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Analyzing Pre- and Post-Pandemic Housing Market Trends in India: A Quasi-Experimental Approach Using ITS and Panel Data Analysis

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The research delves into the influence of pre- and post-pandemic real estate housing price indices of cities in India. Using an interrupted time series analysis and panel data regression, this study evaluates the repercussions of the COVID-19 pandemic on residential housing in ten Indian cities over a span of thirteen years from 2010 to 2023. The results present a medley of outcomes on city-level trends, a prevailing post-pandemic downturn observable across cities, and a subsequent positive shift as compared to pre-pandemic standards. The study brings to light the diverse impact and shock insulation exhibited by smaller cities, thus unveiling the variations among different cities.

Keywords

COVID-19, ITS analysis, Real estate market trend, Pre- and post-COVID

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1. Introduction

Real estate markets are highly sensitive to economic and political events. In recent times, the COVID-19 pandemic has also brought price fluctuations in the global and Indian real estate markets. Although a number of research works have been conducted on COVID-19 and other related factors that influence real price, the literature has presented mixed results due to heterogeneity in the real estate market, such as location and segmentation by low and high prices, as well as commercial and residential properties. Each type of real estate and market segment have exhibited divergent outcomes (Wang, 2023). This phenomenon is confirmed in research where retail and hospitality properties, followed by office buildings, have been most affected by the pandemic. In contrast, the residential and industrial sectors have experienced comparatively smaller impacts. Another strand of research focuses on pandemic-induced psychological factors that affect buying behavior, such as population density, proximity to metro stations, and bike-sharing facilities. Extensive investigation has been conducted on the impact of real estate price on bike-sharing availability in metro stations to residents (Zhou et al., 2022).

However, there is a lack of attention paid to city-specific pre- and post-pandemic impacts of real estate prices on residential housing markets in emerging economies like India with the use of a housing price index. This study aims to address this knowledge gap by uniquely employing an interrupted time series (ITS) analysis, which is a quasi-experimental design approach. The investigation seeks to analyze the pre- and post-pandemic impacts on the residential housing price index across ten Indian cities from Q1 2010-11 to Q1 2023. The study confirms the idiosyncratic behavior of the real estate market, and provides mixed results with negative level changes in some of the major cities and weak positive level changes in others. A significantly negative trend post-pandemic is evident across all cities. The analysis indicates an overall positive quick reversal trend in the post-pandemic scenario compared to pre-pandemic times. The study highlights that small cities remain relatively indifferent to structural shocks and reveals heterogeneity among cities in their insulation to price shocks in the small real estate markets of India. This research is a pioneering study with the use of ITS analysis for analyzing the real estate market. The implications are discussed comprehensively.

2. Literature Review

2.1 COVID-19 Pandemic and Real Estate Market

Wang (2022) conducts an investigation on the impact of COVID-19 on the real estate market in Los Angeles, USA. The findings indicate that areas with lower property prices witness a more significant decrease in housing prices. This phenomenon is correlated with increased service sector involvement and decreased rates of home ownership. For the period of March to May 2020, house prices, demand, and supply decreased, but increased for July and August 2020, which was driven by demand. A heterogeneity analysis revealed diverging impacts, with lower-priced markets showing a significant decline in price and demand before June 2020, while higher-priced markets remain relatively stable. After July 2020, higher-priced markets led the recovery of the housing market, while the lower-priced market struggled to regain pre-pandemic levels. Hoesli and Malle (2022) discuss the impact of COVID-19 on different sectors of the real estate market. They note that the retail and hospitality segments followed by office buildings were most affected by the pandemic. In contrast, the residential and industrial sectors experienced less significant impacts. The study further emphasizes that the future trajectory of prices will vary across sectors and highlights the increasing importance of considering the type and location of assets in their valuation. Croom et al. (2020) develop a hedonic model to investigate the impact of commercial real estate pricing with and without the influence of the pandemic. Their findings indicate that there are no significant changes in the analyzed geographic areas in the United States (U.S.) when COVID-19 parameters are inputted into the model. The result further suggests that the pandemic has not had a substantial impact on the pricing dynamics of commercial real estate in the examined regions. Rosenthal et al. (2021) find that rent premium is correlated with employment density across all of the U.S. cities in their study after the pandemic. Zhou et al. (2022) observe that in neighborhoods situated at a considerable distance from metro stations, there is a rise in house prices that corresponds to the level of shared bike usage. This implies the favorable role of bike sharing in supplementing the metro rail system. Nonetheless, the intensity of shared bike usage also exerts a downward pressure on house prices. This effect is less pronounced in upscale neighborhoods and localities. The pandemic has further accentuated both positive and negative price impacts, likely due to the increased use of shared bikes as a means of social distancing. D'Lima et al. (2022) conduct a difference-in-differences analysis to examine the impact of COVID-19 shutdowns and reopening orders on the U.S. housing market. They find no significant aggregate price effect but observe a significant decrease in transaction volume. The risk aversion of sellers and uncertainty in the market contribute to the decrease in transaction volume, which particularly affects large properties. Yörük (2020) documents a decline in sales of new and pending residential properties in major U.S. cities during the early stages of the pandemic, which highlighted demand-side shocks and suboptimal search behavior by buyers due to COVID-19 restrictions. Hu et al. (2021) find an inverse relationship between previous pandemic cases and daily housing returns in five Australian capital cities by employing a daily hedonic housing price index and in addition, confirm an insignificant relationship between lockdowns and housing return. Del Giudice et al. (2020) conduct an investigation into the repercussions of COVID-19 on the housing markets within the Campania region of Italy. They discern various channels through which COVID-19 exerts influence on these housing markets. These channels encompass the closure of neighborhoods or entire cities, apprehensions regarding persistent contagion risks, skepticism towards sanitation efforts, a general economic downturn, as well as specific factors inherent to the housing market. The decline in home sales is likely propelled by both income-related factors and psychological impacts on the demand side. Over the short term, a reduction of -4.16% in housing prices is observed. Looking ahead to the mid-term, their scenario projection anticipates a price decline of -6.49% up to the beginning of 2021. Allen-Coghlan and McQuinn (2020) project a similar price path for the Irish housing market. Zhao (2020) directs attention to the recuperation of the housing market subsequent to April 2020, and noted a discernible upswing in property prices and heightened housing demand. These shifts are ascribed to the implementation of monetary easing measures by the Federal Reserve as part of its response to the COVID-19 situation. Zhao (2020) validates these trends in terms of house prices, demand, and supply across a spectrum of urban, suburban, and rural domains. Tanrıvermiş (2020) analyzes the impact of the COVID-19 pandemic on demand and supply in the international real estate markets on European counties and China.

2.2 Real Estate Demand and Population Density during COVID-19 Pandemic

Liu and Su (2020) delve into the relationship between housing market demand and population density in the U.S. following the onset of the pandemic. Their study reveals a more pronounced decrease in demand within densely populated neighborhoods and central urban areas. This observation implies a shift in inclination to move away from high density living, influenced by changes in the availability of jobs conducive to remote work and access to amenities for consumption. Layser et al. (2020) offer a comprehensive analysis of the interplay between housing stability and public health strategies in the context of the COVID-19 pandemic. Their assertion is that while social distancing measures effectively curtail the transmission of the virus, they concurrently jeopardize housing stability due to the widespread shuttering of businesses and the consequential surge in unemployment.

2.3 Real Estate Market Demand and Regulation

Nanda and Ross (2012) explore the effect of property condition disclosure laws on house prices by using traditional parametric panel data models and a semiparametric propensity score matching model. They find that compliance with the law leads to an additional increase of 3% to 4% in housing prices in the metropolitan areas of 50 U.S. states over a four-year period of time. Hoesli et al. (2020) investigate the relationship between regulation and asset bubbles in the real estate market following the global financial crisis. The study employs an event study approach and examines the abnormal returns of the 15 largest real estate companies traded on the German, French, and (United Kingdom) UK stock exchanges between January 2009 and April 2015.

Anundsen et al. (2023) analyze sentiment, stock market developments, and prediction errors in the Norwegian housing market with a simple linear regression model. Sentiment changes show a positive and significant correlation with abnormal price movements, while stock market changes have no significant impact. Despite the simplicity of the model, the study suggests that sentiment explains over 5 percent of price variations. The sentiment index and normalized prediction errors exhibit a similar downward trend before the lockdown in Norway, gradually increasing before the reopening. No association is found between changes in house and stock market prices.

3. Research Methodology

The objective of this research study is to ascertain the impact of the COVID-19 pandemic on the real estate price index of ten selected cities in India along with all India quarterly times series data from 2010 to 2023.

3.1 Data and Variables

3.1.1 Dependent Variable

The data for this study are sourced from the Housing Price Index (HPI) developed by the National Housing Bank (NHB) (see Table A1 in Appendix). NHB RESIDEX, the first official housing price index in India, was an initiative of the NHB undertaken at the behest of the Ministry of Finance, Government of India. The index was formulated under the guidance of a technical advisory committee (TAC) which comprised stakeholders from the housing market. It was launched in July 2007 and updated periodically until March 2015, with 2007 as the base year. The HPI is sub dataset of RESIDEX, and consists of registration, assessment and market prices under construction properties but not land prices as this concerns housing prices. Each category has city-wise and composite prices. This study considers the city-wise price. Presently, there are 50 cities in India in the HPI. Furthermore, the NHB sources for the HPI through its primary channels such as registration data collected from the sub-registrar offices (SROs) of the states or union territories (UTs) for HPI@Registered Prices, valuation data collected from primary lending institutions for HPI@Assessment Prices and primary and secondary data collected through market surveys for HPI@Market Prices for Under Construction Properties (National Housing Bank, 2024). The definition of under construction properties under HPI@Market Prices for Under Construction Properties refers to stock/inventory available at different stages of construction with the developers. It refers to only the primary market and does not include resale stock. The index is calculated based on the moving average of four quarters. This NHB data is widely used in past published research studies conducted on the Indian real estate market (Bhavsar, 2023; Pandey and Jessica 2018).

3.1.2 City Selection

We choose all the metro and mini metros which total 10 cities from the available 26 cities in India as per the government classification of metro and mini metro cities with appropriate representation across India, which ranges from South, East, North to West India. We excluded Pune from Maharashtra and Surat from Gujarat due to their proximity to the already represented Mumbai and Ahmadabad.

3.1.3 Control Variables

The study uses the inflation index derived from consumer price index and gross domestic product (GDP) data as the control variable released by Ministry of Statistics and Programme Implementation (MOSPI) and Government of India and the same has been adopted as a control variable in past studies on the housing market in India (Bhavsar, 2023; Pandey and Jessica 2018).

Since the objective is to infer the impact of pre- and post-pandemic periods on the housing price index, we segmented the data into two periods from Q1 2011 to Q1 2019 as the pre-pandemic period and Q2 2019 to Q1 2023 as the post-pandemic period. Since the study is on impact pre- and post-pandemic, the segmented data demands a quasi-experimental based design; hence the most suif method is an interrupted time series (ITS) analysis.

3.2 Interrupted Time Series Analysis

The adopted method, an ITS analysis (Gottman, 1981; Williams and Gottman, 1982, Rushe and Gottman, 1993; Williams and Gottman, 1999) provides capabilities that are best suited to analyzing the pre- and post-pandemic periods which are increasingly adopted in healthcare and policy studies. In this study, we assume the effect of pandemic as an intervention in the time series data set. The study strengthens the ITS analysis by including GDP and inflation as the control variables.

A time series involves the repeated observation of a specific event over a period of time, and can be divided into two segments in the simplest scenario. The first segment represents event rates before an intervention or policy, while the second segment reflects rates after the intervention. The method known as "segmented regression" is utilized to statistically assess the changes in both the level and slope of the event rates during the post-intervention period compared to the pre-intervention period. Essentially, segmented regression is employed to measure immediate changes (level) in the outcome rate as well as changes in the trend (slope) that occur following the intervention. The term "segmented" indicates that the model has distinct intercept and slope coefficients for the pre- and post-intervention time periods. Researchers can apply segmented regression to a single time series that describes only the intervention or policy site, or take a more robust approach and compare the changes at the intervention site with changes at another site where no intervention or policy took place. Since we study each city separately, and there is no comparison study, the ITS analysis regression model assumes the following (Huitema and McKean 2000; Linden and Adams 2011).

The study covers single quarterly housing price index data from Q1 2010-11 to Q1 2022-23 for the 10 cities of India. In addition to the housing price index, the study also includes GDP and inflation. We added a dummy variable X for the ITS of Q2 2019-20 to the housing price index. The time period T was added as another variable. The product of time (T) and the dummy variable (X) is considered as variable time after interruption (XT).

$$Y_t = \beta_0 + \beta_1 T_t + \beta_2 X_t + \beta_3 X_t T_t + \varepsilon_t \tag{1}$$

where T_t = time since the start of the study, X_t= dummy variable which is the intervention period of the study, X_tT_t = is an interaction term, and Y_t is the aggregated outcome variable measured at time t. The dependable variable Y_t is the housing price index (HPI) , which is a quarterly data.

In the context of our analysis, β0 corresponds to the intercept, thus capturing the initial level of the outcome variable. β1 represents the slope of the outcome variable until the intervention period begins. Moving forward, β2 reflects the change in the outcome level immediately after the introduction of the intervention, thus indicating the post-intervention effect. Additionally, β3 accounts for the trend of changes post-intervention. To determine the effectiveness of the intervention, we look for significant p-values in β2, which would suggest an immediate treatment effect, or in β3, which would indicate a treatment effect over time (Linden and Adams, 2011). In order to ensure that the error terms in the regression model do not correlate or depend on one another, we conducted a Breusch-Godfrey Lagrange multiplier (LM) test for autocorrelation up to 8 lags (L8). The LM test result (Table A2 in the Appendix) indicates that for all the cities, the data are free of autocorrelation, and null hypothesis (HO) is accepted and alternative hypothesis is rejected. In addition to the city-wise ITS analysis shown in Table 1 and summary in Table 2, this study also conducts a random effect panel data analysis by including all 10 cities considered with the use of Stata software as shown in Table 3. A Hausman test to identify fixed and random effect choices was conducted and accepted null hypothesis. Hence, we proceeded with random effect choices while conducting the panel data regression.

3.3 Result Analysis

As shown in Table 1 and summarized in Table 2, during the course of the pre-pandemic period, all of the cities exhibited a positive and strong market and all of the cities showed a similar price trend. In the post-pandemic scenario, there is significantly negative level change witnessed for the Mumbai, Delhi and Kochi markets. However, Bangalore, Chennai, and Ahmedabad show a significantly positive level change, which is worth noting. The study also observes that, other than Jaipur, Kolkata, Kanpur, and Kochi, the other major markets show a significantly negative post-trend change which indicates that bigger cities are a major victim of the pandemic. However, there is a robust reversal of the trend back to previous levels. The panel data regression analysis of all of the cities in Table 3 also confirms the same with a strong pre-trend and significantly negative post-trend change and exhibits a strong reversal.

Table 1 City-wise ITS Analysis

	Trend/Level	Factor	Std. Error	Beta	t	Sig.
Mumbai		(Constant)	12.404		7.17	0.00
		GDP	37.418	0.028	1.12	0.27
		Inflation	104.122	0.013	0.34	0.74
	Pre-Trend	T	0.242	1.239	21.03	0.00
	Post-Level Change	X	5.475	-0.174	-4.28	0.00
	Post-Trend Change	XT	0.803	-0.179	-3.95	0.00
	Post-Trend	T+XT		1.060		
Bangalore		(Constant)	20.577		4.208	0.00
		GDP	62.074	0.079	2.270	0.03
		Inflation	172.732	-0.012	-0.223	0.82
	Pre-Trend	T	0.401	0.950	11.564	0.00
	Post-Level Change	X	9.082	0.199	3.521	0.00
	Post-Trend Change	XT	1.332	-0.152	-2.403	0.02
	Post-Trend	T+XT		0.798		
Delhi		(Constant)	32.966		3.590	0.00
		GDP	99.447	0.092	1.882	0.07
		Inflation	276.729	-0.078	-1.041	0.30
	Pre-Trend	T	0.642	1.268	11.070	0.00
	Post-Level Change	X	14.551	-0.148	-1.872	0.07
	Post-Trend Change	XT	2.135	-0.447	-5.070	0.00
	Post-Trend	T+XT		0.82		
Chennai		(Constant)	19.509		7.716	0.00
		GDP	58.851	-0.052	-1.402	0.17
		Inflation	163.765	-0.204	-3.530	0.00
	Pre-Trend	T	0.380	0.800	9.094	0.00
	Post-Level Change	X	8.611	0.174	2.874	0.01
	Post-Trend Change	XT	1.263	-0.133	-1.969	0.06
	Post-Trend	T+XT		0.67		
Ahmedabad		(Constant)	12.561		6.156	0.00
		GDP	37.891	0.018	0.772	0.44
		Inflation	105.439	0.056	1.543	0.13
	Pre-Trend	T	0.245	1.143	20.833	0.00
	Post-Level Change	X	5.544	-0.075	-1.978	0.05
	Post-Trend Change	XT	0.813	-0.080	-1.896	0.06
	Post-Trend	T+XT		1.06		

(Continued…)

(Table 1 Continued)

	Trend/Level	Factor	Std. Error	Beta	t	Sig.
Lucknow		(Constant)	14.436		8.688	0.00
		GDP	43.548	0.007	0.421	0.68
		Inflation	121.179	-0.112	-4.526	0.00
	Pre-Trend	T	0.281	1.044	27.845	0.00
	Post-Level Change	X	**6.372**	**0.025**	**0.964**	**0.34**
	Post-Trend Change	XT	0.935	-0.223	-7.724	0.00
	Post-Trend	T+XT		0.82		
Jaipur		(Constant)	13.792		6.083	0.00
		GDP	41.605	-0.003	-0.049	0.96
		Inflation	115.772	0.142	1.447	0.16
	Pre-Trend	T	0.269	0.998	6.701	0.00
	Post-Level Change	X	**6.087**	**0.166**	**1.615**	**0.11**
	Post-Trend Change	XT	**0.893**	**-0.118**	**-1.028**	**0.31**
	Post-Trend	T+XT		0.88		
Kolkatta		(Constant)	26.383		5.232	0.00
		GDP	79.586	-0.006	-0.123	0.90
		Inflation	221.462	-0.151	-2.072	0.04
	Pre-Trend	T	0.514	0.951	8.555	0.00
	Post-Level Change	X	**11.645**	**-0.123**	**-1.610**	**0.11**
	Post-Trend Change	XT	**1.708**	**0.011**	**0.129**	**0.90**
	Post-Trend	T+XT		0.96		
Kanpur		(Constant)	21.890		2.570	0.01
		GDP	66.033	-0.098	-1.176	0.25
		Inflation	183.749	0.234	1.820	0.08
	Pre-Trend	T	0.426	1.024	5.238	0.00
	Post-Level Change	X	**9.662**	**0.095**	**0.704**	**0.49**
	Post-Trend Change	XT	**1.417**	**-0.090**	**-0.597**	**0.55**
	Post-Trend	T+XT		0.93		
Kochi		(Constant)	33.18		3.041	0.00
		GDP	100.08	-0.135	-2.488	0.02
		Inflation	278.50	-0.029	-0.346	0.73
	Pre-Trend	T	0.65	0.992	7.785	0.00
	Post-Level Change	X	14.64	-0.198	-2.253	0.03
	Post-Trend Change	XT	**2.15**	**0.112**	**1.147**	**0.26**
	Post-Trend	T+XT		1.10		

Notes: T is Time Period, X is Post-level Change, XT= Interaction, and T+XT= Sum of Coefficients of T and X

Table 2 Summary of Result Analysis

City	Pre-Trend	Post-Level Change	Post-Trend Change	Post-Trend
Mumbai	1.24***	-0.17***	-0.18***	1.06
Bangalore	0.95***	0.20***	-0.15**	0.80
Delhi	1.27***	-0.15*	-0.45***	0.82
Chennai	0.80***	0.17**	-0.13*	0.67
Ahmedabad	0.80***	0.17**	-0.13*	0.67
Lucknow	1.04***	0.02ns	-0.22***	0.82
Jaipur	1.00***	0.17ns	-0.12ns	0.88
Kolkatta	0.95***	-0.12ns	0.01ns	0.96
Kanpur	1.02***	0.09ns	-0.09ns	0.93
Kochi	0.99***	-0.20**	0.11ns	1.10
Panel of all Cities	4.66***	-3.38ns	-2.75**	1.91

Notes: *** P<99, ** P<95, and *P< 90

Figure 1 Visualization of Changes in Trends and Level of ITS Analysis

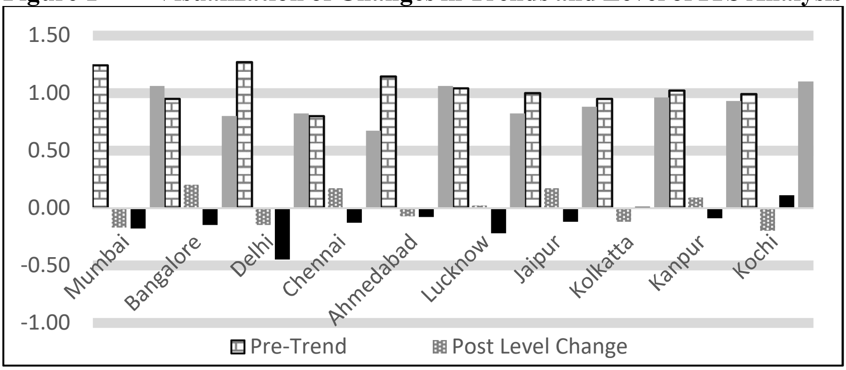

Table 3 Panel Data ITS Analysis

Random-effects GLS regression		Number of obs	= 490
Group variable: ID		Number of groups	= 10
R-sq:		Obs per group :	
within	= 0.0000	min	= 49
between	= 0.0000	avg	= 49.0
overall	= 0.5842	max	= 49
		Wald chi2 (5)	= 2468.81
corr (u_i, X)	= 0 (assumed)	Prob > chi2	= 0.0000

Price	Coef. Std. Err.	Std. Err	Z	P> |Z|	[95% Conf. Interval]	
GDP	-0.3223116	49.36852	-0.01	0.995	-97.0828	96.43822
Inflation	-130.8484	137.377	-0.95	0.341	-400.102	138.4055
SN	4.667191	0.318801	14.64	0.000	4.042351	5.29203
CV	-3.387093	7.223327	-0.47	0.639	-17.5446	10.77037
CVSN	-2.752166	1.059694	-2.60	0.009	-4.82913	-0.67521
_cons	102.624	21.93764	4.68	0.000	59.627	145.6209

4. Discussion

Conducting a quasi-experimental design based on an ITS analysis, this study focuses on the housing price index of ten cities in India. This examination unveils a notably idiosyncratic character within the real estate market, both in terms of its trajectory and overall level. The findings highlight a distinct divergence in price behavior among larger, smaller, and emerging cities. Furthermore, the research affirms that the heterogeneity of the real estate market at the city level is intrinsic and expected. Consequently, the study furnishes a collection of valuable insights into the characteristics of the real estate market in India, both in normal conditions and the aftermath of the pandemic. This finding is consistent with Bhavsar (2023) who employs a co-integration and Granger casualty econometric model to understand the complementary influence and causality among and between eight cities of India. Notably, post-pandemic, all of the Indian cities experienced a significantly positive trend. However, the impact of the pandemic disproportionately affected major cities, while smaller cities, barring Kochi, remained comparatively insulated. The unique behavior of Kochi, which resembled that of a larger city, can be attributed to its reliance on income from Gulf migrants that flows into Kerala. As such, it becomes evident that Kochi is more susceptible to structural shocks compared to the other bigger Indian cities.

This outcome underscores that larger cities, characterized by a significant concentration of economically linked corporate and private sector employees who reside and work there, were adversely affected through various avenues, such as employment losses and reduced compensation packages. Conversely, smaller cities predominantly employ government workers who possess higher savings rates and bear lower burdens of equated monthly installments. This could potentially explain why smaller cities consistently remain resilient to structural shocks. In the post-pandemic period, there is a faint recovery attempt, yet the negative trend persists, particularly for larger cities. Smaller cities, on the other hand, continue to exhibit a degree of indifference to these fluctuations. When we scrutinize the difference in trends before and after the pandemic, a clear indication of substantial reversal emerges, with only minor deviations from the pre-pandemic levels. In its entirety, this study suggests that although the pandemic has impacted the trajectory of the real estate market, this influence is transient. This finding are consistent with Sarkar and Purohit (2022) and Mehta et al. (2023) who claim that housing prices tend to rise and quickly reverse to normal in India with minimal impact from the pandemic. The panel data analysis confirms the generalizability and robustness of our findings at the city-level. The panel data analysis confirms that overall, the Indian markets were stronger pre-pandemic and insignificantly affected by the pandemic, and the Indian housing real estate market has shown remarkable resilience during the pandemic and recovered quickly from the temporary shock and temporary downward trends. This results indicate that the smaller Indian cities show a similar behavior. The noteworthy resilience of the smaller cities and the same trend exhibited overall at the panel-level deserves attention. Consequently, investors might consider incorporating both smaller and larger cities into their portfolio to mitigate the potential impact of future structural shocks and effectively counterbalance risks – a key implication drawn from this study.

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Appendix

Table A1 City-Wise Housing Price Index, Control Variable, GDP, Inflation and Intervention Period as Dummy Variable

QUARTER	MUMBAI	DELHI	BANGALORE	AHEMDABAD	LUCKNOW	KOLKATA	CHENNAI	JAIPUR	KANPUR	KOCHI	GDP	Inflation	T	X	XT
Q1.2010-11	90.6	100.7	98.6	93.2	88.8	77.9	102.7	95.3	91.7	89.6	0.0524	0.0891	1	0	0
Q2.2010-11	99.7	95.6	97.9	102.5	98.7	103.2	109.5	99	99.4	92.4	0.0524	0.0891	2	0	0
Q3.2010-11	100.9	92.1	97.9	102	104.7	106.6	94.6	103.6	103.7	113.8	0.0524	0.0891	3	0	0
Q4.2010-11	108.8	112.1	105.5	102.2	107.8	112.3	93.1	102.1	105.1	104.2	0.0524	0.0891	4	0	0
Q1.2011-12	122.1	126.8	110.7	121.3	118	103	101.2	106.3	104.7	120.9	0.0546	0.0948	5	0	0
Q2.2011-12	131.4	124.8	107.8	130.4	123.1	105	110.4	109.6	106.8	105	0.0546	0.0948	6	0	0
Q3.2011-12	122.8	136.7	138.6	137.1	131.9	103.2	110.7	108.3	108.5	103.1	0.0546	0.0948	7	0	0
Q4.2011-12	143.5	158.2	133.3	141	129.4	106.1	108.2	108.6	114.9	97.8	0.0546	0.0948	8	0	0
Q1.2012-13	147.6	177.3	133.3	140.8	136.4	135.2	119.2	113.4	114.4	98.8	0.0639	0.1002	9	0	0
Q2.2012-13	148.1	183.2	136.6	146.4	156.6	149.1	117.8	117.4	106	127.5	0.0639	0.1002	10	0	0
Q3.2012-13	158.9	200.7	141.2	150.6	169.3	162.5	137.6	118.9	92.8	136.5	0.0639	0.1002	11	0	0
Q4.2012-13	159.5	213.1	141.9	155	166.2	169.4	137.4	129.4	90.9	124.2	0.0639	0.1002	12	0	0

(Continued…)

(Table A1 Continued)

QUARTER	MUMBAI	DELHI	BANGALORE	AHEMDABAD	LUCKNOW	KOLKATA	CHENNAI	JAIPUR	KANPUR	KOCHI	GDP	Inflation	T	X	XT
Q1.2013-14	160	214.8	142.3	161.9	173.9	171.8	138.3	129.4	82.4	127	0.0741	0.0667	13	0	0
Q2.2013-14	169.2	215.7	150.4	171.7	186.7	173.5	150	128	92	161.6	0.0741	0.0667	14	0	0
Q3.2013-14	166.5	211.1	169.3	172.6	203.6	168.2	174.3	127.3	81.6	189.4	0.0741	0.0667	15	0	0
Q4.2013-14	175.4	229.3	184.3	169.4	212.5	169.8	179.3	120	78.4	166.2	0.0741	0.0667	16	0	0
Q1.2014-15	183.2	241.7	180.4	173	223.3	194	179.2	120.6	99.4	166.9	0.08	0.0491	17	0	0
Q2.2014-15	185.9	251	174.6	183.2	238.7	209.3	172.8	131.7	101.8	184.2	0.08	0.0491	18	0	0
Q3.2014-15	188	273.2	183.1	187.7	243.4	210.8	187.3	143.6	107	180.9	0.08	0.0491	19	0	0
Q4.2014-15	194.7	290.1	202.7	185	267.3	224.9	188	140.6	113.5	179.7	0.08	0.0491	20	0	0
Q1.2015-16	203.5	296.5	208.4	186.6	259.8	231.1	186	132.7	104.3	172.6	0.0826	0.0495	21	0	0
Q2.2015-16	205.9	299.3	208	196.8	264.7	224.1	194.2	136	110.4	171	0.0826	0.0495	22	0	0
Q3.2015-16	208.9	300	205.9	207.3	282.5	224.1	202.7	136.1	115.1	184.6	0.0826	0.0495	23	0	0
Q4.2015-16	208	302.1	190	204.1	288.9	222.3	210.7	126.1	111.6	169.8	0.0826	0.0495	24	0	0

(Continued…)

(**Table A1 Continued)**

QUARTER	MUMBAI	DELHI	BANGALORE	AHEMDABAD	LUCKNOW	KOLKATA	CHENNAI	JAIPUR	KANPUR	KOCHI	GDP	Inflation	T	X	XT
Q1.2016-17	219.2	305.7	220.6	207.6	302.6	234.9	230.6	126.8	113	199.7	0.068	0.0333	25	0	0
Q2.2016-17	226.5	314.9	220.1	214.1	311.6	231.9	229.3	127.5	107.8	191.7	0.068	0.0333	26	0	0
Q3.2016-17	235.8	314.6	225.1	217.8	337.1	240.2	224	128.7	120.9	182.6	0.068	0.0333	27	0	0
Q4.2016-17	243.9	312.6	218.3	235.4	335.8	242.3	208.9	129.4	130.8	208.2	0.068	0.0333	28	0	0
Q1.2017-18	246	341.9	227.7	243.1	341.3	251.4	204.8	132.7	133.5	189.1	0.0645	0.0394	29	0	0
Q2.2017-18	254.7	335.3	221	236.1	344.4	248.2	213.3	144.5	144.7	227.4	0.0645	0.0394	30	0	0
Q3.2017-18	257.4	335.6	225.6	256.8	354	253.4	217	149.4	149.1	231.3	0.0645	0.0394	31	0	0
Q4.2017-18	257.3	324.3	232.9	252	362.2	254.7	227.2	159.2	152.3	257.1	0.0645	0.0394	32	0	0
Q1.2018-19	264.2	341.6	244.8	254	360.6	254.5	224.5	155.6	148.7	267	0.0374	0.0373	33	0	0
Q2.2018-19	263.9	342.1	245.8	258.6	370	255.9	238.5	157.6	140.3	274.7	0.0374	0.0373	34	0	0
Q3.2018-19	266	346.7	243.2	261.4	386.3	262	246.9	152.8	154.9	298	0.0374	0.0373	35	0	0
Q4.2018-19	261.4	328.6	256.1	262.4	370.3	265.5	255.3	141	150.1	307.3	0.0374	0.0373	36	0	0

(Continued…)

(Table A1 Continued)

QUARTER	MUMBAI	DELHI	BANGALORE	AHEMDABAD	LUCKNOW	KOLKATA	CHENNAI	JAIPUR	KANPUR	KOCHI	GDP	Inflation	T	X	XT
Q1.2019-20	260.6	342.8	266	264.1	370.7	266.5	256.6	161.5	164.9	287.7	-0.066	0.0662	37	0	0
Q2.2019-20	265	333.1	273.6	262.8	371.9	275.1	257.1	177.3	166	279	-0.066	0.0662	38	1	1
Q3.2019-20	256.8	329.4	283.8	282.3	392	266.5	280.9	175.5	171.4	280.6	-0.066	0.0662	39	1	2
Q4.2019-20	264.4	325.7	273.8	276.1	395.5	272.4	281.5	172.8	172.5	265	-0.066	0.0662	40	1	3
Q1.2020-21	263	319.8	308.8	278.4	396.2	270.9	275.2	172.6	170.4	271.5	0.0895	0.0513	41	1	4
Q2.2020-21	263	314.9	297.7	286.5	397.5	268.1	262.8	172.6	171.1	270.1	0.0895	0.0513	42	1	5
Q3.2020-21	261.3	329.4	319.1	273	398.1	280	278.8	171	170.5	258.9	0.0895	0.0513	43	1	6
Q4.2020-21	266.5	323.2	316.8	284.1	398.4	276.8	279.3	166.7	171.3	286.2	0.0895	0.0513	44	1	7
Q1.2021-22	265.9	315	333.7	302.8	394.9	284	261.2	167.1	169.2	287.3	0.07	0.058	45	1	8
Q2.2021-22	279.8	299.3	313.2	302.6	395.5	278.7	268.7	181.2	171	297.2	0.07	0.058	46	1	9
Q3.2021-22	286	327.7	315.9	302.8	397.2	288.5	267.5	188.5	170.2	310.1	0.07	0.058	47	1	10
Q4.2021-22	281.3	326.2	281	295.7	396.8	329.9	277	187	172	307.4	0.07	0.058	48	1	11
Q1.2022-23(P)**	284.9	312	320.4	317.7	398	329.3	280.2	175.6	173.3	326.3	0.07	0.058	49	1	12

Notes: T denotes Time Variable, X is the Dummy Variable (Intervention Period), and XT is Interaction.

Table A2 LM Test for Autocorrelation (Mumbai)

Lag(p)	Chi2	df	Prob >chi2
1	0.000	1	1.0000
2	0.000	2	1.0000
3	0.000	3	1.0000
4	0.000	4	1.0000
5	0.000	5	1.0000
6	0.000	6	1.0000
7	0.000	7	1.0000
8	0.000	8	1.0000

Note: H0 denotes no serial correlation