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When firms merge, do carbon emissions fall? Insights from China's manufacturing sector

Will W Qiang[1,8], Tianzuo Wen[2,8], Haowen Luo[1], Yuxuan Xiao[1], Bo Huang[3], Steve H L Yim[4,5,6], Shuai Shi[7,*] and Harry F Lee[1,*]

[1] Department of Geography and Resource Management, The Chinese University of Hong Kong, Shatin, New Territories, Hong Kong Special Administrative Region of China, People's Republic of China
[2] Department of Urban Planning and Design, The Social Infrastructure for Equity and Wellbeing (SIEW) Lab and Urban Systems Institute, The University of Hong Kong, Pokfulam Road, Hong Kong Special Administrative Region of China, People's Republic of China
[3] Department of Geography, The University of Hong Kong, Pokfulam Road, Hong Kong Special Administrative Region of China, People's Republic of China
[4] Centre for Climate Change and Environmental Health, Nanyang Technological University, Singapore, Singapore
[5] Asian School of the Environment, Nanyang Technological University, Singapore, Singapore
[6] Lee Kong Chian School of Medicine, Nanyang Technological University, Singapore, Singapore
[7] Department of Real Estate and Construction, The University of Hong Kong, Pokfulam Road, Hong Kong Special Administrative Region of China, People's Republic of China
[8] These authors contributed equally to the work.
[*] Authors to whom any correspondence should be addressed.

E-mail: alexshi@hku.hk and harrylee@cuhk.edu.hk

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Abstract

Manufacturing mergers and acquisitions (M&A) represent a market-driven mechanism for corporate restructuring that facilitates technology transfer, resource reallocation, and the exchange of management knowledge between heterogeneous corporate owners. Unlike complex multi-departmental carbon policies, M&A networks may offer a more manageable pathway for diffusing cleaner production methods across urban systems. This study examines how manufacturing M&A network centrality affects urban carbon emissions using data from 284 Chinese cities (2004–2018). We uncover an inverted U-shaped relationship between M&A network centrality and emissions, indicating that initial network integration increases emissions before deeper connections enable reductions through operational efficiency improvements and the adoption of clean technologies. Using Apple suppliers as an instrumental variable, we establish that M&A network centrality causally reduces carbon emissions. However, unconditional quantile regression reveals striking heterogeneity: emission reductions occur primarily in cities with low to moderate baseline emissions, while high-emission cities show no significant response. The temporal analysis confirms that M&A effects materialize quickly but diminish over time. These findings suggest that for cities with moderate emissions and substantial network integration, facilitating manufacturing M&A offers a cost-effective complement to traditional environmental policies. However, high-emission cities require more direct interventions beyond market-driven restructuring. This evidence highlights the need for tailored policy approaches that harness spontaneous market mechanisms while taking into account both emission contexts and network positions.

1. Introduction

Carbon dioxide is the primary greenhouse gas driving climate change, largely due to anthropogenic emissions. Research has highlighted the major role of corporations in this process (Azar *et al* 2021, Busch *et al* 2022), making corporate emission reduction a global priority. As the world's top manufacturer and largest carbon emitter, China faces growing pressure to reduce emissions (IEA 2021). In response, it pledged to peak carbon emissions by 2030 and achieve carbon neutrality by 2060 (State Council of the People's Republic of China 2021).

Balancing economic growth and emission reduction remains a key challenge, especially for developing countries like China. Since emissions result from economic activity, simply limiting production or consumption contradicts corporate profit motives and consumer utility. A more viable path lies in leveraging green technologies and institutional innovation. In this context, mergers and acquisitions (M&A) have become increasingly important in corporate restructuring and resource allocation. Environmentally responsible firms tend to perform better and attract investment (Chen and Xie 2022, Chen and Gao 2023), and can benefit from carbon trading (Shi *et al* 2022a, Zhang *et al* 2024). However, existing studies often overlook the diversity of corporate ownership in shaping environmental strategies.

Since the 1990s, M&A activity in China has accelerated, driving restructuring and industrial convergence (Weterings and Marsili 2015, Wu *et al* 2020). Post-merger integration reshapes corporate structures and regional industries (Rozen-Bakher 2018, Wu *et al* 2024). This article fills a key gap by examining how M&A networks formed through ownership transfers affect urban carbon emissions.

Manufacturing M&A may offer a more efficient alternative to complex policy tools for reducing emissions. Theoretically, this study expands the concept of externality by examining how deliberate ownership transfers can lead to unintended environmental consequences. It also bridges the gap between corporate finance and environmental science. Practically, within China's institutional framework, top-down policies often fail to align with bottom-up corporate responses (Zhang *et al* 2020, Wu *et al* 2024). Our findings aim to inform policies that reconcile urban growth and carbon reduction through market mechanisms.

To investigate this, we apply an instrumental variable approach using Apple's supply chain in China to identify causal effects. We employ unconditional quantile regression (UQR) to investigate the nonlinear effects of manufacturing M&A on urban carbon emissions. The analysis draws on 14,140 manufacturing M&A transactions (2004–2018) from the Zephyr database and high-resolution carbon emission data from ODIAC (Open-source Data Inventory for Anthropogenic CO_2).

2. Manufacturing M&A-induced capital network and urban carbon emissions

M&A involves ownership transfers for asset restructuring, serving as a useful metric to assess corporate ownership heterogeneity. M&A reflects differences in firm size and knowledge (Cartwright and Schoenberg 2006, Lee and Lieberman 2010), which influence perceptions of carbon economies. It also fosters long-term partnerships, enabling technical learning and the sharing of resources. M&A may reconfigure the geographic identities of firms by redistributing corporate functions and relationships, leading to agglomeration or dispersion of resources, jobs, and networks. This spatial restructuring can address overcapacity and promote industrial concentration (Boschma and Hartog 2014, Wu *et al* 2024). Additionally, M&A has spillover effects on local partners and competitors, impacting broader urban growth (Ellwanger and Boschma 2015, Shi and Pain 2020, Shi *et al* 2022b). However, its influence on carbon emissions, particularly in the manufacturing sector, remains understudied.

From a city network perspective, M&A forms spatial linkages across regions. These transactions are highly concentrated in major urban centers (Böckerman and Lehto, 2006, Wu *et al* 2020), shaped by local factors such as market size, innovation capacity, and policy incentives (McCarthy and Dolfsma 2015, Wu *et al* 2020). M&A networks exhibit co-agglomeration and core-periphery patterns, driven by firms' responses to place-specific advantages (Aquaro *et al* 2023, Wu *et al* 2024). While traditional agglomeration externalities diminish with distance, urban network externalities, enabled by information and communication technology, facilitate the flow of intangible assets, such as knowledge and capital, thereby transcending geographic constraints.

Theories of global cities and network production highlight the complex interconnections among labor, capital, and knowledge. Huggins and Thompson (2014) argue inter-organizational knowledge flows enhance regional growth, introducing the idea of 'network capital'. Endogenous growth theory similarly emphasizes the role of knowledge exchange in long-term development.

Research on urban network relationships is still in its initial stages, with a primary focus on the flow indicators available for urban externalities (Burger and Meijers, 2016). However, these studies have focused on measurable flows, often neglecting intangible drivers like capital and knowledge. Industrial upgrading influences inter-regional M&A trends, with firms favoring regions that boast advanced economic structures (Böckerman and Lehto 2006, Wu *et al* 2020). M&A alters firm-place relationships, creates new hierarchies, and drives urban change (Bruhn *et al* 2017, Wu *et al* 2022). Recent studies have mapped capital flows from M&A to explain urban development (Shi and Pain 2020, Shi *et al* 2022b). These flows generate value through spillovers such as resource sharing and talent mobility, which may also influence carbon emissions.

Despite these insights, research on the impact of manufacturing M&A on carbon emissions is limited. Some studies find that industrial agglomeration can reduce pollution (Cheng 2016, Han *et al* 2022a),

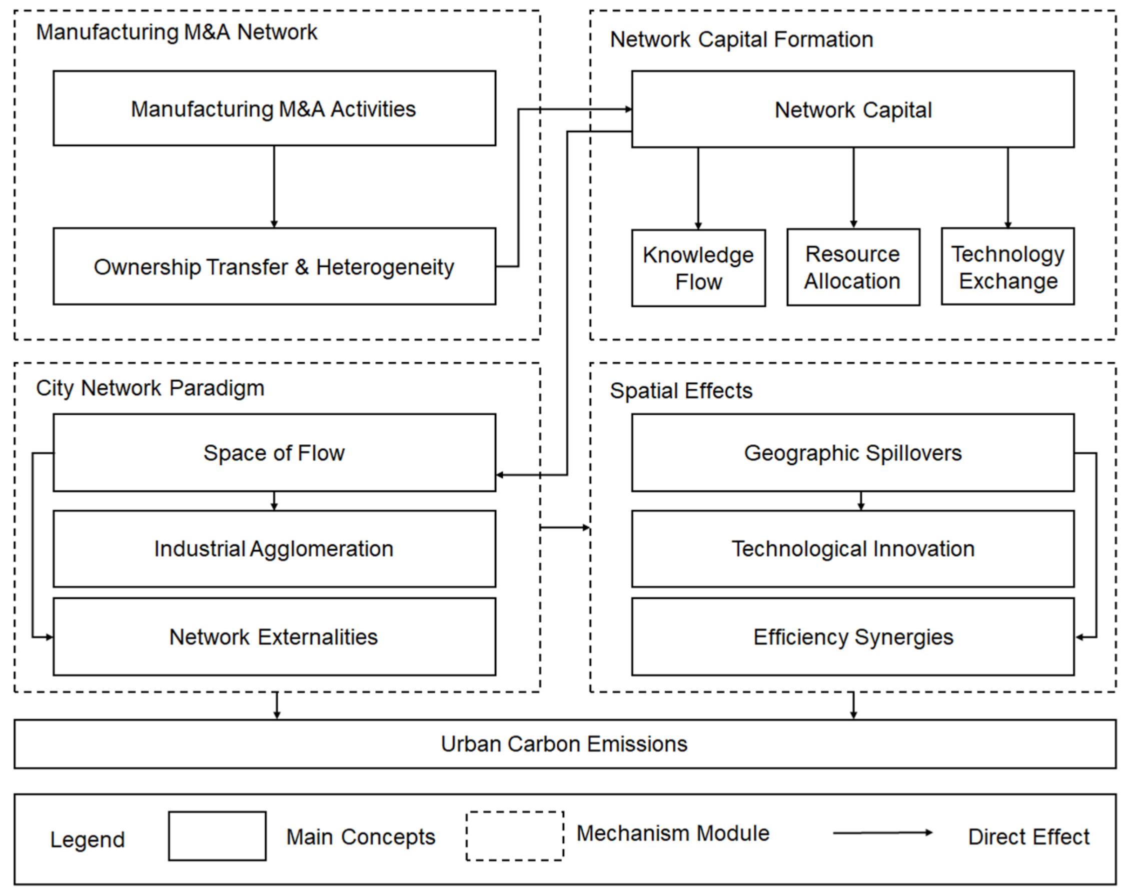

Figure 1. Conceptual framework linking manufacturing M&A to urban carbon emissions reduction.

but overlook the non-linear, networked nature of cross-industry relations. This gap motivates our study on how M&A-driven capital networks, via corporate linkages and spatial patterns, impact urban carbon emissions.

We employ a multi-method approach that combines network analysis, instrumental variables, and UQR. Our conceptual framework (figure 1) outlines how M&A-generated network capital (e.g. knowledge flows, resource allocation) interacts with spillover effects and policy interventions to influence urban carbon outcomes.

3. Study area, variable, and methodology

3.1. Study area

This study examines urban carbon emissions and corporate ownership networks across 284 prefecture-level and above cities in mainland China from 2004 to 2018. As a major manufacturing hub and significant carbon emitter, China provides a relevant context for examining the relationship between manufacturing M&A activity and environmental outcomes. The cities span a range of economic conditions, and prefecture-level units are ideal for analysis due to their key role in implementing industrial policy and regulating the environment.

The period covers critical phases of China's development—post-WTO growth, the global financial crisis, and early sustainability efforts—during which 14,140 M&A transactions reshaped the manufacturing sector. This timeframe enables the assessment of how evolving corporate networks align with carbon emission trends amid rapid industrialization and rising environmental awareness, providing insights into the dynamic between economic integration and environmental performance.

3.2. Variables

3.2.1. Carbon emissions

A major challenge in studying urban carbon emissions in China is the lack of publicly available city-level emissions data. To address this, researchers have developed estimation methods using satellite night lights (e.g. DMSP/ordinary least squares (OLS)) and fossil fuel tracking systems (Wang *et al* 2017, Lv *et al* 2020, Sha *et al* 2020). However, most rely on provincial-level fuel consumption data and default emission factors (e.g. the IPCC 2006 guidelines), which limits accuracy due to the absence of detailed, long-term city-level energy data.

This study utilizes the ODIAC dataset (Oda and Maksyutov 2011), which provides monthly CO_2 emissions at a 1 km × 1 km resolution, combining nighttime lights, power plant data, and geolocation

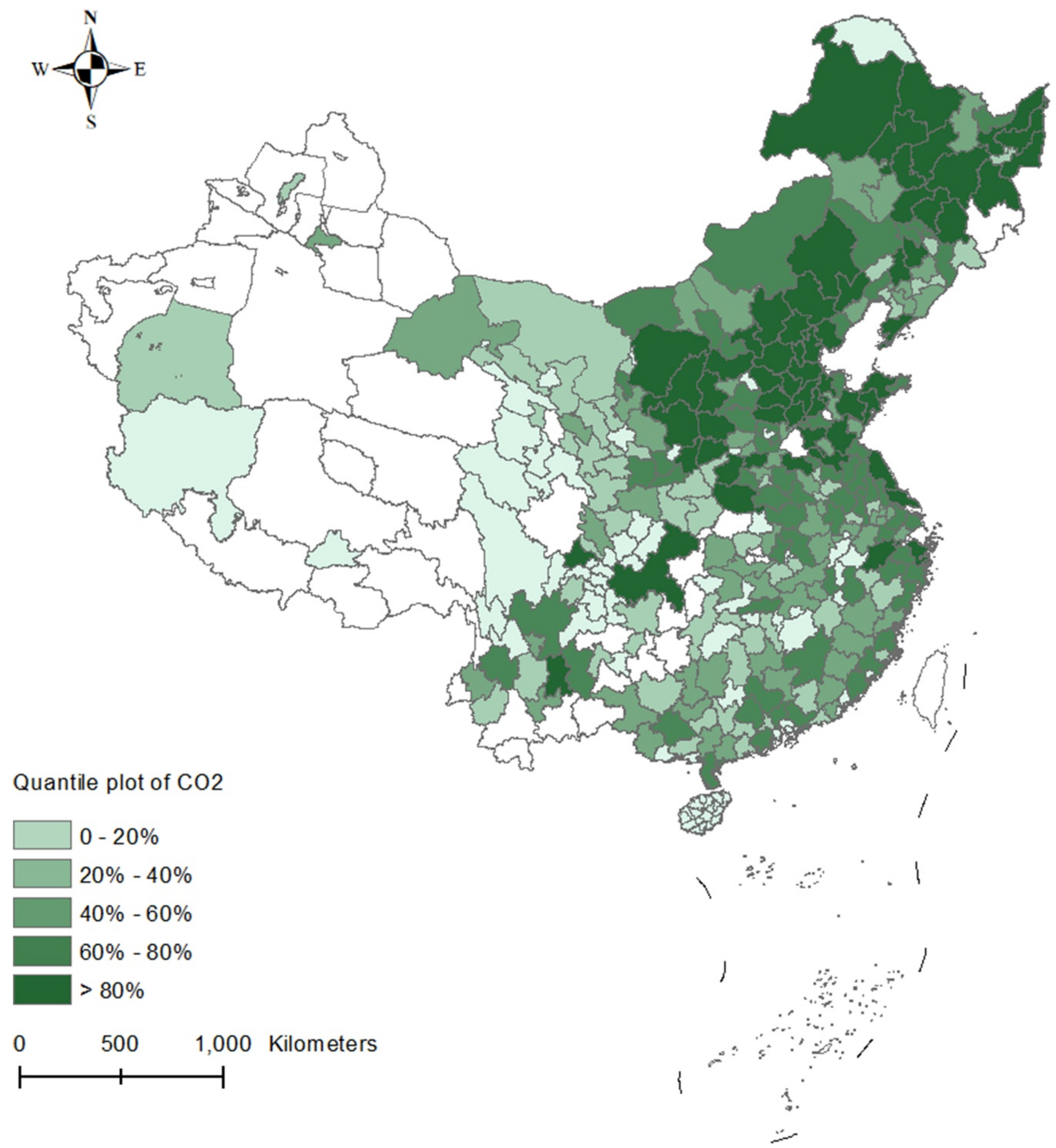

Figure 2. Quantile plot of CO_2.

information. ODIAC is widely utilized in climate and energy research due to its high spatial-temporal resolution, global coverage, and open access (Labzovskii *et al* 2019, Lei *et al* 2021). It includes emissions from major sources, such as coal power plants and cement production.

The study uses ODIAC data from 2004 to 2018, as later years are projected based on 2018 fuel data (Oda and Maksyutov 2015), ensuring reliability. Figure 2 shows the quintile distribution of city-level emissions in 2018.

3.2.2. Manufacturing M&A closeness centrality

M&A, defined as the transfer of ownership between independent entities, plays a crucial role in China's industrial restructuring amid economic transition (Shi *et al* 2022b). This study utilizes data from the Bureau van Dijk Zephyr database (www.cbs.dk/en/library/databases/zephyr), a leading global source for M&A records, particularly those involving complex transactions (Bollaert and Delanghe 2015). Only completed M&A deals involving actual ownership changes are included, excluding minority acquisitions, capital injections, and internal reorganizations. The transaction year reflects the legal completion date, not the announcement or negotiation dates.

Due to incomplete location data (e.g. only phone numbers or simplified addresses), company locations are verified using enterprise search platforms like QCC (www.qcc.com) and Aiqicha (https://aiqicha.baidu.com), enabling accurate assignment to prefecture-level cities. The dataset covers only manufacturing sector M&A, excluding real estate and services. Figure 3 visualizes cross-regional M&A activity

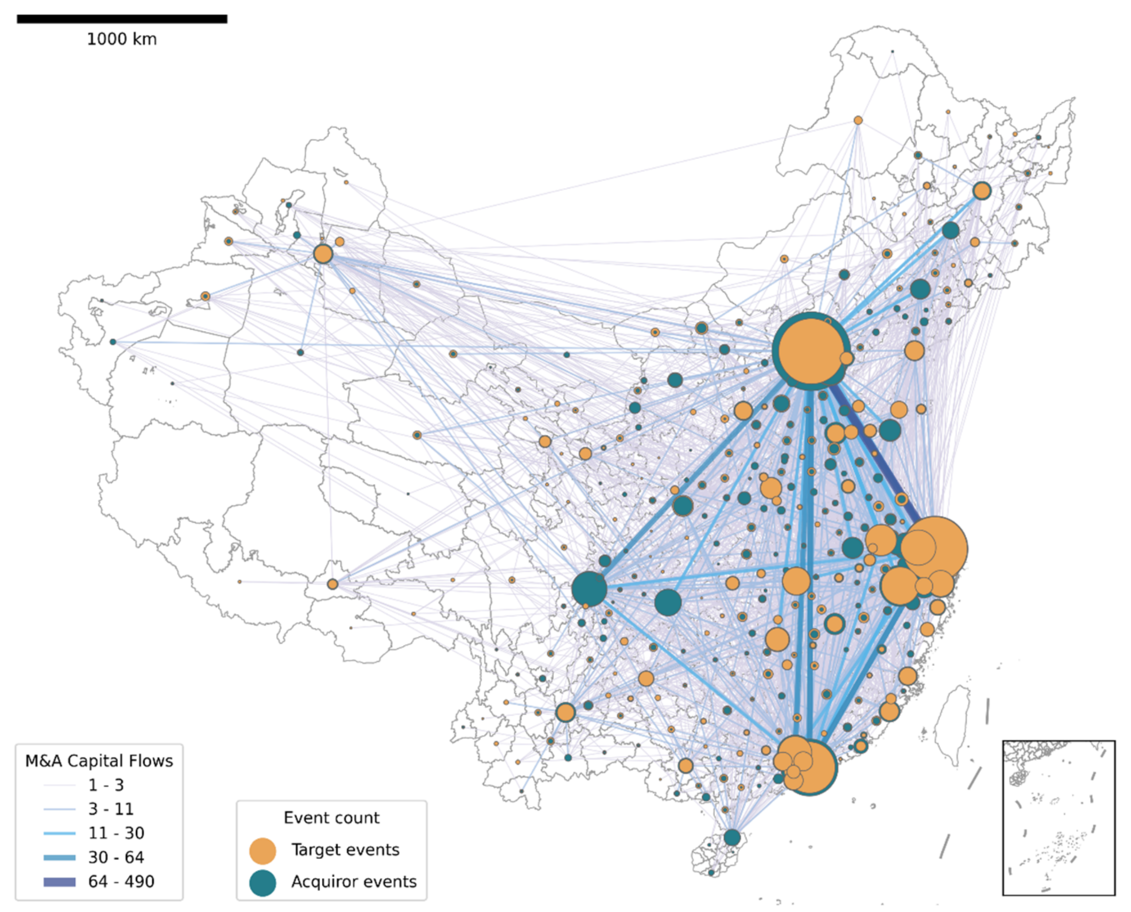

Figure 3. Geographic distribution of M&A capital flows (2004–2018).

(2004–2018), highlighting capital flow intensity and acquirer/target density across cities.

Closeness centrality in the M&A network measures how centrally located a city is based on the shortest path lengths to all other cities through M&A connections, rather than geographical distance. It quantifies how easily a city can reach all other cities in the network through these M&A connections. In our directed network, an edge from city i to city j exists if city i has acquired companies in city j. Its calculation is as follows:

$$\text{Closeness Centrality}_i = \frac{n-1}{\sum_{k\neq i} d_{ik}}$$

where n is the number of cities in the network, and d_{ik} is the length of the shortest directed path from city i to city k. A direct acquisition represents a path of length 1, while indirect connections through intermediary cities have longer path lengths. A higher closeness centrality value indicates that a city is more central in the M&A transaction network, implying shorter M&A chains to reach other cities regarding M&A. By evaluating the closeness centrality of cities based on the M&A network structure, we can determine their strategic importance in the network and explore potential correlations with carbon emissions.

3.2.3. Control variables

We account for key socioeconomic and technological factors: population size (Pop), economic wealth measured by gross domestic product (GDP), technological capability captured through innovation patents (Patents), industrial structure upgrading represented by the ratio of secondary and tertiary industries (Industries), government economic intervention intensity measured by the ratio of fiscal expenditure to GDP (Fiscal), and employment levels (Employment). Log transformations are applied to population, GDP, patents, and employment variables to address scale differences and capture non-linear relationships.

3.3. Baseline model specification

We follow the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) framework to measure the impact of M&A on CO_2 emissions (Dietz & Rosa 1997; Dong, Dong, & Ren 2020):

$$I = \alpha P^b A^c T^d e$$

where i represents cities and t represents years. I stands for environmental impact, P for population size, A for economic output, and T for technological level. The coefficient α and parameters b, c, and d are calculated through modeling, with e being the error term. The original equation can also be expressed using logarithms:

$$\ln I = \ln\alpha + b(\ln P) + c(\ln A) + d(\ln T) + \ln e$$

where b, c, and d represent the percentage change induced by a 1% increase while all other factors remain constant. In the STIRPAT model, other factors related to carbon emissions can be added. Therefore, we expand the model as:

$$\begin{aligned}\ln\mathrm{CO}_2 = \alpha + \beta M\&A + \beta\ln(Pop) + \beta\ln(GDP)\\ + \beta\ln(Patents) + \beta Industries + \beta Fiscal\\ + \beta\ln(Employment) + \varepsilon_{it}\end{aligned}$$

where β is the main parameter estimation. $\ln\mathrm{CO}_2$ is carbon dioxide emissions. *M&A* is the closeness centrality of manufacturing M&A data. $\ln(Pop)$ is the population given as its logarithm. $\ln(GDP)$ indicates the level of wealth, expressed as the GDP logarithm. $\ln(patents)$ is the technological level measured by the logarithm of innovation patents. *Industries* represents the ratio of secondary and tertiary industries, quantifying the upgrading of the industrial structure. *Fiscal* is the ratio of fiscal expenditure to GDP, representing the intensity of government economic intervention. To examine the potential non-linear relationship between M&A network centrality and carbon emissions, we further extend the model to include a quadratic term:

$$\begin{aligned}\ln(\mathrm{CO}_2)_{it} = \alpha + \beta_1 M\&A_{it} + \beta_2 M\&A_{it}^2 + \beta_3\ln(Pop)_{it}\\ + \beta_4\ln(GDP)_{it} + \beta_5\ln(Patents)_{it}\\ + \beta_6 Industries_{it} + \beta_7 Fiscal_{it}\\ + \beta_8\ln(Employment)_{it} + \varepsilon_{it}\end{aligned}$$

where ${M\&A_{it}}^2$ is the squared term of closeness centrality. The inclusion of this quadratic term allows us to test for an inverted U-shaped relationship between *M&A* network centrality and carbon emissions. A positive β_1 and negative β_2 would suggest that cities with moderate centrality in the M&A network experience higher emissions due to increased economic activity. In contrast, highly central cities may benefit from technology spillovers and efficiency gains that reduce emissions. This non-linear specification captures the dual nature of M&A network effects: the scale effect, which increases emissions through economic expansion, and the technology effect, which reduces emissions through technology diffusion and resource optimization.

3.4. Instrumental variable

To address potential endogeneity in assessing the impact of M&A on carbon emissions, this study employs an instrumental variable based on the locations of Chinese Apple suppliers (2013–2018), identified using Amap's geocoding service. The rationale lies in Apple's supply chain dynamics: suppliers must rapidly expand their capacity, optimize production, and enhance research and development to meet Apple's high standards. This drives improvements in management and coordination, potentially increasing local M&A activity. However, supplier entry is unlikely to directly affect local emissions, as the influence operates through corporate restructuring rather than immediate production changes. Thus, the presence of Apple suppliers serves as a valid instrument—theoretically linked to M&A but exogenous to carbon emissions—that meets the key conditions for instrumental variable analysis.

We implement a two-stage least squares approach with the following specification:

$$\begin{aligned}\text{First stage}: M\&A_{it} = \pi_0 + \pi_1 AppleSupplier_{it}\\ + \pi_2\ln(Pop)_{it} + \pi_3\ln(GDP)_{it}\\ + \pi_4\ln(Patents)_{it} + \pi_5 Industries_{it}\\ + \pi_6 Fiscal_{it} + \pi_7\ln(Employment)_{it} + \nu_{it}\end{aligned}$$

$$\begin{aligned}\text{Second stage}: \ln(\mathrm{CO}_2)_{it} = \alpha + \beta_1\widehat{M\&A_{it}}\\ + \beta_2\ln(Pop)_{it}] + \beta_3\ln(GDP)_{it} + \beta_4\ln(Patents)_{it}\\ + \beta_5 Industries_{it} + \beta_6 Fiscal_{it}\\ + \beta_7\ln(Employment)_{it} + \in_{it}\end{aligned}$$

where *AppleSupplier* is our instrumental variable indicating the presence or number of Apple suppliers, and $\widehat{M\&A_{it}}$ represents the predicted values of M&A closeness centrality from the first-stage regression. The validity of our instrument relies on two conditions: relevance (the presence of Apple suppliers significantly predicts M&A activity) and exclusion restriction (Apple suppliers affect carbon emissions only through their impact on M&A networks). To formally test instrument validity, we employ the Anderson canonical correlation LM test for underidentification (Anderson 1951), which tests whether the excluded instruments are correlated with the endogenous regressors, and the Cragg-Donald Wald F statistic for weak identification, comparing it against the Stock-Yogo critical values to ensure our instrument is not weak (Cragg and Donald 1993, Stock and Yogo 2002).

3.5. Unconditional quantile regression (UQR)

While OLS regression assumes uniform city-level effects, quantile regression (QR) provides a more nuanced analysis by assessing how M&A impacts carbon emissions across the entire distribution, from low- to high-emission cities. QR overcomes two key issues: OLS captures only average effects, and subgroup analysis can distort results due to uneven sample sizes (Lee and Li 2012). Additionally, QR does not rely on strict data assumptions, enhancing the robustness of our findings. Based on these advantages, we adopt the following model:

$$Q_\tau\left(\ln CO_{2it}\right) = c_\tau + \beta M\&A + \beta \ln\left(Pop\right) + \beta \ln\left(GDP\right) + \beta \ln\left(Patents\right) + \beta Industries + \beta Fiscal + \beta \ln\left(Employment\right) + \varepsilon_{it}$$

where $Q_\tau\left(\ln CO_2\right)$ is the τth quantile of the carbon emissions distribution. *M&A* is the city's M&A closeness centrality. ε is the error term. β is the main parameter estimation and represents the influence of each explanatory variable on the explained variable at different quantiles.

Conditional quantile regression (CQR) is often used to assess how variables affect different parts of a distribution; however, it conditions on other variables, which can distort the results by altering the outcome distribution. This means percentiles may vary across subgroups, making CQR less effective for studying population-wide effects. To address this, Firpo *et al* (2009) introduced UQR, which uses the recentered influence function to estimate effects without conditioning on covariates, preserving the original distribution. Following Firpo *et al* (2009), this study applies UQR to examine how M&A affects CO_2 emissions across the emissions distribution.

3.6. Robustness tests

3.6.1. Placebo test for instrumental variable

To validate the exogeneity of our Apple supplier instrumental variable, we conduct a placebo test by randomly generating 1000 pseudo-instrumental variables. For each iteration $k = 1, 2, \ldots, 1000$, we randomly shuffle the Apple supplier location data across cities and construct a pseudo-instrument using the shuffled data. We then estimate the following IV regression system:

$$\text{First:}\ \widehat{M\&A}_{it}^{(k)} = \pi_0 + \pi_1 Z_{it}^{(k)} + \pi_2 X_{it} + \nu_{it}$$

$$\text{Second: } \ln\left(CO_2\right)_{it} = \alpha + \beta_1^{(k)} \widehat{M\&A}_{it}^{(k)} + \gamma X_{it} + \varepsilon_{it}$$

where $Z_{it}^{(k)}$ is the kth randomly generated instrumental variable and $M\&A_{it}^{(k)}$ is the predicted M&A value from the first-stage regression. We compare the distribution of the 1000 estimated coefficients $\left\{\beta_1^{(1)}, \beta_1^{(2)}, \ldots, \beta_1^{(1000)}\right\}$ with our actual IV estimate β_1^{IV}. If our instrument is valid, the actual estimate should lie in the extreme tail of the placebo distribution, indicating that the relationship between Apple suppliers and M&A activity is not due to random chance. The visualization of this distribution provides a clear assessment of our instrument's validity relative to randomly assigned alternatives.

3.6.2. Oster test for omitted variable bias

Following Oster (2019), we assess the robustness of our results to potential omitted variable bias by evaluating how much selection on unobservables would be needed to nullify our results, relative to selection on observables. The key parameter is calculated as:

$$\beta^* = \beta^F - \delta \frac{\left(R_{\max} - R^F\right)}{\left(R^F - R^R\right)} \left(\beta^R - \beta^F\right)$$

where β^F is the coefficient from the full model with all controls, β^R is the coefficient from the restricted model with fewer controls, R^F and R^R are the R-squared values from the full and restricted models respectively, $R_{\max}$ is the theoretical maximum R-squared (typically set at $1.3 \times R^F$), and δ represents the degree of selection on unobservables relative to observables. We calculate the value of δ that would make $\beta^* = 0$. If the absolute value of δ exceeds 1, it suggests that selection on unobservables would need to be stronger than selection on observables to eliminate our findings, indicating robustness. The visualization of how the estimated coefficient changes across different values of δ and $R_{\max}$ provides insights into the sensitivity of our results to potential omitted variables.

3.6.3. Dynamic effects with lagged M&A variables

To examine the temporal dynamics of M&A network effects on carbon emissions and address potential reverse causality concerns, we estimate models incorporating lagged M&A variables:

$$\ln\left(CO_2\right)_{it} = \alpha + \beta_j M\&A_{i,t-j} + \gamma X_{it} + \mu_i + \varepsilon_{it}$$

where $j \in \{1,2,3\}$ represents the lag period, $M\&A_{i,t-j}$ is the j-period lag of the closeness centrality measure, X_{it} is the vector of control variables, and μ_i captures city fixed effects. We estimate this model separately for each lag period to examine how the impact of M&A network position on emissions evolves. If M&A network centrality affects emissions with a delay, we expect significant coefficients on the lagged terms. The pattern of coefficients $\{\beta_1, \beta_2, \beta_3\}$ across different lag periods reveals whether M&A effects are immediate, persistent, or cumulative over time.

3.7. Descriptive statistics

Table 1 presents descriptive statistics for the variables used in this study. The data has been sourced from comprehensive and authoritative databases, including the *China Economic and Industry Database* (CEIC) and the Yearly *China City Statistical Yearbooks*.

Table 1. Descriptive statistics of the variables employed in this study.

Variable	Obs	Mean	Std. Dev.	Min	Max
ln(CO_2)	4260	14.047 72	0.686 901	11.7798	15.853 21
M&A	4260	0.156 4858	0.056 0361	0.769 231	0.353 75
ln(*pop*)	4260	5.868 571	0.689 762	2.876 949	8.133
ln(*GDP*)	4260	16.0917	1.057 906	12.789 89	19.604 85
Fiscal	4260	0.159 74	0.099 535	0.026 598	1.936 381
ln(*patents*)	4260	3.973 501	1.937 981	0	10.757 67
Industries	3971	85.972 92	8.898 864	38.51	99.97
Employment	4256	52.920 58	13.142 99	9.91	94.82

Table 2. Baseline regression results.

Variables	Model 1	Model 2
M&A	-0.470^{***}	0.477^{**}
	(0.041)	(0.213)
M&A2		-2.699^{***}
		(0.594)
ln(*pop*)	-0.121^{***}	-0.112^{***}
	(0.030)	(0.030)
ln(*GDP*)	0.208^{***}	0.212^{***}
	(0.007)	(0.007)
Fiscal	0.384^{***}	0.373^{***}
	(0.033)	(0.033)
ln(*patents*)	-0.013^{***}	-0.011^{***}
	(0.003)	(0.003)
Industries	0.001^{**}	0.001^{*}
	(0.001)	(0.001)
Employment	0.003^{***}	0.003^{***}
	(0.000)	(0.000)
Constant	11.211^{***}	11.030^{***}
	(0.181)	(0.185)
VIF	3.19	—
Observations	3970	3970
Number of cities	284	284
Adjusted R-squared	0.493	0.496
Hausman test	142.55^{***}	136.30^{***}
City FE	Yes	Yes

Notes: Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4. Results

4.1. Baseline model

Table 2 presents baseline regression results on the relationship between M&A network centrality and urban carbon emissions. In Model 1 (linear specification), the M&A closeness centrality coefficient is -0.470 ($p < 0.01$), indicating a significant negative association. Model 2 adds a quadratic term to test for nonlinear effects, revealing a positive linear coefficient (0.477, $p < 0.05$) and a negative quadratic coefficient (-2.699, $p < 0.01$), supporting an inverted U-shaped relationship. The mean VIF of 3.19 rules out multicollinearity, and significant Hausman test results (142.55 and 136.30, both at 1%) justify using fixed effects. The adjusted R^2 increases slightly from 0.493 to 0.496 with the inclusion of the quadratic term, indicating an improved model fit.

Figure 4 illustrates the inverted U-shape, with a turning point at a centrality value of 0.0884, below the sample mean of 0.156. This implies most cities have passed the threshold where increased centrality reduces emissions. Below the threshold, growing network integration raises emissions due to expanded activity; beyond it, deeper integration reduces emissions, likely through technology spillovers and efficiency gains. The divergence between the quadratic (solid) and linear (dashed) models, especially at high centrality levels, highlights the importance of capturing nonlinear effects.

4.2. Instrumental variable validation

Table 3 presents instrumental variable regression results, utilizing manufacturing M&A network closeness centrality as the primary explanatory variable. In the first stage, the number of Apple suppliers (instrumental variable) is significantly and negatively associated with M&A network centrality (coefficient = -0.001, $p < 0.01$). The strong correlation is supported by a first-stage F-statistic that exceeds the 1% threshold, validating the instrument's relevance. This aligns with spatial economic logic: while dense Apple supplier networks promote resource integration through M&A, their strict environmental standards may reduce centrality. The instrument is exogenous, as Apple's supplier locations are unrelated to specific city-level carbon trajectories, but influence emissions indirectly through M&A-induced spillovers.

In the second stage, both the Anderson likelihood ratio (18.295, $p < 0.01$) and Cragg-Donald test ($F = 18.352$) confirm identification strength and instrument validity. Controlling for population, economic growth, urban shrinkage, and innovation, the results indicate that a one-unit increase in M&A network centrality is associated with a 2.337-unit reduction in urban carbon emissions ($p < 0.01$). This suggests a negative causal effect, indicating that integration into M&A networks enables the adoption of green technology, environmental knowledge sharing, and the substitution of carbon-intensive assets—collectively reducing regional carbon intensity.

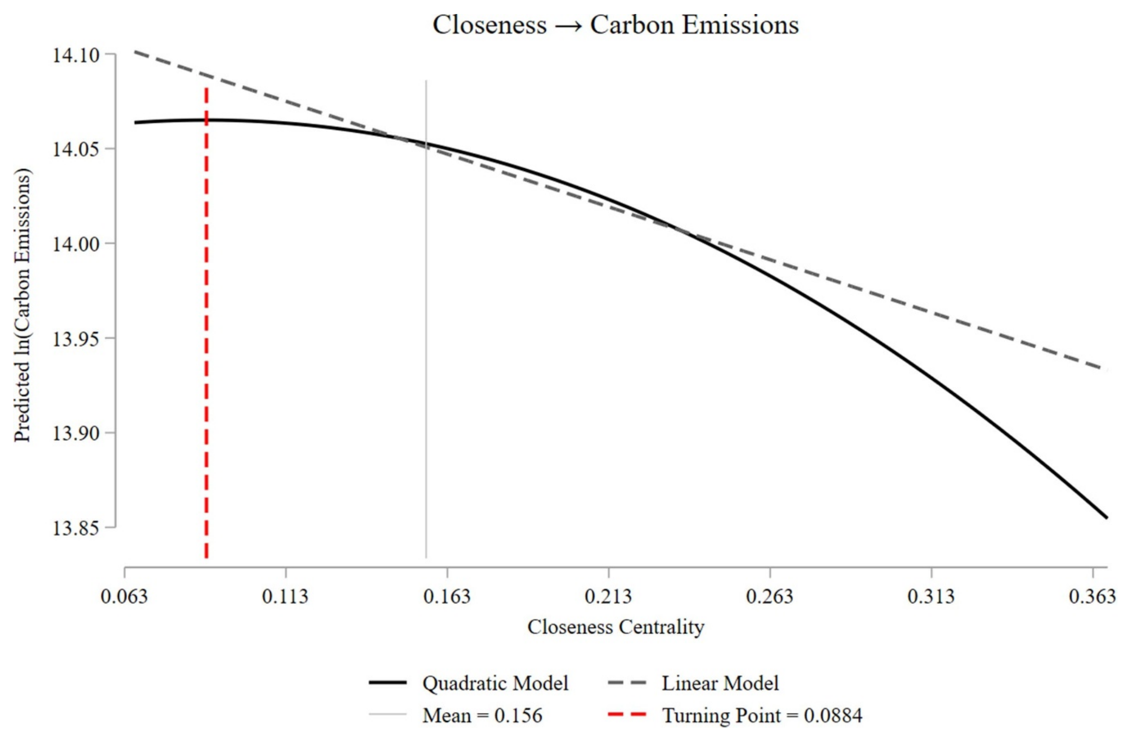

Figure 4. Non-linear relationship between M&A network centrality and carbon emissions.

Table 3. Instrumental variable results.

Variables	IV first stage	IV second stage
M&A		-2.337^{***}
		(0.735)
Apple	-0.001^{***}	
	(0.000)	
ln(*pop*)	-0.028^{**}	-0.064
	(0.012)	(0.044)
ln(*GDP*)	0.001	0.211^{***}
	(0.003)	(0.009)
Fiscal	0.013	0.411^{***}
	(0.013)	(0.043)
ln(*patents*)	0.021^{***}	0.028^{*}
	(0.001)	(0.017)
Industries	-0.000	0.001
	(0.000)	(0.001)
Employment	0.000^{***}	0.004^{***}
	(0.000)	(0.001)
Underidentification test		18.295^{***}
Weak identification test		18.352^{***}
Observations	3899	3899
Number of cities	279	279

Notes: Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.3. UQR results

Table 4 presents UQR results across the 10th, 25th, 50th, 75th, and 90th percentiles of CO_2 emissions, with all models showing strong explanatory power ($R^2 > 0.80$). UQR allows us to assess how the impact of manufacturing M&A closeness centrality varies across cities with different emission levels. We find a significant negative relationship between M&A centrality and CO_2 emissions at the 10th and 25th quantiles, but not at higher quantiles, indicating that M&A-driven emission reductions are more pronounced in lower-emitting cities.

Other emission drivers also vary across the distribution. Population growth is negatively associated with emissions only in the lowest-emitting cities, possibly reflecting efficiency gains. GDP shows a consistent positive relationship at lower quantiles, suggesting emissions may increase with economic growth. Fiscal expenditure raises emissions at the 10th quantile, indicating potential misalignment with low-carbon goals. Innovation, industrial concentration, and employment have limited influence at lower quantiles.

These findings underscore the need for differentiated policy approaches. In lower-emission cities, M&A integration may support carbon reduction, while in high-emission areas, broader structural changes are likely needed. Figure 5 illustrates that the negative impact of M&A on emissions diminishes at higher quantiles, reinforcing that M&A-related emission benefits are concentrated in cities with smaller carbon footprints.

4.4. Robustness test results

4.4.1. Placebo test for instrumental variable

Table 5 presents the results of a robust placebo test validating the Apple supplier instrument. By generating 1000 random pseudo-instruments and comparing

Table 4. UQR estimation results for M&A closeness centrality on CO_2 emissions.

Variables	10th quantile	25th quantile	50th quantile	75th quantile	90th quantile
M&A	-1.225^{***}	-1.120^{***}	−0.158	0.400	−0.166
	(0.339)	(0.322)	(0.250)	(0.246)	(0.287)
ln(*Pop*)	−0.311	0.035	−0.009	−0.109	-0.595^{**}
	(0.199)	(0.276)	(0.205)	(0.177)	(0.284)
ln(*GDP*)	0.372^{**}	0.116	0.168^{**}	0.218^{**}	0.315^{*}
	(0.153)	(0.120)	(0.083)	(0.106)	(0.180)
Fiscal	2.139^{**}	0.462	0.249^{*}	0.137	−0.071
	(0.873)	(0.416)	(0.144)	(0.170)	(0.143)
ln(*patents*)	0.008	0.001	0.025	−0.031	-0.041^{*}
	(0.035)	(0.030)	(0.021)	(0.027)	(0.024)
Industries	0.012	0.014^{*}	0.001	-0.014^{**}	−0.014
	(0.009)	(0.007)	(0.005)	(0.006)	(0.009)
Employment	0.003	0.009^{***}	−0.001	−0.003	0.005
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
Constant	7.581^{***}	9.950^{***}	11.290^{***}	13.017^{***}	14.477^{***}
	(2.263)	(2.233)	(1.900)	(1.806)	(2.745)
Observations	3969	3969	3969	3969	3969
R-squared	0.806	0.829	0.888	0.863	0.859

Notes: Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

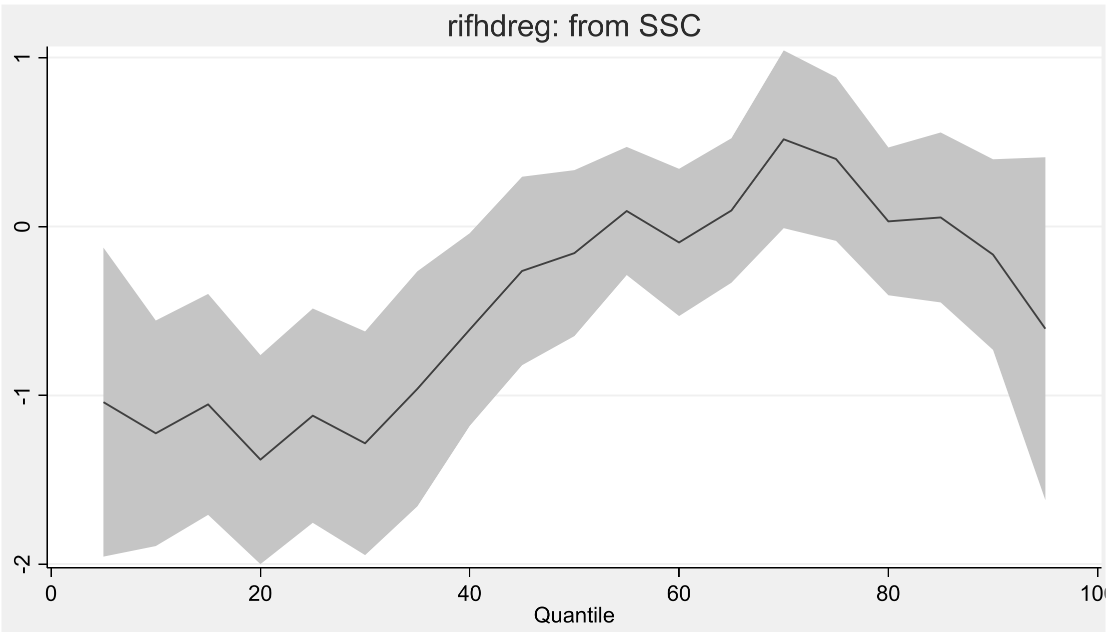

Figure 5. Variation of coefficients for carbon emissions by the target at different quantile levels. The area in dark gray indicates the confidence interval.

their diagnostics with the true instrument, the test confirms the instrument's validity. The Apple supplier instrument yields an Anderson LM statistic of 18.298 ($p < 0.0001$), while random instruments average only 0.959, with 95.5% failing the identification test ($p > 0.05$).

Weak identification results further support this. The Cragg-Donald F statistic for the true instrument is 18.355, exceeding the Stock-Yogo 10% threshold of 16.38. No random instrument meets this benchmark; fewer than 2% surpass even the 25% threshold. The placebo p-value of 0.001 shows the true instrument lies in the extreme tail of the distribution, confirming that its strength is not due to chance but reflects real economic linkages.

Figure 6 visually supports these findings. Kernel density plots show random instruments clustered near zero, while the true instrument's statistics stand out clearly in the right tail, with no overlap—demonstrating statistical distinctiveness. Together, these results confirm that the Apple supplier instrument meets both relevance and exclusion restriction criteria for valid instrumental variable estimation.

Table 5. Placebo test for instrumental variable validity: Apple suppliers vs. random instruments.

Test statistics	True IV (Apple suppliers)	Random IVs (1000 replications)	Interpretation
Underidentification test			
Anderson LM statistics	18.298	Mean: 0.959 (Max: 12.479)	True IV strongly identified
Anderson LM p-value	$p < 0.0001$	95.5% have $p > 0.05$	True IV passes the identification test
Weak identification test			
Cragg-Donald Wald F	18.355	Mean: 0.958 (Max: 12.498)	True IV is not weak
Exceeds 10% SY critical value (16.38)	Yes	0.00%	True IV passes the strictest criterion
Exceeds 15% SY critical value (8.96)	Yes	0.20%	
Exceeds 20% SY critical value (6.66)	Yes	0.90%	
Exceeds 25% SY critical value (5.53)	Yes	1.90%	
Overall performance			
Identified ($p < 0.05$)	Yes	4.50%	True IV strongly outperforms
Placebo p-value	—	0.001	True IV in extreme tail

Notes: IV = instrumental variable; SY = Stock-Yogo. The placebo test randomly generates 1000 pseudo-instruments with similar distributional properties to the Apple supplier variable. The placebo p-value represents the proportion of random instruments that perform as well as or better than the true instrument.

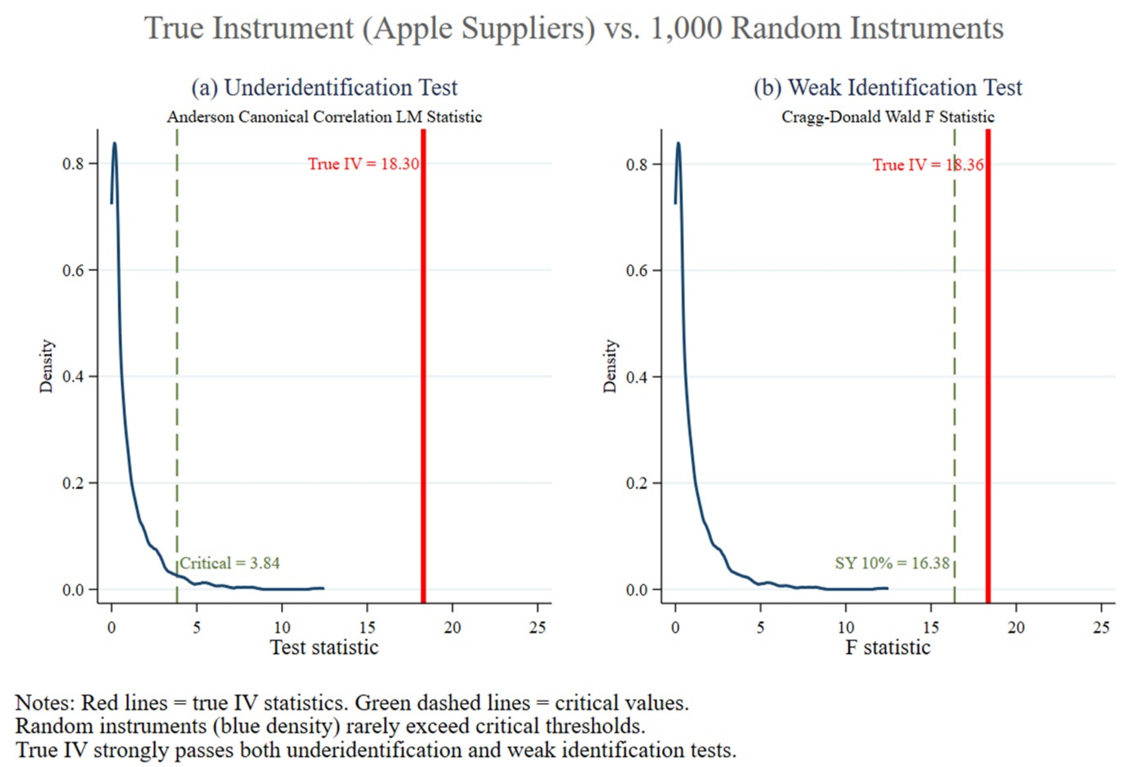

Figure 6. Placebo test for instrumental variable validity: diagnostic statistics distribution.

4.4.2. Oster test for omitted variable bias

Table 6 presents Oster (2019) Test results assessing the robustness of the negative relationship between M&A network centrality and carbon emissions to omitted variable bias. The uncontrolled model yields a positive coefficient of 0.609 ($R^2 = 0.049$), while the full model shows a significant negative coefficient of −0.470 ($R^2 = 0.530$). The estimated selection parameter $\delta = -1.12$ would be required to nullify the effect, assuming Rmax = 0.689 (1.3 × controlled R^2). Across all positive δ values, adjusted coefficients remain negative, ranging from −0.722 ($\delta = 0.5$) to −1.742 ($\delta = 2.0$).

Figure 7 illustrates this relationship: the coefficient becomes increasingly negative as δ rises from −2 to 2, crossing zero only at $\delta = -1.12$, implying that

Table 6. Oster robustness test results.

Specification	Value	Interpretation
Uncontrolled model		
Coefficient	0.609***	Positive correlation
R^2	0.049	Low explanatory power
Controlled model		
Coefficient	−0.470***	Negative effect
R^2	0.530	Substantial explanatory power
Oster test parameters		
Rmax	0.689	$1.3 \times R^2$ (controlled)
δ for $\beta = 0$	−1.12	Selection required for zero effect
Adjusted coefficients		
$\delta = 0.5$	−0.722	Moderate positive selection
$\delta = 1.0$	−1.008	Equal selection
$\delta = 2.0$	−1.742	Strong positive selection

*** $p < 0.01$.

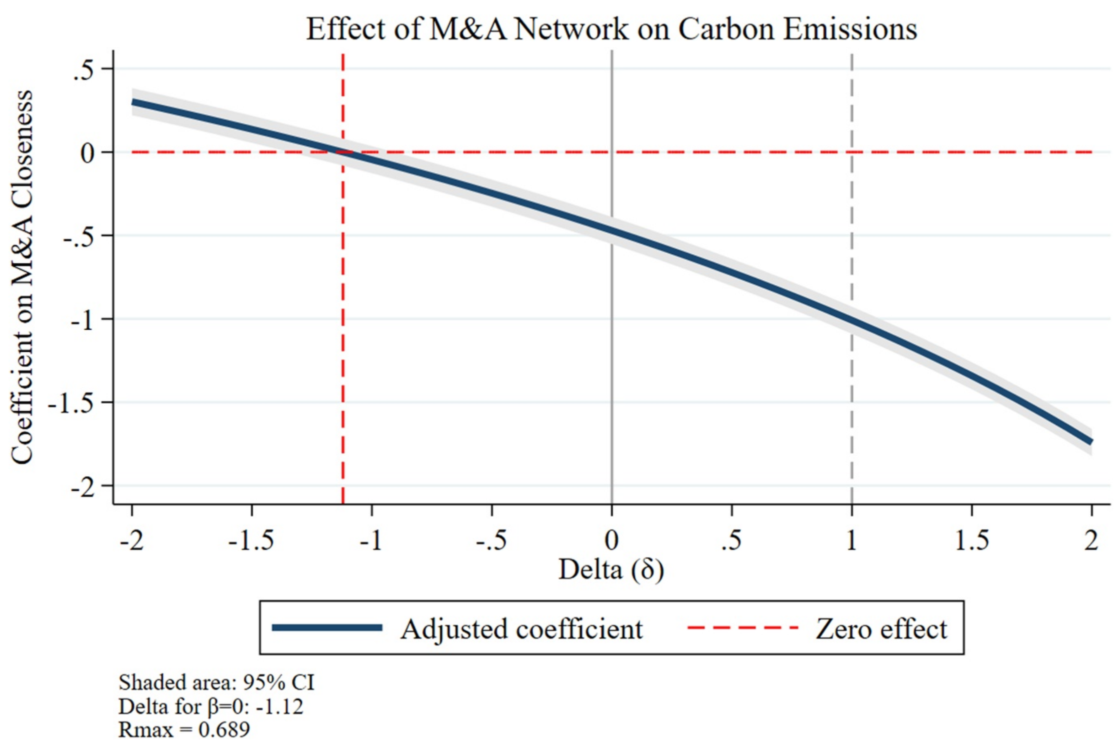

Figure 7. Oster test for selection on unobservables: coefficient stability under alternative selection assumptions.

unobserved factors would have to be negatively correlated with observables to eliminate the effect. The 95% confidence interval excludes zero for $\delta > -0.5$, and even equal selection ($\delta = 1$) yields a more substantial effect (−1.008). These results confirm that the negative impact of M&A network centrality on emissions is robust to omitted variable concerns.

4.4.3. Dynamic effects with lagged M&A variables

Table 7 explores the temporal dynamics of M&A network centrality on carbon emissions using lagged models, controlling for city fixed effects and time-varying covariates. Due to panel structure constraints, the number of observations declines with additional lags. Results show a significant and persistent negative effect of M&A centrality on emissions. The contemporaneous effect ($\beta = -0.471$, $p < 0.01$) and one-period lag ($\beta = -0.467$, $p < 0.01$) are nearly identical, indicating an immediate and stable short-term impact. The effect gradually weakens over time, with coefficients declining to −0.327 ($t - 2$, $p < 0.01$) and −0.247 ($t - 3$, $p < 0.01$), suggesting attenuation but continued influence over multiple periods.

5. Discussion

This study examines the impact of ownership transfers in manufacturing on urban carbon performance. Results reveal a non-linear, inverted U-shaped

Table 7. Dynamic effects with lagged M&A variables.

Variables	Current (t)	Lag 1 ($t-1$)	Lag 2 ($t-2$)	Lag 3 ($t-3$)
M&A	-0.4705^{***} (0.0414)			
M&A ($t-1$)		-0.4673^{***} (0.0414)		
M&A ($t-2$)			-0.3271^{***} (0.0459)	
M&A ($t-3$)				-0.2475^{***} (0.0540)
Constant	11.2110^{***} (0.1806)	11.4171^{***} (0.1973)	11.9010^{***} (0.2259)	12.1873^{***} (0.2371)
Control variables	Yes	Yes	Yes	Yes
Observations	3970	3687	3405	3121
R-squared	0.5302	0.4833	0.4079	0.3337
City FE	Yes	Yes	Yes	Yes
Number of cities	284	284	284	284

Notes: Standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

relationship between M&A network centrality and emissions: early integration raises emissions, while deeper integration reduces them. Instrumental variable analysis confirms a causal negative effect, supporting prior findings that M&A facilitates technology transfer and cleaner processes (Contractor *et al* 2014, Stettner and Lavie 2014, Zhu and Zhu 2016).

UQR highlights heterogeneity, as emission reductions are concentrated in low-emission cities, while high-emission cities experience limited effects, consistent with the influence of institutional and development differences (Yang *et al* 2015, Liu *et al* 2016). The emission-reducing impact of M&A emerges quickly and remains stable in the short term, though it attenuates over time, echoing firm responses to green market signals (Chen and Xie 2022, Shi *et al* 2022a, Zhang *et al* 2024).

Policy implications vary by city type. Most cities in the sample already benefit from network integration, making M&A a cost-effective complement to traditional environmental policy. Geographic proximity enhances the diffusion of technology and management spillovers (DeLong 2001, Pirinsky and Wang 2006, Kalnins and Lafontaine 2013, Han *et al* 2022b), suggesting that targeted support for green M&A could amplify its benefits, especially for early environmental adopters. In contrast, high-emission cities require stronger interventions, as M&A alone is insufficient in the face of weak institutional settings (Vaaler and Schrage 2009, Van Essen *et al* 2012, Yang *et al* 2015). These cities require stricter regulations, enhanced enforcement, and increased public investment in clean technology. The role of local context is crucial, as spatial and institutional characteristics shape M&A's environmental impact (Böckerman and Lehto 2006, Chakrabarti and Mitchell 2013, McCarthy and Dolfsma 2015, Wu *et al* 2020).

Overall, while M&A can drive emissions reductions, its success depends on local conditions, particularly emission levels and existing network integration, highlighting that market-driven restructuring is not a one-size-fits-all solution.

6. Conclusions

This study identifies an inverted U-shaped relationship between manufacturing M&A network centrality and urban carbon emissions: initial integration raises emissions, but beyond a threshold, deeper network ties reduce environmental impact through knowledge spillovers and technology transfer (Zademach and Rodríguez-Pose 2009, Sun *et al* 2012, Dong *et al* 2019, Wu *et al* 2020). Most cities in the sample have surpassed this turning point, positioning them to benefit from further development of their M&A networks.

M&A's emission-reducing effects are uneven across cities. Low-emission cities benefit significantly, while high-emission cities show little to no response, aligning with literature on information asymmetry in M&A outcomes (Coval and Moskowitz 2001, Moeller *et al* 2007, Ragozzino 2009, Bick *et al* 2017). This suggests that cities with stronger baseline conditions are better positioned to leverage M&A for cleaner technologies.

These findings underscore the need for context-sensitive environmental policy. M&A is not a one-size-fits-all solution. Low- and mid-emission cities may benefit from facilitating M&A through regional coordination and infrastructure support (Dennis Wei *et al* 2008, He and Chen 2022, Wu *et al* 2022, Huang *et al* 2023). In contrast, high-emission cities require stronger interventions, including targeted regulations and public investment.

The study has several limitations: (1) it omits post-2020 factors like remote work; (2) it focuses on macro-level outcomes, lacking firm-level process data; (3) its 1 km $\times$ 1 km emission resolution limits facility-level insights; (4) it includes few failed

M&A cases, hindering analysis of unsuccessful integrations; and (5) it cannot empirically test certain mechanisms in the conceptual framework, such as regulatory enforcement or funding impacts. Future research should address these gaps by incorporating enterprise-level data, higher-resolution emissions, and examining geographic barriers to information flows (Kang and Kim 2008, Di Guardo *et al* 2016, Han *et al* 2022a). Studying failed M&A using alternative designs (e.g., difference-in-differences) could also reveal the risks of carbon leakage and resource misallocation. Such insights would help craft more effective, locally tailored policies for green industrial restructuring.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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Author contributions

Will W Qiang 0000-0002-3633-872X
Conceptualization (equal), Data curation (equal), Formal analysis (equal), Investigation (equal), Methodology (equal), Validation (equal), Visualization (equal), Writing – original draft (equal), Writing – review & editing (equal)

Tianzuo Wen 0000-0002-3163-8686
Formal analysis (equal), Investigation (equal), Validation (equal), Writing – original draft (equal), Writing – review & editing (equal)

Haowen Luo 0000-0003-4760-5958
Formal analysis (equal), Investigation (equal), Validation (equal), Writing – original draft (equal), Writing – review & editing (equal)

Yuxuan Xiao 0000-0002-2981-197X
Formal analysis (equal), Investigation (equal), Writing – original draft (equal), Writing – review & editing (equal)

Bo Huang 0000-0002-5063-3522
Formal analysis (equal), Investigation (equal), Validation (equal), Writing – original draft (equal), Writing – review & editing (equal)

Steve H L Yim 0000-0002-2826-0950
Formal analysis (equal), Investigation (equal), Validation (equal), Writing – original draft (equal), Writing – review & editing (equal)

Shuai Shi 0000-0001-6041-8191
Conceptualization (equal), Data curation (equal), Formal analysis (equal), Investigation (equal), Methodology (equal), Project administration (equal), Supervision (equal), Validation (equal), Writing – original draft (equal), Writing – review & editing (equal)

Harry F Lee 0000-0001-5415-7845
Conceptualization (equal), Data curation (equal), Formal analysis (equal), Funding acquisition (equal), Investigation (equal), Methodology (equal), Project administration (equal), Resources (equal), Software (equal), Supervision (equal), Validation (equal), Visualization (equal), Writing – original draft (equal), Writing – review & editing (equal)

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