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Flattening the Curve and the Flight of the Rich: Pandemic-Induced Shifts in US and European Housing Markets

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ABSTRACT: The pattern of increasing suburban house prices relative to urban centers initiated during the pandemic continues to hold across the top 30 US metropolitan statistical areas (MSAs). In contrast, European countries such as Denmark, France, and the United Kingdom did not experience a similar shift in valuations. We posit and find supporting evidence that these divergent patterns partially due to differences in the characteristics of suburban areas, particularly in terms of household income and property sizes; with European suburbs being relatively poorer and characterized by smaller housing units. We show that, in the US, MSAs with suburban features more akin to those in European cities generally experienced little to no increase in suburban housing prices compared to their urban centers. Finally, our findings indicate that migration patterns of the high-income population might have partially influenced the urban-suburban revaluation in the US.

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WORKING PAPERS

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1 Introduction

In the United States, the pandemic exerted a significant influence on property prices, consistent with a noticeable shift in households' relative preferences for urban living. Spurred by lockdowns and facilitated by the newfound ability to work from remote, the demand for suburban homes outpaced that in urban centers. This urban-to-suburban movement disrupted the traditional negative correlation between property prices and distance from city centers, with the average premium for downtown living shrinking significantly, and even turning negative in some cases (Gupta et al. (2022)). These developments raise several questions. First, was the shock to household preferences toward suburban living short-lived or persistent? Second, what lies behind the heterogeneity in experiences documented for American cities? And related, was this phenomenon limited to the United States (US) or it extended to other countries? This paper sheds some light on all these questions.

We extend the analysis in Gupta et al. (2022) seminal paper in several ways. First, with the benefit of almost two extra years of observations, we investigate whether house price gradients in the US—defined as the elasticity of house prices to the distance from the city center—have continued to rise or reverted to their pre-pandemic levels. Second, we broaden the geographical scope of the analysis and examine whether similar trends are observable beyond the US, focusing on selected European countries (Denmark, France, and the United Kingdom (UK)). Finally, guided by the differences in experiences across countries, we identify several factors that can explain the heterogeneity of house-price behavior across American metropolitan areas.

Our first set of results suggests that the effect of the pandemic on relative house prices in American cities is proving highly persistent. On average, price gradients across the top 30 US Metropolitan Statistical Areas (MSAs) continued to increase, even as the pandemic was coming to an end. House prices in the outer regions of these MSAs continued to outpace their inner counterparts in the second half of 2022.

Our second main finding is that this flattening of gradients does not seem to find a counterpart in Europe. Relative house prices in cities in Denmark, the UK , and (to a large extent) France did not follow the same trajectory seen in the US. In these countries, gradients remained consistently negative and statistically significant over the period 2020 to 2022. This suggest that household relative preferences for suburban versus downtown living remained roughly constant during the pandemic.

We hypothesize that the differences in trends between the US and Europe may stem from differences in the characteristics of their suburban areas. In the US, suburbs are often dominated by middle-class families, while European suburbs attract a more diverse socioeconomic mix, including lower-income households. To the extent that household income serves as a proxy for factors like living standards, educational quality, and housing conditions, these differences could explain the limited migration from urban to suburban areas and the stability of price gradients in Europe.

An additional difference between Europe and US suburbs relates to the size of available properties. US suburban areas typically feature properties with larger living spaces, expansive yards, and garages. In contrast, European suburban properties, although varying by country and region, generally offer smaller living spaces with fewer bedrooms and limited outdoor areas. Given that the urban-to-suburban migration during the pandemic was largely motivated by the quest for more spacious living, differences in the size of available homes may also contribute to explain why the revaluation from urban to suburban areas occurred in the US but not in Europe.

To corroborate these hypotheses, we exploit variations in relative house-price patterns across the top 30 MSAs in the US: Some MSAs saw a sustained rise in their price gradients, while others experienced little change during the pandemic or even a decline as conditions improved. According to our hypotheses, we should find that American cities whose suburbs resemble European ones in terms of relative income levels and home sizes should have experienced a lesser increase in the price gradients. Our analysis finds evidence in support of these explanations: MSAs with these characteristics indeed show a more modest rise in their price gradients.

We interpret this evidence as consistent with the notion that the change in pricing gradients was primarily driven by demand shifts by higher income households that had the means and the opportunity (having more often the ability to work remotely) to move to the suburbs. To further corroborate this hypothesis, we, next, examine the extent to which the surge in US suburban house price growth was influenced by the migration of high-income populations. Our findings show that areas that exhibited greater mobility of high-income individuals saw more pronounced suburban house price increases. This complements the findings in Gupta et al. (2022), which identifies the capacity to work from home as a primary factor in the urban exodus (indeed, while household income tends to be correlated with the ability to work from home, changes in mobility of high-income population does not).

The findings in this paper have implications for both commercial and residential real estate markets. Gupta et al. (2023) report a substantial impact on the commercial sector due to the urban-suburban shift reinforced by work from home, noting a 45% decline in office values in 2020 and a longer-term reduction of 39%, equating to $453 billion in lost value for the US. On the residential side, Li and Su (2021) point to a "decongestion" effect that has particularly benefited low-income households by easing housing demand and improving affordability in major cities such as New York, San Francisco, and Los Angeles. Our findings suggest that these effects are relatively persistent and will continue to affect real estate markets in the US. It also points to an asymmetry between American and European cities and the lack (or much weaker presence) of these shifts in Europe.

If proved persistent, remote working and the associated shift in household preferences for urban living and flattening of price gradients present both policy challenges and opportunities. Lower demand for office space and reduced traffic in downtown areas will require an adjustment in the structure of American cities and, during the transition, may lead to stress for the commercial real estate sector and put pressure on cities' fiscal revenues. At the same time, in steady state, reduced price premia for urban living may help taming the affordability crisis that several cities have been facing in recent years allowing for more inclusive urban structures.

Literature review—Our paper contributes to a growing literature on the impact of the pandemic on real estate markets. Gupta et al. (2022) observed a less negative bid-rent function, indicating a shift in the relationship between house prices, rents, and distance from the city during the pandemic. This shift was driven by urban flight and the increased ability to work from home. Similarly, Ramani and Bloom (2021) found a

"Donut Effect," where large US metro areas experienced a shift in households, businesses, and real estate demand from central business districts (CBDs) to lower density suburbs and exurbs. The size of the donut effect varied by city size, with larger effects in large cities, smaller in mid-sized cities, and minimal impact in small cities. Additionally, they find that most households leaving city centers relocated to suburbs within the same city, while some moved to smaller metros and few chose rural areas. For the US, the relative decline in residential rents and prices in the densest areas is confirmed by Liu and Su (2021) and Althoff et al. (2020).

While the mentioned papers focus on the US market, Ziemann et al. (2023) examine the behavior of the price gradient across 16 OECD countries, including those in our analysis. They find that the price gradient increased only in large metropolitan areas, but find no evidence of an increase in the gradient for medium or small-sized cities.[1] Our estimation analysis diverges from theirs, as it aligns more closely with the econometric methodology in Gupta et al. (2022). We focus on estimating the evolution of price gradients *over time* and do this for *each country* individually, instead of calculating the *average* gradient across the *cross-section*. The downside of estimating the average effect is the potential skewness of results towards countries represented by a larger number of postcodes in the sample. Furthermore, the cross-sectional estimates provide only a singular gradient, not capturing its variation over time.

For London, Gokan et al. (2022) find that there was an increase in the price and rent gradients. Although employing somewhat different specification for the interaction of the distance and time variable, the main difference with our analysis is that they focus only on London and the geographic units they consider are neighbourhoods with population between 400-1,200 households, whereas we focus on postcodes as geographic areas.[2] For China, Huang et al. (2023) find that the pandemic reduced the price premium for living in tall buildings.

[1]Their analysis is based on a pooled cross-section regression over all postcodes in the sample of 16 countries. This set up does not allow for observing the evolution of the gradient over the years surrounding the pandemic, potentially leaving out insights into how the pandemic may have influenced property price dynamics over time. Moreover, their sample is heavily weighted towards postcodes from the US, Mexico, and the UK, making up approximately 70%. This skewness may raise concerns about the results being more indicative of trends in these countries, potentially not reflecting the situation in the other 13 countries included in the analysis.

[2]Neighborhoods are identified by lower super output area (LSOA), as defined by the Office for National Statistics. The LSOA is a geographic area containing between 400 and 1,200 households.

A large and growing literature studies the confluence of the pandemic and work from home on real estate markets more generally. Van Nieuwerburgh (2023) documents work from home patterns and its implications for the residential and commercial real estate markets. Brueckner et al. (2023) examines the effects of work from home on the housing market from intercity and intracity viewpoints, finding evidence that confirm their theoretical prediction that work from home lowers housing prices and rents in high-productivity counties, as workers relocate to more affordable metro areas while keeping their desirable jobs. Mondragon and Wieland (2022) finds that the shift to remote work explains over one half of the 23.8 percent national house price increase over this period. Duranton and Handbury (2023) studies the long-term impact of remote work on future urban development, and summarizes evidence on the adjustment of residential and commercial prices and activity at varying distances from city centers during and after the pandemic. Delventhal et al. (2022), using a quantitative model of the Los Angeles metropolitan area, find evidence suggesting that, following a permanent increase in the work from home, (i) jobs move to the core of the city, while residents move to the periphery, (ii) traffic congestion eases and travel times drops, (iii) average real estate prices fall, with declines in core locations and increases in the periphery.

For the commercial real estate, Rosenthal et al. (2022) documents a decline in the commercial rent gradient across 89 U.S. urban areas, whereas Hoesli and Malle (2022) find that retail and hospitality properties and to a lesser extent office buildings were most affected during the pandemic in Europe. Gupta et al. (2023) shows that remote work led to large drops in lease revenues, occupancy, lease renewal rates, and market rents in the commercial office sector, suggesting a valuation decline of New York City office buildings by 44% in long run value.

2 Data

In our analysis, we examine the largest 30 MSAs by population in the US, listed in Table 4 of Appendix A.1. For Denmark, we focus on Copenhagen and Aarhus; for France, on Paris, Lyon, and Marseille; and for the UK, on London, Birmingham, Leeds, Liverpool, Manchester, and Sheffield. The selection of cities in Denmark, France, and the UK is guided by cities' population size, geographic distribution, and economic importance, offering a diverse and robust representation of urban life in these countries. We focus on these larger cities because as Ramani and Bloom (2021) document for the US, it is in the larger cities that we would expect to find the most pronounced changes in price gradients.

House price data. For the US, we use Zillow data at the zip code level to measure prices at monthly frequencies. We rely on the Zillow House Value Index (ZHVI), which adjusts for house characteristics using machine learning techniques. For further details on the Zillow data, refer to Appendix B of Gupta et al. (2022). For Denmark, we use quarterly data at the postcode level from Association of Danish Mortgage Banks, comprising initial listing prices, final listing prices, and transaction prices realized for detached/terraced houses, owner-occupied flats, and holiday homes. In our analysis, we use realized transaction prices for detached/terraced houses and owner-occupied flats. For France, we use transactions of sold properties data from the land values dataset distributed by DGFiP, a national statistics and data publishing entity. The dataset records housing sales, with each entry featuring a unique sale, the transfer date and property characteristics like type, size, and room count. Similarly, for the UK, we use transactions of sold properties data from the HM Land Registry Open Data, with each entry featuring the property's sale price, address, type, and date of ownership transfer. Appendix section A.3 describes the steps used to clean the transaction-level data and section 4.1 describes the construction of the price indices at postcode-level at quarterly frequency.

Distance from city center data. For the US, we use data on distance from city center directly from Gupta et al. (2022), calculated as the logarithm of one plus the distance in kilometers between a zip code's centroid and the city hall (or Grand Central Terminal for New York) of the main city of the metropolitan area. For other countries, we calculate the distance from city center as the logarithm of one plus the distance in kilometers between a given postcode and the central postcode, defined as the postcode where the main square of the city is located. We use the GeoNames Database and the accompanying Python program to generate the distances. Central postcodes for European cities are listed in Table 4 of Appendix A.1.[3]

Zip code/postcode level demographic characteristics. In our baseline regression

[3]In the paper, we use the term city center and central zip code/postcode interchangeably.

analyses for the US, we include zip code level control variables from the 2021 5-year ACS (American Community Survey). These variables include median household income, median age of the head of household, the proportion of black residents, and the proportion of residents earning over \$150k. We also use data on population migration by income groups from the 1-year ACS sample for the period 2019 to 2022. For the UK, we use postcode level control variables from the UK Census. These variables include median household income (from 2018), the median age of the head of household (from 2021), the proportion of non-Western Europe born population (from 2021), and the share of households that earn less than 60% of the median income before housing costs (from 2011/12).[4] Data for these variable is reported based on Middle Layer Super Output Areas (MSOAs), which we map to postcode areas. Since postcodes typically contain multiple MSOAs, we use population-weighted means of the MSOA-level variables within each postcode.

2.1 Definition of city borders

For the US, house price data from Zillow is available at the zip code level, which includes information on the MSAs and states to which these zip codes belong. This allows for clearly defined city boundaries. However, in the case of house price data for Denmark or property transaction data for France and the UK, although they contain information about postcodes, they lack information about the cities associated with these postcodes. Consequently, we have to define city borders ourselves.

In the case of Denmark and France, we link postcodes to NUTS3 regions,[5] which we then associate with metropolitan regions.[6] It is important to note that in Europe, multiple NUTS3 regions can sometimes be associated with a single metropolitan region. To maintain relevance and exclude exceedingly remote regions, we refine our selection of NUTS3 regions to encompass only those within a feasible commuting distance from a central postcode.[7] The guiding principle is that the furthest distance from the central to

[4]We use the most recent observation for which data are available at the time of writing the paper.
[5]To map the postcodes to NUTS3 regions, we use data from Eurostat.
[6]To link NUTS3 regions to metropolitan regions we follow OECD's territorial correspondence table (Territorial Level 2021, TL-2021).
[7]For this we follow OECD territorial grids definition.

Table 1: City and NUTS3 Code

City	NUTS3 2021 Code
Copenhagen	DK011
	DK012
	DK013
Aarhus	DK042
Paris	FR101
	FR105
	FR106
Marseille	FR104
	FR105
Lyon	FRK26

the most remote postcode in a given city should not surpass that of the capital city. Take Paris as an illustrative example: the farthest distance between its central postcode and its most distant postcode is 23km. Consequently, for other French cities we evaluate—each being smaller than Paris—we set a boundary of a 23km radius. The list of the NUTS3 codes included for each city are shown in Table 1.

For the UK, we link postcodes to cities using a dataset compiled by Pope (2017), representing the postal boundaries for 2012.

3 The price gradients in the US

We estimate the price gradient over time for the top 30 US MSAs using data until December 2022, adding two years of additional data relative to Gupta et al. (2022), whose sample period ends in December 2020. We estimate the slope using their empirical specification:

$$ln(p_{ijt}) = \alpha_0 + \delta_t Month_t \times \left[ln(1 + D(z^z_{ij}, z^m_j))\right] + \beta X_{ij} + \alpha_t Month_t + \alpha_j MSA_j + \epsilon_{ijt}. \quad (1)$$

The unit of observation is a zip code-month. p_{ijt} refers to the price in zip code i of MSA j at time t, and $D(z^z_{ij}, z^m_j)$ is the distance in kilometers between the centroid of zip code i and the center of the MSA j, where $i \in j$.[8] The controls include: time fixed effects (Month_t), MSA fixed effects (MSA_j), and zip-code level control variables (X_{ij}). The zip-code controls are: log of annual median household income, median age of the head of

[8]The center of an MSA is defined as the city hall of the MSA, with the exception of New York, where the center is the Grand Central Terminal.

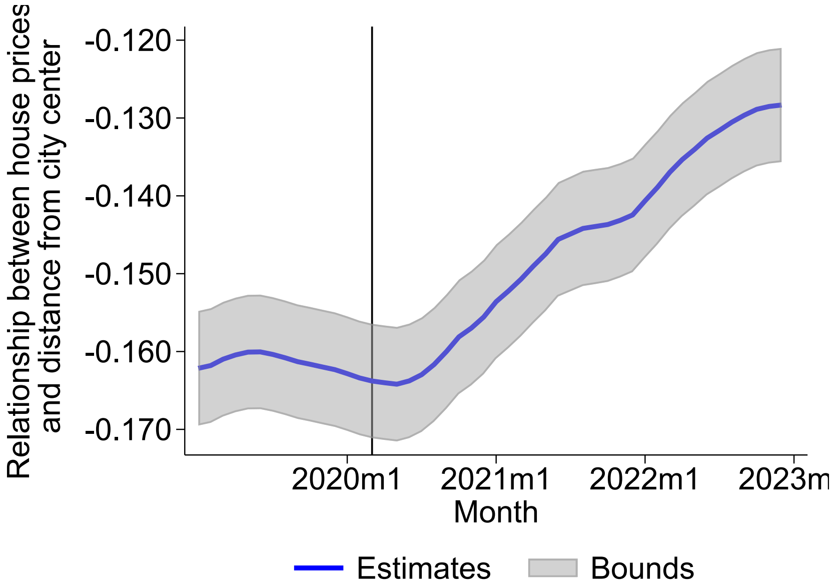


Figure 1: The figure plots the coefficient δ_t in eq. (1) that is the time-varying relationship between house prices and distance from a central zip code. The estimates are obtained from a panel regression based on data from the top 30 MSAs spanning January 2019 to December 2022. The vertical line marks March 2020, noting the start of the pandemic.

household, proportion of Black households, and proportion of households who earn over \$150k. The controls are all based on the latest available data from the 5-year ACS in 2021, and do not vary over time during the estimation window.[9] Unlike in Gupta et al. (2022), the main estimation sample is not restricted to zip code-month observations for which both price and rent data are available. This significantly increases the sample size (almost threefold). The figures plot the coefficient δ_t from the estimated regression, which measures the elasticity of prices to distance between the zip code and the center of the MSA in any given month t. We refer to it as the price gradient.

Figure 1 shows the price gradient obtained from a panel regression at the zip code level for the top 30 MSAs over the period January 2019 to December 2022 following eq. 1. The price gradient began to increase shortly after the start of the pandemic. In December 2019, it was -0.16, and by December 2022, it reached -0.13. The change in slope ($\Delta\delta = 0.03$) implies that house prices 10km from the city center grew by 5.5 percentage points more than house prices in the city center. This result suggests that, albeit the pandemic was nearing its end, average price growth in suburban areas continued to outpace that in city centers.

[9] The control variables in Gupta et al. (2022) are measured as of 2019, which were the latest available at the time their study was done.

4 The price gradient in selected European countries

Next, we estimate price gradients across selected European cities for which house price data at the postcode-level is either readily available or can be constructed from property transaction records. Our analysis focuses on cities in Denmark, France, and the UK. House-price indices at the postcode level at quarterly frequencies are readily available for Denmark. In the case of France and the UK, we generate quarterly house price series using property transaction data. We choose to construct quarterly series as postcode-month combinations tend to have insufficient data for reliable price estimates. First, we outline the methodology used to create these postcode-level price indices, and then we present the estimated price gradients for the three countries.

4.1 France and the UK

We construct house price series at the postcode level at quarterly frequencies using estimates from a hedonic model. In the appendix, we perform also robustness checks, where we build price indices using the median sale prices in each postcode-quarter. We focus on major cities, including Paris, Lyon, and Marseille in France; and London, Birmingham, Leeds, Liverpool, Manchester, and Sheffield in the UK. As mentioned earlier, this selection is driven by two key factors. First, in the US, the trend of rising suburban prices has predominantly been observed in major cities, as opposed to smaller ones, as noted by Ramani and Bloom (2021). Second, the limited number of transactions in postcodes in smaller cities could lead to unreliable estimates.

To estimate our hedonic price model, we estimate the following regression specification for each city j

$$p_{ijt} = \beta_{j0} + \beta_t Quarter_t + \beta_{ij} PostCode_{ij} + \beta_{ijt} Quarter_t \times PostCode_{ij} + \beta_{jx} X_{ijt} + \epsilon_{ijt}, \quad \forall j \tag{2}$$

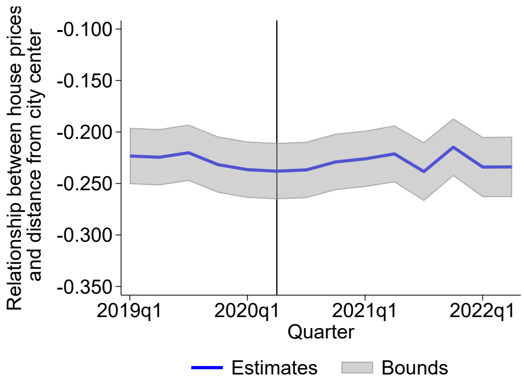
The unit of observation is an individual property transaction (i) within a city (j) and quarter (t). p is the transaction price, $Quarter_t$ is a time fixed effect, $PostCode_{ij}$ is a postcode fixed effect, $Quarter_t \times PostCode_{ij}$ is a time×postcode fixed effect, X is a vector of property level characteristics, and ϵ is the error term. As information on property characteristics varies between France and the UK, for France, X includes the sale type (existing vs. pre-built property), property type (apartment vs. maisonette), size in square meters, and the number of rooms. Meanwhile, for the UK, X consists of the property type (detached, semi-detached, flats/maisonette, terraced), a dummy variable for new or existing properties, and the property's duration (leasehold vs. freehold). Eq. (2) is estimated separately for each city in the dataset for the period 2019Q1 to 2022Q3 for the UK and 2019Q1 to 2022Q2 for France.

For each quarter-postcode pairing, we calculate house prices using their predicted values. These are derived by adding the regression's intercept, the coefficients specific to both the quarter and postcode, and their mutual interaction. Furthermore, we integrate the coefficients from the X vector. As the specifics in the X vector diverge between France and the UK due to differences in transaction data. In France, our pricing model is based on a property characterized by 3 rooms, 100 square meters, a sold status (as opposed to pre-sale), and a maisonette property type. Conversely, in the UK, our pricing pertains to properties that are pre-existing (not new builds), have a freehold tenure (instead of leasehold), and fall under the flats/maisonettes property category.

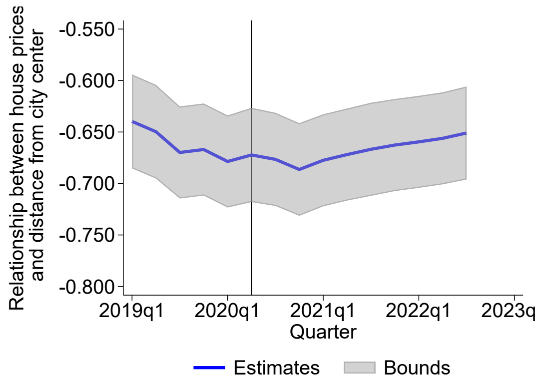
Figure 2 shows the price gradient for France (right top panel) and for the UK (left top panel) obtained from a panel regression at the postcode level for the three largest cities, estimated over the period 2019Q1 to 2022Q2, for France; and for the largest six cities in the UK, estimated over the period January 2019Q1 to 2022Q3 following eq. (1).[10] The bottom panels show the estimates of the price gradient for the capital cities, Paris and London. Owing to data constraints, postcode-level controls are only used for the UK, which include the median share of non-Western European born population, median age, median household income, the share of people living in poverty, while eq. (1) for France is estimated without such controls. In the robustness section 7, we show and discuss the results from estimating our baseline specification using postcode fixed effects.

The results indicate a notable difference in how the pandemic affected price gradients

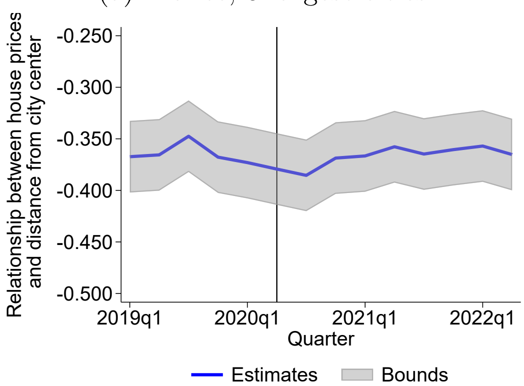
[10]The estimation samples are based on the latest available data points when the analysis were performed for both countries.



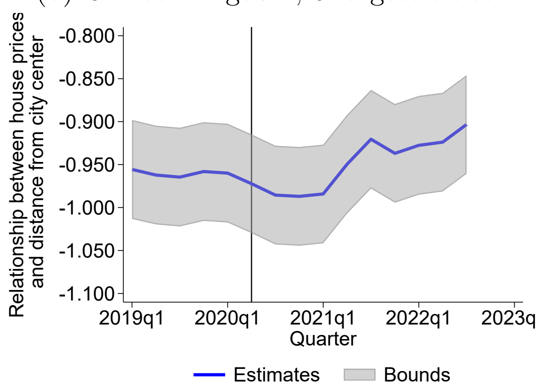
(a) France, 3 largest cities



(b) United Kingdom, 6 largest cities

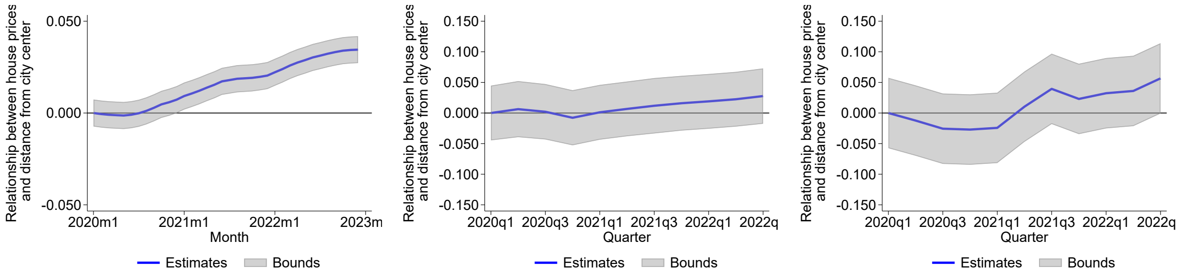


(c) Paris



(d) London

Figure 2: The figure plots the coefficient δ_t in eq. (1) that is the time-varying relationship between house prices and distance from a central postcode. The estimates are obtained from a panel regression based on data from the three largest cities in France and the six largest cities in the UK based on population over the period 2019Q1 to 2022Q2 (2022Q3) for France (UK), estimated at quarterly frequencies. Panels (c) and (d) show the same estimates but when restricting the sample to Paris and London, respectively. The vertical line marks March 2020, noting the start of the pandemic.



(a) US, top 30 MSAs (b) UK, 6 largest cities (c) London

Figure 3: The figures show the difference in the coefficient δ_t at time t and its January 2020 value, estimated using eq. (1), and computed as $(\delta_t - \delta_{Jan2020})$. A positive coefficient indicates a price gradient increase compared to January 2020. The left panel shows the estimates for the US, the middle panel shows the estimate for the UK, and the right panel shows the estimates for London.

in the US, on one hand, and France and UK, on the other. In the US, relative urban-suburban house prices underwent a marked change, with a notable increase in relative suburban property values. Meanwhile, the price gradient of the largest three cities in France remained stable thought the period. The UK followed a path reminiscent of France, but also revealed a subtle indication of an upward shift.[11] Delving deeper into the capital cities suggests that the gradient in Paris remained stable, whereas in London it saw a mild uptick.

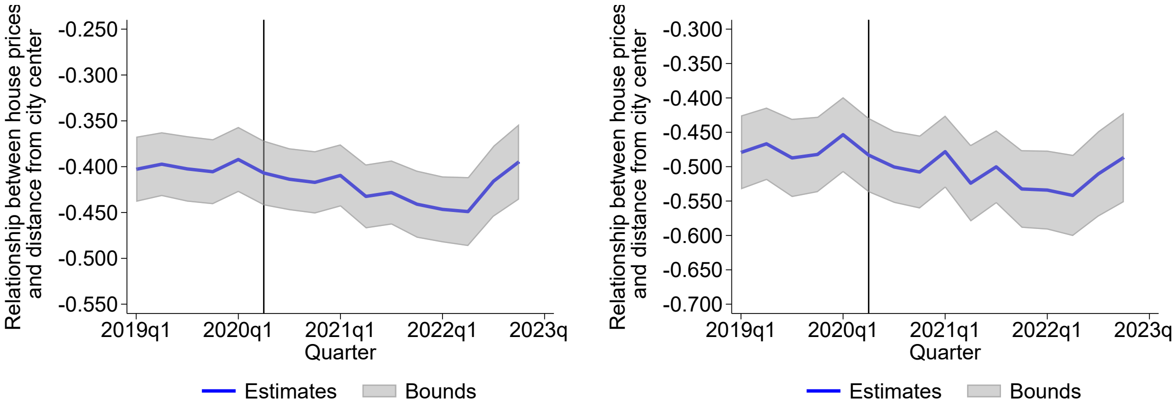
Given the observed minor upward trend in the UK, we further analyze if the deviation of the coefficient δ_t in equation (1) significantly differs from its value in the first quarter of 2020 ($\delta_t - \delta_{2020Q1}$ for the UK; $\delta_t - \delta_{Jan2020}$ for the US). Figure 3 displays these findings. For the US, the deviation change is both positive and significant. In contrast, for the UK and specifically London, the positive change is mild and lacks statistical significance. Section A.2.1 in the Appendix provides the results of a Wald test for the difference in these coefficients over time for all four countries, confirming the findings presented in Figure 3.

4.2 Denmark

Finally, we estimate the price gradient for Denmark by employing readily available house price data at the postcode level and at quarterly frequencies.

Figure 4 presents the price gradient derived from a panel regression conducted at the

[11] When controlling for postcode fixed effects om regression (1), the gradient for France increases, and to a lesser degree, so does that of the UK; but the change in the gradient is still much more pronounced and statistically significant for the US. Section 7 presents and discusses these results.



(a) Denmark, 2 largest cities

(b) Copenhagen

Figure 4: Panel (a) plots the coefficient δ_t in eq. (1) that is the time-varying relationship between house prices and distance from a central postcode. The estimate are obtained from a panel regression based on data from the two largest cities in Denmark based on population over the period 2019Q1 to 2022Q4. Panels (b) shows the same estimates but when restricting the sample to Copenhagen. The vertical line marks March 2020, noting the start of the pandemic. The end data point for each sample is based on the latest available data at the time the analysis were performed for both countries.

postcode level for Copenhagen and Aarhus, encompassing the period from 2019Q1 to 2022Q4, following eq. (1). Similar to France, this panel regression does not incorporate sociodemographic controls due to lack of publicly available data on household demographics at the postcode level. The outcome of this analysis echos those for France and the UK. The price gradient is both markedly negative and statistically significant. But it shows minimal fluctuations since the onset of the pandemic and has broadly remained flat throughout the estimation period.

Overall, these findings suggest a stark difference in the experiences of real estate markets in the US and selected European countries during and after the pandemic. In the next subsection, we discuss potential factors that may underpin these divergent market behaviors.

5 Why do price gradients differ?

The flattening of house-price gradients in the US was likely spurred by the desire for larger homes and the reduced benefits from living downtown associated with lock-downs and the need and ability to work from remote (Gupta et al. (2022)). Based on this interpretation we consider structural characteristics of European cities that may have prevented a similar development in their residential real estate markets. In particular, we focus on two factors that may have reduced the appeal of European suburbs: (i) the size of properties available, and (ii) the socioeconomic composition of the population.

Properties in suburbs. There is much variation in suburban property characteristics between the US and Europe. American suburban homes are typically larger with expansive yards and garages, reflecting the country's ample land resources and preference for sizeable living spaces.[12] Conversely, while European suburban properties vary by country and region, their differences in size between central city areas and suburbs do not seem to differ much. A Eurostat (2016) study documents that the average size of a property in rural areas of the EU-28 was 104sqm, which is only 5sqm larger than in towns and suburbs, and only 15sqm larger than in cities. To the extent that relative increase in demand for suburban homes in the US was driven by the quest for more spacious dwellings, the more limited supply of large properties in European suburbs may contribute to explain the stability of price gradients in Denmark, France, and the UK.

To examine this hypothesis within our dataset, Table 2 reports the percentage of large and small properties in the US and France by distance from city centers.[13] In the US, the percentage of large homes—defined to be those with more than 5 rooms (Table 2, column 2)—rises with the distance from city center, comprising nearly 70 percent of properties 25-30km out.[14] In France, however, property sizes do not consistently increase with distance from the city, and homes with over 4 rooms make up only about 30 percent of all properties, less than half of the US ratio. These findings corroborate the earlier discussion that US properties farther from city centers are generally larger and that large properties tend to represent a growing share of the market as the distance from city centers increases. In contrast, albeit limited, our data from France suggests only a milder increase in the percentage of large properties.

Socioeconomic compositions in suburbs. There are significant differences between the socioeconomic characteristics of the populations living in suburban areas in the US and Europe. American suburbs are typically inhabited by middle-class and upper-

[12]See Urban Living Institute (2016) report on suburban housing characteristics in the US.

[13]We use data for the US from the 5-year ACS for 2011-2021, and data for France from the DGFiP transaction records for 2017m1-2022m6. Despite that the French data only represents sold properties, it is a valuable proxy given the lack of comprehensive data on room count by property by distance from city center.

[14]For the US, we take 5 to be the cutoff value for "large" properties because properties with 4-5 rooms are bundled together in the ACS data.

Table 2: Property size by distance from city center: France vs. US

	US: ≤ 4	US: > 5	FR: ≤ 4	FR: > 4	FR Median Area
Distance From City Center					
< 5	80.0	19.9	92.7	7.0	56.0
5-10	62.2	37.7	89.2	10.8	62.0
10-15	55.4	44.6	81.4	18.6	69.0
15-20	49.0	51.0	76.1	23.9	81.5
20-25	42.6	57.4	74.0	26.0	90.0
25-30	39.3	60.7	75.7	24.2	84.5

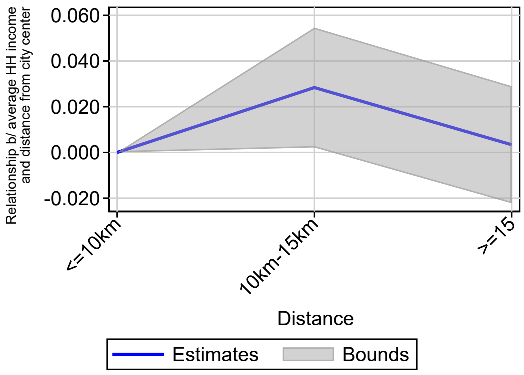
Note: The property size is based on the number of rooms in a property. The category ≤ 4 represents the percentage of homes in the US with fewer than 4 rooms. The category US: > 5 indicates the percentage of properties in the US at the zip code level with more than 5 rooms, as properties with 4-5 rooms are bundled together in the Census data. For France, the category FR: > 4 represents the percentage of properties at the postcode level with more than 4 rooms. FR Median Area refers to the median home area in square meters for France.

middle-class families (Brueckner (2011); Antipova (2018)). This is often associated with greater availability of services and higher-quality public school systems. In Europe, the socioeconomic composition of suburban neighborhoods is more diverse, encompassing both lower-income and higher-income residents, along with a variety of housing types, including public housing.[15] This difference might have played an additional role in deterring people from relocating to suburban areas in Europe.

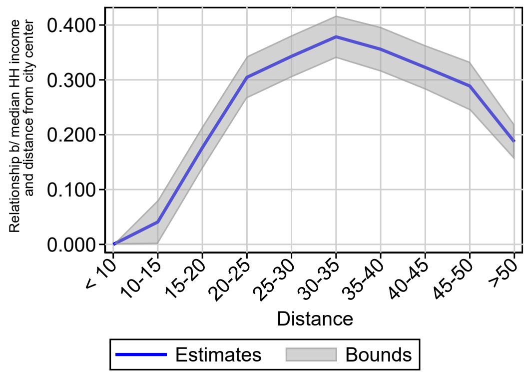
This is evident in our dataset. Figure 5 reports coefficient estimated cross-sectionally at the postcode level. We regress a measure of log household income on dummy variables indicating thresholds for distance from the city center, while controlling for city/MSA fixed effects. We use data from 2018 for consistency as this is the year for which data is available for the UK.

The results for the 6 largest cities in the UK (Figure 5, left top panel) reveal a subtle and almost negligible increase in household income for postcodes 10-15km from the city center compared to those within a 10km radius from the city center. What is even more striking is that when considering London alone, household income in more remote postcodes actually declines significantly at distance beyond 10km from the city center (Figure 5, left right panel). In contrast, the US shows a very distinct pattern, suggesting that household income begins to rise significantly after surpassing 10km from the city center, with this upward trend continuing as the distance increases (Figure 5, bottom

[15]See for example Hochstenbach and Musterd (2018) Tammaru et al. (2021), and Haandrikman et al. (2023) for evidence and discussion on the socioeconomic segregation in Europe.



(a) UK, 6 largest cities



(b) US, top 30 MSAs

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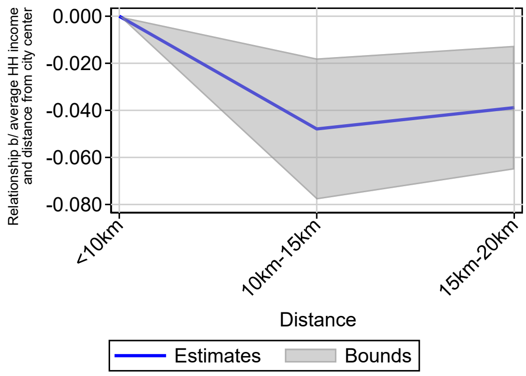


(c) London

Figure 5: The panels show coefficient estimates from a 2018 cross-section regression comparing the largest 6 cities in the UK (top left), the top 30 US MSAs (top right), and London (bottom center). Due to data limitations, household income is measured differently: average for UK at the postcode level and median at the US zip code level. We regress log household income on distance-thresholds dummy variables, while also accounting for city/MSA fixed effects.

center panel).

In summary, there are large differences in the socioeconomic and structural characteristics of European and American suburbs. Next, we turn to testing (indirectly) our hypothesis that these differences played a role in the divergent patterns observed in house price gradients, by focusing on heterogeneity across US cities.

6 Heterogeneity in the gradient across US MSAs

Figure 1 in section 3 showed that the price gradient has continued to trend upwards on average across the top 30 US MSAs. In this section we examine the extent to which this upward trend varies across the top 30 MSAs in our sample. Several factors could explain the variation in gradients across MSAs. For example, Gupta et al. (2022) show that MSAs in which work from home was more prevalent and MSAs that adopted more stringent stay-at-home measures during the pandemic witnessed a larger increase in price gradients.

Figure 6 shows the change in the price gradient over the period January 2020 and December 2022 across all MSAs. In this chart, dark bars show how much prices changed in each of the 30 MSAs from January 2020 to June 2021. Light bars show the changes from June 2021 to December 2022. We divide the changes into these two periods to explore whether, after the initial price rise due to the pandemic (January 2020-June 2021), some areas saw a return of the price gradients to what they were before the pandemic, while in others the gradients kept going up. The solid black line on the chart shows the total change in the gradients over both periods. The blue dot indicates whether the change in the gradient, calculated as $(\delta_t - \delta_{Jan2020})$, is statistically greater than zero at any point over the period January 2020 to December 2022.

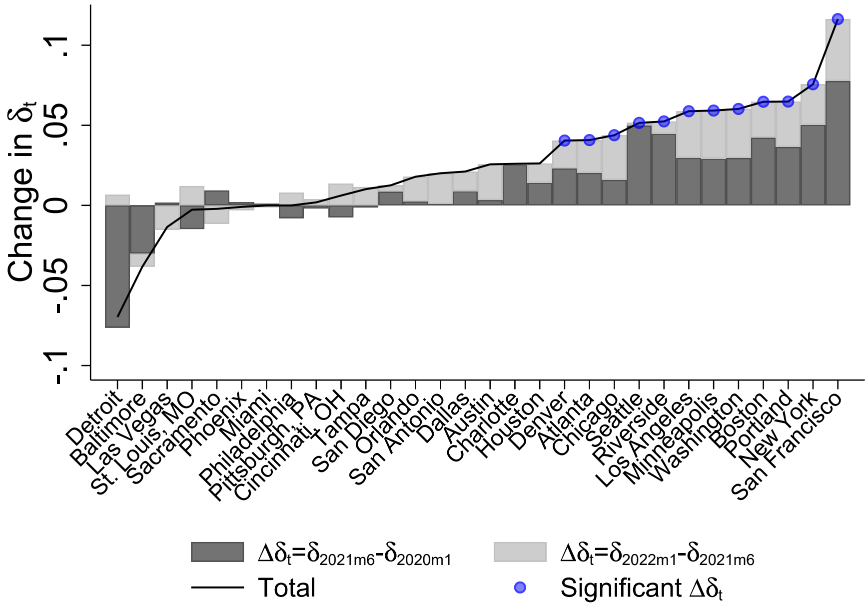


Figure 6: The figure plots changes in the price across the top 30 US MSAs. We first estimate a gradient specification separately for each MSA following eq. 1. We then calculate from this specification, the change in the δ_t coefficient for each MSA between January 2020 and June 2021 (dark shaded bars) and June 2021 and December 2022 (light shaded bar). The black solid line indicates the sum of the two bars. The blue dot indicates whether the gradient δ_t significantly differs from its January 2020 value, i.e. $(\delta_t - \delta_{Jan2020})$.

In the chart, larger positive dark shaded bars indicate a larger increase in the price gradients from January 2020 to June 2021. Larger negative light shaded bars indicate a drop in the gradient between June 2021 and December 2022, suggesting a return of the price gradient to pre-pandemic levels. Interestingly, not many MSAs saw such decrease. In fact, for over half of the sampled MSAs, the gradient either remained high, though at varying magnitudes, or decreased only slightly since January 2020. And for over a third of the MSAs the change in the gradient, $(\delta_t - \delta_{Jan2020})$, was significantly greater than zero.

Among the top 30 MSAs, San Francisco, New York, and Portland have experienced the most sustained increases in their price gradients. Conversely, cities like Miami, Pittsburgh, and Phoenix have seen little or no change in the gradients from January 2020 to December 2022. There are also MSAs like Detroit, Baltimore, and Las Vegas, in which the gradient turned more negative since the offset of the pandemic, suggesting that properties closer to the city core increased in value compared to those in more remote areas.

These findings highlight significant cross-MSA heterogeneity, indicating that the pandemic's influence on urban real estate prices has continued in some areas until December 2022, while in others it never gained much traction.

6.1 Reconciling differences across MSAs

Building on the observed variations in price gradients across US MSAs, we next turn our attention to exploring potential explanations for these disparities. Specifically, we investigate whether the structural differences we identified between the US and selected European real estate markets can also shed light on the divergences seen within US MSAs. In essence, we are interested in examining whether US MSAs, whose suburban income and property size profiles resemble those of European cities, have similarly experienced a more moderate increase in their price gradients.

We ask two questions. First, did MSAs with relatively poorer suburbs (similar to London) experienced a less pronounced uptick in price gradients? Second, did MSAs where property sizes do not substantially increase as one moves away from the urban core—mirroring the property distribution in France—also exhibit a more tempered gradient increase? Note that with "resemblance to European cities" we do not mean to denote an all-encompassing similarity but rather a narrow definition specific to relative income and property size characteristics in suburban areas.

First, we examine whether US MSAs that have relatively poorer suburbs experienced less pronounced increases in their price gradients since the onset of the pandemic. To do so, we calculate the percentage difference between the median household income in suburbs, defined at zip codes 10-30km away from the city center, and the national median household income. Using the national median as a benchmark is particularly important when comparing suburban incomes across MSAs. This approach mitigates the distorting effect of cities like New York, which have extraordinarily high median incomes in their urban cores (zip codes within 10km of the city center). In such MSAs, despite a seemingly large income gap between the core and suburbs, suburban areas often still have incomes considerably higher than the national median. These suburbs remain attractive places to live, especially since higher income is a proxy of factors such as the standard of living, quality of education, and quality of housing.

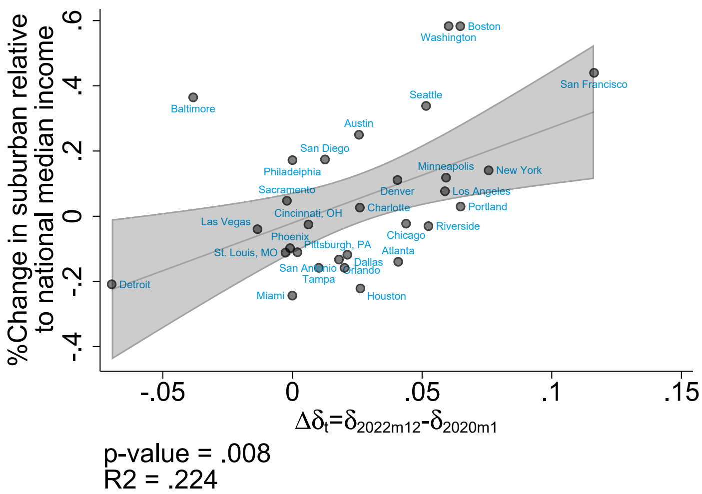
The top panel of Figure 7 illustrates the relationship between the change in the price gradient from January 2020 to December 2022 and the percentage deviation of median household income in the suburbs from the national median, as measured in 2019. This relationship is positively correlated and highly statistically significant, with variations in suburban household income accounting for slightly over 20 percent of the fluctuations in the change of the price gradient across MSAs. This result suggests that suburbs with household incomes below the national median experienced smaller increases in the price gradients consistent with what happened in Europe.

Next, we investigate whether US MSAs with property characteristics similar to European cities experienced less pronounced increases in their price gradients. To quantify the similarity to Europe in suburban property sizes, we calculate the percentage difference between the median share of large homes (with more than three rooms) in areas located 10-30km away from the city center and those within a 10km radius of the center. This metric serves as an indicator of whether homes situated farther from the city center are generally larger than those nearer to it.

The bottom panel of Figure 7 displays the relationship between the change in the price gradient from January 2020 to December 2022 and the percentage difference in the prevalence of large properties between city centers and their surrounding suburbs, as assessed in 2019. This correlation is both positive and highly statistically significant, with suburban property size accounting for close to 20 percent of the across-MSA variation in the change in the price gradient. The data suggests that suburbs with relatively larger properties compared to their city centers experienced more substantial increases in their price gradients. Conversely, MSAs that resemble European cities—where suburban properties are not significantly larger than those in the city center—saw more modest increases in their price gradients.

Finally, we construct a comprehensive "Similarity-to-Europe" index, combining our two key metrics: relative household income and property size. Each MSA is assigned a score based on its decile position within the distribution for these factors. We sum these scores and normalize them, setting the MSA least similar to European cities in suburban income and property size at a high score of 100, while the MSA most resembling European characteristics receives a lowest score.

Figure 8 shows the relationship between the similarity-to-Europe index and the change in the price gradient for the top 30 MSAs. The positive correlation observed implies that



(a) Change in the price gradient vs suburban relative household income

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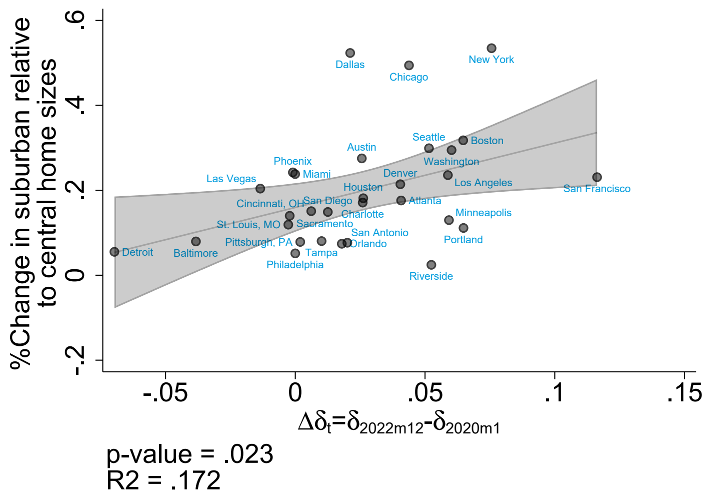


(b) Change in the price gradient vs room size

Figure 7: The scatter plots shows the relationship between the change in the price gradient and the income gap (top panel) and home size gap (bottom panel) across the top 30 MSAs in the US. The gradient is calculated as the change in δ_t coefficient for each MSA between January 2020 and December 2022 following eq. 1. The income gap is calculated as the percentage difference between the median income in suburbs and the median national income. The house size gap is calculated as the percentage difference of the share of houses with more than 3 rooms in suburbs vs core areas. Suburbs are defined as the areas that are 10-30km away from city centers; core areas are defined as the zip codes within 10km away from city centers.

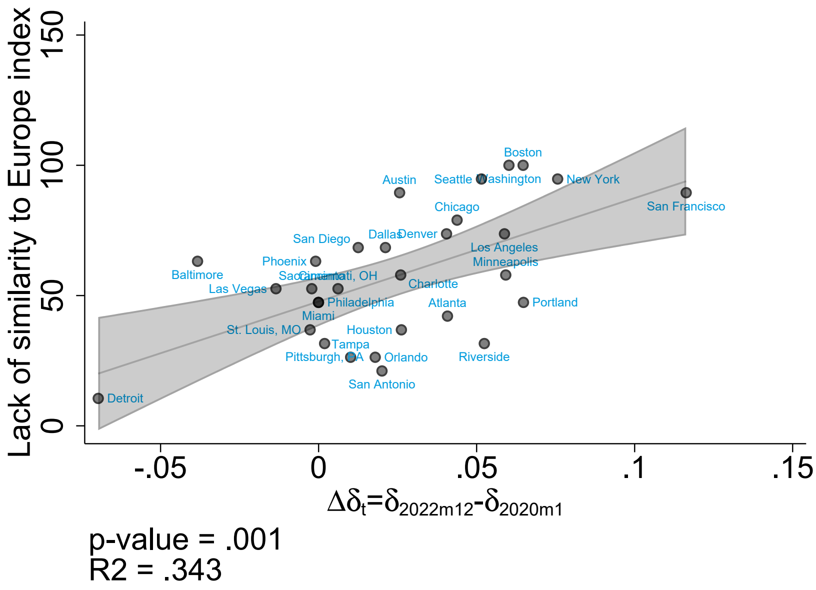
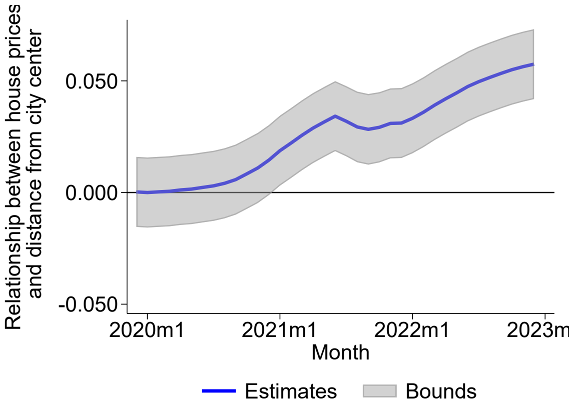


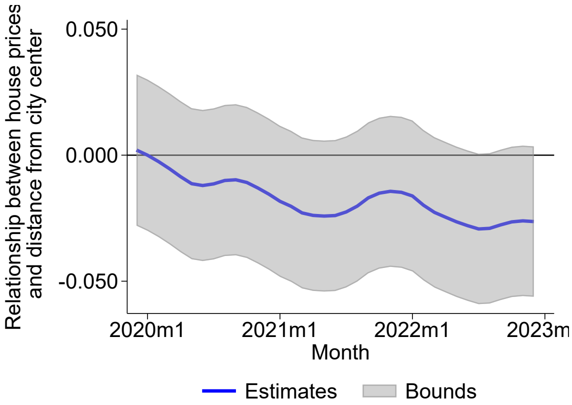
Figure 8: The scatter plot shows the relationship between the similarity-to-Europe index and the change in the price gradient between January 2020 to December 2022 for the top 30 MSAs in the US. A larger value of the index implies lower similarity to Europe. The similarity-to-Europe index is obtained by assigning MSAs a score based on where they belong within the decile of the distribution. We add these scores and normalize them such that the MSA that looks the least like Europe in terms of income in the suburbs and property sizes gets the highest score of 100 and the MSA that looks most like Europe gets the lowest score.

MSAs, where suburbs are characterized with a larger positive deviation in median household income from the national median and larger positive deviation of the size of houses between the urban core and suburbs have experienced more significant increases in their price gradients. Moreover, the high R-squared and p-value imply that the combination of these two factors better explains their relationship to changes in the price gradient.

Finally, Figure 9 shows the price gradients for MSAs based on how closely they align with European cities, as measured by the similarity-to-Europe index. The left side figure displays the price gradient for MSAs that deviate the most from European cities in aspects like income and property size. The MSAs in this subset belong to the top 30th percentile according to our similarity index. The right side figure shows, in contrast, the price gradient for MSAs that most mirror European cities in terms of income and property characteristics, falling within the bottom 30th percentile of our similarity-to-Europe index.



(a) Less like Europe



(b) More like Europe

Figure 9: The figures show the difference in the coefficient δ_t at time t and its January 2020 value, estimated using eq. (1), and computed as $(\delta_t - \delta_{Jan2020})$. The left side figure plots the difference in the gradient for MSAs that look less similar to Europe and belong in the top 30th percentile in the similarity-to-Europe index; the right side figure plots the difference in the gradient for MSAs that look more similar to Europe and belong in the bottom 30th percentile in the similarity-to-Europe index.

This analysis highlights the different trends among these MSAs. In cities that are most unlike European ones, the price gradient has consistently remained higher compared to January 2020 levels. The persistent increase in their price gradients sets them apart from trends observed in Europe. Conversely, MSAs that are more similar to European ones in terms of household income and property size, the price gradient experienced little to no change, mirroring the stability seen in European cities.

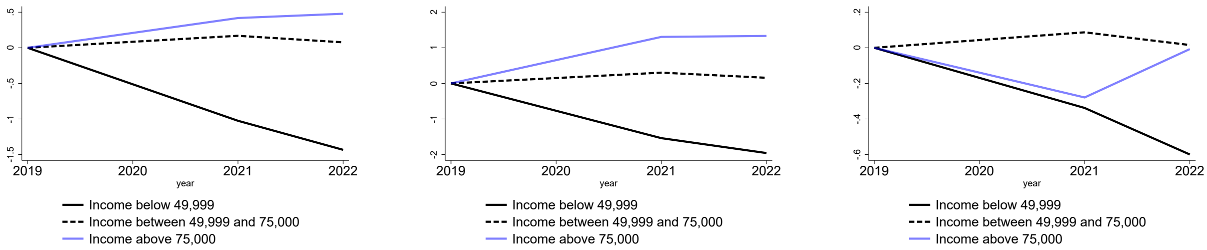
This evidence is also consistent with our hypothesis that differences in suburban structures and socioeconomic composition help explain the highly asymmetric gradient developments in the US and Europe.

6.2 Flight of the rich?

While suburban structural characteristics seem to have played a role in shaping the shifts in residential real estate market during the pandemic, as (Gupta et al. (2022)) document, another significant consideration is the transformation in work modalities. As work from home gained traction, the relative attractiveness of suburban living increases. Notably, the ability to work from home was more prevalent for jobs at the higher end of the income distribution and, hence, it permitted and encouraged a greater mobility primarily for higher-income households. Given the evidence in the previous section, the question then arises of whether in MSAs where these higher-income individuals were less able or willing to move experienced lower increases in price gradients. Put differently, were the gradients flattened by the rich?

To answer this question we next investigate how the mobility of high-income individuals' relates to the changes in price gradients experienced since the pandemic. Using the 1-year ACS sample, we determine the percentage of the population that relocated **in a specific MSAs** within a given year, segmented by income group. This percentage is calculated by comparing the number of individuals who moved within each income category to the overall population for that year. Specifically, our analysis focuses on three income brackets: (i) income below \$49,999, (ii) income between \$49,999 and \$75,000, and (iii) income exceeding \$75,000, as defined by ACS. We define high-income population mobility as the movement of individuals earning \$75,000 or more.

Since wealthier and poorer households tend to move with different frequency, we focus on changes in mobility rather than its level. Figure 10 plots the difference in the percentage of the population that moved in a given year t and 2019 for each income group, calculated by taking the percentage of the population that moved in the given year t and subtracting the percentage that moved in 2019. Panel (a) in 10 indicates that the mobility of high-income individuals increased by about half a percentage point between 2019 and 2021. Conversely, mobility among lower-income individuals dropped by more than 1 percentage points. This trend was more marked in MSAs less similar to Europe, i.e., where suburbs are characterized by higher income and properties are more expansive (Figure 10, panel b). However, in MSAs resembling European suburban settings, mobility for the same income group decreased by about 2 percentage points in 2021, returning to its 2019 level the following year (Figure 10, panel c).



(a) US, top 30 MSAs

(b) MSAs less similar to Europe

(c) MSAs more similar to Europe

Figure 10: The figure shows the percentage of people aged 15 and older who moved either within their county or to another, categorized by income level. Each year's value is presented in relative terms to 2019 by subtracting the 2019 figure.

Next, we investigate if the gradient in MSAs with higher growth in high-income population mobility between 2019 and 2021 also experienced risen and sustained house price gradients. We define the growth in high-income population mobility between the years 2021 and 2019 as the difference in the percentage of the high-income population that moved, relative to the total population. Figure 11 plots the change in the coefficient δ_t relative to its January 2020 value when running regression eq. 1 by splitting the sample to MSAs that experienced the highest growth in high-income population mobility (top 30th percentiles among the 30 MSAs) and those that experienced the lowest growth in high-income mobility (bottom 30th percentile) between 2019 and 2021. The results indicate that in MSAs where the growth in mobility of high-income individuals was more pronounced, the price gradient was considerably above its January 2020 level (shown by the blue line in Figure 11). This sharply contrasts with MSAs where the mobility of high-income individuals was more limited, where the price gradient remained merely unchanged compared to its January 2020 level.

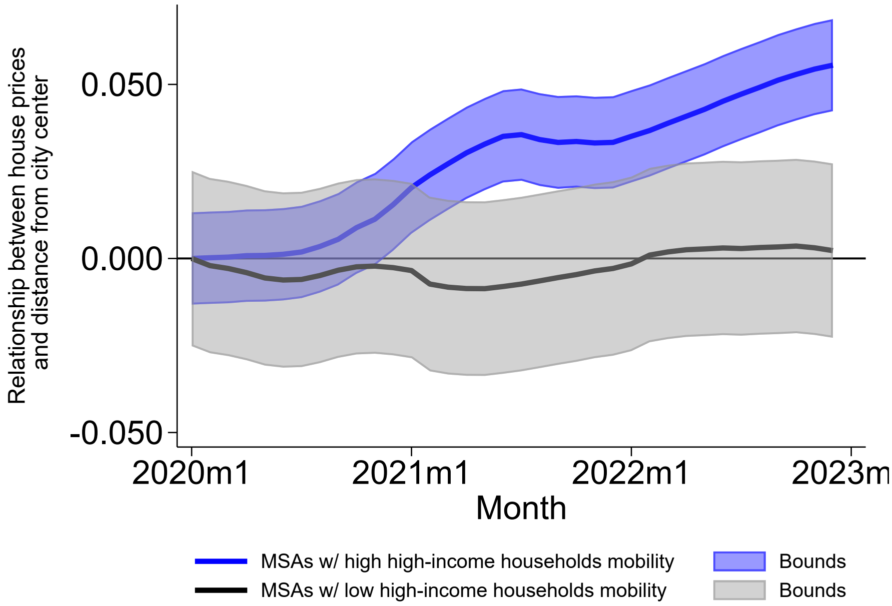


Figure 11: The figure shows the difference in the coefficient δ_t from its value in January 2020, represented as $(\delta_t - \delta_{Jan2020})$. The blue line indicates the gradient difference for MSAs characterized by higher mobility of high-income population, placing them in the top 30th percentile of the MSA sample. The grey line represents the gradient difference for MSAs, characterized by lower mobility of high-income population, ranked in bottom 30th percentile of the MSA sample.

We further investigate our hypothesis using zip code level data. In this analysis, we examine whether price shifts between January 2020 and December 2022 were more marked in zip codes farther from the urban core, particularly in areas with an increased mobility of high-income individuals. We estimate the following regression specification at the cross section of zip codes

$$\begin{aligned}\Delta p_{ij} &= \alpha + \delta_1 ln(1 + D(z^z_{ij}, z^m_j)_{ij}) + \delta_2 ln(1 + D(z^z_{ij}, z^m_j)_{ij}) \times I_{ij} \\ &\quad + \gamma I_{ij} + \beta X_{ij} + \alpha_j MSA_j + \epsilon_{ij}. \end{aligned} \tag{3}$$

The unit of observation is zip code i in MSA j. Δp_{ij} is the percentage change in the price between January 2020 and December 2022, I_{ij} is a dummy variable taking the value of 1 if the change in mobility of high-income individuals between 2019 and 2021 is above the 50th percentile within a given MSA, $ln(1 + D(z^z_{ij}, z^m_j)_{ij})$ is the same measure of distance and X_{ij} is the same set of controls employed in eq. (1), MSA_j is MSA fixed effects, and

ϵ_{ij} is the error term.

The regression analysis, shown in column 1 of Table 3, suggests that during the 2020-2022 period, house prices of properties situated further from city centers rose more than those closer to the urban core as the coefficient on the distance variable, δ_1, is positive and highly statistically significant. Additionally, this increase was even more pronounced—by an additional 25 percent of the house price increase—in areas that saw above the 50th percentile growth in the mobility of high-income individuals as the coefficient on the interaction term between the high-income population mobility indicator and distance from the urban core, δ_2, is positive and highly significant.

Table 3: Zip-Level regressions, using the change in house prices between Jan 2020 to Dec 2022 as a dependent variable

	Δp_{ij}	Δp_{ij}	Δp_{ij}	Δp_{ij}	Δp_{ij}
Log distance	3.383***	3.121***	3.311***	2.736***	3.046***
	(0.177)	(0.184)	(0.174)	(0.214)	(0.190)
High-income mover zip area(=1)	-3.129***			-2.566***	
	(0.758)			(0.763)	
High-income mover zip area(=1) X Log distance	0.840***			0.688***	
	(0.219)			(0.220)	
Median household income	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Median household age	0.068***	0.073***	0.076***	0.073***	0.077***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Median share of black population	14.202***	13.701***	13.755***	13.561***	13.559***
	(0.620)	(0.631)	(0.632)	(0.630)	(0.634)
Share of earners above 150k	7.128**	5.336*	4.775	6.595*	4.915
	(3.571)	(3.046)	(3.045)	(3.573)	(3.051)
High-teleworkable job zip area(=1)		-4.666***		-4.326***	-3.421***
		(0.808)		(0.816)	(1.042)
High-teleworkable job zip area(=1) X Log distance		1.141***		1.044***	0.841***
		(0.228)		(0.230)	(0.291)
High-income zip area(=1)			-4.160***		-2.017*
			(0.803)		(1.034)
High-income zip area(=1) X Log distance			0.963***		0.428
			(0.221)		(0.283)
Constant	10.589***	11.758***	11.101***	13.220***	12.171***
	(0.623)	(0.677)	(0.633)	(0.777)	(0.701)
MSA fixed effects	✓	✓	✓	✓	✓
Observations	5989	6055	6055	5989	6055
R squared	0.603	0.602	0.602	0.605	0.603

The table shows a regression of percent change in zip-level Janury 2020 to December 2022 against a variety of zip level covariates. Explanatory variables include: log distance from a central ZIP code, a dummy indicator that takes the value of 1 if a zip code has above the 50th percentile increase in high-income movers between 2019 and 2021 in a given MSA, a dummy indicator that takes the value of 1 if a zip code has above the 50th percentile share of teleworkable jobs in a given MSA, a dummy indicator that takes the value of 1 if a zip code has above the 50th share of high-income population in a given MSA, an interaction variable between the log distance and the mentioned dummy variables, and a variety of controls from the 2021 ACS, including median household income in thousands, median age of household head, percentage of Black households, and share of high income households, earning above $150,000 (all demeaned). The presence of MSA-fixed effects is indicated in the table bottom.

A legitimate question that arises is whether these results would remain intact if one controlled for the share of jobs that could be performed remotely. Gupta et al. (2022) shows that the ability to telework could explain a significant portion of the cross-MSA and cross-zip variation in the price gradient and price change. To confirm this result in our sample, we modify eq. (3) by replacing the dummy variable indicating the change in mobility of high-income population with a dummy variable indicating the share of jobs that can be done remotely (teleworkable jobs) at the zip code level, as proposed by Dingel and Neiman (2020), using the data from Gupta et al. (2022). Similarly as before, the indicator variable takes the value of 1 if a zip code has a share of teleworkable jobs of above the 50th percentile within a given MSA. Our findings indicate that from January 2020 to December 2022, prices increased more in zip code areas farther from the city center, and particularly in those areas with a higher share of teleworkable jobs as both the coefficient on distance and the interaction between distance and the teleworkable jobs indicator are positive and significant.

Building on this finding, we augment eq. (3) to incorporate an indicator variable of the share of teleworkable jobs at the zip code level and its interaction with distance, while continuing to control for the change in mobility of high-income individuals and its interaction with distance. The estimates from this regression specification are presented in column 4 of Table 3. The coefficient on distance and the interaction term of distance and the change in high-income individual mobility are still positive and significant, with magnitudes similar to our previous findings. The coefficient on the teleworkability indicator and its interaction with distance are also positive and significant. This analysis suggests that even after accounting for the share of teleworkable jobs at the zip code level, the change in high-income mobility continues to play an important role in explaining the disproportional rise in house prices in more remote areas.

Lastly, it is important to distinguish between the change in mobility of the high-income population and the share of high-income population. The latter is strongly associated with the share of teleworkable jobs, typically held by higher earners. In our sample, the correlation between the share of teleworkable jobs and high-income population is 0.77. However, the correlation with the change in high-income mobility is nearly zero. We once again modify eq. (3) to incorporate both the teleworkability and high-income population share indicators, along with their respective interactions with distance, while excluding changes in high-income population mobility. The results, as presented in column 5 of Table 3, reveal that while the coefficient on the interaction of distance and telework is positive and significant, the coefficient on distance and the high-income population share indicator is positive but no longer statistically significant. This finding, again, underscores that even after accounting for teleworkability, the change in mobility of the high-income population continues to explain variations in house prices in more remote areas, whereas the share of high-income population, when interacted with distance, does not.

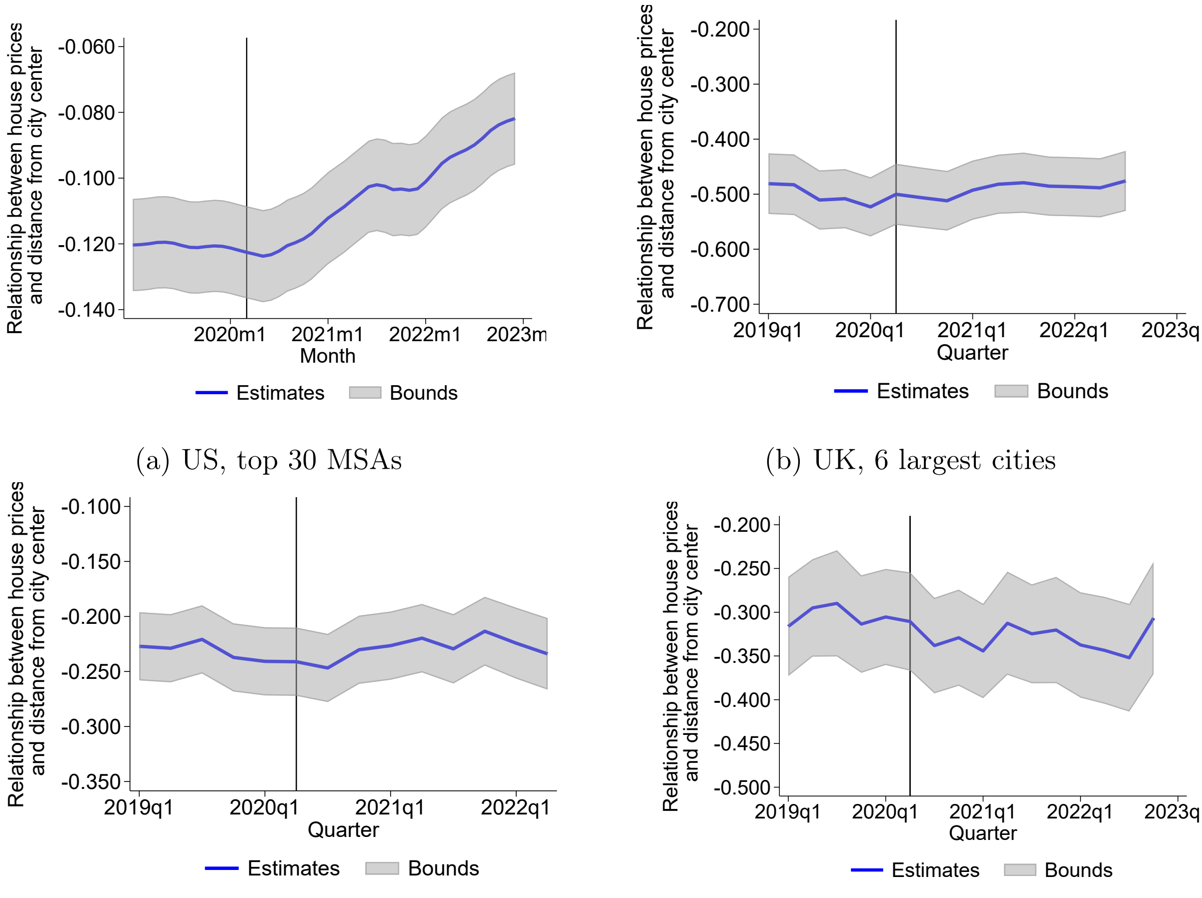
Overall, our analysis highlights a significant interplay between the mobility patterns of high-income movers during the pandemic and shifts in real estate markets. MSAs with pronounced high-income mobility displayed distinct trends in property valuations, with notable price increases in areas distant from city centers, especially where there was a higher presence of affluent movers. These findings underscore the substantial influence of high-income individual mobility on urban and suburban real estate valuations amidst the pandemic.

7 Robustness

In this section we conduct a series of tests to assess the robustness of our results.

Refining the analysis to a closer proximity to city center. An issue that may arise in our analysis involves the effects of potential outliers such as more remote zip codes or postcodes. This could potentially skew the observed real estate price gradient towards a more negative trend prior to the pandemic, and illustrate a more pronounced flattening during the pandemic period. This concern mainly stems from the assumption that properties situated at considerable distances from the city center could be driving these results. This issue is particularly relevant for European cities, given their typically smaller geographical span as compared to their US counterparts.

To address this concern, we rerun our initial specification with a revised geographical limit. For US cities, we limit the furthest distance from the city center to be 30 kilometers, and for European cities, this distance is capped at 15 kilometers. The outcome of this



(a) US, top 30 MSAs

(b) UK, 6 largest cities

(c) France, 3 largest cities

(d) Denmark, 2 largest cities

Figure 12: The figures show the difference in the coefficient δ_t at time t and its January 2020 value, estimated using eq. (1), and computed as $(\delta_t - \delta_{Jan2020})$. A positive coefficient indicates a price gradient increase compared to January 2020. The left panel shows the estimates for the US, the middle panel shows the estimate for the UK, and the right panel shows the estimates for London.

refined analysis is presented in Figure 12. Although there is a minor quantitative change in the results when limiting the distance of the furthest zip code/postcode from the city center, the changes are minor and importantly the qualitative results remain unscathed.

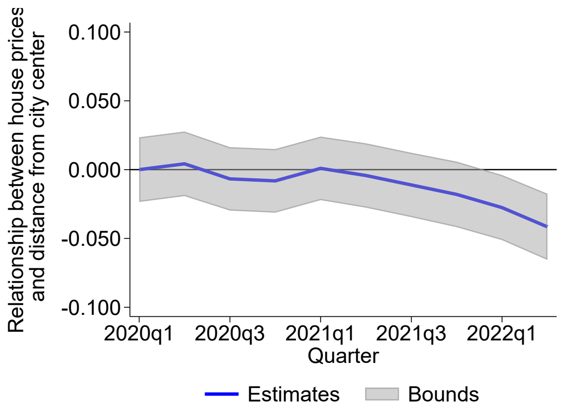
Absence of demographic and socioeconomic controls for Denmark and France. In our analysis, for Denmark and France we do not have access to demographic data at the postcode level, meaning we cannot factor in population characteristics like we do for the UK and the US in our baseline specification, (1). To mitigate the potential omitted variable bias, we re-estimate the baseline regression for each country by incorporating zip/postcode fixed effects instead of the zip/postcode-level controls. This approach effectively controls for all non-time varying variations across regions.

Figure 13 shows the coefficient δ_t in equation (1) when controlling for zip/postcode fixed effects, relative to its 2020Q1 value (January 2020 for the US), $(\delta_t - \delta_{2020Q1})$. Three observations are worth noting. First, the gradients follow a similar trend compared to the one observed under the baseline specification. Second, the coefficient standard errors decrease for all countries. Third, the change in the gradient becomes significant for France and, to a lesser degree, for the UK. Conducting the same analysis at the city-level suggests that the behavior of the gradient in France is predominantly influenced by Lyon and Marseille, as it remains stable in Paris. This could suggest that the observed average effects in France are more reflective of regional rather than national trends, considering the economic and geographical prominence of Paris. In contrast, London's gradient change aligns closely with the UK's national trend.

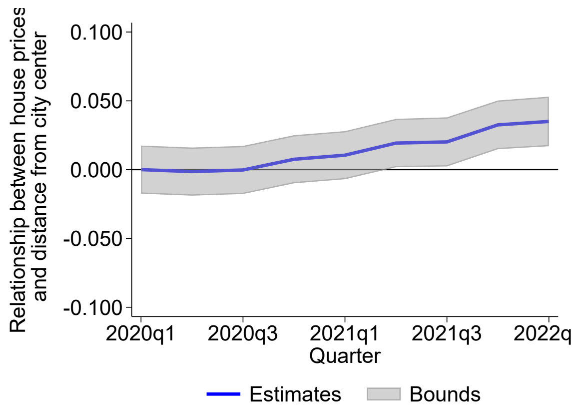
Yet, the change in the gradient for the US remains much more pronounced. Despite the gradient's change increasing for France and becoming slightly positive, all our results comparing US MSAs to European cities in terms of income and house characteristics remain intact. See figures in Section A.2.2 in the Appendix.

Construction of price indices for France and the UK using median sale prices. For France and the UK, in our baseline analysis we employ a hedonic model that considers property-specific characteristics to generate time series of house prices at the postcode-quarter level using transaction level data. Yet, the hedonic model can encounter challenges, particularly when dealing with smaller postcodes that do not have a substantial number of transactions, thus challenging the precision of the model's estimates.

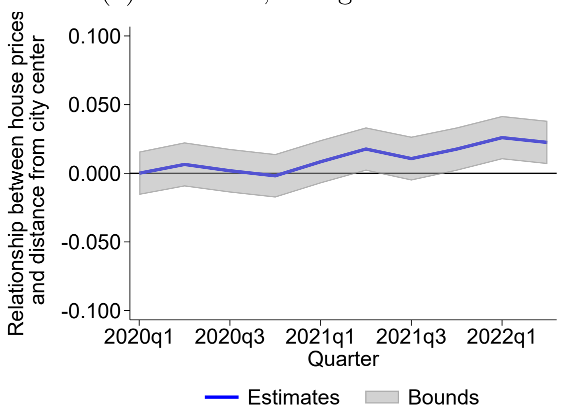
To address this concern, we construct alternative price indices at the postcode-quarter level using the median sale price within a specific postcode-quarter as an estimation of the property value. To ensure a reasonable degree of precision in estimating the median, we restrict the minimum number of observations to at least 25 within each postcode-quarter. Figure 13 illustrates the price gradient for France (right panel) and the UK (left panel), as derived from the time series of house prices that were calculated using the median sale price within each postcode-quarter. We observe that both the level and the trajectory of the price gradient for both countries align closely with those estimated using hedonic prices. This supports the view that the hedonic model provides plausible estimates of house price indices at the postcode-month level.



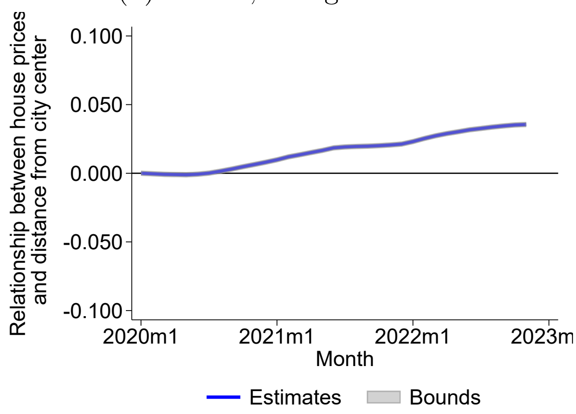
(a) Denmark, 2 largest cities



(b) France, 3 largest cities

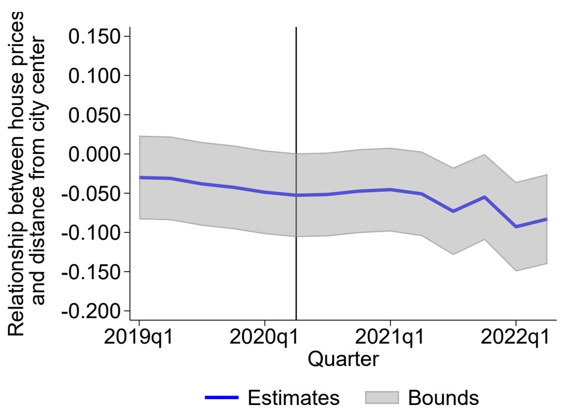


(c) UK, 6 largest cities

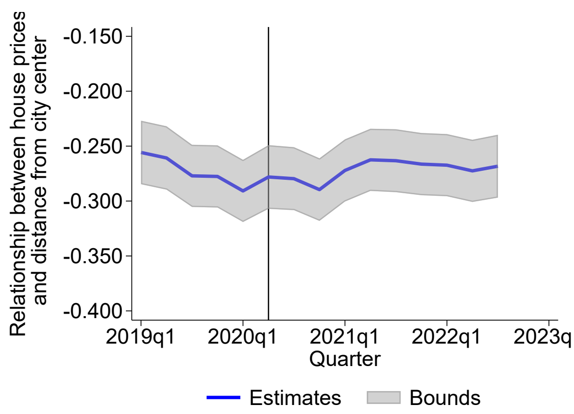


(d) US, top 30 MSAs

Figure 13: The figures show the bid-rent function slope coefficient estimates from a panel regression at the zip code level for top 30 MSAs in the US and top 6 cities in the UK over the period January 2019 to December 2022 for the US and 2019Q1 to 2022Q3 for the UK following eq. (1). Samples are based on the latest available data points when the analysis were performed for both countries. No zip code/postcode level controls are included.



(a) France, 3 largest cities



(b) UK, 6 largest cities

Figure 14: The Figure shows δ_t for prices from a panel regression at the zip code/postcode level for the US and the UK when omitting the zip code/postcode level controls. The regressions are estimated over the period January 2019 to December 2022 following eq. 1.

8 Conclusion

During the pandemic, developments consistent with a shift in household preferences toward suburban living unfolded in US residential real estate markets. Most American cities experienced real estate booms, and in that context had properties located further from city centers appreciating in value relative to their more urban counterparts. While this surge in suburban property values may not be permanent, there is compelling evidence for its persistence as central business districts continue to struggle with office occupancy rates plateauing between 40 and 60 percent across top 10 US MSAs.[16]

We expand the analysis in Gupta et al. (2022) in three directions. First, we investigate whether the growth trend in suburban areas has continued to outpace that in city centers. Secondly, we explore whether these trends are replicated in selected European countries. Finally, we explore some of the factors that led to heterogeneous developments in gradients across the Atlantic and within the US.

Our findings indicate that, as of December 2022, the relative price of suburban relative to urban homes in major US MSAs remained elevate relative to pre-pandemic levels. This is consistent with the notion that the increased appeal of suburban living experienced during the pandemic appears to be persistent.

On the contrary, European cities in Denmark, France, and the UK did not witness as significant a positive uptick in the gradient. We attribute these divergent trends between the two regions to disparities in suburban demographics and property sizes. Specifically, we hypothesize what the lower appeal of European suburbs to higher income households (with their smaller dwelling size and relatively poorer socioeconomic structure) is at the root of this difference.

Moreover, we find that that American cities whose suburbs most resembles European peripheral neighborhoods (that is those characterized by lower median household incomes and smaller properties) experienced a more modest flattening of price gradients. This differential effect is also related to the movement of higher income households. Regions that witnessed a greater increase in mobility of higher-income households were also those

[16] This is based on data by Kastle as of October 2023. Kastle provides information on office occupancy rates across the top 10 US MSAs, obtained by tracking access activity data from KastlePresence app, keycard, and fob usage in the buildings and businesses they secure.

that experienced a more marked flattening of the price gradient, consistent with the notion that the relative change in urban versus suburban house prices was largely driven by wealthier households.

These findings hold wide-ranging implications for both commercial and residential real estate markets, offering valuable insights into the ongoing evolution of property values in both the US and Europe, as they adapt to changing work patterns and housing preferences.

In particular, in the US, the apparent persistence of the rebalancing of urban/suburban house price together with the finding that this is primarily driven by migration by wealthier household associated with remote working presents difficult challenges for American cities. First, there are short-term risks and adjustment cost stemming from the low occupancy rates of office buildings, the associated decreased city-center traffic, and potentially concentrated exposures in regional banks. Second, there is a medium-term challenge for cities facing reduced tax revenues through not only reduced business activity but also because of the flight of the wealthy. On the other side, the rebalancing of house prices can in principle, over time, help ameliorating the house affordability crisis that has plagued cities over the last two decades, allowing for more diverse and inclusive social landscapes.

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A Appendix

A.1 List of MSAs/cities

Table 4: List of MSAs/cities and information on zip-code/postcode distances

2*MSA/city	Central zip code (post code)*	Total number of zip codes (postcodes)**	Most distant zip code (post code) (km)***	% of Zip/postal codes > 30km from center
United States				
Atlanta-Sandy Springs-Alpharetta, GA	30303	212	101	60
Austin-Round Rock-Georgetown, TX	78701	89	69	40
Baltimore-Columbia-Towson, MD	21202	160	67	44
Boston-Cambridge-Newton, MA-NH	02110	281	127	54
Charlotte-Concord-Gastonia, NC-SC	28202	116	92	59
Chicago-Naperville-Elgin, IL-IN-WI	60602	386	132	66
Cincinnati, OH-KY-IN	45203	160	82	47
Dallas-Fort Worth-Arlington, TX	75204	264	115	61
Denver-Aurora-Lakewood, CO	80203	132	117	30
Detroit-Warren-Dearborn, MI	48226	216	109	56
Houston-The Woodlands-Sugar Land, TX	77002	235	112	53
Las Vegas-Henderson-Paradise, NV	89106	72	123	21
Los Angeles-Long Beach-Anaheim, CA	90013	378	91	43
Miami-Fort Lauderdale-Pompano Beach, FL	33133	185	139	59
Minneapolis-St. Paul-Bloomington, MN-WI	55415	226	134	51
New York-Newark-Jersey City, NY-NJ-PA	10017	903	177	57
Orlando-Kissimmee-Sanford, FL	32801	93	72	40
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	19102	373	91	51
Phoenix-Mesa-Chandler, AZ	85003	157	171	48
Pittsburgh, PA	15222	361	87	64
Portland-Vancouver-Hillsboro, OR-WA	97201	120	89	42
Riverside-San Bernardino-Ontario, CA	92501	159	295	67
Sacramento-Roseville-Folsom, CA	95814	122	147	56
San Antonio-New Braunfels, TX	78205	118	111	44
San Diego-Chula Vista-Carlsbad, CA	91950	107	107	50
San Francisco-Oakland-Berkeley, CA	94102	176	77	43
Seattle-Tacoma-Bellevue, WA	98164	169	102	56
St. Louis, MO-IL	63101	238	105	63
Tampa-St. Petersburg-Clearwater, FL	33602	134	78	50
Washington-Arlington-Alexandria, DC-VA-MD-WV	20006	363	133	54
United Kingdom				
Birmingham	B1	55	16	0
Leeds	LS1	24	17	0
Liverpool	L1	37	16	0
London	WC2N	220	28	0
Manchester	M2	43	18	0
Sheffield	S1	21	17	0
France				
Lyon	69001	64	22	0
Marseille	13002	48	23	0
Paris	75004	143	23	0
Denmark				
Aarhaus	8000	87	54	53
Copenhagen	1550	83	53	33

* The central postcode refers to the zip code where the city hall is located or its nearest zip code.
**Total number of postcodes that enter in the regression analysis (no other postcodes).
***The maximum distance between the central and the furthest zip code.

A.2 Additional Figures

A.2.1 Wald Test

The tables show the results of the Wald test, checking if the coefficient δ_t is significantly different from the coefficient δ_{2020Q1} ($\delta_{Jan2020}$ for US) in eq. (1).

Table 5: Wald test for difference in coefficients δ_t vs. δ_{2020Q1} ($\delta_{Jan2020}$ for US)

Denmark

δ_t	F-stat.	p-value
2020Q2#LogDistance	0.24	0.63
2020Q3#LogDistance	0.53	0.47
2020Q4#LogDistance	0.70	0.40
2021Q1#LogDistance	0.34	0.56
2021Q2#LogDistance	1.78	0.18
2021Q3#LogDistance	1.42	0.23
2021Q4#LogDistance	2.49	0.11
2022Q1#LogDistance	3.15	0.08
2022Q2#LogDistance	3.28	0.07
2022Q3#LogDistance	0.55	0.46
2022Q4#LogDistance	0.01	0.94

France

δ_t	F-stat.	p-value
2020Q2#LogDistance	0.00	0.95
2020Q3#LogDistance	0.00	0.99
2020Q4#LogDistance	0.10	0.75
2021Q1#LogDistance	0.20	0.65
2021Q2#LogDistance	0.42	0.52
2021Q3#LogDistance	0.01	0.94
2021Q4#LogDistance	0.84	0.36
2022Q1#LogDistance	0.01	0.92
2022Q2#LogDistance	0.01	0.91

UK

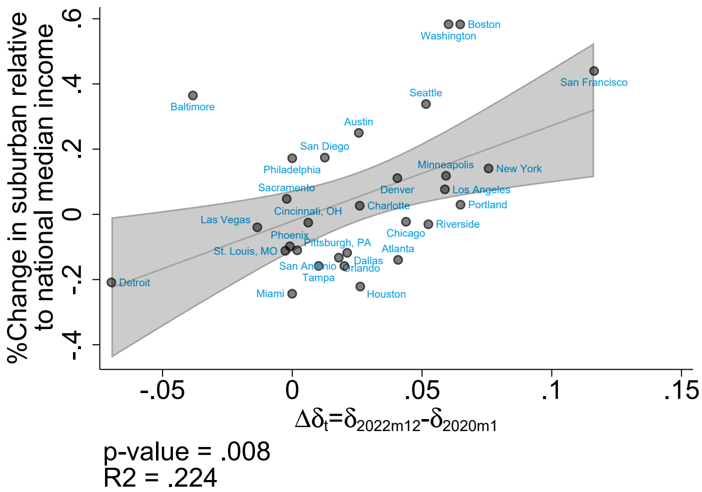
δ_t	F-stat.	p-value
2020Q2#LogDistance	0.03	0.86
2020Q3#LogDistance	0.00	0.95
2020Q4#LogDistance	0.05	0.83
2021Q1#LogDistance	0.00	0.97
2021Q2#LogDistance	0.04	0.85
2021Q3#LogDistance	0.11	0.74
2021Q4#LogDistance	0.20	0.66
2022Q1#LogDistance	0.28	0.59
2022Q2#LogDistance	0.40	0.53
2022Q3#LogDistance	0.59	0.44

US

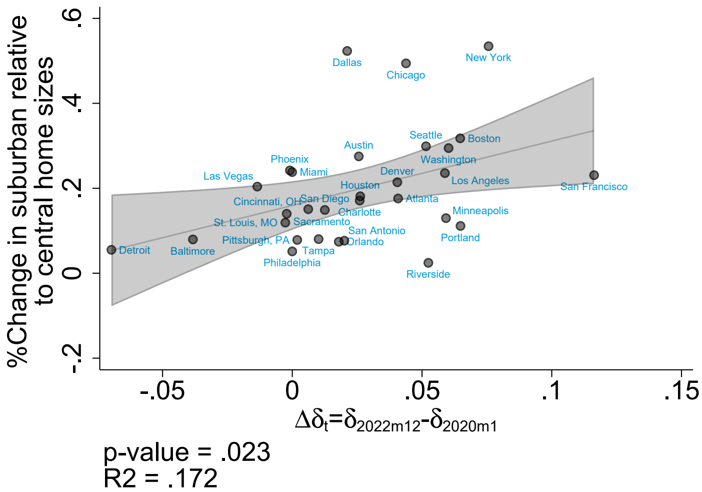
δ_t	F-stat.	p-value
Mar2020#LogDistance	0.02	0.88
Jun2020#LogDistance	0.02	0.88
Sep2020#LogDistance	0.20	0.65
Dec2020#LogDistance	1.34	0.25
Mar2021#LogDistance	3.73	0.05
Jun2021#LogDistance	7.54	0.01
Sep2021#LogDistance	9.00	0.00
Dec2021#LogDistance	10.54	0.00
Mar2021#LogDistance	17.00	0.00
Jun2022#LogDistance	23.24	0.00
Sep2022#LogDistance	27.99	0.00
Dec2022#LogDistance	30.23	0.00

A.2.2 Robustness checks: Specification with Zip/Postcode Fixed Effects

The three scatter plots in figures 15 and 16 show the relationship between the change in the price gradient, obtained from running regression (1) but controlling for zip/postcode fixed effects, and (i) income gap, (ii) home size gap, (iii) similarity-to-Europe index. Figure 17 shows the coefficient δ_t relative to its January 2020 value, with the left panel plotting the results for the gradient for MSAs that look less similar to Europe, and the right plotting those for MSAs that look more similar to Europe.



(a) Change in the price gradient vs household income



(b) Change in the price gradient vs room size

Figure 15: The scatter plots are the same as in Figure 7 in the main text but with the difference that the gradient is obtained from regression (1) that includes zip/postcode fixed effects instead of zip/postcode level controls.

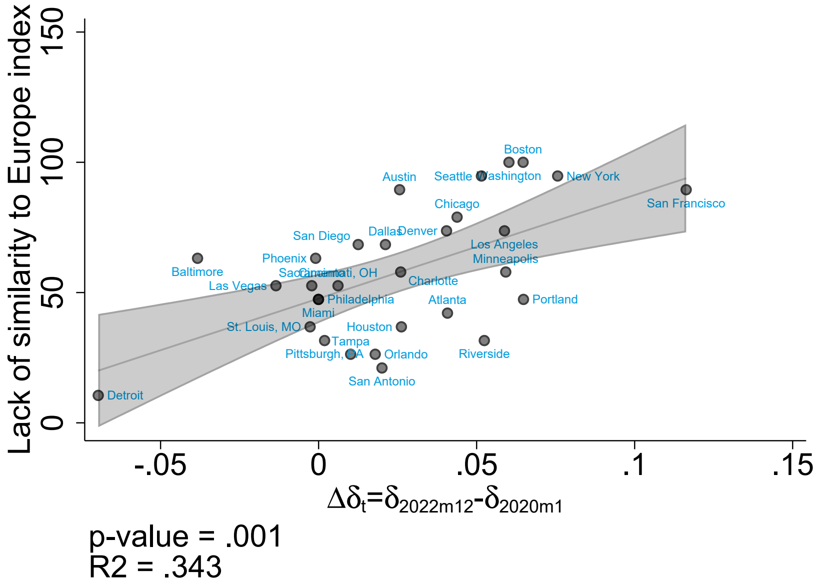
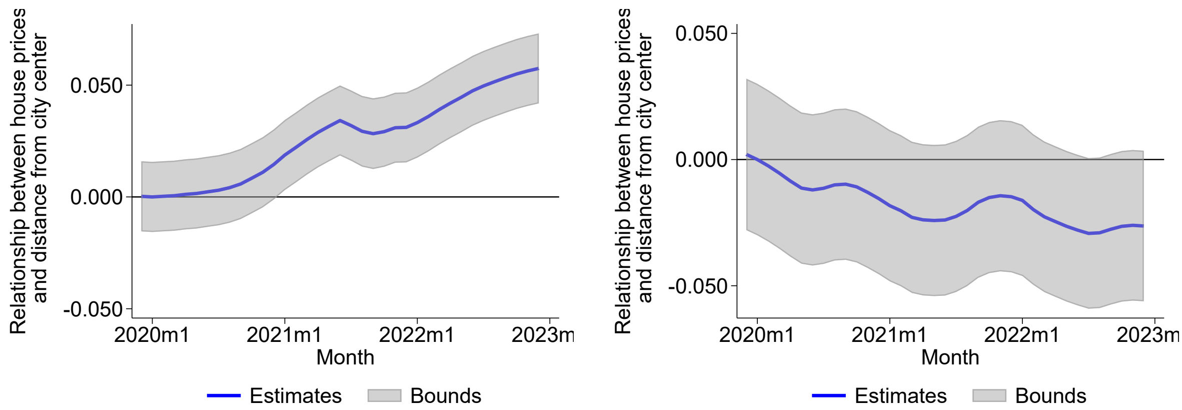


Figure 16: The scatter plots are the same as in Figure 8 in the main text but with the difference that the gradient is obtained from regression (1) that includes zip/postcode fixed effects instead of zip/postcode level controls.



(a) Less like Europe

(b) More like Europe

Figure 17: The scatter plots are the same as in Figure 9 in the main text but with the difference that the gradient is obtained from regression (1) that includes zip/postcode fixed effects instead of zip/postcode level controls.

A.3 France and UK: Data sources and cleaning

A.3.1 France

Data Sources. Real estate transaction data comes from Demandes de valeurs foncières géolocalisées (DVF géolocalisées— data.gouv.fr). This data is produced by Etalab, which is a part of the French government's interministérielle du numérique (DINUM), one of the agencies responsible for publishing national statistics and data. The boundaries of each MSA are defined using the French government's definition of a "Functional Area"

(Definition—Functional areas | Insee). We get each city's functional area using the list of communes within each city's functional area. All information comes form INSEE, France's main national statistical agency.

Steps in cleaning the data. We drop transactions that are missing information on location, price, or property type. We keep only transactions for apartments or maisons. If a single transaction includes both an apartment and a maison, we categorize this as a maison. We keep only transactions that are real estate sales or sales of future real estate (that has not yet been built). Thus, we exclude auctions, expropriations, exchanges/gifts, and sales of land with no buildings on it. We also drop transactions with prices that are below 15,000 euros since these are likely not sales of housing.

A.4 UK

Data Sources. Real estate transactions (for England and Wales) come from Price Paid Data - GOV.UK (www.gov.uk). These data are provided by HM Land Registry. The transaction are pre-labeled by cities, which typically correspond to administrative divisions in the country.

Steps in cleaning the data. Since UK postcodes define very small geographic regions, we only use the first part of each postcode. Specifically, all UK postcodes are in the form XXXX YYY, where the first section (XXXX) is often called the outer code. The outer codes correspond to larger geographic regions so we only use these. Whenever we refer to postcodes for the UK, we refer to the outer code part. We drop transactions that are missing the price, postcode, and the property type. Moreover, we drop transactions with prices that are below 15,000 pounds since these are likely not sales of housing (this decreases the sample by 100 transactions out of >100k). We keep transactions only for property types that are “Detached"/"Semi-Detached" or “Flats/Maisonettes"/"Terraced". We also drop all transactions where property type is denoted as “Other”.

Flattening the Curve and the Flight of the Rich: Pandemic-Induced Shifts in US and European Housing Markets

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