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APARTMENT PRICES, THE BUSINESS CYCLE AND TIME ON MARKET: EVIDENCE FROM BUCHAREST

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Abstract. The issue of time on market (TOM) correlation with the sale price remains under-explored considering the importance and complexity of the housing market. This paper argues that TOM is influenced by variables other than transaction prices and tests the hypothesis that the business cycle is important in explaining the dynamics of TOM and driving transaction prices in the housing market. In testing this hypothesis, the paper investigates the role of transaction prices and TOM in the housing market in Bucharest, Romania using granular observations of 32,000 price listings over the period 2013–2017, a time-scale that captures the economic recovery phase following the global financial crisis. The analysis shows that spatial correlation is strong for TOM rather than weak and that reinforcing spatial effects evidenced among TOM in transactions of closed units would reflect the strong clustering in prices but are balanced in a type of (contrary sign) distribution effect that diminish the whole spatial impact in TOM in similar size, describing a corrective mechanism leading to a more balanced impact on TOM. Results show that GDP affects transaction prices pro-cyclically (0.062%) and with persistence (0.054%), while only GDP growth (the cycle) influences TOM (0.352%).

Keywords: TOM, housing prices, business cycle, spatial error effects.

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1. Introduction

The literature concerning the relationship of the sale price to time on market (TOM) in the housing market is complex and inconsistent suggesting that there is a lack of consensus. Several studies have argued that sale price increases with TOM; that is, the longer the TOM, the higher the prices (Yavas, 1992; Asabare et al., 1993; Taylor, 1999; Forgey et al., 1996; Björklund et al., 2006). In contrast, other studies (McGreal et al., 2009) have indicated an optimal marketing period after which the achieved prices no longer increase and may even decline due to negative perceptions of the property (Sirmans et al., 1995; Huang & Palmquist, 2001; Knight, 2002; Dubé & Legros, 2016), indicating the hypothesis that prices only decline after TOM reaches a maximum.

Long TOM reflects either the characteristics of the property or market conditions. For example, Haurin (1988) discusses the impact of the atypicality of a property affecting TOM. In this context, the literature demonstrates that house prices can be sticky in an economic downturn, with properties staying longer in the market in an effort to maintain price level, whereas in the up-cycle prices are rising fast with correspondingly short TOM with sale prices exceeding list prices (Haurin et al., 2013).

In exploring further, the impact of cycles upon TOM, McGreal et al. (2016) demonstrated that the business cycle is one of the main determinants of TOM, with their findings complementing supporting other literature that has discussed the relationship between TOM and market conditions (Pryce & Gibb, 2006; Zhou et al., 2018). However, in the same paper, McGreal et al. (2016) observed inconsistent results between TOM and transaction prices arising from spatial factors. In particular, their study of the Adelaide (Australia) market identified that TOM was spatially randomly distributed, whereas house prices demonstrated a strong spatial association with spill-over effects.

In this paper, the methodology used by McGreal et al. (2016) is applied to a similar dataset for the city of Bucharest, Romania. Specifically, the paper tests whether the business cycle explains the dynamics of TOM and its role in driving transaction prices in the housing market. The findings of this paper lend support to previous results regarding the significance between transaction prices, list prices and differences with TOM. In particular, the introduction of the business cycle as an explanatory variable is shown to improve the statistical significance of the model.

The rationale behind exploring the link between GDP and liquidity in the residential market is based on the intuition that the economic climate influences the number of transactions in any market. During periods of economic boom, the likelihood of potential buyers deciding to purchase a unit increases, thereby expanding the market size. Conversely, in times of economic contraction, the probability of purchasing decreases. This implies that during periods of economic expansion, the likelihood of buying is higher, resulting in more housing seekers and increased liquidity, which directly leads to a reduction in TOM. This intuition is supported by evidence observed after the global financial crisis, during the initial phase of economic recovery, when housing transactions rose (and TOM decreased) without a substantial increase in prices.

The literature has explored the effect of macroeconomic variables, such as income (which typically rises during economic booms), and other factors that directly impact prices. However, it has not thoroughly examined the effect of market size, which grows during periods of economic expansion, on explaining TOM. This is the focus of the article.

The paper, in Section 2, reviews relevant literature on TOM and explores theoretical principles. Section 3 develops the theory and formulates specific hypotheses to be tested. Section 4 explains the hypothesis to be tested. Section 5 describes the database developed for Bucharest and outlines variable transformation. Section 6 presents the analysis and results from the hedonic estimations relating to asking prices, transaction prices and TOM. Section 7 presents the discussion. Section 8 draws conclusions stemming from this study.

2. Literature and theoretical principles

This literature review builds upon the strong underpinning theoretical and empirical research base in relation to TOM. Reflecting on this previous research, two broad sets of factors appear to influence TOM's behaviour: external (economic conditions) and internal (property-specific and the role of brokers and searching issues) factors.

Regarding the external factors, TOM has been influenced by economic conditions; in boom periods, a higher selling price is associated with shorter TOM (Haurin et al., 2013; Han & Strange, 2014). Björklund et al. (2006) considered that a good selling strategy in a rising market is to set a high list price compared to the expected transaction price. He et al. (2020) found that the price–TOM relationship is non-linear and time-dependent and argued that both the selling price and TOM increased together during a boom period. Making a similar point, An et al. (2013) found that the relationship between price and TOM depends on market conditions, with a positive effect between price and TOM but a negative impact in declining markets. For Glasgow (Scotland) Pryce and Gibb (2006) demonstrated that booming markets tend to have an early peak in the hazard function followed by a steep decline, while Haurin et al. (2013) also using a hazards model established for the Belfast market (Northern Ireland) that unexpected short duration price shocks change the duration of the marketing period with a positive demand shock resulting in rising prices and shorter TOM. An et al. (2013) considered that the effect of search (effectively TOM) on price is positive even in a declining market, suggesting that it is sufficient to offset the negative market impact. McGreal et al. (2016) argued that economic conditions are leading TOM rather than property prices, with the business cycle one of the main determinants of TOM. They also articulated that TOM varies depending on economic momentum, with the GDP being the primary determinant.

Several papers have also discussed the impact of macroeconomic variables on TOM. For example, Taylor (1999) observed that interest rates, employment and exchange rates influence TOM. Likewise, Kalra and Chan (1994) observed that mortgage rate and total unemployment are important factors impacting selling time notably for low-price houses. Kang and Gardner (1989) considered that the selling time of property depended on market conditions due to changes in mortgage interest rates. Using a similar argument, Genesove and Mayer (1997) considered that the higher the loan-to-value associated with the mortgage, the longer the TOM. Macroeconomic trends are captured by income as an explanatory variable of TOM in studies such as Sirmans et al. (2010) and Hayunga and Pace (2019). The role of transparency in housing markets and market conditions was also examined by Nikiforou et al. (2022) and An et al. (2013), while Kalra and Chan (1994) explored the influence of macroeconomic factors on TOM using censored methods. Other studies have investigated the value of TOM, considering the effect of valuation methodologies and the role of experts (Ferreira & Jalali, 2015), tested new empirical methodologies (Cajias & Zeitler, 2023), or examined the role of TOM in market equilibrium within a theoretical context (Lisi, 2021).

From the perspective of internal (property-specific) factors, the literature has primarily followed search theory to explain the relationship between transaction prices and TOM, with a focus on selling conditions, the role of brokers, and the specific characteristics of the property. Given the vast amount of literature on this topic, we reference here only the contributions most relevant to this research. TOM is influenced by factors such as atypical property characteristics (Haurin et al., 2010), which mainly results in significant discounts from the list price. Atypically can be associated with the stigma effect, with Pryce and Gibb (2006) arguing that stigma effects attached to unsold properties lengthen TOM with a signalling effect reducing the chances of a sale. Analysis by Kang and Gardner (1989) found no correlation between the size of the property and marketing time; however, in the same paper, they argued that marketing time is significantly shorter for newer homes. Several authors have argued that factors such as property age, quality, and size impact TOM (Jud et al., 1996; Taylor, 1999; McGreal et al., 2009), while Rossini et al. (2012) were of the opinion that dwelling size and location were major factors determining TOM. Analysis by Dubé and Legros (2016) inferred that better-quality houses stay less TOM.

Whilst literature is abundant on property characteristics, the impact of macroeconomic factors and market cycles on TOM, there has been less emphasis on how TOM varies spatially across metropolitan areas. In this context, the paper by Pryce and Gibb (2006) is important, demonstrating that TOM varies differently with the market cycle depending on the submarket structure. Also, the analysis by Anglin et al. (2003) that TOM is more affected by spatial location and market conditions than property characteristics was a change in thinking regarding those factors that impact TOM. Likewise, Carrillo and Pope (2012) observed substantial heterogeneity in the distribution of TOM across property locations and that there is substantial heterogeneity in the distribution of TOM across property types and property locations within the county.

Housing transaction prices receive multiple influences from several dimensions with the literature extensive on this topic. On the one hand, housing transaction prices are affected by macroeconomic variables associated with monetary conditions (Rubio & Carrasco-Gallego, 2016; Taltavull de La Paz & White, 2012, 2016; Davis & Van Nieuwerburgh, 2015) with real variables (Case et al., 2011, 2005; Adams & Füss, 2010; Piazzesi & Schneider, 2016) and strong spill-over effects at a spatial level (Taltavull de La Paz et al., 2017; Meen, 1999; Cook & Thomas, 2003; Gupta & Miller, 2012). TOM varies depending on the economic momentum, with the county's GDP being the primary determinant of the number of days a property expends being offered (McGreal et al., 2016). Janssen et al. (2015) found that the application of the bottom price strategy compared to the asking price strategy in a cold market leads to a 55% decreasing TOM. Zhou et al. (2018) also explore the timely of TOM and found that patience may lead developers to sell the house at a price premium.

The literature also demonstrates that housing transaction prices and TOM are endogenously related at a spatial level as both are simultaneously determined (Björklund et al., 2006; Dubé & Legros, 2016; Daneshvary & Clauretie, 2013). The existing evidence suggests that transmission of influences between price and TOM could occur, thus, in two dimensions, space and time, supporting the hypothesis that housing transaction price drivers should affect TOM in both directions.

In this context, McGreal et al. (2016) found that spatial effects are asymmetrically related to housing prices showing strong spatial spillovers and randomly distributed TOM. The existence of different spatial distributions for price and TOM[1] is seemingly at variance with the perception that price and TOM are strongly correlated, suggesting the effect of the influence of a third variable and that prices and TOM belong to a different economic mechanism. This infers that the direct correlation between prices and TOM is spurious (by definition), requiring further consideration of basic principles of housing demand theory to these relationships between house prices and TOM.

The literature clearly establishes an endogenous relationship between prices and TOM, both of which are influenced by the specific characteristics of properties, such as features, quality, specificity, and location, among others. Prices are also affected by macroeconomic and microeconomic factors that contribute to their fluctuations, including monetary policy, capital movements, income levels, spillovers, and the structure of submarkets, which subsequently affect TOM. TOM can be influenced by the unique attributes of the property as well as by prices. However, it remains unclear which of these factors initiates the changes, and there is ongoing debate about the order of influence and the individual effects of these two interrelated variables (TOM and housing prices). Identifying the direction and magnitude of this relationship is one of the objectives of this study.

3. Theoretical perspective[2]

Summarizing, the reviewed literature provides clear evidence on housing price reactions to changes in three groups of variables. The first group is economic conditions (EC), which includes primary demand determinants such as interest rates, employment, and economic growth (Taylor, 1999; Kalra & Chan, 1994; Kang & Gardner, 1989). These variables affect the market differently depending on the economic cycle phase, producing varying impacts on transactions and TOM (Haurin et al., 2013; Han & Strange, 2014; An et al., 2013). The second group consists of property characteristics and specific housing market conditions (PMC), including factors like age, quality, size, location, and atypical features. These aspects influence price levels and transaction volume at varying degrees of individual intensity (Dubé & Legros, 2016; Jud et al., 1996; McGreal et al., 2016; Haurin et al., 2010; Pryce & Gibb, 2006). Additionally, the spatial distribution of property-specific factors varies across and within metropolitan areas, introducing significant heterogeneity in price distribution (Pryce & Gibb, 2006; Carrillo & Pope, 2012). The third group, which affects TOM directly, involves brokers and selling strategies (BSC). Established literature indicates that brokers' expertise and pricing strategies can expedite or prolong transactions and TOM (Björklund et al., 2006; He et al., 2020). The literature also emphasizes the simultaneous, complex, and bidirectional relationship between housing prices and TOM, as

[1] Where TOM was randomly distributed among the space while transaction prices show strong spatial correlation.

[2] We want to extend our heartfelt gratitude to the anonymous referee and the editor for their insightful suggestion to add this section. Their valuable input has significantly enhanced the completeness and quality of this paper. We sincerely appreciate their efforts in helping us improve our work.

higher prices associated to shorter TOM during economic booms but large TOM in downturns (An et al., 2013; McGreal et al., 2016).

Economic theory explains how general socio-economic conditions (e.g., GDP, demographics) primarily influence housing demand, which increases in response to positive economic shocks, thereby shifting demand and increasing rents (DiPasquale & Wheaton, 1996). This rise in rents alters the equilibrium cap rate, leading to increasing property values:

$$Ph \Leftrightarrow \Upsilon\left(rents, ir\right). \quad (1)$$

Including the components supported by literature:

$$Ph_t = \Phi\left(rents, ir\right)_t = \Phi\left(EC, ir\right)_t \cdot \Gamma\left(PMC\right)_t \cdot \Lambda\left(BSC\right)_t \cdot \upsilon_t, \quad (2)$$

where: ir refers to a proper capitalization rate; υ_t is an error; Φ, Γ and Λ are matrices of parameters estimating the responses sensibility of housing prices to change in the three group of drivers.

Within the PMC group, the endogenous housing market mechanism highlights that imbalances arise as market activity moves through different cyclical phases, with periods of oversupply typically associated with downturns and economic crises, contributing to disequilibrium (Chinloy, 1996; Wheaton, 1999; Pyhrr et al., 1999)[3]. One indicator of this imbalance is the increase in vacancies at previous price levels during downturns, signaling that prices have not yet adjusted to the current market conditions and remains sticky. Figure 1 presents a graphical representation of market disequilibrium during the crisis phase and the subsequent path toward recovery. At the cycle's low point (left figure), several units remain priced above the new equilibrium established after a negative shock (at price P2, units vacant are H1 to H0). This pricing imbalance (P2–P1) will persists until purchasing capacity is restored, prompting a positive shift in demand (right figure).

Evidence of price stickiness is presented in Genesove and Mayer (1997) who demonstrates that sellers are reluctant to lower listing prices despite changing market conditions, creating prolonged price misalignments. Such price response is associated with extended TOM and higher prices, as demand remains insufficient to absorb excess supply at previous price levels. Zabel (2016) found that prices rise as vacancies fall under excess demand but decline more slowly when vacancies increase due to excess supply. This asymmetry prolongs housing downturns with extended TOM. Sticky prices also dampen the effects of interest rate changes on housing prices, limiting monetary policy's impact on the housing market (Chen et al., 2024; Taltavull de La Paz & White, 2016) and affect future prices in what is known the "anchoring" effect (Shie, 2019).

Thus, following Björklund et al. (2006), the equilibrium between prices and TOM within each housing submarket can be represented as follow:

$$Ph_t = \Phi\left(GDP, ir\right)_t \cdot \Gamma\left(P_{t-1}, vacancies, spatian, OtherPMC\right)_t \cdot \Lambda\left(BSC\right)_t \cdot \upsilon_t; \quad (3)$$

$$TOM_t = \Phi'\left(GDP, ir\right)_t \cdot \Gamma'\left(P_{t-1}, vacancies, spatian, OtherPMC\right)_t \cdot \Lambda'\left(BSC\right)_t \cdot \mu_t. \quad (4)$$

With Ph_t being housing prices, and TOM_t is the time the property has been listed on the market, both are endogenously related as are simultaneously generated when transaction takes place. Both variables are influenced by economic components (EC) measured by GDP, which proxies for employment and purchasing power, as well as by endogenous factors within the property market cycle (PMC). As sticky prices imply a price-anchoring effect that affects price response until vacancies reach the minimum level to prevent new prices from reacting, a reversion component

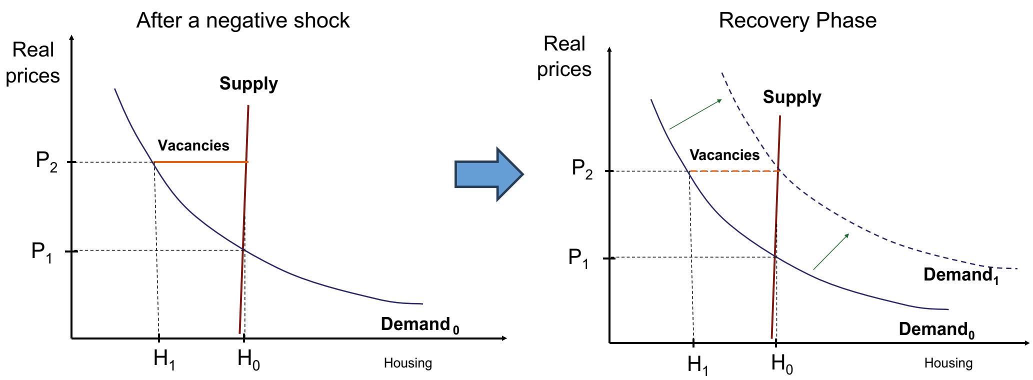

Figure 1. Market mechanism. From crisis to recovery

[3] The disequilibrium has several implications, as it is largely demonstrated by the literature. Implications determine the housing market mechanism itself (White, 2015), or for valuation purposes (d'Amato et al., 2019; d'Amato, 2022).

(P_{t-1}) and the vacancies should be included into the equation. Location and spatial idiosyncratic characteristics also refine the price reaction by housing characteristics.

4. The hypothesis from theoretical discussions

Considering the previous evidence, on the importance of the business cycle as one of the main determinants of TOM (McGreal et al., 2016) this paper contends that market mechanisms led by GDP are important in determining TOM. According to theory, the first shock on the demand side is usually started due to economic activity changes and is invariably associated with changes in GDP with effects on space demand (DiPasquale & Wheaton, 1996). As a fundamental driver, the GDP is one of the determinants of housing prices together with population or finance (Case et al., 2005), thus house price (*ph*) can be represented as a function of GDP and other factors in a reduced form from Equation (3) (see Equation (5)).

$$ph_t = \alpha + \beta gdp_t + \zeta X_t + \varepsilon_t, \quad (5)$$

where: ph_t is transaction prices at time t; gdp_t refers to Gross Domestic Product as a measure of business cycle; X is a matrix with a set of fundamental variables explaining housing prices from the macroeconomic point of view (Case et al., 2005); ε_t is an error measure. Note lower case are variables in logs.

The volume of transactions in essence captures the business cycle effect with a large number of transactions characterising a more liquid market, while fewer transactions capture lower liquidity. Larger liquidity can be associated with lower TOM (that is, the larger the transactions, the lower the TOM), as properties have a greater probability of being sold due to the better conditions in the market and a potential accumulation of buyers (the opposite applies).

Theorising any GDP changes can affect, simultaneously, both TOM and house prices but through different mechanisms suggesting another source of endogeneity. We hypothesise that prices are affected through an increase/decrease in demand derived from the cyclical GDP impact on income and employment, and the latter affects TOM depending on the amount of transactions resulting from the economic growth and the market size namely the number of households with purchasing capacity and availability of finance in the market. This suggests an asymmetry in how TOM responses to changes in prices and would be reflected in the random spatial distribution found in McGreal et al. (2016).

Either market size or economic growth affecting TOM and transaction prices suggest the existence of spurious effects on the direct relationship (Arrow A in Figure 1) while P and TOM are affected simultaneously by the economic dynamics (Figure 2).

The mechanism is shown as follows.

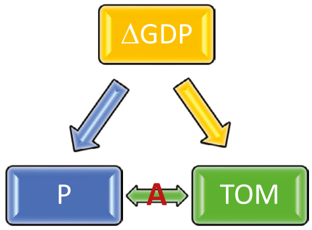

Figure 2. The endogenous relationship between a change in GDP, house price and TOM

Supply conditions in each market determine the intensity of price reactions in the short run, affecting simultaneously transactions and the number of buyers,

GDP → Purchase capacity & number of buyers

$$(1)\nabla GDP \rightarrow \nabla transactions \rightarrow \Delta TOM;$$

$$(2)\nabla GDP \rightarrow \nabla buyers \rightarrow \nabla \%Ph.$$

TOM and housing prices are endogenously determined, and the channel should be (2) → (1). If so, and prices show a strong correlation in the time and space, TOM should also show the same.

This paper tests the hypothesis that TOM simultaneously follows housing transaction prices as represented in Equations (3) and (4), using a two-step analysis. The first step estimates a pooled OLS/2SLS models to find causality between transaction prices and TOM in presence of the business cycle without consider the spatial correlation. The second step tests the spatial autocorrelation between TOM and transaction prices in order to add additional evidence to McGreal et al. (2016) about spatial reaction shown by both variables; It estimates an Spatial regression model to test the simultaneity between the generation of transaction prices and TOM in presence of the economic growth and controlling for the existing spatial spill-over effects.

In essence there are two hypotheses to be tested in the analysis.

H_0^1. TOM-Transaction prices are not related at the time level nor the spatial level.

H_0^2. GDP affects TOM dynamics.

5. Data base and variable transformations

The database for the analysis in this paper comes from Bucharest city and was extracted from a proprietary database, Flexmls, of residential property transactions. The database contains individual information on housing listings and transactions georeferenced for the city. Data covers the period from the first quarter of 2013 to the second quarter of 2017 a period that captures the economic recovery phase following the financial crisis[4]. In total 32,000

[4] The period included in the analysis is the only one available in the dataset. The data is unique and highly detailed, but it belongs to a well-established company, and no more updated statistics are available.

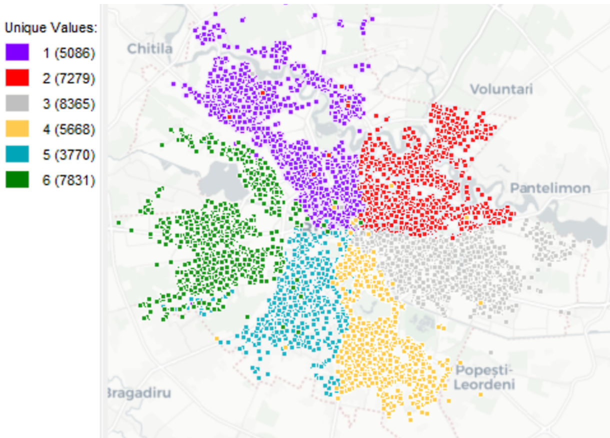

Figure 3. Housing transactions by district in Bucharest

transactions are considered. The database is very rich and contains list prices and transaction prices of each property, mainly apartments, TOM, construction details, age, property type, number of floors and locational characteristics. The distribution of transactions across Bucharest is shown in Figure 3.

The data on TOM is available on a quarterly basis and for six different geographical districts of the city. TOM is variable over time and also varies spatially across the city (Figure 4). From a spatial perspective it is apparent that districts 3, 4 and 6 have TOM below the average and by inference seemingly are more liquid locations, while districts 1, 2 and 5 of Bucharest appear to have lower liquidity. The trend suggested by the Figure 3 is an increase in TOM though cyclicality is apparent.

Regarding price (Figure 5) it is apparent that transaction price lags list price across the time period considered. In this respect, the data for Bucharest is consistent with arguments proposed by authors such as Yavas and Yang (1995) that the list price sets the upper bound or limit and that bids are below list price. The data show an initial drop in prices throughout 2013 and the first half of 2014 thereafter rising at a steady rate up to the end of the period considered (second quarter of 2017). This suggests both increasing house prices, with list and transaction price growing in parallel, and increasing TOM.

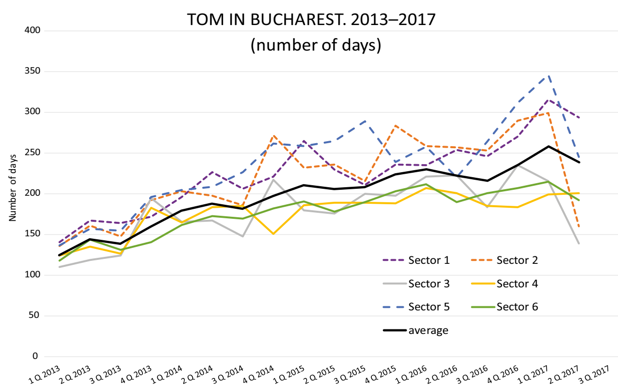

Figure 4. TOM in number of days and by sector, Bucharest 2013–2017

In accordance with the hypothesis advanced in this paper, the core non-property variable, the GDP for the city of Bucharest, is included into the dataset and assigned to each observation accordingly to the time listed. The original data are available on an annual basis but for this analysis has been transformed into a quarterly time series using the official quarterly GDP for Romania (as a surrogate for Bucharest) and applying the Denton (1971) algorithm for interpolated series in the subject data (Bucharest GDP in this case, series *x*) relating the frequency of the benchmark (Romanian GDP, series *y*)[5]. As illustrated (Figure 6), the change in GDP is used as to model the business cycle in Bucharest.

Table 1 presents descriptive statistics for all the variables used in the analysis including property characteristics. The average nominal price for the whole Bucharest (in index form) is used to control the observed prices. In total there are 28 quarterly data points.

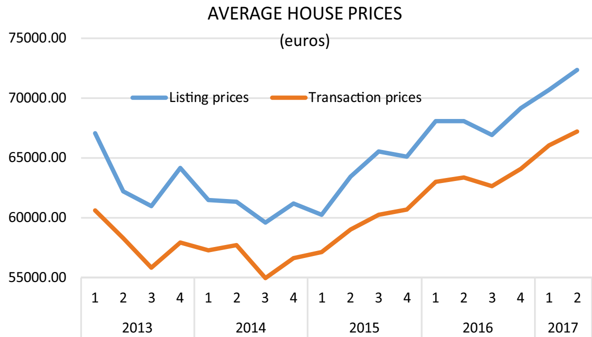

Figure 5. Listing and housing transaction prices in Bucharest 2013–2017

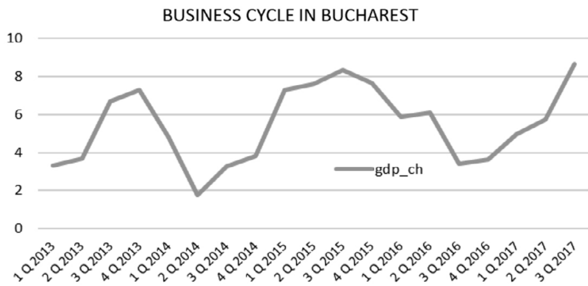

Figure 6. Quarterly business cycle in Bucharest

5 The goal of the Denton interpolation is movement preservation: the interpolated series "*x*" should preserve the movement in the indicator series "*y*" as much as possible producing an interpolated series that closely follows the growth rate of the indicator "*y*". The dynamics between GDP and housing prices (both for Bucharest and Romania).

Table 1. Basic statistics

	N		Mean	Median	Mode	St. Dev.	Assym	Kurtosis	Min	Max
	Valid	Lost/%								
Property type	37999	0								
Address	37999	0								
Construction year	35497	2502	1959	1978	1980	196.286	–9.743	93.83	0	2017
Age	35497	2502	58.28	39	37	196.286	9.743	93.83	0	2017
lage	35486	2513	3.51	3.7	3.6	0.857	–0.424	6.90	0	7.61
Postal code	748	37251	17663.24	0	0	47157.15	9.678	124.15	0	700000
Type of apart:	37999	0								
d_condo	24737	65.1%	0.65	1	1	0.477	–0.634	–1.60	0	1
d_partial_ap	12733	33.5%	0.34	0	0	0.472	0.699	–1.51	0	1
d_circular	264	0.7%	0.01	0	0	0.083	11.872	138.96	0	1
Listing date	37999	0								
Tranzaction date	37999	0								
floor_n	35057	2942	3.84	3	1	3.000	0.517	–0.65	–1	17
D_atic	198	0.50%	0.01	0	0	0.072	13.745	186.94	0	1
d_house	2744	7.20%	0.07	0	0	0.259	3.306	8.93	0	1
Financing:	37999	0								
d_cash	18501	48.70%	0.49	0	0	0.500	0.052	–2.00	0	1
d_inmobiliar	867	2.30%	0.02	0	0	0.149	6.392	38.86	0	1
d_mortgage	2990	7.90%	0.08	0	0	0.269	3.130	7.80	0	1
d_leasing	9	0%	0.00	0	0	0.015	64.957	4217.6	0	1
d_loan_pers	18	0%	0.00	0	0	0.022	45.915	2106.3	0	1
d_public_fin	5418	14.30%	0.14	0	0	0.350	2.045	2.18	0	1
d_rate	16	0%	0.00	0	0	0.021	48.704	2370.2	0	1
Geo Lat	37999	0	44.43	44.43	44.41	0.027	0.298	0.19	44.36	44.53
Geo Lon	37999	0	26.10	26.11	25.99	0.049	–0.188	–1.02	25.95	26.23
County:	37999	0								
S1	5086	13.40%	0.13	0	0	0.340	2.151	2.63	0	1
S2	7279	19.20%	0.19	0	0	0.394	1.568	0.46	0	1
S3	8365	22%	0.22	0	0	0.414	1.351	–0.17	0	1
S4	5668	14.90%	0.15	0	0	0.356	1.970	1.88	0	1
S5	3770	9.90%	0.10	0	0	0.299	2.681	5.19	0	1
S6	7831	20.60%	0.21	0	0	0.404	1.453	0.11	0	1
Bathroom with bathtub	37989	10	0.93	1	1	0.373	1.037	31.77	0	10
Bathroom with shower	37989	10	0.17	0	0	0.403	2.807	16.76	0	9
Nº bathrooms	37987	12	0.17	0	0	0.469	36.732	3922.8	0	52
Number of bedroom	37997	2	1.40	1	1	1.044	1.641	11.44	0	20
Number of floors	37182	817	6.95	8	10	3.214	–0.370	0.20	0	50
Total bathrooms	37997	2	1.26	1	1	0.553	3.350	27.68	0	15
Street	37999	0								
d_alley	3774	9.90%	0.10	0	0	0.299	2.679	5.180	0	1
d_boulev	4314	11.40%	0.11	0	0	0.317	2.437	3.937	0	1
d_way	1902	5.00%	0.05	0	0	0.218	4.127	15.033	0	1
d_road	307	0.80%	0.01	0	0	0.090	10.991	118.8	0	1
d_plaza	71	0.20%	0.00	0	0	0.000			0	0
d_street	23779	62.60%	0.63	1	1	0.484	–0.520	–1.730	0	1
Listing price	37999	0	65025.9	55000.0	55000.0	57930	19.2	1041.2	8000	4500000
Initial price	37988	11	69357.6	57775.0	65000.0	67549	18.1	788.5	0	4500000
Tranzaction price	29283	8716	60249.7	52500.0	60000.0	43729	8.5	161.9	1.0	1600000
l_transp	29283	8716	10.9	10.9	11.0	0.5	0.2	16.4	0.0	14.3
Util urface (SQM) M2	37795	204	61.2	54.0	50.0	43.1	12.3	429.3	0.0	2560.0
Garage	37999	0								
d_parking	414	1.10%	0.01	0	0	0.104	9.424	86.81	0	1
Zone MLS	37996	3	309.96	190	288	270.17	2.173	6.48	100	2110
Energie: rating	708	1.86%								
d_A	432	1.10%	0.01	0	0	0.106	9.218	82.98	0	1
d_B	230	0.60%	0.01	0	0	0.078	12.737	160.24	0	1

End of Table 1

	N		Mean	Median	Mode	St. Dev.	Assym	Kurtosis	Min	Max
	Valid	Lost / %								
d_C	41	0.10%	0.00	0	0	0.033	30.395	921.93	0	1
d_D_G	5	0%	0.00	0	0	0.011	87.163	7595.8	0	1
No_cert	17337	45.80%	0.46	0	0	0.498	0.176	–1.97	0	1
Energie: Thermal isolation (d_solar)	7201	19%	0.19	0	0	0.392	1.585	0.51	0	1
d_front_view	37999	0	0.27	0	0	0.445	1.028	–0.94	0	1
d_side_view	37999	0	0.07	0	0	0.250	3.464	10.0	0	1
d_back_view	37999	0	0.21	0	0	0.407	1.431	0.05	0	1
list_date	37999	0	11/16/2014	11/03/2014	11/11/2015		–0.012	–0.96	07/29/2010	07/12/2017
Trans_date	37999	0	06/08/2015	06/24/2015	07/01/2014		–0.124	–1.05	01/01/2013	07/19/2017
TOM	37999	0	203.74	109	29	258.511	2.561	7.93	0	2287

6. Analysis and results

The analysis tests the hypothesis with and without spatial framework, finding evidence of the relationships between GDP, TOM, and Prices by (a) controlling for endogenous relationship and (b) by spatial association, incorporating both spatial correlation dimensions (lag and error) simultaneously as regressors[6]. The latter models are estimated within a regression framework that employs a spatial functional form, using a first-order spatial Queen matrix constructed from the data.

When both endogenous and exogenous variables are included, estimation is performed using generalized two-stage least squares (2SLS). This method requires an additional set of instruments equal to the number of endogenous variables, along with the corresponding instruments for each variable in the model. When including spatial corrections, this approach became notably complex due to the higher number of parameters (those to the spatial instruments) that need to be calculated. Both spatial correlation dimensions (spatial lags and errors) are incorporated simultaneously, with the first order of the spatial lag operator selected based on the spatial methodology described by Anselin and Rey (2014)[7].

The analysis is done in two steps. The first step utilises pooled OLS and 2SLS econometric analysis to estimate the causality between transaction prices and TOM by defining a simultaneous system of equations that estimate p and TOM simultaneously (Equations (6) and (7)).

$$p_{ht} = \alpha_{1t} + \gamma TOM_t + \vartheta_1 GDP_t + \sum_{i=1}^{n}\sum_{k=1}^{k}\beta_{k,i}X_{k,i,t} + \omega_t; \quad (6)$$

$$TOM_t = \alpha_{2t} + \delta p_{ht} + \vartheta_2 GDP_t + \sum_{i=1}^{n}\sum_{k=1}^{k}\beta'_{k,i}X_{k,i,t} + \upsilon_t, \quad (7)$$

where: *TOM* is time on market; X_i is a matrix of "*k*" housing attributes associated with the quality of the house and district location; *p* is house prices and GDP is the Gross Domestic Product; ω_t and υ_t are a measure of errors.

Following the establishment of the spatial evidence (McGreal et al., 2016), the second step involves the estimation of simultaneous equations (Equations (6) and (7)), in a panel framework and tests for the existence of an association between TOM and the business cycle using a hedonic model with spatial controls, in which TOM and housing prices are controlled by housing attributes. As both equations mentioned above are endogenous, the reduced form is adopted to estimate, controlling for endogeneity, a 2SLS Spatial model (reflected in Equation (8)).

$$\begin{aligned} TOM_{i,t} &= c + \sum_{i=1}^{n}\sum_{m=1}^{k}\beta_{m,i}X_{m,i,t} + \varphi_i ph_{i,t} + \\ &\gamma gdp_t + \rho W\left[TOM_i\right] + \lambda W \mu_i + \varepsilon_{it} \end{aligned} \quad (8)$$

with $\mu_t = \lambda\left(W \cdot \mu_t\right) + \varepsilon_t$.

With *X* being a matrix of "*k*" housing attributes for every "*i*" transaction observations at time *t*; *gdp* is a measure of the business cycle; *ph* is housing prices; *TOM* is time on market and ε_i is a random error measure N(0, σ_e); *W* is the spatial *ixi* matrix of proximity; μ_i is a spatially correlated error measure. The Anselin-Kelejian Test applied in the 2SLS rejects the null of there is no spatial autocorrelation in the residuals (C = 606.033***) and the model introducing the spatial dimension (with a Spatial model including both spatial lags and spatial errors). Lower case represents variables in logs. Functional form is estimated using the Instrumental method for those endogenous variables considered as GDP, housing prices and TOM.

The two steps of the analysis tests two relationships determining TOM and prices, the spatial and the temporal.

[6] Note that vacancies and BSC variables included in the theoretical Equations (2) and (3) are not included in this empirical exercise. Full vacancies data is not available but we consider they are strongly correlated with past prices and it level is captured by TOM. BSC are considered constant due to the period of the analysis.

[7] We do not use STAR models, even though the observations are time-based, because the observed period is relatively short (quarterly data from 2013 Q1 to 2017 Q3). This limited timeframe makes it difficult to accurately identify time patterns in data and compute time correlation as an additional variable, resulting in the loss of nearly one year of data if pursued. Additionally, the data does not capture the full economic cycle, so the potential time autoregression estimated would lack the ability to properly control for time within the STAR framework.

6.1. Spatial relationships testing for spatial autocorrelation

Spatial relationships are estimated using Moran's I at a city level and the existence of local spatial clusters using LISA. The analysis suggests no spatial correlation in TOM, with a low number of properties being spatially correlated at the city level (Moran's I = 0.064) and number of clusters (Figure 7) which represents the point estimations of LISA.

House price presents a different picture with spatial correlation among the transaction prices apparent (Moran's I = 0.137), with evidence of strong price diffusion (Figure 7) having a positive effect on prices notably in the central and northern districts of Bucharest (Figure 8).

The bivariate spatial correlation between TOM and transaction price indicates that the neighbour TOM does not spatially affect transaction prices. This finding contrasts with the presumption that areas with larger TOM have less liquidity and that properties tend to be sold later than in areas with shorter TOM (Figure 9).

Listing prices follow a similar pattern to that for transaction prices they are not correlated spatially with TOM with few clusters where it is possible to find a diffusion

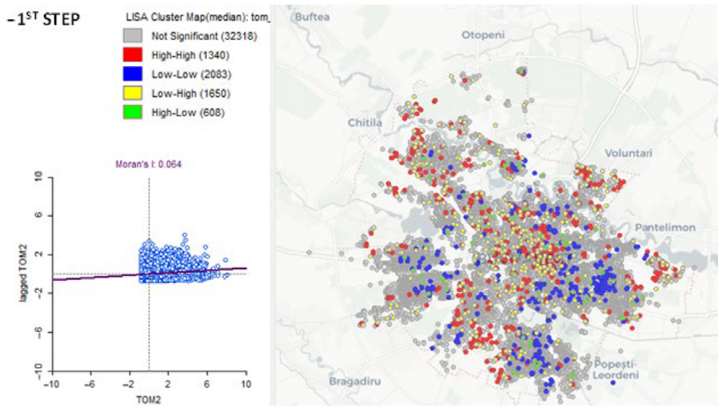

Figure 7. LISA clusters of TOM in Bucharest

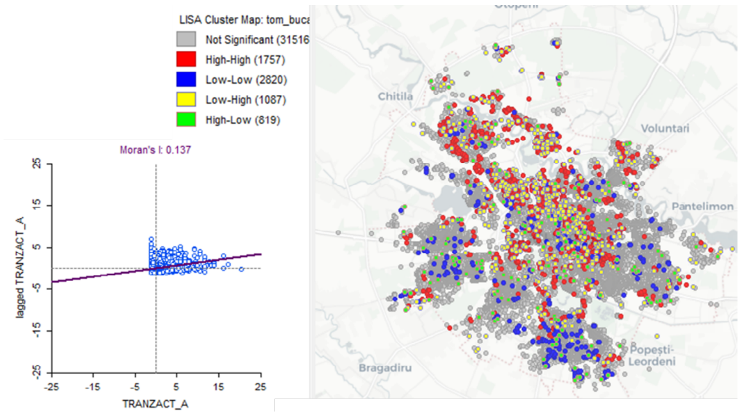

Figure 8. LISA spatial clusters of transaction prices in Bucharest

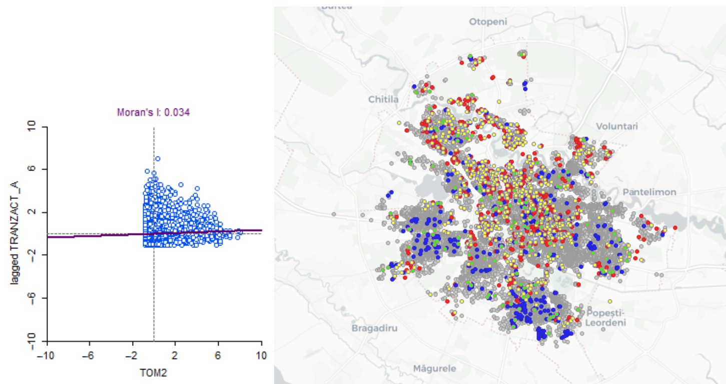

Figure 9. LISA bivariate spatial clusters of TOM and transaction prices in Bucharest

effect. Differences between asking and transaction prices are also randomly distributed spatially, there are few areas where spatial correlation is shown[8]. The bivariate spatial correlation again shows no spatial association between TOM and price reduction or increase over the asking price when properties are transacted and a low number of clusters where it is possible to find any such a relationship.

Thus, the spatial evidence shows that TOM and transaction prices are independent. The hypothesis is that if TOM does not depend on the neighbour price evolution, it should be related to some time-base variable. GDP is taken in this paper as the time-base reference to identify the determinant of TOM.

6.2. Hedonic price models: GDP, TOM and transaction prices

This section presents causal evidence of both hypotheses; H_0^1: TOM and PRICE are not related at the time level, and H_0^2: GDP affects TOM dynamics. For those purposes, two methodologies are employed to identify the two directions of causality, as represented in Equations (6) to (8):

Model 1. The hedonic system represented by Equations (6) and (7) is tested in a Pooled OLS/2SLS regression. The model includes six district variables measuring the location where the transaction occurs and thus captures the market size and allows for testing the hypothesis that TOM and transaction prices vary depending on the market size. The relevance of the transaction of each district allows for testing the hypothesis that TOM and transaction prices vary depending on the market size discussed above (McGreal et al., 2016). The model controls for a set of housing attributes, raising evidence of the responses of the quality-controlled prices to changes in the economic conditions and endogenously determining TOM. Attributes include the property energy efficiency measured from A to G levels and a dummy variable of the A and B is included to control for the impact that a high-efficient property would have over transaction prices, following Rico-Juan and Taltavull de La Paz (2021).

Equations (6)–(7) are estimated with pooled OLS and 2SLS to evidence the effect of the endogenous relationship. Results are consistent in both OLS and 2SLS estimation in either equation explaining transaction prices or TOM with the same signs and quite a similar size of the effects calculated through the parameters.

A total of 20 housing attributes have been used for quality-controlled transaction price computation. Districts dummies have been included (invariant variables, both OLS and 2SLS) to control for time-constant unobserved heterogeneity; A measure of energy efficiency is also included (in the highest levels, A and B) to control this particular attribute's influence on transaction prices. The GDP variable is introduced in levels and yearly changes to test for the reactions to the business cycle. To control for endogeneity, instruments for endogenous components are included. Results in Table 2 give evidence about the nature of the TOM and transaction prices relationship.

Table 2. Pooled-hedonic models results+

Dep. variable:									
Log (transaction prices)					Log (TOM)				
	(1)		(2)			(3)		(4)	
	Pooled OLS		Pooled 2SLS			Pooled OLS		Pooled 2SLS	
	β	St. Error	β	St. Error		β	St. Error	β	St. Error
(Constant)	6.327	0.114***	7.203	0.758***	(Constant)	2.129	0.635***	8.477	3.886**
ltom	–0.018	0.001***	–0.019	0.001***	l_transp	–0.508	0.033***	–0.755	0.040***
lgdp	0.062	0.009***	–0.044	0.090	lgdp	0.074	0.049	–0.478	0.472
lgdp_1lag	0.054	0.009***	0.064	0.012***	lgdp_1lag	0.352	0.047***	0.404	0.061***
District effects:					District effects:				
S1	0.208	0.005***	0.201	0.005***	S1	0.245	0.029***	0.314	0.029***
S2	0.060	0.004***	0.060	0.005***	S2	0.105	0.024***	0.123	0.024***
S3	0.112	0.004***	0.110	0.004***	S3	–0.023	0.023	0.004	0.023
S4	0.013	0.005***	0.015	0.005***	S4	0.002	0.025	0.010	0.026
S5	–0.026	0.005***	–0.024	0.005***	S5	0.142	0.029***	0.132	0.029***
Controls:									
Atributes	Yes		Yes		Atributes	Yes		Yes	
Adj R^2	0.704		0.702		Adj R^2	0.097		0.098	
F	2342.06***		2612.5***		F	102.56***		121.4***	
DW	1.746				DW	0.247			
N	25546		25545		N	25545		25545	
Second-stage SSR			1647.95					38843.96	
Instrument rank			26					26	

Note: + All continuous variables are in logs. ***, ** means parameter is statistically significant at 1% and 5%.

8 Results can be provided under request.

Table 2 presents selected results of the four equations calculated for this Model 1[9]. Overall, the models exhibit acceptable performance, with most explanatory variables being statistically significant, low biases from autocorrelation (indicated by large Durbin-Watson test results), and high F-test values. The estimation of Equation (7) shows autocorrelation issues (DW = 0.247) in the pooled OLS regression. The results from both the pooled OLS and 2SLS models are robust in terms of effect size and direction. The instruments used are typically lagged one period, a common practice; however, in the case of the TOM model, transaction prices are instrumented using asking prices[10].

The analysis shows that transaction prices have a higher explanatory capacity than TOM, suggesting that determinants included in the model largely determine transaction price evolution, explaining 70.2% of the transaction price variability. In the case of TOM, the model explains 9.7% of its variability, suggesting that TOM's main drivers are absent in the model. Furthermore, the transaction price model indicates a negative and statistically significant association between prices and TOM (an increase of 1% in TOM is associated with a 0.018% discount in transaction prices), aligning the results with the literature supporting the contention that the longer the property is in the market, the lower the transaction price. These results seem to be corrected at the district level. As Equations (1) and (2) in Table 2 indicate, districts 1 to 4 positively correct the effect on transaction prices, while district 5 shows a negative correction. To illustrate this further, any transaction that occurred in district 1 increases by 0.208% over the price of the reference (district 6) showing the existence of a location premium in transactions. As all districts are statistically significant, the effect of TOM is generalised across Bucharest.

GDP pro-cyclically affects transaction prices. The 2SLS results indicate that the effect is produced with a time lag of one year inferring that changes in business cycle affect transaction prices during the following year. This positive and lagged effect is robust and persistent in different model specifications and affects both transaction prices and TOM. The effect of the business cycle on prices is smaller with 1% of change in the one-year-lag GDP increasing transaction prices by 0.064% (Equation (2) in Table 2). However, as seen in Equation (4) for TOM, GDP shows a more substantial effect with an increase of 1% of lagged GDP increasing TOM by 0.354% in the following year. These differential effects suggest that TOM is impacted earlier by the business cycle relative to transaction prices.

The reverse equation captures the effect of changes in transaction prices over TOM (Equations (3) and (4), Table 2) showing that an increase of 1% in transaction prices is associated with a reduction of 0.45% in TOM. This represents a more significant effect, and such an asymmetric response underpins the relevance of prices in the market and the complex association between both endogenous variables. At a sub-market level, the mechanism, transaction prices-TOM-GDP (–1) is statistically significant in districts 1, 2 and 5 relative to district 6, but not in districts 3 and 4 suggesting that idiosyncratic variables associated with particular districts affect TOM according to the hedonic model, but does not hold in other districts adding to the complexity of relationships. This result is consistent with Sirmans et al. (2010).

Model 2. This model estimates Equation (8) by using an IV Spatial – hedonic spatial model with spatial lag and spatial error correction. Selected results are in Table 3[11]. For robustness, the equation is estimated using alternatively asking and transaction prices and considers (as demonstrated in the previous Model 1) two variables as endogenous: the lagged GDP and the transaction prices. The spatial model is calculated in two stages with Instruments which fulfil the requirements.

The spatially controlled model is applied to identify how spatial correlation explains the association between prices, TOM and economic cyclical impulses. The Spatial model is estimated using Two-Step Spatial Least Squares considering endogeneity at the spatial level (spatial correlation among the variables in the model) and a non-spatial endogeneity between transaction prices and TOM (Equations (2) and (3) in Table 3) and between transaction prices, TOM and lagged GDP (Equations (4) and (5) in Table 3).

The explanatory power of the models in explaining TOM is modest, consistent with existing literature on TOM and spatial models, ranging from 5% to 10% depending on the functional form. Results are fairly consistent across the models in terms of the size and sign of the effects of the explanatory variables. Both spatial components (lag and error) also show consistent signs and magnitudes. The chosen instruments for the endogenous variables, excluding the spatial components, are asking prices and GDP.

Table 3 provides details of the instruments used in the spatial model. Equation (1) on it represents the baseline model in which only spatial autoregressive relationships are considered among all variables. Estimated parameters confirm the existence of strong spatial autocorrelation in TOM, both between properties and on the unobserved idiosyncratic features highlighted through the rho and lambda parameters (ρ range from 0.383 to 0.433 and λ between –0.41 to –0.044, both strongly significant at 1%). The parameter values are broadly similar in their effect but opposing mathematical signs essentially cancels the respective effects supporting the lack of spatial association in single spatial analysis. Results also identify a highly significant and negative association between transaction prices and TOM, with a small effect size, suggesting that an increase in transaction prices reduces TOM to a negligible degree, by 0.008% (Table 3, Equation (1)). This model

9 Parameters obtained for the whole model specification can be found in Table A1 in the Annex section.

10 The covariance among coefficients is lower than 2.8×10^{-5}, and 2.8×10^{-5} for the price equation and 6.5×10^{-5}, and 6.5×10^{-5} for the TOM equation.

11 The estimated parameters of the rest of variables can be found in Table A2 in the Appendix.

Table 3. Model 2: Spatially weighted two stage least squares (HET) of TOM+

Dep. variable: LTOM	(1) β	(1) Std. Error	(2) β	(2) Std. Error	(3) β	(3) Std. Error	(4) β	(4) Std. Error	(5) β	(5) Std. Error
Constant	–4.202	0.654***	–4.199	0.638***	–2.085	0.689***	–26.386	4.697***	–7.237	3.398***
LGDP	0.123	0.005	0.098	0.049*	0.012	0.042				
LGDP_1LAG	0.015	0.042***	0.450	0.045***	0.390	0.040***	2.993	0.518***	1.003	0.388**
S1	0.105	0.017***	0.063	0.020***	0.125	0.021***	0.047	0.022**	0.132	0.021***
S2	0.026	0.015	0.013	0.015	0.030	0.015**	0.013	0.017	0.033	0.015**
S3	–0.080	0.015***	–0.096	0.016***	–0.069	0.015***	–0.101	0.017***	–0.063	0.016***
S4	–0.033	0.016**	–0.046	0.016***	–0.034	0.015**	–0.079	0.019***	–0.041	0.016**
S5	0.098	0.019***	0.095	0.019***	0.093	0.018***	0.098	0.021***	0.090	0.018***
ρ_W_LTOM	0.383	0.026***	0.435	0.026***	0.405	0.028***	0.433	0.028***	0.415	0.028***
λ_W_ε	–0.410	0.028***	–0.434	0.027***	–0.442	0.027***	–0.380	0.032***	–0.444	0.028***
L_TRANSP	–0.008	0.002***	–0.078	0.020***			–0.117	0.023***		
L_ASKINGP					–0.093	0.067			–0.134	0.070
Controls		Yes		Yes		Yes		Yes		Yes
Non spatial endogenous variables	0		1		1		2		2	
Pseudo-R2	0.1007		0.0788		0.0993		0.0518		0.0957	
Spatial-pseudo R2	0.0937		0.07		0.0936		0.0421		0.0887	
N	37999		37999		37999		37999		37999	
Degrees of freedom	37972		37972		37972		37973		37973	
Endogenous	W_LTOM		W_LTOM, L_TRANSP,		L_ASKINGP, W_LTOM		LGDP_1LAG L_TRANSP, W_LTOM		LGDP_1LAG, L_ASKINGP, W_LTOM	
Non-spatial instruments	NONE		L_ASKINGP		L_TRANSP		L_ASKINGP		L_TRANSP, LGDP	
Spatial instruments	W_BATHROOM_A, W_D_A, W_D_B, W_D_BACK_VIE, W_D_BOULEV, W_D_CASH, W_D_CONDO, W_D_FRONT_VI, W_D_INMOBILI, W_D_PARKING, W_D_PUBLIC_F, W_D_SIDE_VIE, W_D_SOLAR, W_D_STREET, W_FLOOR_N, W_LAGE, W_LGDP, W_LGDP_1LAG, W_LM2, W_L_ASKINGP, W_S1, W_S2, W_S3, W_S4, W_S5									

Note: The instruments used in these exercises are reflected in the two last rows in this table. Model 1 only have the spatial instruments needed to estimate lambda and rho, thus, no extra instrument other than those required by the spatial exercise. As conventional procedure, the spatial analysis requires the same number of instruments than the dependent variables. Those instruments are the spatially lagged variables. Since Model 2, all equations contain one or more endogenous variables (addressing the literature) and the instruments used for each one is defined in the Table 3, the second-to-last row. For instance, Equation (2) considers, as endogenous, the transaction price. The instrument in this case is asking price (both in logs). In Equation (5), there are two endogenous components in the model: lagged GDP and asking prices. The instruments are transaction prices and GDP.

+ All continuous variables are in logs.
***, **, * means parameter is statistically significant at 1%, 5% and 10%.

supports the previous results concerning the effect of the business cycle on transaction momentum, with the lagged GDP inferring that an increase of 1% of GDP in the previous year increases TOM by 0.015%.

Equation (2) controls for spatial association, both taking into account prices and TOM either exogenous and endogenously related. Under this model, an increase of 1% in transaction prices reduces TOM by 0.078% and if GDP increases by 1% in the previous year, TOM increases by 0.45%. Similarly, when the model considers prices and TOM as endogenously related, the association between them is ten times larger, and the spatial effects are similar in value with opposite signs (Model 2, Equations (2) and (3)). In addition, when transaction prices and TOM as endogenously related to GDP (Model 2, Equations (4) and (5)), basically an endogenous triangle relationship appears showing a much stronger association between the three indicators, suggesting that an increase in transaction prices of 1% reduces TOM by 0.117%, while a 1% increase on GDP in the previous year elastically increases TOM by 2.9%.

Results are consistent across all models concerning the effect and direction of the business cycle on TOM and reflective of the study by Anglin et al. (2003). The analysis captures an idiosyncratic situation of Bucharest, in which landlords prefer to maintain their properties unsold until they reach the expected price.

7. Discussion

Modelling without spatial effects gives high explanatory capacity of TOM in predicting transaction prices (Adj R^2 = 70.2%) which is much stronger than the influence of prices on TOM (Adj R^2 = 9.7%), that suggests the determinants included in the model largely explain the evolution of transaction prices but not TOM, indicating that the main drivers of TOM are absent from the model.

However, the influence of TOM on prices is negative and statistically significant (an increase of 1% in TOM is associated with a 0.018% discount in transaction prices), while the effect of transaction prices on TOM is also negative and consistent across all specifications, with a larger impact: a 1% increase in transaction prices reduces TOM by about 0.5% to 0.75%. These results align with literature suggesting that properties remaining on the market longer tend to have lower prices. Spatial differences emerge at the district level, with positive price adjustments in districts 1 to 4 of Bucharest, indicating a location premium, while district 5 shows negative adjustments (relative to district 6). In the TOM equation, districts 1, 2, and 5 are statistically significant and show positive parameters, indicating a non-generalized impact of transaction prices on TOM. When controlling for spatial correlations, the strong effect of transaction prices on TOM nearly disappears. Results in Table 3 are consistent across the five model specifications, suggesting that any increase in transaction prices slightly reduces TOM variation (by only 0.008% to 0.115%). This implies that most of the correlation observed in models without spatial adjustments is due to the spatial correlation of prices themselves, rather than TOM.

The results highlight the influence of the business cycle on TOM. Table 2 shows that GDP affects transaction prices pro-cyclically (0.062%) and with persistence (0.054%), while only GDP growth (the cycle) influences TOM (0.352%). The spatial model in Table 3 more precisely captures a robust effect of the business cycle on TOM, with statistically significant results across all model specifications. This model reveals an elastic response of TOM (+2.993% and +1.003%) to changes in the business cycle when the cycle is treated as endogenous, as shown in columns (4) and (5). The size of the effects estimated in both type of models (with and without spatial effects) suggests that TOM is influenced earlier by the business cycle, with causality running from GDP changes to TOM and then to property prices, as evidenced in the models. This result refers to the intuition of the existence of differing responses to market changes between buyers and sellers. Buyers may react more swiftly to shifts in market conditions, whereas sellers' asking prices might be anchored to the most recent highest selling prices for similar properties in the same submarket. Consequently, TOM may change first, as sellers tend to take longer to adjust their asking prices in response to market fluctuations. This pattern aligns with the anchoring and slow adjustment heuristic[12].

TOM reacts with changes in variables included in the model but not in the whole territory. In Bucharest, the different effect on districts suggests that idiosyncratic variables associated with districts affect TOM (accordingly to the hedonic model) but not in others.

Spatial descriptive analysis supports the evidence that TOM is uncorrelated at the spatial level, while transaction prices appear strongly spatially correlated. Transaction prices positively influence neighbour property prices in districts with significant revaluation and a negative influence in areas with declining prices, extending the impact across adjacent properties, indicating strong spillover effects at the cluster level, and supporting the theory of differences among submarkets. In no district does TOM appear to react spatially with prices when analysed using descriptive statistics (Moran's I) which seems to be contradictory as TOM is generated together with prices and should be influenced as well by closed properties. However, the spatial correlation of TOM becomes apparent in the 2SLS spatial model, where both types of spatial correlations–between neighbouring properties and due to idiosyncratic features (lags and errors)–exert strong but opposing effects, effectively cancelling each other out. This supports the apparent lack of spatial association in TOM.

The interpretation is that while the TOM of neighboring transactions positively influences each other, spatially unobserved factors impacting the area exert a negative influence, balancing out spatial relationships[13]. Thus, the reinforcing spatial effects observed in TOM among close transactions may actually reflect the strong clustering of prices, balanced by opposing forces that reduce the overall spatial impact on TOM. This suggests a corrective mechanism where deviations, both positive and negative, are distributed across districts in Bucharest, leading to a more balanced overall effect. It implies that while TOM may seem spatially clustered, underlying factors work to smooth its spatial effects.

These contrasting effects have been observed across different datasets, underscoring the importance of accurately specifying the spatial model to capture the underlying spatial processes effectively.

8. Conclusions

Whilst there is a rich literature on TOM, there remains many areas of debate and controversy. The originality of this paper lies in testing the hypothesis whether TOM is influenced by variables other than transaction prices and in doing so the paper explicitly explores the influence of the business cycle controlled by spatial autocorrelation. The findings indicate that TOM is not spatially correlated with transaction prices using univariate analysis. However,

[12] We would like to acknowledge the anonymous referee for highlighting this discussion. We fully agree with the interpretation provided, which is entirely his or her contribution.

[13] The unobserved factors are spatial in nature. We do not know exactly what they are, and they are not controlled in the model as its observation is required to test their influence. This is what the parameter lambda (λ) does. The consistent results in all estimation done support the lambda parameter robustness and show that different spatial influences can be canceled out to determine TOM. This is a novelty in this paper and a way to research more in depth. We want to thank an anonymous referee for highlighting this discussion.

findings from empirical models, both with and without spatial controls, suggest that there is strong spatial correlation for TOM stemming from two sources: spatial proximity, which is positive and statistically significant, and unobserved heterogeneous features any idiosyncratic features spatially associated) which is negative. Thus, the spatial correlation by proximity follows that observed by transaction prices, supporting endogenous relationships at the spatial level.

Significantly the results highlight the relevance of the GDP growth in explaining TOM and transaction prices. The estimated effect of transaction price changes is of particular interest with the analysis showing that an increase of 1% in transaction prices reduces TOM by 0.508%. The simultaneously reverse effect shows that a 1% increase in TOM reduces transaction prices by 0.018%. These findings suggest that the direction of the effect is from economic growth affecting transaction prices and simultaneously having an effect on TOM. However, underlining the complexity of TOM, a Spatial model suggests that the effect of changes on transaction prices over TOM being spatially controlled is lower, with a 0.117% reduction in TOM when transaction prices rise 1%. When the model takes GDP growth as exogenous, the effect on rising TOM is similar. However, when GDP is considered endogenous, the impact becomes elastic (2.9%), suggesting a strong association between apartment transactions and economic growth in Bucharest. This result means that the apartment market is closely dependent of the economic growth and that any change in the business cycle is associated with an elastic change in apartment prices. The idea that both are endogenous related drives the attention towards the housing-GDP direct relationships and how (existing) housing simultaneously generates wealth or that GDP growth appears simultaneously with an increase in the effective demand for housing. Those issues fall in the macroeconomic perspective of the housing market which should be deeply investigated.

The implications of this study stem from the significance of the business cycle on TOM. Whilst some previous literature has raised this issue, the significance of this paper using robust modelling techniques is to highlight the role of economic growth as the third dimension in exploring the relationship between TOM and transaction price. In essence, results support the idea that economic growth and transaction prices are affected simultaneously and then, prices determine TOM depending on the neighbourhood characteristics. This is the first paper to give empirical evidence that a multiple endogenous relationship exists between transaction prices, TOM and economic growth and demonstrate the sequence of effects.

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Appendix

Table A1. Pool-hedonic models. Parametres of attribute variables

Dependent variable	L (transaction prices)		L (transaction prices) – 2SLS		LTOM		LTOM – 2SLS		
	β	St. Dev.	β	St. Dev.	β	St. Dev.	β	St. Dev.	
floor_n	–0.006	0.001***	–0.006	0.001***	0.029	0.003***	0.010	0.002***	
d_cash	–0.027	0.005***	–0.027	0.005***	0.011	0.025	0.009	0.027	
d_mortgage	0.001	0.006	0.004	0.007	0.162	0.033***	0.163	0.032***	
d_public_fin	–0.067	0.006***	–0.071	0.006***	0.459	0.029***	0.450	0.028***	
Bathroom with bathtub	0.029	0.004***	0.017	0.003***	0.155	0.021***	0.112	0.020***	
Nº bathrooms	0.019	0.003***	EXCL	EXCL	0.022	0.016	EXCL	EXCL	EXCL
Number of floors	0.008	0.001***	0.007	0.001***	–0.039	0.003***	EXCL	EXCL	EXCL
d_street	0.016	0.003***	0.018	0.003***	–0.061	0.017	–0.015	0.015	
d_parking	0.174	0.020***	0.182	0.021***	0.010	0.106***	–0.013	0.077	
d_solar	0.015	0.004***	0.016	0.005***	–0.256	0.020***	–0.270	0.020***	
d_front_view	0.007	0.003**	0.010	0.004***	–0.093	0.016***	–0.095	0.016***	
d_side_view	0.012	0.005**	0.012	0.006**	–0.058	0.028***	–0.060	0.027**	
d_back_view	0.010	0.003***	0.012	0.004***	–0.104	0.018***	–0.103	0.017***	
d_condo	0.038	0.003***	EXCL	EXCL	–0.099	0.016***	–0.101	0.016***	
d_boulev	0.062	0.005***	0.061	0.005***	–0.047	0.026***	EXCL	EXCL	EXCL
d_A	0.010	0.013			0.283	0.069***	0.260	0.078***	
d_B	–0.026	0.017			0.024	0.087	0.000	0.083	
lage	–0.044	0.002***	–0.050	0.002***	0.017	0.011*	0.033	0.010***	
LM2	*0.915*	*0.004****	*0.920*	*0.004****	*1.087*	*0.037****	*1.045*	*0.055****	

Note: ***, **, * means parameter is statistically significant at 1%, 5% and 10%.

Table A2. Model 2: Spatially weighted two stage least squares (HET) of TOM. Durbin model. Controls' parameter values

Dep. variable: LTOM	(1)		(2)		(3)		(4)		(5)	
	β	Std. Error	β	Std. Error	β	Std. Error	β	Std. Error	β	Std. Error
BATHROOM_A	–2.848	0.515***	0.134	0.016***	0.141	0.017***	0.142	0.017***	0.147	0.017***
D_A	0.134	0.016***	0.410	0.059***	0.385	0.058***	0.447	0.065***	0.391	0.058***
D_B	0.393	0.058	0.051	0.082	0.027	0.081	0.093	0.089	0.032	0.081
D_BACK_VIE	0.034	0.081***	–0.022	0.019	–0.060	0.016***	–0.044	0.020**	–0.070	0.017***
D_BOULEV	–0.058	0.016***	–0.067	0.018***	–0.062	0.019***	–0.048	0.020***	–0.053	0.019***
D_CASH	–0.071	0.018**	0.347	0.132***	–0.160	0.015**	0.655	0.156***	–0.147	0.017***
D_CONDO	–0.105	0.018***	–0.084	0.013***	–0.080	0.015***	–0.091	0.014***	–0.077	0.015***
D_FRONT_VI	–0.090	0.012***	–0.024	0.017	–0.054	0.014***	–0.037	0.018**	–0.062	0.015***
D_INMOBILI	–0.052	0.014	0.513	0.143***	–0.003	0.043	0.876	0.172***	0.022	0.047
D_PARKING	0.052	0.045**	0.185	0.062***	0.177	0.064***	0.127	0.068	0.172	0.064***
D_PUBLIC_F	0.153	0.061***	0.840	0.131***	0.342	0.022***	1.260	0.169***	0.380	0.034***
D_SIDE_VIE	0.402	0.023	0.009	0.027	–0.026	0.025	–0.010	0.029	–0.034	0.026
D_SOLAR	–0.025	0.025***	–0.160	0.016***	–0.168	0.016***	–0.230	0.022***	–0.184	0.019***
D_STREET	–0.173	0.016***	–0.049	0.012***	–0.050	0.012***	–0.049	0.013***	–0.049	0.012***
FLOOR_N	–0.054	0.012***	0.009	0.002***	0.007	0.002***	0.011	0.002***	0.007	0.002***
LAGE	0.007	0.002***	0.129	0.006***	0.119	0.006***	0.141	0.007***	0.119	0.006***
LM2	0.393	0.040***	0.463	0.017***	0.484	0.041***	0.498	0.020***	0.509	0.043***

Note: ***, ** means parameter is statistically significant at 1% and 5%.