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Synchronisation among short-term rental markets, co-movements and cycles in 39 European cities

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ABSTRACT

This paper presents new evidence of the short-term rental market's prices and transactions from a daily time-series perspective in 39 European cities from 2015 to 2020. It uses Airbnb micro datasets to build time-series cycles by extracting the original observations containing total bookings (rent transactions), rental units supply, and asking rent, with a daily periodicity. The cycles show the periods in which short-rental activity was more relevant for each city, and the level of rents across Europe. The paper provides empirical evidence of a long-term relationship among the city variables (tested via mean and variance). Causality supporting co-movements across cities was found by estimating a short-term naïve market equilibrium model using the vector error correction model approach, supporting the hypothesis that the short-term rental market performs according to housing-market principles. Short-run elasticities among rents and contracts across the 39 cities show causal evidence of co-movements among rents and the supply and demand of properties. The market adjustment on the supply side estimates new units responding to changes in prices within 15 lags (days) and longer (350 lags) from the demand side, equivalent to eight to nine months. Evidence of the pandemic's limited effect on housing supply and prices' positive effect is also provided. A robust negative weekend impact on prices was found, suggesting stronger market relevance on weekdays.

1. Introduction: the rise of the short-term rental market (STRM) globally

As the leading platform (Airbnb) has published its data, the literature concerning the short-term rental market (STRM) has increased dramatically over recent years. Most studies have focused on identifying this market's impact on the long-term rental market (LTRM), its influence on rental prices, or its market attractiveness, in relation to removing housing units from the formal LTRM and being one of the causes of the increasing lack of affordable housing across the main European cities. Despite these relationships' relevance, few and recent researches have focused on the market dynamics (Gossen & Reck, 2021, Casamatta et al., 2022 or Sainaghi & Baggio, 2020), the size of the STRM, or its impacts on cities (Gurran et al., 2020), among other relevant aspects. This market is relevant for municipalities due to several effects (positive and negative) on their territory, requiring re-designing and new urban regulations. The potential negative effects of excess visitors are one of the main effects alerting local governments, which have started to regulate this by trying to reduce and control the phenomenon. The argument that many visitors "disturb" the calm environment has also provoked a reaction among municipalities (Filippas & Horton, 2018; Sheppard & Udell, 2016). The lack of information regarding STRM performance has also led to criticism that visitors are not registered, thus highlighting different treatment compared to the hotel sector. However, although this sector has grown rapidly over recent years, the lack of detailed information makes it complex to identify its effects on pollution or agglomeration, as well as the potential benefits to cities. Therefore, municipalities are unsure about the effect of the policies applied to regulate the STRM and the type of regulations to issue.

The reasons for the STRM rapidly expanding across cities are still not deeply known; it remains unclear whether short-term movements captured through platforms are simply a new type of tourism or, on the contrary, if this is evidence of a hidden demand that is now being

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captured thanks to the facilities associated with the platforms (Görög, 2019; PwC, 2014), and which is growing as income recovers. The number of visitors using rented properties, for example, is not counted, as they are not registered. If the number of units is small but they are continuously booked, the number of people using the STRM is large and would create city congestion. If the cities are related and there is spillover to other cities, then the STRM should be developed or regulated regarding this impact. Additionally, extant literature generally suggests that the STRM channels tourism (Lee, 2016). If this is true, the question arises regarding which type of tourism would use the apartments during the whole week. This is relevant as the STRM could be covering housing needs for other reasons, such as labour mobility associated with cities' economic sectors. Labour purposes or other ends, rather than tourism, could be being covered (and may have been being covered for a long period) by using short-term rental (STR).

Thus, questions such as why STR demand has strongly risen simultaneously in major cities and whether STR demands in cities are related to each other still require research to identify whether the technological platforms have triggered a new tourist demand for visiting cities or have revealed the existence of formerly unknown population mobility patterns. A common belief is that the STRM attracts visitors during the weekend (Farronato & Fradkin, 2018; Sainaghi & Baggio, 2020) but more evidence is required to identify why also attract population during the working days.

Many other questions are also of interest. It is said that the STRM is taking many units away from the LTRM, reducing affordability (Sheppard & Udell, 2016), and thus forcing authorities to intervene with regulations to support particular groups of citizens. However, evidence has been recently published showing that only a small proportion of housing stock in each city is available via STR platforms (UNECE, 2022).[1] Whether the STRM provides a substitutive supply when the hospitality industry is overbooked has also been studied (Sainaghi & Baggio, 2020).

This paper adds to STRM knowledge by quantifying and analysing its dynamics. It reveals empirical regularities driving STR activity, evidenced by a long-term relationship with permanent effects between bookings and rents across cities. Using a time-series econometric methodology, this paper estimates the evolution of STR's leading market indicators (prices and contracts) over the last decade for the analysed cities. The hypotheses are related to analysing the implications highlighted by the detailed data in order to: assess whether the STRM is related among cities, revealing the existence of a common reason its growth; and reveal the time pattern of visitors arriving in cities on weekdays, which suggests different reasons for visitors moving into cities.

This study builds a supply–demand model in the short run and finds evidence of long-term causal relationships between supply, demand, and prices. The long-term relationship reveals the existence of common drivers of STR contracts, evidencing flows of population movement simultaneously to the group of analysed cities. The findings demonstrate that STRM performance follows market principles, with different time reactions for supply and demand. It also reveals a phenomenon with wide-ranging policy implications for cities' planning, encompassing congestion in certain periods (over-consumption of public services), mobility among cities (suggesting the need to coordinate transport and urban policies), and fiscal impacts (both national and international).

Our study contributes to the literature in various ways. First, the data description in the exploratory analysis reports relatively new information. A daily time-series dataset of long-term contracts and prices for 39 European cities since 2015 is created. Daily data enables observing the differences among cities in the very short-term contract patterns (and prices), identifying the seasonal components of time series and testing the weekend effect. In this context, this research demonstrates that the STRM not only serves tourism flows but also covers other housing needs, i.e. it enables distinguishing between demand for tourism purposes (weekend) and other reasons.

Second, the high-frequency time series related to the housing market are also new. The housing-market literature has not analysed rents or contracts daily. These data enable estimating the speed of the market in reaching equilibrium by calculating price elasticities in the short run. The sensibility in price reaction reveals the potential STRM drivers.

Third, this is the first paper to empirically demonstrate the existence of co-movements both in prices and contracts in the STRM at the city level. The existence of standard patterns to explain the evolution of contracts is also new, revealing a ripple effect among cities' STRMs. The co-movements demonstrate a causal relationship between STR activity across cities and a long-term association in STRM activity, highlighting and measuring a new form of rental demand previously unaccounted for in the markets. The analysis also identifies the minor effects of the COVID-19 pandemic measures applied during 2020. This is the first paper to present the dynamics of the STRM in a large number of cities, to analyse housing-market equilibrium with high-frequency data (daily), and to provide empirical evidence of the rent elasticities of STRM demand and supply.

This paper is organised as follows. Section 2 reviews the literature regarding the STRM and co-movements, and formulates the hypotheses. Section 3 presents the model and empirical strategy for the analysis. Section 4 explains the dataset and the exploratory analysis of the data. Section 5 presents and discusses the results. Section 6 is devoted to policy implications, and Section 7 provides conclusions.

2. Literature review

The increase in STR activity is a worldwide phenomenon. It appeared during the global financial crisis (GFC) period and has risen since the economic recovery in 2014, including during the pandemic period.

STR activity surfaced some years before the GFC through the creation of technological platforms to share information about available accommodation cheaper than hotel rooms. The arrival of accessible and cheap technological platforms enabled low-cost contact between suppliers and visitors, which is considered the condition that triggered this market and enabled its growth (Botsman, 2015).

The literature suggests that the STRM expanded to complement household incomes by renting available space at home via a sharing activity. This rental type's rising popularity is due to demand and supply reasons. First, increased demand comes from a greater desire for mobility among Millennials [well-educated but with low or medium income owing to lower initial wages (Zilahy, 2016)]. The platforms appear to satisfy such demand through sharing information about the available supply and simplifying the rent-contract processes for more flexible and cheaper accommodation in the desired destination. Second, there was a broad fall in income after the GFC, which pushed homeowners to look for additional resources by renting their homes (Böcker & Meelen, 2016; Görög, 2019). After the GFC ended and economies started to recover, the market networks created through these technological platforms, far from diminishing, showed maximum rent contracts in 2017–2018 (UNECE, 2022).

The tourism field has studied STRM growth from different perspectives over recent years. Sainaghi and Baggio (2020) conducted a literature review, classifying 189 STRM publications into nine topic clusters: conceptual; demand-side, based on the consumer-behaviour approach; supply-side, analysing hosts and exploring spatial patterns; the

[1] UNECE (2022) estimated the role that the STRM is playing in 43 European cities' economies and evaluated the amount of resources it is using to understand the relevance of this market. The project contains a clear description of the market size and some of the characteristics, suggesting that STR activity uses limited housing resources (around 4 % of housing stock), but has been extremely efficient in creating wealth (1 % of GDP at the city level on average) by rotating the use of each housing unit, as well as stressing the population movements in the cities analysed.

determinants of performance; host–guest relationships; analysis of non-commercial platforms; the social impact of P2P; the effects on the hotel sector (economic and strategic); and economic impact. According to Andreu et al.'s (2020) bibliometric study, in 2017, interest in this sector led to a focus on topics related to price management or pricing models, with more sophisticated analytical tools used since 2019, such as spatial models of hedonic pricing, revenue management, behavioural pricing, and price fairness, among others, mainly using Airbnb datasets and accommodation attributes. Jaremen et al.'s (2020) literature review focused on the importance attached to the consequences of STRM; most are externalities produced in cities by the STRM, highlighting the relevance of the impact on the housing market, transport, life quality, gentrification, citizens' innovation, and entrepreneurial initiatives, as well as the effect on local budgets. All these aspects were quantified in a recently published UN report (UNECE, 2022). Another aspect analysed was measuring the effect of STRM expansion in city centres, supporting the idea of the "touristification" of historical cities and its increasing disturbance of city life and gentrification, as well as the role of hosts.

Among these topics, price analysis has often been studied, focusing particularly on potential STRM effects on the hotel sector, the LTRM, and business heterogeneity. For instance, Gibbs et al. (2018) compared the STRM and the hotel market in 2015–2016, concluding that Airbnb hosts have limited capacity to apply price strategies related to the hotel sector, but that this is not the case for hosts managing specific properties (allocated in high-demand areas, full property buildings, or larger portfolios); such differences stress market heterogeneity in the STRM. Mermet (2021) showed that the most profitable listings are advertised by upper-class households, while low-income households are significantly under-represented among hosts and have less profitable listings. Thus, this author confirmed that Airbnb does not benefit homogeneously across population categories and reproduces patterns of inequality in tourist cities. The latter study is a confirmation that STRM activity is combining B2B with P2P, as UNECE (2022) evidenced. Shokoohyar et al. (2020) showed that properties with more rooms, closer to historical attractions, in neighbourhoods with lower minority rates, and better nightlife are more likely to have higher returns if rented through a STR contract. In addition, property location was found to significantly impact rental strategy selection, emphasising the widely known term "location, location, location" in the real-estate market.

The effect of the geographical pattern of STRM business locations has been corroborated in other case studies. Cerezo-Medina et al. (2022) generated a series of concentration maps of four medium-sized Andalusian cities showing that the STR phenomenon coincides with that of traditional tourist accommodations, i.e. in the historical centres. The concentration of STRM businesses in city centres creates spatial spill-over effects on prices, driving inner cities to become "hot" price clusters [tested for 43 European cities by Unece, 2022], and having a substantial influence on prices [see Zhenpeng, 2019 for the US]. Adamiak (2018) mapped the supply in European cities.

Gyódi (2021) analysed price variations during the pandemic among the nine largest European cities (Amsterdam, Barcelona, Berlin, Lisbon, London, Milan, Paris, Venice, and Vienna). This author found that Airbnb was slower to recover tourist numbers than the international hospitality industry, but more flexible in using its accommodation during the pandemic, shifting supplied units from STR accommodation to long-term rental (LTR) apartments, thus reducing the decline in the price of Airbnb properties. Gossen and Reck (2021) supported these results by analysing Berlin between 2019 and 2020, observing that hosts switched from short-term to long-term and rented relatively more full apartments than separate rooms during the pandemic, favouring a counter-cyclical behaviour in this market. Counter-cyclical dynamics in the STRM were also shown by Benítez-Aurioles (2021), who studied the heterogeneity in price determination in Majorca. The study combined Airbnb and official statistics to measure the effect of host professionalism on "price management" as a function of seasonal variations in demand. The results showed that host professionalism has a counter-cyclical effect and that the P2P market has a lower seasonality than the conventional market.

The influences between the STRM and the hotel industry have received much attention. Guttentag et al. (2017) investigated why an increasing number of tourists choose Airbnb services instead of traditional accommodation options. A 2015 survey yielded 800 on-line responses from tourists who had stayed in Airbnb accommodation during the previous year. The results highlighted five motivating factors: interaction; home benefits; novelty; sharing economy ethos; and local authenticity. Sainaghi and Baggio (2020) analysed the substitutive role of both accommodation types' supply from the demand perspective in Milan, testing the synchronisation between hotel occupancy and Airbnb listings over four years. The findings revealed heterogeneous results, demonstrating that during the week both are desynchronised, with hotels working in the business segment and STRM listings accommodating leisure visitors. During weekends and holidays, they found a partial synchronisation with a potential substitution effect between both supply sources of accommodation, with a more competitive capacity of Airbnb in these periods. Thus, the latter seems to partially compete with the former in attracting city visitors during weekends. Dogru, Hanks, et al. (2020) estimated that a 1 % increase in Airbnb listings reduces hotel revenue per room by 0.031 % on average.

The increasing role of professional hosts in the STRM increases the hotel industry's competence (Sainaghi & Baggio, 2020). These authors suggested that there is a de-synchronisation between hotel and STRM supply, with the latter having different seasonal patterns compared to hotel occupation, and supporting other research findings (in the US) regarding the complementarity of Airbnb listing with hotel supply in hot-demand periods when the latter have their capacity overbooked (Farronato & Fradkin, 2018). These studies suggest that both markets (STRM and hotel accommodation) would be different, with a partially common demand.

Demand has been demonstrated to be the main STRM driver, with a considerable influence on market performance (greater than that of the price) (Bruno & Faggini, 2020); rental price is not a significant condition in determining the reasons why properties are non-booked (Leoni et al., 2020). Some research has highlighted the increased number of STRM professional hosts since 2018 (UNECE, 2022). Recent work has suggested that the latter charge prices about 9 % higher than non-professional hosts on average, and that markets with a predominance of professional hosts perform better in the presence of seasonality, increasing in number during the peak season and vanishing during the low season (Casamatta et al., 2022).

Externalities are one of the effects of STRM expansion in recent years, with most literature estimating the negative externalities. For instance, Fernández and Toledano (2020) analysed the geographic and professional concentration during 2018 in Málaga by comparing Airbnb and hotel supply. The study highlighted that Airbnb businesses are concentrated in city centres with higher levels of density than the hotel sector, but also include the main tourist and cultural attractions, such as some specific areas of districts surrounding the downtown district. Such concentration introduces more pressure on the city territory than the traditional hotel sector, suggesting the need for local policies to mitigate the negative impacts. Chica-Olmo et al. (2020) studied Airbnb apartment pricing in Málaga and found, using spatial econometric methods, that accessibility to the city centre, the beach, and places of interest, positively affect the STR price, while noise and certain ethnic groups living near Airbnb apartment negatively impact the price. A positive externality is the capacity of the STRM to create employment in the city. Dogru, Mody, et al. (2020) analysed the effects of Airbnb supply on employment in hospitality, tourism, and leisure sectors in 12 major metropolitan statistical areas in the US between July 2008 and February 2018. The results showed positive (spill-over) effects of increasing employment and the benefits of increasing Airbnb listings in all sectors. Local externalities have also been found to be associated with rental spill-overs in office markets (Mouzakis & Henneberry, 2008).

Researchers have identified the emergence of negative externalities caused by STR activity's rapid growth. These externalities result from population agglomeration in city centres, producing an overuse of public and health services and transport, and negative externalities such as noise and changes in neighbourhoods' quality of life[2] (Filippas & Horton, 2018; Sheppard & Udell, 2016). A further externality is the gentrification of city neighbourhoods resulting from investment incentives to refurbish units rented on the sharing market (Amore et al., 2020; Wachsmuth & Weisler, 2018; Yrigoy, 2019). However, the empirical causal evidence is limited in this literature. For a deeper analysis of short-rental market effects, see UNECE (2022).

The strength of population movements has led to fears that the use of housing for short-term periods will crowd out the formal rental market in the main cities [through the rental-gap mechanism (Smith, 1979) and a reallocation channel (Barron et al., 2021)],[3] worsening the lack of affordable housing in most developed countries (Sheppard & Udell, 2016). Research has suggested that the decreasing affordability of conventional rental housing is due to two mechanisms: the effect of STR prices on conventional LTR prices (demand-side effect); and the absorption of some LTR units from the market for short-term use (supply-side effect) (Barron et al., 2021; Wachsmuth & Weisler, 2018). Both mechanisms contribute to a rise in rental and housing prices. The effect seems to exist but does not have a large effect; Garcia-López et al. (2020) estimated a 1.9 % increase in transaction prices and 7 % in rents, similar to the findings of Liang et al. (2022), Yrigoy (2019), and Sheppard and Udell (2016), among others.

Researchers have also analysed other STRM effects. For instance, technological platforms have overcome housing-market barriers and physical limits to the number of exchanges in some markets, increasing market transparency (PwC, 2014) and increasing trust and credibility in transactions, reducing risk factors (Görög, 2019). The debate concerning how the STRM is supplying space for tourism, in a process called "hotelisation", has been developed by Lee (2016) and Cocola-Gant and Gago (2021).

2.1. Co-movements

The common evolution between prices in different locations has been broadly studied under the hypothesis of the spill-over effect. Economic activity and price spread their influences among geographical areas due to the population, labour, or capital mobility differences. The diffusion of housing prices across the space is called the ripple effect (Meen, 1999), defined as the phenomenon of a perturbance in housing prices in a given market spread out to the rest of the territory over time. In particular, the ripple effect on house prices is shown as a movement (in the same direction) in house prices, affecting other regions' prices. The condition for this spatial diffusion to be recognised as a ripple effect is that it is produced permanently, so that the relative house prices between two locations show a constant relationship in the long term, which reflects housing-demand drivers and household behaviour.

Meen (1999) demonstrated that housing-market prices responded to non-simultaneous changes in fundamentals across the UK, creating a perception that prices in one region follow prices in another region, when, in fact, the ripple is produced due to structural differences between them. Four explanations for the ripple effect were suggested that make each region respond differently to external shocks: migration; equity transfer; spatial arbitrage; and spatial patterns in house prices (Meen, 1999). Moreover, this author demonstrated that the ripple effect could exist irrespective of regional structural differences and growth patterns, suggesting that the empirical fact setting the long-run stable differences still remains despite the ripple effect on prices, supporting the general consensus (Ashworth & Parker, 1997; Canarella et al., 2012; Lean & Smith, 2013).

The literature has demonstrated that structural differences among regions are stable in the long run and are reflected in a long-run constant ratio between residential prices (Holmes & Grimes, 2008); thus, the ripple-effect hypothesis implies the long-run convergence of regional prices (Cook, 2003), revealed as a common movement over time. This suggests a deep association among housing markets in different cities or regions, and that they are affected consecutively by the same drivers.

The evidence that house-price shocks in one area are likely to spread to other areas (price diffusion/ripple effect) is considerable in the literature (Alexander & Barrow, 1994; Ashworth & Parker, 1997; Cook, 2003, 2005; Pollakowski & Ray, 1997; Stevenson, 2004; Tu, 2000; Wilhelmsson, 2008; McGreal & Taltavull, 2013). The ripple effect has been broadly found in other countries (Cameron et al., 2005; Canarella et al., 2012; Gupta & Miller, 2012; Lee & Chien, 2011; Liu et al., 2015; MacDonald & Taylor, 1993; Pollakowski & Ray, 1997). City-level estimations also exists: Taltavull de La Paz et al. (2017) differentiated between the spatial-proximity and far-distance ripple effects on housing prices in Spain; Teye et al. (2017) examined the existence of the ripple effect from Amsterdam to 12 other Dutch regions' housing markets, concluding that Amsterdam housing prices have some level of influence on (or ripple to) most regions in the Netherland; Thaker et al. (2021) found similar results for Malaysian cities' residential prices; and Chiang (2014) found strong evidence that Beijing is the most crucial source of housing-price diffusion in China.

Recent contributions support that the ripple effect occurs when the drivers causing price movements co-move in different areas, demonstrating that common factors cause long-run co-movements between regional land prices (Carmona & Rosés, 2012; Tomal & Gumieniak, 2020). Regarding the synchronisation of prices over time (co-movements) with macroeconomic variables, Byrne et al. (2011) analysed whether the co-movements are due to substitution effects in commodity prices because of common inflation pressure, Ortalo-Magné and Rady (1999) explained their response to income and credit market shocks in the UK, and Milcheva and Zhu (2016) demonstrated the role of bank integration. In contrast, Shi et al. (2009) examined the co-movements among 10 urban areas in Australia using Granger causality and vector error correction models (VECMs), finding evidence that the ripple effect is constrained within regions, with little evidence that it can be spread nationally between main cities.

Note that the above research used low-frequency (quarterly or yearly) data. To the best of our knowledge, no published research has used high-frequency (daily) data to test co-movements. Another issue in the literature is that ripples or co-movements have usually been tested for prices but not for transaction volume [exceptions include Tsai, 2014 and Clayton et al., 2010].

2.2. Hypotheses: evidencing co-movements in the short-term rental market (STRM), prices, and transaction volume

This paper provides empirical evidence of co-movements in STRM prices and transactions in 39 European cities. In this case, and as the cities are distant from each other, the co-movements imply a joint evolution of prices and transactions across faraway locations, suggesting the existence of underlying common factors that causally spread their influence in different cities permanently and at the same time, as well as identifying that spill-over effects link STRM dynamics in different cities, making those markets perform in a synchronised way.

Causality is demonstrated by assessing whether STRM responses follow market principles and by identifying how demand and supply behave. Direct demand is the flow of seekers of available space, and the supply is the total properties that could be supplied (stock) and days (listing). There is no information about any other general determinants at the high-frequency level; thus, this research cannot test the income

[2] A negative externality is a much-used concept in socioeconomic analysis. It appears when an activity developed by one agent negatively affects other people who did not participate in its provision.

[3] UNECE (2022) summarises the economic reasons.

effect in the STRM.

This paper hypothesises that the performance of this market evidences population mobility, and if co-movement exists, it captures the effect of such mobility acting as a demanding force with the market changing in the same way across cities. One source of mobility is tourism attracted from other cities (a common income increase, for instance, would affect cities at the same time), while another is interregional mobility due to business reasons, which produces larger movement as the industries are more related. Both have a large impact on cities and are key to defining municipal policies to appropriately cover public-service needs.

This paper aims to find evidence of co-movements among STRMs. We hypothesise that co-movements and spill-over effects link these markets in different European cities, making them to converge through their influence on each other.

Accordingly, three hypotheses are proposed:

H1. Co-movement among STRMs in the main European cities exists, so STRM is synchronised across these cities. Support for *H1* means that there is a benefit for all linked cities as they would experience similar externalities. Thus, there is an opportunity to coordinate measures and regulations across cities to better deal with this phenomenon.

H2. Causality comes from the market mechanism. Support for *H2* suggests it is possible to predict STRM evolution and its persistency, supporting the implementation of policies to maximise STRM benefits.

H3. The STRM is mainly used for tourism purposes, so the market is "hot" during weekends and holidays and weak or inexistent otherwise. Rejecting *H3* suggests that the STRM is used for other purposes, enabling the identification of hidden population mobility for other purposes and the implementation of measures to support them.

3. Model and empirical strategy

The research strategy to find and quantify the co-movements follows the steps explained below, shortly defined by the following sequence and points:

Comovements ➔tested for cointegration
➔ market model definition ➔ mkt model estimation
➔long term relationship (coint)
➔short term relationship (ECM)

The methodology uses the econometric tools the literature recommends:

1st – For estimating comovements, using a battery of tests to identify cointegration, demonstrating that (1) there is long term association among the analysed variables and that (2) it is causally based.

2nd Once the evidence is found, next step is to add a robustness check finding causal evidence in a STR market mechanism. The mechanism is defined according to the economic theory, and estimated.

3rd The model is estimated using Vector Autoregression (VAR) Models, which is the framework for analysing non-stationary time series with cointegration relationships. The results confirm the previous tests and show the existence of comovement with long-term effects (or cointegration relationships), which are statistically significant, and quantify the long-term mechanism of the market equilibrium.

4rd The quantification of short-term relationship is estimated by an Error Correction Model, which identifies the time lag influence among all variables and quantifies their effects.

H1 is demonstrated in the first step, and it is tested by estimating the existence of long-term components among cities' STRM variables. A cointegration relationship among these variables across the cities proves that these markets move together as their different dynamics converge to a common pattern.

The ripple effect can be defined as a perturbance in house prices in a given market that spread out to the rest of the territory over time. The result is that prices tend to move together, sometimes with time lags, and then maintain their relative value, which is represented by a constant in the long term. This can be expressed as:

$$\frac{Ph_{i,t}}{Ph_{j,t}} = \frac{Ph_{i,t+1}}{Ph_{j,t+1}} = \frac{Ph_{i,t+2}}{Ph_{j,t+2}} = \ldots\ldots = \frac{Ph_{i,t+n}}{Ph_{j,t+n}} = c \tag{1}$$

where *Ph* is the housing price of units *I* and *j*, and *c* is a constant.

When this happens, the long-term evolution of prices seems to evolve in parallel, i.e. they co-move. The literature has determined two conditions to distinguish the ripple effect from other synchronisation movements shown in the data (Cook, 2003; Holmes & Grimes, 2008; Meen, 1999): the movements should be in the same direction (otherwise, there is no co-movement as they could diverge); and changes should appear permanently, and the relative prices should remain unaltered. Accordingly, most research considers the ripple effect as a cointegration relationship among different prices, enabling the determination of a permanent economic relationship and the identification of how the related variables converge in the long term. This can be expressed as:

$$\beta_1 Ph_{1,t} + \beta_2 Ph_{2,t} + .. + \beta_n Ph_{n,t} = 0 \tag{2}$$

With daily data, variances would also be synchronised, showing the long-term influence and reflecting the strength of the spill-over-effect change and better capturing the different movements together. The variance can be seen in the standard and idiosyncratic (or particular and specific) components, with the former revealing systematic influences via variations in the variable, reflecting it in a kind of ripple effect. The first empirical exercise is thus to demonstrate the long-term association of STR prices via mean and variance.

The second step looks for robust results of comovement by re-estimating cointegration within a causal market-mechanism model. Thus *H2* is tested by exploring the reaction of the STRM within a market-mechanism scheme that captures whether cities' variables follow economic principles, and that the reaction is causally based. The market mechanism is represented by a supply–demand scheme that enables quantifying the size of the effects in the reaction of supply and demand when the price changes. This market is characterized by an absence of entry barriers as it is open worldwide and allows infinite demand. The limit is in the supply of units with respect to the existing stock, although if the market incentive is large enough, more units will enter. Those define a competitive monopoly market.[4]

The complete supply–demand model for the STRM is defined below, with the demand equation [Eq. (3)] and the supply equation [Eq. (4)] representing the reactions of quantities (booked properties in the market) and supply units (properties offered) to price changes. If the STRM reacts as a market, there should be a statistically significant relationship between quantities and price changes across cities, and the size of the effect between both will reveal the sensibility degree of such a reaction. The market framework and the sensibility reactions determine the market typology in the STRM. This is the first time this approach has been applied and empirically evidenced for STRMs. The model equations are:

$$log\left(qh^{d}{}_{it}\right) = \alpha_1 - \theta_i log[ph_{it}] + \zeta_i [X_{it}] + FE_i + \mu_{it} \tag{3}$$

$$log\left(qh^{s}{}_{it}\right) = \alpha_1 + \beta_i log[ph_{it}] + \gamma_i [X_{it}] + FE_i + \mu_{it} \tag{4}$$

where qh^s_{it} is the total supply of properties in city *i* at time *t*, qh^d_{it} is the total demand in city *i* at time *t*, and ph_{it} is the rental price of properties in city *i* at time *t*. Regarding the STRM, X_{it} is a matrix of control variables associated with city *i* in period *t*, and FE_i is the fixed effects for city *i*, capturing the idiosyncratic non-observable city features affecting the

[4] We acknowledge an anonymous referee for point this issue.

STRM. Variables are measured in logs to estimate the response elasticities. The parameter θ of the price component in Eq. (3) is the price elasticity of demand, while β in Eq. (4) is the price elasticity of supply.

A long-term relationship is expected between quantities and prices, supporting the idea that the market mechanism is consistent and reflects the theoretical market law. From the perspective of this empirical exercise, finding a statistically significant relationship $[\alpha(Qh_{it}) + \beta[Ph_{it}] + c = 0]$ would suggest co-movements among two main market drivers, show how they move together, and support the causal basis for synchronising housing prices and supply/demand quantities.

The literature has demonstrated that a cointegration relationship, as in Eq. (2), reflects a causal association among the variables included in the linear combination (Dufour & Renault, 1998; Engle & White, 1999), quantifying the market reactions, which reflects how a market mechanism performs following a common pattern across the related cities.

The supply/demand scheme above is quantified in this paper using daily data using a vector autoregression (VAR) methodology. Non-stationary data and cointegration relationships are identified, enabling the estimation of permanent (long-term) and transitory (short-run) demand and supply spill-overs among cities' STRMs using the empirical expressions of Eqs. (3) and (4) under the VAR methodology.

VAR methodology estimates an endogenous system of equations in which the dependent variable is explained by its temporary lags and the independent variables are lagged. The method enables quantifying the time effect in a system both for one variable over the future values of itself and of other determinants. When long-term relationships are statistically significant, a VECM is the correct model specification. This paper applies the VECM method, shown in Eqs. (5) and (6), which explains the changes in endogenous variables directly determined by two components: the long-term component (cointegration relationship), which express the permanent mechanism underlying the data and reflects an economic mechanism; and the short term component (error correction), which captures a transitory effect of changes in the explanatory variables (current and in the past) on the dependent variable. Using this methodology, this paper parametrises short-run spill-overs as follows:

$$\begin{aligned}\Delta qh_{i,t} =&\alpha_1 + \theta_1\left[qh_{t-1} + \beta_i^1 ph_{t-1} + c_1\right] + \sum_{j=1..t-1}\sum\nolimits_{i=1}^{i}\delta_{1,j}\Delta qh_{i,t-j}\\ &+ \sum_{j=1..t-1}\sum_{i=1}^{i}\delta_{2,j}\Delta ph_{i,t-j} + \zeta_i[X_{it}] + \mu_{1,t}\end{aligned} \tag{5}$$

$$\begin{aligned}\Delta ph_{i,t} =&\alpha_1 + \theta_2\left[qh_{t-1} + \beta_i^2 ph_{t-1} + c_1\right] + \sum_{j=1..t-1}\sum\nolimits_{i=1}^{i}\tau_{1,j}\Delta qh_{i,t-j}\\ &+ \sum_{j=1..t-1}\sum_{i=1}^{i}\tau_{2,j}\Delta ph_{i,t-j} + \gamma_i[X_{it}] + \upsilon_{1,t} \qquad \forall\ i\end{aligned} \tag{6}$$

where X is a matrix of exogenous variables for each city, including two bivariate variables capturing the effect of weekends and COVID-19, and μ and ν are error terms.

The condition for co-movement is that the linear long-term relationship (cointegration) in the right-hand side, second term, of Eqs. (5) and (6) (θ_1 and θ_2) is statistically significant. The parameters β_i (1 and 2) are the measure of the long-term elasticity of this market. The remaining parameters have a direct interpretation, with $\delta_{1,j}$ representing the short-term spill-over effect on quantities, $\delta_{2,j}$ the statistically significant parameters measuring the short-term price elasticity, and $\tau_{2,j}$ the spill-over effect of prices among cities, all in the short run. The latter two estimated parameters are the cross-correlations between prices and quantities in the short term, which capture the transitory substitution effect of STR demand affecting prices across European cities. Demand is proxied by the number of units that are booked. In this case, the demand equation cannot test the income effect due to data frequency.

In this step, the market mechanism is tested by checking the market responses to the price defined in the model [Eqs. (5) and (6)]. The causal relationship in these markets implies that local governments can identify trends to adapt their services and develop local policies able to reduce the negative effects and take advantage of the benefits associated with the increase of transient population well in advance.

To the best of our knowledge, this is the first paper presenting the dynamics of the STRM and the first to analyse housing-market equilibrium with high-frequency data (daily). The idea of separating the types of synchronisation and their meaning is also a contribution of the paper.

4. Database and exploratory analysis: evidence

The data used in this paper come from the Airbnb platform, retrieved from Airbnb micro dataset (insideairbnb.com) original files. Both listing and calendar files were analysed at the micro level and merged, resulting in a panel with the key variables for 39 European cities (Table 1 shows the cities and the number of observations after cleaning the original files and eliminating repetitions). The city selection was made in order to test the existing co-movement effect across European cities, which drove the decision to analyse all available cities from each geographical area downloaded (available from the website in early 2021). Once the data were cleaned, time series were produced daily, counting the number of events associated with each day (number of properties booked per day). The events of interest are the number of rental contracts, the number of properties hired, and the average daily price, all at the city level.

Rental contracts were extracted from the variables "available" and "not available" in the calendar file associated with each day,[5] and the obtained measure was considered a proxy of the actual rental activity in the market. The models estimated in this exercise cover the complete observed period (until February 2021).

Extraction and cleaning yielded time series with almost the complete information for 2018–2021 (February), although some cities had information from 2015.[6] The resulting dataset comprises a panel with 39 cross-sections (cities). The basic statistics show the main features of the four main variables extracted: Book_p (booked rent); Ask_p (asking rent); Book_n (number of properties booked per day); and Ask_n (non-booked–available–number of properties per day). Asking rents are the rents associated with each listed property on the platform.[7] We associated the number of booked or non-booked days with the number of properties, as both property modes (booked and listed for rent) are mutually exclusive in a single day. This way of accounting units revealed the number of properties offered through the Airbnb platform.[8] All prices were converted into euros. Table 2 shows the basic statistics.

The time perspective of the data is shown in Figs. 1 and 2, representing selected city time series. Fig. 1 shows the number of booked

[5] The information about price used is the listing or asking price. The number of contracts inferred by the available/non-available information in the calendar files is a proxy of the real contracts, as "non-availability" would be because the property is booked (then rented), is reserved for the owner's use (own-rented), or is unavailable for another reason. Other studies have shown that the own-renting average is extremely stable and <30 % of the total number of non-available days for some Spanish cities (Taltavull de La Paz et al., 2020).

[6] Main European cities with data from 2015 are Amsterdam, London, Paris, Vienna, and others (see Table 1).

[7] Asking rent or price is a well-known, accepted concept to differentiate the transaction prices or rent from those prices or rent published. The housing-market literature considers asking prices as the first reference to start transactions in the market.

[8] The number of properties is the whole house or a room. Such details can also be found by extracting the property references in the dataset. On average, they are 2 %–5 % of the housing stock in each city, although all tourist areas present a larger number of units devoted to this market (UNECE, 2022). Other research has shown that around 35 % of listed properties are also listed on other platforms, such as HomeAway in Valencia, Alicante, and Castellon (Taltavull de La Paz et al., 2020), suggesting that short-rent property use enjoys a stable supply.

Table 1
Database, a summary of data, basic statistics of time series.

	Number of booked contracts (variable Book_n)				Rental price in euros per night, published in the platform (variable Asking_p_e)				Number of listing properties not booked (variable Asking_n)			
	Mean	Median	Std. Dev.	Obs	Mean	Median	Std. Dev.	Obs	Mean	Median	Std. Dev.	Obs
Amsterdam	31,562.54	24,732.50	19,585.68	2504	174.57	172.47	34.66	2504	13,741.29	14,766.00	4850.40	2504
Antwerp	10,766.10	10,195.00	7401.43	2125	175.81	176.44	46.06	2244	18,316.77	16,246.00	11,636.30	2141
Athens	8381.59	7071.00	6683.54	2105	66.88	61.30	17.21	2413	17,113.49	16,633.00	13,022.38	2117
Barcelona	22,171.68	22,479.00	12,259.40	2479	106.02	103.92	20.16	2479	33,407.85	36,426.00	13,328.89	2479
Bergamo	2108.49	2247.50	716.83	1408	75.92	75.26	4.10	1408	4102.75	4220.00	1528.97	1408
Berlin	34,605.65	24,825.50	20,703.86	2336	77.97	75.10	14.03	2336	17,589.20	16,951.00	6928.62	2335
Bologna	6443.83	6943.50	2649.46	1322	97.58	92.53	21.20	1322	7010.93	7985.00	2921.63	1322
Bordeaux	19,711.33	20,965.00	7040.38	1396	92.96	92.20	7.91	1396	10,081.10	10,033.00	3299.29	1396
Bristol	4645.15	4953.00	2448.03	1399	111.36	102.65	30.71	1399	3159.15	3205.00	1266.89	1399
Copenhagen	45,659.66	27,106.00	37,846.14	2070	106.22	104.57	32.71	2070	11,366.91	8436.00	6595.76	2070
Dublin	13,787.22	10,141.00	10,442.26	2186	148.43	128.83	73.67	2244	6518.03	5184.50	4014.78	2170
Edinburgh	18,053.92	10,783.00	13,005.54	2045	143.93	121.28	63.31	2046	11,662.32	11,048.50	6325.69	2046
Florence	15,703.05	17,026.00	6310.32	1409	113.49	112.06	12.92	1409	24,494.79	28,294.00	10,206.54	1408
Geneva	4877.18	3546.00	2959.31	2123	116.42	116.82	5.38	2123	4648.79	5175.00	1554.45	2123
Ghent	2114.76	2341.50	958.42	1414	90.86	89.72	4.48	1414	1656.32	1718.50	725.93	1414
Girona	20,275.07	20,894.00	9631.05	1385	149.09	143.57	24.05	1385	25,026.18	25,236.50	10,610.07	1384
Istanbul	31,588.91	33,058.50	18,871.79	1410	42.72	45.65	13.91	1309	75,339.57	77,556.00	38,680.78	1410
Lisbon	27,257.22	30,294.00	11,833.87	1401	99.68	99.71	11.24	1401	47,537.31	53,315.00	21,555.96	1401
London	104,215.30	82,757.50	72,011.90	2506	192.70	168.13	98.83	2506	84,829.01	97,281.50	37,324.02	2506
Lyon	21,979.75	24,381.00	8521.93	1399	93.28	91.08	8.27	1365	10,396.24	11,083.00	4027.85	1399
Madrid	17,849.95	16,925.00	11,856.42	2248	91.96	85.49	25.53	2404	22,083.60	19,032.00	12,429.44	2247
Malaga	5796.34	6206.50	2273.86	1532	100.81	95.68	23.06	1532	9542.18	10,431.00	4120.34	1532
Mallorca	11,288.13	10,336.50	7292.77	2128	189.88	179.33	51.66	2231	18,673.25	17,376.00	9774.51	2128
Manchester	7334.39	7490.00	3916.85	1411	105.20	96.55	21.23	1411	7216.79	7528.00	3000.08	1411
Menorca	3052.17	3021.00	1419.07	1385	187.64	180.00	49.86	1385	3720.41	3552.00	1628.55	1385
Milan	29,876.27	32,107.00	12,329.51	1381	108.93	106.30	16.38	1408	28,414.12	30,323.50	12,870.28	1408
Naples	8301.61	8873.00	3363.26	1332	73.14	72.19	6.11	1301	17,795.19	18,429.00	7897.49	1332
Oslo	19,655.53	24,330.00	11,314.14	1410	90.47	88.32	23.57	1256	6156.36	7059.00	2741.38	1410
Paris	94,101.06	79,789.00	54,662.97	2476	130.09	127.84	24.94	2476	67,988.71	75,959.00	23,053.03	2476
Porto	11,969.08	13,401.00	4585.66	1334	83.37	81.36	17.07	1336	21,902.15	24,721.50	8296.70	1336
Prague	29,307.82	26,475.00	18,107.67	1403	124.11	131.13	78.37	1302	28,088.34	25,432.00	15,916.50	1403
Puglia	25,984.65	28,408.50	9893.39	1412	95.77	91.48	16.38	1412	49,503.43	48,827.50	16,360.17	1412
Rome	26,665.15	25,205.00	14,143.46	1743	105.80	104.48	10.59	1743	47,966.24	51,145.00	24,013.14	1743
Seville	7968.04	8903.50	3376.50	1410	115.26	101.14	40.81	1410	10,178.82	11,165.50	4481.35	1410
Sicily	31,879.28	34,191.00	10,870.19	1411	86.03	85.41	11.39	1411	87,243.83	82,471.00	34,458.10	1411
Stockholm	15,953.94	15,644.50	9499.43	1410	115.32	115.00	34.42	1410	5665.33	5803.00	2648.75	1410
Valencia	9836.14	10,664.00	3519.16	1089	78.97	78.00	9.82	1089	10,002.80	10,985.00	4199.96	1089
Venice	7067.64	7333.50	4983.51	2102	139.43	140.39	9.88	2399	15,445.90	18,214.50	10,878.08	2102
Vienna	17,659.33	11,020.00	12,941.55	2403	83.21	81.47	12.77	2403	15,763.81	14,762.00	6929.16	2402

Source: Inside AirBnB from platform www.insideairbnb.com, file Calendar, and own extraction.

Table 2
Basic statistics. Common sample in the pool.

	Book_p (booked price)	Book_n (booked number of properties)	Ask_p (asking price)	Ask_n (non-booked -available- number of properties a day)
Mean	118.61	28,755.44	121.75	26,714.62
Median	98.95	18,746.00	108.41	16,683.00
Maximum	1427.59	265,438.00	485.08	151,850.00
Minimum	30.58	39.00	12.46	12.00
Std. Dev.	83.96	36,275.85	50.48	28,162.10
Skewness	6.17	3.24	1.76	1.93
Kurtosis	68.05	14.97	8.01	6.72
Observations	43,607	43,607	43,607	43,607
Cross sections	39	39	39	39

Source: Basic statistics of data obtained from Inside AirBnB from platform www.insideairbnb.com, file Calendar, and own extraction.

properties in the left panel and the remaining available properties in the right panel, all in daily data, for 18 selected cities.

Fig. 2 presents the daily average price. The daily prices are the average of all supplies or bookings in each city without weighting. The left panel contains the price agreed in the booking, while the right panel shows the asking price for non-booked properties. The booked price data were available from 2019 for all cities, while asking prices had observations during the whole period. We used the latter in the models, while the former was used for robustness purposes. Prices are presented in euros after applying the daily exchange rate for each currency.

Figs. 1 and 2 show that the number of booked units in peak times is almost double that of available units every day since 2018, while they were around 50 % before. In contrast, the booking prices seem higher than the asking prices, although with significant heterogeneity among cities. The amount of transactions per day supports the idea of solid market growth until 2019, with a fall since early 2020 when COVID-19 hit the market, although some cities maintained vigorous activity during that period. Prices did not fall after the pandemic, and strongly rose at the end of the analysed decade.

The size of the dataset suggests that it is representative of the total

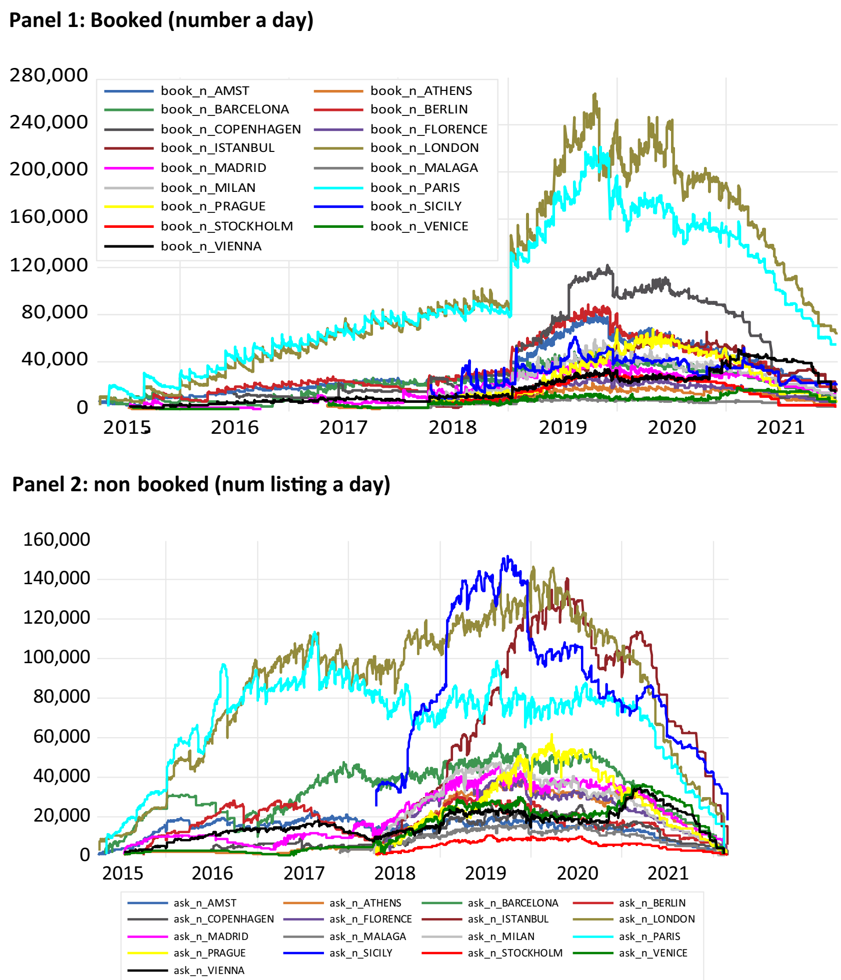

Fig. 1. Short-term rental market activity in 17 selected cities. Booked vs non-booked properties a day.
Panel 1: Booked (number a day).
Panel 2: non-booked (num listing a day).

population. Testing the significance is difficult, however, as the total population movements using the STRM is unknown, and the hidden population movements are also unknown (until the existence of a dataset reveals them). However, we estimated the significance at 95 %, 97 %, and 99 % of the population movements associated with the 39 STRM analysed, with a maximum of 1 % of error, relative to the local registered population and to an infinite population. The results show that the observations used in this paper are fully generalisable.[9]

5. Empirical analysis and discussion

This section presents empirical evidence supporting the market forces driving STRMs in European cities. We identify total units of booked and un-booked properties from the total supply in the market per day, together with their prices. Based on this, we can define the STRM model demand and supply equations following a naïve perspective explained in Eqs. (5) and (6). As the market is operating through a platform (Airbnb) with no barriers, we focus the analysis on the free-market framework where demanders are price-acceptant. There are no entry barriers, and increasing the supply depends on the stock. As a housing market, the available stock in a city is a fundamental limitation for developing this market. A deep study of this dataset (UNECE, 2022) showed that the total units used through the Airbnb platform do not exceed 4 % of each city's primary housing stock on average. Thus, owners or hosts manage the available stock in an efficient way by stablishing a competitive monopoly market, as the amount of property used is small and will be controlled by hosts. Hosts determine the rent to be published (asking price). This is directly connected with the widespread debate regarding whether these prices would be automatically determined by the platform algorithm. The estimated elasticities measure the sensibility of supply (new properties listed) to changes on prices, which is relevant to hypotheses concerning the existence of market control from the hosts' perspective. Thus, the modelling quantifies the supply elasticity, which provides evidence regarding how much the supply market reaction serves to make inferences.[10]

As the dataset is daily, there is no chance of finding fundamental variables to test the economic determinants of supply or demand with the same periodicity. However, by introducing city fixed effects, it is possible to isolate the idiosyncratic features (unobservable variables, such as legal rules or city attractiveness, and differences in size). In addition, the analysed period contains the pandemic effect through a

[9] The results are available on request.

[10] As data limitations do not allow testing the existing market power on the market structure directly. We thank an anonymous referee for highlighting this theoretical issue as the current use of the housing stock potential reduces the unlimited potential response of supply to the market signal. This is an issue for future research.

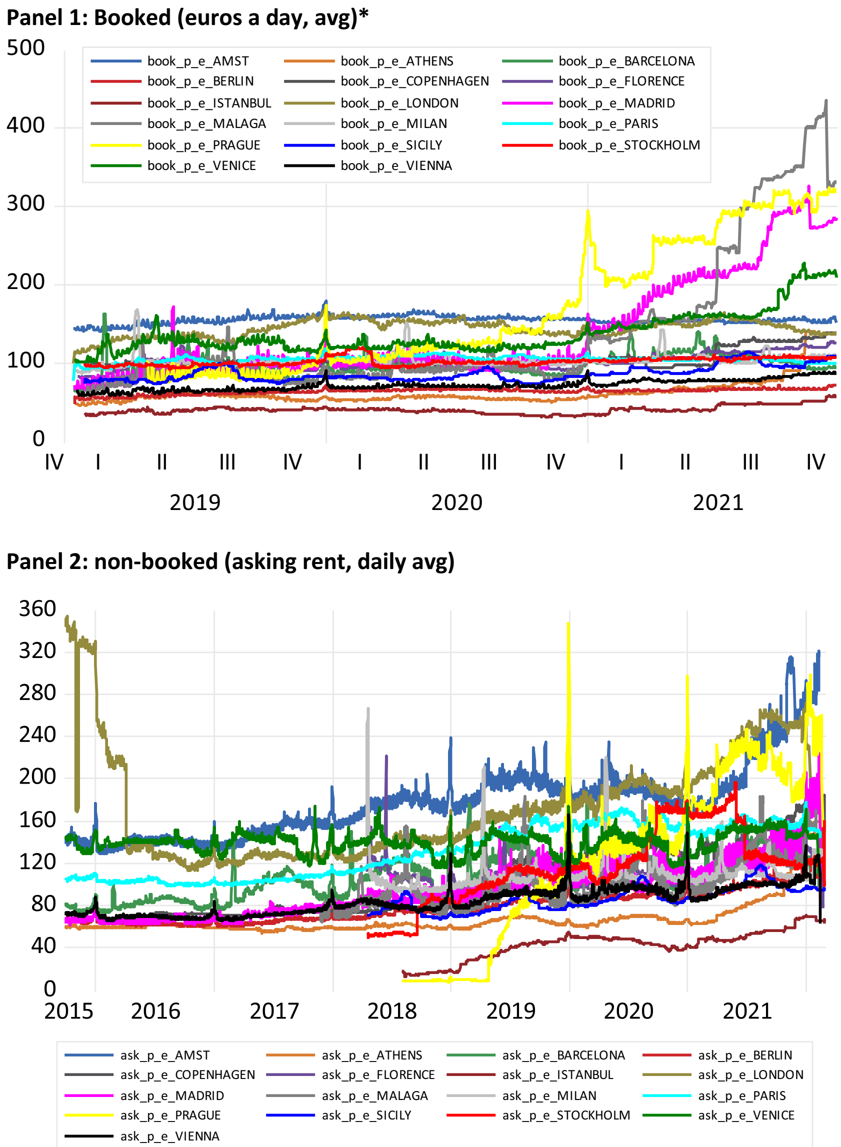

Fig. 2. Short-term rental market daily rents in 39 cities. Booked vs non-booked properties.
Panel 1: Booked (euros a day, avg)*.
Panel 2: non-booked (asking rent, daily avg).

dummy variable to estimate the potential shock in the models.

5.1. Testing H1

Data were pooled to build a panel with $n < t$ dimensions, and the first step was to identify stationary properties for the variables of interest, both with cross-sectional independence and dependence (Table 3). For the former, this paper applied the first-generation panel test, which assumes cross-sectional independence and inter-cross-sectional homogeneity, by applying LLC for common processes and IPS, ADF Fisher, and PP Fisher tests for individual processes (Table 3, panel A). To test stationarity considering cross-sectional dependence, this paper applied second-generation stationarity tests using Bai and Ng's (2004) panel analysis of non-stationary and idiosyncratic components (PANIC) to identify potential common factors in properties supplied and prices in the STRM. PANIC determines the number of common non-stationary factors and the non-stationarity in idiosyncratic components (Table 3, panel B). The direct cointegration test rejected the null hypothesis that all the cross-sections are not, simultaneously, cointegrated. This is initial evidence of a cointegration relationship between cross-section data in each pooled variable.

Common processes for idiosyncratic components are related to the strong volatility, which we hypothesise is associated with the high-frequency data used in this paper. Testing for the existence of common processes in variance with long-run effects, separately, was achieved by estimating the autoregressive conditionally heteroskedastic (ARCH)/generalized ARCH (GARCH) processes (Engle, 1982) or volatility (Bollerslev, 1986). The existence of long-term effects due to processes in variance was examined by estimating a fractionally integrated GARCH (FIGARCH) model (Baillie et al., 1996). Table 4 presents the parameters' results. Following Maheu's (2005) rule, the results support the hypothesis of cointegration in variance for rental asking prices, as the differences in the ARCH parameters tend towards zero, and the differences in the GARCH components tend to unity.

5.2. Testing H2 and H3

H2 was tested by demonstrating causality between supply and

Table 3
Pooled stationary test. Short-term rental market indicators.

	Book_p_e (booked rental price, euros)		Book_n (booked number of properties)		Ask_p_e (Rental asking price, price published in the platform, euros)		Ask_n (non-booked –available units- number of properties a day)	
A. Crossectional independent (statistics)								
39 cross-sections	*levels*	*1st diff*	*levels*	*1st diff*	*levels*	*1st diff*	*levels*	*1st diff*
num obs	43,500		67,069		67,897		67,106	
Null: Unit root (assumes common unit root process)								
Levin, Lin & Chu t*	11.908	−57.74***	1.628	−92.7***	1.588	−79.57***	1.839	−83.28***
Null: Unit root (assumes individual unit root process)								
Im, Pesaran and Shin W-stat	1.899	−143.5***	2.291	−163.2***	−10.21***	−187.8***	3.693	−139.9***
ADF - Fisher Chi-square	210.5***	5809.7***	35.525	7545.1***	499.2***	6498.5***	23.768	7384.4***
PP - Fisher Chi-square	779.29***	4843.***	37.501	1966.4***	884.06***	4485.2***	35.540	6044.68***
Pool individual series	I(1)		I(1)		I(0) with a common root		I(1)	

	Book_p_e (booked rental price, euros)	Book_n (booked number of properties)	Ask_p_e (Rental asking price, price published in the platform, euros)	Ask_n (non-booked –available units- number of properties a day)
B. Crossectional dependent				
Panel unit root tests with cross-sectional dependence: Bai and Ng - PANIC				
Common factors: cardinality of non-stationary factors				
Null hypothesis: retain common factors				
Num Factors	9	9	9	9
test statistic	987.536**	841.363	3326.308	289.357
p-value	1.000	1.000	1.000	1.000
Idiosyncratic elements: pooled test				
Null hypothesis: no cointegration among all cross-sections				
Pooled statistic	+/− Inf	4.41***	+/− Inf	3.17***
p-value	0.000	0.000	0.000	0.002

Note. This table presents the stationarity tests for the four main variables of short-term rental market. Data used is daily from 2015 to 2022 ($N = 39$, $T = 5 * 12$). Section A shows that variables booking and asking supply (numbers) and book rent are I(1) while asking rent reject the null of existence of individual unit root processes. All four variables cannot reject the null of having a common unit root. Those suggest that all but asking rent are I(1). Section B examines the stationarity properties of the panel time series and idiosyncratic nonstationarity. We identify the factor structure using an information criterion from Bai and Ng (2002). For the idiosyncratic component, we reject the null hypothesis of a no cointegration among cross-sections in all cases but in the variable ask-n (number of properties supplied and non-booked).

*** p-value < 0.01.

** p-value < 0.05.

* p-value < 0.1

Table 4
Evidence of common process in variance. Short-term rental market variables of 39 European cities.

Variables		ARCH-GARCH model				FIGARCH				DIFFERENCES	
(Data on averages by day)		RESID(−1)^2		GARCH(−1)		RESID(−1)^2		GARCH(−1)		RESID(−1)^2	GARCH(−1)
		Parameter		Parameter		Parameter		Parameter			
Booked properties	Number	0.8758	***	0.53912	***	0.77097	***	0.26391	***	−0.1048	−0.2752
Non-booked properties	Number	0.8574	***	0.51315	***	0.67921	***	0.19537	***	−0.1782	−0.3178
Booked rent price	Euros	0.3689	***	0.70549	***	0.21254	***	0.56563	***	−0.1564	−0.1399
Rental asking price	Euros	0.3475[a]	***	0.74851[a]	***	0.22825[a]	***	0.97015[a]	***	−0.1193	0.2216
						Differences should tend to…				ZERO	ONE

Estimated parameters suggest that GARCH and FIGARCH show a significant value of parameters with their sum closer to one. These suggest the existence of long-term processes in variance. ARCH and GARCH parameters reach a value larger than one, suggesting that the root plays a more significant role in explaining the long-term memory process. All models contain AR processes (1 to 3), suggesting that the autoregression in the mean is superior to the process in variance, supporting the interpretation above, although only the non-booked supply variable (ask_n) shows the existence of long-term process in variance. Variables measuring property quantities booked and supplied show larger parameters in the innovation process in both GARCH and FIGARCH models, suggesting that short-run events are the primary sources of autoregressive variance in quantities. It does not happen in price indicators, where volatility leads to the autoregression in variance.

[a] No squared root GARCH.

Table 5
Pool test of cointegration relationship among the short-term rental market variables. Supply and demand equations.

	Supply equation				Demand equation			
Pedroni Residual Cointegration Test								
Null hypothesis: no cointegration								
	Statistic	Prob.	Statistic	Prob.	Statistic	Prob.	Statistic	Prob.
Alternative hypothesis 1: common AR coefs. (within-dimension)								
Panel v-Statistic	−1.639	0.949	−1.392	0.918	0.215	0.4149	1.0289	0.1518
Panel rho-Statistic	−28.084	0.000	−4.142	0.000	-25.129	−0.000	-3.7508	0.0001
Panel PP-Statistic	−18.807	0.000	−2.180	0.015	-17.897	0.000	0-2.276	0.0114
Panel ADF-Statistic	−10.612	0.000	−3.348	0.000	-10.071	0.000	-3.2889	0.0005
Alternative hypothesis 2: individual AR coefs. (between-dimension)								
Group rho-Statistic	4.498	1.000			3.5136	0.9998		
Group PP-Statistic	5.028	1.000			3.1594	0.9992		
Group ADF-Statistic	1.563	0.941			−1.009	0.1565		

	Supply equation		Demand equation	
Kao Residual Cointegration Test				
Null hypothesis: no cointegration				
	t-Statistic	Prob.	t-Statistic	Prob.
ADF	3.4075	0.0003	2.3385	0.0097

Supply equation					Demand equation				
Johansen Fisher Panel Cointegration Test									
Hypothesized	Fisher Stat.		Fisher Stat.		Hypothesized	Fisher Stat.		Fisher Stat.	
No. of CE(s)	Trace test	Prob.	Max-eigenvalue test	Prob.	No. of CE(s)	Trace test	Prob.	Max-eigenvalue test	Prob.
None	673.6	0	1031	0		4807	0	920.6	0
At most 1	80.87	0.3896	80.87	0.3896		40.53	0.9999	40.53	0.9999
	Trend assumption: Linear deterministic trend					Trend assumption: Linear deterministic trend (restricted)			

demand and identifying statistically significant long-run and short-term relationships in the panel, which suggests synchronisation of the cities' rents and contracts Table 5. As non-stationary variables, the functional form taken for each equation corresponds to a VECM [Eqs. (5) and (6)],[11] which enables obtaining several measures of elasticities that identify the scope and direction of STRM co-movements. Elasticities also reveal the strength of market forces acting on STR. As already mentioned, a weekend variable (accounting for every Saturday and Sunday along the whole period) was included to identify those "weekend" cities and test *H3*. Finally, a COVID-19 variable (covering March to May 2020[12] when the pandemic appeared) is included to control for the pandemic period.

The VECM comprises two components. One is the long-term relationship, explaining whether co-movement (long-term or cointegrated relationship) significantly contributes to the equilibrium; the other is the set of short-term components, which explains how lagged changes in the model components affect the short-run equilibrium. As a VECM is an endogenous system, the estimated parameters also capture lagged variables affecting each other, which are quantification (as elasticities) of the diffusion or spill-over effects existing in cities.

Table 6 presents the results. As data are daily, estimating the lags contributing to equilibrium results in large periods according to the minimum Akaike test. We identified different lag sensibilities to reach the equilibrium, with shorter periods in the supply eq. (15 lags, which means the influence is concentrated in two weeks) and very long periods in the demand eq. (350 lags, around 11 months). This suggests that hosts (property suppliers) decide the quantity to supply depending on the change in asking prices and other supplies in 15 days' time. On the contrary, changes in demand (or decisions to book a property in a particular city in our sample) are influenced by decisions taken 11 months in advance.

Results support previous evidence concerning the existence of a long-term common relationship both in the supply and demand equations, with the correct signs. The STRM mechanism estimated for the supply equation shows a statistically significant long-term relationship between properties supplied and asking rents, with an elastic parameter suggesting elastic responses of quantities when prices rise by 1 %. The long-term relationship contributes to the equilibrium in the endogenous system with a rapid adjustment (and a small and statistically significant cointegration parameter). The latter is proof of co-movement between STRMs across the cities included in the panel from the perspective of the supply reaction, i.e. both supply and prices moved together across city markets during the analysed period.

The estimated demand side shows a long-term relationship with a negative (as expected) and large statistically significant parameter, suggesting a super-high reaction of contracts to changes in prices (an increase of 1 % in STR prices reduces the demand by 48.1 %). The long-term relationship also contributes to the equilibrium immediately (very

[11] For robustness purposes, the model was also estimated using an ARDL model. Applying automatic selection, the equilibrium model obtained for the demand equation yielded ARDL (12,10,10) and for the supply equation yielded ARDL (10,6,6). These results are consistent with those obtained by the VECM presented here, and are available on request.

[12] The measures were applied on different days depending on the city, and in some of them there were no strong isolation measures until late in this period. However, the impact on international movement appeared in early May, so we maintain the COVID-19 variable definition.

Table 6
Pooled VECM models for supply and demand short-term rental markets.

Dependent variable	Supply Eq.(total listing properties)		Demand Eq. (booked properties)	
	$\Delta(\log q_{hs})$ –daily listing	Δ ($\log p_h$) Asking rents	$\Delta(\log q_{hs})$ - daily booked	Δ ($\log p_h$) Asking rents
Long term				
log($\log p_h$) (−1)	4.504***		−48.13***	
	[8.203]		[−3.845]	
c	−31.213		291.78***	
			[4.921]	
Convergence (co-movement)	−0.00043***	−0.00029***	−0.000012**	0.000022
	[−7.723]	[−6.458]	[−2.170]	[12.35]
Exogenous variables:				
D_covid	−0.001**	0.001***	0.00137	0.00145***
	[−2.144]	[2.531]	[0.894]	[2.978]
Weekend	−0.003***	−0.009***	−0.00492***	−0.00312***
	[−7.893]	[−32.115]	[−5.363]	[−10.649]
Adj. R-squared	0.036	0.683	0.131	0.714
Sum sq. resids	35.29	22.29	217.4283	22.25122
S.E. equation	0.027	0.021	0.066159	0.021165
F-statistic	57.03***	3254.76***	11.85***	176.76***
Lags for the equilibrium	15		350	
Minimum Akaike IC	−9.2861		−7.4466	

Note. t-student in brackets, ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

small convergence parameter) on quantities, showing a quick effect of any change on prices in the long run. However, convergence to the equilibrium is not significant in explaining changes in prices in the short run, suggesting that short-term price changes are determined from the supply side.

The results for exogenous components provide empirical evidence of an asymmetric reaction of this market to the COVID-19 shock. While the supply adjusts, both reducing units supply and increasing prices during the pandemic period, with a more robust reaction of prices, the COVID-19 parameter on the demand side is insignificant in the quantity equation of demand, suggesting that only the price rise is due to the shock. Such a reaction is supported by the posterior evidence of prices rising in the STRMs in several cities.

The weekend effect is consistent in both equations, providing strong evidence suggesting a reduction in supply, demand, and prices during weekends. This indicates less activity in STRMs on weekends than on weekdays on average in cities. In order to find robust results for the weekend effect, the model was re-estimated three times. The results are provided in the Appendix. The first replication (Table A1 in the appendix) includes the weekend variable broken down by quarters, i.e. the original dummy is replaced by four variables capturing the weekends in quarters 1, 2, 3, and 4, both in the supply and demand equations. In all cases but one, the parameters are negative and statistically significant, supporting the previous results. In the demand equation, the only parameter not significant is quarter 3 for the demand equation. The second and third robustness tests were conducted by breaking down the period into two: 2015–2018 (April); and 2018 (May) to 2022 (February). All parameters are statistically significant at the 1 % level and negative, except for both parameters for quarter 2, in the first period, and quarter 4 for demand (all are non-statistically significant but negative). In the second period, only the parameter for the demand equation in quarter 3 is not significant (and negative).The supply equation results are presented in Table A2 (appendix), which shows similar consistent results, with all estimated parameters showing a negative sign and statistically significant, except for quarters 1, 2, and 3 in the first period for quantities. The results thus support the empirical evidence that STRM activity experiences lower levels of bookings and prices during weekends.

The result can be interpreted as the STRM being used for mixed reasons during the week when the labour market requires workers to move to the city. The negative signs suggest that the supply of units during the week dominates those during the weekend.

The whole model is consistent and largely explains the asking prices (explanatory capacity of 68.3 % for changes in asking prices from the supply side, and 71.4 % from the demand side), but a relatively smaller response of the housing quantity changes, lower in the supply eq. (3.6 % of responses) than in the demand eq. (13.1 %). The lower capacity of this model to explain the quantities supplied and absorbed suggests that supply depends mainly on determinants other than price in the medium and long term. This interpretation is consistent with the small amount of units relative to the available stock in this market, and that the units are non-uniquely supplied on one platform as hosts can offer the same property on other platforms. On the other hand, the robust explanation of prices in the model seems to be driven by the lack of supply suggested from the quantities results for the short-run market mechanism.

5.3. Spill-over effects: short-term diffusion among cities' short-term rental markets (STRMs)

The estimated components are shown in Table 7 and reflect two time patterns, with a longer impact on the demand side.

The equilibrium in the supply equation is reached in 15 days, with adjustments both in quantities and prices. The persistency in changes on units offered is statistically significant in almost all lags with negative signs, while the lagged parameter of prices shows alternate signs and less strong persistency to determine quantities, meaning that prices influence the entry of new units to the STRM, but the supply is stable.

The second endogenous equation explaining changes in rents shows a small number of quantities' lagged terms affecting the convergence to rental prices (only three lags out of 15 are statistically significant,[13] the 7th, 10th, and 13th), while almost all components of lagged rental prices are strongly significant, with almost all components being negative. This suggests that rental prices contribute to price convergence in the short run, rather than the new units entering the STRM, so the "price cycle" is recursively determined by the own evolution of prices.

The demand model shows an entirely different pattern. The main difference is the time horizon of 350 days to reach equilibrium, as identified by the minimum Akaike test. This suggests that changes in the properties booked are determined by the market almost 11 months beforehand, which is consistent with the use of the platform to plan future

[13] Only *p*-values of 5 % and 1 % were taken into account as statistically significant parameters.

Table 7
Pooled VECM models for supply and demand short-term rental markets.

Error correction terms	Supply Eq.(total listing properties)		Demand Eq. (booked properties)	
	$\Delta(\log q_{hs})$	Δ $(\log p_h)$ Asking rents	Δ $(\log q_{hs})$	Δ $(\log p_h)$ Asking rents
Lags until equilibrium	15		350	
Δ $(\log q_{hs})(-1)$	0.011***	−0.003	0.335***	0.0228***
	[2.486]	[−0.892]	[59.357]	[12.677]
Δ $(\log q_{hs})(-2)$	−0.068***	0.0009	0.036	0.006***
	[−15.27]	[0.261]	[0.545]	[2.990]
Δ $(\log q_{hs})(-3)$	−0.055***	−0.005	−0.01589***	−0.00043
	[−12.208]	[−1.310]	[−2.269]	[−0.191]
Δ $(\log q_{hs})(-4)$	−0.04983***	0.002508	−0.020867***	0.003377
	[−11.0856]	[0.70189]	[−2.68388]	[1.35764]
Δ $(\log q_{hs})(-5)$	−0.03659***	−0.007202*	−0.018189***	−0.002868
	[−8.13433]	[−2.01467]	[−2.33756]	[−1.15223]
…	…	…	…	…
Δ $(\log p_h)(-1)$	0.022***	0.325***	0.2117***	0.2216***
	[3.918]	[74.43]	[14.5115]	[47.4711]
Δ $(\log p_h)(-2)$	−0.0189***	−0.0544***	−0.0971***	0.004579
	[−3.462]	[−12.523]	[−6.40539]	[0.94414]
Δ $(\log p_h)(-3)$	0.0109**	−0.0526***	−0.02755	−0.03354***
	[2.011]	[−12.159]	[−1.81324]	[−6.90000]
Δ $(\log p_h)(-4)$	−0.001372	−0.10089***	−0.02077	−0.06566***
	[−0.25278]	[−23.3849]	[−1.36451]	[−13.4833]
Δ $(\log p_h)(-5)$	0.002322	−0.1051***	−0.02906	−0.06046***
	[0.42606]	[−24.2654]	[−1.89452]	[−12.3215]
Statistically significant short-term parameters over the total lags (15 for supply and 350 for demand) tested (in %)	73.3 %	63.3 %	14.7 %	19.5 %

Note. t-student in brackets, ***$p > 0.01$, **$p > 0.05$, *$p > 0.1$.

visits. The quantities equation presents lagged persistency, with around 14.7 % of the total lags' parameters being statistically significant and specifically concentrated in three periods: close to the booking date, from three to five and nine to 12 days in advance; between 26 and 36 days (one month) in advance; and between 240 and 280 days (seven to eight months) in advance. The periods clearly show two demand patterns: closer to the property use time; and earlier than the arranged travel plans.

Rent-price changes slightly affect the demand for rental booking, with a less intense influence (6.2 % of the 14.7 % are statistically significant rent parameters). However, the periods when rent increase is significant are matched with those with most intense reservations (the significant parameters are found on the first day, one to two days, and after each month, from 31 to 32 lags, 51 to 64 lags, 91 to 92 lags, and 185 to 186 lags, up to a limit of six months), suggesting that the price mechanism reacts when pre-bookings are accumulated (increasing demand pushes the rents up), although after each hit returning to the equilibrium according to the long-term rules. However, such an increase would increase prices temporarily, but the change would become permanent from the supply perspective due to the strong persistency in the supply equation.

The STR equation of the demand model (column 4 in Table 7) supports the former interpretation. The estimated parameters indicate that changes in rent prices in the short term are weakly influenced by the number of bookings in advance (only 9.1 % are statistically significant lagged quantity parameters out of the total of 19.5 %). In addition, prices show persistency in the very short term (first day and from two to 16 days) and along the whole period, suggesting rent changes determine actual rental prices for periods over 200, 250, and 339 days in advance (between seven and 11 months). The total rental-price equation in the demand model explains 71.4 % of actual price variations.

The results seem to explain the dynamics of prices: booking in advance occasionally increases rents, but such increases remain due to the large persistence of prices in the demand and supply equations.

6. Discussion: urban policy and planning implications of short-term rental market (STRM) spill-overs for cities

The main findings of this paper concern key issues that have several policy implications. First, the time-series data reveal the existence of a previously uncounted portion of the population that has relevance for cities. The number of visitors is large in every city and affects the use of public services. As this transient population was previously unknown, their presence may have overloaded public services, such as transport, health, and others. Services should be increased based on this information, requiring public investment to guarantee service quality. The data also show the wealth in cities created due to such population mobility. The findings demonstrate that these rental activities among the European cities studied follows a common pattern, which is possibly related to the international labour market as well as touristic movements, from the demand side, but also from cross-border business networks operating in STRM, from the supply side.

The results show a segmentation of demand between two groups: one that rents properties well in advance (7–8 months) and another that rents throughout the month prior to the rental date, with a high sensitivity to price changes. Supply does not react to this segmentation and shows a very short-term adjustment to demand pressure (15 days), suggesting that demand for the closest reservations pushes prices upward, triggering the supply response, in the short run. This reaction suggests a market mechanism affecting the short term prices rather than a market power effect exerted by the hosts. The weekend results support this inference, suggesting that the STRM covers accommodation needs for people moving to cities during the week, related to sectors other than tourism. This result provides useful information for municipalities to provide transportation measures and services to facilitate such movements. In addition, it also suggests that any regulation limiting supply will result in further upward price pressure in the short run.

The data do not include information about the origin of the visitors. However, as it can be presumed that many are foreign visitors, the fact that the STRM provides services to non-residents has important international implications as these services are not computed in the balance of payments, nor are they taxed. The fact that STR visits is a global phenomenon between cities suggests that cities should develop common policies to deal with this, which is an opportunity to co-ordinate urban planning between the most closely related cities, such as creating better infrastructure adapted to connectivity between these cities, enhancing transport and communications. Cities can learn from each other in adapting the urban environment to this phenomenon. Results cannot identify the existence of market power but they show a situation of reduced supply with high rotation.

An additional issue is in the fiscal arena. These activities, largely hidden as the agreements are made between individuals or companies (through a platform), need to be completed with transparency to identify the benefits derived from them and to estimate cities' needs.

More detailed data are needed to quantify the income generated and the associated accounting.

7. Conclusions

This paper has analysed, from the time perspective, the evolution of the STRM in 39 European cities using Airbnb data from insideairbnb.com. After cleaning the data, daily time series were created for the cities from 2015 to 2021 (February)[14] with three main variables: total listings per day; total bookings per day; and average daily asking price. The booking price was available only from 2019 and was not used in this paper. The aim was to find empirical evidence of market determinants of co-movements (booking and asking prices) among European cities and their synchronisation. The paper found evidence of long-term common components in booking properties for STR accommodation and its prices, by using the VAR framework and the GARCH and FIGARCH approach to demonstrate the existence of co-movement.

To explore how the short-term synchronicity behaves, a naïve short-term supply–demand model of STRM was also defined and estimated via a pooled VECM framework, estimating elasticities among asking prices and bookings in the city panel. First, a robust long-term relationship was found, affecting both supply and demand equations, supporting the existence of co-movements across European cities' STRMs. Both error-correction equations of quantities (supply and demand models) showed weaker power in explaining the supply units and bookings, while the rental price equations (both models) showed strong explanatory capacity. Thus, the supply of property units is more weakly explained due to the market mechanism compared to rental prices. The estimated parameters in the rental-price equations suggest that prices are strongly affected by the inertia during the year previous to the booking. In addition, the weaker influence of lagged bookings over prices indicates that exogenous factors affecting supply and demand quantities mainly determine the total supply rather than the STRM market equilibrium. Such results could be interpreted as housing supply in the STRM being determined by exogenous conditions, such as the number of units available to be rented in the city or units being simultaneously supplied on other platforms (not accounted for by the data used in this paper). If this is correct, the results reveal a significant STR activity dependence of the hosts' decision about where to advertise the unit although not a market power as such. This would also be influenced by what happens in the "formal" housing market, such as homeownership or the permanent rental market. If the housing market in the city shows affordable conditions, the share or housing stock devoted to the STRM would diminish, constraining the supply; the contrary is also true. The parameters estimated in the model implicitly show a significant dependence of this marked on each city's permanent housing market conditions, and the evidence for the rental-price persistency suggests that prices tend to be established at a new level after experiencing an increase in the demand for the closest reservations.

This phenomenon has important implications (both positive and negative) for cities' policies, requiring re-evaluating the capacity of public services to accommodate short-term visitors while ensuring services for residents. Another potential implication of the study is on the methodology to analyse STRM. If there is a co-movement in market dynamics across cities over time, the current research designs aimed at evaluating the policy impact of a regulation in a city using other cities as controls (for instance, diff-in-diff methodology) could be problematic. That is, if all cities are interrelated (short-term diffusion among cities), then non-regulated cities could be affected by treatments in other cities through induced shifts in demand (violating SUTVA property).[15] Thus, how to measure those markets would be different depending on the city and its relationships with other cities to which it is linked.

CRediT authorship contribution statement

Taltavull de La Paz, Paloma, Conceptualization, Methodology, Validation, Formal analysis, Data Curation, Writing - Original Draft, Writing - Review & Editing, Supervision.

Perez Sanchez, Raul, Resources (literature), Supervision, Data Curation, Writing - Original Draft, Writing - Review & Editing.

Juárez Tárrega, Francisco, Resources (literature), Supervision, Data Curation, Writing - Original Draft, Writing - Review & Editing.

Norman Mora, Eloisa: Resources (literature), Supervision, Writing - Review & Editing.

Su, Zhenyu, Resources (literature), Data Curation, Writing - Original Draft, Writing - Review & Editing.

Author's statement

The authors confirm that this research has not received funds from any public or private institutions and that there is no conflict or interest in none of the authors.

Declaration of competing interest

None.

Data availability

The authors do not have permission to share data.

Appendix A. Appendix A

[14] As the available data varies by city, and the common period for all of them is 2018 onwards, the panel results mainly reflect data responses in 2018–2021.

[15] We acknowledge an anonymous referee for highlighting this implication which is quite right from our perspective.

Table A1
Panel robustness test for the week-end role on daily equilibrium of short-term rental market across 39 cities. Demand equation.

	Period 2015–2022				Period 2015–2018 (April)				Period 2018 (April)–2022(Feb)			
	Baseline model with weekends		weekend AND quarterS		Baseline model with weekends		weekend AND quarter		Baseline model with weekends		weekend AND quarter	
	1		2		3		4		5		6	
Long term relationship												
$(logq_{hs})(-1)$	1		1		1		1		1		1	
$(logp_h\ (-1))$	−48.13***		−46.18***		−9.17***		−6.66***		16.77***		17.09***	
	(12.52)		(11.76)		(4.17)		(3.08)		(5.42)		(5.40)	
C [a]	291.79***		277.92***		42.38***		28.88**		−120.44***		−121.60***	
	(59.29)		(55.72)		(19.06)		(14.06)		(25.75)		(25.63)	
Error correction												
Dependent var.	$\Delta\ (logq_{hs})$	$\Delta\ (logp_h)$	$\Delta\ (logq_{hs})$	$\Delta\ (logp_h)$	$\Delta\ (logq_{hs})$	$\Delta\ (logp_h)$	$\Delta\ (logq_{hs})$	$\Delta\ (logp_h)$	$\Delta\ (logq_{hs})$	$\Delta\ (logp_h)$	$\Delta\ (logq_{hs})$	$\Delta\ (logp_h)$
Convergence (co-movement)	−1.23e−05**	2.24e−05	−1.32e−05**	2.38e−05	0.00011	0.000127	0.00016	0.00017	3.20e−05	−6.06e−05***	3.31e−05	−6.08e−05***
Short run effects (350 lags)	YES		YES		YES		YES		YES		YES	
Exogenous variables[b]:												
D_covid	0.00137	0.00146***	0.001896	0.001605***	no		no		0.000838	0.001475***	0.001621	0.001669***
Weekend	−0.00493***	−0.00313***			−0.00475***	−0.00301***			−0.0047***	−0.00315***		
Weekend*Q1			−0.01085***	−0.00604***			−0.0063***	−0.0064***			−0.01147***	−0.00592***
Weekend*Q2			−0.00489***	−0.00217***			−0.0023	−0.0007			−0.00444***	−0.00212***
Weekend*Q3			−0.0007***	−0.00246			−0.0069***	−0.0024***			−0.00044	−0.00252***
Weekend*Q4			−0.00372***	−0.00218***			−0.0038	−0.0023***			−0.00339***	−0.00242***
Adj. R-squared	0.131	0.710	0.132	0.711	0.135	0.816	0.135	0.818			0.154	0.705
Sum sq. resids	217.428	22.251	217.254	22.217	7.736	0.533	7.731	0.528			186.363	20.189
Log likelihood	65681.9	123099.5	65702.1	123138.3	10306.2	17691.1	10307.8	17720.1			51050.6	95772.3

Notes.
[a] Restricted intercept in cointegration relationship; standard deviation in brackets; ***$p > 0.01$, **$p > 0.05$, *$p > 0.1$.
[b] Standard deviations are omitted in the exogenous variable parameters for simplicity.

Table A2
Panel robustness test for the week-end role on daily equilibrium of short-term rental market across 39 cities. Supply equation.

	Period 2015–2022				Period 2015–2018 (April)				Period 2018 (April)–2022 (Feb)			
	Baseline model with weekends		weekend AND quarterS		Baseline model with weekends		weekend AND quarter		Baseline model with weekends		weekend AND quarter	
	1		2		3		4		5		6	
Long term relationship												
$(logq_{hs})$(-1)	1		1		1		1		1		1	
$(logp_h$ (-1))	4.5***		−46.18***		−9.17***		−6.66***		16.77***		17.09***	
	(0.55)		(11.76)		(4.17)		(3.08)		(5.42)		(5.4)	
C [a]	−31.21***		277.92***		42.38***		28.88**		−120.44***		−121.6***	
Error correction												
Dependent var.	Δ $(logq_{hs})$	Δ $(logp_h)$	Δ $(logq_{hs})$	Δ $(logp_h)$	Δ $(logq_{hs})$	Δ $(logp_h)$	Δ $(logq_{hs})$	Δ $(logp_h)$	Δ $(logq_{hs})$	Δ $(logp_h)$	Δ $(logq_{hs})$	Δ $(logp_h)$
Convergence (co-movement)	−4.29e−04***	−2.85e−04***	−3.32e−04***	−2.56e−04***	−1.11e−05	3.84e−05	−1.85e−05	5.97e−05	−7.59e−04***	−3.60e−04***	−7.39e−04***	−3.55e−04***
Short run effects (15 lags)	YES		YES		YES		YES		YES		YES	
Exogenous variables[b]:												
D_covid	−1.23e−03***	0.001155***	−0.0015***	0.0015***	no		no		−0.00132***	0.001093***	−0.00154***	0.001411***
Weekend	−0.00264***	−0.00852***			−0.0008	−0.0071***			−0.00322***	−0.00913***		
Weekend*Q1			−0.0022***	−0.0128***			−0.00057	−0.0107***			−0.00257***	−0.01355***
Weekend*Q2			−0.0017***	−0.0069***			0.001416	−0.00652***			−0.00261***	−0.0072***
Weekend*Q3			−0.0018***	−0.008***			−0.00095	−0.00666***			−0.00213***	−0.00863***
Weekend*Q4			−0.0049***	−0.0067***			−0.00315***	−0.00543***			−0.00548***	−0.00721***
Adj.												
R-squared	0.036	0.683	0.037	0.686	0.009	0.666	0.01	0.668	0.048	0.687	0.049	0.688
Sum sq. resids	0.027	0.021	34.273	22.016	6.204	2.016	6.196	2.005	26.158	20.006	26.137	19.927
Log likelihood	109945	121389.2	109029.1	119918.3	27523.7	27523.7	27550.2	27550.2	87865.6	93128.6	87881.3	93205.8

Note.
[a] Intercept in cointegration and VAR, Standard deviation in brackets; ***p > 0.01, **p > 0.05, *p > 0.1.
[b] Standard deviations are omitted in the exogenous variable parameters for simplicity.

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