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Special Issue on The Climate Change Challenge to Asia's Development

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The Asia and Pacific region has based its development strategy on a very intensive use of fossil fuels. Consequently, poor air quality affects the daily life of millions of inhabitants of Asia's cities. This poses significant problems for the region's future well-being, especially in the context of how vulnerable it is to the impacts of climate change. At stake are the region's economic development achievements since the second half of the 20th century and improvements in living standards. Climate change may reverse the public health achievements and economic progress of Asia over the last 50 years. A business-as-usual scenario, in which global mean temperature increases by over 4 degrees Celsius by the end of this century, will have very negative consequences for Asia, including prolonged heat waves, coastal sea-level rise, and changes in rainfall patterns that affect human health. From 1996 to 2015, six countries out of the world's ten most affected by extreme weather events in the form of severe heat waves, typhoons, rainfall—were in Asia. For these reasons, efforts must be made to place the Paris Agreement consensus scenario, in which global warming is limited to 1.5–2.0 degrees Celsius above preindustrial levels (which would still have significant negative consequences), on top of the policy agenda. The problem is that the level of public concern about climate change is lower in Asia than in most other regions.

In 2017, the *Asian Development Review* brought together a group of scholars interested in Asia's climate change. Eight of the papers presented at the conference were selected for this special issue on The Climate Change Challenge to Asia's Development. The articles highlight the need for concrete and rapid actions to adapt to climate change.

Deschenes uses cross-country panel data for 1960–2015 to discuss evidence on the relationship between extreme temperatures and mortality in 16 Asian countries. He finds that 1 additional day with a mean temperature above 90 degrees Fahrenheit, relative to 1 day with a mean temperature in the range of 70–79 degrees Fahrenheit, increases the annual mortality rate by about 1%. Deschenes also provides predictions of the impact of climate change (through its effect on temperature and rainfall) on mortality for the 16 Asian countries: while climate change would lead to a modest 4% increase in the annual mortality rate across the 16 countries in the sample over the 2020–2039 period, the impact over the years 2080–2099 would be a much larger 45% increase, which is equivalent to the decline in mortality rates in Asia during 1960–2015.

Costello's paper addresses a critical question for the world's largest fishing region: should Asian countries pursue fishery management reforms or does the prospect of climate change weaken the case for reform? Many Asian fisheries are languishing under outdated management regimes and open access. Estimates put the per year losses of Asian fisheries at $55 billion as a result of inefficient management. Climate change will probably make things worse. Costello analyzes 193 of the most widely harvested species of fish in Asia. Results indicate that about 55% of Asian fisheries will experience reductions. He concludes that, for many Asian fisheries, there is a strong case for adopting fishery management reforms. These could increase the present value of fisheries by 30% and that of food provision by 21%, even under impending climate change.

Jin and Zhang analyze the economic implications of adverse health outcomes as a result of air pollution caused by particulates with aerodynamic diameter $\leq 2.5\ \mu m$ ($PM_{2.5}$). Estimates indicate that 1 million people died in the People's Republic of China (PRC) in 2015 as a result of pollution derived from excessive $PM_{2.5}$. This study uses an integrated exposure-response model to estimate the total cost of $PM_{2.5}$ mortality and the benefits of a reduction in mortality caused by $PM_{2.5}$ in the urban areas of the PRC's 300 major cities. The analysis, using 2016 data, indicates that the total cost of $PM_{2.5}$ mortality in major cities was almost CNY1.2 trillion. They argue that the aggregate benefit of mortality reduction from a uniform $10\ \mu g/m^3$ decrease in $PM_{2.5}$ concentration in these cities is about CNY141 billion. The authors conclude that all cities in the PRC should reduce $PM_{2.5}$ pollution to levels below $10\ \mu g/m^3$.

Arief, Roos, and Horridge evaluate the effects of a land moratorium on the conversion of natural forests to land used for palm oil production in Indonesia. Indonesia is the world's largest producer and exporter of palm oil. Deforestation, and the resultant increase in carbon dioxide (CO_2) emissions, poses a severe problem. The analysis is based on an interregional computable general equilibrium model of the Indonesian economy. Under the baseline of there being no effort to curb deforestation and carbon emissions, 13.1 million hectares of forest land would be converted into oil palm plantation by 2030, leading to increased CO_2 emissions. Under the first alternative scenario, from 2015 onward all land conversion from forest to oil palm plantation would come from managed forests only. There is a decline in CO_2 emissions and palm oil output is smaller than in the baseline. The second alternative scenario adds to the previous simulation a payment in return for lower CO_2 emissions. Under both scenarios, the moratorium leads to a reduction in Indonesia's growth and welfare. However, international transfers can compensate the welfare loss.

Auffhammer and Carleton study crop diversity as a mechanism to increase resilience to the weather shocks that are likely to increase as a result of climate change. They use a panel data set for 270 districts across India during a period of rapid agricultural change, the onset of the Green Revolution, to test whether shifts at the district level in crop diversification improve adaptation. The empirical results suggest that Indian districts with a more diverse crop mix are indeed more resilient in the presence of droughts. They conclude that diversification mitigates yield losses (physical benefit) in times of drought and weakens drought-induced price shocks.

In other words, in drought years, districts with higher levels of agricultural diversity experience higher revenues per hectare. Overall, diversification of crop planting is an effective form of adaptation.

Chen and Xu evaluate the PRC's emissions trading scheme (ETS) pilot projects, which were launched in seven provinces in 2013–2014 and involved 2,012 companies that accounted for a significant percentage of the PRC's emissions. The basis of the ETS mechanism is that individual emitters are allowed to trade their emission allowances. The authors apply the synthetic control method to evaluate whether the program was effective in reducing carbon emissions in each province, finding that success was limited and varied across pilot projects. By province, the most successful were Hubei, Guangdong, and Shenzhen, which reduced emissions from 37 to 60 million tons in 2015; Tianjin did not experience a significant reduction in its carbon emissions. The authors conclude that ETS coverage needs to be expanded beyond petroleum processing, electricity power, and steel. The program was scaled up nationwide in late 2017.

Li and Zhang's paper offers a comparison of the ETSs introduced by Japan, the PRC, and the Republic of Korea. Together, the three countries accounted for one-third of the world's emissions in 2016. Comparisons are made in terms of emission targets and allowances, sectors covered, allowance allocations, monitoring, reporting and verification, compliance and enforcement, and offset markets. The authors also discuss the possibilities for cooperation on carbon markets among these three countries, which would be an important achievement for global climate governance and joint efforts to address regional air pollution concerns. Cooperation can be achieved either by linking well-designed and well-performing markets within the region (e.g., cities like Shanghai and Beijing with Tokyo and Saitama), or by linking carbon markets with similar trading systems.

Finally, Coxhead and Grainger use a general equilibrium model of a small open economy to explore some of the channels through which a fossil fuel subsidy reduction affects welfare and income distribution. Many Asian countries (mostly oil exporters) have used fuel subsidies to help the poor (some countries cut them after the 2014 decline in energy prices), although it is not clear whether the benefits are ultimately offset by negative effects such as the promotion of carbon-based energy sources. To discuss the distributional effects of a subsidy reduction, the authors use data from Viet Nam. Their analysis indicates that (i) a subsidy reform raises the relative prices of nontradables, while the burden of higher consumer prices in the nontradable sector will fall more on wealthier households since they tend to spend more on services, which are nontraded; and (ii) the poor will be substantially affected if rising energy costs reduce profitability and output in traded sectors that intensively employ less-skilled labor. Thus, the overall net distributional impacts of a fuel subsidy change are ambiguous.

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Temperature Variability and Mortality: Evidence from 16 Asian Countries

OLIVIER DESCHENES*

This paper presents an empirical analysis devised to understand the complex relationship between extreme temperatures and mortality in 16 Asian countries where more than 50% of the world's population resides. Using a country-year panel on mortality rates and various measures of high temperatures for 1960–2015, the analysis produces two primary findings. First, high temperatures significantly increase annual mortality rates in Asia. Second, this increase is larger in countries with cooler climates where high temperatures are infrequent. These empirical estimates can help inform climate change impact projections on human health for Asia, which is considered to be highly vulnerable to climate change. The results indicate that unabated warming until the end of the century could increase annual mortality rates by more than 40%, highlighting the need for concrete and rapid actions to help individuals and communities adapt to climate change.

Keywords: Asia, climate change, impact, mortality, temperature
JEL codes: I10, Q54, O13

I. Introduction

Climate change is expected to negatively affect human health in most countries. This ongoing threat is especially significant in South, East, and Southeast Asia (SESA), where more than 50% of the world's population resides and where weather-dependent economic activities such as agriculture remain important contributors to gross domestic product (GDP). Furthermore, the lower levels of income observed in many SESA countries limit opportunities for private and public investment in health-preserving adaptations in response to extreme weather events. While the empirical literature on the predicted health impacts of climate change for the United States (US) and Europe is well developed, the literature for Asia and for lower-income countries is still lacking (see Deschenes 2014 for a review). Most of the existing evidence on climate change impacts for Asia is based on integrated assessment models and other simulation-based approaches rather than data-driven

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empirical estimates (see, for example, ADB 2014, 2017 for a detailed discussion of the results from such quantitative model analyses). This gap in the literature highlights the importance of deriving empirical estimates of climate change impacts based on historical data for Asia.

This paper presents a cross-country panel data analysis of the effects of temperature variability on health in 16 SESA countries.[1] Health data come from the World Development Indicators (WDI) for the period 1960–2015, which includes annual measures of mortality rates across various age groups. An important advantage of using mortality rates as indicators of health is that they are reasonably well measured across many countries for long periods of time. Furthermore, mortality rates are key indicators of a population's ability to smooth consumption; withstand income shocks; and more generally address all changes in health determinants that are driven by weather variability, including effects on human physiology (Burgess et al. 2014).

The empirical results indicate a nonlinear relationship between daily average temperatures (modeled through annual temperature bins) and annual mortality rates. For example, 1 additional day with a mean temperature above 90 degrees Fahrenheit (°F), relative to 1 day with a mean temperature in the 70°F–79°F range, increases the annual mortality rate by roughly 1%. However, given the observed daily average temperature distributions in the sample, such >90°F days are relatively infrequent and concentrated in a handful of countries. A second empirical specification considers cooling degree days as a measure of extreme heat and finds similar evidence for a wider range of SESA countries. In particular, a 10% increase in cooling degree days, with a base of 80°F, leads to a 1.9% increase in the all-age mortality rate. Estimates for infant and adult mortality rates are slightly smaller in magnitude, suggesting that the 65+ population is especially vulnerable to adverse temperature shocks.

The analysis also uncovers important differences across countries in the effects of high temperatures on mortality rates. Countries that experience extreme high temperature events infrequently suffer larger mortality responses compared to countries where high temperatures are more common. This indicates that populations in hotter places may be better adapted to respond to high temperatures than populations in colder places. Importantly, this and all findings in the paper hold true even adjusting for differences in per capita income and other predictors of health and well-being across countries.

The analysis concludes by combining the estimated temperature response functions with output from Global Circulation Models to derive ceteris paribus predictions of the impact of climate change on mortality for the 16 SESA countries

[1]The SESA countries in the sample are Bangladesh, Bhutan, Cambodia, India, Indonesia, Japan, Malaysia, Mongolia, Nepal, Pakistan, the People's Republic of China (PRC), the Philippines, the Republic of Korea, Sri Lanka, Thailand, and Viet Nam. These 16 SESA countries were chosen because data on mortality rates were consistently available in the WDI.

in the sample. It is important to bear in mind that this paper relies on interannual variation in temperature, not on permanent changes in the temperature distributions. This will likely produce an overestimate of the impacts of climate change, because individuals and communities can only engage in a limited set of adaptations in response to interannual variation.

With this caveat in mind, I derive the predicted impacts of climate change on mortality under a business-as-usual scenario from the National Center for Atmospheric Research's (NCAR) Community Climate System Model 3 (CCSM3) Global Circulation Model. The preferred specification suggests that climate change would lead to a 45% increase in the annual mortality rate by the end of the century (i.e., 2080–2099) across the 16 countries in the sample.[2] By comparison, in the near-term future (i.e., 2020–2039), the corresponding estimate is an increase of 4% in the annual mortality rate. Thus, it appears that continued social and economic growth, as well as targeted investments in public health and infrastructure, may help prevent some of the catastrophic predicted increase in the end-of-century mortality rate. A subregional analysis comparing East Asia, Southeast Asia, and South Asia also leads to a similar conclusion: the mortality rate is predicted to increase in all three subregions, ranging from 24% in Southeast Asia to 34% in East Asia.[3] However, two of the three subregional estimates are statistically imprecise and need to be interpreted accordingly. It is also noteworthy that the entire predicted increase in the mortality rate is driven by a change in the temperature distribution, as opposed to a change in the precipitation distribution. This has implications for climate change adaptation policy since ambient temperature (unlike water) is not "storable" and thus cannot be shifted across time periods.

This paper's empirical approach addresses many (though not all) of the empirical challenges that typically make deriving credible estimates of climate change impacts difficult. In general, these challenges arise from the complex nature of the causal link between climate and human health. First, there is a complicated, dynamic relationship between temperature and mortality, which can cause the short-term relationship to differ substantially from the long-term one (Deschenes and Moretti 2009). Second, individuals' locational choices, which determine exposure to local temperature and rainfall distributions, are in part attributable to socioeconomic status and health. This form of locational sorting may confound the effects of temperature, making it difficult to uncover the causal relationship between temperature and mortality. Third, the relationship between temperature and mortality is potentially nonlinear, meaning it may not be well captured by relating mortality rates with average annual temperatures.

[2]As a reference point, a similar exercise suggests that climate change will lead to a roughly 2%–3% increase in the US mortality rate by the end of the century (Deschenes and Greenstone 2011).

[3]The subregion-specific estimates are subregion-specific regression models.

These challenges are addressed as follows. First, estimating regression models for annual mortality rates rather than for daily or weekly mortality rates helps capture the long-term effects of temperature shocks on mortality, as opposed to transitory effects due to near-term mortality displacement or harvesting. Second, the panel constructed from the WDI data permits the inclusion of country fixed effects, year fixed effects, and region-year fixed effects. Accordingly, the temperature variables are identified from unpredictable and presumably random year-to-year variation in weather, and the results account for any permanent differences across countries such as health or socioeconomic status while controlling for yearly shocks at the regional level. Third, relying on daily weather data to construct measures of exposure to extreme temperatures reduces the dependence on functional form assumptions to identify the "temperature–mortality relationship." Fourth, the WDI data allow for the estimation of separate effects for the mortality of specific age groups (including infants) for each country in the sample, which allows for heterogeneity in the estimated temperature–mortality relationship.

There are a few important caveats to these calculations and to the analysis in general that warrant further discussion. First, the country-year panel design used in this paper makes it difficult to control for country-specific shocks. In particular, the main results are not robust to the inclusion of country-specific time trends since those absorb a large component of the underlying variation. Future research may overcome this limitation by using panel data with within-country (e.g., province-level) variation. Furthermore, as discussed above, the estimated climate change impacts likely overstate the mortality costs because the analysis relies on interannual variation in weather, not a permanent change in the distribution of weather. It is possible that individuals and communities would invest in more health-preserving adaptations in response to permanent climate change. On the other hand, climate change is likely to affect many other health outcomes in addition to mortality—for example, it may increase vector-borne diseases such as malaria and dengue that are especially prominent in Asia and the Pacific (ADB 2014, 2017). Finally, climate change will also shift the observed patterns of other climatic variables that may impact health (e.g., changes in monsoon patterns, hurricanes, floods, and other extreme weather events). By focusing only on temperature change, the results reported in this paper could underestimate the overall health costs of climate change for the 16 SESA countries.

II. Literature Review

A. Thermoregulation and the Temperature–Mortality Relationship

The human body's thermoregulation function allows us to cope with extreme high and low temperatures. In particular, exposure to excessive heat triggers an increase in the heart rate in order to increase blood flow from the body to the skin, which reduces body temperature by convection, and increases sweat production, which reduces body temperature by evaporative cooling. These responses allow individuals to pursue physical and mental activities without endangering their health within certain temperature ranges. Temperatures outside of these ranges pose dangers to human health and can result in heat-related illnesses, including heat stroke, seizure, organ failure, and in some cases premature mortality.

A large literature studies the connection between extreme temperatures and mortality, which is sometimes known as the temperature–mortality relationship (see, for example, Basu and Samet 2002, Portier et al. 2010, and Deschenes 2014). A challenge in this literature is that heat-related illness is not part of the International Classification of Diseases that underlies most vital statistics records worldwide. As a result, studies typically relate all-cause mortality rates (or mortality rates for cardiovascular disease) to ambient measures of temperature. Evidence of excess heat-related mortality has been documented in many countries, time periods, and for various subpopulations. Younger and older populations and lower socioeconomic groups generally face higher risks of heat-related mortality. Access to air-conditioning greatly reduces mortality on hot days and the spread of residential air-conditioning in the US explains a large share of the marked reduction in heat-related mortality observed over the 20th century (Barreca et al. 2016).

Empirical studies of the effect of temperature and other environmental insults on mortality need to address the possibility of harvesting or near-term mortality displacement in which the number of deaths immediately caused by a period of very high temperatures is typically followed by a reduction in the number of deaths in the period immediately subsequent to the hot day or days (Basu and Samet 2002, Deschenes and Moretti 2009). This pattern tends to occur because heat shocks firstly affect individuals who are already very sick and would have likely died in the near-term.

Predicting changes in life expectancy due to climate change becomes an important challenge in the presence of harvesting. Studies that correlate day-to-day changes in temperature with day-to-day changes in mortality tend to overstate the mortality effect of climate change, since the dynamics of temperature and mortality are such that episodes of harvesting are generally followed by a reduction in the number of deaths in the period immediately following the temperature shock. The solution to this problem is to design studies that examine intermediate and long-term effects, either through appropriate time aggregation of the data to combine daily temperature shocks with annual mortality rates (Deschenes and Greenstone 2011) or through the use of distributed lag models (Braga, Zanobetti, and Schwartz 2001; Deschenes and Moretti 2009). I follow the former approach in this paper.

In the context of low- and middle-income countries, like most countries in the SESA region, the causal linkages between mortality and high temperatures are even more complex. The relationship not only can reflect the body's physiological thermoregulatory functions, but it is also likely to be driven by socioeconomic factors (e.g., income, nutrition, and access to basic medicines) and biological factors (e.g., vector-borne diseases and infections, including diarrhea) (ADB 2017). The empirical analysis below will therefore also make use of some of the available data on stunting and nutrition deficits in the WDI to shed light on the mechanisms underlying the observed temperature–mortality relationship in SESA countries.

B. Conceptual Framework

The application of the Becker–Grossman model of health production to derive the willingness to pay for improvements in environmental quality, which includes the value of defensive action, is increasingly common in the literature (Deschenes and Greenstone 2011; Graff-Zivin and Neidell 2013; Deschenes, Greenstone, and Shapiro 2017). The formal derivation of the theoretical predictions is presented in these papers and so there is no need to reproduce them here. The key result is that the mortality-related social cost of climate change goes beyond what is indicated by the statistical relationship between temperature and mortality when individuals invest resources in adaptation or self-protection. Indeed, the model shows that the correct measurement of the willingness to pay to avoid climate change requires knowledge of how temperature affects mortality and how it affects self-protection investments that reduce mortality risks.[4] Monetizing such direct and indirect impacts on mortality and all relevant defensive investments comes with tremendous data requirements. Indeed, most empirical studies ignore the economic value of defensive investments altogether while a few studies consider a handful of defensive investments such as residential energy consumption and air-conditioning (Deschenes and Greenstone 2011, Barreca et al. 2016). As panel data on self-protection investments are not consistently available for the sample countries, this sort of analysis is beyond the scope of this paper. Accordingly, the analysis presented here is limited in that it is only informative about the effects of climate change on mortality rates and not directly informative on the economic and social costs of the mortality-related component of climate change.

III. Data Sources, Sample Construction, and Summary Statistics

A. Data Sources

In order to quantify the effect of temperature and rainfall shocks on mortality rates in 16 SESA countries, I have assembled a country-level data set for the

[4]More generally, the correct measure of willingness to pay should consider all the monetized health impacts, and all health-improving defensive investments, not just the components related to mortality.

1960–2015 period. The key inputs to that data set are daily gridded weather variables obtained from the National Centers for Environmental Prediction and National Center for Atmospheric Research (NCEP/NCAR) Reanalysis Project combined with annual mortality rate data from the WDI. The following paragraphs describe these data sources in more detail and present summary statistics.

Sample construction. The empirical analysis focuses on 16 SESA countries for which the relevant outcomes, controls, and weather variables are consistently available: Bangladesh, Bhutan, Cambodia, India, Indonesia, Japan, Malaysia, Mongolia, Nepal, Pakistan, the People's Republic of China (PRC), the Philippines, the Republic of Korea, Sri Lanka, Thailand, and Viet Nam. In 2015, these countries had a combined population of 3.8 billion, which was over half the world's total population.

Weather data. The recent literature has emphasized the importance of nonlinearities in the relationship between temperature and health that make the use of annual or monthly temperature averages inappropriate (Deschenes 2014). Thus, daily data are required. Daily temperature records based on weather station measurements are available for nearly all countries through the Global Historical Climatology Network. Unfortunately, the geographical and temporal consistency of these data is limited in most Asian countries. In particular, many stations have sporadically missing data across days, making the construction of daily temperature bins impossible since those require a consistent set of 365 daily observations for each station.

Instead, I make use of the daily gridded weather variables obtained from the NCEP/NCAR Reanalysis Project (Kalnay et al. 1996).[5] The reanalysis data are available at the daily and subdaily level for a grid of 2.5° (longitude) by 2.5° (latitude).[6] I then assign each grid cell in the NCEP/NCAR data to a subcountry population cell from the Gridded Population of the World.[7] To proceed, I use an inverse distance weighted average of all NCEP/NCAR grid cell variables within 300 kilometers of each population grid cell centroid. Finally, I construct the country-year weather variables (including nonlinear transformation of daily average temperature such as cooling degree days and temperature bins) using a weighted average of all population grid cells within a country, where the weights correspond to the population within each cell. This produces a balanced panel of country-year observations on the relevant weather variables for the period 1960–2015 that is

[5]These data are available from National Oceanic and Atmospheric Administration. Earth System Research Laboratory. http://www.esrl.noaa.gov/psd/ (accessed July 31, 2017).

[6]This includes grid points located above land and oceans due to the many island and coastal countries in the sample. NCEP/NCAR grid points must be located within 300 kilometers of the population centroid grid points to be included in the assigned weather data.

[7]Center for International Earth Science Information Network, Socioeconomic Data and Applications Center. Gridded Population of the World, Version 3. http://sedac.ciesin.columbia.edu/data/collection/gpw-v3 (accessed April 14, 2017).

representative of the within-country population distribution as measured in the Gridded Population of the World file.

World Development Indicators. The data for the main outcome and control variables used in this study are taken from the World Bank's WDI database. These data are compiled by the World Bank from officially recognized international sources and represent the most current and accurate global measures of the key variables in this study. Specifically, I use the WDI data to construct a country-year level panel of annual mortality rates for the 16 countries in the sample over the period 1960–2015. Importantly, the WDI reports mortality rates (per 1,000 population) for three separate age groups: (i) all-age or crude mortality rate, (ii) infant mortality rate (ages 0–1), and (iii) adult mortality rate (ages 15–60).[8]

In addition to the mortality rate data, I also rely on the WDI for control variables and for variables used to construct interaction effects. These include total population (a count of all residents of a country regardless of legal status or citizenship), GDP per capita (expressed in current US dollars), electrification rate (fraction of population with access to electricity), access to an improved water source (fraction of population with access), number of hospital beds (per 1,000 population), access to improved sanitation facilities (fraction of population with access), and urbanization rate (fraction of population living in urban areas as defined by national statistical offices). Finally, I use the prevalence of undernourishment in the population and the prevalence of stunting in children aged 0–4 years to explore the mechanisms connecting temperature and mortality.

Climate change prediction data from Global Circulation Models. Data on "predicted" temperature and precipitation distributions are required to estimate, ceteris paribus, the impact of future climate change on mortality rates. To this end, I rely on model output from the NCAR's CCSM3, which is a coupled atmospheric-ocean general circulation model used in the Intergovernmental Panel on Climate Change's 4th Assessment Report (IPCC 2007). Predictions of future realizations of climatic variables are available for several emission scenarios, which are drivers of the simulations, corresponding to "storylines" describing the way the world (e.g., populations and economies) may develop over the next 100 years. I focus on the A2 scenario, which is a business-as-usual scenario that predicts a substantial rise in global average temperatures similar to the temperature change projections for Asia reported in ADB (2014).

The data are processed in the same manner as in Deschenes and Greenstone (2011), so I omit most details here. Data on daily average temperature and total precipitation for the period 2000–2099 are assigned to each sample country using the same procedure applied to the daily NCEP/NCAR Reanalysis Project data. Specifically, I assign each grid cell in the CCSM3 file to a subcountry population

[8]The crude mortality rate is defined by the WDI as "the number of deaths occurring during the year per 1,000 population estimated at midyear."

cell from the Gridded Population of World file using an inverse distance-weighted average with a radius of 300 kilometers from each population grid cell centroid. The country-year variables are constructed using a weighted sum of all population grid cells within a country, where the weights correspond to the population in each population cell. This produces a balanced panel of country-year observations on the relevant CCSM3 variables for the period 2000–2099. In order to account for any systematic model error, I define the future climatic variables (daily average temperature, realized annual temperature bins, annual cooling degree days, and total annual precipitation) as follows. The model error is calculated for each of the 365 days in a year separately for each country as the average difference between the country-by-day-of-year specific variable from the NCEP/NCAR data and the CCSM3 data during the 2000–2015 period.[9] This country-by-day-of-year specific error is then added back to the CCSM3 data over the 2020–2099 period to obtain an error-corrected climate change prediction.

B. Summary Statistics

Table 1 reports summary statistics on the resident population and average mortality rates across the 16 countries in the sample over the 1960–2015 period. Large differences in country size are evident. For example, average population during 1960–2015 ranges from 0.5 million (Bhutan) to 1.1 billion (PRC). Population growth rates between 1960 and 2015 also vary significantly across countries. These important differences in country size motivate the inclusion of controls for population in the regression models below. The next panel shows average annual crude mortality rates (all ages) ranging from 5.3 deaths per year per 1,000 population in Malaysia to 15.8 deaths per year per 1,000 population in Cambodia. The remarkable improvements in well-being and health are clearly showed by comparing the mortality rates in 1960 and 2015. Across the 16 countries, all-age mortality rates have declined by factors of 2–3 (e.g., the PRC's mortality rate declined from 25.4 to 7.1 during the review period). Similar cross-sectional differences can also be seen in infant mortality rates in the last panel (defined as deaths under the age of 1 divided by number of births). One issue with the infant mortality rate is that data are not available for every country, especially in the first decades of the sample period. As a result, the primary outcome studied in the paper is the all-age mortality rate, which is available for all time periods for all countries. The large cross-sectional differences in the all-age and infant mortality rates may reflect fundamental differences in health determinants across countries, as well as differences in public health infrastructure, economic growth, and the underlying climate. These permanent differences across countries will be addressed by country fixed effects included in all empirical specifications.

[9]This is the only period in which the NCEP/NCAR and CCSM3 data series overlap.

Table 1. **Summary Statistics on Population and Mortality Rates**

	Population (million)				All-Age Mortality Rate per 1,000				Infant Mortality Rate per 1,000			
Country	**1960–2015**	**N**	**1960**	**2015**	**1960–2015**	**N**	**1960**	**2015**	**1960–2012**	**N**	**1960**	**2015**
Bangladesh	102.0	56	48.2	161.0	10.2	56	20.3	5.4	88.1	56	176.3	30.7
Bhutan	0.5	56	0.2	0.8	13.5	56	31.3	6.2	80.3	47	n.a.	27.2
Cambodia	9.6	56	5.7	15.6	15.8	56	21.8	6.0	72.8	41	n.a.	24.6
India	845.3	56	449.7	1,311.1	11.2	56	22.4	7.3	85.7	56	165.1	37.9
Indonesia	171.7	56	87.8	257.6	9.0	56	18.0	7.2	62.0	56	148.4	22.8
Japan	117.5	56	92.5	127.0	7.4	56	7.6	10.2	7.5	56	30.4	2.0
Malaysia	18.0	56	8.2	30.3	5.3	56	10.6	5.0	17.7	56	67.4	6.0
Mongolia	2.0	56	1.0	3.0	10.0	56	19.9	6.1	56.7	38	n.a.	19.0
Nepal	18.5	56	10.1	28.5	12.8	56	27.6	6.3	93.8	56	219.6	29.4
Pakistan	105.1	56	44.9	188.9	10.4	56	20.7	7.3	100.2	56	192.0	65.8
People's Republic of China	1,066.4	56	667.1	1,371.2	7.3	56	25.4	7.1	36.1	47	n.a.	9.2
Philippines	60.2	56	26.3	100.7	7.1	56	11.2	6.8	38.0	56	67.9	22.2
Republic of Korea	40.5	56	25.0	50.6	6.5	56	14.3	5.4	15.7	56	80.2	2.9
Sri Lanka	16.0	56	9.9	21.0	7.1	56	12.3	6.8	26.9	56	72.7	8.4
Thailand	51.7	56	27.4	68.0	7.6	56	13.2	8.0	35.1	56	102.2	10.5
Viet Nam	62.7	56	34.7	91.7	7.1	56	12.0	5.8	34.1	52	n.a.	17.3

n.a. = not available.

Note: The summary statistics are calculated from a sample of 896 country-year observations.

Source: Author's calculations from World Development Indicators data.

The empirical analysis uses daily weather data taken from the NCEP/NCAR Reanalysis Project to develop the relevant country-year level measures for temperature and precipitation variables. Table 2 reports summary statistics on some of the country-year level measures of observed weather during 1960–2015. These are calculated across all country-by-year observations available (896). The first panel of the table reports average daily temperatures in Fahrenheit (°F). The well known climatic differences across the SESA countries are seen by contrasting the averages, which range from 29°F (Mongolia) to 81°F (Cambodia). There is also sizable within-country variation across years, as shown by the minimum and maximum values. (These correspond to the lowest and highest annual average temperatures for each country between 1960 and 2015.) For each country, the range is about ±2°F from the average of daily temperatures across years. This variation will be exploited to identify the country fixed effect regression models reported below.

As noted earlier, the relevant temperature variables to predict mortality rates are measures of exposure to the extremes of the temperature distribution. Figure 1 explores this distribution in more detail. The eight light bars in Figure 1 show the distribution of daily average temperatures across eight temperature categories ("bins") for the 16 sample countries during the 1960–2015 period.[10] The bins correspond to daily average temperatures of less than 30°F, greater than 90°F, and the six 10°F-wide bins in between. The height of the bar reports the mean number of days per year in each bin; this is calculated as the average across country-by-year realizations. The modal bin is 70°F–79°F, with 150 days per year, which is to be expected because many countries in the sample are located in tropical areas along or just north of the equator. As emphasized in the literature review above, recent studies of the effects of temperature on health have highlighted the importance of nonlinear effects, represented by a difference in marginal effects of temperature increases across the temperature distribution. For example, an extra degree of daily average temperature at 90°F may have a much larger impact on mortality than an extra degree of daily average temperature at 70°F. To this end, the number of days in the highest two bins (80°F–89°F and >90°F) are especially important. On average, there are 64 days per year in the 80°F–89°F range and 6 days per year in the >90°F range. The eight bins displayed in Figure 1 form the basis for the flexible modeling of temperature effects on mortality rates as is now commonly used in the literature (Deschenes 2014).

Figure 1 also shows how the full distributions of daily mean temperatures are expected to change. The dark bars report the predicted number of days in each temperature category across the 16 sample countries for the period 2080–2099 under the business-as-usual scenario. The most important changes in the

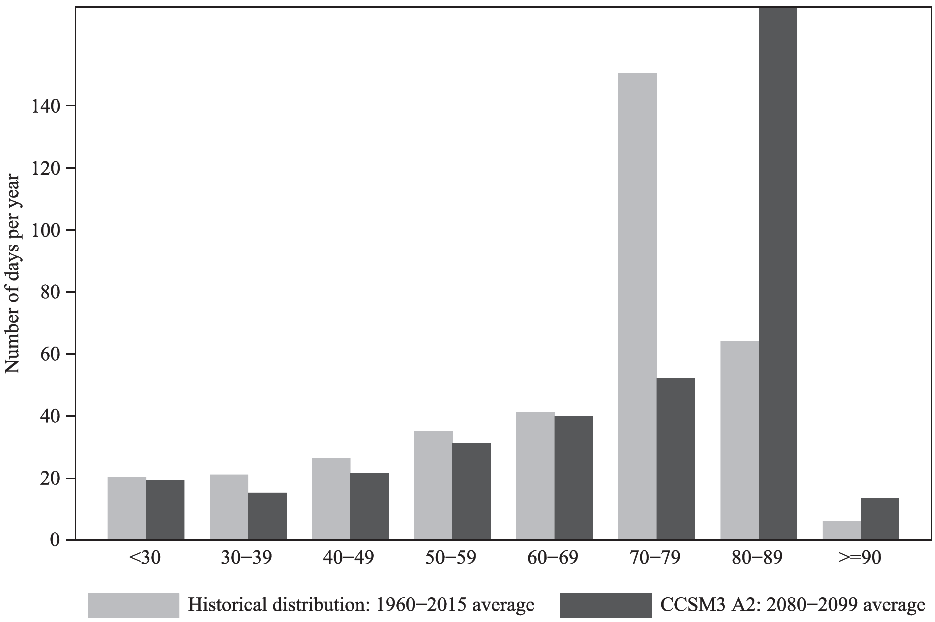
[10] Daily average temperatures are the simple average of the daily minimum and maximum. Therefore, a daily average temperature of 90°F may correspond, for example, to a day with a high of 100°F and a low of 80°F.

Table 2. **Summary Statistics on Temperature and Precipitation Variables**

	Daily Temperature (°F)			Annual Days >80°F			Annual Days >90°F			Annual Precipitation (inches)		
Country	**Average**	**Min**	**Max**	**Average**	**Min**	**Max**	**Average**	**Min**	**Max**	**Average**	**Min**	**Max**
Bangladesh	78.4	76.9	79.6	124.2	84.6	149.2	5.7	0.4	28.7	62.4	44.4	91.7
Bhutan	49.0	47.5	51.0	0.2	0.1	0.4	0.0	0.0	0.1	70.6	33.5	106.6
Cambodia	81.0	79.3	82.6	83.9	29.8	158.4	0.3	0.0	2.7	105.3	72.4	123.5
India	78.0	76.3	79.4	137.5	104.3	157.4	33.5	22.8	42.3	41.2	30.5	51.2
Indonesia	79.2	78.2	80.3	76.0	29.3	144.3	0.0	0.0	0.0	112.1	73.4	161.4
Japan	57.6	56.1	59.5	8.2	1.1	21.8	0.0	0.0	0.0	60.2	36.5	84.4
Malaysia	79.4	78.1	80.7	35.2	9.1	76.4	0.0	0.0	0.0	141.0	102.6	180.0
Mongolia	29.0	25.8	32.7	2.0	0.2	5.9	0.0	0.0	0.7	15.1	11.0	27.0
Nepal	68.4	66.4	70.2	9.1	6.2	13.1	2.0	1.2	3.5	64.7	46.5	84.1
Pakistan	74.3	72.0	76.0	138.2	117.7	156.9	57.4	35.2	77.5	17.3	10.3	31.6
People’s Republic of China	57.4	55.8	59.2	15.0	2.8	28.2	0.1	0.0	0.4	51.2	39.6	70.8
Philippines	80.2	78.8	81.8	147.6	23.9	216.0	0.0	0.0	0.0	72.1	44.9	91.8
Republic of Korea	53.2	50.9	55.4	1.4	0.0	10.0	0.0	0.0	0.0	31.8	18.1	47.3
Sri Lanka	79.8	78.7	81.2	188.0	43.2	265.2	0.1	0.0	0.3	80.0	43.2	109.8
Thailand	79.9	78.3	81.7	83.1	33.7	143.5	0.8	0.0	4.4	102.5	85.1	126.2
Viet Nam	76.6	75.3	78.0	115.9	27.9	153.9	0.0	0.0	0.2	91.2	75.2	106.8

Note: The summary statistics are calculated from a sample of 896 country-year observations.
Source: Author’s calculations from NCEP/NCAR Reanalysis Project data.

Figure 1. **Distribution of Daily Average Temperatures (°F), 1960–2015 and Predicted Distribution of Daily Average Temperatures (°F), 2080–2099**



CCSM3 = Community Climate System Model 3.
Notes: This figure shows the historical average distribution of daily mean temperatures and predicted future distribution of daily mean temperatures across eight temperature bins for the 16 South, East, and Southeast Asian countries in the sample. Light bars represent the average number of days per year in each temperature bin during the period 1960–2015. Darker bars show the corresponding predicted distribution derived using daily data from error-corrected CCSM3 A2 model data for the period 2080–2099.
Sources: Author's calculations from NCEP/NCAR Reanalysis Project data and NCAR CCSM3 data.

distribution are in the last three bins. The CCSM3 A2 model predictions indicate that exposure to daily average temperatures in the 70°F–79°F range will be greatly reduced, dropping from 150 days per year on average to 52 days. It is evident that all of this change is offset by an equally large increase in the number of days per year where the mean daily temperature is between 80°F and 89°F—such exposure is predicted to increase from 64 days to 174 days per year. Finally, another change is the increase in the frequency of days with a mean temperature in excess of 90°F, which is predicted to rise from roughly 6 days to 14 days per year.

Returning to Table 2, the middle two panels report statistics on the number of days per year in each country when the daily average temperature exceeds 80°F and 90°F. Once again, both cross-country and within-country variation is clearly evident. The range in the number of >80°F days per year is between 0.2 (Bhutan) and 188 (Sri Lanka) on average. Within countries, we observe a large degree of interannual variation that is almost as wide as the cross-country variation. For example, in Indonesia the range of the number of annual days with an average daily temperature $>$80°F is between 29 and 144. This within-country variation will drive the identification of the country fixed effects regression models. Similar patterns emerge when examining the cross- and within-country variation in days with temperature $>$90°F. However, it is evident that many countries do not experience such days with high frequency. Only Bangladesh, India, and Pakistan are exposed to more than 5 days per year with mean temperature $>$90°F on average. As such, most of the empirical identification of the $>$90°F impacts will be disproportionally driven by these three countries. As a result, the empirical analysis will consider a few alternative specifications to model the effects of high temperatures on mortality.

IV. Econometric Approach

This section describes the econometric models used in the paper. Specifically, the estimates are obtained from fitting the following equation:

$$Y_{ct} = \sum_{j} \theta_j TMEAN_{ctj} + \sum_{k} \gamma_k PREC_{ctk} + X'_{ct}\delta + \alpha_c + \beta_t + \varepsilon_{ct} \qquad (1)$$

where Y_{ct} is the mortality rate in country c in year t. As mentioned before, we focus on the all-age mortality rate, the infant mortality rate, and the adult mortality rate. The last term in equation (1) is the stochastic error term, ε_{ct}.

The independent variables of interest are the measures of temperature and precipitation, which are constructed to capture the full distribution of annual fluctuations in weather. The variables $TMEAN_{ctj}$ denote the number of days in country c in year t when the daily average temperature is in the j^{th} of the eight temperature bins reported in Figure 1. This functional form imposes the relatively weak assumption that the impact of the daily mean temperature on the annual mortality rate is constant within 10°F-degree intervals. The empirical analysis will also consider a few alternative specifications of the temperature effects. The variables $PREC_{ctk}$ are simple indicator variables based on total annual precipitation in country c in year t that represent the following intervals: less than 30 inches, 30–59 inches, 60–89 inches, 90–119 inches, and more than 120 inches.

The regression model includes a full set of country fixed effects (α_c), which absorb all unobserved country-specific time-invariant determinants of health and mortality rates. For example, the notable differences in climate across countries documented in Table 2 will be controlled for by these fixed effects. Further, any permanent differences in health care provision or infrastructure across countries will not confound the effect of weather on health. The equation also includes year fixed effects (β_t), which will be allowed to vary across subgroups of countries in some specifications. These fixed effects will control for unobserved time-varying factors in the dependent variable that are common across all countries or subgroups of countries.

The validity of the predicted climate change impacts reported in this paper depends crucially on the assumption that the estimation of equation (1) will produce unbiased estimates of the temperature–mortality relationship coefficients (θ_j). Since the estimating equation includes country and year fixed effects (or region-year fixed effects), these coefficients are identified from country-specific deviations in temperature from long-term averages after controlling for shocks common to all countries in a given year. Since year-to-year weather fluctuations in a given location are exogenous (as they are driven by natural variability in the climate system), it seems reasonable to assume that these fluctuations are orthogonal to unobserved determinants of mortality rates.

V. Results

This section is divided in two subsections. The first provides estimates of the relationship between daily temperatures and mortality rates. The second subsection uses these estimated relationships to predict the impacts of climate change on annual mortality in the SESA countries.

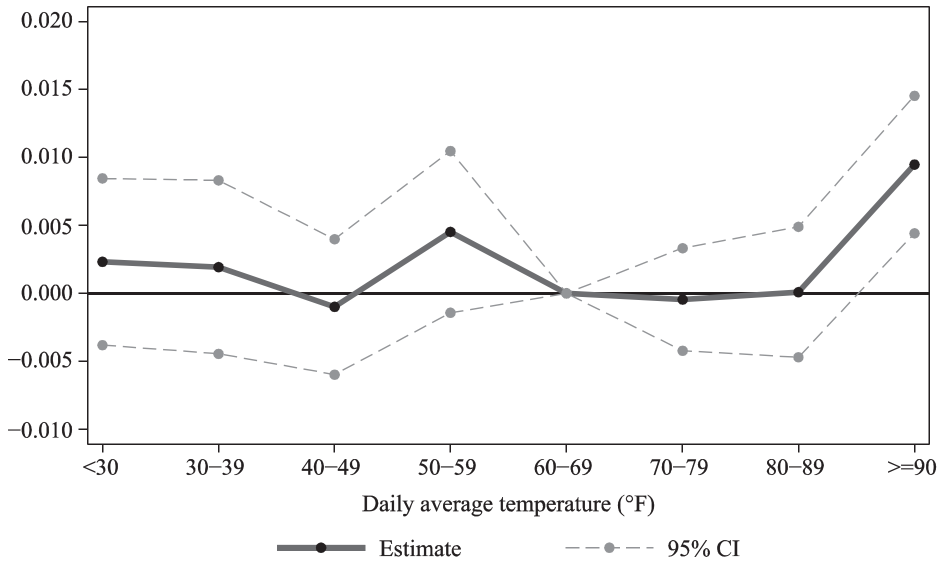
A. Baseline Estimates of the Impact of Temperature on Mortality

Figure 2 presents the estimate of the temperature–mortality relationship obtained from fitting equation (1). The figure reports the estimated regression coefficients associated with the daily temperature bins (i.e., the θ_j's) where the 60°F–69°F bin is the reference (omitted) category. That is, each coefficient measures the estimated impact of 1 additional day in temperature bin *j* on the log annual mortality rate, relative to the impact of 1 day in the 60°F–69°F range. The dashed lines correspond to the 95% confidence intervals when standard errors are clustered at the country level.[11]

The figure reveals a mostly null relationship, with the exception of high mortality risks at extreme temperatures (i.e., for daily average temperatures above 90°F). The point estimates underlying the response function indicate that exchanging 1 day in the 60°F–69°F range for 1 day above 90°F would increase the mortality rate by approximately 1% (i.e., 0.0095 log mortality points). This point estimate is statistically significant with a standard error of 0.0024. However, all other point estimates are close to zero and statistically insignificant at the 5% level. This result is somewhat in contrast with the "U-shaped" relationship found in many studies of the US (see Deschenes 2014 and Portier et al. 2010 for

[11] Since there are only 16 clusters, I also computed standard errors using the wild cluster bootstrap method proposed by Cameron, Gelbach, and Miller (2008). Based on those calculations, it appears that the simple cluster-robust standard errors are understated by about 30%. This does not change the conclusion of the tests of statistical significance for most of the key coefficient estimates presented in the paper.

Figure 2. **Estimated Temperature–Mortality Relationship for 16 SESA Countries, 1960–2015**



CI = confidence interval; SESA = South, East, and Southeast Asia.
Notes: The plotted lines report seven coefficient estimates (circle markers) representing the effect of a single day in each of the corresponding seven temperature bins, relative to the effect of a day in the 60°F–69°F reference bin, on the annual log all-age mortality rate. Dashed lines represent the 95% confidence interval for the estimates. Standard errors clustered by country.
Sources: Author's calculations from World Development Indicators and NCEP/NCAR Reanalysis Project data.

reviews of the literature), although these are the first comprehensive estimates of the temperature–mortality relationship over the entire 20th century.

Table 3 reports the point estimates associated with the key temperature variables underlying Figure 2 in order to better characterize the results and evaluate their robustness across alternative samples and subpopulations. While the underlying regression models include all seven temperature bin variables, the table only reports the coefficient estimates associated with the number of days below 30°F, the number of days between 30°F–39°F, the number of days between 80°F–89°F, and the number of days above 90°F.

Panel A reports the coefficient estimates separately by age group for the baseline specification that includes temperature and precipitation variables, country fixed effects, and year fixed effects. Standard errors clustered at the country level are reported in parentheses. There are several important observations to be made from Panel A. First, the effect of extreme high temperatures on mortality documented in the overall population (all age groups) is also detectable for infants. In particular, the effect of >90°F temperature days is similar (0.0083 versus 0.0095 log mortality rate points). Further, colder temperatures significantly predict increases in infant

Table 3. **Estimates of the Impact of High and Low Temperatures on Log Annual Mortality Rates by Age Group**

	Number of Days Per Year with Mean Temperature				
	<30°F	**30°F−39°F**	**80°F−89°F**	**>90°F**	**N**
A. Baseline Specification Estimates					
1. All-age mortality rate	0.0023	0.0019	0.0001	0.0095**	896
	(0.0029)	(0.0030)	(0.0023)	(0.0024)	
2. Infant mortality rate (0–1)	0.0046	0.0052*	0.0031	0.0083*	841
	(0.0028)	(0.0023)	(0.0021)	(0.0040)	
3. Adult mortality rate (15–60)	−0.0036	−0.0009	−0.0008	−0.0001	878
	(0.0060)	(0.0034)	(0.0025)	(0.0023)	
B. Alternative Specifications, All-Age Mortality					
1. Adding region-year fixed effects	0.0017	0.0002	−0.0006	0.0108**	896
	(0.0027)	(0.0030)	(0.0033)	(0.0031)	
2. Adding additional controls	0.0022	−0.0001	−0.0014	0.0098**	859
	(0.0033)	(0.0031)	(0.0029)	(0.0032)	
3. Adding controls for relative humidity	0.0002	−0.0012	0.0003	0.0115**	859
	(0.0029)	(0.0027)	(0.0023)	(0.0037)	

Notes: The coefficient estimates correspond to the effect of single days with daily temperatures in the <30°F, 30°F–39°F, 80°F–89°F, and >90°F ranges on log annual all-age mortality rate, relative to days with daily temperatures in the 60°F–69°F range. The number of days in the 40°F–49°F, 50°F–59°F, and 70°F–79°F bins are also included in the regressions. Each row corresponds to a single regression. Standard errors are clustered by country. Asterisks denote p-values of <0.05 (*), <0.01 (**), and <0.001 (***).
Sources: Author's calculations from World Development Indicators and NCEP/NCAR Reanalysis Project data.

mortality rates, a pattern not detected for the other age groups. Finally, for adults (defined by the WDI as ages 15–60), the relationship between temperature and mortality is essentially null: none of the point estimates are statistically significant and all are of very small magnitude. Taken together, these results are consistent with the previous literature, which has repeatedly found that younger and older individuals are more vulnerable to extreme temperatures, in part due to their weaker thermoregulatory functions. An important implication of this difference in effects across age groups is that it indicates that climate change will have unequal effects across different demographic groups within the same country, an issue I will investigate below.

Panel B reports on the robustness of the baseline all-age mortality estimates reported in Row 1 of Panel A. In Row 1 of Panel B, the year fixed effects are replaced by region-year fixed effects, where the three regions are defined as follows: Bangladesh, Bhutan, India, Nepal, Pakistan, and Sri Lanka (roughly corresponding to South Asia); the PRC, Japan, the Republic of Korea, and Mongolia (East Asia); Cambodia, Indonesia, Malaysia, the Philippines, Thailand, and Viet Nam (Southeast Asia). The advantage of this specification over "pooled" year fixed effects is that the region-year fixed effects controls for unobserved shocks to health, economic activity, weather, and any other unobserved factor that predicts health and varies regionally over time.

Row 2 of Panel B adds the following country-level control variables to the specification of Row 1: log GDP per capita, the fraction of the population residing in urban areas, and a variable corresponding to the number of hospital beds per 1,000 population as a crude control for the level of health care infrastructure in each country.[12] Finally, Row 3 of Panel B adds controls for relative humidity to the specification of Row 2 by including variables representing the number of days per year of low relative humidity (defined as days below the 25th percentile of the observed relative humidity distribution) and high relative humidity (defined similarly as days above the 75th percentile). This addition is motivated by prior research for the US that shows that the temperature–mortality relationship may be different when humidity is included as a predictor in addition to temperature (Barreca 2012).

It is evident from examining the results in Panel B that none of these alterations to the baseline specification lead to meaningful changes in the estimates of the effect of extreme temperatures on mortality. Some of them modestly change point estimates, but in comparison to the standard errors, none of the alternative estimates appear different than the corresponding baseline estimates. Nevertheless, in order to minimize concerns about omitted variables bias, I will maintain the "preferred specification" that controls for relative humidity and region-year fixed effects (in addition to the controls included in the baseline specification) for the remainder of this paper.

B. Alternative Specification and Heterogeneity of the Temperature Effects

One limitation of the estimates based on the full temperature bins approach is that the >90°F bin is primarily identified by a handful of countries that are exposed to such days with a high enough frequency (i.e., Bangladesh, India, and Pakistan as shown in Table 2). As an alternative, Table 4 considers a specification with a single measure of heat exposure: cooling degree days with a base of 80°F (CDD80).[13] This variable is computed as the annual sum of the deviation between the daily average temperature and the base 80°F. Negative values (temperatures below 80°F) do not contribute to CDD80. For example, a day where the daily average temperature is 81°F contributes one CDD80 and a day where the daily average temperature is 93°F contributes 13 CDD80. These daily deviations are then summed over the entire calendar year by country to form the measure of CDD80 used in the empirical models. The average CDD80 over the entire sample is 246.4. A key advantage of the CDD80 specification over the temperature bin specification, which is very unevenly distributed across countries in the high temperature ranges, is that every

[12]The results including per capita income should be interpreted with caution since studies have shown that temperature fluctuations affect per capita income (Burke, Hsiang, and Miguel 2015; Dell, Jones, and Olken 2012).

[13]Heating and cooling degree days are often used in energy demand analysis.

Table 4. **Estimates of the Impact of Cooling Degree Days on Log Annual Mortality Rates by Age Group and Country**

	Annual Cooling Degree Days with Base 80°F (÷10)	
	Coefficient	**Standard Error**
A. Estimates by Age Group		
1. All-age mortality rate	0.0075***	(0.0017)
2. Infant mortality rate (0–1)	0.0054	(0.0030)
3. Adult mortality rate (15–60)	0.0054*	(0.0022)
B. Estimates by Climate Zones, All-Age Mortality Rate		
Countries below median CDD80 (27.2)	0.0171	(0.0135)
Countries above median CDD80 (465.6)	0.0077***	(0.0017)
C. Country-Specific Estimates, All-Age Mortality Rate		
Bangladesh (430.1)	0.0051***	(0.0011)
Bhutan (0.5)	n.a.	n.a.
Cambodia (191.3)	−0.0049	(0.0044)
India (862.8)	0.0061*	(0.0024)
Indonesia (76.1)	0.0024	(0.0141)
Japan (12.4)	0.0811*	(0.0360)
Malaysia (39.8)	0.0203	(0.0162)
Mongolia (5.6)	n.a.	n.a.
Nepal (53.0)	0.0585**	(0.0156)
Pakistan (1225.2)	0.0108**	(0.0027)
People’s Republic of China (29.0)	0.0585	(0.0457)
Philippines (209.3)	0.0205*	(0.0086)
Republic of Korea (1.3)	n.a.	n.a.
Sri Lanka (391.7)	0.0068	(0.0041)
Thailand (201.0)	0.0096	(0.0059)
Viet Nam (213.0)	0.0083	(0.0085)

CDD80 = cooling degree days with a base of 80°F, n.a. = not available.

Notes: The coefficient estimates correspond to the effects of annual cooling degree days with base 80°F (divided by 10) on log annual mortality rates. The rows in Panel A are from separate regressions. The rows in Panels B and C are from pooled regressions across climate zones (Panel B) and countries (Panel C). Each regression includes country fixed effects; region-year fixed effects; and controls for precipitation, relative humidity, log population, and other country-specific controls. Standard errors are clustered by country. Asterisks denote p-values of <0.05 (*), <0.01 (**), and <0.001 (***).

Sources: Author’s calculations from World Development Indicators and NCEP/NCAR Reanalysis Project data.

country in the sample is exposed to positive amounts of CDD80 every year. While the across-country sample average is 246.4, the country-specific averages ranges from 0.5 (Bhutan) to 1,225 (Pakistan). Given that the empirical support for CDD80 is stronger, the remainder of the paper will focus on the CDD80 specification to model the effects of high temperatures on the various outcomes.

Panel A of Table 4 reports the coefficients and standard errors associated with the CDD80 from models for the three mortality rates variable. For presentation purposes, the CDD80 variable is divided by 10 in the regression and so the estimates correspond to a 10-unit change in the CDD80 variable (about a 5%

change compared to the 246.4 mean). The coefficient in Row 1 of Panel A indicates that a 10-unit increase in CDD80 increases the annual mortality rate by 0.75%.[14] As expected, the estimates from the CDD80 specification are more precise since there is greater population exposure to CDD80 than to days with a daily average temperature above 90 °F. In the case of all-age mortality, the cluster-robust t-statistic is larger than 4. The coefficient estimates for infant and adult mortality rates are both 0.0054, indicating that a 10-unit increase in CDD80 increases the infant and adult mortality rates by about 0.5%. Both of these estimates have larger standard errors and only the one for adult mortality is statistically significant at the 5% level.[15]

Panels B and C explore the extent to which the effects of high temperatures (as captured by the variable CDD80) vary across country-specific exposure to CDD80 (Panel B) and across country (Panel C). The motivation for these additional analyses is that there are important cross-country differences in average CDD80 per year (as shown by the number in parenthesis in Panel C). As a result, different countries or subregions may have undertaken investments that mitigate the impact of extreme temperatures on mortality, or its population may have physiologically acclimatized to different climates. Additional differences across countries in the estimated effects of high temperatures may reflect differences in public health investments, infrastructure, primary types of economic activity, and other factors.

Panel B reports the coefficient estimates of the effect of CDD80 separately for the countries below the sample median exposure to CDD80 (133.7), estimated from a pooled regression with the same set of fixed effects and controls as for the estimates reported in Panel A. The numbers in parenthesis in Panel B are the average CDD80 for the countries below (27.2) and above (465.6) median CDD80. Consistent with the differential adaptation hypothesis listed above, the coefficient estimates are twice as large for countries below the median exposure compared to countries above the median. Notably, the estimated effect for countries below the median exposure is very imprecise with a standard error of 0.0135. As a result, Panel B only provides weak evidence of adaptation to high temperatures based on the underlying climate.

Panel C reports country-specific estimates of the effect of CDD80 on the all-age mortality rate, also estimated from a pooled regression with country and region-year fixed effects.[16] Countries that have fewer than 10 CDD80 per year are omitted from this analysis (i.e., Bhutan, the Republic of Korea, and Mongolia). There is important heterogeneity in the estimated effects of CDD80 on mortality, with coefficient estimates ranging from –0.0049 to 0.0811. The precise

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[14]The corresponding estimate for cooling degree days with a base of 90°F is 0.0133 with a standard error of 0.0058.

[15]Adding interactions between the relative humidity variables and the CDD80 variable increases the estimated coefficient on CDD80 and reduces the marginal effect of CDD80 on the log annual all-age mortality rate.

[16]The country-specific estimates of the CDD80 effects are identified primarily through time series variation.

interpretation of the highest coefficient, for example, is that a 10-unit increase in CDD80 increases annual mortality rates by about 8% in Japan. The estimated impact is positive for 12 out of 13 countries and statistically significant in 6 of 13 cases. Notable estimates include 0.5% for Bangladesh, 0.6% for India, about 1% for Pakistan, and about 2% for the Philippines.

The most straightforward explanation for the differences in the measured effect of high temperatures on mortality across countries is that populations in hotter areas may be better adapted either through technology or physiology to respond to high temperatures than populations in colder areas. For example, in the US, Barreca et al. (2015) find that the impact of extreme heat (defined as days with an average temperature above 90°F) on mortality is notably larger in states that infrequently experience extreme heat. In particular, they find that the measured effect of high temperatures on mortality is more than 10 times larger for states in the lowest decile of the long-term distribution of high-temperature days than it is for states in the highest decile (where such high temperatures are relatively frequent).

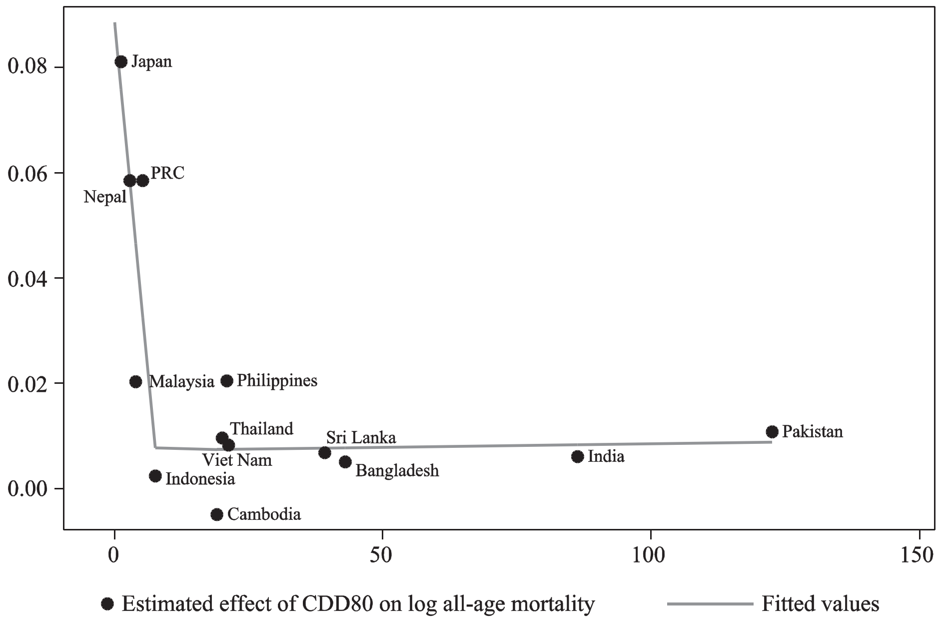
Figure 3 investigates this hypothesis by plotting the country-specific estimated impacts of CDD80 from Panel C in Table 4 against the historical average CDD80 for each country. As before, CDD80 are normalized by 10, so that 100 on the figure represents 1,000 CDD80. The negative relationship between the measured effect of CDD80 on mortality and average CDD80 is evident at first glance. The countries with low average CDD80—Japan, Malaysia, Nepal, and the PRC—are the four countries with the largest estimated mortality effects.

Further investigation of the patterns in Figure 3 reveals a "two-segment" relationship, where we observe a first segment with massive reductions in the measured effect of CDD80 up to about 10 CDD80 (100 in untransformed units): the estimated coefficient for log mortality rates drops from 0.08 (Japan) to about 0.01 (Thailand). This is followed by a second segment where increases in average CDD80 are no longer associated with marked reductions in its effect on mortality. To highlight this pattern, Figure 3 superimposes the fitted line from a piecewise linear regression with a knot at 7.5 CDD80 (75 in untransformed units).[17] The fit of the regression (with 13 observations) is striking: the simple piecewise linear representation explains 75% of the variance in the estimated CDD80 coefficient on log mortality. The first estimated slope segment is –0.011 (with a standard error of 0.0019), while the second estimated slope segment is a statistically insignificant 0.00001. Thus, it appears from this simple exercise that there are limits to mortality-reducing adaptations: the data suggest no further dampening of the temperature–mortality relationship beyond an average exposure of 75–100 CDD80.[18]

[17] The knot point was estimated using a nonlinear regression routine.

[18] This exercise is identified by cross-sectional variation and so the usual caveat to this interpretation applies.

Figure 3. **Country-Specific Estimates of the Effect of High Temperatures on Log Annual Mortality Rates**



CDD80 = cooling degree days with a base of 80°F, PRC = People's Republic of China.
Notes: This figure plots the country-specific estimated impacts of CDD80 from Panel C in Table 4 against the historical average CDD80 for each country, where base 80°F cooling degree days are divided by 10. The country-specific estimated impacts of CDD80 are from the pooled regression across 13 countries. (Bhutan, the Republic of Korea, and Mongolia are excluded due to their low exposure to CDD80.) The regression includes country fixed effects; region-year fixed effects; and controls for precipitation, relative humidity, log population, and other country-specific variables.
Sources: Author's calculations from World Development Indicators and NCEP/NCAR Reanalysis Project data.

C. Explorations into Possible Mechanisms

As highlighted earlier, the mechanisms connecting extreme temperatures and human health are especially complex in developing economies, where large shares of the population are employed in weather-dependent economic activities. With this in mind, a simple framework to understand the effect of high temperatures on mortality should consider two broad channels: (i) a direct channel connecting high temperatures and mortality through human physiology or disease; and (ii) an indirect economic channel through which high temperatures depress real incomes leading to higher incidences of undernutrition, lower levels of investment in health-producing goods, and other income- and nutrition-related health hazards.

The challenge in separating between these two channels is that both contribute to observed mortality, especially given that cause-specific mortality rates are not available in the WDI data. Put another way, the information in the mortality

Table 5. **Estimates of the Impact of Cooling Degree Days on Log Fraction of Population Undernourished and Log Fraction of Stunting in Children Under 5**

	Annual Cooling Degree Days with Base 80°F (÷10)	
	Coefficient	**Standard Error**
Log fraction of population undernourished	0.0088*	(0.0033)
Log fraction of stunting in children age 5 or younger	0.0018	(0.0088)

Notes: The coefficient estimates correspond to the effects of annual cooling degree days with base 80°F (divided by 10) on the log fraction of the population undernourished and the log fraction of stunting in children under the age of 5. Each regression includes country fixed effects; region-year fixed effects; and controls for precipitation, relative humidity, log population, and other country-specific controls. Standard errors are clustered by country. Asterisks denote p-values of <0.05 (*), <0.01 (**), and <0.001 (***).

Sources: Author's calculations from World Development Indicators and NCEP/NCAR Reanalysis Project data.

records used to construct the WDI data does not identify deaths as being due to, for example, a heat stroke (a direct, or physiological, channel) versus deaths due to, for example, chronic malnutrition (an indirect channel). In order to shed light on the mechanisms underlying the relationships documented in Figures 2−3 and Tables 3–4, I make use of information on the prevalence of undernourishment (percent of population) and prevalence of stunting (percent of children under the age of 5) that is available at the country-year level from the WDI. It should be noted that these data are sparser than the mortality rates and are missing in specific countries and years.

Table 5 reports estimates of the effect of high temperatures on the prevalence of undernourishment and stunting based on the same specification as the model in Table 4 (i.e., the base 80°F cooling degree days specification). Panel A of Table 5 reports the coefficients and standard errors associated with the CDD80 variable from panel regression models for the undernutrition indicators. Like in Table 4, the CDD80 variable is divided by 10 in the regression, so the estimates correspond to a 10-unit change in the CDD80 variable (about a 5% change compared to the mean).

The estimates suggest that a 10-unit increase in CDD80 increases the undernourished share of the population by almost 1%. The estimate is statistically significant at the 5% level. In the case of stunting, the point estimate is also positive but not significant. Overall, the estimates in Table 5 are consistent with the notion that the observed temperature–mortality relationship is driven in part by an indirect channel due to undernutrition, as opposed to being entirely driven by a purely physiological relationship. More broadly, this finding has implications for climate change adaptation policy: interventions that increase the availability of nutritional intake (or income) in years of extreme heat, especially among poorer populations, may substantially mitigate the negative health consequences of climate change.

Table 6. **Estimates of the Impact of Climate Change on Log Annual Mortality Rates, Based on Error-Corrected CCSM3 A2 Model**

	Predicted Impact on Log Mortality Rate:		
	Due to ΔCDD80	Due to ΔPrecipitation	Overall Impact
A. Estimates for 2080–2099			
All-age mortality rate	0.4519**	0.0060	0.4579**
	(0.1326)	(0.0049)	(0.1337)
Infant mortality rate (0–1)	0.2000	−0.0061	0.1939
	(0.2735)	(0.0052)	(0.2741)
Adult mortality rate (15–60)	0.3860*	0.0063*	0.3923*
	(0.1817)	(0.0030)	(0.1809)
B. Estimates by Time Period, All-Age Mortality			
2020–2039	0.0475**	−0.0087	0.0388*
	(0.0139)	(0.0072)	(0.0142)
2050–2069	0.2163**	−0.0016	0.2146**
	(0.0635)	(0.0013)	(0.0632)
2080–2099	0.4519**	0.0060	0.4579**
	(0.1326)	(0.0049)	(0.1337)
C. Estimates by Subregion, All-Age Mortality, 2080–2099			
East Asia	0.2428	0.0047	0.2475
	(0.2049)	(0.0412)	(0.1793)
Southeast Asia	0.2704	−0.0462	0.2242
	(0.5311)	(0.0526)	(0.5751)
South Asia	0.3358**	−0.0032	0.3326**
	(0.1042)	(0.0033)	(0.1015)

CCSM3 = Community Climate System Model 3, CDD80 = cooling degree days with a base of 80°F.
Notes: The entries in this table report calculations for the predicted impact of climate change on log annual mortality rates based on the error-corrected CCSM3 A2 model. Underlying regressions include country fixed effects, region-year fixed effects, and controls for precipitation, relative humidity, log population, and other country-specific controls. Standard errors are clustered at the country level. Asterisks denote p-values of <0.05 (*), <0.01 (**), and <0.001 (***). See the text for more details.
Sources: Author's calculations from World Development Indicators, NCEP/NCAR Reanalysis Project data, and NCAR CCMS3 data.

D. Predicted Impacts of Climate Change on Asian Mortality Rates

The relationship between annual temperature fluctuations and mortality rates documented in the previous tables and figures can be combined with scientific predictions about future climate change to develop estimates of the impacts of climate change on mortality rates. This exercise—essentially a ceteris paribus projection—is not without limitations, which are discussed at length in the next section.

Table 6 reports the results of such a calculation, obtained by combining the empirical estimates of the temperature–mortality relationship as shown in Table 4 with the CCSM3 A2 projections for the 16 sample countries over the 2020–2099 period. The estimates are calculations of the predicted change in the annual mortality rate (in percentage terms) due to the predicted change in high temperatures (annual CDD80) and annual precipitation recovered from the

CCSM3 A2 model. The impacts reported are based on country-level predictions calculated as the average of

$$\hat{\theta}_{CDD80}\Delta CDD80_{cj} + \sum_{k}(\hat{\delta}_k \Delta PREC_{ck}) \tag{2}$$

That is, the predicted change in the annual CDD80 in a country ($\Delta CDD80_{cj}$) is multiplied by the corresponding estimated coefficient of its effect on the log mortality rate ($\hat{\theta}_{CDD80}$). A similar calculation is done for the number of days in each precipitation bin. The final estimate corresponds to the weighted average of equation (2) across all countries in the sample. The standard errors of the predictions are calculated accordingly.

The columns in Table 6 break down each component of the calculation: the predicted impact due to the change in CDD80; the predicted impact due to the change in precipitation; and the overall impact, which is the sum of the previous two. Finally, the three panels correspond to predicted climate change impacts across age groups, horizon time periods, and regional subgroups.

The end of century results (i.e., over the 2080–2099 horizon) in Panel A indicate that all-age mortality rates are predicted to increase by 45%. By comparison, Deschenes and Greenstone (2011) find a corresponding effect of 3% for the US; thus, it is clear that climate change poses a much larger risk for human health in Asia than in the US. The rest of panel A decomposes the all-age estimates into a component for infants (Row 2) and a component for the prime-aged population (ages 15–60, Row 3). For both age groups, the estimate is positive and large: 20% for infants and 39% for ages 15–60, though only the latter is statistically significant. This evidence suggest that the burden of climate change on human health in Asia will be distributed more or less the same across all age groups.

Panel B reports predicted impacts on all-age mortality across different time horizons: 2020–2039, 2050–2069, and 2080–2099. These results show that impacts grow over the time horizon in a linear fashion, reflecting the fact that CCSM3 predicts a rising trend in global average temperatures as well as in measures of high temperatures such as CDD80. The fact that the projected impacts grow linearly with the time horizon emphasizes the need for implementing strategies in the near future to avoid large impacts on human health due to climate change.

Finally, Panel C reports estimates for the three subregions of Asia (East, South, and Southeast). The impact estimates are derived from subregion-specific estimates of the temperature–mortality relationship and subregion-specific climate change predictions regarding future levels of CDD80 and precipitation. The predictions are for all-age mortality rates for the 2080–2099 period. Overall, the predicted impacts are similar across subregions, ranging from 24% in Southeast Asia to 34% in East Asia. Only the latter estimate is statistically significant. Thus, it appears each region will be similarly impacted by climate change; therefore, concerns about climate change reinforcing inequality of well-being and economic status across countries are not warranted here in the case of human health impacts.

VI. External Validity of the Projected Mortality Impacts of Climate Change

Are studies based on historical variations in temperature and mortality, such as this one, externally valid to assess the impacts of climate change on mortality? A central issue is that empirical studies are necessarily identified by observed historical variation in weather rather than a permanent future shift in the climate. Absent the random assignment of climates across otherwise identical populations, there is no research design that can fully address this point. At the very least, standard economic theory suggests that this approach leads to an overstatement of the projected human health costs of climate change. This is because the set of health-preserving adaptations that are available to respond to a temperature shock that occurs in the short term is smaller than the set of health-preserving adaptations that are likely to be available in the long term. Indeed, some recent studies attempt at addressing this problem by exploiting exogenous variation in long-term average temperatures, such as the one caused by the "Little Ice Age" (Waldinger 2017).

Therefore, in the case of this analysis with country-year data, it is important to recognize the limitations inherent in using year-to-year variation in weather. Such variation is informative about the health effects related to the "transition" between the current and future climate distribution. However, it is not informative about the complete long-term effects of climate change on health, since the full set of defensive investments an individual can engage in is restrained to a period of 1 year rather than a longer time frame.

The end-of-century predicted mortality impact estimates indicate that climate change will increase mortality rates by about 45%. To put this estimate in some context, the all-age mortality rate declined from 21.6 to 7.2 per 1,000 between 1960 and 2015 (see Table 1), which is a decline of about 0.25 percentage points, or about 1%, per year (relative to 1960 mortality rates). If the point estimates are taken literally, the predicted increase in mortality due to climate change is roughly equivalent to losing half a century's worth of improvement in longevity, which is a remarkably large effect. This finding highlights the urgency to slow down and reverse the strong trend in rising average temperatures documented in Asia and worldwide. Failure to do so threatens to negate multidecade improvements in living standards and economic development in Asia. Furthermore, it underscores the critical role that private and public climate change adaptation will need to assume if these dire predictions are to be avoided.

There are a number of caveats to these calculations, and to the analysis more generally, that must be emphasized. First, the effort to project outcomes at the end of the century requires a number of strong assumptions, including that (i) the climate change predictions are correct, (ii) relative prices (e.g., for all health-improving inputs) will remain constant, (iii) the same health technologies will prevail, and (iv) the geographical distribution of populations in the 16 Asian countries in the sample will remain unchanged. These assumptions are not realistic, but the alternative approach involves making further assumptions about future population growth, mobility patterns, relative prices, technological innovations, and economic growth. Incorporating such additional assumptions in climate change impact predictions is beyond the scope of this paper.

Second, there is still considerable uncertainty about the reliability of the future climate predictions derived from Global Circulation Models. Climate models can produce inconsistent predictions that differ in terms of the magnitude and sign of future changes in key climate variables. As a result, climate change impact estimates based on a projection of the future climate from a single climate model can be unreliable (Burke et al. 2015). One approach proposed by the Burke et al. (2015) study is to compute climate change impact predictions from the 15 or so climate models from which future predictions are available. The range of predicted impacts across the ensemble of all climate models accounts for some (although not all) of the uncertainty inherent in Global Circulation Models. However, this approach is computationally very demanding when daily climate data outputs are required. As a result, this approach is beyond the scope of this paper.

Third, as emphasized before, it is likely that these estimates overstate the increase in mortality due to climate change because the identification strategy relies on interannual fluctuations in weather rather than a permanent change in the weather distribution (climate). As a result, there are a number of mortality-reducing adaptations that cannot be undertaken in response to a single year's weather realization. For example, permanent climate change and continued economic growth in Asia is likely to lead to institutional adaptations (e.g., improvements in public health services and hospitals' ability to treat heat-related illnesses, higher penetration rates of air-conditioning). Another natural response to permanent climate change's impact on heat-related mortality is migration to cooler regions. The empirical approach in this paper fails to account for these adaptations.

Finally, these predicted climate change impacts on mortality do not capture the full impacts of climate change on health. In particular, there may be increases in the incidence of morbidities due to the temperature increases. Additionally, there are a series of indirect channels through which climate change could affect human health, including greater incidence of vector-borne infectious diseases (e.g., malaria and dengue fever). At the same time, many other climatic variables whose distributions are expected to change due to climate change have effects on mortality rates and other health outcomes. For example, changes in the patterns of the monsoon, increased drought incidence, or stronger hurricanes will have their own health impacts. However, this study is not equipped to shed light on these issues.

VII. Conclusion

This paper presents the first empirical analysis devised to understand the complex relationship between extreme temperatures and mortality in 16 Asian countries representing more than 50% of the world's population. Using a country-year panel on mortality rates and various measures of high temperatures for 1960–2015, the paper produces two primary findings. First, high temperatures are strong predictors of increases in mortality rates. Second, this effect is larger in countries where high temperatures are infrequent.

Applying predictions on future temperature and rainfall distributions from a Global Circulation Model to the estimated temperature–mortality relationships provides an opportunity to learn about the possible impacts of climate change on health in Asia. The ceteris paribus predictions reported in the paper indicate that in the short term (i.e., over the 2020–2039 horizon), climate change, through its effects on temperature and rainfall alone, will have modest impacts on mortality rates in Asia, with a predicted increase of 4%. In the long term (i.e., over the 2080–2099), the corresponding predictions are dramatically larger, with a predicted increase of 45%. Such an increase roughly corresponds to the remarkable decline in mortality rates in Asia during the 1960–2015 period. This finding therefore underscores the importance of climate change adaptation to mitigate some of the expected negative effects on human health. Without adaptation, climate change may reverse the public health achievements and economic progress of Asia over the last half-century.

This paper only represents a first attempt at empirically analyzing the temperature–mortality relationship in Asia and providing climate change impact projections that can inform policymaking. Many key implications for future research emerge from this analysis. Future studies should attempt to use panel data with within-country variation in both the outcomes and the climatic variables, as in Burgess et al. (2014). Such within-country analysis will allow the specification of more robust econometric models that control for local unobserved shocks. Additionally, within-country panel analysis can inform climate change adaptation strategies by studying specific policies or technology deployments that can mitigate the effect of temperature extremes on health, as in Barreca et al. (2016).

Finally, as emphasized earlier, climate change will bring changes to a host of climatic variables in addition to temperature, many of which can have significant impacts on health. All of these considerations should be priorities for future research in this area.

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Does Climate Change Bolster the Case for Fishery Reform in Asia?

CHRISTOPHER COSTELLO*

I examine the estimated economic, ecological, and food security effects of future fishery management reform in Asia. Without climate change, most Asian fisheries stand to gain substantially from reforms. Optimizing fishery management could increase catch by 24% and profit by 34% over business-as-usual management. These benefits arise from fishing some stocks more conservatively and others more aggressively. Although climate change is expected to reduce carrying capacity in 55% of Asian fisheries, I find that under climate change large benefits from fishery management reform are maintained, though these benefits are heterogeneous. The case for reform remains strong for both catch and profit, though these numbers are slightly lower than in the no-climate change case. These results suggest that, to maximize economic output and food security, Asian fisheries will benefit substantially from the transition to catch shares or other economically rational fishery management institutions, despite the looming effects of climate change.

Keywords: Asia, climate change, fisheries, rights-based management
JEL codes: Q22, Q28

I. Introduction

Global fisheries have diverged sharply over recent decades. High governance, wealthy economies have largely adopted output controls or various forms of catch shares, which has helped fisheries in these economies overcome inefficiencies arising from overfishing (Worm et al. 2009) and capital stuffing (Homans and Wilen 1997), and allowed them to turn the corner toward sustainability (Costello, Gaines, and Lynham 2008) and profitability (Costello et al. 2016). But the world's largest fishing region, Asia, has instead largely pursued open access and input controls, achieving less long-run fishery management success (World Bank 2017). Recent estimates show that many Asian fisheries continue to languish under outdated management regimes and could benefit from economically optimized fishery management systems such as catch shares. World Bank (2017) estimates that

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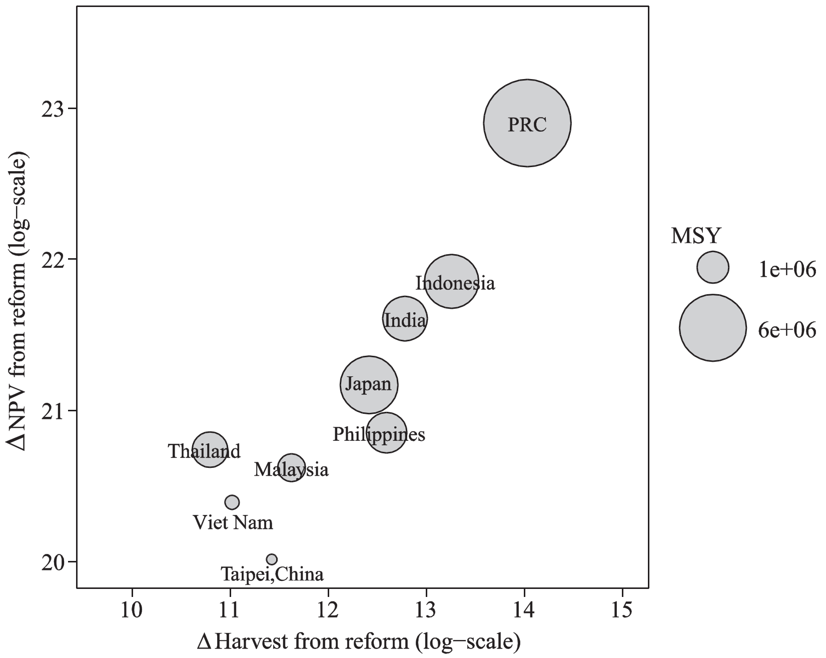
Figure 1. **Hypothetical Benefits of Economically Optimal Fishery Reforms for Select Economies**



MSY = maximum sustainable yield, NPV = net present value, PRC = People's Republic of China.
Note: The figure shows the nine economies with the greatest gains in profit, which all happen to be in Asia.
Source: Calculated from data in Costello, Christopher, Daniel Ovando, Tyler Clavelle, C. Kent Strauss, Ray Hilborn, Michael C. Melnychuk, Trevor A. Branch, Steven D. Gaines, Cody S. Szuwalski, Reniel B. Cabral, Douglas N. Rader, and Amanda Leland. 2016. "Global Fishery Prospects Under Contrasting Management Regimes." *Proceedings of the National Academy of Sciences* 113 (18): 5125–29.

Asian fisheries lose $55 billion per year in inefficient management, which accounts for 65% of the estimated global loss of $85 billion. Figure 1 shows the potential gains from catch shares in the nine economies with the largest economic surplus, all of which are in Asia.

All of the aforementioned benefits of fishery reform were calculated assuming a stationary environment. Yet, climate change promises to dramatically alter the productivity and spatial distribution of most Asian fish stocks (Molinos et al. 2016). These climate-induced changes are expected to play out over the next 100 years or more, but are already starting to take hold. For example, range shifts have been noted in several of the world's oceans, coral bleaching appears to be accelerating, and the productivity of many stocks has sharply changed in recent years. These findings raise an important dilemma for Asian economies interested in the long-run sustainability, food security, and profitability of their fisheries: Should they aggressively pursue fishery management reforms in advance of the most serious predicted effects of climate change? Or does the prospect of climate change weaken the case for reforms such that aggressive reform is no longer necessary?

To shed light on this dilemma, I join newly available data on Asian fishery status with state-of-the-art climate forecasts and bioeconomic models. I largely draw on data and methods in Gaines et al. (2018), though that paper does not single out any results for Asian fisheries, nor does it ask whether the case for reform is strengthened or weakened under climate change. This allows me to conduct a species-by-species analysis for 193 species of the most widely harvested fish in Asia, representing about 29 million metric tons in fish catch.[1]

I begin by estimating biological status and trends for each of these species; this is accomplished by combining retrospective regression approaches (Costello et al. 2012) with dynamic structural models (Martell and Froese 2013). I then use these data as inputs into a bioeconomic model that estimates the potential benefits—in terms of fish conservation, fishery profit, and fish catch—from adopting economically efficient fishery management practices in Asia in the absence of climate change. Essentially, this involves comparing projected fishery performance under business-as-usual (BAU) management with fishery performance under economically optimized management.[2] Results of that analysis largely corroborate previous findings. But because I am primarily interested in how climate change affects these calculations, I then couple to this analysis projections of climate effects on each of the species in my data set from Molinos et al. (2016). These climate models suggest that about 55% of Asian fisheries will experience reductions from climate change, and 29% will experience significant range shifts in the coming decades. By combining the fishery status, models, and climate effects, I can then estimate the potential benefits from adopting fishery management reforms in the face of climate change. Naturally, this involves solving for the economically optimal feedback control rule in each fishery. The final step is to ask whether the strong case for fishery reform is maintained, or undermined, in a future with significant climate change.

Overall, the strong case for fishery management reform is maintained in a world with significant climate change.[3] For the median fishery, both the economic and food provision cases for reform are slightly strengthened by climate change (though by less than 1 percentage point). However, because the effects are not symmetric, the aggregate case is somewhat weakened (by about 3 percentage points for harvest and 4 percentage points for value). While these results suggest that Asian fisheries would still do well to hasten the transition to economically optimized fishery management, they also point to substantial heterogeneity across fisheries due

[1] The species list (shown in the Appendix) is the set of species for which fish catch is reported to the Food and Agriculture Organization (FAO) in at least one of FAO regions 61, 71, or 57 (FAO 2014).

[2] To keep values comparable, I assume that price and cost parameters are the same under BAU and optimized fishery management, and that these parameters are unaffected by climate change.

[3] All results in this paper use the representative concentration pathway 6.0 scenario.

to differences in (i) current status of fish populations, (ii) BAU management, (iii) the biological effects of climate change, and (iv) anticipated geographic movement under climate projections. Taken together, these results suggest that for many Asian fisheries, climate change will strengthen the case for management reforms. But in some cases, I find that the case gets substantially weaker; in these places, motivating governments to undertake costly reforms will have to rely on other arguments or sources of reform capital.

The rest of this paper is organized as follows. Section II discusses the status and trends of major Asian fisheries, and their management. Section III provides theoretical guidance about the conditions under which climate change might strengthen, or weaken, the case for fishery management reform. Section IV then focuses on the empirical estimates of the effects of climate change on Asian fisheries. The estimates of reform with and without climate change are presented in section V. Finally, section VI concludes.

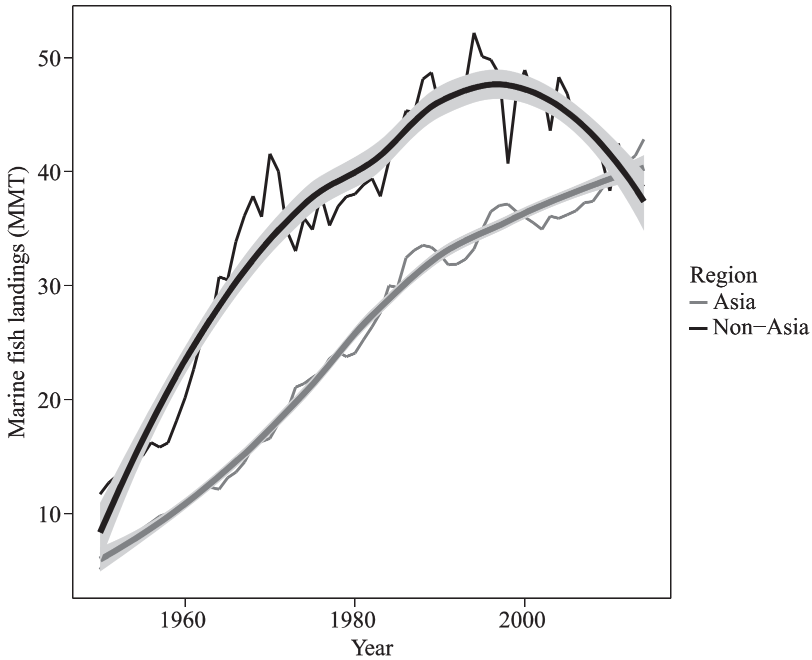
II. Status of and Trends in Asian Fisheries

Official data from the Food and Agriculture Organization (FAO) show a surprising and underrecognized trend in Asian versus non-Asian fish catch. While global catch has been relatively constant over the past few decades (at approximately 80 million metric tons per year), the fraction of global catch produced in Asia has steadily increased (Figure 2). Over the past 5 years, Asian catch has surpassed the rest of the world combined, which represents a dramatic feat for a region focused intently on increasing protein production from the sea (Cao et al. 2017). Yet, questions remain about the underlying reasons for this dramatic divergence in trends between Asia and non-Asian regions. The most common explanation is that Asia's catch is being propped up by increasingly aggressive fishing efforts. Under this explanation, fisheries are progressively being overfished and will eventually collapse. The second possibility is that many large Asian fisheries are thought to have fished-down their immense stocks of predatory fish and that this allows for a "predatory release" (Szuwalski et al. 2016). Under this explanation, catches of smaller-bodied fish can be sustained at a much higher level than was previously thought because their predator numbers have been reduced. But owing to the immense diversity in Asian fish species, fishery management institutions, and economic conditions, the truth is almost certainly somewhere in between.[4] The model I use here will not allow us to distinguish between these underlying causes, but it will allow us to track the likely species-by-species consequences of climate change on Asia's fisheries.

Drawing concrete conclusions about Asian fisheries is significantly hampered by the paucity of evidence on the biological status and trends for species

[4]See Cao et al. (2017) and Costello (2017) for further discussion of Asian fishery objectives and trends.

Figure 2. **Fish Catch over Time—Asia versus the Rest of the World**



MMT = million metric tons.
Source: Food and Agriculture Organization (FAO). 2014. "The State of World Fisheries and Aquaculture." Technical Report of the Food and Agriculture Organization of the United Nations.

of fish harvested in Asia. While individual economies conduct some scientific surveys (Melnychuk et al. 2017), almost no Asian fisheries conduct or report stock assessments. While Asian fisheries supply over half of the global fish catch, among the more than 500 fish stocks represented in the global Ram Legacy Stock Assessment Database (Ricard et al. 2012), only about 1% are from Asia. To overcome these extreme data gaps, recent contributions have provided data-poor methods for estimating stock status and backing out the fishing mortality rate that is implied by reported fish catches. Costello et al. (2016) merge methods from Costello et al. (2012) and Martell and Froese (2013) to estimate current biological status (biomass of a fish stock relative to its biomass under maximum sustainable yield (MSY), denoted as B/B_{MSY}) and current fishing mortality rate (as a fraction of fishing mortality under MSY, denoted as F/F_{MSY}).

For an estimate of the current status of Asian stocks, we follow Gaines et al. (2018) and aggregate fisheries from Costello et al. (2016) at the species level, and extract species whose geographic range extends into Asian waters. Here I make some brief comments about the data underlying this analysis. Biomass and fishing mortality estimates are derived using a panel regression model (Costello et al. 2012) as priors for a structural model from fishery science called the Catch–MSY method (Martell and Froese 2013). This model also provides estimates of the biological parameters for each individual stock, which are then aggregated at the species level for species known to exist in Asian waters. Catch data are from FAO (2014) and the Ram Legacy Stock Assessment Database (Ricard et al. 2012). Price and cost parameters are species-level aggregations from Costello et al. (2016); the resulting database of global fish prices has been published in Melnychuk et al. (2016) and cost parameters are derived to rationalize the level of fishing observed as formalized in Costello et al. (2016). The relevant climate data, which describe the spatial footprint of fish species now and in the future under alternative climate scenarios, are from Molinos et al. (2016), who estimate the change in ocean temperatures over time and associate that with species' temperature preferences to estimate the geographic range of a species in the future. After filtering for the species that reside in Asian waters, this leaves us with 193 species-level bioeconomic models with biological parameters, spatial distributions, and changes in each over time under different climate scenarios.[5]

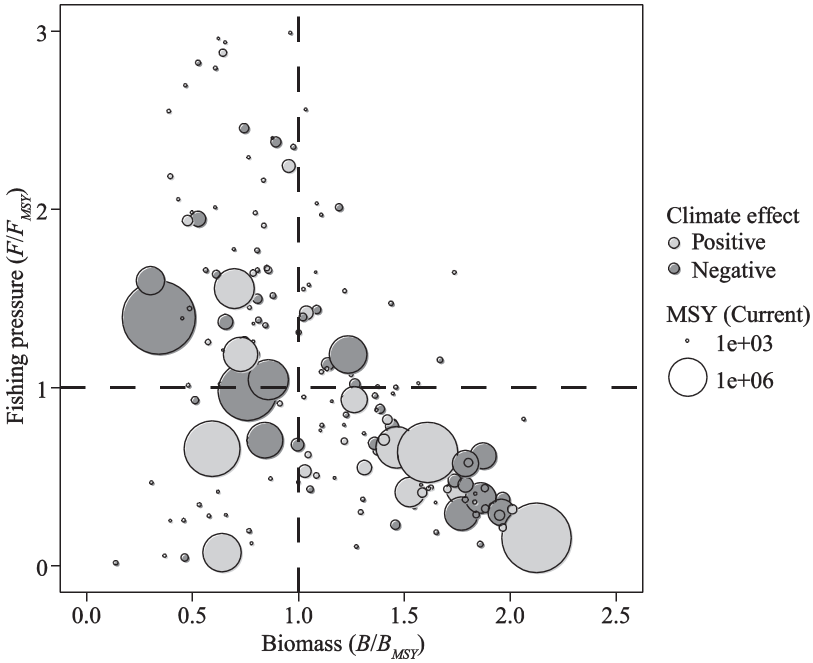
The resulting 193 Asian fish species are displayed in Figure 3, where bubble size indicates the potential size of the species' fish catch (MSY) and shading foretells the future climate effects estimated from the climate model that will be described later (lighter shade for positive effects on carrying capacity and darker shade for negative effects on carrying capacity).[6] Using this approach, the median values for B/B_{MSY} and F/F_{MSY} are both near 1; this may initially suggest that Asian fisheries are in reasonable condition. But a closer inspection of Figure 3 reveals a stark contrast between two classes of fisheries. Those in the top left of Figure 3 are in poor condition. According to this model, these fisheries have been overfished, driving their biomass below levels that which would maximize food provision, and they continue to be fished at an excessive rate.[7] Many of the medium-sized and large Asian fisheries (bubble size), and the fisheries that will be negatively impacted by climate change (darker shade), are in this region of the figure. The second major group consists of fisheries in the bottom right of Figure 3. These fisheries appear to be underfished, at least so far as food production is concerned. Many of these biologically abundant species are expected to be positively affected by climate change. When combined, these features suggest that there may be important possibilities for future growth in some of these fisheries.

[5]I will not repeat here all of the data caveats from these previous papers. But it suffices to say that these estimates are subject to many qualifications, therefore all of these results should be viewed with some degree of caution.

[6]The unit of analysis in this article is technically a species of fish residing in Asian waters as extracted and reported from Gaines et al. (2018). For exposition, I also refer to species as either stocks or fisheries.

[7]As with most bioeconomic models, the one used here finds that the level of fish biomass that maximizes steady state fishery profit exceeds B_{MSY} by about 20%–30%.

Figure 3. **Status and Fishing Pressure for Asian Fish Stocks**



MSY = maximum sustainable yield.
Note: Size indicates MSY and shading indicates whether climate change is expected to have a positive (lighter shade) or negative (darker shade) effect on carrying capacity through 2100.
Source: Author's analysis of data from Gaines, Steven, Christopher Costello, Brandon Owashi, Tracey Mangin, Jennifer Bone, Jorge Garcia Molinos, Merrick Burden, Heather Dennis, Ben Halpern, Carrie Kappel, Kristen Kleisner, and Dan Ovando. 2018. "Fixing Fisheries Management Could Offset Many Negative Effects of Climate Change." *Science Advances.* Forthcoming.

III. Climate Change and Fishery Reforms—Theory

The basic question this paper poses is whether the case for fishery management reform that has been established in the absence of climate change will be maintained in a future with aggressive climate change. In this section, I develop the theory underpinning the empirical analysis that follows. Consider a single fishery in discrete-time with period-t biomass given by B_t. The fraction of the fish stock that is extracted in year t is given by F_t, so the harvest is given by $H_t = F_t B_t$. Price is assumed to be constant, p, and harvesting costs depend on aggregate fishing mortality, so cost is cF_t^B for some constants $c \geq 0$ and $\beta \geq 1$.[8]

[8]This nests the canonical bioeconomic model in which $\beta = 1$, but allows for the possibility that early applications of fishing effort are the most efficient; therefore, additional units of effort are increasingly costly.

This implies that period-t profit of the fishery is

$$\pi_t(F_t, B_t, K_t) = pH_t - cF_t^{\beta} \tag{1}$$

where I have made explicit the dependence on fishing mortality (F_t), biomass of the stock (B_t), and carrying capacity (K_t), which will capture the effects of climate change on the growth of the fish stock.

But the ecosystem places natural constraints on an economy's harvesting decisions. Let the growth of the fish stock be given by the following:

$$B_{t+1} = B(t) + \frac{\phi + 1}{\phi} g B_t \left(1 - \left(\frac{B_t}{K_t}\right)^{\phi}\right) - H_t \tag{2}$$

This biological growth equation (known as the Pella–Tomlinson model) contains three parameters: (i) g, which is related to the maximum (or "intrinsic") growth rate of the stock; (ii) ϕ, which governs the skewness of the familiar hump-shape of growth function; and (iii) K_t, which is the carrying capacity of the stock.[9] This functional form is quite general and nests two familiar examples. First, in equation (2), I have allowed the carrying capacity (K_t) to vary over time; in this paper, K_t reflects the climate state in year t. For example, if climate change is expected to reduce the overall suitable geographic range of a stock by 2% per year, I follow Gaines et al. (2018) and interpret this as a change in carrying capacity (so K_t declines by 2% per year). This interpretation of carrying capacity allows climate impacts to have year-by-year effects on fish stock growth. Second, the special case where $\phi = 1$ delivers the familiar logistic growth equation (with carrying capacity K_t and intrinsic growth rate $2g$).

Naturally, the consequences of climate change on any given fishery will hinge not only on the environmental effects, but also on the way in which the fishery is managed. As a measure of the economic benefit of fishery reform without climate change, I calculate the net present value (NPV) under the BAU fishing mortality rate (again without climate change); denoted as $\bar{F}_{-CC}$, these are the "Fishing Pressure" values in Figure 3 and are compared to the NPV under economically optimized fishery management, denoted as $F^*_{-CC}(B_t)$. To calculate the optimized feedback control rule, $F^*_{-CC}(B_t)$, I use a discrete-time dynamic programming approach, with numerical-value-function iteration and backward induction using $K_t = K_0$, thus assuming that climate change is not occurring. I work backward until the value and policy functions converge. I then forward simulate using the converged policy function from the starting conditions shown in Figure 3 to obtain $\bar{V}_{-CC}$ (NPV under BAU without climate change), V^*_{-CC} (optimized NPV without climate change), $\bar{H}_{-CC}$ (cumulative harvest 2012–2100 under BAU without climate change), and H^*_{-CC} (cumulative harvest 2012–2100 under optimized NPV without climate change).

[9]All parameters were extracted from Gaines et al. (2018).

In a similar manner, when climate change is present, I calculate the NPV and harvest under a BAU policy and an optimized policy. But which policies to use? For the optimized policy, since K_t can change each year in the climate change scenario, it could be treated as a state variable, which would give rise to a policy function that conditioned on K_t (as well as B_t). Under that fully adaptive assumption, the fully optimal policy function would take the form $F^*_{CC}(B_t, K_t)$, so effectively there would be a different optimized harvest control policy function every year that fully anticipated the future effects of climate change. While this may seem farfetched, it would provide a useful benchmark because it would represent the highest possible NPV that any fishery could attain under climate change. But, I do not conduct this additional optimization for three reasons. First, doing so would presume that the fishery manager had perfect foresight about climate effects in all fisheries over the next 80 years and was able to perfectly reoptimize her policy function every year in anticipation of those changes. This seems implausible because of information and policy constraints that often prevent such nimble policy responses. The second reason is that I have conducted this optimization for three fisheries (representing the 5th, 50th, and 95th percentiles of change in K due to climate change) and found that it makes almost no difference in the ultimate NPV of the fishery. The percentage increases in value from using the $F^*_{CC}(B_t, K_t)$ policy instead of the $F^*_{CC}(B_t)$ policy are 0.36%, 0.001%, and 0.02%, respectively, for the 5th, 50th, and 95th percentile fisheries; the commensurate differences in aggregate harvest in 2012–2020 are 3.9%, 0.01%, and 0.04%, respectively.[10] The final reason is that conducting this optimization for all 193 fisheries is very time consuming.

For these reasons, I continue to use the same optimized feedback control rule derived above, so $F^*_{CC}(B_t) = F^*_{-CC}(B_t)$ from the dynamic programming value function iteration procedure described above. For the BAU policy under climate change, I allow for the possibility raised in Gaines et al. (2018), who argue that range shifts induced by climate change could lead to institutional failures that increase fishing pressure. At the same time, it seems irrational to assume that fishing would extend beyond what is economically viable.

To capture these features, I analyze two different models of BAU fishing pressure (Table 1). In both models, BAU fishing pressure is initially $\bar{F}_{-CC}$ (as in the case without climate change). In the first model, I assume fishing pressure for shifting stocks gradually shifts to the open access level of fishing pressure (for which economic profit is zero in steady state) over time as range shifts take hold. In the second model, I assume BAU fishing pressure is unaffected by climate change, so $\bar{F}_{CC} = \bar{F}_{-CC}$ forever.

Across these models, I evaluate two different measures of fishery performance. The first is the NPV of the fishery from 2012 to 2100, and the second

[10] These fisheries are Pacific rudderfish (whose 2100 K is only 62% of its current K), Bartail flathead (whose 2100 K is 99.7% of its current K), and Akiami paste shrimp (whose 2100 K is 110% of its current K).

Table 1. **Fishing Policies with and without Climate Change**

		Climate Change?	
		No	**Yes**
Policy	BAU	$\bar{F}_{-CC}$	$\bar{F}_{-CC}$ to $\bar{F}_{OA}$ or $\bar{F}_{-CC}$ forever
	Optimized	$F^{*}_{-CC}(B_t)$	$F^{*}_{CC}(B_t)$

BAU = business as usual.
Source: Author's compilation.

is the cumulative harvest over the same time period. For any given fishery, these values will depend on the starting conditions (Figure 3), policy function (Table 1), and climate change impact on carrying capacity (Figure 6).

The NPV of the fishery under any climate trajectory and any policy function is given by

$$V = \sum_{t=0}^{T} \left(\frac{1}{1+r} \right)^{t} \pi_t \left(F_t, B_t, K_t \right) \tag{3}$$

where $r = 5\%$ is the discount rate and the equation is subject to equation (2). This implies that there are four relevant values to calculate for the NPV and four relevant values for H:

- NPV calculations
  - No climate change, BAU management $\left(\bar{V}_{-CC}\right)$
  - No climate change, optimized management $\left(V^{*}_{-CC}\right)$
  - Climate change, BAU management $\left(\bar{V}_{CC}\right)$
  - Climate change, optimized management $\left(V^{*}_{CC}\right)$

- Cumulative harvest calculations
  - No climate change, BAU management $\left(\bar{H}_{-CC}\right)$
  - No climate change, optimized management $\left(H^{*}_{-CC}\right)$
  - Climate change, BAU management $\left(\bar{H}_{CC}\right)$
  - Climate change, optimized management $\left(H^{*}_{CC}\right)$

This paper seeks to determine the first differences:

- percentage loss from failing to optimize management without climate change:

$$\Delta\Omega_{-CC} \equiv \frac{\Omega^{*}_{-CC} - \bar{\Omega}_{-CC}}{\Omega^{*}_{-CC}} \left(H^{*}_{CC}\right) \tag{4}$$

- percentage loss from failing to optimize management with climate change:

$$\Delta\Omega_{CC} \equiv \frac{\Omega^{*}_{CC} - \bar{\Omega}_{CC}}{\Omega^{*}_{-CC}} \tag{5}$$

where the outcome variable Ω can either be NPV (V) or cumulative harvest (H) from 2012 to 2100. For example, ΔV_{-CC} provides a measure of what is lost by adhering to BAU management, rather than optimizing the management of the fishery, in the absence of climate change.[11] These values are represented in Figure 7 (where BAU fishing pressure is given by the transition to open access for shifting stocks) and Figure 8 (where BAU fishing pressure is unchanged under climate change).

And our main statistic of interest will be the difference in these differences, expressed as a percentage point change:

$$\Delta\Omega \equiv \Delta\Omega_{CC} - \Delta\Omega_{-CC} \tag{6}$$

For example, if $\Delta V = 5$ percentage points for a particular fishery, this would indicate that the case for fishery reform is 5 percentage points stronger in a world with climate change than it is in a world without climate change. Of course, we expect this statistic to be positive for some fisheries and negative for others. These values are represented in Figures 9 and 10 below.

Theoretical Guidance

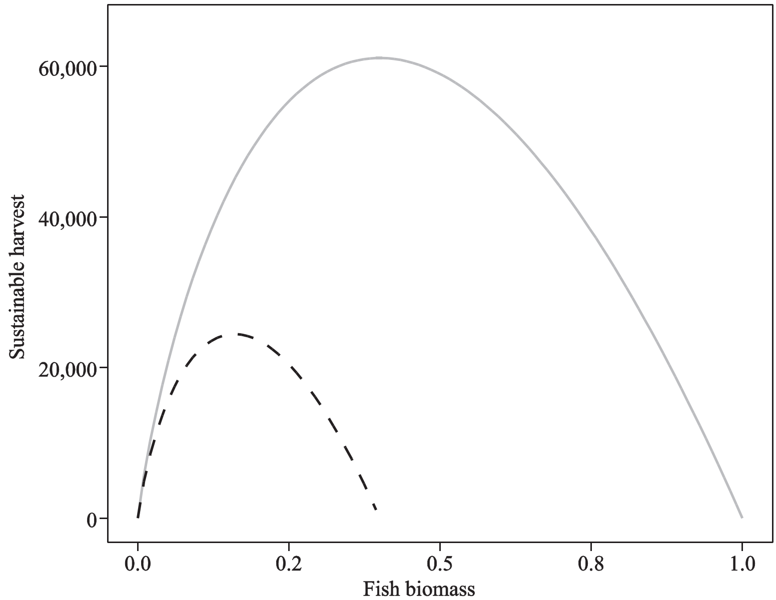
Does theory provide any guidance about how we might expect climate change to affect the value of fishery management optimization? First, whether or not climate change occurs, we expect that optimizing the management of a fishery will lead to an increase in economic value. In other words, we expect $\Delta V_{-CC} > 0$ and $\Delta V_{CC} > 0$. And while we generally expect fishery profit and fishery catch to go hand-in-hand, fishing costs (c in equation 1) imply that it is possible for an intervention to increase profit but decrease catch.[12] But as a general rule, we expect $\Delta H_{-CC} > 0$ and $\Delta H_{CC} > 0$ for most fisheries; when these values are negative, we expect them to be small in absolute value.

But how will ΔV_{-CC} and ΔV_{CC} compare with each other? In other words, calculating $\Delta V \lesseqgtr 0$ will determine whether the presence of climate change increases or decreases the economic case for fishery management reform. Similarly, calculating $\Delta H \lesseqgtr 0$ will determine whether the presence of climate change increases or decreases the food production case for reform. While the answers will turn out to depend on current conditions, BAU management, and the dynamic effects of climate change for any particular fishery, some broad generalizations are possible. First, for fisheries that will experience a reduction in carrying capacity

[11] The denominators in equations (4) and (5) are the same. Normalizing both by the no-climate change scenario facilitates their comparison as percentage point differences later in the paper. Also note that the denominator is the optimized value Ω^*_{-cc} rather than the preoptimized value. This is because under some open access scenarios the preoptimized value can be negative so the percentage would not make sense. The interpretation of these values is the percentage loss from failing to optimize rather than the percentage gain from optimizing.

[12] For example, suppose the fishery is already managed to maximize sustainable yield. Then a management change to optimize NPV will necessarily decrease long-run catch.

Figure 4. **Steady-State Fishery Production with and without Climate Change for a Fishery with Globally Median Parameters**

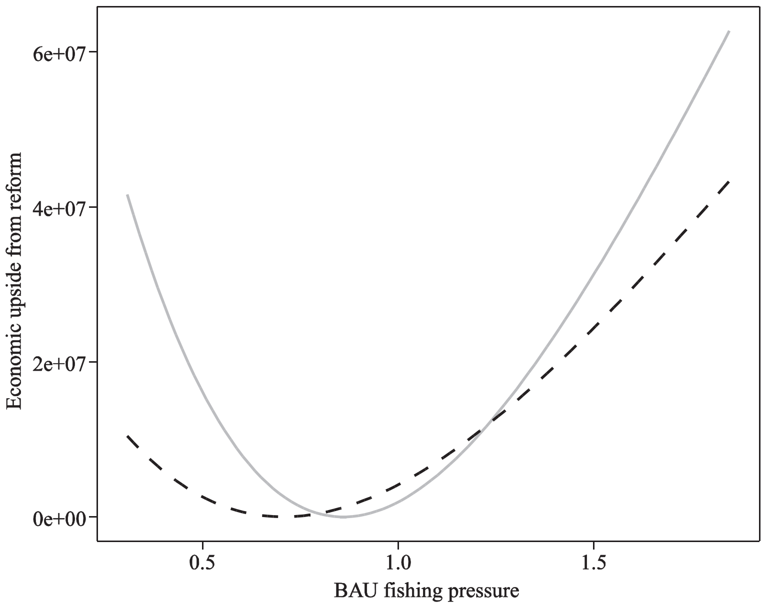


Note: The solid line is without climate change and the dashed line is with a hypothetical 60% reduction in carrying capacity from climate change.
Source: Author's calculations from globally median parameters extracted from Costello, Christopher, Daniel Ovando, Tyler Clavelle, C. Kent Strauss, Ray Hilborn, Michael C. Melnychuk, Trevor A. Branch, Steven D. Gaines, Cody S. Szuwalski, Reniel B. Cabral, Douglas N. Rader, and Amanda Leland. 2016. "Global Fishery Prospects Under Contrasting Management Regimes." *Proceedings of the National Academy of Sciences* 113 (18): 5125–29.

from climate change, it is reasonable to expect a reduction in both the maximum fish catch and the maximum value of the fishery. For example, Figure 4 shows the production function for a fishery with the median global parameters, where the solid line uses current parameters (no climate change) and the dashed line assumes a 60% reduction in carrying capacity resulting from climate change. Production with climate change is everywhere below production without climate change, reflecting the reduction in carrying capacity. This logic seems to suggest that fisheries that will suffer reductions in carrying capacity are likely to gain less from management reform than are fisheries that will experience increases in carrying capacity.

But this logic turns out to depend on the current level of fishing pressure. If BAU fishing pressure is very high (e.g., if the fishery is in open access equilibrium), then the logic holds firmly because the fishery is currently experiencing low (or zero) profit and low catch. Optimizing such a fishery eventually brings about positive increases whether or not climate change occurs, but climate change increases the case for reform only if it will increase carrying capacity. Alternatively,

Figure 5. **Steady-State Economic Upside from Reform for a Fishery with Globally Median Parameters**



BAU = business as usual.
Note: The solid line is without climate change and the dashed line is with a hypothetical 60% reduction in carrying capacity from climate change.
Source: Author's calculations from globally median parameters extracted from Costello, Christopher, Daniel Ovando, Tyler Clavelle, C. Kent Strauss, Ray Hilborn, Michael C. Melnychuk, Trevor A. Branch, Steven D. Gaines, Cody S. Szuwalski, Reniel B. Cabral, Douglas N. Rader, and Amanda Leland. 2016. "Global Fishery Prospects Under Contrasting Management Regimes." *Proceedings of the National Academy of Sciences* 113 (18): 5125–29.

if BAU fishing pressure is very low (take the extreme case when it is zero), then the logic also holds because under BAU both profit and catch are low (or zero). But for intermediate levels of fishing pressure, it turns out that the logic can break down. Figure 5 shows the increase in steady-state profit (again for a fishery with globally median parameters) that arises from fishery management reform as a function of BAU fishing pressure. The solid line depicts the upside from reform without climate change and the dashed line depicts it with a 60% drop in carrying capacity resulting from climate change. To see how a deleterious climate shock could actually increase the benefits from reform, consider the following example. Suppose BAU fishing pressure is about 0.9, which is near the profit-maximizing fishing pressure in the absence of climate change (solid line in Figure 5). In that case, the economic upside from reform (in the absence of climate change) is near zero. But how does the economic upside from reform change after a deleterious climate shock (dashed line)? After climate change, the optimal level of fishing pressure declines (to about 0.75) and the upside from reform, given that BAU fishing pressure is

0.9, is nonnegligible. This example is simply meant to illustrate the possibility that a negative climate shock does not necessarily imply a lower benefit from fishery management reform.

The bioeconomic models I apply to Asian fisheries are substantially more complicated than the simple illustrative examples from Figures 4 to 5. The effects of climate change play out over time, starting conditions differ across fisheries, BAU and optimized policies have effects that evolve over time, and optimal policies are dynamically (not statically) optimized. While the intuition provided above can provide some guidance, it is ultimately an empirical question whether the presence of climate change will strengthen or weaken the case for management reform in any given Asian fishery.

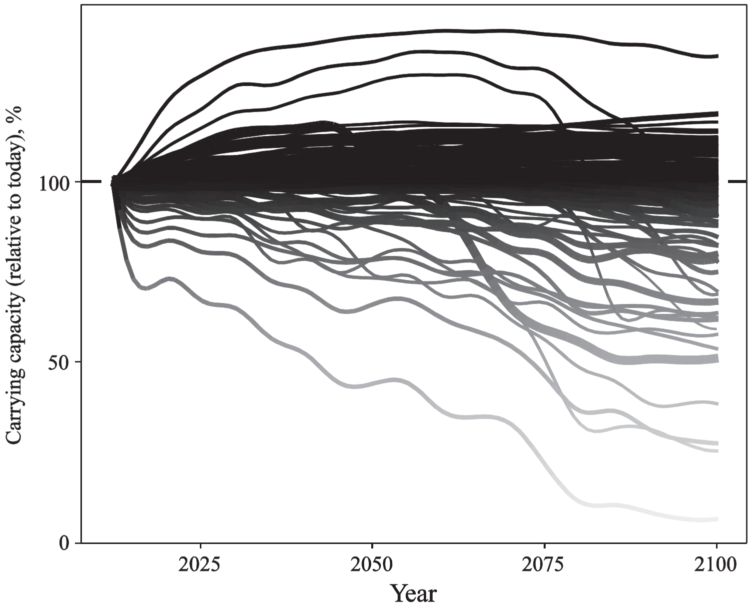
IV. The Effects of Climate Change on Asian Fisheries

Following Gaines et al. (2018), the myriad effects of climate change on global fisheries can be distilled into two categories. The first, and most widely studied, is that climate change may alter the stock growth of a fishery, which is often interpreted as a change in carrying capacity. This can occur through changes in prey abundance, ocean temperatures, acidification, or via other mechanisms. The second consequence of climate change is that it can alter the spatial range of a species in the ocean. Even in the absence of carrying capacity changes, range shifts can have significant consequences to fishery sustainability because as a fish stock crosses international boundaries, institutional failures can lead to overexploitation.

I thus assume that the major effects of climate change can be captured by changes in carrying capacity and shifts in geographic range over time. Changes in the total geographic area suitable for a species correspond to changes in carrying capacity over time. Figure 6 shows the individual trajectories of carrying capacity for each of the 193 species in this analysis under a representative concentration pathway 6.0 climate change scenario; among these species, 55% will decline in carrying capacity and 45% will increase. The line thickness in Figure 6 corresponds to MSY (so it varies over time for each stock, in accordance with changes in K_t) and the shading corresponds to scaled K_t; all values are relative to the 2012 value. Among the species studied, 61% will experience a reduction in carrying capacity and/or significant range shifts as a result of climate change; the other 39% will experience positive effects.

To capture these effects of climate change on a species' carrying capacity and range, we must somehow translate them into the bioeconomic model presented above. First, we keep track of the carrying capacity in each year for each species (Figure 6), and this becomes an input into the model itself (see equation 2). To capture range shifts, we make no changes to the model when a stock is a stationary stock (that is, when it stays within a country's waters). But for the 29% of species

Figure 6. **Effects of Climate Change on Carrying Capacity of Asian Fish Stocks**



Notes: Each line represents an Asian fish species. Shading indicates carrying capacity (relative to 2012 value) and thickness indicates maximum sustainable yield (MSY) of the stock.
Source: Author's analysis of data from Gaines, Steven, Christopher Costello, Brandon Owashi, Tracey Mangin, Jennifer Bone, Jorge Garcia Molinos, Merrick Burden, Heather Dennis, Ben Halpern, Carrie Kappel, Kristen Kleisner, and Dan Ovando. 2018. "Fixing Fisheries Management Could Offset Many Negative Effects of Climate Change." *Science Advances.* Forthcoming.

that are shifting stocks, I run two scenarios. In the first scenario, the BAU fishery policy gets progressively worse as these transboundary shifts start to take hold. In the second scenario, fishing pressure for shifting stocks is unaffected by climate change. All of these assumptions are summarized as follows:

- Changes in fish stock growth
  – Changes in carrying capacity, K, over time: K_t (Figure 6) is an input to the biological model (equation 2) and thus to the forward simulations.
  – BAU policy under climate change: fish at the current fishing mortality rate (except for shifting stocks, see below)
  – Optimized policy under climate change: use the dynamically optimized harvest control rule under current conditions.

- Range shifts
  – "Stationary stocks" have policy functions as indicated above.
  – "Shifting stocks," or those that are expected to cross significantly into multiple jurisdictions (Gaines et al. 2018), are treated as follows:

- Under BAU, the initial fishing mortality rate is the current fishing mortality rate. It either gradually transitions to the fishing mortality rate under open access according to when the shifts are expected to occur, or it is maintained at the current fishing mortality rate; both scenarios are examined below.
- Under optimized management, the harvest policy is optimized (under current conditions), so range shifts are internalized into the policy.

V. The Value of Fishery Management Reform for Asian Species

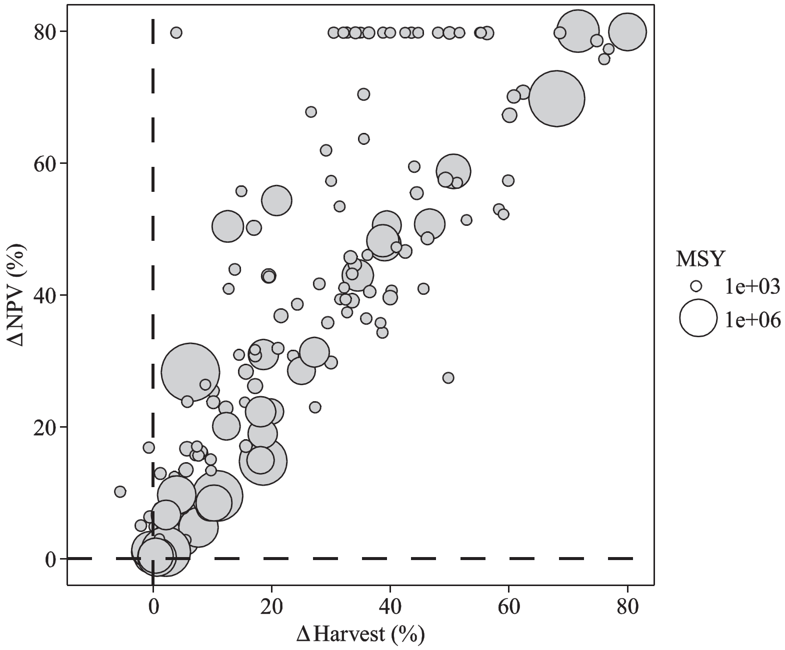
Detailed information on fishery management in Asia is extremely hard to come by. Most available evidence suggests that fishery management institutions are somewhat outdated and rely heavily on input controls such as season length; gear restrictions; and, in some cases, limited licenses. But there seem to be very few cases of feedback control rules, such as harvest control rules, that are now the backbone of fishery policy in Australia, Canada, the United States, and much of Europe and Latin America. I use the model described above to estimate the economic and food provision benefits of adopting fishery management reforms in Asian fisheries.

In the absence of climate change, the benefits of management reforms vary by fishery, but adopting economically rational fishery management generally increases both cumulative harvest (horizontal axis of Figure 7) and economic value (vertical axis of Figure 7) relative to BAU. The average effect of implementing optimized fishery management is expected to increase catch by about 24% and economic value by 34%, though these values range widely across fisheries. The comparable results in a world with climate change are shown in Figure 8, where the shading refers to whether climate change is expected to have a positive (lighter shade) or negative (darker shade) effect on fish stock growth. With climate change, the benefits of reform are still large (visually, there is little difference between Figures 7 and 8). But the average effects of reform are slightly muted here (reform increases catch by 21% and economic value by 30%). The next section explicitly focuses on the difference between these two sets of results.

How Does Climate Change Affect the Value of Fishery Reform in Asia?

The main question this paper seeks to ask is: does climate change undermine the case for fishery management reform in Asia? I conclude with an emphatic “no.” Perhaps the best evidence is from Figure 8, which shows that there remains a large benefit of fishery management reform in nearly all Asian fisheries despite the onset of climate change. A more nuanced question is: does climate change strengthen or weaken the case for fishery management reform? Essentially, this amounts to the difference between Figure 8 and Figure 7, which is depicted in Figure 9 as percentage point changes for each individual fishery.

Figure 7. **The Value of Reforming Asian Fisheries without Climate Change as a Fraction of Optimized Value without Climate Change**

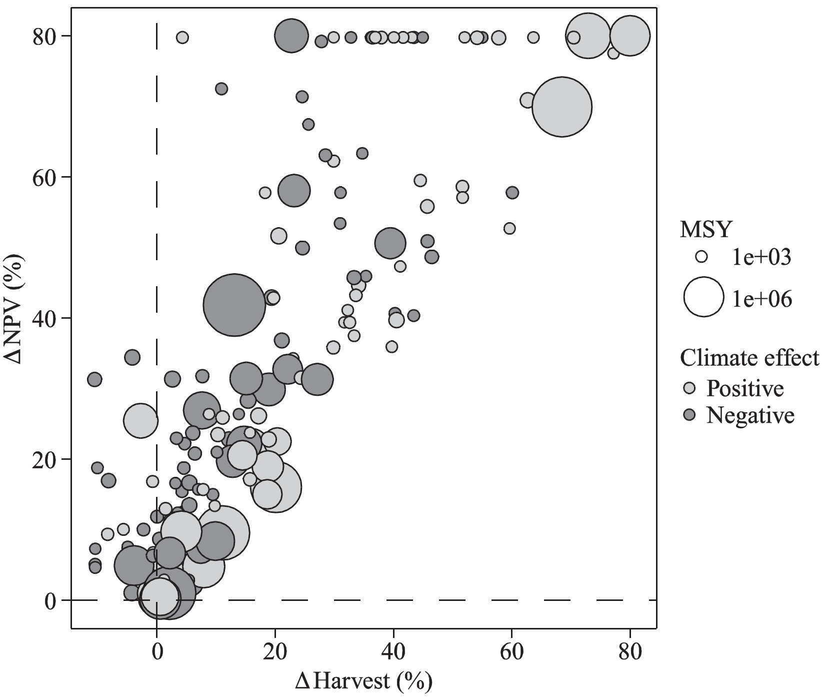


MSY = maximum sustainable yield, NPV = net present value.
Source: Author's analysis of data from Gaines, Steven, Christopher Costello, Brandon Owashi, Tracey Mangin, Jennifer Bone, Jorge Garcia Molinos, Merrick Burden, Heather Dennis, Ben Halpern, Carrie Kappel, Kristen Kleisner, and Dan Ovando. 2018. "Fixing Fisheries Management Could Offset Many Negative Effects of Climate Change." *Science Advances.* Forthcoming.

For stationary stocks (triangles in Figure 9), climate change only affects carrying capacity (it does not affect BAU management). For these stocks, the intuition provided in section III was that carrying capacity increases and the case for reform typically go hand-in-hand. Indeed, this seems to be the case for Asian fisheries: those for which carrying capacity shocks will be positive (lighter triangles) tend to have a stronger case for reform (in both harvest and economic value), and those for which carrying capacity shocks will be negative (darker triangles) tend to have a weaker case for reform. For stationary stocks, the overall conclusion is that climate change will generally bolster the case for fishery management reform in Asia.

But the story can be considerably different for Asian stocks for which we anticipate future range shifts resulting from climate change (circles in Figure 9, which reflect the assumption that BAU fishing pressure gradually shifts to open access for shifting stocks). For those stocks, climate change induces potentially devastating institutional failure, which drives a possibly large wedge between the

Figure 8. **The Value of Reforming Asian Fisheries under Climate Change as a Fraction of Optimized Value without Climate Change**

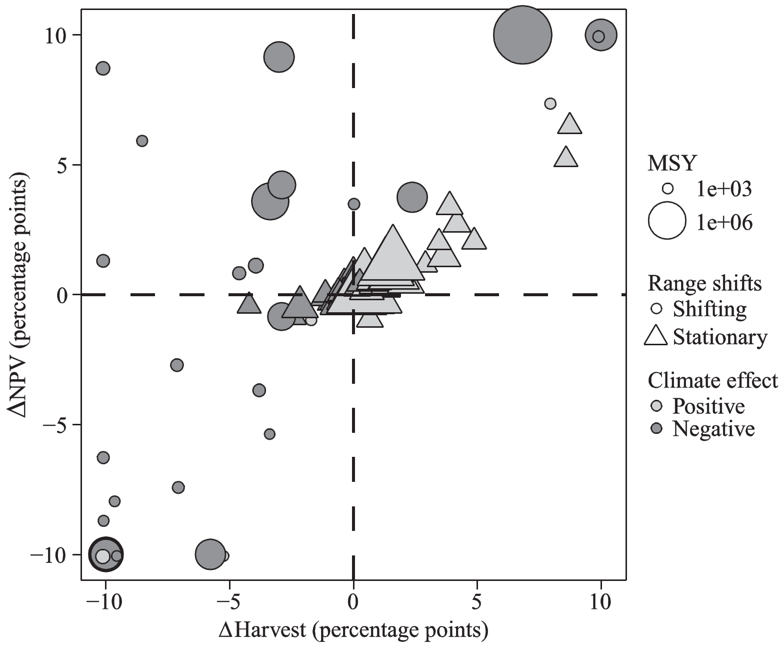


MSY = maximum sustainable yield, NPV = net present value.
Note: Shading indicates whether climate change is expected to have a positive (lighter shade) or negative (darker shade) effect on carrying capacity through 2100.
Source: Author's analysis of data from Gaines, Steven, Christopher Costello, Brandon Owashi, Tracey Mangin, Jennifer Bone, Jorge Garcia Molinos, Merrick Burden, Heather Dennis, Ben Halpern, Carrie Kappel, Kristen Kleisner, and Dan Ovando. 2018. "Fixing Fisheries Management Could Offset Many Negative Effects of Climate Change." *Science Advances.* Forthcoming.

value of the fishery with and without reform. This complicates the calculus. While many shifting stocks are also negatively affected by climate change, the case for reform can either be strengthened (circles in upper right of Figure 9) or weakened (circles in lower left of Figure 9) by the onset of climate change. Taken together, these results suggest that despite climate change, the case for fishery reform remains strong in Asia, though the case can be weakened for some stocks.

To test the importance of the BAU assumption for shifting stocks, I repeat the same analysis for the alternative BAU scenario. In the results depicted in Figure 9, the BAU policy under climate change was for stationary stocks to continue at their current fishing mortality rate and for shifting stocks to transition to open access fishing pressure. The alternative is to treat shifting stocks in the same manner as stationary stocks (so they maintain the current fishing mortality rate). In that case, the basic story stands but the case for reform is even stronger. In both the

Figure 9. **Does Climate Change Strengthen the Case for Fishery Reform in Asia? BAU Fishing Pressure Gradually Shifts to Open Access for Shifting Stocks**

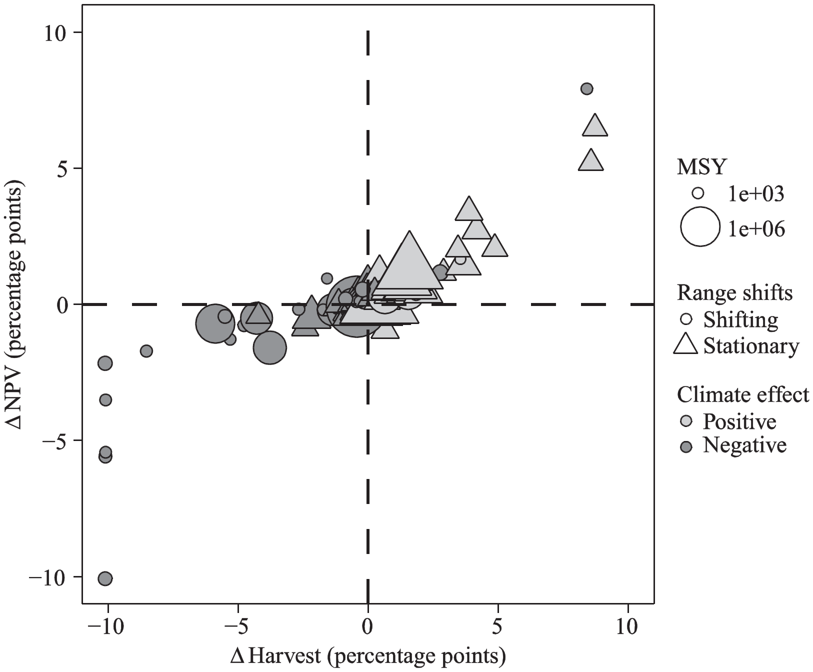


MSY = maximum sustainable yield, NPV = net present value.
Source: Author's analysis of data from Gaines, Steven, Christopher Costello, Brandon Owashi, Tracey Mangin, Jennifer Bone, Jorge Garcia Molinos, Merrick Burden, Heather Dennis, Ben Halpern, Carrie Kappel, Kristen Kleisner, and Dan Ovando. 2018. "Fixing Fisheries Management Could Offset Many Negative Effects of Climate Change." *Science Advances.* Forthcoming.

no-climate change and the climate change scenarios, the benefits of reform are 21%–24% (increase in harvest from reform) and 30%–34% (increase in economic value from reform), suggesting that climate change does not dramatically alter the case for reform. The fishery-by-fishery results for this scenario are depicted in Figure 10, which conform to the theoretical expectation that the case for reform will generally be strengthened for stocks that experience a positive climate shock (lighter shade) and weakened for stocks that experience a negative climate shock (darker shade).

Returning to the original BAU assumption, we can aggregate the data underlying Figure 9 to the FAO fish category level to provide a glimpse into the types of fish for which climate change is likely to strengthen or weaken the case for fishery reforms (recognizing that the case for reform remains strong in nearly all cases). Table 2 reports ΔH and ΔV for the seven fish categories with MSY > 1 million metric tons (reported as percentage point gains as a consequence of climate change). These data suggest that the case for reform is strengthened for the large class of cods, hakes, and haddocks, but weakened (sometimes substantially) for

Figure 10. **Does Climate Change Strengthen the Case for Fishery Reform in Asia?**



MSY = maximum sustainable yield, NPV = net present value.
Note: Plotted for all stocks under the alternative business-as-usual assumption (with climate change, all stocks are fished at their current fishing mortality rate).
Source: Author's analysis of data from Gaines, Steven, Christopher Costello, Brandon Owashi, Tracey Mangin, Jennifer Bone, Jorge Garcia Molinos, Merrick Burden, Heather Dennis, Ben Halpern, Carrie Kappel, Kristen Kleisner, and Dan Ovando. 2018. "Fixing Fisheries Management Could Offset Many Negative Effects of Climate Change." *Science Advances.* Forthcoming.

Table 2. **Effect of Climate Change on the Case for Reform by Major Fish Category**

Category	**Stocks (No.)**	**MSY (MMT)**	**BMSY (MMT)**	**Δ*H***	**Δ*V***
Cod, hake, haddock	5	4.83	72.22	6.03	9.66
Misc. pelagic fishes	23	4.86	48.31	1.75	2.25
Misc. coastal fishes	36	1.48	21.58	−6.50	1.46
Herring, sardines, anchovy	11	3.98	82.49	−0.62	1.44
Tuna, bonito, billfish	18	6.06	35.74	−0.30	0.19
Misc. demersal fishes	21	4.45	36.87	−2.74	−5.59
Salmon, trout, smelt	5	1.02	17.75	−31.48	−23.18

BMSY = biomass under maximum sustainable yield, MMT = million metric tons, MSY = maximum sustainable yield.
Source: Author's analysis of data from Gaines, Steven, Christopher Costello, Brandon Owashi, Tracey Mangin, Jennifer Bone, Jorge Garcia Molinos, Merrick Burden, Heather Dennis, Ben Halpern, Carrie Kappel, Kristen Kleisner, and Dan Ovando. 2018. "Fixing Fisheries Management Could Offset Many Negative Effects of Climate Change." *Science Advances.* Forthcoming.

other groups such as salmon and smelts. Some groups show the interesting pattern that the case for harvest is weakened but the case for economic value is strengthened (e.g., herrings, sardines, and anchovies). The table also provides the number of species composing each category and measures of fishery size (MSY) and overall biomass (BMSY). Four of the five largest classes of fish are expected to have a stronger economic rationale for reform with climate change than without climate change.

VI. Conclusions

The focus of this paper has been on whether climate change undermines the case for fishery management reform in Asia. While the Asia-wide answer is “no,” the answer for any given species turns out to hinge on the exact manner in which climate change will influence the species. For sedentary stocks, the main effect of climate change is on the carrying capacity, and thus the overall growth of the fish stock. If the carrying capacity of a stock is expected to decline under climate change, then the case for fishery reform is generally weakened; the opposite holds for cases when the carrying capacity will increase in the future. While the model results support this prediction, the weakening of the case for reform is quite small (less than 5 percentage point changes), even when climate change will have deleterious effects. The other significant implication of climate change, which has largely gone unnoticed by the previous literature, is that the ranges of some stocks will change. When fish stocks move into new jurisdictions, this can cause a race to fish and may result in worse outcomes than if the same stock had not crossed a jurisdictional boundary. Fisheries for which this second effect is present see a much wider range of outcomes, which largely hinge on how aggressively they are currently managed.

Overall, these results suggest that the vast majority of Asian fisheries, including its largest ones, would benefit economically and in terms of food security by engaging in fishery management reforms. Across Asia, I find that such reforms could lead to increases of 30% in the present value of fisheries and 21% in food provision, even under impending climate change. This implies that Asian fisheries should hasten the transition to sensible, economically rational fishery management under current climate conditions; this will simultaneously secure food and livelihoods across Asia’s diverse fisheries, even in the face of climate change.

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Appendix

This table contains the scientific and common names for each of the 193 species in the Asia data set used in this paper. Among these are several names of economies, which represent aggregated species according to the Food and Agriculture Organization's not elsewhere included (nei) category (e.g., Singapore nei 110).

Table A1. **Scientific and Common Names of Fisheries Used in this Analysis**

	Scientific Name	**Common Name**
1	Argyrosomus hololepidotus	Southern meagre (=Mulloway)
2	Stephanolepis cirrhifer	Threadsail filefish
3	Tenualosa toli	Toli shad
4	Atrobucca nibe	Blackmouth croaker
5	Konosirus punctatus	Dotted gizzard shad
6	Genypterus blacodes	Pink cusk-eel
7	Scomberomorus lineolatus	Streaked seerfish
8	Ruditapes philippinarum	Japanese carpet shell
9	Oncorhynchus gorbuscha	Pink (=Humpback) salmon
10	Nemipterus virgatus	Golden threadfin bream
11	Ilisha elongata	Elongate ilisha
12	Portunus trituberculatus	Gazami crab
13	Scomberomorus niphonius	Japanese Spanish mackerel
14	Todarodes pacificus	Japanese flying squid
15	Oncorhynchus tshawytscha	Chinook (=Spring=King) salmon
16	Muraenesox cinereus	Daggertooth pike conger
17	Psenopsis anomala	Pacific rudderfish
18	Tenualosa ilisha	Hilsa shad
19	Conger myriaster	Whitespotted conger
20	Clupanodon thrissa	Chinese gizzard shad
21	Mene maculata	Moonfish
22	Seriolella punctata	Silver warehou
23	Erimacrus isenbeckii	Hair crab
24	Pennahia argentata	Silver croaker
25	Berryteuthis magister	Schoolmaster gonate squid
26	Paralichthys olivaceus	Bastard halibut
27	Sardinella longiceps	Indian oil sardine
28	Pterygotrigla polyommata	Latchet(=Sharpbeak gurnard)
29	Atheresthes evermanni	Kamchatka flounder
30	Nemadactylus macropterus	Tarakihi
31	Lactarius lactarius	False trevally
32	Crassostrea gigas	Pacific cupped oyster
33	Trochus niloticus	Commercial top
34	Miichthys miiuy	Mi-iuy (brown) croaker
35	Sardinella lemuru	Bali sardinella
36	Psettodes erumei	Indian halibut
37	Chelidonichthys kumu	Bluefin gurnard
38	Jasus edwardsii	Red rock lobster

Continued.

Table A1. *Continued.*

	Scientific Name	Common Name
39	Rastrelliger brachysoma	Short mackerel
40	Rexea solandri	Silver gemfish
41	Ammodytes personatus	Pacific sandlance
42	Singapore	nei_110
43	Seriolella brama	Common warehou
44	Sillago flindersi	Flinders' sillago
45	Arctoscopus japonicus	Japanese sandfish
46	Callorhinchus milii	Ghost shark
47	Makaira nigricans	Blue marlin
48	Chanos chanos	Milkfish
49	Cromileptes altivelis	Humpback grouper
50	Thailand	nei_122
51	Palau	nei_92
52	Haliotis rubra	Blacklip abalone
53	Megalops cyprinoides	Indo-Pacific tarpon
54	Oncorhynchus nerka	Sockeye (=Red) salmon
55	Cololabis saira	Pacific saury
56	Plectropomus leopardus	Leopard coralgrouper
57	Acanthocybium solandri	Wahoo
58	Amblygaster sirm	Spotted sardinella
59	Arripis trutta	Australian salmon
60	People's Republic of China	nei_20
61	Pagrus auratus	Silver seabream
62	Sillago sihama	Silver sillago
63	Cambodia	nei_15
64	Isurus oxyrinchus	Shortfin mako
65	Lates calcarifer	Barramundi (=Giant seaperch)
66	Trachysalambria curvirostris	Southern rough shrimp
67	Taipei,China	nei_120
68	Ruvettus pretiosus	Oilfish
69	Scylla serrata	Indo-Pacific swamp crab
70	Mugil cephalus	Flathead grey mullet
71	Selaroides leptolepis	Yellowstripe scad
72	Euthynnus affinis	Kawakawa
73	Republic of Korea	nei_115
74	Prionace glauca	Blue shark
75	Tonga	nei_124
76	Epinephelus merra	Honeycomb grouper
77	Oncorhynchus keta	Chum (=Keta=Dog) salmon
78	Portunus pelagicus	Blue swimming crab
79	Decapterus russelli	Indian scad
80	Rastrelliger kanagurta	Indian mackerel
81	Eleutheronema tetradactylum	Fourfinger threadfin
82	Pomadasys argenteus	Silver grunt
83	Thunnus obesus	Bigeye tuna
84	Melicertus latisulcatus	Western king prawn
85	Pseudopleuronectes herzensteini	Yellow striped flounder
86	Vanuatu	nei_133
87	Platycephalus conatus	Deep-water flathead

Continued.

Table A1. *Continued.*

	Scientific Name	Common Name
88	Platycephalus indicus	Bartail flathead
89	Indonesia	nei_56
90	Saurida tumbil	Greater lizardfish
91	Selar crumenophthalmus	Bigeye scad
92	Fiji	nei_39
93	Istiompax indica	Black marlin
94	Penaeus semisulcatus	Green tiger prawn
95	Trachurus declivis	Greenback horse mackerel
96	Herklotsichthys quadrimaculatus	Bluestripe herring
97	Scomber australasicus	Blue mackerel
98	Chirocentrus dorab	Dorab wolf-herring
99	Japan	nei_63
100	Timor-Leste	nei_32
101	Federated States of Micronesia	nei_78
102	Megalaspis cordyla	Torpedo scad
103	Zenopsis nebulosa	Mirror dory
104	Beryx decadactylus	Alfonsino
105	Tetrapturus angustirostris	Shortbill spearfish
106	Penaeus monodon	Giant tiger prawn
107	Marsupenaeus japonicus	Kuruma prawn
108	Thunnus albacares	Yellowfin tuna
109	Oncorhynchus kisutch	Coho (=Silver) salmon
110	Zeus faber	John dory
111	Scomberomorus commerson	Narrow-barred Spanish mackerel
112	Istiophorus platypterus	Indo-Pacific sailfish
113	Katsuwonus pelamis	Skipjack tuna
114	Sepioteuthis lessoniana	Bigfin reef squid
115	Thyrsites atun	Snoek
116	Cephalopholis boenak	Chocolate hind
117	Decapterus maruadsi	Japanese scad
118	Kajikia audax	Striped marlin
119	Thunnus alalunga	Albacore
120	Harpadon nehereus	Bombay-duck
121	Philippines	nei_96
122	Pellona ditchela	Indian pellona
123	Mustelus antarcticus	Gummy shark
124	Drepane punctata	Spotted sicklefish
125	Lutjanus argentimaculatus	Mangrove red snapper
126	Carcharhinus longimanus	Oceanic whitetip shark
127	Hoplostethus atlanticus	Orange roughy
128	Kiribati	nei_65
129	Malaysia	nei_73
130	Sri Lanka	nei_117
131	Solomon Islands	nei_112
132	Platycephalus richardsoni	Tiger flathead
133	India	nei_55
134	Carcharhinus falciformis	Silky shark
135	Thenus orientalis	Flathead lobster
136	Ommastrephes bartramii	Neon flying squid

Continued.

Table A1. *Continued.*

	Scientific Name	Common Name
137	Anoplopoma fimbria	Sablefish
138	Panulirus longipes	Longlegged spiny lobster
139	Macruronus novaezelandiae	Blue grenadier
140	Elagatis bipinnulata	Rainbow runner
141	Eleginus gracilis	Saffron cod
142	Epinephelus tauvina	Greasy grouper
143	Seriolina nigrofasciata	Blackbanded trevally
144	Anodontostoma chacunda	Chacunda gizzard shad
145	Sphyraena barracuda	Great barracuda
146	Xiphias gladius	Swordfish
147	Tegillarca granosa	Blood cockle
148	Trichiurus lepturus	Largehead hairtail
149	Centroberyx gerrardi	Bight redfish
150	Arripis georgianus	Ruff
151	Sphyraena jello	Pickhandle barracuda
152	Sardinella gibbosa	Goldstripe sardinella
153	Ariomma indicum	Indian dirtfish
154	Australia	nei_6
155	Papua New Guinea	nei_94
156	Rachycentron canadum	Cobia
157	Scomberomorus guttatus	Indo-Pacific king mackerel
158	Priacanthus macracanthus	Red bigeye
159	Pampus argenteus	Silver pomfret
160	Dussumieria elopsoides	Slender rainbow sardine
161	Acetes japonicus	Akiami paste shrimp
162	Rhynchobatus australiae	Whitespotted wedgefish
163	Coryphaena hippurus	Common dolphinfish
164	Cheilinus undulatus	Humphead wrasse
165	Mallotus villosus	Capelin
166	Thunnus orientalis	Pacific bluefin tuna
167	Fenneropenaeus chinensis	Fleshy prawn
168	Scomber japonicus	Chub mackerel
169	Bregmaceros mcclellandi	Unicorn cod
170	Pleurogrammus azonus	Okhotsk atka mackerel
171	Sardinops sagax	South American pilchard
172	Paralithodes camtschaticus	Red king crab
173	Russian Federation	nei_101
174	Metapenaeus joyneri	Shiba shrimp
175	Democratic People’s Rep. of Korea	nei_88
176	Myanmar	nei_82
177	Hilsa kelee	Kelee shad
178	Lateolabrax japonicus	Japanese seabass
179	Engraulis japonicus	Japanese anchovy
180	Gadus macrocephalus	Pacific cod
181	Thunnus tonggol	Longtail tuna
182	Perna viridis	Green mussel
183	Sardinella zunasi	Japanese sardinella
184	Fenneropenaeus penicillatus	Redtail prawn
185	Paralithodes platypus	Blue king crab
186	Larimichthys crocea	Large yellow croaker

Continued.

Table A1. *Continued.*

	Scientific Name	Common Name
187	Larimichthys polyactis	Yellow croaker
188	Theragra chalcogramma	Alaska pollock (=Walleye poll.)
189	Dussumieria acuta	Rainbow sardine
190	Parastromateus niger	Black pomfret
191	Pseudocaranx dentex	White trevally
192	Trachurus japonicus	Japanese jack mackerel
193	Pagrus major	Japanese seabream

Source: Author's analysis of data from Gaines, Steven, Christopher Costello, Brandon Owashi, Tracey Mangin, Jennifer Bone, Jorge Garcia Molinos, Merrick Burden, Heather Dennis, Ben Halpern, Carrie Kappel, Kristen Kleisner, and Dan Ovando. 2018. "Fixing Fisheries Management Could Offset Many Negative Effects of Climate Change." *Science Advances.* Forthcoming.

An Economic Evaluation of the Health Effects of Reducing Fine Particulate Pollution in Chinese Cities

Yana Jin and Shiqiu Zhang*

Fine particulate pollution ($PM_{2.5}$) is a leading mortality risk factor in the People's Republic of China (PRC) and many Asian countries. Current studies of $PM_{2.5}$ mortality have been conducted at the national and provincial levels, or at the grid-based micro level, and report only the exposure index or attributable premature deaths. Little is known about the welfare implications of $PM_{2.5}$ mortality for urban areas. In this study, we estimate the total cost of $PM_{2.5}$ mortality, the benefit of its reduction achieved through meeting various air quality targets, and the benefit of mortality reduction achieved through a uniform 10 micrograms per cubic meter decrease in $PM_{2.5}$ concentration in the urban areas of 300 major cities in the PRC. Significant heterogeneity exists in welfare indicators across rich versus poor and clean versus dirty cities. The results indicate that cities in the PRC should accelerate the fine particulate pollution control process and implement more stringent air quality targets to achieve much greater mortality reduction benefits.

Keywords: benefit valuation, integrated exposure-response model, mortality risks, People's Republic of China, $PM_{2.5}$
JEL codes: D61, I18, Q51, Q53

I. Introduction

Air pollution, especially the ambient fine particulate matter known as $PM_{2.5}$, which are particulates with aerodynamic diameter ≤ 2.5 micrometers (μm), is a risk to human health (Dockery et al. 1993, Pope et al. 2002). The benefit of reduction in premature mortality risk attributable to lowering $PM_{2.5}$ comprises the vast majority of the overall benefit of air pollution control policies, and has been used to inform

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policy efficiency in various regulatory contexts (United States Environmental Protection Agency 2006, 2011). For example, the cost–benefit analysis of the Clean Air Act in the United States (US) suggests that in 2020 the total annual benefit will reach \$2 trillion (in 2006 prices), more than 30 times the total compliance costs; of the total benefit, 85% is due to reductions in mortality attributable to ambient $PM_{2.5}$ (hereafter $PM_{2.5}$ mortality) (United States Environmental Protection Agency 2011).

Rapid economic growth powered by surges in fossil fuel consumption and urbanization in many developing countries in Asia, such as the People's Republic of China (PRC) and India, have led to increases in air pollution and adverse health outcomes that are much more severe than in developed countries. Of the 1.37 billion people living in the PRC, 83% live in areas where the $PM_{2.5}$ concentration exceeds the PRC's ambient air quality standard (AQS) of 35 micrograms per cubic meter (μg/m^3) (Liu et al. 2016a). The northern, eastern, and central regions of the PRC have been exposed to annual $PM_{2.5}$ concentrations ranging from 40 μg/m^3 to 100 μg/m^3. Meanwhile, fine particulate pollution was associated with 4 million premature deaths worldwide in 2015, including 1 million in the PRC and 1 million in India (Global Burden of Disease Study 2015).

Recently, fine particulate pollution and its impacts have become national concerns and are now among the top political priorities in the PRC (Young et al. 2015; Jin, Andersson, and Zhang 2016). Stringent policies have been implemented on a national scale. Yet, the economic benefit of $PM_{2.5}$ control is unclear, and the effectiveness and efficiency of current policies is still being debated (detailed information is provided in section II). The targets of $PM_{2.5}$ concentration reduction, the prioritization of local interventions across sites and sectors, and the pace of the fine particulate pollution control process have been frequently questioned (Liu 2015; Jin, Andersson, and Zhang 2016, 2017). A sound economic analysis of the benefit of fine particulate pollution control is urgently needed to inform efficient policy design and implementation in the PRC.

In this study, we measure the benefit of fine particulate pollution control by quantifying $PM_{2.5}$ mortality and its welfare implications for the census-registered population in the urban areas of 300 cities at the prefecture level and above (hereafter major cities) in the PRC.[1] We develop an analytical framework that only requires publicly available data on $PM_{2.5}$ concentration and official statistics. We focus on analyzing three monetized benefits of $PM_{2.5}$ mortality reduction: (i) the theoretical maximum benefit, achieved by reducing $PM_{2.5}$ concentration from

[1]Cities in the PRC cover both urban and rural areas. There are 653 cities, including 292 cities at the prefecture level and above, and 361 county-level cities. These two types of cities have used different statistical indicator systems since 1997, and some of these indicators are not comparable. Therefore, the data for the two types of cities are presented separately in the statistical yearbooks. Cities at the prefecture level and above provide statistical information for the total city and for urban areas (districts in the city), whereas county-level cities only have information for the total city. In this study, we focus on the urban areas of the 292 cities at the prefecture level and above.

the current level to zero, which is identical to the total cost of $PM_{2.5}$ mortality;[2] (ii) the total benefit of mortality reduction achieved by meeting the World Health Organization's (WHO) Air Quality Guidelines (AQG) (TB_{AQG}) and three interim targets for fine particulate pollution ($TB_{IT\text{-}1}$, $TB_{IT\text{-}2}$, and $TB_{IT\text{-}3}$);[3] and (iii) the benefit of mortality reduction achieved by a uniform 10 $\mu g/m^3$ decrease in $PM_{2.5}$ concentration (UB_{10}).

Three main considerations motivate our research design. First, we focus on clearly defined city-level jurisdictions across the PRC rather than on provinces or grid-based maps with square cells. Most provinces in the PRC are vast territories, and the distributions of income, population, and pollution are highly uneven within each province. Therefore, the estimates aggregated at the national or provincial levels used in prior studies (see, for example, World Bank 2007, 2016; Xie et al. 2016a) may mask heterogeneity in $PM_{2.5}$ mortality. Furthermore, because it is the municipal governments that implement policies at the local level, it is more useful to provide estimates at the level of these micro jurisdictions. One may naturally think that the recent grid-based studies mapping $PM_{2.5}$ mortality distribution (see, for example, Lelieveld et al. 2015, Liu et al. 2016a, Xie et al. 2016b) are suitable for this purpose, but it is often burdensome to match the estimates of multiple cells with the borders of cities and districts.[4] Therefore, in this study we directly estimate outcomes at the level of city jurisdictions.

Second, we focus on the urban areas of major cities.[5] The greatest benefit of a reduction in $PM_{2.5}$ mortality will occur in urban areas because they have larger populations, more fine particulate pollution, and higher income levels, which are associated with a greater willingness to pay to reduce mortality risks. Further, in developing countries like the PRC, databases of monitored $PM_{2.5}$ concentrations and official statistics on socioeconomic status, which are essential for the validity of welfare estimates, are much more comprehensive for urban areas than rural areas. For simplicity, in the rest of this paper, we use "cities" to refer to the urban areas of major cities, unless indicated otherwise.

Third, in addition to considering the total cost and total benefit, we analyze the benefit of mortality reduction achieved by a uniform 10 $\mu g/m^3$ decrease in $PM_{2.5}$ concentration in cities across the PRC. The distribution of UB_{10} across cities is of both polity and research relevance. Most cities in the PRC are exposed to fine

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[2]The total cost of mortality attributable to $PM_{2.5}$ is only one important part of the total cost of fine particulate pollution; the latter also includes many other elements such as morbidity costs, citizens' defensive and adaptive expenditures, productivity losses, decrease in visibility, and damage to materials and crops.

[3]IT-1, IT-2, and IT-3 refer to WHO targets of $PM_{2.5}$ concentration meeting 35 $\mu g/m^3$, 25 μg/m3, and 15 $\mu g/m^3$, respectively.

[4]As a result, these papers invariably aggregate the cells at the provincial level and then use provincial average socioeconomic data to discuss the likely socioeconomic factors.

[5]In our analysis, urban areas meet the definition of *shi xia qu*, a statistical indicator in the PRC, which refer to city-governed districts, city-controlled districts, or municipal districts that are subdivisions of prefecture-level or larger cities.

particulate pollution levels far above WHO's first interim target (35 μg/m^3), and it may take decades of effort to meet this standard. Therefore, the economic benefit of a unit of pollution reduction, for example, a 10 μg/m^3 $PM_{2.5}$ concentration reduction, is policy relevant. Efficient fine particulate pollution control requires that the cost of reducing $PM_{2.5}$ pollution by one unit should be lower than the estimated UB_{10} for that unit change. However, the estimation of UB_{10} is complicated by two issues. Recent evidence shows that the concentration response (CR) function between fine particulate pollution and mortality risks may be nonlinear (concave), especially at high $PM_{2.5}$ concentrations (Burnett et al. 2014, Pope et al. 2011). The concave CR function indicates that in cites with the same population density, the same reduction in $PM_{2.5}$ concentration will lead to less mortality risk reduction in cities with higher concentrations than in cleaner cities, which is counterintuitive and has raised environmental equity concerns (Pope et al. 2015). However, citizens in dirtier cities can sometimes have higher incomes and may therefore be more willing to pay to reduce health risks. These contradictory effects make the real distribution of UB_{10} among different types of cities a complicated empirical question.

This study contributes to the growing literature on the economic analysis of the health impacts of air pollution in developing countries. In particular, our estimation framework uses only publicly available data; is based on clearly defined jurisdictional urban areas; and considers the total cost of $PM_{2.5}$ mortality, the benefit of meeting different air quality standards, and the benefit outcomes of a uniform reduction in $PM_{2.5}$ concentrations. Our study focuses on the outcomes of annual $PM_{2.5}$ exposure in 2016, but the same approach can be applied to other years and countries. This framework enables us to not only evaluate the environmental benefits of pollution control, but also to provide stakeholders with an easy-to-use tool for generating inputs for policy impact analyses.

Our analysis suggests that ambient $PM_{2.5}$ in the urban areas of major cities in the PRC caused 0.67 million premature deaths in 2016. The percentage of deaths attributable to fine particulate pollution in urban areas is twice the national average, indicating that urban residents face considerably higher mortality risks than the general population. For 2016, the aggregated total cost of $PM_{2.5}$ mortality in major PRC cities was about CNY1,172 billion.[6] The average per capita cost of $PM_{2.5}$ mortality is CNY2,255. The aggregated benefit of mortality reduction from a uniform 10 μg/m^3 decrease in $PM_{2.5}$ concentrations in these cities was about CNY141 billion in 2016, which is equal to a per capita UB_{10} of CNY321. Our results show significant heterogeneity across cities with different characteristics. Cities with medium to high $PM_{2.5}$ concentrations, high per capita income, and large populations have the highest total cost. Cities with lower $PM_{2.5}$ concentrations, high per capita income, and large populations can realize the most benefit from a uniform

[6] \$1 = CNY6.64 at the 2016 average exchange rate.

10 μg/m^3 decrease in $PM_{2.5}$ concentrations. Meeting the PRC's current AQS of 35 μg/m^3 will realize a very limited reduction in $PM_{2.5}$ mortality; therefore, all cities in the PRC should aim at reducing fine particulate pollution to levels below the stringent WHO third interim target and AQG.

The rest of the paper is organized as follows. Section II describes the available data and the challenges of fine particulate pollution in the PRC. Section III develops an analytical framework to quantify the premature deaths from fine particulate pollution and the welfare measures of total cost, total benefit, and the benefit of a uniform 10 μg/m^3 decrease in $PM_{2.5}$ concentration. Section IV presents the results and section V discusses the implications for the literature and policy makers. Section VI concludes the paper. The list of technical terms used in this paper is found in the Appendix.

II. Background and Data

We collect three sets of publicly available data to form a city-level, cross-sectional data set for all the major cities in the PRC in 2016. They include the following data: (i) city-specific annual average $PM_{2.5}$ concentration, (ii) urban census registered population sizes, and (iii) urban per capita disposable income.[7] The fine particulate pollution data are available from the Qingyue Open Environmental Data Center.[8] The urban population and income data are collected from provincial statistical yearbooks.[9] With this data set, we can assess $PM_{2.5}$ mortality, the various welfare indicators, and their heterogeneity across cities with different characteristics. Before presenting our formal estimation, we provide an overview of the PRC's ambient fine particulate pollution, recent policies, and how current pollution levels compare to various air quality targets.

The PRC's economy has been growing rapidly for decades; uneven regional development has concentrated most of the population, fossil fuel consumption, and vehicles in city clusters in the eastern and central PRC. As a result, citizens in these areas enjoy much of the benefit of economic development but have more severe environmental problems such as air pollution. Cities in the northern PRC are exposed to more severe air pollution than the national average, mainly because of the coal consumed by heavy industries and by urban central heating during the winter in these areas. Furthermore, rural households in the northern PRC use coal and biomass for winter space heating. Due to incomplete combustion, these fuels make substantial contributions to ambient fine particulate pollution throughout the

[7]In cities in the PRC there are both citizens with urban *hukou* (household registration) and unregistered rural–urban migrants who live in cities without an urban *hukou*. In this paper, we focus on the urban-registered population. Examining the environmental health impacts of the rural–urban migrants are of importance and a city-level analysis would rely on nonpublicly available data sources, which we direct to future studies.

[8]See https://data.epmap.org.

[9]See, for example, Beijing Municipal Bureau of Statistics (2017) and Jiangsu Bureau of Statistics (2017).

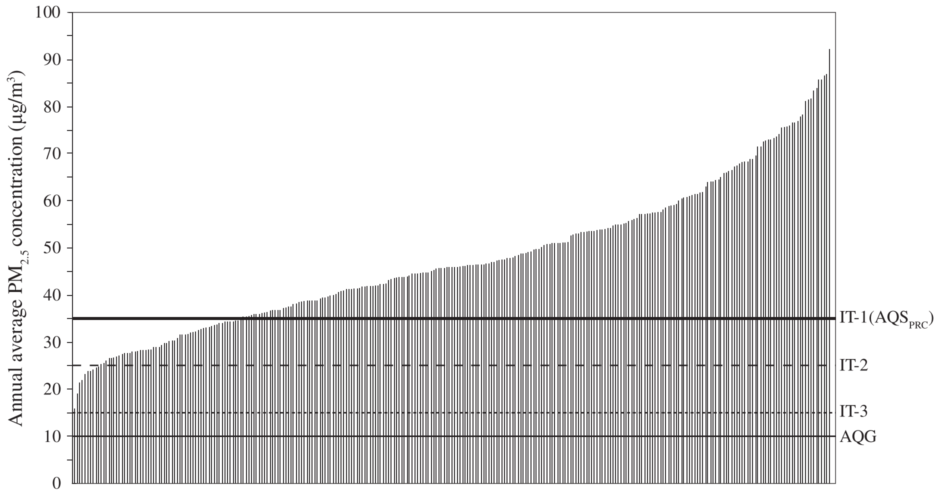
region (Liu et al. 2016b). In addition to coal, vehicle emissions are important contributors to pollution in all cities in the PRC (Shao et al. 2006, Tsinghua University 2006). In megacities such as Beijing and Shanghai, vehicles make the greatest contribution to local fine particulate pollution, exceeding other sources such as coal combustion, road and construction site dust, and industry processes (Beijing MEPB 2014, Shanghai MEPB 2015). Finally, regional-scale transported $PM_{2.5}$ also affects cities in the plains (Xu, Wang, and Zhang 2013), whereas for the basin cities in the central PRC such as Chengdu and Chongqing, meteorological conditions that are unfavorable to pollutant diffusion worsen local pollution (Liang et al. 2016).

In January–February 2013, a winter-long haze caused by extremely high $PM_{2.5}$ concentrations enveloped the whole northern and eastern PRC. Fine particulate pollution and its impacts on health became, for the first time, a nationwide concern (Chris and Elizabeth 2016). The strong political will to control $PM_{2.5}$ pollution was seen in the quick and stringent response from the Government of the PRC. The China State Council (2013) issued the Air Pollution Prevention and Control Action Plan, 2013–2017 (hereafter the Action Plan), which contains compulsory regional air quality improvement goals and 10 key tasks. The goals were largely uniform within each region but varied between regions: the Action Plan required the Beijing–Tianjin–Hebei, Yangtze River Delta, and Pearl River Delta regions to reduce their annual average $PM_{2.5}$ concentration by 25%, 20%, and 15%, respectively, between 2013 and 2017, whereas the rest of the PRC was assigned the more relaxed goal of reducing particulates with aerodynamic diameter $\leq$10 micrometers (PM_{10}) by 10% over the same period. Faced with these mandatory air quality improvement goals, local authorities implemented a variety of regulations. Although improvements were observed at the end of the 5-year policy window, it was difficult for the northern region of Beijing–Tianjin–Hebei, which has much higher $PM_{2.5}$ levels (Tsinghua University and Clean Air Alliance of China 2014), to reach the policy goals even though regulations with very high compliance costs had been implemented (Jin, Andersson, and Zhang 2017; Wang 2017). However, the cleaner region of the Pearl River Delta reached its goals easily (China Environmental Protection Association 2016).

In the long term, the PRC's cities must meet the challenge of more stringent air quality targets. WHO AQG for annual average $PM_{2.5}$ concentration is 10 μg/m^3.[10] WHO also defines three interim targets (IT-3, IT-2, and IT-1) to gauge different countries' progress in reducing fine particulate pollution. In 2012, the PRC updated the AQS and set 35 μg/m^3 as the annual average $PM_{2.5}$ standard, equaling WHO's first interim target level of 35 μg/m^3. Figure 1 shows that the

[10]Although adverse health effects are still observable below this concentration (Di et al. 2017), the 10 μg/m^3 level is recommended as the long-term guideline value as it is only slightly higher than the environmental background $PM_{2.5}$ and has been shown to be achievable in large urban areas in highly developed countries (WHO 2005).

Figure 1. **Annual Average Fine Particulate Pollution Concentration in Chinese Cities at the Prefecture Level and Above, 2016**



AQG = World Health Organization's Air Quality Guidelines, AQS = ambient air quality standard, IT = World Health Organization's Air Quality Interim Target, $PM_{2.5}$ = particulates with aerodynamic diameter ≤2.5 μm, PRC = People's Republic of China.

Source: 2016 Annual Average $PM_{2.5}$ Concentration from Qingyue Open Environmental Data Center. https://data.epmap.org.

$PM_{2.5}$ concentration of all major cities in the PRC in 2016 exceeded the AQG target. Two-thirds did not meet WHO's first interim and the PRC's AQS.

In sum, reducing $PM_{2.5}$ concentration in the PRC's cities will inevitably be a difficult and long-term process. This is evident from the severe and complex nature of the pollution itself, the policy dynamics of the Action Plan, and the large gap between current pollution levels and WHO's interim targets. We examine the economic value of various $PM_{2.5}$ concentration or reduction scenarios to provide a welfare perspective on this long-term $PM_{2.5}$ control process. As defined earlier, we define the values as the total cost, total benefit of WHO's AQG (TB_{AQG}) and three interim targets ($TB_{IT\text{-}1}$, $TB_{IT\text{-}2}$, and $TB_{IT\text{-}3}$), and the benefit of a uniform 10 μg/m^3 decrease in fine particulate pollution concentration (UB_{10}). As discussed in the next sections, total cost, together with the physical estimates of premature deaths, can represent a major part of the welfare loss attributable to fine particulate pollution across cities. The results of UB_{10} answer important questions such as how significant is the benefit of near-term achievable $PM_{2.5}$ control, and why relatively clean cities should further reduce their fine particulate pollution. The relative sizes of the total cost, total benefit, and the benefit of a uniform 10 μg/m^3 decrease in fine particulate pollution concentration have implications for setting targets and choosing appropriate speeds for $PM_{2.5}$ pollution reduction across cities.

III. Methodology

In this section, we build an estimation framework using an integrated exposure-response (IER) model and parameters suitable for the PRC context. We first note that, regardless of the estimation scales used, the economic value of the mortality (or mortality changes) attributable to $PM_{2.5}$ will eventually be composed of the following four sets of information: (i) the exposed population; (ii) the baseline mortality rate; (iii) the CR relationship, which is a monotonic increasing function of $PM_{2.5}$ concentration with its slope usually called the CR coefficient; and (iv) the value of a statistical life (VSL), which represents the willingness to pay for mortality risk reduction aggregated over the affected population. As discussed below, holding other factors unchanged, the economic estimate will grow with an increase in any of the four factors.

A. Premature Deaths Attributable to 1 Year of Exposure to Fine Particulate Pollution

In epidemiological studies of the health effects of ambient air pollution, the relationship between $PM_{2.5}$ exposure and mortality is characterized by the CR function. The conventional view is that the CR function is a linear function of $PM_{2.5}$ concentration, c_i, with a slope defined as the CR coefficient (Dockery et al. 1993, Pope et al. 2002). Pooled estimates from meta analyses, such as the one by Hoek et al. (2013), suggest the CR coefficient is a 6% (95% confidence interval from 4% to 8%) increase in all-cause mortality per 10 $\mu g/m^3$ increase in $PM_{2.5}$ concentration. The constant CR coefficient assumption has been applied in many developed countries where $PM_{2.5}$ concentration generally ranges below 30 $\mu g/m^3$. Accordingly, the relative risk (RR) for premature death at $PM_{2.5}$ concentration c_i can be written as

$$RR(c_i) = 1 + CR\ coefficient * (c_i - c_0) \tag{1}$$

where c_0 is the threshold concentration that causes health impacts.

Recent evidence suggests that the CR function is nonlinear (concave), and the CR coefficient is lower when the $PM_{2.5}$ concentration is higher (Pope et al. 2011, Burnett et al. 2014). This implies that using the constant CR coefficient derived from studies of cleaner developed countries may overestimate the health impacts from fine particulate pollution in places with very high $PM_{2.5}$ concentrations. To better describe the concave characteristics of the CR function, an IER model was developed by Burnett et al. (2014) and Smith et al. (2014). It has been applied in the Global Burden of Disease project (Lim et al. 2013) and recently in PRC-specific studies (Liu et al. 2016a, Xie et al. 2016a, Xie et al. 2016b, and Mu and Zhang 2015). The IER simulates a set of disease-specific RR curves that cover the whole range of $PM_{2.5}$ exposure by integrating available evidence for the health impacts of ambient air pollution, indoor air pollution from household solid fuel use, second-hand smoking, and active smoking. It therefore can be used to estimate the $PM_{2.5}$ mortality risks for cities in the PRC with high concentrations.

The IER describes the RR for several diseases, k, associated with $PM_{2.5}$ pollution.

$$RR_k\,(c_i) = \begin{Bmatrix} 1 + \alpha_k & \left(1 - e^{-\gamma_k (c_i - c_0)^{\delta_k}}\right), & \mathit{if}\, c_i > c_0 \\ & 1, & \mathit{else} \end{Bmatrix} \tag{2}$$

where k is one of the four major adult diseases associated with $PM_{2.5}$: ischemic heart disease, chronic obstructive pulmonary disease, stroke, and lung cancer. α_k, γ_k, and δ_k are the parameters characterizing the shapes of the RR_k curve.

The Global Burden of Disease Study (2013) provides the exact $RR_k\,(c_i)$ value and its 95% confidence interval for disease k at each integer's concentration level for the IER model. Therefore, given city j's 2016 annual average $PM_{2.5}$ concentration (c_i), we know the corresponding $RR_k\,(c_i)$.

The attribution fraction of the mortality risks of disease k from $PM_{2.5}$, AF_k can be written as

$$AF_k = \frac{RR_k(c_i) - 1}{RR_k(c_i)} \tag{3}$$

The disease-specific premature deaths due to the annual exposure to ambient $PM_{2.5}$ in city i, (D_{ki}), is

$$D_{ki} = I_{ki} * P_i * AF_k \tag{4}$$

where I_{ki} is the mortality rate for disease k in city i. Currently, there is no publicly available city-level mortality information for cities in the PRC. We apply the provincial disease-specific mortality estimated by Liu et al. (2016a) to all the cities in the same province. P_i is the population of city i.

B. Total Cost of Mortality Attributable to 1 Year of Exposure to Fine Particulate Pollution

The premature deaths from $PM_{2.5}$ are monetized using the VSL estimates for the PRC. VSL is the marginal rate of substitution between income and micro mortality risk reduction (Hammitt 2000) and is nonconstant across income groups and risk contexts (Cameron and DeShazo 2013). It is obtained by aggregating individuals' willingness to pay for mortality risk reductions over the affected population. Therefore, the higher the income level of the affected population, the higher their willingness to pay and VSL. Meta analyses of VSL empirical estimates show that it increases with the income of the sampled population and decreases with the level of mortality risk reduction in the research (Viscusi and Aldy 2003, Lindhjem et al. 2011). As a result, Cameron (2010), among others, advocates not using a one-size-fits-all VSL for populations across sites and regulatory contexts, and proposes adjusting it to fit the population's income level and a study's risk settings.

Empirical VSL estimates for the PRC are limited, and the data are more than 10 years out-of-date. Reviews of these studies are available in Huang, Andersson, and Zhang (2017); and Jin (2017). Due to the large differences in income and health risks between developed countries and the PRC, and the changes over the last decade, applying VSL values from United States-based or old PRC studies to current PRC data sets using benefit transfer methods would incur large uncertainties. Motivated by this gap, Jin (2017) designed a state-of-the-art discrete choice experiment (DCE) that incorporated the newest IER evidence on the health impacts of air pollution and constructed risk reduction scenarios that are realistic in the PRC setting. Based on online DCE surveys implemented in September 2016 on a representative sample of over 1,000 Beijing citizens, Jin reported the VSL for air pollution mortality impacts in Beijing to be CNY3 million (95% confidence interval from CNY2.2 million to CNY5 million, in 2016 prices).[11] More detailed information of this DCE survey, econometric analysis, and results are available in Jin (2017).[12] This VSL estimate of Beijing's air pollution fits this study's research objective, as it is up-to-date and the risk contexts in the two studies are the same.

As Jin (2017) did not find significant differences in the VSLs of the major adult diseases associated with $PM_{2.5}$, we use her base estimate of CNY3 million as the $VSL_{Beijing,\, air\, pollution}$ to monetize the premature deaths D_{ki}. We then adjust the $VSL_{Beijing,\, air\, pollution}$ to every city i as follows:

$$VSL_i = VSL_{Beijing,\, air\, pollution} * \left(\frac{Y_{Beijing}}{Y_i}\right)^e \tag{5}$$

where $Y_{Beijing}$ and Y_i are, respectively, urban per capita disposable income in Beijing and in city i, and e is the income elasticity of VSL, which in this study is assumed to be 1.[13]

The total cost of the premature deaths for city i (TC_i) can be written as

$$TC_i\,(c_i) = VSL_i * \sum\nolimits_k D_{ki} \tag{6}$$

Finally, combining equation (6) with equation (1) to equation (5), the total cost of premature deaths in city i from 1 year of exposure to the average annual $PM_{2.5}$ concentration c_i is

[11] As the VSL enters estimation in this study as a multiplier, its absolute size only "shifts" the welfare indicators to higher or lower levels. Our conclusions remain.

[12] The full survey questionnaire (in English) is available at yanajin.weebly.com.

[13] Most studies use per capita GDP to adjust the VSL across sites (e.g., Huang, Xu, and Zhang 2012; and Mu and Zhang 2013). We improve this by using per capita disposable income (Hammitt 2000).

$$TC_i\left(c_i\right) = VSL_{Beijing,\, air\, pollution} * \left(\frac{Y_{Beijing}}{Y_i}\right)^e * P_i \sum\nolimits_k \left\{ I_{ki} * \frac{RR_k\left(c_i\right) - 1}{RR_k\left(c_i\right)} \right\} \tag{7}$$

C. Benefit of Mortality Reduction from a Uniform 10 μg/m^3 Decrease in $PM_{2.5}$ Concentration and from Meeting WHO AQG and Interim Targets

In this study, the benefit of mortality reduction from a uniform 10 μg/m^3 decrease in $PM_{2.5}$ concentration in city i is defined as the $TC_i\left(c_i\right)$ in equation (7) minus $TC_i\left(c_i - 10\right)$, i.e., the total cost in the same year with a counterfactual 10 μg/m^3 reduction in $PM_{2.5}$ concentration. The interpretation is as follows: if city i realizes a 10 μg/m^3 reduction in annual average $PM_{2.5}$ concentration, and everything else stays at the 2016 level, then the benefit of prevented premature deaths caused by this specific reduction in $PM_{2.5}$ concentration equals the following:

$$UB_{10,i}\left(c_i\right) = TC_i\left(c_i\right) - TC_i\left(c_i - 10\right) \tag{8}$$

We define UB_{10} as based on a 10 μg/m^3 decrease, rather than on a 1 μg/m^3 decrease of c_i because a 10 μg/m^3 change is more policy relevant. A stable and significant reduction in the $PM_{2.5}$ concentration of 10 μg/m^3 could in most cases only be achieved through policy, whereas a 1 μg/m^3 change may occur due to natural factors such as meteorological fluctuations. Furthermore, the PRC's Action Plan sets air quality improvement goals based on percentage changes that, if transformed into concentration changes, are on a 10 μg/m^3 order of magnitude. Therefore, using a 10 μg/m^3 change in our estimations provides ready-to-use references for local policy economic evaluations.

Likewise, the benefit of reductions in $PM_{2.5}$ mortality achieved by meeting different air quality targets, TB_{AQG}, $TB_{IT\text{-}1}$, $TB_{IT\text{-}2}$, and $TB_{IT\text{-}3}$, are defined as

$$TB_{t,i}\left(c_i\right) = \left\{ \begin{matrix} TC_i\left(c_i\right) - TC_i\left(c_t\right), & if\, c_i > c_t \\ 0, & else \end{matrix} \right\} \tag{9}$$

where t is one of the four air quality targets and c_t is each target's corresponding concentration level, which are WHO's AQG (10 μg/m^3) and interim targets, IT-3 (15 μg/m^3), IT-2 (25 μg/m^3), and IT-1 (35 μg/m^3).

IV. Results

A. Estimated Premature Deaths

Our first set of results is for the estimated premature deaths attributable to 1 year of exposure to ambient $PM_{2.5}$ in 2016 in the major cities in the PRC. Table 1 reports the estimated total reductions and disease-specific reductions. It also compares our results with those of the newest estimates given in the Global

Table 1. **Premature Deaths Attributable to Ambient $PM_{2.5}$—Comparison of National and Urban Estimates**

Estimates and Calculations	**GBD 2015 (a)**	**This Study (b)**	**Urban/National Ratio (b/a)**
Research areas in the People's Republic of China	nationwide	urban areas	—
Population affected (million) [A]	1,370	446	0.3
Total deaths except from injuries (million) [B]	8.6	2.7	0.3
Premature deaths due to $PM_{2.5}$ (million) [C]	1.1	0.7	0.6
Rate of disease-related death (per 100,000) [B]/[A]	630	620	0.9
Percent attributable to $PM_{2.5}$ [C]/[B]	12.8%	25.0%	1.9
Premature Deaths Due to $PM_{2.5}$ by Disease	**GBD 2015**	**Liu et al. 2016**	**This Study**
Stroke	322,228	688,000	349,139
Ischemic heart disease	291,764	381,900	185,860
Lung cancer	145,985	129,400	58,343
Chronic obstructive pulmonary disease	281,703	168,100	76,084

GBD = Global Burden of Disease Study, $PM_{2.5}$ = particulates with aerodynamic diameter $\leq 2.5\ \mu m$.
Source: Authors' calculations.

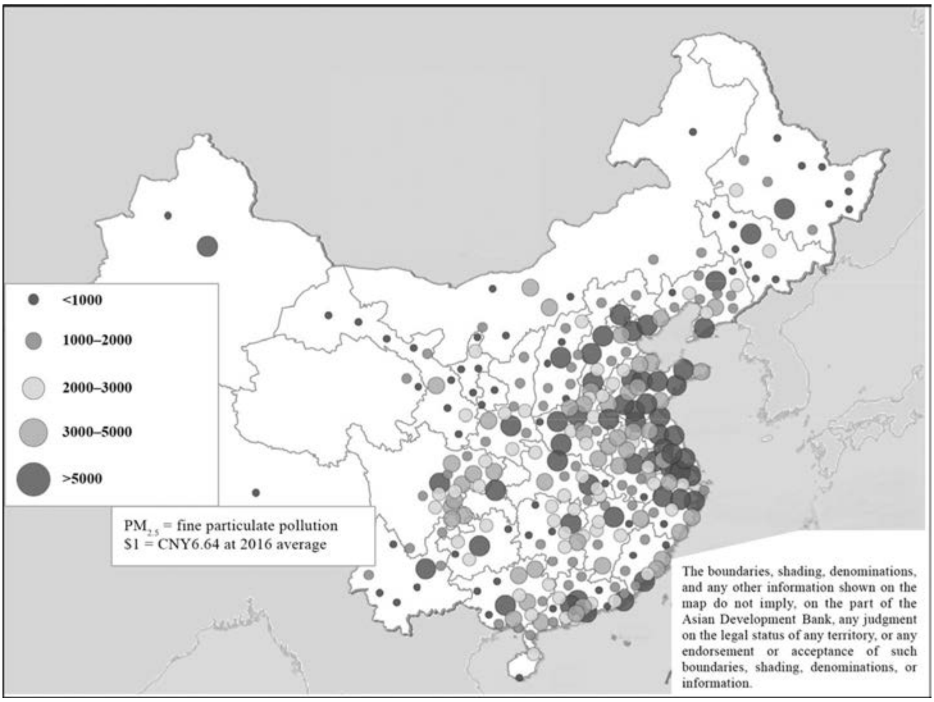
Burden of Disease Study (2015) and in Liu et al. (2016a). In the latter's analysis, the premature deaths are also calculated based on the IER model, but for the entire population of the PRC.

Our results, as shown in Table 1, suggest that 0.67 million premature deaths are attributable to ambient $PM_{2.5}$ in the urban areas of major cities in the PRC cities in the 2016 data set. Although the urban-registered population in our study area is 0.45 billion, which is only 33% of the 1.37 billion people living in the PRC, the premature deaths due to ambient fine particulate pollution account for 60% of the deaths nationally. The rate of disease-related death for urban residents is almost the same as that of the whole population, suggesting that although there is no difference between the baseline mortality risks of urban residents and the national average, the percentage of deaths attributable to ambient $PM_{2.5}$ in urban areas is almost twice the national average. These results indicate that urban residents face considerably higher mortality risks associated with ambient fine particulate pollution than the general population.

The lower part of Table 1 compares disease-specific premature deaths. Stroke accounts for the majority of premature deaths, followed by ischemic heart disease; chronic obstructive pulmonary disease and lung cancer are less common. This is consistent with the fact that the baseline mortality risks for stroke and ischemic heart disease are higher. The relative magnitude of the four types of disease-specific $PM_{2.5}$ mortalities in our study are similar to the patterns in nationwide estimates.

Cities with higher estimates of premature deaths are those with larger populations and higher $PM_{2.5}$ concentrations. The magnitudes and distribution of our results are in accordance with recent grid-based studies such as Liu et al. (2016a) and Xie et al. (2016a).

Figure 2. **Total Cost of Mortality Attributable to 1 Year of Exposure to $PM_{2.5}$, 2016**
(CNY million)

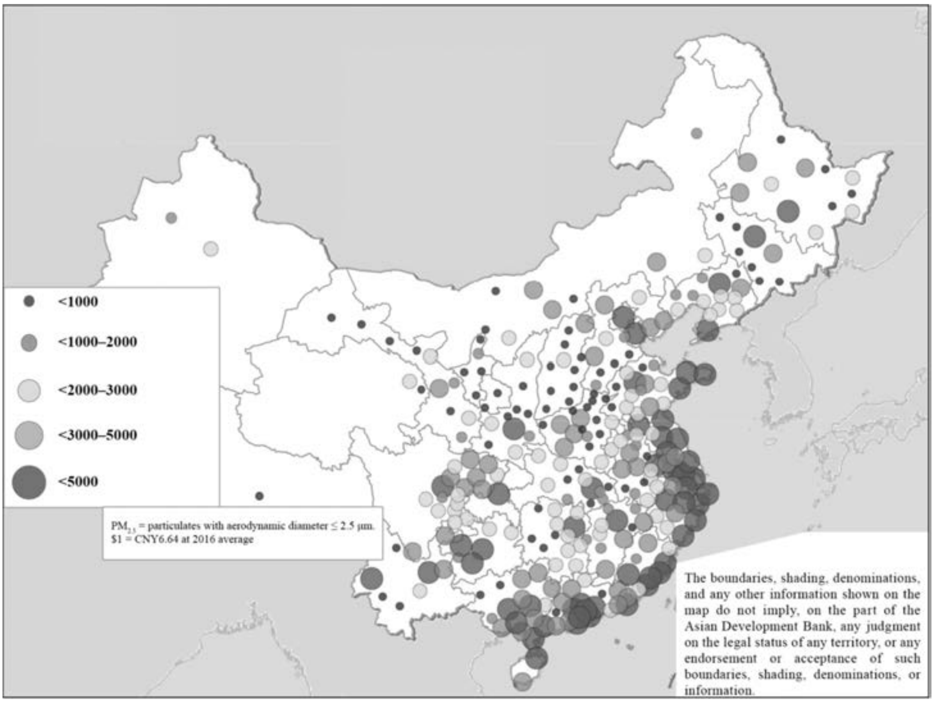


CNY = yuan.
Source: Authors' calculations.

B. Total Cost of $PM_{2.5}$ Mortality, Benefit of a Uniform 10 $\mu g/m^3$ Decrease in $PM_{2.5}$ Concentration, and Benefit of Meeting WHO AQG and Interim Targets

In the second set of results, we determine welfare outcomes by analyzing the monetary terms of different $PM_{2.5}$ mortality impacts. We begin with the total cost estimates; that is, the total cost of $PM_{2.5}$ mortality. It represents a majority of the annual social welfare loss if ambient fine particulate pollution remains unchanged. In other words, total cost is the theoretical maximum benefit that could result from reducing the current $PM_{2.5}$ concentration to zero. In major cities in the PRC in 2016, it aggregated to about CNY1,172 billion. The spatial distribution of total cost is shown in Figure 2. Megacities in the Beijing–Tianjin–Hebei and Yangtze River Delta regions, as well as Chengdu and Chongqing in the central PRC, have the highest total cost. Income, population, and $PM_{2.5}$ concentration are all high in these cities, pulling up their total cost estimates. In the highly developed Pearl River

Figure 3. **The Benefits of Mortality Reduction from a Uniform 10 μg/m^3 Decrease in $PM_{2.5}$ Concentration Reduction** (CNY million)

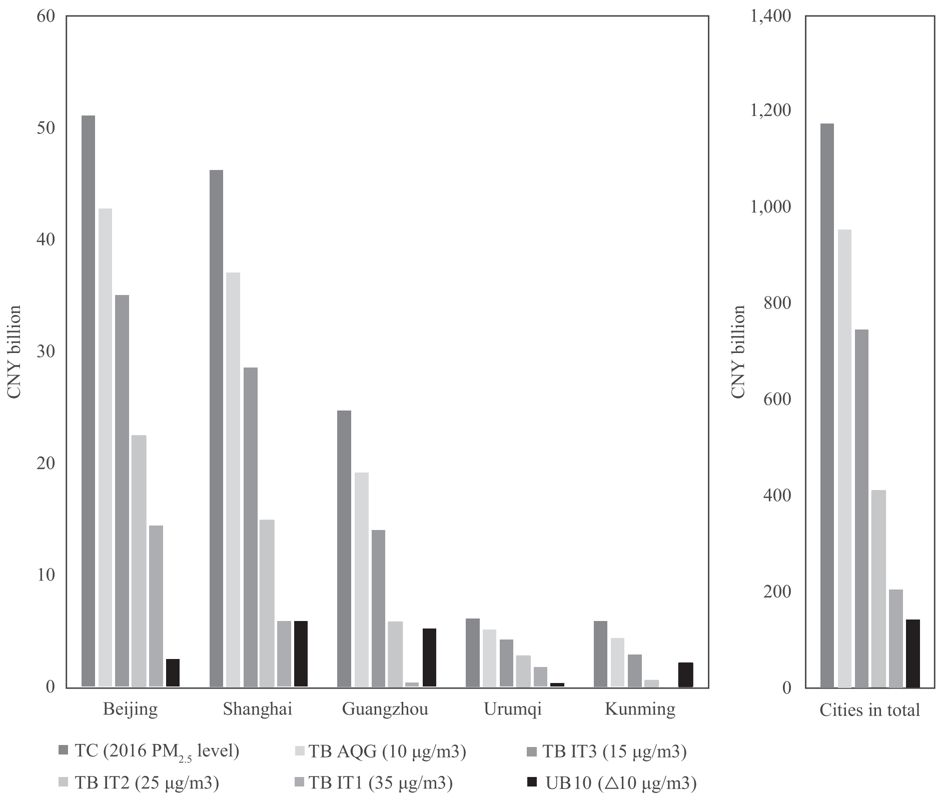


CNY = yuan.
Source: Authors' calculations.

Delta region, although $PM_{2.5}$ concentration is relatively low, populated cities such as Guangzhou and Shenzhen have very high total cost.

We then consider UB_{10}, that is, the benefit of mortality reduction from a uniform 10 μg/m^3 decrease in $PM_{2.5}$ concentration in 2016 in each city. It should be noted that for most of the PRC's cities with currently high $PM_{2.5}$ concentration levels, UB_{10} measures the near-term and achievable benefits of implementing effective fine particulate pollution control measures. In contrast, for cities with a very low $PM_{2.5}$ concentration, a further decline of 10 μg/m^3 is a big reduction and may be difficult to achieve. The total UB_{10} of all cities in 2016 was about CNY141 billion. Importantly, the spatial distribution of the UB_{10}, shown in Figure 3, is very different from that of the total cost, shown in Figure 2. Beijing, Tianjin, Chongqing, and provincial capitals with high $PM_{2.5}$ concentrations such as Chengdu and Shenyang have high UB_{10} values. However, cities with medium and low $PM_{2.5}$ concentrations, high incomes, and high populations, such as those along the eastern and southern coastline, also have very high UB_{10}.

Figure 4. **Total Cost of $PM_{2.5}$ Mortality, Total Benefits of Meeting Different Air Quality Standards, and Benefits of a Uniform 10 $\mu g/m^3$ Decrease in $PM_{2.5}$ Concentration**



AQG = World Health Organization's Air Quality Guidelines, CNY = yuan, IT = World Health Organization's Air Quality Interim Target, $PM_{2.5}$ = particulates with aerodynamic diameter ≤ 2.5 μm, TB = benefit of mortality reduction achieved by meeting certain air quality targets, TC = total cost of $PM_{2.5}$ mortality, UB_{10} = benefit of a uniform 10 $\mu g/m^3$ decrease in $PM_{2.5}$ concentration.
Notes: The scales are different in the vertical axes of the left and right panels. \$1 = CNY6.64 (2016 average prices).
Source: Authors' calculations.

Next, we compare the values for total cost with total benefit, which include the benefit of a reduction of mortality achieved by meeting different air quality targets and a uniform 10 $\mu g/m^3$ decrease in fine particulate pollution concentration for five representative cities and for all cities (Figure 4). Intuitively, it seems that more stringent air quality targets will have greater benefits. However, a disproportionately increasing trend can be seen from $TB_{IT\text{-}1}$ to $TB_{IT\text{-}3}$ and finally TB_{AQG}. This is due to the concavity of the CR relationship between $PM_{2.5}$ concentration and mortality. The current PRC's AQS of 35 $\mu g/m^3$, which is equal to WHO's first interim target, represents a huge reduction in $PM_{2.5}$ concentration for some cities, but the associated benefit ($TB_{IT\text{-}1}$) is very small (less than one-third of the total cost). Cities will achieve a much higher total benefit ($TB_{IT\text{-}3}$) (more than

Table 2. **Top 20 Cities for Attributable Premature Deaths, TC, $TB_{IT\text{-}3}$ (15 $\mu g/m^3$), and UB_{10}**

Attributable Premature Deaths		Total Cost		Total Benefit $_{IT\text{-}3}$ (15 $\mu g/m^3$)		UB_{10}	
Top 20 Cities	**Deaths**	**Top 20 Cities**	**CNY billion**	**Top 20 Cities**	**CNY billion**	**Top 20 Cities**	**CNY million**
Chongqing	36,113	Chongqing	56.0	Chongqing	36.7	Shanghai	5,837
Tianjin	17,032	Beijing	51.1	Beijing	35.0	Guangzhou	5,190
Beijing	17,030	Shanghai	46.2	Shanghai	28.6	Chongqing	4,858
Shanghai	15,302	Tianjin	33.1	Tianjin	22.5	Nanjing	3,494
Chengdu	12,692	Nanjing	29.3	Nanjing	18.6	Shenzhen	3,051
Nanjing	11,190	Guangzhou	24.7	Chengdu	16.1	Beijing	2,452
Xi'an	10,803	Chengdu	23.9	Guangzhou	14.0	Hangzhou	2,192
Guangzhou	9,256	Xi'an	20.2	Xi'an	13.8	Shantou	2,123
Shijiazhuang	9,021	Hangzhou	19.2	Hangzhou	12.2	Kunming	2,076
Zhengzhou	8,417	Wuhan	17.0	Wuhan	11.2	Suzhou	2,057
Wuhan	8,149	Suzhou	16.5	Jinan	10.6	Xiamen	1,912
Shenyang	7,468	Shenyang	15.3	Suzhou	10.4	Tianjin	1,776
Harbin	7,406	Jinan	15.2	Shijiazhuang	10.2	Foshan	1,768
Hangzhou	7,006	Zhengzhou	14.6	Zhengzhou	10.2	Qingdao	1,711
Tangshan	6,802	Shijiazhuang	14.4	Shenyang	9.9	Chengdu	1,634
Jinan	6,752	Qingdao	13.0	Changsha	8.4	Fuzhou	1,561
Xuzhou	6,266	Changsha	12.9	Harbin	8.3	Nanning	1,429
Baoding	6,107	Harbin	12.9	Tangshan	8.3	Shenyang	1,371
Suzhou	5,780	Changzhou	12.5	Qingdao	8.2	Putian	1,336
Qingdao	5,711	Tangshan	12.0	Changzhou	8.1	Wuhan	1,326

CNY = yuan, IT = World Health Organization's Air Quality Interim Target, $PM_{2.5}$ = particulates with aerodynamic diameter $\leq 2.5\ \mu m$, UB_{10} = benefit of a uniform 10 $\mu g/m^3$ decrease in $PM_{2.5}$ concentration.
Notes: Total benefit (TB) refers to the benefit of mortality reduction achieved by meeting certain air quality targets. Total cost refers to the total cost (TC) of $PM_{2.5}$ mortality. \$1 = CNY6.64 (2016 average prices).
Source: Authors' calculations.

one-half of the total cost) if the annual $PM_{2.5}$ concentration is lower than WHO's third interim target level of 15 $\mu g/m^3$. When cities meet WHO's AQG, the TB_{AQG} is about 80% of the total cost. Figure 4 illustrates the welfare implications of the uniform 10 $\mu g/m^3$ decrease in fine particulate pollution concentration for different cities. For dirty cities such as Beijing and Urumqi, UB_{10} is much lower than the total benefit, whereas for clean cities such as Guangzhou and Kunming, it corresponds to a significant pollution reduction and is therefore comparable to the total cost.

In Table 2, we list the 20 cities with the highest estimates of attributable premature deaths along with their corresponding total cost, total benefit of WHO's third interim target (15 $\mu g/m^3$), and the benefit of a uniform 10 $\mu g/m^3$ decrease in $PM_{2.5}$ concentration. The cities' rankings of total cost and total benefit of WHO's third interim target vary slightly from their ranking of premature deaths, but the ranking of UB_{10} is totally different from the other three measures. In fact, among the cities with the most deaths, cleaner and dirtier cities swap rankings for the UB_{10}, and many new cities that are generally cleaner and wealthier appear on the UB_{10}'s top 20 list.

C. Comparing Cities Using per Capita Welfare Indicators

Our third set of results considers per capita welfare indicators. We use them to remove the influence of huge disparities in cities' populations on our results. Due to space limitations, we focus on per capita total cost and per capita UB_{10}. Per capita total cost can be interpreted as the economic cost of the annual attributable mortality risk for an average individual in city *i* in 2016. Per capita UB_{10} represents the economic benefit of this individual's mortality risk reduction from a 10 μg/m^3 decrease in $PM_{2.5}$ concentration. We also study how income and $PM_{2.5}$ pollution levels influence individual welfare. Ideally, we would use subsamples of populations with different socioeconomic statuses within and across cities for this purpose. However, due to data limitations, we only approximately examine this issue by looking at the difference between low- and high-income cities. We equally divide the cities into five income groups with the first group having the lowest income and the fifth group having the highest income. Then we plot the per capita total cost and per capita UB_{10} for these cities against the $PM_{2.5}$ concentration, as shown in Figures 5 and 6, respectively. The areas of the circles represent the city's population.

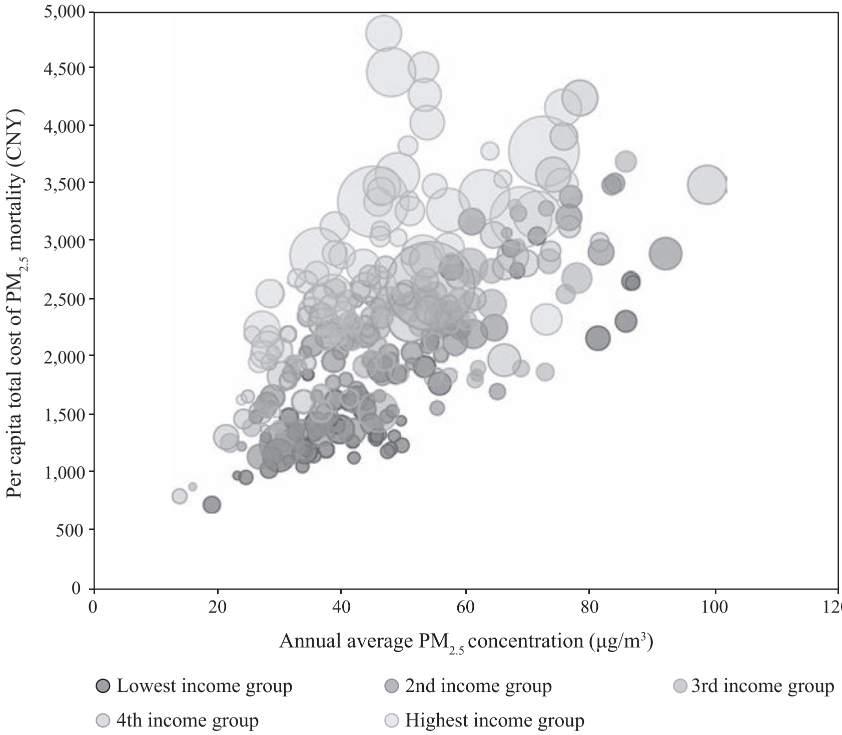
For per capita total cost in Figure 5, we see that cities with the highest per capita total cost are high-income cities with $PM_{2.5}$ concentrations between 40 μg/m^3 and 60 μg/m^3. Residents in low-income and high $PM_{2.5}$ concentration cities (see the circles for the first and second income groups with $PM_{2.5} > 60$ μg/m^3) bear a greater burden in terms of the economic costs of $PM_{2.5}$ mortality.

Figure 6 shows a clear trend of decreasing per capita UB_{10} as $PM_{2.5}$ concentration increases. This is contrary to the conventional understanding that the first unit of pollution reduction has the highest benefit. As indicated in previous analyses, this is due to the concavity of the $PM_{2.5}$ CR function. In each income group, the per capita UB_{10} spans a wide range, from about CNY100 to CNY900.

D. How Do Cities in the People's Republic of China Differ from Cities in Other Countries?

Our last exercise is to compare the results for cities in the PRC with those in other countries. We choose two megacities in developed countries, New York City (population 8.5 million; annual $PM_{2.5}$ concentration in 2016, 13.5 μg/m^3) and Seoul (population 10.3 million; annual $PM_{2.5}$ concentration in 2016, 27 μg/m^3). We also choose Monrovia (population 1.1 million; annual $PM_{2.5}$ concentration in 2016, 22 μg/m^3), the capital city of Liberia, to represent cities in least developed countries. We perform the same total cost and UB_{10} estimation process on the three cities. It should be noted that it is a huge step for cities with low $PM_{2.5}$ concentrations to further reduce them by 10 μg/m^3 (e.g., for New York City, the final $PM_{2.5}$ concentration would be near zero).

Figure 5. **Per Capita Total Cost for Cities with Different Incomes and $PM_{2.5}$ Concentrations**

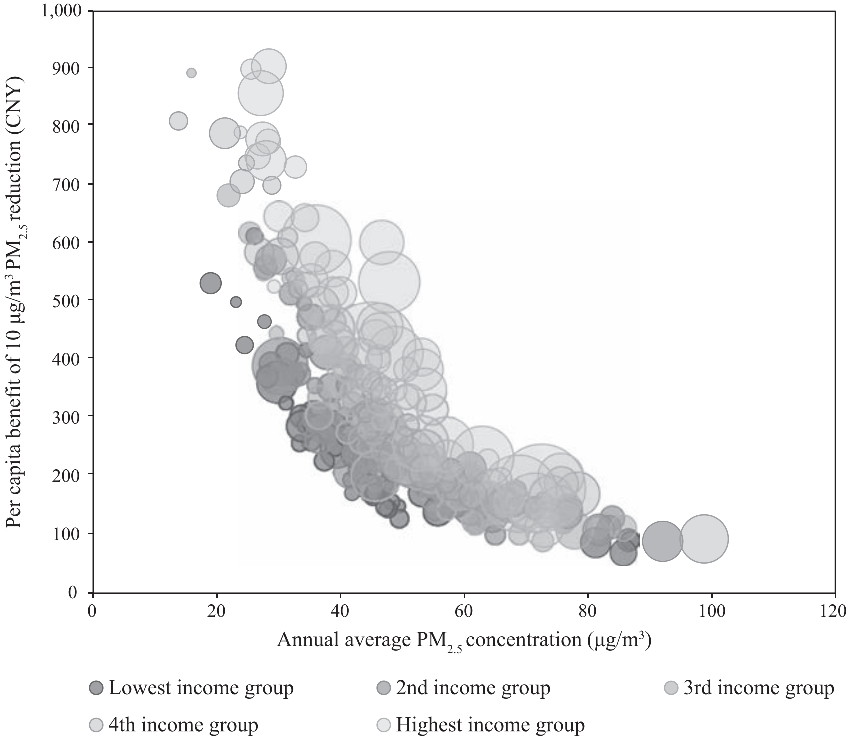


CNY = yuan, $PM_{2.5}$ = particulates with aerodynamic diameter ≤ 2.5 μm.
Notes: Cities are divided into five equal groups according to urban per capita disposable income, from the 1st (lowest income group) to the 5th (highest income group). Circle size represents the affected population in each city. \$1 = CNY6.64 (2016 average prices).
Source: Authors' calculations.

Figure 7 shows the estimated per capita total cost for all these cities. The results for the PRC's cities are well below CNY5,000, whereas they are near CNY15,000 for New York City and CNY20,000 for Seoul. Similarly, Figure 8 indicates that the per capita UB_{10} is much lower in cities in the PRC than in cities in developed countries. The huge differences are mainly due to the concavity of the CR function and the income disparity between cities in the PRC and those in developed countries.

Figure 9 further explains the difference in the benefit of a uniform 10 μg/m^3 decrease in fine particulate pollution concentration between cities. In the right part of Figure 9, we show several typical cities along the per capita UB_{10} curve, from those with low pollution levels (Shenzhen, Sanya, and Kunming), through middle pollution levels (Guangzhou, Shanghai, and Zhangye), to high pollution levels (Chongqing, Beijing, Urumqi, and Hengshui). These cities also vary significantly

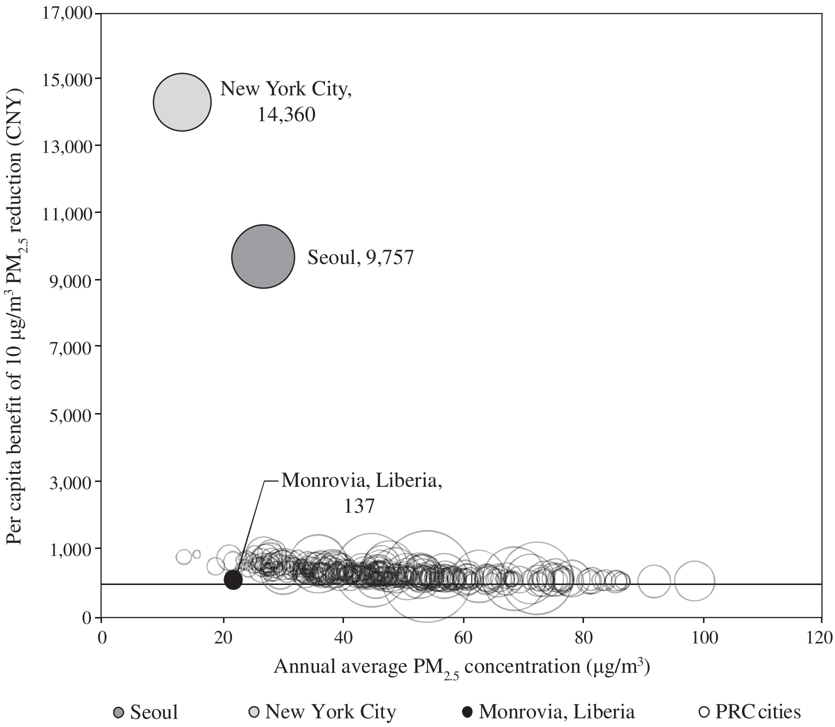
Figure 6. **Per Capita Benefit of Reduction in Mortality from a 10 μg/m^3 Decrease in $PM_{2.5}$ Concentration for Cities with Different Per Capita Incomes and $PM_{2.5}$ Concentrations**



CNY = yuan, $PM_{2.5}$ = particulates with aerodynamic diameter $\leq$2.5 μm.
Notes: Cities are divided into five equal parts according to urban per capita disposable income, from 1st (lowest income group) to 5th (highest income group). Circle size represents the affected population in each city. \$1 = CNY6.64 (2016 average prices).
Source: Authors' calculations.

in per capita income and population. For example, Beijing and Urumqi have almost the same $PM_{2.5}$ concentration levels, but Beijing has a higher per capita income than Urumqi; therefore, the per capita UB_{10} in Beijing is higher. On the left panel of Figure 9, we multiply per capita UB_{10} by each city's population and get squares representing the size of the UB_{10}. In this figure, the difference in the populations of Beijing and Urumqi results in more widely differing UB_{10}. Similarly, all cities with high $PM_{2.5}$ concentrations have relatively lower UB_{10}, and cities with middle to high pollution levels, relatively small populations, and low per capita income have the lowest (e.g., Hengshui, Urumqi, and Zhangye). Figure 9 also suggests that when dirty cities reduce their fine particulate pollution enough to enter the lower $PM_{2.5}$ concentration ranges, the UB_{10} of a further reduction significantly increases. For example, if Beijing's concentration decreases to the level of Shanghai's, they

Figure 7. **Per Capita Total Cost for Cities in the PRC versus Monrovia, New York City, and Seoul**



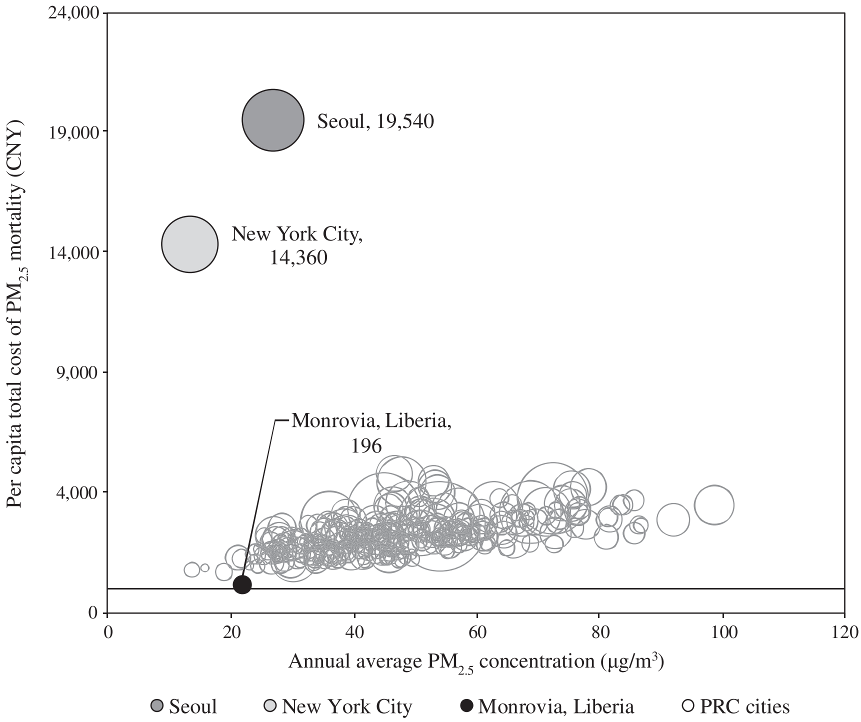
CNY = yuan, $PM_{2.5}$ = particulates with aerodynamic diameter ≤ 2.5 μm, PRC = People's Republic of China.
Notes: \$1 = CNY6.64 (2016 average prices). Circle size represents the affected population in each city.
Source: Authors' calculations.

would have similar UB_{10} values, and if they both become as clean as Shenzhen, they would have very large values.

V. Policy Implications

The first and foremost implication of our results is that when $PM_{2.5}$ pollution is high, the benefit of controlling it is relatively low. Thus, the PRC and other emerging economies with high levels of fine particulate pollution should accelerate their pollution control processes. Although the optimal $PM_{2.5}$ control pathway and speed depend on factors such as projections of changes in a country's technology, economy, and population, the implications of the relative size differences of the total benefit, and the increasing trend of UB_{10} are clear: given compliance costs and assuming steady economic development, the lower the $PM_{2.5}$ concentration, the more beneficial an extra pollution control effort is to society.

Figure 8. **Per Capita UB_{10} for Cities in the PRC versus Monrovia, New York City, and Seoul**

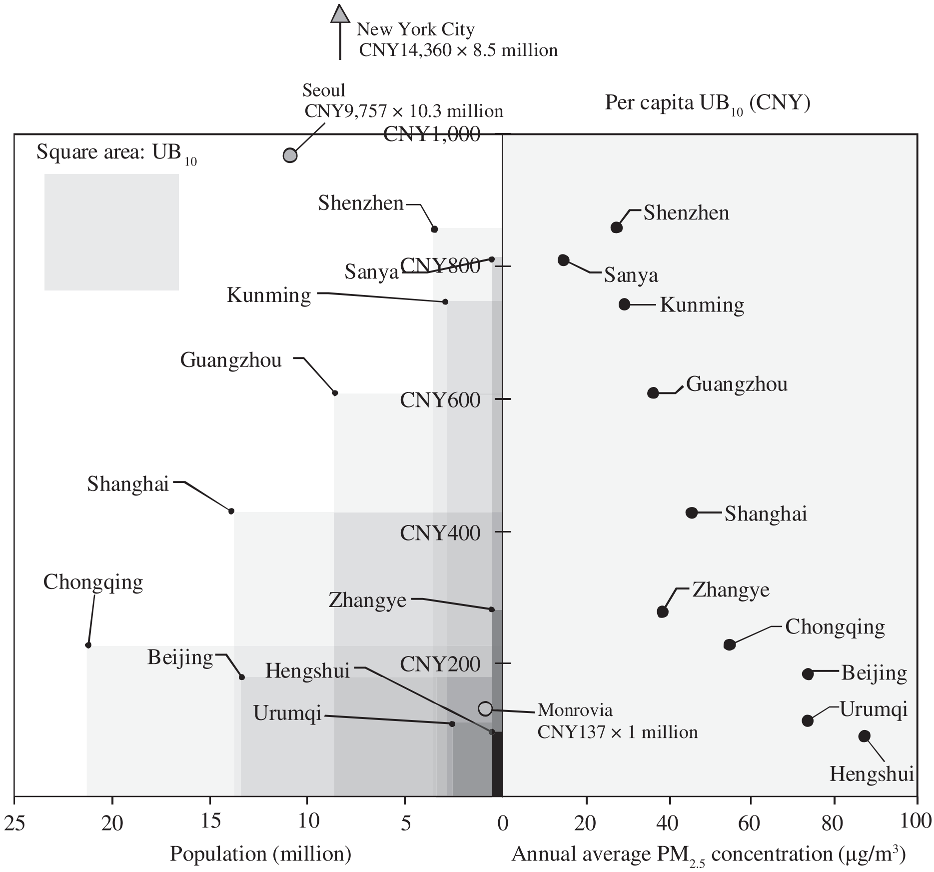


CNY = yuan, $PM_{2.5}$ = particulates with aerodynamic diameter ≤2.5 μm, PRC = People's Republic of China, UB_{10} = benefit of a uniform 10 $\mu g/m^3$ decrease in $PM_{2.5}$ concentration.
Notes: S1 = CNY6.64 (2016 average prices). Circle size represents the affected population in each city.
Source: Authors' calculations.

Second, our results highlight the importance of considering the cost effectiveness of $PM_{2.5}$ control policies. This is especially relevant for cities with high pollution levels. To reach the socially optimal pollution level, an efficient policy requires that the marginal cost of pollution reduction is smaller than the marginal benefit.[14] Thus, for cities with a UB_{10} that is close to the marginal benefit of pollution reduction, policies to reduce high pollution have to be very cost effective. However, in the PRC and many developing countries, the cost of controlling $PM_{2.5}$ across sites and sectors is unclear. Sound economic analyses of the available technologies and policy instruments are urgently needed to enhance the cost effectiveness of $PM_{2.5}$ control. Furthermore, as fine particulate pollution can be transported over long distances, regional control strategies that combine the

[14]This is not necessary in a dynamic efficiency perspective. Dynamic efficiency favors the policy that maximizes the sum of the present value of the net benefit for each period.

Figure 9. **UB_{10} for Typical Cities with Different Characteristics**



CNY = yuan, $PM_{2.5}$ = particulates with aerodynamic diameter ≤2.5 μm, UB_{10} = benefit of a uniform 10 $\mu g/m^3$ decrease in $PM_{2.5}$ concentration.
Note: $1 = CNY6.64 (2016 average prices).
Source: Authors' calculations.

efforts of neighboring cities and provinces are essential to cost-effective reductions in $PM_{2.5}$ concentrations (Wu, Xu, and Zhang 2015).

Third, our estimation scheme can be easily used by the general public and the government. Our approach mainly relies on official statistics and data on $PM_{2.5}$ annual concentrations. We focus on clearly defined jurisdictional urban areas rather than on cells in grids. As pollution control costs are usually calculated for specific programs and projects within certain jurisdictional areas, our approach helps to unify the cost–benefit analyses of $PM_{2.5}$ control. This helps local authorities to understand the trade-offs between the cost and benefit for their own administrative areas, and will help neighboring cities to coordinate their pollution control efforts through economic mechanisms (e.g., transfers).

Fourth, our results imply that current policy targets of uniform percentage reductions in regional $PM_{2.5}$ concentrations do not consider the significant heterogeneity in the welfare impacts of these reductions among cities with different characteristics. We show how income, population, and original fine particulate pollution levels can alter the welfare measures of $PM_{2.5}$ pollution reduction. More efficient pollution control policies could incorporate these factors and set differential targets for different cities. Our results also demonstrate the importance of equity considerations, which are a critical part of the policy-making process. We show that for low-income and high-pollution cities, the benefit of a uniform 10 $\mu g/m^3$ decrease in fine particulate pollution concentration is much lower than that for high-income and low-pollution cities. For the former, the sooner they enter the low $PM_{2.5}$ concentration range, the greater their benefit. However, these less advantaged cities often have more tension between economic growth and pollution control, and are therefore more likely to continue to have high pollution levels. Equity considerations would support the allocation of extra resources to these cities to accelerate the $PM_{2.5}$ control process.

VI. Conclusions

Air pollution, especially ambient $PM_{2.5}$, is one of the most pressing challenges for the PRC and many developing countries. It results in millions of premature deaths annually. Although a growing body of literature provides increasingly precise and high-resolution information on fine particulate pollution exposure and its health impacts at the regional, national, and provincial levels, the social welfare implications of $PM_{2.5}$ mortality in urban areas have remained unclear. Multiplying the estimated premature deaths by monetary values such as VSL does not generate accurate economic results due to the nonlinear concentration response relationship between $PM_{2.5}$ and mortality, disparities in income and population, and the mismatch between the grid cells commonly seen in the literature and the more policy-relevant jurisdictional areas.

This study develops an accessible estimation scheme to provide welfare implications for $PM_{2.5}$ mortality in urban areas of the PRC. Based on the integrated exposure-response model, our approach uses publicly available $PM_{2.5}$ concentration data and city-level socioeconomic statistics to estimate the total cost of $PM_{2.5}$ mortality, the benefit of a uniform $PM_{2.5}$ concentration reduction, and the benefit of meeting WHO AQG and interim targets for the urban areas of nearly 300 major PRC cities. The results suggest that in these cities the aggregated total cost of annual $PM_{2.5}$ mortality for 2016 is about CNY1,172 billion. The average per capita total cost is CNY2,255. The aggregated benefit of mortality reduction resulting from a uniform 10 $\mu g/m^3$ decrease in $PM_{2.5}$ concentration (UB_{10}) in these cities is about

CNY141 billion for 2016; the per capita UB_{10} is CNY321. Cities with high incomes and large populations that are located in areas with severe air pollution suffer the highest welfare losses, and the UB_{10} is lower than for cleaner cities. The benefit of meeting WHO's first interim target is very low relative to the benefit of meeting more stringent air quality targets. As most of the cities in the PRC still have $PM_{2.5}$ concentrations well above WHO's first interim target of 35 $\mu g/m^3$, local authorities need to accelerate fine particulate pollution control in a cost-effective manner. Only in this way can greater benefits of $PM_{2.5}$ mortality reduction be achieved.

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Appendix: List of Technical Terms

AF	attribution fraction of the mortality risks of a disease
CR function	concentration response function
IT-1	interim target of $PM_{2.5}$ concentration meeting 35 $\mu g/m^3$
IT-2	interim target of $PM_{2.5}$ concentration meeting 25 $\mu g/m^3$
IT-3	interim target of $PM_{2.5}$ concentration meeting 15 $\mu g/m^3$
IT	air quality interim target of the World Health Organization
$PM_{2.5}$	particulates with aerodynamic diameter $\leq$2.5 micrometers
$PM_{2.5}$ mortality	mortality attributable to ambient $PM_{2.5}$
PM_{10}	particulates with aerodynamic diameter $\leq$10 micrometers
RR	relative risk
TB_{AQG}	the benefit of mortality reduction achieved by meeting the World Health Organization's air quality guidelines
TB_{IT-1}, TB_{IT-2}, and TB_{IT-3}	the benefit of mortality reduction achieved by meeting the World Health Organization's interim targets 1, 2, and 3, respectively.
TC	total cost of $PM_{2.5}$ mortality
UB_{10}	the benefit of mortality reduction achieved by a uniform 10 $\mu g/m^3$ decrease in $PM_{2.5}$ concentration
VSL	value of a statistical life
$\mu g/m^3$	micrograms per cubic meter

Source: Authors' compilation.

Indonesia's Moratorium on Palm Oil Expansion from Natural Forests: Economy-Wide Impacts and the Role of International Transfers

Arief A. Yusuf, Elizabeth L. Roos, and Jonathan M. Horridge*

Indonesia has introduced a moratorium on the conversion of natural forests to land used for palm oil production. Using a dynamic, bottom-up, interregional computable general equilibrium model of the Indonesian economy, we assess several scenarios of the moratorium and discuss its impacts on the domestic economy as well as on regional economies within Indonesia. We find the moratorium reduces Indonesian economic growth and other macroeconomic indicators, but international transfers can more than compensate the welfare losses. The impacts also vary across regions. Sumatra, which is highly dependent on palm oil and is home to forests that no longer have a high carbon stock, receives fewer transfers and suffers the greatest economic loss. Kalimantan, which is relatively less dependent on palm oil and has forests with a relatively high carbon stock, receives more transfers and gets greater benefit. This implies that additional policy measures anticipating the unbalanced impacts of the moratorium are required if the trade-off between conservation and reducing interregional economic disparity is to be reconciled.

Keywords: carbon emissions, computable general equilibrium, Indonesia, palm oil
JEL codes: R10, R11, R13

I. Introduction

The United Nations Reduction of Emissions from Deforestation and Forest Degradation (REDD) program seeks to reduce carbon emissions resulting from deforestation and enhance carbon stocks in forests, while also contributing to national sustainable development (UN-REDD 2015). REDD supports developing countries in their efforts to mitigate climate change through the implementation of several activities. For example, financial mechanisms have been implemented

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to reduce deforestation and, therefore, carbon dioxide (CO_2) emissions by compensating countries and land owners for actions taken that prevent forest loss or degradation.

Deforestation and forest degradation have been estimated to contribute about 20% of global CO_2 emissions (Van der Werf et al. 2009). The main reason for deforestation is the conversion of forest to agricultural land for commercial and subsistence farming. Hosonuma et al. (2012) find that agricultural production contributes about 80% of deforestation worldwide, followed by mining and urban expansion. In Latin America, the main cause for deforestation is the expansion of cropland and pasture. From 2001 to 2013, it is estimated that 17% of new cropland and 57% of new pasture area was created by converting forest area (Graesser et al. 2015, De Sy et al. 2015). In sub-Saharan Africa, deforestation is mainly driven by the high demand for crop commodities such as cocoa and palm oil (Ordway, Asner, and Lambin 2017). Other determinants of the rates of deforestation in sub-Saharan Africa include population growth and the discovery of extractive resources such as oil and gas (Rudel 2013). In Southeast Asia, deforestation is driven by growth in the consumption of vegetable oil, such as palm oil, which is used in food and biodiesel. Within Southeast Asia, Indonesia contributes significantly to CO_2 emissions. Over the period 1990–2010, the forest cover in the peatlands of Peninsular Malaysia, Sumatra, and Borneo fell from 77% to 36%. Sumatra now only has 28% of its historical forested peatlands left after years of deforestation (Miettinen, Shi, and Liew 2012).

Several studies have been conducted to evaluate the economic viability of an incentive payment to reduce deforestation and CO_2 emissions. The viability and effectiveness of incentive payments depends on the profitability of alternative land uses (Butler, Koh, and Ghazoul 2009) and the price of CO_2 per ton (Sandker et al. 2010). For example, Sandker et al. (2010) developed a systems dynamics model for a cocoa agroforest landscape in southwestern Ghana to explore whether REDD payments are likely to promote forest conservation and what the economic implications would be. They find that in the short term, REDD payments are likely to be preferred by farmers, especially if there is a large annual up-front payment and when the policy only focuses on payments that end deforestation of old-growth forests. However, soon after the up-front payment, there may be an incentive to break the contract due to the higher rental returns from cocoa production. REDD payments may not be effective in avoiding deforestation of degraded forests since this is the type of land required for the expansion of cocoa production. If cocoa prices increase, the carbon prices should be even more than \$55 per ton of CO_2 to stop deforestation of old-growth forests (Sandker et al. 2010). Butler, Koh, and Ghazoul (2009) model and compare the profitability of converting forest to oil palm against conserving forests for a payment. They find that converting a hectare of forest to palm oil production is more profitable to land owners than preserving it for carbon credits. They suggest that giving REDD credits price parity with traded carbon credits would boost the profitability of avoiding deforestation (Butler, Koh, and Ghazoul 2009). Bellassen and Gitz (2008) calculate the breakeven price of carbon, which yields comparable revenue for preserving forests or shifting cultivation in Cameroon. They calculate that a breakeven price of $2.85 per ton of CO_2 would generate similar revenue values. They suggest that at current CO_2 prices it could be more profitable to preserve the primary forest rather than converting it to crops (Bellassen and Gitz 2008). In general, it seems difficult to provide a framework for REDD, which is based on long-term contracts, given the fluctuation in agricultural commodity prices in the short term.

In this paper, we develop and apply a regional dynamic computable general equilibrium (CGE) model for Indonesia to investigate two scenarios regarding the moratorium placed on the conversion of managed and natural forest to oil palm plantations. In the first scenario, we model the moratorium in the absence of a once-off REDD payment. In the second scenario, we model the moratorium on land conversion and the role of a once-off REDD payment, while assuming a price of $10 per ton of CO_2 emissions.

The rest of this paper is structured as follows. Section II provides a background on the palm oil sector in Indonesia. This section discusses both the general development of the sector as well as how it relates to Indonesia's carbon emissions. The methodology used in this paper is discussed in section III, which mainly describes the CGE model used in the analysis. The data used for the model are described separately in section IV, while section V provides a detailed description of the construction of scenarios simulated using the model. Section VI discusses the results of the simulations and section VII concludes.

II. Palm Oil Sector in Indonesia

Indonesian economic growth has been highly dependent on its resource-based sectors.[1] In recent years, the palm oil sector has become one of the country's leading economic sectors and an important export-oriented industry. Palm oil is extracted from the bunches of plum-sized fruit borne by oil palm trees, which grow mostly in Malaysia and Indonesia.[2] Output has grown rapidly since the 1960s and it is now the world's highest-volume vegetable oil. It can be used for food, fuel, and other industrial purposes.

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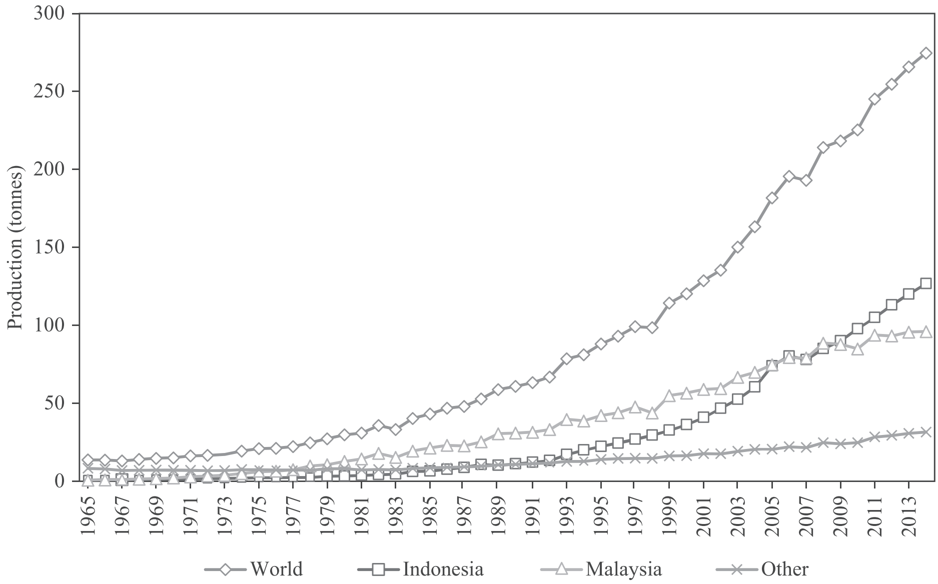
[1]Indonesia has significant natural resource reserves. It is a leading exporter of steam coal, tin, nickel, gold, bauxite, lead, copper, and zinc. In recent years, over 40% of Indonesian exports were mineral and petroleum products. Globally, Indonesia is also the largest palm oil producer and exporter, and the second-largest exporter of rubber, robusta coffee, and fish products (Dutu 2015).

[2]See Malaysian Palm Oil Board. Malaysian Palm Oil Industry. http://www.palmoilworld.org/about_malaysian-industry.html.

Figure 1. **Global Production of Palm Oil, 1965–2014**



Source: Food and Agriculture Organization of the United Nations (FAO). 2017. FAOSTAT Online Statistical Service. http://www.fao.org/faostat/en/#home (accessed July 15, 2015).

A. Development of the Palm Oil Sector in Indonesia

The development of the Indonesian palm oil sector dates to the early 1960s when 70,000 hectares were developed for harvesting. With an average productivity of 13.4 tons per hectare, Indonesia was able to produce approximately 936,000 tons of palm oil (Food and Agriculture Organization [FAO] 2017). Rapid developments in this sector occurred in 1980, when the government changed the plantation scheme. Before 1980, only the state-owned plantation company could operate. After 1980, however, both private plantations and smallholder plantations could also operate.

The immediate impact of this policy was an increase in plantation area to 204,000 hectares, with a production of 3.4 million tons, in 1980. In 2014, Indonesia was the world's largest producer of palm oil with a production capacity of 126.7 million tons on 7.4 million hectares of cultivated land (FAO 2017). Figure 1 shows global production of palm oil, which is dominated by Indonesia and Malaysia. Other producers include Cameroon, Colombia, Ghana, Nigeria, and Thailand, which collectively account for less than 15% of global production.

The increase in Indonesia's production of palm oil has partly been driven by transforming natural forests into plantation land. While FAO data show an increase in the area harvested from 204,000 hectares in 1980 to 7.4 million hectares in 2014, there was hardly any change in productivity during this period. The productivity from oil palm plantation in Indonesia increased from 11.1 tons per hectare in 1965 to an average of 17 tons per hectare in 2014. Over the last 2 decades, there has been little productivity improvement in Indonesia.

In contrast, Malaysia has a well-developed palm oil sector. Not only has Malaysia increased its production area, it also focused on increasing productivity. A contributing factor to Indonesia's low productivity is the involvement of small-scale palm oil producers. In 2010, 42% of total oil palm plantation holders were small-scale producers (Burke and Resosudarmo 2012). On one hand, the small-scale producers increase community involvement and provide economic benefits to rural communities, especially those in Sumatra and Kalimantan (Burke and Resosudarmo 2012). However, small-scale plantation owners typically have below-average levels of productivity (Burke and Resosudarmo 2012, Rudel et al. 2009).

Palm oil production is an important driver of Indonesian growth. Indonesia is also the world's largest exporter of palm oil (Burke and Resosudarmo 2012). In 2013, exports of Indonesian palm oil products reached 20.5 million tons and were valued at about $17 billion (FAO 2017).

Palm oil production in Indonesia is mainly located on the islands of Sumatra and Kalimantan. In 2012, Sumatra contributed approximately 73% to the national production of palm oil. Within Sumatra, Riau is the province with the greatest planted area and highest level of production. This province has 1.9 million hectares of palm plantations and produces 5.8 million tons of palm oil. Kalimantan (Borneo) contributes approximately 23% to the country's total palm oil production. Most recently, the government has also promoted palm oil production in the eastern part of Indonesia. Over the last 5 years, the area under cultivation in Central Sulawesi and Southeast Sulawesi increased annually by 17.8% and 15.4%, respectively.

B. Indonesia's Palm Oil Sector and Carbon Emissions

Indonesia contributes significantly to deforestation in Southeast Asia via the conversion of peat swamp forests for commercial use. Over the period 1990–2010, the proportion of forest cover in the peatlands of Malaysia and Indonesia (Sumatra and Borneo) fell from 77% to 36% (Miettinen, Shi, and Liew 2012). Miettinen et al. (2012) suggest that if current levels of peatland deforestation continue, then Southeast Asian peat swamp forests will disappear by 2030. This conversion has serious consequences for the environment by releasing greenhouse gases and damaging forest ecosystems and the communities that rely on forests for survival (Miettinen et al. 2012, Burke and Resosudarmo 2012, Carlson et al. 2013, Rudel et al. 2009).

Focusing on Indonesia, Miettinen et al. (2013) use historic analysis to show that 70% of all industrial plantations have been established since 2000, while only

4% of the current plantation area existed in 1990. They estimate that if future conversion rates are similar to historic conversion rates, 6–9 million hectares of peatland in insular Southeast Asia could be converted into plantations by 2020, leading to increased annual CO_2 emissions of 380–920 million tons by the same year. Miettinen et al. (2013) present a time series of peatland conversion and degradation in the Air Hitam Laut peatland in Jambi Province located in Sumatra. They use high-resolution satellite imagery to map land cover and degradation status between 1970 and 2009. They find that forest cover declined from 90% to 43% in the study area during the review period. Within the Berbak National Park, forest area fell from 95% to 73%; outside the national park, it fell from 86% to 25%. They also find that large-scale oil palm plantations and smallholder producers accounted for 21% and 8%, respectively, of the conversion (Miettinen et al. 2013).

Abood et al. (2015) compare the magnitude of forest and carbon loss, and forest and carbon stocks remaining, in four key industries: palm oil, logging, fiber, and coal mining. They find that the four industries accounted for 44.7% of forest loss in Kalimantan, Sumatra, Papua, Sulawesi, and Moluccas between 2000 and 2010. They rank third in the palm oil industry in terms of deforestation and second in terms of CO_2 emissions.

A recent study by Carlson et al. (2013) found that net cumulative greenhouse gas emissions from oil palm plantations in 2010–2020 are projected to reach 1.52 gigatons of CO_2. They also projected that during the same period, the carbon emissions from oil palm plantations in Kalimantan would rise by 284% and contribute 27% of Indonesia's projected land-based emissions in 2020. This undermines the government's efforts to reduce greenhouse gas emissions by 26% relative to the business-as-usual scenario by 2020. Considering the entirety of Indonesia's plantation area, the emissions from palm oil alone will prevent the country from reaching its 2020 target.

III. Modeling the Moratorium on Land Conversion in Return for a Payment

Capturing the regional impact of a moratorium on land conversion in return for a payment requires a detailed regional multisector model of Indonesia that accounts for changes in land availability and CO_2 emissions.[3] For this paper, we use INDOTERM, a multiregional, recursive dynamic general equilibrium model based on the well-known TERM model developed by Horridge (2012). This section provides a more detailed description of the INDOTERM model and the modeling of the land supply used in palm oil production.

[3]A more comprehensive discussion on the model's description can be read in the earlier and longer version of this paper in Yusuf, Roos, and Horridge (2017).

While the complete model is too large to describe in this paper, a comprehensive description is contained in Horridge (2012) and Horridge, Madden, and Wittwer (2005). The TERM model was created for Australia (Horridge, Madden, and Wittwer 2005; Wittwer 2012) and adopted for South Africa (Stofberg and Van Heerden 2016); Poland (Zawalinska, Giesecke, and Horridge 2013); Brazil (Ferreira Filho, dos Santos, and do Prado Lima 2010); the People's Republic of China (Horridge and Wittwer 2008); and Indonesia (Pambudi and Smyth 2008; Pambudi, McCaughey, and Smyth 2009; Pambudi 2005). As the theory of the TERM model and data structures are well documented, in this paper we provide an overview only.

INDOTERM consists of two interdependent modules. The first module describes the core model equations related to the region-specific behavior of producers, investors, households, governments, and exporters at a regional level. It also describes the dynamic mechanism in the model: capital accumulation and labor market adjustment. The second module describes the treatment of land-use change, emissions, and REDD payments.

The core model equations describe the behavior of producers, investors, households, governments, and exporters at a regional level. Producers in each region are assumed to minimize production costs subject to a nested constant returns to scale production technology. In this nested structure, each regional industry's inputs of primary factors are modeled as a constant elasticity of substitution (CES) aggregate of labor, capital, and land inputs. Commodity-specific intermediate inputs to each regional industry are modeled as CES composites of foreign and domestic varieties of the commodity. Labor inputs used by each regional industry are distinguished by occupation, with substitution possibilities over occupation-specific labor described via CES functions specific to each regional industry. In each region, the representative households are assumed to choose composite commodities to maximize a Klein–Rubin utility function. Households and firms consume composite commodities that are assumed to be CES aggregations of domestic and imported varieties of each commodity. The allocation of investment across regional industries is guided by relative rates of return on capital. For each region-specific industry, new units of physical capital are constructed from domestic and imported composite commodities in a cost-minimizing fashion, subject to constant returns to scale production technologies. Region-specific export demand for each commodity is modeled via constant elasticity demand schedules that link export volumes from each region to region-specific foreign currency export prices. Regional demand for commodities for public consumption purposes is modeled exogenously or linked to regional private consumption. For a detailed description of the input–output structure, see Horridge (2012).

As mentioned above, the core section includes equations determining the demand for factor inputs by industry. Typically, we model the demand for primary factors via the following optimization problem:

Each industry in all regions chooses $XPRIM_{(i,d)}$ to minimize total primary cost $\sum_i XPRIM_{(i,d)} * PPRIM_{(i,d)}$,[4] subject to

$$XPRIM_{(i,d)} = CES(LAB_{(i,d)}, CAP_{(i,d)}, LND_{(i,d)}) \tag{1}$$

where *LAB*, *CAP*, and *LND* are the overall labor, capital, and land demand, respectively. *PPRIM* and *XPRIM* are the primary factor price and quantity, respectively, in industry *i*. The percentage change form of the optimization problem yields the following demand equation for land:

$$xlnd_{(i,d)} = xprim_{(i,d)} - \sigma[plnd_{(i,d)} - pprim_{(i,d)}] \tag{2}$$

Equation (2) implies that in the absence of any price changes the demand for land moves in proportion to the overall demand for primary factors. The second term on the right-hand side shows the price-induced substitution effect between the primary factors. An increase in the price of land relative to the cost-weighted average of all three factors leads to substitution away from land in favor of the others. The magnitude of the change depends on the elasticity of substitution. It is common in CGE models to assume that the total quantity of land available for agricultural purposes are fixed.

The core model includes two dynamic mechanisms: capital accumulation and labor market adjustment. In each region, industry-specific capital is linked to industry-specific investment. Industry-specific investments are linked to changes in industry-specific rates of return. The labor market mechanism guides the labor market from a short-run environment (sticky real wages, flexible labor) to a long-run environment (flexible wage, fixed employment). Therefore, in the short run, positive (negative) outcomes are reflected in positive (negative) changes in employment (with no change in real wage), and in the long run are reflected as positive (negative) changes in real wage (with employment unchanged).

The second module describes the treatment of land-use change, emissions, and REDD payment. INDOTERM identifies five types of land use: crops, estate crops, oil palm plantation, managed forest, and natural forest. Below we specify a set of core equations that allow for the conversion of land use, emissions, and REDD payment. Specifically, we model (i) the conversion of natural forest to oil palm plantation; and (ii) the REDD payment, which is a once-off payment for the promise of not converting natural forest to oil palm plantations.

[4]In the INDOTERM database, Indonesia can be disaggregated regionally into 33 provinces. However, in this simulation we aggregate the provinces into 12 regions: West Sumatra (Aceh, Sumatra Utara, Sumatra Barat); East Sumatra (Riau, Kepulauan Riau, Jambi, Sumatra Selatan, Kep. Bangka Belitung, Bengkulu, Lampung); Northwest Java (DKI Jakarta, Jawa Barat, Banten); East Java (Jawa Tengah, DI Yogyakarta, Jawa Timur); West Kalimantan (Kalimantan Barat, Kalimantan Tengah); East Kalimantan (Kalimantan Selatan, Kalimantan Timur); North Sulawesi (Sulawesi Utara, Gorontalo, Sulawesi Tengah); South Sulawesi (Sulawesi Selatan, Sulawesi Barat, Sulawesi Tenggara); Bali Nusa Tenggara (Nusa Tenggara Barat, Nusa Tenggara Timur); Maluku (Maluku, Maluku Utara); and Papua (Papua Barat, Papua).

In this module, we do not explicitly model the supply of land available for agricultural purposes as a function of land rents. In other words, we do not model a supply curve. Instead, we take the quantity of total land available as exogenous and change the allocation of land between uses of land.

Our module begins with an equation that determines the change in land area, measured in thousands of hectares by industry and region as

$$\Delta AREA_{(i,d)} = \left[\frac{LNDAREA_{(i,d)}}{100}\right] * xlnd_{(i,d)} \text{ for } d \in REG, i \in \text{land using } IND \qquad (3)$$

where

- $\Delta AREA_{(i,d)}$ is the change in the amount of land available by industry i and region d,[5]
- $LNDAREA_{(i,d)}$ is the initial amount of the land available by industry i and region d, and
- $xlnd_{(i,d)}$ is the percentage change in the land rental value by industry i and region r (see equation 2).

Land may be used for either commercial purposes such as the cultivation of crops, estate crops, oil palm, managed forest, or classified as natural forest, which is defined as an undisturbed forest free of commercial activity.

Equation (4) determines the change in CO_2 emissions due to land-use change by region.[6] CO_2 intensity is measured as tons of CO_2 emissions per hectare. This equation states that the total change in CO_2 intensity by region is the sum of the product of the change in land area allocated to various land-using industries, including natural forest, and multiplied with the CO_2 intensity for each of these activities:

$$\Delta CO2_{(d)} = \sum_{i \in IND} CO2INT_{(i,d)} * \Delta AREA_{(i,d)} + CO2INTNF_{(d)} * \Delta NFAREA_{(d)} \qquad (4)$$

for $d \in REG$, $i \in$ land using IND
where

- $\Delta CO2_{(d)}$ is the total change in CO_2 emissions by region,

[5] A percentage change for the variable called x is defined as $x = \frac{\Delta X}{X} * 100$, where ΔX is the change in X and X is the initial value. The ordinary change in X can therefore be written as $\Delta X = (x * X) * 0.01$.

[6] As explained in section IV, converting land cover from one use (e.g., forest) to another (e.g., oil palm plantation) causes the volume of CO_2 stored in (or emitted from in the reverse case) the land cover to change. For example, natural forests store more CO_2 than plantations. If a natural forest is transformed into an oil palm plantation, which stores less CO_2 than a forest, more CO_2 is then emitted into the atmosphere.

- $CO2INT_{(i,d)}$ is the total CO_2 intensity measured as tons of emission per hectare for all industries using land,

- $CO2INTNF_{(d)}$ is the CO_2 intensity measured as tons of emissions per hectare of natural forest, and

- $\Delta NFAREA_{(d)}$ is the ordinary change in the natural forest area by region r.

Equations (5) and (6) allow us to impose two rules to simulate the different land conversion scenarios. The first rule (equation 5) states that half of the area allocated to oil palm plantations comes from managed forests. For example, if the land area for palm oil production increases by 2 hectares, 1 hectare of land will come from managed forest area. The remaining hectare comes from the conversion of natural forest to palm oil production. When this equation is operational in the business-as-usual scenario, we assume that both natural and managed forests contribute, in equal shares, to the oil palm plantation:

$$\Delta AREA_{(\text{“}Forestry\text{”},d)} = -0.5 * \Delta AREA_{(\text{“}OilPalm\text{”},d)} + f\_rule1_{(d)} \text{ for } d \in REG \tag{5}$$

The second rule is shown in equation (6). This equation states that an increase in the land allocated to palm oil production comes from only managed forests. When this rule is activated in the policy simulation, we place a moratorium on the areas converted from forest to palm oil production, allowing only the conversion from managed forests to palm oil production while conserving natural forests:

$$\Delta AREA_{(\text{“}Forestry\text{”},d)} = -\Delta AREA_{(\text{“}OilPalm\text{”},d)} + f\_rule2_{(d)} \text{ for } d \in REG \tag{6}$$

where

- $\Delta AREA$ is the change in the land area allocated to managed forestry and oil palm plantations by region, and

- f_rule1 and f_rule2 are shift variables used to activate or deactivate the respective equations.

Equation (7) calculates the change in the REDD payment by region as the difference between the REDD payment between 2 consecutive years:

$$\Delta REDD_{(d)} = REDD^{t}_{(d)} - REDD^{t-1}_{(d)} \text{ for } d \in REG \tag{7}$$

where

- $\Delta REDD$ is the change in the REDD payment between years t and $t-1$ by region d, and

- $REDD^{t}_{(d)}$ and $REDD^{t-1}_{(d)}$ are the REDD payments in 2 consecutive years by region d.

Equation (8) determines the REDD payment in year t as the carbon price per ton of CO_2 emissions multiplied by the fall in CO_2 emissions for that year. *BaseEmit* captures the base level of CO_2 emissions and is determined via equation (9). Equation (8) is activated in the policy simulation and states that if CO_2 emissions are above the base level of emissions, then the REDD payment will decline. Alternatively, if the CO_2 emissions fall in the policy simulation relative to the base level of emissions, then the REDD payment will increase. If the emissions in the policy simulation are fixed at the base level of emissions, the change in the REDD payment is zero:

$$REDD^{t}_{(d)} = CO2PRICE * \left[-\Delta CO2_{(d)} + BaseEmit_{(d)}\right] \text{ for } d \in REG \tag{8}$$

where

- $CO2PRICE$ is the carbon price per ton of CO_2 emissions,
- $\Delta CO2$ is the change in CO_2 emissions from changing the use of land and is determined in equation (4), and
- *BaseEmit* is the level of CO_2 emissions in the baseline simulation and determined via equation (9).

Equation (9) is operational only in the baseline simulation and determines the base level of CO_2 emissions. Baseline emissions by region are determined by the ordinary change in CO_2 emissions in the business-as-usual simulation (determined in equation 4) and a shift variable:

$$BaseEmit_{(d)} = \Delta CO2_{(d)} + f\_BaseEmit_{(d)} \text{ for } d \in REG \tag{9}$$

where

- *BaseEmit* is the base level of CO_2 emissions by region, and
- *f_BaseEmit* is a shift variable used to activate or deactivate the equation.

In the baseline simulation, the shift variable is exogenous and *BaseEmit* is endogenous. In the policy simulation, this equation is inoperative with the shift variable set endogenously and *BaseEmit* set exogenously.

In our theory, the REDD payment is directly paid to households in each region. Equation (10) determines the value of household income by region as the sum of labor income and the REDD payment. This equation also includes two exogenous shift variables that allows for uniform or region-specific changes to household income to be imposed.

$$HOUTOT_{(d)} = WAGE_{(d)} + f\_HOU_{(d)} + f\_HOU\_D + \Delta REDD_{(d)} \text{ for } d \in REG \tag{10}$$

where

- *HOUTOT* is the value of household income by region.
- *WAGE* is the wage income by region,
- Δ*REDD* is the ordinary change in the REDD payment by regions as determined in equation (7), and
- *f_HOU* by region and *f_HOU_D* are naturally exogenous shift variables that can be used to impose uniform or region-specific changes to household income.

The REDD payment is a payment to Indonesian households from a foreign donor and therefore we include the REDD payment with other net transfers from the rest of the world.[7] The final equation shows that the share of the nominal change in the balance of trade (BOT) and REDD payment to gross domestic product (GDP):

$$SHRBOTGDP = \frac{[\Delta BOT + \Delta NTROW]}{GDP} \tag{11}$$

where

- *SHRBOTGDP* is the share of the sum of *BOT* and *NTROW* to *GDP*,
- Δ*BOT* is the nominal change in the balance of trade, which is defined as exports minus imports,
- Δ*NTROW* is the change in net transfers abroad which is the sum of net remittances and the REDD payment, and
- *GDP* is nominal GDP.

In the policy simulations, we hold the *SHRBOTGDP* exogenous. This captures the idea that on a national level, Indonesia faces an external balance

[7]Net transfers from the rest of the world include payments received such as remittances and aid, as well as payments from Indonesia to the rest of the world.

constraint. We also note that assuming there is no change in *GDP* or *SHRBOTGDP*, an increase in the *NTROW* implies a fall in the nominal *BOT*.

IV. Description of the Database

Two large databases form the initial solution to the INDOTERM model. The base year in each is 2005.

A. The Core Database

The core TERM database is calibrated using various sources. These sources include the following:

(i) Indonesian National Input–Output Table 2005,

(ii) Indonesian Interregional Input–Output Table 2005,

(iii) regional share of production for each commodity for various years, and

(iv) Indonesian Social Accounting Matrix 2005.

The process of the construction of the INDOTERM database can be found in Horridge (2012) and Horridge and Wittwer (2008). The regional database consists of a set of matrices, capturing the 2005 structure of the Indonesian economy. We begin by creating a USE matrix valued at producers' price. This matrix shows the flow of commodity *c* from source *s* to user *u*. Values at producers' price are the sum of the flows of commodity *c* from source *s* to user *u* at basic price and the associated indirect tax. We also have a matrix capturing the margins that facilitate the flow of commodities. Value-added matrices include labor payments by industry and occupation, capital, and land rentals by industry, and production taxes by industry. The database is balanced in that the costs equal sales for each sector. From the national database we create regional input–output data and interregional flows of commodities. Detailed regional data are not available in the required format. We use regional output shares to inform us on the regional distribution of inputs and outputs. We then construct interregional trade matrices that show the trade of commodities between regions. Our task is made easier by assuming that industry-specific technologies are similar across regions. Given these assumptions, we ensure that regional data are consistent with national data with regard to land use and the CO_2 database. For a detailed description of the TERM database, see Horridge (2012).

B. Land Use and Carbon Dioxide Database

In parameterizing the land-use module, we require data on

(i) land area, measured in hectares, used for commercial purposes by region;

(ii) land area, measured in hectares, identified as natural forest by region; and

(iii) the CO_2 intensities per hectare by land use and region.

As mentioned before, land is used for either commercial purpose (crops, estate crops, oil palm, and managed forests) or classified as natural forest, which is defined as an undisturbed forest free of commercial activity.

For this study, we need to know the initial carbon stock stored in different land-use activities (e.g., crops, oil palm, and natural forests). Drawing on literature, CO_2 is stored in plant biomass and soil. For example, Agus et al. (2009) describe the carbon stored in various biomass and soils. They note that the amount of carbon stored varies by region and growth stage (e.g., oil palm) and depends on climate conditions, soil fertility, elevation and drainage, and land use.

CO_2 emissions occur when there is a change in land use. The amount of CO_2 emissions depends on the carbon stock of the biomass of the initial land before conversion takes place. For example, converting peatland, which stores a high level of carbon, to oil palm plantations will increase greenhouse gas emissions in the atmosphere, especially CO_2.

We do not have data on the CO_2 intensities per hectare by land use and region. To infer the CO_2 intensities per hectare and region, we use the following data: (i) carbon stock map, and (ii) land-use map. We obtained these maps from Minnemeyer et al. (2009).

We estimate the carbon intensity (CO_2 per hectare) by land-using sector (agriculture) and natural forest (forest area that is not used by any of the industries). To do that using geographic information system software, we overlay the two maps and calculate the average of carbon intensity.[8]

V. Simulation Design: Business-as-Usual, Moratorium, and Reduction of Emissions from Deforestation and Forest Degradation Payment

We run three simulations with the INDOTERM model:

[8]Here, we do not distinguish between peatland or other types of land since whether the land is peat or non-peat has implicitly been accounted for in the carbon stock map.

(i) **SIM0—the baseline simulation.** This simulation shows the growth of the Indonesian economy in the absence of the moratorium and REDD scheme. We assume that oil palm lands grow between 3% and 8% per annum, depending on the region, until 2030. We use regional oil palm land data to come up with this scenario. Higher growth regions include provinces in Kalimantan and lower growth regions are in Sumatra. We assume that half the oil palm land originates from natural forest and the other half from managed forest. This is roughly based on Carlson et al. (2013).

(ii) **SIM1–moratorium without international transfers.** This simulation reproduces the growth path of (i) but without further conversion of natural forest to oil palm. We assume that oil palm land still grows but from the conversion from managed forest.

(iii) **SIM2–moratorium with international transfers.** This simulation reproduces the growth path of (ii) but with a REDD payment proportional to the emissions saved by (ii). Therefore, in this simulation we convert the avoided deforestation into avoided CO_2 emissions and translate it into international transfers by multiplying the avoided emissions with the price of carbon (see equations 4 and 8). We used \$10 per ton of CO_2 emissions and distribute the transfers to the regions according to their magnitude of emissions reduction.[9] The transfers are given directly to representative households who will spend the money received as consumption spending (equation 10).

SIM0: Baseline Simulation

The baseline simulation is designed to serve as a plausible business-as-usual scenario for the future path of the Indonesian economy in the absence of the REDD scheme, or the absence of additional efforts to curb deforestation and carbon emissions. This baseline is used as a benchmark against which the economic impacts of reduced forest clearing with and without a REDD payment are measured.

Our baseline forecast is driven by projected changes in population, labor force, productivity, and foreign demand that are roughly consistent with Indonesia's recent GDP growth rates of 6% per annum. We impose the following exogenous changes for each year of the baseline simulation:

[9]The choice of \$10 per ton of CO_2 emissions was chosen based on similar earlier work for Indonesia that uses economic modeling such as in Busch et al. (2012). To our knowledge, this is the best study published that we can use as a reference. Busch et al. (2012) estimate the impacts that alternative national and subnational economic incentive structures for reducing emissions from deforestation (REDD+) in Indonesia would have had on greenhouse gas emissions and national and local revenue if they had been in place from 2000 to 2005. Throughout the analysis, Busch et al. (2012) use the carbon price of \$10 per ton of CO_2 emissions.

(i) The labor force and population grow at 2.5% and 1.5% per annum, respectively, over the entire simulation period. The higher growth rate for the labor force reflects (a) Indonesia's relatively young population, and (b) the idea that over time workers will migrate from informal to formal sectors, becoming more productive.

(ii) There is a continued increase in foreign demand for Indonesian commodities, including edible oils.

(iii) Labor productivity improves for all service industries by 3% per annum and for nonservice industries by 6% per annum.

Of special importance in our simulations are our assumptions regarding natural resource endowment and productivity. Natural resources not only refer to land as defined in section IV, but also include ore bodies, fish stocks, and other water activities. We assume the following:

(i) Land productivity rises by 3% per annum in all agricultural sectors, including crops, estate crops, oil palm, and managed forests. Improved land productivity is another way of increasing output in, for example, the palm oil sector.

(ii) Land productivity in all extractive sectors, except for oil and gas, rises by 2% per annum. The assumption of no growth in land productivity in the oil and gas sector reflects our view that Indonesian oil reserves offer little scope for an output increase.

(iii) For all land-using sectors, except the palm oil sector, we assume that the land area under cultivation is fixed. Although current Indonesian policy is to not allocate more land to the palm oil sector, we increase the land allocated to this sector. This is because there are still substantial natural forest areas previously allocated for oil palm that have not actually yet been converted. This factor, and perhaps a flouting of the policy, could allow the area under cultivation to rise. We assume that the land area for oil palm increases on a per annum basis by 8% in Kalimantan and Papua, 4% in East Sumatra and Sulawesi, and 3% in West Sumatra.

All regions expand during the simulation period but at different growth rates. Regional performance is dependent on the type of economic activity that is dominant in that particular region. For example, palm oil production is mainly located in Sumatra (78.5%) and Kalimantan (17.5%). Therefore, any changes, such as a moratorium on the expansion of oil palm plantations, would affect the regional growth of Sumatra and Kalimantan. The extent of this impact depends on these regions dependence on palm oil production and related sectors such as the edible oils industry since palm oil is used as an input into the production of edible oils. Kalimantan's economy is less palm oil dependent, whereas Sumatra has a higher dependency on palm oil and related industries such as edible oils industry. Kalimantan, for example, has a higher share of mining (20%) and manufacturing other than edible oils (28%) as part of its economy.

Another difference between Sumatra and Kalimantan is the tons of CO_2 per hectare that is stored in their respective forests. As mentioned in section IV, the CO_2 stock stored in Kalimantan's forests is much higher than in Sumatra's. This does not have a direct impact on economic growth, but as we shall see in the policy simulations, it will affect the REDD payment to Sumatra and Kalimantan and alter welfare via changes in household income. We surmise that if Kalimantan converts fewer forests into oil palm plantations, more carbon would be stored in Kalimantan forests. With a higher carbon intensity, the level of CO_2 emissions would be lower and the transfer payments to Kalimantan households higher. Sumatran households would benefit from REDD transfers, but not at the same level as in Kalimantan since the carbon intensity of Sumatran forests are slightly lower.

Our baseline simulation results show that Java's output is more than 3 times larger in 2030 than in 2005, while Papua and Maluku double in size. Java has the highest growth rate over the period because it hosts the majority of Indonesia's manufacturing and service industries. These industries show strong growth over the simulation period, while Papua and Maluku, which grow at a lower rate, mainly produce output that does not benefit greatly from employment and productivity improvements.

In the baseline simulation, Kalimantan and Sumatra show the highest levels of land-use conversion from forests to oil palm plantations. Papua and Sulawesi show the lowest levels of land conversion. The increase in the land area designated for oil palm implies a loss of managed and natural forest area. With the change in land use, we expect a change in the level of CO_2 emissions. The change in CO_2 emissions follows a similar path to the change in oil palm land area. Based on the carbon stock of natural forests, the level of CO_2 emissions is the highest in Kalimantan and Sumatra. Regions with the lowest CO_2 emissions are Papua and Sulawesi.

The growth paths of economic indicators generated in SIM1 and SIM2, which are detailed in the next section, move away from the baseline, making it possible to evaluate the impact of the policy. Policy effects are reported as percentage deviations from the baseline forecast.

VI. Consequences of the Moratorium and Reduction of Emissions from Deforestation and Forest Degradation Payment

A. SIM1: Imposing a Land Moratorium in the Absence of REDD

In the first policy simulation, we simulate the economic impacts of the moratorium on converting natural forests to oil palm plantations in the absence of a once-off REDD payment. The features of the policy simulation are the same as the baseline but now we assume that from 2015 all land conversion from forest to oil palm plantation comes from managed forests only—no land will be allocated from natural forests. Following normal practice, we report policy results as differences from the baseline scenario.

Because land for oil palm is now sourced from managed forests only, the land area used for palm oil production grows half as fast as in the baseline simulation. Thus, the differences between the baseline and policy simulations include:

(i) there is 1 less hectare of land converted to oil palm;

(ii) the converted land only comes from managed forests;

(iii) no natural forest is converted to oil palm, avoiding deforestation and conserving this area;

(iv) there is a decline in CO_2 emissions; and

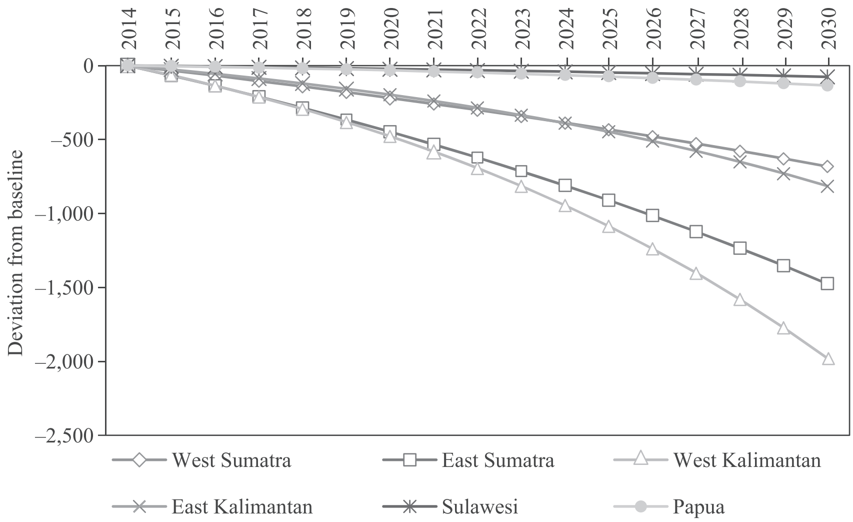
(v) there are varied regional economic impacts.

Figure 2 shows that the total area converted to oil palm is less than in the baseline simulation. The natural forest area, which is not converted to oil palm land, is higher in SIM1 than in the baseline. By the end of the simulation period, approximately 5 million hectares of forest have been conserved, with the bulk of this amount located in Kalimantan and Sumatra.

In the baseline, this land area grows to 18.6 million hectares in 2030, while in the policy simulation this area grows to 13.4 million hectares. The difference of 5.2 million hectares is the natural forest area that was conserved due to the moratorium. Therefore, instead of oil palm land area growing at an annual average of 4.9% as in the baseline simulation, oil palm land area grows at an average rate of 2.9% per annum.

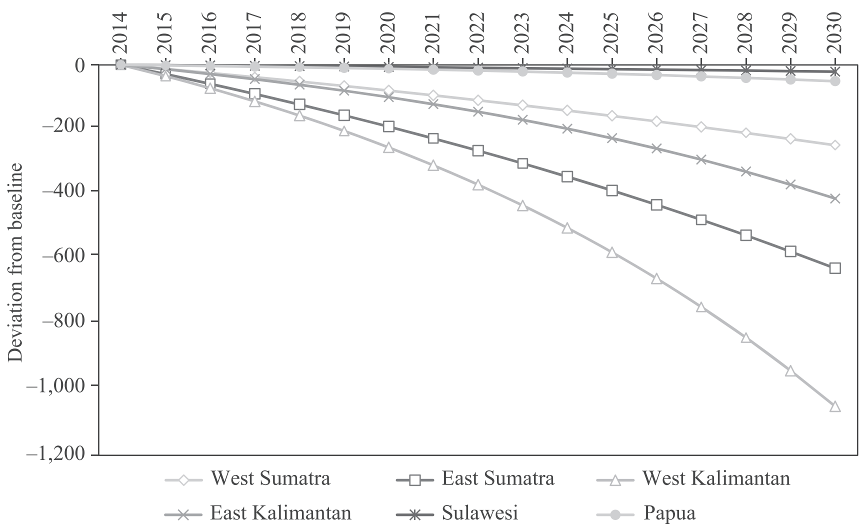
Due to the conservation of natural forests, CO_2 emissions fall relative to the baseline in all regions (although at different levels) (Figure 3). The change in the level of CO_2 emissions depends on the carbon stock intensity of each type of land

Figure 2. **Oil Palm Land Area by Region**



Source: Authors' calculations from model simulations.

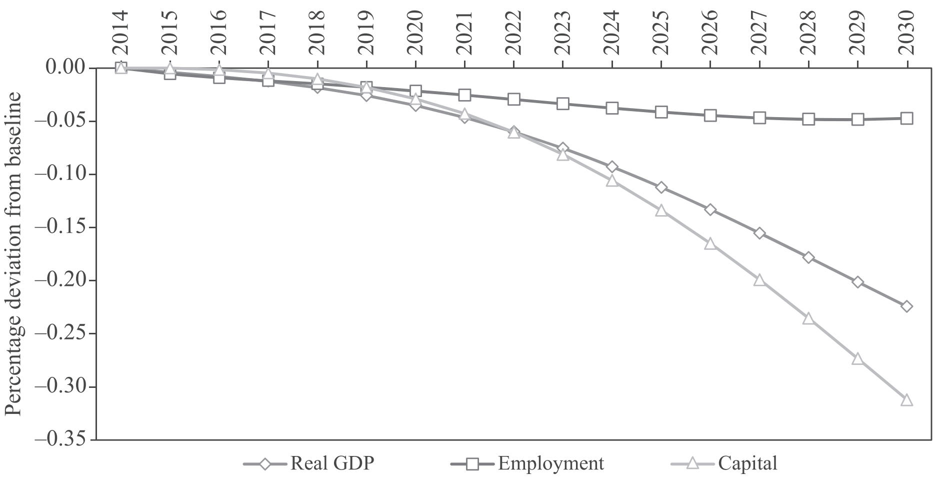
Figure 3. **Carbon Dioxide Emissions by Region**



Source: Authors' calculations from model simulations.

use (see section IV). This is because natural forests store more carbon stock than oil palm plantations. CO_2 emissions fall the most in West Kalimantan, followed by East Sumatra. These results are determined by the:

Figure 4. **Gross Domestic Product from the Income Side**



GDP = gross domestic product.
Source: Authors' calculations from model simulations.

(i) hectares of natural forests saved from deforestation, and

(ii) carbon stock stored in natural forests in different regions.

Our initial setting of CO_2 intensities show that the carbon stock stored in natural forests is highest for West Kalimantan at 800 tons per hectare.

On a macro level, the impacts of a moratorium on land conversion seem small. However, as we shall see, there are regional disparities that are significant, especially in Kalimantan and Sumatra. We next focus on the main macroeconomic variables before moving on to the regional impacts of the moratorium. Figure 4 shows the results for GDP components from the income side. The results show that capital and real GDP fall in the long run and are 0.3 and 0.23 percentage points below the baseline, respectively. Our assumption is that employment is fixed in the long run. With employment effectively unchanged and with no productivity improvements, capital adjusts given fixed rates of returns.

The percentage of GDP calculated as the share weighted sum of capital and oil palm land is

$$gdp = SHRlab * xlab + SHRcap * xcap + SHRlnd * xlnd + a \tag{12}$$

where *gdp*, *xlab*, *xcap*, *xlnd,* and *a* are the percentage changes in real GDP, labor, capital, land, and productivity, respectively. These percentage change values are simulation results. *SHRlab*, *SHRcap*, and *SHRlnd* are the shares of labor, capital, and land in total primary factor costs, respectively. These numbers are calculated from the database values for the respective factors. With *xlab* and *a* fixed, the percentage change is dependent on the share capital and land and the percentage change in capital and land, specifically oil palm land.

$$gdp = SHRcap * xcap + SHRlnd * xlnd \quad (13)$$

$$gdp = 0.45 * -0.31 + 0.003 * -21 \quad (14)$$

$$gdp = -0.21 \quad (15)$$

We note that the percentage change in capital contributes the most to the change in GDP. For each \$1 of land lost, \$2 of capital is lost, given that capital is mobile and adjusts to fixed rates of return.

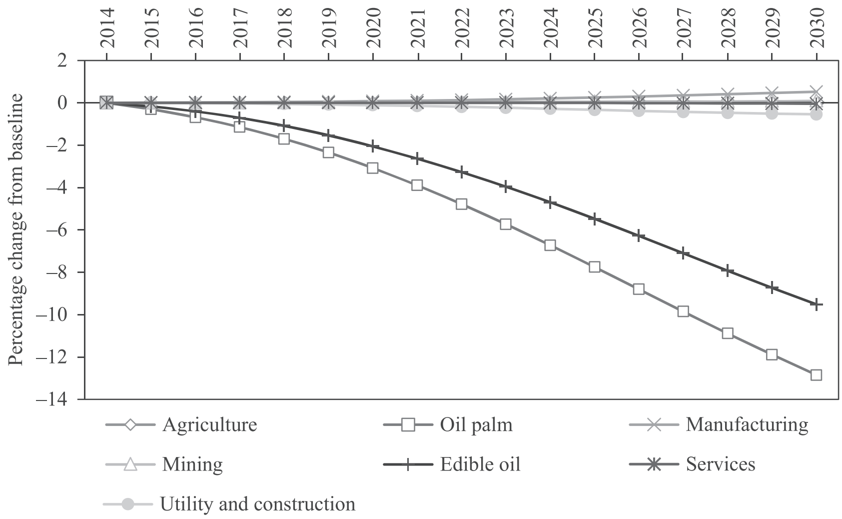
A point to note is that even though the long-run change in national employment is negligible, this does not mean that employment at the individual industry level remains close to baseline values. In most industries, there are permanent employment responses to the moratorium. In the long run, employment in the edible oils industry falls by 10% from the baseline. This result is explained by the underlying input–output linkage captured in the database, which shows that palm oil is mainly used as an input in the edible oils industry. With the change in aggregate employment negligible, the fall in employment in the edible oils and palm oil industries, implies an increase in employment in other industries such as manufacturing. In terms of regional employment, Sumatra shows the largest negative deviation due to the prominence of the palm oil and edible oils industries in this region.

Figure 5 shows the percentage deviation in output from the baseline for the main industries. Not surprisingly, the palm oil and edible oils industries show the largest declines in output. Regions that rely on palm oil production and related industries (such as the edible oils sector) for employment and economic growth show the strongest decline in regional employment and output.

In our simulation, wages adjust to hit the target employment rate while holding domestic employment fixed at base levels. Therefore, the loss of jobs in palm-oil producing areas means gains elsewhere. The regions making gains probably do not produce much palm oil, instead they produce, for example, other manufacturing commodities as is the case in Java. As mentioned before, most oil palm plantations and edible oils industries are located in Sumatra and Kalimantan. It is therefore not surprising that Sumatra's growth is below the baseline throughout the simulation period (Figure 6). Kalimantan, however, shows little change in regional growth. This is because Kalimantan is less dependent than Sumatra on palm oil production and more diversified in its productive activities. Therefore, it can better adjust to the land moratorium.

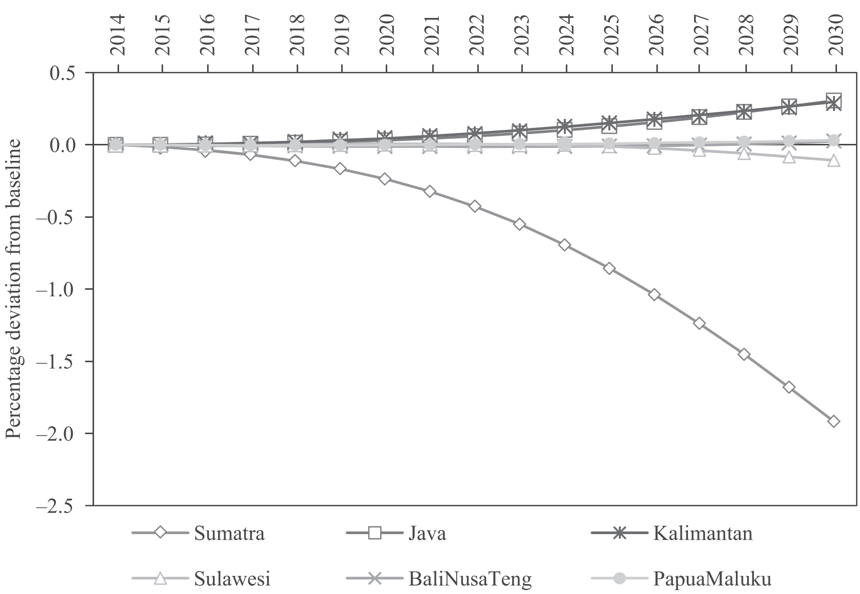
In the next simulation, we translate the moratorium on land conversion into a monetary reward to those regions with lower levels of CO_2 emissions.

Figure 5. **Output of Main Industries**



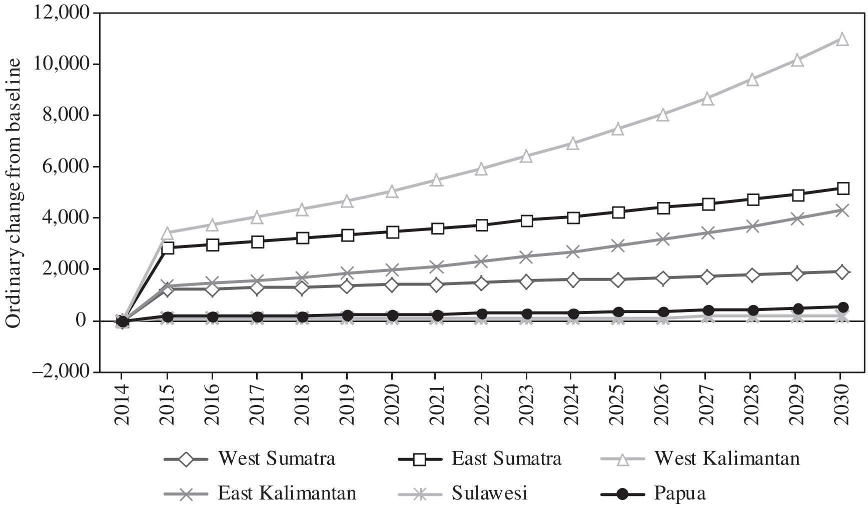
Source: Authors' calculations from model simulations.

Figure 6. **Gross Domestic Product by Region**



Source: Authors' calculations from model simulations.

Figure 7. **REDD Payments by Region**



REDD = Reduction of Emissions from Deforestation and Forest Degradation.
Source: Authors' calculations from model simulations.

B. SIM2: Imposing a Land Moratorium in Return for a REDD Payment

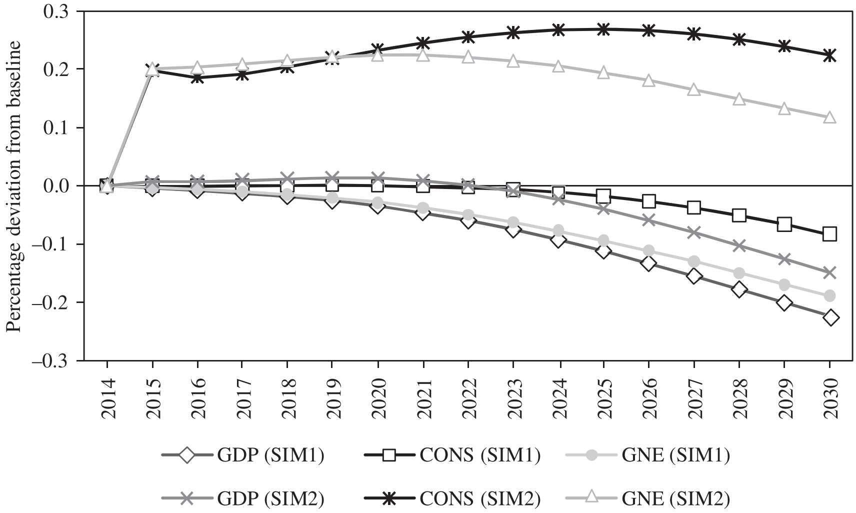
In this simulation, we evaluate the impact of a moratorium on the land used for palm oil production, which is similar to SIM1, but now it is accompanied with a gift of foreign exchange (REDD payment) in return for lower CO_2 emissions. The payment is directly awarded to households in region *r* (see equation 10).

As shown in Figure 3, West Kalimantan and East Sumatra shows the largest reductions in CO_2 emissions. Therefore, it is not surprising that the largest REDD payments are to West Kalimantan, followed by East Sumatra (Figure 7). West Kalimantan receives the most REDD payments because it has (i) a relatively high level of CO_2 emissions reduction, and (ii) the highest level of carbon storage per ton in natural forests among all regions (see section IV).

As shown in Figure 8, the moratorium reduces Indonesia's economic growth and negatively impacts other macroeconomic indicators such as gross national expenditure (GNE) and welfare.[10] International transfers ($10 per ton of CO_2 emissions avoided) can more than compensate for these welfare losses as measured by declines in consumption or GNE. However, the fall in GDP due to the moratorium cannot fully be compensated. In this context, GNE and consumption

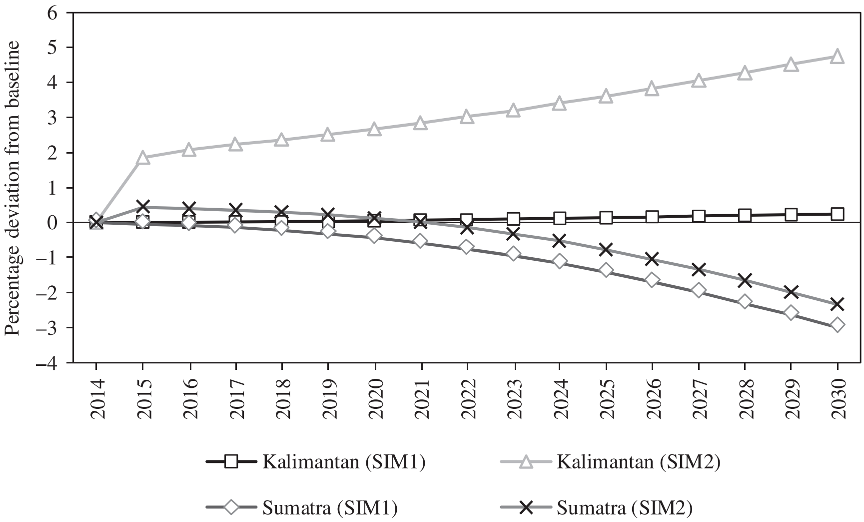
[10]GNE is the total value of private and public expenditure in the economy. It is different from GDP because GNE includes expenditures on imported commodities and excludes exports of commodities produced within a country. GDP is the total value of production within a country, which includes exports of commodities and excludes the imports of commodities.

Figure 8. **Gross Domestic Product, Gross National Expenditure, and Consumption**



Source: Authors' calculations from model simulations.

Figure 9. **Consumption in Sumatra and Kalimantan**



Source: Authors' calculations from model simulations.

are a better measure of welfare as the international transfers impact the current account deficit.

The impact of the moratorium with international transfers varies across regions; Kalimantan wins, Sumatra loses (Figures 8 and 9). Sumatra is highly dependent on palm oil and its economy is less broad based. The carbon stocks of its forests are no longer high compared to the past. Consequently, it receives a smaller amount of transfers than Kalimantan. Kalimantan, on the other hand, is not yet too dependent on palm oil as its economy is more broad based. In addition, the carbon stock of its forests is still high; therefore, it receives more transfers.

VII. Conclusion

The objectives of this paper are to (i) identify the macroeconomic effects on the Indonesian economy of a land moratorium, including how the effects are distributed across different regions in the country; and (ii) determine to what extent international transfers, which are payments for ecosystem services in which the international community pays for avoided deforestation and additional carbon storage services, can mitigate the effects of the moratorium.

We use the INDOTERM model—a bottom-up, multiregional CGE model of the Indonesian economy—to conduct three experiments. The first simulation is the business-as-usual simulation where we model the growth of the Indonesian economy in the absence of a moratorium and REDD payments. In the baseline simulation, we assume that both natural and managed forests are converted to oil palm plantations. We then use this model to evaluate alternative growth paths where we simulate a moratorium on converting forest area to oil palm plantation in the absence of REDD payments (SIM1), and in return for a REDD payment that is proportional to the fall in CO_2 emissions (SIM2).

Our results show that in the baseline simulation, 13.4 million hectares of forest land are converted to oil palm. Of the total land converted, half comes from managed forest and the other half from natural forest.

The results suggest that the moratorium reduces Indonesian economic growth and other macroeconomic indicators, but international transfers ($10 per ton of CO_2 emissions avoided) can more than compensate the welfare loss. However, the impact varies across regions. Sumatra, which is highly dependent on palm oil given that its economy is relatively less broad based than other regions and the carbon stock of its forests is no longer high, receives less transfers and suffers greater economic loss. Kalimantan, which is relatively less dependent on palm oil than Sumatra and has forests with a high carbon stock, receives more transfers, and enjoys greater benefits. This result suggests that additional policy measures anticipating the imbalanced impacts of the transfers are required if the trade-off between conservation and reducing interregional economic disparity is to be reconciled.

In the future, it may be useful to run several scenarios simulating different levels of REDD payments based on different prices for reducing CO_2 emissions. In the policy simulations in this paper, we also do not improve palm oil productivity over time. It would be interesting to see the regional and domestic impacts if productivity gains in the palm oil sector were to reach those in Malaysia.

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Regional Crop Diversity and Weather Shocks in India

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Agriculture in both the developing and developed country context is highly sensitive to weather shocks. The intensity of these shocks is likely to increase under climate change, leading to an ongoing debate regarding the ability of farmers to insulate yields and income against accelerating environmental extremes. We study crop diversity as an avenue for increased resilience. Diversity in agricultural systems has been suggested in the agroecology and environmental economics literatures as a powerful means of on-farm insurance, both through physical and market-based channels. However, large-scale empirical evidence of its effectiveness is lacking, and crop diversity is largely absent from the empirical climate impacts literature. We examine the insurance benefits of crop diversity in the context of India at the height of the Green Revolution, a period of rapid change in agricultural diversification due to the increased penetration of a small set of high-yielding variety crops. Building on a basic empirical model from the climate impacts literature, we show that areas with higher crop diversity of planted area display measurably more drought resilience, both in terms of gross and net revenues. We decompose this aggregate result to show that diversification has implications for farmer welfare both through physical (yield) and market (price) channels.

Keywords: agriculture, climate change, crop diversity, weather shocks
JEL codes: Q10, Q15

I. Introduction

Food production, and hence farmer welfare, is highly vulnerable to weather shocks, particularly in the developing world, where few insurance mechanisms exist to buffer farmers against extreme weather events. The link between climatic conditions and agricultural yields has been extensively empirically documented for major crops in the North American context (Burke and Emerick 2016, Schlenker and Roberts 2009), and these findings have been replicated across the globe (Carleton and Hsiang 2016, Auffhammer and Schlenker 2014,

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IPCC 2014). Indian agriculture is particularly susceptible to yield damage under adverse climate events, as production is heavily dependent on uncertain monsoon rainfall (Fishman 2016; Auffhammer, Ramanathan, and Vincent 2012), crop-damaging temperatures regularly depress yields (Carleton 2017; Welch et al. 2010; Auffhammer, Ramanathan, and Vincent 2006), and formal crop insurance is rare. By increasing the intensity of extreme climate conditions, global climate change is likely to exacerbate this vulnerability, raising important questions regarding whether and how the agricultural sector will adapt.

There are many adaptive behaviors and technologies that enable farmers to cope with weather-based uncertainty. These include investment in irrigation; development and use of new drought- and/or submergence-tolerant crop varieties (Dar et al. 2013); transfer of land and labor to nonagricultural sectors (Colmer 2016; Mendelsohn, Nordhaus, and Shaw 1994); shifting timing of planting or harvesting (Wright and Gardner 1995); and investment in formal crop insurance (Annan and Schlenker 2015). However, recent empirical work focusing on crop-specific avenues of adaptation has uncovered little to no evidence that farmers have successfully reduced yield sensitivity to accelerating climate change (Burke and Emerick 2016; Lobell et al. 2014; Schlenker, Roberts, and Lobell 2013; Schlenker and Roberts 2009). In contrast, a parallel body of work in agroecology has turned attention to across-crop solutions, suggesting that crop diversity has the potential to buffer both productivity (Bellora et al. 2017; Zimmerer 2010; Di Falco and Chavas 2008, 2009) and income (Baumgärtner and Quaas 2009, Di Falco and Perrings 2003) from adverse climate conditions. While researchers have proposed many mechanisms through which diversification of crop portfolios can enable adaptation, there is a dearth of large-scale empirical evidence of its effectiveness. Here, we use rich panel data from 270 districts across India during a period of rapid agricultural change to test whether shifts in macroscale (i.e., district-level) crop diversification have observable impacts on farmer income in times of extreme weather. Consistent with prior farm-level analyses (see, for example, Di Falco, Bezabih, and Yesuf 2010), we detect benefits of macroscale diversification for farmer revenues. In a novel test that isolates physical and market-based mechanisms, we show that diversification mitigates aggregate yield losses in times of drought, while simultaneously weakening drought-induced price shocks.

Our findings contribute to two distinct bodies of literature, which to date have remained independent. First, our results suggest that crop diversity is an effective, yet understudied, form of adaptation in the rapidly growing empirical literature on the agricultural impacts of climate change. This literature has demonstrated that while high temperatures and low rainfall are generally damaging to staple crops, there is substantial heterogeneity across crops in the weather–yield relationship. For example, rice in India is sensitive to rising nighttime temperatures (Welch et al. 2010; Auffhammer, Ramanathan, and Vincent 2006), while other major staple crops like maize, soy, and cotton suffer disproportionately under extreme daytime heat in

India and the United States (Burgess et al. 2014, Schlenker and Roberts 2009). Rice production throughout South and Southeast Asia has been found to be sensitive to the availability of rainfall during the monsoon season for nonirrigated systems, and to the availability of economically viable groundwater and surface water resources for irrigated systems (Auffhammer, Ramanathan, and Vincent 2012; 2006). Rainfall appears, however, much less important for crop production relative to temperature when researchers consider other crops and other regions of the world (Schlenker and Lobell 2010).

This heterogeneity suggests that diversification of crop planting, either at the farm level or at a more aggregate scale, may facilitate the resilience of total production and farm income to adverse climate conditions. However, this literature has focused on other means of adaptation. For example, the breeding of new crop varieties, which can more easily withstand climatic extremes, has received substantial attention. Dar et al. (2013) use a randomized field experiment in Orissa (now known as Odisha), India to show that a novel submergence-tolerant rice variety has substantial positive impacts on the mean and variance of rice yield. Maybe the most obvious avenue of adaptation to more uncertain rainfall regimes available to farmers is the installation of irrigation infrastructure, which has been observed throughout the major agricultural production areas globally. While demonstrably beneficial, irrigation as adaptation ceases to be feasible in the presence of insufficient groundwater or surface water (Fishman 2018). Other hypothesized forms of adaptation include shifting the planting calendar, switching crops, or exiting agriculture altogether. In this paper, we focus on the possibility that crop diversification may provide a means of adaptation that has thus far remained absent from climate change impacts research.

The second body of literature we contribute to is the active area of research on the benefits of biodiversity. Diversification is often cited as a means of reducing vulnerability to shocks, both within agriculture and in ecological systems more broadly (Bellora et al. 2017, Tilman et al. 2001, and Tilman and Downing 1994). Similarly, diversification as insurance is a well-accepted principle in finance and underlies modern portfolio theory. In the agricultural and agroecology literatures, crop diversification has been argued to enhance the ability of farmers and food production systems to respond to climatic variability by increasing the efficiency of water and nutrient use, enhancing species complementarities, and ensuring that species with heterogeneous climatic sensitivities exist jointly (Di Falco, Bezabih, and Yesuf 2010). However, much of the empirical agroecology literature has focused on a relatively narrow spatial scale and spectrum of crops (Gil et al. 2017), with findings often diverging (Di Falco, Bezabih, and Yesuf 2010). This is an active area of research with empirical studies covering much of the globe (Zimmerer 2010).

A number of economic studies have examined the benefits of crop diversification at various temporal and spatial scales. One literature builds on the seminal paper by Rosenzweig and Binswanger (1993) looking at crop choice, farm level profitability, and weather risk. The majority of these papers have engaged in case studies of single farms or local production systems, which often specialize in a small number of crops. Gaudin et al. (2015) find significant yield benefits from cropping sequence diversification over a 31-year period of field trials in Ontario, Canada. They found that diversification led to yield increases of 7% for corn and 22% for soybeans. Di Falco and Chavas (2008) show that for cereals in Southern Italy, higher biodiversity is consistent with better production outcomes during negative rainfall events. Di Falco, Bezabih, and Yesuf (2010) demonstrate similar findings for a panel of farms in Ethiopia. They show that higher crop diversity leads to better production outcomes during bad rainfall events, suggesting that diversity is consistent with higher resilience. These papers and the references cited therein comprise a flourishing literature, which appears to suggest empirical evidence of the benefits to resilience from higher crop diversification. The advent of massive new data sets of high resolution land cover imagery will certainly revolutionize this literature as one will be able to look at both temporal and spatial changes in crop diversity locally and globally.

In this paper, we seek to make a modest contribution to the literature with two innovations. First, we test whether we can detect evidence of increased resilience at a macroscale of diversification, in contrast to the field- and farm-level analyses that dominate previous work.[1] Second, we separately identify two key pathways linking diversity and climate resilience. Nearly all studies focus on the production benefits of diversification, citing or testing for particular mechanisms like the species complementarities discussed above. However, the manner in which these production effects manifest as changes in farmer welfare depend critically on endogenous price responses. Baumgärtner and Quaas (2009) describe a model in which formal market insurance and "natural insurance" realized through diversification of a crop portfolio are substitutes. In this conceptual framework, farmers adopt diversification in the presence of uncertain climate conditions when formal market insurance is absent or costly, as is the case in much of India. However, the advantages of such natural insurance depend on the extent to which local prices move in tandem with diversity-moderated yield shocks. To our knowledge, we provide the first empirical evidence that diversification influences both physical production and local price levels.

Our study is set in the context of India during the onset of the Green Revolution, which dramatically transformed Indian agriculture. Following decades of frequent famines, the early 1960s saw the rollout of high-yielding varieties (HYVs) of cereals (particularly wheat), increased rollout of irrigation infrastructure,

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[1]See Zimmerer (2010) for a discussion of the role of geographic scale in agroecological studies of crop diversity.

and more frequent use of pesticides and fertilizers as well as machinery. On the institutional side, this period saw land reforms and the related consolidation of landholdings as well as the broad availability of credit access for farmers. As a consequence, diversity generally fell through increased adoption of HYVs and other agricultural inputs that facilitated a transition toward more monoculture-based production systems. This transition was particularly stark in North India. We use these spatial and temporal differences as a source of variation in crop diversity at the district level, where the average Indian district is slightly larger than the average county in the United States.

We use annual weather, agricultural price, production, and cost data measured in each district and each year to test whether district-level crop diversity is correlated with higher gross or net farm revenues per hectare in years of drought. Our estimation results suggest that in drought years, districts with higher levels of agricultural diversity experience higher gross and net revenues per hectare. These aggregate results can arise not only through physical benefits of diversification on crop yields, but also through changes in local prices to the extent that markets are not fully integrated across space. In what we believe is a novel decomposition of the income effect, we test whether the impacts of diversity during drought periods affect crop yields and agricultural prices simultaneously. We find evidence that revenues are affected both through physical impacts on yields and through a farm gate price mechanism. Our estimation results show that these impacts are robust across space and to the inclusion of controls for unobservables in the form of district and year fixed effects as well as regional trends. The remainder of the paper is organized as follows. Section II briefly describes the data employed in our estimation. Section III describes the empirical model. Section IV presents and discusses the results. Section V concludes with some suggestions for further research.

II. Data

The agricultural data at the district level used in this paper come from the India Agriculture and Climate Data Set. We use the original data set created by Sanghi, Kumar, and McKinsey (1998), which covers the period 1956–1987. These data contain area planted, output, and farm gate prices for major crops (pearl millet, sorghum, maize, rice, and wheat) as well as minor crops (barley, cotton, groundnut, chickpea, jute, potato, finger millet, pigeon pea, rapeseed and mustard, sesame, soy, sugarcane, sunflower, tobacco, and a collective category called “other pulses”). Area planted is reported in thousands of hectares, output is reported in thousands of tons.

As Zimmerer (2010) discusses, the study of crop diversity and how it is measured depends greatly on the spatial scale of analysis. Studies of single crops often extend down to the level of different types of strawberry plants. We do not have data at this scale. Also, indicators of diversity often take into account different spatial arrangements of planting patterns for individual crops—the "surrounding landscape," which is thought to play an important ecological role. We do not have a field-level database, which would allow us to generate an indicator to take these important dimensions into account. Finally, there is the diversity in crop rotation studied by Gaudin et al. (2015), which looks at temporal measures of diversity. We only observe annual data and hence cannot investigate the order of planting and harvest. Given these limitations, we create a simple yet widely used indicator of concentration, the Herfindahl–Hirschman Index (HHI), based on area planted to different crops in a given year and district. While this measure is relatively coarse when compared with field-level analyses, it enables us to investigate whether the microscale findings from the existing literature scale to an aggregate level. Moreover, this macroscale indicator enables us to investigate the market response to diversification, as measured by local prices.

Our HHI for district i and year t is defined as follows:

$$HHI_{it} = \sum_{j=1}^{J} s_{ijt}^{2} \tag{1}$$

where $s_{ijt} = \frac{a_{ijt}}{\sum_{j=1}^{J} a_{ijt}}$ is the share of total planted area in district i dedicated to crop j in year t. J is the total number of crops, which in our data set comprises the 20 major and minor crops listed above.[2]

Our weather data are monthly averages and were aggregated up from weather stations to districts and weighted by the inverse squared distance from district centroid to each station. We define the kharif (monsoon crop) growing season as June through September and rabi (winter crop) as November and December (Carleton 2017, Guiteras 2009). We use cumulative growing season rainfall and average growing season temperature as explanatory climatic variables. We create an indicator for extremely low levels of rainfall, using the lowest tercile of kharif season rainfall for each district as the cutoff value, following Auffhammer, Ramanathan, and Vincent (2012), and Burgess et al. (2014).

Our agricultural price index is based on Burgess et al. (2014), which is a simple index with time-invariant crop weights. Each crop j in each district i is weighted by the average percentage of total crop revenue derived from crop j. That is, the weight for crop j in district i is calculated by

$$w_{ji} = \frac{1}{T} \sum_{t=1}^{T} \frac{P_{jit} Q_{jit}}{\sum_{j=1}^{J} P_{jit} Q_{jit}} \tag{2}$$

[2]We used the HHI over the Shannon Index since our data contain many crop and year combinations with zero area planted.

The price index for each district *i* in year *t* is calculated as

$$P_{it} = \sum_{j=1}^{J} P_{jit} w_{ji} \tag{3}$$

where P_{jit} is the crop-specific price (in rupees/quintal) as reported in the raw data (Sanghi, Kumar, and McKinsey 1998).

We first conduct our analysis for all districts with available data across India. To test for spatial heterogeneity based on the location of emergence of the Green Revolution, we split India into North (Gujarat, Haryana, Punjab, Rajasthan, and Uttar Pradesh) and South (Andhra Pradesh, Bihar, Karnataka, Madhya Pradesh, Maharashtra, Odisha, Tamil Nadu, and West Bengal). We run versions of our models allowing the effect of crop diversity during drought years to vary between the North and the South. Table 1 provides the complete summary statistics for our sample of districts and also breaks them out by geographic region. The summary statistics indicate that the northern districts are significantly drier during the kharif season on average and in terms of extremes. This is not surprising since the southern states are part of the monsoon belt, where much of the rain-fed rice agriculture is based. The northern districts are also warmer during the kharif season with an average monthly temperature that is almost 1.5 degrees Celsius higher than the southern states.

To create indicators of farmer income, we construct measures of both gross and net revenues per hectare of planted area. Gross revenues are simply the sum of all production returns for each crop, where prices and quantities are taken directly from the India Agriculture and Climate Data Set. Net revenues subtract estimated labor and fertilizer costs from gross revenues. However, these input costs are heavily interpolated and results for net revenues should therefore be interpreted with caution. The statistics on net revenue per hectare in Table 1 indicate similar net and gross revenues per hectare in the North and the South. Yields in terms of tons per hectare are not statistically different in the North than in the South. There is no statistical difference in area planted per district between the two groupings of states. If we consider the share of irrigated crops across the two groupings, 24% of area planted was irrigated in the North across the entire sample, while the same average is only 18% for the South. Further, the farm gate price index is slightly higher in the South, although the difference is not statistically significant.

Figure 1 displays our main variable of interest, the HHI of crop diversification across time, separately for the North and South. We see a trend consistent with the onset of the Green Revolution in the mid-1960s. The North experienced a steady increase in HHI over time. Two things stand out. First, there is the drastic increase in the index over time in the North, which is indicative of a move toward more monoculture. This relationship is not clear in the South, where the HHI stays somewhat constant on average. Figure 2 displays the HHI plotted against the share

Table 1. **Summary Statistics—All India, North India, and South India**

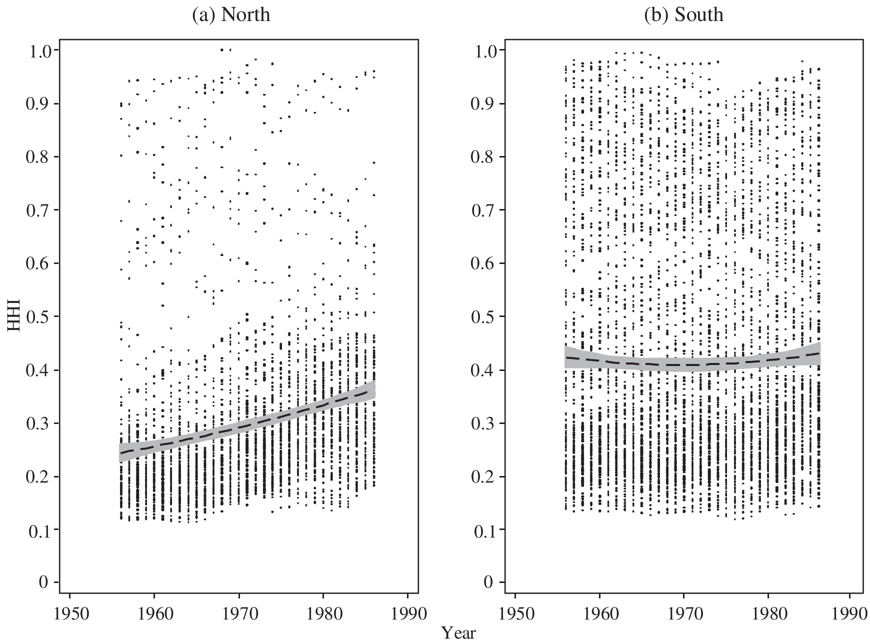
	All India					North		South	
Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Precip JJAS	8,401	0.86	0.51	0.01	5.43	0.71	0.36	0.96	0.57
Precip ND	8,401	0.04	0.07	0.00	0.76	0.01	0.02	0.05	0.09
Temp JJAS	8,401	28.53	2.07	21.10	34.52	29.92	1.50	27.62	1.88
Temp ND	8,401	20.64	2.41	10.57	27.66	19.28	2.22	21.55	2.07
Total Revenue/ha (thousands)	8,401	1.07	0.95	0.00	29.24	1.02	0.88	1.09	1.00
Net Revenue/ha (thousands)	8,401	0.19	1.13	−44.07	19.56	0.20	0.68	0.19	1.35
Yield (tons/ha)	8,401	0.86	0.46	0.00	15.08	0.89	0.45	0.84	0.46
Area (thousand ha)	8,401	535.35	293.89	3.10	2,177.41	540.69	275.03	531.82	305.72
Share irrigated	8,401	0.20	0.16	0.00	0.92	0.24	0.15	0.18	0.16
Price Index	8,401	134.75	85.74	6.36	832.35	129.47	84.31	138.25	86.51
HYVs Share of Area Planted	8,401	0.11	0.12	0.00	0.58	0.12	0.13	0.10	0.12
HHI Diversification Index	8,401	0.37	0.21	0.11	1.00	0.30	0.16	0.42	0.23

ha = hectare; HHI = Herfindahl–Hirschman Index (calculated over area planted to 20 different crops); HYVs = high-yielding varieties; JJAS = June, July, August, and September; ND = November and December.

Notes: "Precip" refers to cumulative seasonal rainfall measured in meters. "Temp" refers to average seasonal temperature measured in degrees Celsius.

Source: Authors' own calculation from data constructed by Sanghi, Apurva, K. S. Kavi Kumar, and James W. McKinsey Jr. 1998. *India Agriculture and Climate Data Set*. Washington, DC: World Bank.

Figure 1. **Time Series of Crop Diversity Index**



HHI = Herfindahl–Hirschman Index (calculated over area planted to 20 different crops).
Notes: North India includes Gujarat, Haryana, Punjab, Rajasthan, and Uttar Pradesh. South India includes Andhra Pradesh, Bihar, Karnataka, Madhya Pradesh, Maharashtra, Odisha, Tamil Nadu, and West Bengal.
Source: Authors' own calculation from data constructed by Sanghi, Apurva, K. S. Kavi Kumar, and James W. McKinsey Jr. 1998. *India Agriculture and Climate Data Set.* Washington, DC: World Bank.

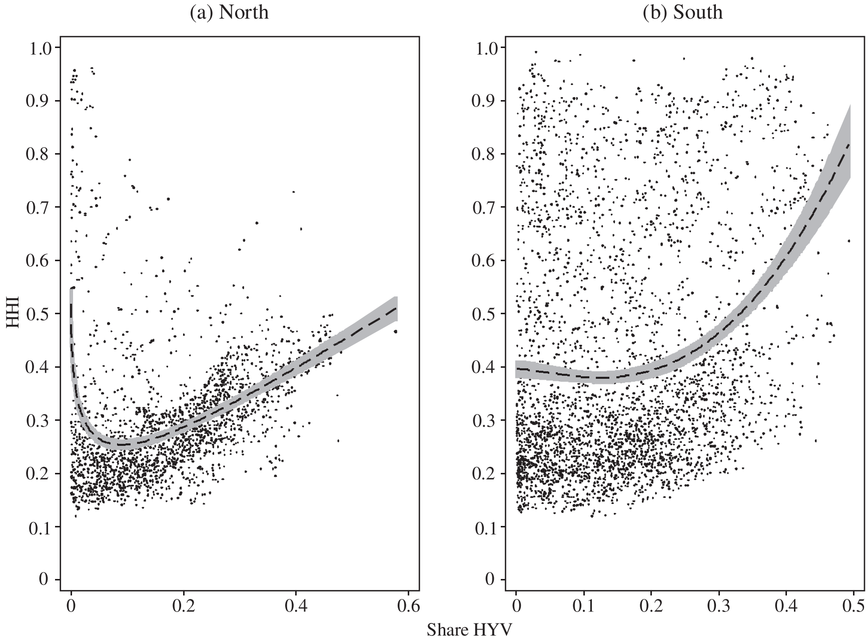
of HYVs in terms of area planted. The HYVs rollout in the North correlates strongly with decreased diversity, as is evidenced by the increase in the HHI from 0.20 to 0.34 for the districts in Punjab, Uttar Pradesh, and Haryana. This means that while Green Revolution technologies were taken up at relatively similar rates across India, only in the North did this imply lower crop diversity. Second, there is significantly more variability in the South in the HHI than in the North.

We now use these data to examine whether more diverse cropping systems are more resilient to rainfall shocks in the form of a drought.

III. Empirical Model

Auffhammer, Ramanathan, and Vincent (2012) previously examined the role of rainfall extremes on rice yields throughout India using aggregate state-level data. They show that higher incidence of drought and an increase in more intense rainfall events, conditional on total monsoon rains, lead to measurable depressed yields for

Figure 2. **Crop Diversity Index and Share of Area Planted to HYVs**



HHI = Herfindahl–Hirschman Index (calculated over area planted to 20 different crops), HYVs = high-yielding varieties.
Notes: North India includes Gujarat, Haryana, Punjab, Rajasthan, and Uttar Pradesh. South India includes Andhra Pradesh, Bihar, Karnataka, Madhya Pradesh, Maharashtra, Odisha, Tamil Nadu, and West Bengal.
Source: Authors' own calculation from data constructed by Sanghi, Apurva, K. S. Kavi Kumar, and James W. McKinsey Jr. 1998. *India Agriculture and Climate Data Set.* Washington, DC: World Bank.

rain-fed rice. We adopt a similar econometric specification as a starting point, which is given by

$$\begin{aligned} y_{it} = \alpha_i + \theta_t + \beta_1 HHI_{it-1} + \beta_2 HHI_{it-1} * drought_{it} + \beta_3 drought_{it} \\ + \beta_4 Temp_{it} + \beta_5 Precip_{it} + \varepsilon_{it} \end{aligned} \tag{4}$$

where y_{it} is one of our four outcome variables (gross revenue per hectare, net revenue per hectare, yield per hectare, and price index) in district i and year t; α_i, and θ_t are district and year fixed effects, respectively;[3] $drought_{it}$ is a dummy variable indicating a low rainfall year; $Temp_{it}$ is a vector of seasonal (kharif, rabi) average temperature; and $Precip_{it}$ is a vector of seasonal (kharif, rabi) cumulative rainfall. The additive error term ε_{it} is assumed to be serially correlated across time, yet independent across districts.

[3]For robustness, we show additional results including region-specific time trends in place of year fixed effects.

The variable y_{it} will be one of four different variables. In a first set of regressions we will use gross revenues (in rupees) per area planted, which is simply the sum of revenues from all crops grown in a district-year. In a second set of regressions, we will use net revenues, which account for costs of major inputs to production. In a third set of regressions we will use yield, which is simply total output (in tons) aggregated across crops and measured per unit of area planted. This measure of course does not directly link to farmer income, as weight in tons and the economic value of crops are not necessarily positively correlated. In a final set of regressions, we will put our price index based on equation (3) as the dependent variable. We will run all regressions for all of India and then examine whether there is evidence of spatial heterogeneity between the North and South, and between more and less heavily irrigated areas.

The variable *drought* is a dummy equal to 1 when cumulative kharif season rainfall is in the first tercile of rainfall for district *i* in year *t*, based on the distribution of that district's rainfall over the entire sample time period. $Temp_{it}$ comprises two variables, kharif and rabi average monthly temperature, and is an important control, given the negative impacts of heat on yields in India (Burgess et al. 2014; Guiteras 2009; Auffhammer, Ramanathan, Vincent 2006).

The variables of interest in these regressions are HHI_{it-1} and $HHI_{it-1} * drought_{it}$. The coefficient β_1 will measure the relationship between lower crop diversity and each dependent variable directly and hence is of interest in itself. The coefficient β_2 will measure the relationship between lower crop diversity during drought years and each dependent variable, and is the main coefficient of interest. If higher diversity makes districts more resilient to droughts, we would expect a negative coefficient on this interaction term for the net and gross revenue and yield regressions.[4]

In our regressions we include HHI and its interaction with the drought variable as lagged by one period, which makes them econometrically predetermined in the time series sense. We estimate all equations with district and year fixed effects to control for temporal effects within each district and time-invariant state characteristics, respectively. Identification hence comes from within-district variation, conditional on the year fixed effects and other observable controls. The coefficients on all weather variables—*Temp*, *Precip*, and *drought*—can be interpreted causally as these within-location realizations are plausibly exogenous (Carleton and Hsiang 2016). However, given significant temporal dependence in the diversity measure, our use of a lagged independent variable is imperfect and β_2 may be affected by unobserved heterogeneity. In the absence of a readily available instrument, we see this approach as the best one can do to assuage endogeneity concerns. We interpret all our findings regarding the HHI interaction

[4] Recall that a higher HHI indicates higher concentration in area planted, and hence lower diversity.

Table 2. **Ordinary Least Squares Estimation Results—All India**

	Gross Revenue	Gross Revenue	Net Revenue	Net Revenue	Yield	Yield
HHI	−0.059	−0.255	−1.212**	−2.371***	0.107	−0.417
	(0.831)	(1.057)	(0.516)	(0.698)	(0.452)	(0.546)
HHI × Drought	−0.211***	−0.160**	−0.565*	−0.565*	−0.077***	−0.074***
	(0.072)	(0.070)	(0.323)	(0.306)	(0.027)	(0.025)
Drought	0.027	0.003	0.155	0.126	0.003	−0.010
	(0.026)	(0.027)	(0.105)	(0.095)	(0.012)	(0.011)
Temp JJAS	−0.006	0.170***	0.055*	−0.019	−0.030**	0.003
	(0.024)	(0.015)	(0.034)	(0.021)	(0.012)	(0.006)
Precip JJAS	0.011	0.092**	0.021	−0.034	0.016	0.054***
	(0.050)	(0.042)	(0.055)	(0.061)	(0.024)	(0.017)
Temp ND	−0.018	−0.062***	−0.072***	−0.066***	−0.007	−0.019***
	(0.012)	(0.006)	(0.026)	(0.008)	(0.005)	(0.003)
Precip ND	0.413	0.019	−0.714	−0.602	−0.014	−0.041
	(0.349)	(0.318)	(1.140)	(0.889)	(0.168)	(0.141)
District FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	No	Yes	No	Yes	No
Region Trends	No	Yes	No	Yes	No	Yes
Observations	8,401	8,401	8,401	8,401	8,401	8,401
R-squared	0.711	0.683	0.388	0.373	0.697	0.699

FEs = fixed effects; HHI = Herfindahl–Hirschman Index (calculated over area planted to 20 different crops); JJAS = June, July, August, and September; ND = November and December.
Notes: "Precip" refers to cumulative seasonal rainfall. "Temp" refers to average seasonal temperature. "Drought" refers to a binary indicator defined as equal to 1 when cumulative JJAS season rainfall is in the first tercile of the district-specific rainfall distribution. Gross and net revenues are measured in thousands of rupees per hectare; yield is measured in tons per hectare. Standard errors are clustered by administrative district and are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.1$.
Source: Authors' calculations.

as correlational. All of our estimates cluster standard errors by district. The next section discusses the results from estimating different versions of equation (4).

IV. Estimation Results

Table 2 displays the estimation results for our main specification. The first two columns show the estimation results from estimating equation (4) using gross revenues per hectare as the dependent variable for all of India, controlling for year fixed effects (column 1) versus region-specific trends (column 2). All models control for district fixed effects. We find a negative yet statistically insignificant parameter estimate on the diversity index, suggesting that there is no correlation between crop diversity and gross revenues per hectare, conditional on the included observables and fixed effects or trends. The interaction of the HHI indicator and the drought dummy is significantly different from zero and negative, which is consistent with more diverse districts having higher gross revenues per hectare during drought years. Its point estimate suggests that a one sample standard deviation higher HHI during a drought year would result in 4.4% less gross revenue per hectare for that district. If we use net revenues, the sign of the interaction term is similar, yet the point estimate and associated uncertainty are larger. A one standard deviation increase in the HHI has a roughly two and a half times larger negative effect during drought years, which of course works through gross revenues as well as labor and input expenditures. The latter are not well measured in the data set, which leads us to suggest that the gross revenue regressions provide a more reliable estimate of impacts. The last two columns in the table conduct a simple yield regression and the results carry the same sign and statistical significance. In average years, diversity has no distinguishable impact on crop yields, but in times of drought, districts with lower diversity suffer substantially lower yields. The standardized magnitude of the effect on yields is smaller than that for gross revenues, suggesting that a one standard deviation increase in the HHI is consistent with a 1.9% decrease in yields.

Table 3 examines whether there is heterogeneity in the estimated effects in terms of location of the district or how heavily irrigated the district is. To test whether the northern districts are more or less resilient than the southern districts, we include an interaction term of our variable of interest with a dummy for the northern states. The first three columns of the table show these results. The point estimates on the interaction term of interest between the drought dummy and the HHI are almost identical to those in Table 2. The interaction term with the North India dummy is not statistically different from zero, suggesting that there is little evidence of heterogeneity in terms of a North–South divide, despite substantial differences in the rollout of Green Revolution technologies.

We then generate a dummy variable called "Irrig," which equals 1 if more than 30% of a district's area is irrigated. This represents the top quartile of the districts in terms of the share of area irrigated. The interaction is included in the last three columns of Table 3. In the gross revenue and yield regression, the point estimate on the interaction term is opposite in sign to the now slightly larger point estimates on the regular interaction, which suggests that the resilience benefit from higher diversification appears to be concentrated in districts with lower shares of irrigated area.

The effect of crop diversification on revenue resilience in light of drought depends both on physical responses of crops to the diversity of the local portfolio, as well as on the degree to which diversity can moderate the influence of weather shocks on local prices. For example, if markets throughout India were perfectly integrated, local prices would fail to reflect local climatic conditions and diversification would matter for farming households only through its effects on crop yields. However, if local prices were fully determined by local production, negative supply shocks in drought years would be accompanied by price increases, helping to buffer income effects through a natural market mechanism. To test whether and

Table 3. **Ordinary Least Squares Estimation Results—All India Heterogeneity Effects**

	Gross Revenue	Net Revenue	Yield	Gross Revenue	Net Revenue	Yield
HHI	−0.069	-1.206^{**}	0.098	−0.097	-1.176^{**}	0.090
	(0.831)	(0.533)	(0.452)	(0.832)	(0.492)	(0.452)
HHI × Drought	-0.213^{***}	-0.564^{*}	-0.079^{***}	-0.293^{***}	-0.486^{**}	-0.114^{***}
	(0.073)	(0.327)	(0.028)	(0.069)	(0.224)	(0.025)
HHI × Drought × North	0.061	−0.040	0.055			
	(0.116)	(0.274)	(0.041)			
HHI × Drought × Irrig				0.303^{***}	−0.293	0.136^{***}
				(0.100)	(0.418)	(0.041)
Drought	0.021	0.159^{*}	−0.003	0.023	0.159	0.001
	(0.032)	(0.093)	(0.013)	(0.027)	(0.109)	(0.012)
Temp JJAS	−0.007	0.056	-0.032^{***}	−0.007	0.056^{*}	-0.031^{***}
	(0.024)	(0.036)	(0.012)	(0.024)	(0.033)	(0.012)
Precip JJAS	0.010	0.022	0.014	0.003	0.029	0.012
	(0.050)	(0.056)	(0.024)	(0.050)	(0.055)	(0.024)
Temp ND	−0.018	-0.072^{***}	−0.007	−0.015	-0.075^{***}	−0.006
	(0.012)	(0.026)	(0.005)	(0.012)	(0.029)	(0.005)
Precip ND	0.415	−0.716	−0.011	0.424	−0.725	−0.009
	(0.349)	(1.132)	(0.168)	(0.348)	(1.144)	(0.170)
District FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,401	8,401	8,401	8,401	8,401	8,401
R-squared	0.711	0.388	0.698	0.712	0.389	0.698

FEs = fixed effects; HHI = Herfindahl–Hirschman Index (calculated over area planted to 20 different crops); JJAS = June, July, August, and September; ND = November and December.
Notes: “Precip” refers to cumulative seasonal rainfall. “Temp” refers to average seasonal temperature. “Drought” refers to a binary indicator defined as equal to 1 when cumulative JJAS season rainfall is in the first tercile of the district-specific rainfall distribution. “North” refers to a binary indicator defined as equal to 1 when the district is within Gujarat, Haryana, Punjab, Rajasthan, or Uttar Pradesh. “Irrig” refers to a binary indicator defined as equal to 1 when more than 30% of a district’s planted area is irrigated. Gross and net revenues are measured in thousands of rupees per hectare; yield is measured in tons per hectare. Standard errors are clustered by administrative district and are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.1$.
Source: Authors’ calculations.

how local prices are influenced by crop diversity in addition to the yield effects documented above, we regress our price index on the same set of covariates we use in the previous two tables. The first two columns in Table 4 use the pooled all-India sample. Columns 3 and 4 look at whether the price response varies across space. These regressions suggest a statistically significant correlation between the price index and the interaction of the diversification index with the drought indicator. However, this effect is quantitatively small: a one standard deviation increase in the HHI during a drought year is consistent with a roughly 1.5% higher price index. If we look at the interaction in the last two columns, this effect is much larger in North India, where the effect is 4%. The interaction between the drought variable and the diversification index suggests that in drought years, less diverse districts see slightly higher farm gate prices, alongside lower yields.

Table 4. **Ordinary Least Squares Estimation Results—Price Index**

	Price Index	Price Index	Price Index	Price Index
HHI	-53.558^{***}	16.505	-55.131^{***}	15.207
	(12.050)	(15.445)	(11.951)	(15.355)
HHI × Drought	10.101^{**}	12.103^{***}	9.801^{**}	11.637^{***}
	(4.235)	(4.046)	(4.141)	(3.998)
HHI × Drought × North			9.940^{*}	14.588^{**}
			(5.598)	(5.945)
Drought	−1.135	−1.496	−2.176	−3.003
	(2.002)	(2.007)	(2.127)	(2.144)
Temp JJAS	6.788^{***}	19.910^{***}	6.583^{***}	19.511^{***}
	(1.729)	(1.300)	(1.730)	(1.306)
Precip JJAS	1.959	7.306^{**}	1.701	6.936^{*}
	(3.232)	(3.592)	(3.235)	(3.590)
Temp ND	−0.779	-2.801^{***}	−0.807	-2.811^{***}
	(0.983)	(0.591)	(0.987)	(0.591)
Precip ND	−5.210	-33.327^{***}	−4.779	-32.741^{***}
	(12.539)	(10.959)	(12.525)	(10.928)
District FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	No	Yes	No
Region Trends	No	Yes	No	Yes
Observations	8,401	8,401	8,401	8,401
R-squared	0.816	0.782	0.816	0.782

FEs = fixed effects; HHI = Herfindahl–Hirschman Index (calculated over area planted to 20 different crops); JJAS = June, July, August, and September; ND = November and December.
Notes: "Precip" refers to cumulative seasonal rainfall. "Temp" refers to average seasonal temperature. "Drought" refers to a binary indicator defined as equal to 1 when cumulative JJAS season rainfall is in the first tercile of the district-specific rainfall distribution. "North" refers to a binary indicator defined as equal to 1 when the district is within Gujarat, Haryana, Punjab, Rajasthan, or Uttar Pradesh. Total and net revenues are measured in thousands of rupees per hectare; yield is measured in tons per hectare. Standard errors are clustered by administrative district and are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.1$.
Source: Authors' calculations.

V. Conclusions

Our empirical results suggest that Indian districts with a more diverse crop mix are indeed more resilient in the presence of droughts. We show economically small, yet statistically significant, effects on gross and net revenues. We document that these impacts materialize both through a physical effect on yields, as well as through changes in local prices. We see no heterogeneity between North India and South India in the revenue and yield regressions, but do detect a higher price response in the North compared to the South. We show some suggestive evidence that these benefits seem to be negated in heavily irrigated districts, where irrigation serves as a backstop for bad rainfall outcomes, as long as irrigation water is available from groundwater or surface sources. These findings contribute both to the literature seeking to understand possible adaptation pathways for agriculture under anthropogenic climate change, as well as to the body of research quantifying the benefits of increased diversification in agricultural and agroecological systems.

There are several caveats to our analysis. This observational study suggests correlations only, as we have to rely on the fact that our lagged diversification index is predetermined. A proper, and hugely costly, experimental design would randomly encourage farmers in different districts to increase the diversity of crops grown. This is clearly not feasible in the short run at this scale. A meta-analysis of the studies listed in Zimmerer (2010) might serve as an interesting next step for future research.

Many outstanding questions regarding the resiliency benefits of crop diversity go beyond the resources available for this study. They include a more careful examination of which type of heterogeneity is responsible for the largest gains in resilience. For example, are the aggregate gains from diversification due to heterogeneity in minor crops? Or, are the observed benefits only realized when minor and major crops together provide a diversified portfolio? We hope that increased availability of satellite imagery over time will allow us to more closely examine these questions for large-scale panel data. Closer collaboration between ecologists, agricultural economists, and data scientists might provide a fruitful path forward to disentangle the mechanisms behind these effects and better understand the associated economic benefits and costs.

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Carbon Trading Scheme in the People's Republic of China: Evaluating the Performance of Seven Pilot Projects

XING CHEN AND JINTAO XU*

The People's Republic of China (PRC) launched seven emissions trading scheme (ETS) pilot projects in 2013–2014 to explore a cost-effective approach for low-carbon development. The central government subsequently announced its plans for the full-fledged implementation of ETS in the entire PRC in late 2017. To ensure the success of ETS in the PRC, it is necessary to gain a better understanding of the experiences and lessons learned in the pilot projects. In this paper, we provide a policy overview of the seven pilot projects, including policy design, legislative basis, and market performance. We use the synthetic control method to evaluate the carbon mitigation effect of each of the seven ETS pilots. Our findings are that success has been limited and uneven across the pilot projects, which warrants deeper evaluation of the differences between them and caution in scheme expansion. Results from the analysis also shed light on policy improvements that can benefit the nationwide development of ETS.

Keywords: cap-and-trade, climate change, emissions trading schemes, synthetic control method
JEL codes: Q51, Q54, Q56

I. Introduction

The need to address climate change and reduce greenhouse gas (GHG) emissions has become the consensus of the world's major countries. Policy makers are employing or contemplating the use of market-based instruments for climate policy. In recent years, cap-and-trade schemes have commanded attention in discussions related to climate change. The theoretical attraction of cap-and-trade is its potential to reduce emissions at lower cost than conventional, direct regulations such as mandated technologies or performance standards.

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In October 2011, the National Development and Reform Commission (NDRC) of the People's Republic of China (PRC) designated seven provinces and cities—Beijing, Chongqing, Guangdong, Hubei, Shanghai, Shenzhen, and Tianjin—as regional pilot projects in a carbon emissions trading scheme (ETS) that is consistent with the logic of a cap-and-trade system (NDRC 2011). The Government of the PRC also established a nationwide carbon emissions trading market at the end of 2017. While there is a wide agreement among economists as to the potential advantages of market-based instruments, there is much debate as to whether ETS is the best policy option for the PRC.

This article provides an overview and analysis of the PRC's carbon market based on 4 years of pilot testing. We introduce the background and market performances of ETS, along with a comparison of the seven pilot projects in different regions of the PRC. We use the synthetic control method to evaluate emissions reduction achievements at the regional level. Challenges that exist in the PRC carbon market are identified and policy recommendations to further improve the market are also provided.

The rest of this paper is organized as follows. The next section lays out the legislation that supports the PRC's ETS system and analyzes existing regulations. Section III focuses on the actual market performances of the seven pilot projects. Section IV evaluates the carbon mitigation effect of the seven pilot projects based on the synthetic control method. The final section provides highlights of key conclusions from the analysis, the main challenges to successful implementation of ETS, and policy recommendations to support the program's expansion nationwide.

II. Policy Overview

Theoretically, ETS affects total GHG emissions by creating a market for emissions permits allocated to individual emitters under an aggregate emissions cap. The regulatory authority stipulates the total allowable quantity of emissions. In doing so, the level of scarcity of allowable GHG emissions is determined; total allowable emissions are then divided into a certain number of emissions permits that are allocated to individual emitters based upon certain rules. Recognizing differences in marginal costs of implementing the permits by different individual emitters, the trading of permits is allowed and an equilibrium price for the permits emerges. This equilibrium price provides a signal as to the level of scarcity of the emissions permits, guiding individual emitters (firms most likely) to choose between reducing or increasing GHG emissions, and to identify technologies corresponding to their choices. Moreover, an effective ETS achieves the set cap with minimum social costs.

In 2009, the PRC pledged to reduce by 2020 the intensity of carbon dioxide (CO_2) emissions per unit of gross domestic product (GDP) by 40%–45% from

Table 1. **Legislative Basis of Seven Emissions Trading Scheme Pilots**

Pilot Province or City	Legal Document
Beijing	Resolution on Beijing to Carry Out Carbon Trade Pilot under the Premise of Strictly Controlling Total Carbon Emissions (Beijing Municipal People's Congress Standing Committee) (31 December 2013)
Shanghai	Shanghai Carbon Emission Management Interim Guidelines (Shanghai Municipal People's Government Order No. 10) (18 November 2013)
Guangdong	Guangdong Province Carbon Emission Management Interim Guidelines (Guangdong Provincial People's Government Order No. 197) (15 January 2014)
Shenzhen	Regulation on Carbon Emission Management for the Shenzhen Special Economic Zone (Shenzhen Municipal People's Congress) (30 December 2012)
Tianjin	Notice on Issuing the Interim Measures on Carbon Emissions Trading in Tianjin (General Office of Tianjin Municipal People's Government) (21 May 2013)
Hubei	Hubei Province Carbon Emissions and Trade Management Interim Measures (Hubei Provincial Government Order No. 371) (25 April 2014)
Chongqing	Chongqing Carbon Emission and Trade Management Interim Measures (Chongqing Municipal People's Government 41st Executive Meeting) (27 March 2014)

Sources: All data are from the following local municipal government websites. For Beijing, http://www.bjrd.gov.cn/zdgz/zyfb/jyjd/201312/t20131230_124249.html; for Shanghai, http://www.shanghai.gov.cn/nw2/nw2314/nw2319/nw2407/nw31294/u26aw37414.html; for Guangdong, http://zwgk.gd.gov.cn/006939748/201401/t20140117_462131.html; for Shenzhen, http://www.sz.gov.cn/zfgb/2013/gb817/201301/t20130110_2099860.htm; for Tianjin, http://qhs.ndrc.gov.cn/qjfzjz/201312/t20131231_697047.html; for Hubei, http://fgw.hubei.gov.cn/ywcs2016/qhc/zg_gzdt/bgs_wbwj/201404/t20140425_76918.shtml; and for Chongqing, http://www.cq.gov.cn/publicinfo/web/views/Show!detail.action?sid=3874934.

2005 levels. In December 2011, the PRC suggested for the first time in its 12th Five-Year Plan for National Economic and Social Development to "gradually establish a carbon emissions trading market" as a way to control GHG emissions. The GHG Emissions Control Work Schedule for the 12th Five-Year Plan specifically points to establishing a "carbon emissions trading pilot" and developing the PRC's "overall program for [a] carbon trading market." This indicates that the PRC's carbon trading policy will follow the principle of "first pilot at the local level, then scale up." In October 2011, a Notice on Conducting Carbon Trading Pilots by the NDRC confirmed seven designated pilots. The pilot provinces and cities established an institutional basis for carbon trading and officially launched trading in 2013–2014. Building on the pilot experience, the PRC accelerated the construction of a national carbon trading market, which began operation on 19 December 2017.

Establishing the legal basis of ETS is an important prerequisite for successful implementation. The legal documents listed in Table 1 carry different legal weight: some are resolutions passed by the local People's Congress Standing Committees, while others are government orders. In addition to legal tools, some pilot ETSs also use administrative methods such as confiscation of the following year's permits and public shaming to promote compliance among firms.

The science, rationality, and effectiveness associated with ETS design is also critical for the success of each pilot and of the future national carbon market. In addition to learning from existing markets globally, including the European ETS and the Regional GHG Initiative in the United States, the PRC has conducted in-depth studies into its own conditions in order to establish locally appropriate markets. Overall, the cap-and-trade schemes in the PRC's seven pilots have the following characteristics:

- **Executive entity.** In most cases, the executive entity is the local Development and Reform Commission, generally its department in charge of resources, environment, and energy. Local finance bureaus and other departments provide support to implementation.

- **Industries regulated.** Almost all energy-intensive industries are covered in the pilot trading schemes, including electricity, steel, cement, and chemicals. The Beijing, Shanghai, and Tianjin ETSs also include the construction and services industries.

- **Government intervention**. Government intervention in the carbon market includes emissions data collection, emissions permit allocation and auction, and interventions in market pricing when necessary. For example, the Beijing, Shanghai, and Shenzhen ETSs put forward market conditions and methodologies to regulate prices for emissions permits.

- **Permit allocation methodology**. All pilots adopted the historical emissions method to allocate permits, while the benchmarking method was used for new facilities and certain industries. The Guangdong, Hubei, and Shenzhen ETSs conducted auctions for emissions permit allocation. Other pilots generally distributed permits free of charge.

- **Transaction and reporting thresholds**. The pilots also set market access conditions for companies involved in the trading scheme and announced thresholds for emissions reporting for other large emitters that were not covered by the trading system (referred as "reporting companies"). These companies must report their emissions to the government on an annual basis so the latter can determine whether they should be included in the future carbon trading scheme or not. The emissions of companies involved in carbon trading (referred to as "emissions control companies") account for about 60% of total regional emissions in Guangdong and Tianjin, and for more than 40% in other pilot regions (Table 2).

Table 2. **Carbon Emissions Cap and Number of Covered Companies in Seven Pilots**

Pilot Province or City	Carbon Emissions Cap (CO_2 million tons/year)	Number of Covered Companies	Proportion of Allowance in Total Emissions
Beijing	70	490	40.0%
Shanghai	510	191	57.0%
Guangdong	350	202	58.0%
Shenzhen	30	635	40.0%
Tianjin	150	114	60.0%
Hubei	120	138	35.9%
Chongqing	100	242	39.5%

CO_2 = carbon dioxide.
Notes: Most pilots increased their number of covered companies each year. The information in this table is for the initial year of each pilot. All pilots were launched in 2013, except for Hubei and Chongqing, which were launched in 2014.
Source: Carbon Emissions Allowance Management Rules (Interim) published by the local government in each pilot region.

Table 3. **Trading Indicators of the Seven Emissions Trading Scheme Pilots**

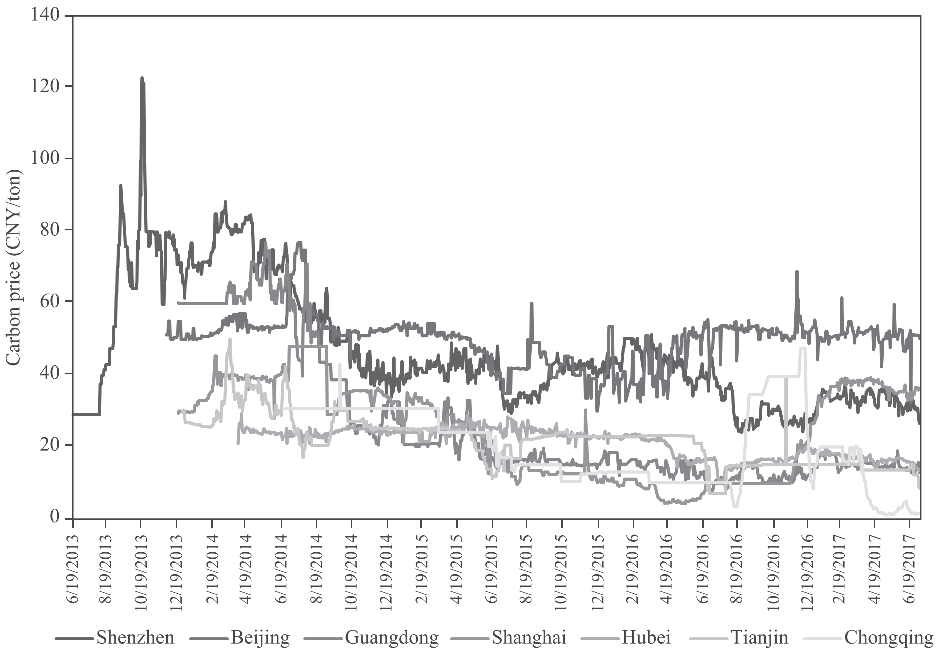
Pilot Province or City	Starting Date	Active Ratio[a]	Average Trading Price (CNY/ton CO_2)	Average Trading Volume (ton/day)	Share of Total Volume
Shenzhen	19 Jun 2013	90%	47	18,604	16%
Beijing	28 Nov 2013	69%	50	7,869	6%
Shanghai	19 Dec 2013	63%	25	11,819	9%
Guangdong	19 Dec 2013	71%	26	34,399	26%
Tianjin	26 Dec 2013	52%	22	3,450	3%
Hubei	2 Apr 2014	96%	21	50,163	35%
Chongqing	16 Jun 2014	18%	20	6,644	5%
Average	…	66%	30	18,992	…

CNY = yuan, CO_2 = carbon dioxide.
[a] Active ratio refers to the number of days that have trading volume divided by the total number of trading days.
Source: China Carbon Trading Platform. http://k.tanjiaoyi.com/ (accessed June 30, 2017).

III. Market Performance

The effectiveness of ETS pilots relies not only on institutional design, but also on the actualities of policy implementation. The intermediate effects of the carbon trading policy can be observed through the market performances of the seven ETS pilots. This study selected carbon price and trading volume to evaluate market performance of each of the seven pilots (Table 3).

Figure 1. **Historical Trend of Carbon Prices in the Seven Emissions Trading Scheme Pilots**



CNY = yuan.
Source: China Carbon Trading Platform. http://k.tanjiaoyi.com/ (accessed June 30, 2017).

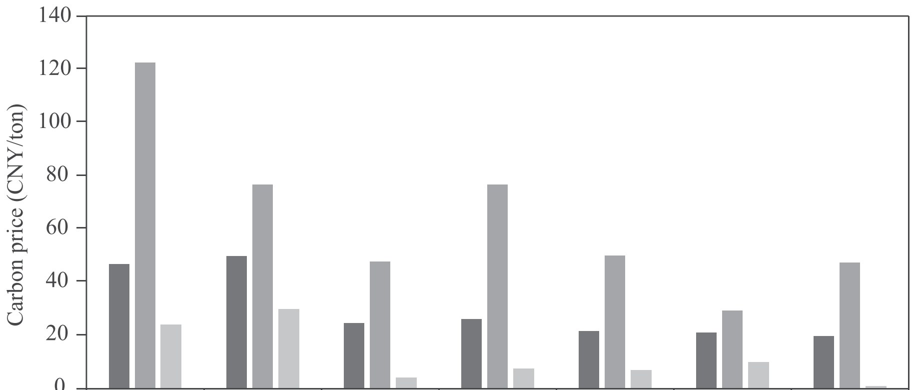
A. Carbon Price

Price fluctuations were observed to be normal in most ETS pilots. Overall, the price fluctuated wildly in 2013; subsequently, price fluctuations were smaller. This is because in the early stage of ETS in the PRC, there was only one pilot project (Zhao et al. 2016). With the subsequent launching of other ETS pilots, the price fluctuations moderated (Figure 1).

Price differences are obvious among the seven ETS pilots, with the overall average price in the review period (June 2013–June 2017) being CNY30 per ton. The average price was CNY50 per ton in Beijing, which ranks the highest, followed by Shenzhen at CNY47 per ton. The average price in Chongqing in June 2017 was CNY20 per ton, which ranks the lowest. The lowest price observed in Beijing during the review period was CNY44 per ton, which is still higher than the national average price and the peak price observed in Chongqing.

As can be seen from Figure 2, among the seven pilot ETSs, prices fluctuated the most in Tianjin and Shenzhen, while price movements in Hubei ETS were relatively small. However, when approaching the compliance deadline (mainly in

Figure 2. **Peak Price, Average Price, and Lowest Price of the Seven Emissions Trading Scheme Pilots**



	Shenzhen	Beijing	Shanghai	Guangdong	Tianjin	Hubei	Chongqing
Average price	46.88	49.87	24.73	26.27	21.73	21.20	19.87
Peak price	122.97	77.00	48.00	77.00	50.10	29.35	47.52
Bottom price	24.13	30.00	4.20	7.57	7.00	10.07	1.00

■ Average price ■ Peak price ■ Bottom price

CNY = yuan.
Source: Authors' calculations based on data from China Carbon Trading Platform. http://k.tanjiaoyi.com/ (accessed June 30, 2017).

June or July each year), the carbon price always rose.[1] Although price fluctuations are common in the early stage of ETSs globally, excessive price fluctuations are not conducive to reflecting the actual cost of carbon emissions. They create huge risks for market participants and uncertainty for the covered companies.

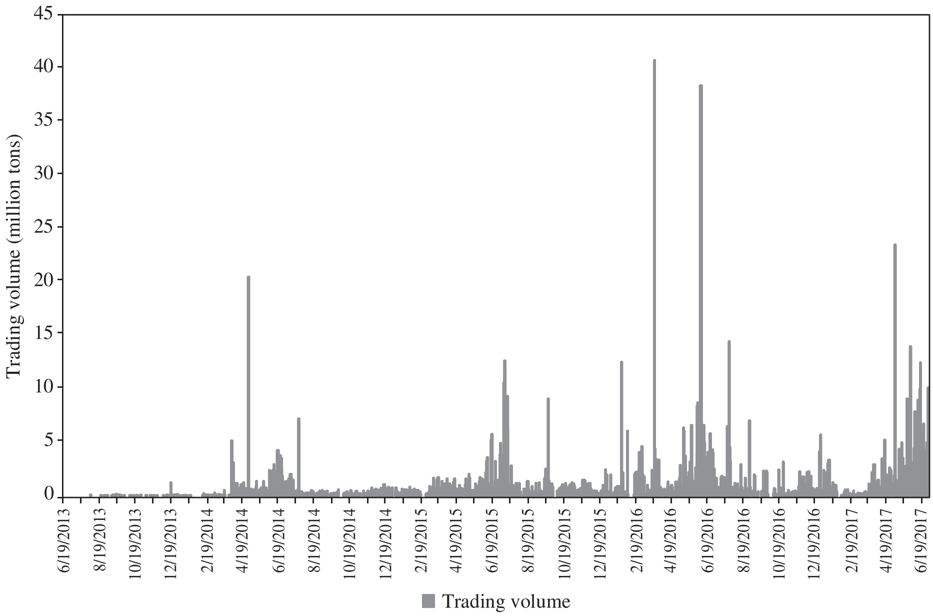
B. Trading Volume

Another characteristic of ETS pilots is their low trading volumes, which seems to be a big challenge for the PRC's carbon market. There is little or even no trading volume on most days. However, the trading volume of each ETS pilot increased sharply before its respective compliance period (Figure 3).

Although the overall size of the PRC's seven pilot carbon markets is substantial, companies were not enthusiastic in participating in carbon trading, as evidenced by the ratio of cumulative trading volumes to carbon emissions cap. Zhao et al. (2016) depicted this phenomenon: for the Shenzhen ETS, the cumulative trading volume only accounted for 5.6% of the carbon emissions cap, which is the highest among the seven ETS pilots. In the other six pilots, the ratios were

[1] When approaching compliance deadline, all participants must ensure that they have followed the procedural steps or they may get penalized.

Figure 3. **Historical Trend of Trading Volumes in the Seven Emissions Trading Scheme Pilots**

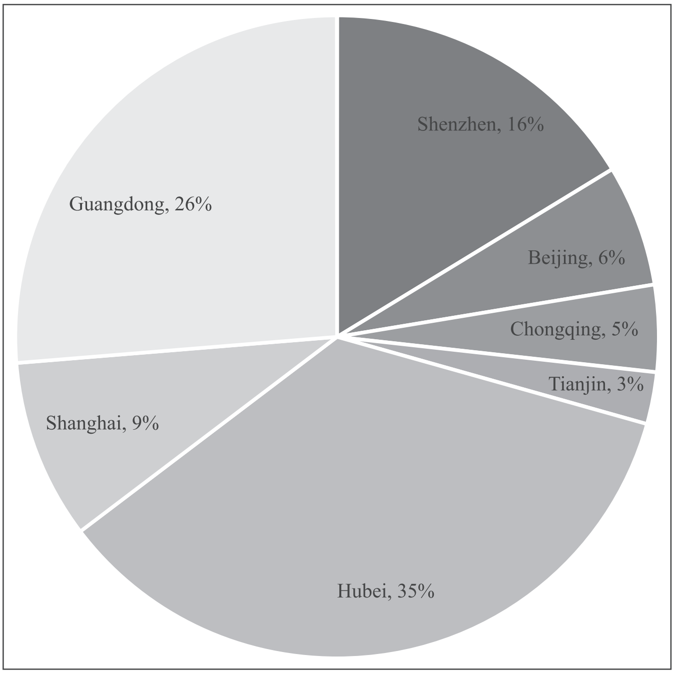


Source: Authors' calculations based on data from China Carbon Trading Platform. http://k.tanjiaoyi.com/ (accessed June 30, 2017).

4.9% in Hubei, 3% in Beijing, 2% in Shanghai, and less than 1% in each of the other three pilot locations. The total cumulative trading volume of seven ETS pilots only accounted for 1.4% of the total carbon emissions cap. Thus, the ratio is rather low and most of the allowances have not been traded. It is partly because of policy uncertainty during the pilot period of ETS, so it is difficult for covered companies to stay cautious. In addition, during the pilot period, covered companies are pressured by other existing energy conservation policies (e.g., energy saving targets) so ETS may not substantially influence companies' behavior.

Comparing compliance across the seven pilot ETSs—from the start date until the end date of the trading period—reveals that the Hubei, Guangdong, and Shenzhen ETSs had the most active trading. From the perspective of secondary market performance, the design and operation of the Hubei ETS has been successful. By 30 June 2017, cumulative nationwide trading volume was 114.6 million tons, among which the cumulative trading volume of the Hubei ETS was 40.4 million tons, or about 35% of the total. The Guangdong and Shenzhen ETSs also both had a larger trading volume than either the Beijing, Shanghai, Chongqing, or Tianjin ETSs (Figure 4). At the same time, Tianjin and Chongqing seems to be far behind the average level, reflected by fairly low market liquidity in the two places.

Figure 4. **Trading Volume Shares of the Seven Emissions Trading Scheme Pilots**



Source: Authors' calculations based on data from China Carbon Trading Platform. http://k.tanjiaoyi.com/ (accessed June 30, 2017).

IV. Emissions Reduction Achievements

With important implications for global climate change mitigation, the development of ETS in the PRC has attracted increasing attention in recent years. Before ETS was actually implemented, many researchers discussed the mechanism design and regional linkages from a theoretical perspective. With the establishment of ETS in the PRC, researchers began evaluating its emissions reduction achievements. In this section, we focus on the carbon mitigation effect of the seven pilot ETSs.

A. Research on Emissions Trading Scheme Impact Assessment

Perhaps because the PRC's ETS pilots only covered a short amount of time from preparation to commissioning, most attention has been paid to estimating the potential (ex ante) impacts of the regional ETSs and the hypothetical nationwide ETS (Jiang et al. 2016). There are few studies conducting an impact assessment from ex post empirical perspectives.

Many researchers have used computable general equilibrium (CGE) or CGE-based models to assess the PRC's upcoming national ETS. Tang and Wu (2013) established an interregional CGE model to simulate social welfare impacts of different climate policies. They found that ETS can moderate the economic and social welfare losses regardless of the allocation of emissions permits. Liu et al. (2013) used a Sino-TERMCO2 model to investigate carbon abatement effects of separated and linked markets. Their results showed that the linked market can improve social welfare and reduce carbon emissions intensity, but this system may distribute welfare more unevenly among different industries.

As current research mainly focuses on individual ETS pilots, a comprehensive comparison of all seven pilots is needed. For the Shanghai ETS, for example, Zhou (2015) simulated the economic impacts and cobenefits under alternative employment conditions. The results illustrated that a double dividend from carbon emissions trading is available if the labor released from ETS-affected sectors is absorbed immediately. Otherwise, GDP will decrease 1.5%–2.4% compared to the baseline. For the Guangdong ETS, Wang et al. (2015) used a GD_CGE model to simulate the effects of carbon mitigation through ETS under the carbon intensity target. The results show that with an abatement target, implementation of ETS can reduce abatement costs and decrease GDP losses, which constitutes a cost-effective way to achieve carbon reduction. Ren, Dai, and Wang (2015) used a dynamic two-region CGE model and the results showed that if a carbon trading policy is implemented in a low-carbon scenario GDP declines 0.8% relative to the baseline. For the Hubei ETS, Tan, Liu, and Wang (2016) used a multiregional general equilibrium model (Term-CO_2) to simulate economic and environmental impacts. The results showed that the carbon emissions of Hubei are reduced by 1% and GDP declines slightly by 0.06%. For the Tianjin ETS, Liu et al. (2017) simulated the impacts on the economy and environment using a Term-CO_2 model. The results showed that carbon emissions decrease by 0.62% and GDP declines a marginal 0.04%.

To sum up, these studies showed that ETS has the potential to lower the total economic costs and social welfare losses caused by carbon emissions abatement in the PRC, but its impact significantly varies by province and sector. Among these studies, however, only a small number of such impact assessments have been conducted and most of them have drawn qualitative conclusions. Empirical ex post impact assessments of the pilot ETSs are needed to guide the operation of the PRC's nationwide ETS (Jiang et al. 2016).

B. Method and Data

To estimate the effects of events and policy interventions at the aggregate level, researchers often use comparative case studies. In such studies, researchers estimate the evolution of aggregate outcomes (in this case, CO_2 emissions) for a unit affected by an occurrence of the event and compare it to the evolution of the same aggregates estimated for some control group of unaffected units. However, it is difficult to estimate the carbon mitigation effect of carbon trading because of the lack of solid control groups in this case.

The synthetic control method is used for effect estimation in settings where a single unit (e.g., state, country, or firm) is exposed to an event or intervention. The synthetic control method was first introduced and implemented in Abadie and Gardeazabal (2003). Other comparative studies include investigating the economic impacts of German reunification (Abadie, Diamond, and Hainmueller 2015) and the local impacts of nuclear power facilities (Ando 2015). There is also a series of research focusing on the PRC. Liu and Fan (2013) examine the economic impacts of the PRC's house property tax pilot program in Chongqing. Zhang, Zhong, and Yi (2016) used this same method to answer the question of whether the Olympic Games improved air quality in Beijing.

Based on Abadie, Diamond, and Hainmueller (2011), we use a simple model providing a rationale for the use of the synthetic control method. Suppose that we observe $J+1$ regions, and the first region is exposed to the intervention of interest, so that we have J remaining regions as potential controls. Suppose Y_{it}^N is the outcome that would be observed for region i at time t without treatment for units $i = 1, 2, \ldots J+1$, and time periods $t = 1, 2, \ldots T$. Let T_0 be the number of preintervention periods, with $1 < T_0 < T$. Let Y_{it}^I be the outcome that would be observed for region i at time t with treatment in periods $T_0 + 1$ to T. We assume that the intervention has no effect on the outcome before the implementation period, so for all i in period $t \in \{1, 2, \ldots T_0\}$, we have $Y_{it}^N = Y_{it}^I$. Let $\alpha_{it} = Y_{it}^I - Y_{it}^N$ be the effect of the intervention for unit i at time t, and let D_{it} be an indicator that takes a value of 1 if unit i is exposed to the intervention at time t and zero otherwise. The observed outcome for unit i at time t is

$$Y_{it} = Y_{it}^N + D_{it}\alpha_{it} \tag{1}$$

We aim to estimate $(\alpha_{1T_0+1}, \ldots \alpha_{1T})$. For $t > T_0$,

$$\alpha_{1t} = Y_{1t}^I - Y_{1t}^N = Y_{1t} - Y_{1t}^N \tag{2}$$

Because Y_{it}^I is observed, to estimate α_{1t} we just need to estimate Y_{1t}^N; suppose that Y_{it}^N is given by a factor model:

$$Y_{it}^N = \partial_t + \theta_t Z_i + \lambda_t \mu_i + \varepsilon_{it} \tag{3}$$

where Z_i is a $(r \times 1)$ vector of observed covariates (not affected by the intervention), ∂_t is an unknown common factor with constant factor loading across units, λ_t is a $(1 \times F)$ vector of unknown parameters, μ_i is a $(F \times 1)$ vector of unobserved factor loadings, and the error term ε_{it} represents unobserved transitory shocks at the regional level with zero mean.

We have to estimate Y_{it}^N. Consider a $(J \times 1)$ vector of weights $W^* = (w_2^*, \ldots w_{j+1}^*)$ such that $W_J \geq 0$ for $j = 2, \ldots, J+1$ and $w_2 + \cdots + w_{J+1} = 1$. Each value of the vector W^* represents a potential synthetic control, that is, a particular weighted average of control regions. The value of the outcome variable for each synthetic control indexed by W^* is

$$\sum_{j=2}^{J+1} w_j Y_{it} = \partial_t + \theta_t \sum_{j=2}^{J+1} w_j Z_j + \lambda_t \sum_{j=2}^{J+1} w_j \mu_i + \sum_{j=2}^{J+1} w_j \varepsilon_{it} \tag{4}$$

Suppose that there are $W^* = (w_2^*, \ \ldots \ w_{j+1}^*)'$ such that

$$\sum_{j=2}^{J+1} w_j^* Y_{jt} = Y_{11}, \ \ldots \sum_{j=2}^{J+1} w_j^* Y_{jT_0} = Y_{1T_0} \quad \text{and} \quad \sum_{j=2}^{J+1} w_j^* Z_j = Z_1 \tag{5}$$

If $\sum_{i=1}^{T_0} \lambda'_t \ \lambda_t$ is nonsingular, then

$$Y_{1t}^N - \sum_{j=2}^{J+1} w_j^* Y_{jt} = \sum_{j=2}^{J+1} w_j^* \sum_{s=1}^{T_0} w_j^* \lambda_t \left(\sum_{i=1}^{T_0} \lambda'_t \ \lambda_t \right)^{-1} \lambda'_s \left(\varepsilon_{js} \varepsilon_{is} \right) - \sum_{j=2}^{J+1} w_j^* \left(\varepsilon_{jt} - \varepsilon_{it} \right) \tag{6}$$

Abadie, Diamond, and Hainmueller (2011) proved that, under the general condition, the right-hand side of equation (6) will approach zero. As a result, $\sum_{j=2}^{J+1} w_j^* Y_{jt}$ is the unbiased estimation of Y_{it}^N, where $T_0 < t \leq T$. So $\alpha_{1t} = Y_{it} - \sum_{j=2}^{J+1} w_j^* Y_{jt}$ is the unbiased estimation of α_{1t}.

Take Hubei as an example. We construct the synthetic Hubei as a weighted average of potential control provinces, with weights chosen so that the resulting synthetic Hubei best reproduces the values of a set of predictors of CO_2 emissions in Hubei before the carbon trading system was implemented (i.e., before 2013). Because the synthetic Hubei is meant to reproduce the CO_2 emissions that would have been observed for Hubei in the absence of a carbon trading pilot, we discard from the donor pool provinces that adopted a carbon trading system during our sample period. Therefore, Beijing, Chongqing, Guangdong, Shanghai, and Tianjin are excluded from the donor pool. Finally, our donor pool includes the remaining 24 provinces.

Our outcome variable of interest is annual CO_2 emissions, calculated based on energy consumption at the provincial level. We use annual provincial-level data of energy consumption during the 1995–2015 period from the *China Statistical Yearbook* (National Bureau of Statistics of China 2016). Since seven pilots went into effect beginning in late 2013, we mark 2013 as the treatment year. This gives us 17 years of preintervention data. Our sample period begins in 1995 because it is the first year for which data on energy consumption are available for all our control provinces. It ends in 2015 because newer data have not yet been published. Based

Table 4. **Social and Economic Characteristics of Actual and Synthetic Emissions Trading Scheme Pilots**

Pilot Province or City		GDP per Capita (CNY)	Share of Secondary Industry in Total GDP (%)
Hubei	(real)	13,703.1	42.6
Hubei	(synthetic)	13,746.8	42.8
Beijing	(real)	42,862.0	29.9
Beijing	(synthetic)	17,454.5	33.5
Shanghai	(real)	47,094.2	46.5
Shanghai	(synthetic)	21,964.8	50.4
Tianjin	(real)	37,534.3	52.8
Tianjin	(synthetic)	14,944.7	48.9
Chongqing	(real)	13,678.4	44.2
Chongqing	(synthetic)	13,286.3	44.3
Guangdong	(real)	24,596.6	48.4
Guangdong	(synthetic)	24,505.5	49.0

CNY = yuan, GDP = gross domestic product.
Source: Authors' calculations.

on the method proposed by the Intergovernmental Panel on Climate Change, we calculate annual CO_2 emissions for all provinces. We choose our predictors of CO_2 emissions based on Auffhammer and Carson (2008): GDP per capita and share of secondary industry in total GDP.

Using the techniques described above, we construct a synthetic for each of Beijing, Chongqing, Guangdong, Hubei, Shanghai, and Tianjin that mirrors the values of the predictors of CO_2 emissions for themselves before the introduction of a carbon trading system. We estimate the carbon mitigation effect of carbon trading pilots as the difference in CO_2 emissions between Hubei and its synthetic version after 2013. We then perform a series of placebo studies that confirm that our estimated effects for carbon trading pilots are unusually large relative to the distribution of the estimate that we obtain when we apply the same analysis to the provinces in the donor pool. Then we repeat the process for Beijing, Chongqing, Guangdong, Shanghai, and Tianjin.

C. Results

As explained above, we construct the synthetic Hubei as the convex combination of provinces in the donor pool that most closely resemble Hubei in terms of prepilot values of CO_2 emissions predictors. The results are displayed in Table 4, which compares the pretreatment characteristics of the actual Hubei with that of the synthetic Hubei, as well as comparisons for the other five pilots. Table 5 displays the weight for each synthetic pilot.

Because social and economic characteristics vary substantially across provinces, different synthetic results emerge. Generally, the closer to the average

Table 5. **Synthetic Weight for Each Synthetic Pilot**

Province	Hubei_ weight	Beijing_ weight	Shanghai_ weight	Tianjin_ weight	Chongqing_ weight	Guangdong_ weight
Anhui	0.036	0	0	0	0.027	0.003
Fujian	0.025	0	0	0	0.030	0.008
Gansu	0.019	0	0	0	0.047	0.003
Guangxi	0.033	0	0	0	0.031	0.003
Guizhou	0.025	0	0	0	0.042	0.003
Hainan	0.096	0.682	0	0	0.080	0.133
Hebei	0.026	0	0	0	0.020	0.003
Heilongjiang	0.018	0	0	0	0.034	0.003
Henan	0.045	0	0	0	0.015	0.003
Hunan	0.059	0	0	0	0.023	0.004
Inner Mongolia	0.024	0	0.018	0	0.036	0.011
Jiangsu	0.057	0	0	0	0.012	0.052
Jiangxi	0.025	0	0	0	0.034	0.003
Jilin	0.017	0	0	0.566	0.040	0.003
Liaoning	0.024	0	0	0	0.026	0.007
Qinghai	0.013	0	0.352	0.381	0.301	0.003
Shaanxi	0.020	0	0	0	0.036	0.003
Shandong	0.027	0	0	0	0.010	0.005
Shanxi	0.017	0	0	0	0.039	0.003
Sichuan	0.322	0	0	0	0.020	0.003
Xinjiang	0.021	0	0	0	0.043	0.004
Yunnan	0.025	0	0	0	0.036	0.003
Zhejiang	0.029	0.318	0.629	0.052	0.020	0.734

Source: Authors' calculations.

level of the whole country, the better the synthetic result is. For example, Hubei, Guangdong, and Tianjin each have a better synthetic result than either Shanghai, Beijing, or Chongqing.

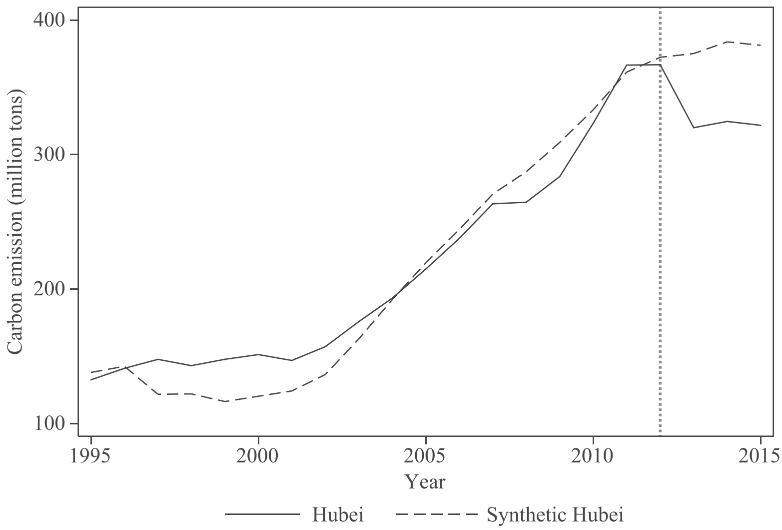
Figure 5 plots the trends in CO_2 emissions in Hubei and the synthetic Hubei. Since 2013, CO_2 emissions in Hubei and synthetic Hubei have differed notably, indicating Hubei reduced CO_2 emissions by about 59.5 million tons in 2015 due to the carbon trading scheme.

Figure 6 shows that before 2013 the synthetic data fit the actual data quite well for Guangdong. After 2013, the gap between the CO_2 emissions of Guangdong and that of synthetic Guangdong emerges, which shows a deviation from the synthetic data. Guangdong (including Shenzhen) reduced CO_2 emissions by 37.1 million tons in 2015.

From the perspective of trading indicators, Hubei and Guangdong (including Shenzhen) had more active trading than the other five pilots. The synthetic results support our expectation that more trading volume results in more emissions reduction.

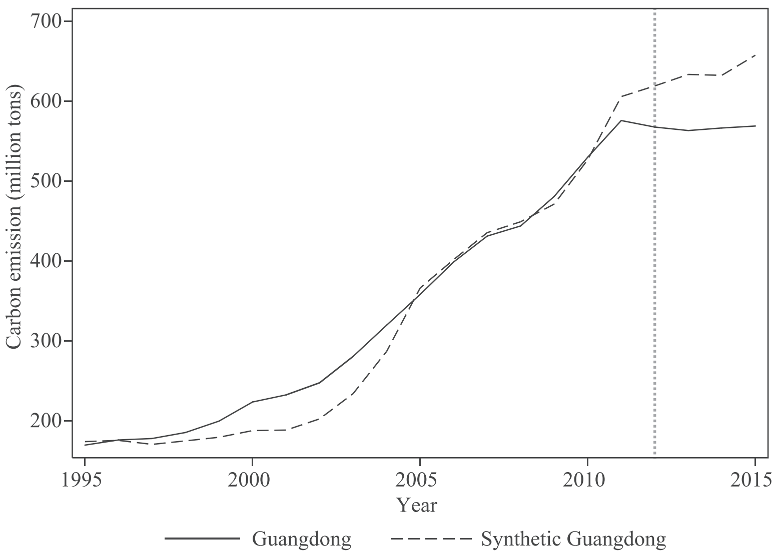
Figure 7 plots the trends in CO_2 emissions in Tianjin and synthetic Tianjin. Since 2013, CO_2 emissions in Tianjin seemed to have outpaced those in synthetic

Figure 5. **Carbon Dioxide Emissions in Hubei versus Synthetic Hubei**



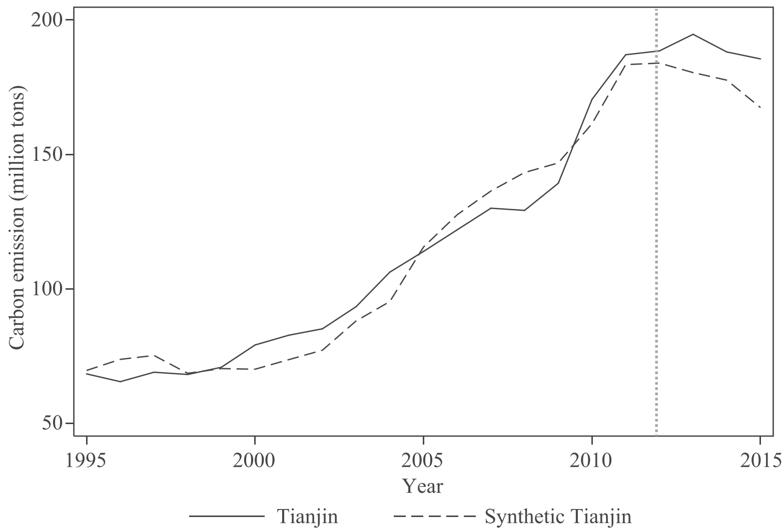
Source: Both actual emissions and synthetic emissions are authors' estimates based on data from the National Bureau of Statistics of China. 2016. *China Statistical Yearbook, 1995–2015*. Beijing.

Figure 6. **Carbon Dioxide Emissions in Guangdong versus Synthetic Guangdong**



Source: Both actual emissions and synthetic emissions are authors' estimates based on data from the National Bureau of Statistics of China. 2016. *China Statistical Yearbook, 1995–2015*. Beijing.

Figure 7. **Carbon Dioxide Emissions in Tianjin versus Synthetic Tianjin**



Source: Both actual emissions and synthetic emissions are authors' estimates based on data from the National Bureau of Statistics of China. 2016. *China Statistical Yearbook, 1995–2015*. Beijing.

Tianjin. The result is expected given the lack of liquidity in the Tianjin trading market.

However, we cannot get good synthetic results before 2013 for Beijing, Chongqing, and Shanghai. Therefore, we cannot say anything about their respective performances yet and are still searching for a better synthetic control strategy for these three municipalities. The existing results are included in the Appendix.

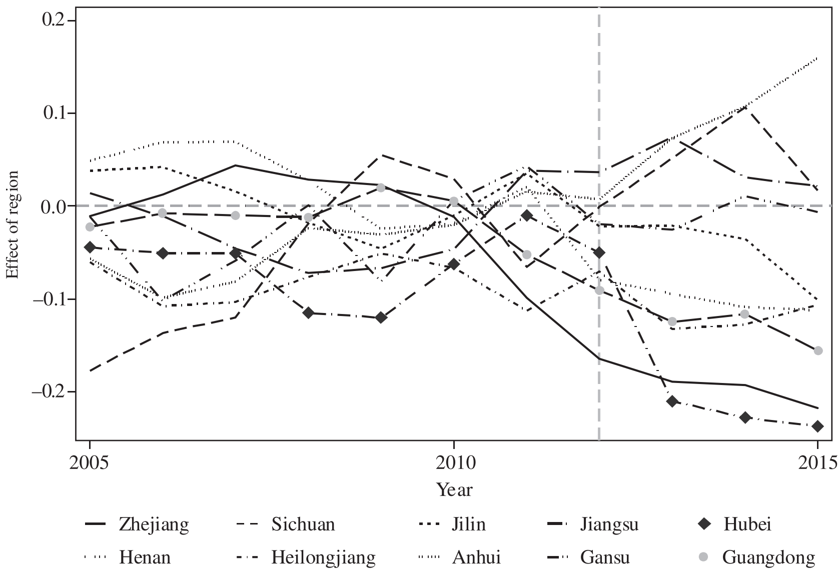
D. Robustness Test

The empirical results in the last section reveal a gap between the CO_2 emissions of Hubei and those of synthetic Hubei. In this context, we will use a placebo test to check the statistical significance of our results.

For example, are there any other provinces among the donor pool that show a gap between real CO_2 emissions and synthetic CO_2 emissions when these provinces are viewed as a treatment group? We iteratively apply the synthetic control method to estimate the impact of the carbon trading pilot on every other province. We can get the difference between real emissions and synthetic emissions, and then we divide the difference by real emissions.

Before doing this test, we need to exclude the provinces that do not fit the original CO_2 emissions data before 2012. The bad fit before the treatment means that the gap after the treatment may not be caused by the treatment itself. Therefore,

Figure 8. **Distribution of Carbon Emissions Forecast Changes in Guangdong, Hubei, and Other Provinces**



Source: Both actual emissions and synthetic emissions are authors' estimates based on data from the National Bureau of Statistics of China. 2016. *China Statistical Yearbook, 1995–2015*. Beijing.

we exclude the provinces whose mean squared prediction error before 2012 are larger than 100. Finally, we obtain nine provinces as a potential control group.

In Figure 8, each gray line represents the difference in CO_2 emissions between each province in the donor pool and its respective synthetic version. The estimated gap for Hubei is unusually large relative to the distribution of the gaps for other provinces in the donor pool. Similarly, Guangdong shows the same pattern since 2013, when its ETS went into effect.

V. Conclusions

Generally, the low trading volume in the PRC's carbon trading market shows that it is not liquid enough to be well functioning. The sharp increase in trading volume before the compliance period shows that the covered companies are unenthusiastic about ETS and view it as a routine government inspection that they must comply with. At the same time, the prohibition on cross-provincial trade reduces the attractiveness of the PRC carbon market to investors, especially institutional investors.

The awareness and participation of companies in the carbon market is still relatively low (China Emissions Exchange 2014). The high trading volume in the month before the compliance period shows that companies still treat carbon emissions trading as a means of compliance rather than an investment. Because the PRC's carbon market is still in an early stage of development, companies' views of carbon asset values will evolve with the development and maturing of the carbon market.

The seven pilot ETSs have achieved different emissions reduction results. Hubei stands out in many aspects as its ETS pilot has been very influential. Based on our synthetic result, Hubei reduced emissions by 59.5 million tons in 2015 through its carbon trading scheme. Guangdong (including Shenzhen) also performed reasonably well, reducing emissions by 37.1 million tons in 2015. On the other hand, Tianjin did not notably reduce its carbon emissions.

For policy recommendations, we suggest the following measures.

The expansion of coverage of the PRC's ETS is necessary. For now, most sectors covered by ETS are energy-intensive sectors such as petroleum processing, electricity, and steel. However, for Beijing, Shanghai, and Shenzhen, where energy-intensive sectors account for a low share of emissions, it is difficult to see an active market with a limited coverage. In these three pilots, the transport sector accounts for a large share of total emissions. According to China Emissions Exchange (2014), the transport sector accounted for 27.9% of Shenzhen's total emissions in 2010. Therefore, including the transport sector in the nationwide ETS is sensible.

Allowing multiple products to activate the ETS system. The PRC's seven ETS all use a single spot product, which may limit the liquidity of carbon markets. On the contrary, for the European Union ETS, forward trading accounts for 80%–90% of the shares traded while spot trading accounts for only about 10% (Aatola, Ollikainen, and Toppinen 2013). We suggest that authorities investigate the possibility to permit necessary derivative products in carbon trading markets. Shanghai and Shenzhen both have a stock exchange and therefore an advantage in promoting financial innovation compared with other pilots. Shanghai and Shenzhen should seize the chance to become the largest carbon futures exchange centers in the world.

Improving market transparency is the foundation to releasing market signals. Not all pilots clearly post information about each covered company. At the same time, although the carbon price and trading volume for each day are posted online, we find it difficult to know the exact trading parties. Improving market transparency would help enhance the efficacy of the system.

Despite the limited success of the ETS program, this has been extended nationwide, starting December 2017. There are two main differences between the nationwide scheme and the seven pilot programs. First, the supervision of the nationwide ETS program has shifted from NDRC to the newly established Ministry of Ecology and Environment. Second, the power generation sector is the only sector in the nationwide scheme, including 1,700 power companies. The coverage of only the power sector is due to two reasons. One is that the power sector is typically energy intensive and accounts for a large share of the PRC's carbon emissions. The other reason is that the power sector has better data. If the initial strategy to include only the power sector goes smoothly, the central authorities intend to extend the market to cover more sectors.

Finally, the PRC began implementing environmental taxes on 1 January 2018. The joint effects of the taxation system and carbon trading schemes on domestic pollution and carbon emissions warrant close monitoring and assessment. Analysis of the joint effects will shed light on needed policy changes and the country's prospects in the battle against pollution and climate change.

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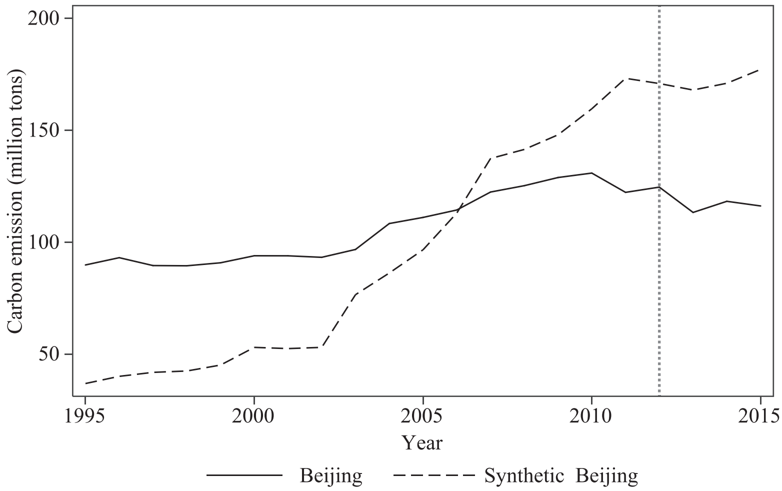
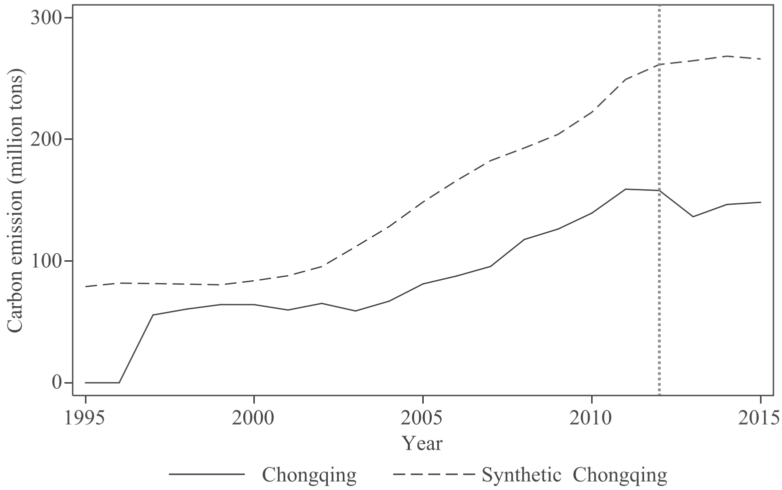
Appendix

Figure A.1. **Comparison of Emissions, Beijing**



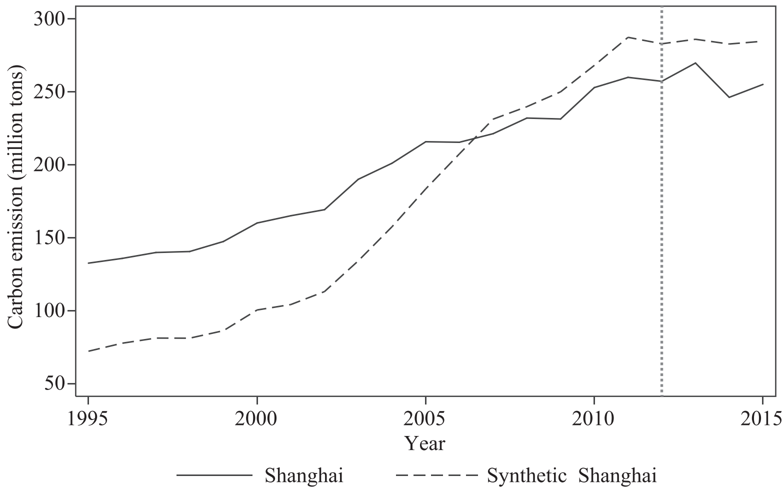
Source: Both actual emissions and synthetic emissions are authors' estimates based on data from the National Bureau of Statistics of China. 2016. *China Statistical Yearbook, 1995–2015*. Beijing.

Figure A.2. **Comparison of Emissions, Chongqing**



Source: Both actual emissions and synthetic emissions are authors' estimates based on data from the National Bureau of Statistics of China. 2016. *China Statistical Yearbook, 1995–2015*. Beijing.

Figure A.3. **Comparison of Emissions, Shanghai**



Source: Both actual emissions and synthetic emissions are authors' estimates based on data from the National Bureau of Statistics of China. 2016. *China Statistical Yearbook, 1995–2015*. Beijing.

Regional Cooperation on Carbon Markets in East Asia

Jiajia Li and Junjie Zhang*

The People's Republic of China, Japan, and the Republic of Korea have launched individual emission trading schemes to control greenhouse gas emissions cost-effectively. This paper reviews key carbon market design elements in the three countries in terms of emission allowances, covered sectors, allowance allocations, monitoring, reporting and verification, compliance and penalties, and offset markets. We assess the performances of the emission trading schemes among the three countries based on secondary-market allowance transactions. Considering heterogeneous climate policy designs in the region, we explore various approaches for the linkage of East Asian carbon markets. Cooperation on carbon markets is instrumental for regional and global climate governance. It could not only help achieve cost-effective emission reductions in the region, but also signal the commitment of the three countries to climate change mitigation.

Keywords: carbon markets, climate change, East Asia, linkage
JEL codes: Q54, Q58

I. Introduction

The People's Republic of China (PRC), Japan, and the Republic of Korea together account for almost a quarter of global gross domestic product (GDP) and a third of global greenhouse gas (GHG) emissions. In order to control GHG emissions cost-effectively, each country has started to pilot emission trading schemes (ETSs). Japan launched two regional ETSs in 2010 and 2011. The PRC has launched seven regional ETSs since 2013 and announced the initiation of a national market in 2017. The Republic of Korea started its nationwide ETS in 2015. The three countries' active engagement in climate actions not only contributes to global efforts in tackling climate change, but also ameliorates concerns that the major East Asian countries might race to the bottom in climate policy.

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A major incentive for the three countries to pilot carbon markets is a desire to curb their ever-increasing GHG emissions. The PRC, Japan, and the Republic of Korea are among the leading GHG emitters in the world. Their combined emissions accounted for over 33% of global emissions in 2016. Individually, the PRC overtook the United States to become the world's largest emitter in 2007. Japan has been the fifth-largest global emitter for a long period of time. The Republic of Korea was the eighth-largest emitter in 2015 (Olivier, Janssens-Maenhout, and Peters 2016). While Japan's emissions have stabilized, the GHG emissions of the PRC and the Republic of Korea continue to grow rapidly.

All three countries have signed and ratified the major climate agreements such as the Kyoto Protocol, Copenhagen Accord, and Paris Agreement. With pressure from international climate negotiations, Japan was the first East Asian country subject to legally binding emission reduction requirements in the Kyoto Protocol. Although the PRC and the Republic of Korea had no obligations under the Kyoto Protocol, the two countries pledged to reduce carbon emissions in the recent treaties. In particular, the PRC agreed in the Paris Agreement to peak its GHG emissions around 2030. Likewise, the Republic of Korea committed to reduce its GHG emissions by 37% from the business-as-usual (BAU) level by 2030.

Carbon markets can minimize the cost of compliance for the PRC, Japan, and the Republic of Korea to achieve their GHG emission targets. Compared with command-and-control policies, market-based instruments allow more flexibility for emitters to reduce emissions. By equalizing marginal abatement costs among emitters, the overall cost of carbon emission control can be minimized. Carbon markets also enable low-carbon industries to gain a comparative advantage, which facilitates the efforts of these countries, especially the PRC, to upgrade industrial structures.

The cobenefit of reducing local and regional air pollution is another important incentive for the three countries to control their GHG emissions. Since GHG is mainly emitted through the burning of fossil fuels, reducing carbon emissions will result in the abatement of many other toxic air pollutants. Air pollution in the PRC has drawn international attention in recent years as Chinese cities rank among the most polluted in the world. The transboundary air pollution problem is also complicating the already complex diplomatic relationships among the three countries. Therefore, coordinated regional carbon markets have the potential to mitigate regional air pollution concerns.

The PRC, Japan, and the Republic of Korea have engaged in separate endeavors in controlling GHG emissions. The timing is ripe for the three countries to explore possible carbon market linkage in order to achieve greater efficiency. The benefits of market linkage mainly lie in the following two aspects. First, market linkage in East Asia can increase the cost-effectiveness and stability of carbon markets; different marginal abatement costs among the firms being regulated by each market in different countries can lead to cost savings. A lower cost of climate mitigation achieved by market linkage can incentivize these countries to engage in more aggressive GHG emission control. Second, geographic proximity is a crucial factor for linkage among the PRC, Japan, and the Republic of Korea. The three countries have close ties in economic exchanges, and a linked carbon market will contribute to these relationships. Consequently, the expanding carbon markets ensure "Factory Asia" will grow in an environmentally sound and climate-friendly manner.

Carbon markets in East Asia could be linked in two ways. The first approach is to link the well-performing markets such as the Shanghai, Beijing, Guangdong, and Shenzhen ETSs in the PRC, and the Tokyo and Saitama ETSs in Japan. These are well-designed pilots in regions with similar levels of economic development. Another approach is to link the carbon markets with similar trading systems. Specifically, Japan and the Republic of Korea have adopted the cap-and-trade system, and the markets within these two countries could be linked more smoothly. However, the PRC's carbon markets are basically a system of tradable performance standards, which is more difficult to be linked with a cap-and-trade system. Thus, as expected, the power generation industry of the seven pilots in the PRC just started to combine in 2017. In the long term, multilateral links could be achieved in East Asia through establishing cross-regional links and bilateral links.

However, linking these carbon markets still presents major challenges and obstacles. First, heterogeneous and even incompatible market designs across countries makes linkage quite difficult. In particular, the PRC, Japan, and the Republic of Korea have distinct rules on monitoring, reporting, and verification (MRV); allowance allocation; and covered sectors. Second, the potential transboundary wealth transfer among linked markets is another controversial issue. Third, some countries might have incentives to overallocate allowances, which depresses market prices and transaction volumes. Lastly, the linkage could fall victim to geopolitical conflicts and disputes. The successful linkage of East Asian carbon markets needs to overcome these obstacles.

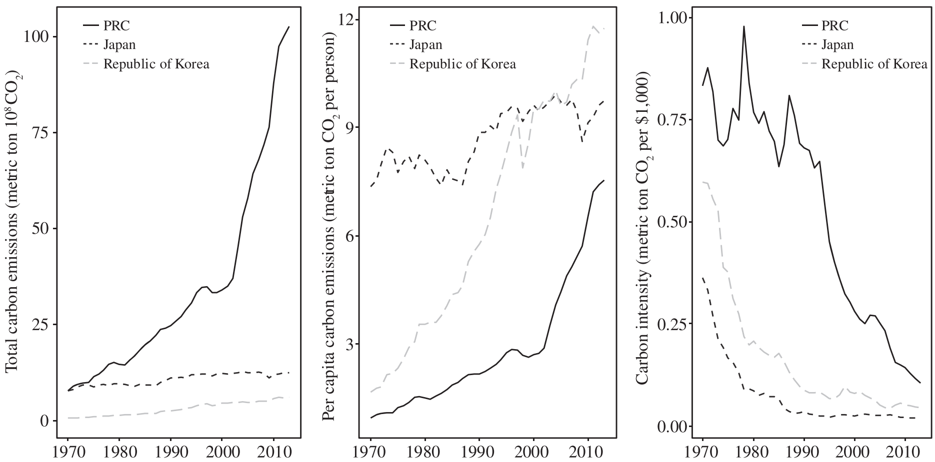
The remainder of the paper proceeds as follows. Section II introduces carbon emissions and international climate treaty participation in East Asia. Section III compares six design elements of carbon markets. Section IV assesses market performances by analyzing general trends of carbon prices and trading volumes. Section V discusses the potential benefits and concerns of linkage in East Asia. Section VI concludes the paper with further discussions.

II. Background

A. Carbon Emissions

The PRC, Japan, and the Republic of Korea are among the major GHG emitters in the world (Figure 1). Japan has had relatively stable total and per capita

Figure 1. **Carbon Emissions and Carbon Intensities in the PRC, Japan, and the Republic of Korea**



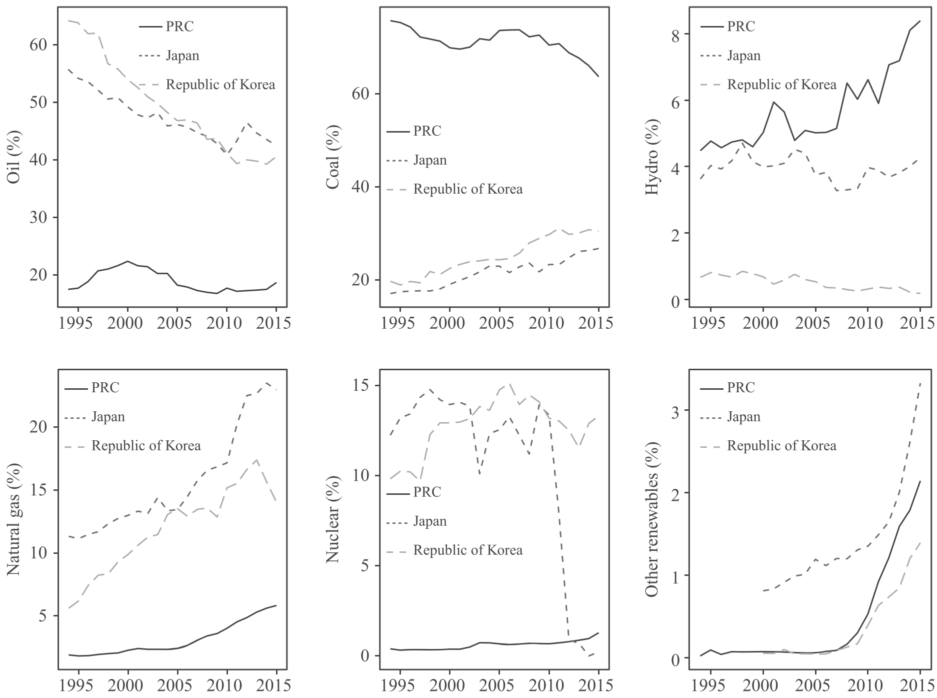
CO_2 = carbon dioxide, PRC = People's Republic of China.
Sources: United States Department of Energy, Carbon Dioxide Information Analysis Center.

emissions since 1970. In comparison, GHG emissions in the PRC have grown dramatically over the past 40 years. The PRC's total emissions were about the same as Japan's in 1970, but had grown to more than 8 times that of Japan's by 2013. The PRC used to have low per capita emissions, but is now quickly approaching Japan's level. Additionally, per capita emissions in the Republic of Korea have grown rapidly and since 2005 it has been the highest per capita emitter among the three countries, averaging 11.75 tons of carbon dioxide equivalent (tCO_2e)/person in 2013. All three countries have massively reduced carbon intensity (emissions per unit of GDP) in the past 3 decades. In 2013, Japan had the lowest carbon intensity (less than 0.03 metric tons of CO_2 per $1,000), while the PRC had the highest intensity (more than 0.1 metric tons of CO_2 per $1,000).

GHG emissions are determined by population, per capita income, energy intensity (energy consumption per unit of GDP), and energy mix (emissions per unit energy consumption). While the PRC surpassed Japan in 2010 to become the world's second-largest single-country economy, the PRC's per capita GDP is still much lower than the two developed countries in East Asia. Although, the PRC's per capita GDP growth has been more stable in the last 2 decades.

In terms of energy consumption and energy intensity, the PRC has the largest total energy consumption, with an annual growth rate of about 1.5% since 2000. The Republic of Korea and the PRC had similar per capita energy consumption in 1970, but the Republic of Korea's per capita consumption has since grown much faster than the PRC's. Recently, energy consumption in the Republic of Korea exceeded 5 tons oil equivalent per person, while Japan's per capita energy consumption peaked

Figure 2. **Energy Mix for the PRC, Japan, and the Republic of Korea**



PRC = People's Republic of China.
Source: Data were obtained from the BP Statistical Review of World Energy.

in 2000. The energy intensity of the PRC is approaching the level of the Republic of Korea, while Japan remains the lowest among the three countries.

Figure 2 illustrates the energy mix for the three countries between 1995 and 2015. Coal accounted for more than 60% of the PRC's total energy consumption during the review period. Although the PRC's coal consumption declined rapidly between 1995 and 2015, it remained much higher than that of Japan and the Republic of Korea. The percentage of natural gas in the energy mix rose in all three countries during the review period. The overall shares of fossil fuels have declined across the three countries. By contrast, renewable energy has gained a share of the energy mix in the past decade in all three countries. The PRC has become the world's largest renewable energy producer. It has the most wind power installations and the highest growth rate in solar power use in the world. As for the share of hydropower in the energy mix, only the PRC has experienced significant growth, while the share in Japan has been stable and it has declined in the Republic of Korea. Furthermore, Japan's nuclear power industry collapsed in 2011 after the Fukushima nuclear accident.

Table 1. **Commitments of the PRC, Japan, and the Republic of Korea in Major Climate Treaties**

Treaty	PRC	Japan	Republic of Korea	Target Year
Kyoto Protocol	No requirement	Reduce emissions by 6% compared to 1990	No requirement	2012
Copenhagen Accord	Reduce emissions intensity by 40%–45% compared to 2005	Reduce emissions by 25% compared to 1990	Reduce emissions 30% below the BAU level	2020
Paris Agreement	Peak emissions around 2030	Reduce emissions by 26% compared to 2013	Reduce emissions 37% below the BAU level	2030

BAU = business as usual, PRC = People's Republic of China.
Sources: The State Council of the People's Republic of China (2013); and Environmental Defense Fund, Institute for Global Environmental Strategies, and Climate Challenges Market Solutions (2016a, 2016b).

B. Participation in Climate Treaties

The PRC, Japan, and the Republic of Korea have joined major international climate treaties and taken various domestic actions to control carbon emissions. The most important international climate agreements include the United Nations Framework Convention on Climate Change, Kyoto Protocol, Copenhagen Accord, and Paris Agreement. Table 1 lists the emission targets of the PRC, Japan, and the Republic of Korea under these last three climate treaties.

Following the principle of common but differentiated responsibilities in the United Nations Framework Convention on Climate Change, the Kyoto Protocol signed in 1997 set legally binding quantified emission limitations and reduction targets for Annex B parties, which are mainly industrialized countries. Japan was required to reduce emissions by 6% before 2012 compared to its 1990 level. The non-Annex B parties, such as the PRC, have no obligations to control emissions in the early stage. However, developing countries can be involved through the Clean Development Mechanism (CDM), which is a project-based carbon market that allows developed countries to partially comply with their emission reduction targets by investing in qualified mitigation projects in developing countries. The Republic of Korea is also a non-Annex B party under the Kyoto Protocol because it was not a member of the developed country club when the treaty was being negotiated.

The Copenhagen Accord signed in 2009 requires signatories to submit emission targets, but these pledges are not legally binding. In this agreement, the PRC pledged to reduce its carbon intensity, measured by emissions per unit of GDP, by 40%–45% by 2020 compared to the 2005 level (Yang, Zhang, and Wang 2018). Japan pledged to reduce carbon emissions by 25% from the baseline of 1990, while the Republic of Korea aimed to reduce its GHG emissions by 30% from the BAU level by 2020.

In addition to the above international treaties, the 2016 Paris Agreement is the first comprehensive climate treaty that requires the actions of both developed and developing countries. Each country determines and regularly reports its own contribution to global climate mitigation. The contributions of each country to achieve the global climate target are called nationally determined contributions. However, there is no enforcement mechanism for a country to set a specific target by a specific date, but all the participants are required to draw up stricter targets than their previous ones.

As part of the Paris Agreement, the PRC pledged that its carbon emissions would peak no later than 2030, and that it would reduce its emission intensity by 60%–65% from the 2005 level. In addition, nonfossil fuel energy should account for around 20% of total energy consumption, and forest coverage will rise to 4.5 billion cubic meters. Japan pledged to reduce GHG emissions by 26% by 2030 compared to the 2013 level. Furthermore, emissions of energy-originated CO_2 should eventually be reduced by 25%. The Republic of Korea also planned to reduce its GHG emissions by 37% from the BAU level across all economic sectors before 2030.

III. Comparison of Key Design Elements

A. Overview of Carbon Markets

The PRC, Japan, and the Republic of Korea have started piloting ETSs to limit GHG emissions in recent years. The PRC launched seven municipal or provincial carbon markets in 2013. The first phase of the experiment covered all four direct-controlled municipalities (Beijing, Shanghai, Tianjin, and Chongqing); two provinces (Guangdong and Hubei); and one special economic zone (Shenzhen). The total regulated emissions are about 1.2 billion tons of CO_2, or about 11.4% of total national emissions. At the end of 2017, the PRC launched the national carbon market that only covers the power generation industry. Japan established the Tokyo ETS in 2010 and the Saitama ETS in 2011. Tokyo is the largest municipality in Japan with annual emissions of 67.3 metric tons of CO_2e; the annual emissions of Saitama total 38.5 metric tons of CO_2e. The Republic of Korea launched its nationwide ETS in 2015, which covers 525 business entities that are together responsible for 68% of national GHG emissions.

The three countries have distinctive characteristics in terms of economic development and energy consumption. The PRC has the lowest GDP per capita ($7,400) and the highest energy intensity. The Republic of Korea is approaching Japan in some key economic and energy indicators. Although energy intensity is not a perfect indicator for energy efficiency, combining many other factors such as higher GDP per capita and a lower percentage for the secondary industry that reflect a higher industrialized economy, Japan is comparably more energy efficient.

Table 2. **Carbon Intensity Reduction Targets and Total Allowances Issued**

Country	Region	By 2015	By 2020	By 2030	Annual Allowances
PRC	Beijing	18.0%	38.5%	nil	5.5 mt
	Shanghai	19.0%	39.5%	nil	510 mt (for 3 years)
	Tianjin	19.0%	39.5%	nil	100 mt
	Chongqing	17.0%	36.5%	nil	131 mt (2013) 126 mt (2014) 121 mt (2015)
	Guangdong	19.5%	40.0%	nil	388 mt
	Hubei	21.0%	40.5%	nil	324 mt
	Shenzhen	17.0%	37.5%	nil	30 mt
Japan	Tokyo	10.0%	39.0%	nil	56 mt (2014)
	Saitama	nil	22.4%	nil	33 mt (2014)
Republic of Korea	Republic of Korea	nil	42.5%	56.0%	573 mt (2015) 562 mt (2016) 559 mt (2017)

mt = metric ton, nil = data are not available or applicable, PRC = People's Republic of China.
Sources: The State Council of the People's Republic of China (2013, 2016); International Carbon Action Partnership (2017a, 2017b, 2017c); and Government of the Republic of Korea, Ministry of Environment (2016).

With respect to regional markets, Beijing, Shanghai, and Shenzhen are prosperous metropolises in the PRC, as the three pilots have relatively higher levels of GDP per capita (above \$14,500) and lower levels of energy intensity (below 3 tons of standard coal equivalent [tce] per \$10,000).[1] Among the carbon markets, Tokyo is one of the most developed cities in the world, with GDP per capita of \$63,789 and energy intensity of 0.25 tce per \$10,000 in 2014. Some Chinese cities (Beijing, Shanghai, and Shenzhen) have similar levels of economic development as the Republic of Korea and Saitama; hence, their carbon markets are possibly more comparable.

B. Emission Targets and Allowances

Each carbon market has set its emission target to a certain degree (Table 2). In general, the PRC aims for the most ambitious intensity reduction targets, compared with Japan and the Republic of Korea, because of its higher carbon intensity at the baseline stage. Based on the emission intensity targets, each pilot determines the amount of its annual emission allowance.

In the near-term, Japan set a moderate target to reduce its carbon intensity (10% for Tokyo by 2015) because its energy efficiency was already advanced. For example, Japan's industrial sectors, such as steel and cement, have attained the world's highest level of energy efficiency. The Research Institute of Innovative Technology for the Earth (2008) finds fossil fuel power generation in Japan has

[1]Energy intensity indicates the amount of output (normally measured in terms of GDP) given an amount of energy input. Based on this definition, the unit for energy intensity is tce per \$10,000. A smaller number for this indicator suggests greater economic benefits and higher energy utilization.

achieved one of the highest levels of energy efficiency among all developed countries. Hence, it is challenging for Japan to make further improvements.

In the aftermath of the Fukushima nuclear accident, the phasedown of nuclear power further limited the options for Japan to reduce its emissions. In 2012, Japan's nuclear power generation dropped to zero. However, in the long term, with booming energy demand, especially in the summer months, the supply of nuclear energy will resume under stricter regulations. Therefore, Tokyo seeks to achieve a more ambitious target with a 39% reduction in carbon intensity by 2020.

C. Covered Sectors

The three countries cover a wide range of industrial sectors with slight variations. The Republic of Korea and the PRC mainly focus on energy, transport, and building industries. Japan regulates almost all industrial sectors and some commercial sectors (Table 3).

The regulated entities are determined by the magnitude of their emissions or energy consumption. All pilots in the PRC except Hubei use annual emissions as the threshold; using energy consumption as the threshold is mainly due to concerns over data availability (Zhang, Wang, and Du 2017). The Republic of Korea uses annual emissions of 150 kilotons as the threshold. The threshold for the two pilots in Japan is 1,500 kiloliters of crude oil equivalent.

Overall, the Republic of Korea's ETS covers the highest percentage of total emissions. The PRC's regional ETS pilots cover 33%–60% of municipal or provincial emissions. Japan's two ETSs cover the lowest percentages: Tokyo's carbon market covers 20% of emissions and Saitama's covers only 18%.

D. Allowance Allocation

Allowances can be allocated using benchmarking, grandfathering, or auction. By setting performance standards, benchmarking rewards environmentally friendly entities and penalizes inefficient ones. It is also a useful way to measure the emission performances of peer firms. Benchmarks can be set through several approaches, among which the most popular is to follow the European Union (EU) ETS by establishing the 10% most efficient installations as a benchmark. Grandfathering allocates allowances according to historical emissions or intensities. Auction assigns allowances to the highest bidder, which is preferred by many researchers because it can quickly discover marginal social abatement costs.

The methods of allowance allocation for each carbon market are summarized in Table 4. Most pilots in the PRC use grandfathering, except for the electricity and cement sectors in Beijing, Guangdong, Shanghai, Shenzhen, and Tianjin, which use benchmarking. Guangdong is the PRC's only regional ETS that auctions partial allowances, but the percentage of allowances by auction is below 3%. Similarly, the

Table 3. **Covered Sectors in the Carbon Market**

Country	Region	Sectors Covered	Threshold	Number of Entities	Emissions Covered
PRC	Beijing	Electricity, heating, cement, petrochemical and other industries, and large public buildings including hospitals, schools, and government buildings	>10 kt	415 (2013); 543 (2014)	40.0%
	Shanghai	Electricity, iron and steel, petrochemical and chemical industries, metallurgy, building materials, papermaking, textile, aviation, airports and ports, public and office buildings, and railway stations	Industries >20 kt, nonindustries >10 kt	191	57.0%
	Tianjin	Electricity, heating, iron and steel, chemical and petrochemical industries, and oil and gas exploration	>20 kt	114	60.0%
	Chongqing	Electricity, metallurgy, chemical industries, cement, and iron and steel	>20 kt	242	39.5%
	Guangdong	Electricity, cement, iron and steel, petrochemical industries, and public services including hotels, restaurants, and business	In 2013 >20 kt; since 2014: industries >10 kt, nonindustries >5 kt	202 (2014); 193 (2015)	58.0%
	Hubei	Electricity, heating, metallurgy, iron and steel, automobile and equipment, chemical and petrochemical industries, cement, medicine and pharmacy, food and beverage, papermaking	Energy consumption >60k tce	138	33.0%
	Shenzhen	Electricity, building, manufacturing, water supply	Industries >5 kt, public buildings >20 km^2, office buildings >10 km^2	635	40.0%
Japan	Tokyo	Commercial and industrial sectors	1,500 kl of crude oil equivalent	1,300	20.0%
	Saitama	Commercial and industrial sectors	1,500 kl of crude oil equivalent	568	18.0%
Republic of Korea	Republic of Korea	Steel, cement, petroleum-chemistry, refinery, power, buildings, waste, and aviation	>150 kt	525	67.7%

kl = kiloliter, km^2 = square kilometer, kt = kiloton, PRC = People's Republic of China, tce = ton of standard coal equivalent.

Sources: Information compiled from official documents and relevant reports from 10 carbon markets, including Beijing Development and Reform Commission (DRC) (2014); China-Beijing Environmental Exchange (2014); General Office of the Beijing People's Government (2013, 2014); Chongqing DRC (2014); Hubei DRC (2014); Shanghai DRC (2013); Guangdong DRC (2013); Tianjin DRC (2013); Tianjin People's Government (2013); Shanghai People's Government (2013); Committee of the Shenzhen People's Congress (2012); Hubei People's Government (2013); Chongqing People's Congress (2014); and International Carbon Action Partnership (2017c).

Table 4. **Allowance Allocation**

Country	Region	Benchmarking	Grandfathering	Auction
PRC	Beijing	New entrants	Existing entities	
	Shanghai	Electricity, aviation, airports, ports	Other sectors	
	Tianjin	Electricity, heating	Other sectors	
	Chongqing		All sectors	
	Guangdong	Electricity, cement, iron and steel	Other sectors	8 mt (2.06% in 2014), 2 mt (0.51% in 2015)
	Hubei		All sectors	
	Shenzhen	Electricity, heating, water supply, manufacturing	Other sectors	
Japan	Tokyo		All sectors	
	Saitama		All sectors	
Republic of Korea	Republic of Korea	Cement, oil refinery, aviation	Other sectors	0% 2015–2017, 3% 2018–2010, >10% 2021–2025

mt = metric ton, PRC = People's Republic of China.
Sources: Information compiled from official documents and relevant reports from 10 carbon markets, including Beijing Development and Reform Commission (DRC) (2014); China-Beijing Environmental Exchange (2014); General Office of the Beijing People's Government (2013, 2014); Chongqing DRC (2014); Hubei DRC (2014); Shanghai DRC (2013); Guangdong DRC (2013); Tianjin DRC (2013); Tianjin People's Government (2013); Shanghai People's Government (2013); Committee of the Shenzhen People's Congress (2012); Hubei People's Government (2013); Chongqing People's Congress (2014); and International Carbon Action Partnership (2017c).

Republic of Korea mainly uses benchmarking and grandfathering. Benchmarking is mainly applied to cement, oil refineries, and aviation, while grandfathering is used in other sectors. Furthermore, the Republic of Korea plans to auction allowances in the coming years, with the percentage of allowances awarded via auction increasing to 10% by 2025. In Japan, grandfathering has been adopted for all sectors at the current stage.

E. Monitoring, Reporting, and Verification

The PRC, Japan, and the Republic of Korea have each established their own MRV systems to ensure credible emission reductions. Table 5 summarizes the key features of MRV in each ETS. At the national level, the PRC's Standardization Administration has published general guidelines for GHG emissions accounting, with detailed protocols for 10 industries having been finalized. Some Chinese pilots require the covered firms to submit their monitoring plans, including the boundaries for emissions accounting. This may help to improve the quality of MRV.

The Government of the Republic of Korea issued a national decree to standardize the MRV system. Different from the PRC, after the third-party verifier has verified the report, it is submitted to a competent authority. Then, the competent authority is responsible for validating the report. If the company fails to submit

Table 5. **Monitoring, Reporting, and Verification**

Country	Region	Threshold for Reporting	Threshold for Verification
PRC	Beijing	Energy consumption >2,000 tce	>10 kt
	Shanghai	>10 kt	>20 kt
	Tianjin	>10 kt	>20 kt
	Chongqing	>20 kt	>20 kt
	Guangdong	>10 kt or energy consumption >5,000 tce	>20 kt or energy consumption >10,000 tce
	Hubei	Energy consumption >60,000 tce	Energy consumption >60,000 tce
	Shenzhen	>1 kt	Industries >1 kt Public buildings >10 kt
Japan	Tokyo	1,500 kl of crude oil	1,500 kl of crude oil
	Saitama	1,500 kl of crude oil	1,500 kl of crude oil
Republic of Korea	Republic of Korea	Total emissions >125 kt or facility emissions >25 kt	Total emissions >125 kt or facility emissions >25 kt

kl = kiloliter, kt = kiloton, PRC = People's Republic of China, tce = ton of standard coal equivalent.
Sources: Information compiled from the official documents and relevant report from 10 carbon markets, including Beijing Development and Reform Commission (DRC) (2014); China Beijing Environment Exchange (2014); General Office of the Beijing People's Government (2013, 2014); Chongqing DRC (2014); Hubei DRC (2014); Shanghai DRC (2013); Guangdong DRC (2013); Tianjin DRC (2013); Tianjin People's Government (2013); Shanghai People's Government (2013); Committee of the Shenzhen People's Congress (2012); Shenzhen Department of Housing and Urban-Rural Development (2013); Hubei People's Government (2013); Chongqing People's Congress (2014); and International Carbon Action Partnership (2017c).

the requested report, the authority shall conduct the fact-finding survey and only certify the actual amount of GHG emissions. Thus, the duty of report verification is transferred from the third-party verifier to the government. In Japan, besides reporting annual emissions, the covered firms shall also report their emission reduction plans to the government.

F. Compliance and Enforcement

The carbon markets in the three countries have different built-in penalties for noncompliance (Table 6). The entities that are eligible for an allowance allocation are required to keep their total emissions below the caps. This is a mandatory obligation.

In cases of violating MRV protocols or noncompliance with the emission target, financial and other penalties are applied in two stages. In the first stage, the regulators in Beijing, Tianjin, Chongqing, Guangdong, Tokyo, and the Republic of Korea order the entities to correct their excessive emissions. The Tokyo ETS orders the entities to reduce emissions by the amount of the shortfall multiplied by 1.3. Beijing, Shanghai, and Guangdong adopt financial penalties for failing to comply with the MRV protocols. Some pilots in the PRC also apply other penalties, including recording noncompliance in the business credit report system,

Table 6. **Penalties for Noncompliance**

Country	Region	Financial Penalty	Deduction from Allowance
PRC	Beijing	3–5 times	Yes
	Shanghai	CNY50,000–CNY100,000	
	Tianjin		
	Chongqing	3 times	
	Guangdong	CNY50,000	Yes
	Hubei	3 times but not to exceed CNY150,000	Yes
	Shenzhen	Up to 3 times	Yes
Japan	Tokyo	¥500,000 and a surcharge of 1.3 times the shortfall	
	Saitama		
Republic of Korea	Republic of Korea	Up to 3 times but not to exceed $91 per ton of CO_2e	Yes

¥ = yen, CNY = yuan, CO_2e = carbon dioxide equivalent, PRC = People's Republic of China.
Sources: Information compiled from official documents and relevant reports from 10 carbon markets, including Beijing Development and Reform Commission (DRC) (2014); China Beijing Environment Exchange (2014); General Office of the Beijing People's Government (2013, 2014); Chongqing DRC (2014); Hubei DRC (2014); Shanghai DRC (2013); Guangdong DRC (2013); Tianjin DRC (2013); Tianjin People's Government (2013); Shanghai People's Government (2013); Committee of the Shenzhen People's Congress (2012); Hubei People's Government (2013); Chongqing People's Congress (2014); and International Carbon Action Partnership (2017c).

annulling the qualification for government support, and recording noncompliance in the performance appraisal system for state-owned enterprises. In the second stage, any noncompliance by entities will be subject to financial penalties and possible surcharges, except in the Tianjin and Saitama ETSs. Other penalties are also adopted by more carbon markets at this stage.

Financial penalties are the most common measures taken by all ETSs. In this case, the regulators charge various financial penalties according to the market value of the excessive emissions, except in Guangdong. Nonfinancial penalties also play a crucial role. The deduction of the excessive emissions from future allowances can also be a credible threat because of the increasing difficulties in future compliance. Recording noncompliance in the business credit report system will increase an entity's cost of financing in financial markets. The Government of the PRC gives fewer grants and less support to entities that either violate MRV protocols or do not comply with the emission allowance.

G. Offset Market

Offsets may be used to meet compliance obligations in the PRC, Japan, and the Republic of Korea (Table 7). In the PRC, the voluntary emission trading market generates China Certified Emissions Reductions (CCERs). Like CDM, the CCER market is a project-based offset market that is dominated by wind, small hydropower, solar photovoltaic, and forest carbon sinks. Eligible entities can use CCER offsets, but the PRC's regional pilots limit the use of offset credits in terms

Table 7. **Requirements of Using Offset Credits**

Country	Region	Offset Credit	Limit	Local Source	Other Restrictions
PRC	Beijing	CCER; energy conservation and forestry offsets	<5% of allowance	>50% from Beijing	Offsets generated after 1 January 2013, excluding industry, gas, and hydro projects
	Shanghai	CCER	<5% of allowance	Not from covered firms	Offsets generated after 1 January 2013
	Tianjin	CCER	<10% of verified emissions	Priority for Beijing, Tianjin, and Hubei offsets	Excluding hydro and pre-CDM projects
	Chongqing	CCER	<8% of verified emissions		Offsets generated after 31 December 2010 (except for carbon sinks); excluding hydro projects
	Guangdong	CCER	<10% of verified emissions	>70% from Guangdong	>50% from CO_2 and CH_4, excluding hydro, fossil fuel, and pre-CDM projects
	Hubei	CCER	<10% of allowance	All	Only small hydro
	Shenzhen	CCER	<10% of verified emissions		Offsets from renewables, clean transport, ocean, forestry offsets, and agriculture
Japan	Tokyo	Small and Midsize Facility Credit	Without limit	Within Tokyo	Generated since FY2010
		Renewable Energy Certificate	Without limit	Either within or outside Tokyo	Issued in and after FY2008
		Outside Tokyo Credit	Up to one-third of the reduction amount	Outside Tokyo	Emission reductions since 2010
		Saitama Credit	Without limit	Outside Tokyo	Emission reductions since 2010
	Saitama	Small and Midsize Facility Credit	Without limit	Within Saitama	Generated in Saitama since FY2011
		Outside Saitama Credit	Up to one-third (offices), or to one-half (factories)	Outside Saitama	Generated from large facilities from FY2015
		Renewable Energy Credit	Without limit	Either within or outside Saitama	Credits from solar (heat, electricity), wind, geothermal, or Hydro (under 1,000 kW) electricity production are counted at 1.5 times the value of regular credits.

Continued.

Table 7. *Continued.*

Country	Region	Offset Credit	Limit	Local Source	Other Restrictions
		Forest Absorption Credit	Without limit	Either in or outside Saitama	Credits from inside the Saitama Prefecture are counted at 1.5 times the value of regular credits
		Tokyo Credit	Without limit	Outside Saitama	Excess Credits from TMG ETS from FY2015, Small and Midsize Facility Credits issued by TMG ETS from FY2012
Republic of Korea	Republic of Korea	KCU	<10% of allowance, international credit <5% (phase III)	Domestic (phases I and II), international offsets permitted (phase III)	Activities implemented after 14 April 2010

CCER = China Certified Emissions Reductions, CDM = Clean Development Mechanism, CH_4 = methane, CO_2 = carbon dioxide, FY = fiscal year, KCU = Korea Credit Unit, kW = kilowatt, PRC = People's Republic of China, TMG ETS = Tokyo Metropolitan Government Cap-and-Trade Program.

Sources: Information compiled from official documents and relevant reports from 10 carbon markets, including Beijing Development and Reform Commission (DRC) (2014); China-Beijing Environmental Exchange (2014); General Office of the Beijing People's Government (2013, 2014); Chongqing DRC (2014); Hubei DRC (2014); Shanghai DRC (2013); Guangdong DRC (2013); Tianjin DRC (2013); Tianjin People's Government (2013); Shanghai People's Government (2013); Committee of the Shenzhen People's Congress (2012); Hubei People's Government (2013); Chongqing People's Congress (2014); and International Carbon Action Partnership (2017c).

of percentage, location, and issuing date. In Japan, offset credits from emission reduction activities in small and midsize facilities are qualified, including the credits from activities outside Tokyo and Saitama. Renewable energy credits can be used without limits. Forest credits are also qualified in the Saitama ETS. Meanwhile, the Korean ETS comprises three phases: phase I (2015–2017), phase II (2018–2020), and phase III (2021–2025). Domestic offset credits are only allowed in phases I and II for non-ETS entities.

Although offsets can reduce an entity's cost of compliance by providing access to a greater set of cost-effective mitigation opportunities, the use of offset credits is often constrained. All ETSs in the PRC and the Republic of Korea limit the proportion of offset credits in the total allowances. In contrast, many offsets in the Tokyo and Saitama ETSs can be used without limits.

IV. Market Performances

The PRC, Japan, and the Republic of Korea have set up institutions for carbon emissions trading. In the PRC, each of the seven pilots owns a local carbon exchange. In Japan, the Tokyo Metropolitan Government Cap-and-Trade Program defines reduction obligations in Japan; Tradable Reduction Credits are released only if these obligations are exceeded. Thus, the emission right is granted for free. Besides Tradable Reduction Credits, four sorts of offset markets are also traded on the Tokyo Metropolitan Government Cap-and-Trade Program ETS and another five are dealt in the Saitama ETS. In the Republic of Korea, three types of credits are available in its secondary market: Korea Allowance Units (KAUs), Korea Offset Credits (KOCs), and Korea Credit Units (KCUs). The Korea Exchange is the official trading market designated by the Government of the Republic of Korea.[2] In principal, only KAUs and KCUs can be traded on the Korea Exchange, while KOCs are traded over the counter.

Carbon prices in the PRC and Japan follow a similar pattern: the price rises at the opening stage of a carbon market and then declines gradually. In contrast, the carbon price in the Korean ETS kept rising in its first compliance year, which could be due to more stringent allowance allocation. Table 8 reports the average carbon price of each market. Due to data limitations, the carbon prices in Japan and the Republic of Korea are only partly available. Among the three countries, the PRC's market stays at the lowest price, with a price-declining trend from \$6.92/tCO_2e in 2013 to \$3.38/tCO_2e in 2016. The average carbon prices in Shenzhen and Beijing in 2016 were higher than in the PRC's other five pilots at \$5.85/tCO_2e and \$7.05/tCO_2e, respectively. Japan had the highest average carbon price in 2015 at

[2]KAUs are allowances allocated to firms according to emission targets under the Korean ETS. KOCs are credits that are mainly issued from offset markets authorized by the government. KCUs are credits that transform from KOCs, but they cannot be transformed back to KOCs (Environmental Defense Fund, Institute for Global Environmental Strategies, and Climate Challenges Market Solutions 2016a).

Table 8. **Annual Carbon Prices**

Country or Region	Average Price	Country or Region	Average Price
Beijing	\$7.70 (2013)	Hubei	\$3.41 (2014)
	\$8.16 (2014)		\$3.65 (2015)
	\$6.93 (2015)		\$2.71 (2016)
	\$7.05 (2016)		
Shanghai	\$4.45 (2013)	Shenzhen	\$9.11 (2013)
	\$5.71 (2014)		\$8.69 (2014)
	\$3.17 (2015)		\$6.00 (2015)
	\$1.24 (2016)		\$5.85 (2016)
Tianjin	\$4.38 (2013)	PRC	\$6.92 (2013)
	\$4.28 (2014)		\$6.06 (2014)
	\$3.31 (2015)		\$4.16 (2015)
	\$2.08 (2016)		\$3.38 (2016)
Chongqing	\$4.60 (2014)	Japan	\$31.50 (2015)
	\$3.15 (2015)		nil
	\$1.96 (2016)		nil
Guangdong	\$7.54 (2014)	Republic of Korea	\$14.60 (2015)
	\$2.92 (2015)		\$18.03 (2017)
	\$2.02 (2016)		\$20.66 (Jan 2018)

nil = data are not available or applicable, PRC = People's Republic of China.
Sources: The data for the PRC's carbon prices are available from the Carbon Market Analysis Platform. http://k.tanjiaoyi.com/ (accessed August 1, 2017). The data for the Republic of Korea's carbon prices in 2017 are available from the Korea Exchange. http://ets.krx.co.kr (accessed July 26, 2017). The data for Japan's carbon prices are from Environmental Defense Fund, Institute for Global Environmental Strategies, and Climate Challenges Market Solutions (2016a).

\$31.50/tCO_2e. The Republic of Korea's average carbon prices in 2015 and 2017 were \$14.60/tCO_2e and \$18.03/tCO_2e, respectively.

In summary, the PRC is still at a very early stage of carbon market experimentation. The allowances are generally abundant across the seven pilots. Once the regulated companies realized this, the price, as expected, declined. Tokyo's declining carbon price could be mainly due to energy-saving activities, especially after the Tohoku Earthquake and the nuclear meltdown in Fukushima in 2012. The allowance allocation in the Republic of Korea was not sufficient in 2015. Thus, the Government of the Republic of Korea released 900,000 tCO_2e of allowances between June 2015 and June 2016 to stabilize the market. Recently, the Republic of Korea published its carbon emission target for 2018 (0.54 billion tons of CO_2e), which is a 2.3% reduction compared with 2017.

Trading volume is another important indicator to assess the performance of a carbon market. Both the PRC and the Republic of Korea have observed dramatic increases in carbon allowance trading before the compliance date of each year. The volatility of trading volume around the compliance date in the PRC and Republic of Korea might be caused by (i) carbon markets in both countries banning third-party participants, which could decrease market liquidity; (ii) regulated companies having more flexibility in the PRC and the Republic of Korea, which may encourage them to bank the credits rather than make transactions; and (iii) both countries being in their early stage of emission trading, with companies taking full advantage of trading opportunities. As for the Japanese ETSs, detailed secondary market information is not available except for the annual volume of transactions, which steadily increased from 2011 to 2015.

V. Linking Carbon Markets

A. Incentives for Market Linkage

The PRC, Japan, and the Republic of Korea can together build a strong regional economy. Furthermore, the three countries have already collaborated on energy and environmental issues over the past 3 decades. As early as the late 1980s, the PRC and Japan started to work together on natural gas development through Japanese Official Development Assistance. Since then, more areas of environmental collaboration have been initialized. The three countries have strengthened cooperation in recent years by forming regional agreements such as the Acid Deposition Monitoring Network in East Asia, Tripartite Environment Ministers Meeting, and Long-Range Transboundary Air Pollutants in East Asia. These existing cooperative programs paved the way for the three countries to link their carbon markets. In the long term, linked East Asian carbon markets have the potential to rebalance international carbon markets, implement global climate policies, and stimulate regional economic prosperity (Massetti and Tavoni 2012).

It is crucial for the PRC, Japan, and the Republic of Korea to strengthen cooperation in tackling climate change for the following three reasons. First, manufacturing is the key industry in each of the three countries. Regional climate collaboration ensures that no country will intend to make their manufacturing sector more competitive by relaxing climate regulations, thus avoiding the concern of a race to the bottom. Second, the collaboration will send a strong signal to the world about the determination of East Asian countries in mitigating climate change. This is particularly crucial for global climate governance after the United States announced its withdrawal from the Paris Agreement. Third, it will also benefit the regional environment. The deterioration of regional air quality has become a contentious debate among the three countries. The cobenefits of climate actions will help the region to improve air quality and solve potential environmental conflicts.

To date, East Asian countries have had limited regional collaboration on climate change, mainly through the Kyoto Protocol. In particular, the CDM plays an important role in climate actions, in which the PRC and the Republic of Korea were the host countries of CDM projects and Japan was an investor. Although the CDM was not designed for regional climate cooperation, its implementation provided important experiences for establishing interconnected carbon markets in the region. Furthermore, the CDM shed light on the indirect linkage between cap-and-trade and emission-reduction-credit systems. Building upon the climate collaboration initialized by the CDM, linkage among the existing trading systems of the PRC, Japan, and the Republic of Korea can create an additional climate cooperation channel (Perdan and Azapagic 2011).

The PRC, Japan, and the Republic of Korea have engaged in separate endeavors in establishing carbon markets to curb their GHG emissions. Market linkage should become an important policy option for collaboration on this notable market-based instrument (Flachsland, Marschinski, and Edenhofer 2009). Carbon market linkage is associated with economic, environmental, and strategic benefits. From the economic perspective, linkage creates a cost-effective system for firms to reduce the cost of compliance. Heterogeneities among the firms being regulated by each market suggest different marginal abatement costs. This creates an opportunity for improving cost-efficiency and achieving the minimum cost in reducing carbon emissions (Stavins 2016). For example, the ETS with higher marginal abatement costs can benefit from purchasing relatively inexpensive allowances from other ETSs, thus achieving emission reduction goals at a lower cost. The differences among the PRC, Japan, and the Republic of Korea make inter-ETS trading appealing. The EU's ETS provides a good case study of where the heterogeneous size of installations enables cost savings for a unified market (Trotignon and Delbosc 2008).

In the long term, carbon market linkage can increase the liquidity of markets and decrease the volatility of prices because networked markets are broadened with more buyers and sellers, especially for those small-scale carbon markets. Admittedly, individual winners and losers exist within one linked market. Generally speaking, linked markets reduce regional costs of compliance and ultimately achieve reduction targets at the minimized cost.

The three East Asian countries are well positioned to link their carbon markets because of geographic proximity, which is an important strategic benefit in creating a universal linked market (Ranson and Stavins 2015). Geographic proximity can facilitate information interchanges. The similarity in cultures could also enhance mutual trust in climate collaboration. In this case, East Asian countries are geographically and culturally close to each other and therefore likely to link. Further, carbon market linkage among the three countries could foster cooperation in other aspects, for instance in international trade and investment.

B. Roadmap of Linkage

Climate collaboration mainly includes top-down (among governments) and bottom-up (among regions and firms) channels, with linkage belonging to the latter case (Jaffe, Ranson, and Stavins 2009). The bottom-up development of climate policy leads to fragmented carbon markets, which can be indirectly linked or formally linked (Flachsland, Marschinski, and Edenhofer 2009). This section focuses on the roadmap for carbon market linkage in East Asia, accounting for the heterogeneous market designs that have been introduced in the previous sections. Specifically, we explore the possibility of evolving from unilateral markets to multilateral links, and propose frameworks for direct and indirect linkages.

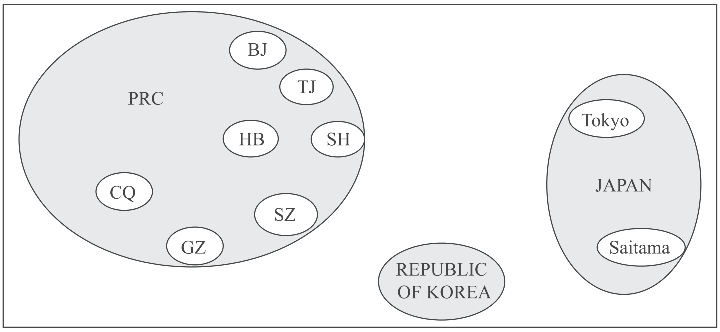
The complexity of market linkage is partly caused by different types of tradable permit systems. Japan and the Republic of Korea adopt the cap-and-trade system; the PRC adopts the tradable-performance-standard system. The direct linkage of cap-and-trade systems is common and economically viable (Montagnoli and de Vries 2010). Alternatively, indirect linkage across cap-and-trade and tradable-performance-standard systems is also conceivable but with uncertain results (Reuters 2012). For example, industrialized countries obtain carbon credits by investing mitigation projects in developing countries in the CDM. However, it is challenging to demonstrate that the proposed project results in real emission reductions compared with the baseline scenario. Nevertheless, linkage between the PRC and Japan could still be possible with an appropriate mechanism design. Jaffe, Ranson, and Stavins (2009) argued that mutual recognition and unified policy design are notable issues that can determine the possibility of linking.

In addition to the conceptual debate, there exists a large strain of literature that uses models to assess the possibility of linking carbon markets in Asia. For instance, Calvin, Fawcett, and Jiang (2012) and Calvin et al. (2012) evaluated the economic and environmental impacts of climate mitigation under the framework of the Asia Modeling Exercise, which provides insight for the consequence of linking heterogeneous carbon markets. Paltsev et al. (2012) investigated various scenarios of mitigating carbon emissions and their impacts on economic growth in the PRC. Their result suggests that the PRC has played a crucial role in climate collaboration and market linkage within Asia. Hübler, Löschel, and Voigt (2014) employ computable general equilibrium models to compare different climate policy scenarios for the PRC, highlighting the economic gains of linking the PRC's ETS to the EU's ETS.

Carbon market linkage can be implemented at the international, national, or regional level. It is beneficial to start from piloting subnational market linkage, which will engender economic, environmental, and strategic benefits. Currently, carbon markets in the PRC, Japan, and the Republic of Korea are unilateral without any linkage. Figure 3 plots each carbon market in the three countries. Japan is home to two carbon markets, while the Republic of Korea has one nationwide market. Although the Government of the PRC is establishing a national emission trading system, the national carbon market will not be fully functioning until 2020 and the seven provincial pilots are not currently linked with each other. Therefore, the seven carbon market pilots in the PRC are treated unlinked, but they are expected to be unified in a couple of years.

There are mainly two pathways for developing a cluster of carbon markets in East Asia. One approach is for the well-behaved carbon markets to establish two-way or one-way linkages. In Figure 4a, we suggest the ETSs in Beijing,

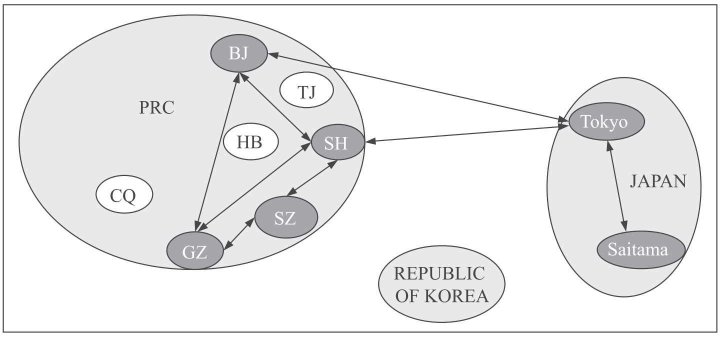
Figure 3. **Unilateral Carbon Markets in the PRC, Japan, and the Republic of Korea**



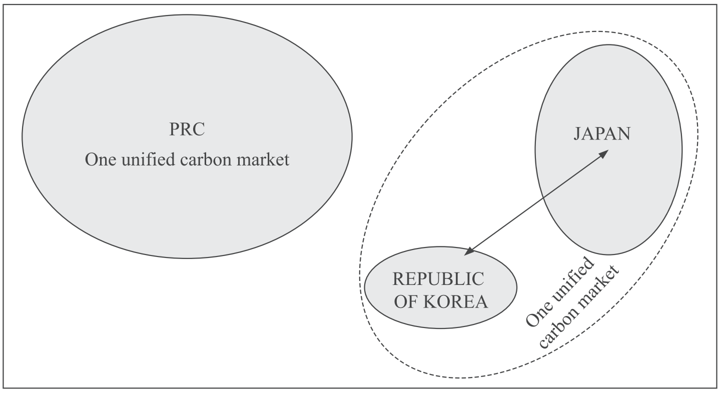
BJ = Beijing, CQ = Chongqing, GZ = Guangzhou, HB = Hubei, PRC = People's Republic of China, SH = Shanghai, SZ = Shenzhen, and TJ = Tianjin.
Source: Authors' illustration.

Figure 4. **Cross-Regional Links between the PRC, Japan, and the Republic of Korea**

(a) Well-developed markets links

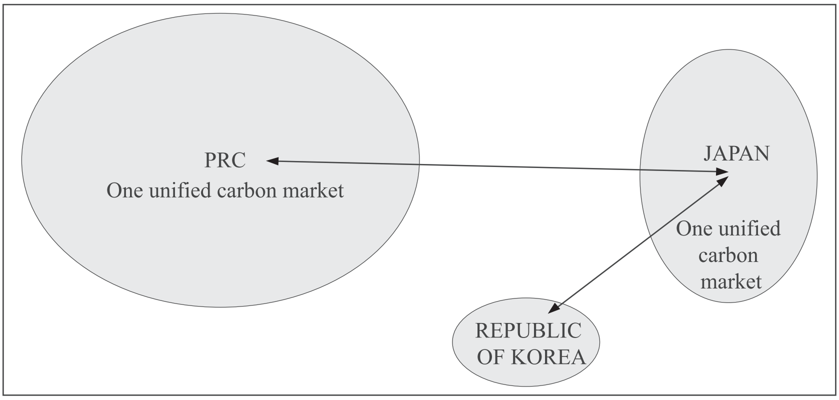


(b) Same tradable permit system markets links



BJ = Beijing, CQ = Chongqing, GZ = Guangzhou, HB = Hubei, PRC = People's Republic of China, SH = Shanghai, SZ = Shenzhen, and TJ = Tianjin.
Source: Authors' illustration.

Figure 5. **Chained Bilateral Links in the PRC, Japan, and the Republic of Korea**



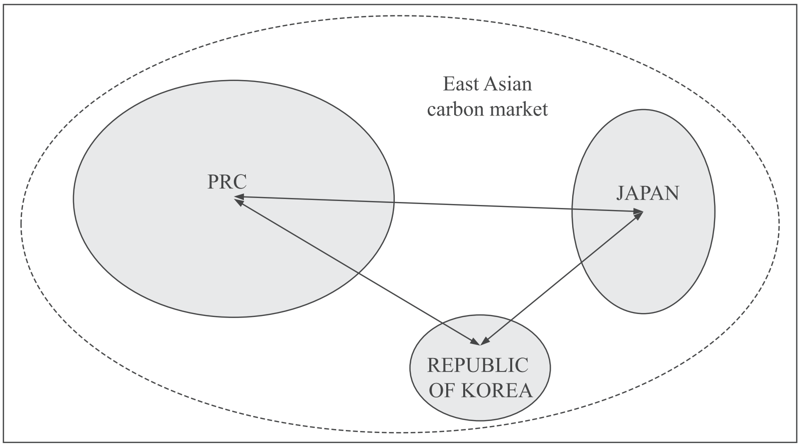
PRC = People's Republic of China.
Source: Authors' illustration.

Shanghai, Guangdong, and Shenzhen show potential opportunities for linking within the PRC. Those four pilots could also be linked with the carbon markets in Tokyo and Saitama. These cities tend to set ambitious targets on emission reductions and have the ability to accomplish such goals. Alternatively, carbon markets under the same tradable permit system could link first, which is less challenging and has a lower risk (Figure 4b). Since both Japan and the Republic of Korea adopt the cap-and-trade system, they can start working together by promulgating compatible market regulations. Similarly, the seven pilots in the PRC could successfully combine into a national carbon market first.

The linkages above lead to chained bilateral links in which Japan builds a two-way linkage with the PRC and the Republic of Korea. The bilateral relationships set a promising vision for a fully linked carbon market in the final stage. Carbon markets in the PRC and the Republic of Korea can also be indirectly linked, as shown in Figure 5, with Japan as the common partner. However, this linkage is also associated with risks since either of the original linking partners can link with a third party; therefore, both of the original participants could access new and unlimited supplies of allowances from the third party. This indirect system becomes less efficient as the transaction costs gradually grow, but more firms could gain from the bilateral linkage in various aspects. The trade-offs between indirect linkage and direct linkage are discussed by Jaffe, Ranson, and Stavins (2009) in detail.

Consequently, Figure 6 illustrates full multilateral links between the PRC, Japan, and the Republic of Korea. Although it is premature to create this full linkage at present, it should be the ultimate goal of linking East Asian carbon markets.

Figure 6. **Full Multilateral Links in the PRC, Japan, and the Republic of Korea**



PRC = People's Republic of China.
Source: Authors' illustration.

C. Challenges and Recommendations

Linking carbon markets can improve liquidity, efficiency, and stability. However, market linkage in East Asia is not fully ready. If linked, the East Asian carbon market could be the largest in the world; hence, it would be more difficult to build and manage. First, incompatible market designs create difficulties since each carbon market has individual climate goals, which drives diverse emission targets and distinct levels of stringency of regulations. Various covered sectors, allowance allocations, MRVs, and even different market stabilization mechanisms cause fragmented markets as well. Second, some markets tend to overallocate allowances, arousing the moral hazard concern. Third, emission leakage is a serious threat to the carbon market, since linkage can make some firms relocate to other regions outside the scope of the linkage, causing emissions in other regions to increase (Aldy 2016). Fourth, carbon market linkage could lead to transboundary wealth transfers. Finally, geopolitics can be a concern when geopolitical conflicts and disputes complicate climate cooperation.

Nevertheless, linking East Asian carbon markets would be distinctly important and there are positive signals for such market linkage. In theory, heterogeneities among different markets suggest the expected cost savings in the linkage market could be large. In practice, Japan has prior experience in international carbon market linkage. Furthermore, the PRC launched the national ETS pilot in 2017, which makes inter-ETS linkages more convenient, while the Republic of Korea intends to link its domestic ETS with international markets. As a first step, it is forming agreements with other ETSs that are recognized for credible GHG emission reductions.

We make the following recommendations in terms of carbon market linkage. The PRC, Japan, and the Republic of Korea should recognize each other's trading allowances reciprocally. Since it is politically infeasible to link carbon markets through legally binding international treaties, the mutual recognition of emission allowances is a sensible strategy toward connected carbon markets in East Asia. It is worth noting that carbon market linkage can lead to low-quality emission reductions in some markets without a uniform MRV system. For international linkage, participants can use global principles that provide key features and model rules in order to solidify the foundation of future market linkage. The conditions mentioned above do not have to restrain linkage among the PRC, Japan, and the Republic of Korea. Economic and political concerns are underlying problems that can prevent efforts to link markets or lead to their failure. Therefore, efforts to link carbon markets in East Asia do not need to be overhasty.

VI. Conclusion

This paper reviews and compares carbon markets in the PRC, Japan, and the Republic of Korea. The designs of these carbon markets are based on unique economic, industrial, and demographic backgrounds. In this context, we review the key elements of these markets including GHG emission targets, allowance allocations, MRVs, and offset markets. We assess the performances of these markets in terms of carbon prices and trading volumes. Based on this information, we explore the possibility of market linkage among the three ETSs by analyzing incentives, identifying obstacles, and providing policy suggestions.

Developing linked carbon markets in East Asia is essential and beneficial, but also challenging. Some questions remain for carbon market linkage in East Asia. For example, how can the MRV systems, ETSs, or new organizations take actions to ensure the integrity of the linkage? How can the linkage require national markets to give up some control over prices and GHG emission targets? How can small markets survive and be protected at the very beginning? These questions entail further study of linkage among East Asian ETSs.

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Fossil Fuel Subsidy Reform in the Developing World: Who Wins, Who Loses, and Why?

Ian Coxhead and Corbett Grainger*

Fossil fuel subsidies are widespread in developing countries, where reform efforts are often derailed by disputes over the likely distribution of gains and losses. The impacts of subsidy reform are transmitted to households through changes in energy prices and prices of other goods and services, as well as through factor earnings. Most empirical studies focus on consumer expenditures alone, and computable general equilibrium analyses typically report only total effects without decomposing them by source. Meanwhile, analytical models neglect important open-economy characteristics relevant to developing countries. In this paper, we develop an analytical model of a small open economy with a preexisting fossil fuel subsidy and identify direct and indirect impacts of subsidy reform on real household incomes. Our results, illustrated with data from Viet Nam, highlight two important drivers of distributional change: (i) the mix of tradable and nontradable goods, reflecting the structure of a trade-dependent economy; and (ii) household heterogeneity in sources of factor income.

Keywords: distribution, energy subsidy, household income, labor, real exchange rate, trade
JEL codes: F18, H20, O25, Q43

I. Introduction

A large and growing literature assesses the distributional implications of energy policies. Where developing economies are concerned, most (though not all) of these studies rely heavily, if not exclusively, on household expenditure data to quantify changes in well-being. In this paper, we advance the claim that where developing countries are concerned, focusing on changes in household cost of living

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alone may be insufficient to account for the distributional effects of a major energy price reform. Our key point is that energy's primacy as an input to production in lower-income economies means that it is also reasonable to expect that a meaningful change in energy subsidies or tax rates will also have macroeconomic impacts through economy-wide changes in sectoral relative prices and factor demands, and thus on key sources of household income. Since the sources of household earnings from factors are heterogeneous across the income distribution, ignoring changes through factor market channels may overlook an important source of distributional impact.

There is no question that in many countries the scale of fossil fuel subsidies merits an economy-wide perspective. They are remarkably widespread in the developing world. The global value of these subsidies was estimated at about $300 billion in 2015 after having peaked in prior years at over $500 billion (International Energy Agency [IEA] 2017). While countries at the top of the subsidy rankings are mostly oil exporters, in the mid-2000s several Asian economies—among them Bangladesh, India, Indonesia, Malaysia, Pakistan, the People's Republic of China (PRC), Thailand, and Viet Nam—were all in the IEA's "top 40" countries in terms of energy subsidy-to-gross domestic product (GDP) ratios despite being either net energy importers or marginal exporters. Despite substantial subsidy reductions in recent years, in many Asian economies subsidies remain large, both in absolute terms and in relation to total spending and government outlays. In the most recent global rankings of subsidy spending compiled by the IEA, the PRC, India, and Indonesia were the top three among net energy importers, with 2015 subsidy outlays of about $19 billion, $19 billion, and $15 billion, respectively. In 2015, Indonesia spent 1.8% of GDP on fossil fuel subsidies; the respective share for India was 0.9%, for Bangladesh 1.2%, and Pakistan 1.3%.[1]

Eliminating or significantly reducing fossil fuel subsidies has long been a prominent feature of the global policy reform agenda. In 2009, the G20 heads of state agreed to joint efforts to reduce "inefficient" fuel subsidies.[2] Lowering subsidies is predicted to have a measurable impact on aggregate income; Coady et al. (2015) calculated the total global gain from the removal of subsidies in 2015 at $2.9 trillion, or 3.6% of global GDP. Among world regions, they found that the largest proportional gains (about 9% of regional GDP) would be in emerging Asian economies, along with oil-exporting regions in the Middle East and the Commonwealth of Independent States. Reducing subsidies would also reduce global greenhouse gas emissions by 8% by 2050, according to Burniaux

[1]IEA. Energy Subsidies Database. http://www.iea.org/statistics/resources/energysubsidies/ (accessed August 2, 2017).

[2]The G20 heads of state (and later in the same year, Asia-Pacific Economic Cooperation heads of state) committed to "phase out and rationalize over the medium-term inefficient fossil fuel subsidies while providing targeted support for the poorest" (Eilperin 2009).

and Chateau (2014), even excluding the savings from subsidy reductions that would be invested in renewables and improved efficiency. This has been discussed in the economics literature for many years (Larsen and Shah 1992, Poterba 1993), but interest has deepened considerably along with concerns over the effects of global climate change. A multiagency analysis issued in 2010 estimated that global energy consumption could be cut by as much as 5% in 2020 if fossil fuel subsidies were completely phased out (IEA, OECD, and World Bank 2010). The scale of potential global benefits from subsidy reduction was one of the key motivating forces behind the recent global agreement on reducing greenhouse gas emissions, the so-called Paris Agreement.

The persistence of fossil fuel subsidies in many countries in spite of the magnitude of potential benefits has a variety of explanations. These include promoting industrial growth and lowering and stabilizing consumer prices of fuel, electricity, and heating. Advocates often claim that fossil fuel subsidies disproportionately help the poor by reducing their living costs and by helping address "energy poverty," or a lack of access to ready sources such as electricity. These perceptions are widespread, and as a result, proposals to reduce subsidies encounter considerable popular and political resistance due to concerns that higher prices will undermine efforts to achieve economic growth and poverty reduction (Pradiptyo et al. 2015). Opponents of subsidies point to efficiency costs, the opportunity costs of fiscal outlays, additional off-budget costs such as those associated with policy support for state-owned energy generators, and impacts on local copollutants (e.g., sulfur dioxide, nitrogen oxide, and particulate matter) due to the promotion of cheap carbon-based energy sources. They also question whether subsidies really benefit the poor relative to other groups. There are thus active debates over the merits of subsidies as tools of economic growth, and whether their removal would have positive or negative effects on income distribution. The lack of consensus on the welfare and distributional effects of subsidy reform has inhibited effective and timely policy measures in many countries.

The empirical literature on the incidence of environmental taxes or subsidies does not provide a clear signal on this important question. This literature takes a variety of approaches, from single-market (or partial equilibrium) empirical studies using household survey data, to simulations using computable general equilibrium models or macro models. There is substantial disagreement over the incidence of fossil fuel (or energy) subsidies. Partial equilibrium calculations based on household consumption changes often find that higher environmental tax rates (i.e., lower rates of subsidy) would be progressive in developing countries (Datta 2010, Sterner 2011, Rentschler 2016). Others, however, find the opposite, or yield inconclusive results (see Dennis 2016, Table 1). In addition, calculations of incidence based only on changes in household cost of living lack a full accounting of the channels through which households are impacted (Fullerton 2011, Parry et al. 2006). Estimates from a multicountry survey of reform efforts (Arze del

Granado, Coady, and Gillingham 2012) and from single-country models (e.g., Jiang, Ouyang, and Huang 2015) show that the indirect elements of a subsidy account for about 60% of its total impact. Some studies include impacts through the prices of nonenergy consumption goods (e.g., Metcalf 1999, West and Williams III 2004, Grainger and Kolstad 2010). A representative view holds the following:

> The impact of increasing domestic fuel prices on the welfare of households arises through two channels. First, households face the direct impact of higher prices for fuels consumed for cooking, heating, lighting, and personal transport. Second, an indirect impact is felt through higher prices for other goods and services consumed by households as higher fuel costs are reflected in increased production costs and consumer prices. The magnitude of these impacts depends on the importance of cooking, lighting, heating, and personal transport costs in total household consumption, as well as on the fuel intensity of other goods and services consumed by households. The distribution of the impacts across different income groups will depend on the relative importance of these factors across income groups (Coady, Flamini, and Sears 2015, 6).

These claims notwithstanding, the factor market consequences of energy pricing policies are especially likely to matter in developing countries. First, industrial consumers of electricity in developing countries represent a much larger share of total energy use than in wealthy countries. In the average wealthy country, residential, commercial, and transport end-uses account for 60% of total energy use, compared to 40% for industry. In the average developing country, it is industry that accounts for the largest share (62%), with residential and transport accounting for 15% each, and commercial just 7%. In the PRC, a relatively highly industrialized emerging economy, industrial usage is 76% of the total (Table 1).

Second, because factor earnings directly affect incomes and because factor ownership is not uniformly distributed, we should also expect factor market impacts to be both important and heterogeneous across households.

After taking these general equilibrium effects into account, the ex ante incidence of subsidy reform is neither as clear, nor as easily measured, as in studies using expenditure data alone. This ambiguity is reflected in the empirical general equilibrium literature, where some studies of a carbon tax or energy subsidy reform find regressive effects, others progressive effects, and others still no effects at all (Solaymani and Kari 2014; Coxhead, Wattanakuljarus, and Nguyen 2013; Yusuf and Resosudarmo 2015).[3] What is surprising is that none of these studies

[3]A common finding from this literature is that subsidy reform is only progressive when budgetary gains from lower subsidy rates are applied to a specific form of compensation for poorer households; that is, the first-order effects

Table 1. **Energy Use by End-Use Sector, 2011** (%)

	Developing Countries	Developed Countries	United States	People's Republic of China[a]
Residential	15	20	22	11
Commercial	7	16	19	7
Industrial	62	40	32	76
Transport	15	25	28	8

[a]Data for the People's Republic of China for 2007.
Sources: United States Energy Information Administration data compiled by Wolfram, Catherine, Orie Shelef, and Paul Gertler. 2012. "How Will Energy Demand Develop in the Developing World?" *Journal of Economic Perspectives* 26 (1): 119–37. For the People's Republic of China, 2007 data from ChinaFAQs. http://www.chinafaqs.org/library/energy-consumption-major-end-use-sector-china-1980-2007-and-us-2007 (accessed September 15, 2017).

provide a quantitative breakdown of the changes in real household incomes.[4] This lack of detail, in turn, reduces the power of these analyses as bases for policy recommendations.

Uncertainty over the distribution of gains and losses motivates a deeper analytical examination of the channels through which reforms affect household welfare. Analytical general equilibrium models of the kind we will present below can contribute insights. Although highly stylized, they help identify structural characteristics that may be ignored in partial equilibrium studies, or whose influence in numerical general equilibrium simulations may be conflated with other effects. We shall demonstrate that trade, by imposing limits on some, but not all, domestic price adjustments to a policy shock, plays a major role in predictions of the incidence of a fossil fuel policy—and, in particular, that its factor market effects are likely to be felt in household incomes.

The rest of this paper is organized as follows. Section II presents the economic intuition behind the incidence of subsidy reform. In section III, we develop a formal model. Section IV provides an illustration using data from Viet Nam, and section V discusses some more general issues arising from the model and empirical illustration. Section VI concludes the paper.

II. Intuition on Trade, Energy Subsidies, and Household Welfare

Before presenting the model, we develop some of the intuition behind the distribution of energy tax burden in a trade-dependent developing economy.

of the reform may be regressive and/or increase poverty (Bruvoll and Vennemo 2014, ADB 2016). In addition to the studies cited in the text, IEA, OECD, and World Bank (2010) and ADB (2016) both provide surveys and discussions of many other related studies.

[4]Plante (2014) presents a macroeconomic model of subsidy reform that identifies several of the key channels discussed here, but for the case of a single representative household.

The economic incidence of a tax differs from its statutory incidence because the net tax burden is passed on through product and factor markets. The extent to which tax burden is passed forward (to consumers) or backward (to factor owners) depends on behavioral and technological responses to the tax—for example, the elasticity of consumer demand for a product, or the substitutability of a less highly taxed input for a more highly taxed one. In general, tax burden is distributed according to relative magnitudes of relevant elasticities of demand or supply. The definition of a small open economy is that it is a price-taker in global markets; that is, the price elasticity of demand for its exports and the elasticity of supply for goods that it imports are both very high. This eliminates the capacity of domestic producers of tradable goods for price-shifting, since any attempt to do so will simply result in substitution to lower-priced suppliers. This feature of a small open economy plays a central role in the analysis of tax incidence.

In an economy with competitive markets, economic profits are zero in equilibrium. In the short run, with technology fixed, an increase in the price of energy used as an input to some productive activity creates negative profits. To restore equilibrium, either the price of that activity's output must rise or the price of an input or inputs must decline—or both. Whether the output price will rise or not depends on whether domestic producers can pass higher energy costs forward to consumers. Industries that compete directly with foreign producers at prices that are determined in world markets cannot do this. Instead, their adjustment to the tax or subsidy change will be deflected back onto other inputs, especially factors used intensively relative to other sectors, or those (such as fixed capital or land) that are used exclusively in the affected industries.[5]

This constraint on tradable-producing sectors stands in contrast to conditions facing producers of nontradables, whose markets are by definition protected from international competition. If the producers of nontradables can pass additional tax burden forward in the form of higher prices while producers of tradables cannot, then in a small open economy a higher tax (or lower subsidy rate) applied to a widely used input such as energy causes an increase in the relative price of nontradables to tradables—a change referred to as a real exchange rate appreciation, or simply a real appreciation. For net energy importers, lowering the subsidy reduces fuel import demand. In the short run, this creates a current account surplus that is resolved by a real appreciation.[6] This diminishes the competitiveness of domestically produced tradable goods and services relative to those supplied elsewhere in the world market; as a result, exports decline and imports increase (Burniaux, Chateau, and Savage 2011). The negative effect on exports is scaled by their energy intensity, since a

[5]In the limit, when some input is used exclusively in the affected industry, this is merely a restatement of an insight from the Ricardo–Viner–Jones specific factors model that a change in output price has a magnified effect on returns to the specific factor in that industry.

[6]If a country is large enough to influence world prices, this causes a deterioration in the external terms of trade.

larger energy cost share results in a proportionally greater increase in production costs. The implications of the subsidy reform for trade, which are intuitively understood by many policy makers, are nonetheless absent from most ex ante carbon tax models since these assume either that prices are all symmetrically either fixed or (more commonly) endogenous (Fullerton and Heutel 2007, Metcalf 2009, Heutel and Kelly 2016).[7]

The same phenomena can be equivalently described in terms of macroeconomic adjustments. If higher domestic energy prices raise costs in tradable sectors, their resulting loss of international competitiveness creates (or widens) a trade deficit, with a matching excess of domestic aggregate expenditure over income. To eliminate these deficits, assuming no international capital flows or factor payments, requires some combination of lower aggregate expenditure and a fall in domestic relative prices, so as to restore the equilibrium real exchange rate. Among tradable industries, higher costs and lower profits cause the tax burden to be passed back in the form of lower factor prices. Accordingly, the shifting incidence of the tax affects not only the structure of production and trade, but also factor prices and employment, and ultimately, through this channel, the distribution of household income and welfare.[8]

In addition to the foregoing structural responses, there is also a fiscal dimension, and this may be important in countries where the costs of financing a subsidy are large. To the extent that a subsidy must be financed from the public budget, it limits opportunities to compensate losers and crowds out other development-related spending. The problem is more severe when a subsidy policy fixes domestic energy prices in nominal terms, as is common in some countries, since this is equivalent to a variable subsidy rate that is an increasing function of the world energy price. During global energy price booms, the cost of defending a fixed domestic price can absorb a large share of the public sector's discretionary spending (Clements et al. 2013). This was the case in several Asian economies, most notably Indonesia, in the early 2000s.[9] Thus, an energy subsidy raises a different set of distributional and welfare issues, drawing attention to the trade-off between job

[7]Several models of carbon policy highlight the importance of international trade, though they generally do not focus on distributional impacts (e.g., Böhringer, Lange, and Rutherford 2014). To our knowledge, there are no analytical models that address the questions on which we focus here.

[8]In the case of an environmental tax, some adverse distributional or welfare impacts can be offset through revenue recycling and other policy packages financed by tax revenues, an issue extensively explored in the "double dividend" literature (e.g., Bovenberg and Goulder 1996). A subsidy, however, imposes costs rather than raising revenues, and so creates no such opportunity.

[9]During the run-up in global energy prices that took place between 2003 and 2008, pass-through from global to domestic prices varied greatly across the developing world. Among the Asia and Pacific countries, the average rate was high at almost 95%; in some individual countries, however, it was much lower. India and Indonesia each passed through only about one-third of the world price change on all or some fossil fuel products (Arze del Granado, Coady, and Gillingham 2012). In 2009–2012, India (except gasoline), Indonesia, Malaysia, and Thailand (for kerosene and liquefied petroleum gas) all showed extremely low pass-through rates ranging from 13% to 30%, compared with median rates of 76%–84% for a group of 65 developing countries (Kojima 2015).

creation (caused by cheaper energy) and diminished capacity for public spending on development goods such as education, infrastructure, and antipoverty programs.

The foregoing discussion draws our attention to the roles played by factor intensity, energy intensity, and price endogeneity—especially that associated with the distinction between traded and nontraded goods in a small open economy—in the supply-side determination of tax incidence. These three features emerge clearly in a general equilibrium analysis, as we show in the next section.

III. An Analytical Framework

In this section, we present a stylized model of the incidence of energy subsidy reform in an open developing economy. Our goal, as already noted, is to identify the effects of an energy policy change on responses by industries that use different technologies and face different market conditions, and the economy-wide consequences of these responses including their impacts on real household incomes. We address only the case of a net energy-importing country. We make several simplifying assumptions with the goal of capturing the major relevant phenomena without imposing a burdensome level of complexity; these assumptions are noted in the text.

The model assumes two primary factors; two final goods; and a third good, energy, that is both used by industry as an intermediate input and consumed directly by households. We assume constant returns to scale and competitive markets and ignore international trade in factor services. We also assume that energy is imported but not produced domestically. Equivalently, we can suppose that there is domestic energy production, but whether through small size or market segmentation, the energy sector has no influence on domestic factor markets.

The economy is endowed with fixed quantities of two factors v_i, $i = 1, 2$, with prices w_i. These are used to produce two composite goods with quantities g_j and domestic prices p_j. The first, labeled T, is a Hicksian composite of tradable goods on the assumption that their relative price in world markets does not change. The second is a nontraded good, N. Energy, E, is imported as just described. The price of energy is subject to a subsidy at rate s. We define the subsidy using the "price-gap" approach; that is, the domestic price is $p_E = p_E^* (1 - s)$, where p_E^* is the world market price in local currency terms.[10] With this structure, analysis of the producer effects of an energy tax change is analogous to that in models of effective protection in the international trade literature (e.g., Corden 1966); that is, a policy change alters the net output price received.

[10]The price-gap approach is a widely used benchmark that captures the most common forms taken by fossil fuel subsidies in the developing world. For further discussion of the advantages and disadvantages of this approach, see Burniaux, Chateau, and Savage (2011).

Following trade models developed by Woodland (1982) and Dixit and Norman (1980), the supply side of the economy can be summarized by an aggregate revenue (or GDP) function $g(p, \upsilon)$, where $p = \{p_T, p_N, p_E\}$ is the vector of domestic prices and υ is a vector of factor endowments. This function is the result of profit maximization by a representative producer subject to factor endowment constraints and is increasing in υ and homogeneous of degree 1 in prices. It is increasing and convex in p_T and p_N. Differentiation with respect to these prices yields, by Shephard's lemma, final good supply functions $y_j = g_j(p, \upsilon) = \partial g(p, \upsilon)/\partial p_j$. Similarly, the gradient of $g(p, \upsilon)$ with respect to any factor endowment gives the shadow price (or under the assumption of complete and competitive markets, the market-clearing price) of that factor, so we have $w_i(p, \upsilon) = \partial g(p, \upsilon)/\partial \upsilon_i$, $i = 1, 2$.[11] Finally, the derivative with respect to p_E is the negative of the total quantity of energy demanded for intermediate use.

Consumers derive income from ownership of labor and capital, and maximize utility subject to their factor-income budget constraint. Representing each household's decisions by an expenditure function, we can define total household spending by an aggregate expenditure function equal to total income, $e(p, U) = Y$. The derivative of $e(p, U)$ with respect to each price is the quantity demanded of the corresponding good for final consumption. These derivatives are written $e_j(p, U) = \partial e(p, U)/\partial p_j$.

With this set of derivatives, we can construct comparative-static predictions of the direction of change in variables of interest to our story: factor prices, household incomes, and real expenditures. To maintain focus on the subsidy reform policy experiment, we assume that growth in factor endowments and changes in technology are exogenous and set them to zero.

Household real income effects. Households earn income from factor endowments υ_i^h and their real incomes are the sum of factor incomes deflated by household-specific consumer price indices, $R^h \equiv \sum_i w_i \upsilon_i^h / P^h$, where $P^h = \prod_j p_j^{\alpha_j^h}$ is a cost-of-living index and each α_j^h is the share of good j in the total expenditures of household h. Expressed in proportional changes of variables using $\hat{x} = dx/x$ for all variables x, the change in each household's real income, with $d\upsilon_i^h = dp_T^* = 0$, is

$$\hat{R}^h = \sum_i \delta_i^h \hat{w}_i - \alpha_N^h \hat{p}_N - \alpha_E^h \hat{p}_E \tag{1}$$

where δ_i^h is the share of factor i in the income of household h. For convenience choosing quantities such that $p_E^* = 1$, the proportional change in energy prices due to subsidy reform is $\hat{p}_E = \frac{-s}{1-s}\hat{s}$. Using this in equation (1) reveals the total effect of subsidy reform on real household income, expressed in terms of household income

[11] This assumption need not hold if there are unaccounted environmental externalities. Our analysis abstracts from these in order to focus on the economic incidence of the subsidy.

and budget shares, and the general equilibrium elasticities of income and prices with respect to the subsidy rate:

$$\hat{R}^h = \sum_i \delta_i^h \hat{w}_i - \alpha_N^h \hat{p}_N + \alpha_E^h \frac{s}{1-s} \hat{s} \tag{2}$$

Equation (2) provides a decomposition, for each household, of the general equilibrium impact of a subsidy change. The magnitude of the direct "pump-price" effect is captured in the third right-hand side term, which is the product of the household's expenditures on fuel and a term capturing the proportional impact of the subsidy change on the consumer fuel price. The other two right-hand side terms capture general equilibrium impacts through factor markets and changes in those consumer prices that are determined within the domestic economy. We will investigate signs and magnitudes of these price effects next.

Equation (2) also helps us begin to identify likely winners and losers among households, in terms of expenditure patterns and the distribution of factor endowments. This information is captured by interhousehold variation in the values of the expenditure and income parameters, α and δ. Consider an n-household economy, where for each household real income changes depend on factor earnings and consumer prices as just described. So long as all households face the same price changes for factors and goods, the incidence of a subsidy change depends on the extent to which households differ in the structure of income and expenditure. If we compare each household h's experience to that of the national mean (denoted by superscript μ), for example, we have

$$\hat{R}^h - \hat{R}^u = \sum_i \left(\delta_i^h - \delta_i^\mu\right) \hat{w}_i - \left(\alpha_N^h - \alpha_N^\mu\right) \hat{p}_N - \left(\alpha_E^h - \alpha_E^\mu\right) (1-s) \tag{3}$$

This is the relevant construct for assessing distributional outcomes due to a shock that changes economy-wide product and factor prices. To illustrate, consider the subsidy change term on its own. In equation (3), $\alpha_E^h - \alpha_E^\mu > 0$ indicates that household h spends more than the average on fuel, so a lower subsidy rate will reduce h's real income relative to the population mean. Obviously, if most households have similar values for some parameter, then the distributional effects of a change in the associated price or wage variable will necessarily be small.

Factor price changes. As noted earlier, factor prices are found from the derivative of the revenue function with respect to endowments. Thus, for factor i, the effect of a change in the subsidy on its price, holding other exogenous variables constant, is

$$dw_i = g_{iN} dp_N + g_{iE} dp_E \tag{4}$$

Converting to proportional changes and again substituting in the subsidy change expression:

$$\hat{w}_i = \varepsilon_{iN} \hat{p}_N - \frac{s}{1-s} \varepsilon_{iE} \hat{s} \tag{5}$$

where ε_{ij} is the elasticity of wage *i* with respect to price *j*. Assuming that factor inputs and energy are complementary inputs, the sign of $\varepsilon_{iE} = \partial \hat{w}_i / \partial \hat{p}_E$ is negative. In this two-factor model, the sign of $\varepsilon_{iN} = \partial \hat{w}_i / \partial \hat{p}_N$ is positive for the factor used intensively in N production and negative for the other.[12] In this case, reducing the energy subsidy will unambiguously reduce w_1, used intensively in T production, and could either increase or reduce w_2, depending on the relative magnitudes of the two right-hand side terms. In the event that there is no change in p_N, both factors will see their prices fall, a consequence of reduced demand as the price of a complementary input goes up.[13]

Aggregate income and price-shifting. To complete the analysis, we need an expression for the general equilibrium change in the price of nontradables relative to that of tradables. This change will affect households both through prices of consumption goods and through changes in demand (and thus returns to) factors of production from which they derive income.

The change in p_N has several contributing elements. An increase in the price of energy reduces profitability in nontradable production; for a given quantity demanded, supply of nontradables diminishes, raising p_N. A lower subsidy rate also induces consumers to substitute away from energy in their consumption choices; this cross-price effect in final demand also raises p_N. Finally, if subsidy reform increases aggregate income by reducing deadweight losses, then demand for all normal goods increases, and this too tends to increase p_N. All of these components of the relative price effect depend critically on differences in the markets for tradables and nontradables. Producers of tradables face elastic demand (for exports) or supply (for imports), so their output prices are effectively fixed relative to prices in world markets. Producers of nontradables face domestic demand that may be quite inelastic with respect to price; this guarantees that changes in the profitability of nontradables' production will be met at least in part through changes in their prices. This part of the analysis highlights the importance of the distinction between endogenously priced nontradables and exogenously priced tradables.

Recalling our assumption that fuel is imported, define the fiscal cost of the subsidy as the unit subsidy rate times the number of units imported, or $s\,[e_E\,(p, U) + g_E\,(p, v)]$.[14] The terms within brackets are the quantities of imports for final and intermediate consumption, respectively.

[12]By the symmetry of second partial derivatives of the revenue function, these "Stolper–Samuelson" elasticities are dual to the "Rybczinski elasticities," ε_{Ni}, and have the same signs.

[13]When energy is an intermediate input, as in this model, a rise in its price when output price is fixed is equivalent to negative total factor productivity growth for primary factors. See Coxhead and Grainger (2017) for more details.

[14]Our focus rests on the case of fuel-importing countries. In fuel exporters—especially those where mining and refining is carried out by a state or quasi-state enterprise—the true fiscal cost is likely to be lower in that the subsidy is now a transfer among domestic entities and may be recovered through some other tax or pricing instrument. Unsurprisingly, the highest fossil fuel subsidy rates, by far, are found in exporting countries such as the Gulf States, the Russian Federation, Central Asian oil producers, Iran, Venezuela, and others.

The aggregate budget constraint of the economy states that aggregate expenditure on final consumption be just equal to aggregate net income from production less the cost of the subsidy, or

$$e(p, U) \equiv g(p, v) - s\left[e_E(p, U) + g_E(p, v)\right] \tag{6}$$

Before proceeding, it helps to denote the excess domestic demand for any good, j, by $z_j = e_j(p, U) - g_j(p, v)$. With respect to trade, $z_j > 0$ indicates a net import and $z_j < 0$ a net export. The derivative of z_j with respect to another variable k is the difference between the derivatives of the respective demand and supply functions, i.e., $z_{jk} = e_{jk}(p, U) - g_{jk}(p, v)$. The properties of the excess demand functions are carried through from those of their components.

By definition, the market for nontradables must clear domestically, so in equilibrium

$$z_N = e_N(p, U) - g_N(p, v) \equiv 0 \tag{7}$$

Equilibrium. The aggregate expenditure and revenue functions defined earlier represent optimizing behavior by firms and consumers, and thus satisfy full employment of factors and binding consumer budget constraints. Accordingly, if equations (6) and (7) both hold, then external trade is also in balance by Walras' law. Since by construction there are no leakages through savings or externalities, the model as described represents general equilibrium.

Effect on aggregate welfare. To evaluate the general equilibrium effects of a change in the subsidy, we take the total derivatives of the foregoing two expressions, holding world prices and factor endowments constant at their initial levels. From equation (6), the complete derivative after collecting terms is

$$\begin{aligned}(e_U + se_{EU})\,dU = {} & -z_T\,dp_T^* - z_N\,dp_N - (e_E + g_E)\,dp_E - (e_E + g_E)\,ds \\ & - s\,(e_{EE} + g_{EE})\,dp_E - s\,(e_{EN} + g_{EN})\,dp_N \end{aligned} \tag{8}$$

Energy is a normal good for consumers, so we know that $e_{EU} > 0$. With $dp_T^* = 0$ by assumption, $z_N = 0$ by equation (7), and $dp_E = -ds$ because $p_E^* = 1$; the first four terms on the right-hand side sum to zero. The own-price derivatives e_{EE} and g_{EE} are both negative. If energy and nontradables are substitutes in consumption, then $e_{EN} > 0$. Finally, the sign of g_{EN} is unknown a priori, but more likely to be negative if tradables are more energy intensive than nontradables, so that a rise in the latter's relative price reduces overall industry demand for energy, other things equal.

To see the net effect of a subsidy reduction on welfare and to identify the parameters whose values govern this effect, we convert the remaining terms to log changes and again use $\hat{p}_E = \frac{-s}{1-s}\hat{s}$. This gives

$$\beta\hat{Y} = \left(\varepsilon_{EE}^H\alpha_E^H + \varepsilon_{EE}^F\alpha_E^F\right)\hat{s} - s\left(\varepsilon_{EN}^H\alpha_E^H + \varepsilon_{EN}^F\alpha_E^F\right)\hat{p}_N \tag{9}$$

where $\beta = (1 + se_E) > 0$ scales the welfare effect of a subsidy change when $s > 0$. Where needed, superscripts H and F refer to households in the aggregate (i.e., consumer demand) and firms in the aggregate (intermediate demand), respectively. In this expression $\hat{Y}$ is, as noted, a money metric of change in utility equal to $e_U dU/Y$.[15]

Equation (9) provides an unambiguous indication of the direct effect of a subsidy reduction on aggregate income: a lower subsidy rate increases Y. This effect is larger, the more elastic is energy demand for either final or intermediate uses and the larger is its share in aggregate household spending or production costs. The net welfare effect, however, depends on the sign and relative magnitude of the indirect effect, through $\hat{p}_N$, which remains to be solved.

Effect on nontradable price. From equation (7), by total differentiation, using $e_{NU} dU = e_N dY$ and rearranging terms, we obtain

$$e_N dY = -z_{NN} dp_N - (e_{NE} - g_{NE})\, dp_E \tag{10}$$

Converting once again to proportional changes:

$$\left(\varepsilon^H_{NN} - \varepsilon^F_{NN}\right)\hat{p}_N = -e_N \hat{Y} + \frac{s}{1-s}\left(\varepsilon^H_{NE} - \varepsilon^F_{NE}\right)\hat{s} \tag{11}$$

The interpretation of this expression is again intuitive. Note that $(\varepsilon^H_{NN} - \varepsilon^F_{NN}) < 0$ because its elements are the own-price elasticities of demand (negative) and supply (positive) for N. Assume that income remains constant at its base level. Reducing the subsidy rate raises the price of energy relative to other prices. It has a positive effect on p_N through household expenditures to the extent that energy is a substitute in consumption for nontradables, i.e., $\varepsilon^H_{NE} > 0$. On the production side, if energy is a normal input to production of N, then $\varepsilon^F_{NE} > 0$. Combining these results, when aggregate income is unchanged, a lower subsidy rate raises the price of N from both demand and supply sides. Finally, higher aggregate income raises p_N since nontradables are normal goods. The prediction of an increase in p_N is supported by empirical studies confirming real appreciations among net energy importers following unilateral subsidy removal (Burniaux, Chateau, and Savage 2011, Table 2; ADB 2016).

Equations (9) and (11) comprise a two-equation system with two unknowns, $\hat{Y}$ and $\hat{p}_N$. There is ambiguity over the general equilibrium signs of both changes, since a rise in p_N is seen in equation (9) to be associated with a decline in Y. The ambiguity comes from second-order effects that should not be expected to dominate the outcomes described above, but cannot be ruled out except through empirical investigation. This, in turn, conveys ambiguity to changes in the price of factors from which household income changes are derived. The distributional impact of a

[15]The derivative is the reciprocal of the marginal utility of income $\partial V/\partial Y$, so the term on the left-hand side measures the additional income required to maintain utility V.

Table 2. **Regional Subsidies on Fossil Fuel Usage, 2011**

Country	Subsidy Rate (%)	Value ($ billion)	Share of GDP (%)	Share of Gov. Exp. (%)
Indonesia	23.2	21.3	2.5	14.3
Thailand	20.0	10.3	3.0	15.2
Malaysia	18.4	7.2	2.6	10.1
Viet Nam	15.5	4.1	3.4	12.8
Philippines	4.3	1.5	0.7	4.4

GDP = gross domestic product.
Note: Subsidy rates are calculated for 2009–2011 when world petroleum prices were about 50% of the levels prior to the global financial crisis.
Sources: International Institute for Sustainable Development. http://www.iisd.org/gsi/sites/default/files/ffs_gsibali_meetingreport.pdf; World Energy Subsidy database. http://www.iea.org/subsidy/index.html (accessed December 2, 2013); government expenditure data are from Asian Development Bank. Statistical Database System. https://www.adb.org/data/sdbs (accessed July 22, 2014).

subsidy change will depend on parameter values that are unique to each country and case.

IV. Incidence of Subsidy Reduction: An Illustration from Viet Nam

From the foregoing analysis, it is easy to see that households may experience the effects of subsidy reform through several channels beyond changes in consumer fuel prices. In this section, we consider possible distributional effects of a subsidy change, highlighting the channels described in the model.

In developing countries, wealthier households typically have larger fuel expenditure shares. (This is confirmed in the numerous country studies presented in Sterner 2011.) Data from developing country household surveys show fuel expenditure shares ranging from about 3% for households in the lowest expenditure groups to 8%–10% for those in wealthier groups. By this measure, equation (1) suggests that the direct effects of a subsidy reduction (i.e., $\hat{s} < 0$) are progressive; that is indeed the most frequent finding from studies on lower-income economies. However, direct effects need not be large, either in absolute or relative terms. Data compiled by the IEA showed 2011 fossil fuel subsidy rates in five Southeast Asian countries ranging from 4.3% in the Philippines to 23.2% in Indonesia (Table 2).[16]

Including other consumer price effects (e.g., increased cost of transportation services) will increase cost-of-living impacts. Since markets for nontradables clear domestically, their prices may adjust in the wake of a policy shock, whereas domestic prices of tradable goods are limited by those established in global markets. In the United States, goods and services (mainly the latter) classed as nontradable

[16] It follows that in Indonesia, where subsidy rates were highest, the direct impacts of a 10% subsidy cut range from –0.23% for quintile 1 households with a 3% fuel expenditure share to –0.77% for quintile 5 households with a 10% share.

account for 63% of total household expenditures (Johnson 2017). In that case, the effect on real household income of a 10% rise in nontradables' prices is about 20 times greater than the direct impact of a 10% rise in fuel prices. But the distributional impact of these changes depends also on the extent to which expenditure shares vary across households at different levels of income.

Finally, we have emphasized that a subsidy change has additional distributional implications insofar as it exerts asymmetric effects on industries that are heterogeneous in terms of factor intensity, and insofar as households are heterogeneous in terms of income sources. This brings to the fore what is arguably the least studied question pertaining to the structural incidence of subsidy reforms: in which direction, and by how much, can factor prices be expected to move as a subsidy rate is reduced?

A complete assessment of incidence requires a general equilibrium model in which the total effect of a given change is decomposed into contributions through the various adjustment channels. In this section, we conduct a more limited exercise. Using the most recent data available from one subsidy-affected country, Viet Nam, we compute values of the most important parameters in the model developed above. We then use these values to sketch the likely distributional outcomes from a policy shock.

Data are from the 2012 Viet Nam Social Accounting Matrix (SAM), published in CIEM-WIDER (2016). The SAM is constructed from data obtained in surveys of households, firms, and other entities and activities, and provides a consistent database of production and factor demand, household income and expenditures, and other relevant data from which we can compute necessary parameter values. The 2012 SAM is disaggregated into 164 industries and commodities, 6 labor types as well as several forms of capital, and 20 household types.

In the spirit of the stylized facts in the foregoing model, we aggregate all nonenergy agricultural and manufactured goods into a traded goods category, and all services into one nontraded category. Energy consists of coal, oil, gas, refined petroleum products, and electricity. Labor is classified as rural or urban, and as one of three skill levels based on reported educational achievements. However, defining skills based on educational achievement really reflects only the educational attainment of the population, not the skills they bring to the labor force, so we combine the lowest two levels—based on primary and secondary schooling—into one category. Moreover, labor in Viet Nam is mobile among industries, so for each skill level we combine rural and urban labor within each skill category. Households are sorted into five quintiles by expenditure, and each quintile is subdivided into rural and urban subgroups. These are each further subdivided by primary income source into farm and nonfarm households, a useful distinction since it identifies households' capital income by sector. Of course, these groups are not equal in size (Table 3); rather, they are representative of the distribution of the population of Viet Nam, the large majority of which remains rural and farm based.

Table 3. **Distribution of Households by Type and Expenditure Quintile, Viet Nam**

Type	Rural, Farm	Rural, Nonfarm	Urban, Farm	Urban, Nonfarm	Total
Poorest 20%	0.168	0.013	0.012	0.008	0.20
Quintile 2	0.147	0.021	0.016	0.016	0.20
Quintile 3	0.129	0.022	0.016	0.033	0.20
Quintile 4	0.095	0.029	0.018	0.058	0.20
Richest 20%	0.053	0.028	0.011	0.108	0.20
Total	0.592	0.112	0.074	0.222	1.00

Source: Authors' calculations from Government of Viet Nam, General Statistics Office of Viet Nam. Viet Nam Household Living Standards Survey 2012. http://www.gso.gov.vn/default_en.aspx?tabid=483&idmid=4&ItemID=13888.

Table 4. **Household Expenditure Shares on Energy, Traded Goods, and Services, Viet Nam**

	All	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Energy	0.046	0.034	0.047	0.052	0.051	0.045
Traded	0.587	0.700	0.619	0.595	0.532	0.490
Services	0.367	0.266	0.333	0.353	0.418	0.466

Source: Authors' calculations from CIEM-WIDER. 2016. *2012 Social Accounting Matrix for Viet Nam*. Ha Noi: Finance Publishing House.

In Viet Nam, the data indicate a range of expenditure shares for fuel from 3.2% for rural farm households in quintile 1 up to 7.1% for urban nonfarm households in quintile 2. (Table 4 summarizes these data, for succinctness aggregating over household types within each quintile.) Fuel expenditure shares in the upper three quintiles vary between 3.5% and 6.6% over all household types. There is, therefore, some variation in fuel expenditure shares. However, this variation is not strongly correlated with income and, moreover, even the largest shares are relatively small as a percentage of total household expenditure. It follows that even a large change in energy prices can have only a limited effect on distributional incidence. Using these expenditure data, the direct impact of a hypothetical 10% increase in pump prices ranges only from 0.32% to 0.71% of household expenditures.

There is more variation among households in their expenditures on traded and nontraded goods, and it is more systematically associated with income. Table 4 shows that 70% of total spending by quintile 1 households is on traded goods and less than one-third on services. Unlike fuel expenditures, these shares do change monotonically across quintiles; wealthier households spend proportionally more on services, so that in quintile 5 the shares are almost equal. It follows that the real appreciation effect of an energy price change, as discussed in the previous section, will have a proportionally larger effect on upper-quintile households, whose expenditure share on nontraded services is almost double that of the poorest quintile. Moreover, all households' expenditure shares for services are, very

Table 5. **Factor Shares in Household Income by Quintile, Viet Nam**

	All	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
High-skill labor	0.297	0.118	0.182	0.268	0.369	0.551
Low–Medium-skill labor	0.527	0.723	0.662	0.569	0.452	0.228
Agricultural capital	0.113	0.147	0.129	0.120	0.097	0.072
Nonagricultural capital	0.063	0.012	0.027	0.044	0.082	0.150

Source: Authors' calculations from CIEM-WIDER. 2016. *2012 Social Accounting Matrix for Viet Nam*. Ha Noi: Finance Publishing House.

roughly, an order of magnitude larger than those for fuel. A 10% increase in fuel prices that also generated a 1% increase in the prices of services would result in two effects of roughly similar magnitude on household welfare. But whereas the fuel price increase would have a similar effect on the cost of living for all quintiles, the effect of a services price increase would be about double for quintile 5 relative to quintile 1 households, generating a more strongly progressive impact.

In contrast to the fuel expenditure data, there is a great deal of variation in the sources of household factor incomes. Across the 20 household types, the coefficient of variation in factor incomes is 70% for high-skill labor; 28% and 74%, respectively, for medium- and low-skill labor; 107% for agricultural capital; and 86% for other (nonagricultural) capital. Moreover, factor shares in household income for labor, the most important income source by far, show strong and predictably monotonic variation from the poorest to the richest households. Table 5 summarizes this variation over quintiles. Most strikingly in these data, quintile 1 households derive 87% of their income from low- to medium-skill labor and agricultural capital; in quintile 5, only 30% of income comes from these sources. It follows that the effects of an asymmetric shock to factor prices, even one that is fairly modest in magnitude, may have a more far-reaching distributional impact than the direct impacts of changes in energy prices, or even of changes in the relative prices of traded goods and services.

The likelihood of asymmetric factor price changes is an increasing function of the heterogeneity of factor intensity in production across industries. Table 6 summarizes factor intensity and energy intensity for traded goods, services, and energy. (Since transportation services are heavily energy dependent, we also consider these as a distinct category.) The energy and transport sectors together account for 13% of value added and are highly energy dependent. The traded and nontraded sectors are of similar size. The traded sector, however, is much more intensive in its use of less skilled labor and capital, but more dependent on intermediate inputs. (The share of value added in total costs, 32%, is nearly half that of nontraded goods.)

Interestingly, direct spending on fuel is about equal in both sectors (4%–6% of total cost). The direct effect of an energy price shock will be similar in the two sectors; differences between them, therefore, will depend more on indirect

Table 6. **Factor Intensity of Production in Sector Aggregates, Viet Nam**

	Energy	Traded	Nontraded	Transport
Sector share in total VA	0.10	0.44	0.43	0.03
Factor shares in sector VA				
High-skill labor	0.36	0.23	0.44	0.27
Low–Medium-skill labor	0.06	0.45	0.25	0.37
Agricultural capital	0.00	0.11	0.00	0.00
Other capital	0.58	0.21	0.31	0.36
Total	1.00	1.00	1.00	1.00
VA share in total cost	0.52	0.32	0.57	0.32
Energy share in total cost	0.41	0.04	0.06	0.44

VA = value added.
Notes: Factor shares computed using value-added weights. Energy shares computed using total cost weights.
Source: Authors' calculations from CIEM-WIDER. 2016. *2012 Social Accounting Matrix for Viet Nam*. Ha Noi: Finance Publishing House.

Table 7. **Sectoral Distribution of Factor Employment**

	Energy	Traded	Nontraded	Transport	Total
High-skill labor	0.11	0.30	0.56	0.02	1.00
Low–Medium-skill labor	0.02	0.61	0.34	0.03	1.00
Agricultural capital	0.00	1.00	0.00	0.00	1.00
Other capital	0.20	0.32	0.45	0.03	1.00

Source: Authors' calculations from CIEM-WIDER. 2016. *2012 Social Accounting Matrix for Viet Nam*. Ha Noi: Finance Publishing House.

effects—price changes in upstream industries and the capacity to pass on cost increases through higher prices to purchasers. This provides a reminder of the potential importance of cost pass-through in response to policy change.

Finally, we recall that heterogeneity in factor employment across sectors plays a critical role in determining the incidence of subsidy reform. Table 7 shows the factor employment shares for high- and low-skill labor, as well as agricultural and nonagricultural capital, for each of the composite sectors. The traded part of the economy is both more intensive in the use of low- and medium-skill labor, and accounts for 61% of its employment. Thus, low- and medium-skill workers (who tend to be from low-income households) would be most impacted through changes in factor returns in the traded sectors.

V. Discussion

The previous section walks through key predictions from the model developed earlier in this paper by highlighting the key parameters from Viet Nam. We now briefly discuss the implications.

As discussed earlier, many of the Asian countries facing energy subsidy reform are small open economies. These emerging economies are increasingly specializing in manufactured goods requiring low- or medium-skill labor for export to world markets. These industries—plus agriculture, fishery, and forestry—typically account for around half of domestic value added. Of the other half, much is generated in a broad set of service industries that range from low skill, labor intensive (e.g., personal services, wholesale and retail trade, and local transportation) through construction, hotels and restaurants, and other medium-skill activities, to white-collar and professional services such as finance, education, and government.[17] Much employment in the fastest-expanding subsectors of services is at the low end of the skill range, and capital investment per worker is low relative to manufacturing. Although there are exceptions, it is reasonable to assume for the purposes of a stylized account that tradables are relatively less labor intensive overall, but that they are more intensive in the use of low-skill labor relative to higher skilled.[18]

If, as our model predicts, subsidy reform raises the relative price of nontradables, the effects across the income distribution will be mixed. The burden of higher consumer prices in the nontradables sector will fall more on wealthy than on poor households. But on the production side of the economy, reform will tend to reduce returns on most sector-specific capital relative to those on labor, and to reduce the return on low-skill labor relative to high skilled. Since low-skill labor is provided primarily by poor households, whereas the rich earn mainly from capital or skills, the labor market adjustment could cause poorer households to lose in a relative sense—and by more, if they are agricultural households deriving significant income from land or other agriculture-specific capital. Even a relatively small decline in factor earnings could be sufficient to leave poorer households worse off from subsidy reform, after taking account of pump-price effects and increases in the overall cost of living.

This back-of-the-envelope calculation comes with many obvious caveats, but it makes the case that a significant subsidy reform applied to purchasers of fuels as intermediates as well as to consumers may well have more profound impacts on households, and especially on poorer households, through factor markets in general, and the labor market in particular, than through changes in the consumer prices of goods and services that they purchase.

We also note that the results shown are short and medium run in nature. In the long run, firms and consumers will respond to relative price changes in the usual ways, for example, by adopting new technologies and through interfuel substitution. Nevertheless, it is short-run effects (or perceptions of them) that are most relevant to politically charged debates over subsidy reform, or energy tax increases. Many debates over incidence are also defined along other recognizable criteria besides tiers of the expenditure distribution—notably, rural and urban populations are often

[17]The remainder comes from heavy industry sectors producing processed ores, basic metals, chemicals and plastics, paper and other timber products, machinery, fertilizer, and cement.

[18]An important exception is transportation, which is both highly capital and energy intensive, and also largely nontradable.

regarded separately—and the illustrative data used in this section reveal substantial variation across those categories. One gain is that these variations should help in debates where energy policy intersects other areas of policy concern, such as agricultural or rural development.

Our illustrative calculations underscore the point that there is considerable ambiguity in the distributional consequences of the subsidy reform. Ex ante predictions become less clear as the dimensions of the model increase. While we can gain a degree of ex ante analytical power from the model, for detailed empirical results it is necessary to go to a computable general equilibrium approach.[19] One outcome that we can hope for is that future general equilibrium analyses of the incidence of energy policies provide more detailed decompositions of their results. This will permit a more focused discussion of the sources of distributional change, leading perhaps to better targeting of ameliorative policies.

VI. Conclusions

Fossil fuel subsidies have been widespread in the developing world, especially in Asia, and have made a substantial contribution to excessive energy demand. The broad direction of current policy favors reducing subsidies and/or introducing carbon taxes. In 2014, the governments of India, Indonesia, Malaysia, and several other regional economies took advantage of sharply declining world energy prices to cut back or eliminate fossil fuel subsidies. These moves have the potential to reduce both localized air pollution (with substantial local cobenefits) and global greenhouse gas emissions in line with commitments made in global emissions reduction agreements. There are other economic rationales as well for such policy measures.

However, impediments to progress in subsidy reduction remain. Prominent among these are doubts about their impacts on other measures of development progress and concerns about the distribution of gains and losses from reform. These doubts have not yet been conclusively resolved through empirical studies.

In this paper, we provide a structured discussion backed by a stylized formal model to clarify and explore the main channels through which energy policy reforms affect welfare and income distribution in a developing country setting. Our focus is on the interactions of policies and prices in a trade-dependent developing economy. The characteristic features of such an economy, we argue, are such that the stylizations adopted in partial equilibrium analyses and in closed economy general equilibrium models provide misleading guidance as to the incidence of energy policy reform.

[19]Among computable general equilibrium models addressing carbon taxes and energy subsidies, Yusuf and Resosudarmo (2015) is exemplary in integrating detailed household data to generate continuous distributional results. Yusuf, Patunru, and Resosudarmo (2017) provide a regionally disaggregated analysis, also for Indonesia.

We show that the constraints placed on an economy through its trade with the global market play an important role in the economic response to energy policy reform. Industries that produce for the global marketplace find that their response to higher energy prices is constrained by prices in world markets; these limit producers' capacity to pass tax increases forward. Producers of nontradables, on the other hand, are able (up to a point) to pass higher energy costs on as higher prices since their purchasers cannot switch to substitutes in external markets. This difference, and the associated macroeconomic linkages expressed in the real exchange rate, condition the economy's aggregate response to subsidy reform and exert a potentially large influence over the distribution of gains and losses from that reform.

We have modeled the distributional impacts of fuel subsidy reform in general equilibrium with emphasis on the role of trade and factor markets in determining incidence. This is a neglected point in the analytical literature, and one that is typically not readily accessible in currently published simulation results from computable general equilibrium models. The greater importance of industry as a source of energy demand in developing countries relative to wealthier countries makes factor market linkages a prime target for analytical attention.

In the case of Viet Nam, our analysis of household expenditures on fuel and other items by quintile of the expenditure distribution indicates that a lower fuel subsidy rate would have a relatively larger impact on the living costs of wealthier households. These spend proportionally more on services, which are nontraded and whose prices would thus rise with energy costs. On the household income side, the poor will be heavily affected if rising energy costs reduce profitability and output in traded sectors. Those sectors are the largest and most intensive employers of low- and medium-skill labor, which is the primary income source for poor households. Thus, in Viet Nam the net distributional effect of an across-the-board fuel subsidy reduction would be ambiguous.

For the purpose of guiding the design of real-world empirical and policy research, several additional considerations outside the scope of the model are worth noting. First, some important welfare gains or losses are ignored in the model—specifically those associated with reduced emissions and associated changes in expenditures for pollution abatement or adaptation. Studies in many developing countries indicate that particulate matter and gaseous emissions from industries and vehicles have large and costly impacts on human health and longevity and reduce the productivity of labor. If reducing the fuel subsidy rate lowers emissions growth, then it also delivers benefits in the form of a healthier and more productive workforce and lower rates of depreciation of some forms of capital.

Second, for simplicity we have not modeled the policy choices that a government faces when the fiscal burden of a subsidy is reduced. In the real world, the government's budget constraint means that spending on fuel subsidies crowds out other potentially growth-enhancing expenditures, such as on infrastructure, education, and health. Increased spending on these (or indeed, other fiscal policy responses such as lowering income taxes or making direct cash transfers to households) will have different implications for aggregate income growth and the distribution of welfare changes.

Third, in focusing on the real exchange rate mechanism, our model has aggregated many industries into a few categories, ignoring within-category heterogeneity. Unpacking the details of this stylized result is a task for numerical general equilibrium modelers. The model likewise neglects long-run responses to a policy shock, including interfuel substitution and other adaptive changes by firms and households, that tend to minimize losses or increase gains.

Finally, lower subsidies move an economy onto a less carbon-intensive growth path, but may come at a cost in terms of aspirations for industrial growth. Unilateral subsidy reform may reduce a country's potential for globally connected economic growth, which has consequences for development in the long run. Even though one country's subsidy reform is likely to have a negligible impact on global greenhouse gas emissions, there is nevertheless a case to be made for compensation from the international community, as the total effect of fossil fuel subsidies is indeed substantial. Such compensation could be used to increase overall income, reduce energy poverty, or further amend distributional inequality.

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