Housing Price Gradients in Mexico City During the COVID-19 Pandemic

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Abstract

The COVID-19 pandemic flattened the negative relationship between distance to the city center and housing prices in developed-country cities, increasing the prices in suburbs while decreasing them in central areas. We showthat this relationship flattening did not occur in Mexico City. We estimate the slope of the housing price gradient with respect to the distance to the center and to employment density using administrative and survey data on housing prices in Mexico City from 2019 Q1 to 2022 Q4. Ourestimates rule out statistically significant changes in the slope of the housing price gradient after 2020 Q1 with respect to the pre-pandemic period. We outline possible mechanisms behind this lack of gradient change, such as differences in pandemic restrictions relative to other countries, a reduced potential for remote work, lack of access to finance housing purchases, and supply shocks in the suburbs.

Keywords: Housing prices, housing price gradients, COVID-19

JEL Codes: R23, R51, R12

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1 Introduction

Cities around the world exhibit higher housing prices around the centers of economic activity. In standard urban economics models, this price pattern arises as a consequence of commuting to work: prices are higher near city centers and lower in the suburbs to compensate for the additional commuting cost when living far from places of work. During the COVID-19 pandemic with the rise of remote work, commuting patterns were disrupted and the separation between places of work and places of residence became blurry. Such disruption changed housing price gradients with respect to distance to centers of economic activity in developed-country cities (Gupta et al. 2022; Brueckner et al. 2023), giving rise to new dynamics in housing markets around the world. In each particular country and city, however, these patterns responded to local pandemic dynamics and to the idiosyncrasies of each city's housing market.

We examine the changes in these housing price gradients in Mexico City. There are several reasons why housing price gradients may have reacted differently in Mexico relative to other countries, making Mexico an interesting setting to evaluate housing price responses to the pandemic. First, Mexico's COVID-19 mobility restrictions were less stringent than those of other Latin-American countries and than those of developed countries in Europe and North America.[1] Restrictions on individual mobility were less strict than in other countries, and business closure restrictions were hard to enforce in the informal sector, where 55% of workers were employed in 2021. Second, the share of jobs that can be done remotely is substantially smaller in Mexico than in the US (Leyva and Mora 2021), limiting the potential effects of worker relocation because of remote work on housing markets. Third, Mexico's housing market has a small volume of transactions relative to the United States or Europe, with a smaller housing demand and workers with limited financial capacity to acquire housing.[2] As such, we expect that the overall housing price gradients in Mexican cities and their

[1] According to data from Hale et al. (2023), during 2021, Mexico's COVID-19 restrictions were the least stringent relative to the largest 7 Latin-American countries, and to the US, Canada, and the largest European countries.

[2] According to the Mexican 2010 decennial census, Mexico exhibited one of the largest vacancy rates among OECD countries (OECD 2015). INFONAVIT (2020) points out that the Mexican labor market's composition

evolution during and after the pandemic may be different from the well-documented flattening in US cities –an increase in prices in the suburbs relative to prices in the city centers (Gupta et al. 2022).

To study housing price gradients, we use administrative data on all housing sales where the property was appraised to sign a mortgage contract. We combine this dataset with census data on economic activity and neighborhood-level data on amenities. Then, we estimate parametric and non-parametric housing price gradients and evaluate how they changed during and after the pandemic. Our analysis period covers 2019 Q1 to 2022 Q4.

We do not find evidence of a change in the slope of the housing price gradient in Mexico City. Although our estimates are noisy, we can rule out that the slope of the relationship between prices and distance flattened during the COVID period with respect to the pre-COVID period at the 95% confidence level. In contrast, the slope of the housing price gradient changed from -0.103 before COVID to -0.090 in December 2020 in the US (Gupta et al. 2022). Our results also contrast with those of Ziemann et al. (2023), who observe gradient flattening for a sample of OECD country cities between the latter half of 2019 and the latter half of 2021, driven mainly by large metropolitan areas. We note, however, that the share of housing that is purchased through a mortgage contract in Mexico is much smaller than in the US or other developed countries (INFONAVIT 2020), and as such, there may have been price responses that our data from mortgage appraisals does not capture.

The lack of changes in the price gradient slope remains when we use density instead of distance to the city center as a measure of economic activity. Although we find increased housing sales in peripheral areas at the beginning of the pandemic, these sales increases were not accompanied by rising prices relative to central areas. Instead, we see price decreases consistent with a relative positive supply shock in places far from the center. We outline possible reasons behind the lack of a gradient change in Mexico City. Fewer pandemic restrictions than in developing countries, a more limited potential for remote work, supply

negatively impacts housing demand: a large share of informal workers without access to formal housing loans granted translates into a large share of self-built houses financed by household savings. Moreover, INFONAVIT (2020) highlights the limited financial capacity of formal workers who may purchase housing through Infonavit, a government housing agency.

shocks in suburban areas, and migration to Mexico City may have played a role. We cannot, however, rule out alternative explanations, such as an adjustment via the rental market instead of the sales market.

Our paper contributes to the literature on housing markets during the pandemic. In the US, these studies have focused on changes in housing demand and the effects of remote work on housing prices. Ramani and Bloom (2021) identify a "doughnut effect" of the pandemic on US cities, with increased demand for housing in suburban areas and lower-density neighborhoods. Althoff et al. (2022) argue that these changes are associated with the decline of business service industries, usually located in the densest areas. Outside the US, and beyond the changes documented in Ziemann et al. (2023), Gokan et al. (2022) document a flattening of the housing-price distance gradient in London; Alves and San Juan del Peso (2021) observed a similar shift for Spain, and Huang et al. (2023) and Ou et al. (2023) document flattening in Chinese cities. We contribute to this literature by documenting these changes for Mexico City, where there were fewer pandemic-related restrictions.

We also contribute to the literature on changes in city structure because of remote work. This literature argues that the flattening in housing price gradients spurs from the fact that central locations lose their advantage relative to other locations if workers no longer have to commute to workplaces, which are usually located in city centers (Brueckner et al. 2023; Davis et al. 2023; Delventhal et al. 2022; Howard et al. 2023; Mondragon and Wieland 2022). In the US, Brueckner et al. (2023) find that high-productivity counties where jobs had a high work-from-home potential experienced smaller price and rent changes, suggesting a relocation of residents from expensive places to more affordable locations. Mondragon and Wieland (2022) indicate that areas with significant exposure to remote work exhibited higher house price growth during the COVID-19 crisis. Our findings on the limited change in housing price gradients in Mexico suggest that the mechanisms driving changes in city structure due to remote work may operate differently in a developing country city, with a large share of informal work where fewer jobs that can be done remotely (Leyva and Mora 2021). Last, we contribute to the literature on Mexican housing markets during the pandemic. Malpezzi (2023) documents a slowdown of the growth in housing prices and rents for Mexico between

2019 Q4 and 2020 Q4. Chiu et al. (2020) document a negative performance of real estate investment trusts in Mexico in 2020. In addition to the academic literature, several reports have documented the aggregate dynamics of the housing sector in Mexico during the pandemic (BBVA Research 2021a,b; INFONAVIT 2020, 2021, 2022). These reports highlight decreases in housing construction and mortgage lending during 2020, accompanied by a positive rebound in 2021 that was somewhat mitigated by higher construction costs. They also document rebounds in housing rental prices to their pre-pandemic levels by 2022. We contribute by providing a detailed characterization of housing price dynamics for Mexico City around the pandemic.

The rest of the paper proceeds as follows. Section 2 describes our data sources. Section 3 provides an overview of the evolution of housing markets during and after the pandemic in Mexico City. Section 4 outlines our estimation strategy for housing price gradients. Section 5 shows the housing price gradient estimates and looks at how they changed during the pandemic. Section 6 concludes.

2 Data

This section describes the data sources for housing prices and covariates in Mexico City.

Property Prices and Characteristics. Our main data source is the universe of fair market values from home appraisals required to issue mortgages in the Mexico City metropolitan area, which contains 16 municipalities/boroughs in the administrative boundaries of Mexico City, and 60 municipalities in the neighboring states of Mexico State, Morelos, and Hidalgo.[3] The data is provided by Mexico's Sociedad Hipotecaria Federal (SHF) through an agreement with Banco de México. SHF is a government banking institution affiliated with Mexico's treasury, whose function is to provide credit for housing development. Every time a mortgage contract is processed, the mortgaged property is appraised and its data are recorded in the SHF database. Therefore, the dataset contains all housing properties (used and new) that were

[3] The appraisals occur as part of the process to purchase housing with a mortgage contract. Most housing that is appraised is eventually purchased. Housing for sale that has not yet been appraised is not included.

bought through a mortgage. Strictly speaking, however, the dataset is not a sales dataset: we may observe properties that were appraised but failed to be sold, and we do not observe properties that were sold without a mortgage contract.

We observe fair market values by property, property location, property characteristics, and neighborhood characteristics for the new appraisals in each quarter. Therefore, our dataset can be thought of as measuring the "flow" of appraisals. For property characteristics, we observe the number of bedrooms, bathrooms, house type (house, apartment, condo), parking spaces, number of floors, and building age. For neighborhood characteristics, we observe urban infrastructure and urban amenity indexes calculated by SHF. We focus on the period from 2019 Q1 to 2022 Q4. We exclude the last quarter of 2019 because of an unusual change in the number of properties. For some of the analyses, we divide the sample into three time periods: a "pre-pandemic" period from 2019 Q1 to 2020 Q1, a "pandemic restrictions" period from 2020 Q2 to 2022 Q1, and a "post-pandemic-restrictions" period from 2022 Q2 to 2022 Q4.[4] We filter out observations with extreme price values and with inconsistent built areas and terrain areas. Appendix A provides details about sample selection.[5]

There are some limitations of our dataset in terms of following housing market dynamics. First, we do not observe housing that was sold outside of a mortgage contract, nor do we observe self-built housing. Both segments are important in Mexico. According to data from the National Survey of Housing 2020, at the country level, 38% of acquired housing was self-financed, and 57.3% of housing was self-built. For Mexico City, 52.3% of housing was self-built. A second limitation is the inability to observe the stock of housing. A last limitation is that some of the appraisals we see in the dataset may not have led to actual sales. We expect this to be a small percentage of observations, since appraisals occur late in the process of purchasing housing only for mortgage purposes, at the stage where potential buyers have

[4] We choose 2022 Q1 as the ending of the "pandemic restrictions" period because this is the quarter when most of Mexico's pandemic-related restrictions were lifted. Mexico ended its "traffic light" COVID warning system in 2022 Q2. However, some of the pandemic restrictions or their enforcement may have eased before 2022 Q2.

[5] We use the date of each property's appraisal as the date of the price quote. Appraisals typically use information from sales of similar properties up to 6 months before the appraisal, so the price dynamics we observe may have some lag.

already chosen a property.

To complement SHF data, we use two alternative data sources. First, we use survey data on housing prices from Dinámica del Mercado Inmobiliario (DIME). DIME contains quarterly information on the price and characteristics on units in housing developments throughout the country. Specifically, the data contains information on 65,283,928 units.[6] The data is collected by surveyors acting as mystery shoppers, and it mostly covers mid- and high-price units. We map every property to a location using its address, managing to georeference 1.46% of the observations.

Second, we also compare the overall trends in Mexico City's housing markets from the SHF data with data from the Unique Housing Registry (RUV). This dataset contains information on new housing developments that received government funding. Because this data does not contain precise location information, we do not use it for the estimation of housing price gradients.

Neighborhood-level covariates. We obtain additional covariates from Mexico's Housing and Population Census of 2020 at the postal code level to control for income differences across neighborhoods. The covariates include the neighborhood-level proportions of adults and neighborhood-level proportions of houses with: dirt floors, toilets, washing machines, cars, computers, and cell phones. We also include neighborhood-level robbery/burglary rates and homicide rates obtained from Mexico City's police department (Attorney General's Office, Mexico City 2023).

3 Housing Markets in Mexico City During the COVID-19 Pandemic

In this section, we provide an overview of prices and property transactions in Mexico City from 2019 to 2022, focusing on changes from the pandemic restrictions and post-pandemic-restrictions periods relative to the pre-pandemic period.

[6] In the dataset, each observation represents a specific type of unit offered by the housing developments included in the dataset. Then, each observation corresponds to multiple units.

We start by providing an overall picture of price and quantity dynamics in the SHF dataset for Mexico City and the Mexico City metro area. Figure 1, panel (a) shows the evolution of average prices per square meter in the city from 2019 to 2022. The average price per square meter in Mexico City 's metro area was $18,005 pesos in the first quarter of 2019, about $1,493 USD at the average exchange rate of $19.42 MXN per USD for the period. Average prices per square meter experienced a sharp decline during the first quarter of the pandemic restrictions period in 2020 Q2, dropping by 14.7%. They remained depressed throughout the pandemic restrictions period and experienced a sharp rebound by 2022 Q2. At the end of 2022, the average price per square meter was $28,891.43, close to its value at the beginning of the analysis period.

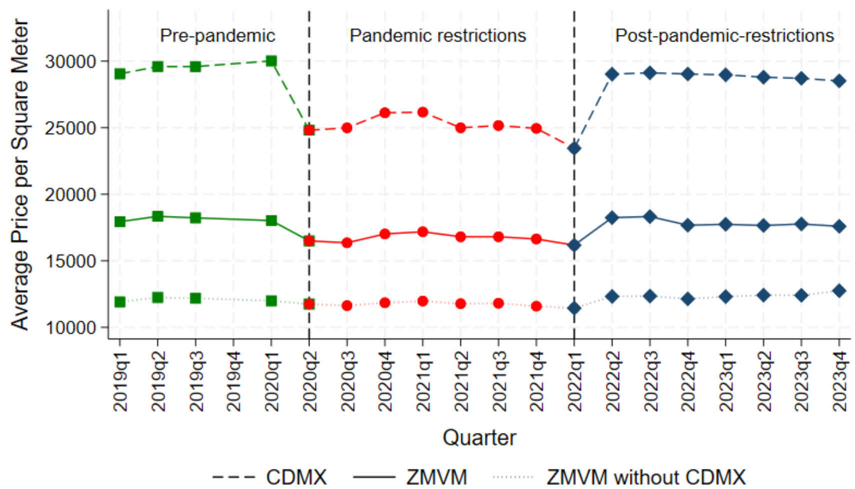
For properties in the metro area outside of Mexico City, prices did not change as much during the pandemic. The average price per square meter in these areas was $12081 pesos ($622 USD) in the pre-pandemic period, $11727 pesos ($603 USD) in the pandemic restrictions period, and $12385 pesos ($637 USD) in the post-pandemic-restrictions period. Overall, average prices in the Mexico City metro area dropped by 8% during the pandemic restrictions period and then rose above their pre-pandemic levels.

Figure 1, panel (b) shows the evolution in the number of properties in the SHF database. In contrast to the evolution of prices, the number of properties in Mexico City remained at around 7,000 properties per quarter during the pandemic restrictions period, and decreased after 2022. The number of properties in the metro area as a whole increased because of an increase in appraised properties in the metro area outside the city. The aggregate pattern masks heterogeneity in the evolution of the number of properties by property price. Figure 2 shows that the number of properties in the first and second quartiles of the price distribution (using quartiles based on pre-pandemic prices) rose substantially during the pandemic and then decreased, while the number of properties for the third and fourth quartiles remained stable.[7]

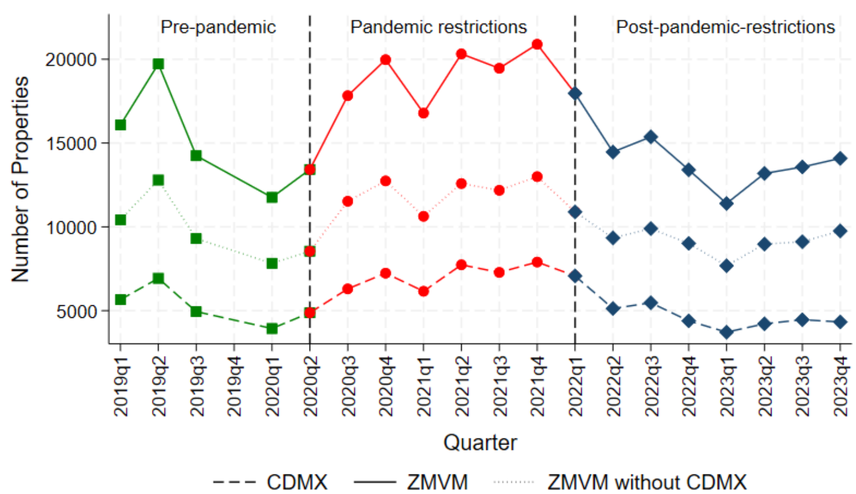
[7] Appendix Figure E.1 shows average prices and the number of properties separating properties by type: 2 Bedrooms, 1 Bathroom; 2 Bedrooms, 2 Bathrooms; and 3 Bedrooms, 2 Bathrooms. The first two types of properties show similar patterns in prices and quantities. 3-Bedroom 2-bathroom properties show less sharp changes in prices and quantities.

Figure 1: Average real prices and number of properties, Mexico City, 2019 Q1 - 2023 Q4

(a) Average price per square meter.



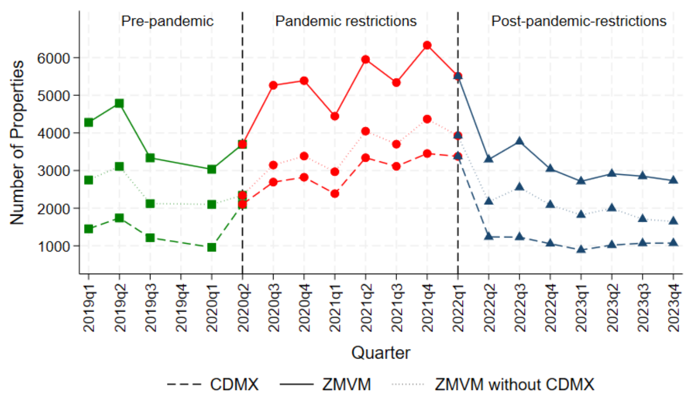
(b) Number of properties.



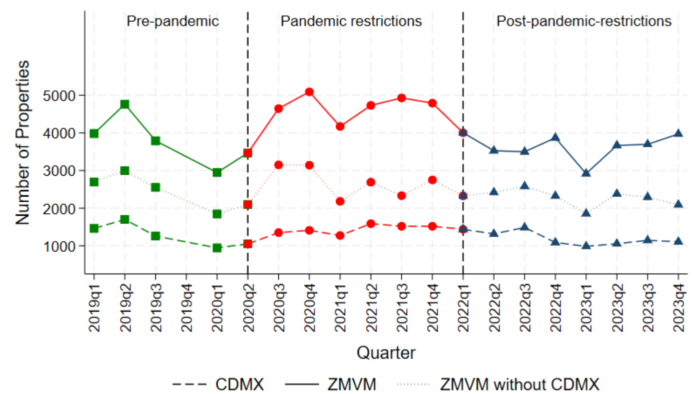
Source: SHF, authors' calculations. Pesos of July 2018. We exclude 2019 Q4 because of an unusual change in the number of properties in this period.

Figure 2: Number of properties by price quartile, Mexico City, 2019 Q1 - 2023 Q4.

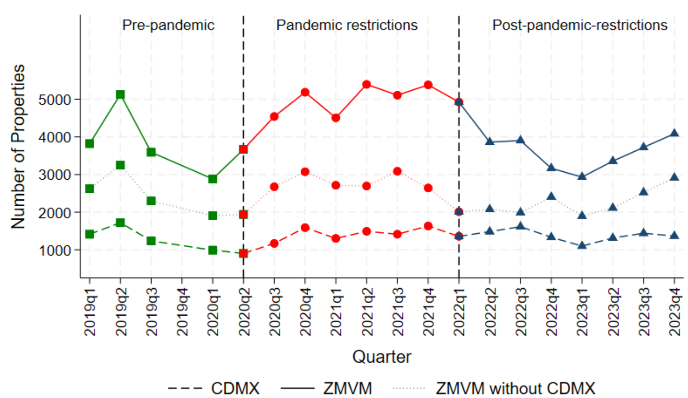
(a) Number of properties. First quartile.



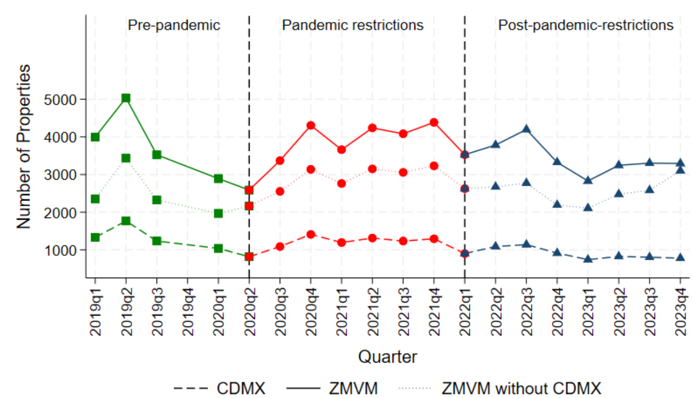
(b) Number of properties. Second quartile.



(c) Number of properties. Third quartile.



(d) Number of properties. Fourth quartile.



Source: SHF, authors' calculations. We calculate the quartiles using the distribution of real prices for the pre-pandemic period (2019 Q1 to 2020 Q1). We exclude 2019 Q4 because of an unusual change in the number of properties.

There is also substantial heterogeneity in these price and quantity dynamics across the city. Figure 3 shows the evolution of prices and quantities by distance to the city center, *Zócalo*.[8] The price drops were sharper in neighborhoods near the city center. Quantities rose during the pandemic everywhere in the metro area.

Although these patterns are informative of the segment of the residential housing market that is purchased through credit, they may be uninformative of overall price and quantity dynamics in the entire housing market, which includes properties that are not covered in the SHF dataset. For comparison, in Section C of the Appendix we compare the price and quantity dynamics with alternative data sources. In general, the price dynamics for housing in the SHF dataset and alternative sources in the pre-pandemic period are similar, but during the pandemic restricions period, other sources display different price dynamics, presumably from composition changes in these alternative datasets.

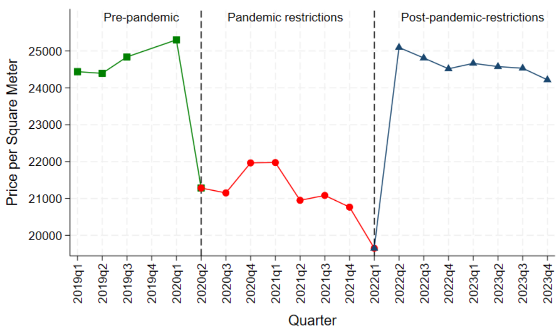
Table 1 shows descriptive statistics for prices and quantities in the pre-pandemic, pandemic restrictions, and post-pandemic-restrictions periods. Most of the housing in our dataset is used: the share of used housing in the dataset increased from 69% to 86% in the pandemic restrictions period, coming back to 80% in the post-restrictions period.[9] The average price per square meter decreased by 7.8% during the pandemic restrictions period relative to the pre-pandemic period and then recovered sharply. In contrast, the average number of properties per quarter increased during the pandemic restrictions period, from about 15,300 properties per quarter to about 18,100 properties per quarter. A decrease in prices, together with an increase in quantities, would be consistent with positive supply shocks in the market during the pandemic restrictions period. Anecdotal evidence suggests that part of this supply shock was explained by people migrating away from Mexico City, and from people selling properties to cope with the negative financial shock from the pandemic (El Universal 2020). Together with these price changes, the variance in prices decreased in the post-pandemic-restrictions

[8] We classify properties as near, mid, or far from the city center according to the distance to the center. The full classification is in Appendix Table E.1.

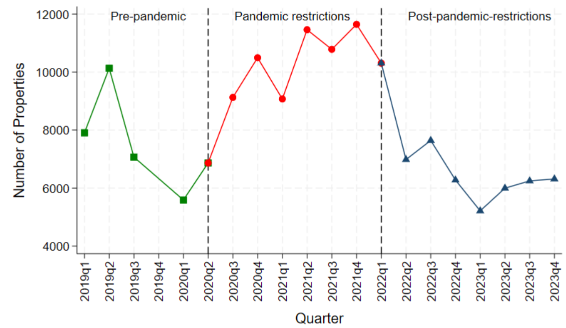
[9] The share of new housing is higher in the Mexico City metropolitan area: it was 36.5% in the pre-pandemic period. Moreover, the share of new housing in the dataset has been decreasing over time: from 2008 to 2020, the share of new housing in the dataset was close to 50%.

Figure 3: Average prices and number of properties by distance to the city center, Mexico City, 2019 Q1 - 2023 Q4

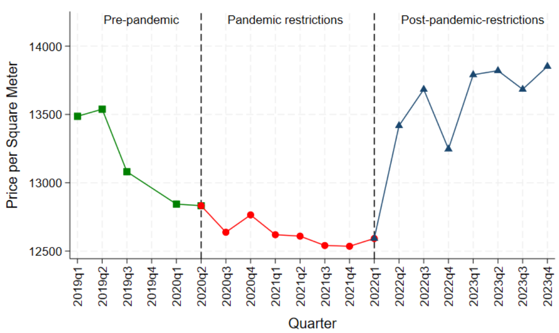
(a) Average price per square meter. Near the city center



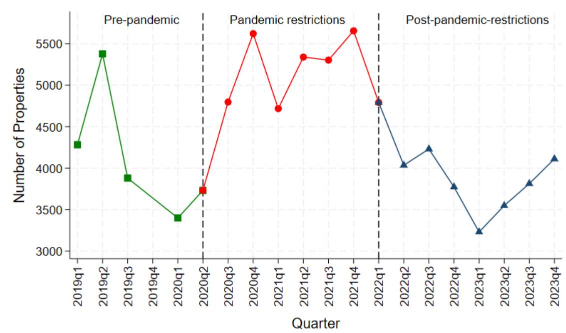
(b) Number of properties. Near the city center.



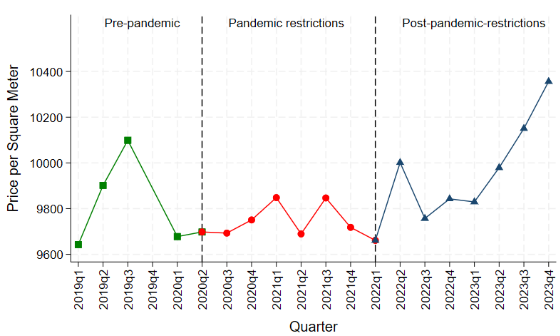
(c) Average price per square meter. Mid distance to city center.



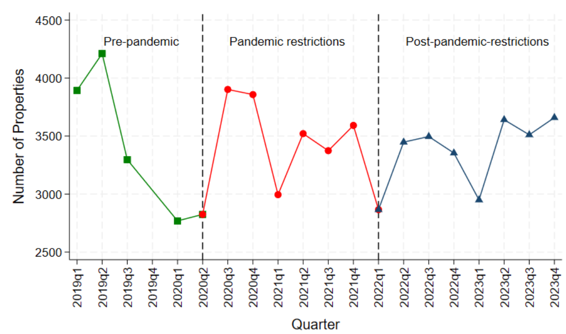
(d) Number of properties. Mid distance to city center.



(e) Average price per square meter. Far from the city center.



(f) Number of properties. Far from the city center.



Source: SHF, authors' calculations. We exclude 2019 Q4 because of an unusual change in the number of properties. Prices are in pesos of July 2018. Table E.1 in the Appendix shows the distance of each municipality to the city center, *Zócalo*.

period relative to the pre-pandemic period, with lower variance in prices, particularly in municipalities close to the city center.

The pandemic restrictions period also involved changes in the composition of properties sold in the market. During this period, the share of properties sold close to the city center increased by five p.p., while the share of properties sold far from the center decreased by the same share. This composition change was temporary, however, as the shares of properties sold by distance to the center changed again in the post-pandemic-restrictions period, with an increase in the share of properties sold far from the center.

Figures 4 and 5 show the spatial patterns of prices and the number of properties during the three analysis periods. Figure 4 shows price patterns. Mexico City's metro area shows a polycentric pattern with prices being higher in the northwest part of the city (North of *Bosque de Chapultepec*, in *Las Lomas* neighborhoods) and along *Avenida Insurgentes*, a north-south corridor that concentrates economic activity. Panels (a) and (b) show this spatial pattern: comparing the panels highlights the sharp price decrease during the pandemic restrictions period. The price drop is somewhat uniform around the city and does not display a pattern by distance to the center. Panel (c) shows price levels similar to those in panel (a), with a relative increase in prices in the western part (inside the city boundaries) and in the north of the metro area (outisde the city boundaries).

Figure 5 shows the average number of properties in the SHF dataset per quarter in each period. The quantities pattern is scattered, with higher numbers of properties in residential centers in the center, south, and west of the city. During the pandemic restrictions period, as shown in panel(b), more properties were appraised in the western and southern parts of the metro area, away from the city center, relative to the pre-pandemic period displayed in panel (a). This change reverted in the post-pandemic-restrictions period, and panels (a) and (c) display similar patterns.

Figures 6, 7, and 8 shows the percentage variation in prices in the three analysis periods. The decrease in prices in the pandemic restrictions period relative to the pre-pandemic period was uniform, except for relative increases in eastern peripheral areas. During the recovery period, prices in the peripheral areas of the metropolitan area increased relatively more than

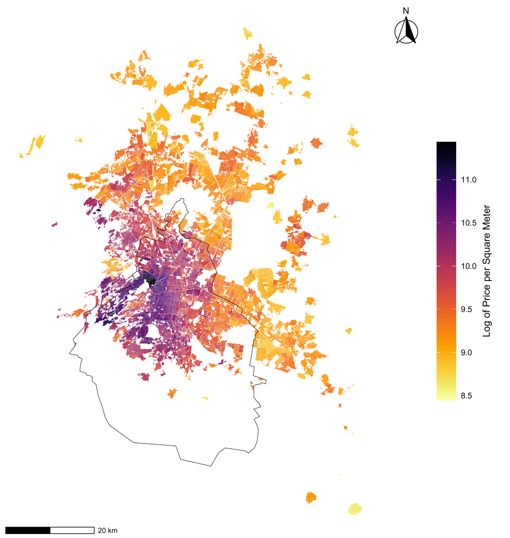
Table 1: Descriptive statistics. Mexico City metro area.

	Pre-pandemic 2019-Q1 to 2020-Q1	Pandemic restrictions 2020-Q2 to 2022-Q1	Post-pandemic-restrictions 2022-Q2 to 2023-Q4
Mean of price per square meter (pesos of Jul 2018)	18203.8	16767.5	17968.2
Standard deviation of price per square meter	12204.8	11360.0	11303.0
Number of observations	61272	145137	94330
Number of observations per quarter	15318.0	18142.1	13475.7
Mean of price per square meter by distance to city center			
Nearby municipalities	24673.0	21076.1	24642.5
Intermediate municipalities	13284.5	12648.4	13642.8
Far-away municipalities	9820.2	9758.6	10008.7
Standard deviation of price per square meter by distance to city center			
Nearby municipalities	13720.3	13163.9	12704.5
Intermediate municipalities	6251.8	5959.1	5587.2
Far-away municipalities	1498.0	1834.3	1655.9
Share of housing by distance to city center			
Nearby municipalities	0.50	0.55	0.47
Intermediate municipalities	0.27	0.27	0.28
Far-away municipalities	0.23	0.18	0.24
Mean of price per square meter by type of property			
2 bedrooms, 1 bathroom	14331.6	13797.2	13944.2
2 bedrooms, 2 bathrooms	33753.1	30825.7	32506.7
3 bedrooms, 2 bathrooms	24583.6	20975.2	24091.3
Other	17409.2	16091.2	17624.2
Standard deviation of price per square meter by type of property			
2 bedrooms, 1 bathroom	7956.2	7811.3	7324.2
2 bedrooms, 2 bathrooms	14365.5	14763.6	12188.6
3 bedrooms, 2 bathrooms	12515.5	12119.9	11164.8
Other	11799.9	10960.6	11178.1
Share of housing by type of property			
2 bedrooms, 1 bathroom	0.37	0.36	0.39
2 bedrooms, 2 bathrooms	0.09	0.08	0.09
3 bedrooms, 2 bathrooms	0.06	0.06	0.06
Other	0.48	0.50	0.45

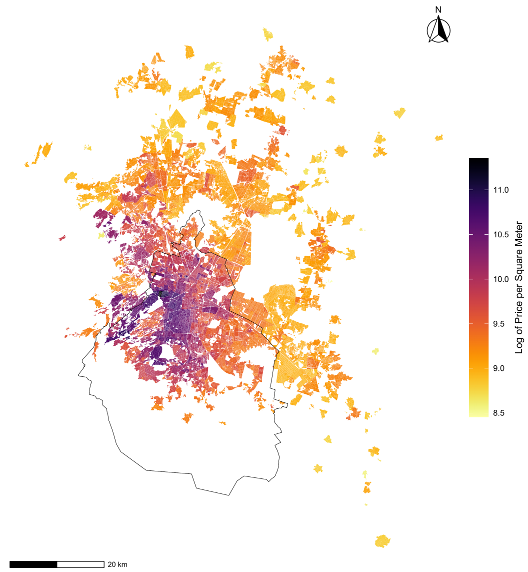
Source: SHF, authors' Calculations. Prices are in pesos of July 2018. We exclude 2019 Q4 because of an unusual change in the number of properties. The ranking of close, intermediate, and far municipalities is based on the distance between the city center (*Zócalo*) and each municipality's town hall. Table E.1 shows the distance for each municipality.

Figure 4: Log price per square meter, Mexico City metropolitan area, 2019 Q1 - 2023 Q4

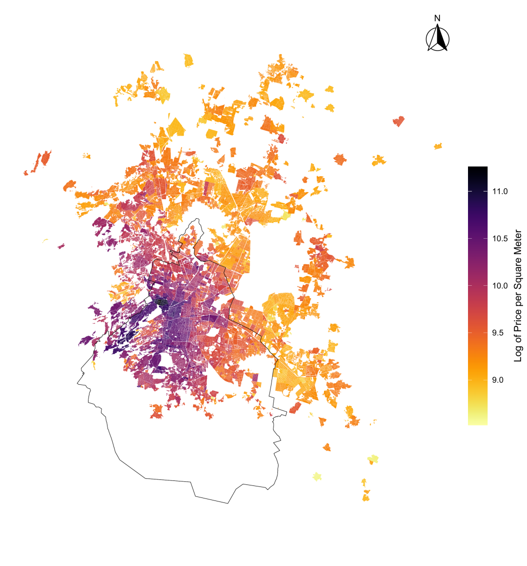
(a) Pre-pandemic period: 2019 Q1 - 2020 Q1



(b) Pandemic restrictions period: 2020 Q2 - 2022 Q1



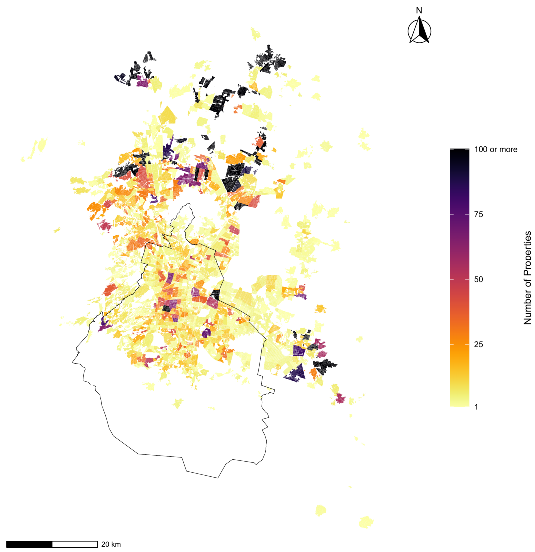
(c) Post-pandemic-restrictions period: 2022 Q2 - 2023 Q4



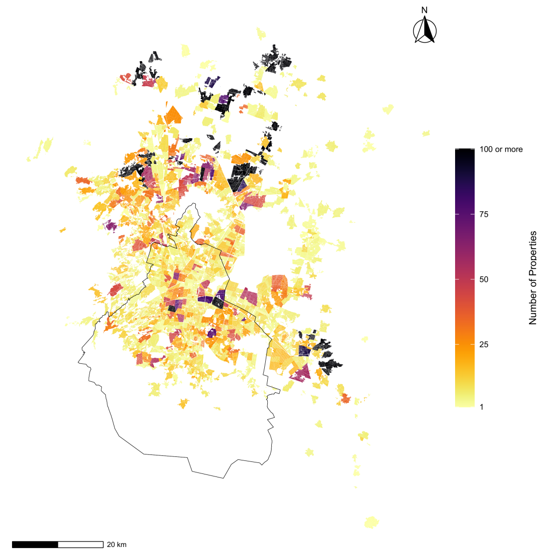
Source: SHF, authors' calculations. Observations are quarterly average log prices by postal code. We exclude 2019 Q4 because of an unusual change in the number of properties.

Figure 5: Number of properties appraised in SHF data, Mexico City, 2019 Q1 - 2023 Q4

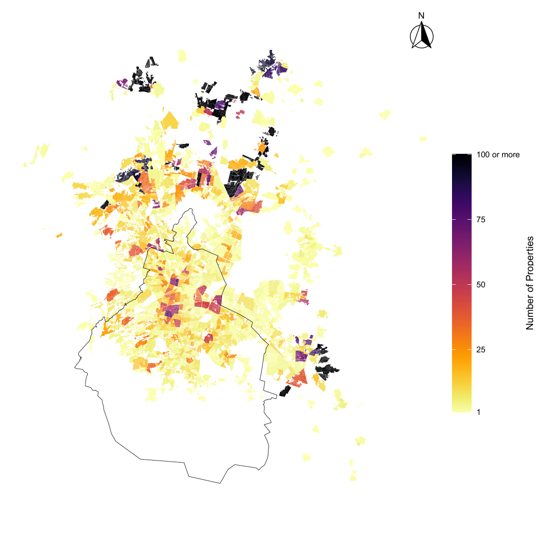
(a) Pre-pandemic period: 2019-Q1 - 2020 Q1



(b) Pandemic restrictions period: 2020 Q2 - 2022 Q1



(c) Post-pandemic-restrictions period: 2022 Q2 - 2023 Q4

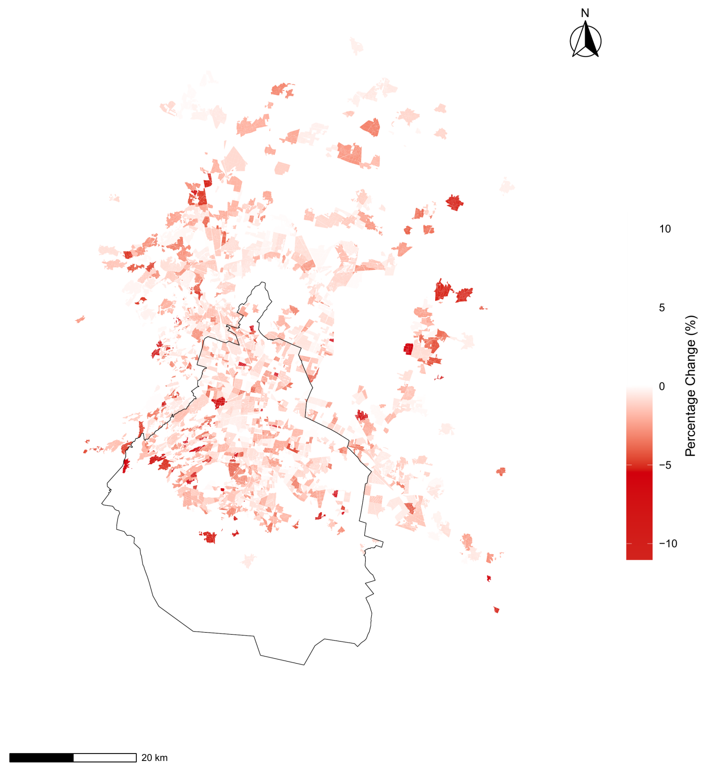


Source: SHF, authors' calculations. Quarterly average number of observations by postal code. We exclude 2019 Q4 because of an unusual change in the number of properties.

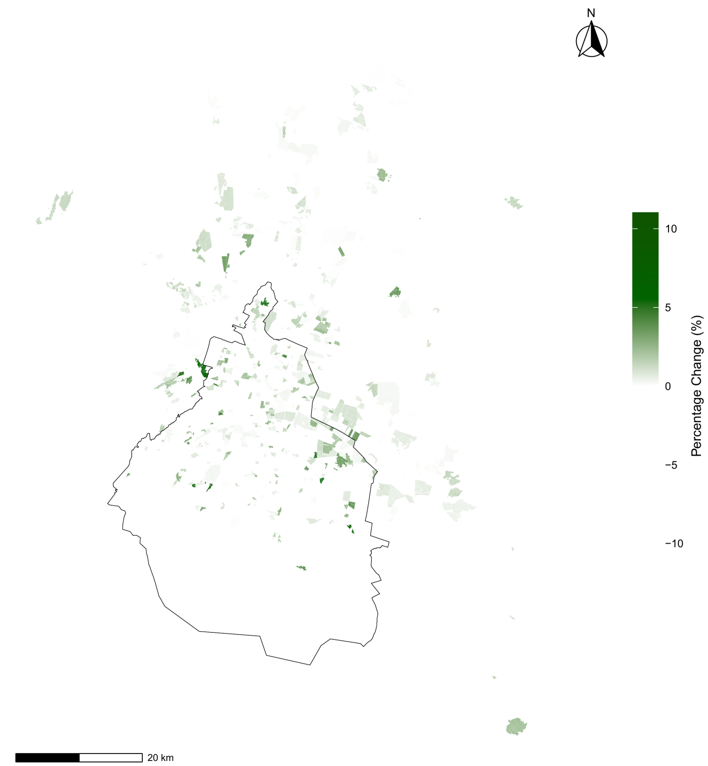
prices in the central areas. Comparing the pre-pandemic to the post-pandemic-restrictions period, prices in the eastern part of the city increased more. These patterns suggest that there may have been a flattening of the price gradient. Nevertheless, in Section 5 we will show that gradient changes are small and not statistically significant.

Figure 6: Percent change in prices, Mexico City, Pre-pandemic period (2019 Q1 - 2020 Q1) to Pandemic Restrictions period (2020Q2 - 2022 Q1).

(a) Negative changes



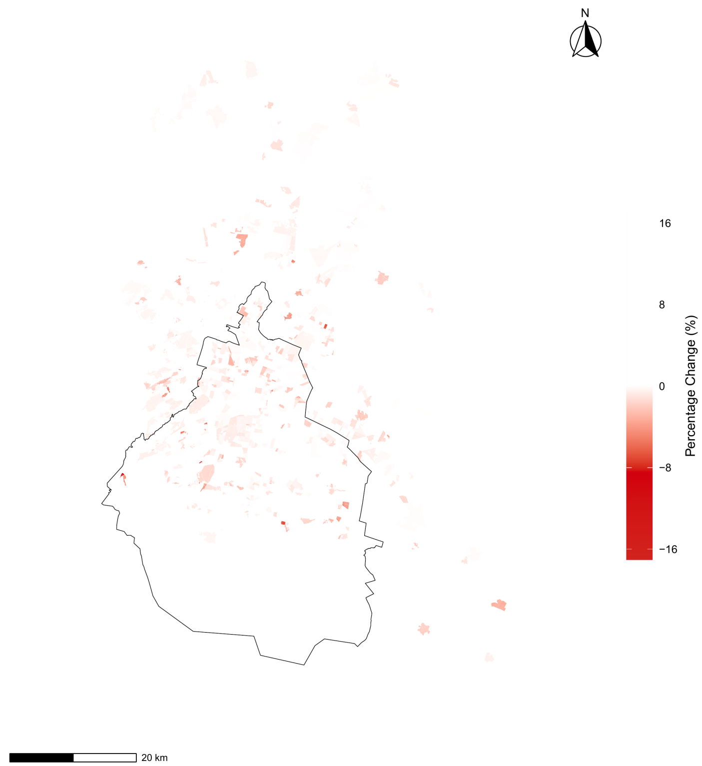
(b) Positive changes



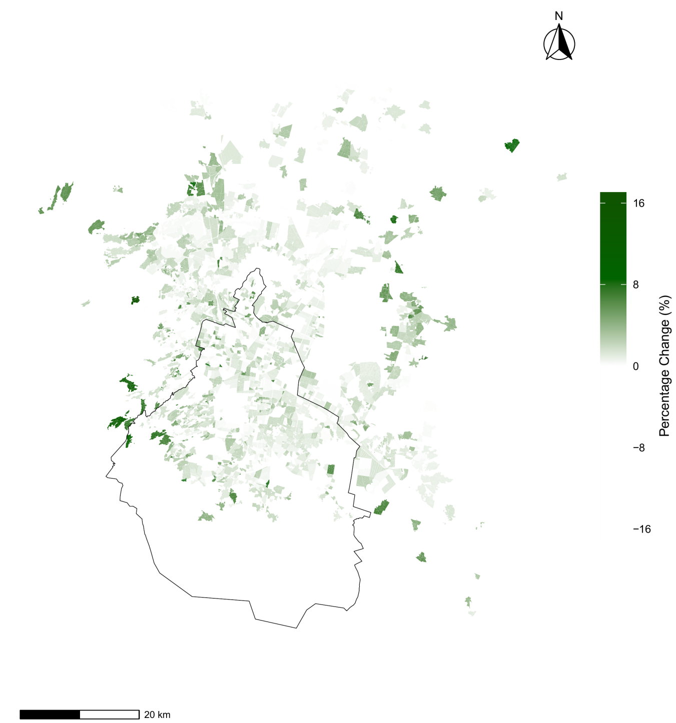
Source: SHF, authors' calculations. Quarterly average number of observations by postal code. We exclude 2019 Q4 because of an unusual change in the number of properties.

Figure 7: Percent change in prices, Mexico City, Pandemic Restrictions period (2020 Q2 - 2022 Q1) to Post-pandemic-restrictions period (2022 Q2 - 2023 Q4).

(a) Negative changes



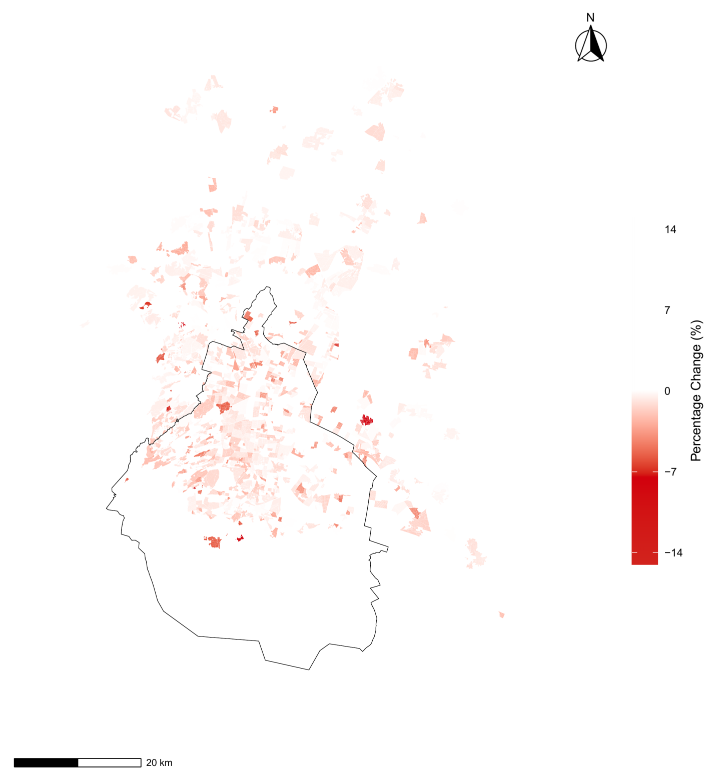
(b) Positive changes



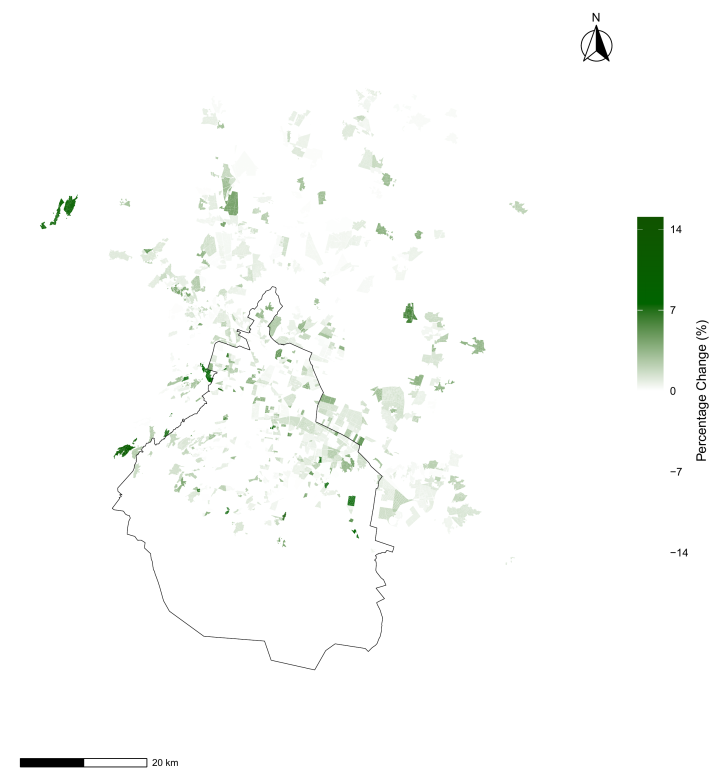
Source: SHF, authors' calculations. Quarterly average number of observations by postal code. We exclude 2019 Q4 because of an unusual change in the number of properties.

Figure 8: Percent change in prices, Mexico City 2019 Q1 - 2023 Q4, Pre-pandemic period to Post-pandemic-restrictions period.

(a) Negative changes



(b) Positive changes



Source: SHF, authors' calculations. Quarterly average number of observations by postal code. We exclude 2019 Q4 because of an unusual change in the number of properties.

4 Gradient Estimation

This section outlines our empirical strategy for estimating price gradients with respect to distance to the center and to employment density for Mexico City. To estimate gradients with respect to distance to the center, we follow Gupta et al. (2022) and estimate log-linear regressions of prices on distance to the center and covariates:

$$\ln\left(P_{it}\right) = \alpha_t + \delta \ln\left(1 + D_{c(i)}\right) + X_{it}'\beta + Z_{c(i)}'\gamma + \varepsilon_{it}. \tag{1}$$

Here, $P_{i,t}$ is the price per square meters of built area i at quarter t. The variable $D_{c(i)}$ is the distance from the centroid of property i's postal code $c(i)$ to the city center (*Zócalo*). The variables X_{it} are controls at the property level. These include number of bedrooms, number of bathrooms, elevators, number of floors, building age, a quality index of nearby infrastructure and housing type dummies that categorize properties according to the quality of the construction materials (e.g. basic, luxury, etc ...). The variables $Z_{c(i)}$ are controls that vary at the postal code level. These include the share of population over 18 years of age; the share of houses with: dirt floors, washing machines, toilets, cars, computers, and cell phones; robbery rates; and homicide rates per 100,000 people. We allow for different intercepts per quarter α_t. The coefficient of interest is δ, the percentage change in price per square meter for a 1% increase in distance to the city center, after controlling for differences in housing and neighborhood characteristics. We estimate equation (1) separately for the pre-pandemic, pandemic restrictions, and post-pandemic-restrictions periods. We cluster standard errors by postal code.

We also estimate a semi-parametric version of (1), where we allow for (conditional) average prices to vary across bins of distance to the city center:

$$\ln\left(P_{it}\right) = \tilde{\alpha} + \sum_k \tilde{\delta}_k^j \mathbb{1}\left(D\text{Km}_{c(i)} = k\right) \mathbb{1}\left(t \in j\right) + X_{it}'\tilde{\beta} + Z_{c(i)}'\tilde{\gamma} + \tilde{\varepsilon}_{it}. \tag{2}$$

In this equation, $D\text{Km}_{c(i)}$ is the distance from the centroid of postal code $c(i)$ to the city center, rounded to the nearest kilometer, such that the variables $\mathbb{1}\left(D\text{Km}_{c(i)} = k\right), k =$

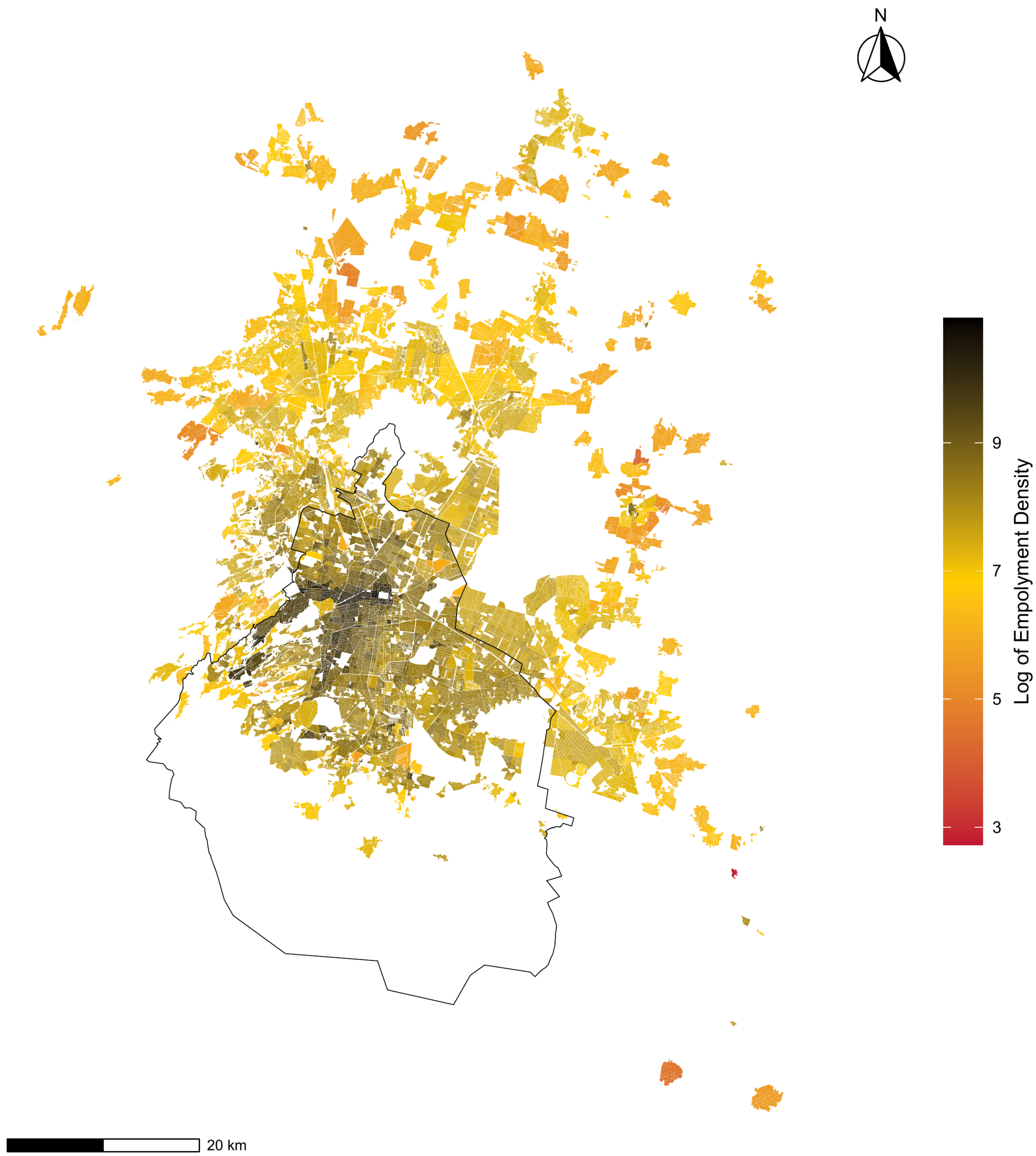
$1, 2, 3, \ldots$ are indicators for 1 Km bins of distance to the center. The variables $\mathbb{1}(t \in j), j \in \{\text{pre, pandemic, post}\}$ are dummies for the pre-pandemic, pandemic restrictions, and post-pandemic-restrictions periods. The coefficients $\tilde{\delta}_k^j$ measure the average log price per square meter of built area in each bin after controlling for property and neighborhood characteristics in each of the three analysis periods.

While informative, the analysis in equations (1) and (2) may be inadequate for a polycentric city like Mexico City. Prevous analyses of employment density patterns in Mexico City suggest that it has a polycentric structure, with disperse employment centers based on economic activities (Aguilar and Hernández-Lozano 2016; Escamilla et al. 2016). In polycentric cities, prices are higher near centers of economic activity that may or may not coincide with administrative city centers. While in Mexico City the *Zócalo* –the central square where the national and city government halls locate– concentrates a fair share of economic activity, there are other areas with high employment, such as those along *Avenida Insurgentes Sur*, around Santa Fe –a financial center–, and around the city's main food market. Figure 9 shows a map of employment density before the pandemic, using data from the National Directory of Economic Units (DENUE). We measure employment density as the log of the number of workers over the area in squared kilometers for each geo-statistical area (AGEB).[10] The figure displays a scattered pattern of employment density.

To deal with the polycentricity of the city, we estimate variants of equations (1) and (2) using density as an independent variable. For equation (2), we group postal codes into vingtiles of employment density.

[10]DENUE contains geo-referenced information on number of workers per registered establishment. Note that DENUE only includes data on establishments with a fixed physical location, and excludes establishments with mobile locations. It also excludes workers in the agricultural sector, bus and cab drivers, domestic workers, political associations, and diplomats. The number of workers is recorded in intervals: 0-5, 6-10, 11-30, 31-50, 51-100, 101-250, and over 251. We assign a value of 3 for the first bin, and we take the lower bound of the interval for all other bins.

Figure 9: Employment density in the Mexico City metropolitan area. Pre-pandemic period.



Source: DENUE, authors' calculations. Log of number of workers over are in squared kilometers per geo-statistical area (AGEB). DENUE employment data only includes establishments with a fixed physical location, and excludes establishments with mobile locations. It also excludes workers in the agricultural sector, bus and cab drivers, domestic workers, political associations, and diplomats. The number of workers is recorded in intervals: 0-5, 6-10, 11-30, 31-50, 51-100, 101-250, and over 251. We assign a value of 3 for the first bin, and we take the lower bound of the interval for all other bins.

5 Housing Price Gradients in the Mexico City metropolitan area

In this section, we show our estimates of housing price gradients for the Mexico City metropolitan area for the pre-pandemic, pandemic restrictions, and post-pandemic-restrictions periods. We show that, unlike other countries, there is little flattening of the housing price gradient during the pandemic restrictions period in Mexico City.

Parametric estimates for the pre-pandemic, pandemic restrictions, and post-pandemic-restrictions periods. Table 2, panel A, shows the results of our estimation of price gradients with respect to distance to the city center. Column (1) shows estimates for the pre-pandemic period without any controls. The estimate of the distance elasticity of housing prices is about -0.57, meaning that house prices per square meter in properties 10% farther from the city center are 5.7% lower on average. Once property-level controls are added in column (2), the elasticity drops to about -0.33. Gupta et al. (2022) estimate an elasticity of housing prices to distance to the center of around -0.13 for the largest 30 metropolitan areas in the US, after controlling for some neighborhood covariates. When we control for the whole set of neighborhood and property covariates in column (3), we find a negative elasticity of -0.24.

Columns (4) to (6) show analog estimates during the COVID-19 pandemic restrictions period. The uncontrolled price-distance slope drops in absolute value to about -0.51 during this period, while the estimate with controls becomes slightly more negative . In other words, if anything, the price gradient became *steeper* during the pandemic restrictions period. Columns (7) to (9) show estimates for the post-pandemic-restrictions period from 2022 Q2 to 2022 Q4. The estimate for the model with the full set of controls is similar to the one for the pandemic restrictions period, and more negative than the one for the pre-pandemic period.[11]

[11] These regressions are equivalent to specifications where built area appears on the right hand side of the equation with a coefficient of 1. In Appendix E, table E.2 we also estimate these regressions with log price as the dependent variable and log built area as a control, without restricting the coefficient on built area. While in many cases we reject that the coefficient on log built area is 1, we do not see evidence of gradient flattening in regressions controlling for area. We chose to focus on the regressions with price per square meter as a dependent variable for ease of interpretation.

Table 2: Distance and density gradient estimates, Mexico City metropolitan area, 2019-2023.

	Pre-pandemic			**Pandemic restrictions**			**Post-pandemic-restrictions**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A									
log(distance + 1)	-0.571***	-0.331***	-0.237***	-0.516***	-0.358***	-0.254***	-0.549***	-0.339***	-0.255***
	(0.022)	(0.017)	(0.024)	(0.023)	(0.012)	(0.016)	(0.019)	(0.015)	(0.020)
N	61308	61308	60377	145194	145194	142991	94374	94374	94007
R-squared	0.521	0.791	0.849	0.388	0.703	0.760	0.550	0.791	0.844
Panel B									
log(employment density)	0.353***	0.168***	0.062***	0.316***	0.184***	0.066***	0.319***	0.159***	0.051***
	(0.020)	(0.014)	(0.016)	(0.022)	(0.010)	(0.012)	(0.021)	(0.010)	(0.014)
N	57807	57807	57722	138545	138545	138383	88739	88739	88654
R-squared	0.403	0.768	0.836	0.310	0.677	0.745	0.417	0.767	0.830
Number of quarters	4	4	4	8	8	8	7	7	7
Controls									
Property		Yes	Yes		Yes	Yes		Yes	Yes
Neighborhood			Yes			Yes			Yes
Fixed Effects									
Quarter	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: SHF, authors' calculations. The table displays estimates of δ, the relationship between log housing prices and distance to the center or employment density, from equation (1). Panel A shows estimates of the relationship between housing prices and log distance to the center. Panel B shows estimates of the relationship between log housing prices and log employment density. We exclude 2019 Q4 because of an unusual change in the number of properties.

We test whether the changes across periods in the *estimated* distance gradients from our sample suggest a change in the underlying *population* gradients in Table 3. After including property and neighborhood controls, we do not find a significant flattening of the distance gradient between the before-COVID and during-COVID periods. We can rule out that the relationship flattened by more than 0.016 at the 95% confidence level. We also do not find a flattening of the distance gradient in the after-COVID period relative to the before-COVID period, although the standard errors around this gradient difference are wide. These results contrast with those from Gupta et al. (2022) for the United States, who find that the slope of the distance gradient flattened by 0.013 by Dec 2020 relative to the pre-COVID period in a sample of US cities.

The estimates of the gradient with respect to employment density in panel B of Table 2 paint a similar picture. Prices per square meter were about 3.5% higher for places with 10% higher employment density before the pandemic. After controlling for covariates, this figure drops to about 0.62%. During the pandemic restrictions period, the relationship between employment density and prices became steeper before bouncing back in the post-pandemic-restrictions period. We also test the statistical significance of these changes in density gradients in Table 3. We do not find statistically significant changes when comparing the pandemic restrictions periods with either the pre-pandemic or post-pandemic-restrictions periods, although the estimates are noisy. When comparing the pre-pandemic and post-pandemic-restrictions periods, we do find evidence of flattening, although the magnitude is small: in the post-pandemic-restrictions period a 10% higher employment density is associated with a 0.51% increase in prices.

In appendix C, we compare these estimates with estimates from DIME data. The estimates for the distance gradient are similar to those with the SHF data in the pre-pandemic period, but slightly smaller in the post-pandemic-restrictions period. The density gradients are much steeper. We do not find significant flattening of these gradients between the pre-pandemic period and the post-pandemic-restrictions period in either case. One possible reason for the lack of evidence of flattening are the limitations of the SHF and DIME data, which only covers mortgage appraisals, and does not cover self-built housing. To check if more ag-

Table 3: Differences in distance and density gradient estimates, Mexico City metropolitan area, 2019-2023.

	No controls	Property	Property and neighborhood
Distance (difference$>0 \implies$ gradient flattening)			
Pandemic restrictions - Pre-pandemic	0.055***	-0.027**	-0.017
	(0.028, 0.083)	(-0.049, -0.005)	(-0.050, 0.016)
Post-pandemic-restrictions - Pre-pandemic	0.022	-0.008	-0.018
	(-0.011, 0.054)	(-0.030, 0.014)	(-0.055, 0.019)
Post-pandemic-restrictions - Pandemic restrictions	-0.034**	0.019**	-0.001
	(-0.060, -0.007)	(0.001, 0.037)	(-0.025, 0.023)
Employment Density (difference $<0 \implies$ gradient flattening)			
Pandemic restrictions - Pre-pandemic	-0.037**	0.016*	0.004
	(-0.067, -0.008)	(-0.002, 0.034)	(-0.018, 0.027)
Post-pandemic-restrictions - Pre-pandemic	-0.034*	-0.009	-0.011
	(-0.071, 0.003)	(-0.029, 0.011)	(-0.036, 0.015)
Post-pandemic-restrictions - Pandemic restrictions	0.003	-0.025***	-0.015**
	(-0.014, 0.020)	(-0.035, -0.016)	(-0.027, -0.003)

Source: Authors' calculations based on the estimates from Table 2. Numbers in parentheses are confidence intervals for the change in the corresponding gradient at the 95% confidence level. Stars $**$ and $***$ represent significance at 95% and 99% respectively. We obtain the covariance between the estimates using seemingly unrelated estimations. Standard errors clustered by postal code. Before COVID is the period from 2019 Q1 to 2020 Q1. During COVID is the period from 2020 Q2 to 2022 Q1. After COVID period is from 2022 Q2 to 2022 Q4. We exclude 2019 Q4 because of an unusual change in the number of properties.

gregate evidence was consistent with flattening in the self-built housing market, we obtained average estimated housing rents data for self-built houses from the income-expenditure survey. This data fails to suggest any evidence of flattening: the ratio of estimated rents for self-built housing in the suburbs (Mexico state) relative to the central areas (Mexico City) remained relatively constant, at about 52% in 2020 and 53% in 2022. This evidence, however, does not rule out that the bulk of the flattening happened in the rental market, as opposed to the sale market.

An additional reason behind the lack of change in the gradient estimates is a change in the shares of housing of each type. However, we do not see major changes in the share of housing by property type in Table 1. We do not obtain separate estimates of the gradient by housing type according to number of bedrooms and bathrooms because the sample sizes are small. We do, however, obtain estimates for different housing types for which we have sufficient data (apartments, condo houses, and houses), as well as for different housing classes (subsidized housing, mid-range housing, and semi-luxury housing). We provide detailed estimates in appendix D. We do not find evidence of flattening for apartments or houses, nor for semi-luxury or subsidized housing. For condo houses and for mid-range housing, the point estimates of the gradient slopes suggest flattening, but only the changes for the density gradient are statistically significant, yet small.

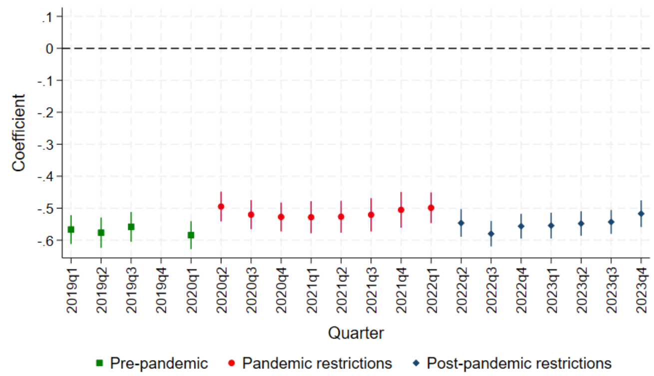
Quarterly estimates. To visualize if the slopes of the relationship between housing prices and distance to the city center or employment density are changing over time, we estimate cross-sectional analogs of equation (1) by quarter and plot the evolution of the slope coefficient over time. Figure 10 shows the results for distance to the center. Panels (b) and (c) confirm the pattern in Table 2: after controlling for property and neighborhood characteristics, if anything, the price-distance gradient became steeper during the pandemic restrictions period, while reverting in the post-pandemic-restrictions period.

Figure 11 displays quarterly estimates for the price-employment density relationship. Both the uncontrolled and controlled estimates are relatively stable over time, although there is some evidence of steepening during the pandemic restrictions period.[12]

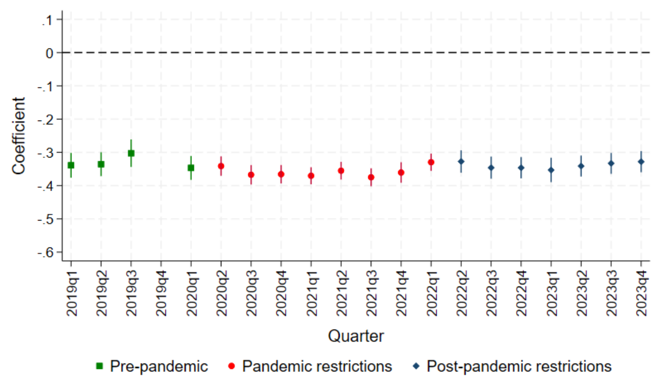
[12]We show estimates for apartments and condo houses in Appendix figure **??**. These do not show significant

Figure 10: Quarterly estimates of the slope of the log price-distance to the center relationship. Mexico City, 2019 Q1-2023 Q4.

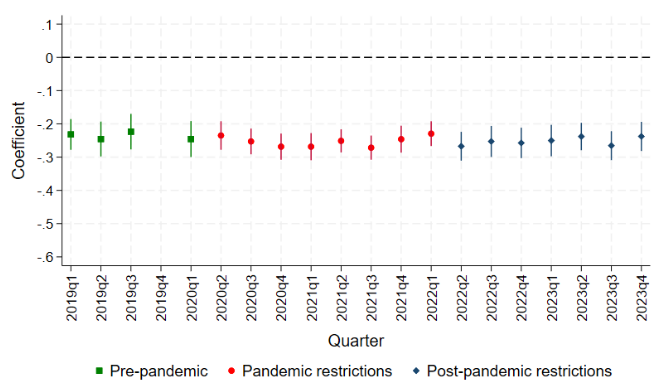
(a) No controls.



(b) Property-level controls.



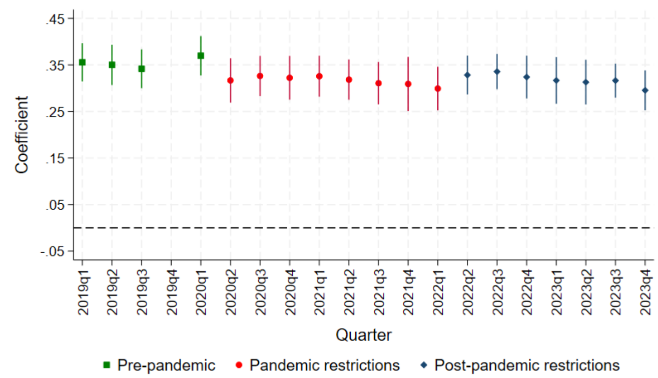
(c) Property- and neighborhood-level controls.



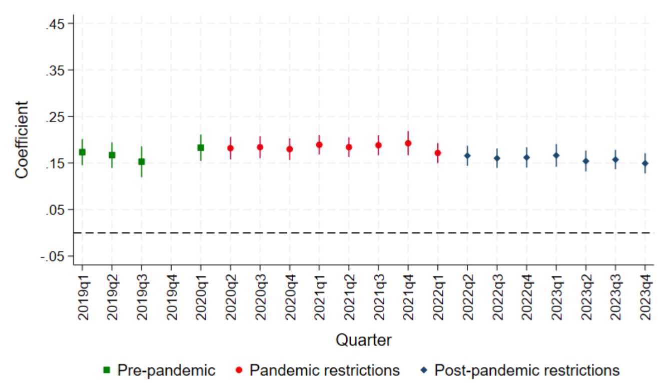
Source: SHF, authors' calculations. Each coefficient is the estimate of δ, the relationship between log housing prices and distance to the city center from equation (1) in each quarter. The bars are confidence intervals at the 95% confidence level. Standard errors clustered by postal code. We exclude 2019 Q4 because of an unusual change in the number of properties.

Figure 11: Quarterly estimates of the slope of the log price-employment density relationship. Mexico City, 2019 Q1-2023 Q4.

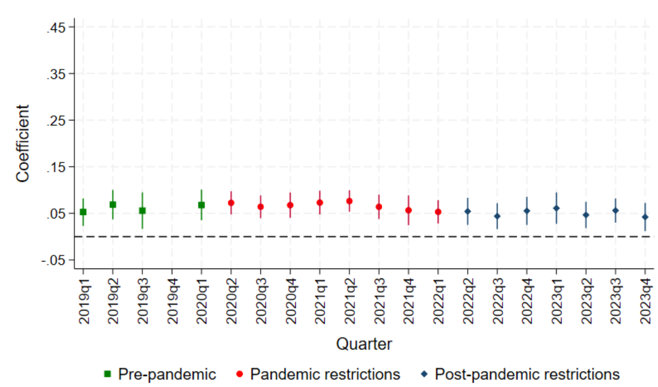
(a) No controls



(b) Property-level controls



(c) Property- and neighborhood-level controls.



Source: SHF, authors' calculations. Each coefficient is the estimate of δ, the relationship between log housing prices and employment density from equation (1) in each quarter. The bars are confidence intervals at the 95% confidence level. Standard errors clustered by postal code. We exclude 2019 Q4 because of an unusual change in the number of properties.

Semiparametric estimates. Figure 12 shows estimates of the price gradient with respect to distance to the city center by 1-km bins.[13] For each bin, we show estimates for the pre-pandemic, pandemic restrictions, and post-pandemic-restrictions periods. We normalize the coefficient for the city-center before the pandemic to zero, so the coefficient can be interpreted as log differences of prices relative to prices in the city center before the pandemic. In these figures, flattening would imply that the coefficients for small distances from the city center in the restrictions and post-restrictions periods would be systematically below their pre-pandemic counterparts, and coefficients for large distances should show the opposite pattern.

Panel (a) shows uncontrolled estimates. On average, prices are lower for properties farther from the city center. Before COVID-19, prices 15 km from the city center were 10 log points lower than those in the center. Without controls, however, the relationship between distance and prices is non-linear, as evidenced by the pattern in the figure. This is due to different property and neighborhood characteristics along the distance to the city center axis. Once we control for property- and neighborhood-level characteristics, the relationship becomes smoother and closer to linear, as shown in panels (b) and (c). Net of controls, prices 15 km from the center were 19 log points lower than at the center.

The estimated gradients are similar across the three analysis periods. Across distance bins, most coefficient estimates are close in size and have confidence intervals that overlap. The similarity is more striking when controls are added in panel (c). The only differences in coefficients are in high distances from the city center in sparsely populated areas.

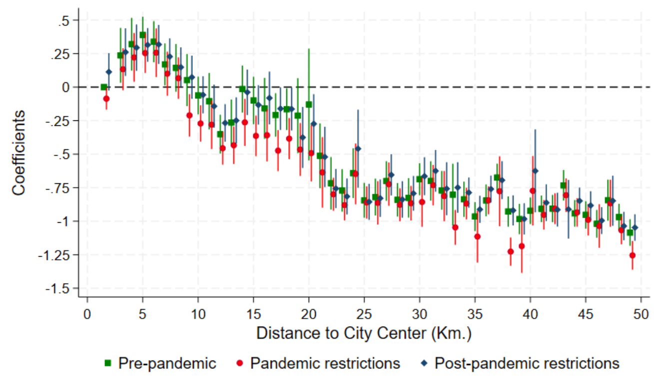
Figure 13 shows semiparametric housing price gradients with respect to employment density. Panel (a) shows the uncontrolled price differences across vingtiles of employment density. Going from the densest areas to areas with median density, in the 10th vingtile, is associated with a price decrease of about 126 log points in the pre-pandemic period. The relationship between density and prices is steeper for areas with above-median density, and tapers off in areas with below-median density. In these uncontrolled estimates, the gradient

changes either.

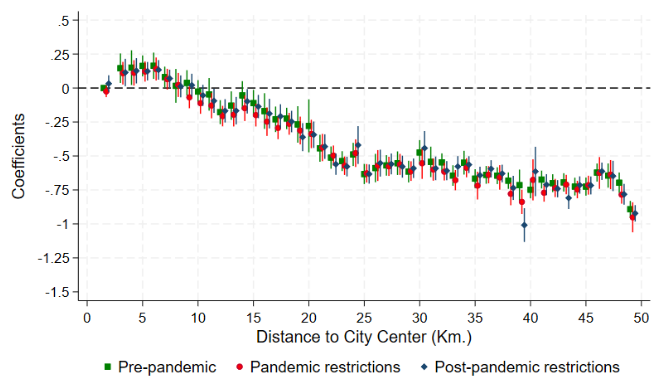
[13]We combine the 1km and 2km bins because of small sample sizes.

Figure 12: Semiparametric estimates of the slope of the log price - distance to center relationship. Mexico City, 2019-2023.

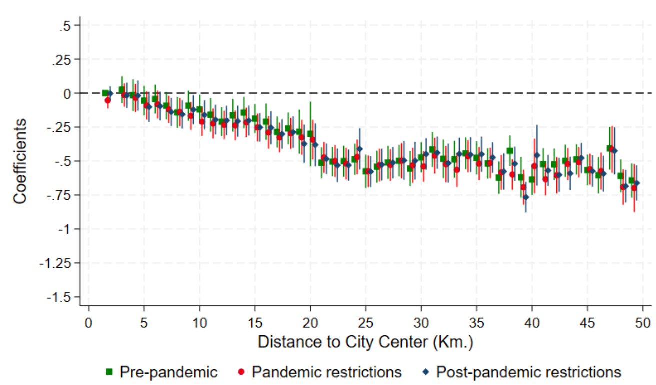
(a) No controls.



(b) Property-level controls.



(c) Property- and neighborhood-level controls.



Source: SHF, authors' calculations. Each coefficient is the estimate of $\tilde{\delta}_k^j$, from equation (2). Pre-pandemic is the period from 2019 Q1 to 2020 Q1. Pandemic restrictions is the period from 2020 Q2 to 2022 Q1. Post-pandemic-restrictions is the period from 2022 Q2 to 2022 Q4. The bars are confidence intervals at the 95% confidence level. Standard errors clustered by postal code. We group the first two bins of distance to the center (1km and 2km) into a single bin and a single coefficient because of small sample sizes, and we omit the coefficients for distances larger than 50km. We exclude 2019 Q4 because of an unusual change in the number of properties.

before the pandemic is flatter than the gradients in the other periods.

The differences across periods disappear once property- and neighborhood-level controls are added in panels (b) and (c). With controls, places with median density have prices only 26 log points lower than prices in the highest employment density vingtile. The coefficients do not show substantial differences across time periods.

Discussion. Our estimates show that the slope of the relationship between housing prices and distance to the city center or employment density did not change during the COVID-19 pandemic, and that by 2022 Q2, the slope of this relationship was similar to its level in the pre-pandemic period.

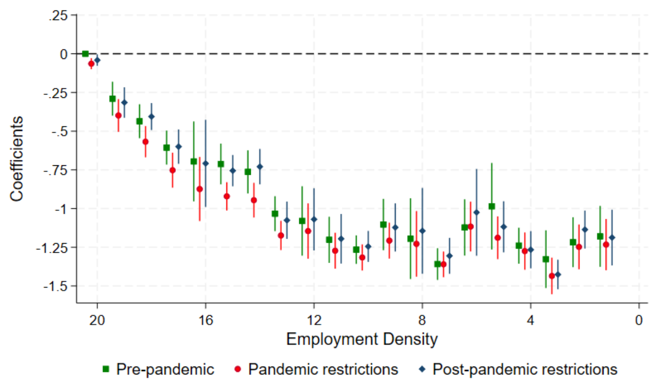
We note at least three differences between Mexico's housing market dynamics during the pandemic and those in the US and other developed countries. First, there were fewer mobility restrictions in Mexico than in other countries, as shown in data from Hale et al. (2023). The less-stringent restrictions may have contributed to smaller changes in worker mobility, commuting behavior and equilibria in the housing market.

Second, remote work may have been less appealing in Mexico City than in other cities from other countries. Adrjan et al. (2023) show that as of September of 2022, only 5.7% of job postings in Mexico were for remote work, whereas the average country in their sample had about 10.6% of remote work job postings. Leyva and Mora (2021) show that only about 10% of jobs in Mexico could be done from home, half of the share of jobs that could be done remotely in the US. A smaller share of remote workers may have implied a smaller demand shock for properties in Mexico City's periphery and may have prevented Mexico City from moving to a new equilibrium with a higher share of people living in the suburbs (Monte et al. 2023). A large share of informal work may also have contributed to the lack of changes in the housing market, as informal work is harder to do remotely.

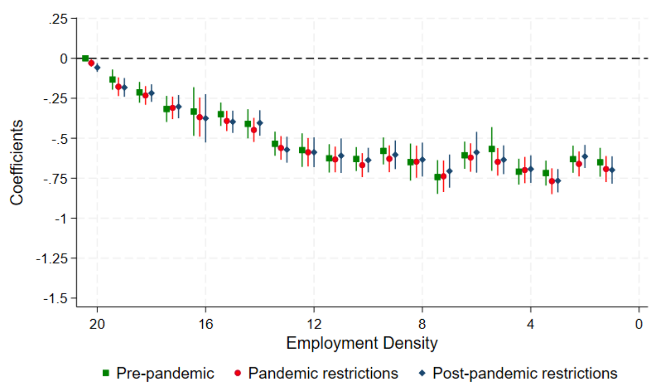
Third, households in Mexico City may be less mobile because of lack of access to funding to acquire new housing. INFONAVIT (2020) points out that a large of informal workers without access to formal housing translates into a large share of self-built houses financed by household savings. Households with self-built houses may have fewer resources to change houses. Formal workers who buy housing with government support via Infonavit usually

Figure 13: Semiparametric estimates of the slope of the log price-employment density relationship. Mexico City, 2019-2023.

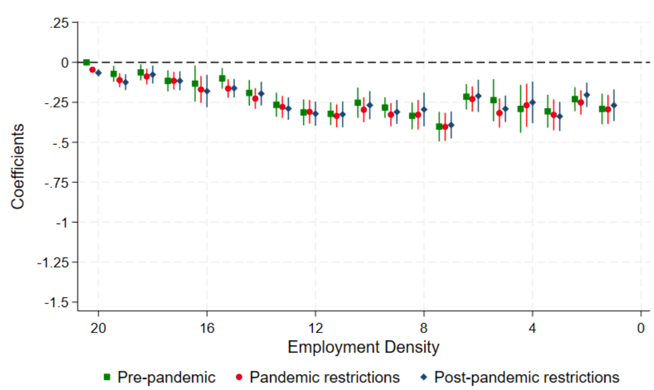
(a) No controls



(b) Property-level controls



(c) Property- and neighborhood-level controls.



Source: SHF, authors' calculations. Each coefficient is the estimate of $\tilde{\delta}_k^j$, from equation (2) by vingtiles of employment density. Before COVID-19 is the period from 2019 Q1 to 2020 Q1. During COVID-19 is the period from 2020 Q2 to 2022 Q1. After COVID-19 is the period from 2022 Q2 to 2022 Q4. The bars are confidence intervals at the 95% confidence level. Standard errors clustered by postal code. We exclude 2019 Q4 because of an unusual change in the number of properties.

have limited additional sources of financing (INFONAVIT 2020).

Beyond these differences between Mexico and other countries, there are other possible explanations for the lack of gradient flattening in Mexico City. The price and quantity dynamics in Figure 3 suggest a supply mechanism behind these findings. From 2019 Q3 to 2020 Q3, average prices fell by 14.85% in boroughs near the city center, while they fell by 4.02% in boroughs far from the city center. The number of appraised properties (to be eventually sold) increased by 29.11% near the center and increased by 18.35% far from the center. These patterns suggest the presence of positive supply shock for properties away from the city center. This supply shock may have absorbed the increase in demand for properties away from the city center.

A possible additional source of lack of flattening in the housing price gradient in Mexico City is an increase in the number of international residents in Mexico City during the pandemic. The number of foreigners that applied for temporary or permanent residence in Mexico increased from 37,903 in 2019 to 44,322 in 2020 (Brooks 2022). Brooks (2022) documents that foreigners tend to migrate to central neighborhoods in Mexico City located in the boroughs close to the city center, which showed only moderate price changes in our analysis period, as seen in Table 1. Migration to Mexico City may have increased the relative appeal of these central neighborhoods, which may have helped offset the negative demand shock from COVID-19. Nevertheless, if most of the foreigners entered the rental housing instead of the sale market, the impact on sale prices may have been limited. A more detailed analysis of this phenomenon would require geo-referenced data on housing demand by migrants to Mexico City.

6 Concluding Remarks

We estimate the housing price gradient –the relationship between housing prices and distance to economic activity– in Mexico City during the COVID-19 pandemic. Our estimates rely on administrative data for appraised properties. We show that housing prices are higher closer to the city center and to centers of economic activity, as observed in other cities around the world. However, we do not see evidence of a flattening of this relationship during the COVID-19 pandemic, in contrast to what has been observed in other cities (Gupta et al. 2022; Ziemann et al. 2023).

We outline possible mechanisms behind the lack of change in housing price gradients in Mexico City. The different degree of mobility restrictions in Mexico relative to other countries, compared to differences in remote work potential and in the potential of the mortgage housing market to react may have played a role, although we cannot rule out other explanations such as reactions in other segments of the housing market, such as sales through other channels or rents. Our evidence from the mortgage housing market points towards supply shocks in the areas of Mexico City far from the city center that may have dampened the housing price increases coming from increased demand for remote locations. Further work in this area could examine the quantify the role of these potential mechanisms on the dynamics of the housing market in the city in the post-pandemic era.

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Online Appendix - Not for Publication

A SHF Sample Selection

The SHF database contains 8,253,575 observations for the entire country, covering the period from January 2008 to December 2023. We select our estimation sample in two steps. In the first step, we remove properties with missing or inconsistent data.

- We exclude 514 observations from properties without bedrooms or bathrooms.
- We exclude 1,660 observations with missing values in the number of elevators variable.
- We discard 4,053 observations from properties with a completion year greater than the current year.
- We drop 20,127 observations from properties with more than 5 floors.
- We drop 132,356 observations from subsidized housing properties with areas above 1,000 square meters, since by law these types of properties cannot have more than 1,000 square meters of area.
- We exclude observations with inconsistent postal codes.

After the first step, we retain 8,010,850 observations, 97.05% of the original database. In the second step, we remove outliers in the distribution of price per square meter, land area, and built area to land area. Specifically:

- We exclude 52 observations where the price per square meter exceeds 150,000 pesos.
- We drop 160,141 observations with land areas below the 1st percentile or above the 99th percentile of the national land surface area distribution.
- We calculate the ratio of built area to land area per state and drop 389,620 observations below the 2.5th or above the 97.5th percentile of each state's built/land area ratio distribution.

At this stage, the dataset has 7,461,037 observations. The dataset for Mexico City metropolitan area from 2019 to 2023 contains 300,876 observations.

B DIME Sample Selection

The DIME dataset comprises 315,100 observations covering the entire country from 2006 Q4 to 2023 Q4. Each observation represents a specific type of unit offered by the housing developments included in the dataset. To account for this dataset's structure, we apply frequency weights to adjust and expand the data. We begin by filtering the dataset:

- Removing 147 observations with missing values in the state variable.
- Excluding 452 observations where the price per square meter exceeds 150,000 pesos.
- Dropping 6,262 observations with land areas outside the 1st and 99th percentiles of the national land surface area distribution.

Next, we georeference the housing developments, focusing on municipalities in the Mexico City metropolitan area:

- Georeferencing 22,314 housing developments.
- Dropping 1,066 observations with latitude and longitude values falling outside the 2nd and 98th percentiles of their respective distributions.

After merging the georeferenced data with the filtered DIME dataset, we retain 45,741 observations. Finally, limiting the dataset to observations from 2019 Q1 to 2023 Q4 reduces the sample to 14,628 observations.

C Comparison with Alternative Data Sources

In this section, first, we compare the evolution of prices and quantities between our main data source, the SHF dataset, and two alternative data sources: The Unique Housing Registry

(RUV, from its Spanish acronym) and the Housing Market Dynamics dataset (DIME from its Spanish acronym). Then, we obtain estimates of housing price gradients from georeferenced DIME data. We do not find evidence of a flattening housing price gradient with the DIME data.

The RUV dataset contains information on new housing development starting in 2004. Every developer who is interested in receiving government funding has to register new housing construction projects in this dataset. The data is monthly and includes information on the number of units, bedrooms, and bathrooms for each unit type, built area, terrain area, and prices.

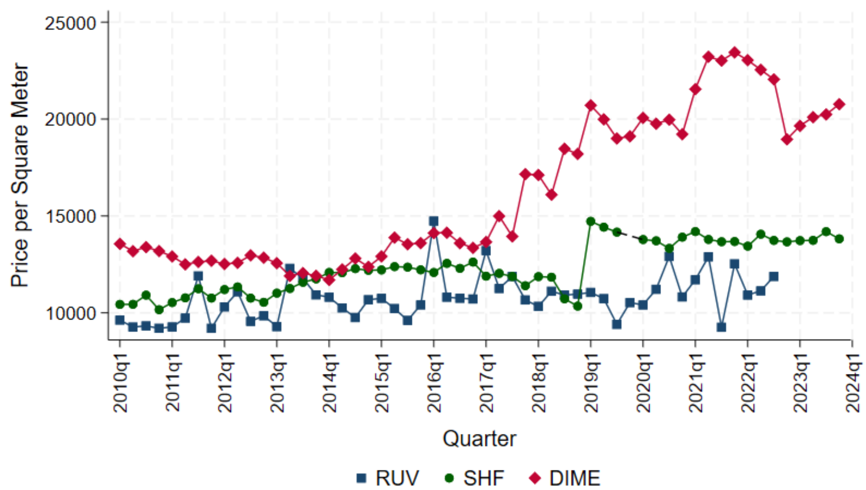
The DIME dataset is a proprietary database on housing developments collected by Softec. It is aimed at mid- and high-price units and is collected by mystery shoppers.

Figure C.1 compares prices and quantities between the different datasets for 2 bed-1 bath properties. Prices evolve similarly across datasets up to 2017, when average prices in the DIME dataset start increasing, at the same time as the number of properties in the dataset decrease.

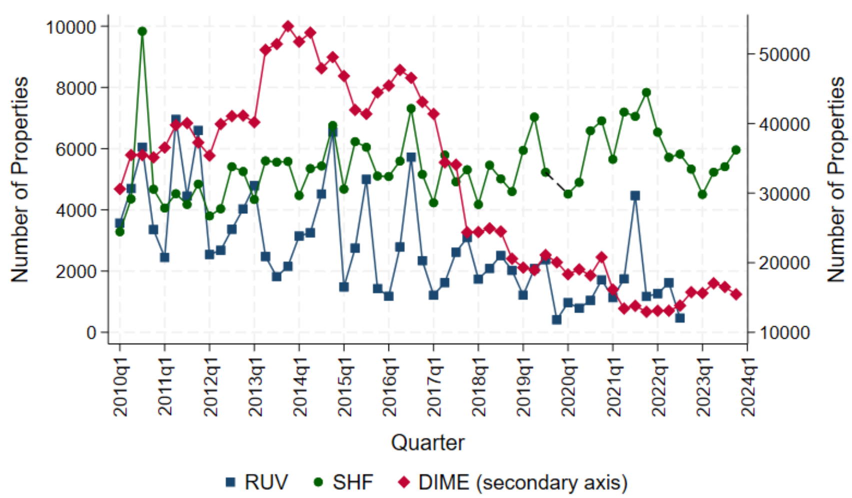
Table C.1 shows gradient estimates with the DIME data. After controlling for housing and neighborhood characteristics, the estimate of the slope of distance gradient is remarkably similar to that obtained from SHF data in the pre-pandemic period: a 10% higher distance to the center is associated with a 2.3% decrease in prices. However, for the DIME dataset, the point estimate of this slope does decrease in absolute value in the pandemic restrictions and post-pandemic-restrictions periods. Nevertheless, this decrease is not statistically significant, as shown in table C.2. Density gradients in the DIME data are remarkably different from those in the SHF data. One possible reason behind this difference is the fact that DIME data targets higher-income multifamily housing. These gradients show some evidence of flattening, but the difference between the post-pandemic-restrictions period and the pre-pandemic period is not statistically significant.

Figure C.1: Number of properties and average prices, Mexico City 2019 Q1 - 2023 Q4. 2 bedroom - 1 bathroom properties. Comparison between datasets.

(a) Average price per square meter.



(b) Number of properties.



Source: SHF, authors' calculations. Prices are in pesos of July 2018. We exclude 2019 Q4 because of an unusual change in the number of properties.

Table C.1: Distance and density gradient estimates, Mexico City metropolitan area, 2019-2023. DIME data.

	Pre-pandemic			**Pandemic restrictions**			**Post-pandemic-restrictions**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A									
log(distance + 1)	-0.608***	-0.295***	-0.239***	-0.582***	-0.292***	-0.184***	-0.547***	-0.305***	-0.160***
	(0.066)	(0.041)	(0.063)	(0.058)	(0.026)	(0.049)	(0.064)	(0.034)	(0.044)
N	336542	336285	274838	400931	400811	352132	215408	215253	193121
R-squared	0.512	0.879	0.919	0.500	0.858	0.901	0.542	0.856	0.917
Panel B									
log(employment density)	3.218***	1.494***	0.678***	2.628***	1.120***	0.306	2.681***	1.311***	0.112
	(0.476)	(0.237)	(0.247)	(0.516)	(0.161)	(0.223)	(0.560)	(0.181)	(0.246)
N	305168	304911	256625	383460	383340	343424	206608	206453	186995
R-squared	0.450	0.862	0.901	0.327	0.838	0.895	0.426	0.835	0.909
Number of quarters	4	4	4	8	8	8	7	7	7
Controls									
Property		Yes	Yes		Yes	Yes		Yes	Yes
Neighborhood			Yes			Yes			Yes
Fixed Effects									
Quarter	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: DIME, authors' calculations. The table displays estimates of δ, the relationship between log housing prices and distance to the center or employment density, from equation (1). Panel A shows estimates of the relationship between housing prices and log distance to the center. Panel B shows estimates of the relationship between log housing prices and log employment density.

Table C.2: Differences in distance and density gradient estimates, Mexico City metropolitan area, 2019-2023. DIME data

	No controls	Property	Property and neighborhood
Distance (difference$>0 \implies$ gradient flattening)			
Pandemic restrictions - Pre-pandemic	0.026	0.003	0.055
	(-0.102, 0.154)	(-0.073, 0.078)	(-0.034, 0.144)
Post-pandemic-restrictions - Pre-pandemic	0.061	-0.011	0.079
	(-0.091, 0.212)	(-0.113, 0.092)	(-0.046, 0.203)
Post-pandemic-restrictions - Pandemic-restrictions	0.035	-0.013	0.023
	(-0.091, 0.160)	(-0.084, 0.057)	(-0.080, 0.127)
Employment Density (difference $<0 \implies$ gradient flattening)			
Pandemic restrictions - Pre-pandemic	-0.591**	-0.373**	-0.372*
	(-1.054, -0.128)	(-0.702, -0.045)	(-0.802, 0.058)
Post-pandemic-restrictions - Pre-pandemic	-0.537	-0.182	-0.567**
	(-1.471, 0.396)	(-0.644, 0.280)	(-1.110, -0.023)
Post-pandemic-restrictions - Pandemic-restrictions	0.053	0.191	-0.194
	(-0.782, 0.889)	(-0.123, 0.505)	(-0.592, 0.203)

Source: Authors' calculations based on the estimates from Table C.1. Numbers in parentheses are confidence intervals for the change in the corresponding gradient at the 95% confidence level. Stars $**$ and $***$ represent significance at 95% and 99% respectively. We obtain the covariance between the estimates using seemingly unrelated estimations. Standard errors clustered by postal code. Before COVID is the period from 2019 Q1 to 2020 Q1. During COVID is the period from 2020 Q2 to 2022 Q1. After COVID period is from 2022 Q2 to 2022 Q4.

D Results by property types and classes

Table D.1: Distance and density gradient estimates, Mexico City metropolitan area 2019-2023. Apartments only.

	Pre-pandemic			**Pandemic restrictions**			**Post-pandemic-restrictions**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A									
log(distance + 1)	-0.562***	-0.276***	-0.183***	-0.509***	-0.280***	-0.181***	-0.528***	-0.280***	-0.196***
	(0.032)	(0.023)	(0.029)	(0.026)	(0.015)	(0.022)	(0.021)	(0.017)	(0.024)
N	27659	27659	27633	54835	54835	54721	46795	46795	46731
R-squared	0.485	0.829	0.883	0.434	0.799	0.853	0.560	0.850	0.889
Panel B									
log(employment density)	0.381***	0.179***	0.061***	0.346***	0.182***	0.052***	0.335***	0.173***	0.061***
	(0.038)	(0.022)	(0.022)	(0.027)	(0.012)	(0.013)	(0.022)	(0.010)	(0.013)
N	26090	26090	26074	52401	52401	52372	43473	43473	43451
R-squared	0.408	0.814	0.868	0.392	0.788	0.840	0.491	0.839	0.875
Number of quarters	4	4	4	8	8	8	7	7	7
Controls									
Property		Yes	Yes		Yes	Yes		Yes	Yes
Neighborhood			Yes			Yes			Yes
Fixed Effects									
Quarter	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: SHF, authors' calculations. The table displays estimates of the relationship between log housing prices, distance to the center and employment density, controlling for area. Panel A shows estimates of the relationship between housing prices and log distance to the center. Panel B shows estimates of the relationship between log housing prices and log employment density. We exclude 2019 Q4 because of an unusual change in the number of properties.

Table D.2: Distance and density gradient estimates, Mexico City metropolitan area 2019-2023. Condo houses.

	Pre-pandemic			Pandemic restrictions			Post-pandemic-restrictions		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A									
log(distance + 1)	-0.558***	-0.417***	-0.350***	-0.477***	-0.384***	-0.323***	-0.518***	-0.425***	-0.335***
	(0.043)	(0.026)	(0.044)	(0.046)	(0.022)	(0.040)	(0.049)	(0.026)	(0.055)
N	24311	24311	23954	45820	45820	44846	35945	35945	35725
R-squared	0.362	0.722	0.769	0.266	0.668	0.716	0.314	0.671	0.724
Panel B									
log(employment density)	0.184***	0.115***	0.046**	0.133***	0.087***	0.025	0.125***	0.078***	0.006
	(0.034)	(0.017)	(0.018)	(0.037)	(0.019)	(0.021)	(0.040)	(0.021)	(0.022)
N	23192	23192	23161	43089	43089	43033	33987	33987	33945
R-squared	0.128	0.659	0.742	0.068	0.609	0.691	0.064	0.606	0.706
Number of quarters	4	4	4	8	8	8	7	7	7
Controls									
Property		Yes	Yes		Yes	Yes		Yes	Yes
Neighborhood			Yes			Yes			Yes
Fixed Effects									
Quarter	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: SHF, authors' calculations. The table displays estimates of the relationship between log housing prices, distance to the center and employment density, controlling for area. Panel A shows estimates of the relationship between housing prices and log distance to the center. Panel B shows estimates of the relationship between log housing prices and log employment density. We exclude 2019 Q4 because of an unusual change in the number of properties.

Table D.3: Distance and density gradient estimates, Mexico City metropolitan area 2019-2023. Houses only.

	Pre-pandemic			Pandemic restrictions			Post-pandemic-restrictions		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A									
log(distance + 1)	-0.380***	-0.311***	-0.205***	-0.443***	-0.399***	-0.266***	-0.435***	-0.336***	-0.224***
	(0.026)	(0.019)	(0.035)	(0.041)	(0.017)	(0.019)	(0.018)	(0.019)	(0.028)
N	9338	9338	8790	44539	44539	43424	11634	11634	11551
R-squared	0.285	0.528	0.711	0.216	0.440	0.544	0.292	0.511	0.693
Panel B									
log(employment density)	0.211***	0.130***	0.065***	0.267***	0.214***	0.100***	0.206***	0.145***	0.067***
	(0.049)	(0.019)	(0.015)	(0.017)	(0.010)	(0.009)	(0.038)	(0.016)	(0.012)
N	8525	8525	8487	43055	43055	42978	11279	11279	11258
R-squared	0.107	0.475	0.698	0.171	0.413	0.530	0.114	0.463	0.677
Number of quarters	4	4	4	8	8	8	7	7	7
Controls									
Property		Yes	Yes		Yes	Yes		Yes	Yes
Neighborhood			Yes			Yes			Yes
Fixed Effects									
Quarter	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: SHF, authors' calculations. The table displays estimates of the relationship between log housing prices, distance to the center and employment density, controlling for area. Panel A shows estimates of the relationship between housing prices and log distance to the center. Panel B shows estimates of the relationship between log housing prices and log employment density. We exclude 2019 Q4 because of an unusual change in the number of properties.

Table D.4: Distance and density gradient estimates, Mexico City metropolitan area 2019-2023. Subsidized housing.

	Pre-pandemic			Pandemic restrictions			Post-pandemic-restrictions		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A									
log(distance + 1)	-0.266***	-0.356***	-0.363***	-0.242***	-0.379***	-0.352***	-0.218***	-0.397***	-0.388***
	(0.019)	(0.019)	(0.030)	(0.022)	(0.014)	(0.019)	(0.027)	(0.019)	(0.038)
N	27283	27283	27217	64881	64881	64443	43667	43667	43559
R-squared	0.296	0.455	0.528	0.182	0.362	0.429	0.183	0.418	0.494
Panel B									
log(employment density)	0.111***	0.097***	0.029	0.129***	0.151***	0.065***	0.069***	0.102***	0.027
	(0.018)	(0.022)	(0.018)	(0.017)	(0.015)	(0.015)	(0.020)	(0.020)	(0.022)
N	25103	25103	25047	61178	61178	61061	39040	39040	38973
R-squared	0.112	0.278	0.436	0.112	0.244	0.361	0.054	0.247	0.424
Number of quarters	4	4	4	8	8	8	7	7	7
Controls									
Property		Yes	Yes		Yes	Yes		Yes	Yes
Neighborhood			Yes			Yes			Yes
Fixed Effects									
Quarter	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: SHF, authors' calculations. The table displays estimates of the relationship between log housing prices, distance to the center and employment density, controlling for area. Panel A shows estimates of the relationship between housing prices and log distance to the center. Panel B shows estimates of the relationship between log housing prices and log employment density. We exclude 2019 Q4 because of an unusual change in the number of properties.

Table D.5: Distance and density gradient estimates, Mexico City metropolitan area 2019-2023. Mid-range housing.

	Pre-pandemic			**Pandemic restrictions**			**Post-pandemic-restrictions**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A									
log(distance + 1)	-0.444***	-0.309***	-0.185***	-0.413***	-0.330***	-0.186***	-0.406***	-0.307***	-0.180***
	(0.020)	(0.019)	(0.026)	(0.022)	(0.014)	(0.019)	(0.022)	(0.017)	(0.023)
N	27559	27559	26719	65809	65809	64141	40658	40658	40462
R-squared	0.420	0.624	0.757	0.303	0.547	0.661	0.391	0.610	0.738
Panel B									
log(employment density)	0.297***	0.213***	0.080***	0.254***	0.203***	0.058***	0.235***	0.176***	0.030**
	(0.019)	(0.014)	(0.016)	(0.024)	(0.012)	(0.013)	(0.023)	(0.012)	(0.014)
N	26486	26486	26475	63276	63276	63251	39959	39959	39957
R-squared	0.359	0.617	0.750	0.238	0.529	0.649	0.298	0.586	0.724
Number of quarters	4	4	4	8	8	8	7	7	7
Controls									
Property		Yes	Yes		Yes	Yes		Yes	Yes
Neighborhood			Yes			Yes			Yes
Fixed Effects									
Quarter	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: SHF, authors' calculations. The table displays estimates of the relationship between log housing prices, distance to the center and employment density, controlling for area. Panel A shows estimates of the relationship between housing prices and log distance to the center. Panel B shows estimates of the relationship between log housing prices and log employment density. We exclude 2019 Q4 because of an unusual change in the number of properties.

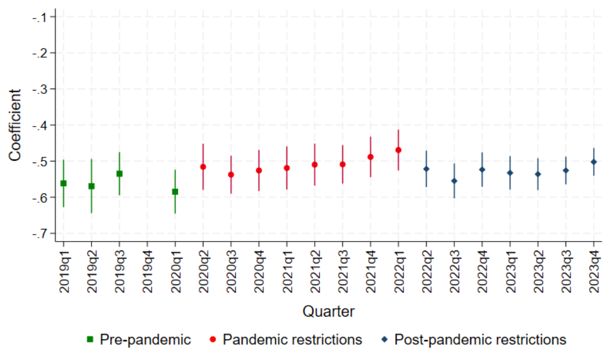
Table D.6: Distance and density gradient estimates, Mexico City metropolitan area 2019-2023. Semi-luxury housing.

	Pre-pandemic			**Pandemic restrictions**			**Post-pandemic-restrictions**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A									
log(distance + 1)	-0.271***	-0.178***	-0.027	-0.328***	-0.228***	-0.068*	-0.320***	-0.257***	-0.114***
	(0.053)	(0.056)	(0.058)	(0.032)	(0.032)	(0.039)	(0.027)	(0.026)	(0.036)
N	5528	5528	5519	10082	10082	10023	8796	8796	8758
R-squared	0.157	0.475	0.592	0.230	0.497	0.600	0.225	0.480	0.563
Panel B									
log(employment density)	0.130***	0.093***	0.041	0.161***	0.115***	0.057***	0.154***	0.125***	0.071
	(0.032)	(0.031)	(0.027)	(0.019)	(0.018)	(0.017)	(0.014)	(0.013)	(0.014)
N	5330	5330	5328	9760	9760	9752	8528	8528	8520
R-squared	0.176	0.497	0.601	0.274	0.524	0.615	0.277	0.507	0.580
Number of quarters	4	4	4	8	8	8	7	7	7
Controls									
Property		Yes	Yes		Yes	Yes		Yes	Yes
Neighborhood			Yes			Yes			Yes
Fixed Effects									
Quarter	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

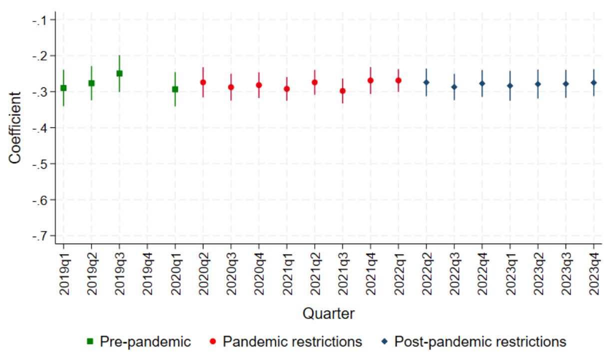
Source: SHF, authors' calculations. The table displays estimates of the relationship between log housing prices, distance to the center and employment density, controlling for area. Panel A shows estimates of the relationship between housing prices and log distance to the center. Panel B shows estimates of the relationship between log housing prices and log employment density. We exclude 2019 Q4 because of an unusual change in the number of properties.

Figure D.1: Quarterly estimates of the slope of the log price - distance to center relationship by property type. Mexico City metropolitan area, 2019-2023.

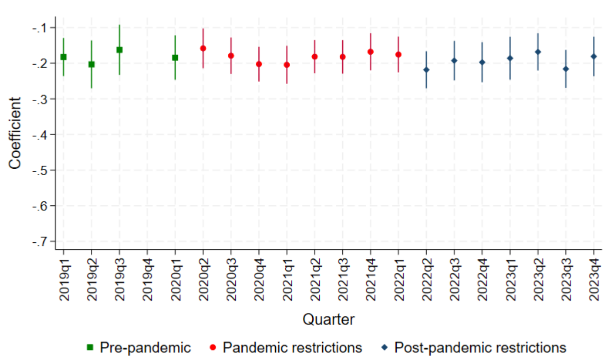
(a) Apartments only, no controls



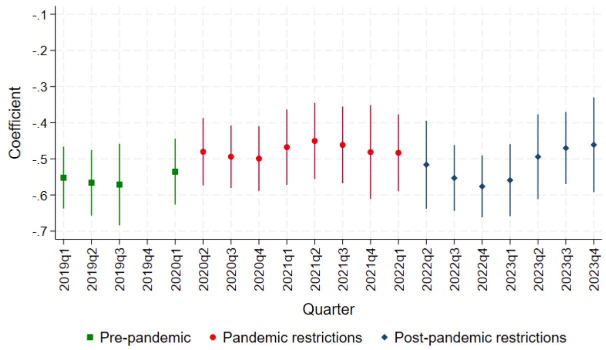
(b) Apartments only, property-level controls



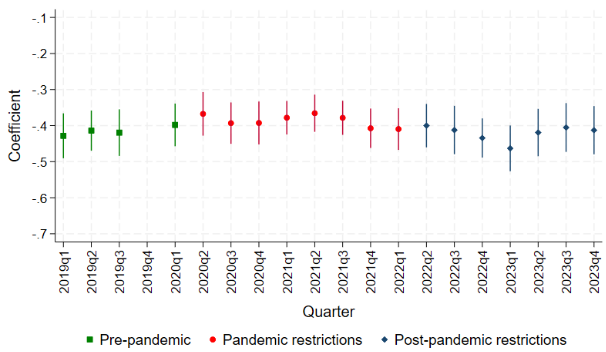
(c) Apartments only, property- and neighborhood-level controls.



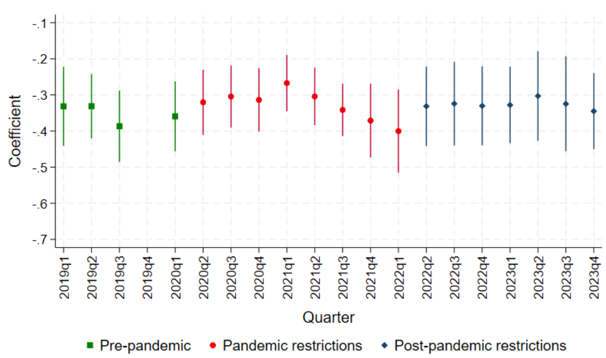
(d) Condo houses, no controls



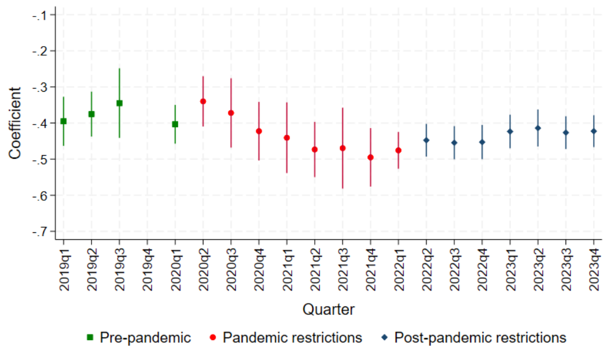
(e) Condo houses, property-level controls



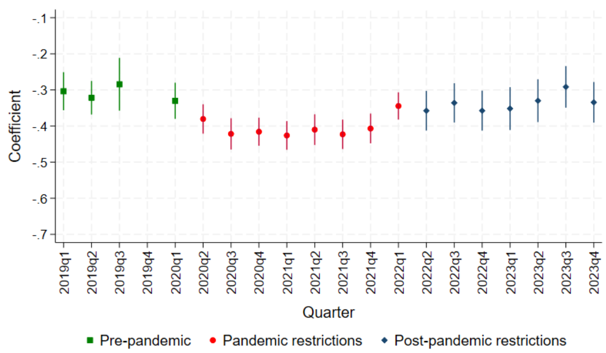
(f) Condo houses, property- and neighborhood-level controls.



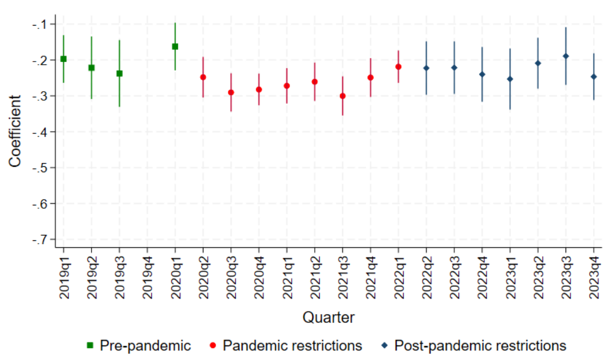
(g) Houses only, no controls



(h) Houses only, property-level controls



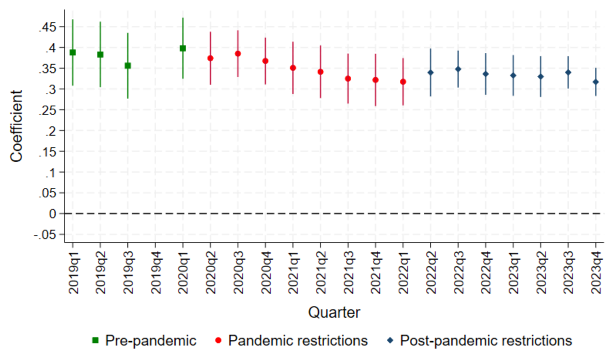
(i) Houses only, property- and neighborhood-level controls.



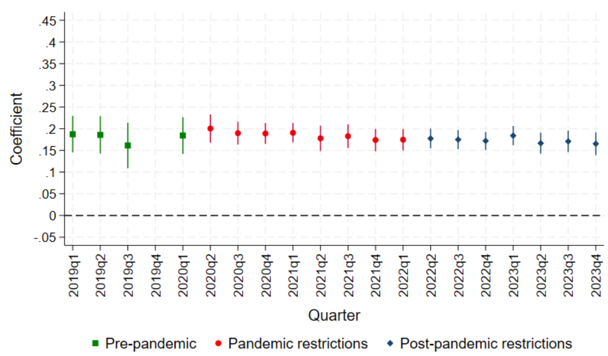
Source: SHF, authors' calculations. Each coefficient is the estimate of δ, the relationship between log housing prices and distance to the city center from equation (1) in each quarter. The bars are confidence intervals at the 95% confidence level. Standard errors clustered by postal code. We exclude 2019 Q4 because of an unusual change in the number of properties.

Figure D.2: Quarterly estimates of the slope of the log price - employment density relationship by property type. Mexico City metropolitan area, 2019-2023.

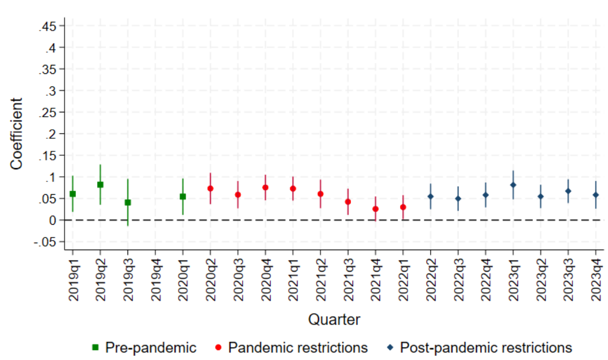
(a) Apartments only, no controls



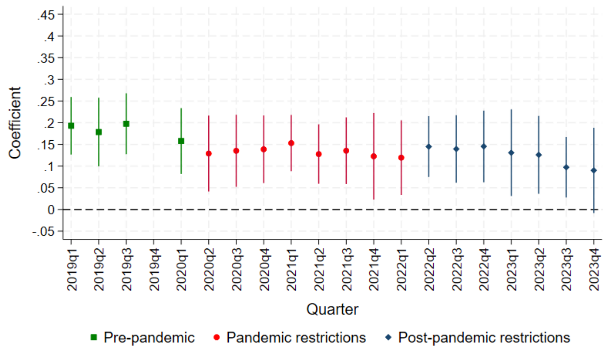
(b) Apartments only, property-level controls



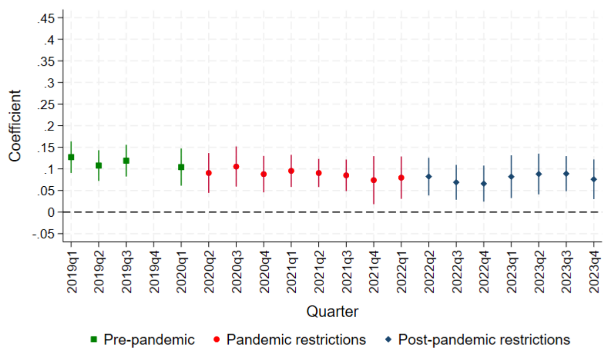
(c) Apartments only, property- and neighborhood-level controls.



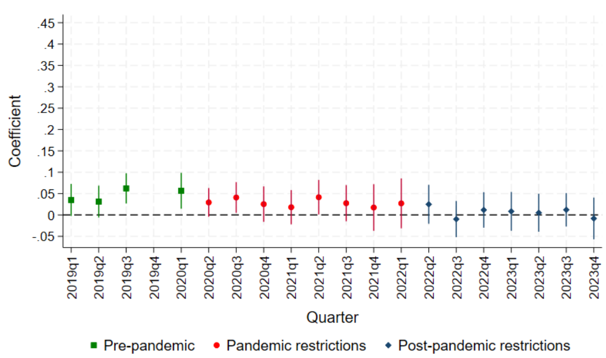
(d) Condo houses, no controls



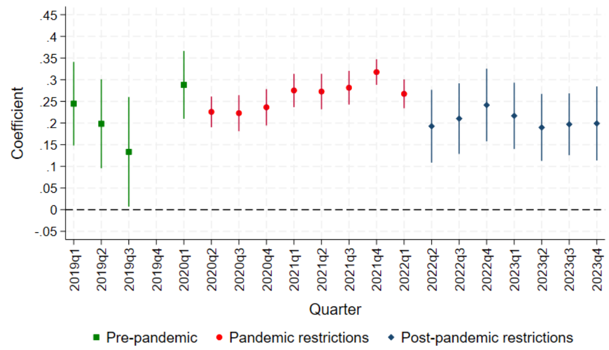
(e) Condo houses, property-level controls



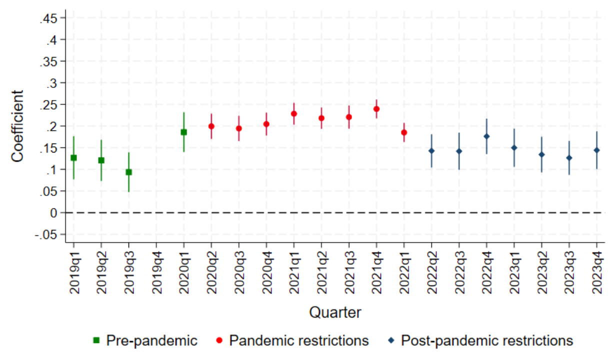
(f) Condo houses, property- and neighborhood-level controls.



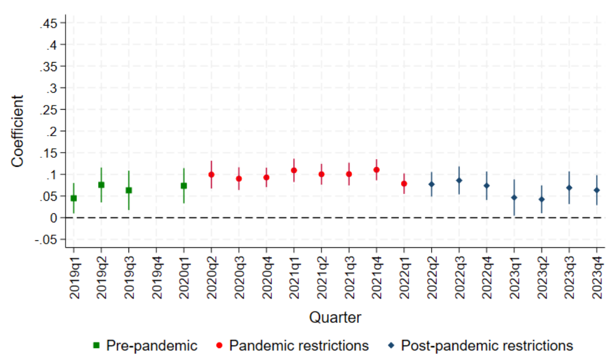
(g) Houses only, no controls



(h) Houses only, property-level controls



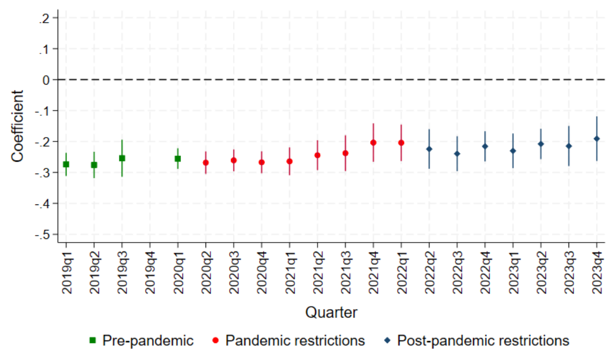
(i) Houses only, property- and neighborhood-level controls.



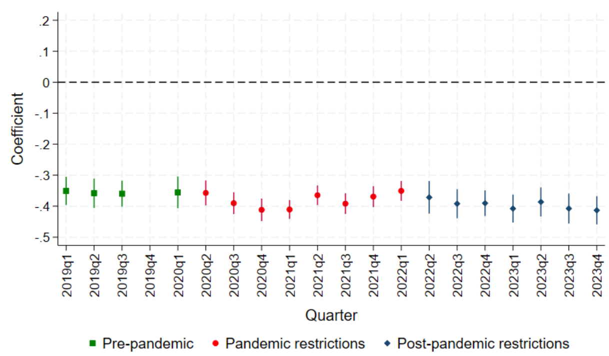
Source: SHF, authors' calculations. Each coefficient is the estimate of δ, the relationship between log housing prices and employment density from equation (1) in each quarter. The bars are confidence intervals at the 95% confidence level. Standard errors clustered by postal code. We exclude 2019 Q4 because of an unusual change in the number of properties.

Figure D.3: Quarterly estimates of the slope of the log price - distance to center relationship by property class. Mexico City metropolitan area, 2019-2023.

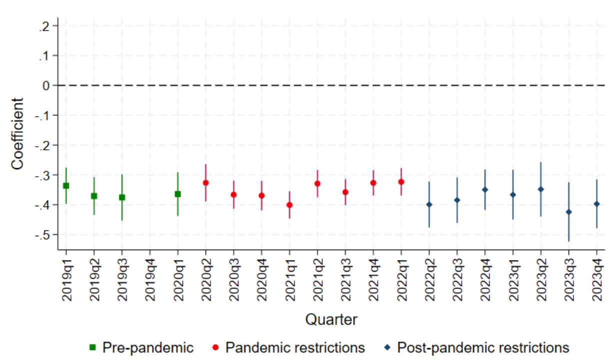
(a) Subsidized housing, no controls



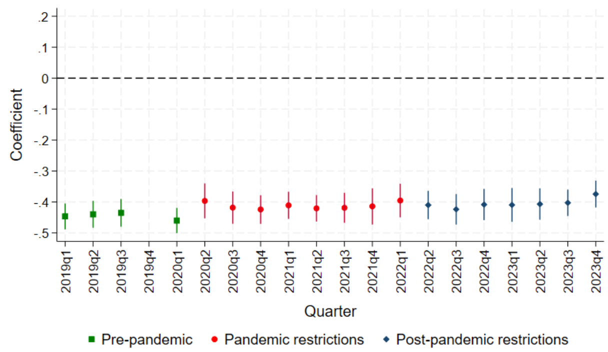
(b) Subsidized housing, property-level controls



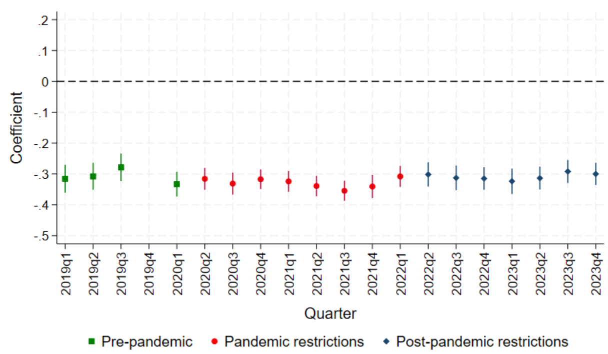
(c) Subsidized housing, property- and neighborhood-level controls.



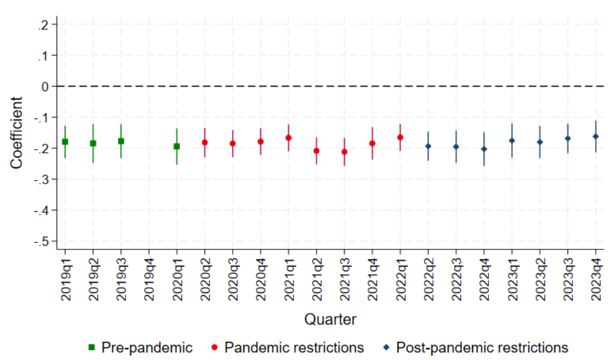
(d) Mid-range housing, no controls



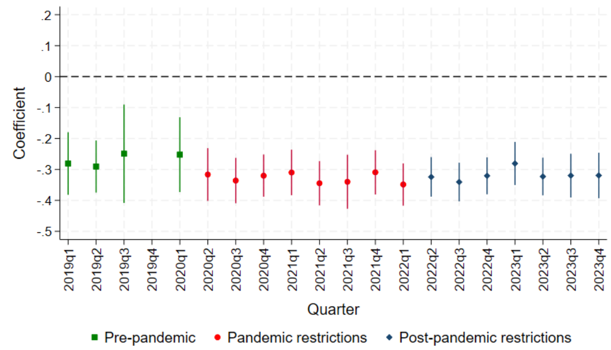
(e) Mid-range housing, property-level controls



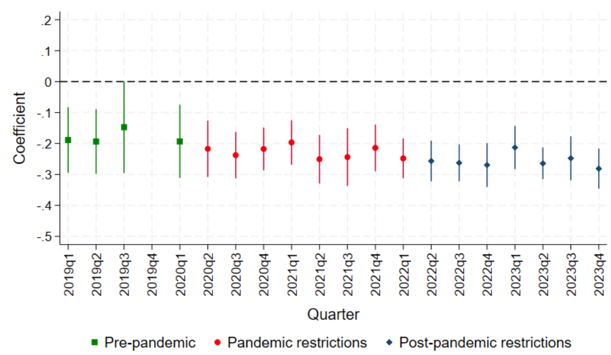
(f) Mid-range housing, property- and neighborhood-level controls.



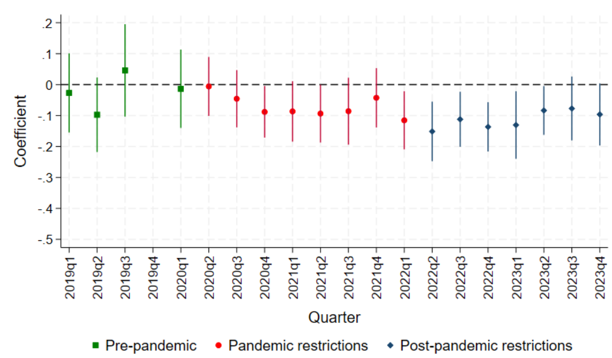
(g) Semi-luxury housing, no controls



(h) Semi-luxury housing, property-level controls



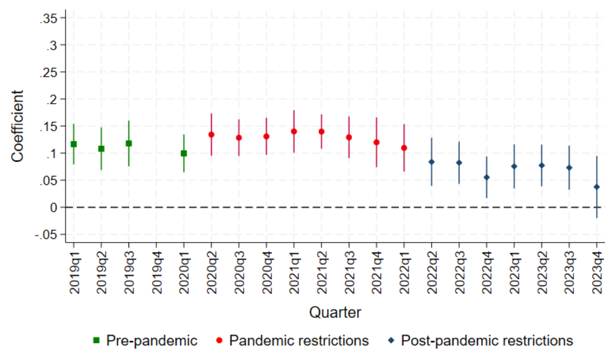
(i) Semi-luxury housing, property- and neighborhood-level controls.



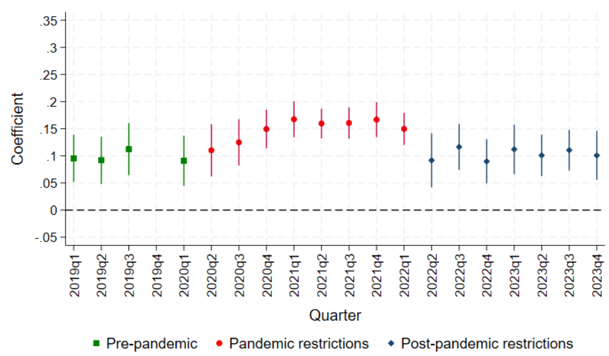
Source: SHF, authors' calculations. Each coefficient is the estimate of δ, the relationship between log housing prices and distance to the city center from equation (1) in each quarter. The bars are confidence intervals at the 95% confidence level. Standard errors clustered by postal code. We exclude 2019 Q4 because of an unusual change in the number of properties.

Figure D.4: Quarterly estimates of the slope of the log price - employment density relationship by property class. Mexico City metropolitan area, 2019-2023.

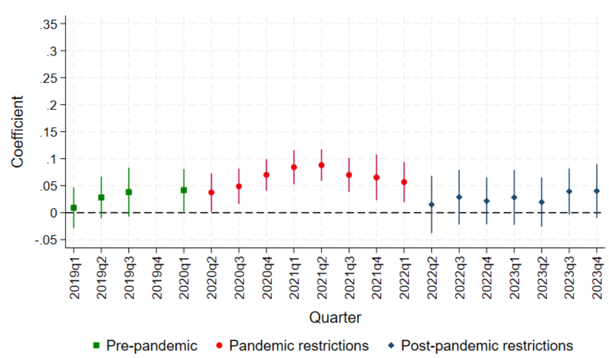
(a) Subsidized housing, no controls



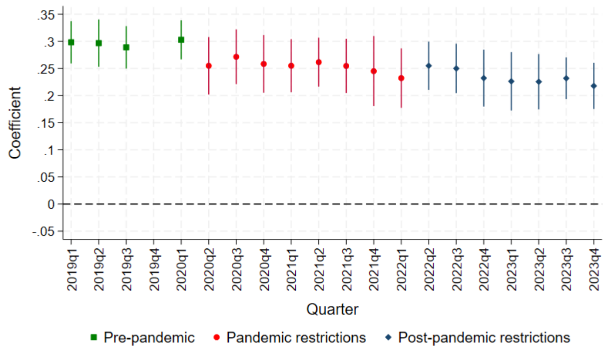
(b) Subsidized housing, property-level controls



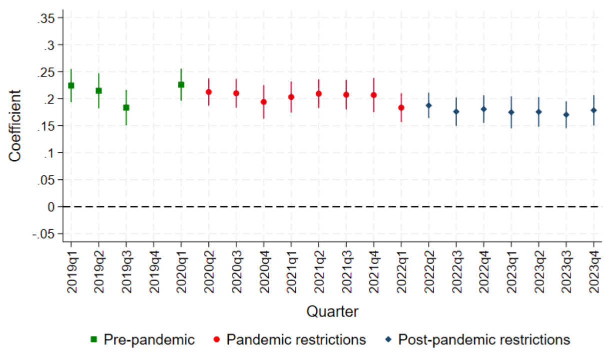
(c) Subsidized housing, property- and neighborhood-level controls.



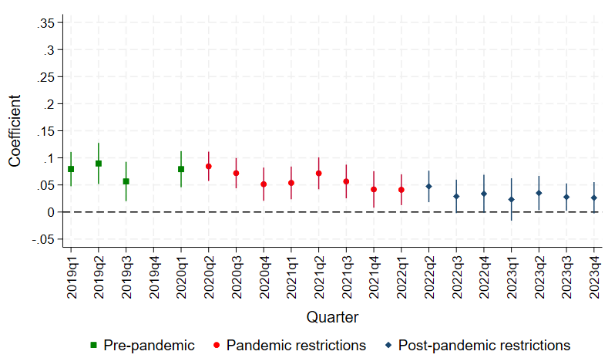
(d) Mid-range housing, no controls



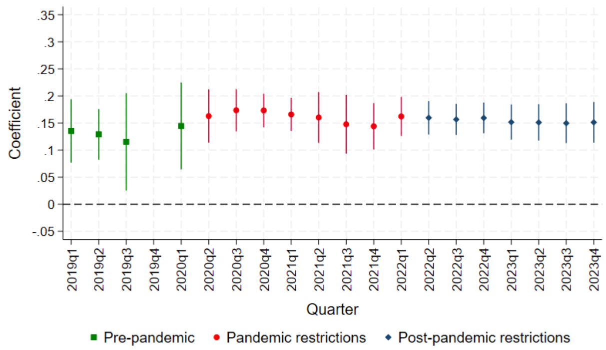
(e) Mid-range housing, property-level controls



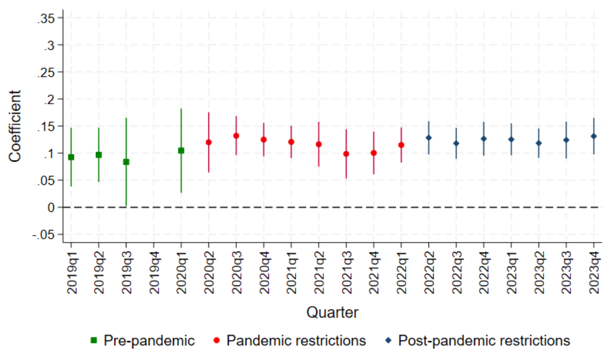
(f) Mid-range housing, property- and neighborhood-level controls.



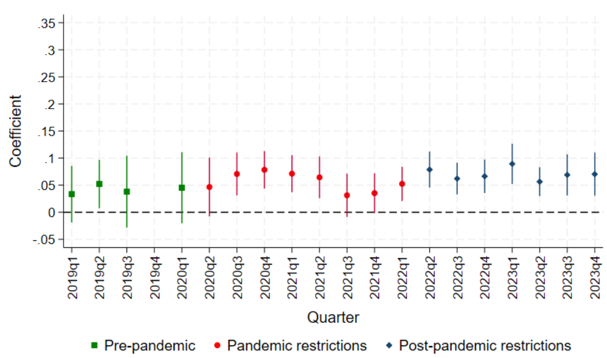
(g) Semi-luxury housing, no controls



(h) Semi-luxury housing, property-level controls



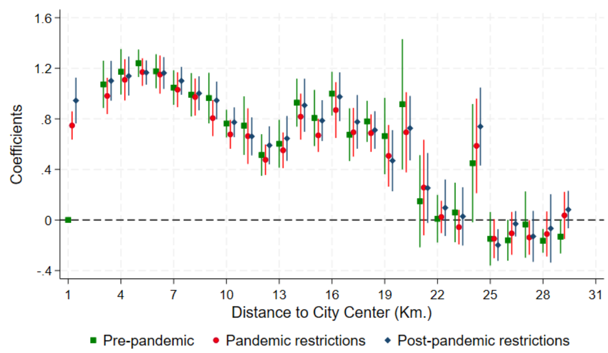
(i) Semi-luxury housing, property- and neighborhood-level controls.



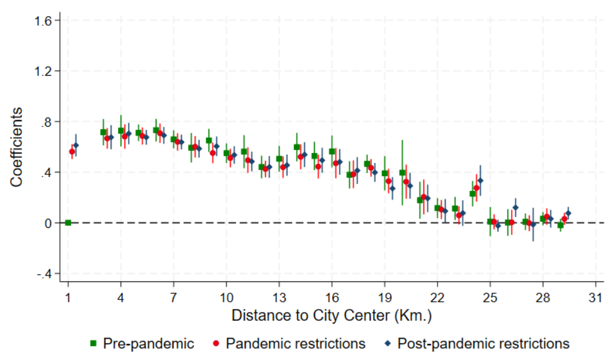
Source: SHF, authors' calculations. Each coefficient is the estimate of δ, the relationship between log housing prices and distance to the city center from equation (1) in each quarter. The bars are confidence intervals at the 95% confidence level. Standard errors clustered by postal code. We exclude 2019 Q4 because of an unusual change in the number of properties.

Figure D.5: Semiparametric estimates of the slope of the log price - distance to center relationship by property type. Mexico City metropolitan area, 2019-2023.

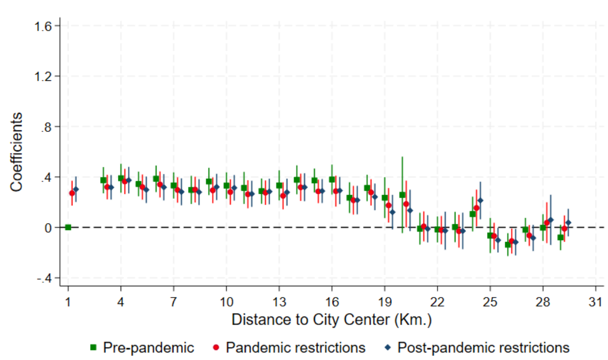
(a) Apartments only, no controls



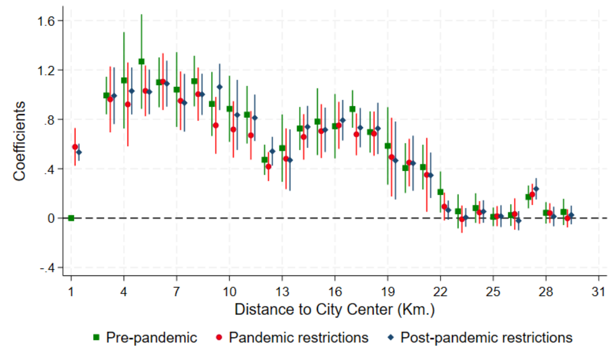
(b) Apartments only, property-level controls



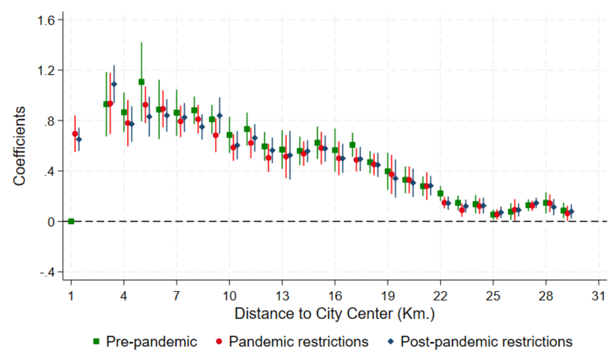
(c) Apartments only, property- and neighborhood-level controls.



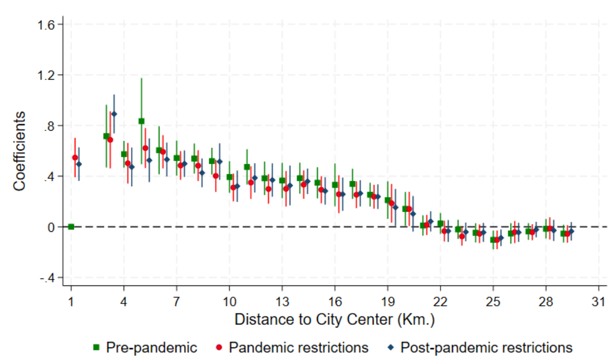
(d) Condo houses, no controls



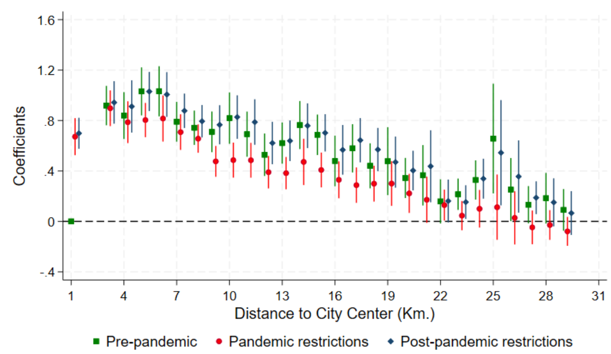
(e) Condo houses, property-level controls



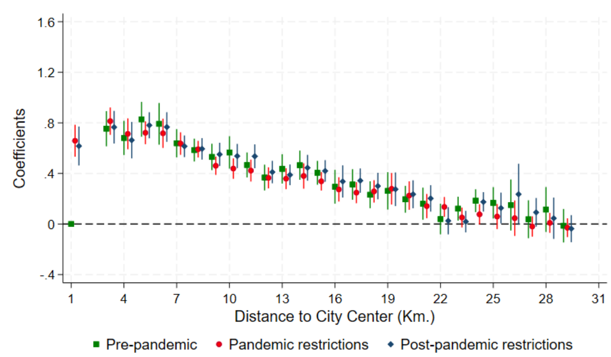
(f) Condo houses, property- and neighborhood-level controls.



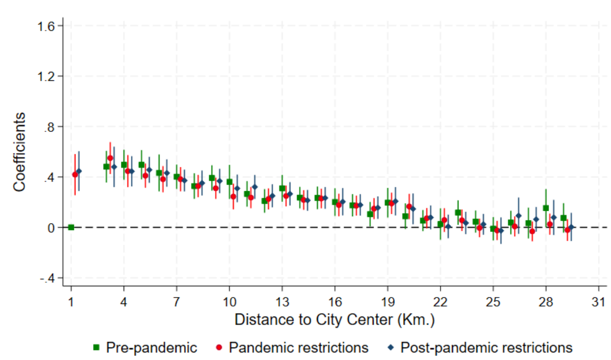
(g) Houses only, no controls



(h) Houses only, property-level controls



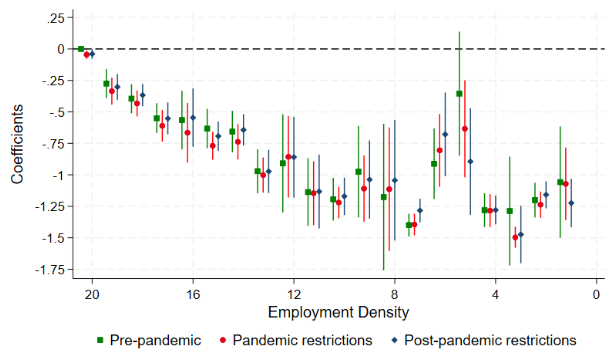
(i) Houses only, property- and neighborhood-level controls.



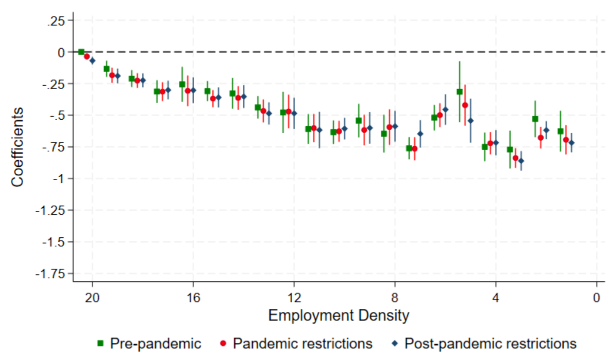
Source: SHF, authors' calculations. Each coefficient is the estimate of δ, the relationship between log housing prices and distance to the city center from equation (2) in each quarter. The bars are confidence intervals at the 95% confidence level. Standard errors clustered by postal code. We exclude 2019 Q4 because of an unusual change in the number of properties.

Figure D.6: Semiparametric estimates of the slope of the log price - employment density relationship by property type. Mexico City metropolitan area, 2019-2023.

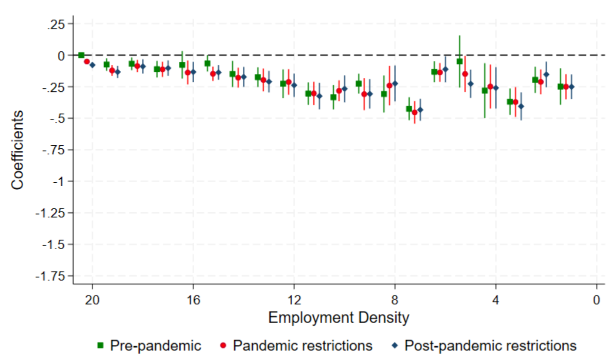
(a) Apartments only, no controls



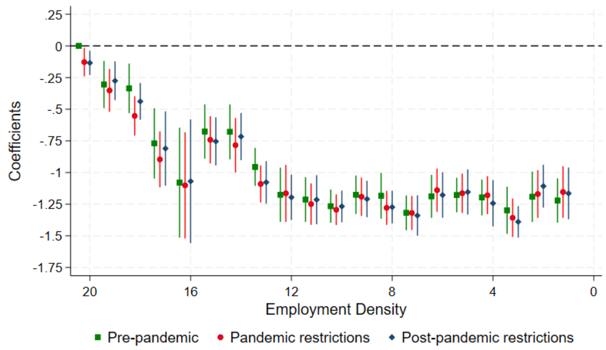
(b) Apartments only, property-level controls



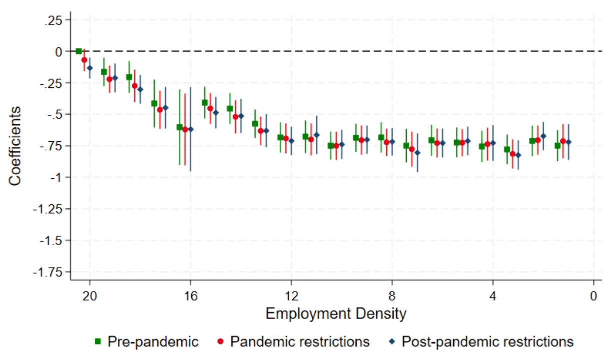
(c) Apartments only, property- and neighborhood-level controls.



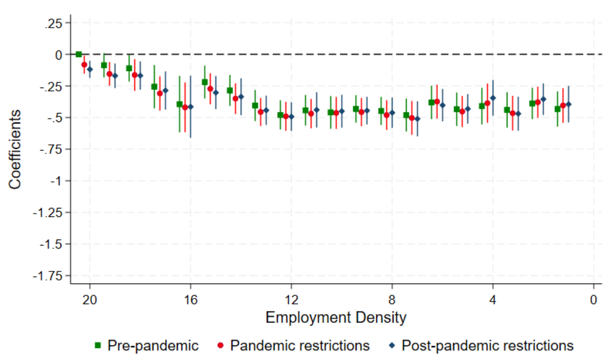
(d) Condo houses, no controls



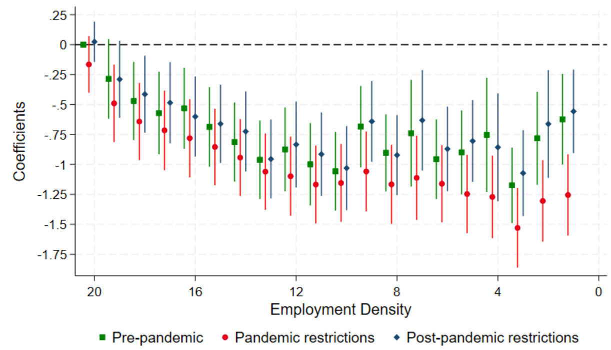
(e) Condo houses, property-level controls



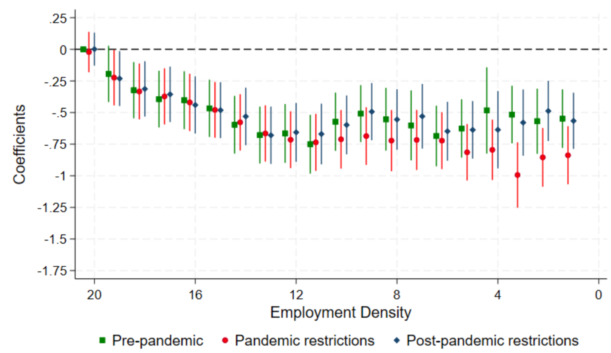
(f) Condo houses, property- and neighborhood-level controls.



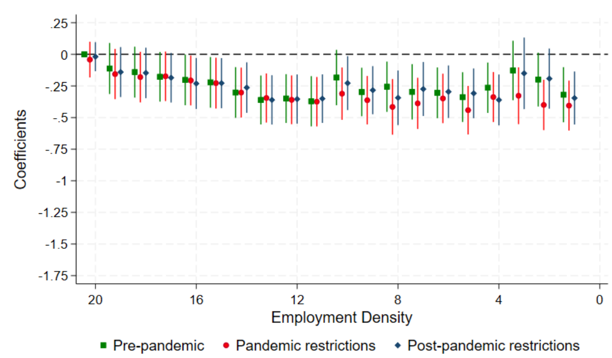
(g) Houses only, no controls



(h) Houses only, property-level controls



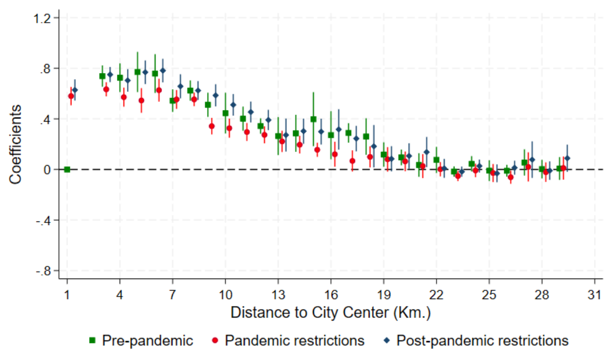
(i) Houses only, property- and neighborhood-level controls.



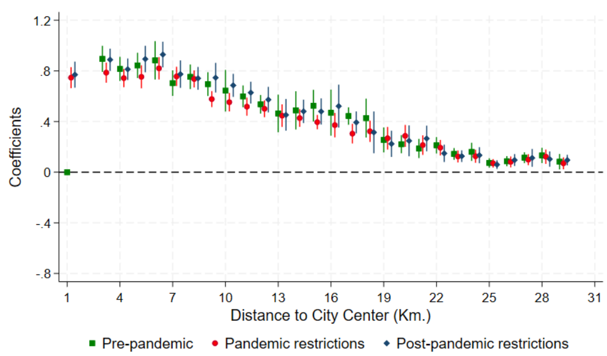
Source: SHF, authors' calculations. Each coefficient is the estimate of δ, the relationship between log housing prices and employment density from equation (2) in each quarter. The bars are confidence intervals at the 95% confidence level. Standard errors clustered by postal code. We exclude 2019 Q4 because of an unusual change in the number of properties.

Figure D.7: Semiparametric estimates of the slope of the log price - distance to center relationship by property class. Mexico City metropolitan area, 2019-2023.

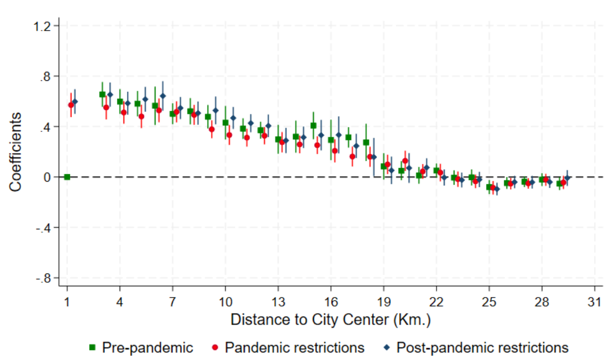
(a) Subsidized housing, no controls



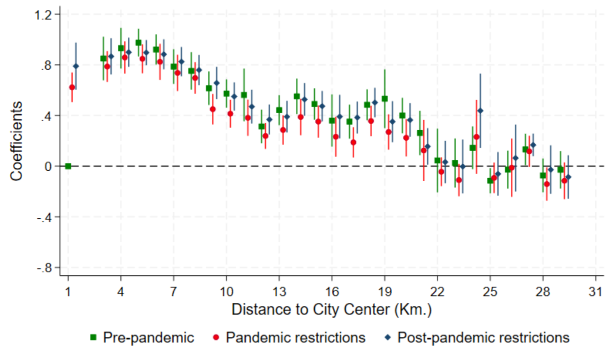
(b) Subsidized housing, property-level controls



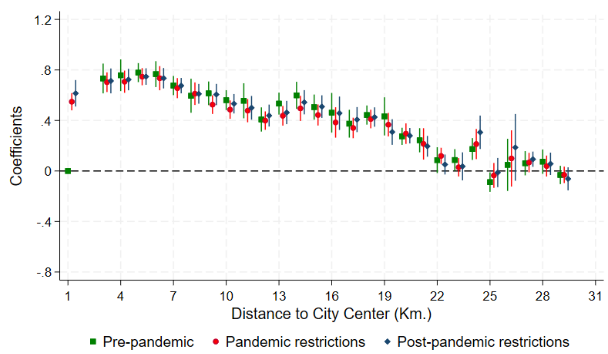
(c) Subsidized housing, property- and neighborhood-level controls.



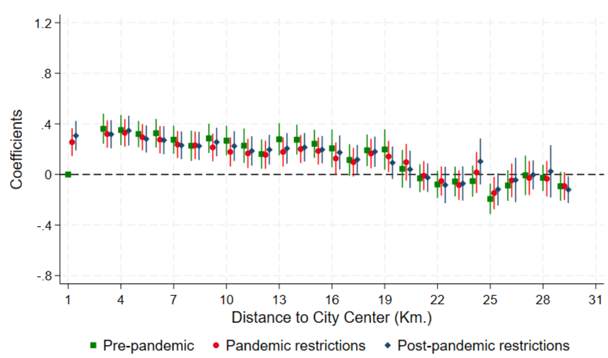
(d) Mid-range housing, no controls



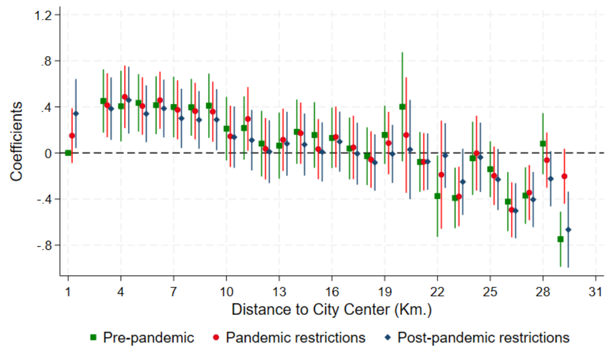
(e) Mid-range housing, property-level controls



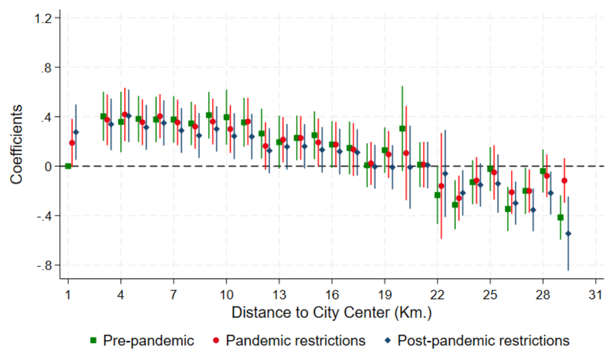
(f) Mid-range housing, property- and neighborhood-level controls.



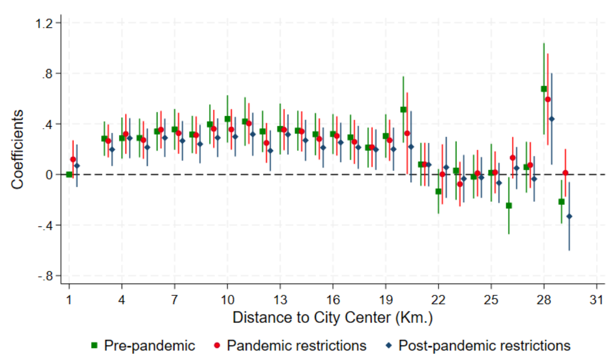
(g) Semi-luxury housing, no controls



(h) Semi-luxury housing, property-level controls



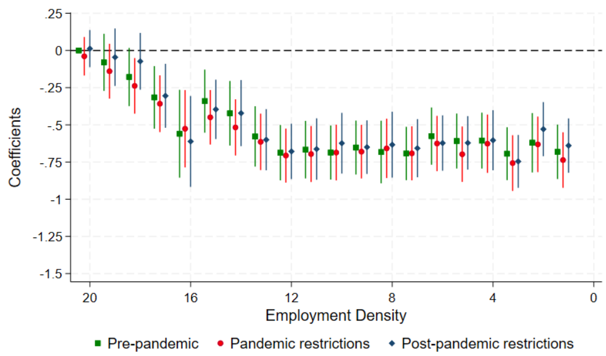
(i) Semi-luxury housing, property- and neighborhood-level controls.



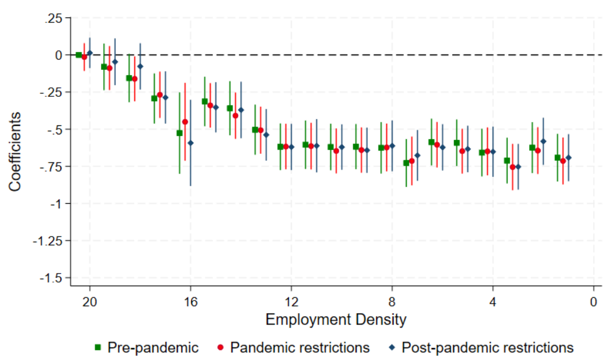
Source: SHF, authors' calculations. Each coefficient is the estimate of δ, the relationship between log housing prices and distance to the city center from equation (2) in each quarter. The bars are confidence intervals at the 95% confidence level. Standard errors clustered by postal code. We exclude 2019 Q4 because of an unusual change in the number of properties.

Figure D.8: Semiparametric estimates of the slope of the log price - employment density relationship by property class. Mexico City metropolitan area, 2019-2023.

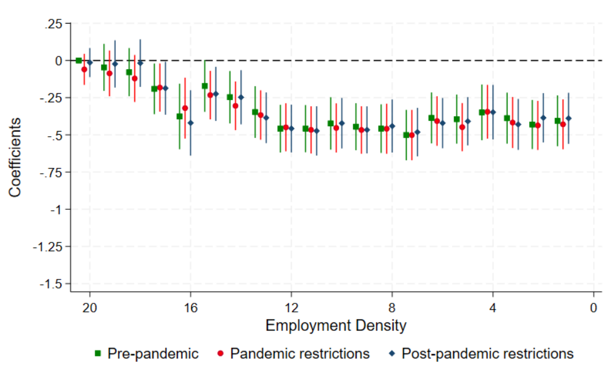
(a) Subsidized housing, no controls



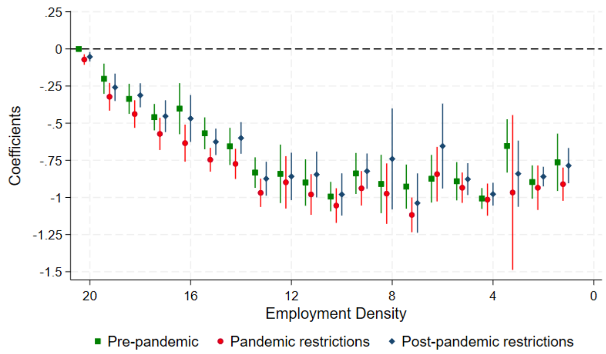
(b) Subsidized housing, property-level controls



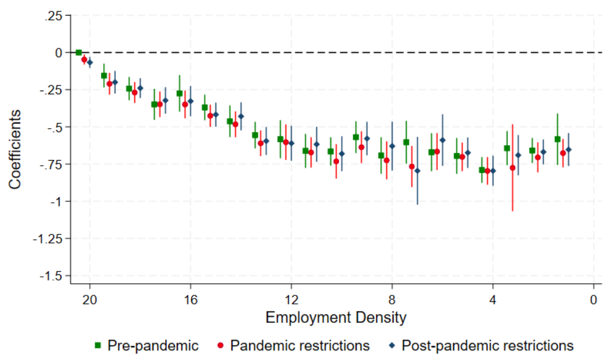
(c) Subsidized housing, property- and neighborhood-level controls.



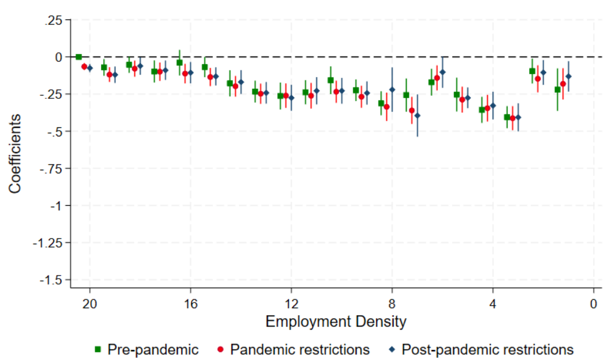
(d) Mid-range housing, no controls



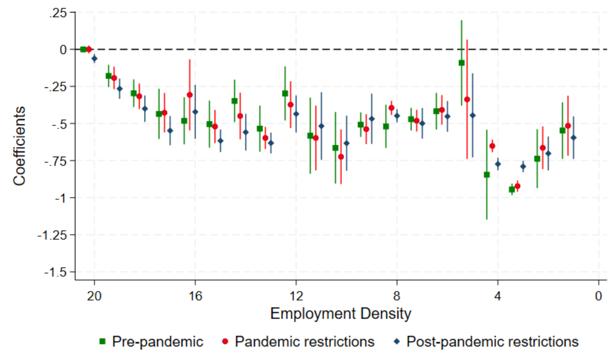
(e) Mid-range housing, property-level controls



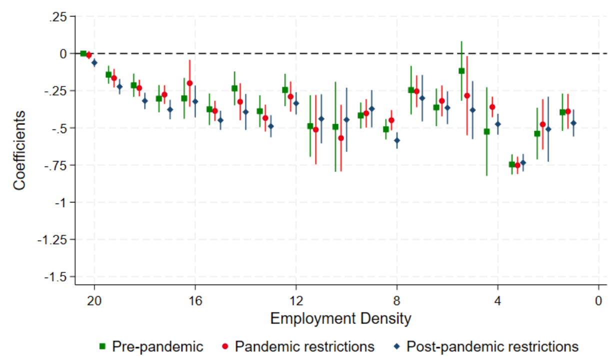
(f) Mid-range housing, property- and neighborhood-level controls.



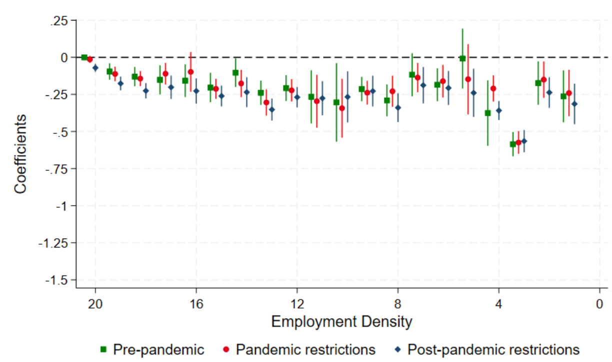
(g) Semi-luxury housing, no controls



(h) Semi-luxury housing, property-level controls



(i) Semi-luxury housing, property- and neighborhood-level controls.

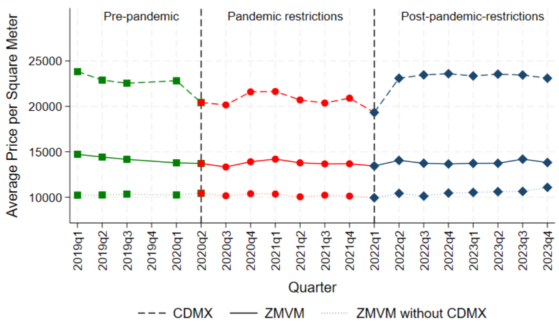


Source: SHF, authors' calculations. Each coefficient is the estimate of δ, the relationship between log housing prices and distance to the city center from equation (2) in each quarter. The bars are confidence intervals at the 95% confidence level. Standard errors clustered by postal code. We exclude 2019 Q4 because of an unusual change in the number of properties.

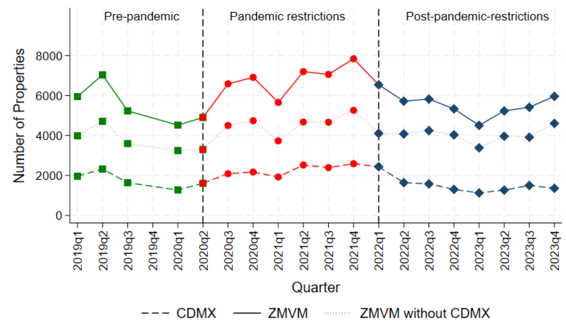
E Additional Figures and Tables

Figure E.1: Average prices and number of properties by property type, Mexico City metropolitan area, 2019 Q1 - 2023 Q4

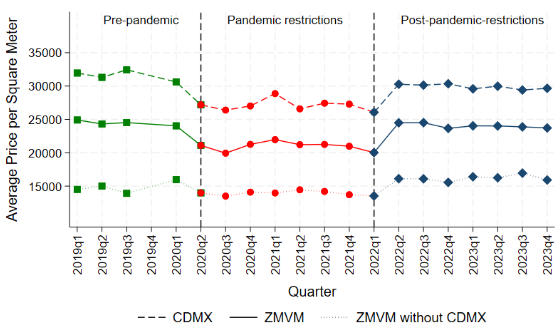
(a) Average price per square meter. 2 bedroom - 1 bathroom properties.



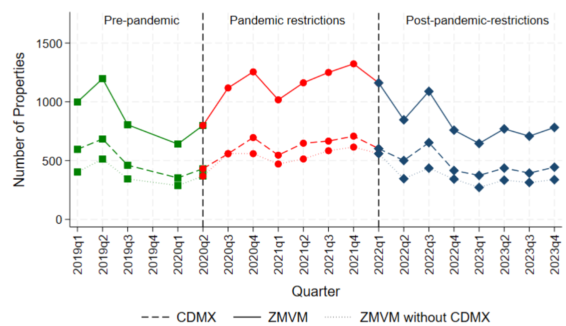
(b) Number of properties. 2 bedroom - 1 bathroom properties.



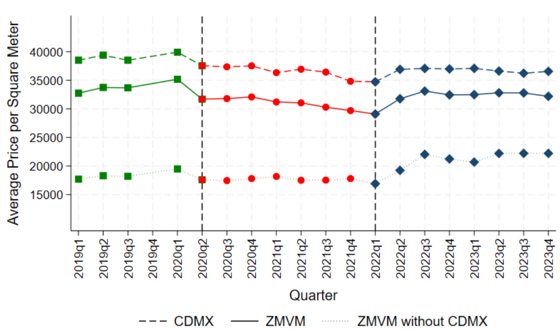
(c) Average price per square meter. 3 bedroom - 2 bathroom properties.



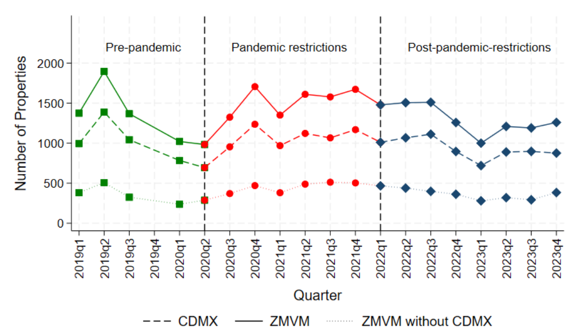
(d) Number of properties. 3 bedroom - 2 bathroom properties.



(e) Average price per square meter. 2 bedroom - 2 bathroom properties



(f) Number of properties. 2 bedroom - 2 bathroom properties



Source: SHF, authors' calculations. We exclude 2019 Q4 because of an unusual change in the number of properties. Prices are July 2018 pesos.

Table E.1: Distance from Mexico City's boroughs and metro area municipalities to city center

Municipality	Distance to Zócalo (km)	Municipality	Distance to Zócalo (km)	Municipality	Distance to Zócalo (km)
Nearby municipalities		**Intermediate municipalities**		**Far-away municipalities**	
Cuaútemoc	1.647	Valle de Chalco Solidaridad	25.986	Temamatla	37.589
Venustiano Carranza	4.234	Cuautitlán Izcalli	26.439	Ixtapaluca	38.512
Iztacalco	5.659	Tlalpan	26.989	Teotihuacán	39.393
Benito Juárez	6.401	Chicoloapan	27.019	Coyotepec	40.695
Miguel Hidalgo	7.489	Tultepec	27.400	Tepetlaoxtoc	41.483
Azcapotzalco	7.800	Tezoyuca	27.968	Tenango del Aire	41.588
Gustavo A. Madero	8.172	Jilotzingo	28.202	Zumpango	42.228
Nezahualcóyotl	11.674	Chinconcuac	28.395	Juchitepec	44.559
Coyoacán	11.810	Tonanitla	28.740	San Martín de las Pirámides	44.862
Iztapalapa	12.209	Chiautla	30.485	Huehuetoca	45.072
Tlalnepantla de Baz	12.839	Cuautitlán	30.684	Ayapango	47.663
Álvaro Obregón	15.964	Melchor Ocampo	30.721	Otumba	48.297
Naucalpan de Juárez	17.272	Acolman	31.630	Villa del Carbón	48.306
Ecatepec de Morelos	18.221	Papalotla	32.196	Tlalmanalco	48.888
Chimalhuacán	19.630	Texcoco	32.398	Tizayuca	49.920
Atizapán de Zaragoza	20.826	Milpa Alta	33.533	Temascalapa	50.355
La Paz	21.148	Nextlalpan	33.541	Tequixquiac	52.335
Xochimilco	21.187	Tecámac	33.992	Amecameca	55.466
Tultitlán	21.520	Jaltenco	34.257	Tepetlixpa	55.924
Coacalco de Berriozábal	21.738	Nicolás Romero	34.512	Axapusco	56.668
Atenco	21.921	Isidro Fabela	34.948	Ozumba	56.764
Tláhuac	21.980	Teoloyucan	36.721	Hueypoxtla	58.644
Cuajimalpa de Morelos	22.107	Cocotitlán	36.777	Nopaltepec	60.647
Huixquilucan	22.304	Tepotzotlán	37.167	Apaxco	61.168
La Magdalena Contreras	22.967	Chalco	37.355	Atlautla	62.343
				Ecatzingo	66.182

Source: Author's calculations.

Table E.2: Distance and density gradient estimates, Mexico City metropolitan area 2019-2022. Log area as a control.

	Pre-pandemic			Pandemic restrictions			Post-pandemic-restrictions		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A									
log(distance + 1)	-0.535***	-0.334***	-0.245***	-0.509***	-0.372***	-0.269***	-0.515***	-0.342***	-0.264***
	(0.021)	(0.018)	(0.024)	(0.023)	(0.013)	(0.017)	(0.018)	(0.015)	(0.020)
log(Built surface)	1.202***	0.964***	0.824***	1.046***	0.792***	0.722***	1.171***	0.948***	0.822***
	(0.020)	(0.022)	(0.021)	(0.019)	(0.011)	(0.011)	(0.017)	(0.017)	(0.022)
p-value log(Built surface) = 1	0.000	0.095	0.000	0.016	0.000	0.000	0.000	0.002	0.000
N	61308	61308	60377	145194	145194	142991	94374	94374	94007
R-squared	0.807	0.911	0.937	0.712	0.864	0.894	0.830	0.917	0.939
Panel B									
log(employment density)	0.328***	0.168***	0.063***	0.309***	0.190***	0.069***	0.293***	0.160***	0.054***
	(0.019)	(0.014)	(0.016)	(0.022)	(0.011)	(0.012)	(0.021)	(0.010)	(0.014)
log(Built surface)	1.259***	1.014***	0.853***	1.078***	0.820***	0.739***	1.215***	0.975***	0.852***
	(0.032)	(0.027)	(0.023)	(0.024)	(0.013)	(0.012)	(0.025)	(0.021)	(0.020)
p-value log(Built surface) = 1	0.000	0.603	0.000	0.001	0.000	0.000	0.000	0.240	0.000
N	57807	57807	57722	138545	138545	138383	88739	88739	88654
R-squared	0.765	0.901	0.930	0.674	0.849	0.885	0.784	0.908	0.934
Number of quarters	4	4	4	8	8	8	7	7	7
Controls									
Property		Yes	Yes		Yes	Yes		Yes	Yes
Neighborhood			Yes			Yes			Yes
Fixed Effects									
Quarter	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: SHF, authors' calculations. The table displays estimates of the relationship between log housing prices, distance to the center and employment density, controlling for area. Panel A shows estimates of the relationship between housing prices and log distance to the center. Panel B shows estimates of the relationship between log housing prices and log employment density. We exclude 2019 Q4 because of an unusual change in the number of properties.