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Bigerna, Simona and D'Errico, Maria Chiara and Polinori, Paolo

University of Perugia; Department of Economics, University of Perugia; Department of Economics, University of Perugia; Department of Economics

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Simona Bigerna[a,*], Maria Chiara D'Errico[a], Paolo Polinori[a]

[a] *University of Perugia, Department of Economics*

Abstract

Accounting for the 55% of global population and the 70% of global emissions cities are on the forefront of the climate change mitigation policies and have a pillar role in meeting global targets. The role of cities for a sustainable economy has become more urgent with the Covid-19 pandemic, highlighting that cities cannot go back to business as usual. There are many policy options for city to address climate change, such as improving energy saving, reducing emissions, advocating low-carbon life. Cities need to find the appropriate low-carbon development pathways for their sustainable development, therefore, their actions must be tailored according to multiple criteria, including socio-economic factors, spillover effects, the structure of source of emissions, etc. The objective of this study is therefore to identify the most appropriate pathways cities should follow when designing their climate mitigation programs, accounting for their specific characteristics, including their carbon dioxide emissions. Using data from the CDP-ICLEI Unified Reporting System 2020 and the Global Human Settlement Urban Centre database, the fuzzy-set qualitative comparative analysis identifies the configurations of city- and program-specific factors according to which urban climate actions set more ambitious climate goals in terms of emissions reduction. In this way, the study provides policy recommendations to local governments to select and support the most appropriate climate mitigation programs.

Keywords: climate change, city mitigation program, Fuzzy-set qualitative comparative analysis

JEL: codes: C83, O38, O21, Q58, R11

*Corresponding author

Email addresses: simona.bigerna@unipg.it (Simona Bigerna), mariachiara.derrico@unipg.it (Maria Chiara D'Errico), paolo.polinori@unipg.it (Paolo Polinori)

1. Introduction

Sustainable development has a global dimension and it is recognized that there is a close mutual interaction between local and global processes. Cities are open systems impacting on all other areas and on the earth as a whole, and vice-versa. Cities host more than 50% of the world's population, and it is expected to increase to almost 70% by 2050. Cities are responsible for both around the 70% of global carbon dioxide (CO2) emissions and for 80% of global GDP representing an opportunity to accelerate towards ambitious climate goals. All these factors make the decarbonisation of cities a global priority and a special opportunity to achieving national and international climate objectives and commitments.
Over the past decade, the efforts of local governments to build resilience against climate change have stepped up, endorsing Green Innovation and Climate-Tech through a set of urban programs. The Global covenant of mayors (GcoM), which gather more than 10000 cities worldwide, intends to reduce its annual CO2 emissions of 2.3 billion tons by the 2030.
We aim to formulate, from the available climate mitigation programs cities have already worldwide experienced, transferable policy recommendations helping to support the long-term strategies to tackle climate change.
We provide a methodology for evaluating the urban climate mitigation programs and their interactions with city-specific factors, based on configurational approach and the fuzzy-set qualitative comparative analysis (fsQCA). The configurations of the critical city- and program-specific factors according to which the urban climate mitigation actions set more ambitious climate goals in terms of emissions reduction are identified. The detection of the paths leading to high expected levels of emissions reduction will have important implications for policy-maker at local level providing guidance to select and support the most appropriate climate mitigation solutions.
A large number of climate actions exist to enhance the environmental and energy sustainability of cities. Urban planning comprises a variety of different and complementary strategies such as industrial co-generation, district heating, combined heat and power generation, photovoltaic systems, combined urban waste management

and energy production. Current practices demonstrate overwhelming variety of initiatives and policies, so that the actual success of such strategies in a cross-sectional comparative perspective is hard to evaluate. Therefore, it is crucial to extract, from the current worldwide urban policies, the critical information to summarize the best paths supporting policy-makers to address carbon neutrality. Several reasons exist why we have chosen energy-environmental plans at urban level as focus of the analysis. First, most production, consumption and transport activities take place in urban areas. Second, city is a natural institutional decision- making unit, with well-defined competence and without a composite policy structure horizontally organized in many planning agencies. Thus, the involvement of a unique and identifiable decision-making unit allows for consistent assessments on the effectiveness of the climate actions undertaken at urban level. Third, most programs are based on a bottom-up approach and the direct involvement of locality. Therefore, we focus on those actions that will enhance the support of the general public in favour of changes in energy production, distribution and/or consumption and in lifestyles.

There are many initiatives undertaken by local governments aiming at promoting a resilient and low-emission society such as: the Cities Climate Leadership Group (C40) that connects more than 97 mega-cities; the Local Governments for Sustainability (ICLEI) a global network of more than 2500 cities in 125; the Eurocities which is a network of more than 200 European cities and finally, the GCoM that is a global alliance for city climate leadership, built upon the commitment of over 10,000 cities and local governments sprawled upon 6 continents and 140 countries (representing more than 900 million people). Urban action plans place urgent demand on the scientific community to provide multi- and inter- disciplinary analyses and discussions useful to implement urban mitigation actions within the global climate policies. Nevertheless, literature has not yet defined the pathway cities should follow, leading to contradictory results. This inconsistency among studies suggests that tailored and multi-dimensional planning is required, that is, urban policy-makers must design programs that are appropriate to both, the peculiar configuration of the city and the climate goals they expect to achieve. Some authors focus on case studies of specific area. Hendrickson et al. (2016) apply life cycle assessment to evaluate San

Francisco's climate change mitigation strategy; Lee and Painter (2015) compare the urban policies of four different cities (Seoul, Busan, Seattle and Anheim); Nagorny-Koring and Nochta (2018) analyse in a case study two EU-funded projects involving eight EU cities to evaluate the urban transitions theoretically and practically. Damsø et al. (2016) examine the GHG emission targets of the climate action plans undertaken by local governments in Denmark, while Coelho et al. (2018) examine the Sustainable Energy Action Plan submitted by 124 Portuguese municipalities. Other studies use broader dataset. Pablo-Romero et al. (2018) use the GCoM database to study the main benchmark actions of nearly 1300 cities; Reckien et al. (2018) collected the climate mitigation and adaptation plans across 885 urban areas of the EU. However, a crucial knowledge gap remains in this field: few studies consider the sector-wise structure of emissions at city-level, when they analyse the relationship between the city form and CO2 emissions. In this study we try to fill this gap. In parallel with controlling for socio-economic factors, we consider the sector-wise CO2 emissions share as determinant variable affecting the goal of climate actions undergone at city-level. The configurational approach of the fsQCA allows to broaden the set of critical factors used since it acknowledges the important role of the context and allows for explaining the relationships among multiform factors, and how they are related to a given outcome. Paper is structured as follows, Section 2 describes the variables employed in the analysis and the methodological framework. Section 3 provides the results their discussion. Section 4 is devoted to Conclusions.

2. Material and Methods

We are interested in identifying how the city-specific attributes are combined with the specific features of the urban mitigation programs to increase the cities' efforts towards emissions reduction. In this context, the configurational approach involved by the fsQCA employs the city- and program-specific factors as causal conditions and the expected emissions reduction defined by each climate action as outcome. Using Boolean logic, fsQCA examines the relationship between the outcome and all binary combinations of causal conditions. Then, fsQCA selects the combinations of causal conditions that consistently lead to high levels of expected climate outcome.

The advantage of fsQCA is that it allows researchers to find distinct combinations of causal conditions which, in turn, suggest different pathways to reach a given outcome. In a fsQCA framework, the term "set" is used rather than "variable", to emphasize the idea that each variable will be transformed to represent the level of membership in a given condition.

2.1. The Sets

Two datasets are employed to conduct the analysis. Information about the mitigation programs cities have undertaken during the 2020 is sourced from CDP-ICLEI Unified Reporting System 2020. From this platform we collect the data concerning the expected outcome of the analysis (expressed in terms of emissions reduction) and the specific characteristics of the mitigation programs that are used as causal conditions. Information about the main features of the cities undertaking the mitigation programs is sourced from the Global Human Settlement Urban Center Database (GHS-UCDB). From this platform we collect the data concerning the specific features of the cities that are used as causal conditions.

The CDP-ICLEI Unified Reporting System 2020 accounts for 522 cities and 776 programs, however, for most of the cities, data about the expected outcomes of the undertaken mitigation programs are missing. Therefore, from the raw dataset we can select only a subsample of 145 cities and 571 programs. Moreover, when we merge it with the GHS-UCDB, the sample further shrinks to 90 cities that account for 184 programs. Table S.1 in the section Supplementary Material lists the cities belonging to the considered subsample, that are the cities reporting all the necessary information for the configurational analysis.

The mitigation programs cover a wide range of climate actions promoting decarbonization and sustainability in most of the green-house gas emitting sectors: building; energy supply; transportation; industrial production; agriculture, forestry and land use. Table 1 lists, by regions, the main green house gas emitting sectors where climate-tech actions are involved and the corresponding sample sizes.

Table 1: Urban Mitigation Actions by Regions

				Regions			
Actions	Australia/New Zealand	Central America	Eastern Africa	Eastern Asia	Eastern Europe	Middle Africa	Northern America
Buildings	1	3	0	20	1	0	18
Community Development	0	2	0	13	0	0	2
Energy Supply	1	2	0	7	0	0	7
Finance-Economic Development	1	1	0	1	0	0	0
Food-Agricolture	0	0	0	1	0	0	1
Mass Transit	0	1	1	2	0	0	1
Outdoor Lighting	1	2	0	2	1	0	2
Private Transport	0	3	0	4	0	0	4
Waste	0	4	0	6	0	1	3
Water	0	1	0	0	0	0	0
Actions	Northern Europe	South America	South-Central Asia	South-Eastern Asia	Southern Europe	Western Europe	World
Buildings	8	2	2	1	6	1	63
Community Development	0	2	0	0	0	0	19
Energy Supply	7	1	0	0	4	0	29
Finance-Economic Development	0	0	0	0	0	0	3
Food-Agricolture	0	0	0	1	0	0	2
Mass Transit	1	2	0	0	0	0	8
Outdoor Lighting	0	2	0	1	6	0	17
Private Transport	3	0	0	0	3	1	18
Waste	1	2	0	0	5	0	22
Finance-Economic Development	0	0	0	0	0	0	1

2.1.1. The Set of Climate Outcome

For each mitigation program, city can disclose three different expected outcomes, expressed in terms of CO2 emissions reduction, energy saving, and RES production. We select as outcome the CO2 emissions reduction variable since it is the most reported information in the questionnaire.

Intensity. By dividing the CO2 emissions reduction variable by the urban GDP at Purchase Power Parity (PPP) we obtain the variable Intensity that is the outcome of our fsQCA. Respect to the variable in levels, Intensity controls for the effects of the scale of economic activities, therefore, it is not greatly affected by business cycle fluctuations. *Intensity* is measured in terms of metric tonnes per year/US dollar (2007).

Table S.2 in the section Supplementary Materials shows the main summary statistics for the emissions reduction expected outcome according to the regions which mitigation programs are spread in.

2.1.2. The Set of the Program-specific Causal Conditions

We relate the outcome set of the Intensity to two causal conditions characterizing the urban mitigation programs: the sector which the climate mitigation actions turn to and the number of means of implementation used. Both factors come from CDP-ICLEI Unified Reporting System 2020 database.

Sectors. Each climate mitigation action covers a specific sector which can be buildings, food and agriculture or waste, etc... To obtained a factorized attribute, we rank sectors according to their number of employees (their contribution to the overall national employment).[1] This ranking variable ranges between 1 and 10. The higher the rank, the more employees the sector hires.

Table S.3 in the section Supplementary Materials shows the main summary statis-

[1]Ranking is sourced from https://www.statista.com/statistics/1195197/employment-by-sector-in-europe/.

tics of the factor variable *Sector* according to the regions which programs are implemented in.

Means of Implementation. There are 12 different types of means that the Reporting System identifies for implementing urban programs. These instruments are quite heterogeneous and range from financial mechanisms to education, regulation and monitoring activities. Table S.4 in the section Supplementary Materials lists all possible means of implementation and their frequency in the sample. The grater the number of instruments, the more complex the program is, as it involves multiple practices to achieve the climate target. Therefore, to proxy its degree of complexity, we construct the variable *N-means* that counts the number of means of implementation used in each program. Figure 1 provides a graphical representation of the relative frequency of climate programs based on the number of tools used. As the number of instruments increases (or we can say as the complexity increases), actions become less frequent. Programs using more than 5 means of implementation are only 19, less than the 10% of the sample.

Figure 1: Relative Frequency of Mitigation Actions According the Number of Means of Implementation Used.

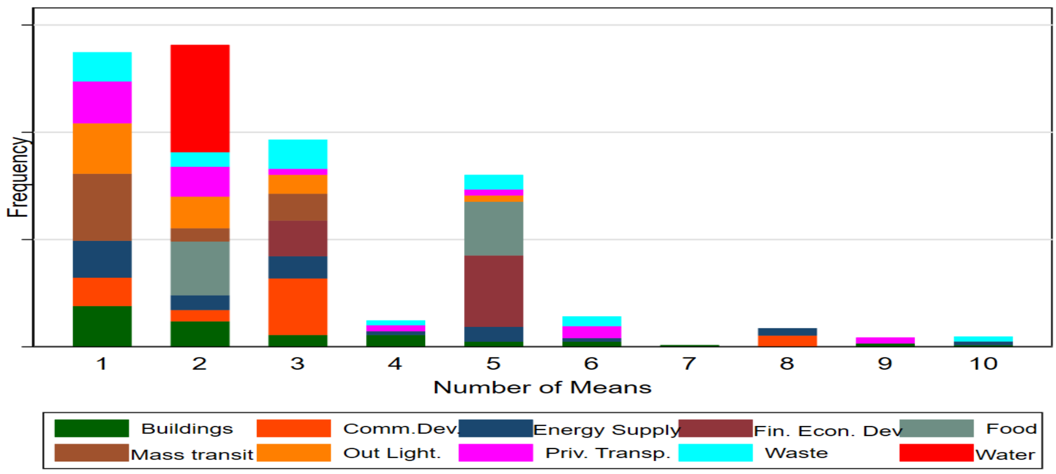


Table S.5 in the section Supplementary Materials shows the main summary statistics of the causal condition *N-Means* by world regions.

2.1.3. The Set of City-specific Causal Conditions

Data used to construct the causal conditions defining the urban forms and the city-specific characteristics are sourced from the GHS-UCDB. Factors defining the urban forms related to CO2 emissions are several, and scholars have used different attributes and indexes to investigate the link between emissions and their urban determinants (see Bhatta et al. (2010), Siedentop and Fina (2010), Shahbaz et al. (2015), Zhang and Lin (2012), Nguyen et al. (2021), Meng et al. (2017), and Meng and Huang (2018)). Nevertheless, literature has not yet drawn definitive recommendations.

Density. Recent studies use urban population density as main attribute of urbanization (Glaeser and Khan, 2010; Marcotullio et al., 2014; Iwata and Managi, 2016; Ahmad et al., 2015; Cuberes, 2012). Following this latter framework, we use population density as a proxy variable of urban agglomeration (Fritsch and Mueller, 2008; Melo et al, 2009; Uchida and Nelson, 2010). It is expressed in terms of number of people for square kilometers.

Table S.6 in the section Supplementary Materials shows the main summary statistics of the causal condition *Density* according to the regions in which programs are spread in.

Urban Sprawl Rate. Density is complemented with a spatial metric expressing the extent and the compactness of urban settlements (Yin et al., 2005; Makido et a., 2016; Lee and Lee, 2014). We use as causal condition the built-up area cover rate that proxies the spatial urban sprawl. It is constructed as the share of the total built-up area on the total urban area.

Table S.7 in the section Supplementary Materials shows the main summary statistics of the causal condition *Sprawl Rate* according to the regions which mitigation programs are implemented in.

Sector-wise Emissions Structure. Several studies highlight how the effects of urban conditions such as density or sprawl rate on CO2 emissions differ according to the sector-wise structure of emissions, leading to mixed results. (see among others Fujii et al. (2017), Cole and Neumayer (2004) and Poumanyvong et al. (2012), Cervero and Murakami (2010), Brownstone and Golob (2009), Yamamoto (2009) and Fang (2008), Lee and Lee (2014), Ahmad et al. (2015), and Makido et a. (2016). Following previous scholars, our fsQCA includes the CO2 emissions shares from energy, transport and residential sector as causal conditions that are potentially related to the climate outcome set.

Table S.8 shows the main summary statistics of the sector-wise shares of urban CO2 emissions by world regions.

2.2. Fuzzy QCA

High levels of expected climate outcome may be sourced from different configurations of causal conditions (the different combinations of program-specific and city specific factors); that is, paths leading to a given outcome are multiple. The final objective of the present study is to analyse which conditions are necessary and/or sufficient for high levels of intensity in CO2 emissions reduction to occur. To do that, we use fsQCA, an analytic technique that identifies the minimum combinations of causal conditions that contribute to a given outcome (Ragin, 2000, 2008).

Grounded in the set theory, this approach well fits for examining connections between multiple and complex conditions and a given outcome. Indeed, fsQCA allows for significant levels of causal complexity in the social and economic phenomena by analysing how much one factor, combined with other factors, is associated to a specific outcome.

FsQCA provides a novel way of analysing data, bringing together quantitative or qualitative variables, and broadening the methodological approaches.[2] Compared with the traditional regression analysis, fsQCA shows several advantages when analysing

[2]Recently, fsQCA has been used to calibrate and analyse quantitative and qualitative data (e.g., Guerola Navarro et al. (2021), Lee et al (2021), Long et al. (2021), Llopis et al. (2021), Pappas et al. (2020), Dwekat et al. (2020)), forecasting (Pappas and Woodside, 2021; Yu et al., 2021), and mixed-method studies (Ma and Pa, 2021; Cairns et al., 2017)

social realities with high degree of complexity. First, it allows for equifinality, because factors are assumed to be not independent on one another and to not compete with one another to explain variation in the outcome. Rather, the configurational approach assumes that there may be different clusters of attributes that work together to achieve the same outcome (Fiss, 2007; Ragin, 2000, 2008). Second, fsQCA does not assume the uniformity of the causal effects; on the contrary, given the complex interactions among factors, it recognizes that the same factor may lead to different outcomes, according to the different combinations with other attributes (Fiss, 2007).[3] Third, it relaxes the assumption of causal symmetry that is typical of regression analysis. Rather, the presence and absence of the outcome need different explanations (He and Fu, 2021).

Generally, variance-based methods examine variables in a competing environment as they compute the net effect between variables in a model, fsQCA focuses instead on the complex and asymmetric relations between the outcome of interest and its causal conditions (El Sawy et al., 2010; Liu et al., 2017; Woodside, 2014).

2.2.1. Statistical Background

FsQCA evaluates the relationship between sets: the outcome set and the set of all possible Boolean combinations of causal conditions.

Two descriptive measures evaluate the strength of the empirical support for setting theoretic relations: consistency and coverage.

Consistency assesses the degree to which observations sharing a given configuration of causal conditions agree in displaying a given outcome; if the configuration is a subset of the outcome set, then, this configuration is consistent with the outcome, that means, this configuration is one of the possible paths leading to the given outcome. Consistency is given by the following fuzzy membership score:

$$Consistency(X, Y) = \sum_i min(x_i, y_i) / \sum_i x_i \tag{1}$$

[3] One factor, in combination with different others, sometimes leads to the presence of the outcome, and sometimes, if combined differently, leads to the absence of the outcome.

where X identifies a particular configuration of factors, Y signifies a specific outcome set, x_i and y_i are the degrees of membership into the set of predictors X and outcome Y, respectively.[4] $Cons(X, Y)$ evaluates the degree of subsetness of each configuration in a given outcome. The closer the value of $Cons(X, Y)$ to unity, the greater the consistency of the data with the assertion that X is a subset of Y or, in logical terms, with the statement "if X, then Y".

Coverage, by contrast, assesses the degree to which a configuration of factors "accounts for" a given outcome. Allowing for equifinality usually involves that a given outcome may be sourced from different consistent configurations of factors treated as logically equivalent; coverage gauges the empirical relevance of each combination. Coverage is given by the following fuzzy membership score:

$$Coverage(X_i, Y_i) = \sum_i min(x_i, y_i) / \sum_i x_i \tag{2}$$

In both formulas, the membership score with the minimum operator defines the degree to which any observation accounts for ("experiences") the configuration under question.

The two formulas imply that data need to be transformed in a fuzzy set; instead of working with probabilities, fsQCA calibrates raw data into a set of membership scores, ranging from 0 to 1 that show if and how much an observation belongs into a specific set. A case with a fuzzy membership score of 1 is a full member of a fuzzy set (fully in the set), and a case with a membership score of 0 is a full non-member of the set (fully out of the set). A case with membership score of 0.5 represents the maximum of ambiguity as neither in nor out of a fuzzy set. Following the principle of direct calibration, three anchors are defined to calibrate variables according to their distributions (Woodside, 2013; Crespo and Crespo, 2016). We set as anchors the 95th, the 50th and the 5th percentiles of variables' distributions, corresponding to full membership set (calibrated value=1), intermediate membership set (calibrated

[4]See Ragin (2000, 2006) for discussions of other methods.

value=0.5), and the full non-membership set (calibrated value=0), respectively.[5]

Then, the truth table computes the all logically possible combinations of factors leading to the set of full membership in the intensity in the emissions reduction (the full-membership outcome set). For a number of factors equal to k, there may be 2^k logically possible configurations. As the number of causal conditions increases, the number 2^k of possible configurations increases exponentially. For each configurations, the accompanying consistency scores are computed from eq.(1) (see tables S.9-S.11 in the section Supplementary Materials).

Boolean minimization is then performed from the truth table in order to reduce the set of all logically possible configurations to a more parsimonious solution (the "final reduction set").[6] First, the Wald test selects the configurations with consistency scores statistically significant. Following Ragin (2000, 2006), Wald tests compares the consistency score of each configuration with the numeric benchmark of 0.8. Configurations with p-values lower than 0.05 are then selected; these configurations represent the combinations of factors with statistically significant consistency.[7] Second, once consistent configurations have been determined, Quine–McCluskey algorithm reduces these latter to their common logical elements.[8] This final reduction set represents the logical description of the conditions sufficient to produce a given outcome; quoting Ragin (2006), they are "the recipes to achieve a defined outcome".

Our analysis concludes with the partitioning coverage procedure, that computes the portion of the outcome set covered by each causally relevant configuration using eq.(2). As high levels of intensity can be conform to more than one configuration, partitioning coverage makes explicit the empirical relevance of each path.

[5] We do not use exactly 1 and 0 as breakpoints because the two membership scores would correspond to positive and negative infinity, respectively, for the log of the odds (Ragin, 2008). The calibration is performed using the software STATA, `fuzzy` package.

[6] Depending on how we decide to deal with the logical remainders there are three different solutions: parsimonious, complex and intermediate, all compatible with each other.

[7] Test is unilateral and compares the null hypothesis that the consistency is equal to the benchmark value (0.8) against the alternative hypothesis that consistency is larger.

[8] See Ragin (1987).

3. Results and Discussion

In this section we present the results of the three fsQCA performed. All analyses employ as outcome the percentile variable of emissions reduction intensity, and, as causal conditions, the percentile variables of the program-specific factors (the *Sector* and *N-Means*), and city-specifi factor (*Density* and *Sprawl rate*). The three models differ in the causal condition represented by the CO2 emissions share, we use the percentiles of the CO2 emissions share from energy, residential and transport sector in the first, second and the third model, respectively.

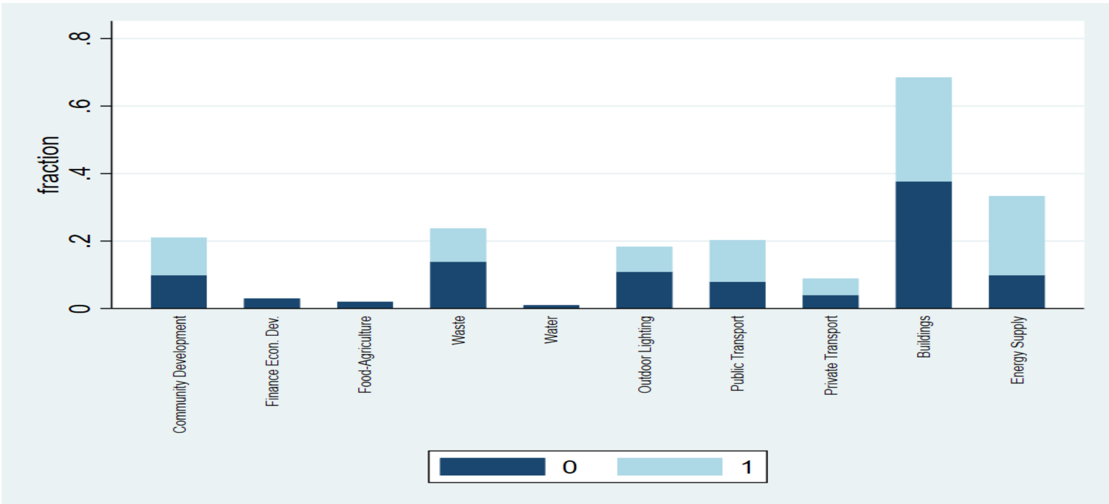
Table 2 shows the summary statistics of the original variables (the expected climate outcome and causal conditions) and the corresponding calibrated variables (the membership score variables) denoted by the fuzzy-set acronym *f-s*.

Table 2: Operational Variables, Summary statistics.

	mean	sd	min	max
Intensity	.0000544	.0006642	0	.0090072
f-s Intensity	.4484238	.3161184	.0474259	.9525741
Actions	7.395604	2.495318	1	10
f-s Actions	.5176353	.3402703	.0474259	.9525741
N-means	2.76087	2.100583	1	10
f-s N means	.395576	.3320464	.0474259	.9498448
Density	3732.699	2651.716	946.8936	16307.6
f-s Density	.4885422	.3119465	.0474259	.9525741
Sprawl Rate	36.76573	13.56187	21.02761	80.01614
f-s Urban sprawl	.4685573	.3243611	.0474259	.9514577
Share Energy Sct.	13.97516	17.60553	.0366454	78.21275
f-s Share CO2 Energy Sct.	.5264037	.29656	.0474259	.9485679
Share Residential Sct.	20.90291	8.882999	1.696213	41.87497
f-s Share CO2 Resid. Sct.	.4891405	.2968774	.0474259	.9525741
Share Transport Sct.	24.7721	10.56381	3.803092	60.64493
f-s Share CO2 Transp. Sct.	.4588625	.2867812	.0500559	.9485778
Observations	184			

Focus on the emissions reduction intensity, local climate mitigation programs vary significantly in the definition of the expected outcomes. Figure 2 depicts the size of both the sets of membership - in and out - of the causal condition *f-s Sector* to the set*Intensity* in emissions reduction. Programs are identified by the sector in which they operate and are sorted by their rate of employment, showing sectors with lower rate on the left and sectors with higher rate on the right.

Figure 2: Membership Scores of Intensity in Emissions Reduction and Mitigation Actions.



*Observations identified by 0 define membership scores smaller than 0.5. They indicate the set of cases more out than in the set of intensity.
*Observations identified by 1 define membership scores greater than 0.5. They indicate the set of cases more in than out of the set of intensity.

All possible configurations and their accompanying frequencies are shown in the three truth tables in the section Supplementary Materials. Moreover, for all configurations, consistency scores are computed. For each analysis, all configurations with statistically significant consistency scores and the accompanying p-values are presented in tables 3, 5, 7. Tables 4, 6 and 8 show instead the results from the partitioning coverage procedure, that are the consistency score, the raw and the unique coverage scores of the highly consistent configurations (the configurations belonging to the final reduction set).

3.1. Energy Sector

In the first analysis, the truth table S.9 lists all logically possible configurations, their frequencies and the consistency scores. Then, table 3 lists all configurations of causal conditions that pass Wald test. Each configurations is described by five letters, and each letter identifies a causal condition (see the note of Table 3 to know which letter stands for each factor). The lower case of the letter denotes a low membership score of the causal condition. The upper case of the letter denotes instead a high membership score of the causal condition. There are eleven configurations of factors that are assumed to be sufficient in determining the full-membership in the outcome set: amdSc, amdSC, amDSC, aMdSc, aMdSC, aMDSc, AmdSC, AmDSc, AMdSc, AMdSC, AMDSc. To give an example, the first row means that mitigation actions with low levels of employment (a) and few means (m) of implementation, referring to cities that show low levels of urban density (d), low shares of CO2 emissions from the energy sector (c), and high levels of urban sprawl rate (S) is a combination that consistently leads to high levels of emissions reduction.

Table 4 lists instead the reduced final solution set and its accompanying coverage. We show the parsimonious solution, where remainders (the configurations with frequency lower than three) are excluded.

Algorithm identifies three configurations in the final reduction set: MSc, amSC and amDC. The first combination states that programs with several means of implementation (M), undertaken by diffused cities (S) where the CO2 emissions share from the energy sector are low (c) are consistent conditions to achieve high levels of intensity in the emissions reduction. The second combination that is consistent with full membership outcome set is more complex, since it adds another factor. This configuration defines climate mitigation programs covering sectors with low rates of employment(a) and few means implementation (m), undertaken by diffused cities (S) with high levels of CO2 emissions sourced from the energy sector (C). The last configuration defines programs covering sectors with low rates of employment (a), low number of means of implementation (m), concerning cities with high levels of urban density (D) and CO2 emissions share (C).

Table 3: Consistency with Sufficiency. Energy Sector.

Y-Consistency vs. Set Value.					
Configuration	Y-Consistency	Set Value	F-statistic	p-value	Freq.
amdSc	0.879	0.8	9.82	0.002	6
amDSC	0.856	0.8	4.13	0.044	3
aMdSc	0.917	0.8	27.95	0	1
aMDSc	0.884	0.8	10.81	0.001	4
AmdSC	0.921	0.8	36.09	0	2
AMdSc	0.896	0.8	13.38	0	4
AMdSC	0.928	0.8	23.85	0	1
AMDSc	0.873	0.8	4.8	0.03	7

Factor list:
a/A stand for the sector of the mitigation program set;
m/M stand for the number of means set;
d/D stand for the urban density set;
s/S stand for the urban sprawl rate set;
c/C stand for the set of CO2 emissions share from energy sector.
Capital letter stands for set of high-membership scores, lower case letter stands for set of low membership scores.

Table 4: Final Reduction Set. Energy Sector.

Final Reduction Set			
Set	Raw Coverage	Unique Coverage	Solution Consistency
MSc	0.304	0.135	0.798
amSC	0.277	0.019	0.861
amDC	0.321	0.067	0.77
Total Coverage = 0.479			
Solution Consistency =	0.748		

The total coverage describes the extent to which the outcome of interest may be explained by all the three relevant configurations, it is comparable with the R-square reported on regression-based methods (Woodside, 2013). Here, the union set of all causally relevant configurations cover less than half of the full-membership outcome set (0.479), with a consistency score equal to 0.788.
The "raw coverage" assessment is complemented with the "unique coverage" assessment. Since the outcome can be sourced from three alternate paths, the unique coverage measures the coverage that is exclusively due to one single configuration, discarding the overlapping part with the others. For each relevant configuration, unique coverage is computed taking the difference between the coverage of the union set (Total Coverage) and the coverage of the complement exclusive set.[9] For two configurations (amSC and amDC) the unique coverages are low, meaning that most of the outcome is sourced from the overlapping part, while MSc shows alone a coverage of the 0.135 and a consistency of 0.798, meaning that cities with high levels of sprawl rate and low shares of CO2 emissions from the energy sector, that grant complex programs with several means of implementation, tend to define high levels of climate outcome measured in terms of intensity of black carbon emissions reduction.

3.2. Residential Sector

Second analysis employs as factor the CO2 emissions share from residential sector. From the truth table S.10 in the Supplementary Materials, the Wald test selects nine configurations of predictors causally relevant that are listed in table 5.

Boolean minimization leads to three configurations of predictors that roughly cover the half of full-membership outcome set (Total coverage equal to 0.498): MdS, amdC and aMSc (table 6).

MdS identifies programs with high degree of complexity (high number of means of implementation-M), undertaken by geographically wide-spread cities (S) with low

[9]This template is very similar to that provided by regression analysis to access the contribution of each independent regressor to the variation of the dependent variable.

Table 5: Consistency with sufficiency. Residential Sector.

Y-Consistency vs. Set Value.					
Configuration	Y-Consistency	Set Value	F-statistic	p-value	Freq.
amdSC	0.881	0.8	9.93	0.002	6
aMdSC	0.931	0.8	40.31	0	1
aMDSc	0.872	0.8	4.78	0.03	2
AmdSc	0.91	0.8	28.67	0	3
AMdSc	0.922	0.8	19.14	0	1
AMdSC	0.91	0.8	18.83	0	4

Factor list:
a/A stand for the sector of the mitigation program set;
m/M stand for the number of means set;
d/D stand for the urban density set;
s/S stand for the urban sprawl rate set;
c/C stand for the set of CO2 emissions share from energy sector.
Capital letter stands for set of high-membership scores, lower case letter stands for set of low membership scores.

levels of urban density (d). Generally, cities with wide-spread urban area and low urban population density show buildings with high degree of heterogeneity that imposes to differentiate the means of implementations if they want to reach a certain level of climate outcome. The second configuration, amdC, concerns mitigation actions covering sectors with low rates of employment (a) and few means of implementation (m), undertaken by cities with low density (s) and high share of emissions from the residential sector (C). Lastly, aMSc defines programs with several instruments that cover sectors with low employment rate (a), undertaken by concentrated cities (s) with low shares of CO2 emissions sourced from residential sector.

Among the three configurations, the amdC set covers alone more than 17% of the full-membership set of the outcome even if it has the lowest consistency score. It means that programs that cover sectors with low levels of employment (a) and adopt few means of implementation (m), combined with cities with low levels of density (d) and high levels of CO2 emissions share from residential sector (C) represent a consistent and causally relevant configuration for high levels of emissions reduction intensity.

Table 6: Final Reduction Set. Residential Sector.

	Final Reduction Set		
Set	Raw Coverage	Unique Coverage	Solution Consistency
MdS	0.301	0.086	0.872
amdC	0.355	0.172	0.74
aMSc	0.213	0.025	0.864
Total Coverage = 0.498			
Solution Consistency =	0.741		

3.3. Transport Sector

The last analysis consider as causal condition the CO2 emissions share from the transport sector. All configurations are listed in table S.11 in section Supplementary Materials and the selected consistent configurations are shown in table 7.

The final reduction set covers the 37% of the outcome set and it is defined by only two configurations: aSC and MSC with coverage scores lower than 10% (table 8). This means that the two consistent combinations are not supported by high number of observations and most of the coverage comes from the overlapping part set expressed by the two conditions: high levels of sprawl rate (S) and high levels of emissions share from the transport sector (C). Both combinations include only three causal predictors assumed to be sufficient. The first combination (aSC), consistent with high levels of climate outcome, identifies mitigation actions that cover sectors with low rates of employment (a), undertaken by diffused cities (S) with high levels of CO2 emissions sourced from the transport sector (C). The second configuration (MSC) concerns instead programs with many instruments (M), undertaken by diffused cities (S) with high levels of CO2 emissions shares from the transport sector (C).
It is not surprising that both configurations identify cities with high share of CO2 emissions from the transport sector. As the transport sector is one of the main responsible of black carbon emissions, cities with high CO2 emissions shares from this sector tent to define ambitious climate outcomes in terms of intensity in emissions

Table 7: Consistency with sufficiency. Transport Sector.

Y-Consistency vs. Set Value.					
Configuration	Y-Consistency	Set Value	F-statistic	p-value	Freq.
amdSc	0.907	0.8	26.56	0	1
amdSC	0.889	0.8	12.31	0.001	5
amDSC	0.867	0.8	5.31	0.022	2
aMdSC	0.914	0.8	25.81	0	1
AmdSc	0.918	0.8	33.91	0	2
AMdSc	0.943	0.8	82.53	0	1
AMdSC	0.874	0.8	6.06	0.015	4
AMDSC	0.89	0.8	8.53	0.004	6

Factor list:
a/A stand for the sector of the mitigation program set;
m/M stand for the number of means set;
d/D stand for the urban density set;
s/S stand for the urban sprawl rate set;
c/C stand for the set of CO2 emissions share from energy sector.
Capital letter stands for set of high-membership scores, lower case letter stands for set of low membership scores.

reduction. Moreover, both configurations associate high levels of CO2 emissions share from the transport sector with high levels of urban sprawl rate; this configuration is quite intuitive: public and private transport pollute more in cities with wide-spread urban area.

Table 8: Final Reduction Set. Transport Sector.

	Final Reduction Set		
Set	Raw Coverage	Unique Coverage	Solution Consistency
aSC	0.306	0.089	0.852
MSC	0.281	0.064	0.834
Total Coverage = 0.370			
Solution Consistency = 0.814			

It is noteworthy that all relevant configurations differ according to the gas-emitting sector considered (energy, residential and transport). This highlights the pillar role of the structure of emissions sources when analysing urban mitigation actions, their climate goals, the means of implementations and their link with other city-specific conditions.

4. Conclusions

In this study we identify the most relevant pathways that cities can follow to promote goal-oriented climate mitigation programs, that are those actions involving the highest efforts and the most ambitious climate outcomes in terms of intensity in the emissions reduction.

Using configurational approach, from the climate programs recorded in the CDP-ICLEI Unified Reporting System 2020, we identify the configurations of causal conditions that are consistent with the presence of high levels of intensity in the emissions reduction. Recognizing the strategic role of local governments, this method provides urban policy-makers transferable recommendations that will help to support the long-term strategy against climate change.

This study tries to broaden the analysis on the environmental efforts undertaken by cities and the related expected reductions in CO2 emissions, using a wide group of critical factors. Indeed, differencing from the existing literature, we use as determinants both program-specific and city-specific attributes, and we analyse their potential combinations that consistently lead to the most performing climate mitigation actions. As the relation between urban forms and urban black carbon emissions differs according to the emitting sector which they are sourced from, we complement the city-specific factors commonly used in the literature with untapped variables: the sector-wise shares of CO2 emissions computed at urban-level. Therefore, three different fsQCAs are performed, one for each gas-emitting sector (energy, residential and transport). In all analyses we employ as outcome the intensity in the emissions reduction, and, as causal conditions, the program-specific factors, the urban density and the urban sprawl rate; whilst, we use the CO2 shares from energy, residential and transport sector in the first, second and the third model, respectively. In this way we are able to identify which configurations best fit with the specific environmental footprint that cities record in the three gas-emitting sector.

From the fsCQA analysis and the Quine-McCluskey algorithm we derive the the final reduction sets of causal conditions that consistently lead to high levels of environmental outcome. All relevant configurations differ according to the gas-emitting sector considered (energy, residential and transport). In the first analysis, the consistent configuration with the highest coverage is given by the set of diffuse cities, with low shares of black carbon emissions from the energy sector, that have undertaken programs with several means of implementation. In the second analysis, the set of cities with low levels of urban density, high values of emissions share from the residential sector, that have promoted programs covering sectors with low rates of employment and few means of implementation account alone for the 17% of the full-membership outcome set. In the third analysis, the final reduction set show two configurations, both identify the set of diffuse cities with high levels of CO2 emissions share from the transport sector. They differ in the program-specific characteristics: the first set concerns programs covering sectors characterized by low levels of employment rate; the second identifies instead composite programs, employing several means of implementation. Nevertheless, both configurations are characterized by unique coverage lower than the 10%.

The upcoming global efforts to shape a more sustainable future after the pandemic need the strong engagement on the part of mayors and their urban systems, both in the design and in the implementation of recovery programs. Many cities have been able to use crisis as opportunity to rethink their future as more sustainable places their for citizens. Our study aims to identify the crucial city-driven strategies that contribute to the new global challenges of energy efficiency, renewable energies, digitalisation. While recovery strategies can be crucial in setting up a clear vision for the future of cities, it is the allocation of resources for their implementation that can make the difference. Accordingly, this study contributes to define the most appropriate pathways cities should follow when select the climate mitigation programs to fund.

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Supplementary Material

This supplementary section deepens the analysis of the data used as causal conditions in the fsQCA.

The main information about the climate mitigation programs is sourced from the CDP-ICLEI Unified Reporting System 2020 database, that is a platform which collects self-reported and standardized information about the climate mitigation programs cities have worldwide undertaken during 2020.[1] By compiling a questionnaire, cities disclose to the system information concerning the main characteristics of the mitigation actions such as the magnitude and the time scale of the expected outcomes, the sector involved, the means and the status of implementation.[2]

The CDP-ICLEI dataset is then integrated with the GHS-UCDB that provides information on urban centers accordingly to a set of multi-temporal thematic attributes gathered from multiple sources available in the open scientific domain (Florczyk et al., 2019). The database represents the global status on urban centres by offering the cities location, their extent (surface, shape), and describing each city with a set of geographical, socio-economic and environmental attributes, many of them going back 25 or even 40 years in time. Urban Centres are defined in a consistent way across geographical locations and over time, according to the "Global Definition of Cities and Settlements" developed by the European Union. The GHSL project produces information for more than 11 thousand cities, based mainly on two quantitative factors: i) the spatial distribution (density) of built-up structures, and ii) the spatial distribution (density) of resident population. It also includes the sector-wise amounts of CO2 emissions at urban-level.[3]

[1] This data was collected in partnership by CDP and ICLEI - Local Governments for Sustainability.

[2] Few cities of the sample also report the total cost of the action and how much has been funded by the local government.

[3] Bottom-up methodology is applied in order to make comparable the emissions from all different urban settlements, considering their respective levels of detail, uncertainties or data limitations. All human activities leading to climate relevant emissions are included, combustion in the power, industry, buildings, transport and agricultural sectors.

Table S.1 shows the sample of cities considered for the fsQCA, divided by the 13 word regions. Some regions account only for one single city; they are Eastern Africa, Eastern Europe and Western Europe that account for Dar es Salaam, Sofia and Bruxelles, respectively.

The Outcome Set

The outcome set of the fsQCA is given by the intensity in the expected emissions reduction, that is the expected CO2 emission reduction divided by the urban GDP. Both datasets (the CDP-ICLEI and GHS-UCDB) are used to construct this variable. Data about CO2 emissions reduction variable are sourced from the CDP-ICLEI and they are measured in terms of tonnes per year. Urban GDP (PPP) estimates comes instead from the GHS-UCDB, and it is expressed in US dollars (2007).[4] Therefore, *Intensity* is measured in terms of metric tonnes per year/US dollar (2007). Table S.2 in the section Supplementary Materials shows the main summary statistics for the emissions reduction expected outcome according to the regions which mitigation programs are spread in.

The Set of the Program-specific Causal Conditions

Two causal conditions are used to define the urban mitigation programs: the sector which the climate mitigation actions turn to and the number of means of implementation used. Data come from CDP-ICLEI Unified Reporting System 2020 database, for both factors.

Sector. *Sector* is a factor variable that ranks the climate mitigation programs according to the number of employees hired by the sector which the program refer to.[5] Table S.3 shows the main summary statistics of *Sector* by world regions.

[4]These estimates are computed using the global grids on total annual GDP (PPP), available at 30 arc-sec resolution (approx. 60 km at the equator) (Kummu et al., 2018). The global grids were harmonised with the Urban Centre grid (i.e., projected with resampling to 1×1 kilometre grid in World Mollweide projection).

[5]Ranking is sourced from https://www.statista.com/statistics/1195197/employment-by-sector-in-europe/. We also classify mitigation actions according to other aspects that are their general contribution to environmental damage and GDP. Analyses undertaken with these different ranking variables lead to the same, robust results.

Table S.1: List of the Cities included in the study-sample.

City	Freq.	Percent	Cum.
Australia/New Zealand			
Adelaide	1	25	25
Melbourne	1	25	50
Newcastle	1	25	75
Sydney	1	25	100
Total	4	100	
Central America			
Celaya	1	12.5	12.5
Escuintla	1	12.5	25
Hermosillo	1	12.5	37.5
Mexico City	1	12.5	50
Morelia	1	12.5	62.5
San José	1	12.5	75
Uruapan	1	12.5	87.5
Xalapa	1	12.5	100
Total	8	100	
Eastern Africa			
Dar es Salaam	1	100	100
Total	1	100	
Eastern Asia			
Hong Kong	1	25	25
Taichung	1	25	50
Tokyo	1	25	75
Toyama	1	25	100
Total	4	100	
Eastern Europe			
Sofia	1	100	100
Total	1	100	
Middle Africa			
Yaounde	1	100	100
Total	1	100	

Northern America			
Abington	1	3.85	3.85
Albuquerque	1	3.85	7.69
Boston	1	3.85	11.54
Boulder	1	3.85	15.38
Cleveland	1	3.85	19.23
Columbus	1	3.85	23.08
Dallas	1	3.85	26.92
Denver	1	3.85	30.77
Edmonton	1	3.85	34.62
Halifax	1	3.85	38.46
Houston	1	3.85	42.31
Las Vegas	1	3.85	46.15
London_CAN	1	3.85	50
Milwaukee	1	3.85	53.85
Nashville	1	3.85	57.69
New Bedford	1	3.85	61.54
Philadelphia	1	3.85	65.38
Phoenix	1	3.85	69.23
Portland	1	3.85	73.08
Providence	1	3.85	76.92
Rochester	1	3.85	80.77
San Jose_USA	1	3.85	84.62
Santa Cruz_USA	1	3.85	88.46
Saskatoon	1	3.85	92.31
Toronto	1	3.85	96.15
Winston-Salem	1	3.85	100
Total	26	100	

Northern Europe			
Birmingham	1	7.14	7.14
Bournemouth	1	7.14	14.29
Bristol	1	7.14	21.43
Copenhagen	1	7.14	28.57
Helsinki	1	7.14	35.71
London	1	7.14	42.86
Lund	1	7.14	50
Manchester	1	7.14	57.14
Newcastle upon Tyne	1	7.14	64.29
Nottingham	1	7.14	71.43
Riga	1	7.14	78.57
Turku	1	7.14	85.71
Uppsala	1	7.14	92.86
Örebro	1	7.14	100
Total	14	100	
South America			
Barrancabermeja	1	6.67	6.67
Belo Horizonte	1	6.67	13.33
Cuenca	1	6.67	20
Goiânia	1	6.67	26.67
Itatiba	1	6.67	33.33
Londrina	1	6.67	40
Montevideo	1	6.67	46.67
Recife	1	6.67	53.33
Rio de Janeiro	1	6.67	60
Sertãozinho	1	6.67	66.67
Sorocaba	1	6.67	73.33
Sumaré	1	6.67	80
Talca	1	6.67	86.67
Valdivia	1	6.67	93.33
Villavicencio	1	6.67	100
Total	15	100	

South-Central Asia			
Kochi	1	50	50
Nagpur	1	50	100
Total	2	100	
South-Eastern Asia			
Balikpapan	1	25	25
Bangkok	1	25	50
Banyuwangi	1	25	75
Pakse	1	25	100
Total	4	100	
Southern Europe			
Athens	1	12.5	12.5
Barcelona	1	12.5	25
Barreiro	1	12.5	37.5
Braga	1	12.5	50
Ferrara	1	12.5	62.5
Ljubljana	1	12.5	75
Murcia	1	12.5	87.5
Porto	1	12.5	100
Total	8	100	
Western Europe			
Brussels	1	50	50
Dijon	1	50	100
Total	2	100	
Western Europe			
Brussels	1	100	100
Total	1	100	

Table S.2: Summary Statistics of the Emission *Intensity* Outcome by Region.

	min	mean	max	sd*
Australia/New Zealand	2.84e-09	7.39e-07	2.11e-06	1.19e-06
Central America	2.54e-10	3.53e-07	8.37e-07	3.10e-07
Eastern Africa	3.43e-10	3.43e-10	3.43e-10	.
Eastern Asia	3.96e-07	7.05e-07	1.31e-06	5.23e-07
Eastern Europe	7.66e-07	7.66e-07	7.66e-07	.
Middle Africa	.0000195	.0000195	.0000195	.
Northern America	1.34e-08	1.91e-06	.0000141	3.72e-06
Northern Europe	0	.0000356	.0003563	.0001065
South America	0	3.03e-06	.0000129	4.73e-06
South-Central Asia	4.72e-08	1.68e-06	3.31e-06	2.31e-06
South-Eastern Asia	7.46e-10	1.56e-08	3.04e-08	2.10e-08
Southern Europe	2.09e-09	5.10e-07	1.98e-06	6.48e-07
Western Europe	3.14e-09	3.14e-09	3.14e-09	.
Total	0	7.65e-06	.0003563	.0000448
Observations	90			

*Note: Missing standard deviations (sd) regard regions encompassing only one city.

Table S.3: Summary Statistics of the *Sector* Set by Region.

	min	mean	max	sd*
Australia/New Zealand	3	7.333333	10	3.785939
Central America	5	6.4	10	2.19089
Eastern Africa	8	8	8	.
Eastern Asia	5	8	10	2.645751
Eastern Europe	7	7	7	.
Middle Africa	5	5	5	.
Northern America	2	8.066667	10	2.250926
Northern Europe	5	8.727273	10	1.53889
South America	2	6.333333	10	3
South-Central Asia	9	9	9	0
South-Eastern Asia	7	8	9	1.414214
Southern Europe	7	8.428571	10	1.397276
Western Europe	7.5	7.5	7.5	.
Total	2	7.745902	10	2.224153
Observations	90			

*Note: Missing Standard deviations (sd) regard regions encompassing only one city.

Means of Implementation. Table S.4 lists all possible means of implementation and their frequency in the sample. Cities can choose among different kinds of instruments

Table S.4: List and Frequency of the Means of Implementation.

Means of implementation	Freq.	Percent	Cum.
Assessment and evaluation activities	5	2.72	2.72
Awareness raising program or campaign	17	9.24	11.96
Capacity building and training act.	12	6.52	18.48
Development and implementation of act.	14	7.61	26.09
Education	16	8.7	34.78
Financial mechanism	14	7.61	42.39
Infrastructure development	68	36.96	79.35
Monitor activities	3	1.63	80.98
Policy and regulation	7	3.8	84.78
Stakeholder engagement	18	9.78	94.57
Sustainable public procurement	9	4.89	99.46
Verification activities	1	0.54	100
Total	184	100	

and the larger the range of employed instruments, the more complex the programs is. Table S.5 shows the main summary statistics about the number of instruments used according to the region which programs are implemented in.

The Set of City-specific Causal Conditions

Factors defining the urban forms related to CO2 emissions are several, and scholars have used different

Some studies consider the share of urban population on the total as the main urban attribute affecting emissions and energy consumption (Shahbaz et al., 2015; Shahbaz and Lean, 2012; Zhang and Lin, 2012).[6] Others instead define urbanization using

[6]Using the share of urban population, Shahbaz et al. (2015), find a Granger causality relation between urbanization and the per-capita energy consumption in Malaysia. Same results in Shahbaz and Lean (2012) and in Zhang and Lin (2012) for Tunisia and Chinese urban areas, respectively.

Table S.5: Summary Statistics of the *N-Means* Set by Region.

	min	mean	max	sd*
Australia/New Zealand	5	6	8	1.732051
Central America	1	2.666667	5	1.966384
Eastern Africa	3	3	3	.
Eastern Asia	1	2	3	1
Eastern Europe	3	3	3	.
Middle Africa	10	10	10	.
Northern America	1	2.6	6	1.638815
Northern Europe	1	2.818182	10	2.78633
South America	1	2.777778	6	1.715938
South-Central Asia	2	2	2	0
South-Eastern Asia	1	1.5	2	.7071068
Southern Europe	1	2.625	10	3.067689
Western Europe	1	1	1	.
Total	1	2.857143	10	2.292042
Observations	90			

*Note: Missing Standard deviations (sd) regard regions encompassing only one city.

the GDP per-capita (Meng et al., 2017; Meng and Huang, 2018).[7]

We opt for the urban *Density* as suggest by Glaeser and Khan (2010), Marcotullio et al. (2014), Iwata and Managi (2016), Ahmad et al. (2015), and Cuberes (2012). Glaeser and Khan (2010), Marcotullio et al. (2014) and Iwata and Managi (2016) find inverse correlation between urban density and vehicular CO2 emissions (from private transport).[8] Ahmad et al. (2015) confirm the inverse relation between density and per-capita CO2 emissions from residential sector India. Cuberes (2012) finds instead a positive relation between urban density and vehicular CO2 emissions.[9] This variables is obtained by divided the urban population by the urban area. Urban population is given by the total population calculated within the spatial domain of the Urban Centre, it is expressed in number of people[10]. Urban area is instead expressed in terms of square kilometers. Therefore, the causal condition *Density* is expressed in terms of people/square kilometers. Table S.6 shows the main summary statistics of *Density* by world regions.

Urban Sprawl Rate. Yin et al. (2005), Makido et a. (2016) and Lee and Lee (2014) highlight the need to a more comprehensive way to represent the urban form that accounts for spatial metrics. These authors employ indexes expressing the extent and the compactness of urban settlement.[11] Following these scholars, we use as causal

[7]In the first, using a consumption based approach, authors find that Chinese megacities act as net exporters of CO2 emissions: most of the black carbon emissions related to Chinese megacities's consumption is formed outside their boundaries. In the second, using instead spatial econometric techniques, authors find that the increase in the urban GDP causes an increase in the urban CO2 emissions.

[8]Dense cities are characterized by the lower use and ownership of vehicles as well by lower levels of per-capita miles. As policy implication iwata2016can suggest to increase urban density through property taxes and land use regulation.

[9]The increase in urban GDP and residential wealth turns into the increase in the demand of private vehicles.

[10]It is generated by spatial disaggregation (downscaling) of census spatial data to 250x250 metres resolution grid, using the GHS Layer Population (GHS-POP) grids as principal spatial covariate (Freire et al., 2016). Per each Urban Centre population is calculated by intersecting the Urban Centre polygon with the population grid (Florczyk et al., 2019) at 1 km resolution.

[11]Makido et a. (2016) find that dense and compact settlements lead to lower per-capita CO2 emissions sourced from transport sector and higher per-capita CO2 emissions from residential sector.

Table S.6: Summary Statistics of the *Density* Set by Region.

	min	mean	max	sd*
Australia/New Zealand	1496.026	1828.739	2154.089	329.0933
Central America	4319.424	6345.606	9252.396	1712.693
Eastern Africa	8099.265	8099.265	8099.265	.
Eastern Asia	2264.584	8443.147	16307.6	7171.698
Eastern Europe	4521.372	4521.372	4521.372	.
Middle Africa	13805.77	13805.77	13805.77	.
Northern America	946.8936	1638.165	2216.778	394.786
Northern Europe	2637.749	3360.684	5155.379	658.8372
South America	3662.79	5672.85	7636.743	1544.132
South-Central Asia	3508.048	7347.923	11187.8	5430.404
South-Eastern Asia	5736.308	5741.494	5746.679	7.333471
Southern Europe	2497.84	4234.488	7568.948	1900.406
Western Europe	5193.675	5193.675	5193.675	.
Total	946.8936	4335.869	16307.6	2990.095
Observations	90			

*Note: Missing Standard deviations (sd) regard regions encompassing only one city.

condition the built-up area cover rate that proxies the spatial urban sprawl. Data are sourced from GHS-UCDB, the built-up area is computed within the spatial domain of the urban centre and it is expressed in square kilometres.[12] The built-up area cover rate is then constructed as the share of the total built-up area on the total urban area. Table S.7 shows the main summary statistics *Sprawl Rate* by world regions.

Table S.7: Summary Statistics of *Sprawl Rate* Set by Region.

	min	mean	max	sd
Australia/New Zealand	28.31551	33.65499	43.55461	8.582167
Central America	29.86068	39.22876	50.91729	7.80788
Eastern Africa	60.07728	60.07728	60.07728	.
Eastern Asia	24.67703	43.313	63.69761	19.56897
Eastern Europe	54.92958	54.92958	54.92958	.
Middle Africa	40.03811	40.03811	40.03811	.
Northern America	21.02761	33.04431	41.74366	6.107077
Northern Europe	30.19274	44.87683	72.51785	14.02783
South America	36.66143	58.17599	80.01614	14.57512
South-Central Asia	58.34681	65.24568	72.14455	9.756476
South-Eastern Asia	59.2802	69.09328	78.90636	13.87779
Southern Europe	25.54341	44.00041	61.61747	11.13469
Western Europe	26.53949	26.53949	26.53949	.
Total	21.02761	44.14978	80.01614	14.75544
Observations	90			

Sector-wise Emissions Structure. Fujii et al. (2017) highlight how the effects of urban conditions such as density or sprawl rate on CO2 emissions differ according to the sector-wise structure of emissions, leading to mixed results. Studies analysing CO2 emissions at urban level that takes into account the sector-wise differences are several. Most studies recognize the transport sector as the most responsible of ur-

[12] Data are generated by spatial aggregation (upscaling) of the information collected at various decametric spatial resolution satellite image data records (10-15-30-80 metres) available for different years and different satellite platforms (Corbane et al., 2020), to the 250x250 metres and 1x1 kilometer resolution grids, aggregated separately per each year.

ban CO2 emissions at urban-level (see among others Cole and Neumayer (2004) and Poumanyvong et al. (2012)). Cervero and Murakami (2010), Brownstone and Golob (2009), Yamamoto (2009) and Fang (2008) highlight instead an inverse relation between density and CO2 emissions from transport sector.[13] Heterogeneous results are also found in Lee and Lee (2014), Ahmad et al. (2015) and Makido et a. (2016). Lee and Lee (2014) find that the urban population weighted density is negative related to the urban CO2 emissions but its effect are more pronounced in the private transport sector than the household (residential energy use) sector. Ahmad et al. (2015) find instead an inverse relation between density and per-capita CO2 emissions from the residential sector in India. Makido et a. (2016) state that compact and dense cities have lower per-capita urban emissions from the transport sector than sprawled and sparse cities. On the other hand, monocentric and dense cities have greater per-capita urban emissions from the residential sector. Consistently with this literature, in the fsQCA, we use as causal conditions the shares of the urban CO2 emissions from energy, transport and residential sector .

GHS-UCDB provides data on CO2 emissions that are sourced from the European Commission's Emissions Database for Global Atmospheric Research (EDGAR v5.0), which estimates the CO2 emissions from usage of fossil fuels (i.e., non-shortcycle-organic) for different reference years (Muntean et al., 2018). The calculation of the emissions includes all human activities, except large scale biomass burning and land use, land-use change, and forestry. Emissions are differentiated by emitting-sectors, the sector definition is based on the following IPCC 1996 codes: energy - Power Industry (IPCC 1A1a), residential - Energy for buildings (IPCC 1A4), waste (IPCC 6), industry - Oil refineries and Transformation industry (IPCC 1A1b, 1A1c), Combustion for manufacturing (IPCC 1A2), Fuel exploitation (IPCC 1B), Industrial Processes (IPCC 2), Solvents and products use (IPCC 3), transport - Transport (IPCC 1A3), and agriculture - Agriculture (IPCC 4). The comparability among cities is guaranteed by the bottom-up compilation methodology of sector-specific

[13] Density is in fact negative related with the vehicle ownership, and population in dense cities tend to own smaller and less pollutant vehicles.

emissions applied consistently for all world countries. Emissions are expressed in tonnes per year. The shares of the three selected sectors are computed on the total of CO2 emissions. Table S.8 shows the main summary statistics of the sector-wise shares of urban CO2 emissions according to the world regions which programs are implemented in.

Table S.8: Summary Statistics of Sector-wise Emissions *Shares* Set by Region.

	min	mean	max	sd*
Australia/New Zealand				
Share Energy Sct.	2.008401	5.085512	6.998875	2.691086
Share Residential Sct.	12.98144	14.29619	15.12331	1.151191
Share Transport Sct.	26.00457	28.78467	32.90003	3.636487
Central America				
Share Energy Sct.	1.948297	12.98251	24.01672	15.60473
Share Residential Sct.	7.523683	9.369511	11.21534	2.610396
Share Transport Sct.	21.59924	39.38612	57.17301	25.15445
Eastern Africa				
Share Energy Sct.	31.09742	31.09742	31.09742	.
Share Residential Sct.	3.79397	3.79397	3.79397	.
Share Transport Sct.	34.48425	34.48425	34.48425	.
Eastern Asia				
Share Energy Sct.	.0838866	5.314087	10.54429	7.396621
Share Residential Sct.	17.06474	18.08861	19.11247	1.447966
Share Transport Sct.	23.05387	24.41209	25.7703	1.920805
Eastern Europe				
Share Energy Sct.	20.42586	20.42586	20.42586	.
Share Residential Sct.	9.364652	9.364652	9.364652	.
Share Transport Sct.	26.85289	26.85289	26.85289	.
Middle Africa				
Share Energy Sct.	19.87959	19.87959	19.87959	.
Share Residential Sct.	16.24611	16.24611	16.24611	.
Share Transport Sct.	22.4146	22.4146	22.4146	.
Northern America				
Share Energy Sct.	.0366454	9.707535	38.12908	12.8316
Share Residential Sct.	19.47683	29.17333	36.47176	5.535843
Share Transport Sct.	10.98211	22.27149	35.96896	7.704993
Northern Europe				
Share Energy Sct.	.173144	23.30804	73.50476	24.44432
Share Residential Sct.	4.852516	22.47187	41.19059	12.81423
Share Transport Sct.	3.803092	24.68574	43.91841	12.06866

South America				
Share Energy Sct.	.1246937	13.44838	48.71039	23.58848
Share Residential Sct.	5.396255	8.924954	11.49654	2.554025
Share Transport Sct.	15.59881	44.58479	60.64493	19.86392
South-Central Asia				
Share Energy Sct.	15.08618	41.28168	67.47718	37.04603
Share Residential Sct.	7.848647	8.099325	8.350003	.3545127
Share Transport Sct.	4.690582	9.975563	15.26054	7.474092
South-Eastern Asia				
Share Energy Sct.	.7351919	8.60183	16.46847	11.12511
Share Residential Sct.	1.696213	2.721051	3.745888	1.449339
Share Transport Sct.	10.98025	19.68211	28.38397	12.30629
Southern Europe				
Share Energy Sct.	.4031861	16.23064	78.21275	26.29609
Share Residential Sct.	4.587373	18.0891	29.65955	8.599346
Share Transport Sct.	4.454291	25.65949	39.87795	11.91588
Western Europe				
Share Energy Sct.	21.93687	21.93687	21.93687	.
Share Residential Sct.	31.26377	31.26377	31.26377	.
Share Transport Sct.	22.33273	22.33273	22.33273	.
Total				
Share Energy Sct.	.0366454	15.60338	78.21275	19.56733
Share Residential Sct.	1.696213	19.22504	41.19059	10.80099
Share Transport Sct.	3.803092	26.0136	60.64493	12.56924
Observations	90			

*Note: Missing Standard deviations (sd) regard regions encompassing only one city.

Truth Tables

The truth tables of the three analyses are shown below.

Table S.9: Truth Table of fsQCA with Emission Reduction Intensity as Outcome and Action, Number of Means, Urban Density, Urban Sprawl Rate and the CO2 Emission Share from the Energy sector as Factors.

Action	N Means	Density	Sprawl Rate	CO2% Energy	Red Intensity	Freq.	Consistency
0	0	0	0	0	1	2	0.751
0	0	0	0	1	1	16	0.709
0	0	0	1	0	1	6	0.879
0	0	1	0	0	1	7	0.683
0	0	1	0	1	1	1	0.765
0	0	1	1	0	1	7	0.808
0	0	1	1	1	1	3	0.856
0	1	0	0	0	1	2	0.779
0	1	0	0	1	1	17	0.71
0	1	0	1	0	1	1	0.917
0	1	1	0	0	1	3	0.779
0	1	1	0	1	1	1	0.813
0	1	1	1	0	1	4	0.884
0	1	1	1	1	1	4	0.864
1	0	0	0	0	1	2	0.796
1	0	0	0	1	1	22	0.756
1	0	0	1	0	1	8	0.828
1	0	0	1	1	1	2	0.921
1	0	1	0	0	1	3	0.777
1	0	1	0	1	1	1	0.801
1	0	1	1	1	1	12	0.814
1	1	0	0	0	1	4	0.842
1	1	0	0	1	1	9	0.836
1	1	0	1	0	1	4	0.896
1	1	0	1	1	1	1	0.928
1	1	1	0	0	1	2	0.848
1	1	1	1	0	1	7	0.873
1	1	1	1	1	1	8	0.844

For both factors and outcome the number 1 stands for full-membership score and 0 for full non-membership score.
Cases with membership score equal to 0.5 are excluded because classified as undetermined.

Table S.10: Truth Table of fsQCA with Emission Reduction Intensity as Outcome and Action, Number of Means, Urban Density, Urban Sprawl Rate and the CO2 Emission Share from the Residential Sector as Factors.

Action	N Means	Density	Sprawl Rate	CO2% Resid.	Red Intensity	Freq.	Consistency
0	0	0	0	0	1	16	0.725
0	0	0	0	1	1	2	0.736
0	0	0	1	1	1	6	0.881
0	0	1	0	0	1	7	0.672
0	0	1	0	1	1	1	0.769
0	0	1	1	0	1	3	0.839
0	0	1	1	1	1	7	0.806
0	1	0	0	0	1	16	0.71
0	1	0	0	1	1	3	0.781
0	1	0	1	1	1	1	0.931
0	1	1	0	0	1	2	0.752
0	1	1	0	1	1	2	0.831
0	1	1	1	0	1	2	0.872
0	1	1	1	1	1	6	0.856
1	0	0	0	0	1	23	0.768
1	0	0	0	1	1	1	0.787
1	0	0	1	0	1	3	0.91
1	0	0	1	1	1	7	0.834
1	0	1	0	0	1	3	0.759
1	0	1	0	1	1	1	0.804
1	0	1	1	0	1	8	0.864
1	0	1	1	1	1	4	0.798
1	1	0	0	0	1	8	0.828
1	1	0	0	1	1	5	0.865
1	1	0	1	0	1	1	0.922
1	1	0	1	1	1	4	0.91
1	1	1	0	0	1	2	0.817
1	1	1	1	0	1	7	0.845
1	1	1	1	1	1	8	0.845

For both factors and outcome the number 1 stands for full-membership score and 0 for full non-membership score.
Cases with membership score equal to 0.5 are excluded because classified as undetermined.

Table S.11: Truth Table of fsQCA with Emission Reduction Intensity as Outcome and Action, Number of Means, Urban Density, Urban Sprawl Rate and the CO2 Emission Share from the Transport Sector as Factors.

Action	N Means	Density	Sprawl Rate	CO2% Transp.	Red Intensity	Freq.	Consistency
0	0	0	0	0	1	14	0.714
0	0	0	0	1	1	4	0.755
0	0	0	1	0	1	1	0.907
0	0	0	1	1	1	5	0.889
0	0	1	0	1	1	8	0.661
0	0	1	1	0	1	8	0.803
0	0	1	1	1	1	2	0.867
0	1	0	0	0	1	14	0.719
0	1	0	0	1	1	5	0.774
0	1	0	1	1	1	1	0.914
0	1	1	0	0	1	2	0.813
0	1	1	0	1	1	2	0.772
0	1	1	1	0	1	8	0.831
1	0	0	0	0	1	20	0.763
1	0	0	0	1	1	4	0.796
1	0	0	1	0	1	2	0.918
1	0	0	1	1	1	8	0.838
1	0	1	0	0	1	0	0.83
1	0	1	0	1	1	4	0.751
1	0	1	1	0	1	9	0.836
1	0	1	1	1	1	3	0.852
1	1	0	0	0	1	6	0.826
1	1	0	0	1	1	7	0.846
1	1	0	1	0	1	1	0.943
1	1	0	1	1	1	4	0.874
1	1	1	0	1	1	2	0.845
1	1	1	1	0	1	9	0.825
1	1	1	1	1	1	6	0.89

For both factors and outcome the number 1 stands for full-membership score and 0 for full non-membership score.
Cases with membership score equal to 0.5 are excluded because classified as undetermined.

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