Beyond national climate action: the impact of region, city, and business commitments on global greenhouse gas emissions

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Supplemental online material

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# S1: Detailed methods on the subnational actors’ commitments dataset preparation

Cities are local governments that are administrative units of a specific geographical territory. In our analysis, the term “cities” includes towns, urban communities, districts, and counties, as defined by the actors themselves and often also defined in the country’s legal system. Regions are subnational administrative units that are generally broader in population and in scope than cities. They usually have separate governing bodies from national and city governments but encompass lower administrative levels of government; often, they are the first administrative level below the national government. “Regions” in this report includes US and Indian states, German Länder, and Chinese provinces. Regions can also include councils of subnational governments acting together.

The emissions inventory totals and data for quantifiable climate commitments used for the calculations were mostly self-reported by entities through one of the reporting platforms presented in Table S-1.

Table S-1: Data sources for individual non-state and subnational actor commitments

| Climate Action Platform  | Data source |
| --- | --- |
| Alliance of Pioneer Peaking Cities | Alliance of Pioneer Peaking Cities (2016). Accessed from: http://www.huanjing100.com/p-1307.html. Peak emissions years were used in the calculation of the cities’ projected carbon emissions. |
| C40 Cities for Climate Leadership Group | C40 Cities for Climate Leadership. Accessed June 2019 from: https://www.c40.org/cities. |
| ICLEI Local Governments for Sustainability carbon*n*® Climate Registry | ICLEI Local Governments for Sustainability carbon*n*® Climate Registry (www.carbonn.org). (Data provided directly by ICLEI in June 2019). Individual targets and action plans for carbon*n* participants based on 2018 GPC Inventory responses. In cases where baseline information for participating actors was absent, it was supplemented with baseline information from data collected from carbon*n*’s reporting members (individual targets, action plans, and progress data) in March 2018. |
| CDP Cities  | CDP. (2019). 2018 Cities Emissions Reduction Targets; 2018\_Cities Community-wide Emissions Map; 2018 Cities Renewable Energy Targets Map.csv; 2018 City-wide Electricity\_Mix. Accessed May 2019 from: www.data.cdp.net. |
| CDP 2018 Disclosure Survey | CDP. (Provided directly from CDP in July 2019). *GHG emissions and action data for companies based on the 2018 responses*. |
| Compact of States and Regions | Compact of States and Regions. (Data provided directly by the Compact of States and Regions in February 2019). 2018 States and Regions Open Portal Dataset, collected via CDP States and Regions 2018 Information Request.  |
| EU Covenant of Mayors for Climate & Energy | EU Covenant of Mayors for Climate & Energy. Individual targets and emissions data for reporting members. Accessed April 2019 from: www.globalcovenantofmayors.org. |
| Under2 Coalition | Under2 Coalition (Secretariat The Climate Group). Membership and action data collected from signatories’ appendices. Accessed June 2019 from: https://www.under2coalition.org/members.  |
| Global Covenant of Mayors for Climate & Energy | Global Covenant of Mayors for Climate & Energy. (Data provided directly by Global Covenant of Mayors in June 2019). Individual targets and emissions data for reporting members. |
| US Climate Alliance | U.S. Climate Alliance. Accessed July 2019 from: https://www.usclimatealliance.org/state-climate-energy-policies. Information from this source was supplemented through desk research of participants’ climate action targets or plans. |
| US Climate Mayors | US Climate Mayors. Accessed July 2019 from: www.climatemayors.org and http://climatemayors.org/actions/climate-action-compendium/.Information from this source was supplemented through desk research of participants’ climate action targets or plans. |

Different platforms report participants’ climate actions in different formats and to different levels of detail: CDP Cities report the breakdown of direct (scope 1) emissions and electricity use-related (scope 2) emissions of subnational actors, whereas others do not include information on emissions scopes if inventory information is reported by an actor. Climate action platforms also capture different types of targets, that span absolute GHG emissions reduction, energy efficiency, renewable energy, and intensity-based targets, among others.

To address the inconsistencies in each platform’s method of categorising targets and to include as many subnational actors’ targets as possible, we chose the most common targets across platforms. We included region- or city-wide absolute GHG emission reduction targets and quantified emission levels under each target using the following variables: actor's base year scope 1 and scope 2 emissions, the target percent reduction, the target base year, the target year, and the actor’s most recent GHG inventory year and the 2015 inventory scope 1 and scope 2 emissions. Sector-level and government-operations targets for cities and regions were excluded if city- or region-wide emissions reduction targets existed. This study did not consider energy efficiency and renewable energy targets without GHG emission reduction targets.

In sum, the we have applied the following hierarchy of data selection:

1. Region- or city-wide absolute GHG emissions reduction targets, in terms of:
	* Absolute emissions reduction
	* Reduction relative to base year emissions
2. Government (e.g., direct and indirect GHG emissions from buildings and other government-owned sources) GHG emission reduction targets, in terms of:
	* Absolute emissions reduction
	* Reduction relative to base year emissions

We also supplemented data from other sources. Chinese subnational commitments were derived from the C40 Cities for Climate Leadership Group, the iGDP China Policy Mapping Tool (IGDP, 2019), and the Chinese cities and provinces participating in the Alliance of Pioneer Peaking Cities (2016). China's 2012 emissions inventory data (including both scopes 1 and 2) of these cities in 2012 were taken from Liu & Cai (2018). GDP data were derived from the China Economic Database (CEIC, 2019). For US subnational actors, we filled some data gaps on baseline emissions and climate action commitments through internet desk research of city climate action plans and progress reports.

The emissions data for the subnational commitments was carefully examined for their correctness. We applied filters to exclude commitments with historical per capita GHG emissions lower than 0.2 tCO2e/capita and higher than 40 tCO2e/capita, with a few exceptions for which were able to verify the correctness of the data (e.g., many GHG commitments for local government operations, which often had very low per capita GHG emissions values, were still included in the analysis).

To calculate the emissions time series for individual subnational actors, we used three tiers of interpolation between the starting year of our projections (=2016) and the quantifiable emissions reduction targets, depending on data reported by individual actors.

* Tier 1: if inventory year and inventory emissions are both available, we interpolate between the latest inventory emissions reported and the target year emissions, assuming a constant rate of decrease.
* Tier 2: if inventory emissions are known but not inventory year, we assume that inventory year is 2010, and apply the same interpolation as Tier 1 (the average year of last inventories was 2013; we assumed an earlier year of 2010 in order to not overestimate the emissions reductions for 2016 and consequently the emissions reductions between 2016 and 2030).
* Tier 3: for cases with no inventory emissions or inventory year, we base our interpolations on base year emissions and base year.

For regions and cities that only report one target year, we assume a constant rate of reduction until the target year, after which we assume emissions have the same trend as the current national policies scenario. For regions and cities that have multiple targets, we interpolate from either the inventory or baseline emissions, whichever is available, up to the first target year (i.e., 2030). If a longer-term target (i.e., 2050) is available, we interpolate from the first target year (i.e., 2030) to the second target year (i.e., 2050) by assuming different rates of reduction between the target years. This approach indicates that there would be limited, if not zero, additional emissions reductions compared to the current policies scenario if actors do not have targets beyond 2020.

For Chinese cities, because of the nature of China’s Alliance of Pioneer Peaking Cities' peak emissions year targets, we had to calculate the emissions reductions differently. We extrapolated emissions from 2012 until 2030, assuming the rate of change in emissions is identical to the rate of change in population. The population projection time series data is obtained from UN World Urbanization Prospects (UN DESA, 2014). For two Chinese cities (Nanping and Jinchang) and two provinces (Sichuan and Hainan) that did not have population projections available, we used national level emissions growth rates based on the TIMER BAU model to extrapolate future emissions pathway. After the last target year, we assumed that the emission levels follow current national policies scenario emission projections until 2030. For subnational actors that report inventory-year emissions that are lower than the estimated target-year emissions, we assumed that these actors have achieved their target emissions reductions in the inventory year and then assumed a constant emissions level after the inventory year (i.e., no additional reductions are assumed).

# S2: Detailed methods on the companies’ commitments dataset preparation

CDP used three separate datasets to develop the country-specific climate action dataset used in this analysis. First, there are the **raw response data** that companies provide annually through CDP’s climate change questionnaire at the request of investors or purchasers. These data include targets, reporting year and base year GHG emissions global inventories, and scope 1 and 2 country-level emissions breakdowns for the reporting year.

Second, there are two separate datasets that result from CDP’s annual data cleaning processes that follows the disclosure cycle:

* The **clean and complete dataset (CCDS)** is the full GHG dataset (Griffin and Taylor, 2016; Sawbridge et al., 2016a, 2016b, 2016c; Sawbridge and Griffin, 2016). The final output includes cleaned emissions data from responding companies, as well as estimated emissions values (see the statistical framework and bottom-up estimation methodology documents) for non-responding companies included in the corporate sample.
* The **cleaned corporate targets dataset (CCTD)** uses similar internal consistency checks to validate and clean the data describing emissions reduction and renewable energy targets. This dataset also employs relevant and available emissions data from current and previous years’ responses and CCDS to better contextualize the target data.

The **country-specific climate action dataset** used for this analysis essentially combines the CCTD with the country-level scope 1 / scope 2 emissions breakdowns provided in the raw response data. Elements of the CCTD also incorporate global emissions data from raw responses or the CCDS, based on the approach described in CDP (2018) .

While CDP is not necessarily comprehensive of all corporate global climate action, they report that over 6,900 companies responded to their climate change questionnaire (CDP, 2019). Of these companies, about half reported that they had an absolute or intensity GHG emissions reduction target in place (CDP, 2019).

The CDP questionnaire for companies encourages the use of GWPs from the IPCC’s Fifth Assessment Report (AR5) (IPCC, 2014) for reporting emissions. We consider these data to be comparable with that reported in terms of AR4 GWPs as most companies are categorised to be emitting predominantly CO2, with only a minimal amount of tracked emissions (<1%) coming from non-CO2 emissions from the waste sector.

The current reporting year (inventory) emission values were calculated as the sum of total scope 1 and 2 emissions in the country of operation, while target year emission values were calculated using the company’s target percentage in emissions reduction for absolute targets, anticipated emissions reduction for emission intensity targets.

As some companies make multiple commitments, we selected one reduction target from the dataset, for each country branch, based on the following priority order:

* Target years after 2017 were preferred to those before 2017
* Absolute emission reduction targets were preferred to intensity targets
* scopes preferred in order of “scope 1+2”, “scope1+2+3”, “scope 1”, “scope 1+3”, “scope 2”, “scope 2+3”
* Targets closest just before and closest to 2030 are preferred

Those records from the CDP dataset that were reported as “poor quality” or reported higher company GHG emissions from the operating branch than the total company were removed from the dataset.

Based on historical emissions and the selected commitments, an emission pathway was constructed of each company branch. This pathway consists of interpolated emissions between base year, start year and the selected target year. If the target year is before 2030, emission growth in line with the current policies scenario is assumed.

As with subnational actor commitments, we assumed a linear interpolation of emission levels between the starting year (2016) and the short- to mid-term target year (between 2016 and 2030), as well as between the short- to mid-term target year and the long-term target year. After the last target year, we assumed that the emission levels follow current national policies scenario emission projections until 2030.

We also collected company-level revenue data to estimate the aggregate scale of companies with commitments in economic terms. The revenue data were collected from the 2019 Fortune Global 500 (Fortune, 2019), Forbes Global 2000 (Murphy et al., 2019), and Hoovers datasets (D&B Hoovers, 2019), supplemented, when possible, with desk research. Companies’ combined revenue estimated for each country reflects companies making quantifiable commitments to reduce GHG emissions, whose headquarters are in that country, and whose revenue data is publicly available.

# S3: Additional information on the calculation of net aggregate GHG impact of commitments

## S3.1: Quantification of total emissions from subnational actors and companies with commitments after accounting for overlaps

The total GHG emissions from individual actors’ commitments (*E*NSA(t)) are calculated as:

$E\_{NSA}(t)=E\_{R}(t)+\left\{\left(E\_{C}\left(t\right)-E\_{C,R}\left(t\right)\right)-E\_{C,R}^{\*}\left(t\right)\right\}+\left\{\left(E\_{B}\left(t\right)-E\_{B,RC}\left(t\right)\right)-E\_{B,RC}^{\*}\left(t\right)\right\}+\left\{\left(E\_{P}\left(t\right)-E\_{P,RCB}\left(t\right)\right)-E\_{P,RCB}^{\*}(t)\right\}$ (2)

where

*E*NSA(t): total projected GHG emissions from non-state actors with commitments in year *t*.

*E*R(t): aggregate of projected GHG emissions from regions with commitments in year *t*;

*E*C(t): aggregate of projected GHG emissions from cities with commitments in year *t*;

*E*C,R(t): aggregate of projected GHG emissions from cities with commitments geographically overlapping with *E*R(t) in year *t*;

*E\**C,R(t): additional GHG emissions reductions from cities with commitments overlapping with *E*R(t) in year *t*, after comparing the level of ambition;

*E*B(t): aggregate of projected GHG emissions from energy end-use companies with commitments (excluding electricity-generating companies) in year *t*;

*E*B,RC(t): aggregate of projected GHG emissions from energy end-use companies with commitments geographically overlapping with *E*R(t) and *E*C(t) in year *t*;

*E\**B,RC(t): additional GHG emissions reductions from energy end-use companies with commitments overlapping with *E*R(t) and *E*C(t) in year *t*, after comparing the level of ambition;

*E*P(t): aggregate of projected GHG emissions from electricity-generating companies with commitments in year *t*;

*E*P,RCB(t): aggregate of projected GHG emissions from electricity-generating companies with commitments geographically overlapping with *E*R(t), *E*C(t) and *E*B(t) in year *t*; and

*E\**P,RCB(t): additional GHG emissions reductions from electricity-generating companies with commitments overlapping with *E*R(t), *E*C(t) and *E*B(t) in year *t*, after comparing the level of ambition.

## S3.2: Share of electricity-related GHG emissions in total direct and electricity-related GHG emissions from cities

Table S-2: Share of electricity-related GHG emissions in total direct and electricity-related GHG emissions from cities.

|  |  |  |
| --- | --- | --- |
| Country | Value | Source |
| Brazil | 17% | average of 14 cities data from CDP (2019) |
| Canada | 20% | average of 15 cities data from CDP (2019) |
| China | 45% | Authors' estimate from Liu (2016) on four major cities (Beijing, Shanghai, Tiangjin, Chongqing) in 2009 |
| EU28 | 34% | average of 53 cities data from CDP (2019) |
| India | 20% | Authors' estimate from Ramachandra et al. (2015) on seven cities (Delhi, Mumbai, Hyderabad, Chennai, Kolkata, Bangalore, Ahmedabad) in 2009-2010 |
| Indonesia | 57% | average of 2 cities data from CDP (2019) |
| Japan | 54% | average of 2 cities data from CDP (2019) |
| Mexico | 25% | average of 5 cities data from CDP (2019) |
| South Africa | 60% | average of 5 cities data from CDP (2019) |
| US | 38% | average of 81 cities data from CDP (2019) |

## S3.3: Detailed description of the “partial effect” method

**The partial effect method** only counts the additional reductions of cities to regions if they are unambiguously more ambitious. Ideally, we would compare a city’s commitment to the emissions reductions of that city expected under the region-level commitment, but such information does not exist. Therefore, we implement this approach by considering only reductions if a city’s target is more ambitious than a long-term emission trajectory consistent with the 2 °C goal. Country-specific long-term trajectories are estimated from Höhne, den Elzen and Escalante (2014) by taking roughly the central estimates of all effort-sharing approaches; the values for 2030 used in the analysis are presented in Table S-3.

Table S-3: Indicative 2030 emission levels implied by 2 °C-consistent emission trajectories under a range of effort sharing approaches used as a threshold for quantifying net additional impact. Source: authors’ estimate based on Höhne et al. (2014).

|  |  |
| --- | --- |
| Country | Emissions in 2030 relative to 2015 levels |
| Brazil | -40% |
| Canada | -50% |
| China | -20% |
| EU28 | -50% |
| India | +50% |
| Indonesia | -30% |
| Japan | -50% |
| Mexico | -40% |
| South Africa | 0% |
| USA | -50% |

## S3.4: Detailed description of the “partial conservative effect” method

**The partial conservative effect method** assumes that there is always a group with “laggard” subnational actors and companies that do not implement any climate action. We assume that this group accounts for the same amount of 2016 GHG emissions as the actors with commitments (“frontrunners”). So, a group of frontrunners, a group of laggards, and a group of followers in between exist. Implicitly, the group of followers implement climate action in line with the national current policies scenario (or NDCs). The assumption on the size of these groups is not based on statistical data, as such data on progress is not available. These size assumptions can be improved when this data comes available. Therefore, we have assumed that the group of laggards have the same size, in terms of emissions, as the group of frontrunners.

This “laggard” group is assumed to follow a business-as-usual scenario, which is derived from the TIMER model, which forms part of the integrated assessment model IMAGE 3.0 (Stehfest et al., 2014). It describes future energy demand and supply for 26 global regions, of which some are large countries (e.g., US, China), and can assess the implications of energy system trends for all major greenhouse gases and air pollutants. The model is built up from different modules, including energy demand modules for transport, industry, buildings and modules for energy supply, industrial processes and emissions.

For this study, no policy, business-as-usual scenario projections for cities and companies were developed by calculating a weight average of a selection of sub‑sectors. The weighting factors to

Table S-4: Weight (as percentage of total emissions coming from urban areas) applied to total sub-sector CO2 emissions from TIMER Model to construct (per country) aggregated CO2 emission projections for cities (for scope 1 and scope 2 emissions)

|  |  |  |  |
| --- | --- | --- | --- |
| Sector | Sub-sector | Weight scope 1 | Weight scope 2 |
| Industry | Cement | 0% | 0% |
|  | Steel | 0% | 0% |
|  | Other | 75% | 75% |
| Transport | Bus | 75% |  |
|  | Train | 50% |  |
|  | Car | Share of urban population | 75% |
|  | High speed train | 50% |  |
|  | Air | 0% |  |
|  | Trucks | 50% |  |
|  | Other freight | 0% |  |
| Residential | Urban | 100% | 100% |
| Services |  | 100% | 100% |
| Other |  | 75% | 75% |
| Losses/leakages |  | 0% | 0% |
| Bunkers |  | 0% | 0% |

develop the business-as-usual projections is provided Table S-5 and Table S-4.

Table S-5: Weight applied to total sub-sector CO2 emissions from TIMER Model to construct (per country) aggregated CO2 emission projections for companies (for scope 1 and scope 2)

|  |  |  |  |
| --- | --- | --- | --- |
| Sector | Sub-sector | Weight scope 1 | Weight scope 2 |
| Industry | Cement | 100% | 100% |
|  | Steel | 100% | 100% |
|  | Other | 100% | 100% |
| Transport | Bus | 0% |  |
|  | Train | 0% |  |
|  | Car | 5% | 25% |
|  | High speed train | 0% |  |
|  | Air | 0% |  |
|  | Trucks | 0% |  |
|  | Other freight | 0% |  |
| Residential | Urban | 0% | 0% |
| Services |  | 100% | 100% |
| Other |  | 100% | 100% |
| Losses/leakages |  | 100% | 100% |
| Bunkers |  | 0% | 0% |

For illustration purposes, we show an example of calculating aggregated additional city impact relative to the region (see top panel in Figure 1 of the article). Suppose the “forerunner” cities in area (C-R) cover 120 MtCO2e/year in 2015, and this group has committed to an annual 2.8% emission reduction rate below 2015 by 2030; the “laggard” cities group which by definition also covers 120 MtCO2e/year in 2015, follows a lower 0.2% business-as-usual emission reduction rate below 2015 by 2030. Further suppose the group of regions (area (C-R)) have on average committed to a 1.4% emission reduction rate below 2015 by 2030. This method assumes that the “forerunner” cities in area (C-R) would deliver emissions reductions additional to those of the regions only when the average emissions reduction rate of “forerunner” cities in area (C-R) and the “laggard” cities, i.e. 1.5% (*2.8%+0.2%*)/2), is larger the regions’ 1.4%. In this case the additional mitigation impact is 0.12MtCO2e/year (0.1%\*120).

# S4: Supplementary data on the GHG emissions coverage per actor group

## S4.1: Regions and cities

The regions and cities included in this study represent a population of 579 million, while participating regions hold nearly 514 million people.In other words, they represent populations that rival those of large countries**;** only China and India have larger populations.Cities taking climate action hold more people than the US and Brazil combined, while regions taking climate action represent a population about four times the size of Japan’s (World Bank, 2019).



Figure S-1: Population of cities and regions making quantifiable commitments to reduce GHG emissions by geographic region. Data source: various.

Europe and North America host the greatest number of cities and regions making quantifiable commitments to reduce GHG emissions. Subnational governments in East Asia and the Pacific, however, represent the largest collective population (Figure S-1). Many of the participating actors in this region are megacities – urban areas home to more than 10 million people – that exercise huge influence over their countries and region’s emissions. While relatively few actors are making quantifiable commitments in South Asia and Latin America these cities and regions also represent large populations, giving their efforts substantial influence within their countries. Cities making quantifiable climate commitments in Latin America and the Caribbean collectively hold 41 million people, roughly 4 million more than Canada’s 2018 population (World Bank, 2019b).

The vast majority (93% percent) of subnational governments’ quantifiable emission reduction commitments focus on short-term targets, aiming to reduce emissions by or in 2020.The remaining 7% of targets are split relatively evenly between mid-term targets – which set target years between 2021 and 2030 – and long-term post-2030 targets (Figure S-2). In terms of the share of emissions, subnational actors with only short-term (by or in 2020) targets, and no mid- or long-term targets, represent 34 % of all subnational actors’ base year emissions in 2015. Among subnational actors, the most common short-term emissions reduction target is 22%, while the most common midterm (2021-2030) emissions reduction target is 40%, and the most common target for longer-term targets (set after 2030) is 80%.

The heavy focus on short-term targets reflects, in large part, high levels of adoption of a 2020 goal by the European participants in the Global Covenant of Mayors for Climate and Energy, which are mostly small towns and communities with relatively low emissions. This trend also applies – less dramatically – across other geographic locations. One exception is the US, which leads in terms of the number of cities and states making long-term quantifiable commitments. More than half of the US cities and states with 2050 targets also had mid-term targets for years after 2025.



Figure S-2: Number and target years of cities and regions’ quantifiable commitments to reduce GHG emissions in the ten major emitting economies.

## S4.2: Companies

Nearly 1,500 companies, operating within 10 of the world’s major emitting economies, have made quantifiable commitments to reduce GHG emissions through CDP. Their combined revenue totals over $21 trillion US Dollars (USD), roughly the size of the US GDP (World Bank, 2019a). More than 450, or just over 20%, of the world’s largest companies – defined in terms of their membership in the 2019 Fortune Global 500 and Global Forbes 2000 lists – are included in this total.

Across the 10 major emitting economies this report considers, the EU28, the US, and China host the greatest number of companies making quantifiable GHG reduction commitments. Targets set by companies headquartered in the US and the EU28 cover markedly more (self-defined) baseline emissions than companies in other regions, likely reflecting the high level of participation in these locations. Similarly, the largest concentration of revenue is found among companies headquartered in the US, the EU28, and Japan.

As with commitments by regions and cities, most company commitments focus on short-term timelines, up to or in 2020. Across the GHG emissions reduction commitments made by companies reporting quantifiable emissions reductions to CDP in the 10 major emitting economies, 58% have targets up to or in 2020; 40% aim for target years between 2021 and 2030; and 2% set targets after 2030. The most common GHG emissions reduction target aims to cut GHG emissions by roughly 20%, with varying base years between 1990 and 2018 (the most common base year is 2014). Company branches with only short-term (by or in 2020) targets, and no mid- or long-term targets, represent 45.2 % of all companies’ base year emissions.

Commitments span a wide range of sectors, with particularly high concentration in the manufacturing and services sectors (Figure S-3). More than 500 commitments each reference renewable energy and fuel efficiency, while over 350 commitments in energy efficiency, and nearly 200 mention transport.



Figure S-3: The distribution of companies making quantified GHG emissions reduction commitments by sector. Data source: CDP Corporate Climate Targets Dataset 2018

# References

CDP (2018). “Appendix C: Developing climate action datasets,” in *Non-State and Subnational Action Guidance: Guidance for integrating the impact of non-state and subnational mitigation actions into national greenhouse gas projections, targets and planning*, eds. NewClimate Institute, World Resources Institute, CDP, and The Climate Group (NewClimate Institute, World Resources Institute, CDP, The Climate Group), 1–117. Available at: http://www.climateactiontransparency.org/wp-content/uploads/2017/07/ICAT-Non-State-and-Subnational-Action-Guidance-26-JUL-2017.pdf.

CDP (2019). Global Climate Change Analysis 2018. Available at: https://www.cdp.net/en/research/global-reports/global-climate-change-report-2018 [Accessed September 10, 2019].

CEIC (2019). China Premium Database. Available at: https://www.ceicdata.com/en/products/china-economic-database [Accessed August 1, 2019].

D&B Hoovers (2019). Company Search Database. Available at: http://www.hoovers.com/company-information/company-search.html [Accessed October 20, 2019].

Fortune (2019). Fortune Global 500. Available at: https://fortune.com/global500/2019/ [Accessed October 20, 2019].

Griffin, P., and Taylor, H. (2016). The Clean and Complete Dataset 2016. Technical Annex II: Bottom-up Estimation Methodology. CDP.

Höhne, N., den Elzen, M., and Escalante, D. (2014). Regional GHG reduction targets based on effort sharing: a comparison of studies. *Clim. Policy* 14, 122–147. doi:10.1080/14693062.2014.849452.

IGDP (2019). China Policy Mapping Tool. Available at: http://www.igdp.cn/policy-mapping-tool/ [Accessed August 1, 2019].

IPCC (2014). Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. , eds. R. K. Pachauri and L. A. Meyer Geneva, Switzerland, Switzerland: IPCC.

Liu, Z., and Cai, B. (2018). High-resolution Carbon Emissions Data for Chinese Cities. Environment and Natural Resources Program, Belfer Center Available at: https://www.belfercenter.org/publication/high-resolution-carbon-emissions-data-chinese-cities.

Murphy, A., Ponciano, J., Hansen, S., and Touryalai, H. (2019). GLOBAL 2000: The World’s Largest Public Companies. Available at: https://www.forbes.com/global2000/#1309417e335d [Accessed October 20, 2019].

Ramachandra, T. V., Aithal, B. H., and Sreejith, K. (2015). GHG footprint of major cities in India. *Renew. Sustain. Energy Rev.* 44, 473–495. doi:10.1016/j.rser.2014.12.036.

Sawbridge, H., and Griffin, P. (2016). CDP Full GHG Emissions Dataset 2016. Technical Annex IV : Scope 3 Overview and Modelling. CDP.

Sawbridge, H., Griffin, P., Van der Vlugt, I., Peirano, J., Shannon, R., Crocker, T., et al. (2016a). The CDP Clean and Complete Dataset 2016: Summary. CDP.

Sawbridge, H., Shannon, R., and Griffin, P. (2016b). CDP Clean and Complete Dataset 2016. Technical Annex I : Data Cleaning Approach. CDP.

Sawbridge, H., Shannon, R., and Griffin, P. (2016c). CDP Clean and Complete Dataset 2016. Technical Annex III : Statistical Framework. CDP.

Stehfest, E., van Vuuren, D., Kram, T., Bouwman, L., Alkemade, R., Bakkenes, M., et al. (2014). Integrated Assessment of Global Environmental Change with IMAGE 3.0 - Model description and policy applications. Bilthoven, the Netherlands: PBL Netherlands Environmental Assessment Agency Available at: http://www.pbl.nl/sites/default/files/cms/publicaties/pbl-2014-integrated assessment of global environmental change with image30\_735.pdf.

UN DESA (2014). World Urbanization Prospects. doi:10.4054/DemRes.2005.12.9.

World Bank (2019a). GDP (current US$). Available at: https://data.worldbank.org/indicator/ny.gdp.mktp.cd [Accessed August 1, 2019].

World Bank (2019b). World Development Indicators. Population, total. Available at: https://data.worldbank.org/indicator/SP.POP.TOTL?view=chart [Accessed September 5, 2019].