PERCEPTION OF PUBLIC INSECURITY AND HOUSING PRICES IN MEXICO

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ABSTRACT

This paper evaluates the impact of the perception of public insecurity on housing prices in Mexico. To that end, two dynamic panel data models involving 27 Mexican cities are assembled. The first model corresponds to the pre-pandemic period, while the second to the pandemic period. The specification of the model is based on a supply- and demand-side approach, whereas its estimation relies on the Arellano-Bond technique to address endogeneity problems. The evidence is consistent in showing that: 1) Housing prices fall as the perception of public insecurity rises, and 2) higher construction costs and income levels raise home prices. Moreover, the provision of public infrastructure and the real mortgage interest rate generate demand- and supply-side effects, so the net effect of these two variables on housing prices is negative before the pandemic and positive during the pandemic. Finally, housing prices involve a strong inertial component.

Keywords: Perception of public insecurity, housing prices, panel data models, instrumental variables estimation.
JEL Classification: C23, C26, K42, R31.

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PERCEPCIÓN DE INSEGURIDAD PÚBLICA Y PRECIOS DE LAS CASAS EN MÉXICO

RESUMEN

Este trabajo evalúa el impacto de la percepción de inseguridad pública en los precios de las viviendas en México. Para tal fin, se emplean dos modelos dinámicos de datos en panel que involucran 27 ciudades. El primero corresponde al periodo pre-pandemia, mientras que el segundo al periodo de la pandemia. La especificación del modelo se basa en un enfoque de oferta y demanda, mientras que la estimación se realiza mediante el procedimiento Arellano- Bond para atender problemas de endogeneidad. La evidencia indica que: 1) los precios de las viviendas caen conforme aumenta la percepción de inseguridad pública, y 2) mayores costos de construcción y niveles de ingreso encarecen las viviendas. Asimismo, la provisión de infraestructura pública y el costo real del crédito hipotecario generan efectos de oferta y demanda, por lo que el efecto neto de estas dos variables sobre el precio de las casas es negativo antes de la pandemia y positivo durante la pandemia. Finalmente, los precios de las casas involucran un fuerte componente inercial.

Palabras clave: percepción de inseguridad pública, precios de las casas, modelos de datos en panel, estimación por variables instrumentales.

Clasificación JEL: C23, C26, K42, R31.

1. INTRODUCTION

This research focuses on the impact of the perception of public insecurity and other key variables on home prices in Mexico. To that end, two-panel data sets with 27 Mexican cities in the cross-section dimension are assembled[1]. The first dataset contains pre-pandemic quarterly data from Q1 2016 to Q2 2019, while the second covers the pandemic period from Q3 2019 to Q3 2023. Although the pandemic in Mexico did not start until early 2020, the way to calculate the level of public insecurity in Mexico City (which is one of the 27 cities of the

[1] Those cities are listed in Appendix 1.

sample) changed in the third quarter of 2019. Such a change had to do with the degree of data disaggregation[2] and brought about a sudden shift in the measure of public insecurity, making it convenient to separate the first and second data sets at that juncture. The use of these two estimation periods allows for making historical comparisons and properly employing the Arellano-Bond (AB) estimator, which requires the number of cities to be significantly larger than the number of periods in the panel. The central hypothesis here is that the perception of public insecurity bears a negative relationship with housing prices, after controlling for the effects of other relevant variables.

Broadly speaking, urban areas in Mexico are plagued by crime and insecurity. High crime rates tend to raise the perception of danger in streets and pathways, restaurants and bars, public transportation hubs, commercial centers, street automated teller machines (ATMs), and parks. The perception of insecurity is also linked to the frequency of homes being broken into, either to steal valuables or to inflict property damage. As the perceived risk in certain locations rises, potential homebuyers become more discouraged. This, in turn, lowers demand for housing in dangerous cities and neighborhoods, thereby pushing property prices down. Furthermore, the pervasive environment created by extreme crime and violence tends to bring down private investment and employment opportunities, giving rise to social fabric deterioration and flight of residents. In contrast, a relatively higher perception of safety in certain cities tends to attract not only more buyers but also wealthier buyers, which pushes property prices up through an enhanced demand.

Most papers examining the effects of local crime on house prices involve cities in developed countries. In fact, there is a shortage of studies focused on cities in developing countries, and even more so in the case of Latin America (Margaretic and Sosa, 2023, p. 1; Atuesta and Carrasco, 2023, p. 1203). Moreover, most of those studies rely on aggregated data rather than panel data (Atuesta and Carrasco, 2023, p. 1203). Therefore, it is relevant to conduct further research on this matter, especially in the

[2] From Q1 2016 to Q2 2019, the level of public insecurity in Mexico City was calculated as the average across its four broad regions: North, South, East and West. Nonetheless, as of Q3 2019, the level of public insecurity is calculated as the average across the 16 boroughs (*i.e.*, alcaldías) of Mexico City.

case of Mexican cities where widespread criminal activity has become a major concern.

It is worth noting that housing prices are influenced by a wide range of factors associated with different theories, which are not necessarily mutually exclusive. One strand of the literature mainly focuses on the role played by consumer preferences and budget constraints (Rosen, 1979; Maclennan, 1982). A closely related approach is the one referred to as the hedonic price theory, according to which home prices respond to structural attributes such as the number of rooms and bathrooms, the lot size, and the quality of construction materials (Rosen, 1974; Baltagi, 2015). The locational theory regards houses as investment opportunities and, therefore, takes account of other determinants of home prices, such as proximity to parks and commercial centers, the availability of good public infrastructure, and other external amenity variables that could potentially lead to property appreciation in the long term (Alonso, 1964; Brueckner, 1987). Lastly, the rule-of-law perspective emphasizes the importance of developing strong institutions, particularly in areas such as criminal justice, poverty reduction, education, job creation, and political stability, given that high crime rates and widespread public insecurity can lower property values in certain cities and neighborhoods (Gibbons and Machin, 2008; Delgado-Fernández and Wences-Nájera, 2018; Ceccato and Wilhelmsson, 2011, 2020; González-Juárez *et al.*, 2021; Atuesta and Carrasco, 2023).

Along these lines, some papers combine the hedonic approach, which is mostly based on the structural characteristics of homes, with the governance perspective, highlighting the impact of crime, violence, and weak governance (mainly in terms of law and order) on property prices (Tita, Petras and Greenbaum, 2006; Ceccato and Wilhelmsson, 2011; Delgado-Fernández and Wences-Nájera, 2018; González-Juárez *et al.*, 2021).

Since this paper relies on housing price indices instead of individual house prices, our model is not based on a hedonic price approach that involves the structural characteristics of homes or their locational advantages. As we shall see here, the selection of variables is based on a supply- and demand-side model similar to the one used by Donald and Winkler (2002). Moreover, in addition to the impact of urban danger, this paper assesses the effect of the following variables on home prices: Construction costs, public physical infrastructure[3], income level, and real mortgage interest rates. For each of these variables, it was possible to find or construct disaggregated information for the 27 cities of the sample. Nonetheless, such a selection is restricted by the availability of disaggregated data.

To obtain more robust empirical evidence, a dynamic panel data model is specified and then estimated by the AB estimator. The AB estimator is also known as difference Generalized Method of Moments (GMM). Under certain conditions, the AB estimator is robust to endogeneity problems and consistent, regardless of the behavior of the model's residuals (Arellano and Bond, 1991; Baltagi, 2008, p. 150). This paper makes sure that such conditions are reasonably satisfied. Along these lines, the empirical evidence points to the following conclusions:

1. The perception of public insecurity has a negative impact on home prices, which are measured through the housing price indices provided by the Sociedad Hipotecaria Federal (SIF). In other words, rising crime rates bring down the market value of houses, apartments, and condominiums, which is consistent with the central hypothesis of this investigation.
2. Higher construction costs result in higher home prices, given that more expensive materials, machinery and labor make it more costly to build new homes and provide maintenance to the existing ones.
3. State-level economic activity, which is used as a proxy for the income level of each city, yields a positive effect on house prices.
4. The provision of public infrastructure[4] and the real mortgage interest rate are considered to affect both the demand and the supply of housing. In this context, both variables generate a negative effect on housing prices in the pre-pandemic period and a positive effect in the pandemic period. Therefore, sections 4 and 5 examine the channels through which these two variables can influence housing demand and supply.

This paper is divided into four sections. Section 2 briefly reviews the empirical literature. Section 3 explains the model, the data, and the

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[3] This variable can be regarded as an external amenity variable.

[4] As section 3 explains, this is a composite variable reflecting different types of foundational physical systems provided by the government in each city.

econometric procedures, whereas section 4 presents the econometric evidence. Finally, the conclusions are devoted to interpreting the empirical findings and discussing their policy implications.

2. LITERATURE REVIEW

Many papers investigate the impact of crime on housing prices, but most of them are devoted to developed nations and are limited to a single city. In this context, based on data regarding 2,800 house sales in Jacksonville, Florida, during the period July 1994-June 1995, Lynch and Rasmussen (2001) analyze the impact of crime on home prices. To that end, they gathered crime data from 89 police beats in the city. To avoid specification errors, home selling prices are regressed not only on crime data but also on a vector of structural and neighborhood characteristics. Therefore, the model is hedonic because the attributes of the houses and the neighborhoods of Jacksonville are being considered. Such a model is estimated through Ordinary Least Squares (OLS) and is one of the earliest investigations showing the negative impact of crime on property values.

Tita, Petras, and Greenbaum (2006) contend that local housing markets are an early indicator of neighborhood deterioration due to crime. Based on data for the city of Columbus, Ohio, during the period 1995-1998, they specify a hedonic model of house prices including the following regressors: House characteristics (such as square feet and number of bedrooms), location characteristics (such as population), per capita income, and crime rates. Moreover, these authors disaggregate crime data and per capita income to the census tract level. All in all, they considered 43,577 housing sales in 189 tracts during the reference period (1995-1998). In this context, they make use of instrumental variables estimation to address endogeneity issues. Lastly, this paper differentiates between property and violent crime, showing that the latter has a stronger negative impact on home market values. The rationale behind this finding is that violent crime engenders a greater psychological impact in the neighborhoods (Klimova and Lee, 2014).

Ihlanfeldt and Mayock (2010) also addressed the effects of different types of crime on property prices. In this perspective, they employ panel data stemming from Miami-Dade County, Florida. The panel considers all house transactions over the period 1999-2007 in each neighborhood of such a county, so disaggregated data are utilized. Moreover, the following types of crime occurring in each neighborhood are recorded: Burglary, motor theft, larceny, vandalism, rape, aggravated assault, and murder. Therefore, by means of instrumental variables estimation, these authors show that more violent crimes, such as aggravated assault and murder, exert greater downward pressure on home prices, which is consistent with the findings of Tita, Petras, and Greenbaum (2006) for Columbus, Ohio.

In the same vein of research, Ceccato and Wilhelmsson (2011) study the impact of fear of crime, on the one hand, and vandalism, on the other, on apartment prices in Stockholm, the capital of Sweden. To that end, they specify a hedonic price model involving the structural characteristics of the homes (such as the number of bedrooms) as well as the characteristics of the neighborhoods (such as the quality of public services) in which they are located. To estimate the model, they also employ data regarding apartment sales prices and different crime-related variables. All the information pertains to the year 2008 and is disaggregated across the different neighborhoods of Stockholm. Their main result is that not only vandalism leads to lower apartment prices but also the mere fear of crime.

Boggess, Greenbaum, and Tita (2013) maintain that property prices are not the best indicator of the impact of crime rates on the housing market. According to them, high crime rates influence not only house prices but also housing turnover. Therefore, these authors assess the impact of violent and property crime on housing transactions rather than housing prices. Using data from Los Angeles neighborhoods during the period 1993-1997 and the OLS method, they show that crime rates bear a positive relationship with home sales. In this context, they conclude that widespread crime brings about "homeowner instability."

Buonanno, Montolio, and Raya-Vílchez (2013) study the impact of crime perception in Barcelona, using data from the different districts of such a city from 2004 to 2006. During this period, 1,653 apartment transactions were undertaken across the city. For each transaction, the authors collect data on structural attributes (*e.g.*, square meters and number of bedrooms) and the district where the apartment was sold. Such information is combined with a victimization survey, which allows them to estimate the crime perception in each district. To address endogeneity issues, these authors employ instrumental variables estimation. The evidence here shows that district security is associated with higher apartment values and vice versa.

Delgado-Fernández and Wences-Nájera (2018) evaluate the effect of insecurity on housing prices in Acapulco de Juárez, Mexico. To assess the level of insecurity, they make use of the distance of homes to the most unsafe neighborhood in Acapulco, which is Ciudad Renacimiento. Their model is hedonic because it considers the main physical characteristics of each house and its locational advantages, such as proximity to the beach, view of the beach, and whether it is in a relatively safe private area or not. Based on the OLS method and a sample of 184 homes sold in December 2016, this paper concludes that home prices tend to fall as they get closer to Ciudad Renacimiento.

Within this line of research, Ceccato and Wilhelmsson (2020) establish that proximity to "crime hot spots" lowers property market values. This finding is based on data for the metropolitan region of Stockholm, Sweden, during the period January-December 2013. Within this region and timeframe, these authors recorded 118,520 property transactions involving single- and multi-family homes. In this context, based on OLS estimations, they conclude that proximity to crime hot spots has a greater negative influence on Stockholm's property prices than the crime rates themselves.

As opposed to previous studies, Wong *et al.* (2020) assess the impact of crime activity on home market values at a national level, using the case of Malaysia through the 1988-2016 period. Moreover, rather than collecting individual home prices, this investigation resorts to state-level property indices as the model's dependent variable, whereas the state-level reported crime rate is the key regressor. In this context, two different types of crimes are considered: Violent crimes (*i.e.*, murder, rape, robbery, and aggravated assault) and property crimes (*i.e.*, burglary, theft, auto theft, and snatching). Therefore, panel OLS estimations show that violent crimes deliver a more robust negative impact on property prices.

González-Juárez *et al.* (2021) employ a hedonic price approach with structural and environmental variables to estimate the impact of public insecurity on housing prices across six municipalities of Guanajuato, Mexico. The data collected comprised 273 house listings across the municipalities of Celaya, Salamanca, Silao, León, Irapuato, and San Miguel de Allende in 2019. The structural variables included here are number of bedrooms, bathrooms, parking spaces, square meters of land area, and green areas. Other environmental amenities, such as the availability of schools and commercial centers, are also incorporated into the model, together with data regarding two types of crimes: Intentional homicides and theft. Therefore, OLS estimations indicate that the number of intentional homicides and the number of thefts (both measured per 100,000 population) bear a strong negative relationship with housing prices.

Finally, Atuesta and Carrasco (2023) make use of three different proxies for crime, assessing the impact of each on new home prices in Mexico City during the period December 2006-November 2011. The three proxies for crime are: 1) The proximity of the home to the nearest execution point, 2) the proximity of the home to the nearest narco-message attached to the executed person, and 3) the number of murders between the home and the nearest narco-message. In this context, they assign geographic coordinates to house sales and violent occurrences with a view to gathering disaggregated data and, therefore, estimate a dynamic panel data model through the AB estimator. In addition to the proxies for criminal activity, these authors incorporate other variables concerning the structural characteristics of the homes, and the sociodemographic characteristics of the neighborhoods where they are situated. Along these lines, they find that home prices are negatively associated with: 1) The number of executions surrounding the housing project, and 2) the proximity to the nearest narco-message associated with a fatality.

Our study fills a small gap in the empirical literature on three grounds. First, it is focused on Mexico, which is a developing country. There is a lack of research addressing developing nations, especially Latin American nations such as Mexico (Margaretic and Sosa, 2023, p. 1; Atuesta and Carrasco, 2023, p. 1203). Secondly, our paper comprises 27 Mexican cities, which is relevant given the shortage of investigations involving more than one city. And third, it includes two critical estimation periods: The pre-pandemic period and the pandemic period. On the other hand, we employ the AB estimator, which is robust to endogeneity problems. As is well known, the AB estimator applies to dynamic panel data models, which capture the predetermined component of housing prices through the inclusion of a lagged dependent variable among the regressors. By the same token, urban danger in many Mexican cities has become a day-to-day reality, propelled by the rampant criminal activities of organized groups linked to drug trafficking as well as many other illicit operations. Given the pervasive nature of criminal activities in Mexico, it is crucial to provide further insights into its impact on home prices while controlling for the effects of other key variables.

3. MODEL, DATA, AND ECONOMETRIC METHOD

3.1. The model

The selection of variables is based on a supply- and demand-side model, similar to the one employed by Donald and Winkler (2002). As a broad external amenity variable, we constructed a composite measure of public infrastructure provision, which captures three types of basic physical systems provided by the government in each city: 1) Water, irrigation, and sanitation, 2) electricity and telecommunications services, and 3) transportation and urbanization. Nonetheless, this paper does not include a measure of wealth due to the lack of disaggregated data. Instead, it relies solely on state-level economic activity indices as a proxy for the income level of each city. The demand for housing in city *i* at quarter *t*, denoted Q_{it}^{D}, is represented by equation [1]:

$$Q_{it}^{D} = \propto_{0i} + \propto_{1} P_{it} + \propto_{2} Y_{it} + \propto_{3} R_{it} + \propto_{4} PIP_{it} + u_{it} \qquad [1]$$

Where P_{it} is the housing price index of city *i* at time *t*, whereas Y_{it} is the economic activity index of state *i* and is used as a proxy for the income level of city *i*. So, it is a demand-side variable. Moreover, R_{it} is the real mortgage interest rate, PIP_{it} is the composite variable of public infrastructure provision, u_{it} is the stochastic disturbance term, and $\propto_{0i}$ is an intercept term that varies across cities, so that it captures their heterogeneity (like in a fixed effects panel data model). The expected parameter signs of equation [1] are the following: $\propto_1 < 0$, $\propto_2 > 0$, $\propto_3 < 0$, and $\propto_4 > 0$.

The supply of housing, denoted Q_{it}^{S}, is given by equation [2]:

$$Q_{it}^{S} = \gamma_{0i} + \gamma_{1} P_{it} + \gamma_{2} R_{it} + \gamma_{3} CC_{it} + \gamma_{4} PIP_{it} + v_{it} \qquad [2]$$

Where CC_{it} stands for construction costs while v_{it} is the disturbance term. Like before, γ_{0i} captures the heterogeneity across cities. The expected parameter signs here are the following: $\gamma_1 > 0$, $\gamma_2 < 0$, $\gamma_3 < 0$, and $\gamma_4 > 0$. In addition to the housing price index (P_{it}), there are two variables entering both the demand- and the supply-side equations:

1. The real mortgage interest rate (R_{it}). Broadly speaking, a rise in the mortgage interest rate reflects a change in the country's overall credit conditions. Therefore, credit becomes more expensive not only for home buyers but also for home builders and real estate developers, which explains that the mortgage interest rate is negatively related to the demand and the supply of housing.
2. Public infrastructure provision (PIP_{it}). An enhancement in public infrastructure encourages builders and developers to invest more in new projects and raises the supply of houses. On the other hand, given that people are more likely to purchase houses in cities with good infrastructure, this variable has a positive impact on housing demand as well.

Lastly, construction costs are assumed to be negatively related to the supply of housing because they make it more expensive not only to build new homes but also to provide maintenance to the existing ones. In any event, all the variables of the model will enter the reduced-form equation which, in turn, will be estimated. Equation [3] represents the equilibrium condition:

$$Q_{it}^{D} = Q_{it}^{S} \qquad [3]$$

Next, we substitute equations [1] and [2] into [3] and then solve for P_{it}. In this way, we obtain equation [4], which is the reduced-form equation for the price of houses:

$$P_{it} = \beta_{0i} + \beta_1 CC_{it} + \beta_2 PIP_{it} + \beta_3 Y_{it} + \beta_4 R_{it} + w_{it} \qquad [4]$$

Finally, to assess the effects of the perception of public insecurity, denoted $INSEC_{it}$, we specify the following amplified equation:

$$P_{it} = \beta_{0i} + \beta_1 CC_{it} + \beta_2 PIP_{it} + \beta_3 Y_{it} + \beta_4 R_{it} + \beta_5 INSEC_{it} + w_{it} \qquad [5]$$

Where β_{0i} is the new intercept term that changes from one city to another, whereas w_{it} is the new stochastic disturbance term. Equation [5] is a housing price equation, so the expected parameter signs are: $\beta_1 > 0$, $\beta_2 > 0$, $\beta_3 > 0$, $\beta_4 >< 0$, and $\beta_5 < 0$. Therefore, the perception of public insecurity would lower housing prices.

3.2. Econometric method

The AB procedure requires two transformations to equation [5]. First, the intercept, β_{0i}, must be replaced by a cross-sectional error term, μ_i, which now reflects the heterogeneity across cities. Second, a lagged dependent variable (P_{it-1}) must be added as a regressor:

$$P_{it} = \gamma P_{it-1} + \beta_1 CC_{it} + \beta_2 PIP_{it} + \beta_3 Y_{it} + \beta_4 R_{it} + \beta_5 INSEC_{it} + \mu_i + w_{it} \quad [6]$$

The inclusion of P_{it-1} in equation [6] transforms the model into a dynamic panel data model, where γ is the autoregressive parameter. This new model includes two disturbance terms. The first varies across cities but is constant overtime (μ_i) while the second varies across cities and across time (w_{it}). According to Baltagi (2008, pp. 147-150), to solve the endogeneity problem, we must eliminate all sources of correlation between the regressors and the two error terms in equation [6]. The first step is to remove μ_i, because it influences the dependent variable and can thus be correlated with the lagged dependent variable. As shown in equation [7], this is accomplished by first differencing all the variables:

$$\Delta P_{it} = \gamma \Delta P_{it-1} + \beta_1 \Delta CC_{it} + \beta_2 \Delta PIP_{it} + \beta_3 \Delta Y_{it} + \beta_4 \Delta R_{it} + \beta_5 \Delta INSEC_{it} + \Delta w_{it} \quad [7]$$

The second step is to ensure that all the regressors in equation [7] are uncorrelated with the new error term, Δw_{it}. This is achieved by generating several instrumental variables fulfilling two key criteria: 1) They must be highly correlated with the regressors, and 2) they must be uncorrelated with the disturbance term. Under the AB method, those instrumental variables are given by the lags of the regressors in equation [7], with the proviso that those lags are in levels rather than first differences.

If the number of cross-section units (N) is much larger than the number of periods (T), then the AB estimator is robust to endogeneity problems and consistent despite the behavior of the model's residuals (Arellano and Bond, 1991; Baltagi, 2008, p. 150). In this context, our two panel data sets involve 27 Mexican cities, meaning that N = 27. Moreover, the use of a lagged dependent variable and a set of instruments brings down the number of time series observations in each data set. Therefore, the adjusted sample period runs from Q3 2016 to Q2 2019 (*i.e.*, T = 12) in the pre-pandemic model, and from Q1 2020 to Q2 2023 (*i.e.*, T=14) in the pandemic model. As a result, in both cases N is much greater than T.

The selection of the AB estimator over other alternatives was based on the finding that crime is an endogenous variable, so we need an estimator that is robust to endogeneity problems. Aliyu *et al.* (2016) contend that crime is an endogenous variable on the following grounds. First, most criminals reside in low-income neighborhoods or cities because these areas are more affordable, so they may be inclined to commit some of their felonies in the vicinity. Nonetheless, according to these authors, high-income neighborhoods provide greater incentives for criminals due to the higher value of goods that can eventually be stolen. Lastly, they assert that high-income victims are more likely to report a crime than low-income victims, so the under-reporting phenomenon is more acute in poor areas. Therefore, endogeneity is a key issue to be addressed.

In this context, alternative estimators such as Pooled Mean Group (PMG) and Common Correlated Effects (CCE) are not specifically designed to deal with the critical issue of endogeneity. The PMG estimator works well when T and N are both large and the purpose is to estimate long-run coefficients that are identical across cross-section units while allowing the short-run parameter estimates to vary from one cross-section unit to another (Pesaran, Shin and Smith, 1999). Furthermore, the CCE estimator can be robust to cross-sectional dependence even when N and T are relatively small (Pesaran, 2006). However, neither the PMG nor the CCE methodologies perform better than the AB procedure in the presence of endogeneity.

3.3. Data issues

The dependent variable in equation [6] is given by the housing price indices of 27 Mexican cities (P_{it}), so this is not a typical hedonic pricing model. Since we are dealing with average housing prices rather than the sale prices of individual houses, we do not need to consider their structural attributes (*e.g.*, the number of rooms). However, we do include an external amenity variable: Public infrastructure provision (PIP_{it}). As previously stated, this is a composite variable, which was constructed to reflect changes in three basic physical systems afforded by the government of each city: 1) Water, irrigation, and sanitation, 2) electricity and telecommunications services, and 3) transportation and urbanization. Rather than using three different external amenity variables, we chose to construct a single composite variable to alleviate multicollinearity problems. Such a task was undertaken by calculating the average of these three dimensions of public infrastructure, which are reported by the Instituto Nacional de Estadística y Geografía (INEGI).

Residential construction costs (CC_{it}) by city are measured through a specific producer price index reflecting the costs of three factors: Construction materials, machinery rental for that purpose, and labor. Moreover, the state-level economic activity index (Y_{it}), which is a measure of the real output generated by each state, is used here as a proxy for the income level of the city corresponding to that state. To obtain the real mortgage interest rate for city i (R_{it}), we deflated the nominal mortgage interest rate using the inflation rate of city i. Lastly, the perception of public insecurity ($INSEC_{it}$) in each city is given by the percentage of the population aged 18 and older who perceive the city they live in to be unsafe or insecure. This measure of public insecurity takes account of the perception of urban danger in the following spaces: ATMs on the street, banks, schools, workplaces, homes, cars, public transportation, highways, recreational centers or parks, and shopping malls (National Survey on Victimization and Perception of Public Security, 2024, p. 65). As can be seen, some of these locations are public while others are private.

Along these lines, quarterly data was gathered for each variable of equation [6]. The housing price indices were obtained from the SIF. The real mortgage interest rate for each city was calculated using nominal mortgage interest rate data from the Banco de México (Banxico) and city-level inflation rates provided by the INEGI. The residential construction costs indices for each city, the state-level economic activity indices, and the perception of public insecurity for each city were all collected from INEGI. Lastly, the composite index of public infrastructure was calculated (in the way described earlier) using data from INEGI. All the variables are seasonally adjusted, and, except for the real mortgage interest rate and the perception of public insecurity, they are stated in natural logarithms. No logarithms were applied to these two variables because they are measured as percentages.

4. ECONOMETRIC ANALYSIS

4.1. Parameter estimation and hypothesis testing

The first step here is to estimate equation [7] through the AB estimator. In equation [7], all the variables are expressed in first differences. Table 1 shows the estimation results for the pre-pandemic and the pandemic periods.

Table 1. Dynamic panel data models
Dependent variable: Housing price index ($\Delta \ln P_{it}$)
Method: Arellano-Bond estimator
GMM weights: White period instrument weighting matrix
Coefficient covariance method: Ordinary
GMM iterations: 2-step (update weights once)

	Pre-pandemic period	Pandemic period
Adjusted estimation period	2016Q3-2019Q2	2020Q1-20223Q2
Cross-section units	27	27
Periods	12	14
Total panel (balanced) observations	324	378
Regressors	Coefficients	Coefficients
Lagged housing price index ($\Delta \ln P_{it-1}$)	0.989375***	0.915871***
Construction costs ($\Delta \ln CC_{it}$)	0.034239***	0.112251***
Public infrastructure provision ($\Delta \ln PIP_{it}$)	–0.001173***	0.002400***
State-level economic activity ($\Delta \ln Y_{it}$)	0.021663*	0.017996***
Real mortgage interest rate (ΔR_{it})	–0.000992***	0.000954***
Perception of public insecurity ($\Delta INSEC_{it}$)	–0.000239***	–5.29E-05***
Instrument rank	27	28

Notes: Asterisks *, **, and *** indicate statistical significance at the 10%, 5% and 1% significance levels, respectively. Δ = First difference operator, ln = Natural logarithm, and Q = Quarter. No logarithms are applied to the real mortgage interest rate and the perception of public insecurity, given that these two variables are expressed in percentages.
Source: Own estimations based on data from the INEGI, the Banxico, and the SIF.

Before interpreting the empirical findings, we must address the instrument proliferation problem that occurs when T is too large. Put differently, an excessive number of instruments tends to overfit the original regressors, in which case the instruments fail to correct endogeneity and thus result in finite sample bias (Windmeijer, 2005; Roodman, 2009a)[5]. There are two general guidelines for determining whether the instrument count or rank is too high. The first is when the number of instruments exceeds the number of cross-section units (N) in the panel (Roodman, 2009a). Nevertheless, the validity of this rule of thumb can be questioned when N is too high as well. According to Roodman (2009a), in the case of a panel with T = 5 and N = 100, the number of individuals is so high that it cannot work as a reliable limit for the number of instruments. The second guideline is when the probability value of the Sargan-Hansen test is close to 1, suggesting a result that is "too good to be true" (Roodman, 2009b). Given the practical and imprecise nature of these guidelines and the absence of more formal methods, in some cases Roodman (2009b) recommends testing the robustness of the findings by reducing the number of instruments.

In this context, Table 2 reports the outcome of the Sargan-Hansen tests. The null hypothesis here is that the instruments are uncorrelated with the error term, which means that they are reasonably valid. The resulting probability value is 0.181758 in the pre-pandemic period and 0.054264 in the pandemic period. This means that the null hypothesis

Table 2. Sargan-Hansen tests

Null hypothesis: The instruments are uncorrelated with the error term

Pre-pandemic period (2016Q3-2019Q2)		Pandemic period (2020Q1-20223Q2)	
J-statistic	Probability value	J-statistic	Probability value
26.67827	0.181758	33.57233	0.054264

Notes: Q = Quarter. The intervals reported for the two periods are sample-adjusted due to the inclusion of lags and the use of instrumental variables.

Source: Own estimations based on data from the INEGI, the Banxico, and the SIF.

5 As is well known, to solve the endogeneity issue the instruments must be correlated with the regressors and uncorrelated with the error term.

cannot be rejected for the first period but can be rejected for the second at the 10% significance level. Therefore, there is a problem in the pandemic period, perhaps because the instrument rank is slightly greater than the number of cross-section units (*i.e.*, 28 *vis-à-vis* 27).

To correct the problem identified in the pandemic period, we follow the suggestion of Windmeijer (2005) and Roodman (2009b), which is to reduce the value of T and thus the instrument count when necessary, that is, when the null hypothesis of the Sargan-Hansen test is rejected. To accomplish this task, we must re-estimate the model for such a period with semi-annual rather than quarterly data, which unfortunately entails an information loss. Estimation results are shown in Table 3.

Table 3. Dynamic panel data model

Dependent variable: Housing price index ($\Delta \ln P_{it}$)

Method: Arellano-Bond estimator

GMM weights: White period instrument weighting matrix

Coefficient covariance method: Ordinary

GMM iterations: 2-step (update weights once)

Adjusted estimation period for the pandemic period	2020S2-2023S1
Cross-section units	27
Periods	6
Total panel (balanced) observations	162
Regressors	
Lagged housing price index ($\Delta \ln P_{it-1}$)	0.826500***
Construction costs ($\Delta \ln CC_{it}$)	0.207230***
Public infrastructure provision ($\Delta \ln PIP_{it}$)	0.009239***
State-level economic activity ($\Delta \ln Y_{it}$)	0.011065
Real mortgage interest rate (ΔR_{it})	0.002230***
Perception of public insecurity ($\Delta INSEC_{it}$)	–0.001129***
Instrument rank	27

Notes: Asterisks *, **, and *** indicate statistical significance at the 10%, 5% and 1% significance levels, respectively. Δ = First difference operator, ln= Natural logarithm, and S = Semi-annual. No logarithms are applied to the real mortgage interest rate and the perception of public insecurity, given that these two variables are expressed in percentages.

Source: Own estimations based on data from the INEGI, the Banxico, and the SIF.

As can be seen, now the instrument rank is the same as the number of cities in the panel (*i.e.*, 27). So, the next step is to assess to what extent this is useful to alleviate the correlation between the instrumental variables and the model's residuals. To make that determination, we must perform the Sargan-Hansen test for the pandemic period based on semi-annual data. Table 4 shows that the probability value for the null hypothesis that the instruments are uncorrelated with error term is 0.204336, which is much higher than before. In fact, this time the null hypothesis cannot be rejected, so we can conclude that the instruments are reasonably valid.

Ideally, we would like to have higher probability values for these tests, even though values approaching 1 may also be the symptom of an underlying problem (Roodman, 2009b). Therefore, in addition to the nonrejection of the null hypothesis in the Sargan-Hansen tests, we also rely on the asymptotic properties of the AB estimator. As stated earlier, if N is sufficiently larger than T, then the AB estimator is unbiased and consistent irrespective of the behavior of the residuals (Arellano and Bond, 1991; Baltagi, 2008, p. 150). As reported in Table 1, N equals 27 and the adjusted value of T is 12 in the pre-pandemic period. What is more, once we estimate the model for the pandemic period with semi-annual data (Table 3), not only does the outcome of the Sargan-Hansen test improve, but the adjusted value of T goes down from 14 to 6.

Finally, the available software allows for conducting AB tests for serial correlation, given that this problem may be a source of inefficiency in relatively small samples. Appendices 2 and 3 display the results of these tests, which are applied to equation [7], where the error term is represented by Δw_{it}. Now, according to Arellano and Bond (1991), if the

Table 4. Sargan-Hansen test

Null hypothesis: The instruments are uncorrelated with the error term

Pandemic period (2020S2-2023S1)	
J-statistic	**Probability value**
26.05563	0.204336

Notes: S = Semi-annual. The interval reported here is sample-adjusted due to the inclusion of lags and the use of instrumental variables.

Source: Own estimations based on data from the INEGI, the Banxico, and the SIF.

error term (w_{it}) in equation [6] is identically independently distributed, then Δw_{it} in equation [7] must display first-order serial correlation and no second-order serial correlation. These two requirements are satisfied when working with quarterly data, regardless of whether we are dealing with the pre-pandemic or the pandemic period. However, when working with semi-annual data in the case of the pandemic period, the null hypothesis of "no second order autocorrelation" is rejected.

4.2. Empirical findings

Tables 1 and 3 lay the foundation to establish the following relationships:

1. The estimated coefficient of the lagged dependent variable ($\Delta \ln P_{it-1}$), which is an elasticity, is above 0.90 when working with quarterly data and above 0.80 when working with semi-annual data. Moreover, it is statistically significant at the 1% level in all cases. The economic interpretation here is that housing prices involve a strong predetermined or inertial component.
2. In every regression, perception of public insecurity ($\Delta INSEC_{it}$) has a negative estimated coefficient, which is statistically significant at the 1% level. Therefore, a higher perception of public insecurity brings down housing prices, and this evidence is robust.
3. The parameter estimate of construction costs is positive and statistically at the 1% level in the three regressions, so this variable exerts an upward pressure on home prices.
4. The state-level economic activity index has a positive coefficient, which is statistically significant when working with quarterly data only (see Table 1). However, the level of statistical significance rises from 10% in the pre-pandemic period to 1% in the pandemic period. The rationale behind this finding is that this variable works as a proxy for the income level, which, in turn, is directly related to the demand for housing. And higher demand leads to higher home prices.
5. During the pre-pandemic period, public infrastructure provision had a negative impact on home prices, which is statistically significant at the 1% level. However, in the pandemic period, regardless of whether we work with quarterly or semi-annual data, this variable yields a positive effect on housing prices, which is statistically significant at the 1% level.

As explained below in greater detail, this variable influences the supply as well as the demand for housing. On the demand side, people are more willing to buy houses in cities with good public infrastructure, given that it improves their quality of life. On the supply side, better physical infrastructure translates into lower costs of construction, maintenance and transportation, on the one hand, and higher productivity and investment levels in the construction industry, on the other. Therefore, *ceteris paribus*, the net effect of this variable is ambiguous and contingent on the circumstances analyzed in the conclusions.

6. Lastly, during the pre-pandemic period, the real mortgage interest rate renders a negative effect on housing prices, whereas during the pandemic period (irrespective of whether we use quarterly or semi-annual data) it renders a positive effect. In all the cases, the coefficient associated with this variable is significant at the 1% level. The ambiguous impact of this variable on home prices can be explained on the grounds that rising mortgage interest rates are usually associated with a tightening of overall credit conditions, and vice versa. Therefore, more expensive loans not only lower the demand for houses by discouraging home buyers, but they also reduce the supply of houses by discouraging real estate developers and home builders.

5. CONCLUSIONS AND POLICY IMPLICATIONS

Many Mexican cities are plagued by criminal activity. Yet there is a lack of research concerning the impact of crime on property prices in the case of Mexico and other developing nations (Margaretic and Sosa, 2023, p. 1; Atuesta and Carrasco, 2023, p. 1203). Moreover, most of those studies are devoted to a single city. This investigation comprises 27 Mexican cities and two different estimation periods for comparison purposes.

As is well known, housing prices depend on numerous factors linked to different theories, which tend to complement one another. One line of research primarily studies the influence of buyer preferences and income constraints (Rosen, 1979; Maclennan, 1982). For their part, the hedonic price approach underscores the relevance of the physical attributes of homes such as lot size, number of bedrooms and bathrooms, building materials, and other amenity variables like garages and gardens (Rosen, 1974; Baltagi, 2015). From the investors' standpoint, the locational theory considers the proximity of houses to good schools, recreation areas, and commercial centers as these factors tend to raise home market values over time (Alonso, 1964; Brueckner, 1987). Finally, the rule-of-law strand of the literature focuses on the need to develop sound institutional frameworks to enhance poverty reduction efforts, education, job creation, political stability, and the overall criminal justice system, given that high crime rates and the perception of urban insecurity tend to reduce property values, particularly in the most violent cities and neighborhoods (Gibbons and Machin, 2008; Delgado-Fernández and Wences-Nájera, 2018; Ceccato and Wilhelmsson, 2011, 2020; González-Juárez *et al.*, 2021; Atuesta and Carrasco, 2023).

As stated earlier, this investigation resorts to housing price indices rather than individual house prices. Therefore, our model does not rely on the hedonic price approach, even though an external amenity variable is included among the regressors (*i.e.*, public infrastructure provision). In this context, the supply- and demand-side model estimated here points to several conclusions. The most relevant is that housing prices decrease as the perception of public insecurity rises. The negative impact of this variable on home market values is highly significant in the pre-pandemic and pandemic periods, which is consistent with the central hypothesis of this investigation. Therefore, our finding is relatively consistent with at least three previous studies for the case of Mexico. Delgado-Fernández and Wences-Nájera (2018) and González-Juárez *et al.* (2021) resort to a hedonic price approach and to the OLS method to show that crime and violence lower home prices. As stated earlier, both studies are d voted to a single city, and each of them relies on a different measure of criminal activity. Moreover, their main shortcoming is that the OLS method employed is not robust to endogeneity. For their part, Atuesta and Carrasco (2023) make use of the AB estimator to study the impact of three different proxies for crime, but their study is restricted to case of Mexico City. Even though our investigation comprises 27 cities and two important periods of analysis, its main limitation is that the AB estimator suffers from the so-called instrument proliferation problem, which as previously explained may prevent us from "fully" resolving¿ the endogeneity problem.

As is widely acknowledged, fear of crime in urban areas responds to several factors, and the actual crime rates are one of them. Nonetheless, media coverage, coupled with the lack of trust in law enforcement, tends to magnify the perception of urban danger and, therefore, the impact of crime on Mexican real estate markets. What is more, home prices are a key determinant of homeowners' wealth, which, in turn, can have a multifaceted impact on the economy. These considerations highlight the need to tackle public insecurity and restoring public confidence through more effective and visible policing as well as comprehensive crime prevention programs, especially in the cities and neighborhoods hit by crime. Public infrastructure investments to upgrade street lighting, transportation services, and recreational facilities, along with information campaigns to raise awareness about city safety improvements, can be useful to shorten the time lag between crime rate reductions and positive shifts in public sentiment.

Another finding has to do with the positive impact of construction costs on home prices. As pointed out earlier, this variable encompasses construction materials, machinery rental for that purpose, and labor. Therefore, improving the sources of materials, granting tax incentives to enhance machinery and equipment, and raising labor productivity through education and training can be useful to provide affordable and higher quality housing to low- and middle-income families. Moreover, the state-level economic index has a positive impact on housing prices, given that this variable works as a proxy for the income level, which, in turn, is positively related to housing demand.

Public infrastructure provision and the real mortgage interest rate deliver a negative effect on housing prices in the pre-pandemic period, and a positive effect in the pandemic period. In both cases, the effect is statistically significant at the 1% level. As previously explained, these two variables generate supply- and demand-side effects, so both are included in the housing demand and the housing supply equations (*i.e.*, equations [1] and [2]). As the reader may recall, public infrastructure provision captures three types of foundational physical systems afforded by the government in each city: 1) Water, irrigation, and sanitation; 2) electricity and telecommunications services; and 3) transportation and urbanization. Therefore, on the demand side, an enhancement in these services raises the quality of life in a city, makes it more desirable, and, ultimately, exerts an upward pressure on property prices. On the supply side, a solid infrastructure in the aforementioned areas stimulates private investment in the construction industry, reduces transportation and maintenance costs, and raises productivity levels. While the demand-side effect pushes prices up, the supply-side effect pushes prices down. Therefore, the net effect is indeterminate, and further research is required to ascertain why the effect of public infrastructure provision changed from being negative in the pre-pandemic period to being positive in the pandemic period.

As for the real mortgage interest rate, Donald and Winkler (2002) explain that the impact of this variable on property prices can be either positive or negative. The rationale, according to them, is that higher real interest rates raise the cost of credit not only to home buyers but also to home builders and real estate developers. As explained before, increasing mortgage interest rates often take place amid a large-scale tightening of credit conditions, so loans become more expensive for everyone. Furthermore, in addition to pre-selling, home builders often depend on loans from banks and other financial institutions to start or complete a costly project. Therefore, according to Donald and Wrinkler (2002), higher interest rates shift the house supply and demand curves simultaneously to the left. Given that the supply curve moves upwardly and the demand curve downwardly, the net effect on home prices depends on the relative magnitude of each movement. Like public infrastructure provision, real mortgage interest rates generate a negative effect in the pre-pandemic period and a positive effect in the pandemic period. So, in this case further research is also needed to explain the role played by the pandemic in shifting the sign of the net effect of interest rates on home prices.

Finally, the strong impact of the model's lagged dependent variable indicates that housing prices entail a predetermined or inertial component. Despite this inertial behavior, the impact of the perception of public insecurity and the other regressors is not only statistically significant but also meaningful from the theoretical standpoint. ◄

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Appendix 1. Cities of the sample along with their respective states

City	State	City	State
1. Aguascalientes	Aguascalientes	15. Toluca de Lerdo	Estado de México
2. Mexicali	Baja California	16. Morelia	Michoacán de Ocampo
3. Tijuana	Baja California	17. Tepic	Nayarit
4. La Paz	Baja California Sur	18. Monterrey	Nuevo León
5. San Francisco de Campeche	Campeche	19. Heroica Puebla de Zaragoza	Puebla
6. Colima	Colima	20. Querétaro	Querétaro
7. Tapachula	Chiapas	21. San Luis Potosí	San Luis Potosí
8. Chihuahua	Chihuahua	22. Culiacán Rosales	Sinaloa
9. Juárez	Chihuahua	23. Hermosillo	Sonora
10. Mexico City		24. Villahermosa	Tabasco
11. Durango	Durango	25. Tlaxcala de Xicohténcatl	Tlaxcala
12. León de los Aldama	Guanajuato	26. Veracruz	Veracruz de Ignacio de la Llave
13. Acapulco de Juárez	Guerrero	27. Mérida	Yucatán
14. Guadalajara	Jalisco		

Appendix 2. Arellano-Bond test for serial correlation for the pre-pandemic and the pandemic periods using quarterly data

	Pre-pandemic period (2016Q3-2019Q2)		Pandemic period (2020Q1-20223Q2)	
Null hypothesis	***m*-statistic**	**Prob. value**	***m*-statistic**	**Prob. value**
No first-order autocorrelation	−3.443660	0.0006	−1.754593	0.0793
No second-order autocorrelation	1.387296	0.1654	0.074004	0.9410

Notes: Q = Quarter. The intervals reported for the two periods are sample-adjusted due to the inclusion of lags and the use of instrumental variables.
Source: Own estimations based on data from the INEGI, the Banxico, and the SIF.

Appendix 3. Arellano-Bond test for serial correlation for the pandemic period using semi-annual data

Pandemic period (2020S2-2023S1)		
Null hypothesis	***m*-statistic**	**Prob. value**
No first-order autocorrelation	−2.458893	0.0139
No second-order autocorrelation	−3.172539	0.0015

Notes: S = Semi-annual. The interval reported here is sample-adjusted due to the inclusion of lags and the use of instrumental variables.
Source: Own estimations based on data from INEGI, the Banxico, and the SIF.