Investigating whether CME Home Price Index Futures are at Surplus

Fu Shuen Shie

Abstract

This study primarily investigates the hedging problems of the S&P / Case–Shiller Home Price Indices. We provide useful suggestions for the problem of low trading volumes in the current 10 metropolitan home price index futures and one home price composite index future introduced by the Chicago Mercantile Exchange. In addition, we also provide solutions to the lack of relevant home price index futures for hedging in the newly added 10 metropolitan areas. Results show that the 11 current index futures can be further reduced into six index futures, which can also be used as the optimal hedging target of the newly added 10 metropolitan home price indices.

Keywords cointegration, unequal variance test, home price indices

I. Introduction

Among various national economic indices, stock and real estate markets are the most reliable indicators for reflecting economic conditions. Between stock and real estate markets, the economic climate of the real estate market has even been considered an "economic locomotive." The development of the real estate market influences the development of numerous industries such as real estate agencies and the steel, cement, construction material, and financial industries. The subprime mortgage crisis showed that when a real estate market bubble emerges, the credit market was impacted first, which further evolved into a global financial crisis. Thus, the financial industry must further analyze and monitor the developments in the real estate market. The emergence of a real estate market bubble causes constantly rising inflation and the possibility of severe recession when the bubble bursts. Ultimately, this exposes the banking industry to increased risks. Investors in the financial, real estate-related, and real estate industries possess relatively expansive portfolios. Thus, studying how those in the financial or related industries or even public real estate owners can implement hedging at an opportune moment is one of the motives of this study.

Based on the results of previous research, the fluctuation risks of real estate spot prices seem to be avoidable in forward house or presale contract markets. This is particularly common in several Asian countries (Lai et al. 2004; Chau et al. 2007; Fan et al. 2012). Forward house or presale contract markets refer to advanced contract signing and prearranged transaction prices and transfer dates before the completion of real estate construction processes. This is identical in concept to forward contracts or futures. The difference with forward contracts is that a deposit with a specific proportion of the agreed real estate price must be paid at the time of signing in forward house or presale contracts. Contrary to the concept of futures, the biggest difference is that all forward house or presale contracts are provided with a series of payment schedules; ultimately, the remaining amount is paid on the transfer date. This method of delivery is completely different to forward contracts and futures. Fan et al. (2012) also indicated that four differences exist between standard and real estate forward transactions. Their investigation also exposed drastic differences between forward house or presale contracts and forward contracts or futures in hedging.

Furthermore, Edelstein et al. (2012) indicated that before the subprime mortgage crisis, the prosperity of the U.S. real estate market has driven house or presale contracts to become the main transaction method in numerous housing markets in the United States. This included the apartment markets in San Diego, Washington, D.C., and South Florida. However, along with the subprime mortgage crisis, the real estate downturn in the United States indicated that forward house or presale contracts are not the optimal instruments for hedging. Thus, the importance of developing real estate derivatives has become apparent.

This shows that fluctuation risks in real estate spot prices may be avoided through forward house or presale contract markets; however, these types of markets involve increased costs. Moreover, large sums of penalties must be paid in breach of contract cases. Except for breaches of contract, buyers are indifferent to average real estate owners, who must also confront the risks of falling prices. By contrast, sellers also expose themselves to the risks of rising prices, especially the prices of raw building materials. Thus, buyers and sellers still require low-cost and suitable hedging instruments even in forward house or presale contract markets. As indicated by Ortalo-Magné and Rady (2002), the hedging effects of real estate stocks or relevant financial securities are ineffective toward the idiosyncratic risks of local housing markets. In addition, real estate stocks or relevant financial securities have high costs. Thus, the possibility of developing increasingly local real estate derivatives such as local real estate index derivatives can improve hedging effects (Case and Shiller, 1996). Englund et al. (2002) and Shiller (2003) have also indicated that real estate indices are required for risk hedging real estate prices. Thus, suitable hedging targets were emphasized in this study, specifically home price index derivatives.

As mentioned by McDuff (2012) in a previous study regarding home price indices, Bailey et al. (1963) were the first to propose calculation methods for repeat-sales home price index by using regression.[1] However, home price indices became the common calculation method, which was proposed by Case and Shiller (1987, 1989). Between these two authors, Shiller became one of the three winners of the 2013 Nobel Memorial Prize in Economic Sciences. Case et al. (1993) further indicated that to enable real estate owners to effectively hedge, real estate derivative markets must be quickly developed. Subsequently, Case, Shiller, and Weiss formed a company, Case Shiller Weiss, by adopting Case and Shiller’s (1987, 1989) methodology, which used repeat sales pricing to organize and subsequently sell real estate market data. In 2002, Fiserv bought Case Shiller Weiss and introduced the commercial natured Case–Shiller indices. In 2006, Standard & Poor’s (S&P) became partners of Fiserv, who statistically analyzed and published the S&P/Case–Shiller Home Price Indices. Since 1987, these indices have been available to primarily provide statistical analyses on home price indices in 10 major U.S. metropolitan areas as well as their respective composite indices (Composite-10, CSXR). Since January 2000, 20 major metropolitan home price indices and their respective composite indices (Composite-20, SPCS20R)[2] were added. In addition, 10 major U.S. metropolitan home price index futures and their respective composite home price index futures were introduced in the Chicago Mercantile Exchange (CME).

Although the S&P/Case–Shiller Home Price Indices introduced 20 metropolitan home price indices, the corresponding home price index futures of the 10 newly added metropolitan areas were not introduced. Thus, real estate owners in these 10 metropolitan areas were unable to determine optimal hedging strategies. The primary reason may be related to a viewpoint provided by McDuff (2012), which indicated the insufficient trading volume in the 10 newly

[1]Repeat sales pricing refers to data obtained from real estate properties that have been sold more than twice: When a real estate property was repeatedly sold, its new price was compared with the previous price after a period of time, from which real estate price change data were then obtained.
[2]Indices were statistically analyzed monthly and published 2 months later.

added metropolitan areas. Thus, we considered this as the primary reason that the CME did not introduce the home price index futures of these areas. However, because lacking such an instrument is disadvantageous, determining relevant hedging instruments by using present indices has become crucial. Consequently, two motives for this study have emerged: 1) to investigate why the CME home price index future trading volumes are low and 2) to devise a method for providing the 10 newly added metropolitan areas with related home price index futures for hedging.

Previous studies on futures have mentioned that the optimal target for avoiding risks in spot commodities is through their respective derivatives. If a spot commodity does not have its own derivative, financial instruments with strong relevance must be found to obtain the optimal hedging effect. When spot commodity indices exhibit nonstationary properties (i.e., unit root), spurious regression can result in regression analyses. A majority of previous studies on stock indices has adopted cointegration models to investigate their relationships. However, cointegration models cannot solve the problems specified in this study. Instead, cointegration models can only determine the existence of long-run equilibrium relationship between each capital market. The extent of the dependency between long-run equilibrium relationships cannot be distinguished. Specifically, cointegration models cannot identify which relevant home price index future is the optimal relevant hedging instrument. A testing method proposed by Lee et al. (2012) solved this problem; they derived a new test in the cointegration framework, which was named the unequal variance test (UVT). This test was used as the empirical basis of this study.

The remainder of this paper is organized as follows: The next section introduces the methodology. The third section provides a description of the data and the empirical results, and the last section presents the conclusion.

II. Methodology

We conducted an empirical study based on the research method proposed by Lee et al. (2012). Because unit root and cointegration tests are fairly mature, the relevant models are not listed in this study. Among these models, the Augmented Dickey Fuller (ADF) and Phillips and Perron (PP) unit root tests were adopted in this study. Moreover, because the UVT was derived from the Engle–Granger methodology (Engle and Granger, 1987), the Engle–Granger methodology was used for conducting cointegration tests for determining the existence of equilibrium relationships.

Cointegration can only determine whether each index exhibits long-run equilibrium relationships. If all the variables were input into the model, only a few cointegration relationships can be determined. However, this was not the purpose of this investigation. Thus, we paired the S&P/Case–Shiller Home Price Indices and identified optimal hedging targets from cointegrated indices by using the UVT analysis. The home price indices studied are shown in Table 1.

Table 1 The 20 major metropolitan home price indices and the two composite home price indices.

Index	Home Price Index Description	Metropolitan Statistical Area (MSA) Designation
BO	Greater Boston	Boston–Cambridge–Quincy, MA
CH	Chicago metropolitan area	Chicago–Naperville–Joliet, IL–IN–WI
DN	Denver-Aurora Metropolitan Area	Denver–Aurora, CO
LV	Las Vegas metropolitan area	Las Vegas, NV-AZ
LX	Greater Los Angeles	Los Angeles–Long Beach–Santa Ana, CA
MI	South Florida metropolitan area	Miami–Fort Lauderdale–Pompano Beach, FL
NY	New York metropolitan area	New York–Northern New Jersey–Long Island, NY–NJ–PA
SD	San Diego County, California	San Diego–Carlsbad–San Marcos, CA
SF	San Francisco	San Francisco–Oakland–Fremont, CA
WD	Washington Metropolitan Area	Washington–Arlington–Alexandria, DC–VA–MD–WV
AT	Atlanta metropolitan area	Atlanta–Sandy Springs–Marietta, GA
CR	Charlotte metropolitan area	Charlotte-Gastonia-Concord, NC-SC
CE	Greater Cleveland	Cleveland–Elyria–Mentor, OH
DA	Dallas/Fort Worth Metroplex	Dallas–Fort Worth–Arlington, TX
DE	Metro Detroit	Detroit–Warren–Livonia, MI
MN	Minneapolis-Saint Paul	Minneapolis–St. Paul–Bloomington, MN–WI
PH	Phoenix metropolitan area	Phoenix–Mesa–Scottsdale, AZ
PO	Portland metropolitan area	Portland–Vancouver–Beaverton, OR–WA
SE	Seattle metropolitan area	Seattle–Tacoma–Bellevue, WA
TP	Tampa Bay Area	Tampa–St. Petersburg–Clearwater, FL
CS10	Composite-10	A composite index of the top 10 MSA's in the country
CS20	Composite-20	A composite index of the top 20 MSA's in the country

Source: S&P Dow Jones Indices

The model used in this study was set up as follows:

$$HPI_{kt} = \alpha_i + \beta_i HPI_{it} + \gamma_i t + \varepsilon_{k\_i,t},$$
$$HPI_{kt} = \alpha_j + \beta_j HPI_{jt} + \gamma_j t + \varepsilon_{k\_j,t}. \quad i \neq j \neq k \quad t = 1, 2, 3, ..., T \qquad (1)$$

where HPI_{kt} represents the home price index of k at time t; α_i, α_j, β_i, β_j, γ_i, and γ_j are coefficients; HPI_{it} and HPI_{jt} represent the home price indices of i and j at time t; $i, j, k \in (\text{BO}, \text{CH}, ..., \text{CS10}, \text{CS20})$; and $\varepsilon_{k\_i,t}$ and $\varepsilon_{k\_j,t}$ are residual terms of the regression model. For further information regarding these two residual terms, please refer to Hypothesis 1 by Lee et al. (2012).

Therefore, the null and alternative hypotheses to be investigated in this study from the above investigation were formed as follows:

$$H_0 : \sigma^2_{k\_i} = \sigma^2_{k\_j} \quad \text{v.s.}$$
$$H_1 : \sigma^2_{k\_i} < \sigma^2_{k\_j}. \quad i \neq j \neq k$$

In these hypotheses, $\sigma^2_{k\_i}$ and $\sigma^2_{k\_j}$ represent the respective population variances of $\varepsilon_{k\_i,t}$ and $\varepsilon_{k\_j,t}$.

The least squares method was used to estimate the parameters of model (1): $(\hat{\alpha}_i, \hat{\beta}_i, \hat{\gamma}_i)$ and

$(\hat{\alpha}_j, \hat{\beta}_j, \hat{\gamma}_j)$. As derived by Hansen (1992) and Davidson (2000), the rate of convergence of these two sets of parameters were both $(T^{1/2}, T^{3/2}, T)$. Thus, the population variance estimators $\sigma^2_{k\_i}$ and $\sigma^2_{k\_j}$ for $\varepsilon_{k\_i,t}$ and $\varepsilon_{k\_j,t}$ were obtained as follows:

$$\hat{\sigma}^2_{k\_i} = \frac{1}{T-3}\sum_{t=1}^{T}(HPI_{kt} - \hat{\alpha}_i - \hat{\beta}_i HPI_{it} - \hat{\gamma}_i t)^2$$
$$\hat{\sigma}^2_{k\_j} = \frac{1}{T-3}\sum_{t=1}^{T}(HPI_{kj} - \hat{\alpha}_j - \hat{\beta}_j HPI_{jt} - \hat{\gamma}_j t)^2 . \quad i \neq j \quad t = 1,2,3,...,T \qquad (2)$$

Assume that $\hat{\varepsilon}_{k\_i,t} = HPI_{kt} - \hat{\alpha}_i - \hat{\beta}_i HPI_{it} - \hat{\gamma}_i t$ and that $\hat{\varepsilon}_{k\_j,t} = HPI_{kt} - \hat{\alpha}_j - \hat{\beta}_j HPI_{jt} - \hat{\gamma}_j t$ are the respective estimators for $\varepsilon_{k\_i,t}$ and $\varepsilon_{k\_j,t}$. The following were obtained by substituting these estimators into (2).

$$\hat{\sigma}^2_{k\_i} = \frac{1}{T-3}\sum_{t=1}^{T}\hat{\varepsilon}^2_{k\_i,t}$$
$$\hat{\sigma}^2_{k\_j} = \frac{1}{T-3}\sum_{t=1}^{T}\hat{\varepsilon}^2_{k\_j,t} . \quad i \neq j \neq k \quad t = 1,2,3,...,T \qquad (3)$$

Lastly, test statistic (Z_0) theorized by Lee et al. (2012) can be obtained from the above results:

$$Z_0 = \frac{(\hat{\sigma}^2_{k\_i} - \hat{\sigma}^2_{k\_j})}{(\frac{\hat{V}_{\varepsilon_{k\_i}}}{T} + \frac{\hat{V}_{\varepsilon_{k\_j}}}{T})^{1/2}} \sim N(0,1), \quad i \neq j \neq k \qquad (4)$$

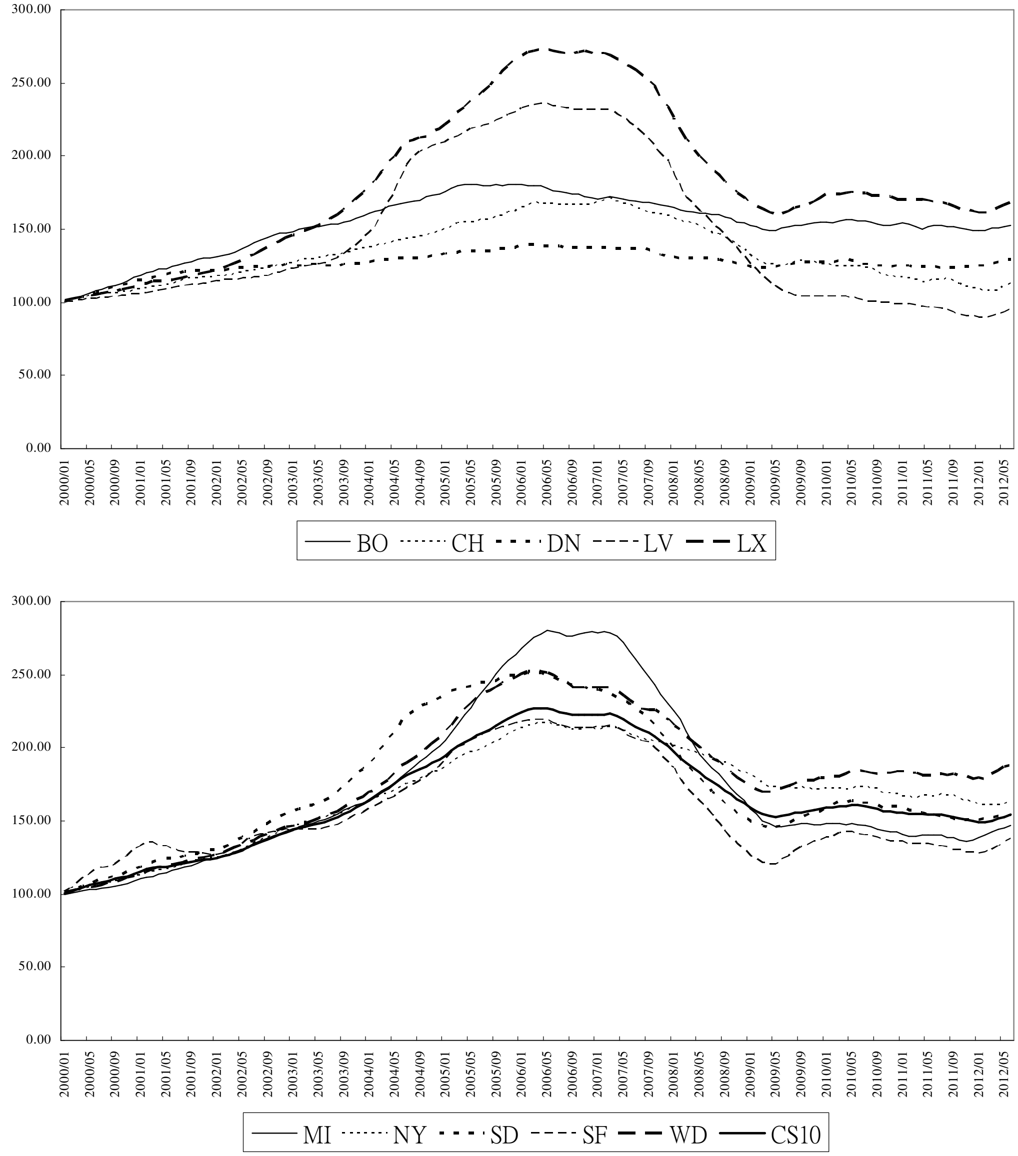
where $\hat{V}_{\varepsilon_{k\_i}} = \mathrm{var}(T^{-1/2}\sum_{t=1}^{T}\hat{\varepsilon}^2_{k\_i,t})$ and $\hat{V}_{\varepsilon_{k\_j}} = \mathrm{var}(T^{-1/2}\sum_{t=1}^{T}\hat{\varepsilon}^2_{k\_j,t})$. This study adopted (4) as the primary test method.

III. Data and Empirical Results

Data and Descriptive Statistics

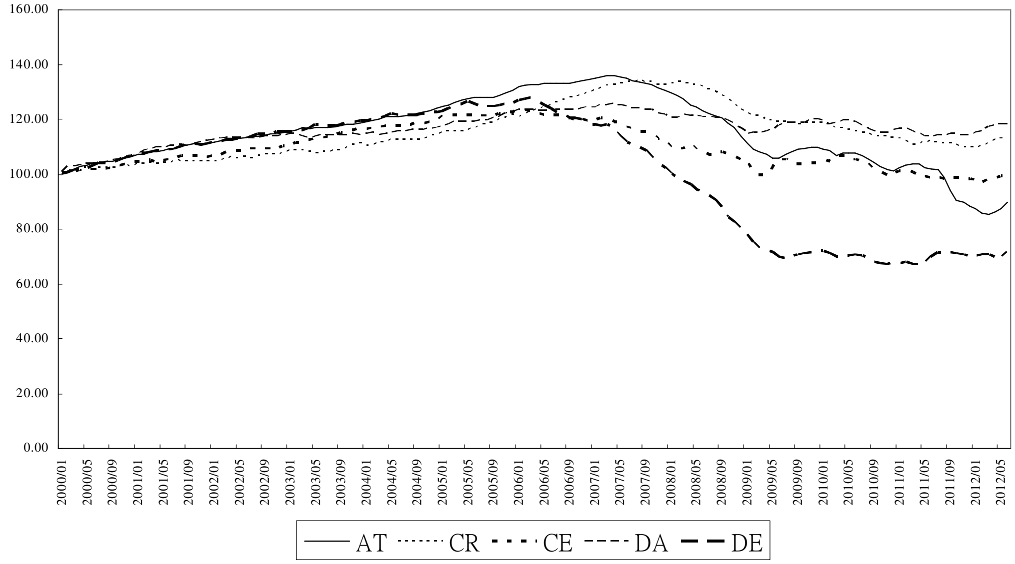
The study data were obtained from the S&P/Case–Shiller Home Price Indices provided by S&P Dow Jones Indices, which comprised 20 major metropolitan home price indices and two composite home price indices (CS10 and CS20). S&P Dow Jones Indices added 20 major US metropolitan home price indices since January 2000; thus, the data covered a study period that ranged from January 2000 to June 2012 (a total of 150 months). To eliminate seasonal factors, this study adopted seasonally adjusted data provided by the S&P Indices. As indicated by the S&P Indices in the S&P/Case–Shiller Home Price Indices and Seasonal Adjustment descriptions, the "seasonal adjustment of economic time series is typically achieved using a computer program, Census X-12-ARIMA, which is distributed and maintained by the U.S. Census Bureau." Figure 1 and Figure 2 show the graphical depictions of these chosen home price indices. The descriptive statistics for home price indices are shown in Table 2.

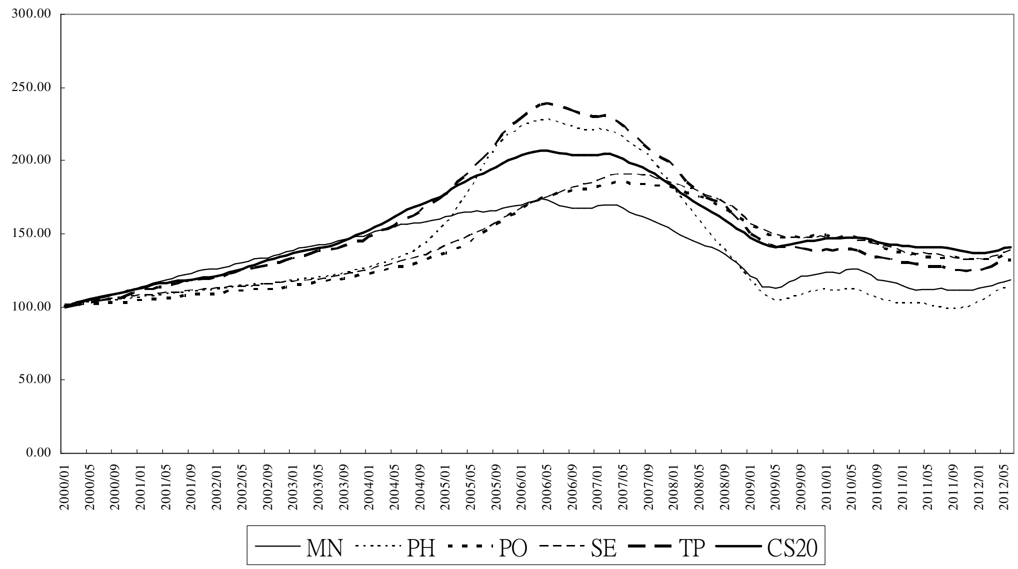
Figure 1 Ten earlier major metropolitan areas home price indexes and 10-City Composites home price index.



Notes: The ten regions used in the Composite of 10 (CS10) are: Boston (BO), Chicago (CH), Denver (DN), Las Vegas (LV), Los Angeles (LX), Miami (MI), New York (NY), San Diego (SD), San Francisco (SF), and Washington DC (WD).

Figure 2 Other ten major metropolitan areas home price indexes and 20-City Composites home price index.





Notes: The ten additional regions used in the Composite of 20 (CS20) are: Atlanta (AT), Charlotte (CR), Cleveland (CE), Dallas (DA), Detroit (DE), Minneapolis (MN), Phoenix (PH), Portland (PO), Seattle (SE), and Tampa (TP).

Table 2 Descriptive statistics for the 20 major metropolitan home price indices and the two composite home price indices.

Panel A	10 earlier major metropolitan areas and 10-City Composites									
	BO	CH	DN	LV	LX	MI	NY	SD	SF	WD	CS10
Mean	152.9627	133.6055	126.8926	145.9631	181.5821	172.5663	167.5903	175.2671	156.1940	179.3987	164.8856
Median	153.7000	127.5550	126.8350	121.1900	170.8700	148.1350	171.7250	159.7050	141.6100	181.4350	156.8950
Maximum	180.8000	171.2000	139.3600	235.7600	273.1100	280.1500	216.5900	251.7100	219.2500	252.8700	226.9000
Maximum date	2005/11	2007/03	2006/03	2006/04	2006/04	2006/05	2006/05	2006/03	2006/03	2006/03	2006/04
Minimum	100.9200	100.5600	100.6600	90.1500	101.0300	99.9400	100.3400	101.1000	101.4500	100.8700	100.7500
Std. Dev.	19.8225	20.5097	8.0061	51.0998	51.3536	54.5003	32.8232	44.3032	33.8640	42.4990	35.4948
Skewness	-0.8075	0.3369	-0.9598	0.6593	0.3691	0.7804	-0.3745	0.3974	0.7076	-0.0478	0.2266
Kurtosis	3.1659	1.8059	4.4895	1.7837	2.1025	2.3339	2.2170	1.9150	2.0511	2.1450	2.1080
Panel B	**Other 10 major metropolitan areas and 20-City Composites**										
	AT	CR	CE	DA	DE	MN	PH	PO	SE	TP	CS20
Mean	115.0908	115.4454	109.8593	116.2831	101.1025	136.4662	138.7368	139.5233	141.5960	155.3528	153.2286
Median	114.0900	113.0800	108.1600	115.9000	109.0000	132.3450	116.0300	136.3000	137.6450	139.4000	145.2400
Maximum	136.0400	133.8700	123.3500	125.6800	127.7500	173.8200	228.0700	185.4400	190.6000	239.0400	206.6400
Maximum date	2007/04	2007/08	2006/01	2007/04	2006/03	2006/04	2006/05	2007/04	2007/05	2006/05	2006/04
Minimum	85.2500	100.6600	97.1800	100.7100	67.2400	100.1900	99.1200	100.5900	101.0800	100.0800	100.5900
Std. Dev.	12.6681	9.6008	7.8984	5.4404	21.2374	21.8133	42.8814	26.3106	26.4471	40.1864	30.0515
Skewness	-0.1915	0.5081	0.2255	-0.5645	-0.5159	0.2189	1.0414	0.2609	0.3543	0.7742	0.3437
Kurtosis	2.4581	2.1830	1.7171	3.1977	1.6556	1.6375	2.5087	1.8818	1.9987	2.3497	2.0906

Notes: The ten regions used in the Composite of 10 (CS10) are: Boston (BO), Chicago (CH), Denver (DN), Las Vegas (LV), Los Angeles (LX), Miami (MI), New York (NY), San Diego (SD), San Francisco (SF), and Washington DC (WD), and the ten additional regions used in the Composite of 20 (CS20) are: Atlanta (AT), Charlotte(CR), Cleveland (CE), Dallas (DA), Detroit (DE), Minneapolis (MN), Phoenix (PH), Portland (PO), Seattle (SE), Tampa (TP).

As indicated by Edelstein et al. (2012), the U.S. real estate market prospered prior to the subprime mortgage crisis. This can be seen in Fig. 1–2 and Table 2 in which all maximum indices appeared before the occurrence of the crisis. From the time of occurrence of the maximum value in Table 2, the prosperous period spanned from November 2005 to August 2007. Since August 2007, all the indices presented an overall decline. By contrast, the maximum values stated in this study (see Table 2) were obtained during March 2006 and May 2006: the period of March 2006 comprised maximum values from DN, SD, SF, WD, and DE; the period of April 2006 comprised maximum values from LV, LX, CS10, MN, and CS20; and the period May 2006 comprised maximum values from MI, NY, PH, and TP. Thus, after eliminating CS10 and CS20, the maximum values from 12 out of 20 major metropolitan areas occurred between March 2006 and May 2006. This showed that the most prosperous time point for each real estate market region occurred within the same period. Based on the standard deviations shown in Table 2, the South Florida metropolitan area (MI) presented the most drastic index fluctuation, which reached 54.5003; Greater Los Angeles (LX) and the Las Vegas metropolitan area (LV) followed with the second and third most drastic index fluctuations, respectively, with 51.3536 and 51.0998. This showed that the real estate price limits in these three areas were relatively large. By contrast, real estate prices in the Dallas/Fort Worth Metroplex (DA), Greater Cleveland (CE), and the Denver-Aurora Metropolitan Area (DN) were relatively stable; the real estate fluctuations in these regions were respectively 5.4404, 7.8984, and 8.0061. The aforementioned data analysis showed the inclusion of information before and after the subprime mortgage crisis; thus, the empirical results are expected to be a highly valuable reference.

This study used the ADF and PP unit root tests to test whether each index is a unit root, and the results are presented in Table 3.

Panel A from Table 3 shows that all home-price indices below 10% significance cannot reject the nonstationarity hypothesis, which refers to the inclusion of unit roots in all variables. Panel B shows that after first difference, all the indices from the results of the ADF and PP were below 10% significance and rejected the nonstationarity hypothesis. Generally, all home price indices were confirmed to be integrated of order one, I(1). This is similar to the statement by Lee et al. (2012) that the traditional regression model can therefore not be adapted to discuss the relationships between pairs of metropolitan areas, and a spurious regression model is necessary.

Next, this study used the Engle–Granger cointegration test and the UVT to respectively identify the existence of long-run equilibrium relationships between each index and determine the optimal alternative indices.

Optimal Hedging Indices for the 10 Newly Added Home Price Indices

A purpose of this study was to identify the optimal hedging channels for the 10 newly added indices. Thus, determining relevant hedging targets by using current indices is the optimal method. Model (1) was used to test the newly added 10 major metropolitan home price indices as well as the other 10 indices (i.e., BO, CH, DN, LV, LX, MI, NY, SD, SF, WD, and the addition of CS10). After pairing the indices, the Engle–Granger cointegration test was adopted to identify the cointegration relationships, which were $k \in (\text{AT}, \text{CR}, \text{CE}, \text{DA}, \text{DE}, \text{MN}, \text{PH}, \text{PO}, \text{SE}, \text{TP})$ and $i \in (\text{BO}, \text{CH}, \text{DN}, \text{LV}, \text{LX}, \text{MI}, \text{NY}, \text{SD}, \text{SF}, \text{WD}, \text{CS10})$. The results are presented in Table 4.

Table 4 shows that the newly added 10 major metropolitan home price indices and the other 11 indices below a 10% significance collectively exhibited cointegration relationships (i.e., long-run equilibrium relationships). However, as Lee et al. (2012) stated, the different levels of co-movement among these home price indices relative to other specific home price indices cannot be distinguished. Thus, UVT was subsequently used to analyze and identify the optimal hedging indices: (4) was used to test and determine the relative indices with minimum variation. To prevent a lengthy presentation of the results, paired comparisons of each index $k \in (\text{AT}, \text{CR}, \text{CE}, \text{DA}, \text{DE}, \text{MN}, \text{PH}, \text{PO}, \text{SE}, \text{TP})$ relative to $i, j \in (\text{BO}, \text{CH}, \text{DN}, \text{LV}, \text{LX}, \text{MI}, \text{NY}, \text{SD}, \text{SF}, \text{WD}, \text{CS10})$ were organized and presented using the three first indices, which had the least variation. These results are presented in Table 5.

Table 5 shows that by considering only the magnitude of the negative signs in the test statistics without considering significance, the optimal hedging index for four indices (i.e., AT, CR, PO, and SE) were CH; the optimal hedging index for two indices (i.e., PH and TP) were MI; and the optimal hedging indices for the remaining indices (i.e., CE, DA, DE, and MN) were respectively BO, DN, SD, and CS10. Thus, the 10 new indices that we suggest adding can serve as the hedging indices as indicated by the present analysis. This means that these indices can be hedged using their corresponding futures. Relative to other indices, $\hat{\sigma}^2_{\text{AT\_CH}}$, $\hat{\sigma}^2_{\text{PH\_MI}}$, and $\hat{\sigma}^2_{\text{TP\_MI}}$ collectively showed less significance. Thus, AT, PH, and TP supposedly possess exceptional hedging effects. However, this did not solve the present problem of low future trading volumes; attempted resolutions are presented in the following sections.

Table 3 Unit root tests in S&P/ Case–Shiller home price indices

Panel A	Price level										
	BO	CH	DN	LV	LX	MI	NY	SD	SF	WD	CS10
ADF	0.382	0.069	1.013	-0.703	-0.305	-0.571	0.284	-0.536	-0.302	0.115	-0.027
PP	1.137	0.122	1.302	-0.375	0.193	-0.044	0.852	0.156	0.085	0.707	0.404
	AT	CR	CE	DA	DE	MN	PH	PO	SE	TP	CS20
ADF	-0.354	0.238	-0.206	0.984	-0.728	-0.011	-0.486	0.235	0.059	-0.361	-0.182
PP	-0.452	0.560	-0.108	1.402	-0.927	0.163	-0.251	0.531	0.481	0.039	0.358
Panel B	First difference										
	BO	CH	DN	LV	LX	MI	NY	SD	SF	WD	CS10
ADF	-2.268 ***	-3.012 ***	-4.716 ***	-1.901 *	-1.801 *	-1.669 *	-2.069 **	-2.273 **	-2.527 **	-1.938 *	-1.734 *
PP	-4.216 ***	-4.154 ***	-4.630 ***	-2.067 **	-1.943 *	-1.741 *	-2.806 ***	-2.091 **	-2.602 ***	-2.278 **	-1.698 *
	AT	CR	CE	DA	DE	MN	PH	PO	SE	TP	CS20
ADF	-3.363 ***	-2.252 **	-4.128 ***	-3.906 ***	-2.074 **	-2.880 ***	-2.096 **	-1.670 *	-1.817 *	-1.884 *	-1.801 *
PP	-3.853 ***	-7.710 ***	-8.280 ***	-7.621 ***	-4.335 ***	-4.277 ***	-1.868 *	-2.674 ***	-3.336 ***	-2.268 **	-1.704 *

Notes: The ten regions used in the Composite of 10 (CS10) are: Boston (BO), Chicago (CH), Denver (DN), Las Vegas (LV), Los Angeles (LX), Miami (MI), New York (NY), San Diego (SD), San Francisco (SF), and Washington DC (WD), and the ten additional regions used in the Composite of 20 (CS20) are: Atlanta (AT), Charlotte (CR), Cleveland (CE), Dallas (DA), Detroit (DE), Minneapolis (MN), Phoenix (PH), Portland (PO), Seattle (SE), Tampa (TP). ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

The Possibility of Further Reducing the Number of Present Future Indices

The previous section shows that indices such as BO, CH, DN, MI, SD, and CS10 can be used as optimal hedging indices for the newly added 10 metropolitan indices. Based on this result, we determined whether the other five indices (i.e., LV, LX, NY, SF, and WD) can be further hedged by other indices. We emphasize that a commodity's own derivative remains as the optimal hedging commodity. Similarly, the Engle–Granger cointegration test was applied to identify cointegration relationships: $k \in (\mathrm{LV, LX, NY, SF, WD})$ and $i \in (\mathrm{BO, CH, DN, MI, SD, CS10})$ (shown in Table 6). Similar to Table 4, cointegration relationships that have a significance of below 10% are collectively shown in Table 6. Thus, the UVT can be used to analyze the optimal hedging indices. These results were organized in Table 7. In Table 7, with the exception of the optimal hedging index for NY being CH, the optimal hedging index for all remaining indices was CS10. Thus, CH can be selected as the optimal hedging target for NY and CS10 can be selected as the optimal hedging target for the remaining indices. Furthermore, as a suggestion, the volumes of the LV, LX, NY, SF, and WD index futures can be reduced.

IV. Conclusion

The major contribution of this study is applying the model by Lee et al. (2012) for solving the problem of low home price index future trading volumes and identifying the most suitable hedging targets for the newly added 10 metropolitan indices.

The results showed that the maximum values for each index occurred between November 2005 and August 2007, during which the maximum values for 12 major metropolitan areas were concentrated between March 2006 and May 2006. This observation was identical to that by Edelstein et al. (2012). All home price indices consisted of I(1). Thus, traditional regression analysis can result in spurious regressions. Thus, this study adopted the Engle–Granger cointegration test and UVT to identify long-run equilibrium relationships between each index and determine the optimal hedging indices, respectively.

The results also showed that indices such as BO, CH, DN, MI, SD, and CS10 can be used as optimal hedging indices for the newly added 10 primary metropolitan home price indices. In addition, we suggest that the volumes of the five index futures of LV, LX, NY, SF, and WD be reduced; therefore, the present 11 index futures can be reduced to six index futures.

Table 4 Engle-Granger cointegration test in 10 newly added indices between different home price indices

Index		BO	CH	DN	LV	LX	MI	NY	SD	SF	WD	CS10
AT	ADF	-2.207 **	-2.268 **	-2.283 **	-2.815 ***	-2.571 **	-2.778 ***	-3.061 ***	-2.161 **	-1.635 *	-2.294 **	-2.397 **
	PP	-2.603 ***	-2.042 **	-2.214 **	-1.693 *	-2.530 **	-2.760 ***	-3.069 ***	-2.064 **	-2.519 **	-2.237 **	-2.340 **
CR	ADF	-2.344 **	-1.632 *	-1.712 *	-1.862 *	-2.002 **	-2.003 **	-1.992 **	-1.977 **	-1.632 *	-1.935 *	-1.902 *
	PP	-2.993 ***	-1.768 *	-2.254 **	-2.128 **	-2.299 **	-2.303 **	-2.168 **	-2.280 **	-2.003 **	-2.270 **	-2.155 **
CE	ADF	-2.719 ***	-2.314 **	-2.848 ***	-2.305 **	-2.422 **	-1.969 **	-1.796 *	-2.930 ***	-1.736 *	-2.335 **	-2.211 **
	PP	-2.745 ***	-3.717 ***	-3.010 ***	-2.498 **	-2.605 ***	-2.183 **	-1.914 *	-3.142 ***	-1.768 *	-2.544 **	-2.351 **
DA	ADF	-2.212 **	-3.118 ***	-2.105 **	-2.729 ***	-2.729 ***	-3.018 ***	-3.011 ***	-2.301 **	-2.447 **	-2.493 **	-3.373 ***
	PP	-2.317 **	-3.682 ***	-1.935 *	-3.392 ***	-3.430 ***	-3.797 ***	-3.554 ***	-2.773 ***	-2.875 ***	-3.191 ***	-2.775 ***
DE	ADF	-2.316 **	-2.937 ***	-2.657 ***	-1.679 *	-1.842 *	-1.894 *	-1.957 **	-2.890 ***	-2.927 ***	-2.140 **	-1.939 *
	PP	-4.246 ***	-39.004 ***	-2.784 ***	-2.205 **	-2.110 **	-2.048 **	-1.815 *	-2.038 **	-2.784 ***	-2.126 **	-15.624 ***
MN	ADF	-2.397 **	-1.745 *	-3.340 ***	-3.436 ***	-3.368 ***	-2.856 ***	-2.443 **	-3.227 ***	-2.785 ***	-3.047 ***	-2.970 ***
	PP	-2.561 **	-1.640 *	-3.476 ***	-3.355 ***	-3.283 ***	-2.918 ***	-2.887 ***	-3.293 ***	-2.577 **	-3.027 ***	-2.962 ***
PH	ADF	-3.420 ***	-2.849 ***	-2.499 **	-3.155 ***	-2.654 ***	-3.139 ***	-2.696 ***	-3.263 ***	-2.709 ***	-3.093 ***	-3.083 ***
	PP	-3.413 ***	-2.655 ***	-2.876 ***	-3.358 ***	-3.039 ***	-3.302 ***	-5.154 ***	-3.079 ***	-3.050 ***	-5.681 ***	-3.286 ***
PO	ADF	-2.890 ***	-3.267 ***	-2.079 **	-2.089 **	-2.564 **	-1.934 *	-2.866 ***	-2.579 **	-2.077 **	-3.439 ***	-2.702 ***
	PP	-4.416 ***	-3.536 ***	-2.245 **	-2.489 **	-2.608 ***	-3.655 ***	-4.355 ***	-3.277 ***	-2.487 **	-2.744 ***	-3.644 ***
SE	ADF	-3.924 ***	-3.350 ***	-2.413 **	-2.504 **	-2.669 ***	-2.933 ***	-3.133 ***	-2.906 ***	-2.302 **	-3.599 ***	-3.315 ***
	PP	-3.662 ***	-13.021 ***	-2.452 **	-2.621 ***	-2.265 **	-3.177 ***	-4.298 ***	-2.720 ***	-2.428 **	-2.125 **	-2.216 **
TP	ADF	-2.928 ***	-3.600 ***	-2.113 **	-4.317 ***	-2.923 ***	-1.875 *	-3.449 ***	-1.964 **	-2.920 ***	-1.774 *	-2.444 **
	PP	-3.363 ***	-2.738 ***	-2.924 ***	-4.278 ***	-2.934 ***	-2.324 **	-2.159 **	-2.636 ***	-3.444 ***	-1.896 *	-2.589 ***

Notes: The ten regions used in the Composite of 10 (CS10) are: Boston (BO), Chicago (CH), Denver (DN), Las Vegas (LV), Los Angeles (LX), Miami (MI), New York (NY), San Diego (SD), San Francisco (SF), and Washington DC (WD), and the other are Atlanta (AT), Charlotte(CR), Cleveland (CE), Dallas (DA), Detroit (DE), Minneapolis (MN), Phoenix (PH), Portland (PO), Seattle (SE), Tampa (TP). ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

International Research Journal of Applied Finance ISSN 2229 – 6891
Vol. VI Issue – 6 June, 2015

Table 5 The unequal variances tests in 10 newly added indices between different home price indices

AT		$\hat{\sigma}^2_{AT\_BO}$	$\hat{\sigma}^2_{AT\_CH}$	$\hat{\sigma}^2_{AT\_DN}$	$\hat{\sigma}^2_{AT\_LV}$	$\hat{\sigma}^2_{AT\_LX}$	$\hat{\sigma}^2_{AT\_MI}$	$\hat{\sigma}^2_{AT\_NY}$	$\hat{\sigma}^2_{AT\_SD}$	$\hat{\sigma}^2_{AT\_SF}$	$\hat{\sigma}^2_{AT\_WD}$	$\hat{\sigma}^2_{AT\_CS10}$
	$\hat{\sigma}^2_{AT\_CH}$	-2.7550 ***	0.0000	-2.4863 ***	-2.2455 **	-2.1809 **	-1.9265 **	-1.2962 *	-2.4941 ***	-2.1772 **	-2.3656 ***	-1.9401 **
	$\hat{\sigma}^2_{AT\_NY}$	-2.3156 **	1.2962	-2.0430 **	-1.5657 *	-1.5165 *	-1.2558	0.0000	-2.0604 **	-1.6810 **	-1.7815 **	-1.1295
	$\hat{\sigma}^2_{AT\_CS10}$	-1.5464 *	1.9401	-1.2824 *	-0.5147	-0.4893	-0.2510	1.1295	-1.3143 *	-0.8620	-0.8305	0.0000
CR		$\hat{\sigma}^2_{CR\_BO}$	$\hat{\sigma}^2_{CR\_CH}$	$\hat{\sigma}^2_{CR\_DN}$	$\hat{\sigma}^2_{CR\_LV}$	$\hat{\sigma}^2_{CR\_LX}$	$\hat{\sigma}^2_{CR\_MI}$	$\hat{\sigma}^2_{CR\_NY}$	$\hat{\sigma}^2_{CR\_SD}$	$\hat{\sigma}^2_{CR\_SF}$	$\hat{\sigma}^2_{CR\_WD}$	$\hat{\sigma}^2_{CR\_CS10}$
	$\hat{\sigma}^2_{CR\_CH}$	-2.0264 **	0.0000	-1.8621 **	-1.0700	-1.1943	-0.7503	-0.6718	-1.7867 **	-1.4377 *	-1.4407 *	-1.1460
	$\hat{\sigma}^2_{CR\_NY}$	-1.5822 *	0.6718	-1.3564 *	-0.4613	-0.6482	-0.1504	0.0000	-1.3375 *	-0.9149	-0.9066	-0.5541
	$\hat{\sigma}^2_{CR\_MI}$	-1.4186 *	0.7503	-1.1768	-0.2901	-0.4826	0.0000	0.1504	-1.1781	-0.7448	-0.7335	-0.3816
CE		$\hat{\sigma}^2_{CE\_BO}$	$\hat{\sigma}^2_{CE\_CH}$	$\hat{\sigma}^2_{CE\_DN}$	$\hat{\sigma}^2_{CE\_LV}$	$\hat{\sigma}^2_{CE\_LX}$	$\hat{\sigma}^2_{CE\_MI}$	$\hat{\sigma}^2_{CE\_NY}$	$\hat{\sigma}^2_{CE\_SD}$	$\hat{\sigma}^2_{CE\_SF}$	$\hat{\sigma}^2_{CE\_WD}$	$\hat{\sigma}^2_{CE\_CS10}$
	$\hat{\sigma}^2_{CE\_BO}$	0.0000	-2.0559 **	-1.7478 **	-2.0747 **	-1.8613 **	-2.4761 ***	-1.6154 *	-0.0409	-2.0411 **	-1.5531 *	-1.2270
	$\hat{\sigma}^2_{CE\_SD}$	0.0409	-2.0671 **	-1.7587 **	-2.0839 **	-1.8799 **	-2.4852 ***	-1.6293 *	0.0000	-2.0587 **	-1.5670 *	-1.2425
	$\hat{\sigma}^2_{CE\_CS10}$	1.2270	-1.1828	-0.7980	-1.2515	-0.8054	-1.7378 **	-0.5671	1.2425	-1.0453	-0.4821	0.0000
DA		$\hat{\sigma}^2_{DA\_BO}$	$\hat{\sigma}^2_{DA\_CH}$	$\hat{\sigma}^2_{DA\_DN}$	$\hat{\sigma}^2_{DA\_LV}$	$\hat{\sigma}^2_{DA\_LX}$	$\hat{\sigma}^2_{DA\_MI}$	$\hat{\sigma}^2_{DA\_NY}$	$\hat{\sigma}^2_{DA\_SD}$	$\hat{\sigma}^2_{DA\_SF}$	$\hat{\sigma}^2_{DA\_WD}$	$\hat{\sigma}^2_{DA\_CS10}$
	$\hat{\sigma}^2_{DA\_DN}$	-2.0592 **	-0.2541	0.0000	-1.9322 **	-1.7508 **	-1.1867	-1.0977	-2.4071 ***	-1.7294 **	-1.8882 **	-1.3809 *
	$\hat{\sigma}^2_{DA\_CH}$	-1.9120 **	0.0000	0.2541	-1.7589 **	-1.5704 *	-0.9931	-0.8657	-2.2441 **	-1.5326 *	-1.6981 **	-1.1614
	$\hat{\sigma}^2_{DA\_NY}$	-1.3030 *	0.8657	1.0977	-1.0541	-0.8450	-0.2420	0.0000	-1.5667 *	-0.7503	-0.9342	-0.3188
DE		$\hat{\sigma}^2_{DE\_BO}$	$\hat{\sigma}^2_{DE\_CH}$	$\hat{\sigma}^2_{DE\_DN}$	$\hat{\sigma}^2_{DE\_LV}$	$\hat{\sigma}^2_{DE\_LX}$	$\hat{\sigma}^2_{DE\_MI}$	$\hat{\sigma}^2_{DE\_NY}$	$\hat{\sigma}^2_{DE\_SD}$	$\hat{\sigma}^2_{DE\_SF}$	$\hat{\sigma}^2_{DE\_WD}$	$\hat{\sigma}^2_{DE\_CS10}$
	$\hat{\sigma}^2_{DE\_SD}$	-0.5639	-2.0820 **	-1.2097	-1.5626 *	-1.4312 *	-1.9696 **	-1.6770 **	0.0000	-1.0936	-1.0743	-1.0243
	$\hat{\sigma}^2_{DE\_BO}$	0.0000	-1.6149 *	-0.6377	-1.0489	-0.8455	-1.4356 *	-1.2201	0.5639	-0.4651	-0.4766	-0.4094
	$\hat{\sigma}^2_{DE\_CS10}$	0.4094	-1.3150 *	-0.2582	-0.7117	-0.4685	-1.1007	-0.9153	1.0243	-0.0526	-0.0781	0.0000

Notes: The ten regions used in the Composite of 10 (CS10) are: Boston (BO), Chicago (CH), Denver (DN), Las Vegas (LV), Los Angeles (LX), Miami (MI), New York (NY), San Diego (SD), San Francisco (SF), and Washington DC (WD), and the other are Atlanta (AT), Charlotte(CR), Cleveland (CE), Dallas (DA), Detroit (DE). ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5 Continued

MN	$\hat{\sigma}^2_{MN\_BO}$	$\hat{\sigma}^2_{MN\_CH}$	$\hat{\sigma}^2_{MN\_DN}$	$\hat{\sigma}^2_{MN\_LV}$	$\hat{\sigma}^2_{MN\_LX}$	$\hat{\sigma}^2_{MN\_MI}$	$\hat{\sigma}^2_{MN\_NY}$	$\hat{\sigma}^2_{MN\_SD}$	$\hat{\sigma}^2_{MN\_SF}$	$\hat{\sigma}^2_{MN\_WD}$	$\hat{\sigma}^2_{MN\_CS10}$
$\hat{\sigma}^2_{MN\_CS10}$	-0.4202	-0.8623	-0.8432	-1.2478	-0.9876	-1.5866 *	-0.5987	-0.2687	-1.0926	-0.9861	0.0000
$\hat{\sigma}^2_{MN\_SD}$	-0.2014	-0.6442	-0.6502	-1.0989	-0.8051	-1.4417 *	-0.3845	0.0000	-0.9019	-0.7921	0.2687
$\hat{\sigma}^2_{MN\_BO}$	0.0000	-0.3773	-0.4166	-0.8890	-0.5680	-1.2114	-0.1612	0.2014	-0.6397	-0.5388	0.4202
PH	$\hat{\sigma}^2_{PH\_BO}$	$\hat{\sigma}^2_{PH\_CH}$	$\hat{\sigma}^2_{PH\_DN}$	$\hat{\sigma}^2_{PH\_LV}$	$\hat{\sigma}^2_{PH\_LX}$	$\hat{\sigma}^2_{PH\_MI}$	$\hat{\sigma}^2_{PH\_NY}$	$\hat{\sigma}^2_{PH\_SD}$	$\hat{\sigma}^2_{PH\_SF}$	$\hat{\sigma}^2_{PH\_WD}$	$\hat{\sigma}^2_{PH\_CS10}$
$\hat{\sigma}^2_{PH\_MI}$	-3.3426 ***	-3.2460 ***	-3.3709 ***	-1.6267 *	-1.7511 **	0.0000	-3.2214 ***	-2.7453 ***	-2.4151 ***	-2.1512 **	-2.1649 **
$\hat{\sigma}^2_{PH\_LX}$	-2.8135 ***	-1.3231 *	-2.6759 ***	-0.3563	0.0000	1.7511	-1.3598 *	-1.8962 **	-0.2451	-0.2562	-0.3181
$\hat{\sigma}^2_{PH\_SF}$	-2.7594 ***	-1.1892	-2.6137 ***	-0.1854	0.2451	2.4151	-1.2294	-1.8139 **	0.0000	-0.0287	-0.1003
PO	$\hat{\sigma}^2_{PO\_BO}$	$\hat{\sigma}^2_{PO\_CH}$	$\hat{\sigma}^2_{PO\_DN}$	$\hat{\sigma}^2_{PO\_LV}$	$\hat{\sigma}^2_{PO\_LX}$	$\hat{\sigma}^2_{PO\_MI}$	$\hat{\sigma}^2_{PO\_NY}$	$\hat{\sigma}^2_{PO\_SD}$	$\hat{\sigma}^2_{PO\_SF}$	$\hat{\sigma}^2_{PO\_WD}$	$\hat{\sigma}^2_{PO\_CS10}$
$\hat{\sigma}^2_{PO\_CH}$	-2.6311 ***	0.0000	-2.5131 ***	-1.1190	-1.2532	-0.4148	-0.7429	-2.2392 **	-1.6616 **	-1.6078 *	-1.2700
$\hat{\sigma}^2_{PO\_MI}$	-2.3877 ***	0.4148	-2.2131 **	-0.7232	-0.8691	0.0000	-0.2931	-1.9593 **	-1.2981 *	-1.2314	-0.8475
$\hat{\sigma}^2_{PO\_NY}$	-2.2430 **	0.7429	-2.0410 **	-0.4746	-0.6310	0.2931	0.0000	-1.7925 **	-1.0813	-1.0072	-0.5913
SE	$\hat{\sigma}^2_{SE\_BO}$	$\hat{\sigma}^2_{SE\_CH}$	$\hat{\sigma}^2_{SE\_DN}$	$\hat{\sigma}^2_{SE\_LV}$	$\hat{\sigma}^2_{SE\_LX}$	$\hat{\sigma}^2_{SE\_MI}$	$\hat{\sigma}^2_{SE\_NY}$	$\hat{\sigma}^2_{SE\_SD}$	$\hat{\sigma}^2_{SE\_SF}$	$\hat{\sigma}^2_{SE\_WD}$	$\hat{\sigma}^2_{SE\_CS10}$
$\hat{\sigma}^2_{SE\_CH}$	-2.5281 ***	0.0000	-2.4497 ***	-1.1085	-1.2861 *	-0.4912	-0.8105	-2.1919 **	-1.6442 *	-1.6317 *	-1.2990 *
$\hat{\sigma}^2_{SE\_MI}$	-2.2426 **	0.4912	-2.0873 **	-0.6207	-0.8266	0.0000	-0.2697	-1.8582 **	-1.2095	-1.1877	-0.7922
$\hat{\sigma}^2_{SE\_NY}$	-2.1149 **	0.8105	-1.9334 **	-0.3876	-0.6112	0.2697	0.0000	-1.7094 **	-1.0144	-0.9892	-0.5604
TP	$\hat{\sigma}^2_{TP\_BO}$	$\hat{\sigma}^2_{TP\_CH}$	$\hat{\sigma}^2_{TP\_DN}$	$\hat{\sigma}^2_{TP\_LV}$	$\hat{\sigma}^2_{TP\_LX}$	$\hat{\sigma}^2_{TP\_MI}$	$\hat{\sigma}^2_{TP\_NY}$	$\hat{\sigma}^2_{TP\_SD}$	$\hat{\sigma}^2_{TP\_SF}$	$\hat{\sigma}^2_{TP\_WD}$	$\hat{\sigma}^2_{TP\_CS10}$
$\hat{\sigma}^2_{TP\_MI}$	-3.4175 ***	-3.0611 ***	-3.4358 ***	-1.9608 **	-2.4616 ***	0.0000	-3.1994 ***	-3.2086 ***	-2.9216 ***	-2.8290 ***	-2.4943 ***
$\hat{\sigma}^2_{TP\_CS10}$	-3.0095 ***	-0.8424	-2.9366 ***	-0.5052	-0.1683	2.4943	-0.7043	-2.4535 ***	-1.3747 *	-0.7332	0.0000
$\hat{\sigma}^2_{TP\_LX}$	-2.9645 ***	-0.6543	-2.8810 ***	-0.3730	0.0000	2.4616	-0.5071	-2.3693 ***	-1.2205	-0.5552	0.1683

Notes: The ten regions used in the Composite of 10 (CS10) are: Boston (BO), Chicago (CH), Denver (DN), Las Vegas (LV), Los Angeles (LX), Miami (MI), New York (NY), San Diego (SD), San Francisco (SF), and Washington DC (WD), and the other are Minneapolis (MN), Phoenix (PH), Portland (PO), Seattle (SE), Tampa (TP). ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6 Engle-Granger cointegration test in LV, LX, NY, SF, and WD between different home price indices

Index		BO	CH	DN	MI	SD	CS10
LV	ADF	-2.379 **	-2.968 ***	-2.899 ***	-3.459 ***	-2.293 **	-3.876 ***
	PP	-2.108 **	-2.073 **	-3.044 ***	-2.478 **	-1.744 *	-2.811 ***
LX	ADF	-2.744 ***	-2.461 **	-2.561 **	-2.346 **	-2.846 ***	-3.335 ***
	PP	-2.184 **	-1.917 *	-3.149 ***	-1.918 *	-1.836 *	-3.042 ***
NY	ADF	-2.009 **	-1.936 *	-2.416 **	-2.647 ***	-2.212 **	-2.205 **
	PP	-1.636 *	-2.274 **	-2.409 **	-3.015 ***	-2.433 **	-2.689 ***
SF	ADF	-3.300 ***	-2.237 **	-2.753 ***	-3.589 ***	-2.605 ***	-3.198 ***
	PP	-3.890 ***	-2.392 **	-3.073 ***	-4.151 ***	-2.838 ***	-4.025 ***
WD	ADF	-2.528 **	-2.065 **	-3.038 ***	-2.531 **	-2.688 ***	-2.491 **
	PP	-2.892 ***	-2.127 **	-3.287 ***	-2.921 ***	-2.875 ***	-3.161 ***

Notes: The ten regions used in the Composite of 10 (CS10) are: Boston (BO), Chicago (CH), Denver (DN), Las Vegas (LV), Los Angeles (LX), Miami (MI), New York (NY), San Diego (SD), San Francisco (SF), and Washington DC (WD). ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7 The unequal variances tests in LV, LX, NY, SF, and WD between different home price indices

LV		$\hat{\sigma}^2_{LV\_BO}$	$\hat{\sigma}^2_{LV\_CH}$	$\hat{\sigma}^2_{LV\_DN}$	$\hat{\sigma}^2_{LV\_MI}$	$\hat{\sigma}^2_{LV\_SD}$	$\hat{\sigma}^2_{LV\_CS10}$
	$\hat{\sigma}^2_{LV\_CS10}$	-3.0868 ***	-2.7729 ***	-3.1623 ***	-0.9735	-2.5220 ***	0.0000
	$\hat{\sigma}^2_{LV\_MI}$	-2.6744 ***	-1.2943 *	-2.8001 ***	0.0000	-1.1110	0.9735
	$\hat{\sigma}^2_{LV\_SD}$	-2.2328 **	-0.1860	-2.4026 ***	1.1110	0.0000	2.5220
LX		$\hat{\sigma}^2_{LX\_BO}$	$\hat{\sigma}^2_{LX\_CH}$	$\hat{\sigma}^2_{LX\_DN}$	$\hat{\sigma}^2_{LX\_MI}$	$\hat{\sigma}^2_{LX\_SD}$	$\hat{\sigma}^2_{LX\_CS10}$
	$\hat{\sigma}^2_{LX\_CS10}$	-3.2373 ***	-2.8738 ***	-3.0878 ***	-1.7489 **	-2.8358 ***	0.0000
	$\hat{\sigma}^2_{LX\_MI}$	-2.9473 ***	-2.1147 **	-2.8424 ***	0.0000	-1.6043 *	1.7489
	$\hat{\sigma}^2_{LX\_SD}$	-2.4288 ***	-0.9213	-2.4015 ***	1.6043	0.0000	2.8358
NY		$\hat{\sigma}^2_{NY\_BO}$	$\hat{\sigma}^2_{NY\_CH}$	$\hat{\sigma}^2_{NY\_DN}$	$\hat{\sigma}^2_{NY\_MI}$	$\hat{\sigma}^2_{NY\_SD}$	$\hat{\sigma}^2_{NY\_CS10}$
	$\hat{\sigma}^2_{NY\_CH}$	-3.7050 ***	0.0000	-3.1945 ***	-2.8157 ***	-2.5536 ***	-1.1870
	$\hat{\sigma}^2_{NY\_CS10}$	-3.2207 ***	1.1870	-2.8905 ***	-1.6800 **	-2.0802 **	0.0000
	$\hat{\sigma}^2_{NY\_MI}$	-2.2908 **	2.8157	-2.2602 **	0.0000	-1.1509	1.6800
SF		$\hat{\sigma}^2_{SF\_BO}$	$\hat{\sigma}^2_{SF\_CH}$	$\hat{\sigma}^2_{SF\_DN}$	$\hat{\sigma}^2_{SF\_MI}$	$\hat{\sigma}^2_{SF\_SD}$	$\hat{\sigma}^2_{SF\_CS10}$
	$\hat{\sigma}^2_{SF\_CS10}$	-3.0544 ***	-2.1616 **	-3.0748 ***	-1.0192	-1.3716 *	0.0000
	$\hat{\sigma}^2_{SF\_MI}$	-2.6730 ***	-1.6542 **	-2.6425 ***	0.0000	-0.5050	1.0192
	$\hat{\sigma}^2_{SF\_SD}$	-2.3801 ***	-1.2881 *	-2.3108 **	0.5050	0.0000	1.3716
WD		$\hat{\sigma}^2_{WD\_BO}$	$\hat{\sigma}^2_{WD\_CH}$	$\hat{\sigma}^2_{WD\_DN}$	$\hat{\sigma}^2_{WD\_MI}$	$\hat{\sigma}^2_{WD\_SD}$	$\hat{\sigma}^2_{WD\_CS10}$
	$\hat{\sigma}^2_{WD\_CS10}$	-3.3761 ***	-2.7824 ***	-1.4274 *	-1.9447 **	-1.9937 **	0.0000
	$\hat{\sigma}^2_{WD\_DN}$	-3.1221 ***	-2.3804 ***	0.0000	-1.0728	-1.2173	1.4274
	$\hat{\sigma}^2_{WD\_MI}$	-2.7036 ***	-1.7386 **	1.0728	0.0000	-0.2042	1.9447

Notes: The ten regions used in the Composite of 10 (CS10) are: Boston (BO), Chicago (CH), Denver (DN), Las Vegas (LV), Los Angeles (LX), Miami (MI), New York (NY), San Diego (SD), San Francisco (SF), and Washington DC (WD). ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

References

Bailey, M., R. Muth and H. Nourse. 1963. A Regression Model for Real Estate Price Index Construction. *Journal of the American Statistical Association* 58(304): 933-942.

Case, K.E. and R.J. Shiller. 1987. Prices of Single-family Homes Since 1970: New Indexes for Four Cities. *New England Economic Review* Sep/Oct: 45-56.

Case, K.E. and R.J. Shiller. 1989. The Efficiency of the Market for Single-family Homes. *American Economic Review* 79(1): 125-137.

Case, K.E. and R.J. Shiller. 1996. Mortgage Default Risk and Real Estate Prices: the Use of Index-based Futures and Options in Real Estate. *Journal of Housing Research* 7(2): 243-258.

Case, K.E., R.J. Shiller and A.N. Weiss. 1993. Index-based Futures and Options Trading in Real Estate. *Journal of Portfolio Management* 19: 83-92.

Chau, K.W., S.K. Wong and C.Y. Yiu. 2007. Housing Quality in the Forward Contracts Market. *Journal of Real Estate Finance and Economics* 34(3): 313–325.

Davidson, J. 2000. Econometric Theory. Blackwell Publisher.

Edelstein, R., P. Liu, and F. Wu. 2012. The Market for Real Estate Presales: A Theoretical Approach. *Journal of Real Estate Finance and Economics* 45(1): 30-48.

Engle, R.F. and C.W.J. Granger. 1987. Cointegration and Error Correction Representation, Estimation, and Testing. *Econometrica* 55(2): 251- 276.

Englund, P., M. Hwang and J.M. Quigley. 2002. Hedging Housing Risk. *Journal of Real Estate Finance and Economics*. 24(1): 167-200.

Fan, G., M. Pu and S.E. Ong. 2012. Optimal Portfolio Choices, House Risk Hedging and the Pricing of Forward House Transactions. *Journal of Real Estate Finance and Economics*, 45(1): 2-29.

Hansen, B.E. 1992. Consistent Covariance Matrix Estimation for Dependent Heterogeneous Processes. *Econometrica* 60(4): 967-972.

Lai, R.N., K. Wang and Y.Q. Zhou. 2004. Sale before Completion of Development: Pricing and Strategy. *Real Estate Economics* 32(2): 329-357.

Lee, C., F.S. Shie and C.Y. Chang. 2012. How Close a Relationship Does a Capital Market Have with Other Such Markets? The Case of Taiwan from the Asian Financial Crisis. *Pacific-Basin Finance Journal* 20(3): 349-362.

McDuff, D. 2012. Home Price Risk, Local Market Shocks, and Index Hedging. *Journal of Real Estate Finance and Economics* 45(1): 212-237.

Ortalo-Magné, F. and S. Rady. 2002. Tenure Choice and Riskiness of Non-housing Consumption. *Journal of Housing Economics* 11(3): 266–279.

Shiller, R.J. 2003. The New Financial Order: Risk in the 21st Century. Princeton University Press, Princeton, NJ.

Author

Fu Shuen Shie
Department of Finance, National Taichung University of Science and Technology, Taichung City, Taiwan, R.O.C., fsshie@nutc.edu.tw

The author thanks the financial support of Ministry of Science and Technology (MOST) of the Republic of China (Taiwan) to this work under Grant Nos. MOST 102-2410-H-025-004.