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Long–range dependence in the returns and volatility of the Finnish Housing Market

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Abstract

Purpose – The purpose of the paper is to examine the evidence of long–range dependence behaviour in both house price returns and volatility for fifteen main regions in Finland over the period of 1988:$Q1$ to 2018:$Q4$. These regions are divided geographically into forty–five cities and sub–areas according to their postcode numbers. The studied type of dwellings is apartments (block of flats) divided into one–room, two–rooms, and more than three rooms apartments types.
Design/methodology/approach – For each house price return series, both parametric and semiparametric long memory approaches are used to estimate the fractional differencing parameter d in an Autoregressive Fractional Integrated Moving Average (ARFIMA (p,d,q)) process. Moreover, for cities and sub–areas with significant clustering effects (ARCH effects), the semiparametric long memory method is used to analyse the degree of persistence in the volatility by estimating the fractional differencing parameter d in both squared and absolute price returns.
Findings – A higher degree of predictability was found in all three apartments types price returns with the estimates of the long memory parameter constrained in the stationary and invertible interval; implying that the returns of the studied types of dwellings are long–term dependent. This high level of persistence in the house price indices differs from other assets, such as stocks and commodities. Furthermore, the evidence of long–range dependence was discovered in the house price volatility with more than half of the studied samples exhibiting long memory behaviour.
Research limitations/implications – Investigating the long memory behaviour in both returns and volatility of the house prices is crucial for investment, risk, and portfolio management. One reason is that, the evidence of long–range dependence in the housing market returns suggests a high degree of predictability of the asset. The other reason is that, the presence of long memory in the housing market volatility aids in the development of appropriate time series volatility forecasting models in this market. The study outcomes will be used in modelling and forecasting the volatility dynamics of the studied types of dwellings. The quality of the data limits the analysis and the results of the study.
Originality/value – To the best of the authors' knowledge, this is the first research that assesses the long memory behaviour in the Finnish housing market. Also, it is the first study that evaluates the volatility of the Finnish housing market using data on both municipal and geographical level.
Keywords – House prices, Returns, Volatility, Long memory, Finland
Paper type – Research paper

1 Introduction

The Finnish property investment market is booming. It amounted up to EUR 69.5 billion at the end of 2018; that is an increase of 9.1 per cent compared to the previous year (Kaleva, 2019). In terms of property sector, currently, the residential properties are the largest sector in the Finnish property investment market. They represented 29 per cent of the total property investment market in 2018. The high demand for small and well–located apartments boosts this strong residential property investment as young or working–age population are moving towards urban areas. In 2018, up to 75 per cent of the newly constructed dwellings were for studios and one–bedroom flats (Statistics Finland, 2019). Moreover, according to the freshest statistics from 2016; housing consisted 50.3 per cent of the Finnish households' total wealth (Statistics Finland, 2016). Therefore, understanding the dynamics of the Finnish house prices, especially, investigating whether the returns and volatility of those types of dwellings preferred by investors exhibit long memory behaviour is crucial; for investment, risk, and portfolio management. One reason is that, the evidence of long–range dependence in the housing market returns suggests a high degree of predictability of the asset based on historical information. The other reason is that, the presence of long memory in the housing market volatility is the key element in the development of appropriate time series volatility forecasting models in this market; which can have substantial impacts of macroeconomic activity.

Previous research has examined the evidence of long memory in either returns or volatility of different assets classes; such as stocks (Hiemstra and Jones, 1997; Ólan, 2002; Christodoulou-Volos and Siokis, 2006), commodity futures (Baillie et al., 2007), and energy futures (Cunado et al., 2010). Moreover, the presence of persistence has been analysed in real state returns and volatility (Elder and Villupuram, 2012), and in individual housing markets (Milles, 2011; Feng and Baohua, 2015). While previous studies in different countries such as the United Kingdom and the United States have tested the evidence of long memory in housing markets using data sets at the state or metropolitan level of the family–home property type; for housing investment and portfolio allocation purposes; this study uses the Finnish house price indices data on both metropolitan and geographical level of the apartments in the block of flats property type which has increased its investors' attractiveness in the Finnish residential properties sector.

The general purpose of the study is to provide to the investors, risk managers, policymakers, and consumers the information regarding diversifying a housing investment portfolio across Finland and by apartment type; as many investors are often highly concentrated in narrow geographical regions such as Helsinki. In other words, the aim is to answer the following research question: "What type of apartments, geographically located in which area of Finland, should be included in the investment portfolio to acquire the best possible risk–return relationships?" This question is answered using appropriate modelling and forecasting approaches to understand the dynamics of the market. Thus, specifically, this article analyses the long–range behaviour in both returns and volatility of the Finnish housing market by the size of the apartments; that is, single–room apartments, two–rooms apartments, and apartments with more than three rooms. The study outcomes will be used in modelling and forecasting the volatility dynamics of the studied types of dwellings. Plus precisely, in an in–sample and out–of–sample forecasting test and performance comparison of different univariate time series models. The employed methodology is as follows. For each house price return series, both parametric and semiparametric long memory approaches are used to estimate the fractional differencing parameter d in an Autoregressive Fractional Integrated Moving Average (ARFIMA (p,d,q)) process. Moreover, for cities and sub–areas with significant clustering effects (ARCH effects), the semiparametric long memory method is used to analyse the degree of persistence in the volatility by estimating the fractional differencing parameter d in both squared and absolute price returns.

The study contributes to the literature by being the first attempt to assess the long memory behaviour in the Finnish housing market. Also, it is the first study that evaluates the volatility of the Finnish housing market using both municipal and geographical data level of the investors' favoured property type. Results reveal strong supportive evidence of the long memory behaviour in both returns and volatility of the studied apartment types. The high degree of persistence found in the house price returns differs from other assets, such as stocks and commodities. For house price volatility, the strong evidence of long memory is following other assets volatility dynamics. However, the degree of long–range dependence found is much higher.

The remainder of the article is organised as follows. Section 2 reviews the relevant literature. Section 3 describes the data and the methodology to be employed. Section 4 presents and discusses the results. Section 5 concludes the article.

2 Literature review

There has been extensive research on the housing market; whether the focus is on modelling the price dynamics, capturing the price volatility, or investigating the presence of substantial persistence in returns and/or volatility. The examination of these issues is done on individual housing markets or across different housing markets. For instance, Lin and Fuerst (2014) and Hossain and Latif (2009) examined Canadian house price volatility; Lee (2009), Lee (2017), and Lee and Reed (2013) studied Australian house price volatility. Guirguis et al. (2007) have investigated house price and volatility spillovers between two cities in the Spanish housing market, Madrid and Coslada; while Coskun and Ertugrul (2016) modelled the volatility properties of the house price of Turkey, Istanbul, Ankara, and Izmir. Apart from extensive studies on the house price volatility in developed countries; the dynamic of the housing market in small countries such as the Cyprus island (Savva and Michail, 2017) and developing countries such as Malaysia (Reen and Razali, 2016) have also been studied. However, the United States (US) and the United Kingdom (UK) are the two countries that have drawn more attention in terms of residential real state studies.

Regarding modelling house price volatility; authors who have studied US house prices include Dolde and Tirtiroglu (1997) who found evidence of time–varying volatility of the house price in the towns in Connecticut and San Francisco area. Moreover, Dolde and Tirtiroglu (2002) identified volatility shifts in the house price returns for four regions, and concluded that these shifts were due to regional conditions rather than national economic conditions. Miller and Peng (2006) and Milles (2008) investigated the evidence of ARCH effects in home prices at the metropolitan statistical area (MSA) level and state level, respectively. They found proof of ARCH effects in 34 MSAs out of 277 and 28 states out of 50. Furthermore, studies such as Miao et al. (2011), Karoglou et al. (2013), Webb et al. (2016), and Zhu et al. (2013) investigated different issues associated with shocks, price jump, and risk–return relationships in the various US areas and cities throughout different sample periods. The investigations of house price volatility in the UK include the works of Milles (2010), Milles (2011b), Milles (2015), Tsai (2014), Willcocks (2010), and Morley and Thomas (2011).

Regarding investigating whether house prices exhibit long–memory behaviour; Tsai et al. (2010) studied the volatility persistence in the UK housing market by older and newer homes. The authors employed the switch ARCH model and found a high magnitude of the high volatility regime for both the older and new housing market. In the US housing market, Milles (2011) found that over half of the 62 studied MSAs exhibit long memory in the conditional volatility, especially the West Coast MSAs. Elder and Villupuram (2012) examined the evidence of long–term behaviour of house price for 14 city indices and 10–city composite indices and found a higher degree of long–range dependence in both house price returns and volatility. Barros et al. (2015) evaluated the long–range dependence of house price volatility employing both data on state and metropolitan level. They found stationary long memory behaviour in the studied sample; to encompass each state and additional metropolitan areas; their analysis and results parallels to the Elder and Villupuram (2012) findings.

The outcomes of the above studies suggest evidence of volatility clustering in housing markets and long–range dependence in a limited number of countries. For Finland, there have been no investigations of house price volatility in general and of the long–term dependence behaviour in both returns and volatility in particular. Therefore, this paper aims to extend the current literature on countries' housing market volatility analysis. Moreover, in the literature, different studies employed data on the state, national, regional, or metropolitan level. However, few studies have been undertaken on house price volatility series using cross–level data for the seek of comparative analysis. Hence, this article attempts to fill that gap by using data on both metropolitan and geographical level for housing market investment and portfolio allocation purposes. Furthermore, as pointed out by Katsiampa and Begiazi (2019), few studies have attempted to analyse house price dynamics by property type level; hence to extend the extremely limited literature, this study uses data on apartments in the block of flats property type which has increased its investors' attractiveness in the Finnish residential properties sector.

3 Data and Methodology

Data

The study employs the Statistics Finland quarterly house price indices data of fifteen main regions in Finland; throughout 1988:$Q1$ to 2018:$Q4$, for a total of 124 observations. The studied regions are ranked according to their number of inhabitants. There are four regions with more than 250,000 inhabitants: Helsinki, Tampere, Turku, and Oulu; of which the three first make up the so–called growth triangle in Southern Finland, and Oulu is the growth center of Northern Finland. Seven regions with more than 100,000 inhabitants: Lahti, Jyväskylä, Kuopio, Pori, Seinäjoki, Joensuu, and Vaasa. Four regions with a population number between 80,000 – 90,000: Lappeenranta, Kouvola, Hämeenlinna, and Kotka. These regions are then divided geographically into cities and sub–areas according to their postcodes number (see Table 8 in Appendix A); to form a total of forty–five cities and sub–areas. The considered type of dwellings is apartments (block of flats) because they are the most homogenous assets in the housing market compared to other housing types, such as detached and terraced. Additionally, in Finland, flats are favored by investors. The apartments types are divided into single–room, two–rooms, and more than three rooms apartments.

Tables 1–3 provide the summary statistics of the quarterly house price returns for single–room, two–rooms, and more than three rooms flats respectively. Note that cities and sub–areas without available data for at least 20 years (80 observations) have been removed from the analysis. Over the studied period, Pori–area1 leads the one–room apartments type group with the highest average return (1.33 percent per quarterly). Kuopio–area1

follows with 1.32 percent per quarterly average return. Vaasa–area1, Lahti–area1, and Helsinki–area1 come in third place with an average return of at least 1.2 percent per quarterly. In terms of volatility dimension, Pori–area1 also recorded the highest risk measure (standard deviation), followed by Lahti–area1. The largest cities, such as Helsinki and Tampere, as well as Helsinki–area2, appear to be less volatile as they have the lowest risk level; suggesting a less significance of the ARCH effects in these cities and area.
The Two–rooms apartments type group appears to have less quarterly average returns, in general; compare to one–room and more than three rooms flats types. Helsinki–area1 scores the highest average return (1.30 percent per quarterly), followed by Helsinki–city, Helsinki–area2, Tampere–area1, and Turku-area1 with at least 1.0 percent per quarterly average return. Kotka–area2 leads the group in terms of risk measure. Same as in one–room apartments type group, the biggest cities (Helsinki, Tampere, Turku, and Oulu) and their surrounding areas seem to be less volatile. Helsinki–area1 also comes on top with 1.29 percent per quarterly average return in the more than three rooms apartments type group, followed by Lappeenranta–area2 and Tampere–area1. Hämeenlinna–area1, Joensuu–area1, and Seinäjoki–city are the more volatile areas of the group.

The house price movement of a sample of the three most volatile cities/sub–areas in each of the apartments categories over the studied period is shown in Figure 1. Those are Pori–area1, Pori–city, Jyväskylä–area2 in one–room apartments type group; Kotka–area2, Pori–area1, Kotka–area1 in two–rooms apartments type group; and Hämeenlinna–area1, Joensuu–area1, Seinäjoki–city in more than three rooms apartments type group. Initial evidence of volatility clustering effects is observed in all sample cities and sub–areas as they exhibit high fluctuations with certain time periods of high volatility followed by low volatility for other periods. A similar pattern is observed in all the graphs from the end of the 1980s until mid–1993, the period that Finland experienced financial market deregulation which induces a structural break in house price dynamics (Oikarinen, 2009a; Oikarinen, 2009b).

Methodology

The methodology employed in this study is presented as follows: first, we filter first order autocorrelations from the returns with an ARMA model of appropriate order determined by Akaike information criteria (AIC) and Bayesian information criteria (BIC). Thereafter, we test ARCH effects on the ARMA filtered returns. Next, an analysis of long memory behaviour in both returns and volatility is undertaken. That is, for each house price return series, both parametric and semiparametric long memory approaches are used to estimate the long memory parameter d of individual ARFIMA process. Lastly, for cities and sub–areas with significant clustering effects (ARCH effects), the semiparametric long memory method is used to analyse the degree of persistence in the volatility by estimating the fractional differencing parameter d in both squared and absolute price returns. All analysis was conducted in R (R Core Team, 2019).

Cities/Sub–areas	Abbrevations	Mean	Maximum	Minimum	Sd	nobs
Helsinki–city	hki	1.12	10.5	-9.1	3.5	124
Helsinki–area1	hki1	1.25	12.9	-8.7	4.1	124
Helsinki–area2	hki2	1.15	9.6	-9.0	3.6	124
Helsinki–area3	hki3	0.96	12.6	-12.6	4.1	124
Helsinki–area4	hki4	0.78	11.1	-12.0	4.3	124
Tampere–city	tre	1.01	11.6	-10.9	3.9	123
Tampere–area1	tre1	1.12	13.7	-13.8	4.9	123
Tampere–area2	tre2	1.13	15.8	-16.1	5.9	119
Tampere–area3	tre3	0.91	17.6	-11.9	5.0	123
Turku–city	tku	0.99	15.0	-9.6	4.4	124
Turku–area1	tku1	1.10	16.7	-11.7	5.5	124
Turku–area2	tku2	1.02	25.3	-19.3	6.9	111
Turku–area3	tku3	1.01	15.4	-23.0	6.4	114
Oulu–city	oulu	0.79	12.6	-10.3	4.3	124
Oulu–area1	oulu1	0.81	16.0	-12.0	5.1	124
Oulu–area2	oulu2	0.89	16.8	-16.7	5.7	116
Lahti–city	lti	0.80	17.6	-14.4	5.4	124
Lahti–area1	lti1	1.27	44.1	-24.6	8.1	109
Lahti–area2	lti2	0.55	17.9	-19.6	6.2	124
Jyväskylä–city	jkla	0.87	14.3	-10.1	4.7	124
Jyväskylä–area1	jkla1	0.99	15.7	-13.0	5.1	124
Jyväskylä–area2	jkla2	1.13	31.1	-18.5	7.4	91
Pori–city	pori	0.96	25.5	-23.5	7.6	124
Pori–area1	pori1	1.33	32.9	-23.6	8.7	100
Kuopio–city	kuo	0.95	17.9	-11.7	4.4	123
Kuopio–area1	kuo1	1.32	18.9	-18.6	5.9	111
Kuopio–area2	kuo2	1.12	16.6	-17.0	6.7	87
Joensuu–city	jnsu	0.88	17.1	-14.6	5.0	122
Joensuu–area1	jnsu1	0.93	18.7	-14.5	5.5	117
Vaasa–city	vaasa	1.01	15.7	-14.8	6.8	121
Vaasa–area1	vaasa1	1.29	18.8	-15.9	7.6	105
Kouvola–city	kou	0.39	16.5	-15.5	6.8	118
Lappeenranta–city	lrta	0.68	13.5	-12.9	4.9	124
Lappeenranta–area1	lrta1	1.01	18.6	-18.4	6.9	97
Hämeenlinna–city	hnlina	0.86	13.8	-15.7	5.9	124
Hämeenlinna–area1	hnlina1	1.07	13.3	-17.9	6.4	103
Kotka–city	kotka	0.71	18.2	-11.8	5.7	121
Kotka–area1	kotka1	1.11	17.5	-14.3	6.9	95

Notes: This table presents summary statistics on the one–room flats price index returns. Units are quarterly returns in percentage points. The sample is 1988:$Q1$ to 2018:$Q4$.

Table 1: One–room flats quarterly house price returns – Summary statistics (%).

Cities/Sub–areas	Abbrevations	Mean	Maximum	Minimum	Sd	nobs
Helsinki–city	hki	1.02	10.9	-8.8	3.2	124
Helsinki–area1	hki1	1.30	18.9	-14.2	4.8	124
Helsinki–area2	hki2	1.07	10.6	-8.3	3.3	124
Helsinki–area3	hki3	0.89	9.5	-10.7	3.7	124
Helsinki–area4	hki4	0.72	9.6	-9.7	3.6	124
Tampere–city	tre	0.93	10.5	-8.5	3.1	124
Tampere–area1	tre1	1.07	12.7	-7.9	3.7	123
Tampere–area2	tre2	0.85	10.4	-15.5	4.4	123
Tampere–area3	tre3	0.81	11.4	-11.8	3.6	123
Turku–city	tku	0.85	11.6	-8.3	3.4	124
Turku–area1	tku1	1.02	12.6	-11.6	4.2	124
Turku–area2	tku2	0.80	10.5	-12.2	4.6	124
Turku–area3	tku3	0.77	14.5	-8.3	4.7	124
Oulu–city	oulu	0.70	9.2	-6.2	3.1	124
Oulu–area1	oulu1	0.73	11.3	-6.9	3.6	124
Oulu–area2	oulu2	0.67	11.9	-9.8	4.2	124
Lahti–city	lti	0.58	10.9	-8.4	3.5	124
Lahti–area1	lti1	0.78	13.3	-10.8	4.5	124
Lahti–area2	lti2	0.46	11.9	-7.4	3.9	124
Jyväskylä–city	jkla	0.67	9.4	-8.6	3.3	124
Jyväskylä–area1	jkla1	0.79	12.4	-9.6	3.8	124
Jyväskylä–area2	jkla2	0.55	20.5	-18.6	4.7	124
Pori–city	pori	0.85	22.5	-15.5	5.2	124
Pori–area1	pori1	0.96	24.6	-17.4	6.4	124
Pori–area2	pori2	0.84	18.5	-15.9	6.3	122
Kuopio–city	kuo	0.75	12.9	-12.3	3.5	124
Kuopio–area1	kuo1	0.96	16.7	-15.5	4.8	123
Kuopio–area2	kuo2	0.60	11.5	-9.3	3.7	124
Joensuu–city	jnsu	0.76	14.8	-11.8	4.9	124
Joensuu–area1	jnsu1	0.80	16.8	-12.8	5.7	124
Seinajöki–city	seoki	0.88	20.9	14.4	6.0	118
Vaasa–city	vaasa	0.78	10.0	-8.6	4.1	123
Vaasa–area1	vaasa1	0.88	10.2	-9.3	4.3	121
Kouvoula–city	kou	0.42	27.0	-18.0	5.6	124
Lappeenranta–city	lrta	0.60	16.1	-10.8	3.9	124
Lappeenranta–area1	lrta1	0.72	21.1	-15.8	5.4	123
Lappeenranta–area2	lrta2	0.62	20.9	-17.9	5.7	122
Hämeenlinna–city	hnlina	0.73	12.1	-14.4	4.5	124
Hämeenlinna–area1	hnlina1	0.76	14.1	-16.8	5.2	124
Kotka–city	kotka	0.71	14.1	-10.5	5.1	124
Kotka–area1	kotka1	0.90	18.2	-16.1	6.4	121
Kotka–area2	kotka2	0.84	21.4	-23.7	8.1	96

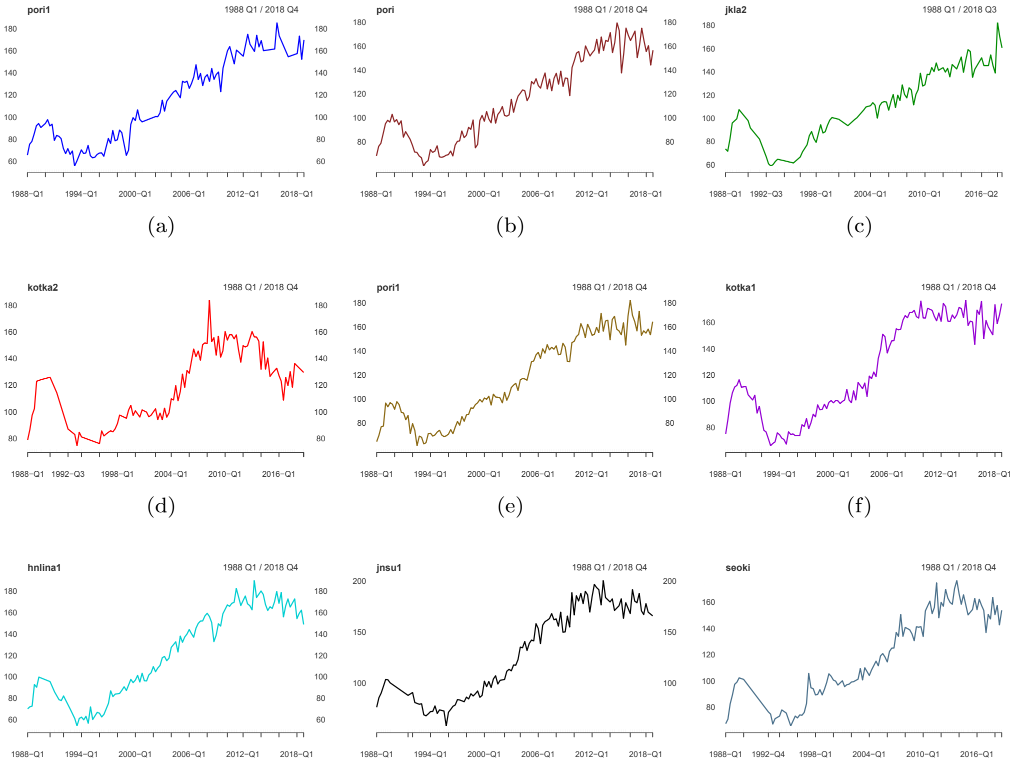
Notes: This table presents summary statistics on the two–rooms flats price index returns. Units are quarterly returns in percentage points. The sample is 1988:$Q1$ to 2018:$Q4$.

Table 2: Two–rooms flats quarterly house price returns – Summary statistics (%).

Cities/Sub–areas	Abbrevations	Mean	Maximum	Minimum	Sd	nobs
Helsinki–city	hki	1.01	12.9	-9.7	3.6	124
Helsinki–area1	hki1	1.29	15.3	-14.5	5.1	124
Helsinki–area2	hki2	1.02	13.9	-8.5	3.7	124
Helsinki–area3	hki3	0.83	12.4	-9.0	3.9	124
Helsinki–area4	hki4	0.72	12.7	-11.2	3.8	124
Tampere–city	tre	0.94	11.7	-11.7	3.7	123
Tampere–area1	tre1	1.09	15.1	-14.6	4.7	123
Tampere–area2	tre2	1.07	12.4	-14.2	5.5	116
Tampere–area3	tre3	0.73	13.3	-12.0	3.5	123
Turku–city	tku	0.85	13.4	-10.2	3.9	124
Turku–area1	tku1	1.08	16.8	-15.8	5.3	124
Turku–area2	tku2	0.84	16.6	-14.8	4.9	124
Turku–area3	tku3	0.76	12.6	-10.5	4.5	124
Oulu–city	oulu	0.77	13.1	-12.4	3.8	124
Oulu–area1	oulu1	0.81	15.2	-14.6	4.6	123
Oulu–area2	oulu2	0.80	10.6	-13.5	4.5	123
Lahti–city	lti	0.66	12.3	-11.5	4.4	124
Lahti–area1	lti1	0.84	16.9	-13.8	5.7	124
Lahti–area2	lti2	0.51	10.6	-11.0	4.5	124
Jyväskylä–city	jkla	0.72	15.1	-9.3	4.4	124
Jyväskylä–area1	jkla1	0.79	17.0	-12.1	5.1	122
Jyväskylä–area2	jkla2	0.79	19.5	-17.4	6.3	122
Pori–city	pori	0.88	16.6	-16.7	5.7	124
Pori–area1	pori1	1.02	18.2	-18.3	6.6	116
Kuopio–city	kuo	0.69	14.61	-14.5	4.4	124
Kuopio–area1	kuo1	0.99	16.5	-27.9	6.9	115
Kuopio–area2	kuo2	0.62	16.7	-18.5	4.9	122
Joensuu–city	jnsu	0.85	19.3	-18.2	6.2	124
Joensuu–area1	jnsu1	0.98	22.6	-19.8	7.2	108
Seinajöki–city	seoki	1.06	27.5	-24.2	7.2	103
Vaasa–city	vaasa	0.81	15.8	-15.4	5.1	123
Vaasa–area1	vaasa1	0.97	19.1	-13.8	5.9	116
Vaasa–area2	vaasa2	1.09	14.8	-20.4	6.9	82
Kouvoula–city	kou	0.37	15.1	-13.9	6.7	121
Lappeenranta–city	lrta	0.59	12.7	-15.7	5.5	121
Lappeenranta–area2	lrta2	1.14	23.7	-22.2	6.9	80
Hämeenlinna–city	hnlina	0.80	22.0	-15.8	6.2	122
Hämeenlinna–area1	hnlina1	0.97	27.5	-16.2	7.4	108
Kotka–city	kotka	0.69	21.6	-17.5	6.4	120

Notes: This table presents summary statistics on the more than three rooms flats price index returns. Units are quarterly returns in percentage points. The sample is 1988:$Q1$ to 2018:$Q4$.

Table 3: More than three rooms flats quarterly house price returns – Summary statistics (%).



(a) (b) (c)

(d) (e) (f)

(g) (h) (i)

Figure 1: The house price movement of the most volatile cities/sub–areas.

Testing for ARCH effects

After filtering serial correlations from the returns series; the squared residual series are used to check the autoregressive conditional heteroscedasticity, also known as ARCH effects. If the null hypothesis of constant variance is rejected, then volatility modelling is required. Two tests are available. The first test, called Portmanteau *Q(m)*, is to examine whether the squares of the residuals are a sequence of white noise. It is the usual Ljung–Box test on the squared residuals, (see Mcleod and Li, 1983). The null hypothesis of the test statistic is that "there is no autocorrelation in the squared residuals up to lag m," that is, the first m lags of the autocorrelation function (ACF) of the squared residuals are zeros. A small p–value (smaller than the considered critical value) suggests the presence of autoregressive conditional heteroscedasticity (strong ARCH effects).

The second test is the Lagrange Multiplier test of Engle (1982), also known as ARCH–LM Engle's test. This test is to fit a linear regression model for the squared residuals and examine that the fitted model is significant. It is equivalent to the usual F statistic for testing $\gamma_i = 0$ $(i = 1, ..., m)$ in the linear regression

$$\hat{e}_t^2 = \gamma_0 + \gamma_1 \hat{e}_{t-1}^2 + ... + \gamma_m \hat{e}_{t-m}^2 + v_t, \quad t = m + 1, ...N,$$

where $\hat{e}_t^2$ is the estimated residuals, v_t is the random error, m is a prespecified positive integer, and N is the sample size. The null hypothesis of the test is that "there are no ARCH effects," that is, $H_0 : \gamma_1 = ... = \gamma_m = 0$, and the alternative hypothesis is $H_1 : \gamma_i \neq 0$ (there are ARCH effects). Again, the null hypothesis is rejected if a p–value smaller than the considered critical value is obtained at the specified number of lags. The ARCH–LM tests were performed using the function ArchTest() from the *FinTs* package (Graves, 2019).

Testing for long–range dependence in returns

The methodology employed is based on the concept of long–term dependence, also called long memory or long–range persistence. This phenomenon describes time series processes whose autocorrelation function (ACF) decays slowly to 0 at a polynomial rate as the number of lag increases. One of the best–known classes of these processes, referred to as *the long–memory time series*, is the Autoregressive Fractionally Integrated Moving Average process of order (p,d,q), denoted by ARFIMA (p,d,q); proposed independently by Granger and Joyeux (1980) and Hosking (1981).
An ARFIMA (p,d,q) can be represented as

$$\Phi(B)(1-B)^d X_t = \Theta(B)u_t, \ t = 1, 2, ..., \tag{1}$$

where u_t is a white noise with $\mathbb{E}(u_t) = 0$, and variance σ_u^2. B is the lag operator or back–shift operator such that $BX_t = X_{t-1}$. $\Phi(B)$ and $\Theta(B)$ denotes finite polynomials of order p and q respectively with unit roots outside the unit circle. That is, $\Phi(B) = 1 - \phi_1 B - .... - \phi_p B^p$ and $\Theta(B) = 1 - \theta_1 B - ... - \theta_q B^q$. The studied discrete valued time series is denoted as X_t.

The estimation procedures of the fractional differencing parameter d can be classified into two groups: parametric and semiparametric approaches. In the former group where all the parameters (autoregressive, differencing, and moving average) are estimated simultaneously; the exact maximum likelihood estimation is used. The most commonly used methods within this group are those proposed by Fox and Taqqu (1986) and Sowell (1992). In the latter group, the most widely used estimator is the one developed by Geweke and Porter-Hudak (1983), usually referred to as the GPH estimator. Two steps are followed in the semiparametric estimation: first, the fractional parameter d is estimated alone, and other parameters are estimated in the second step.
The parametric approach involves the challenge of choosing the appropriate ARMA specification as it requires an explicit identification and estimation of the p and q values, parameters of $\Phi(B)$ and $\Theta(B)$ respectively. In the semiparametric method, however, the estimation of the long memory parameter d may be done without a full specification of the data generating process. Hence, in the long–range dependence analysis, different researchers have considered different semiparametric estimators (Elder and Villupuram, 2012; Christodoulou-Volos and Siokis, 2006) or a combination of both approaches (Barros et al., 2015). Additionally, parametric procedures have been found to require heavy computations, while semiparametric methods are easy to implement (Reisen et al., 2001). Reisen et al. (2001) conducted a simulation study on the estimation of parameters in ARFIMA processes; where they compared the performance of estimating all the ARFIMA parameters based on Hosking's algorithm (Hosking, 1981) and the parametric Whittle estimator proposed by Fox and Taqqu (1986). The semiparametric estimators used in the study are the Geweke and Porter-Hudak (1983) estimator, Smoothed Periodogram estimator by Reisen (1994), Robinson (Robinson, 1995a) estimator, and Robinson's estimator based on the smoothed periodogram. The results of the study indicated that regression methods (semiparametric) performed better than parametric Whittle's approach. In the light of the above research, this article employs both parametric and semiparametric

estimators to analyse the presence of long memory in the house price returns. The semiparametric estimator used is the GPH estimator, while the parametric one is the Whittle estimator. The GPH estimator, also known as the Periodogram estimator, is based on the regression equation using the periodogram function as an estimate of the spectral density. The Whittle estimator is due to Whittle (1953) with modifications suggested by Fox and Taqqu (1986). This estimator is also based on the periodogram, and it involves the spectral density function. The Whittle estimator is the value which minimises the spectral density function. For more details, (see Fox and Taqqu, 1986; Beran, 1994; Dahlhaus, 1989).

The outcome of the estimation is assessed as follows: if $d = 0$ in Equation 1, the process exhibits short memory; corresponding to stationary and invertible ARMA modelling. The process is described as "anti–persistence" if $d \in (-0.5, 0)$. If $d \in (0, 0.5)$, the process is said to manifest long–range positive dependence or long memory as the decay of the autocorrelation is hyperbolically slow. If $d \in [0.5, 1)$, the process is mean reverting, even though it is no longer covariance stationary. That is, shocks will disappear in the long run. Finally, if $d \geq 1$, the process is nonstationary without mean reversion. The estimations of the GPH estimators were performed using the function fdGPH() in the *fracdiff* package (Fraley et al., 2015), while the Whittle estimators were estimated using the function arfima.whittle() in the *afmtools* package (Contreras-Reyes and Palma, 2013).

Testing for long–range dependence in volatility

The presence of high persistence or long memory in the volatility of those cities and sub–areas with significant ARCH effects is analysed using the semiparametric approach to estimate the long memory parameter d in the squared and absolute price returns. For volatility series, the autocorrelation of the squared and absolute returns exhibit similar decay at high lags (Harvey, 1998); which justifies the use of the long memory parameter of any of these metrics. For our purposes, we use both squared and absolute returns for the seek of comparison of the estimated parameters; even though Wright (2002) claimed the strong Monte–Carlo evidence support of using absolute returns, as squared returns can cause a severe negative bias.

Previous studies have examined the persistence nature of the house price volatility employing different Generalized Autoregressive Conditional Heteroscedasticity (GARCH)–type models (Milles, 2011). Within the GARCH–family models, the most used ones which account for long memory in the conditional variance of the assets are Integrated GARCH (IGARCH) model of Engle and Bollerslev (1986), Component GARCH (CGARCH) model of Lee and Engle (1999), and Fractionally Integrated GARCH (FIGARCH) model of Baillie et al. (1996). FIGARCH and CGARCH have been applied more often of late than the IGARCH mainly because; in the IGARCH model, shocks persist forever, meaning that the model implies infinite persistence on the conditional variance; and hence, it is too restrictive (Tayefi and Ramanathan, 2012). The use of the above long memory GARCH–types models, however, to measure the degree of house price volatility persistence can be challenging to interpret as these models require to obtain convergent parameter estimates in the conditional variance equation. Moreover, the results obtained from these GARCH–types models are not directly comparable to the ones from the parametric or semiparametric estimators. Therefore, as we aim to estimate the degree of long–range dependence in the house price volatility; rather than modelling the process governing the studied types of dwellings volatility dynamics, this article employs the semiparametric method to examine the evidence of long memory in the volatility of the studied types of dwellings. The semiparametric estimator used is the GPH estimator described above. Again, the estimations of the GPH estimators were performed using the function fdGPH()

in the *fracdiff* package (Fraley et al., 2015).

4 Results and discussions

Testing for ARCH effects

Table 4 displays the p–values and their lag orders (in parentheses) of the two tests employed to investigate whether there is volatility clustering in each house price return series. Those tests are the Ljung–Box (LB) test and the Engle's Lagrange Multiplier (LM) test. The null hypothesizes of no serial correlation in squared residuals of the LB test and no ARCH effects of the LM test are rejected; in twenty–eight out of thirty–eight studied cities and sub–areas in the one–room flats category; in twenty–nine out forty–two in the two–rooms flats category; and in thirty–three out of forty in the more than three rooms flats category. Thus, strong evidence of volatility clustering (ARCH) effects is evident in over half of the cities and sub–areas in all three apartments types.
In some cases, one of the tests is inconclusive; for instance, in the case of Tampere–area1 (in the one–room flats category) and Turku–area2 (in the two–rooms flats category), the Portmanteau test is inconclusive (we fail to reject the null hypothesis because of the higher p–values); however, the Lagrange Multiplier values are statistically significant. Similarly, in the case of Lahti–area1 (in the more than three rooms flats category), this time, however, it is the Lagrange Multiplier test which is inconclusive. In these cases, the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots of the squared residuals (Figure 2) are used to show that there might be some autocorrelations left even though the significance might be small.

Testing for long–range dependence in returns

Table 5 gives the GPH estimates of the fractional differencing parameter d in the house price returns with their standard errors (in parentheses). Results reveal strong evidence of long–range dependence in most return series in all three apartment type categories. In approximately 68% (twenty–six out of thirty–eight) of the return series, in the one–room flats group; there is long–range positive dependence with values of d in the stationary and invertible interval (d is varying from 0.045 to 0.445). An anti–persistence behaviour is present in nine returns series; which implies a relatively quick dissipate of shocks in the house price returns. Three house price returns series (marked in bold) are mean reverting; however, they may no longer be covariance stationary as the estimates of the long memory parameter are greater than 0.5. Those return series are Turku–area3 ($d = 0.665$), Kuopio–area1 ($d = 0.529$), and Kotka–area1 ($d = 0.510$). In these three sub–areas, shocks will wear off in the long run. Approximately 83% (thirty–five out of forty–two) and 77.5% (thirty–one out of forty) of the return series exhibit stationary long memory behaviour in the two–rooms and the more than three rooms flats category, respectively. Further, in the two respective groups, seven out of forty–two cities/sub–areas and nine out of forty cities/sub–areas display long–range negative dependence or anti–persistence behaviour; which implies unpredictability of future returns based on historical returns.

Table 6 presents the Whittle estimates of the long memory parameter d with their p–values (in parentheses). The evidence of long–range dependence ($d \in (0, 0.5)$) is observed for most of the cities and sub–areas. Plus precisely, 80% (thirty out of thirty–eight), 83% (thirty–five out of forty–two), and 77.5% (thirty–one out of forty) return series exhibit long memory behaviour in the one–room, the two–rooms, and the more than three rooms flats

Regions	Cities/sub–areas	One room flats		Two rooms flats		Three rooms flats	
		LB p–values	LM p–values	LB p–values	LM p–values	LB p–values	LM p–values
Helsinki	hki	0.01724**(1)	0.01873**(1)	0.00037***(1)	0.00046***(1)	0.01916**(6)	0.01009**(6)
	hki1	0.04039**(1)	0.04302**(1)	0.02057**(4)	0.05578*(4)	0.00343***(2)	0.00367***(2)
	hki2	0.01778**(2)	0.01814**(2)	0.00361***(1)	0.00414***(1)	0.732	0.7356
	hki3	0.4441	0.5261	0.04761**(6)	0.03667**(12)	0.00744***(16)	0.03479**(16)
	hki4	0.01691**(2)	0.01927**(2)	0.08855*(3)	0.08347*(3)	0.03538**(1)	0.03665**(1)
Tampere	tre	0.4679	0.8395	0.7761	0.7786	0.07745*(1)	0.08072*(1)
	tre1	0.4878	0.0309**(11)	0.04128**(15)	0.07986*(15)	0.01222**(1)	0.0127**(1)
	tre2	0.992	0.7463	0.00801***(6)	0.00853***(10)	0.02761**(7)	0.05303*(7)
	tre3	0.09774*(1)	0.04147**(3)	0.2478	0.2204	0.0353**(11)	0.01721**(11)
Turku	tku	0.00579**(10)	0.00826**(10)	0.06687*(3)	0.08406*(3)	0.04951**(1)	0.04706**(1)
	tku1	0.06488*(5)	0.02419**(5)	0.5635	0.5692	0.07016*(1)	0.06882*(1)
	tku2	0.07601*(1)	0.08109*(1)	0.1173	0.0827*(16)	0.05191*(1)	0.05502*(1)
	tku3	0.08333*(15)	0.0791*(15)	0.09212*(2)	0.103	0.00029***(1)	0.00035***(1)
Oulu	oulu	0.00641**(1)	0.00589**(1)	0.3195	0.3242	0.00691***(4)	0.00947***(4)
	oulu1	0.08368*(1)	0.08781*(1)	0.5811	0.5853	0.06343*(9)	0.07595*(11)
	oulu2	0.03907**(1)	0.03648**(1)	0.08702*(11)	0.7267	0.25	0.2545
Lahti	lti	0.00397**(1)	0.00437**(1)	0.05585*(2)	0.08992*(13)	0.003756***(1)	0.003697***(1)
	lti1	0.00154**(1)	0.00185**(1)	0.4088	0.412	0.03861**(16)	0.3479
	lti2	0.9878	0.588	0.9908	0.9995	0.9251	0.9793
Jyväskylä	jkla	0.02683**(2)	0.00648**(2)	0.01422**(1)	0.00958***(1)	0.07133*(1)	0.07546*(1)
	jkla1	0.01705**(2)	0.00302**(2)	0.02106**(1)	0.02135**(1)	0.04016**(18)	0.08492*(18)
	jkla2	0.5235	0.03161**(9)	$5.42*10^{-7}$***(1)	$6.57*10^{-7}$***(1)	0.00879***(1)	0.00968***(1)
Pori	pori	0.01178**(2)	0.01481**(2)	0.00783***(14)	0.00057***(11)	0.8245	0.8272
	pori1	0.01847**(2)	0.02341**(2)	0.03601**(14)	0.02325**(7)	0.0135**(1)	0.01498**(1)
	pori2	–	–	0.03395**(1)	0.03511**(1)	–	–
Kuopio	kuo	0.02197**(2)	0.02043**(2)	0.02826**(3)	0.01974**(3)	$9.37*10^{-5}$***(3)	$8.99*10^{-5}$***(3)
	kuo1	0.0332**(2)	0.0343**(2)	0.00983***(3)	0.00361***(3)	0.00570***(1)	0.00651***(1)
	kuo2	0.01171**(1)	0.01355**(1)	0.7606	0.7552	0.05511*(3)	0.06738*(3)
Joensuu	jnsu	0.9552	0.8945	0.4816	0.4866	0.3902	0.3952
	jnsu1	0.02472**(1)	0.0229**(1)	0.06071*(15)	0.1541	0.09813*(17)	0.1872
Seinäjoki	seoki	–	–	0.02307**(2)	0.02324**(2)	0.07986*(14)	0.2042
Vaasa	vaasa	0.7668	0.7694	0.06089*(1)	0.06419*(1)	0.09783*(1)	0.1031
	vaasa1	0.8042	0.8075	0.2579	0.264	0.0145**(1)	0.01613**(1)
	vaasa2	–	–	–	–	0.00897***(2)	0.01832**(2)
Kouvola	kou	0.8457	0.8458	0.00059***(1)	0.00065***(1)	0.9867	0.9868
Lappeenranta	lrta	0.01867**(1)	0.02028**(1)	0.00166***(1)	0.00196***(1)	0.06448*(2)	0.06807*(2)
	lrta1	0.02763**(1)	0.03062**(1)	0.00393***(1)	0.00452***(1)	–	–
	lrta2	–	–	0.9146	0.916	0.00360***(1)	0.00450***(1)
Hämeenlinna	hnlina	0.00286**(1)	0.00331**(1)	0.08782*(6)	0.08461*(6)	0.8803	0.8821
	hnlina1	0.9694	0.9699	0.03765**(6)	0.03006**(6)	0.02362**(7)	0.01233**(4)
Kotka	kotka	0.117	0.08195*(3)	0.1482	0.109	0.0379**(3)	0.02734**(3)
	kotka1	0.8425	0.8342	0.4851	0.04158**(7)	0.04078**(1)	0.04221**(1)
	kotka2	–	–	0.1751	0.1834	–	–

Notes: This table reports the p–values from the Portmanteau (Ljung–Box) and Lagrange Multiplier tests. The values in parentheses are the lag orders of each test. *, **, and *** indicate respectively 10%, 5%, and 1% levels of significance.

Table 4: ARCH effects tests results.

group respectively. Considering the semiparametric approach (GPH estimator), an observation of the results reveals a geographical pattern regarding which cities and sub–areas exhibit long–term dependence in the returns series; densely populated regions Helsinki, Tampere, Turku, and Oulu display long memory behaviour in all three studied types of apartments. Except for Turku–area1, Oulu–city, and Oulu–area2 in the one–room flats category where the anti–persistence behaviour is observed and Turku–area3 with the long memory parameter greater than 0.5.

Similar results of high degrees of persistence in the house price returns were found in the United States house prices indices by Elder and Villupuram (2012) on the metropolitan level. Their estimates of the fractional differencing parameter d were restricted between 0 and 0.5, and even higher than 0.5 in some cities. Moreover, a similar conclusion to Elder and Villupuram's can be drawn in case of the Finnish housing market. That is, this high level of persistence in the house price indices differs from other assets, such as stocks, energy futures, and metal futures. Energy and metal futures assets classes generally display anti–persistence and modest long memory behaviour as documented by

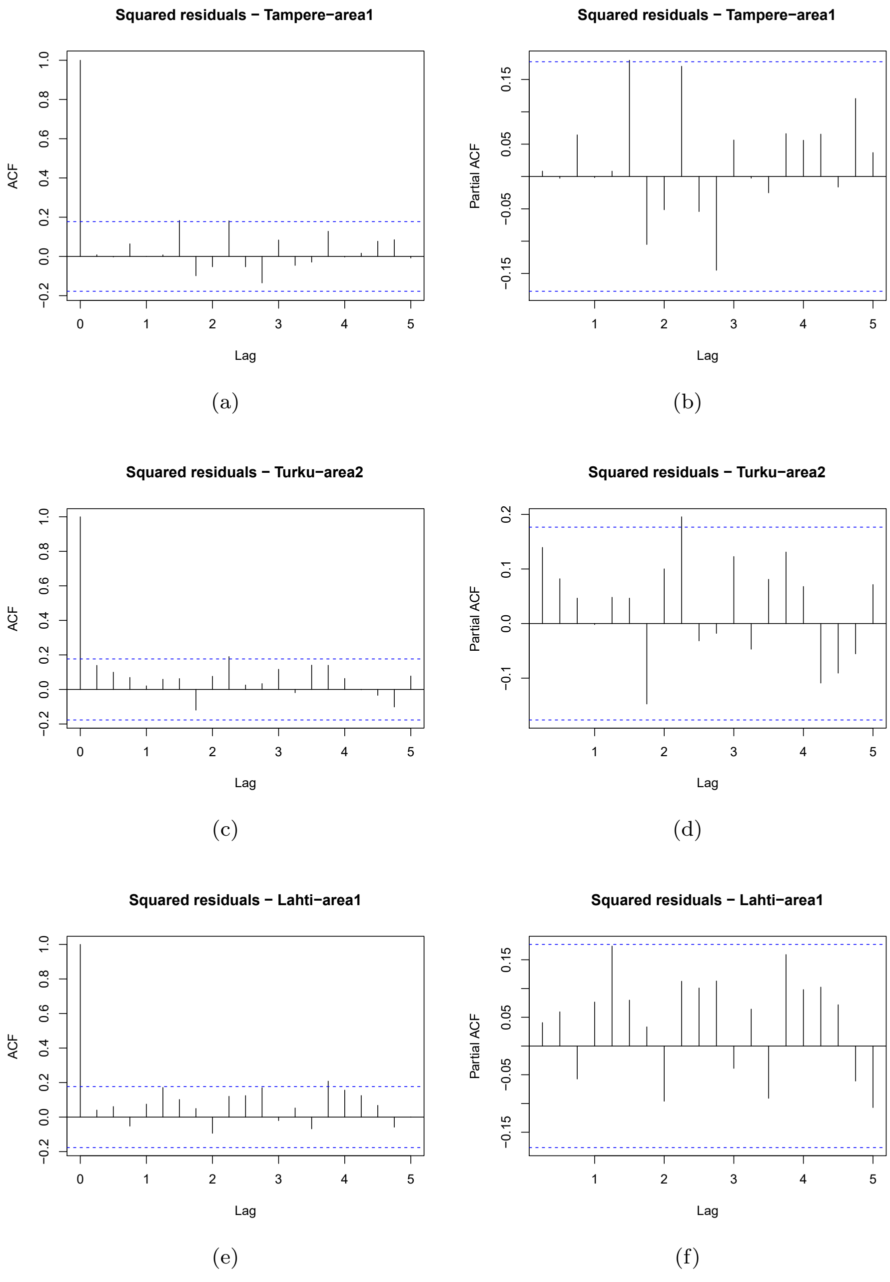


Figure 2: ACF and PACF of the squared residuals.

Barkoulas et al. (1999), Crato and Ray (2000), and Elder and Jin (2009). Also, stocks assets have been found to have the fractional differencing parameter d in the interval of -0.2 to 0.2, see Barkoulas and Baum (1996), Lo (1991), and Hiemstra and Jones (1997). Therefore, as stressed by Elder and Villupuram (2012), the long memory in real estates index returns is notable, and it is a relevant feature for issues such as constructing hedge ratios for risk management. It is worth mentioning again the challenge of specifying the appropriate ARMA *(p,q)* order in the parametric approach as different lag orders lead to varying estimations of the long memory parameter.

Testing for long–range dependence in volatility

Table 7 displays the estimates of the fractional differencing parameter in both squared and absolute returns of house prices in all three apartment types with their standard errors (in parentheses). As with house price returns, results indicate very persistent long memory for house price volatility. In the one–room flats group, the d estimates in squared and absolute returns place respectively, nineteen and eighteen out of twenty–eight cities/sub–areas into the stationary and invertible interval ($d \in (0, 0.5)$); which implies stationary long memory behaviour. An anti–persistence behaviour is present in four (for d in squared returns) and five (for d in absolute returns) cities/sub–areas; which implies a relatively quick disappearance of shocks in house price volatility. Both squared and absolute returns estimate equally place five cities/sub–areas into the interval of d between 0.5 and 1; where shocks in the house price volatility will disappear in the long run.

In the two–rooms flats category, for d estimates in both squared and absolute returns, twenty–five out of twenty–nine cities/sub–areas have long–range positive dependence with values of d in the stationary and invertible interval. Two and three cities/sub–areas, for d estimates in squared and absolute returns respectively, display long–range negative dependence. Further, in the two respective estimates, the house price volatility of two and one cities/sub–areas are mean–reverting but no longer covariance stationary. There is an exception in the more than three rooms flats group, the d estimate in two sub–areas (marked in bold) is higher than one; implying that the house price volatility process in these two sub–areas is nonstationary without mean reversion. Those sub–areas are Vaasa–area2 and Kotka–area1. Otherwise, up to twenty–four cities/sub–areas in this category exhibit stationary long memory behaviour; two cities/sub–areas are anti-persistent; and up two seven cities/sub–areas are mean–reverting. Regarding overall comparison, an inspection of the results of both squared and absolute returns fails to reveal any regional pattern as regards to the degree of persistence in volatility. However, there is some evidence to suggest that regions such as Helsinki–city, Jyväskylä–city, Kuopio–area1, and Hämeenlinna–area1 come on top in terms of house prices volatility persistence in at least two out three types of apartments. Moreover, the estimated d parameters for squared and absolute returns are quite close in most of the cases. However, there are cases where the two estimated parameters place the corresponding city or sub–area into two different intervals. For instance, Turku–area2 (in the one–room flats), d estimate for absolute returns puts it into the stationary and invertible range while the one for squared returns puts it into the mean–reverting, no longer covariance stationary interval. Therefore, as the estimated parameters will be considered in modelling and forecasting house price volatility of the studied types of apartments; both estimates will be used in the recognised model and assessing the best one will be based on the information criteria or other tools for models specification.

In summary, in twenty–eight, twenty–nine, and thirty–three cities/sub–areas which exhibited significant ARCH effects in the one–room, two–rooms, and more than three rooms flats group respectively; over half exhibit long memory in the house price volatility. Moreover, contrasting with other asset classes; such as stocks, for example, Cotter and Stevenson (2008) reported an estimate of the parameter d equalling 0.42 for volatility persistence of the S&P 500 index. Therefore, the higher estimates of long–run dependence found in our study suggest that persistence in house price volatility is much stronger than for stock prices.

Regions	Cities/Sub–areas	d estimates (GPH)		
		One room flats	Two rooms flats	Three rooms flats
Helsinki	hki	0.140 (0.274)	0.155 (0.274)	0.121 (0.274)
	hki1	0.123 (0.273)	0.150 (0.274)	0.107 (0.274)
	hki2	0.140 (0.273)	0.178 (0.274)	0.117 (0.274)
	hki3	0.120 (0.273)	0.094 (0.274)	0.147 (0.274)
	hki4	0.232 (0.274)	0.166 (0.274)	0.146 (0.274)
Tampere	tre	0.169 (0.273)	0.245 (0.274)	0.245 (0.274)
	tre1	0.164 (0.273)	0.160 (0.274)	0.091 (0.274)
	tre2	0.271 (0.293)	0.252 (0.274)	0.221 (0.293)
	tre3	0.066 (0.274)	0.273 (0.274)	0.426 (0.274)
Turku	tku	0.071 (0.274)	0.118 (0.274)	0.209 (0.274)
	tku1	-0.008 (0.274)	0.035 (0.274)	0.190 (0.274)
	tku2	0.264 (0.293)	0.168 (0.274)	0.265 (0.274)
	tku3	**0.665** (0.293)	0.110 (0.274)	0.142 (0.274)
Oulu	oulu	-0.017 (0.274)	0.282 (0.274)	0.313 (0.274)
	oulu1	0.058 (0.274)	0.378 (0.274)	0.264 (0.274)
	oulu2	-0.605 (0.293)	0.081 (0.274)	0.187 (0.274)
Lahti	lti	0.436 (0.274)	0.233 (0.274)	0.321 (0.274)
	lti1	0.445 (0.293)	0.147 (0.274)	0.267 (0.274)
	lti2	0.208 (0.274)	0.331 (0.274)	0.347 (0.274)
Jyväskylä	jkla	0.045 (0.274)	0.095 (0.274)	0.341 (0.274)
	jkla1	-0.005 (0.274)	0.102 (0.274)	0.499 (0.274)
	jkla2	-0.509 (0.317)	0.087 (0.274)	0.390 (0.274)
Pori	pori	-0.124 (0.274)	-0.063 (0.274)	0.098 (0.274)
	pori1	0.059 (0.317)	-0.280 (0.274)	-0.272 (0.293)
	pori2	–	-0.074 (0.274)	–
Kuopio	kuo	-0.107 (0.274)	0.037 (0.274)	0.190 (0.274)
	kuo1	**0.529** (0.293)	-0.166 (0.274)	-0.198 (0.293)
	kuo2	-0.154 (0.318)	0.176 (0.274)	0.215 (0.274)
Joensuu	jnsu	0.056 (0.274)	0.291 (0.274)	0.230 (0.274)
	jnsu1	0.311 (0.293)	0.287 (0.274)	-0.065 (0.293)
Seinäjoki	seoki	–	-0.358 (0.293)	-0.551 (0.293)
Vaasa	vaasa	0.101 (0.293)	0.188 (0.274)	0.077 (0.274)
	vaasa1	-0.327 (0.293)	0.174 (0.293)	-0.160 (0.293)
	vaasa2	–	–	-0.296 (0.318)
Kouvola	kou	0.053 (0.293)	0.401 (0.274)	0.370 (0.293)
Lappeenranta	lrta	0.174 (0.274)	0.186 (0.274)	0.089 (0.293)
	lrta1	0.424 (0.317)	0.247 (0.274)	–
	lrta2	–	-0.027 (0.274)	-0.686 (0.347)
Hämeenlinna	hnlina	0.281 (0.274)	0.425 (0.274)	0.197 (0.274)
	hnlina1	0.068 (0.293)	0.401 (0.274)	-0.171 (0.293)
Kotka	kotka	0.248 (0.293)	0.116 (0.274)	0.0813 (0.293)
	kotka1	**0.510** (0.317)	0.216 (0.293)	-0.307 (0.347)
	kotka2	–	-0.329 (0.317)	–

Notes: This table reports the GPH estimates of the long memory parameter d in the house price returns. The values in parentheses are their standard errors. If $d \in (-0.5, 0)$, the series is described as "anti–persistence". If $d \in (0, 0.5)$, the process manifests the long–range dependence. If $d \in [0.5, 1)$, the process is mean reverting, even though it is no longer covariance stationary.

Table 5: Estimates of fractional differencing parameter (GPH).

Regions	Cities/Sub–areas	d estimates (Whittle)		
		One room flats	Two rooms flats	Three rooms flats
	hki	0.194 (0.188)	-0.281 (0.057)	0.256 (0.084)
	hki1	0.037 (0.801)	0.179 (0.224)	0.362 (0.014)
Helsinki	hki2	0.315 (0.032)	0.296 (0.045)	0.198 (0.180)
	hki3	0.265 (0.072)	0.499 (0.000)	0.377 (0.011)
	hki4	0.468 (0.001)	-0.166 (0.260)	0.499 (0.001)
	tre	-0.345 (0.020)	-0.195 (0.187)	0.426 (0.004)
Tampere	tre1	0.033 (0.820)	0.382 (0.010)	0.251 (0.091)
	tre2	0.247 (0.101)	0.044 (0.762)	0.305 (0.046)
	tre3	-0.377 (0.011)	0.195 (0.189)	-0.344 (0.021)
	tku	-0.523 (0.000)	0.307 (0.037)	0.499 (0.001)
Turku	tku1	0.185 (0.210)	0.327 (0.027)	0.151 (0.305)
	tku2	0.055 (0.721)	0.078 (0.594)	-0.369 (0.013)
	tku3	0.178 (0.247)	0.499 (0.000)	0.090 (0.543)
	oulu	0.235 (0.112)	0.309 (0.036)	0.406 (0.006)
Oulu	oulu1	0.034 (0.816)	0.324 (0.028)	-0.333 (0.024)
	oulu2	0.102 (0.502)	-0.016 (0.909)	0.036 (0.810)
	lti	0.116 (0.432)	0.499 (0.000)	0.091 (0.539)
Lahti	lti1	0.014 (0.929)	0.405 (0.006)	0.149 (0.312)
	lti2	0.092 (0.534)	0.183 (0.217)	0.404 (0.006)
	jkla	0.091 (0.535)	0.209 (0.158)	0.136 (0.356)
Jyväskylä	jkla1	0.025 (0.865)	0.248 (0.093)	0.277 (0.063)
	jkla2	-0.108 (0.533)	-0.207 (0.161)	0.147 (0.323)
	pori	-0.045 (0.758)	0.312 (0.035)	-0.002 (0.984)
Pori	pori1	0.064 (0.695)	0.245 (0.097)	-0.054 (0.722)
	pori2	–	0.187 (0.208)	–
	kuo	0.111 (0.455)	0.437 (0.003)	0.041 (0.777)
Kuopio	kuo1	0.241 (0.122)	0.043 (0.769)	0.005 (0.974)
	kuo2	-0.040 (0.819)	0.147 (0.319)	0.299 (0.045)
Joensuu	jnsu	0.169 (0.257)	0.281 (0.057)	0.026 (0.857)
	jnsu1	0.209 (0.170)	0.311 (0.035)	0.001 (0.990)
Seinäjoki	seoki	–	0.029 (0.846)	-0.583 (0.000)
	vaasa	-0.008 (0.952)	-0.132 (0.373)	0.255 (0.085)
Vaasa	vaasa1	-0.306 (0.056)	0.115 (0.441)	-0.021 (0.886)
	vaasa2	–	–	-0.127 (0.484)
Kouvola	kou	0.189 (0.212)	0.074 (0.614)	0.244 (0.102)
	lrta	0.073 (0.620)	0.093 (0.527)	0.201 (0.181)
Lappeenranta	lrta1	0.017 (0.914)	0.065 (0.659)	–
	lrta2	–	0.125 (0.401)	-0.153 (0.409)
Hämeenlinna	hnlina	0.293 (0.047)	-0.387 (0.008)	0.241 (0.106)
	hnlina1	0.294 (0.069)	0.354 (0.016)	0.021 (0.891)
	kotka	0.279 (0.063)	0.355 (0.016)	0.300 (0.046)
Kotka	kotka1	0.259 (0.125)	0.015 (0.918)	0.171 (0.365)
	kotka2	–	0.032 (0.848)	–

Notes: This table reports the Whittle estimates of the long memory parameter d in the house price returns. The values in parentheses are their standard errors. If $d \in (-0.5, 0)$, the series is described as "anti–persistence". If $d \in (0, 0.5)$, the process manifests the long–range dependence. If $d \in [0.5, 1)$, the process is mean reverting, even though it is no longer covariance stationary.

Table 6: Estimates of fractional differencing parameter (Whittle).

Regions	Cities/sub–areas	One room flats		Two rooms flats		Three rooms flats	
		d – Squared returns	d – Absolute returns	d – Squared returns	d – Absolute returns	d – Squared returns	d – Absolute returns
Helsinki	hki	0.696 (0.274)	0.536 (0.274)	0.327 (0.274)	0.381 (0.274)	0.334 (0.274)	0.410 (0.274)
	hki1	0.381 (0.274)	0.439 (0.274)	0.278 (0.274)	0.229 (0.274)	0.685 (0.274)	0.654 (0.274)
	hki2	0.493 (0.274)	0.535 (0.274)	0.652 (0.274)	0.646 (0.274)	–	–
	hki3	–	–	0.113 (0.274)	0.017 (0.274)	0.396 (0.274)	0.565 (0.274)
	hki4	0.742 (0.274)	0.631 (0.274)	-0.056 (0.274)	-0.0411 (0.274)	0.024 (0.274)	0.029 (0.274)
Tampere	tre	–	–	–	–	0.501 (0.274)	0.353 (0.274)
	tre1	0.378 (0.274)	0.182 (0.274)	0.178 (0.274)	0.306 (0.274)	0.236 (0.274)	0.296 (0.274)
	tre2	–	–	0.374 (0.274)	0.225 (0.274)	0.166 (0.293)	0.241 (0.293)
	tre3	0.152 (0.274)	0.247 (0.274)	–	–	0.157 (0.274)	0.257 (0.274)
Turku	tku	0.106 (0.274)	-0.044 (0.274)	0.168 (0.274)	0.262 (0.274)	0.345 (0.274)	0.331 (0.274)
	tku1	0.083 (0.274)	-0.116 (0.274)	–	–	0.366 (0.274)	0.405 (0.274)
	tku2	0.721 (0.293)	0.347 (0.293)	0.137 (0.274)	0.085 (0.274)	0.511 (0.274)	0.393 (0.274)
	tku3	0.217 (0.293)	0.184 (0.293)	0.156 (0.274)	0.20 (0.274)	0.571 (0.274)	0.541 (0.274)
Oulu	oulu	-0.146 (0.274)	-0.193 (0.274)	–	–	0.480 (0.274)	0.365 (0.274)
	oulu1	0.017 (0.274)	0.019 (0.274)	–	–	0.635 (0.274)	0.423 (0.274)
	oulu2	0.006 (0.293)	0.449 (0.293)	0.013 (0.274)	0.125 (0.274)	–	–
Lahti	lti	0.025 (0.274)	0.087 (0.274)	0.125 (0.274)	0.163 (0.274)	0.036 (0.274)	-0.048 (0.274)
	lti1	0.354 (0.293)	0.853 (0.293)	–	–	0.123 (0.274)	0.005 (0.274)
Jyväskylä	jkla	0.151 (0.274)	0.257 (0.274)	0.320 (0.274)	0.343 (0.274)	0.305 (0.274)	0.414 (0.274)
	jkla1	-0.072 (0.274)	-0.049 (0.274)	0.559 (0.274)	0.409 (0.274)	0.312 (0.274)	0.396 (0.274)
	jkla2	0.304 (0.317)	0.391 (0.317)	0.073 (0.274)	0.240 (0.274)	-0.261 (0.274)	0.253 (0.274)
Pori	pori	-0.142 (0.274)	-0.218 (0.274)	0.078 (0.274)	0.188 (0.274)	–	–
	pori1	0.135 (0.317)	0.184 (0.317)	0.0009 (0.274)	-0.021 (0.274)	0.362 (0.293)	0.252 (0.293)
	pori2	–	–	0.355 (0.274)	0.150 (0.274)	–	–
Kuopio	kuo	0.363 (0.274)	0.315 (0.274)	0.147 (0.274)	0.243 (0.274)	0.202 (0.274)	0.296 (0.274)
	kuo1	0.309 (0.293)	0.288 (0.293)	0.316 (0.274)	0.391 (0.274)	0.358 (0.293)	0.411 (0.293)
	kuo2	0.757 (0.318)	0.626 (0.318)	–	–	0.159 (0.274)	0.137 (0.274)
Joensuu	jnsu1	-0.123 (0.293)	0.008 (0.293)	-0.133 (0.274)	0.003 (0.274)	-0.421 (0.293)	-0.184 (0.293)
Seinäjoki	seoki	–	–	0.249 (0.293)	0.428 (0.293)	0.255 (0.293)	0.218 (0.293)
Vaasa	vaasa	–	–	0.338 (0.274)	0.327 (0.274)	0.140 (0.274)	0.105 (0.274)
	vaasa1	–	–	–	–	0.331 (0.293)	0.109 (0.293)
	vaasa2	–	–	–	–	**1.05** (0.318)	**1.22** (0.318)
Kouvola	kou	–	–	0.360 (0.274)	0.432 (0.274)	–	–
Lappeenranta	lrta	0.539 (0.274)	0.426 (0.274)	0.158 (0.274)	0.242 (0.274)	0.199 (0.293)	0.299 (0.293)
	lrta1	0.403 (0.317)	0.422 (0.317)	0.096 (0.274)	-0.332 (0.274)	–	–
	lrta2	–	–	–	–	0.884 (0.347)	0.722 (0.347)
Hämeenlinna	hnlina	0.072 (0.274)	0.146 (0.274)	0.274 (0.274)	0.089 (0.274)	–	–
	hnlina1	–	–	0.408 (0.274)	0.362 (0.274)	0.459 (0.293)	0.470 (0.293)
Kotka	kotka	0.157 (0.293)	0.235 (0.293)	–	–	0.933 (0.293)	0.732 (0.293)
	kotka1	–	–	0.365 (0.293)	0.390 (0.293)	**1.26** (0.347)	0.679 (0.347)

Notes: This table reports the estimates of the long memory parameter d in both squared and absolute returns of house prices. The values in parentheses are their standard errors. If $d \in (-0.5, 0)$, the series is described as "anti–persistence". If $d \in (0, 0.5)$, the process manifests the long–range dependence. If $d \in [0.5, 1)$, the process is mean reverting, even though it is no longer covariance stationary. If $d \geq 1$, the process is nonstationary without mean reversion.

Table 7: Estimates of d in the Squared and Absolute returns house prices.

5 Conclusion

The presence of long memory in the asset returns implies that the considered asset returns may be predictable at long horizons; which is why investigating this issue is crucial in the development of appropriate time series forecasting models in the financial market. With this motivation, this study examines the persistence or long memory behaviour of the house price returns and volatility for fifteen main regions in Finland. The study employs both parametric and semiparametric long memory approaches to estimate the degree of long–range dependence in both returns and volatility. The results reveal strong supportive evidence of long memory in the returns; suggesting that the house price return series, contrary to other asset classes such as stocks, are strongly autocorrelated and hence highly forecastable. Moreover, in the majority of the cities and sub–areas with significant clustering effects, the long memory behaviour was found in the volatility using either squared or absolute returns. The evidence of high degree of persistence found in the house price volatility is essential higher than that exhibited by other assets categories.

In the standpoint of developing appropriate time series volatility forecasting models in this housing market; for further research, these results will be used in modelling and forecasting the volatility dynamics of the studied types of dwellings. That is, for cities and sub–areas with no significant ARCH effects, meaning those cities with constant mean and variance, and with long–range dependence in the returns; a short memory ARMA (p,q) model and a long memory ARFIMA (p,d,q) model will be used to examine which model leads to the best results in modelling house price returns. The long memory parameter d estimated in the house price returns will be incorporated in the ARFIMA (p,d,q) estimation procedure. However, as the model which fits better does not necessarily mean it will forecast well, an in–sample and out–of–sample forecasting performance of both univariate models will be assessed. Furthermore, for those cities and sub–areas with significant ARCH effects, and exhibiting long memory behaviour in the volatility; a short memory GARCH model will be employed to capture the house price volatility dynamics, and it will be compared to the other GARCH–type models which account for long memory in the conditional variance such as the Fractionally Integrated GARCH (FIGARCH) model, and the Component GARCH (CGARCH) model. Again, long memory parameter d estimated in the house price volatility will be incorporated in the FIGARCH estimation procedure, and a forecasting test will be performed to provide information regarding which forecasting methods delivers superior volatility forecasts of the studied types of apartments.

Appendices

A

Regional division of quarterly house price index data		
Cities/Sub–areas	Abbreviations for cities and sub–areas	Postcode numbers
Helsinki	hki	City area
Helsinki–area1	hki1	100, 120, 130, 140, 150, 160, 170, 180, 220, 260
Helsinki–area2	hki2	200, 210, 250, 270, 280, 290, 300, 310, 320, 330, 340, 500, 510, 520, 530, 540, 550, 560, 570, 580, 590, 610, 810, 850, 990
Helsinki–area2	hki3	240, 350, 360, 370, 400, 430, 440, 440, 620, 650, 660, 670, 680, 690, 730, 780, 790, 800, 830, 840, 950
Helsinki–area4	hki4	Other postcodes
Tampere	tre	City area
Tampere–area1	tre1	33100, 33180, 33200, 33210, 33230, 33240, 33250, 33500, 33540
Tampere–area2	tre2	33270, 33400, 33530, 33560, 33610, 33700, 33730, 33820, 33900, 34240
Tampere–area3	tre3	Other postcodes

Regional division of quarterly house price index data		
Cities/Sub–areas	Abbreviations for cities and sub–areas	Postcode numbers
Turku	tku	City area
Turku–area1	tku1	20100, 20500, 20700, 20810, 20900
Turku–area2	tku2	20200, 20250, 20300, 20380, 20400, 20520, 20720, 20880, 20960
Turku–area3	tku3	Other postcodes
Oulu	oulu	City area
Oulu–area1	oulu1	90100,90120, 90130, 90140, 90230, 90400, 90410, 90420, 90510
Oulu–area2	oulu2	Other postcodes
Lahti	lti	City area
Lahti–area1	lti1	15100, 15110, 15140, 15160, 15320, 15340, 15610, 15850, 15900
Lahti–area2	lti2	Other postcodes
Jyväskylä	jkla	City area
Jyväskylä–area1	jkla1	40100, 40200, 40500, 40520, 40530, 40600, 40700, 40720
Jyväskylä–area2	jkla2	Other postcodes
Pori	pori	City area
Pori–area1	pori1	28100, 28130, 28300, 28430, 28540, 28660, 28900
Pori–area2	pori2	Other postcodes
Kuopio	kuo	City area
Kuopio–area1	kuo1	70100, 70110, 70300, 70600, 70800, 70840
Kuopio–area2	kuo2	Other postcodes
Joensuu	jnsu	City area
Joensuu–area1	jnsu1	80100, 80110, 80200, 80220
Joensuu–area2	jnsu2	Other postcodes
Seinajöki	seoki	City area
Vaasa	vaasa	City area
Vaasa–area1	vaasa1	65100, 65170, 65200, 65410
Vaasa–area2	vaasa2	Other postcodes
Kouvola	kou	City area
Lappeenranta	lrta	City area
Lappeenranta–area1	lrta1	53100, 53130, 53500, 53600, 53900, 55330
Lappeenranta–area2	lrta2	Other postcodes
Hämeenlinna	hnlina	City area
Hämeenlinna–area1	hnlina1	13100, 13130, 13200, 13220, 13270
Hämeenlinna–area2	hnlina2	Other postcodes
Kotka	kotka	City area
Kotka–area1	kotka1	48100, 48210, 48310, 48710
Kotka–area2	kotka2	Other postcodes

Source: Statistics Finland

Table 8: Regional division by postcode numbers.

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