nature sustainability

Article

https://doi.org/10.1038/s41893-025-01658-x

Housing exchange framework to reduce carbon emissions from commuting

Received: 6 October 2024

Accepted: 12 September 2025

Published online: 16 October 2025

Check for updates

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Prevailing strategies for commuting efficiency focus predominantly on land-use and transportation policies, whereas research on the environmental benefits of housing reallocation strategies to mitigate excess commuting remains critically underexplored. Here this study proposes an information-enabled housing exchange framework and quantifies the potential reduction of commuting-related carbon emissions it can achieve. Leveraging housing and travel survey data from Beijing ($n = 2,032$), Munich ($n = 3,131$) and Singapore ($n = 7,418$), at the household level, our analysis reveals that commuting distances could be reduced by approximately 10.49%–12.70%, corresponding to CO_2 emissions reductions of 11.33%, 12.09% and 13.42%, respectively. Crucially, strategic relocation of the households with the 5% highest carbon reduction potential could yield more than 50% of total achievable emissions reduction. These results demonstrate that enhancing housing market efficiency through information transparency can generate substantial environmental co-benefits. The integration of conventional policies with this approach would enable a viable pathway to sustainable urban development.

Excess commuting, defined as unnecessary travel resulting from the mismatch between housing and job locations[1], remains a persistent challenge in urban areas worldwide[2,3]. This phenomenon not only exacerbates transportation costs and increases travel times but also contributes substantially to environmental degradation through elevated carbon emissions[4,5]. According to the US Environmental Protection Agency, reducing commuting distance by just 1 mile can cut annual carbon emissions by approximately 200 kg per car commuter. Hence, addressing excessive commuting patterns supports sustainable urban development and advances climate objectives[6,7].

Traditional explanations for excess commuting often highlight policy-induced inefficiencies, such as sprawl-inducing land-use regulations and transport subsidies[8,9]. Various interventions have been proposed to enhance commuting efficiency[10], such as advocating for compact urban development and implementing cordon pricing in monocentric cities[9,11]. In polycentric cities, more complex commuting patterns arise[12], but differentiated road pricing and robust public transportation systems can still improve commuting efficiency[13–16]. Whereas these 'top-down' approaches have proven effective in certain contexts[17], the evolving complexity of urban economies calls for a more comprehensive exploration of the factors influencing commuting patterns.

Beyond policy-induced factors, housing market inefficiencies also play a critical role in excessive commuting[18,19]. These inefficiencies primarily stem from information imperfections[20,21], which hinder the optimal matching of workers to housing that is closer to their workplaces[22]. A major information imperfection within the housing market is the invisibility of unlisted occupied housing, which comprises a substantial portion of the total housing stock, contributing to suboptimal housing allocations and commuting inefficiencies[23]. However, research on the potential benefits of incorporating unlisted occupied housing information into housing reallocation strategies to reduce commuting-related carbon emissions remains sparse.

This article seeks to fill this gap by proposing a household housing exchange framework that incorporates better information on unlisted occupied housing and assessing its potential environmental benefits. We make two key assumptions: (1) driven by emerging digital technologies (for example, artificial intelligence, big data and blockchain), timely and transparent access to information—such as

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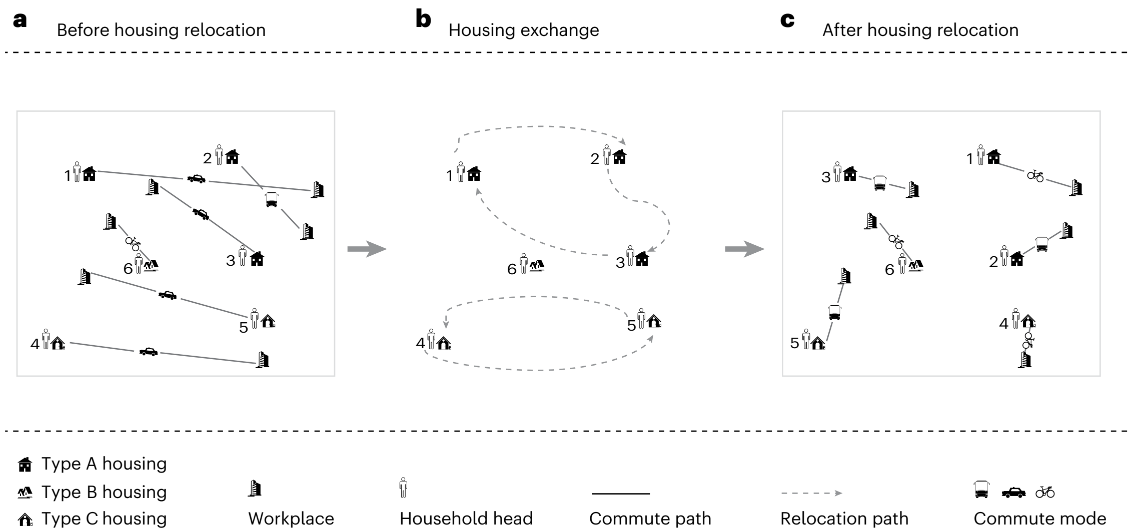

Fig. 1 | Illustration of the impact of household housing exchange on commuting distance reduction. a, Current commuting pattern. **b**, Utility-maximizing households/individuals housing exchange among similar housing type that minimize the aggregate commuting distance. Housing type consists of macro (for example, CBD distance), meso (neighbourhood amenities) and micro level (dwelling size) attributes. **c**, Optimal commuting pattern.

neighbourhood amenities and prices—ensures that all households can obtain relevant details about unlisted occupied housing. That is, each household can access good information pertaining to other households' housing conditions and (2) households base their relocation decisions on utility maximization principles[24]. The central research question guiding this paper is: what are the potential benefits of housing reallocation, facilitated by better information availability, in reducing commuting-related carbon emissions?

Our proposed housing exchange framework reallocates households to higher-utility housing options while minimizing overall commuting distances and emissions (Fig. 1). Housing utility includes the willingness to pay (WTP) for residential amenities, generalized commuting costs[25] and expected capital gains. We employ a modified price regression model[26] to estimate the willingness to pay for residential amenities (Supplementary Information 5). We adopt a discrete choice model (DCM) to estimate people's choice of commuting modes[27] after the relocation and value of commuting time (Supplementary Information 6). The DCM is used to capture people's commuting mode change and calculate the generalized commuting costs. Expected capital gains are estimated based on housing location (Supplementary Information 4.2). Specifically, we assume a rational household would consider relocating if (1) the relocation increases overall utility, even accounting for relocation costs; (2) the associated costs (relocation cost plus price difference) remain within budget (assumed to be 2 years' after-tax discretionary income; details in Supplementary Information 4.2); and (3) the new residence meets acceptable size and amenity standards (that is, same number of rooms and dwelling type, and at most 10% worse WTP). Utility and cost are measured over a 5-year time horizon (representing typical job tenure) and discounted to present value. For all viable relocation pairs of individuals/households that satisfy these conditions, we solve a minimum-weight-matching problem to minimize total commuting distance after relocation. We then estimate potential reductions in emissions (for example, CO_2, fine particulate matter ($PM_{2.5}$)) based on resulting mode-specific commuting distances for each hypothetical scenario. Detailed formulations are shown in the Methods section.

We investigate our central research question from three perspectives:

- To what extent can commuting-related carbon emissions be reduced through the proposed housing exchange framework?
- Is the carbon emissions reduction robust to variations in individuals' amenity preference parameters, value of time and location-based expected capital gains?
- What is the efficient participation rate for such a housing exchange framework?

Using household housing and travel survey data from Beijing (n = 2,032), Munich (n = 3,131) and Singapore (n = 7,418), we find robust reductions in average commuting-related carbon emissions: 11.33% in Beijing, 12.09% in Munich and 13.42% in Singapore. These reductions correspond to annual CO_2 savings of 64.47 kg, 42.59 kg and 124.97 kg per capita, respectively. Furthermore, we identify an efficient participation rate for voluntary housing exchange across the three cities: targeting only the top 5% of households, those with the highest carbon reduction potential, could yield more than 50% of total achievable emissions reductions. This strategy could reduce commuting distances by an average of over 14 kilometres per relocated individual, resulting in an annual reduction of more than 1.30 tons of per capita carbon emissions.

Our study demonstrates how enhancing housing market efficiency through better information of unlisted occupied houses can lead to significant environmental benefits, particularly by reducing commuting-related carbon emissions. By expanding the focus beyond traditional policy interventions, our research explores how better housing reallocation in the market can shape sustainable urban mobility patterns and reduce global carbon emissions.

Results

Commuting distance and emissions reduction

There is a notable spatial mismatch between individual jobs and residences in Beijing, Munich and Singapore, as evidenced by the widespread cross commuting between sampled individuals (Fig. 2a–c). The average commuting distances are 10.99 km in Beijing, 8.59 km in Munich and 12.97 km in Singapore (Fig. 2g–i). Notably, despite Singapore's smaller spatial scale, it exhibits the longest average commuting distance, partly due to its higher concentration of jobs in the city centre and relatively homogeneous dwelling type.

In the optimal consumption–investment scenario, we assume households are willing to exchange their housing if the new one offers a higher overall utility (composed of WTP for residential amenities, generalized commuting costs and expected capital gains) and satisfies the three conditions defined in the 'Main' section. The share of cross

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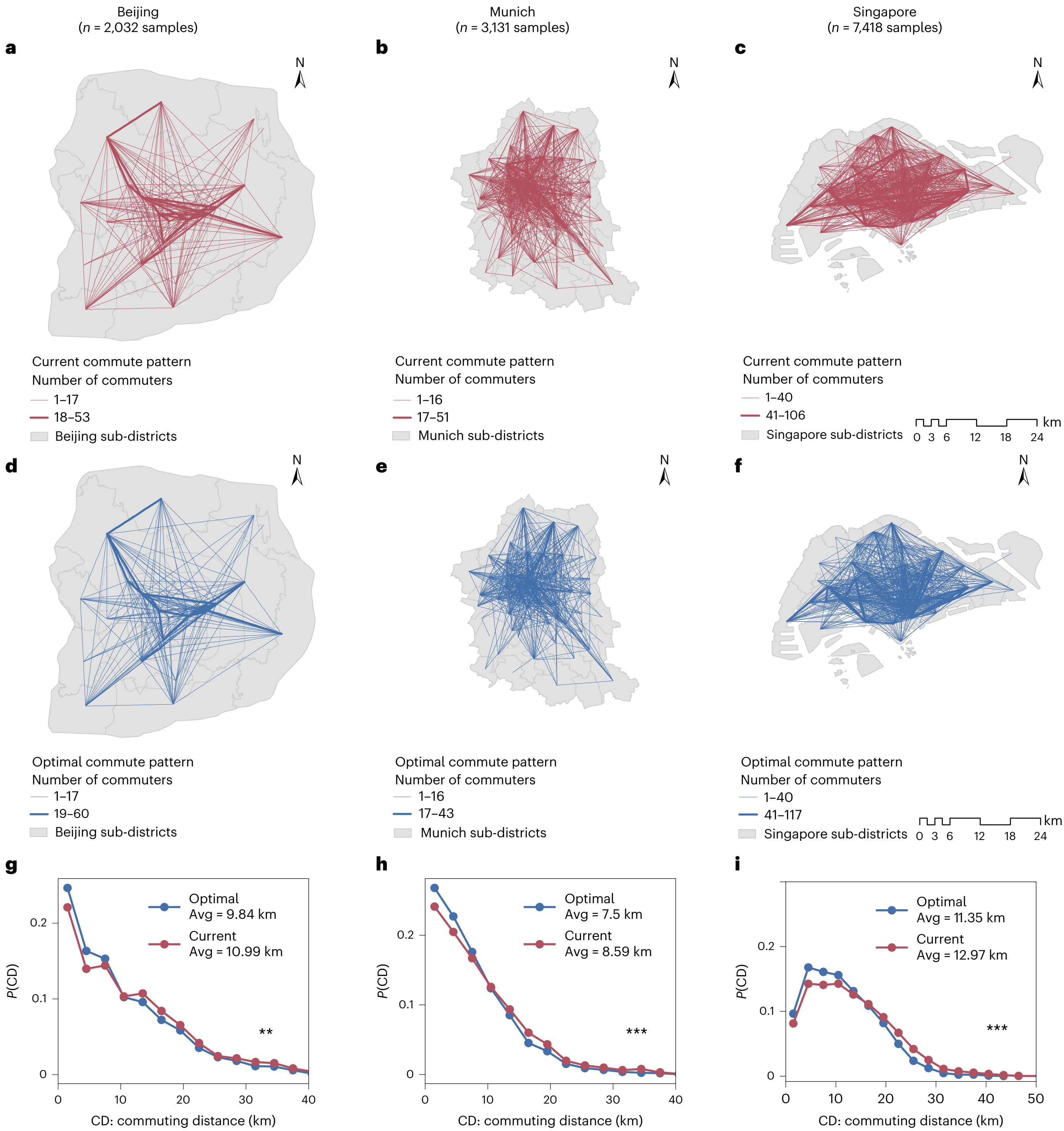

Fig. 2 | Commuting patterns and distance distribution in Beijing, Munich and Singapore before and after the housing exchange. **a**–**c**, Current commuting pattern between sub-districts. **d**–**f**, Optimal commuting pattern after housing exchange. Line width represents the number of commuters. **g**–**i**, Comparison between current and optimal distribution (Avg, average) of commuting distance. The Kolmogorov–Smirnov test indicates a significant difference between the two commuting distance distributions. *** implies $P < 0.001$ and ** implies $P < 0.01$. Map data in **a**–**f** from OpenStreetMap (https://openstreetmap.org/copyright).

commuters between each sub-districts has limited to 71.7%, 53.1% and 88.4% in Beijing, Munich and Singapore, respectively (Fig. 2d–f). The average commuting distance decreases by 10.49% in Beijing (from 10.99 km to 9.84 km), 12.70% in Munich (from 8.59 km to 7.50 km) and 12.46% in Singapore (from 12.97 km to 11.35 km). These reductions correspond to approximate CO_2 emissions reductions of 11.33% (0.14 kg), 12.09% (0.11 kg) and 13.42% (0.27 kg) per one-way commute trip in Beijing, Munich and Singapore, respectively (Fig. 3a–h). Assuming individuals make two commute trips per weekday, this translates to annual per capita emissions reductions of 138.17 kg (Beijing), 71.47 kg (Munich) and 54.77 kg (Singapore). Additionally, the housing exchange framework leads to notable reductions in other pollutants, as illustrated in Fig. 3i–t. For carbon monoxide (CO), individual annual reductions range from 62.88 g to 550.01 g, for nitrogen oxides (NO_x) from

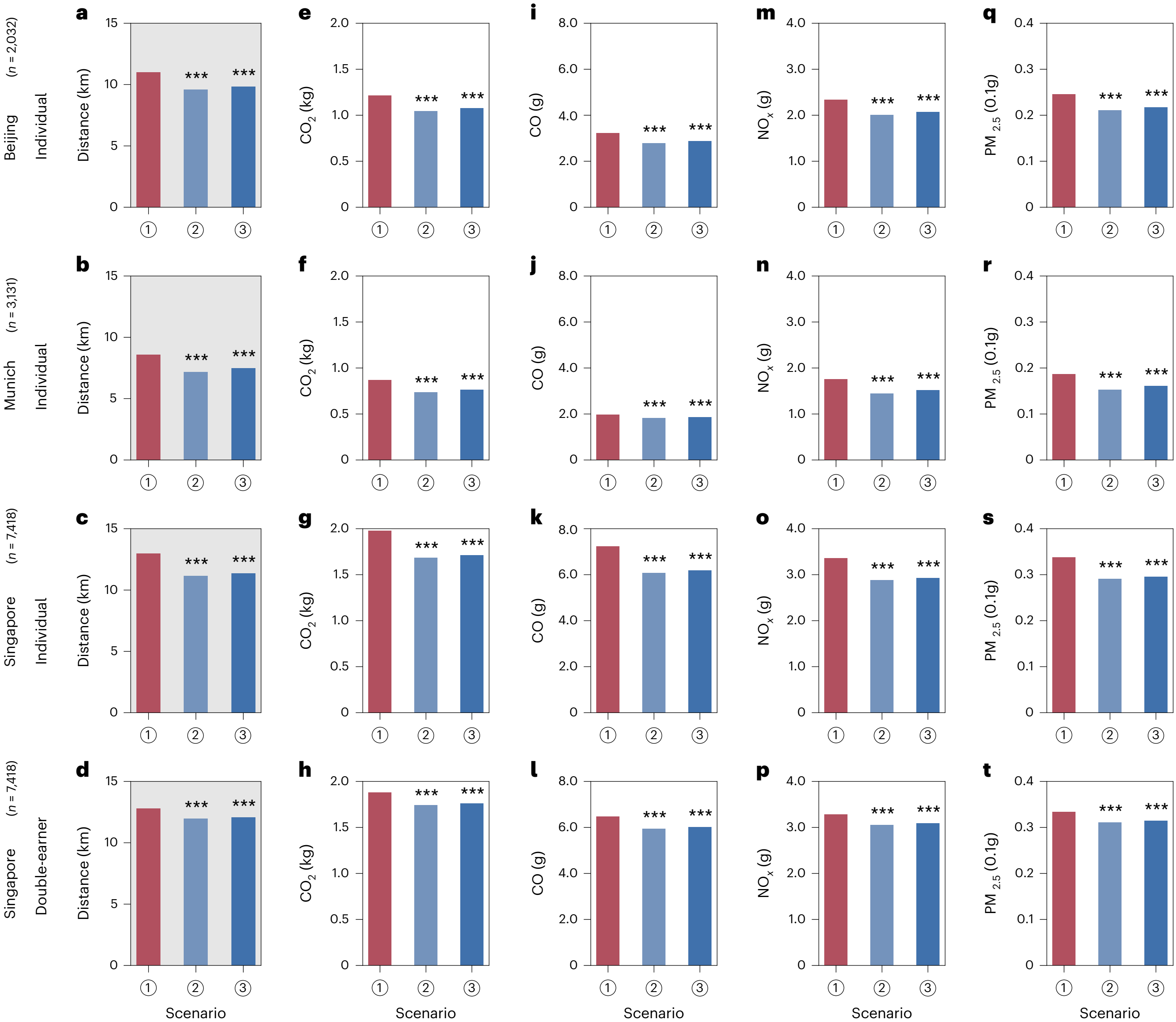

Fig. 3 | Average commuting distance and emissions under current, near-optimal consumption-focused and optimal consumption–investment scenarios in Beijing, Munich and Singapore for individuals and households. Scenario 1 is current. Near-optimal consumption-focused scenario (2): people are willing to relocate given the three conditions defined in the 'Main' section. The utility consists of the willingness to pay and generalized commuting cost. Optimal consumption–investment scenario (3): the utility further includes expected capital gains of housing. We use a paired-wise two-sided *t*-test to evaluate whether the average commuting distance and corresponding emissions in scenarios 2 and 3 are significantly different from scenario 1. *** implies $P < 0.001$. **a**–**d**, Average commuting distance (the grey background indicates that relevant emissions are derived from it). **e**–**h**, Average CO_2 emissions per trip. **i**–**l**, Average CO emissions per trip. **m**–**p**, Average NO_x emissions per trip. **q**–**t**, Average $PM_{2.5}$ emissions per trip.

124.30 g to 224.37 g and for fine particulate matter ($PM_{2.5}$) from 1.37 g to 2.22 g across three cities.

Compared to the optimal consumption–investment scenario, our near-optimal consumption-focused scenario differs solely by omitting expected housing capital gains from the utility maximization framework. Our analysis shows no significant difference between these two scenarios. This suggests that present residential amenity values, rather than expected capital gains, are the primary determinants in household location choice. This phenomenon may be attributed to the combined effect of large housing costs and low property appreciation rates in the market.

We also consider a scenario where the housing exchange decision is made jointly by both earners in double-income households. This exchange considers the utilities and constraints of both earners in the exchange model (as opposed to only considering the household head). It has an additional requirement that both earners must relocate to the same house. Under this scenario, the average reduction in commuting-related CO_2 emissions is lower. Specifically, in Singapore, the reduction drops from 13.42% to 6.25% when both earners participate in the decision-making process.

Sensitivity test for commute emissions reductions

We conduct several sensitivity tests from different aspects (the summary of all tests is provided in Supplementary Information 2). First, for the near-optimal consumption-focused scenario, we test the sensitivity to estimated WTP for the residential amenity and value of time.

We also test different levels of amenity deterioration standard (condition 3 in the 'Main' section). Furthermore, for the optimal consumption–investment scenario, we test the sensitivity of carbon reduction to alternative expected capital gains, varying time spans and stricter amenity constraints.

In reference to near-optimal consumption-focused scenario, when individuals show larger willingness to pay for the overall residential amenities, there would be fewer households (approximately 7.63%–8.57%) exchanging their housing (Supplementary Information 7). The average commuting distance increases by approximately 0.59 km to 0.78 km across three cities, which corresponds to an approximately 4.56%–9.10% decrease in the overall commute reduction (Fig. 4a–c). In contrast, when individuals place a higher value on their time, approximately 4.07%–4.95% additional households would exchange their housing, contributing to 1.47%–3.99% additional commuting-related emissions reductions. Our analysis reveals that commuting distance and emissions reductions are more sensitive to household willingness to pay for amenities than to the value of time. Furthermore, when the amenity standard is relaxed—from being at most 10% worse than the current housing to 20% or 30% worse—no further reductions in commuting distances are observed. These findings can be attributed to the relatively higher housing prices compared to the generalized commuting costs.

In the optimal consumption–investment scenario, we assume the property appreciation rates of houses vary by their distances to the central business district (CBD), and core locations increase faster. In an alternative scenario where core locations increase slower, the average commuting distance decreases by 11.06% in Munich (Fig. 4a–c), because some households are willing to compromise the current housing amenity (with higher expected capital gains) for shorter commutes. This corresponds to an additional reduction of 0.10 kg CO_2 emissions per commuting trip (Fig. 4d–f). Beijing and Singapore show limited change in commuting distance or carbon emissions, which is expected given the city's monocentric structure, where property value is predominantly driven by proximity to the CBD. Second, we also test time span of 3 years and 8 years. Whereas a longer time span expects a larger commuting-related carbon reduction (an increase of 6.91% in Beijing, 10.98% in Munich and 3.92% in Singapore), a shorter time span corresponds to a smaller reduction (a decrease of 6.71% in Beijing, 9.23% in Munich and 5.98% in Singapore). Overall, the optimal reduction in commuting carbon emissions is most sensitive to the time span in Munich. This may be attributed to the smaller disparity between the income growth rate (2.6%) and housing price growth rate (4.5%) in Munich, where the trade-off between commuting costs and housing costs relaxes over a longer time horizon. Last, rather than only regarding the overall willingness to pay for amenity as the exchange feasibility, we further constraining the revealed preferences[28] for each residential amenity, that is, requiring similar (at most ± 30% difference) community income level, distance to CBD and number of nearby points of interest. The additional constraint yields a notable compromise in CO_2 emissions reduction (almost 10% in Beijing and Munich, 5.61% in Singapore).

Emission reductions by random versus targeted relocation

Even if relocation offers potential benefits, some households may not have access to such housing information. Hence, in reality, we may see fewer households participating in the housing exchange framework. To capture this effect, we incrementally include a proportion of households who decide to participate (from 1% to 100%). When households are randomly selected for the exchange, both total and average reductions in commuting distance increases (Fig. 5a–c). This implies a 'network effect' where more participants could increase the efficiency of the housing exchange and benefit everyone.

On the other hand, to identify the efficient participation rate among relocated households, we focus on selecting targeted households whose relocation contributes the most to overall commute reduction. As shown in Fig. 5d–f, just relocating the top 5% of individuals accounts for more than half of the total commute reduction potential in these three cities (61.08% in Beijing, 73.23% in Munich and 56.12% in Singapore). Moreover, the average commuting distance reduction among the relocated individuals is respectively 14.17 km, 16.04 km and 18.23 km. Their commuting patterns are significantly optimized, with the share of trips bypassing the city centre markedly reduced (Fig. 5g–i). This substantial improvement in commuting conditions may serve as a strong incentive for these individuals to relocate. Nevertheless, if more 'targeted selected' individuals are included in the exchange scheme, though the total commute reduction increase, the average commute reduction will decrease rapidly, implying a decreased exchange efficiency.

Discussion

For a long time, researchers have viewed long-distance commuting as a necessary compromise for better jobs and affordable housing[29,30]. In the context of booming technological innovations reducing the information frictions, we proposed a household housing exchange framework, enabled by better information on unlisted occupied housing, to reduce excess commuting-related carbon emissions[31]. Our study demonstrates how enhancing housing market efficiency through better information can lead to significant environmental benefits. By integrating housing reallocation into the broader discourse on sustainable urban mobility, we offer a valuable complementary strategy to traditional policy interventions.

Our findings reveal that an information-enabled housing reallocation can lead to substantial reductions in commuting distances and, consequently, CO_2 emissions. Despite variations in spatial scales, population densities and transportation infrastructure across the cities studied, we observe consistent reductions in commuting-related CO_2 emissions: 11.33% in Beijing, 12.09% in Munich and 13.42% in Singapore. This consistency highlights the robustness of the housing exchange framework. Our results align with previous studies, such as White's (1988)[32] research on 25 US cities and Merriman et al. (1995)[33] on Tokyo. Furthermore, our findings are comparable to the impact of policy interventions such as road pricing (13%) (ref. 34,35) and even larger than the effects of density regulations[36]. Another important contribution of our study is the identification of an efficient participation rate. We show that focusing on a relatively small proportion of the population—just 5%—can achieve at least 50% of the total emissions reductions. Households participating in the housing exchange experience an average reduction of more than 14 km in commuting distances, resulting in an annual reduction of greater than 1.30 tons of CO_2 per car commuter.

Policy implication

The decentralized housing market is characterized by heterogeneous assets trading infrequently with high transaction costs, rendering it vulnerable to much larger information costs and frictions compared to the labour market[20,37]. It manifests through two critical dimensions: first, information asymmetry enables better-informed parties to strategically exploit informational advantages[38,39]. For example, potential buyers might lack information regarding the occupancy status of the school admission entitlement linked to the property. Second, households only have access to area-specific housing pools and lack the comprehensive property data[40], such as complete transaction histories or high-resolution environment risk exposure. These information gaps, combined with heterogeneity in housing and households result in inefficient, multi-stage search and matching that relies on both off-site research and on-site verification. The process is further strained by idiosyncratic preferences, subjective neighbourhood perceptions and search congestion externalities. Despite technology diminishing certain search and match frictions[41–44], imperfect information persists due to inherent institutional barriers, particularly confidentiality protections and data fragmentation.

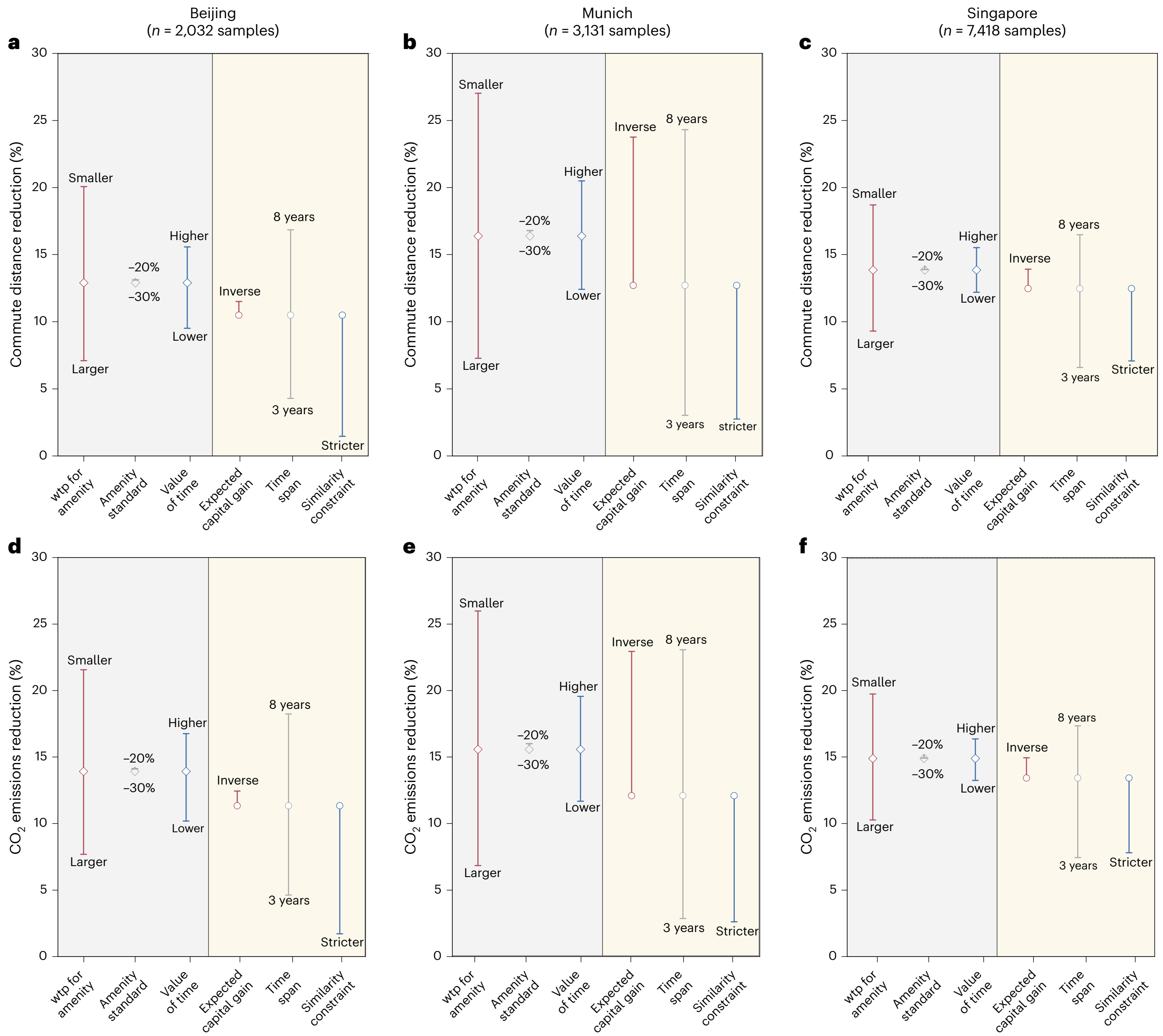

Fig. 4 | Sensitivity test of average commuting distance and CO_2 emissions reduction in reference to the near-optimal consumption-focused and optimal consumption–investment scenarios in Beijing, Munich and Singapore. **a**–**f**, The percentage change in average commuting distance (**a**–**c**) and CO_2 emissions (**d**–**f**). In the grey background, near-optimal consumption-focused scenario is the benchmark (diamond mark) for sensitivity analyses on parameters including 'wtp for amenity', 'amenity standard' and 'value of time'. The length of red lines above (below) the diamond mark represent the increase (decrease) of commuting distance and CO_2 reduction in response to 30% smaller (larger) willingness to pay for residential amenity. When varying the 'amenity standard' from 'being 10% worse than current amenity value' to 'being 20% and 30% worse', there is no change of the commuting distance and CO_2 emissions reduction. The blue lines above (below) the diamond mark represent the sensitivity test of higher or lower value of time (30.3%–68.2%). In the yellow background, optimal consumption–investment scenario is the benchmark (circle mark) for sensitivity analyses on parameters including 'expected capital gain', 'time span' and 'similarity constraint'. The length of the red lines shows the decrease in commuting distance and CO_2 emissions resulting from slower, as opposed to faster, expected capital gains of housing in core locations. The length of the grey lines above (below) the circle mark represents the sensitivity test for changing the time span from 5 years to 8 years (3 years), respectively. The length of blue lines represents the decrease of commuting and carbon reduction when exposing stricter similarity constraint on each residential amenity (for example, regional income, CBD distance and neighbourhood points of interest) for housing exchange.

Even when search and matching efficiency improves, additional transaction costs might still prohibit many households from engaging in such housing exchanges. In Beijing, for instance, short-term property holders are subject to value-added and income tax surcharges, whereas non-citizen households in Singapore must pay an additional buyer's stamp duty (60% of the property value). Other barriers includes Germany's mandatory notarial requirements, which add approximately 1%–2% to property values. Because most households' current housing is leveraged with mortgage debt, the associated financing costs also constrain their residential mobility[45]. Additionally, declining commuting benefits due to increased job mobility and behavioural factors such as status-quo bias further suppress such housing exchange. These frictions collectively discourage optimal housing allocation and may contribute to higher carbon emissions.

To address the aforementioned barriers for the proposed housing exchange framework, targeted policy interventions should be designed

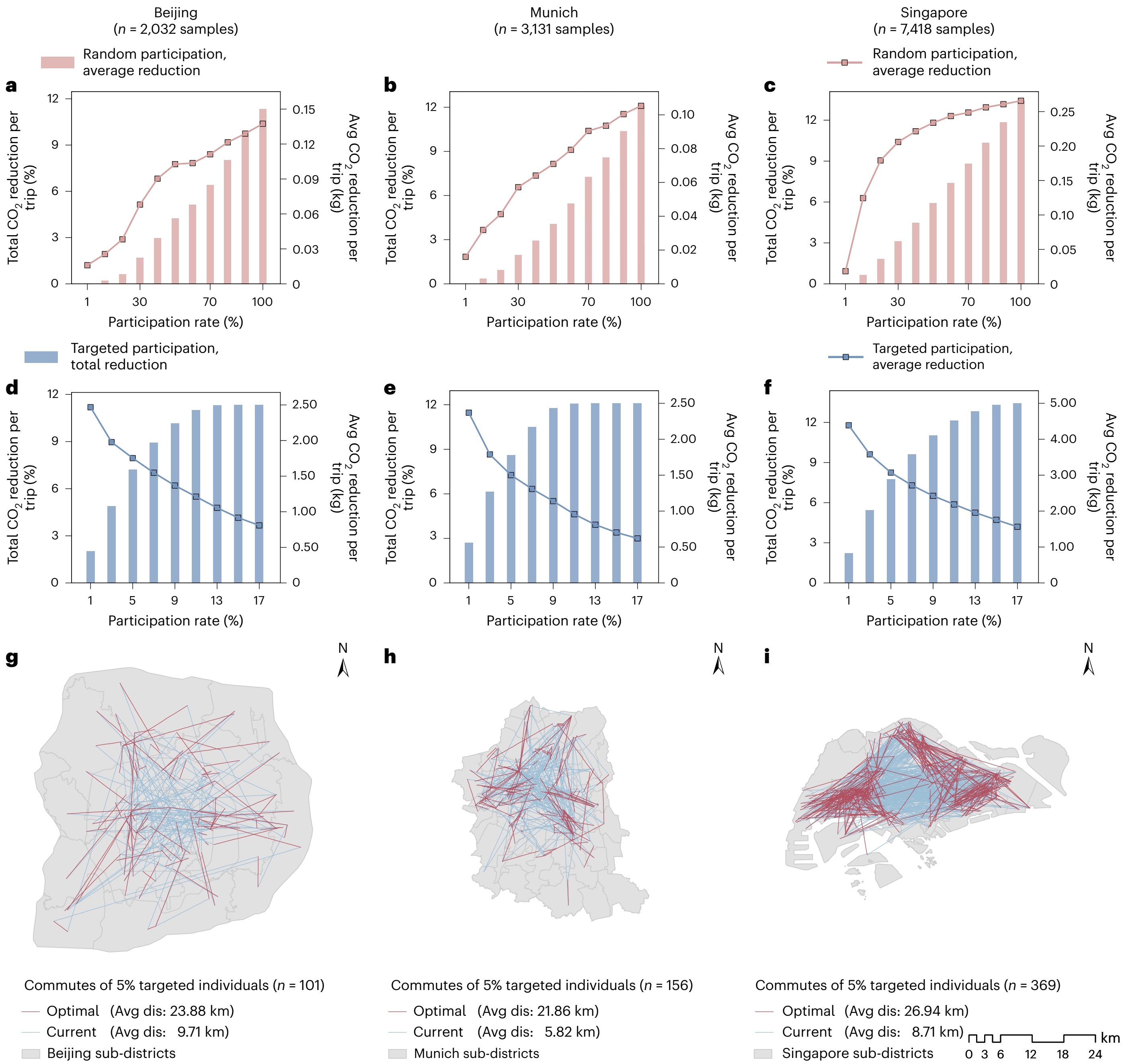

Fig. 5 | CO_2 emissions reduction between randomly and targeted selected individuals for housing exchange and current vs optimal commuting patterns among targeted 5% of households. a–c, Red bars represent the percentage of total reduction in commuting-related carbon emissions when individuals are randomly selected for exchange. Red lines show the average commuting-related carbon emissions reduction among the random participants. **d–f**, Total (blue bars) and average (blue line) reduction in commuting-related carbon emissions among targeted participants. **g–i**, Commuting paths of the top 5% of targeted households with the highest carbon emissions reductions potential before (blue lines) and after (red lines) housing exchange. Map data in **g–i** from OpenStreetMap (https://openstreetmap.org/copyright).

to enhance the housing market efficiency via the proposed environmentally friendly housing exchange. First, reducing information and search frictions should be prioritized[46]. This could involve mandating the disclosure of standardized property conditions in quantity and quality, especially regarding aspects with inherent information asymmetry. Enforcing industry-led housing certifications and inspections (for example, Energy Performance Certificates) and developing a public Geographic Information System (GIS) platform to provide automatically synchronized, scalable data on neighbourhood amenities and disamenities (for example, school quality, pollution sources) would further enhance transparency. Moreover, governments should drive core housing platform integration while enabling industry innovation via controlled application programming interface (API) access and data sharing, which also enhances the matching efficiency. Second, reducing the additional transaction costs is crucial. Policymakers should consider removing or loosening restrictive measures, such as differential taxation based on citizenship or holding periods, and simplifying legal procedures or introducing tax incentives to facilitate such 'low-carbon' housing exchanges. In addition, public–private partnerships could also streamline mortgage transitions to reduce liquidity constraints. These interventions could yield substantial carbon reduction benefits, as illustrated by our

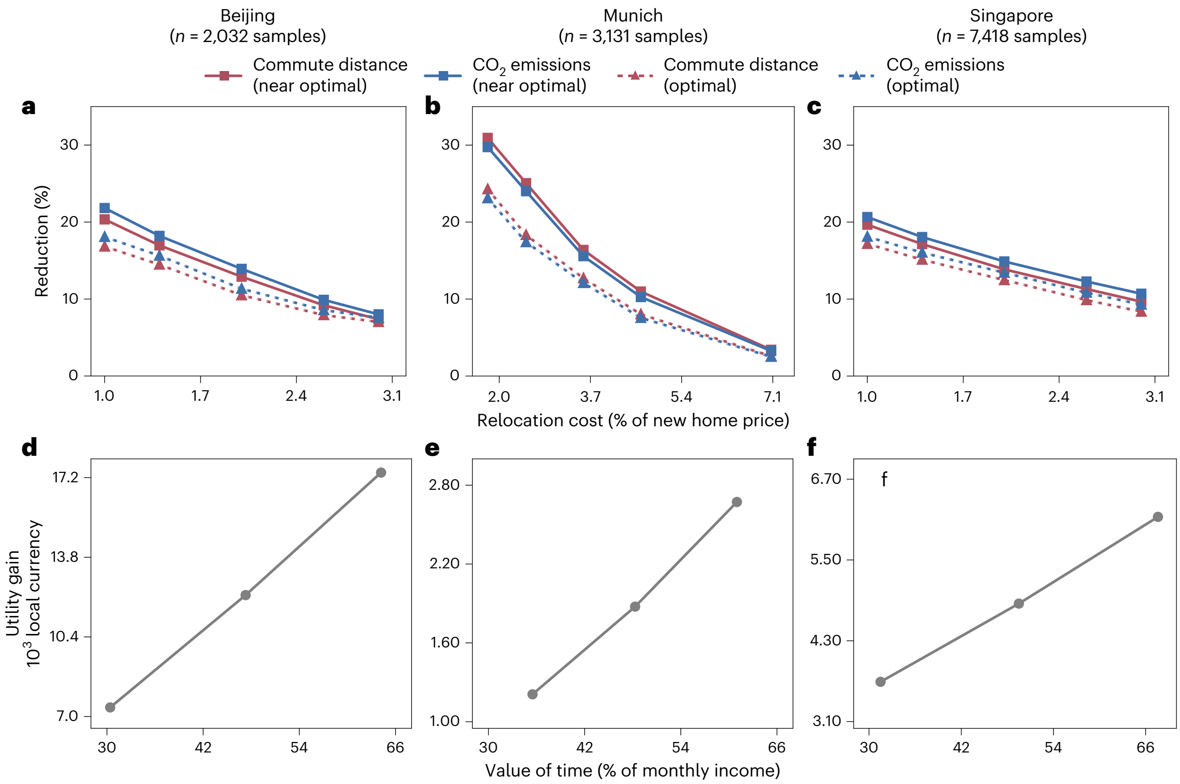

Fig. 6 | Commuting reduction and utility gains under different constraints. **a**–**c**, Red and blue lines represent change of commuting distance and CO_2 emissions in response to relocation cost under the near-optimal consumption-focused scenario. Red and blue dotted lines represent change of commuting distance and CO_2 emissions under optimal consumption–investment scenario. **d**–**f**, Grey lines represent the change of utilities per person (in their respective currencies across the three cities) in response to the value of time.

analysis showing a 30% decrease in relocation costs would elevate CO_2 emissions reductions from current levels (11% in Beijing, 12% in Munich and 13% Singapore) to 16%, 17% and 16%, respectively (Fig. 6a–c). More aggressive measures that halve the relocation costs could achieve even greater reductions (18% in Beijing, 23% in Munich, and 18% in Singapore), demonstrating the substantial policy leverage to simultaneously improve housing market efficiency and environmental outcomes. Third, behavioural nudges and operational improvements could also facilitate such housing exchange. Reframing the exchange as climate action may help counteract households' status-quo bias, while enhanced government regulation would strengthen public trust in property transactions. Leveraging existing brokerage networks and incentivizing temporary 'buffer' housing arrangements could also ease matching difficulties. Last, as shown in Fig. 6d–f, when value of time range from ~30% to ~70% of the income, utility gains could increase by roughly 2–3 times. To maximize emissions reduction, efficiency-oriented policies should incentivize especially high-value-of-time households to optimize location choices through measures such as transit-oriented development incentives or green mortgages.

Limitations

There are several limitations to this study. First, our utility estimate is based on a fixed five-year period for job tenure, which may not fully account for varying job mobility across different sectors[47], potentially skewing our results. Second, the price regression model used in this analysis does not include factors such as building age or subjective neighbourhood attachment, both of which could introduce estimation bias. Furthermore, future research should explore more nuanced dimensions of housing decision-making. Whereas our analysis assumes economically incentivized residential relocation, it would be valuable to fully capture household idiosyncratic preferences in housing choices[48,49]. Last, this study does not fully account for the shift in work patterns. Therefore, more accurate estimations of carbon mitigation potential in the future must integrate the prevailing trend of working from home in the post-COVID-19-pandemic era[50].

Methods

Study area and data

The three study areas—Beijing, Munich and Singapore—are characterized by various spatial scales, populations and densities. Urban Beijing exemplifies cities with larger spatial scales and higher population densities, whereas Singapore represents small, densely populated city-states. Munich serves as a typical example of cities with medium spatial scales and lower population density.

The sample of Beijing was drawn from a household housing and travel survey conducted by the authors' research team in Beijing between 9 October 2020 and 16 March 2021. All participants provided written informed consent before the survey. The study protocol was approved by the Ethics Review Committee of Capital Normal University (approval number CNU-IRB-2020-1812). Both on-street surveys and web surveys are applied. On-street surveys were conducted at main subway stations and large industrial/cultural parks, whereas web surveys were distributed via major social media (that is, WeChat). Using the convenience sampling, the survey gathered 3,369 responses and filtered out 2,032 valid questionnaires. Whereas the sample aligns closely with the population in the gender composition, we recognize that the samples are relatively more educated and younger compared to those of the general population (Supplementary Table 3 in Supplementary Information 3). In addition, because the coordinates collected through the platform of 'wenjuanwang' are encoded, they were first projected to the World Geodetic System (WGS) coordinates to proceed with further spatial analysis in ArcGIS 10.8.

The sample of Munich was drawn from a household housing and travel survey (named 'Wohnen–Arbeiten–Mobilität Survey') jointly conducted by the chair of urban development and chair of land use and transport at the Technical University of Munich between 27 November 2014 and 19 April 2015 in Munich. All participants provided written informed consent before the survey. The study protocol was approved by the Ethics Committee of TUM School of Social Sciences and Technology (approval code EK-SSWT-2017-1317). Both web surveys and post surveys are applied. The web survey was posted on a public portal site (www.wam.tum.de) and promoted through newsletters, press conferences and social media, whereas postcards with quick response (QR) codes were sent to residential communities with the help of partner municipalities. This survey uses snowball sampling. Our web survey mainly consists of four sections: individual current residential location (with geographical coordinates), travel attitudes, travel modes and individual socio-economic profile. The housing and travel costs are also included. Out of 9,623 participants, 7,302 individuals from the European Munich Metropolitan region filled out the survey, and the response rate was 76%; only 3,131 of those were samples whose residence and workplace are both located within Munich region. Whereas the sample aligns closely with the population in the proportion of gender and household type, we recognize that the samples are relatively more educated, richer and younger compared to those of the general population (Supplementary Table 4 in Supplementary Information 3). Nevertheless, the spatial representativeness is acceptable (Supplementary Fig. 1).

The Singapore sample was drawn from a Household Interview Travel Survey (HITS) conducted by Singapore Land Transport Authority between 1 October 2012 and 30 September 2013. Its data collection activities strictly comply with the Singapore Personal Data Protection Act and other relevant national regulations. The secondary analysis of this data was approved by the Capital Normal University (approval number CNU-IRB-2020-1812). The survey uses a stratified random sampling method to ensure that the survey captures a diverse range of households. The sample is stratified based on key demographic factors such as: geographical locations (includes households from across all of Singapore's planning regions), housing type, income levels and household size and structure. The HITS collects information on housing location and various aspects of travel, including how respondents commute to work, school and town centres. Among 5.31 million of the population in 2012, 9,635 households (35,714 individuals) participated in the HITS survey. Among which, 7,418 households include full-time workers. Both statistical and spatial representativeness of the sample is relatively good (Supplementary Table 5 in Supplementary Information 3).

The housing transaction price of each individual household's house is provided only in the Munich survey. In contrast, we estimate the transaction price of the sample's house by spatially matching them in ArcGIS 10.8 with other adjacent similar housing (within 1-km distance from the sample's housing) and calculate the mean of their transaction records ('Realis' database in Singapore and 'Fang tianxia' real estate information platform in Beijing). The commuting distance (along the road network) between workers and each housing are crawled from 'OpenStreetMap' using Python 3.6 and Java 1.8. The commuting cost for public transport is estimated using tiered public transport fares in each city. The commuting time for public transport is estimated using linear regression on commuting distance along the road network.

Matching algorithm for housing exchange framework

Given two individuals i, j who are household heads, define the utility of individual i living in the house of individual j as

$$u_{i,j} = v_{i,j} - \int_{\tau \in \mathcal{T}} (c_{i,j} + \beta_i(\tau) \times t_{i,j})\, d\tau + e_j(\mathcal{T}) + O_i, \quad (1)$$

where $v_{i,j}$ is the individual i's willingness to pay for the house of j. It is estimated using a linear regression model with house trading price as a dependent variable and social-demographics and house amenities as independent variables (Supplementary Information 5). $v_{i,j}$ captured people's utility of residential neighbourhood amenities. $c_{i,j}$ and $t_{i,j}$ are the commuting cost and time per trip if living in house j, respectively. They are calculated based on the location of houses and offices. It also captures the impact of people's travel mode switch after relocation, which are captured using a discrete choice model (DCM). The DCM is calibrated using travel surveys of the same group of people (Supplementary Information 6). $\beta_i(\tau)$ is the value of time for commuting, which will grow with time τ based people's income growth and be discounted to today's value based on the city's discount factor. $\beta_i(\tau)$ is calculated based on the estimated parameters of travel time and travel cost in the DCM (Supplementary Information 6). $\mathcal{T}$ is the time span for evaluating the commuting cost. It is assumed to be 5 years for all scenarios except for the sensitivity testing cases. $e_j(\mathcal{T})$ is the total expected capital gain during the time span $\mathcal{T}$ discounted to present. The capital growth rates are proportional to the proximity to CBD (Supplementary Information 4.2), except for the alternative capital gain scenario in the 'Sensitivity test for commute emissions reductions' section. O_i represents all other factors, which will be cancelled out when deciding housing relocation.

We assume an individual i is willing to switch to the house of j if (1) relocation gives them better utility: $u_{i,j} - u_{i,i} \geq r_{i,j}$, where $r_{i,j}$ is the relocation cost. (2) The associated costs (transaction cost plus price difference) remain within budget: $v_{i,j} - v_{i,i} + r_{i,j} \leq b_i$. b_i is the budget of individual i, setting as 2 years' after-tax income minus the essential living cost (Supplementary Information 4.2). (3) The new residence meets acceptable size and amenity standards. Mathematically, $s_i = s_j$ and $v_{i,j} - v_{i,i} \geq \alpha \times v_{i,i}$, where s_i is the build type and floor plan category of house i, α is the tolerance parameter. It is set to be 0.9 for all scenarios except for the sensitivity testing cases, meaning that we assume people only wish to accept at most 10% worse residential amenities (measured by wiliness to pay). For all pairs of (i, j) that satisfy these conditions, we solve a minimum-weight-matching problem to minimize the total commuting distance after relocation. The specific formulations are:

$$\min_{x} \sum_{i,j \in \mathcal{N}} x_{i,j} \times d_{i,j} \quad \text{(Minimize total commuting distance)} \quad (2)$$

$$\text{s.t.} \quad (u_{i,j} - u_{i,i}) \times x_{i,j} \geq r_{i,j} \times x_{i,j}, \quad \forall i,j \in \mathcal{N} \quad \text{(Better utilities)} \quad (3)$$

$$(v_{i,j} - v_{i,i}) \times x_{i,j} \geq \alpha \times v_{i,i} \times x_{i,j}, \quad \forall i,j \in \mathcal{N} \quad \text{(Adequate residential amenities)} \quad (4)$$

$$(s_i - s_j) \times x_{i,j} = 0, \quad \forall i,j \in \mathcal{N} \quad \text{(Same building type and floor plan)} \quad (5)$$

$$(v_{i,j} - v_{i,i} + r_{i,j}) \times x_{i,j} \geq b_i \times x_{i,j}, \quad \forall i,j \in \mathcal{N} \quad \text{(Budget constraints)} \quad (6)$$

$$\sum_{j \in \mathcal{N}} x_{i,j} = 1 \quad \forall i \in \mathcal{N} \quad \text{(Every individual has exactly one house matched)} \quad (7)$$

$$\sum_{i \in \mathcal{N}} x_{i,j} = 1 \quad \forall j \in \mathcal{N} \quad \text{(Every house has exactly one individual/household matched)} \quad (8)$$

$$x_{i,j} \in \{0,1\} \quad \forall i,j \in \mathcal{N} \quad (9)$$

where $x_{i,j}$ is the binary decision variable on whether individual i is relocated to the house of j. $\mathcal{N}$ is the set of all individuals. $d_{i,j}$ is the commuting distance if individual i live in the house of j. The matching problem is solved with the Google OR-tools package implemented in python 3.8.

After relocation, we calculate the new mode choice probabilities and evaluate how the emissions (for example, CO_2, $PM_{2.5}$) will change. For example, the emissions of CO_2 for an individual i living in house j over a 5-year period is calculated as:

$$E_{CO_2^{(i,j)}} = \sum_{k\in e_i} P_{i,j,k} \times d_{i,j} \times \mathrm{CO_2\ Emission\ rate}_k \cdot \mathrm{Num\ commuting\ trips\ in\ 5\ years}, \quad (10)$$

where $P_{i,j,k}$ is the probability of individual i choosing mode k when living in house j, estimated from the DCM elaborated in Supplementary Information 6. CO_2 Emission rate$_k$ is the emissions of CO_2 for travel mode k (per km). Suppose j^* is the allocated new house of individual i. The CO_2 emissions reduction is simply $E_{CO_2^{(i,j^*)}} - E_{CO_2^{(i,i)}}$. Details can be found in Supplementary Information 4.1.

For a double-earner housing exchange, we require the two earners to switch to the same house. This can be done by first eliminating all houses that do not meet the three conditions for both of them. Then, we aggregate the calculation of utility at the household level. Specifically, $\upsilon_{i,j}$ will be the average willingness to pay of both earners in household i living in the house of household j. The generalized commuting cost (defined as $\mathrm{GC}_{i,j}(\mathcal{T}) := \int_{\tau\in\mathcal{T}} (c_{i,j} + \beta_i(\tau) \times t_{i,j})\,d\tau$), commuting distance $d_{i,j}$ and budget b_i are calculated for both earners in household i and summed together. Note that $r_{i,j}$ and $e_i(\mathcal{T})$ are calculated at house level, and their values are the same as the individual-based house exchange.

For the 'targeted relocation', we define a new decision variable y_i indicating whether individual i switches houses ($y_i = 1$ means switching). For top K 'purposely target' individuals, we solve the following matching problem with an additional constraint to limit the maximum relocated individuals:

$$\min_{\boldsymbol{x},\boldsymbol{y}} \sum_{i,j\in\mathcal{N}} x_{i,j} \times d_{i,j} \quad \text{(Minimize total commuting distance)} \quad (11)$$

$$\text{s.t.} \quad \text{Constraints } (3) \sim (9) \quad (12)$$

$$x_{i,i} \geq (1 - y_i) \quad \forall i \in \mathcal{N} \quad (\text{Relationship bwteen } \boldsymbol{x} \text{ and } \boldsymbol{y}) \quad (13)$$

$$\sum_{i\in\mathcal{N}} y_i \leq K \quad (\text{At most } K \text{ individuals switching houses}) \quad (14)$$

$$y_i \in \{0, 1\} \quad \forall i \in \mathcal{N} \quad (15)$$

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

Household travel surveys—including work location, home location and key socio-demographic variables—for Beijing and Munich, along with the corresponding network-based commuting matrices, are available via Code Ocean at https://doi.org/10.24433/CO.4363875.v1 (ref. 51). The Household Interview Travel Survey (HITS) data for Singapore were provided by the Land Transport Authority (LTA) of Singapore under license. Researchers interested in using these data must submit a formal application to the LTA specifying the intended research purpose and use. The LTA will provide information on response timelines and any applicable data use restrictions through a formal data agreement. Raw transaction data for Singapore can be accessed from the Urban Redevelopment Authority (URA) of Singapore via their subscription-based service available at https://eservice.ura.gov.sg/reis/index. Raw housing transaction data for Beijing are available through a subscription to the 'Fang tianxia' Real Estate Information Platform at https://www1.fang.com/. Source data are provided with this paper.

Code availability

The code used for the analyses is available via Code Ocean at https://doi.org/10.24433/CO.4363875.v1 (ref. 51.).

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Acknowledgements

This work was partly supported by the National Research Foundation (NRF) Singapore under its Campus for Research Excellence and Technological Enterprise (CREATE) programme, and Mens, Manus and Machina (M3S), an Interdisciplinary Research Group (IRG) within the Singapore-MIT Alliance for Research and Technology (SMART) centre. Additional support was provided by the National Natural Science Foundation of China (grant number 41901188 to Juanjuan Zhao). We would like to express our sincere gratitude to J. Liang, A. Thierstein, T. Dai, L. You, H. Zhang, X. Liu, T. Zhu and D. Cui for their insightful comments upon the revision. In addition, we also appreciate the research team members of 'Wohnen–Arbeiten–Mobilität' project (especially A. Thierstein, G. Wulfhorst, M. Bentlage, F. Wenner, B. Büttner and J. Kinigadner) at Technical University of Munich for designing and collecting the Munich survey. We are also deeply grateful to X. Wang, H. Zhao, L. Xu, M. Tang, K. Chen and K. Guan for their contributions to cartography and formatting.

Author contributions

Juanjuan Zhao, B.M., N.S.C. and Jinhua Zhao conceived and designed the study theme and analytical framework. Juanjuan Zhao and B.M. conducted all statistical analyses and data visualization. The first draft of the manuscript was prepared by Juanjuan Zhao and B.M. All authors contributed to subsequent revisions and approved the final version.

Competing interests

The authors declare no competing interests.

Additional information

Supplementary information The online version contains supplementary material available at https://doi.org/10.1038/s41893-025-01658-x.

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Peer review information *Nature Sustainability* thanks the anonymous reviewer(s) for their contribution to the peer review of this work.

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Policy information about availability of computer code

Data collection	Data collections are completed using the Python 3.6 and Java 1.8; Code available at: https://doi.org/10.24433/CO.4363875.v1
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Household travel surveys—including work location, home location, and key sociodemographic variables—for Beijing and Munich, along with the corresponding network-based commuting matrices, are available at https://doi.org/10.24433/CO.4363875.v1 (ref.51). The Household Interview Travel Survey (HITS) data for Singapore were provided by the Land Transport Authority (LTA) of Singapore under license. Researchers interested in using these data must submit a formal application to the LTA specifying the intended research purpose and use. The LTA will provide information on response timelines and any applicable data use restrictions through a formal data agreement. Raw transaction data for Singapore can be accessed from the Urban Redevelopment Authority (URA) of Singapore via their subscription-based service available at: https://eservice.ura.gov.sg/reis/index. Raw housing transaction data for Beijing are available through a subscription to the “Fangtianxia” Real Estate Information Platform at: https://www1.fang.com/.

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Reporting on sex and gender	The research findings are applicable to all genders. Gender information was obtained through participant self-reporting. Disaggregated gender data for Beijing and Munich were provided in the source data with participant consent. The overall gender distribution across the surveys is as follows: the Beijing sample consists of 54.6% male and 45.4% female participants; the Munich sample includes 47.1% male and 52.9% female participants; and the Singapore sample comprises 46.5% male and 53.5% female participants. Analysis using a modified hedonic price model on the Beijing sample indicates that households with female heads tend to transact at significantly higher housing prices than those with male heads. Furthermore, discrete choice modeling of the Beijing sample reveals that females show a greater preference for public transport over walking. Similarly, female participants in the Singapore sample are more inclined to walk to their workplaces than using other travel modes compared to males.
Reporting on race, ethnicity, or other socially relevant groupings	In addition to gender, several other socially relevant groupings were considered in each case study. For Beijing, these include household type (e.g., nuclear family, three-generation family, single-person household, dual-earner household without children), age, and education level. In the Munich study, the groupings comprise age, household size (i.e., number of individuals), income, and education. For Singapore, the categories include age, ethnicity (Chinese, Indian, Malay, and others), occupation (e.g., service and sales workers, associate professionals and technicians), and citizenship status (e.g., Singapore citizen, permanent resident, employment pass holder). All demographic information was provided directly by the survey participants through self-reporting. These variables were selected due to their established influence on residential preferences (e.g. willingness to pay for specific amenities) and travel mode choices. It should be noted that these variables are not used as proxies for other socially constructed categories. To mitigate potential confounding effects, modified hedonic regression and discrete choice models were employed to control for relevant factors in the analysis.
Population characteristics	See below.
Recruitment	Informed consent was obtained from all participants. The Beijing sample was derived from a household housing and travel survey conducted by the authors’ research team between October 9, 2020, and March 16, 2021. Data were collected through both on-street and web-based surveys. On-street surveys were administered at major subway stations and large industrial or cultural parks, while web surveys were disseminated via popular social media platforms, notably WeChat. The Munich sample originated from the “Wohnen–Arbeiten–Mobilitaet” survey, jointly administered by the Chair of Urban Development and the Chair of Land Use and Transport at the Technical University of Munich. The survey was conducted from November 27, 2014, to April 19, 2015, utilizing both online and postal survey methods. The Singapore sample was obtained from an existing dataset—the Household Interview Travel Survey (HITS)—provided by the Land Transport Authority (LTA) of Singapore. The survey took place between October 1, 2012, and September 30, 2013, and employed a stratified random sampling strategy to ensure the representation of diverse household types. It is noteworthy that younger individuals—who typically exhibit shorter commuting distances—are overrepresented in the sample, likely due to the higher accessibility of web-based surveys. This may lead to a potential underestimation of commuting distances, as the sample contains a larger share of respondents with shorter commutes.
Ethics oversight	The research involving Beijing samples received ethical approval from the Ethics Review Committee of Capital Normal University (Approval No. CNU-IRB-2020-1812). The study using Munich samples was approved by the Ethikkommission der TUM School of Social Sciences and Technology (Approval Code: EK-SSWT-2017-1317). The Singapore travel data analyzed in this study were originally collected and provided by the Land Transport Authority (LTA) of Singapore. As a governmental agency, LTA adheres strictly to the Singapore Personal Data Protection Act (PDPA) and other relevant national regulations in its data collection practices. The secondary use of these data in the current study was approved by the Ethics Review Committee of Capital Normal University (Approval No. CNU-IRB-2020-1812).

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Study description	This article proposes a household housing exchange framework that incorporates perfect information in housing market and assesses its potential environmental benefits in terms of commuting distance and carbon emissions. For all viable relocation pairs of individuals/households that satisfy these conditions, we solve a minimum-weight matching problem to minimize total commuting distance after relocation. We then estimate potential reductions in emissions (e.g., CO2, PM2.5) based on the current and optimized mode-specific commuting distances.
Research sample	The study samples comprise 2,032 households/individuals from Beijing, 3,131 from Munich, and 7,418 from Singapore. These three cities were selected to represent diverse spatial scales, population sizes, and density profiles: Beijing exemplifies large-scale, high-density mega-cities; Singapore represents compact and highly dense city-states; while Munich serves as a typical medium-scale city with lower population density. This variation enhances the potential generalization of the research findings to other urban contexts. Additionally, the study focuses primarily on full-time workers, as commuting-related carbon emissions among this group constitute a substantial portion of overall urban carbon emissions. In Beijing, the sample aligns closely with the general population in terms of gender composition. However, respondents are relatively more educated (44.9% hold a master's degree or higher) and younger (39.0% are under 30 years old) compared to the city's overall demographic profile. The Munich sample is representative in gender and household type structure, but participants are also more highly educated (55.3% hold a university degree), have higher incomes (35.8% report monthly earnings exceeding €4,000), and are younger (64.6% are under 40 years old) than the general population. The Singapore sample was drawn from the 2012 Household Interview Travel Survey (HITS) provided by the Land Transport Authority (LTA). It demonstrates relatively strong representativeness: 46.5% of respondents are male, 10.5% are over 60 years old, and the ethnic composition is 69.2% Chinese, 13.9% Indian, and 12.7% Malay.
Sampling strategy	Convenience sampling and snowball sampling were employed for the Beijing (n=2032) and Munich (n=3131) surveys, respectively. A formal a priori sample size calculation was not conducted for these two surveys. Instead, the sample sizes were determined primarily based on practical considerations related to feasibility, including the time frame for data collection, available resources, and the accessibility of the target population during the study period. Nevertheless, we consider the obtained sample sizes to be sufficient for the following reasons: (1) The on-street survey locations in Beijing and the postcard-based survey in Munich covered a diverse range of sub-districts ensuring strong spatial representativeness. This is supported by the close alignment between the average commuting distance in the sample and that of the overall city population. (2) The sample includes participants from all predefined strata (e.g., age, gender, and education groups), thereby capturing the diversity of the target population. Although some demographic characteristics are almost consistent with those of the general population, some discrepancies exist. Specifically, the overrepresentation of younger respondents may slightly reduce the observed commuting distance, while the higher proportion of highly educated respondents may inflate it. Overall, these effects on the representativeness of the average commuting distance are minimal. (3) The sample size provides adequate statistical power for the primary descriptive analyses planned in this study (e.g., estimating proportions with an acceptable margin of error). (4) The sample sizes are consistent with those reported in several key studies in our field that used similar methodological approaches. In contrast, stratified random sampling was used in Singapore's Household Interview Travel Survey (HITS). The survey included 9635 households, representing approximately 1% of Singapore's resident household population. The sample size was determined through the following statistical approaches: (1) Proportion Estimation: The standard formula for estimating a population proportion under simple random sampling was applied to confirm that a ~1% sample (with a ±1% margin of error) is statistically adequate. (2) Stratified Sampling and Design Effect: Stratified sampling was used to ensure representation across subgroups, and the sample size was adjusted using the design effect (Deff) to account for increased variance resulting from the complex survey design. (3) Multiple Objective Optimization: Required sample sizes were calculated for key survey indicators (e.g., mode share, commuting distance), and the largest value was selected to meet precision requirements for all study objectives.
Data collection	In Beijing, samples were collected through both on-street and web-based surveys. On-street surveys were conducted using paper-based questionnaires at major subway stations and large industrial or cultural parks. Web surveys, designed via the "wenjuanwang" platform, were distributed through major social media channels such as WeChat. Convenience sampling was employed for the Beijing survey. Only the research participants and members of the research team were present during data collection in Beijing.

	In Munich, the web survey was hosted on a public portal (www.wam.tum.de) and promoted through newsletters, press conferences, and social media. Additionally, postcards containing survey QR codes were distributed to mailboxes of targeted large residential communities with assistance from partner municipalities. Only research participants and members of the research team were present during the Munich survey. For Singapore, the existing dataset from the 2012 Household Travel Survey (HTS), conducted by the Land Transport Authority (LTA), was utilized. Data in the original survey were collected through standardized questionnaires and interviews. Only LTA-trained interviewers and participating household members were present during the data collection process. Commuting distances—calculated along the road network—between workers and each alternative housing option, as well as POI data across all three cities, were obtained using Python 3.6 and Java 1.8 through web crawling from OpenStreetMap. Housing transaction records for Beijing were scraped using Python 3.6 from the "Fangtianxia" platform. Singapore's housing transaction records, sourced from the "Realis" database, were acquired via a subscription-based service on the website of Singapore's Urban Redevelopment Authority. Blinding was not applicable to this study, since all variables (e.g., commuting distance, housing transactions) were objectively measured or recorded without any subjective assessment, thus eliminating the potential for researcher bias during data analysis.
Timing	The survey data for Beijing were collected from October 9, 2020, to March 16, 2021. The Munich survey was conducted between November 27, 2014, and April 19, 2015. The Singapore survey data span from October 1, 2012, to September 30, 2013. Commuting distance and POI data were obtained from July 18 to July 25, 2021. Beijing housing transaction records were collected from October 14 to October 19, 2021.
Data exclusions	There are no data exclusion applied to the Beijing and Munich's survey. For Singapore's HITs dataset, we pre-establish an exclusion criteria that "those households which do not have commute trips are excluded from the analysis" . Thus, the original 9635 Singapore households are reduced to 7418 households.
Non-participation	Response rates varied across the three surveys, reflecting differences in administration methods and institutional support. The Munich survey employed a multi-channel dissemination strategy—including newsletters and postcards—which resulted in the highest response rate of 75.8%. The Singapore survey, conducted by the Land Transport Authority, achieved a response rate of 60.3%. In contrast, the Beijing survey, which was administered solely by the author's research team, had a response rate of 30.2%.
Randomization	The participants are not allocated into experiment groups in this study.

Reporting for specific materials, systems and methods

We require information from authors about some types of materials, experimental systems and methods used in many studies. Here, indicate whether each material, system or method listed is relevant to your study. If you are not sure if a list item applies to your research, read the appropriate section before selecting a response.

Materials & experimental systems

n/a	Involved in the study
☒	☐ Antibodies
☒	☐ Eukaryotic cell lines
☒	☐ Palaeontology and archaeology
☒	☐ Animals and other organisms
☒	☐ Clinical data
☒	☐ Dual use research of concern
☒	☐ Plants

Methods

n/a	Involved in the study
☒	☐ ChIP-seq
☒	☐ Flow cytometry
☒	☐ MRI-based neuroimaging

Plants

Seed stocks	*Report on the source of all seed stocks or other plant material used. If applicable, state the seed stock centre and catalogue number. If plant specimens were collected from the field, describe the collection location, date and sampling procedures.*
Novel plant genotypes	*Describe the methods by which all novel plant genotypes were produced. This includes those generated by transgenic approaches, gene editing, chemical/radiation-based mutagenesis and hybridization. For transgenic lines, describe the transformation method, the number of independent lines analyzed and the generation upon which experiments were performed. For gene-edited lines, describe the editor used, the endogenous sequence targeted for editing, the targeting guide RNA sequence (if applicable) and how the editor was applied.*
Authentication	*Describe any authentication procedures for each seed stock used or novel genotype generated. Describe any experiments used to assess the effect of a mutation and, where applicable, how potential secondary effects (e.g. second site T-DNA insertions, mosiacism, off-target gene editing) were examined.*