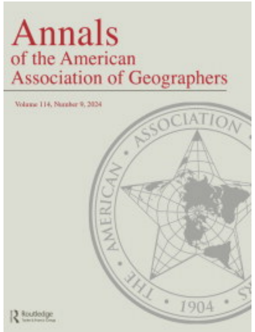

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Transferred Bias Uncovers the Balance Between the Development of Physical and Socioeconomic Environments of Cities

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Evaluating the balance between a city's physical and socioeconomic environmental development is crucial for creating sustainable and livable urban spaces. Although they might appear contradictory, they jointly support the comprehensive sustainable urban development strategy. Traditional methods usually focus on assessing this balance from a specific perspective, such as how neighborhood greenery shapes real estate value. Yet, they fail to deliver a holistic balance assessment in developing the physical and socioeconomic dimensions. To fill this gap, this study introduces a research framework that measures this balance through house prices based on transferred bias. Using house price as an indicator shaped by both physical and socioeconomic environments, the framework first constructs a series of deep learning models to estimate house prices through street view images for each city. These models capture the relationship between neighborhood appearance and house price. Second, by leveraging transfer inference, we introduce neighborhood appearance from one city into the model trained from another city. This process identifies the transferred bias, which is the disparity between inaccurate inference resulting from a mismatched neighborhood appearance and the trained model. Through transferred bias, we can quantify the differences in physical and socioeconomic environments across cities and evaluate the urban balances of these two environments. The results show that the transferred bias effectively quantifies the disparities among cities in physical and socioeconomic environments, thereby facilitating further investigation into the urban balance between these two environments. *Key Words: deep learning, place, street view image, sustainable urban development, transfer learning.*

Sustainable urban development emphasizes achieving a balance among the physical and socioeconomic domains (Brown et al. 1987; Porter and Linde 1995; Goodland and Daly 1996; Basiago 1998; Mensah 2019). This balance fosters the creation of inclusive and healthy communities (McHarg 1969; Jacobs 2016), ensures long-term sustainable development (Kaur and Garg 2019; W. Zhou, Pickett, and McPhearson 2021), and promotes economic growth and prosperity that benefits all residents (Basiago 1998; Pearce, Markandya, and Barbier 2013; Purvis, Mao, and Robinson 2019). It also represents the parity between a city's physical and socioeconomic environments and reflects how these two dimensions harmoniously coexist and support each other in urban development. By synergistically developing the urban physical, including urban appearance and infrastructure, and socioeconomic environment, including social, economic, and cultural atmosphere, cities can provide a higher quality of life, reduce social disparities, and mitigate adverse environmental impacts (Thompson 2002; Kaivo-Oja et al. 2014; Prieto-Curiel, Patino, and Anderson 2023).

Previous studies evaluate urban development balance by proposing city development indexes based on the physical and socioeconomic factors (Garau and Pavan 2018; Yan et al. 2018; Benites and Simões 2021). As Funtowicz and Ravetz (1994)

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noted, however, "No single perspective can fully encompass the reality of the whole system" (575). Diverse sustainable development frameworks assess the balance between urban physical and socioeconomic factors from varying perspectives, often leading to differing and sometimes contradictory outcomes (Gasparatos and Scolobig 2012; Rodrigues and Franco 2020). Wilson, Tyedmers, and Pelot (2007) compared six sustainable development indicator frameworks that can evaluate the balance between urban physical and socioeconomic environments, producing different or even contradictory results. This highlights a significant challenge in identifying cities or countries that achieve balanced development.

Transfer learning, a concept wherein knowledge gained in one domain is applied to another related domain (Pan and Yang 2010; Weiss, Khoshgoftaar, and Wang 2016), can potentially serve as a novel approach to assessing different aspects of cities' balance (Reia, Rao, and Ukkusuri 2022; Y. Ma et al. 2024). In the process of transfer learning, the adaptation enables a model trained in one domain, such as a city with its specific characteristics, to be effectively used in another. Such adaptation significantly reduces the potential biases due to differences between domains (Pan and Yang 2010). These *transferred biases*, however, can be instrumental in highlighting the differences between domains (cities) because they reflect each domain's unique characteristics. They can be used to evaluate disparities in urban development, especially in comparing the physical and socioeconomic environments of different cities.

To address the subjectivity in different urban balance evaluating methods and leverage the insights offered by transferred bias, this work introduces a new framework for assessing the balance between the physical and socioeconomic environments across different cities. This framework focuses on analyzing house price due to its specific position as an indicator influenced concurrently by both the physical and socioeconomic environments of a city. This dual aspect of house prices makes them particularly effective in assessing urban balance, offering insights into the complex relationship between a city's built environment, its social fabric, and its economic landscape (Ryan and Weber 2007; Nilsson 2014; Lockwood et al. 2018; Law, Paige, and Russell 2019).

Our methodology is based on a fundamental idea: By training deep learning models to estimate house prices in various cities, each based on the specific neighborhood appearance as captured through street view images (SVIs), we can establish a relationship between the physical environment and house prices within each city (Kang, Zhang, Gao, et al. 2021; Kang, Zhang, Peng, et al. 2021). This relationship inherently reflects the socioeconomic conditions, as the distinct correlations between physical environment and house prices in different cities are primarily influenced by their respective socioeconomic settings. Consequently, transferred bias emerges when we evaluate one city's neighborhood appearance through the model fitted in another city, thereby reflecting the separated impacts of physical and socioeconomic factors on house prices. By comparing these distinct impacts from urban physical and socioeconomic environments, we can assess the balance of development between these environments across different urban settings.

In this study, we apply our framework to ten U.S. cities in different developmental statuses, assessing the balance between their physical and socioeconomic environments. The results indicate a varied spectrum of urban balance of developments among these cities, demonstrating the effectiveness of our framework in distinguishing the different states of balance. The framework proves to be a reliable and efficient method for comprehensively unveiling the relationship between the physical and socioeconomic aspects of urban areas, providing practical advice for policymakers and urban planners for evaluating and guiding the balanced development of urban physical and socioeconomic environments.

Related Works

Evaluations on Urban Balance and Sustainable Development

Sustainable urban development is significantly influenced by the balance of both physical and socioeconomic environments (Scharlemann et al. 2020). This harmonious progression in these two environments fosters a foundation that synergistically advances toward sustainable development goals (Griggs et al. 2013; Wu et al. 2022). Such balance is crucial for achieving not only environmental sustainability but also socioeconomic prosperity (United Nations 2015b).

Numerous studies contribute to introducing indicators that quantify the balance between these two environments (Mori and Christodoulou 2012;

Phillis, Kouikoglou, and Verdugo 2017; Verma and Raghubanshi 2018). Several indicators provide a global outlook on cities' balanced development through both their physical and socioeconomic environments proposed by various authoritative global organizations and commercial research institutions (Pissourios 2013; Phillis, Kouikoglou, and Verdugo 2017). For instance, the City Prosperity Initiative (CPI), introduced by the United Nations, offers a framework for evaluating the balanced development of the physical and socioeconomic environments (United Nations 2015a). The CPI includes seventeen indicators distributed across six dimensions: productivity, infrastructure, quality of life, equity and social inclusion, environmental sustainability, and urban governance and legislation. Another representative assessment tool is the Spatial Adjusted Livability Index (SALI), developed by the Economist Intelligence Unit (2012), which evaluates relative comfort based on six categories and more than forty qualitative and quantitative factors, including stability, health care, culture and environment, education, infrastructure, and spatial characteristics. To deal with the ambiguity or subjectivity of these indicators, the sustainability assessment by fuzzy evaluation (SAFE) proposes a method to effectively evaluate the development levels of the physical, social, and economic environments in cities using fuzzy logic (Phillis, Kouikoglou, and Verdugo 2017).

These global indicators are overly distilled, making it challenging to apply them for assessing specific situations within a single country or a particular region (Verma and Raghubanshi 2018). As a result, many studies focus on developing indexes for cities or local areas within their countries. The United Nations' Sustainable Cities Development Index (SCDI) assesses urban development in seventy-seven Brazilian cities through the physical and socioeconomic environments (United Nations 2023). The SCDI provides insights into each city's progress and improvement areas, aiding the government in creating tailored development strategies and prioritizing actions. Benita, Kalashnikov, and Tuncer (2021) proposed a Spatial Livability Index for the 203 core urban areas in Singapore, which incorporates geographically weighted principal component analysis to assess livability based on the physical environment, socioeconomic environment, and subjective perceptions.

The subjectivity of each index and the varying emphasis of each evaluation system led to different assessment results (Gasparatos and Scolobig 2012). Indicators that are suitable for one region are often difficult to transfer to another region (Wilson, Tyedmers, and Pelot 2007; Mori and Christodoulou 2012). Tanguay et al. (2010) investigated seventeen relevant indicators along with 188 specific evaluation criteria, and the results showed that 72 percent of the indicators were only applicable to one or two studies, with very few indicators appearing in five or more studies.

Transfer Learning in Urban Analysis

All cities operate based on some common principles (Batty 2008, 2013; Schläpfer et al. 2021). Yet, each city is specifically shaped by its own history, geography, and human activities, resulting in diverse characteristics despite some shared patterns (W. Zhou, Pickett, and Cadenasso 2017; Reia, Rao, and Ukkusuri 2022). The transfer learning approach enables us to not only discern these universal urban principles but also to understand how each city's distinct features contribute to its identity (Rountree and Land 2000; Wang et al. 2018). Building on this, transfer learning is also widely employed to detect shifts in specific urban dynamics, including traffic flow, human mobility patterns, and economic activities, across various urban scenarios (Xie et al. 2016; R. Jiang et al. 2021). It also adapts deep learning models for a series of similar yet distinct urban sensing tasks, ranging from monitoring urban air pollution to predicting traffic flow in multiple transit systems, thereby expanding the scope and applicability of these models (J. Ma et al. 2019; Y. Zhang et al. 2023).

On the other hand, when comparing the actual situation of a city with the general principles of urban development, we can identify the characteristics and environments that correspond to each city. These corresponding aspects might manifest as inconsistencies or deviations from the universal principles in certain aspects of urban development (B. Jiang 2015). By recognizing and analyzing such transferred bias between a city's actual situation and these universal principles, we gain a deeper understanding of each city's specific development status, including its strengths, challenges, and unique needs, which provides us with urban development strategy implications (F. Zhang and Ye 2022).

Exploring Urban Physical and Socioeconomic Environment through Street View Images

SVIs directly record the physical environment of a city. Through deep learning techniques, though, we can infer the implicit influence of the socioeconomic environment on the city from the physical environment (Gebru et al. 2017; F. Zhang et al. 2020). SVIs have emerged as an outstanding tool for studying urban environments owing to their extensive coverage, high quality, and human-like observation perspective (Kang et al. 2020; Hou, Li, and Zhang 2024; F. Zhang et al. 2024). By applying machine learning and geospatial artificial intelligence techniques to these SVIs, we can further extract valuable insights to deepen our understanding and analysis of urban spaces (F. Zhang et al. 2020; Wang et al. 2024). Consequently, in recent years, SVIs have become increasingly important in urban science, transportation, architecture, and human perception and behavior (F. Zhang et al. 2018; Wang et al. 2022; N. Yang et al. 2024; H. Zhou et al. 2024).

Applying deep learning to SVIs helps us to efficiently extract detailed depictions of the urban physical environment and unveil the underlying urban socioeconomic characteristics (Zhang, Xie, and Long 2023). This combination provides a comprehensive evaluation of both the physical and the socioeconomic environments in urban areas. SVIs have been proven valuable in various applications: They can assess urban commercial behavior (J. Yang et al. 2021), analyze street walkability (Wei et al. 2024), and identify characteristics like building age and style (Sun et al. 2022). Additionally, these images are effective in detecting broader social issues such as poverty and inequality (Suel et al. 2019), criminal activities (De Nadai et al. 2020), physical disorder (J. Chen et al. 2023), and social segregation (Yao et al. 2021).

Methodology

We develop a two-stage framework to examine the balance of developments between a city's physical and socioeconomic environments using house prices, as illustrated in Figure 1. All the cities in our study are categorized into two types: the measured City m (the city whose physical or socioeconomic environment status we wish to evaluate) and the referenced City r (the city we set as a baseline for comparison). A city can be classified as either a measured city or a referenced city by different processes in our analysis. In the first stage, our framework involves training a series of deep learning models that focus on the relationship between the physical environment (represented by SVIs) and house prices for all the cities, respectively. In the second stage, we apply the transfer inference, which inputs neighborhood appearances from the measured City m into models trained in referenced City r to infer the house price. This process allows us to identify the transferred bias, which refers to differences between the inferred house prices in the measured City m when using its own model versus the model in the referenced City r. In this process, the distribution of neighborhood appearances across different cities is homogeneous, allowing various deep learning models to transfer and infer results effectively. Meanwhile, the heterogeneity shaped by the unique neighborhood appearances of different cities ensures that the transferred bias accurately reflects the differences in these cities. By analyzing this transferred bias through different comparison strategies, we can separately evaluate the physical and socioeconomic environments across various cities and further evaluate the balance of urban developments (underdeveloped vs. well-developed) between urban physical and socioeconomic environments.

Modeling the Relationship between Physical Environment and House Prices

We employ a deep convolutional neural network (DCNN) to capture the relationship between neighborhood appearances and house prices for each city. The model $f(\cdot)$ is trained by taking SVIs X as the model's input to predict house prices Y of the respective neighborhoods. The predicted house price is denoted as $\hat{Y}$. This process can be described as Equation 1. All models are adequately trained to capture the relationship between SVIs and housing prices effectively. Consequently, this relationship across different cities is primarily shaped by their specific socioeconomic contexts, allowing the model to accurately reflect the cities' socioeconomic environment.

$$\hat{Y} = f(X) \tag{1}$$

Assessing the Balance between Urban Physical and Socioeconomic Environment through "Transferred Bias"

The evaluation of the balance between physical and socioeconomic environments involves quantifying the disparities in these environments, which are

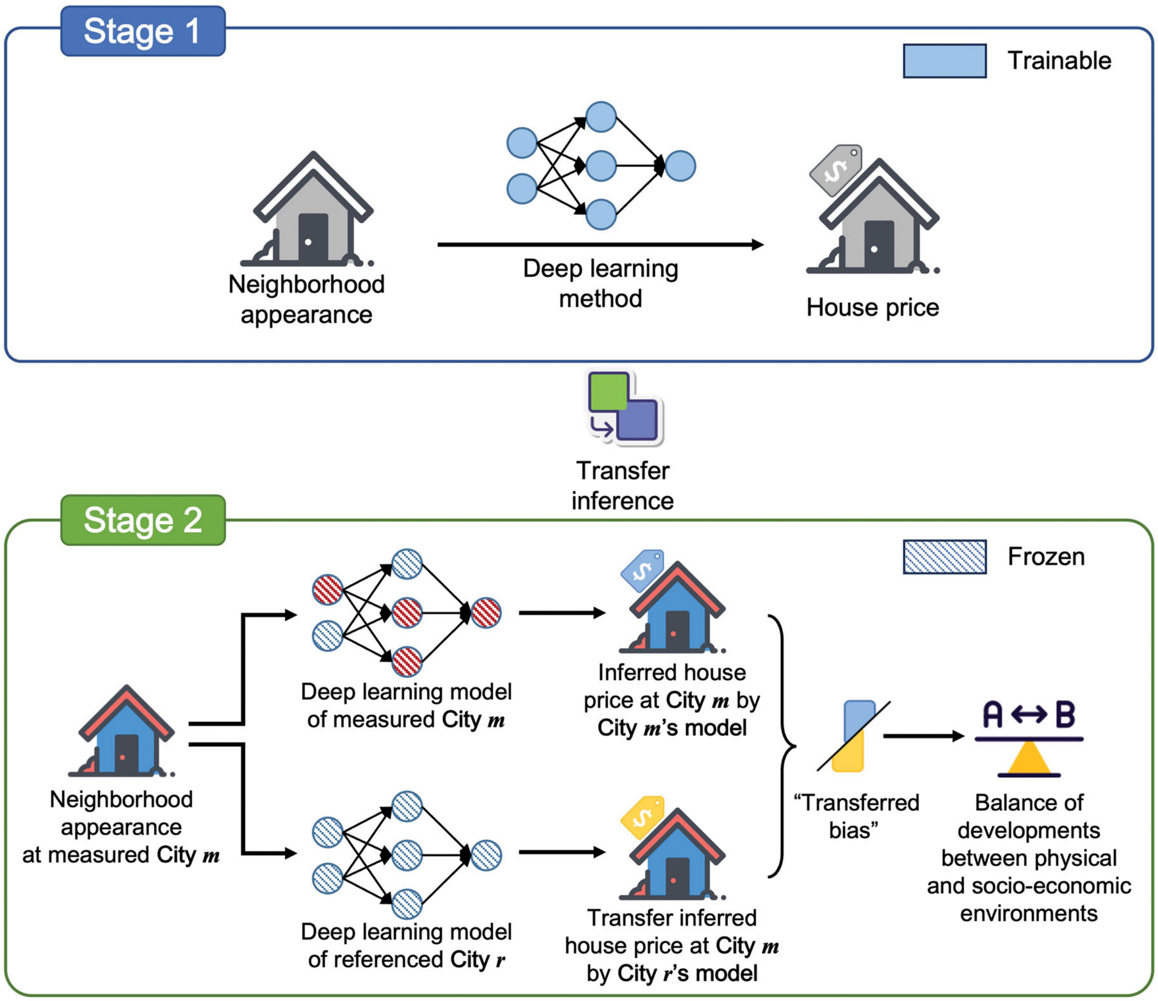

Figure 1. A two-stage conceptual framework for leveraging deep learning to quantify differences in physical and socioeconomic environments between cities using house price data. In Stage 1, a deep learning model is trained using neighborhood appearance data to predict house prices in a given city, thereby establishing a relationship between the city's physical environments and its housing market dynamics. This relationship in different cities inherently reveals their disparity in socioeconomic conditions, captured by the deep learning models. In Stage 2, this trained model in a referenced City r is applied to a different City m (the measured city). In this process, the models are "frozen," which means the model's structure and parameters are fixed when being applied to other cities. By comparing the differences between the inferred house prices in the measured City m when using its own model versus the model in the referenced City r, the framework quantifies the city-to-city variations in both physical and socioeconomic environments. This method highlights the concept of transferred bias as a tool to further evaluate the balance of developments between urban physical and socioeconomic environments.

detected through the transferred bias from both environments. The transferred bias refers to the discrepancies between inaccurate inferences resulting from a mismatch between neighborhood appearance and model, which is quantified through transfer inference. The transfer inference result, represented as $Y\hat{}mr$, is calculated by introducing SVIs X_m from the measured city (City m) into the model $f_r(\cdot)$ trained in the referenced city (City r). The whole process can be described by Equation 2. When $m = r$, the model predicts the actual house price, whereas when $m \neq r$, it represents transfer inference. We introduce different strategies to identify the transferred biases from their physical and socioeconomic environments, respectively.

$$\hat{Y}_{mr} = f_r(X_m) \tag{2}$$

Transferred bias in the socioeconomic environment $\delta_s(r, m)$ can be calculated as the difference between the inferred house prices in the measured City m when using its own model versus the model in the referenced City r. As illustrated in Figure 2A, when the inferred house price $\hat{Y}_{mr}$ is compared with $\hat{Y}_{mm}$ (we use the inferred house price $\hat{Y}_{mm}$ instead of the actual house price Y_m in City m to avoid the bias from the model estimation when comparing it to $\hat{Y}_{mr}$), the difference between the results $\hat{Y}_{mr}$ and $\hat{Y}_{mm}$ originates from using different models, which reflects the specific socioeconomic settings in corresponding cities (Neyshabur, Sedghi, and Zhang 2020). In this manner, we can evaluate the

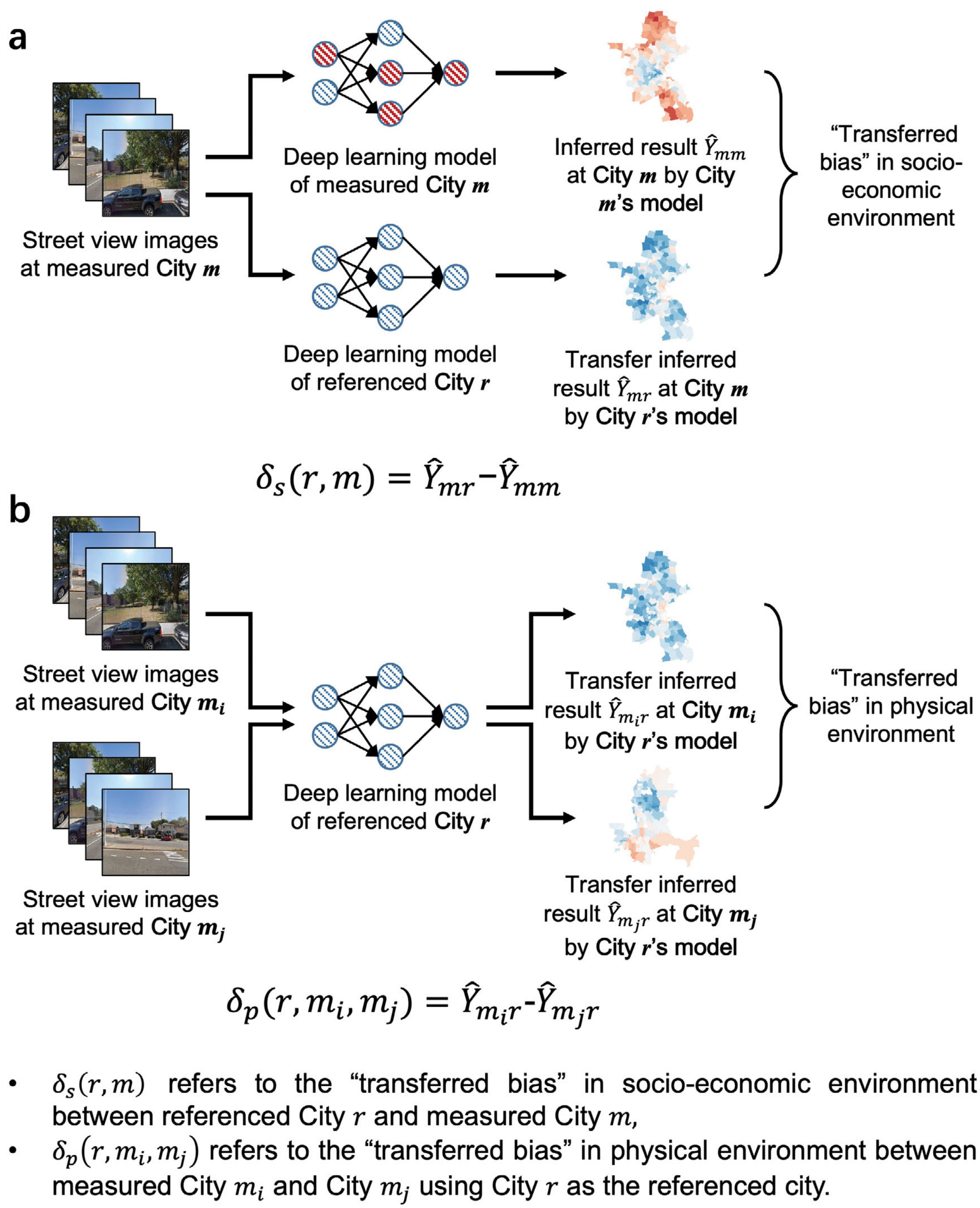

Figure 2. The process of calculating transferred bias from both physical and socioeconomic environments. (A) The transferred bias in the socioeconomic environment emerged by the difference between the inferred house price at City m by using the model in measured City m and referenced City r. (B) The transferred bias in the physical environment comes from the difference between the two inferred results $Yˆm_ir$ and $Yˆm_jr$ using one referenced City r.

transferred bias from the socioeconomic environment $\delta_s(r, m)$, which can be computed using Equation 3:

$$\delta_s(r, m) = \hat{Y}_{mr} - \hat{Y}_{mm} = f_r(X_m) - f_m(X_m) \tag{3}$$

On the other hand, transferred bias in the physical environment $\delta_p(r, m_i, m_j)$ emerges when we compare two transfer inference results from City m_i and m_j when using the same referenced City r's model. As depicted in Figure 2B, when we infer the house prices in measured cities City m_i and City m_j through the model trained in referenced City r, the difference between inferred house price in measured cities $Y\hat{}\,mir$ and $Y\hat{}\,m\ jr$ are both inferred by the model in referenced City r. In this situation, the transferred bias originated from different cities City m_i and City m_j's neighborhood appearances, which reflects the differences in physical environments when viewed from the perspective of City r. Hence, we can quantify the "transferred bias" attributed to the physical environment $\delta_p(r, m_i, m_j)$ using Equation 4. When $m_j = r$, this transferred bias measures the differences in physical environments between City m_i and City r.

$$\delta_p(r, m_i, m_j) = \hat{Y}_{m_i r} - \hat{Y}_{m_j r} = f_r(X_{m_i}) - f_m(X_{m_j}) \tag{4}$$

Experiments

Research Area

This work involves ten U.S. cities as the research area: Miami, Atlanta, Boston, Detroit, Seattle, Denver, San Jose, Austin, Knoxville, and Madison, as depicted in Figure 3. These cities were chosen due to their diverse physical and socioeconomic characteristics, ensuring they represent a broad spectrum of urban types and housing markets. These cities encompass different areas in the United States, including cities on the West Coast (Seattle, San Jose), East Coast (Boston, Miami), and the Midwest (Madison, Detroit). These ten cities also belong to different housing market types, such as tier one (Boston, San Francisco) and tier two (Seattle, Austin), among others. We also include both large metropolitan areas (Miami, Atlanta) and smaller towns (Knoxville, Madison), as well as cities experiencing growth (Boston) and those facing decline (Detroit). This diversity in physical and socioeconomic features enables a comprehensive representation of various city types and housing market dynamics.

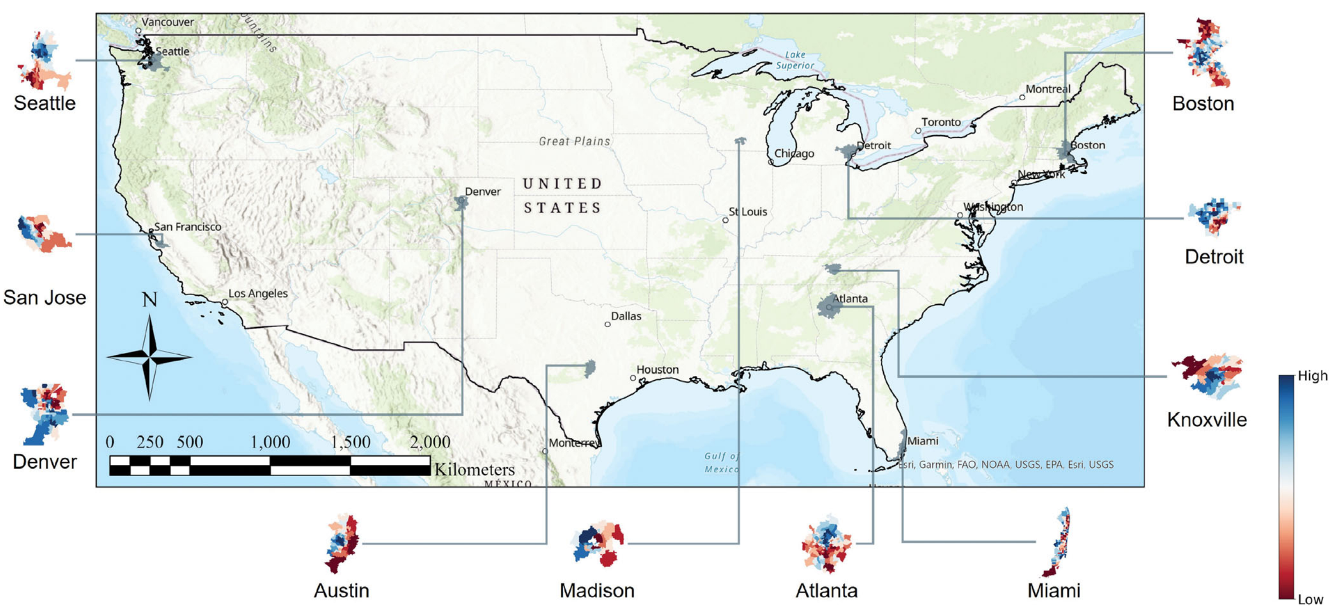

Figure 3. The distribution of the ten-city study area and their house price distribution pattern in the United States. The map for different cities with their ZIP Code Tabulation Area (ZCTA)-level average house price in 10 decile ranking. The palette shows the decile ranking of urban housing prices in each city. "High" refers to housing prices in this ZCTA, which is located in the top 0–10 percent range, and "low" refers to housing prices in the top 90–100 percent range.

Data Set: Real Estate and Street View Image

The house price data set is requested from Zillow, a leading online real estate market company known for their detailed evaluations of house values across the United States (Zillow 2012). This data set is widely used in housing market research (Raymond, Wang, and Immergluck 2016; Holt and Borsuk 2020; Gale and Roy 2023), allowing for a detailed analysis of housing market trends. Here we employ the average neighborhood-level house prices in 2018 across ten cities to obtain a fine-grained representation of the housing market.

To assess the physical environment, we employ SVIs from Google Street View (GSV) to explore the urban environment within each neighborhood. GSV provides a comprehensive view of urban landscapes from a human perspective, offering high coverage and volume, low data bias, and cost-effective data collection compared to traditional data sources (Biljecki and Ito 2021). Each SVI from GSV captures the cityscape from a human viewpoint, facilitating an overall assessment of the neighborhood's visual appearance without semantic segmentation. Our study employs SVIs to observe and evaluate the visual appearance, aiming to quantify the relationship between the physical environment and housing prices. We generate a set of georeferenced sampling points along road networks at 150-m intervals using OpenStreetMap (OSM). At each point, four SVIs facing different directions are captured to ensure a thorough representation of the neighborhood's physical attributes. We request the latest recorded SVIs to ensure the timeliness of physical environment information. To ensure uniformity, SVI data sets from all ten cities are collected using the same method.

DCNN Model Establishment and Validation

A DCNN model was trained to capture the relationship between the neighborhood appearance in each city and the corresponding house prices. Each SVI's corresponding neighborhood house price was input into the DCNN for training. The DCNN model is renowned for its excellent ability to deal with the images, and hence it is widely used for investigating the complex relationship between neighborhood appearances and house prices (Kang, Zhang, Gao, et al. 2021). Our model establishment involves two preprocessing steps to make sure all models can accurately capture the relationship between neighborhood appearances and house prices.

Before beginning the model establishment process, we conducted a preliminary data preprocess to exclude SVIs that were extensively obscured or irrelevant to the urban physical environment. We then thoroughly investigated the sampling years and months of these images to ensure that the physical environments depicted were consistent with those at the time the housing price data were collected. This step also helped us to avoid any potential impacts of seasonal variations on our predictive results. Such measures not only enhanced the accuracy of our model but also ensured consistency and comparability across the data.

Considering that high spatial heterogeneity of neighborhood appearances can interfere with modeling their corresponding house prices (W. Zhou, Pickett, and Cadenasso 2017; Boivin 2018), we first filter the most representative SVIs for each ZIP Code Tabulation Area (ZCTA) through training another DCNN-based classifier for each city. This classifier is designed to classify SVIs into their corresponding ZCTA. SVIs that correctly match their corresponding ZCTA are considered to be representative in that area. Initially, we randomly sampled the same number of SVIs for each ZCTA to form the training data set for each city. Only those images identified as representative were retained for further analysis.

Second, we normalize the neighborhood house prices by converting them into decile ranking and use a classification strategy to model the relationship between SVIs and neighborhood house prices effectively. In this step, all neighborhood house price values within each city were transformed into their respective decile ranges, denoted as $D \in \{1; 2; 3; \ldots ; 10\}$. For instance, if the average house price of a neighborhood falls within the top 10 percent of one city, the corresponding decile ranking D is set to 10. Conversely, if another neighborhood's average house price is in the lowest 10 percent, D is 1. We then use the representative SVIs to predict their corresponding decile ranking of neighborhood house prices. The result is a ten-dimensional vector $D = [d_1, d_2, \ldots , d_{10}]$ indicating the probability of the decile ranking to which the result belongs. Subsequently, we integrated the decile ranking results of predicted house prices at the neighborhood level into the ZCTA and city levels for further analysis.

In addition, we validate the model's performance and robustness in each city from three perspectives. First, we calculate the top-two accuracy for the predicted house price decile rankings, achieving approximately 90 percent accuracy in all ten cities, which indicates a high level of precision. Second, we compute the mean absolute percentage error (MAPE) by comparing the predicted house price with the ground truth house prices. The absolute value of the predicted value of neighborhood house price $\hat{Y}$ can be computed as the product of the predicted probability of house prices in decile rankings d_i and the values of house prices at each decile w_i within the city, as depicted in Equation 5. The MAPE in the ten cities is less than 10 percent, suggesting that the discrepancy between the predicted and actual house prices is minimal. Finally, we compared the distributions of predicted and real-world house prices, finding them to be very similar, which confirms the effectiveness of the DCNN models trained in all ten cities. In summary, our DCNN models can effectively establish the relationship between the SVIs and the house prices in all ten cities.

$$\hat{Y} = \sum_{i=1}^{10} w_i d_i \tag{5}$$

Transferred Bias across Multiple Cities

Here, we conduct different analyses of transferred bias at ZCTA and city levels. We calculate the pairwise transferred bias in both physical and socioeconomic environments. For the transferred bias in the physical environment, we calculate it by comparing the inferred house price $\hat{Y}mr$ at measured City m by City r's model and the inferred house price $\hat{Y}rr$ in City r; that is, $\hat{Y}mr - \hat{Y}rr$. Similarly, the transferred bias in socioeconomic environments is evaluated by $\hat{Y}mr - \hat{Y}mm$. For the city level, we used hierarchical clustering to compare the similarity of trends in transferred bias in physical and socioeconomic environments among the ten cities, thereby assessing the balance of cities in these two environments. At the ZCTA level, calculating transferred bias in the physical environment poses challenges due to the need to establish correspondences between ZCTAs in different cities. Here, we focus solely on transferred bias in the socioeconomic environment at this level. We discuss the spatial distribution of transferred bias and the similarity between different ZCTAs.

Results

Transferred Bias across U.S. Cities

Figure 4 visualizes the city-level pairwise transferred bias in physical and socioeconomic environments among ten U.S. cities. Hierarchical clustering reveals different patterns in the transferred bias of both physical and socioeconomic environments. The physical environments of cities like Seattle, Boston, Atlanta, and Madison, along with the socioeconomic environments of Seattle, Boston, Atlanta, Knoxville, and San Jose, show an obvious negative transferred bias compared to cities outside their cluster. This negative bias suggests that their physical or socioeconomic environment development is underestimated by others, highlighting their urban environments as superior to those in the other cluster. Therefore, these cities are recognized as well-developed in their respective physical or socioeconomic areas. Conversely, the physical environments of cities such as Knoxville, San Jose, Denver, Austin, Detroit, and Miami, and the socioeconomic environments of Denver, Madison, Detroit, Austin, and Miami display a noticeable positive transferred bias when compared with cities outside their cluster. This positive bias indicates that the development of their physical or socioeconomic environments is overestimated by others, suggesting that their urban environments are relatively inferior. Consequently, these cities are classified as having underdeveloped physical or socioeconomic environments.

The Balance between Urban Physical and Socioeconomic Environment

To evaluate the balance of the urban physical and socioeconomic environment of these ten cities, we categorize their development statuses based on their well- or underdeveloped conditions of physical and socioeconomic environments provided by Figure 4. Cities that exhibit either well-developed or underdeveloped conditions in both environments are classified as balanced. In contrast, cities that own a mismatched result, such as a well-developed physical environment alongside an underdeveloped socioeconomic environment or vice versa, are labeled unbalanced. This classification is visually represented in Figure 5A. Furthermore, we delineate the balanced cities based on their development status in both the physical and socioeconomic environments. Cities

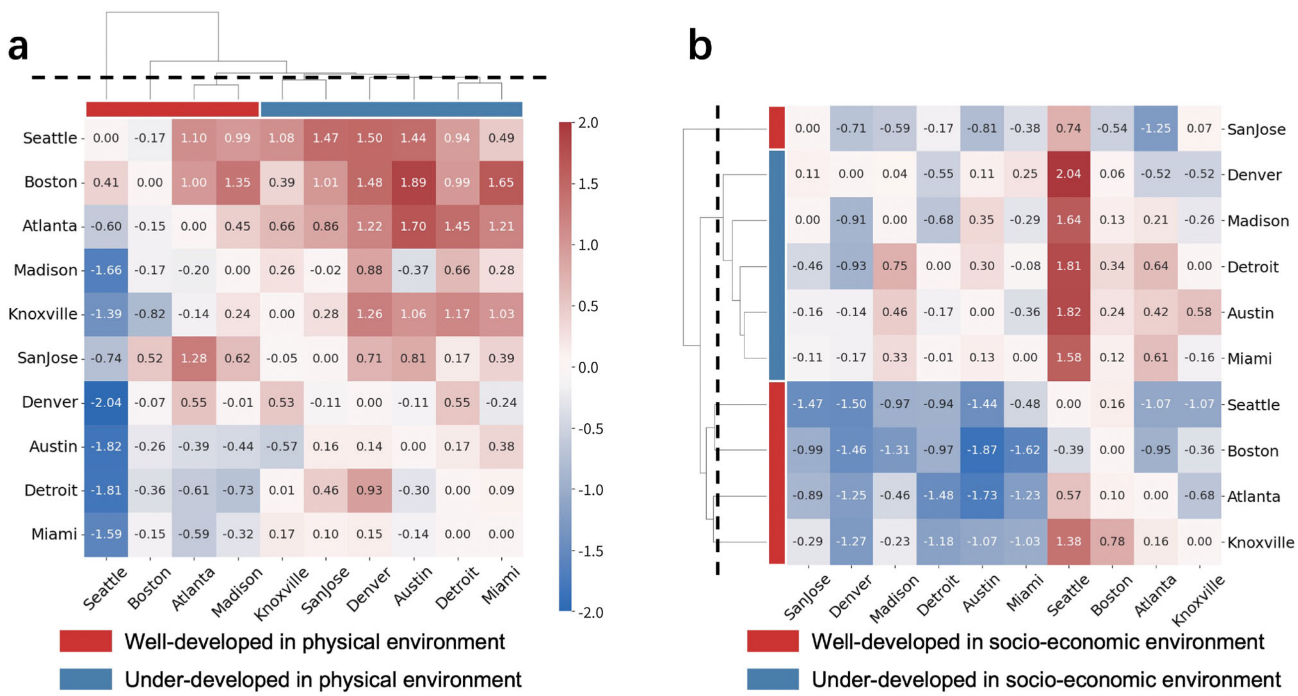

Figure 4. Hierarchical cluster map of the city-level transferred bias matrix from physical and socioeconomic environments. (A) The element at position (i, j) is denoted as the transferred bias in physical environment $\delta_p = \hat{Y}_{ij} - \hat{Y}_{jj}$. (B) The element at position (i, j) is denoted as the transferred bias in socioeconomic environment $\delta_s = \hat{Y}_{ij} - \hat{Y}_{ii}$.

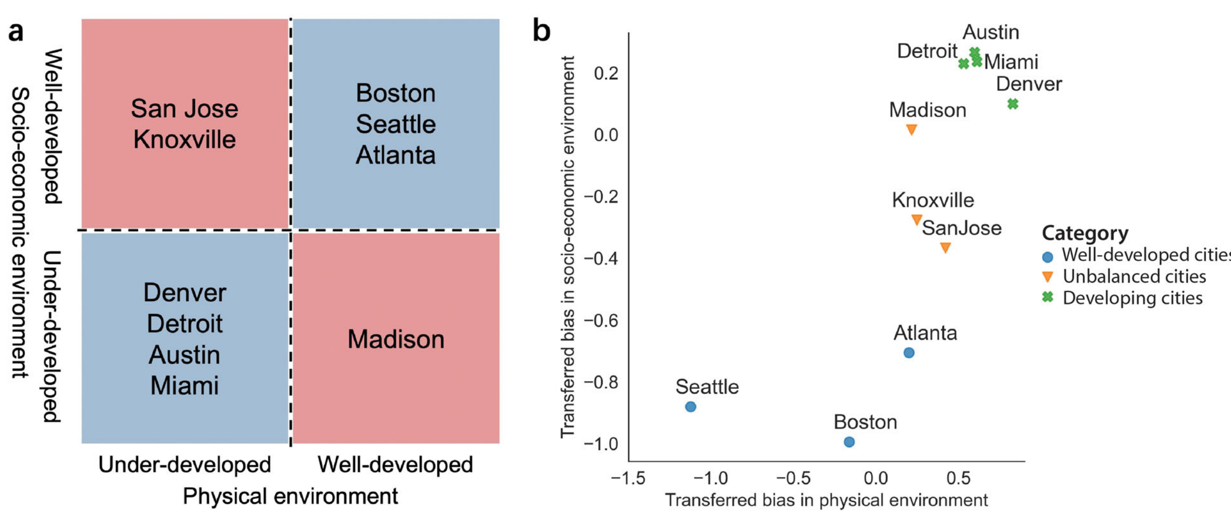

Figure 5. (A) A quadrant map categorizing cities based on their urban physical and socioeconomic development levels. Cities are classified within a 2×2 matrix, depending on whether their physical and socioeconomic environments are well-developed or underdeveloped. (B) The scatter plot of overall transferred bias from the physical and socioeconomic environments. Cities are categorized through their physical and socioeconomic environment status.

characterized by well-developed conditions in both physical and socioeconomic environments are characterized as well-developed cities; whereas those with underdeveloped conditions in both two environments are noted as "developing" cities. It is important to note that here, the terms balanced or unbalanced and well-developed or developing refer to a relative measurement within the context of the cities involved; we acknowledge that absolute balanced or developing conditions do not exist.

We also find that cities with the same development status tend to cluster with each other from the perspective of transferred bias. This clustering pattern is highlighted in Figure 5B, which is made by averaging ten cities' transferred bias in physical and socioeconomic environments according to the directional cues from hierarchical clustering shown in Figure 4 separately and plotted them on a scatter plot. The result also shows that balanced cities, which include both developing cities and well-developed cities, occupy the top and bottom positions on the plot, respectively. In contrast, unbalanced cities are positioned between these two groups, which indicates the intermediate stage of urban development.

The Local Spatial Pattern of Transferred Bias

Figure 6 describes the transferred bias in the socioeconomic environment among cities at the ZCTA level. The ZCTA-level transferred bias in the physical environment is achieved by transferring the same model between two regions. When the spatial regions are inconsistent, however, it becomes difficult to investigate the transferred bias between them. This inconsistency hinders our understanding of the spatial characteristics of the transferred bias. Therefore, we only present the transferred bias within the socioeconomic environment here. The result shows that transferred bias by evaluating the neighborhood appearances of the same city with different referenced cities (each column in Figure 6) exhibits consistent local spatial patterns and spatial autocorrelation. The differences in these similar transferred bias local patterns, however, reflect disparities in the socioeconomic environments among the referenced cities. For example, when focusing on Boston's transferred bias (the third column of Figure 6), we observe a consistent pattern across various models estimating the city's house prices. There is a tendency for the central urban areas to be overestimated, whereas the suburban peripheries are underestimated. The underestimation is deepened in cities with less appealing socioeconomic environments, however, such as Denver, Detroit, and Miami.

Conversely, in cities with socioeconomic environments similar to Boston, like Seattle and Atlanta, the transferred bias is closer to zero, indicating a more accurate prediction by the models for these areas. On the other hand, when we examine Detroit's transferred bias, as depicted in the fifth column of Figure 6, the spatial pattern of bias remains consistent. Yet, in contrast to Boston, cities with socioeconomic environments similar to Detroit, such as Denver and Miami, exhibit transferred biases closer to zero. This suggests a more accurate estimation for these locations. In contrast, cities like Seattle and Boston, which have different socioeconomic environments from Detroit, display obvious transferred biases. Furthermore, the local-level transferred bias reflects the fine-grained similarities in the socioeconomic environment between cities. A prominent example comes from the transferred bias by evaluating San Jose through Seattle as the referenced city. The transferred bias in the eastern region is nearly zero, indicating that these areas are very similar to Seattle in terms of their socioeconomic environment.

Discussion

Transferred Bias Effectively Helps Us to Evaluate the Balance of Urban Environments

The results from the transferred bias effectively distinguish the different states of cities, offering clear insights into their development status. Here is a brief characterization of all the city types based on the classification previously illustrated:

- *Well-developed cities:* Cities like Boston, Seattle, and Atlanta are classified as well-developed cities due to their exceptional physical environments and thriving socioeconomic environments. These cities are renowned worldwide for their strong economic power and appealing urban and natural landscapes, positioning them well for sustained growth and development.
- *Developing cities:* Denver, Austin, Miami, and Detroit fall into the category of developing cities. These cities tend to face challenges in both economic growth and physical environment quality. In addition, this part also includes some declining cities. Cities like Detroit and Miami have seen significant downturns from their previous prosperity. Others struggle to establish stable economic sectors and urban infrastructure, indicating a pattern of ongoing decline.

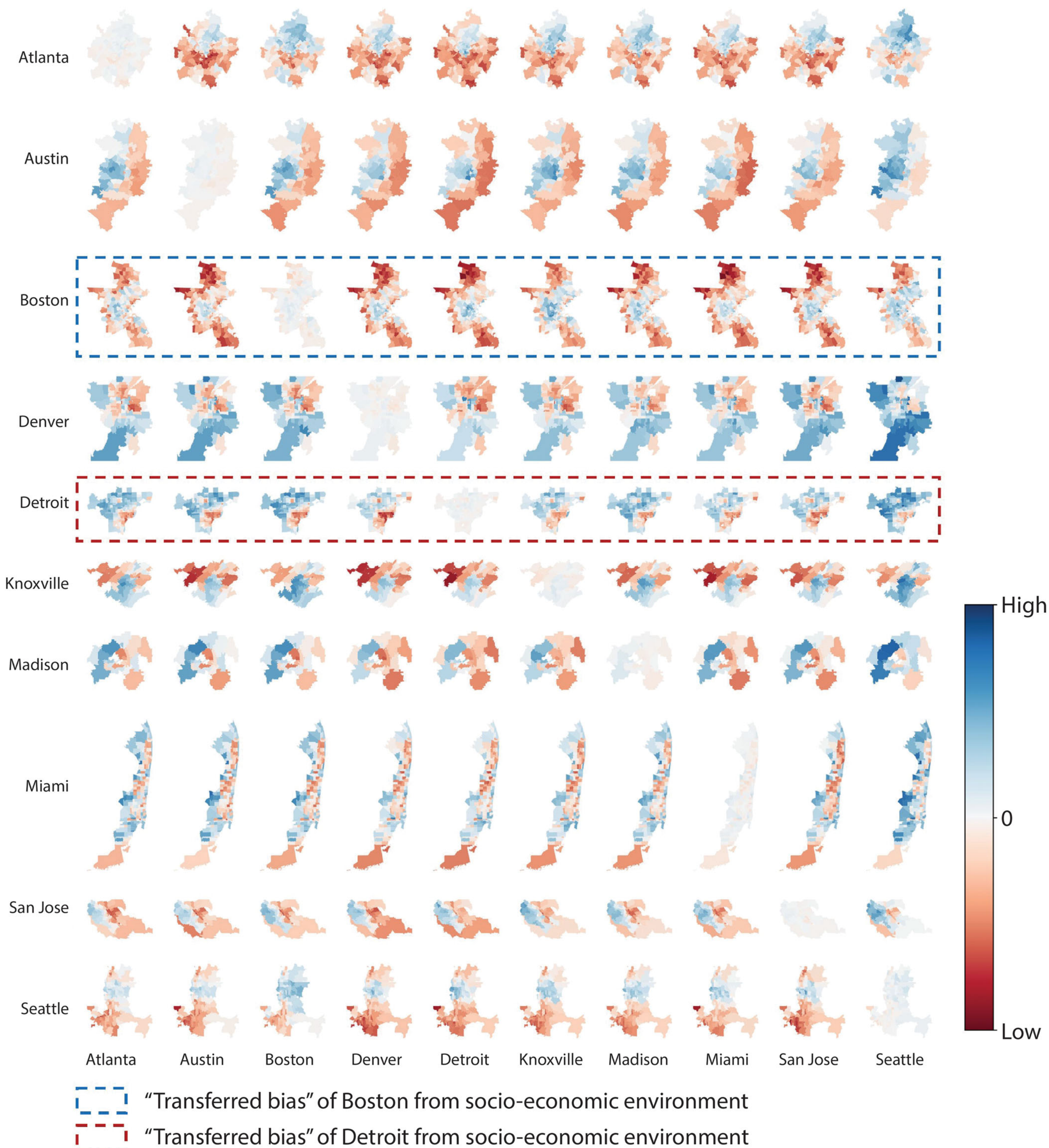

Figure 6. The transferred bias in the socioeconomic environment across ten cities at ZIP Code Tabulation Area (ZCTA) level. The map at position (i, j) represents the transferred bias generated by evaluating the street view images of i row cities with j column cities as referenced cities; i.e., $\delta_s = \hat{Y}_{ij} - \hat{Y}_{ii}$.

- *Unbalanced cities:* According to our analysis, San Jose, Knoxville, and Madison are identified as cities with a mismatch between their physical and socioeconomic development. San Jose, for instance, might not have the most impressive urban landscapes but it is experiencing rapid economic expansion. Conversely,

> Madison, with its appealing urban aesthetics, lags in socioeconomic development. These cities are actively working to address the imbalance between their physical and socioeconomic environments.

Additionally, an interesting phenomenon is that the transferred bias can not only reflect the status of urban development but also show the process of urban evolution. A good example is the unbalanced cities positions between developing cities and well-developed cities in Figure 5B. The mismatch between the city's physical and socioeconomic environments represents an unstable state that is difficult to detect but crucial. Unlike developing cities and well-developed cities that have achieved a stable development and resource utilization phase (Wiechmann and Pallagst 2012), these unbalanced cities are facing a transitional phase, potentially evolving into stable states of either developing or well-developed cities as their urban development progresses (Cohen 2004; Z. Chen and Lu 2016). It is particularly important for policymakers to guide these cities toward becoming well-developed cities and transferred bias can be an effective and insightful tool for them. Developing cities and well-developed cities have reached different types of balanced urban development. Well-developed cities enjoy the advantages brought by balanced urban development, whereas developing cities face the drawbacks of their balanced development. Balanced and well-developed cities like Boston and Seattle are more likely to achieve sustainable and livable urban development, which is attributed to the harmonious balance between their physical and socioeconomic environments (Puleo 2011; Sale 2019). Developing cities like Detroit, however, encounter many challenges, which arise from a long-term lack of adequate physical and socioeconomic developed motivation, often resulting in unsustainable development status. Such a type of development exacerbates resource distribution inequalities and contributes to the "Matthew effect" in urban development, which can significantly affect residents' quality of life (Glaeser et al. 1992; Glaeser 2012; Florida, Mellander, and King 2020).

Figure 7 shows that the Matthew effect drives cities into divergent paths of urban development. In Boston, a typical trend is observed where downtown house prices are higher than those in the suburbs. Conversely, Detroit presents an opposite trend, where suburban house prices are higher than those

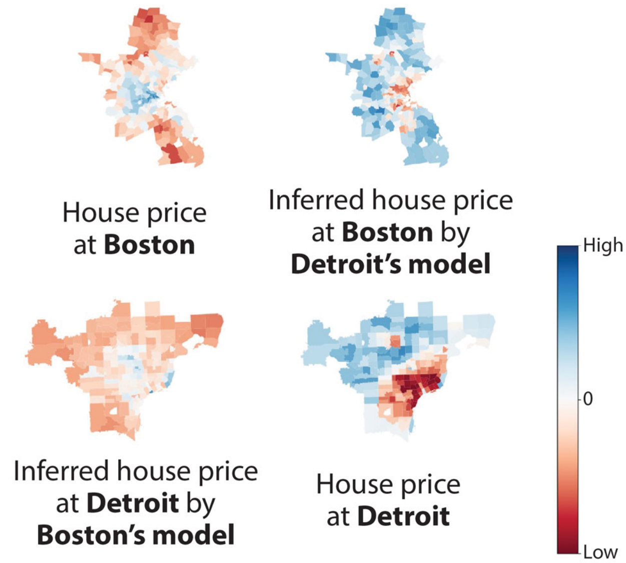

Figure 7. The house price patterns in Boston and Detroit (figures in upper left and lower right) and the transfer inference house price by applying Boston's (Detroit's) neighborhood appearance into Detroit's (Boston's) model (figures in upper right and lower left).

in the city center. This inversion becomes even more apparent when Boston's house price is inferred with Detroit as the referenced city. This phenomenon suggests that the reversed trend originates not from the disparity in the physical environment, but from the socioeconomic environment shaping each city. Detroit's long-term economic downturn has fueled a suburbanization trend within its urban area (Cooke and Denton 2015), leading to an abnormal socioeconomic structure, highlighting the profound impact of socioeconomic environments on urban evolution.

Implications to Sustainable Urban Development

Both physical and socioeconomic environments are crucial for sustainable urban development (Cheng 2003). Interestingly, sometimes the imbalance between these environments can act as a catalyst for development, particularly with strategic urban management and government intervention (Bertaud 2010). This indicates the importance of proactive and targeted governmental actions, especially in cities with clear mismatches between their physical and socioeconomic conditions. Our study particularly highlights such imbalances in cities like San Jose and Madison. San Jose experiences remarkable economic growth and social welfare, yet its physical environment lags behind. This environmental imbalance has contributed to social segregation and widened wealth disparities within the city (Himmelberg, Mayer, and Sinai 2005; Rothwell 2019). To mitigate these issues, it is vital for San Jose to use its economic prosperity to improve urban infrastructure and services, thereby aligning its physical environment with its socioeconomic achievements. Conversely, Madison presents a contrasting scenario with its commendable physical environment but relatively lower socioeconomic performance. Challenges in spurring robust economic growth and sustaining urban infrastructure are prominent here (Barker et al. 2021; Immergluck 2022). Economic stabilization policies could leverage Madison's solid infrastructure to unlock its growth potential (McManamay et al. 2019).

For developing cities, immediate governmental intervention is essential to stimulate urban redevelopment (Fekade 2000). This involves policies focusing on economic diversification, job creation, infrastructure development, and revitalization of housing and neighborhoods. Such strategies are crucial to stimulate economic growth, attract businesses, and foster community ownership, with stakeholder collaboration being key to their success. It is also crucial, though, for governments in currently thriving cities to assess their environments and remain careful about potential imbalances continuously. This forward-looking approach is necessary to ensure sustainability and to prevent future challenges.

Limitation and Future Work

Although the transferred bias demonstrates its unique value, it inevitably comes with limitations. The primary challenge lies in its applicability and scalability to different cities with greater discrepancies in physical and socioeconomic environments. We recognize that the effectiveness of transferred bias is dependent on the degree of homogeneity or heterogeneity between cities. If cities are too similar, the method struggles to effectively distinguish discrepancies between them. Conversely, quantifying transferred bias between extremely heterogeneous cities might also be challenging in getting valuable insights, such as using Boston as the referenced city to measure non-Western cities like Naples or Tokyo. This is because these cities share few commonalities in both physical and socioeconomic environments. In this article, our study addressed the impact of city heterogeneity by specifically selecting a series of dispersed cities across the United States for our experiments, and this approach yielded promising results. The experimental outcomes indicate that, although these cities generally show high homogeneity in their featured representations, they exhibit significant heterogeneity in specific areas of feature space, which helps the transferred bias to effectively capture the difference of their developmental condition in physical and socioeconomic environments as illustrated in Figure 8. It is still worth discussing, however, whether the transferred bias is still effective when applied to cities with greater heterogeneity, such as cities disseminated around the world. For example, if we apply the transferred bias to more complex and dynamic environments, such as those encompassing cities, rural areas, and even wastelands, we must consider whether we can still effectively discern the differences in urban development and distinguish between different types of regions. From a fundamental perspective, the challenges posed by the transferred bias also touch on the profound question of what a city is, encouraging us to rethink this question from the dimension of differences. Above all, defining a city from the perspective of transferred bias provides a fresh perspective for reillustrating cities, which is also an important direction for our explorations in the future.

Another limitation of transferred bias is the lack of interpretability, as selecting different cities as references can result in variations in the ranking of other cities. For instance, Denver and Madison are identified as cities with similar socioeconomic environments in this study. When using Denver as the reference city for evaluating other cities' socioeconomic environment, San Jose ranks sixth, suggesting a relatively favorable socioeconomic condition. When Madison was chosen as the reference city, however, San Jose ranked third, indicating a comparatively poorer socioeconomic environment. This phenomenon suggests that the dimensions emphasized by the transferred bias could vary depending on the referenced city. In this study, we primarily focused on the overall pattern presented by the transferred bias to explore the general physical and socioeconomic environment development of various cities, providing us with an effective result. This macro perspective, however, inevitably overlooks subtle differences in the rankings

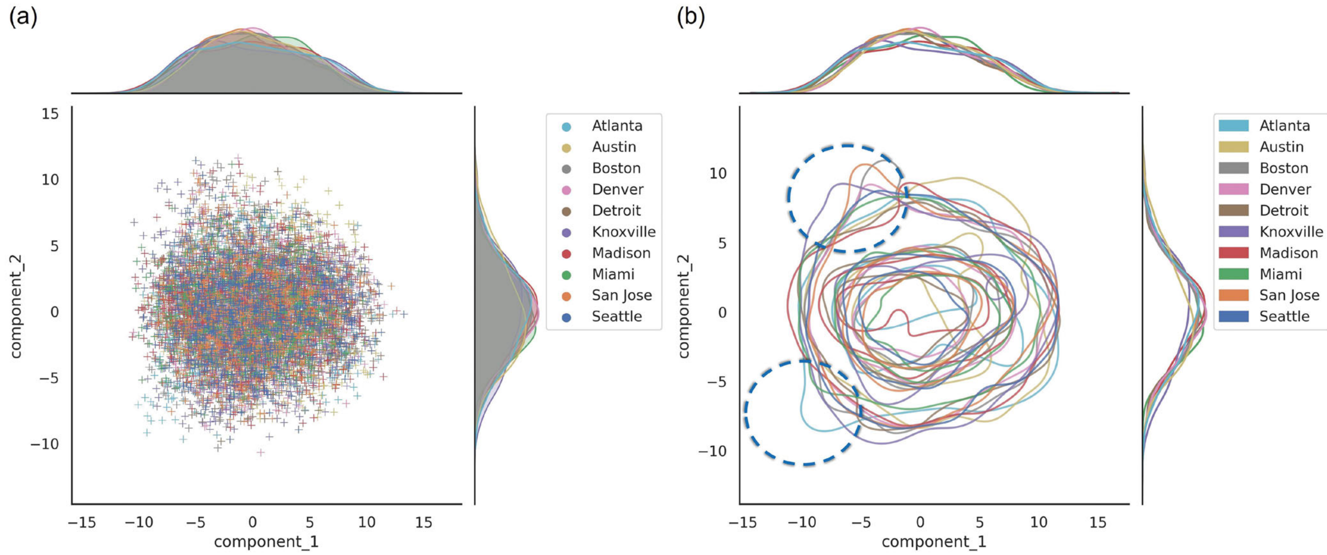

Figure 8. The spatial distribution of the street view images of ten cities. (A) Point scatter distribution; (B) contour line map. The characteristics highlighted in circles reflect obvious differences among different cities.

of individual cities, which reflect unique characteristics in specific dimensions of these cities. Future research will focus on enhancing the interpretability of the transferred bias, aiming to uncover the specific dimensions and features emphasized and captured by the model during the transfer process. This effort is expected to build a more transparent and understandable framework, thereby providing more practical guidance and insights for policymakers, industry practitioners, and researchers.

Conclusion

In summary, our study introduces a novel framework that leverages transferred bias to understand the balance between a city's physical and socioeconomic environments. This framework first captures the relationship between the neighborhood appearance and house prices in different cities, then quantifies the transferred bias in physical and socioeconomic environments by comparing the transfer inference result with the inference result between the measured city and referenced city. Based on the transferred bias, we can further evaluate the balance between the physical and socioeconomic environments. The result shows that transferred bias is effective for evaluating the balance of physical and socioeconomic environments, thereby facilitating further investigation into sustainable urban development and the evolution process. The primary challenge lies in its applicability and scalability to different cities with greater discrepancies in physical and socioeconomic environments, as well as weak interpretability. Despite these challenges, this approach is valuable for stakeholders and policymakers aiming for a comprehensive understanding of urban development at a broader scale. Furthermore, although our research predominantly focuses on housing markets, the concept of transferred bias has the potential for wider application. It also has the potential to investigate the balance of reciprocal factors in the context of urban studies, such as the dynamics between commercial and residential zones or the interplay between globalization and localization. Sustainable urban development requires a synergistic relationship between physical and socioeconomic environments, emphasizing the need for government efforts to create a balance between physical and socioeconomic environments, a key objective for sustainable urban development.

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