

Article

Asymmetric Wealth Effect between US Stock Markets and US Housing Market and European Stock Markets: Evidences from TAR and MTAR

Pedro Coelho ¹, Luís Gomes ^{2,*}  and Patrícia Ramos ³ 

¹ ISCAP, Polytechnic of Porto, 4465-004 S. Mamede de Infesta, Portugal; pedro.coelho@finantech.pt

² CEOS.PP, ISCAP, Polytechnic of Porto, 4465-004 S. Mamede de Infesta, Portugal

³ CEOS.PP, ISCAP, Polytechnic of Porto and INESC TEC, 4465-004 S. Mamede de Infesta, Portugal; patricia@iscap.ipp.pt

* Correspondence: pgomes@iscap.ipp.pt

Abstract: Evidence of the asymmetric wealth effect has important implications for investors and continues to merit research attention, not least because much of the evidence based on linear models has been refuted. Indeed, stock and house prices are influenced by economic activity and react non-linearly to positive/negative shocks. This problem justifies our research. The objective of this study is to examine evidence of cointegrations between the US housing and stock markets and between the US and European stock markets, given the international relevance of these exchanges. Using data from 1989:Q1 to 2020:Q2, the Threshold Autoregression model as well as the Momentum Threshold Autoregression model were calculated by combining the US Freddie, DJIA, and SPX indices and the European STOXX and FTSE indices. The results suggest a long-term equilibrium relationship with asymmetric adjustments between the housing market and the US stock markets, as well as between the DJIA, SPX, and FTSE indices. Moreover, the wealth effect is stronger when stock prices outperform house prices above an estimated threshold. This empirical evidence is useful to portfolio managers in their search for non-perfectly related markets that allow investment diversification and control risk exposure across different assets.

Keywords: threshold autoregression; momentum threshold autoregression; cointegration; asymmetric error correction; risk; financial markets



Citation: Coelho, Pedro, Luís Gomes, and Patrícia Ramos. 2023.

Asymmetric Wealth Effect between US Stock Markets and US Housing Market and European Stock Markets: Evidences from TAR and MTAR.

Risks 11: 124. <https://doi.org/10.3390/risks11070124>

Academic Editors: Tomas Kliestik, Katarina Valaskova and Katarina Zvarikova

Received: 19 May 2023

Revised: 20 June 2023

Accepted: 5 July 2023

Published: 10 July 2023



Copyright: © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Since the end of the 20th century, financial markets have increased the flow of money through growth in the number of participants, financial instruments, and access to capital markets. In a competitive world, investment decisions determine the (in)success of portfolio managers and investors in general.

The market transfers wealth from “one hand to another”, so knowledge of how the market moves and reacts has attracted the attention of agents. Diversification is a weapon available to investors to mitigate losses during market downturns and can be achieved by spreading the budget across several assets with imperfect correlations.

An opportunity is seen as combining the stock and housing markets. In addition, international diversification also became a focus of attention following Grubel (1968). By understanding these movements, investors can implement portfolio strategies to improve returns for a given risk. However, diversification does not guarantee full protection against political and macroeconomic events or investor behaviour.

The housing market and the stock market are linked by two mechanisms through which financial flows are transferred. First, the value added to the housing market when stock market returns rise (wealth effect). Second, real estate growth leads to a rise in the stock market (credit price effect). Housing portfolios are built on the basis of the

investor's wealth, so their diversification is not as effective as that of stock portfolios. In both portfolios, monetary policies affect asset values, although the housing market reacts more slowly than the stock market to shocks (Tsai et al. 2012).

In recent decades, the number of cointegration studies between markets has increased, although much of the evidence has been refuted as the methods employed have evolved (Srivastava 2007; Tsai et al. 2012). The objective of this study is to examine evidence of cointegrations between the US housing and stock markets and between the US and European stock markets, given the international relevance of these exchanges and the lack of consistency in international empirical evidence. For this purpose, the Threshold Autoregression (TAR) model as well as the Momentum Threshold Autoregression (MTAR) model were calculated by combining the US Freddie Mac House Price (Freddie), Dow Jones Industrial Average (DJIA) and Standard & Poor's 500 (SPX) indices and the European Euro STOXX 50 (STOXX) and Financial Times Stock Exchange 100 (FTSE) indices. Given that stock and house prices are influenced by economic activity and react non-linearly to shocks, the use of these models to pursue the objective is a contribution of the study.

Cointegration was studied for the first time by Granger (1981), but it was only after the stock market crash of 1987 that portfolio managers and investors became aware of this effect (Kanas 1998). However, it is important to note that the roots of cointegration are much older and are inextricably linked to the concept of "spurious correlation", highlighting the work of Yule (1926) in the early 20th century.

Cointegration is defined as the probability that two non-stationary time series move in the same direction in the long-term, the discovery of which may lead to a change in portfolio construction for risk mitigation (MacKinnon 2010). Although the variables may diverge in the short term, market forces will bring them together for a long-term equilibrium.

The remainder of the paper is structured as follows. Section 2 presents a review of the literature on cointegration, highlighting some empirical evidence related to financial and housing markets. Section 3 presents the research results and discussion, taking into account the hypotheses established. Section 4 identifies the research methodology used in the empirical study, with details of the sample, data, and hypotheses, as well as a description of the linear cointegration analysis, the threshold cointegration analysis, and the asymmetric error correction model with threshold cointegration. Finally, Section 5 summarizes the main findings.

2. Cointegration

Cointegration is defined as the probability that two non-stationary time series move in the same direction in the long term, with benefits in portfolio construction to reduce risk (MacKinnon 2010). Although the variables may diverge in the short term, market forces will tend to bring them into equilibrium in the long term.

Granger (1981) defines cointegration as the possibility that two non-stationary time series move together in the same direction in the long-term. Cointegration could have strong implications for the construction of international portfolios to diversify risk (MacKinnon 2010). On the other hand, Liu et al. (1990) define integration as the possibility that prices in both the housing market and the stock market are driven by the systematic risk of the overall market index.

Engle and Granger (1987) prove that cointegration series have an error representation and recommend several techniques to test whether two or more series are not cointegrated (null hypothesis). These techniques approximate some tests presented by Fuller (1976) and Dickey and Fuller (1979). Both tests do not follow a tabulated distribution.

Time series do not always follow linear behaviour, so exponential autoregressive and TAR processes have become increasingly common. In addition, non-linear models such as TAR and MTAR have been studied due to their uniqueness. However, the TAR model has not been widely used because of the difficulty in identifying the threshold variable and its associated estimation. Tong (1978) was the first to study this model, which was later extended by Tong and Lim (1980) and Tong (1983).

2.1. Cointegration in Financial Markets

[Stehle \(1997\)](#) computed the first empirical test to segmentation and integration of the US stock market and global market, not being able to reject the null hypothesis. The methodology was based on the traditional model of [Fama and MacBeth \(1973\)](#).

Studying the effects of the crash (1987), [Lee and Kim \(1994\)](#) concluded that markets became more interrelated and that whenever the US stock market has bigger volatility, the co-movements between countries are stronger.

Later, [Cheung and Ng's \(1992\)](#) work on the dynamic properties of stock returns in Tokyo and New York concluded that the US market has more impact on global returns.

[Hatemi-J \(2008\)](#) examined the possibility of integration between the UK and US financial markets. The author does not follow the conventional cointegration tests, which have been calculated for only one change of regime between the time series. Instead, he added three residual-based test statistics to account for two possible regime shifts. The study identified two structural breaks (one in 1991 and the other in 1992, eventually justified by the Gulf War and the exchange rate crisis in Europe) and appears to exist a long and steady relation between these two markets.

On the other hand, [Kanas \(1998\)](#) tested the pairwise cointegration between the US and European (UK, Germany, France, Switzerland, Italy, and The Netherlands) stock markets. Using the Johansen method and the Bierens nonparametric approach, the author found no cointegration between these two markets. [Arshanapalli and Doukas \(1993\)](#) studied interdependencies between UK, Germany, France, and US markets. The results indicated a bivariate cointegration between European markets as well as between US and European markets. In contrast, [Taylor and Tonks \(1989\)](#) do not find evidence of a bivariate cointegration between UK and US markets.

[Kim \(2005\)](#) found that the US market has a greater influence in Asian markets rather than just Japan, although the Asian crisis has had a strong impact on the short-term connections between these markets ([Yang and Lim 2004](#)). In the same sense, [Srivastava \(2007\)](#) studied the possible integration between eight Asian markets and the US markets during 1997 and 2006. The results suggest that the integration differs between periods and that has strengthened in the last years of the sample.

Using a multivariate cointegration model between stock markets indices of the US, the UK, Japan, Germany, Canada, and The Netherlands, [Byers and Peel \(1993\)](#) and [Kasa \(1992\)](#) reached different conclusions.

On the other hand, [Arshanapalli et al. \(1995\)](#) and [Ghosh et al. \(1999\)](#) demonstrated the influence of US market in the Asia-Pacific markets, whose integration started after the market crash (in 1987) or the Gulf War (in 1991). Furthermore, [Choudhry et al. \(2007\)](#), [Ghosh et al. \(1999\)](#) and [Phylaktis and Ravazzolo \(2005\)](#) also detected cointegrations between Asian markets both with US and Japan markets.

2.2. Cointegration in Housing Market

[Li et al. \(2015\)](#) point out that studies on the relationship between the stock market and the housing market fall into three main areas of research: (1) the initial correlation tests, (2) the Granger causality tests in vector autoregressive (VAR), vector error-correction (VEC), and threshold error-correction (TEC) models to identify links between markets and (3) linear and non-linear tests to ascertain whether markets are integrated or segmented.

[Ibbotson and Siegel \(1984\)](#), [Worzala and Vandell \(1993\)](#) confirmed that the US stock market and the housing market are neither negatively nor significantly correlated. Similarly, no strong relationship between the US stock and housing markets was found by [Quan and Titman \(1997\)](#). Although correlation can show co-movement between variables, it has limitations in analysing long-term and lead-lag relationships.

[Green \(2002\)](#) found a wealth effect between the Californian housing market and the stock market from 1989 to 1998. In contrast, the VAR model used by [Sim and Chang \(2006\)](#) found no evidence of a wealth effect in Korean markets.

Liu et al. (1990) were the first to examine the integration between the housing market and the stock market and found evidence of segmentation between the two. The fractional cointegration tests used by Ambrose et al. (1992) differed from these results and indicated the possibility of integration between the stock market and the securitised real estate market.

More recent studies have adjusted error-correction modelling and cointegration approaches and found signs of cointegration (Liow 2006; Liu and Su 2010; Tsai et al. 2012; Ding et al. 2014; Bahmani-Oskooee and Wu 2017). However, Bahmani-Oskooee and Ghodsi (2018) question the findings of some previous studies that used data from only one specific country. Looking at indices from several countries, the authors found stronger results supporting the existence of a wealth effect in the short term than in the long term.

Tsai et al. (2012) studied the long-run equilibrium between the US stock market and housing prices and found evidence of cointegration between these markets, but the long-term adjustments are asymmetric. The authors emphasise that the different results obtained in previous studies may be due to the use of linear econometric models. Indeed, stock and housing prices are influenced by economic activity and react in a non-linear way.

In a different procedure, using a wavelet approach to study the relationship between the property market and the stock market from 1890 to 2012, Li et al. (2015) found that comovement and causality vary across frequencies and evolve over time. Xu and Zhang (2023) also examined the cointegration between monthly housing prices in 100 Chinese cities from 2010 to 2019 using time-invariant and time-varying approaches. Their wavelet transformations showed heterogeneous cointegrating patterns across the pairs tested, despite the existence of many relatively stable cointegrating relationships, which tend to be aggregated results of price relationships at different scales.

Gueye (2021) implemented first-generation tests (tests that assume independence between sections) and second-generation tests (tests that assume dependence between sections) on house prices from 20 OECD countries. The second procedure evidenced stationarity and cointegration in the data series. In addition, the author notes that changes in the housing market also can have a significant impact on the economy.

McCord et al. (2019) applied the Johansen cointegration, Granger causality, and vector error correction model to quarterly house price data for the Northern Ireland housing market between Q1:1995 and Q2:2018. The results indicated that there are market filtration transmission pricing signals in operation in a Granger-causal fashion.

Agoraki et al. (2019) develop a comprehensive Vector Autoregression Model and apply the test methodology on monthly data for the US, UK, Germany, and Japan over the period January 1980 to May 2019. The main findings provided partial support for cointegration, and therefore for capital markets integration, among stock market indices.

3. Research Results and Discussion

Table 1 shows the descriptive statistics of the indices from the first quarter of 1989 to the third quarter of 2020.

Table 1. Descriptive statistics of indices levels.

Statistics	Freddie Mac	DJIA	SPX	FTSE	STOXX
Mean	23.624	11,244.93	1287.64	5090.34	2570.72
Std. Deviation	25.348	6581.62	736.25	1580.65	986.25
Minimum	0.225	2293.62	294.87	1990.20	807.74
Maximum	72.990	28,538.44	3363.00	7687.77	5059.11
Skewness	0.656	0.7817	0.8175	−0.3929	−0.0730
Kurtosis	−1.275	0.040	0.097	−1.007	−0.461

On average, the largest index in the sample is the DJIA and the smallest is Freddie. The standard deviations indicate the high variability of the series, especially for the housing market. Interestingly, the asymmetry of the US indices reveals a fatter right tail distribution,

while the European indices reveal a fatter left tail. Moreover, the positive kurtosis of the DJIA and SPX indices reveals a leptokurtic manifestation, suggesting that the market is classified into a group of hedging noise traders (Gomes et al. 2018) providing liquidity and a group of large speculative position takers consisting of institutional investors and wealthy interveners (Los and Yu 2008).

Table 2 shows the results of the ADF (Dickey and Fuller 1979), PP (Phillips and Perron 1988), and KPSS (Kwiatkowski et al. 1992) tests for stationarity of the time series.

Table 2. Time-series stationarity.

Indexes	ADF	PP	KPSS
	<i>p</i> -Value	<i>p</i> -Value	Test-Statistic Value
Freddie Mac	0.597	0.5937	1.0925 ***
DJIA	0.5661 [5]	0.4887 [4]	2.3051 [4] ***
SPX	0.5007 [5]	0.5221 [4]	2.2070 [4] ***
FTSE	0.4757 [5]	0.5013 [4]	1.8786 [4] ***
STOXX	0.6464 [5]	0.6533 [4]	1.3059 [4] ***

Critical values (intercept) for KPSS test: 0.739 for 1% (***) significance level.

The lag lengths for the tests (in brackets) were determined using the AIC statistic and Ljung-Box Q test. The first two tests (ADF and PP) clearly fail to reject the unit-root hypothesis for all series. However, the KPSS test statistics reveal that the null hypothesis of stationarity is rejected at the 1% significance level for all indices.

The first step in examining the existence of cointegration is to test the null hypothesis of no cointegration against the threshold cointegration. If the null hypothesis is rejected, there is evidence of a long-term relationship between the indices. Afterwards, it is tested whether the adjustments processes are symmetric across markets. If the null hypothesis is rejected, there is a threshold effect between the markets and therefore the adjustments are asymmetric. Finally, the threshold vector error correction of Enders and Granger (1998) is applied to examine the wealth effect.

As mentioned above, markets may react differently to positive and negative shocks, which could lead to asymmetric adjustments in the long-term. Therefore, these types of movements may not be captured by a linear model based on symmetric adjustment. Nevertheless, the Engle–Granger linear cointegration test is carried out for each combination of indices. In the first stage of estimating the long-term relationship between the US and European indices, the latter were chosen to be on the right-hand side of the cointegration regression, assuming that they are the driving force. The number of lags in the unit root tests was chosen so that there was no correlation in the regression of the residuals by means of the BIC criterion. One lag was sufficient to deal with the serial correlation in all index pairs. Table 3 shows the results of the linear cointegration tests.

These results indicate that the Engle–Granger tests fail to reject the null hypothesis at any significance level, regardless of whether a time trend is included in the cointegration model, providing evidence that there is no cointegration or wealth effect between the market pairs. These results do not support any of the three hypotheses established for this study. The Freddie/DJIA results are consistent with Tsai et al. (2012). Even so, the Engle–Granger test may be biased towards finding no cointegration if the adjustment process of the two markets is asymmetric (Enders and Siklos 2001).

The non-linear cointegration analysis is carried out using the threshold autoregressive models TAR and MTAR as well as their consistent counterparts. A diagnostic analysis of the residuals through AIC, the BIC, and the Ljung-Box Q statistics showed that three lags were sufficient to deal with any possible autocorrelation. Threshold values for consistent TAR and MTAR were estimated using the Chan (1993) method. Table 4 shows the results of the nonlinear cointegration tests.

Table 3. Linear cointegration tests.

Panel A—Results of Linear Cointegration Tests: Values of Test Statistics										
Index Pairs	None			Drift			Trend			
	τ_1			τ_2	φ_1		τ_3	φ_2	φ_3	
Freddie/DJIA	−1.740			−1.735	1.520		−1.974	1.411	2.101	
Freddie/SPX	−1.710			−1.705	1.465		−1.964	1.382	2.063	
SPX/FTSE	0.645			0.715	0.764		−0.194	2.157	2.710	
SPX/STOXX	0.795			0.873	1.411		−0.827	2.536	2.743	
DJIA/FTSE	−0.314			−0.271	0.399		−1.211	1.771	2.284	
DJIA/STOXX	0.043			0.088	0.717		−1.449	1.986	2.246	

Panel B—Statistical Tests: Critical Values for Test Statistics											
None	Drift						Trend				
	1%	5%	10%		1%	5%	10%		1%	5%	10%
τ_1	−2.58	−1.95	−1.62	τ_2	−3.46	−2.88	−2.57	τ_3	−3.99	−3.43	−3.13
				φ_1	6.52	4.63	3.81	φ_2	6.22	4.75	4.07
								φ_3	8.43	6.49	5.47

Table 4. TAR and MTAR cointegration tests.

Panel A									
Freddie/DJIA					Freddie/SPX				
Item	TAR	Consistent TAR	MTAR	Consistent MTAR	TAR	Consistent TAR	MTAR	Consistent MTAR	
Lag	3	3	3	3	3	3	3	3	
Threshold	0	0.421	0	0.065	0	−1.09	0	0.187	
ρ_1 (coef+)	−0.001	0.009	−0.022	−0.054 **	−0.016	−0.005	−0.025	0.049	
ρ_1 statistic value	(−0.046)	(0.379)	(−1.318)	(−1.988)	(−0.559)	(−0.187)	(−0.855)	(0.860)	
ρ_2 (coef−)	−0.030 *	−0.032 *	−0.011	−0.006	−0.054	−0.071 *	−0.046	−0.049 *	
ρ_2 statistic value	(−1.671)	(−1.905)	(−0.430)	(−0.342)	(−1.892)	(−2.371)	(−1.551)	(−2.210)	
AIC	−229.744	−230.688	−228.853	−231.070	116.660	114.866	117.329	115.057	
BIC	−212.871	−213.815	−211.980	−214.197	133.533	131.739	134.202	131.930	
Q _{LB} (LB test_4)	0.997	0.999	0.987	0.986	0.619	0.742	0.638	0.395	
Q _{LB} (LB test_8)	0.796	0.823	0.758	0.624	0.771	0.761	0.815	0.661	
Q _{LB} (LB test_12)	0.732	0.748	0.686	0.658	0.911	0.889	0.943	0.894	
H0: no CI	1.404	1.870	0.969	2.059	1.932	2.827	1.601	2.731	
p-value	0.250	0.159	0.383	0.132	0.150	0.063	0.206	0.069	
H0: SAP	0.975	1.891	0.116	2.264	0.914	2.6610	0.269	2.474	
p-value	0.326	0.172	0.734	0.135	0.341	0.106	0.605	0.118	

Panel B									
SPX/FTSE					SPX/STOXX				
Item	TAR	Consistent TAR	MTAR	Consistent MTAR	TAR	Consistent TAR	MTAR	Consistent MTAR	
Lag	3	3	3	3	3	3	3	3	
Threshold	0	−0.136	0	0.004	0	−0.143	0	−0.037	
ρ_1 (coef+)	0.105	0.104 *	0.084	0.094	0.038	0.040	0.003	0.007	
ρ_1 statistic value	(1.879)	(2.033)	(1.588)	(1.782)	(1.802)	(1.947)	(0.165)	(0.409)	
ρ_2 (coef−)	−0.088	−0.134 *	−0.095	−0.106	−0.031	−0.04	0.019	0.036	
ρ_2 statistic value	(−1.537)	(−2.149)	(−1.52)	(−1.73)	(−1.269)	(−1.579)	(0.707)	(0.647)	
AIC	−299.651	−302.832	−298.448	−299.971	−359.686	−361.218	−354.981	−355.02	
BIC	−282.778	−285.959	−281.574	−283.098	−342.813	−344.345	−338.108	−338.147	
Q _{LB} (LB test_4)	0.995	0.995	0.951	0.934	0.961	0.956	0.962	0.951	
Q _{LB} (LB test_8)	0.994	0.993	0.979	0.971	0.791	0.821	0.732	0.743	
Q _{LB} (LB test_12)	1.000	0.998	0.999	0.998	0.609	0.613	0.527	0.545	
H0: no CI	3.373	5.007	2.766	3.536	2.568	3.340	0.257	0.276	
p-value	0.038 *	0.008 **	0.067	0.032 *	0.081	0.039 *	0.7736	0.759	
H0: SAP	6.674	9.941	5.461	7.000	4.828	6.368	0.219	0.256	
p-value	0.011 *	0.002 **	0.021 *	0.009 **	0.030 *	0.013 *	0.641	0.614	

Panel C									
DJIA/FTSE					DJIA/STOXX				
Item	TAR	Consistent TAR	MTAR	Consistent MTAR	TAR	Consistent TAR	MTAR	Consistent MTAR	
Lag	3	3	3	3	3	3	3	3	
Threshold	0	0.159	0	−0.009	0	−0.124	0	−0.002	
ρ_1 (coef+)	0.032	0.061	0.025	0.032	0.022	0.025	−0.019	−0.02	
ρ_1 statistic value	(0.561)	(1.03)	(0.518)	(0.683)	(0.987)	(1.111)	(−0.927)	(−0.992)	

Table 4. Cont.

Panel C								
DJIA/FTSE				DJIA/STOXX				
ρ_2 (coef-)	-0.084	-0.094	-0.128 *	-0.162 *	-0.038	-0.043	0.022	0.027
ρ_2 statistic value	(-1.593)	(-1.877)	(-2.057)	(-2.475)	(-1.564)	(-1.737)	(0.772)	(0.916)
AIC	-267.038	-269.068	-268.754	-270.962	-326.23	-327.1	-324.112	-324.505
BIC	-250.165	-252.195	-251.881	-254.089	-309.357	-310.227	-307.239	-307.632
Q _{LB} (LB test_4)	0.999	0.997	0.961	0.968	0.999	0.999	0.999	0.998
Q _{LB} (LB test_8)	0.977	0.987	0.955	0.94	0.812	0.802	0.697	0.668
Q _{LB} (LB test_12)	0.995	0.998	0.992	0.991	0.724	0.727	0.607	0.585
H0: no CI	1.536	2.544	2.387	3.499	1.789	2.221	0.751	0.943
p-value	0.2194	0.083	0.096	0.033 *	0.172	0.113	0.474	0.393
H0: SAP	2.483	4.488	4.176	6.389	3.480	4.343	1.406	1.788
p-value	0.118	0.036 *	0.043 *	0.013 *	0.065	0.039 *	0.238	0.184

CI means cointegration and SAP means symmetric adjustment process; *, ** denote significance at the 10%, 5% and 1% level, respectively.

The TAR consistent model presents the lowest AIC and BIC values for the Freddie/SPX pair with the housing market and for the SPX/FTSE, SPX/STOXX, and DJIA/STOXX stock market pairs, and is therefore selected as the best. Using the same information criteria, the consistent MTAR model is the best for the Freddie/DJIA and DJIA/FTSE pairs.

The *F*-test for the null hypothesis of no cointegration ($H_0 : \rho_1 = \rho_2 = 0$) against the alternative of cointegration for all pairs (except for the DJIA/STOXX pair) provides evidence at least at the 5% level that the US and European stock indices are cointegrated with threshold adjustment. This means that there is a long-term equilibrium between these market pairs. Furthermore, the *F*-test statistic for the null hypothesis of symmetric adjustment ($H_0 : \rho_1 = \rho_2$) is rejected in all stock pairs at least at the 5% level, suggesting that the process is asymmetric when the two indices adjust to reach the long-term equilibrium. This means that reversions to equilibrium occur at different paces and that our Hypotheses 1 and 2 are supported, except for the DJIA/STOXX pair.

The next step is to estimate an asymmetric error correction model, whose results are shown in Table 5.

Table 5. Error correction model.

Panel A								
Item	Freddie/DJIA				Freddie/SPX			
	DJIA.est	DJIA.t	Freddie.est	Freddie.t	SPX.est	SPX.t	Freddie.est	Freddie.t
(Intercept)	0.012	0.552	0.023	0.251	-0.002	-0.082	0.026	0.297
α_1^+	0.02	0.088	2.551 *	2.584	0.137	0.615	2.046 *	2.220
α_2^+	0.374	1.674	-0.131	-0.135	0.594 **	2.665	0.421	0.457
α_3^+	0.185	0.812	-0.148	-0.15	0.092	0.416	-0.306	-0.334
α_4^+	-0.331	-1.601	-0.713	-0.791	-0.256	-1.236	-0.675	-0.788
α_1^-	-0.401 *	-2.266	1.686 *	2.186	-0.335	-1.846	1.943 *	2.594
α_2^-	-0.311	-1.583	0.141	0.165	-0.362	-1.823	-0.547	-0.668
α_3^-	0.058	0.267	0.278	0.295	0.259	1.23	0.891	1.025
α_4^-	0.263	1.213	-0.129	-0.137	0.121	0.573	-0.618	-0.709
β_1^+	-0.013	-0.301	-0.087	-0.456	-0.036	-0.800	-0.086	-0.468
β_2^+	0.011	0.268	0.016	0.089	0.024	0.573	0.014	0.079
β_3^+	0.014	0.344	-0.094	-0.532	0.014	0.331	-0.084	-0.486
β_4^+	-0.010	-0.250	0.027	0.152	0.006	0.141	0.022	0.129
β_1^-	0.074 *	2.362	0.356 **	2.610	0.065	1.942	0.356 *	2.583
β_2^-	0.010	0.315	-0.149	-1.056	0.006	0.169	-0.109	-0.762
β_3^-	0.001	0.039	0.352 *	2.468	-0.004	-0.122	0.338 *	2.366
β_4^-	0.002	0.056	-0.258	-1.825	0.018	0.534	-0.245	-1.760
Φ^+	0.005	0.340	-0.010	-0.163	0.000	-0.026	0.014	0.233
Φ^-	-0.012 *	-2.102	-0.034	-1.421	-0.011	-1.911	-0.036	-1.526
H ₀₁ : $\alpha_1^+ = \alpha_2^+ = 0$ for all lags	1.591	[0.14]	3.276 **	[0.00]	1.563	[0.14]	3.652 **	[0.00]
H ₀₂ : $\beta_1^+ = \beta_2^+ = 0$ for all lags	0.844	[0.57]	1.602	[0.13]	0.684	[0.7]	1.564	[0.14]

Table 5. Cont.

Panel B								
Item	SPX/FTSE				SPX/STOXX			
	FTSE.est	FTSE.t	SPX.est	SPX.t	STOXX.est	STOXX.t	SPX.est	SPX.t
(Intercept)	−0.014	−0.727	−0.024	−1.198	−0.027	−1.119	−0.018	−0.88
α_1^+	0.568	1.925	0.881 **	2.949	0.431	1.38	0.464	1.776
α_2^+	−0.315	−1.087	−0.341	−1.163	−0.436	−1.525	−0.260	−1.087
α_3^+	−0.042	−0.144	0.06	0.203	0.197	0.698	0.151	0.639
α_4^+	0.432	1.49	0.114	0.388	0.092	0.327	−0.046	−0.192
α_1^-	−0.904 **	−2.628	−0.829 *	−2.378	−0.486	−1.329	−0.464	−1.515
α_2^-	0.333	0.996	0.252	0.744	0.054	0.147	−0.073	−0.236
α_3^-	0.345	0.987	0.181	0.511	0.278	0.772	0.234	0.776
α_4^-	−0.608	−1.702	−0.496	−1.371	0.244	0.679	0.298	0.991
β_1^+	−0.225	−0.809	−0.261	−0.925	−0.121	−0.352	−0.162	−0.562
β_2^+	0.534	1.952	0.784 **	2.827	0.817 *	2.388	0.808 **	2.818
β_3^+	0.04	0.146	0.111	0.402	0.082	0.238	0.056	0.195
β_4^+	−0.399	−1.511	−0.271	−1.013	−0.168	−0.521	−0.172	−0.635
β_1^-	0.665	1.918	0.442	1.26	0.336	0.763	0.216	0.586
β_2^-	−0.320	−0.966	−0.435	−1.293	−0.119	−0.264	−0.195	−0.516
β_3^-	−0.266	−0.793	0.033	0.097	−0.218	−0.477	−0.060	−0.158
β_4^-	0.527	1.578	0.623	1.841	−0.091	−0.204	−0.123	−0.329
Φ^+	−0.046	−0.738	0.008	0.128	0.028	0.840	0.041	1.477
Φ^-	0.134	1.791	0.122	1.619	−0.025	−0.219	0.055	0.563
H ₀₁ : $\alpha_i^+ = \alpha_i^- = 0$ for all lags	1.692	[0.11]	1.960	[0.06]	0.968	[0.47]	1.123	[0.35]
H ₀₂ : $\beta_i^+ = \beta_i^- = 0$ for all lags	1.345	[0.23]	1.576	[0.14]	0.845	[0.56]	1.139	[0.34]

Panel C								
Item	DJIA/FTSE				DJIA/STOXX			
	FTSE.est	FTSE.t	DJIA.est	DJIA.t	STOXX.est	STOXX.t	DJIA.est	DJIA.t
(Intercept)	−0.018	−0.911	−0.017	−0.841	−0.021	−0.814	−0.008	−0.386
α_1^+	0.705 **	2.653	0.775 **	2.885	0.538 *	2.114	0.351	1.675
α_2^+	0.100	0.399	0.172	0.679	−0.151	−0.577	0.003	0.015
α_3^+	0.126	0.505	0.159	0.631	0.233	0.921	0.165	0.794
α_4^+	0.347	1.399	0.123	0.49	0.122	0.480	0.146	0.701
α_1^-	−0.407	−1.157	−0.150	−0.421	0.110	0.305	0.273	0.918
α_2^-	0.659	1.868	0.210	0.588	0.077	0.214	−0.209	−0.706
α_3^-	0.091	0.254	−0.151	−0.418	−0.009	−0.023	−0.128	−0.413
α_4^-	−0.770 *	−2.181	−0.608	−1.705	−0.127	−0.327	−0.006	−0.018
β_1^+	−0.343	−1.375	−0.308	−1.224	−0.295	−0.913	−0.126	−0.473
β_2^+	0.308	1.212	0.296	1.151	0.455	1.441	0.403	1.551
β_3^+	0.006	0.022	0.104	0.412	0.107	0.337	0.083	0.317
β_4^+	−0.430	−1.781	−0.357	−1.463	−0.268	−0.880	−0.388	−1.545
β_1^-	0.098	0.273	−0.254	−0.695	−0.399	−0.888	−0.653	−1.765
β_2^-	−0.722	−1.977	−0.339	−0.918	−0.138	−0.302	0.098	0.260
β_3^-	−0.004	−0.011	0.232	0.621	0.032	0.063	0.149	0.354
β_4^-	0.926 *	2.581	0.905 *	2.495	0.444	0.871	0.341	0.811
Φ^+	−0.007	−0.145	0.029	0.587	0.035	1.021	0.019	0.658
Φ^-	0.135	1.881	0.039	0.54	0.016	0.308	0.065	1.485
H ₀₁ : $\alpha_i^+ = \alpha_i^- = 0$ for all lags	1.870	[0.07]	1.295	[0.25]	0.780	[0.62]	0.691	[0.70]
H ₀₂ : $\beta_i^+ = \beta_i^- = 0$ for all lags	1.799	[0.09]	1.402	[0.20]	0.711	[0.68]	1.158	[0.33]

est means estimated and t means t-ratio; *, ** denote significance at the 10%, 5% and 1% level, respectively.

The estimated coefficient Φ^+ does not present statistical significance at any reasonable level. However, the estimated coefficient Φ^- is significant at least at the 10% level for the Freddie index (Freddie/DJIA and Freddie/SPX pairs) and for the FTSE index (SPX/FTSE and DJIA/FTSE pairs). The statistical significance of Φ^- means that the price only reacts to a negative deviation. In response to a negative deviation, where the price of one index outperforms the other “by an estimated threshold level, error correction occurs, triggering an increase in the second index and then the two markets are cointegrated” (Tsai et al. 2012,

p. 1018). Moreover, the causality relation given by H_{01} presents a “one-way relationship” with the US markets.

On the one hand, the empirical results on the relationship between the Freddie and DJIA markets are similar to those of Tsai et al. (2012), except for the insignificance of the Φ^+ coefficient, whereas the results between the housing market and the two US stock markets are similar to each other. These results confirm the existence of an asymmetric wealth effect between the housing market and the American stock markets, supporting our Hypothesis 3.

On the other hand, the empirical results for the FTSE (SPX/FTSE and DJIA/FTSE pairs) are comparable to those for the US stock indices. There is evidence of cointegration in a one-way causal relationship given by H_{01} and the coefficient Φ^- is significant at the 10% level, supporting our Hypothesis 3 for these indices.

Regarding the results for the STOXX (SPX/STOXX and DJIA/STOXX pairs), almost none of the values are statistically significant, contradicting our Hypothesis 3.

4. Research Methodology

4.1. Sample, Data and Hypothesis

The US nationwide housing price index (obtained from Freddie Mac’s online database) on the one hand, and the Dow Jones Industrial Average (DJIA), and Standard and Poor’s 500 (SPX) indices on the other, are used to measure American housing and stock prices, respectively. In addition, the Financial Time Stock Exchange 100 (FTSE) index and the Euro STOXX 50 (STOXX) index are used to measure European stock prices. These information are summarised in Table 6.

Table 6. Indexes.

Zone	Stock Market	Housing Market
US	DJIA SPX	Freddie Mac
Europe	STOXX FTSE	–

To avoid correlational memory processes between returns over the analysis period, the sample includes data from 1989:Q1 to 2020:Q3, with a total of 127 quarterly observations obtained through the Refinitiv database.

The period of analysis has a great extent, during which several significant events occurred, such as more or less pronounced crises on the international markets. Following the same procedure as Tsai et al. (2012), the data used in the empirical study consist of the simple transformation of the stock index through the first log difference of their levels $\ln(P_t)$. The growth of a dispersion index with increasing index value is typical for this type of financial data and, therefore, the adoption of logarithms in the original series is usually necessary to stabilise the variance (Matos et al. 2004).

The relationship between price variations has been studied through cointegration models, such as the Johansen test and Engle–Granger two-step approach. Balke and Fomby (1997) extended the original approach of Engle and Granger (1987). Later, Enders and Granger (1998) and Enders and Siklos (2001) further generalized the standard Dickey–Fuller by allowing for the “possibility of asymmetric movements in time-series data”, and thus making it possible to test for cointegration by discarding “the hypothesis of a symmetric adjustment to a long-term equilibrium” (Sun 2011, p. 481). This type of model has been used in research on asymmetric price transmission, such as stock market indices (Shen et al. 2007).

We follow the same modelling path to examine the dynamics between US and Europe markets.

Hypothesis 1. *There is a long-term equilibrium relationship between the housing index and stock indices in the US market, although the adjustments from disequilibrium errors are asymmetric.*

Hypothesis 2. *There is a long-term equilibrium relationship between the US stock indices and European stock indices, although the adjustments from disequilibrium errors are asymmetric.*

Hypothesis 3. *The wealth effect between indices is most pronounced when one market outperforms the other.*

The statistical analysis was carried out using the *RStudio* (version 2023.06.1+524) software and package “*atp*” was used to perform the threshold cointegration analyses as well as to estimate the asymmetric correction model (Sun 2011).

4.2. Linear Cointegration Analysis

The Augmented Dickey–Fuller (ADF) test can be used to examine the non-stationarity hypothesis and the order of integration of the variables (Dickey and Fuller 1979). A cointegration analysis is applicable when both series appear to have a unit root. In addition, the Engle–Granger two-step approach is one of the most commonly used cointegration tests (Enders 2004), which focuses on the time-series property of the residuals from the long-term equilibrium relationship (Sun 2011):

$$U_t = \alpha_0 + \alpha_1 W_t + \varepsilon_t \quad (1)$$

$$\Delta \hat{\varepsilon}_t = \rho \hat{\varepsilon}_{t-1} + \sum_{i=1}^P \varphi_i \Delta \hat{\varepsilon}_{t-i} + \mu_t \quad (2)$$

where α_0 , α_1 , ρ , and φ_i are coefficients, W represents the indices levels, ε_t is the error term, and $\hat{\varepsilon}_t$ is the estimated residuals, which are used in the unit root test on a second stage (Engle and Granger 1987). The Δ is the first difference and μ_t represents a white noise term. Finally, P is the number of lags, being selected according to an Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), or Ljung-Box Q test.

The residual series is considered stationary if the null hypothesis ($\rho = 0$) is rejected, meaning that both variables are cointegrated. The value of the lags is chosen in order to prevent serial correlation in the residual’s regression.

4.3. Threshold Cointegration Analysis

In order to establish asymmetric adjustments as an inherent part of cointegration analysis, Enders and Siklos (2001) considered a two-regime threshold cointegration from Equation (2):

$$\Delta \hat{\varepsilon}_t = \rho_1 I_t \hat{\varepsilon}_{t-1} + \rho_2 (1 - I_t) \hat{\varepsilon}_{t-1} + \sum_{i=1}^P \varphi_i \Delta \hat{\varepsilon}_{t-i} + \mu_t \quad (3)$$

$$I_t = 1 \text{ if } \hat{\varepsilon}_{t-1} \geq \tau, 0 \text{ otherwise} \quad (4)$$

or

$$I_t = 1 \text{ if } \Delta \hat{\varepsilon}_{t-1} \geq \tau, 0 \text{ otherwise} \quad (5)$$

where P is the number of lags, as previously presented. The ρ_1 , ρ_2 , and φ_i are coefficients, τ is the threshold value, and I_t is the Heaviside indicator. The indicator I_t can be based on two definitions of τ , using either the lagged residual ($\hat{\varepsilon}_{t-1}$) or the change in this lag ($\Delta \hat{\varepsilon}_{t-1}$).

The pair of Equations (3) and (4) represent a TAR model, and the pair of Equations (3) and (5) represent a MTAR model. The TAR model is able “to capture potential asymmetric deep movements in the residuals” and MTAR is useful “to consider steep variations in the residuals” (Sun 2011, p. 482). The second statistic is particularly important when the adjustment exhibits more momentum in one of the directions. Whenever there is a negative

depth ($|\rho_1| \leq |\rho_2|$) of the residuals, the increases tend to recur, while the decreases cause a much sudden recovery to the equilibrium (Enders and Granger 1998).

Chan (1993) proposed a method to obtain a consistent estimate of the threshold value, which can be specified as zero. The first step is to sort the threshold variable in ascending order for TAR or MTAR, and the second step is to determine the threshold values. If the threshold value is meaningful, the threshold variable must actually cross the threshold value (Sun 2011). In order to ensure an acceptable number of observations from both sides, the top 15% and the last 15% of the values sorted in the first step are excluded. To complete the process, the TAR and MTAR models must be estimated by calculating the sum of squared errors and examining the relationship with the threshold values. The consistent value is the threshold value that minimises the sum of squared errors.

Our study includes four models: TAR ($\tau = 0$), consistent TAR (τ estimated), MTAR ($\tau = 0$), and consistent MTAR (τ estimated). Following Enders and Siklos (2001), the AIC and BIC values are calculated and the model with the lowest values is selected. Two cointegration tests are computed: the F -test to examine cointegration under the null hypothesis ($H_0 : \rho_1 = \rho_2 = 0$) that there is no evidence of cointegration, against the alternative of cointegration with adjustments (TAR and MTAR); and the standard F -test to examine the symmetric adjustments in the long-term equilibrium, where the null hypothesis is defined by $H_0 : \rho_1 = \rho_2$. If H_0 is rejected, there is evidence of an asymmetric adjustment process.

4.4. Asymmetric Error Correction Model with Threshold Cointegration

Engle and Granger (1987) argue that it is possible to estimate an error correction model if all the variables are cointegrated. Furthermore, Sun (2011) states that the adjustment process due to disequilibrium between the variables is symmetric.

There are two extensions to the analysis of asymmetric price transmission, one developed by Granger and Lee (1989) and the other by Balke and Fomby (1997) and Enders and Granger (1998). The first extension stated that both the first differences on the variables and the error correction can be decomposed into either negative or positive components. This extension provides information on the asymmetric effects that can be caused by these differences in the dynamic behaviour of the indexes. The second extension states that whenever the presence of the cointegration threshold is confirmed, the error correction terms are further modified (Sun 2011):

$$\begin{aligned} \Delta W_t = & \theta_w + \delta_W^+ E_{t-1}^+ + \delta_W^- E_{t-1}^- \\ & + \sum_{j=1}^J \alpha_{Wj}^+ \Delta W_{t-j}^+ \\ & + \sum_{j=1}^J \alpha_{Wj}^- \Delta W_{t-j}^- + \sum_{j=1}^J \beta_{Wj}^+ \Delta U_{t-j}^+ + \sum_{j=1}^J \beta_{Wj}^- \Delta U_{t-j}^- + \vartheta_{Wt} \end{aligned} \quad (6)$$

$$\begin{aligned} \Delta U_t = & \theta_U + \delta_U^+ E_{t-1}^+ + \delta_U^- E_{t-1}^- \\ & + \sum_{j=1}^J \alpha_{Uj}^+ \Delta U_{t-j}^+ \\ & + \sum_{j=1}^J \alpha_{Uj}^- \Delta U_{t-j}^- + \sum_{j=1}^J \beta_{Uj}^+ \Delta W_{t-j}^+ + \sum_{j=1}^J \beta_{Uj}^- \Delta W_{t-j}^- + \vartheta_{Ut} \end{aligned} \quad (7)$$

where ΔW_t represents the first difference of the US indices and ΔU_t represents the first difference of the European indexes, θ , δ , α , and β are coefficients, and ϑ is the error term. Time is represented by t , the subscripts' values of W and U differentiate the coefficients of the indexes, and j represents lags. The first difference of the lags can be either positive or negative, being represented by the subscripts $+$ and $-$ in W and U . The J is the maximum lag, being chosen by AIC, BIC, and Ljung-Box Q test to ensure that the residuals have no serial correlation. The error correction term E_t is calculated from the threshold cointegration (Equations (3)–(5)). The interpretation of the estimated coefficients can lead to different

results, such as the existence of asymmetric price behaviour and the response of individual variables to the disequilibrium in previous periods (Sun 2011).

5. Conclusions

Evidence of the asymmetric wealth effect has important implications for portfolio managers. This effect allows investors to ride booming markets and hedge against adverse economic conditions. On the one hand, investors can benefit from capital gains and property appreciation if they are exposed to the stock market and the housing market. On the other hand, investors can benefit from diversification when markets are falling. Indeed, searching for international correlations can improve portfolio diversification due to imperfect correlation between different national markets.

Previous studies have examined a long-term relationship between the housing market and the stock market. However, several of these studies used a linear approach, which could lead to misinformation if the long-term equilibrium relationship is non-linear. Following Tsai et al. (2012), we used the MTAR and TAR non-linear models in view of the different responses of the stock and housing markets to a shock (positive or negative) and the potential impact of the asymmetry on the long-term relationship.

The first step was to test for the presence of asymmetric cointegration. The results suggest a long-term equilibrium relationship with asymmetric adjustments between the housing market and US stock markets. As for the tests between stock markets, the threshold cointegration hypothesis is rejected only for the STOXX index (SPX/STOXX and DJIA/STOXX pairs). The second step was to run an asymmetric error correction model to verify the wealth effect. Whenever stock prices outperform housing above an estimated threshold, the wealth effect is stronger. In addition, when a certain level is reached between the stock price and the housing price, the latter falls, given the cointegration between the markets under these conditions.

In general, the competitiveness and liquidity that characterise these relevant international markets seem to lead them (with the exception of the STOXX) towards a long-term equilibrium relationship with asymmetric adjustments. This means that reversals to equilibrium occur at different rates and may provide better opportunities for short-term risk diversification. These findings are useful for portfolio managers and investors in general, especially as these diversification opportunities have diminished due to globalisation and the increasing correlation between emerging markets (Srivastava 2007).

Further research should continue to test for cointegration between markets at different levels of development and between financial and non-financial indices, using alternative approaches and different time horizons and frequencies.

Author Contributions: Conceptualization, L.G.; methodology, L.G., P.R. and P.C.; software, P.R. and P.C.; validation, L.G. and P.R.; formal analysis, L.G.; investigation, P.C.; resources, P.C.; data curation, P.C.; writing—original draft preparation, P.C.; writing—review and editing, L.G.; visualization, L.G.; supervision, L.G. and P.R.; project administration, L.G. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

References

- Agoraki, Maria-Eleni, Dimitris Georgoutsos, and Georgios Kouretas. 2019. Capital Markets Integration and Cointegration: Testing for the Correct Specification of Stock Market Indices. *Journal of Risk and Financial Management* 12: 186. [CrossRef]
- Ambrose, Brent, Esther Ancel, and Mark Griffiths. 1992. The fractal structure of real estate investment trust returns: A search for evidence of market segmentation and nonlinear dependency. *Journal of the American Real Estate and Urban Economics Association* 20: 25–54. [CrossRef]

- Arshanapalli, Bala, and John Doukas. 1993. International stock market linkages: Evidence from the pre- and post-October 1987 period. *Journal of Banking and Finance* 17: 193–208. [\[CrossRef\]](#)
- Arshanapalli, Bala, John Doukas, and Larry Lang. 1995. Pre and Post-October 1987 Stock Market Linkages between U.S. and Asian Markets. *Pacific-Basin Finance Journal* 3: 57–73. [\[CrossRef\]](#)
- Bahmani-Oskooee, Mohsen, and Tsung-Pao Wu. 2017. Housing prices and real effective exchange rates in 18 OECD countries: A bootstrap multivariate panel Granger causality. *Economic Analysis and Policy* 60: 119–26. [\[CrossRef\]](#)
- Bahmani-Oskooee, Mohsen, and Seyed Hesam Ghodsi. 2018. Asymmetric causality between the U.S. housing market and its stock market: Evidence from state level data. *Journal of Economic Asymmetries* 18: e00095. [\[CrossRef\]](#)
- Balke, Nathan, and Thomas Fomby. 1997. Threshold cointegration. *International Economic Review* 38: 627–45. [\[CrossRef\]](#)
- Byers, David, and David Peel. 1993. Some evidence of interdependence of national stock markets and the gains from international portfolio diversification. *Applied Financial Economics* 3: 239–42. [\[CrossRef\]](#)
- Chan, Kung-Sik. 1993. Consistency and limiting distribution of the least squares estimator of a threshold autoregressive model. *The Annals of Statistics* 21: 520–33. [\[CrossRef\]](#)
- Cheung, Yin-Wong, and Lilian Ng. 1992. Stock Price Dynamics and Firm Size: An Empirical investigation. *The Journal of Finance* 47: 1985–97. [\[CrossRef\]](#)
- Choudhry, Taufiq, Lin Lu, and Ke Peng. 2007. Common Stochastic Trends among Far East Stock Prices: Effects of the Asian Financial Crisis. *International Review of Financial Analysis* 16: 242–61. [\[CrossRef\]](#)
- Dickey, David, and Wayne Fuller. 1979. Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association* 74: 427–31.
- Ding, Haoyuan, Terence Tai-Leung Chong, and Sung Park. 2014. Nonlinear Dependence between Stock and Real Estate Markets in China. *Economics Letters* 124: 526–29. [\[CrossRef\]](#)
- Enders, Walter. 2004. *Applied Econometric Time Series*. New York: John Wiley & Sons, Inc.
- Enders, Walter, and Clive Granger. 1998. Unit-root tests and asymmetric adjustment with an example using the term structure of interest rates. *Journal of Business & Economic Statistics* 16: 304–11.
- Enders, Walter, and Pierre Siklos. 2001. Cointegration and threshold adjustment. *Journal of Business and Economic Statistics* 19: 166–76. [\[CrossRef\]](#)
- Engle, Robert, and Clive Granger. 1987. Co-Integration and Error Correction: Representation, Estimation, and Testing. *Econometrica* 55: 251–76. [\[CrossRef\]](#)
- Fama, Eugene, and James MacBeth. 1973. Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy* 81: 607–36. [\[CrossRef\]](#)
- Fuller, Wayne. 1976. *Introduction to Statistical Time Series*. New York: Wiley, State Publisher.
- Ghosh, Asim, Reza Saidi, and Keith Johnson. 1999. Who Moves the Asia-Pacific Stock Markets: U.S. or Japan? Empirical Evidence Based on the Theory of Cointegration. *The Financial Review* 34: 159–70. [\[CrossRef\]](#)
- Gomes, Luís, Vasco Soares, Sílvia Gama, and José Matos. 2018. Long-term memory in Euronext stock indexes returns: An econophysics approach. *Business and Economic Horizons* 14: 862–81. [\[CrossRef\]](#)
- Granger, Clive. 1981. Some properties of time series data and their use in econometric model specification. *Journal of Econometrics* 16: 121–30. [\[CrossRef\]](#)
- Granger, Clive, and Tae-Hwy Lee. 1989. Investigation of production, sales, and inventory relationships using multicointegration and non-symmetric error correction models. *Journal of Applied Economics* 4: 145–59. [\[CrossRef\]](#)
- Green, Richard. 2002. Stock prices and house prices in California: New evidence of a wealth effect? *Regional Science and Urban Economics* 32: 775–83. [\[CrossRef\]](#)
- Grubel, Herbert. 1968. Internationally Diversified Portfolios: Welfare Gains and Capital Flows. *The American Economic Review* 58: 1299–314.
- Gueye, Ghislain Nono. 2021. Pitfalls in the cointegration analysis of housing prices with the macroeconomy: Evidence from OECD countries. *Journal of Housing Economics* 51: 101748. [\[CrossRef\]](#)
- Hatemi-J, Abdunasser. 2008. Tests for cointegration with two unknown regime shifts with an application to financial market integration. *Empirical Economics* 35: 497–505. [\[CrossRef\]](#)
- Ibbotson, Roger, and Laurence Siegel. 1984. Real estate returns: A comparison with other investments. *AREUEA Journal* 12: 219–42. [\[CrossRef\]](#)
- Kanas, Angelos. 1998. Linkages between the US and European equity markets: Further evidence from cointegration tests. *Applied Financial Economics* 8: 607–14. [\[CrossRef\]](#)
- Kasa, Kenneth. 1992. Common stochastic trends in international stock markets. *Journal of Monetary Economics* 29: 95–124. [\[CrossRef\]](#)
- Kim, Suk-Joong. 2005. Information Leadership in the Advanced Asia-Pacific Stock Markets: Return, Volatility and Volume Information Spillovers from the US and Japan. *Journal of the Japanese and International Economies* 19: 338–65. [\[CrossRef\]](#)
- Kwiatkowski, Denis, Peter Phillips, Peter Schmidt, and Yongcheol Shin. 1992. Testing the null hypothesis of stationarity against the alternative of a unit root. *Journal of Econometrics* 54: 159–78. [\[CrossRef\]](#)
- Lee, Sang Bin, and Kwang Jung Kim. 1994. Does the October 1987 crash strengthen the co-movement in stock price indexes. *Quarterly Review of Economics and Business* 3: 89–102.

- Li, Xiao-Lin, Tsangyao Chang, Stephen Miller, Mehmet Balcilar, and Rangan Gupta. 2015. The co-movement and causality between the U.S. housing and stock markets in the time and frequency domains. *International Review of Economics & Finance* 38: 220–33. [\[CrossRef\]](#)
- Liow, Kim Hiang. 2006. Dynamic relationship between stock and property markets. *Applied Financial Economics* 16: 371–76. [\[CrossRef\]](#)
- Liu, Crocker, David Hartzell, Wylie Greig, and Terry Grissom. 1990. The integration of the real estate market and the stock market: Some preliminary evidence. *The Journal of Real Estate Finance and Economics* 3: 261–82. [\[CrossRef\]](#)
- Liu, Yu-Shao, and Chi-Wei Su. 2010. The relationship between the real estate and stock markets of China: Evidence from a nonlinear model. *Applied Financial Economics* 20: 1741–49. [\[CrossRef\]](#)
- Los, Cornelis, and Bing Yu. 2008. Persistence characteristics of the Chinese stock markets. *International Review of Financial Analysis* 17: 64–82. [\[CrossRef\]](#)
- MacKinnon, James. 2010. *Critical Values for Cointegration Tests*. Queen's Economics Department Working Paper, No. 1227. Kingston: Queen's University, Department of Economics.
- Matos, José, Sílvio Gama, Heather Ruskin, and José Duarte. 2004. An econophysics approach to the Portuguese Stock Index PSI-20. *Physica A: Statistical Mechanics and its Applications* 342: 665–76. [\[CrossRef\]](#)
- McCord, Michael, Daniel Lo, John McCord, Peadar Thomas Davis, and Martin Haran. 2019. Measuring the cointegration of housing types in Northern Ireland. *Journal of Property Research* 36: 343–66. [\[CrossRef\]](#)
- Phillips, Peter, and Pierre Perron. 1988. Testing for a Unit Root in Time Series Regression. *Biometrika* 75: 335–46. [\[CrossRef\]](#)
- Phylaktis, Kate, and Fabiola Ravazzolo. 2005. Stock Market Linkages in Emerging Markets: Implications for International Portfolio Diversification. *Journal of International Financial Markets, Institutions and Money* 15: 91–106. [\[CrossRef\]](#)
- Quan, Daniel, and Sheridan Titman. 1997. Commercial real estate prices and stock market returns: An international analysis. *Financial Analysts Journal* 53: 21–34. [\[CrossRef\]](#)
- Shen, Chung-Hua, Chien-Fu Chen, and Li-Hsueh Chen. 2007. An empirical study of the asymmetric cointegration relationships among the Chinese stock markets. *Applied Economics* 39: 1433–45. [\[CrossRef\]](#)
- Sim, Sung-Hoon, and Byoung-Ky Chang. 2006. Stock and real estate markets in Korea: Wealth or credit–price effect. *Journal of Economic Research* 11: 99–122.
- Srivastava, Aman. 2007. Cointegration of Asian Markets with US Markets: International Diversification Perspectives. *Global Business Review* 8: 251–65. [\[CrossRef\]](#)
- Stehle, Richard. 1997. An Empirical Test of the Alternative Hypotheses of National and International Pricing of Risky Assets. *Journal of Finance* 32: 493–502. [\[CrossRef\]](#)
- Sun, Changyou. 2011. Price dynamics in the import wooden bed market of the United States. *Forest Policy and Economics* 13: 479–87. [\[CrossRef\]](#)
- Taylor, Mark, and Ian Tonks. 1989. The internationalisation of stock markets and the abolition of U.K. exchange control. *Review of Economics and Statistics* 71: 332–36. [\[CrossRef\]](#)
- Tong, Howell, and Kok Sing Lim. 1980. Threshold Autoregression, Limit Cycles and Cyclical Data. *Journal of the Royal Statistical Society Series B* 42: 245–92. [\[CrossRef\]](#)
- Tong, Howell. 1978. On a threshold model. In *Pattern Recognition and Signal Processing*. Edited by C. Chen. NATO ASI Series E: Applied Sciences; Alphen aan den Rijn: Sijthoff & Noordhoff, vol. 29, pp. 575–86. ISBN 9789028609785.
- Tong, Howell. 1983. *Threshold Models in Nonlinear Time Series Analysis*. Lecture Notes in Statistics No. 21. New York: Springer.
- Tsai, I-Chun, Cheng-Feng Lee, and Ming-Chu Chiang. 2012. The asymmetric wealth effect in the US housing and stock markets: Evidence from the threshold cointegration model. *The Journal of Real Estate Finance and Economics* 45: 1005–20. [\[CrossRef\]](#)
- Worzala, Elaine, and Kerry Vandell. 1993. International direct real estate investments as alternative portfolio assets for institutional investors: An evaluation. Paper presented at the 1993 AREUEA Meetings, Anaheim, CA, USA, June 28–July 1.
- Xu, Xiaojie, and Yun Zhang. 2023. Cointegration between housing prices: Evidence from one hundred Chinese cities. *Journal of Property Research* 40: 53–75. [\[CrossRef\]](#)
- Yang, Tracy, and Jamus Jerome Lim. 2004. Crisis, Contagion, and East Asian Stock Markets. *Review of Pacific Basin Financial Markets and Policies* 7: 119–51. [\[CrossRef\]](#)
- Yule, Udny. 1926. Why do we sometimes get nonsense-correlations between time series?—A study in sampling and the nature of time series. *Journal of the Royal Statistical Society* 89: 11–63. [\[CrossRef\]](#)

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.