Is the Sustainability of External Environment Priced in Commercial Real Estate?

By:

Hainan Sheng
Pamplin College of Business
Virginia Tech
Blacksburg, VA 24061
Email: hsheng@vt.edu

Abstract

This paper examines whether a sustainable external environment is priced into commercial real estate (CRE) by assessing properties' exposure to the carbon dioxide from local car emissions, making it among the first to explore how sustainable external environment impacts future CRE returns. Using a comprehensive dataset of US CRE properties over the period from 2002 to 2019, I find that properties situated in lower car emission areas yield an average of 1.5% higher annual returns compared to those in higher emission areas. These results hold even after accounting for property attributes, local economic conditions, environmental policies, public transportation usage, and potential endogeneity concerns. Furthermore, I explore the mechanisms through which car emissions impact CRE performance and find that high levels of greenhouse gas emissions primarily shape CRE performance by adversely influencing the future price appreciation of properties. Overall, this study helps bridge the gap in sustainable real estate literature by highlighting how CRE investors consider external environmental transition risks in their investment decisions.

JEL Codes: R33, Q54, Q51, G11, G12
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1. Introduction

In recent years, the environmental impact of human activities has come under increasing scrutiny, particularly in the context of climate change (e.g., Rothacker et al. (2018), Cao et al. (2021), Gulis et al. (2022), Abrahms et al. (2023), and Ramadorai and Zeni (2024)). One of the primary culprits behind the rising levels of atmospheric carbon dioxide (CO_2) is human-made emissions (e.g., Solomon et al. (2009), Hansen et al. (2013), and Yoro and Daramola (2020)). Amidst these environmental concerns, a large stream of real estate research focuses not only on how green buildings could impact real estate firm and property performance but also on understanding the impact of getting environmental certification on real estate values (e.g., Kok, McGraw and Quigley (2011); Holtermans and Kok (2019); Devine, Sanderford and Wang (2022)). Yet, few studies have explored whether and how a sustainable external environment might also influence their performance.[1] While buildings, particularly commercial structures, are often highlighted as significant contributors to greenhouse gas emissions due to their energy consumption patterns (An and Pivo (2020)), it is equally essential to acknowledge the substantial role of transportation in these human-made emissions. In U.S., the largest source of emissions of carbon dioxide is the transportation sector, where motor vehicles accounted for 83% of CO_2 emissions from transportation in 2019 and 80% in year 2022.[2]

From the literature perspective, there is a growing scientific consensus attributing significant climate transition risks to greenhouse gas emissions.[3] Extensive research, as exemplified by studies such as those conducted by Nordhaus (2007), Weitzman (2007), and Stern (2008), strongly support the notion that

[1] Yang et al. (2023) study the impact of urban street-level greenery on the commercial office building prices in New York city. They measure street-level greenness through Google Street View images and find that offices with relative high street-level greenness enjoys a positive transaction and rent premium. In a similar vein, Cvijanović, Rolheiser and Van de Minne (2024) investigate the air pollution using changes in local wind direction and find that an increase in fine particulate matter exposure leads to a contemporaneous decrease in CRE market values.

[2] https://www.cbo.gov/publication/58861 ; https://nepis.epa.gov/Exe/ZyPDF.cgi?Dockey=P101AKR0.pdf; https://www.epa.gov/greenvehicles/fast-facts-transportation-greenhouse-gas-emissions

[3] Climate transition risk generally refers to financial and operational risks associated with the transition to a low-carbon economy (https://www.epa.gov/climateleadership/climate-risks-and-opportunities-defined#transition). These risks are forward-looking, arising from policy changes, market shifts, technological advancements, and changes in consumer preferences aimed at addressing climate change.

reducing individual carbon footprints can effectively mitigate the risk of substantial climate changes on Earth. This mitigation effort, in turn, could contribute to the creation of a more environmentally friendly living environment, underscoring the interconnectedness between individual actions aimed at reducing carbon footprints and the broader implications of green spaces on real estate property values. The findings presented in this paper strongly support this notion.

Generally, this paper finds that commercial real estate (CRE) properties located in more sustainable core-based statistical areas (CBSAs), where car CO_2 emissions per household are lower, tend to yield higher future property returns compared to properties in less sustainable CBSAs. This holds true even after accounting for property characteristics, local economic context, existing environmental policies, usage of public transportation in the area, and potential endogeneity concerns. Furthermore, this study delves further into the key findings and explores the mechanisms through which local car emissions impact future CRE performance. Overall, the findings imply that higher car CO_2 emissions could lead to more adverse environmental policies, posing external climate transition risks for commercial real estate investors.[4] Specifically, the study shows that the negative impact of a less sustainable external environment on CRE performance is most pronounced in states with a Democratic political leaning, where the Democratic Party tends to prioritize environmental issues more heavily than the Republican Party. Furthermore, I find that the exposure to such high levels of local car carbon dioxide emissions primarily affects commercial real estate performance by negatively influencing its future price appreciation. Conversely, no significant effects on future CRE operating income returns are observed, indicating that operating income is less susceptible

[4] It is important to recognize that CO_2 is not the only pollutant from transportation impacting the environment. Other pollutants, such as volatile organic compounds (VOCs) and particulate matter (PM), may also play a significant role in contributing to air pollution and environmental degradation (e.g., Gilman et al. (2013) and Maung et al. (2022). In this study, CO_2 serves as an instrument to capture the broader impact of car emissions on the commercial real estate (CRE) market, acknowledging that other pollutants may also influence real estate outcomes (e.g., Cvijanović, Rolheiser and Van de Minne (2024)). The study's goal is not to imply that CO_2 alone drives the observed effects but rather to capture the general emissions profile and its impact on CRE performance. While car CO_2 emissions serve as a key indicator in this study, the adverse impacts of car emissions are likely influenced by a combination of pollutants, not CO_2 alone. To ensure robustness, an additional test reported in Table 4 Panel E replicates the main results by incorporating local air quality as a control variable, and the findings remain consistent.

to the local negative environmental externalities stemming from greenhouse gas emissions.[5] These findings collectively suggest that CRE investors factor in external environmental transition risks when making real estate investments.[6] To ensure the robustness of these empirical results, various analyses are conducted. I assess the robustness of the findings by employing alternative econometric specifications, incorporating additional control variables, and utilizing a propensity score matching strategy. Notably, all of these testing approaches yield results that closely align with the central findings of the study.

This article contributes to literature in several areas. Firstly, the findings of this study contribute to an emerging body of literature that explores the ramifications of sustainability, climate change risk, and ESG factors on financial performance of asset investments. This study adds to the growing strand of research that underscores the interconnectedness between environmental sustainability and real estate asset performance. Additionally, this study makes a unique contribution by focusing on the pricing of external environmental transition risk in the CRE market, which is new in the literature. While previous research has explored the influence of environmental factors on housing prices (e.g., Crompton (2001), Crompton (2005), Ye et al. (2019), Lin, Jensen and Wachter (2022), and Kang et al. (2021)), the commercial real estate market's response to the sustainability of external environment has not been directly explored. This study bridges the gap by shedding light on how the CRE market prices external environmental transition risk, adding a new dimension to the literature.

According to Goetzmann, Spaenjers and Van Nieuwerburgh (2021), the U.S. CRE market was valued at $32.8 trillion as of the third quarter of 2020. Furthermore, Addoum et al. (2023) indicate that the majority of assets in the CRE market are held by public and private institutions, along with other professional

[5] Negative externalities usually refer to current unintended and uncompensated costs imposed on third parties or society at large due to economic activities (Encyclopedia Britannica). In the context of environmental issues, these often refer to health impacts, pollution, and degradation of natural resources caused by production and consumption activities.
[6] Throughout the paper, the terms, external climate transition risks' and 'external environmental transition risks, are used interchangeably.

investors. Thus, CRE investors are likely to be sophisticated entities equipped with the necessary skills and resources to assess and price investment risks. Nevertheless, prior research on the impact of greenery exposure on real estate prices has largely overlooked the CRE market, and the majority of the work has focused on the evidence of a relationship between green building practices and "green price premiums." (e.g., Eichholtz, Kok and Quigley (2010), Fuerst and McAllister (2011), Eichholtz, Kok and Quigley (2013), Deng and Wu (2014), Holtermans and Kok (2019), Brolinson, Palmer and Walls (2023) and Devine and Yönder (2023)). As such, this article contributes to the literature by introducing a new perspective to the existing body of work, providing insights into how the CRE market incorporates pricing for the sustainability of external environment.

Lastly, this study sheds light on the mechanisms through which external environmental transition risk affects CRE performance. In line with the findings, this paper demonstrates that high car emissions could lead to more adverse environmental policies and such high levels of greenhouse gas emissions primarily influences future CRE's price appreciation, reflecting higher risk premiums demanded by investors. These findings contribute to a deeper comprehension of the relationship between sustainable external environment and real estate market performance. Such insights are vital for investors seeking to navigate the complexities of environmental considerations in commercial real estate investment in an increasingly environmentally conscious global landscape (Hartzmark and Sussman (2019)).

2. Literature Review

In the existing literature, researchers consistently demonstrate that a green environment has a positive influence on the housing market. Spatial factors affect CRE financial outcomes (e.g., Cashman et al. (2019)), and numerous studies have shown that proximity to green spaces leads to a significant increase in residential property values. For example, Crompton (2001) and Crompton (2005) estimated that parks may yield a significantly positive impact on adjacent properties compared to the average price in the same area. Similarly, Morancho (2003) find that there is an inverse relationship between the selling price of the dwelling and its distance from a green area, while Turner and Seo (2021) show that both private and public forms of green space increase house prices. In line with this, Arvanitidis et al. (2009) demonstrate that a high-quality green environment enhances urban life quality, making cities more appealing to residents, employees, tourists, investors, and businesses. In more recent studies, Zhang and Dong (2018) and Ye et al. (2019) have demonstrated that the presence of visible street greenery and easy street accessibility have notably positive effects on housing prices in China. Additionally, Kang et al. (2021) also demonstrate that street view images are capable of capturing environmental factors that have a positive impact on house price appreciation rates in the United States. All these studies provide pertinent examples of how spatial factors affect financial outcomes.

While previous studies have explored the relationship between environmental factors and their impact on housing prices, there has been a notable absence of research examining the consequences of sustainability in the external environment on the commercial real estate. According to Addoum et al. (2023), the majority of assets within the CRE market are owned by public and private institutions, as well as other seasoned professional investors. As a result, it can be inferred that CRE investors possess the requisite expertise and resources to evaluate and price investment risks effectively. Nonetheless, prior research on the influence of greenery exposure on real estate prices has primarily neglected the CRE market, with most studies concentrating on the evidence of the relationship between green building practices and "green price premiums".

For example, Fuerst and McAllister (2011) investigate the price effects of environmental certification on commercial real estate assets and find that, compared to buildings in the same submarkets, eco-certified buildings have both a rental and sale price premium. This result finds support in Eichholtz, Kok and Quigley (2010) who analyze clusters of certified green and nearby buildings and identify that a direct positive link between increased energy efficiency and elevated selling prices. Brolinson, Palmer and Walls (2023) similarly find that while Energy Star certification increases building rents, utility expenditures remain unchanged, indicating that the certification identifies already energy-efficient buildings rather than prompting further energy-saving investments. This is further evidenced by Ghosh and Petrova (2023), who examine how green certification impacts cash flows and transaction prices in the Western European office markets, and find that properties with green certification enjoy a statistically significant green building premium. Building on this foundation, Eichholtz, Kok and Quigley (2013) further analyze the economics of green building, finding that increases in the supply of green buildings and the volatility in property markets have not affected the returns to green buildings. From a developer's vantage point, Deng and Wu (2014) shed light on the temporal dynamics of the "green price premium" in residential developments, revealing that it predominantly manifests during the resale phase. Extending the perspective to the certified commercial real estate, Holtermans and Kok (2019) examine the adoption and financial performance of certified commercial real estate, highlighting the market's efficiency in integrating environmental characteristics. Additionally, Devine and Yönder (2023) extend the discussion to real estate investment trusts (REITs), demonstrating that environmentally-sustainable portfolios enhance market valuation, with Cashman et al. (2024) highlighting that such value-relevant information can come from REIT annual reports for market participants. In a related vein, Devine, Sanderford and Wang (2022) underscores the predictive power of environmental, social, and governance (ESG) participation and performance on private equity real estate fund returns.

Shifting the focus to the real estate debt market, Eichholtz et al. (2019) and An and Pivo (2020) emphasize the efficient pricing of environmental risk in the real estate debt market and the favorable loan terms associated with green buildings in the commercial mortgage-backed securities (CMBS) market, respectively. Expanding the perspective to the hospitality industry, Zhang et al. (2020) investigate the value of going green in the hotel industry and find that green hotels enjoy a significant room rate premium of 6.5% without reducing occupancy rates. Finally, turning the attention to urban development, Lin, Jensen and Wachter (2022) examine the effects of greening vacant lots on nearby housing prices. Their findings reveal a substantial increase of approximately 4% in housing prices for homes within 1,000 feet of a green vacant lot. Collectively, this body of research highlights the economic benefits surrounding environmentally-conscious practices in the real estate market. In this study, the research addresses the gap in the literature concerning environmental externalities stemming from exposure to car carbon dioxide emissions in the commercial real estate market.

3. Theoretical Framework and Hypothesis Development

Theoretically, as proposed by Blomquist, Berger and Hoehn (1988), implicit markets capture compensation for intraurban and interregional differences in amenities, resulting in differences in housing prices and wages. Extending the spirit of compensating differential theory to professional investors implies that commercial real estate asset valuations would also factor in these variations by adjusting the net operating income through an appropriate capitalization rate. This rate would account for the inherent amenity differences associated with the investment. Holding all other factors constant, commercial properties exposed to greater negative environmental externality would necessitate higher capitalization rates to compensate investors.

On the other hand, drawing from the basic theory of spatial environmental externalities, if local CO_2 emissions don't offer a global warming-related rationale for government policies to show preference to one location over another and there's no policy-based incentive to address greenhouse gas emissions in different regions, the impacts of local car CO_2 emissions on commercial real estate performance might be disregarded, and professional investors would not demand a higher environmental transition risk premium.[7] Yet, in the real world, these conditions are likely not met. Using tax as a proxy for the impact of government policy on local environmental sustainability, the proof of proposition presented below demonstrates that a uniform

[7] While both local pollutants and greenhouse gas (GHG) emissions are part of the broader environmental externalities that may affect commercial real estate through mechanisms such as local regulations, investor preferences, and transition risks, I acknowledge that more research is necessary to examine how local pollutants and GHG emissions interact and their combined impact on local businesses.

tax policy on local car CO_2 emissions across regions is needed to prevent the implementation of additional adverse political policy in that area.[8]

To outline the interactions between location choice and environmental externalities, it is assumed that there is a fixed population of N identical households that must choose between I regions. These households choose their own counties and their level of car gas consumption "C". Household i maximize a quasi-liner utility function:

$$U_i = y_i - h_I^H - \left(h_i^C + t\right)C + V(C; a_i) + t\hat{C} - G(N\hat{C}), \tag{1}$$

Where y_i refers to income in region i. h_I^H and h_i^C are the housing costs and car gas consumption cost in region i. t refers to car emission tax which is initially independent of regions. $\hat{C}$ is the average global car gas consumption. $V(C; a_i)$ represents the region-specific benefits from car gas consumption, where a_i are the attributes of the region which households treat as exogenous.[9] $G(N\hat{C})$ reflects the costs of global car gas consumption associated with global warming (i.e., climate change).

To derive income and housing costs, it is assumed that each region has e_i identical employers whose revenues are concave with the number of people hired. Similarly, it is also assumed that each region has b_i

[8] In the current model, all vehicles are treated as emitting gasoline-related emissions, which does not fully capture the growing presence of electric vehicles (EVs) that have significantly lower greenhouse gas (GHG) emissions compared to internal combustion engine (ICE) vehicles. While extending the model to distinguish between vehicles with different emissions profiles—such as lower-emission EVs and higher-emission ICE vehicles—would offer a more nuanced representation of the market, this is beyond the scope of the present study. Given that EV adoption was relatively low during the study period, as discussed in Section 4, the impact of EVs on gasoline emissions was minimal at that time. Thus, the current model focuses on gasoline-related emissions, which offers a more accurate estimation of car CO_2 emissions for the study period. Future research could expand on this by examining how the increasing adoption of EVs impacts GHG emissions and CRE performance, particularly in regions with higher EV usage.

[9] While treating a_i as exogenous simplifies the model, I acknowledge that households optimize their location choices based on local attributes. In reality, households might respond to changes in these attributes, such as environmental quality, local amenities, or infrastructure improvements, when deciding where to live. If I relax the exogeneity assumption, it would imply that local attributes a_i are determined endogenously, potentially influenced by household behavior, policy interventions, or market dynamics. This change could introduce feedback loops, where households' choices further alter local attributes, which in turn influence future location decisions. Incorporating this dynamic would likely lead to more complex equilibria in the model, as the distribution of households across regions could affect the evolution of attributes in each region. While this extension is beyond the scope of the current analysis, it would be interesting to explore these dynamics in future research, which could provide deeper insights into the interaction between location choice and environmental externalities.

identical builders whose building costs are convex in the number of properties built. It is further assumed that both employers and builders are collectively owned by all the people in equal shares. Given these assumptions, both marginal product of labor and the cost of building housing can be written as follows $f'\left(\frac{N_i}{e_i}\right)$ and $k'\left(\frac{N_i}{b_i}\right)$. To achieve equilibrium, households must choose their own car gas consumption to maximize their utility levels, and these households must also be indifferent among the various regions. This implies that:

$$h_i^C + t = V_1\,(C_i^o;\ a_i), \tag{2}$$

$$\varphi \equiv f'\left(\frac{N_i}{e_i}\right) - k'\left(\frac{N_i}{b_i}\right) - \left(h_i^C + t\right)C_i^o + V(C_i^o; a_i), \tag{3}$$

where $V_1\,(C_i^o;\ a_i)$ is the derivative of the region-specific benefits from car gas consumption regarding its first argument. C_i^o refers to the optimal household car gas consumption conditional on prices and taxes in region i. φ is a constant across locations. As all households are identical, the focus can be placed on an additive social welfare (W) function as follows:

$$W = \sum_i e_i f\left(\frac{N_i}{e_i}\right) - \sum_i b_i k\left(\frac{N_i}{b_i}\right) - N_i(V(C_i^o; a_i) - h_i^C - G(N\hat{C})). \tag{4}$$

Then, the first-order condition for car gasoline consumption and social optionality locations, respectively, are:

$$h_i^C + NG'(N\hat{C}) = V_1\,(C_i; a_i), \tag{5}$$

$$\varphi \equiv f'\left(\frac{N_i}{e_i}\right) - k'\left(\frac{N_i}{b_i}\right) - \left(h_i^C + NG'\left(N\hat{C}\right)\right)C_i + V(C_i; a_i), \tag{6}$$

Where:

$$t = NG'(N\hat{C}). \tag{7}$$

There is no need for any additional government policies if car emissions are taxed at $NG'(N\hat{C})$ across all regions.[10] However, in reality, this condition is unlikely to hold, as each county has its own local tax policy,

[10] In this paper, the emissions tax primarily refers to greenhouse gas emissions from local CO_2, given their significant role in contributing to climate change and their centrality to global environmental policies. However, I acknowledge that other tailpipe emissions, such as nitrogen oxides (NOx), volatile organic compounds (VOCs), and particulate matter (PM), also contribute to local air pollution and may be subject to similar regulatory measures.

including property tax policy. Environmental externalities resulting from rising levels of human-made emissions may lead to more adverse environmental policies, creating higher environmental transition risks for commercial real estate investors in that area.[11] This, in turn, could result in higher risk premiums, reflected in higher capitalization rates for commercial real estate investors. In light of the aforementioned considerations, this study proposes the main hypothesis that: high car emissions are expected to have a negative effect on future CRE performance.

*** Insert Figure 1 About Here ***

4. Data and Empirical Methodology

To operationalize the empirical analysis and ensure comparability across all areas, I employ a strategy that build upon the theoretical foundation in section 3, which involves estimating car emissions for a typical household across various geographic settings throughout the U.S. to proxy for the sustainability of external environment. Generally, I start by estimating car emissions for a typical household at the county level and then aggregate these estimates to the CBSA level by taking averages. This aggregated data is then matched with the CRE data for the final sample.

Specifically, the car emission estimation first involves determining the average gasoline consumption for a standardized household in a particular year if it were located in each zip code for a given county. Utilizing data from the American Community Survey (ACS), a typical household is defined as one with sample

[11] This is based on the implicit assumption that CRE businesses in a more environmentally regulated economy tend to perform worse. From the existing literature, Aghion, Bergeaud and Van Reenen (2023) show that there is a reduction in the innovation response of firms to regulations, where the regulation is equivalent to a tax on profit. Furthermore, Ramiah, Pichelli and Moosa (2015) illustrate that the capital market reacts negatively to the announcement of green policies. Similarly, Guo, Kuai and Liu (2020) find the stock market reacts negatively to stricter environmental regulations. To provide more direct empirical evidence, in Table 5, I include a variable indicating states that have implemented policies aimed at mitigating greenhouse gas emissions and find that the variable are negatively significant associated with CRE returns across all columns, suggesting that adverse environmental policies negatively impact on CRE performance, at least in the short run. The findings in Table 8, which show that the focal results are most pronounced within states expressing stronger support for environmental policies, also provide further evidence that CRE businesses in a more environmentally regulated economy tend to perform worse.

means of household income, head age, and household members for a given year.[12] Figure 1 depicts the average household income (Graph A) and the average household size & head age (Graph B) over time throughout the sample period from 2002 to 2019. The sample ends in 2019 to avoid the pandemic's impact on car usage and to minimize the influence of electric vehicle (EV) adoption on car gasoline emissions estimation in this study.[13] It appears that over the past two decades, household income has consistently risen, while household size has been on a declining trend. Regarding the age of household heads, it generally increased over time, suggesting that U.S. society is moving towards an older demographic profile.

4.1. Car Emission Estimation

The primary dataset used to assess household car gasoline consumption is derived from the 2001, 2009, and 2017 National Household Transportation Surveys (NHTS), conducted by the U.S. Department of Transportation, Federal Highway Administration. This proprietary dataset contains a wealth of information related to zip code-specific household attributes and records annual miles driven. To estimate annual car gasoline consumption, the NHTS relies on information about the types of vehicles owned by households. I then use this data to further estimate average gasoline usage for a typical household in a given county. Specifically, for each household in the NHTS sample, it reports the annual gallons of gasoline consumed by each vehicle. This information is then aggregated by household for all vehicles listed in the dataset. The final sample of this study is filtered to include only those households for which complete demographic and

[12] https://www.census.gov/programs-surveys/acs

[13] The COVID-19 pandemic led to widespread changes in transportation habits due to lockdowns, remote work, and social distancing measures, which would have affected car usage patterns significantly (https://www.iea.org/articles/changes-in-transport-behaviour-during-the-covid-19-crisis and Barbieri et al. (2021)). Furthermore, EV adoption remained relatively low as of 2019. From the 2017 National Household Transportation Surveys, only 2.51% of vehicles in the survey used hybrid, electric, or alternative fuels, while the majority of vehicles are gas-powered. Additionally, in the United States, as of 2019, EVs comprised only about 2% of total vehicle sales (https://www.energy.gov/) and 1.54% market share (https://evadoption.com/) Thus, for the duration of this study's sample period, the influence of EV adoption on the estimation of car gasoline emissions is expected to be trivial. Additionally, the 2022 NHTS, which is the latest available survey as writing of this study, marks a methodological shift with a much smaller sample size and a biennial data collection cycle. This new design makes the data less comparable to previous years and may not provide a consistent basis for analysis. Given these factors, incorporating data from 2020-2024 would likely introduce distortions without adding significant value to the findings. The current study period offers a clearer and more stable representation of typical car usage and emissions trends.

geographic data are available. This yields a sample of 420,294 observations, comprising 81,193 for 2001, 173,442 for 2009, and 165,659 for 2017 NHTS, respectively.

The primary approach for estimating gasoline usage for a typical household is based on individual household characteristics and zip code levels, which are then averaged to the county level using zip code level population density serving as the weighting factor. Federal Highway Administration (FHWA) indicates that travel patterns do not change dramatically in short periods, and the frequency for NHTS is suitable for observing significant societal and technological changes that can influence travel behavior.[14] Furthermore, the average length of car ownership in US is about 10 years.[15] As such, the estimation of car gasoline usage for the periods when National Household Transportation Surveys are not conducted (i.e., 2002 to 2008, 2010 to 2016, and 2018 to 2019) relies on the estimated factor loadings from 2001, 2009, and 2017 National Household Transportation Surveys, respectively. Mathematically, for each period, I first run the general car gasoline model specification as follows:

$$Car\ Gasoline = \sum_j \beta_j X_m^j + \sum_i \gamma_i Y_n^i + \mu_m + \varepsilon_n \, , \tag{8}$$

where $Car\ Gasoline$ refers to the reported annual car gasoline consumption for a household.[16] X_m^j represents the value of zip code characteristic j in zip code m, Y_n^i refers to the value of individual characteristic i for household n, μ_m and ε_n are individual level and zip code level error terms. Specifically, household size (HHsize), household income (HHincome), and household head age (Head Age) are incorporated as household characteristics. Additionally, indicators for major MSA areas (Major MSA), dummies for each region (Midwest, South, West, Northeast), zip code level population density (Density), an indicator for urban areas (Urban), and interaction terms for population density with Major MSA, regions, and urban dummy are included. Major MSA is set to 1 if the household is situated in a metropolitan or

[14] https://www.fhwa.dot.gov/policyinformation/nhts.cfm.
[15] https://www.iseecars.com/how-long-people-keep-cars-study
[16] To reduce the impact of extraordinary outliers, Car Gasoline is top coded at the top 1% of the sample. Results are qualitatively similar when top coding is not applied.

consolidated metropolitan statistical area with a population of 1 million or more.[17] To enhance the accuracy and representativeness of NHTS results, statistical weights from the survey are employed when performing the analysis. [18]

*** Insert Table 1 About Here ***

Table 1 presents the results. In line with the findings in Brownstone and Golob (2009), there's a notable reduction in gasoline usage associated with higher population density. [19] Furthermore, significant positive impacts on gas consumption are observed with both family size and income, while the age of the household head shows a negative association with gasoline usage across all three NHTS datasets.[20] When examining various regions, an interaction with population density shows that families living in the Midwest and South regions generally experience higher gasoline expenditures. However, increased population density in these areas tends to reduce their gas consumption. The findings for Urban areas indicate that, for early years, households located in large cities tend to have lower gasoline consumption, but a higher population in the area tends to increase their gas consumption.

*** Insert Figure 2 About Here ***

Next, utilizing the factor loadings from Columns 1, 2, and 3 in Table 1, I estimate annual gasoline usage for an average household across three distinct periods: from 2002 to 2006, from 2007 to 2016, and from 2017 to 2019. Intuitively, the estimation involves estimating the average gasoline consumption for a standardized household in a particular year if it lived in each zip code in a given county. The standardized

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[17] MSAs were based on the 1999 Metropolitan Areas: Cartographic Boundary Files.
[18] Please refer to NHTS website for more comprehensive construction details of statistical weights.
[19] This paper acknowledges that individuals who choose to live in lower-density areas may do so because they have a preference for driving. In such cases, there could be an overestimation of the impact of population density on reducing gasoline consumption.
[20] While the findings imply a negative correlation between household age and car gasoline consumption, it's essential to recognize that the precise nature of this relationship remains uncertain. Since the age of the household head isn't the primary focus of the study, other omitted factors may influence this association, such as the family's lifestyle. Given these potential influences, further research is necessary to obtain a more comprehensive understanding of the relationship between household age and car gasoline consumption.

household is defined as one with the sample means of house income, head age, and household size for a given year, as shown in Figure 1. The standardized family approach enables comparability of local car emissions across areas. To convert gallons of gasoline into carbon dioxide emissions, a standard conversion factor of 17.86 is applied, which is commonly utilized by the U.S. Energy Information Administration (EIA).[21] This conversion factor accounts for emissions from a gallon of motor gasoline with fuel ethanol included.

Figure 2 illustrates the estimated car emissions of a typical family throughout this study's sample period. Generally, the estimated car emissions for an average family (*Car_CO2*) are on the rise over time, with a particularly quicker rise during the early period of the sample. When comparing counties across the nation, a typical household would produce relatively lower car emissions if located in Yukon-Koyukuk county in Alaska, Ellis county in Oklahoma, or Hyde county in South Dakota. Figure 3 presents the geographical distribution of the car CO_2 emissions for an average family (*Car_CO2*) during the period of 2002 to 2019. Table 2 presents the summary statistics of *Car_CO2* in the final sample, showing a mean of 17,797 lbs of CO_2 per year for a typical family and a median value of 16,865 lbs of CO_2.

*** Insert Table 2 About Here ***

*** Insert Figure 3 About Here ***

However, due to the limited availability of NHTS data, one potential concern in estimating car emissions over time in this study would be the need to extrapolate car gasoline consumption for the missing NHTS years. To address this issue and evaluate the reliability of this study's *Car_CO2* measure in capturing greenhouse gas emissions over time, local air quality data from the US Environmental Protection Agency (EPA) is obtained for the validity testing.[22] It's widely recognized that internal combustion engines in

[21] https://www.eia.gov/environment/emissions/co2_vol_mass.php

[22] Unfortunately, EPA does not monitor carbon dioxide (CO_2) levels directly. However, EPA monitors other pollutants, such as CO and VOCs.

various vehicles, including cars, trucks, and motorcycles, are significant sources of carbon monoxide (CO) emissions. Despite the implementation of stringent emissions regulations over the past few decades, CO remains a major contributor to gasoline vehicle emissions, alongside industrial processes, residential heating and cooking, wildfires, biomass burning, and more. Thus, given that CO is a byproduct of the combustion process in internal combustion engines, the expectation is that if *Car_CO2* effectively captures greenhouse gas emissions over time, it should exhibit a positive and statistically significant association with local CO levels over time. Conversely, volatile organic compounds (VOCs), another type of critical gas monitored by the EPA, are not expected to show a significant association with local greenhouse gas emissions over time. This expectation arises from the definition of VOCs, which encompasses any carbon compound excluding carbon monoxide, carbon dioxide, carbonic acid, metallic carbides or carbonates, and ammonium carbonate, participating in atmospheric photochemical reactions.[23] Thus, a significant positive association of *Car_CO2* with CO but no relationship with VOCs would strongly indicate that the *Car_CO2* effectively captures greenhouse gas emissions over time.

The EPA's Air Quality System (AQS) provides daily reports of both CO and VOCs data. I compute the average CO and VOCs values for each county in a given year and then merge them with the *Car_CO2* dataset where CO or VOCs data is available. Since AQS reports CO and VOCs data based solely on the county where the monitor is located, the number of observations is reduced to 6,719 and 5,909, respectively. To examine the relationship between CO (VOCs) and the car emission metric, panel regression analysis is used next. This involves regressing contemporary CO (VOCs) on the car emission metric presented in this paper, alongside year and county fixed effects. The results of this analysis are presented in Table 3. Columns 1 and 2 report the results for CO, while Columns 3 and 4 replicate the results for VOCs. As shown in the table, both Columns 1 and 2 display positive and strongly significant coefficient estimates. However, the coefficient estimates for car emissions in Columns 3 and 4 are statistically insignificant. These findings

[23] https://www.epa.gov/air-emissions-inventories/what-definition-voc

provide strong evidence that the car emissions metric (*Car_CO2*) in this paper effectively captures greenhouse gas emissions over time.

*** Insert Table 3 About Here ***

4.2. Commercial Real Estate Performance

To measure the performance of commercial real estate, quarterly National Council of Real Estate Investment Fiduciaries (NCREIF) Property Indices (NPI) return data is utilized and then aggregated into the annual level (*PropRet*). These returns represent estimated composite total unleveraged returns for properties held for investment purposes. Since the NPI return data is reported at the CBSA level, the car emission data is next aggregated to the CBSA level by calculating the average and then matched with CRE return data accordingly.

When conducting the multivariate analysis, various property characteristics are controlled for. The data for these property attributes is sourced from the NCREIF database. Specifically, the following variables are included: property capital expenditures per sqft (*CAPEX*), loan-to-value ratio (*LTV*), occupancy rate (*Occupancy*), market value of property per sqft (*MV*), net operating income growth rate (*NOI Growth*), rent growth rate (*Rent Growth*), operating expenses scaled by net operating income (*OPExp Ratio*), and the number of properties in the area *(# of Prop*).[24] Furthermore, to account for the influence of property transactions on local property performance, the property turnover rate (*Prop Turnover*) is calculated by counting the number of properties transacted over the total number of properties *(# of Prop*) in the area.

From a macroeconomic standpoint, it is expected that both inflation and the local economy will have significant implications for the real estate market. To account for these influences, two additional variables are created. Specifically, state-level PCE percentage changes (*ΔPCE%*) are employed to gauge local

[24] To mitigate the impact of outliers, *LTV* ratio, occupancy rate, *NOI Growth*, *Rent Growth*, *OPExp Ratio* are winsorized at 1% and 99% levels.

inflation rate fluctuations, and average county-level GDP percentage changes (*ΔGDP%*) are used to further assess local economic conditions.[25] The data for PCE and GDP is sourced from the Bureau of Economic Analysis (BEA). After merging the commercial real estate dataset with the car emissions dataset and removing observations with missing values for the aforementioned variables, the final sample yields 2,504 observations for the period of 2002 to 2019.[26]

5. Empirical Analysis

5.1. Baseline Results

The initial empirical analysis starts by employing panel regression to investigate whether local car emissions are associated with future commercial real estate performance. Below is the general model specification:

$$PropRet_{i,t+1} = \alpha + \beta_1 Car\_EM_{i,t} + \sum_{j=2} \beta_j X_{i,j,t} + FE + \varepsilon_{i,t} \quad (9)$$

where $PropRet_{i,t+1}$ refers to the NPI total returns in year t+1 in CBSA i. $X_{i,j,t}$ is one of the control variables aforementioned in section 4.2. FE refers to property type, year, and CBSA fixed effects. Table 4 reports the results, where Panel A presents the baseline findings, Panels B and C replicate the baseline results using inflation-adjusted car emission estimation and Fama-MacBeth cross-sectional regressions, respectively, and Panel D includes population density (*PopDensity*) as an additional control variable.

*** Insert Table 4 About Here ***

In Panel A of Table 4, Column 1 presents the raw car CO_2 emissions for a standardized household (denoted as *Car_CO2*) as the focal variable of interest. In Column 2, logarithm is used for *Car_CO2* to account for

[25] CPI and PCE generally exhibit a parallel trend. The rationale behind the selection of PCE over CPI is that CPI often tends to exaggerate the actual inflation rate, whereas PCE provides a more precise measurement by accounting for substitution effects. Additionally, PCE is the preferred measure of the Federal Reserve. A more comprehensive discussion comparing CPI and PCE provided by St. Louis Fed's President could be found here: https://www.stlouisfed.org/publications/regional-economist/july-2013/cpi-vs-pce-inflation--choosing-a-standard-measure .

[26] BEA's PCE data begins in 2001, but to calculate the percentage changes for PCE, the final sample starts from the year 2002.

potential outlier effects. Notably, both Columns 1 and 2 yield significant negative coefficient estimates, indicating that properties within areas characterized by lower greenhouse gas emissions tend to exhibit higher CRE returns in the subsequent year. This observation holds true even after accounting for the current year's performance (*PropRet*$_t$), which should help to mitigate unobservable confounding bias, as shown in Columns 3 and 4. From the economic significance perspective, if the average annual car CO_2 emissions for a typical household were to increase from 8,930 lbs of CO_2 (equivalent to 500 gallons) to 17,860 lbs of CO_2 (equivalent to 1,000 gallons) per year, representing an approximate addition of 1.37 gallons per day to their driving habits, this shift would be linked to an average of 1.57% reduction in CRE property returns in the subsequent year across all the Columns in Panel A. With the average property return in this study's sample being 8.76%, this decrease would result in a property return decline of 17.92% in magnitude, which is economically meaningful.[27]

With regard to the control variables, it is observed that properties with higher occupancy rates, lower market prices per square foot, greater rent growth, and higher number of properties in the vicinity exhibit higher future CRE property returns. Additionally, noteworthy are the statistically significant positive coefficient estimates for the current year's property returns, indicating the presence of momentum returns in the CRE market. In other words, this implies that CRE properties with higher returns in a given year are inclined to maintain higher returns in the subsequent year. Turning to the local economic variables, as expected, CRE outperforms when the local economy demonstrates strength, and inflation rates are higher. This also reinforces the notion that real estate assets serve as a robust hedge against inflation risk (e.g. Hoesli (1994)) . In all, the baseline results in Table 4 Panel A demonstrate that local car carbon dioxide emissions negatively impact the future performance of commercial real estate. This suggests that sustainable external environment plays a vital role in commercial real estate investments, which is in line with the theoretical work discussed in Section 3. In Appendix A, to address concerns about the potential influence of ride-

[27] 17.92% is the result of dividing 1.57% by 8.76%.

hailing services on household car usage, I replicate the baseline analysis from Panel A of Table 4 using a subsample from the period before ride-hailing services were launched, and the results are highly consistent.

To further assess the robustness of the baseline findings, alternative modeling approaches are employed. Panel B of Table 4 adjusts car emission estimates by incorporating inflation-adjusted home income while Panel C replicates the analysis in Panel A using Fama-MacBeth cross-sectional regressions. Specifically, in Panel B, the household income used to estimate car carbon dioxide emissions is adjusted for inflation to represent base year dollars, where the inflation is measured by state-level PCE data from BEA. Table 1 illustrates that household income is significantly related to car usage. Considering that inflation can impact the purchasing power and economic well-being of families over time, it may lead to an overestimate of household car gas consumption in this study. However, the results in Panel B, based on inflation-adjusted household income, are highly consistent with the baseline findings. This suggests that changes in household purchasing power have a limited effect on the relationship between local car CO_2 emissions and commercial real estate performance. Similarly, the Fama-MacBeth cross-sectional regression results in Panel C provide further support for the baseline findings in Panel A. They continue to indicate that higher local car emissions have a negative association with CRE returns in the subsequent year.

Moreover, as shown in Table 1, population density is significantly related to car usage. To address the potential concern that population density might impact the relationship between local car emissions and commercial real estate performance, I next include population density as an additional control variable and replicate the main analysis in Panel D of Table 4.[28] Compared to the baseline results, the findings are highly consistent: CRE properties situated in lower car emission areas consistently yield higher future returns without losing much power, either in statistical or economic significance.[29]

[28] The population density is calculated as the average zip code level population density in a CBSA region.

[29] To further address the concern of population density in the area, in the untabulated table, I replicated the main analysis by aggregating car emissions for a standard household in a county to the total car emissions for a county by

To further address potential endogeneity related to local economic activity, the main results are replicated with the inclusion of CBSA * Year fixed effects. This interaction controls for unobserved heterogeneity specific to each geographic area and year, which could influence both economic activity and CO2 emissions. Including these fixed effects better isolates the impact of car CO2 emissions on property values. As presented in Table 4 Panel E, the results remain consistent with the main findings.

Additionally, existing literature highlights that other pollutants, such as volatile organic compounds (VOCs) and particulate matter (PM2.5), play significant roles in contributing to air pollution and environmental degradation (Chay and Greenstone (2005); Gilman et al. (2013); Sager (2019); Maung et al. (2022); and Cvijanović, Rolheiser and Van de Minne (2024)). While CO_2 emissions serve as a proxy for broader car emissions in this study, it's essential to consider the potential confounding effects of other air pollutants, such as VOCs, Ozone, and PM2.5, on CRE outcomes. To enhance the robustness of the main findings, Table 4, Panel F introduces an additional control for overall local air quality through the air quality index from EPA, while Panel F adds VOC, Ozone, and PM2.5 levels as further controls. After replicating the main analysis with these controls, I continue to find negatively significant coefficient estimates for car CO2 emissions across all columns. Moreover, the results in Panel G reveal that VOCs also have a significantly negative impact on CRE outcomes across the board. These findings provide further strong evidence that local car CO2 emissions play a crucial role in shaping commercial real estate investments, even after considering the effects of local air quality and other main air pollutants. Overall, the findings in Table 4 strongly support the main hypothesis that a less sustainable external environment has a detrimental impact on future CRE market performance.

To further enhance the robustness of the study, in Appendix B, I also replicate the baseline results by accounting for local business activities and green building concentration in the area. This is to address the

multiplying the number of households in a county. I then aggregated these values to the CBSA level by taking the average. The findings are also qualitatively similar.

potential concerns that the relationship between car emissions and future CRE performance could be driven by other emitters in the area, such as the level of local business activity and green building concentration. To operationalize the analysis, I manually collect data on the number of total employer establishments, the number of agricultural-related employer establishments (NAICS=11), and the number of employees per county over the years from County Business Patterns Datasets. I then aggregate these data to the CBSA level by taking averages. I next collect data on ENERGY STAR-certified buildings from the registry of ENERGY STAR Certified Buildings and Plants. I create an indicator variable, High Green Bldg, which is set to 1 if a CBSA has a number of ENERGY STAR-certified buildings higher than the average for a given year, and 0 otherwise. I also create a continuous variable, Green Bldg, which is equal to the average number of ENERGY STAR-certified buildings scaled by the total number of employees per county within a CBSA for a given year. The results are reported in Appendix B, where Panel A presents the results after controlling for local business activities while Panel B illustrates the results after accounting for both local business activities and green buildings concentration in the areas. Compared to the baseline results, the coefficient estimates for car emission variables are not only statistically significant, but their magnitudes are also stronger after controlling for other emitters in the area. This provides strong evidence to support the main hypothesis that high local car emissions have a negative effect on future CRE performance.

5.2. State Greenhouse Gas Emissions Targets

In the theoretical framework of Section 3, I posit that more new adverse environmental policies would have a negative impact on local business, resulting in higher risk premiums demanded by commercial real estate investors. This is based on the implicit assumption that CRE businesses in a more regulated economy tend to perform worse. From the exiting literature, Aghion, Bergeaud and Van Reenen (2023) show that there is a reduction in the innovation response of firms to regulations, where the regulation is equivalent to a tax on profit. Additionally, Ramiah, Pichelli and Moosa (2015) illustrate that capital market reacts negatively to the announcement of green policies. Similarly, Guo, Kuai and Liu (2020) find the stock market reacts negatively to stricter environmental regulations. Yet, there is no direct empirical evidence showing that stricter environmental regulations would negatively affect CRE business. Furthermore, the focal finding of this study that the negative impact of local car emissions on CRE performance might be driven by the current stricter local environmental regulations, not potential future stricter local environmental regulations.

To address these concerns, I obtain data on U.S. State Greenhouse Gas Emissions Reduction Targets from National Conference of State Legislatures. Over the years, several states have implemented a variety of policies aimed at mitigating greenhouse gas (GHG) emissions.[30] Maine was the first state to enact legislation setting specific GHG reduction targets in 2003, followed by California in 2006. Since then, several other states have enacted statutory targets, with Virginia being the most recent. To operationalize the analysis, I first manually collect the data for states with GHG reduction targets and then create an indictor variable (State_GHG_target) for states that have implemented GHG reduction targets over the years. I next replicate the baseline results of Table 4 Panel A by including State_GHG_target as an additional variable in the panel regression analysis. The results are reported in Table 5 Panel A.

*** Insert Table 5 About Here ***

As expected, I find that the coefficient estimates of State_GHG_target are significantly negative across all columns, suggesting that stricter environmental policies have a negative impact on CRE performance, at least in the short term. Furthermore, after accounting for states that currently have stricter environmental policies, I continue to find that CRE properties located in areas with lower car emissions consistently yield higher future returns. This implies that the negative impact of car emissions on CRE performance is more

[30] As of May 2024, at least 16 states and Puerto Rico have enacted legislation establishing GHG emissions reduction requirements.

likely related to potential new adverse environmental regulations rather than the current strict environmental policies.

To further validate the findings, I introduce an interaction term between State_GHG_target and car CO2 emissions. If existing environmental policies were driving the results, I would expect the interaction term to be negatively significant. Additionally, if car CO2 emissions were primarily influenced by current policies, the direct effect of car CO2 emissions would become insignificant once the interaction term is included. However, as shown in Table 5, Panel B, the interaction term is not significant, and the effect of car CO2 emissions remains negative and significant. This suggests that the potential for new environmental policies, rather than the impact of existing ones, is likely driving the results. [31]

I next also replicate the main analysis, focusing solely on states and years where GHG emissions reduction targets were already in place. If current policies were the primary driver, I would expect car CO2 emissions to have no impact on CRE performance in this subsample. However, as reported in Table 5, Panel C, the results still show a significant negative relationship between car CO2 emissions and CRE returns, further supporting the conclusion that the threat of new environmental policies is more likely influencing the outcomes. Overall, the findings in Table 5 strongly support the notion that the prospect of new adverse environmental policies could negatively impact local businesses, leading to higher risk premiums demanded by commercial real estate investors.

5.3. Public Transportation

Up until this point, the focus of this study has been centered on the notion that the selection of car emissions for a typical household is predominantly influenced by the choices made by individuals. However, it's

[31] To further address the potential endogeneity of GHG targets due to state-specific characteristics, I replicated the analysis using state fixed effects. Although the results are not tabulated to save space, they remain consistent with the main findings.

essential to acknowledge that the availability and efficiency of local public transportation can associate with a household's car usage patterns. A household's reduced reliance on personal vehicles may not necessarily stem from a lack of environmental awareness but rather from the convenience of using private cars compared to public buses. This shift in preference is not solely a matter of personal choice but is deeply intertwined with the accessibility and efficiency of public transportation options. [32]

On the other hand, public transportation systems are designed to be more energy-efficient and eco-friendly, as they carry multiple passengers in a single vehicle, thereby reducing the overall carbon footprint per commuter. Thus, it’s reasonable to assume that the carbon dioxide emissions generated by public transportation per household are substantially lower than those produced by driving individual cars. This further highlights the importance of considering the potential impact of local public transportation infrastructure on household car usage patterns, which can potentially bias the primary findings discussed earlier. To address this concern, the analysis next proceeds with estimating the greenhouse gas emissions associated with public transportation usage per household.

Given that the individual surveys regarding the energy consumption of bus and train commuters is limited, aggregated data from the National Transit Database for each of the nation's public transit systems is utilized. This data offers insights into the energy consumption of all nationwide public transit systems annually, predominantly in the form of gasoline for buses.[33] I next match the National Transit Database by county and then aggregates the total bus gasoline consumption by public transit systems within each county. Then, I apply the standard conversion factor of 17.86 converts gallons of gasoline into carbon dioxide emissions.

[32] I knowledge that the relationship between household vehicle usage patterns and the availability and efficiency of local public transportation is potentially bidirectional. While the availability of public transportation can influence a household's car usage patterns, the reverse can also be true—household vehicle usage patterns may impact the design and efficiency of local public transit systems. Thus, the interpretation of the findings in this section focuses more on associations rather than definitive causal relationships.

[33] However, this data does not encompass information for private modes of public transportation, such as taxi services and private bus lines.

To express this on a household level, I next divide the value by the number of households within a county, estimated from US Census data. Finally, to align with the CRE return data, the public bus emissions per household are averaged at the CBSA level.

*** Insert Table 6 About Here ***

To account for the potential impact of local public transportation usage on the relationship between car emissions and CRE performance, a newly created variable, public bus emissions per household (*Bus_CO2*), is incorporated into the panel regression analysis. Additionally, to address the intertwined nature of car and public transportation usage, another new variable (*Car_Bus_CO2*) is introduced, which sums up the car and bus emissions for a household. Table 6 A reports the results, where Columns 1 and 3 assess the impact of car and public bus emissions separately, while Columns 2 and 4 consider the combined impact of car and public bus emissions.[34] Notably, in Columns 1 and 3, even after accounting for the effects of local public transportation usage as a separate factor, the coefficient estimates for car emissions remain significantly negative, though the magnitude is slightly reduced compared to the baseline findings.

Given that public transportation systems are intentionally designed for enhanced energy efficiency and environmental friendliness, as they efficiently transport multiple passengers in a single vehicle, thereby diminishing the overall carbon footprint per commuter, one might naturally anticipate that increased bus utilization would associate with a reduced influence of environmental externalities linked to greenhouse gas emissions on CRE performance. This is supported by the findings in Columns 1 and 3, where both the coefficient estimates for public bus emissions are positively significant. This suggests that public transportation systems significantly reduce the overall carbon footprint per household, thereby mitigating the adverse impact of environmental externalities from greenhouse gas emissions on future CRE performance. When considering the intertwined impacts of car and public transportation usage, Columns 2

[34] For the sake of brevity, this study concentrates on logarithmically transformed emission variables. The results for raw emission variables are qualitatively similar.

and 4 continue to reveal a significant negative association between the combined car and bus emissions for a household and future CRE returns. This implies that public transportation systems positively influence the impact of household car usage on future CRE performance, but such influence does not fully offset the negative impact of car emissions on future CRE returns.

Given that local economic conditions and property attributes may potentially associated with local car emissions, including the car emission variable along with local economic condition and property attribute variables in the same regression analysis might not purely examine the impact of car emissions on future CRE performance. In order to mitigate such potential cofounding effects, I first regress each control variable in the set of local economic conditions and property characteristics separately on the car emission variables (i.e., Ln(*Car_CO2*) and Ln(*Car_Bus_CO2*)) and then obtain the residuals of each control variable.[35] Next, I replicate Table 6 Panel A by replacing the local economic condition and property attribute variables with their respective residuals. This approach ensures that the car emission variables are independent of other control variables and simply capture the association between car CO2 emissions and future CRE performance, if any. The results are reported in Panel B of Table 6. Consistent with the findings in Panel A of Table 6, I continue to find the negative association of car greenhouse gas emissions with future CRE performance after controlling for the potential observable confounding factors.[36] Overall, Table 6 provides another strong evidence to support the notion that sophisticated investors in the CRE market tend to incorporate the sustainability of external environment risk in CRE investments.

Additionally, to further address the potential bias resulting from other unobservable confounding variables that remain unaccounted for in the analysis, in Appendix D, I conduct an instrumental variable analysis,

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[35] Results are consistent if raw car emission variables are used.

[36] To further enhance the robustness of the findings, I also replicate Table 6 Panel A by using the residuals of emission variables. In the first stage, I regress emission variables on the control variables to obtain residuals. I then replicate Table 6 Panel A by replacing the emission variables with their residuals in the second stage. The results of the second stage are reported in Appendix C. The results are highly consistent with the baseline findings.

where is the average number of public transit agencies (NumPTA) in a county for a given CBSA is used as an instrumental variable for the car emission metric. [37] The findings reinforce the notion that less sustainable external environment impedes future commercial real estate performance. In Appendix E, I also investigate the impact of local car emissions on longer-term CRE performance by looking into the next two, three, and four-year cumulative CRE returns. The results show that the negative impact persists for at least the next four years, albeit with diminishing magnitude.

5.4. Propensity Score Matching Approach

To further draw causal inferences regarding the effects of a less sustainable external environment (i.e., high car emission exposure) on the CRE market, the next set of robustness tests replicates the main analyses using a propensity score matching (PSM) strategy. This approach aims to test whether the CRE performance would have been worse in areas with high car emission exposure than if it were located in areas with low car emission exposure.

To construct the matched sample, the propensity score estimated from a probit model is utilized to assess whether CRE properties located in areas with high car emissions are more likely to exhibit better or worse performance than their counterparts in low car emission areas. Mathematically, the general form of the probit model is:

$$P(Y_i = 1|X_i) = F(X_i\beta), \tag{10}$$

where F(·) is the cumulative density function (CDF) of the normal distribution. The dependent variable Y equals to one if the *Car_ EM* (*Car_Bus_CO2*) for a household above the average and zero otherwise for a given year.[38] X is the set of observable variables including capital expenditure ratio, LTV, occupancy rate, market value per sq.ft., NOI growth rate, rent growth rate, operating expense ratio, number of properties,

[37] Although I show that the instrumental variable meets both the relevance and exogeneity criteria for the IV approach, I acknowledge that this IV may not be the ideal choice. Thus, I consider this as a supplementary robustness test with limitations.

[38] Results are consistent when the top tercile, rather than the average, is used as the treatment.

property turnover, PCE percentage changes, and GDP percentage changes. The results of this analysis are presented in Table 7, where Panel A reports the results for *Car_CO2* and Panel B presents the results for combined car and bus emissions per household (*Car_Bus_CO2*).

Overall, the average treatment effect estimate results presented in Table 7 are once again entirely consistent with those outlined above, indicating that CRE properties in areas with high car emission exposure exhibit poorer performance in the following year.[39] Specifically, in Panel A, it is observed that properties located in relatively high car emissions areas have next year returns that are 1.96% (1.92%) lower than properties located in relatively low car emissions areas using the nearest neighbor matching approach (Kernel matching approach). Turning to Panel B with the combined car and bus emission measure, this paper finds that properties located in relatively high *Car_Bus_CO2* have next year returns that are 2.43% lower than their low *Car_Bus_CO2* counterparts. Given the average property return of 8.76%, this implies an overall reduction of 27.74% in magnitude.[40] Taken together, these results suggest environmental externalities stemming from greenhouse gas emissions are indeed driving the observable decrease in future performance of CRE properties.

*** Insert Table 7 About Here ***

5.5. Channels of Future CRE Return Impact

The evidence thus far well supports the primary hypothesis that a less sustainable external environment negatively impacts CRE performance, even after considering alternative model approaches, additional other emitter factors, public transportation usage, and potential endogeneity concerns. In this section, this paper turns to investigate the potential underlying mechanisms through which this may occur.

[39] The average selection bias (not tabulated) across all specifications ranges from 0.9% (0.3%) to 6.7% (4.3%) for nearest neighbor matching for *Car_CO2* (*Car_Bus_CO2*) and .1% (0.1%) to 5.8% (5.9%) for kernel matching for *Car_CO2* (*Car_Bus_CO2*) , which means that the results are reliable.

[40] This is calculated as 2.43%/8.76%=27.74%.

5.5.1. Political Inclination of States

Public opinion research suggests that there is often a partisan divide in the United States regarding climate change, with individuals in Democratic-leaning "blue" states typically expressing more concern about climate change and more support for climate policies than those in Republican-leaning "red" states (e.g., Sugg and Weir (2023)). This pattern is consistent with the general policy positions of the two major political parties, as the Democratic Party tends to prioritize environmental issues more heavily than the Republican Party.[41] As such, the physical impact of high emissions on the sustainable environment and people's willingness to pay may represent a potential channel in explaining the main findings of this study. Based on the theoretical framework in section 3, if adverse environmental policies posing risks for commercial real estate investors, the adverse impact of car emissions on CRE returns is expected to be more concentrated in Democratic-leaning states than in Republican-leaning states as Republican-leaning states might encounter lower climate transition risks compared to those in Democratic-leaning states.[42] To test this hypothesis, states in my sample are categorized into "blue" (Democratic-leaning), "red" (Republican-leaning), and "purple" (swing or battleground) based on presidential and midterm election results between 2002 and 2019. Table 9 Panel A illustrates the political leanings of states used in this study.

Next, the main results are replicated based on subsamples categorized by the political inclination of the states. The findings are presented in Panels B, C, and D of Table 9 for blue, red, and purple states,

[41] See examples: https://www.pewresearch.org/short-reads/2020/02/28/more-americans-see-climate-change-as-a-priority-but-democrats-are-much-more-concerned-than-republicans/ and https://blueandgreentomorrow.com/environment/where-do-republicans-and-democrats-stand-on-environmental-issues/ Furthermore, there is minimal overlap between red states and those with committed GHG reduction goals. Red states have largely refrained from committing to these targets, whereas blue states have steadily embraced them since 2003, with an average of 9 states leading the charge. This pattern indicates that blue states are more focused on climate change initiatives and are likely to continue implementing more environmental policies in the future.

[42] While this paper assumes that blue states currently face higher short- to medium-term transition risks due to their proactive environmental policies and stricter regulations, I acknowledge that red states may face greater transition risks in the future. If red states delay climate action, they may encounter significant 'catch-up' risks as federal or international climate mandates become stricter. However, the current federal policy landscape allows states considerable autonomy, which contributes to the varying levels of transition risk across states. As such, this paper focuses on the immediate risks associated with blue states' aggressive climate policies, while recognizing that the balance of risk could shift over time as federal policies evolve.

respectively. As expected, the results across all these panels confirm that the negative impact of high car emission on CRE returns is indeed concentrated in Democratic-leaning states. More specifically, in Panel B the car emission metrics are found to be inversely related to the magnitude of the next year's property returns, while in Panel C and D neither of the car emission metrics approaches statistical significance at conventionally accepted levels for the subsamples of red or purple states.[43] Once again, as outlined above, these findings confirm the focal results are most pronounced within states that express more concern about climate change and more support for environmental policies. This is also consistent with the notion presented in theoretical framework of section 3 that transition risk arising from more adverse environmental policies would result in a negative impact of high car emissions on future CRE performance.

*** Insert Table 8 About Here ***

5.5.2. Capital Return vs. Income Return

The performance of CRE is influenced by two key factors: the operating cash flow generated by the property (income return) and the rate at which these cash flows are capitalized (capital return), where the latter takes into account a risk premium. Given that operating cash flow for a property tends to be more stable and transparent as compared to its expectation from price appreciation, changes in local market conditions are likely to have a more immediate impact on the return derived from capital gains. Building on the aforementioned findings that transition risk serves as the channel through which a sustainable external environment influences CRE property performance, it is expected that such risk would more likely be factored into property valuation rather than daily operating income. To gain a deeper understanding of the channel through which a sustainable external environment influences future CRE performance, the next

[43] An alternative hypothesis for these findings is that that investors in blue states place a higher value on properties in areas with better air quality, implying that as car emissions increase, returns would decrease. However, in unreported tables, I have indirectly tested this alternative hypothesis and find no significant evidence to support it. Specifically, the coefficient estimates for blue states, as well as the interaction between blue states and local air quality, are statistically insignificant, indicating that blue states do not value properties with better air quality more than other states.

step is to break down CRE returns (i.e. property return) into two components: income return and capital return, both sourced from NCREIF.[44] The results are presented in Table 9.

*** Insert Table 9 About Here ***

Panel A replicates the main results for next year's property's capital return (Capital Ret_{t+1}) while Panel B reports the results for property's income return in the following year (Income Ret_{t+1}). As expected, a striking negative association is observed between local car emissions and future CRE capital returns in Panel A. This implies that commercial properties situated in areas with higher car emission exposure tend to exhibit a price depreciation. Conversely, Panel B reveals that there is no significant association between car emission and future income returns. These findings suggest that the environmental transition risk associated with greenhouse gas emissions is reflected in price depreciation, leading to higher capitalization rates demanded by investors. This observation aligns perfectly with the idea that adverse local environmental factors can adversely affect the value of commercial properties, and sophisticated investors in the CRE market respond by increasing the capitalization rate.

The overall capitalization rate could increase under various conditions. As highlighted in Addoum et al. (2023), it mainly increases when property's current income rises, when the risk premium escalates, or when the expected growth rate of future income diminishes. Since this study controls for factors such as current income, income growth prospects, and local economic growth prospects, it is unlikely that the decrease in capital return can be attributed to an upswing in current operating income or an anticipation of declining future income growth. Thus, the most plausible explanation for the findings is an increase in the risk premium demanded by CRE investors due to the environmental transition risk. This again aligns closely with the theoretical framework presented in section 3.

[44] In the NCREIF, income return refers to the part of property return derived from a property's net operating income, mainly from tenant rent. Capital return, on the other hand, represents the change in the property's market value over a given period.

6. Summary

Recent years have seen heightened attention to the environmental impact of human activities, especially in the context of climate change. Various studies have underscored the role of human-made emissions, especially carbon dioxide (CO_2), in contributing to the rise in atmospheric CO_2 levels. While much research has explored the influence of green buildings and environmental certifications on real estate values and performance, limited attention has been given to how a sustainable external environment affects commercial real estate.

This study investigates the impact of local environmental externalities resulting from car carbon dioxide emissions on commercial real estate (CRE) performance. This article finds that CRE properties located in areas with lower car emissions tend to yield higher future returns, even after accounting for property characteristics, local economic context, existing environmental policies, usage of public transportation in the area, and potential endogeneity concerns. This underscores the importance of considering environmental factors when evaluating the performance and investment potential of CRE properties.

Furthermore, this article uncovers the mechanisms through which local car carbon dioxide emissions impact future CRE performance. It indicates that high car emissions could lead to more adverse environmental policies and such high levels of greenhouse gas emissions primarily shapes CRE by adversely influencing the future price appreciation of properties. This suggests that investors in the CRE market factor environmental transition risks in their real estate investments.

This study is part of the growing body of research that explores the ramifications of climate change risk and environmental, social, and governance (ESG) factors on financial performance in the real estate market. It stands out by specifically examining how an external sustainable environment is priced in the CRE market and elucidating the underlying mechanisms at play. This study offers insights for investors navigating environmental considerations in commercial real estate investment within an increasingly environmentally conscious global context. For future research, it would be interesting to further investigate how specific local environmental policy interventions would impact the performance of CRE, and how emerging technologies and transportation innovations would intersect with sustainable environmental factors in shaping CRE investment decisions.

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Table 1
Annual Gallons of Car Gasoline Consumption

This table presents cross-sectional regression results with dependent variables of a household's annual car gasoline usage from 2001, 2009, and 2017 National Highway Travel Survey (NHTS), respectively. HHsize is the household size calculated as the number of family members in a household. HHincome is the annual household income. Head age is the household head age. Major MSA is a dummy variable which is set to 1 if a household is situated in a metropolitan or consolidated metropolitan statistical area with a population of 1 million or more, and zero otherwise. Midwest is a dummy variable which is set to 1 if a household is situated in the Midwest region which is defined by Census. South is a dummy variable which is set to 1 if a household is situated in the South region which is defined by Census. West is a dummy variable which is set to 1 if a household is situated in the West region which is defined by Census. Ln (density) is the logarithm-transformed population density at zip code level. Urban is a dummy variable which is set to 1 if a household is situated in the Urban area which is defined by NHTS. The robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
		Household's Car Gasoline Usage	
	2001 NHTS	2009 NHTS	2017 NHTS
HHsize	29.6726***	49.8916***	30.1132***
	(6.69)	(12.30)	(6.59)
HHincome	21.9767***	17.4040***	14.8887***
	(16.54)	(16.45)	(6.29)
Head Age	-5.7762***	-5.5903***	-6.1944***
	(-15.85)	(-15.72)	(-19.54)
Major MSA	424.1767**	173.4581	-199.7471
	(2.58)	(1.28)	(-1.47)
Ln(density)	-87.5404***	-78.0083***	-70.6135***
	(-5.50)	(-4.75)	(-3.95)
Ln(density) * Major MSA	-49.4705**	-11.6487	3.7174
	(-2.12)	(-0.57)	(0.19)
Midwest	704.3112***	2,807.8808***	531.4823*
	(7.15)	(33.20)	(1.92)
South	583.4787***	2,390.9727***	446.0245*
	(4.70)	(31.27)	(1.76)
West	898.5156***	79.9348	162.8165
	(5.44)	(1.34)	(0.66)
Ln(density) * Midwest	-125.1978***	-108.7091***	-114.7766***
	(-6.00)	(-4.74)	(-5.11)
Ln(density) * South	-67.4282***	-88.3567***	-77.0690***
	(-3.18)	(-4.25)	(-3.50)
Ln(density) * West	-17.3039	2.2493	-9.2713
	(-0.88)	(0.12)	(-0.51)
Urban	-1,252.5581***	-716.4208***	-83.9327
	(-3.65)	(-3.12)	(-0.43)
Ln(density) * Urban	156.3995***	90.0246***	10.9390

	(3.66)	(3.12)	(0.45)
Constant	1,133.3721***	940.2389***	1,457.0037***
	(10.90)	(14.33)	(7.65)
County Dummy	Yes	Yes	Yes
Observations	81,193	173,442	165,659
Adjusted R-squared	0.372	0.323	0.263

Table 2
Summary Statistics

This table shows summary statistics of key variables used in the empirical analysis of this study. PropRet is the NCREIF's NPI return at annual level. Car_CO2 is the estimated car emissions (lbs/CO_2) for a standardized household. Please refer to section 4.1 for a detailed explanation of this variable. CAPEX is the capital expenditure scaled by market value of properties. LTV is the loan to value ratio. Occupancy is the occupancy rate. MV is market value of properties per square footage. NOI Growth is the net operating income growth rate, Rent Growth is the rent growth rate. OPExp Ratio is the ratio of operating expense to net operating income. # of Prop refers to the total number of properties. Prop Turnover is the ratio of # of property sold to total number of properties. ΔPCE% is state-level PCE percentage changes. ΔGDP% is the average county-level GDP percentage changes for a given CBSA.

	Mean	1st Pctl	25th Pctl	50th Pctl	75th Pctl	99th Pctl	Std Dev
Main Variables:							
$PropRet_{t+1}$	0.0876	-0.2569	0.0438	0.0981	0.1437	0.4071	0.1194
Car_CO2	17797	9243.9	13472	16865	21947	30440	5423.8
Property Characteristics:							
CAPEX	0.9214	0.0046	0.2693	0.5356	1.0662	6.1485	1.7753
LTV	0.4962	0.2738	0.4255	0.4838	0.5540	0.8057	0.1056
Occupancy	0.9125	0.7295	0.8856	0.9248	0.9486	0.9972	0.0533
MV	198.92	32.925	89.791	159.28	247.84	831.42	175.10
NOI Growth	0.0148	-0.1329	-0.0072	0.0107	0.0278	0.2788	0.0573
Rent Growth	0.0080	-0.0697	-0.0014	0.0090	0.0169	0.0858	0.0251
OPExp Ratio	0.6282	0.1956	0.4217	0.5640	0.7766	1.5237	0.3126
# of Prop	24.625	3.0000	6.0000	13.250	31.000	184.75	31.211
Prop Turnover	0.0028	0.0000	0.0000	0.0000	0.0000	0.0547	0.0110
Local Economic Conditions:							
ΔPCE%	4.1440	-3.1992	3.2235	4.2884	5.3679	8.491	2.0538
ΔGDP%	2.3798	-6.484	0.7922	2.3537	4.0237	11.519	3.2304

Table 3
Car Emissions vs. CO and VOC Level

This table presents panel regression results on the relationship between carbon monoxide (volatile organic compounds) and estimated carbon dioxide emissions from vehicles for a typical household. The dependent variables, carbon monoxide (CO) and volatile organic compounds (VOCs),, represent EPA's annual average daily CO and VOC level for a given county. Car_CO2 denotes the estimated car emissions (in lbs/CO_2) for a standardized household in a given county. For a detailed explanation of this variable, please refer to section 4.1. Ln(Car_CO2) represents the logarithm-transformed car emission for a standardized household. To facilitate the readability, Car_CO2, is scaled by 1000. The numbers in parentheses represent robust t-statistics. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	CO		VOCs	
Car_CO2	0.0023***		0.0458	
	(8.20)		(0.81)	
Ln (Car_CO2)		0.0340***		0.7047
		(8.14)		(0.79)
Constant	0.5379***	0.2497***	-1.2278	-7.2328
	(70.15)	(6.27)	(-0.34)	(-0.81)
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Observations	6,719	6,719	5,909	5,909
Adjusted R-squared	0.728	0.728	0.327	0.327

Table 4

Car Emissions and Future CRE Performance

This table presents regression results on the relationship between future CRE returns and estimated carbon dioxide emissions from cars for a typical household. Panel A presents the baseline findings using panel regressions while Panels B and C using inflation-adjusted car emission estimation and Fama-MacBeth (FMB) cross-sectional regressions, respectively. Panel D further replicates baseline results of Panel A by adding population density (PopDensity) as additional control, where PopDensity is the average zip code level population density in a CBSA. Panel E replicates baseline results of Panel A by including CBSA × Year fixed effects. Panel F replicates baseline results of Panel A by adding local air quality measures, air quality index from EPA data (AQI), while Panel G adds volatile organic compounds (VOCs), Ozone, and particulate matter (PM2.5) as additional controls, where AQI (VOCs, Ozone, or PM2.5) is the average county levels in a CBSA. The dependent variable, $PropRet_{t+1}$, represents NCREIF's NPI annual return in the following year. Car_CO2 denotes the estimated car emissions (in lbs/CO_2) for a standardized household. For a detailed explanation of this variable, please refer to section 4.1. Ln(Car_CO2) represents the logarithm-transformed car emission for a standardized household, and $PropRet_t$ represents NCREIF's NPI annual return in the current year. Other control variables are defined as in Table 2. To facilitate the readability, Car_CO2 and # of Prop are scaled by 1000. The numbers in parentheses represent robust t-statistics. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Baseline Results

	(1)	(2)	(3)	(4)
		$PropRet_{t+1}$		
Car_CO2	-0.0015***		-0.0015***	
	(-3.35)		(-3.65)	
Ln (Car_CO2)		-0.0263***		-0.0259***
		(-3.12)		(-3.42)
$PropRet_t$			0.3394***	0.3396***
			(7.02)	(7.02)
Property Characteristics:				
CAPEX	-0.3137	-0.3076	0.0803	0.0862
	(-0.27)	(-0.26)	(0.07)	(0.08)
LTV	0.0284	0.0287	0.0338	0.0341*
	(1.30)	(1.32)	(1.64)	(1.66)
Occupancy	0.3219***	0.3221***	0.1930***	0.1931***
	(7.83)	(7.83)	(4.63)	(4.63)
MV	-0.0001***	-0.0001***	-0.0001***	-0.0001***
	(-3.84)	(-3.79)	(-3.58)	(-3.53)
NOI Growth	0.0044	0.0046	-0.0195	-0.0193
	(0.14)	(0.15)	(-0.63)	(-0.63)
Rent Growth	0.3310***	0.3302***	0.2305***	0.2297***
	(5.66)	(5.63)	(3.91)	(3.89)
OPExp Ratio	-0.0090	-0.0088	-0.0008	-0.0006
	(-0.88)	(-0.86)	(-0.09)	(-0.07)
# of Prop	0.1512**	0.1502**	0.1356**	0.1346**
	(2.44)	(2.42)	(2.48)	(2.46)
Prop Turnover	0.1597	0.1632	-0.0063	-0.0030
	(1.32)	(1.35)	(-0.06)	(-0.03)
Local Economic Conditions				
ΔPCE%	0.0123***	0.0123***	0.0066**	0.0066**
	(4.11)	(4.09)	(2.37)	(2.36)

ΔGDP%	0.0016**	0.0016**	0.0014**	0.0014**
	(2.43)	(2.39)	(2.24)	(2.19)
Constant	-0.2421***	-0.0132	-0.1333***	0.0918
	(-5.61)	(-0.16)	(-3.26)	(1.13)
Year FE	Yes	Yes	Yes	Yes
CBSA FE	Yes	Yes	Yes	Yes
Property Type FE	Yes	Yes	Yes	Yes
Observations	2,504	2,504	2,504	2,504
Adjusted R-squared	0.629	0.628	0.666	0.666

Panel B: Inflation Adjusted Car Emission Estimation

	(1)	(2)	(3)	(4)
		$PropRet_{t+1}$		
Car_CO2	-0.0015***		-0.0014***	
	(-3.25)		(-3.52)	
Ln (Car_CO2)		-0.0262***		-0.0258***
		(-3.04)		(-3.33)
$PropRet_t$			0.3394***	0.3396***
			(7.02)	(7.02)
Property Characteristics	Yes	Yes	Yes	Yes
Local Economic Conditions	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
CBSA FE	Yes	Yes	Yes	Yes
Property Type FE	Yes	Yes	Yes	Yes
Observations	2,504	2,504	2,504	2,504
Adjusted R-squared	0.628	0.628	0.666	0.666

Panel C: FMB Regressions

	(1)	(2)	(3)	(4)
		$PropRet_{t+1}$		
Car_CO2	-0.0014***		-0.0006**	
	(-4.39)		(-2.81)	
Ln (Car_CO2)		-0.0258***		-0.0109***
		(-4.78)		(-3.48)
$PropRet_t$			0.4650***	0.4641***
			(8.24)	(8.27)
Property Characteristics	Yes	Yes	Yes	Yes
Local Economic Conditions	Yes	Yes	Yes	Yes
Property Type FE	Yes	Yes	Yes	Yes
Observations	2,504	2,504	2,504	2,504
Adjusted R-squared	0.250	0.250	0.456	0.456

Panel D: Population Density

	(1)	(2)	(3)	(4)
		PropRet$_{t+1}$		
Car_CO2	-0.0015***		-0.0015***	
	(-3.33)		(-3.63)	
Ln (Car_CO2)		-0.0262***		-0.0258***
		(-3.11)		(-3.41)
PropRet$_t$			0.3391***	0.3393***
			(7.02)	(7.02)
PopDensity	0.0096*	0.0099*	0.0078	0.0081
	(1.73)	(1.80)	(1.35)	(1.40)
Property Characteristics	Yes	Yes	Yes	Yes
Local Economic Conditions	Yes	Yes	Yes	Yes
Property Type FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
CBSA FE	Yes	Yes	Yes	Yes
Observations	2,504	2,504	2,504	2,504
Adjusted R-squared	0.250	0.250	0.456	0.456

Panel E: CBSA × Year fixed effects

	(1)	(2)	(3)	(4)
		PropRet$_{t+1}$		
Car_CO2	-0.0217**		-0.0179***	
	(-2.50)		(-2.63)	
Ln (Car_CO2)		-0.3672***		-0.3166***
		(-2.67)		(-2.81)
PropRet$_t$			0.3995***	0.4005***
			(5.90)	(5.95)
Property Characteristics	Yes	Yes	Yes	Yes
Local Economic Conditions	Yes	Yes	Yes	Yes
Property Type FE	Yes	Yes	Yes	Yes
CBSA × Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	2,504	2,504	2,504	2,504
Adjusted R-squared	0.699	0.699	0.742	0.743

Panel F: Overall Air Quality

	(1)	(2)	(3)	(4)
		$PropRet_{t+1}$		
Car_CO2	-0.0014***		-0.0014***	
	(-3.08)		(-3.41)	
Ln (Car_CO2)		-0.0251***		-0.0248***
		(-2.93)		(-3.24)
$PropRet_t$			0.3376***	0.3376***
			(6.98)	(6.98)
AQI	-0.0002	-0.0002	-0.0001	-0.0001
	(-0.59)	(-0.54)	(-0.28)	(-0.23)
Property Characteristics	Yes	Yes	Yes	Yes
Local Economic Conditions	Yes	Yes	Yes	Yes
Property Type FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
CBSA FE	Yes	Yes	Yes	Yes
Observations	2,493	2,493	2,493	2,493
Adjusted R-squared	0.631	0.631	0.668	0.668

Panel G: VOCs, Ozone, and PM2.5

	(1)	(2)	(3)	(4)
		$PropRet_{t+1}$		
Car_CO2	-0.0019***		-0.0018***	
	(-3.08)		(-3.31)	
Ln (Car_CO2)		-0.0361***		-0.0334***
		(-3.18)		(-3.38)
$PropRet_t$			0.3704***	0.3702***
			(6.71)	(6.71)
VOC	-0.0001***	-0.0001***	-0.0001***	-0.0001***
	(-4.69)	(-4.68)	(-5.56)	(-5.58)
Ozone	-2.4142**	-2.4429**	-1.0862	-1.1078
	(-2.36)	(-2.38)	(-1.18)	(-1.19)
PM2.5	0.0023	0.0024	0.0027	0.0028
	(1.21)	(1.27)	(1.52)	(1.58)
Property Characteristics	Yes	Yes	Yes	Yes
Local Economic Conditions	Yes	Yes	Yes	Yes
Property Type FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
CBSA FE	Yes	Yes	Yes	Yes
Observations	1,740	1,740	1,740	1,740
Adjusted R-squared	0.648	0.648	0.690	0.690

Table 5
State Greenhouse Gas Emissions Targets

This table replicates the baseline results of Table 4 Panel A by additionally controlling for states that have implemented policies aimed at mitigating greenhouse gas emissions. Panel A presents the baseline results after controlling for states with greenhouse gas emissions reduction targets. Panel B presents the results with the interaction between car CO2 emission variables and states with greenhouse gas emissions reduction targets. Panel C replicates the baseline results of Table 4, Panel A, by focusing only on the states and years where GHG emissions reduction targets were already in place. The dependent variable, $PropRet_{t+1}$, represents NCREIF's NPI annual return in the following year. Ln(Car_CO2) represents the logarithm-transformed car emission variable (Car_CO2). For a detailed explanation of Car_CO2, please refer to section 4.1. State_GHG_target is an indicator set to 1 if a state has implemented policies aimed at mitigating greenhouse gas emissions for a year, and zero otherwise, where the U.S. State Greenhouse Gas Emissions Reduction Targets data is obtained from National Conference of State Legislatures. $PropRet_t$ represents NCREIF's NPI annual return in the current year. Property characteristic and local economic condition variables are defined as in Table 2. The numbers in parentheses are robust t-statistics. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: State GHG Emissions Targets

	(1)	(2)	(3)	(4)
	$PropRet_{t+1}$			
Car_CO2	-0.0017***		-0.0016***	
	(-3.68)		(-3.93)	
Ln (Car_CO2)		-0.0290***		-0.0283***
		(-3.41)		(-3.67)
$PropRet_t$			0.3387***	0.3389***
			(7.03)	(7.02)
State_GHG_target	-0.0151**	-0.0143*	-0.0133*	-0.0125*
	(-1.97)	(-1.87)	(-1.85)	(-1.75)
Property Characteristics	Yes	Yes	Yes	Yes
Local Economic Conditions	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
CBSA FE	Yes	Yes	Yes	Yes
Property Type FE	Yes	Yes	Yes	Yes
Observations	2,504	2,504	2,504	2,504
Adjusted R-squared	0.629	0.629	0.667	0.666

Panel B: Condition on GHG Emissions Reduction Targets

	(1)	(2)	(3)	(4)
		$PropRet_{t+1}$		
Car_CO2	-0.0011**		-0.0010**	
	(-2.13)		(-2.11)	
Car_CO2 * State_GHG_target	-0.0017		-0.0017	
	(-1.38)		(-1.57)	
Ln (Car_CO2)		-0.0212**		-0.0199**
		(-2.06)		(-2.05)
Ln (Car_CO2) * State_GHG_target		-0.0185		-0.0197
		(-0.91)		(-1.06)
$PropRet_t$			0.3389***	0.3391***
			(7.06)	(7.04)
State_GHG_target	0.0151	0.1660	0.0182	0.1802
	(0.73)	(0.85)	(0.93)	(1.00)
Property Characteristics	Yes	Yes	Yes	Yes
Local Economic Conditions	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
CBSA FE	Yes	Yes	Yes	Yes
Property Type FE	Yes	Yes	Yes	Yes
Observations	2,504	2,504	2,504	2,504
Adjusted R-squared	0.630	0.629	0.667	0.666

Panel C: States with GHG Emissions Reduction Targets Already in Place

	(1)	(2)	(3)	(4)
		$PropRet_{t+1}$		
Car_CO2	-0.0049***		-0.0040***	
	(-3.65)		(-3.45)	
Ln (Car_CO2)		-0.0709***		-0.0579***
		(-3.29)		(-3.08)
$PropRet_t$			0.4233***	0.4252***
			(5.11)	(5.11)
Property Characteristics	Yes	Yes	Yes	Yes
Local Economic Conditions	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
CBSA FE	Yes	Yes	Yes	Yes
Property Type FE	Yes	Yes	Yes	Yes
Observations	799	799	799	799
Adjusted R-squared	0.661	0.658	0.721	0.719

Table 6
Public Transportation

This table presents panel regression results examining the relationship between future CRE property returns and estimated carbon dioxide emissions from cars for a typical household, while also accounting for public transportation usage. Panel A replicates the baseline results of Table 4 Panel A by adding bus emission variables, while Panel B replicates Panel A by using the residuals of property characteristics and local economic condition variables after regressing them on car emission variables. The dependent variable, $PropRet_{t+1}$, represents NCREIF's NPI annual return in the following year. Ln(Car_CO2) represents the logarithm-transformed car emission variable (Car_CO2). For a detailed explanation of Car_CO2, please refer to section 4.1. Ln(Bus_CO2) represents the logarithm-transformed public bus emission per household. Ln(Car_Bus_CO2) represents the logarithm-transformed car emissions plus public bus emissions per household. For a detailed explanation of the Bus_CO2 and Car_Bus_CO2 variables, please refer to section 5.2. $PropRet_t$ represents NCREIF's NPI annual return in the current year. Property characteristic and local economic condition variables are defined as in Table 2. To facilitate the readability, # of Prop is scaled by 1000. The numbers in parentheses are robust t-statistics. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Replication of Baseline Results

	(1)	(2)	(3)	(4)
	$PropRet_{t+1}$			
Ln(Car_CO2)	-0.0242***		-0.0236***	
	(-2.87)		(-3.13)	
Ln(Bus_CO2)	0.0052**		0.0055**	
	(1.98)		(2.11)	
Ln(Car_Bus_CO2)		-0.0263***		-0.0259***
		(-3.11)		(-3.42)
Property Characteristics:				
$PropRet_t$			0.3398***	0.3396***
			(7.05)	(7.02)
CAPEX	-0.2248	-0.3078	0.1733	0.0860
	(-0.19)	(-0.26)	(0.15)	(0.08)
LTV	0.0274	0.0287	0.0327	0.0341*
	(1.26)	(1.32)	(1.60)	(1.66)
Occupancy	0.3228***	0.3221***	0.1937***	0.1931***
	(7.83)	(7.83)	(4.65)	(4.63)
MV	-0.0001***	-0.0001***	-0.0001***	-0.0001***
	(-3.85)	(-3.79)	(-3.59)	(-3.53)
NOI Growth	0.0037	0.0046	-0.0203	-0.0193
	(0.12)	(0.15)	(-0.66)	(-0.63)
Rent Growth	0.3330***	0.3302***	0.2326***	0.2297***
	(5.67)	(5.63)	(3.94)	(3.89)
OPExp Ratio	-0.0096	-0.0088	-0.0015	-0.0006
	(-0.94)	(-0.86)	(-0.16)	(-0.07)
# of Prop	0.1504**	0.1502**	0.1348**	0.1346**
	(2.43)	(2.42)	(2.47)	(2.46)
Prop Turnover	0.1606	0.1632	-0.0058	-0.0030
	(1.34)	(1.35)	(-0.05)	(-0.03)
Local Economic Conditions:				
ΔPCE%	0.0125***	0.0123***	0.0068**	0.0066**
	(4.14)	(4.09)	(2.44)	(2.36)

ΔGDP%	0.0016**	0.0016**	0.0014**	0.0014**
	(2.37)	(2.39)	(2.17)	(2.19)
Constant	-0.0339	-0.0133	0.0703	0.0917
	(-0.40)	(-0.16)	(0.87)	(1.12)
Year FE	Yes	Yes	Yes	Yes
CBSA FE	Yes	Yes	Yes	Yes
Property Type FE	Yes	Yes	Yes	Yes
Observations	2,504	2,504	2,504	2,504
Adjusted R-squared	0.629	0.628	0.666	0.666

Panel B: Residuals

	(3)		(4)	(1)
		PropRet$_{t+1}$		
Ln (Car_CO2)	-0.0160*		-0.0162**	
	(-1.96)		(-2.19)	
$\epsilon_{Ln(Bus\_EM)}$	0.0052**		0.0055**	
	(1.98)		(2.11)	
Ln(Car_Bus_CO2)		-0.0161*		-0.0163**
		(-1.96)		(-2.20)
$\epsilon_{PropRet_t}$			0.3398***	0.3396***
			(7.05)	(7.02)
Property Characteristics:				
ϵ_{CAPEX}	-0.2248	-0.3078	0.1733	0.0860
	(-0.19)	(-0.26)	(0.15)	(0.08)
ϵ_{LTV}	0.0274	0.0287	0.0327	0.0341*
	(1.26)	(1.32)	(1.60)	(1.66)
$\epsilon_{Occupancy}$	0.3228***	0.3221***	0.1937***	0.1931***
	(7.83)	(7.83)	(4.65)	(4.63)
ϵ_{MV}	-0.0001***	-0.0001***	-0.0001***	-0.0001***
	(-3.85)	(-3.79)	(-3.59)	(-3.53)
$\epsilon_{NOI\ Growth}$	0.0037	0.0046	-0.0203	-0.0193
	(0.12)	(0.15)	(-0.66)	(-0.63)
$\epsilon_{Rent\ Growth}$	0.3330***	0.3302***	0.2326***	0.2297***
	(5.67)	(5.63)	(3.94)	(3.89)
$\epsilon_{OPExp\ Ratio}$	-0.0096	-0.0088	-0.0015	-0.0006
	(-0.94)	(-0.86)	(-0.16)	(-0.07)
$\epsilon_{\#\ of\ Prop}$	0.1504**	0.1502**	0.1348**	0.1346**
	(2.43)	(2.42)	(2.47)	(2.46)
$\epsilon_{Prop\ Turnover}$	0.1606	0.1632	-0.0058	-0.0030
	(1.34)	(1.35)	(-0.05)	(-0.03)
Local Economic Conditions:				
$\epsilon_{\Delta PCE\%}$	0.0125***	0.0123***	0.0068**	0.0066**
	(4.14)	(4.09)	(2.44)	(2.36)
$\epsilon_{\Delta GDP\%}$	0.0016**	0.0016**	0.0014**	0.0014**
	(2.37)	(2.39)	(2.17)	(2.19)
Constant	0.2537***	0.2541***	0.2554***	0.2558***
	(3.19)	(3.19)	(3.55)	(3.56)
Year FE	Yes	Yes	Yes	Yes
CBSA FE	Yes	Yes	Yes	Yes
Property Type FE	Yes	Yes	Yes	Yes
Observations	2,504	2,504	2,504	2,504
Adjusted R-squared	0.629	0.628	0.666	0.666

Table 7
Propensity Score Matching

This table presents estimates of differences in CRE performance measured by next year property returns ($PropRet_{t+1}$) between the treatment group (high levels of car emissions) and the control group (low levels of car emissions) in Panel A, and between the treatment group (high levels of combined car and bus emissions) and the control group (low levels of combined car and bus emissions) in Panel B. The matched sample is constructed by either nearest-neighbor and Kernel score matching, with scores given by a probit model. The observable characteristics used in estimating propensity scores include capital expenditure ratio, LTV, occupancy rate, market value, NOI growth rate, rent growth rate, operating expense ratio, number of properties, property turnover, year and property type fixed effects. Table 2 provides a detailed description of each observable variable. Standard errors are calculated using a 200-bootstrap replication and are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels respectively.

Panel A: Estimated Car Emissions

	$PropRet_{t+1}$	
	Nearest Neighbor Matching	Kernel Matching
High vs. Low Car_CO2	-0.0196**	-0.0152***
	(0.0066)	(0.0045)
Observations	1913	2499

Panel B: Estimated Both Car and Bus Emissions

	$PropRet_{t+1}$	
	Nearest Neighbor Matching	Kernel Matching
High vs. Low Car_Bus _EM	-0.0243***	-0.0149***
	(0.0062)	(0.0045)
Observations	1936	2499

Table 8
Political Inclination of States

This table employs panel regressions to examine whether the political inclination of a state influences the impact of local car emissions on future CRE performance. Panel A shows the political leanings of states. Panel B reports the results for Blue states (i.e., Democratic-leaning states), while Panels C and D present the results for Red (i.e., Republican-leaning) and Purple (i.e., swing) states, respectively. Across all panels, the dependent variable is $PropRet_{t+1}$ which represents NCREIF's NPI annual return in the following year. Ln(Car_CO2) is the logarithm-transformed car emission for a standardized household (Car_CO2). For a detailed explanation of Car_CO2, please refer to section 4.1. Ln(Bus_CO2) represents the logarithm-transformed public bus emission per household. Ln(Car_Bus_CO2) represents the logarithm-transformed car emissions plus public bus emissions per household. For a detailed explanation of the Bus_CO2 and Car_Bus_CO2 variables, please refer to section 5.2. $PropRet_t$ represents NCREIF's NPI annual return in the current year. Property characteristic and local economic condition variables are defined as in Table 2. The robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels respectively.

Panel A: Political Leanings of States

Political Leaning	**State Names**
Blue	California, New York, Illinois, Massachusetts, Washington, Oregon, Maryland, Connecticut, New Jersey, Vermont, Rhode Island, Delaware, Hawaii, Maine, Minnesota
Red	Texas, Utah, Wyoming, Idaho, Alabama, Mississippi, Louisiana, Arkansas, Tennessee, Kentucky, South Carolina, Alaska, Indiana, Kansas, Missouri, Montana, Nebraska, North Dakota, Oklahoma, South Dakota, West Virginia
Purple	Florida, Ohio, Pennsylvania, Michigan, Wisconsin, North Carolina, Virginia, Iowa, Nevada, New Hampshire, Colorado, Arizona, Georgia

Panel B: Blue States

	(1)	(2)	(3)	(4)
		$PropRet_{t+1}$		
Ln(Car_CO2)	-0.0260**		-0.0263**	
	(-2.09)		(-2.38)	
Ln(Bus_CO2)	0.0079**		0.0064*	
	(2.07)		(1.80)	
Ln(Car_Bus_CO2)		-0.0287**		-0.0285**
		(-2.31)		(-2.58)
$PropRet_t$			0.4337***	0.4348***
			(6.17)	(6.19)
Property Characteristics	Yes	Yes	Yes	Yes
Local Economic Conditions	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
CBSA FE	Yes	Yes	Yes	Yes
Property Type FE	Yes	Yes	Yes	Yes
Observations	995	995	995	995
Adjusted R-squared	0.654	0.654	0.716	0.716

Panel C: Red States

	(1)	(2)	(3)	(4)
		$PropRet_{t+1}$		
Ln(Car_CO2)	0.0050		0.0026	
	(0.24)		(0.11)	
Ln(Bus_CO2)	0.0057		0.0024	
	(0.90)		(0.42)	
Ln(Car_Bus_CO2)		0.0021		0.0014
		(0.10)		(0.06)
$PropRet_t$			0.3663***	0.3675***
			(5.42)	(5.49)
Property Characteristics	Yes	Yes	Yes	Yes
Local Economic Conditions	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
CBSA FE	Yes	Yes	Yes	Yes
Property Type FE	Yes	Yes	Yes	Yes
Observations	501	501	501	501
Adjusted R-squared	0.562	0.562	0.612	0.613

Panel D: Purple States

	(1)	(2)	(3)	(4)
		$PropRet_{t+1}$		
Ln(Car_CO2)	-0.0177		-0.0163	
	(-1.43)		(-1.36)	
Ln(Bus_CO2)	0.0009		0.0017	
	(0.18)		(0.34)	
Ln(Car_Bus_CO2)		-0.0179		-0.0168
		(-1.43)		(-1.37)
$PropRet_t$			0.1657**	0.1651**
			(2.17)	(2.18)
Property Characteristics	Yes	Yes	Yes	Yes
Local Economic Conditions	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
CBSA FE	Yes	Yes	Yes	Yes
Property Type FE	Yes	Yes	Yes	Yes
Observations	1,006	1,006	1,006	1,006
Adjusted R-squared	0.642	0.642	0.649	0.650

Table 9
Capital Return vs. Income Return

This table presents panel regression results examining the channels through which local car emission would impact the future CRE returns, where Panel A presents results for capital return (Capital Ret_{t+1}) and Panel B presents the results for operating income return (Income Ret_{t+1}). Ln(Car_CO2) represents the logarithm-transformed car emission for a standardized household (Car_CO2). For a detailed explanation of Car_CO2, please refer to section 4.1. Ln(Bus_CO2) represents the logarithm-transformed public bus emission per household. Ln(Car_Bus_CO2) represents the logarithm-transformed car emissions plus public bus emissions per household. For a detailed explanation of Car_CO2, Bus_CO2, and Car_Bus_CO2, please refer to sections 4.1 and 5.2, respectively. Capital Ret_t and Income Ret_t represent the NCREIF's NPI's capital return and operating income return in the current year, respectively. Other control variables are defined as in Table 2. # of Prop is scaled by 1000. The numbers in parentheses are robust t-statistics. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Capital Return

	(1)	(2)	(3)	(4)
	Capital Ret_{t+1}			
Ln(Car_CO2)	-0.0246***	-0.0232***	-0.0230***	
	(-2.96)	(-2.82)	(-3.06)	
Ln(Bus_CO2)		0.0034	0.0045*	
		(1.34)	(1.78)	
Ln(Car_Bus_CO2)				-0.0248***
				(-3.26)
Capital Ret_t			0.3407***	0.3397***
			(6.51)	(6.48)
Income Ret_t			-0.0873	-0.0787
			(-0.48)	(-0.44)
Property Characteristics	Yes	Yes	Yes	Yes
Local Economic Conditions	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
CBSA FE	Yes	Yes	Yes	Yes
Property Type FE	Yes	Yes	Yes	Yes
Observations	2,504	2,504	2,504	2,504
Adjusted R-squared	0.618	0.618	0.654	0.654

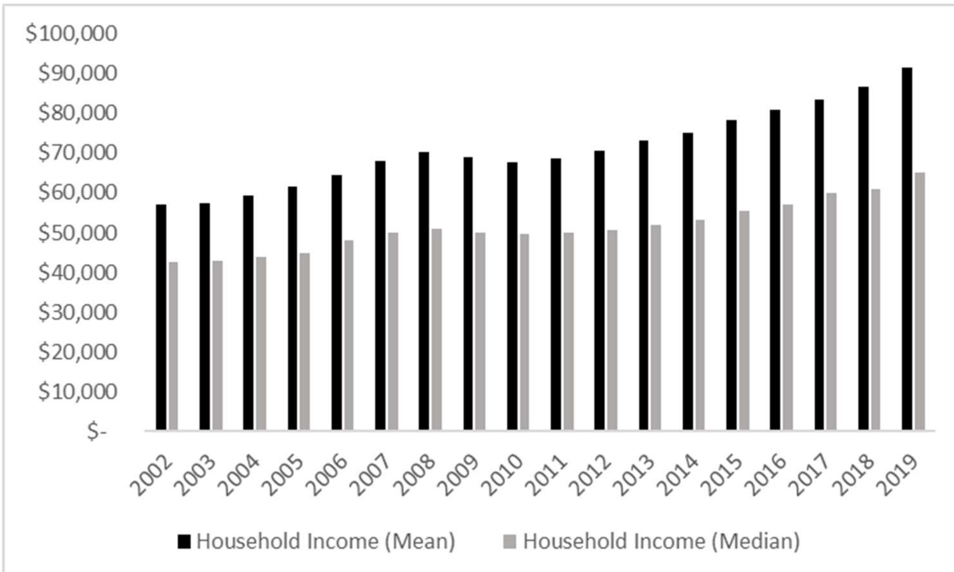
Panel B: Income Return

	(1)	(2)	(3)	(4)
		Income Ret_{t+1}		
Ln(Car_CO2)	-0.0017	-0.0009	-0.0005	
	(-0.97)	(-0.54)	(-0.40)	
Ln(Bus_CO2)		0.0018***	0.0004	
		(2.65)	(0.98)	
Ln(Car_Bus_CO2)				-0.0006
				(-0.55)
Capital Ret_t			-0.0232***	-0.0233***
			(-3.85)	(-3.87)
Income Ret_t			0.6919***	0.6927***
			(21.76)	(21.86)
Property Characteristics	Yes	Yes	Yes	Yes
Local Economic Conditions	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
CBSA FE	Yes	Yes	Yes	Yes
Property Type FE	Yes	Yes	Yes	Yes
Observations	2,504	2,504	2,504	2,504
Adjusted R-squared	0.516	0.516	0.518	0.760

Figure 1
Household Characteristics

This figure shows the time-series trends in the distribution of annual household income (Graph A) and household size & household head age (Graph B) for the period of 2002 through 2019.

Graph A: Household Income



Graph B: Household Size and Head Age

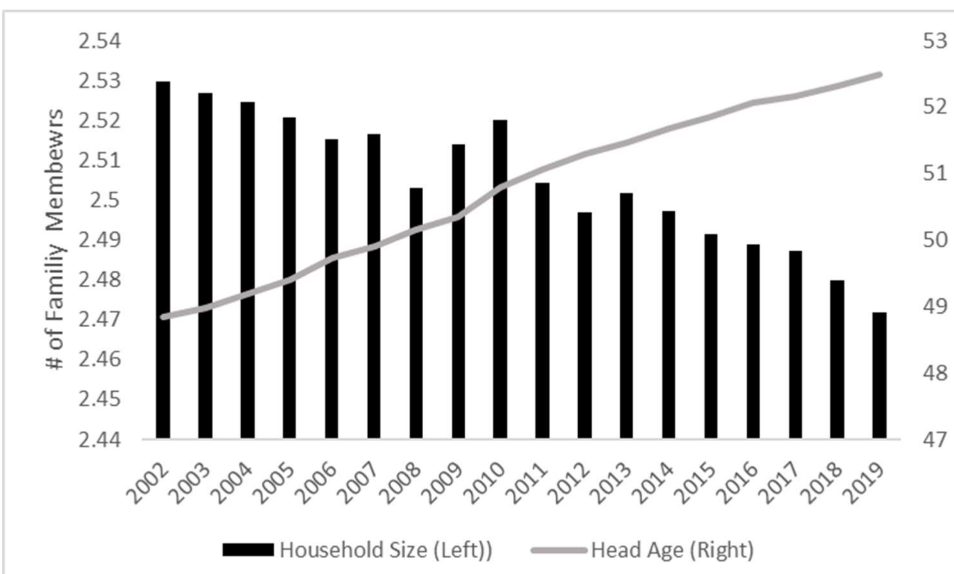


Figure 2
Estimated Car Emissions (lbs of CO2) for an Average Household

This figure illustrates the time-series trends in the distribution of estimated annual carbon dioxide (CO2) emissions from cars for an average family over the period from 2002 to 2019. For a detailed explanation of the estimation of an average family's annual car emissions, please refer to section 4.1.

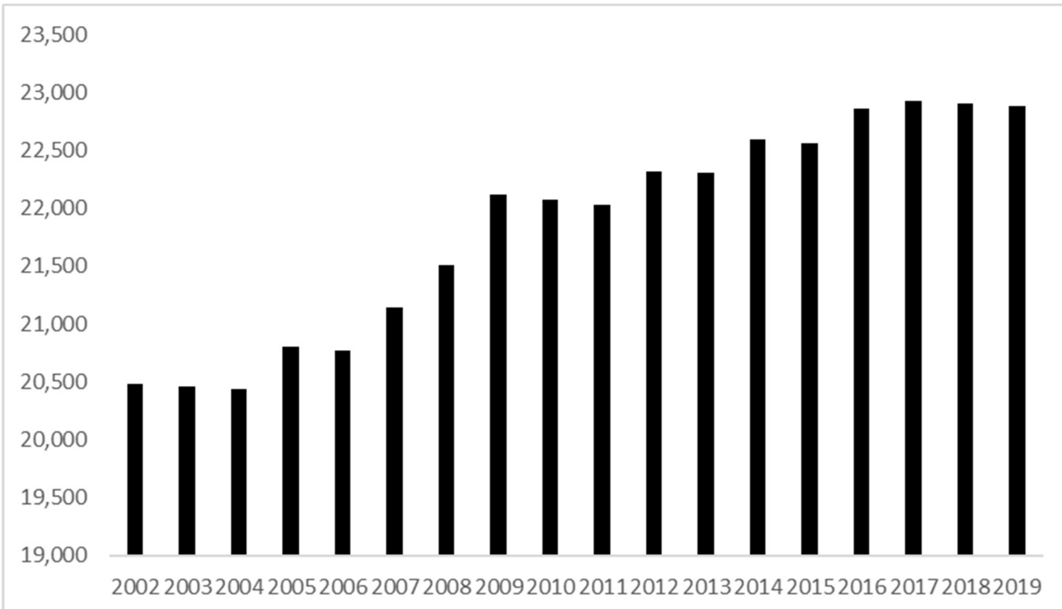
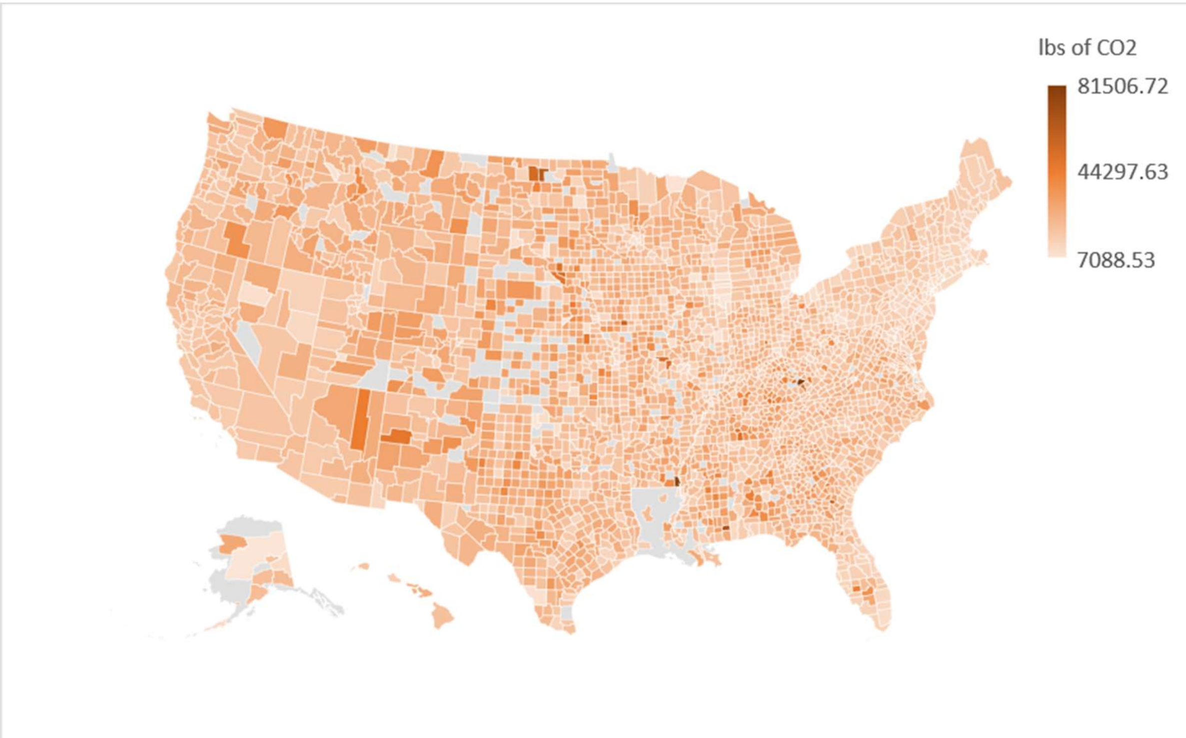


Figure 3
Estimated Car Emissions per Household

This figure presents the geographical distribution of the estimated carbon dioxide (CO_2) emissions from cars for an average family during the period of 2002 to 2019. Higher value (darker color) means higher level of CO_2. The gray-colored area indicates that no data is available. Please refer to section 4.1 for a detailed explanation of the estimation of an average family's annual car emissions.



Appendix A

The introduction of ride-hailing, with Uber launching its first ride in July 2010 and Lyft in June 2012, has raised questions about their environmental impact (e.g. Krishnamurthy and Ngo (2023)). These services have the potential to alter household car usage patterns, which, in turn, could potentially affect relationship of car emissions with CRE performance. In order to address this potential concern, this study revisits the analysis from Table 4 Panel A, focusing on the period before 2010—prior to the launch of Uber and Lyft—to ensure the results are not skewed by the advent of ride-hailing. The findings are reported in Appendix A Table. It shows that the coefficient estimates of car emission metrics are still negatively significant across all columns with similar magnitudes. These findings are highly consistent with the baseline results in Panel A of Table 4, suggesting that ride-hailing services have a limited effect on the relationship between local household car emissions and future commercial real estate performance.

Appendix A Table
Car Emissions and Future CRE Performance Prior to the Launch of Ride-hailing

This table presents regression results on the relationship between future CRE returns and estimated carbon dioxide emissions from cars for a typical household by using subsample from the period before ride-hailing service was launched (i.e. year before 2010). The dependent variable, $PropRet_{t+1}$, represents NCREIF's NPI annual return in the following year. Car_CO2 denotes the estimated car emissions (in lbs/CO_2) for a standardized household. For a detailed explanation of this variable, please refer to section 4.1. Ln(Car_CO2) represents the logarithm-transformed car emission for a standardized household, and $PropRet_t$ represents NCREIF's NPI annual return in the current year. Property characteristic and local economic condition variables are defined as in Table 2. To facilitate the readability, Car_CO2 is scaled by 1000. The numbers in parentheses represent robust t-statistics. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
		$PropRet_{t+1}$		
Car_CO2	-0.0015***		-0.0014***	
	(-3.25)		(-3.52)	
Ln (Car_CO2)		-0.0262***		-0.0258***
		(-3.04)		(-3.33)
$PropRet_t$			0.3394***	0.3396***
			(7.02)	(7.02)
Property Characteristics	Yes	Yes	Yes	Yes
Local Economic Conditions	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
CBSA FE	Yes	Yes	Yes	Yes
Property Type FE	Yes	Yes	Yes	Yes
Observations	1,014	1,014	1,014	1,014
Adjusted R-squared	0.687	0.687	0.699	0.699

Appendix B
Local Business Activity and Green Building Concentration

This table replicates the main regression analysis by adding local business activity (Panel A) and green building concentration (Panel B) as additional control variables. The dependent variable, $PropRet_{t+1}$, represents NCREIF's NPI annual return in the following year. Car_CO2 denotes the estimated car emissions (in lbs/CO_2) for a standardized household. For a detailed explanation of this variable, please refer to section 4.1. Ln(Car_CO2) represents the logarithm-transformed car emission for a standardized household. Total Businesses refers to the average number of total employer establishments in a county across a given CBSA for a given year. Agricultural Business refers to the average number of agricultural-related employer establishments (NAICS=11) in a county across a given CBSA for a given year. Avg. # of Employees refers to the average number of employees per business establishment in a county across a given CBSA for a given year, while Avg. # of Agricultural Employees refers to the average number of employees per agricultural-related business establishment in a county for a given CBSA and year. The local business data is obtained from County Business Patterns Datasets from the Census. High Green Bldg is an indicator variable that equals 1 if a CBSA has a number of ENERGY STAR-certified buildings higher than the average for a given year, and zero otherwise. Green Bldg refers to the average number of ENERGY STAR-certified buildings scaled by the total number of employees in a county within a CBSA for a given year, with the data for ENERGY STAR-certified buildings obtained from the registry of ENERGY STAR Certified Buildings and Plants. $PropRet_t$ represents NCREIF's NPI annual return in the current year. Other control variables are defined as in Table 2. The numbers in parentheses represent robust t-statistics. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Local Business Activity

	(1)	(2)	(3)	(4)
	$PropRet_{t+1}$			
Ln (Car_CO2)	-0.0291***	-0.0284***	-0.0280***	-0.0268***
	(-3.32)	(-3.39)	(-3.54)	(-3.57)
Total Businesses	-0.0001		-0.0001	
	(-0.96)		(-1.18)	
Agricultural Business	0.0007		0.0004	
	(1.15)		(0.71)	
Avg. # of Employees		0.0052		0.0021
		(1.41)		(0.58)
Avg. # of Agricultural Employees		-0.0010**		-0.0007
		(-2.14)		(-1.54)
$PropRet_t$			0.3398***	0.3369***
			(7.08)	(6.96)
Property Characteristics	Yes	Yes	Yes	Yes
Local Economic Conditions	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
CBSA FE	Yes	Yes	Yes	Yes
Property Type FE	Yes	Yes	Yes	Yes
Observations	2,504	2,504	2,504	2,504
Adjusted R-squared	0.629	0.630	0.666	0.666

Panel B: Green Building Concentration

	(1)	(2)	(3)	(4)
	$PropRet_{t+1}$			
Ln (Car_CO2)	-0.0289***	-0.0289***	-0.0279***	-0.0278***
	(-3.30)	(-3.28)	(-3.52)	(-3.50)
High Green Bldg	0.0056		0.0035	
	(1.29)		(0.84)	
Green Bldg		0.0050		0.0053
		(0.27)		(0.29)
$PropRet_t$			0.3391***	0.3398***
			(7.08)	(7.08)
Total Businesses	-0.0001	-0.0001	-0.0002	-0.0001
	(-1.01)	(-0.96)	(-1.21)	(-1.18)
Agricultural Business	0.0007	0.0007	0.0004	0.0004
	(1.18)	(1.15)	(0.73)	(0.70)
Property Characteristics	Yes	Yes	Yes	Yes
Local Economic Conditions	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
CBSA FE	Yes	Yes	Yes	Yes
Property Type FE	Yes	Yes	Yes	Yes
Observations	2,504	2,504	2,504	2,504
Adjusted R-squared	0.629	0.629	0.666	0.666

Appendix C

Residuals of Car Emissions

This table presents panel regression results examining the relationship between future CRE property returns and residuals of estimated carbon dioxide emissions from cars (and/or buses) for a typical household. The table below presents the second stage results. In the first stage, each of the residual emission variables ($\varepsilon_{Ln\,(Car\_EM)}$, $\varepsilon_{Ln(Bus\_EM)}$, and $\varepsilon_{Ln(Car\_Bus\_EM)}$) is obtained by regressing the emission variables on property characteristics and local economic conditions, respectively. In the second stage, each of the residual emission variables is used to replace the emission variables in the model specifications of Table 6 Panel A, where the dependent variable, $PropRet_{t+1}$, represents NCREIF's NPI annual return in the following year. Ln(Car_CO2) represents the logarithm-transformed car emission variable (Car_CO2). For a detailed explanation of Car_CO2, please refer to section 4.1. Ln(Bus_CO2) represents the logarithm-transformed public bus emission per household. Ln(Car_Bus_CO2) represents the logarithm-transformed car emissions plus public bus emissions per household. For a detailed explanation of the Bus_CO2 and Car_Bus_CO2 variables, please refer to section 5.2. $PropRet_t$ represents NCREIF's NPI annual return in the current year. Property characteristic and local economic condition variables are defined as in Table 2.. The numbers in parentheses are robust t-statistics. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	$PropRet_{t+1}$			
$\varepsilon_{Ln\,(Car\_EM)}$	-0.0242***		-0.0236***	
	(-2.87)		(-3.13)	
$\varepsilon_{Ln(Bus\_EM)}$	0.0052**		0.0055**	
	(1.98)		(2.11)	
$\varepsilon_{Ln(Car\_Bus\_EM)}$		-0.0263***		-0.0259***
		(-3.11)		(-3.42)
$PropRet_t$			0.3398***	0.3396***
			(7.05)	(7.02)
Property Characteristics	Yes	Yes	Yes	Yes
Local Economic Conditions	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
CBSA Fixed Effects	Yes	Yes	Yes	Yes
Property Type Fixed Effects	Yes	Yes	Yes	Yes
Observations	2,504	2,504	2,504	2,504
Adjusted R-squared	0.629	0.628	0.666	0.666

Appendix D

Instrumental Variable (IV) Analysis

In addition to public transportation usage along with property attributes, local economic conditions, local business activities, population density, existing environmental policies, and green building concentrations in the area, there may be other unobservable confounding variables that remain unaccounted for in the analysis. To further address the potential bias resulting from endogeneity, the average number of public transit agencies (*NumPTA*) in a county for a given CBSA is used as an instrumental variable for the car emission metric.[45] The data for public transit agencies is obtained from the National Transit Database.

The use of *NumPTA* as an instrument for a typical household car emission can be justified in several ways. First, a household's car gas consumption should be negatively related to the number of public transportation agencies in the area. In this study, the average correlation between *NumPTA* and car emission variable is negative and statistically significant.[46] Second, the error term $\varepsilon_{i,t}$ across all columns in Table 6 exhibits no significant correlation with *NumPTA*.[47] Also, there is little reason to believe that the number of public transit agencies in the area would have a direct relationship with future commercial real estate performance, as public transit agencies are often supported and regulated by governmental bodies. Changes to these agencies typically require extensive planning, public consultation, and legislative action.[48] All of these factors suggest that *NumPTA* satisfies both the relevance and exogeneity criteria for the IV approach.

The instrumental variable estimator is then implemented using 2SLS analysis. Appendix D Table presents the results. Columns 1 and 3 depict the first stage, where *Car_CO2* and *Car_Bus_CO2* are regressed on the

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[45] Although I show that the instrumental variable meets both the relevance and exogeneity criteria for the IV approach, I acknowledge that this IV may not be the ideal choice. Thus, I consider this as a supplementary robustness test with limitations.
[46] The correlation between *NumPTA* and car emission variable is -0.1463 ($p < .0001$).
[47] On average, the correlation between the error term $\varepsilon_{i,t}$ across all columns in Appendix E Table and *NumPTA* is 0.0047 with a p value of 0.8156.
[48] https://www.transit.dot.gov/regulations-and-guidance/environmental-programs/public-transit-united-states

average number of public transit agencies (*NumPTA*), along with other control variables. As indicated by the simple correlation above, the coefficient estimates of the instrument shows negative significance in the first stage. Furthermore, the first-stage F-statistic, assessing the 'weak instrument rule of thumb', is strongly significant (well above ten). This rejects the hypothesis that the instrument can be excluded from the first-stage regressions, affirming that it is not weak. Columns 2 and 4 present coefficient estimates for the second stage, where endogeneity is controlled. In line with the main findings, Columns 2 and 4 exhibit a consistent pattern: significant negative coefficient estimates for both predicted car emission and combined car and bus emission metrics. This reinforces the main notion that negative environmental externality stemming from greenhouse gas emissions impedes future commercial real estate performance.

Appendix D Table
Instrumental Variable Analysis

This table presents 2SLS regression results examining the relationship between future CRE returns and estimated carbon dioxide emissions from cars for a typical household, The instrumental variable used in first stage regression is average number of public transportation agencies in a county within a CBSA. The dependent variable in first state regressions are either Ln (Car_CO2) or Ln(Car_Bus_CO2), where Ln(Car_CO2) represents the logarithm-transformed car emission for a standardized household (Car_CO2) while Ln(Car_Bus_CO2) represents the logarithm-transformed car emissions plus public bus emissions per household. Ln(Bus_CO2) represents the logarithm-transformed public bus emission per household. For a detailed explanation of Car_CO2, Bus_CO2, and Car_Bus_CO2, please refer to sections 4.1 and 5.2, respectively. Ln($\widehat{Car\_EM}$) and Ln ($\widehat{Car\_Bus\_EM}$) are predicted values from first stage regressions. The second stage dependent variable, $PropRet_{t+1}$, represents NCREIF's NPI annual return in the following year. $PropRet_t$ represents NCREIF's NPI annual return in the current year. Property characteristic and local economic condition variables are defined as in Table 2. The numbers in parentheses are robust t-statistics. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) 1st Stage Ln (Car_CO2)	(2) 2nd Stage $PropRet_{t+1}$	(3) 1st Stage Ln(Car_Bus_CO2)	(4) 2nd Stage $PropRet_{t+1}$
$Ln\ (\widehat{Car\_EM})$		-0.0506**		
		(-2.39)		
$Ln\ (\widehat{Car\_Bus\_EM})$				-0.0398*
				(-1.86)
Ln(Bus_CO2)	-0.0377***			
	(-3.20)			
$PropRet_t$	0.0018	0.3393***	0.0044	0.3394***
	(0.03)	(7.28)	(0.07)	(7.25)
NumPTA	-0.1095***		-0.1174***	
	(-9.25)		(-9.96)	
Property Characteristics	Yes	Yes	Yes	Yes
Local Economic Conditions	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
CBSA FE	Yes	Yes	Yes	Yes
Property Type FE	Yes	Yes	Yes	Yes
Observations	2,504	2,504	2,504	2,504
Adjusted R-squared	0.576	0.664	0.572	0.665

Appendix E
Long-Term CRE Performance

This table presents panel regression results on the relationship between long-term future CRE returns and estimated carbon dioxide emissions from cars for a typical household. The dependent variables, $PropRet_{t+2}$, $PropRet_{t+3}$, and $PropRet_{t+4}$, represent NCREIF's NPI cumulative returns in the following two years (Panel A), three years (Panel B), and four years (Panel C), respectively. Ln(Car_CO2) denotes the lonarithm-transformed car emissions (in lbs/CO_2) for a standardized household. For a detailed explanation of Car_CO2, please refer to section 4.1. Ln(Bus_CO2) represents the logarithm-transformed public bus emission per household. Ln(Car_Bus_CO2) represents the logarithm-transformed car emissions plus public bus emissions per household. For a detailed explanation of Car_CO2, Bus_CO2, and Car_Bus_CO2, please refer to sections 4.1 and 5.2, respectively. $PropRet_t$ represents NCREIF's NPI annual return in the current year. Property characteristic and local economic condition variables are defined as in Table 2. To facilitate the readability, # of Prop is scaled by 1000. The numbers in parentheses represent robust t-statistics. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Cumulative Next Two-year Returns

	(1)	(2)	(3)	(4)
	$PropRet_{t+2}$			
Ln (Car_CO2)	-0.0386***		-0.0378***	
	(-2.87)		(-2.95)	
Ln(Bus_CO2)	0.0037		0.0041	
	(0.78)		(0.87)	
Ln(Car_Bus_CO2)		-0.0400***		-0.0395***
		(-3.00)		(-3.11)
$PropRet_t$			0.3605***	0.3601***
			(5.32)	(5.31)
Property Characteristics	Yes	Yes	Yes	Yes
Local Economic Conditions	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
CBSA FE	Yes	Yes	Yes	Yes
Property Type FE	Yes	Yes	Yes	Yes
Observations	2,450	2,450	2,450	2,450
Adjusted R-squared	0.624	0.624	0.637	0.637

Panel B: Cumulative Next Three-year Returns

	(1)	(2)	(3)	(4)
		$PropRet_{t+3}$		
Ln (Car_CO2)	-0.0456**		-0.0452**	
	(-2.35)		(-2.38)	
Ln(Bus_CO2)	0.0070		0.0075	
	(1.03)		(1.11)	
Ln(Car_Bus_CO2)		-0.0485**		-0.0483**
		(-2.53)		(-2.58)
$PropRet_t$			0.3933***	0.3926***
			(4.74)	(4.72)
Property Characteristics	Yes	Yes	Yes	Yes
Local Economic Conditions	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
CBSA FE	Yes	Yes	Yes	Yes
Property Type FE	Yes	Yes	Yes	Yes
Observations	2,420	2,420	2,420	2,420
Adjusted R-squared	0.584	0.584	0.592	0.592

Panel C: Cumulative Next Four-year Returns

	(1)	(2)	(3)	(4)
		$PropRet_{t+4}$		
Ln (Car_CO2)	-0.0455*		-0.0452*	
	(-1.84)		(-1.85)	
Ln(Bus_CO2)	0.0120		0.0125	
	(1.36)		(1.42)	
Ln(Car_Bus_CO2)		-0.0504**		-0.0503**
		(-2.07)		(-2.09)
$PropRet_t$			0.3353***	0.3341***
			(3.53)	(3.51)
Property Characteristics	Yes	Yes	Yes	Yes
Local Economic Conditions	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
CBSA FE	Yes	Yes	Yes	Yes
Property Type FE	Yes	Yes	Yes	Yes
Observations	2,381	2,381	2,381	2,381
Adjusted R-squared	0.557	0.557	0.562	0.562