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Marginal abatement cost of urban emissions under climate policy: Assessment and projection for China's 2030 climate target

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ABSTRACT

This study evaluates the effectiveness of Low-Carbon City Pilot programme and predicts its future trajectory through 2030, using the marginal abatement cost of CO_2 as the outcome indicator to address policy anticipation effects. Drawing on Chinese city-level panel data (2006–2019), we estimate and forecast marginal abatement cost through a hybrid approach combining machine learning regression, autoregressive integrated moving average and quadratic directional distance function. A Difference-in-Differences model is used to assess the policy's impact, while a cost-intensity matrix is employed to explore cities' low-carbon transition stages and pathways to 2030. The results reveal that Low-Carbon City Pilot programme significantly increased the marginal abatement cost of CO_2 in pilot cities, driven by green technology innovation and industrial structure upgrading. These effects are more pronounced in developed, eastern, non-resource-based and non-industrial cities. Under the carbon peaking target, most cities will experience rising abatement costs, with widening inter-city divergence. By 2030, fewer than one-fifth of cities will achieve low-carbon transition, while the majority will remain in mid- or early-transition phrases. We recommend exploring emission reduction potential in central, western, and resource-based cities, addressing transition barriers, and formulating city-specific policies that account for unique underlying costs while enhancing synergies to avoid carbon leakage and worsening climate inequality.

1. Introduction

Human-caused global climate change continues to break records for "the world's hottest year" (Reuters, 2024a). Since 2024, record-breaking high temperatures have hit across many cities worldwide. For instance, several cities in India, including Delhi, have faced extreme heat exceeding 50°C (Reuters, 2024b). Evidently, these persistent climate threats serve as a stark reminder that global efforts to combat climate change still need to be strengthened. On 22 September 2020, as a pivotal actor in the global climate action, China announced its carbon peaking and carbon neutrality goals, accelerating a society-wide shift towards low-carbon transformation. Cities are the fundamental administrative units for implementing a low-carbon economy and addressing climate change (Song et al., 2022). The Low-Carbon City Pilot (LCCP) programme is one of China's most representative climate policies at the prefecture level (Li et al., 2018). It was first implemented in 2010, and then the following two batches were launched in 2012 and 2017 by the National Development and Reform Commission (NDRC), respectively. The list of pilot cities in three batches are provided in **S1 Supplementary Material**. Pilot cities were required to make local decarbonisation plans where specific milestones would be separately assigned to economic sectors and territories under their jurisdiction, facilitating China's carbon neutrality target in a bottom-up manner. Therefore, evaluating the effectiveness of LCCP is important because it is a key to verify the effectiveness of China's carbon reduction actions at the city level, which is essential for devising reasonable decarbonisation strategies for cities.

Despite these efforts, most recent studies evaluating the implementation effects of the LCCP face challenges related to policy anticipation effects. For the second and third batches of pilots, the prerequisites for cities to apply were publicly clarified (Li et al., 2018). Candidate cities were required to meet specific criteria, including targets for reducing carbon emission intensity, total CO_2 emissions, and the

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share of fossil energy in primary energy consumption. Additionally, these cities were mandated to set region-specific milestones in their local decarbonisation plans to ensure the achievement of these targets. This process introduced a non-random element to the selection of pilot cities, potentially creating anticipation effects in empirical analyses. Cities vying to be selected as pilot cities may have strategically improved their performance on the disclosed selection criteria. If these selection criteria are later used as outcome indicators for evaluating LCCP effectiveness, it could lead to severe endogeneity issues in causal inference for policy evaluation. Despite this significant concern, few studies have explicitly addressed the issue of anticipation effects in the context of LCCP. This oversight is notable, given that pilot policies in China generally exhibit anticipated effects (Tao & Goh, 2023).

In addition, predicting and assessing the future trajectory of climate policies is essential for designing effective emission reduction strategies that align with national strategic development goals. In 2023, the Ministry of Ecology and Environment of China released two key reports: the “Progress Assessment Report on the National Low-Carbon City Pilot programme” (i.e., the Progress Report) and the “Responding to Climate Change: China’s Policies and Action Annual Report 2023,” evaluating and reporting on China’s contributions to climate change mitigation and the progress and achievements of urban decarbonisation. Although there has been much progress in the decarbonisation of key cities in China, achieving the carbon peaking and carbon neutrality targets at the city level still poses numerous challenges. By forecasting and evaluating the future trajectory of climate policies and identifying the phased characteristics of urban low-carbon transition can help pinpoint deficiencies in current policies and make necessary adjustments to ensure cities remain on the right path toward emission reductions. This provides forward-looking insights for policy improvement. Currently, most studies focus solely on the ex-post evaluation of the LCCP, as demonstrated in Table 1. However, such studies fail to offer sufficient guidance for formulating effective city-level emission reduction strategies and long-term decarbonisation plans, which are critical for achieving China’s dual carbon goals.

Based on this background, our study aims to assess the effectiveness of the LCCP and its future trajectory up to 2030, while avoiding policy anticipation effects. The findings are intended to provide actionable insights for improving policy design. First, we select the marginal abatement cost (MAC) as the outcome indicator to mitigate the issue of anticipation effects, as it is not among the indicators tied to the pilot’s prerequisites or the targets imposed on local authorities. Moreover, MAC symbolises a city’s emission reduction potential and exhibits substantial heterogeneity across cities, making it a valuable metric to inform the design of future climate policies. Second, we employed a hybrid-methods approach to predict MAC trends through 2030. By constructing a cost-intensity matrix, we classified cities based on their decarbonisation progress and evaluated their transition trajectories, enabling the assessment of the long-term impact of climate policies and the development of differentiated transition strategies.

This study makes two key contributions. First, it refines the methodology for evaluating the LCCP’s effectiveness by addressing policy anticipation effects. We identify the factors contributing to these effects, propose a solution by using MAC, and articulate its advantages as an outcome indicator. Second, the study extends the scope of analysis to include the future trajectory of climate policies, whereas previous research has predominantly focused on ex-post evaluations. By leveraging predicted MAC values and constructing a city classification matrix, we identify the phased characteristics of urban emission reductions and predict the LCCP’s policy effects through 2030. This allows us to pinpoint policy gaps and areas for improvement to ensure the realisation of national long-term emission reduction strategies. Our findings provide critical reference and guidance for designing policies to achieve city-level carbon neutrality goals in China.

The remainder of the paper is organised as follows, in Section 2, reviews related literature and proposes research hypotheses. Section 3

Table 1
Varying causal effects attributed to different samples and outcome selection.

Outcome	Causal effect [size]	Significance [$p<0.01$]	Data description	Reference
Carbon emissions				
Carbon emissions	Negative [2.7 %]	Yes	238 cities, 2007–2022	Cao et al. (2025)
Carbon emissions	Negative [3.0 %]	Yes	268 cities, 2000–2021	Chen et al. (2024)
Carbon emissions	Negative [2.7 %]	Yes	286 cities, 2005–2017	Huo et al. (2022)
Carbon emissions [*residents*]	Negative [7.3 %]	Yes	281 cities, 2004–2020	Li and Xing (2024)
Carbon emissions	Negative [5.2 %]	*No*	285 cities, 2006–2016	Liu et al. (2022)
Carbon emissions	Negative [6.5 %]	Yes	331 cities, 2005–2019	Lyu et al. (2023)
Carbon emission per capita				
Carbon emissions per capita	Negative [7.3 %]	Yes	331 cities, 2005–2019	Lyu et al. (2023)
Carbon emissions per capita	Negative [-]	*No*	245 cities, 2003–2017	Zhang et al. (2024)
Carbon emission intensity				
Carbon emission intensity	Negative [1.3 %]	Yes	-, 2005–2017	Dong et al. (2023)
Carbon emission intensity	Positive [15–20 %]	Yes	49 cities, 2005–2018	Feng et al. (2021)
Carbon emission intensity	Negative [8.1 %]	Yes	285 cities, 2006–2016	Liu et al. (2022)
Carbon emission intensity	Negative [12.9 %]	Yes	48 cities, 2007–2017	Ren et al. (2024)
Carbon emission intensity	Negative [0.13 %]	Yes	283 cities, 2006–2017	Zeng et al. (2023)
Carbon emission intensity	Negative [-]	*No*	245 cities, 2003–2017	Zhang et al. (2024)
Carbon emission efficiency				
Carbon emission efficiency	Positive [2.1 %]	Yes	210 cities, 2008–2016	Fu et al. (2021)
Carbon emission efficiency [*industry*]	Positive [11.1 %]	Yes	266 cities, 2006–2018	Shi and Xu (2022)
Carbon emission efficiency	Positive [6.6 %]	Yes	208 cities, 2003–2016	Wen et al. (2022)
Carbon emission efficiency	Positive [1.7 %]	Yes	251 cities, 2003–2018	Yu and Zhang (2021)
Carbon emission efficiency	Positive [2.0 %]	Yes	285 cities, 2003–2018	Zhang et al. (2022)
Other outcomes				
Fine particulate matter	Negative [2.9 %]	Yes	268 cities, 2000–2021	Chen et al. (2024)
Energy efficiency	Positive [2.6 %]	Yes	249 cities, 2004–2016	Niu et al. (2023)
Energy efficiency	Positive [6.5 %]	Yes	199 cities, 2003–2016	Wang et al. (2023)
Household electricity consumption	Negative [9.5 %]	Yes	266 cities, 2005–2015	Shen and Sun (2023)
Urban energy transition indicator	Positive [1.3 %]	Yes	277 cities, 2006–2020	Liu et al. (2024)
Marginal abatement cost of carbon emissions	Positive [5.3 %]	Yes	282 cities, 2003–2018	Xu et al. (2022)

Note: The column "Causal effect" refers to the impact of LCCP implementation on outcome indicators (positive or negative), and "[size]" indicates the magnitude of the effects. For example, "Negative [2.7 %]" in the third row means that the implementation of LCCP led to a 2.7 % reduction in carbon emissions based on the reference.

introduces research methodology and data sources. Section 4 presents empirical results, robustness tests, city-level MAC projection and classification matrix. Section 5 provides policy implications and concludes.

2. Literature review

2.1. Multidimensionality and anticipation effect in policy evaluation of LCCP

The evaluation of the LCCP programme is multifaceted. While most empirical findings from recent literature align with the conclusions of the Progress Report—highlighting the contribution of the LCCP to emission reductions and efficiency improvements—some studies present contradictory results, as evidenced by the references listed in Table 1. These inconsistencies may stem from several factors, including differences in sample selection methods and the choice of outcome indicators.

Moreover, the selection of pilot cities for the LCCP programme was largely based on their pre-existing or planned carbon emission reduction targets, as noted in the Progress Report. This non-random selection process may introduce an anticipation effect in empirical analyses, raising critical concerns for policy evaluation (Zhang et al., 2024). Candidate cities may have been incentivised to improve task metrics to qualify for selection, potentially distorting *ex ante* trends (Roth et al., 2023). However, many studies, as shown in Table 1, used these pre-existing or planned carbon emission reduction targets, such as total carbon emissions and carbon emission intensity, as outcome indicators to evaluate the effectiveness of the LCCP. This may violate one of the fundamental assumptions of causal inference in policy evaluation, leading to biased conclusions.

2.2. Selecting abatement cost as the outcome indicator

Regarding the potential anticipation effects, we argue that the focus of evaluating the LCCP should not be on its effect on carbon emission or carbon emission intensity as it can be anticipated and explicitly disclosed in the pilot prerequisites and tasks. Although the conclusion of Zhang et al. (2024) shows that no valid anticipation effect was identified when choosing carbon emission per capita and carbon emission intensity as outcome indicators, the insignificant regression results suggest that there are alternative ways to measure the effect of the LCCP on cities' low-carbon transition. In this sense, following the idea of Xu et al. (2022), we adopt the MAC as the outcome indicator, which is widely applied to measure potential costs and benefits of a climate policy to inform policymakers and to help achieve the best results and avoid the worst (Aldy et al., 2021). The advantage of using the MAC for assessment lies in three main aspects. First, it is not one of the indicators bound with the requirements of the pilot or the targets imposed on the local authorities. Second, it represents a city's abatement potential by measuring the cost of one additional unit of CO_2 emission or the cost of the last abated unit of CO_2 emission. Third, according to Ma and Hailu (2016) and Xu et al. (2022), estimates of the MAC vary widely at the city level, being conditional on the economic and geographic characteristics of cities. Xu et al. (2022) note that China is generally located on the left side of the marginal abatement cost curve (MACC), while cities will be able to move up along the curve if dramatic emission reduction continues. This indicates that heterogeneous policy outcomes across cities may be observed, and identification of the heterogeneity could help better design future climate policies.

2.3. Policy evaluation with MAC and hypotheses development

The MAC is defined as the opportunity cost required to reduce an additional unit of pollutant emissions, which entails the corresponding increase in input or decrease in desired output (Hailu & Veeman, 2000). It is a fundamental concept extensively applied in the evaluation of climate policies and scenario-based analysis (Dai et al., 2020; Z. Wang et al., 2020; Zhang et al., 2023). These studies show that higher emission reduction targets typically imply escalating abatement costs (Z. Wang et al., 2020). A higher MAC reflects the reduced economic feasibility of emission control and indicates the limited potential for further emission reduction (Duan et al., 2025; Zhang et al., 2023).

According to previous studies in Table 1, the LCCP has been shown to reduce carbon emissions, lower carbon intensity, and improve carbon efficiency. This suggests that emission reduction measures are advancing rapidly. The easier-to-address aspects of carbon mitigation, such as solar and wind energy, are gradually being overcome. However, the remaining challenges, including carbon capture and storage (CCS) and carbon conversion technologies, are significantly more difficult to tackle. Compared to earlier stages of carbon mitigation, addressing these harder-to-abate areas requires substantially greater financial investment, resulting in a higher MAC.

Moreover, research indicates a U-shaped relationship between MAC and carbon intensity, as represented by the MACC (Cheng et al., 2022; Du et al., 2015; Xu et al., 2022). China is currently positioned on the left side of the MACC (Du et al., 2015; Xu et al., 2022), and carbon intensity has been observed to decline under the influence of the LCCP (Dong et al., 2023; Ren et al., 2024). This implies that the overall MAC of Chinese cities are likely to rise along the curve as carbon intensity decreases.

Regarding how the LCCP affects the MAC, on one hand, the LCCP can increase the MAC by fostering green technology innovation. According to the Porter Hypothesis, appropriately designed environmental regulations can incentivise firms to engage in green innovation (Porter & van der Linde, 1995). By creating regulatory pressure and internalising the external costs of pollution, LCCP could drive high-energy-consuming enterprises to innovate and adopt cleaner technologies (Liu et al., 2023; Liu et al., 2025; Ma et al., 2021). Besides, the effect of green technology innovation on MAC depends on the level of abatement. As demonstrated in the mathematical models by Baker et al. (2008) and Bréchet and Jouvet (2008), environmental innovation reduces MAC only at low abatement levels; otherwise, innovation increases MAC. At lower levels of abatement, green innovation focuses on reducing easier, cheaper emissions and benefits from economies of scale, thereby lowering MAC. Conversely, at higher abatement levels, innovation shifts to addressing inherently more difficult and expensive emissions, leading to increased MAC (Wang et al., 2022). China's position on the left side of the MACC suggests that the country has moved beyond low abatement levels and is progressing toward more advanced stages of development. As a result, green technology innovation in China is likely to increase MAC.

On the other hand, LCCP influences MAC through industrial structure upgrading. Under the LCCP, firms are incentivised to reallocate production resources from high-pollution, energy-intensive industries to low-pollution, low-energy-consumption sectors, thereby facilitating industrial structure upgrading (Zheng et al., 2021; Zhong et al., 2024). This upgrading eliminates "double-high" industries and increases the share of the tertiary sector, which is typically more technologically advanced and operates closer to optimal efficiency. However, achieving further emission reductions in the tertiary sector requires advanced, high-cost technologies and processes, which raises MAC.

Based on the above analysis, the following hypotheses are proposed:

Hypothesis 1: The LCCP increases the MAC of carbon emissions.
Hypothesis 2: The LCCP increases the MAC of carbon emissions by green technology innovation.
Hypothesis 3: The LCCP increases the MAC of carbon emissions by industrial structure upgrading.

2.4. Measuring the phased low-carbon transition of cities under climate policy

Analysing city-level climate policies and their effectiveness is essential for assessing the efforts and achievements of cities in climate action. Current research evaluating the implementation of urban climate or environmental policies primarily relies on ex-post assessments. For example, empirical studies often focus on evaluating the outcomes of the LCCP initiative as shown in Table 1 or examining the effectiveness of emission trading policy on city-level carbon reduction effort (Feng et al., 2024; Zhang et al., 2020). However, such ex-post evaluations can only determine whether policies are effective in the present and fail to provide guidance for cities to develop long-term decarbonisation strategies. Therefore, predicting and assessing the future trajectory of LCCP is essential. Such analysis can assist in designing long-term low-carbon transition strategies for cities and accurately reveal the policy's contribution to achieving China's dual carbon goals. Several studies have integrated climate policy evaluations with the current status of urban low-carbon transitions to describe the phased characteristics of policy-driven urban transformations and explore how to optimise future carbon reduction pathways.

For instance, Duan et al. (2025) constructed a classification matrix using CO_2 emission efficiency and the MAC to categorise cities into three groups, thereby assessing their carbon reduction potential and establishing region-specific low-carbon transition pathways. Cities with low carbon efficiency and high MAC are recommended to adopt low-rate carbon reduction pathways, whereas those with high carbon efficiency and low MAC could pursue more aggressive mitigation strategies. Similarly, Xu et al. (2024) employed the Boston matrix method to classify LCCP performance based on effectiveness and efficiency values, exploring diverse development paths for LCCP implementation. For cities with high effectiveness but low efficiency, strategies should focus on either improving results without increasing inputs or maintaining outcomes while reducing inputs. Moreover, Xu et al. (2022) illustrated the evolving relationship between MAC and carbon intensity by plotting MACCs over four periods. Their analysis revealed that future MACCs are likely to shift further toward the lower-left quadrant, with MAC increasing as carbon intensity decreases. Drawing from these studies, we combine the city classification matrix proposed by Duan et al. (2025) and Xu et al. (2024) with Xu et al. (2022)'s phase-based analysis of MACCs. Using predictive data, we assess the future trajectory of LCCP development through 2030. This approach provides a comprehensive framework for understanding the long-term implications of LCCP on China's low-carbon transition and its contribution to national carbon neutrality goals.

3. Method

Considering the continuity of the MAC estimation, we first use multiple models to forecast the relevant variables needed for the MAC estimation up to 2030. Then, we employ the parametric quadratic directional distance function (QDDF) to estimate city-level MAC from 2006 to 2030, followed by using a time-varying Difference-in-Differences (DID) model to examine the effect of the LCCP on the MAC. The multiple models used in the first step include the stochastic impacts by regression on population, affluence, and technology (STIRPAT) model, machine learning regression (MLR) and autoregressive integrated moving average (ARIMA) model. Specifically, considering that carbon emissions, a key variable for MAC estimation, are not merely a function of time but are influenced by a complex interplay of multiple driving factors such as economic growth, population dynamics, and technological advancements (York et al., 2003), we use the STIRPAT model and MLR to identify driving factors and construct a regression model for carbon emissions based on raw data. This approach effectively captures the non-linear interactions among multiple drivers of emissions, rather than relying directly on ARIMA, which, being dependent on historical trends, cannot account for such complex interactions (Zhang, 2003). Then, linear interpolation is applied to impute missing data, creating a complete dataset from 2006 to 2019. Subsequently, the ARIMA model is employed to predict the forecasted values of the variables required in the regression model, which are then integrated with the STIRPAT and MLR models to estimate carbon emissions up to 2030. Additionally, the ARIMA model is used to forecast other variables with consistent temporal patterns and trends that are critical for MAC estimation.

3.1. STIRPAT model

The impact by population affluence and technology (IPAT) model demonstrates that the primary factors impacting environmental conditions are population size, economic development, and technological progress (Ehrlich & Holdren, 1971). The STIRPAT model extends the classic IPAT model by allowing the decomposition of these variables, as well as other relevant factors, to analyse the environmental situation based on the specific context of the study. This method has been widely utilised to analyse factors influencing carbon emissions in time-series data (Huang et al., 2021; Wang et al., 2017; Yu et al., 2022; Zhou et al., 2023). The expression of the STIRPAT model is as follows:

$$I = aP^bA^cT^de \tag{1}$$

where a is the constant term of the model; b, c and d represent the coefficients of population (P), affluence (A) and technology (T), respectively; and e denotes the model error.

By taking the natural logarithm of both sides of the equation, we obtain the equation as follows:

$$lnI = lna + blnP + clnA + dlnT + lne \tag{2}$$

Drawing from the existing literature and considering the perspectives of population, wealth, and technology, combined with the characteristics of China's urban carbon emissions, we select seven factors: total population (P), per capita GDP ($PGDP$), fixed asset investment (FAI), proportion of the secondary industry ($SIND$), intensity of energy consumption (ECG), share of scientific and technological expenditures (SEG), and infrastructure construction (BOP), to develop an extended STIRPAT model. Table 2 lists the selected factors. The equation can be decomposed as follows:

$$\begin{aligned} lnCO_2 = {} & lna + blnP + clnPGDP + dlnFAI + elnSIND + flnECG + glnSEG \\ & + hlnBOP + lne \end{aligned} \tag{3}$$

where CO_2 is the urban carbon emissions; a is the constant term of the model; b to h represent the coefficients of seven factors, respectively; and e is the model error.

3.2. Machine Learning Regression

To avoid potential multicollinearity problems between economic and environmental variables, we employ machine learning regression (MLR) to select variables, following the ideas of Dong and Zhang (2023) and Chang et al. (2023). The least absolute shrinkage and selection operator (LASSO) (Tibshirani, 2018), elastic net (EN) (Zou & Hastie, 2005), and ridge regression (RR) (Hoerl & Kennard, 1970) are commonly used techniques in MLR. These approaches impose constraints on the parameters to enhance the least-squares estimator,

Table 2
Variables affecting city carbon emissions.

Variables	Definition	Symbol
Population size	Year-end population	P
Economies scale	Per-capita GDP	$PGDP$
Fixed-asset investment	Fixed-asset investment	FAI
Industry structure	Secondary industry proportion	$SIND$
Energy intensity	Energy consumption/GDP	ECG
Science expenditure share	Science expenditure/GDP	SEG
Infrastructure construction	Bus ownership per capita	BOP

thereby reducing variance (Ding et al., 2014; Hastie et al., 2009). EN represents a compromise between the LASSO and RR penalties, offering a comprehensive penalised shrinkage method that easily and quickly fits large datasets with multiple correlations (Fernández-Delgado et al., 2019). According to Friedman et al. (2010), the EN algorithms are shown in equation (4) and equation (5).

$$\min_{(\beta_0,\beta)\in\mathbb{R}^{p+1}}\left[\frac{1}{2N}\sum_{i=1}^{N}\left(y_i-\beta_0-\sum_{j=1}^{p}\beta_j x_{ij}\right)^2+\lambda P_\alpha(\beta)\right] \tag{4}$$

where:

$$P_\alpha(\beta)=\alpha\|\beta\|_{\ell_1}+(1-\alpha)\frac{1}{2}\|\beta\|_{\ell_2}^2 =\sum_{j=1}^{p}\left[\alpha|\beta_j|+\frac{1}{2}(1-\alpha)\beta_j^2\right] \tag{5}$$

y_i is the response variable for the i-th sample, for $i=1,\cdots,N$, and N is the total number of samples; x_{ij} is the j-th predictor for the i-th sample, for $j=1,\cdots,p$, and p is the total number of predictors; β_0 is the intercept term; $\beta=(\beta_1,\cdots,\beta_p)$ is the vector of regression coefficients; λ is the regularisation parameter that controls the strength of the EN regularisation; $P_\alpha(\beta)$ is the EN penalty (Zou & Hastie, 2005), combining both the L1 norm ($\|\beta\|_{\ell_1}$) and the L2 norm ($\|\beta\|_{\ell_2}^2$); α is the parameter that controls the relative contribution of the L1 and L2 penalty terms. When $\alpha=1$, EN becomes to LASSO, while when $\alpha=0$, EN becomes to RR.

3.3. ARIMA model

The ARIMA model, proposed by Box and Jenkins in 1970, is a well-known method for time series forecasting and is widely utilised in studies related to the prediction of pollutant emissions (Chen et al., 2022; Jian et al., 2012; Q. Wang et al., 2020; Zhang et al., 2018). Based on historical data from 2006 to 2019, we use the ARIMA model to forecast the trends of GDP, population, capital stock, labour force, secondary industry share, per capita GDP, fixed asset investment, energy consumption, science and technology expenditures, and bus ownership for 221 cities in China. These forecasted values are subsequently input into the regression model built using the STIRPAT model and MLR to predict future carbon emissions up to 2030, ensuring that the predictions align with the identified causal relationships. Additionally, they are also input into the parametric QDDF model to estimate MAC. The forecast period spans from 2020 to 2030. The detailed model is presented in **S2 Supplementary Material**.

3.4. Time-varying DID model

The LCCP is considered a 'quasi-natural experiment', and a time-varying DID model is used to explore the effect of the LCCP on the city-level MAC of CO_2, explicitly examining the difference in the MAC between pilot cities (treatment group) and non-pilot cities (control group) before and after policy implementation. The first level of difference is at the city level, and the second level of difference is at the year level. Therefore, the baseline model is constructed as follows (Beck et al., 2010):

$$MAC_{it}=\alpha+\beta_1 did_{it}+\beta_2 X_{it}+\mu_i+\lambda_t+\varepsilon_{it} \tag{6}$$

where i represents the city, t represents the year; MAC_{it} is the dependent variable, representing the city-level MAC; did_{it} is a dummy variable with a value of one when the city i is the pilot city in the year t, and zero otherwise; X_{it} is a vector of control variables related to city characteristics; μ_i represents city-related fixed effects; λ_t represents time-related fixed effects; and ε_{it} is the random error term.

3.4.1. Dependent variable

The MAC of CO_2 emissions is the dependent variable in this study. The parametric QDDF is used to estimate the MAC as follows:

$$\begin{aligned}\vec{D}(x,y,b;g)=&a_0+\sum_{n=1}^{3}a_n x_{nk}^t+\beta_1 y_k^t+\gamma_1 b_k^t+\frac{1}{2}\sum_{n=1}^{3}\sum_{n'=1}^{3}a_{nn'}x_{nk}^t x_{n'k}^t+\frac{1}{2}\beta_2\left(y_k^t\right)^2\\&+\frac{1}{2}\gamma_2\left(b_k^t\right)^2+\sum_{n=1}^{3}\delta_n x_{nk}^t y_k^t+\sum_{n=1}^{3}\eta_n x_{nk}^t b_k^t+\mu y_k^t b_k^t+\sum_{k=1}^{K-1}\lambda_k City_k\\&+\sum_{t=1}^{T-1}\tau_t Time_t\end{aligned} \tag{7}$$

where x_{nk}^t is the n-th input for city k at time t, for $n=1,\cdots,3$, and n is the number of inputs; y_k^t is the desirable output for city k at time t; b_k^t is the undesirable output for city k at time t; a_0 is the constant term in the model; a_n, β_1, γ_1, a_{nn}, β_2, γ_2, δ_n, η_n and μ are the corresponding coefficients for their respective linear, quadratic, or interaction terms; $City_k$ is a dummy variable indicating the presence of city k; $Time_t$ is a dummy variable indicating time t; λ_k and τ_t are the fixed effect coefficients; K is the total number of cities and T is the total number of time periods. In our study, the three inputs include labour (x_1), capital stock (x_2) and energy consumption (x_3), while the two outputs are GDP (y) and CO_2 emissions (b), representing desirable and undesirable outputs, respectively.

Once the parameters are estimated, the MAC of CO_2 emissions can be calculated as:

$$q=-p\frac{\partial\vec{D}/\partial b}{\partial\vec{D}/\partial y} \tag{8}$$

where p represents the price of desirable output, while q represents the price of undesirable output. The detailed model settings and variable descriptions are provided in **S3 Supplementary Material.**

3.4.2. Independent variable

Dummy variable (did_{it}) is used to indicate whether a city has implemented the LCCP or not, which equals one if city i is a pilot city in year t, and zero otherwise. We include all three batches of the LCCP in this study. Specifically, the first batch was implemented in 2010, encompassing five provinces (Guangdong, Liaoning, Hubei, Shaanxi, and Yunnan) and eight cities (Tianjin, Chongqing, Shenzhen, Xiamen, etc.); the second batch was implemented in 2012, including Hainan Province and 28 other cities; the third batch was implemented in 2017 and included 45 cities, including Wuhai City in Inner Mongolia, as shown in **S1 Supplementary Material**. However, it is unreasonable to include all cities in the five provinces in the first batch because the scope is too broad to cover every city effectively. Therefore, we only include those cities in the five provinces that have explicitly published documents related to the implementation of low-carbon initiatives. Consequently, the first batch of pilot cities is identified as the initial eight cities plus Guangzhou, Zhuhai, Heyuan, and Jiangmen.

3.4.3. Control variables

Based on previous studies (Wen et al., 2022; Xu et al., 2022; Yu & Zhang, 2021), this study selects the following control variables: industrial structure is represented by the share of tertiary sector output in GDP; science development is represented by science and technology expenditure; education level is represented by education expenditure; city greenery level is represented by green area; economic development is represented by GDP per capita; government budget is represented by government revenue and expenditure; infrastructure construction is represented by bus ridership; investment level is represented by fixed-asset investment; and carbon intensity is represented by the ratio of carbon emissions to GDP. Table 3 presents the descriptive statistics of the variables. Among these variables, *P*, *PGDP*, *FAI*, *SIND*, *EC*, *GDP*, *SE* and *BO* are used to calculate seven variables required for forecasting carbon emissions to 2030 in the STIRPAT model, as shown in equation (3). For example, $BOP = BO/P$. Meanwhile, *L*, *CS*, *EC*, *GDP* and CO_2 are used in equation (7) for MAC estimation. Additionally, *TIND*, *SE*, *EE*, *GA*, *PGDP*, *CI*, *PFR*, *PFE*, *BP*, *FAI*, *Patent_A* and *Patent_G* are employed in the DID regression and mechanism analysis.

3.5. Data sources

The sample for this study consists of panel data from 221 Chinese cities over the period from 2006 to 2019. Data on pilot cities and pilot years are obtained from policy documents issued by the National Development and Reform Commission of the People's Republic of China. Data on carbon emissions and energy consumption are from the China Emission Accounts and Datasets (CEADs) (Shan et al., 2018; Shan et al., 2022). Other data are collected from Chinese Research Data Services (CNRDS), China Statistical Yearbook and China City Yearbook.

4. Result

4.1. Estimation result of the MAC

Based on the MLR results (see **S4 Supplementary Material**) and ARIMA forecasting results (see Table 4 for three inputs and two outputs for the MAC estimation and see **S5 Supplementary Material** for other variables required for CO_2 emissions forecasting), we estimate the parameter values from equation (7) and summarise them in **S6 Supplementary Material**. To avoid convergence problems in the linear programming model, the three inputs and two outputs are normalised by dividing each by their average value (Färe et al., 2005). This normalisation implies that for a hypothetical city, mean inputs generate mean outputs. The QDDF and the MAC can then be calculated based on these parameters. The MAC estimation results are presented in Table 4.

Fig. 1 demonstrates the spatial distribution of the MAC at the prefecture level in China for 2006 and 2019. The results show a general increase in MAC across cities during this period, with a more pronounced rise in the eastern coastal regions.

4.2. Impact of the LCCP policy on the MAC

The results of the benchmark model are presented in Table 5. Column 2 reports the coefficient of the LCCP as 0.0764 at the 1 % significance level, including all control variables and fixed effects, indicating that after the implementation of the LCCP, the MAC of CO_2 in pilot cities has significantly increased, compared with non-pilot cities.

Regarding control variables, tertiary sector proportion, science expenditure, education expenditure, economic development, and greenery level are found to significantly increase the MAC of CO_2, while carbon intensity and fixed asset investment are observed to significantly decrease the MAC. In China, shifting from secondary to tertiary industry is a crucial national strategy to achieve carbon neutrality. Thus, an increase in the share of the tertiary sector indicates a city's progress in its low-carbon transition and the development of technologies to reduce emissions, which could increase the MAC. Science and education expenditures encourage low-carbon technology development through financing and talent cultivation, thereby increasing the MAC. As China's economic development is accompanied by increased productivity, measured as GDP output per unit of emissions (i.e., MAC) in this study, per capita GDP has a positive effect on the MAC. Cities with more greenery tend to depend less on heavy industry and perform well in low-carbon transitions, leading to higher MAC. However, carbon intensity, a measure of emission efficiency, negatively impacts the MAC. High carbon intensity in areas with underdeveloped low-carbon technology indicates a higher potential for emission reduction, leading to lower MAC. The negative relationship for fixed asset investment may be explained by the maximised impact of investments in the secondary industry, while investments in the tertiary industry have not been fully utilised, possibly due to limited technological development. The effects of public finance revenue and expenditure, as well as infrastructure construction, on the MAC are insignificant.

To avoid biased regression results, we conducted several robustness checks, including a parallel trend test, placebo test, CSDID check, and

Table 3
Descriptive statistics of the variables.

Variables	Code	Measurement	Unit	Obs.	Mean	Std.	Min	Max
Secondary industry proportion	*SIND*	Secondary sector output divided by GDP	-	3,094	0.48	0.10	0.11	0.86
Tertiary industry proportion	*TIND*	Tertiary sector output divided by GDP	-	3,094	0.40	0.10	0.11	0.84
Labour	*L*	Total number of employees at the end of the year	10,000 people	3,094	61.61	86.74	4.21	986.87
Capital stock	*CS*	Capital stock	100 million Yuan	3,094	6,319.41	7,944.13	390.32	72,271.09
Energy consumption	*EC*	Energy consumption	10,000 tons of standard coal	2,849	2,097.71	2,155.81	55.30	23,423.97
GDP	*GDP*	Real gross domestic product	100 million Yuan	3,094	2,040.44	2,733.19	98.66	28,297.35
Carbon emissions	CO_2	Carbon emissions	1 million tons	2,737	39.07	37.69	1.17	415.98
Carbon intensity	*CI*	Carbon emissions divided by GDP	Ton/10,000 Yuan	2,737	2.91	2.79	0.20	31.91
Fixed-asset investment	*FAI*	Fixed-asset investment	100 million Yuan	3,094	1,560.00	1,780.00	39.03	19,700.00
Population	*P*	Population at the end of the year	10,000 people	3,094	481.36	329.45	17.61	3,416.00
Per-capita GDP	*PGDP*	Per-capita GDP	Yuan	3,094	43,264.74	35,897.05	4,009.00	274,226.60
Public finance revenue	*PFR*	Public finance revenue	100 million Yuan	3,088	219.35	498.87	2.95	7,165.10
Public finance expenditure	*PFE*	Public finance expenditure	100 million Yuan	3,088	354.67	604.12	5.76	8,351.54
Science expenditure	*SE*	Science expenditure	10,000 Yuan	3,088	99,822.51	340,177.90	0.13	5,549,817.00
Education expenditure	*EE*	Education expenditure	10,000 Yuan	3,088	597,615.00	859,082.80	1,255.00	11,400,000.00
Green area	*GA*	Green area	10,000 square meters	3,049	8,085.64	16,620.53	130.00	168,027.00
Bus passenger number	*BP*	Total bus or tram passenger traffic	10,000 people	3,061	25,299.62	49,420.11	18.00	516,517.00
Bus ownership	*BO*	Number of vehicles operated by public buses or trams in operation	1 vehicle	3,074	1,715.51	3,264.86	24.00	38,728.00
Patent application	*Patent_A*	Number of patent applications	10,000 units	3,094	0.74	1.83	0.0007	25.57
Patent granted	*Patent_G*	Number of granted patents	10,000 units	3,094	0.48	1.16	0.0007	16.69

Table 4
Variables and results for the MAC estimation from 2006 to 2030.

Variable	Unit	Obs.	Mean	Std. dev	Min	Max
Labour	10,000 people	5,525	67.15	101.22	4.21	1,095.69
Capital stock	100 million Yuan	5,525	9,781.74	13,371.77	390.32	132,187.20
Energy Consumption	10,000 tons of standard coal	5,525	2,350.96	2,598.91	55.30	23,423.97
GDP	100 million Yuan	5,525	3,101.69	4,304.17	98.66	45,916.45
Carbon emissions	1 million tons	5,525	43.75	42.37	1.17	415.98
MAC	Yuan/ton	5,525	722.21	1,716.12	153.95	56,159.34

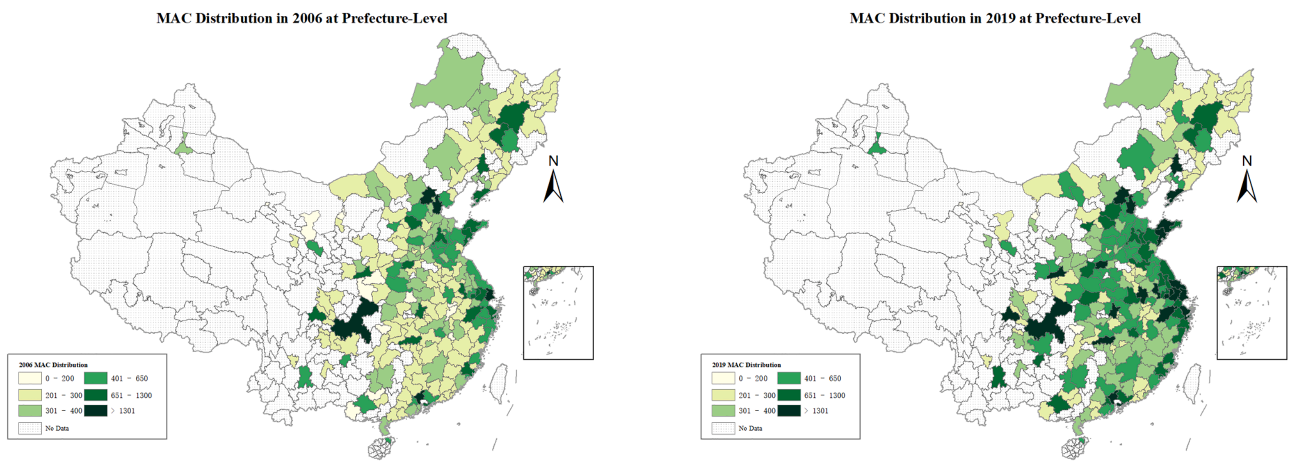

Fig. 1. Spatial distribution of city-level MAC in 2006 and 2019.
Note: 221 cities are included in the maps. Grey areas are cities without data while the coloured areas are divided into six classes according to the range of MAC.

Table 5
Baseline regression result.

Variables	(1) lnMAC	(2) lnMAC
LCCP	0.0915***	0.0764***
	(0.0249)	(0.0223)
TIND		0.256**
		(0.126)
lnSE		0.0328***
		(0.00950)
lnEE		0.0645**
		(0.0267)
lnGA		0.0191*
		(0.0113)
lnPGDP		0.390***
		(0.103)
lnCI		-0.0485***
		(0.0156)
lnPFR		0.0247
		(0.0218)
lnPFE		-0.0490
		(0.0317)
lnBP		-0.00984
		(0.00744)
lnFAI		-0.0714***
		(0.0192)
Constant	5.986***	2.162**
	(0.00333)	(1.044)
City FEs	YES	YES
Year FEs	YES	YES
Observations	3,094	3,094
Adjusted R-squared	0.967	0.970

Note: The parentheses are the standard errors. ***, **, and * represent significant levels at 1 %, 5 %, and 10 %, respectively.

tests for other three overlapping pilot policies. All results confirmed the robustness of our findings. Due to space limitations, these robustness checks are provided in the **S7 Supplementary Material**.

4.3. Heterogeneous effect

The implementation effects of the LCCP exhibit significant heterogeneity across cities with varying levels of development, geographical locations, resource endowments, and industrialisation levels. Developed cities, with advanced industrial systems and stronger technological foundations, are better equipped to support LCCP implementation, resulting in higher MAC due to their ability to attract talent and prioritise research and development. Similarly, cities in eastern regions, with superior infrastructure, are more effective at leveraging technological innovation and industrial restructuring to achieve greater carbon reductions and higher MAC compared to central and western cities. Resource-based cities, however, often face a "resource curse" that constrains the transition into low-carbon industries and limits the effectiveness of LCCP (Zeng et al., 2023). Conversely, non-resource-dependent cities, free from such constraints, are more likely to experience increased MAC under LCCP policies. Industrialisation levels further contribute to these variations, with industrial and non-industrial cities, as well as backup and non-backup cities, demonstrating differing outcomes. Additionally, cities recognised as perform-well pilots are expected to lead in emission reductions and achieve higher MAC if they genuinely progress in low-carbon development. The classification criteria of city types is provided in **S8 Supplementary Material**.

Table 6 presents the results of the heterogeneous effect of the LCCP on the MAC. Columns 1–6 indicate a significantly positive effect of the LCCP on the MAC in developed, eastern and northeastern cities. This can be attributed to their superior technological foundations, abundant talent resources, and significant advantages in low-carbon technology innovation. Additionally, firms in these regions face more intense competition, making it easier for LCCP to incentivise greater energy-

Table 6
The heterogeneous impact of the LCCP on the MAC.

Variables	Economic segment		Geographic segment				Resource dependence and industrialisation segment						Performance segment	
	(1) Developed	(2) Developing	(3) Eastern	(4) Middle	(5) Western	(6) North-Eastern	(7) Resource-Based	(8) Non-Resource-Based	(9) Industrial City	(10) Non-Industrial City	(11) Back-up City	(12) Non-Back-up City	(13) Perform-well City	(14) Underperform City
LCCP	0.202***	0.0146	0.124***	0.0255	0.0681	0.0822***	-0.0457**	0.114***	-0.00141	0.0956***	-0.0179	0.0834***	0.138***	0.0295
	(0.0457)	(0.0170)	(0.0290)	(0.0363)	(0.0630)	(0.0310)	(0.0226)	(0.0260)	(0.0268)	(0.0259)	(0.0328)	(0.0235)	(0.0359)	(0.0245)
TIND	0.151	0.263**	0.283**	0.179	0.324**	0.236*	0.266**	0.186	0.236*	0.286**	0.277**	0.242*	0.282*	0.202*
	(0.140)	(0.119)	(0.130)	(0.132)	(0.142)	(0.135)	(0.129)	(0.132)	(0.131)	(0.132)	(0.135)	(0.128)	(0.143)	(0.121)
lnSE	0.0380***	0.0275***	0.0353***	0.0329***	0.0239**	0.0298***	0.0279***	0.0309***	0.0215***	0.0409***	0.0285***	0.0328***	0.0246**	0.0369***
	(0.00857)	(0.00832)	(0.00755)	(0.00793)	(0.00957)	(0.00774)	(0.00728)	(0.00978)	(0.00771)	(0.00851)	(0.00762)	(0.00962)	(0.00953)	(0.00827)
lnEE	0.0581**	0.0263	0.0391	0.0464*	0.0504**	0.0287	0.0331	0.0611**	0.0330	0.0608**	0.0326	0.0646**	0.0633**	0.0280
	(0.0260)	(0.0246)	(0.0261)	(0.0265)	(0.0248)	(0.0254)	(0.0240)	(0.0269)	(0.0245)	(0.0266)	(0.0246)	(0.0269)	(0.0273)	(0.0251)
lnGA	0.0108	0.0210**	0.0154	0.0170	0.0149	0.0145	0.0149	0.0180	0.0169	0.0152	0.0151	0.0198*	0.0112	0.0219**
	(0.0116)	(0.0101)	(0.0116)	(0.0105)	(0.0107)	(0.0106)	(0.0104)	(0.0113)	(0.0105)	(0.0115)	(0.0105)	(0.0114)	(0.0117)	(0.0103)
lnPGDP	0.431***	0.311***	0.406***	0.420***	0.381***	0.392***	0.339***	0.424***	0.387***	0.392***	0.372***	0.398***	0.453***	0.313***
	(0.109)	(0.0870)	(0.0982)	(0.104)	(0.0953)	(0.0973)	(0.0956)	(0.104)	(0.0956)	(0.107)	(0.0991)	(0.103)	(0.111)	(0.0913)
lnCI	-0.0360**	-0.0367**	-0.0451***	-0.0281*	-0.0321**	-0.0324**	-0.0296**	-0.0433***	-0.0348**	-0.0462***	-0.0281*	-0.0484***	-0.0361**	-0.0389***
	(0.0172)	(0.0146)	(0.0166)	(0.0160)	(0.0149)	(0.0159)	(0.0150)	(0.0165)	(0.0155)	(0.0160)	(0.0156)	(0.0161)	(0.0167)	(0.0146)
lnPFR	0.0198	0.0252	0.0289	0.0170	0.0261	0.0238	0.0169	0.0294	0.0263	0.0205	0.0230	0.0227	0.0318	0.0203
	(0.0231)	(0.0195)	(0.0217)	(0.0216)	(0.0217)	(0.0211)	(0.0202)	(0.0221)	(0.0206)	(0.0222)	(0.0208)	(0.0221)	(0.0223)	(0.0206)
lnPFE	-0.0598	-0.0428	-0.0591*	-0.0428	-0.0325	-0.0498	-0.0403	-0.0544	-0.0487	-0.0440	-0.0472	-0.0479	-0.0439	-0.0481
	(0.0391)	(0.0267)	(0.0325)	(0.0345)	(0.0360)	(0.0352)	(0.0319)	(0.0334)	(0.0348)	(0.0317)	(0.0348)	(0.0319)	(0.0336)	(0.0336)
lnBP	-0.00107	-0.00160	-0.00374	-0.000276	-0.000839	0.00176	0.00422	-0.00850	0.00313	-0.0112	0.00262	-0.00884	-0.00538	-0.00259
	(0.00704)	(0.00728)	(0.00710)	(0.00752)	(0.00715)	(0.00731)	(0.00725)	(0.00722)	(0.00733)	(0.00750)	(0.00729)	(0.00746)	(0.00747)	(0.00706)
lnFAI	-0.0727***	-0.0305**	-0.0647***	-0.0458**	-0.0321	-0.0376**	-0.0252	-0.0761***	-0.0336**	-0.0707***	-0.0283*	-0.0724***	-0.0754***	-0.0395**
	(0.0207)	(0.0152)	(0.0190)	(0.0183)	(0.0199)	(0.0164)	(0.0165)	(0.0191)	(0.0168)	(0.0196)	(0.0168)	(0.0193)	(0.0219)	(0.0162)
Constant	2.047*	2.586***	2.223**	1.563	1.482	1.973**	2.170**	1.992*	1.893**	2.107*	1.916*	2.092**	1.509	2.775***
	(1.096)	(0.876)	(0.999)	(1.025)	(0.976)	(0.991)	(0.962)	(1.060)	(0.954)	(1.074)	(0.989)	(1.049)	(1.123)	(0.905)
Observations	2,492	2,744	2,576	2,380	2,366	2,198	2,338	2,898	2,310	2,926	2,198	3,038	2,632	2,604
R-squared	0.974	0.961	0.977	0.958	0.955	0.961	0.957	0.973	0.958	0.973	0.957	0.972	0.973	0.963

Note: The parentheses are the standard errors. ***, **, and * represent significant levels at 1 %, 5 %, and 10 %, respectively.

saving investments, enhance emission reduction innovations, and increase MAC. Columns 7–12 suggest that the LCCP effects are more pronounced in non-resource-based, non-industrial, and non-energy-back-up cities. Unlike resourced-based cities that rely on high-pollution and high-emission industries for economic growth, these cities are not hindered by resource dependence or industrial structure lock-in. This enables them to transition to low-carbon industrials more effectively under LCCP implementation. These findings align with prior studies (Song et al., 2022; Xu et al., 2022; Zhang et al., 2022). Moreover, Columns 13–14 show that high-rating pilot cities experience a more significant increase in the MAC under the influence of LCCP, confirming the accuracy of the Progress Report's assessment of the pilot cities' performance.

4.4. Mechanism analysis

To test hypotheses 2 and 3, we use the number of patent applications and the number of granted patents as proxies for green technology innovation and use the ratio of secondary sector output to GDP to measure industrial structure upgrading. The staggered DID model is employed to examine the impact of the LCCP on these two aspects. The regression results are presented in Table 7.

The results in Columns 1–2 indicate that LCCP has a significantly positive effect on patent application and patent granted, suggesting that the LCCP effectively promotes green technology innovation. Meanwhile, the results in Column 3 show a significantly negative impact on the proportion of secondary industry, indicating that the LCCP contributes to industrial structure upgrading by facilitating a shift away from traditional, resource-intensive industries. These findings support hypotheses 2 and 3.

4.5. Future trajectory of the impact of LCCP and cities' MAC

Considering the verified positive impact of the LCCP on cities' MAC and its heterogeneous effects, cities may perform differently in their long-term low-carbon transitions. In addition, it is crucial to analyse the evolving features of MAC throughout the transition process and the impact of the LCCP on cities' decarbonisation roadmaps.

4.5.1. The widening disparity in MAC across high-rating cities

Forty cities were rated as excellent in the Progress Report due to their outstanding performance in low-carbon transition actions, particularly in areas such as institutionalisation, implementation and efficiency, capability building and innovation (MEE, 2023). Consequently, this study matches 35 out of the 40 cities and presents their MAC projections toward 2030 in Fig. 2. The results indicate that MAC and the inter-city disparity in MAC will continue to rise across all cities by 2030, and simultaneously the abatement costs and their growth rates differ significantly. The reasons for this phenomenon could be: first, MAC represents the cost of a city's implementation of additional emission control measures and it is argued that high-rate emission reductions are only attributed to the high emission efficiency and relatively low MAC in cities (Duan et al., 2025). Even in pilot cities, due to economic and technological disparities, developed cities and those with lower carbon intensity tend to have relatively higher MACs than developing cities or cities with lower emission efficiency. Second, the U-shaped relationship between MAC and cities' carbon emission intensity implies that cities in the middle of low-carbon transition own relatively low MAC, but the abatement costs will grow as the transition progresses further.

Table 7
The impact of LCCP on green technology innovation and industrial structure upgrading.

Variables	(1) Patent application	(2) Patent granted	(3) Secondary industry proportion
LCCP	1.3280***	0.8302***	-0.6337***
	(0.0772)	(0.0486)	(0.1550)
Constant	7.645**	7.0496***	-51.4304***
	(3.355)	(2.1140)	(6.7385)
Controls	YES	YES	YES
City FEs	YES	YES	YES
Year FEs	YES	YES	YES
Observations	3094	3094	3094
$R-squared$	0.783	0.785	0.969

Note: The parentheses are the standard errors. ***, **, and * represent significant levels at 1 %, 5 %, and 10 %, respectively.

4.5.2. Spatial distribution of cities' MAC by 2030

In addition to the high-rating cities nominated by the government, we also focus on the long-term abatement performance of other cities and the spatial pattern of future MACs at the national level. Fig. 3 illustrates that most cities will see a continuous increase in the MAC from 2020 to 2030, which aligns with the strategic planning of national emission mitigation targets. However, the average MAC in the southern regions is higher than that in the northern regions; similarly, the eastern regions have a higher average MAC compared to the western regions.

Furthermore, it is also interesting to observe that the MAC of cities in the central regions will rapidly grow in 2025 and 2030, bridging the significant spatial gap between the coastal and inland areas. Meanwhile, only a few cities in the western regions have increasing abatement costs that keep pace with the overall trend. Conversely, the MAC in the north-eastern cities seems to stop growing in the future and remains at a relatively low level, indicating that their decarbonisation strategies may fall behind the national goal of carbon peaking by 2030. The findings also inform that in addition to the pilot cities, more supportive climate policies are required to facilitate other cities to align with decarbonisation targets, particularly for those in inland and developing regions in the northeast.

4.5.3. Cost-intensity matrix for cities

Given the quantitative relationship between MAC and carbon emission intensity, the long-term impact of the LCCP on cities' MAC and decarbonisation strategies can be captured through the evolving relationship between the aforementioned variables. Based on the classification approach proposed by Y. Wang et al. (2020) and Duan et al. (2025), we establish cost-intensity matrices using the historic and future trajectory of MAC and carbon emission intensity for 2006, 2019, and 2030, as shown in Fig. 4.

Cities in the second quadrant are classified as Type I – "Pioneering Cities". These cities exhibit high MAC and low carbon intensity, generally positioned in the upper left area of the MACC. This indicates that these cities possess advanced emission reduction technologies and demonstrate significant mitigation effects, placing them at the forefront of the decarbonisation process.

Cities in the third quadrant fall under Type II – "Catch-up Cities". These cities have relatively low carbon intensity but also low MAC, located in the lower left area of the MACC. This reflects lower economic costs for emissions reduction and suggests that these cities still have unfulfilled low-hanging abatement tasks. By advancing clean energy development and green technological progress, they have the potential to further reduce carbon intensity while increasing MAC, ultimately transitioning into Type I.

Cities in the first and fourth quadrants are classified as Type III – "Transition-Challenged Cities". These cities face high carbon intensity and lower MAC, situated near the turning point of the MACC. This positioning implies low economic costs for emissions reduction but significant untapped abatement potential. However, these cities have yet to make substantial progress in the decarbonisation journey.

We find that, under the guidance of the LCCP, cities as a whole are transitioning from Type III to Type II and Type I. In 2006, 96.38 % of cities were classified as Type III. By the present day, more than one-third of these Type III cities have evolved into Type II (25.79 %) or even

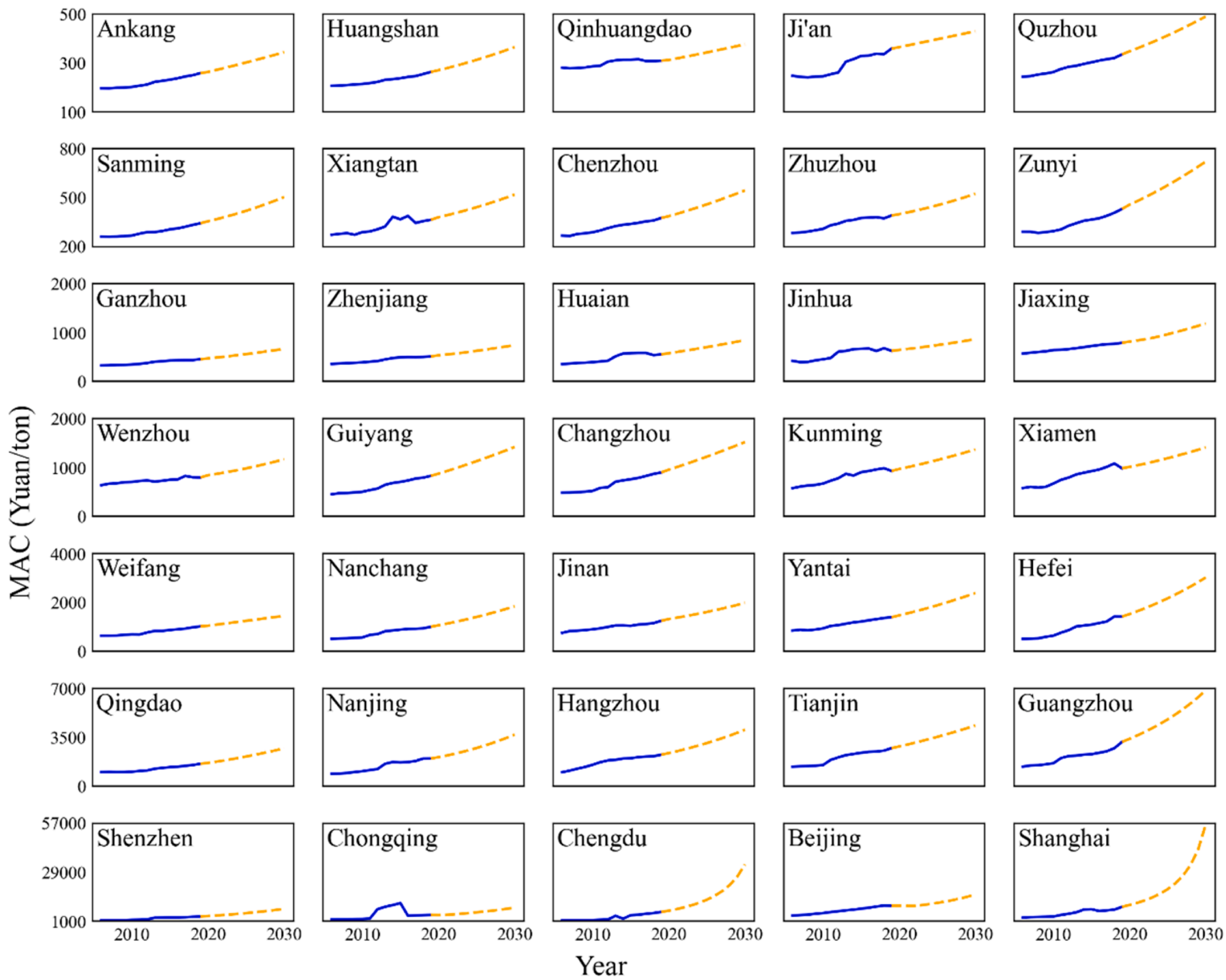

Fig. 2. MAC projection in 2030 for 35 high-rating cities from the Progress Report.
Note: Cities are ascendingly ordered regarding their MAC projections. Blue solid lines represent calculated MAC values based on the real-world data while yellow dashed lines are MAC projections.

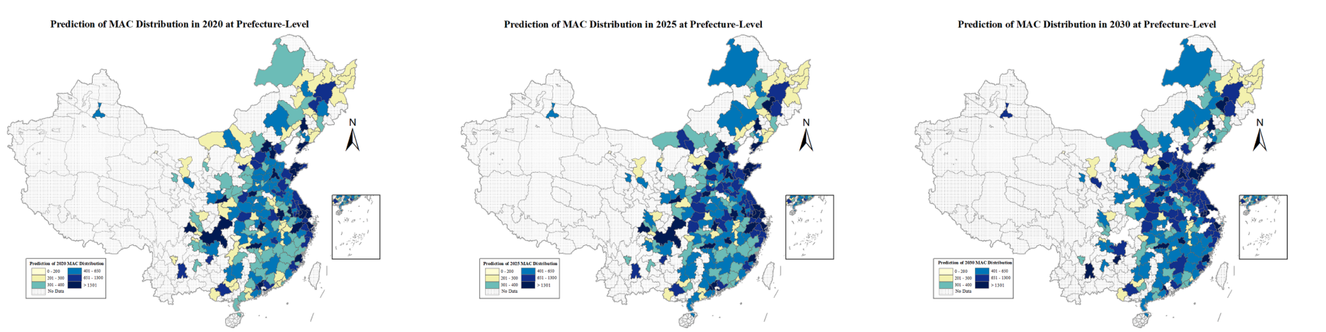

Fig. 3. Maps for MAC projections for 2020, 2025 and 2030.
Note: 221 cities are included in the maps. Grey areas are cities without data while the coloured areas are divided into six classes according to the range of MAC projections, which are as follows: 0–200 (light yellow), 201–300 (light green), 301–400 (light blue), 401–650 (blue), 451–1300 (dark blue), >1300 (black).

leaped directly to Type I (9.05 %). Looking ahead to 2030, over half of the cities are expected to move beyond Type III, with 15.84 % reaching Type I. This indicates that an increasing number of cities are engaging in decarbonisation, continually developing emission reduction technologies, and achieving meaningful results. It demonstrates the significant impact of the LCCP in promoting both short-term emissions reductions and long-term progress toward 2030 goals.

Among these cities, the emission reduction outcomes for pilot cities are significantly stronger than those for non-pilot cities. By 2030, more than one-third of pilot cities are projected to reach Type I, while another third will have transitioned from Type III to Type II. In contrast, although non-pilot cities exhibit a slight overall shift toward the upper-left quadrant, there is no clear trend of crossing into Type I by 2030. Fewer than 10 % of non-pilot cities are expected to successfully

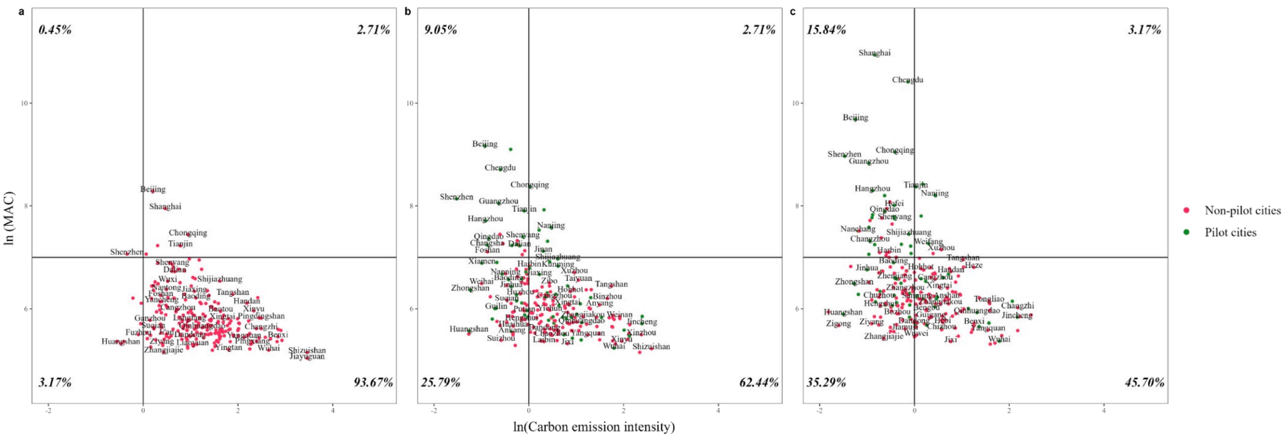

Fig. 4. The cost-intensity classification matrices. (a), (b), and (c) illustrate classification results in 2006, 2019 and 2030, respectively.
Note: The percentage figures are the proportion of cities falling in each of the four quadrants.

transition to Type I, with more than half remaining in Type III. This comparison highlights the strong role the LCCP plays in accelerating emissions reductions in pilot cities.

At present, the effects of the LCCP on pilot cities are primarily reflected in their transition from Type III to Type II. Over the longer term to 2030, the program's impact becomes more evident in transitions from Type II to Type I. As emission reduction technologies advance and easy abatement tasks are completed, the process becomes increasingly challenging. While most pilot cities are steadily progressing in their decarbonisation journeys, some cities—such as Urumqi, Liuzhou, and Jilin—remain in Type III. This suggests that the current LCCP framework may not be well-suited to their specific contexts. For these cities, tailored emission reduction strategies need to be developed based on their unique characteristics and economic development needs.

5. Conclusion and discussion

This study evaluates the effectiveness of the LCCP programme and its future trajectory while addressing the issue of policy anticipation effects. Anticipation effects arise from the non-random assignment of the LCCP, can lead to severe endogeneity issues in causal inference by using dependent variables that coincide with or are highly correlated with the criteria determining city eligibility for the pilot cities (e.g., carbon intensity, a key criterion) for the DID analysis. To address the anticipation effects problem, we select the MAC of CO_2 as the outcome indicator. Although the computation of the MAC is based on various variables related to energy use and carbon emissions which are candidates for determining pilot city status, the correlation between the MAC and these variables is modest. This substantially mitigates concerns about the endogeneity arising from treating the LCCP as a shock to cities. Additionally, MAC represents a city's emission reduction potential, making it a valuable metric for informing future climate policy design. Moreover, we forecast future urban abatement costs by 2030 and construct a cost-intensity matrix based on the quantitative relationship between MAC and carbon emission intensity. This matrix categorises cities into three groups: Type I – "Pioneering Cities," Type II – "Catch-up Cities," and Type III – "Transition-Challenged Cities." By identifying the transitional stages of low-carbon development across cities, the matrix facilitates the development of targeted long-term emission reduction strategies. Our results reveal two key findings: (1) the LCCP significantly increased the MAC of CO_2 in pilot cities, driven by green technology innovation and industrial structure upgrading, although the effect exhibits heterogeneity across cities; (2) by 2030, most cities will experience continued growth in abatement costs, accompanied by widening inter-city disparities. However, the majority of cities will remain in transitional stages, with a significant number still in the early phases of their low-carbon transformation.

Policymakers should prioritise specific target cities to enhance their emission reduction capabilities. Heterogeneity analysis reveals significant variation in the abatement potential of different regions and city types in China. Therefore, greater support should be directed toward central and western regions, resource-based cities, and industrial cities, which includes increasing investment in technology, improvements in current energy consumption structure, and higher adoption rates of clean fuels. Since these regions and cities are generally in the early stages of transition, they possess substantial potential for cost-effective emission reductions. Focusing on these areas can maximise the economic benefits of emission reductions while reducing the inequality in low-carbon development across regions and cities, achieving a win-win situation. Notably, policies must fully consider the spatial mismatch between energy resource production areas and consumption areas. Non-resource-based areas and eastern consumption regions should also share the corresponding responsibilities. Additionally, considering the economic and technological strength of the eastern regions, their emission reduction standards can be appropriately raised to align with those of developed countries.

In addition, policymakers should adopt tailored strategies for each city to optimise their low-carbon transition pathways. By 2030, disparities in MAC across cities are expected to widen further. Most cities will remain in the mid-transition stage, with some still in the early stages, and even a few low-carbon pilot cities will fall short of achieving their anticipated transformation. This underscores the need for more city-specific decarbonisation strategies. The government should analyse the challenges hindering low-carbon transitions in struggling cities and design policies tailored to their unique characteristics. Policy implementation plans should also include strengthened supervision to ensure systematic and orderly low-carbon transitions nationwide, enabling the achievement of China's dual carbon goals. During this process, policymakers need to address the following key issues: first, as China's climate policies become increasingly stringent, energy-intensive enterprises may seek to relocate their production from cities with high MAC to those with low MAC. Such relocations could result in inter-city carbon leakage and weaken the effectiveness of decarbonisation strategies in developing areas. Second, our findings emphasise the underlying costs of urban emission mitigation policies. While developed cities can achieve low-carbon transitions despite high abatement costs, cities struggling in transition face significant challenges. For these cities, high costs may render emissions-based targets unfeasible. Instead, they should focus on improving emission efficiency or enhancing energy efficiency. Third, policymakers should pay more attention to the inequality of abatement costs across cities. Cities should be better synergised in terms of climate policy implementation to prevent the deterioration of climate inequality.

We acknowledge the following limitation in our assumptions and methodology, which are supposed to be addressed in further studies. The data of energy consumption inventory applied in this study is aggregated to the city level based on energy-specific input-output relationships, which serves as an alternative method for estimating city-level energy consumption data. We acknowledge that this method may lead to statistical biases regarding the actual energy consumption of energy-exporting cities, particularly when their actual energy consumption is much lower than the energy supplied to other cities. Nevertheless, this approach has been adjusted to address the deficiencies in energy consumption statistics where the inter-city energy supply-demand information is usually overlooked.

CRediT authorship contribution statement

Yixuan Zhang: Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Data curation. **Xiangjie Zhu:** Writing – original draft, Visualization, Software, Methodology. **Di Liu:** Writing – review & editing, Validation. **Yuli Shan:** Supervision, Resources. **Yi Wu:** Writing – review & editing, Supervision, Project administration, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.scs.2025.106319.

Data availability

Data will be made available on request.

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