RESEARCH ARTICLE

Diffusion of Hong Kong Office Property Prices Across Quality Classes: Ripple Down or Ripple Up?

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Abstract: This study explores whether and how office property prices diffuse across quality classes in Hong Kong. The empirical results reveal that the trends in office property prices are stochastic and demonstrate significant price lead-lag relationships among office property classes. The lead-lag patterns are apparent in both the long run and the short run. In addition, shocks from Class C prices have the strongest and longest-lasting impact on office prices in Hong Kong. In addition to providing new evidence on the ripple effect of commercial property prices across quality classes, this is the first study to explore the ripple effect of commercial property prices in both the short run and the long run. This study is also the first to employ the Vogelsang test (1998) and impulse response analysis to investigate the diffusion of commercial property prices. The findings have implications for government authorities, investors, and financial institutions in terms of policy formation, the timing of office property investments, and the diversification of their office-property-related portfolios.

Keywords: Office; Commercial Property; Ripple Effect; Quality Class; Filtering Down; Trading Up.

JEL Classifications: G00; R30

In the real estate literature, the "ripple effect" refers to the ways in which property booms begin in one area/quality tier and spread outwards to influence others over time (Ho, Ma, & Haurin, 2008), like the ever-expanding ripples that occur when a pebble hits the water. To maximize their profit, property investors typically prefer to buy on a market downtrend and sell on an uptrend (Hoover, 2006). Therefore, they are keen to know where property prices are rising and falling. Obviously, knowledge on the ripple effect can provide

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property market timing information and is, therefore, valuable to property market participants.

In particular, the ripple effect can allow property investors who missed out on the initial boom market to seize their slice of the pie through investing in markets close to the prime market that has surged in price (Tolhurst, 2011; Real Estate Investar, 2012). These effects also represent an opportunity for property developers, particularly those who can presale developments by purchasing, developing, and selling in markets that are expected to surge in price. In addition, the ripple-like effects may potentially have impacts on corporate financial strengths through significant real estate holdings (Chang & Chen, 2011). However, the ripple effect can also be a challenge for financial institutions aiming to diversify their mortgage lending risk (Quigley & Van Order, 1991).

Existing studies on spatial ripple effects in housing prices are intensive, particularly those on the UK housing market, including Alexander and Barrow (1994), Cook (2003; 2005), Cook and Speight (2007), Drake (1995), Giussani and Hadjimatheou (1991), Holmes (2007), Holmes and Grimes (2008), MacDonald and Taylor (1993), and (Meen, 1999). Similar subsequent investigations have been explored in Australia (Luo, Liu, & Picken, 2007), Finland (Oikarinen, 2004), Ireland (Stevenson, 2004), Malaysia (Hui, 2010), New Zealand (Shi, Young, & Hargreaves, 2009), the United States (Pollakowski & Ray, 1997; Holmes, Otero, & Panagiotidis, 2011; Miao, Ramchander, & Simpson, 2011), South Africa (Balcilar, Beyene, Gupta, & Seleteng, 2013), and Spain (Guirguis, Giannikos, & Garcia, 2007). Empirical studies on the ripple effect across quality tiers are relatively sparse, including Ho et al. (2008), Coulson and McMillen (2007), and Sing, Tsai, and Chen (2006) for Hong Kong, the US, and Singapore, respectively. Moreover, these studies present contradicting evidence on both the existence of the ripple effect and the ripple direction. More importantly, because firms might differ from households, findings for housing markets cannot be directly generalized to office markets. Therefore, it is important to study the ripple effect on commercial property markets (Leung, Cheung, & Ding, 2008).

Despite extensive studies on housing markets, the ripple effect in commercial property markets has not yet been adequately explored. Existing studies traditionally utilize correlation analysis to examine the geographical linkages in commercial property prices (Hartzell, Shulman, & Wurtzebach, 1987; Williams, 1996; Wolverton, Cheng, & Hardin, 1998; Brown, Li, & Lusht, 2000). Two exceptions are Tarbert (1998) and Chaudhry, Christie-David, & Sackley (1999), who employed cointegration tests and showed evidence of the convergence of commercial property prices in the UK and mixed evidence for the US. However, existing studies explore neither the lead-lag dynamics of property prices nor the dynamics across quality classes. Regarding trends in commercial property prices, Tarbert (1998) was silent, and Chaudhry et al. (1999) incorporated deterministic trends.

To the best of our knowledge, Leung et al. (2008) is the only exception; they studied the lead-lag transmission of office price changes across price tiers in Hong Kong by employing bivariate Granger causality tests; they found no evidence of this type of transmission in Hong Kong office property markets in the short run. However, Leung and colleagues did not examine the long-run lead-lag relationships. In contrast to existing studies, this study investigates price lead-lag dynamics in both the long run and the short run and asks the following questions: (1) Do office property prices ripple across quality tiers in Hong Kong? (2) If so, do they ripple up or ripple down?

This study employs error correction (VEC) models and impulse response functions (IRFs) to examine the ripple-like dynamics of commercial properties in Hong Kong. Hong Kong has one of the deepest and most liquid property markets in the world (Chau, Macgregor, & Schwann , 2001). This exploration is interesting not only to Hong Kong's local investors but also to international commercial real estate investors. Due to its special link to China and its status as one of the freest business centers in the world, Hong Kong is experiencing a flood of capital and companies investing in its commercial real estate markets (Blazkova, 2017). Hong Kong was ranked 7th among global office property investment cities in terms of attracting the most foreign capital (Rishiwala, 2011).

The present study contributes to the ripple effect literature as follows. First, to the best of our knowledge, this is the first study to explore the ripple effect of commercial property prices in both the short run and the long run. The majority of existing studies focus on house prices. The sparse studies on commercial property markets either fail to explicitly inspect the lead-lag dynamics or examine only the short-run dynamics. In this study, the joint inspection of the short-run and long-run effects fills this gap in the literature.

Second, this study provides new evidence on the ripple effect of commercial property prices across quality class. Similar studies are relatively sparse and focus on housing markets. Moreover, existing studies have produced contradictory evidence. Only one such study focuses on commercial property markets. An additional study on the ripple effect of commercial property prices is clearly needed to enhance the understanding of the ripple direction across quality tiers in property markets.

Third, this study is the first to employ impulse response analysis to investigate the diffusion of commercial property prices. This extension is important because Granger causality may not illustrate the complete story about the interactions between commercial property prices.[1] It is often interesting to highlight the response of one quality tier to an impulse in another quality tier in a market that also involves further quality tiers.

Fourth, previous empirical studies devoted little attention to the trend properties of commercial property prices and neglected the consequence of misspecifying the deterministic components of a VEC model. In contrast, the current study employs the Vogelsang test (1998) to formally inspect whether office property prices exhibit linear deterministic time trends. By applying this test, this study offers more convincing evidence of the ripple effect on office property prices.

Possible Explanations for Ripple Effects Across Quality Classes

Given that properties are not homogenous and that properties of different quality have different demand and supply characteristics, is it reasonable to ask why property prices of different quality should be linked. The filtering-down theory, which is based on the seminal papers of Sweeney (1974) and O'Flaherty (1996), is one of two explanations receiving the most attention. In this theory, the housing market is separated into distinct sets of quality levels. Income characterizes the households. Each household has a bid-rent function that determines the willingness-to-pay for any quality level. Houses of varying quality are matched to households according to their income levels and willingness-to-pay. As the marginal cost of quality is increasing, maintenance is usually a profitable investment for properties of higher quality and not profitable for lower-quality properties (O'Flaherty, 1996). Moreover, lower-quality houses are typically more cheaply supplied as a result of filtering from better-quality houses rather than new construction (O'Flaherty, 1996). Since higher-quality houses are maintained, the building is usually completed during this phase of the quality distribution (Coulson & McMillen, 2007). As consumers with rising income move from lower-quality houses to better-quality houses, the prices of lower-quality houses will fall in order to maintain equilibrium. Therefore, a ripple effect ensures that causality runs from the higher-quality housing price down to the lower-quality housing price.

The other explanation to receive the most attention in the literature is the trading-up theory, which is based on life cycle models of Stein (1995) and Ortalo-Magné and Rady (2004). Similar to the filtering-down theory, the trading-up theory separates the housing market into distinct sets of quality levels and characterizes households by wealth. Distinctively, the trading-up theory begins with two sets of observations in the housing market: (1) homebuyers typically need to make a significant down payment, and (2) housing represents a substantial portion of household net worth. While homeowners are eager to climb the housing ladder, they are credit-constrained. When homeowners sell their old houses, they must repay their outstanding mortgages immediately. Suppose an initial positive shock boosts house prices. The ensuing capital gains on their existing homes allows constrained would-be movers to make down payments on more expensive, higher-quality homes. This, in turn, leads to a demand increase that further boosts the prices of higher-quality housing. Therefore, a ripple effect ensures that causality runs from the lower-quality housing price down to the higher-quality housing price.

The above two theories involve household mobility from lower-quality houses to higher-quality houses and predict the long-run co-movement of different-quality housing prices. Consistent with this prediction, Coulson and McMillen (2007) and Sing et al. (2006) provided cointegration evidence supporting the filtering-down theory in the US and the trading-up theory in Singapore. In contrast, Ho et al. (2008) found no evidence of cointegration of different-quality house prices in Hong Kong. Although the above two theories may also be applicable to commercial property markets, Leung et al. (2008) argued that office buyers might face less severe financial constraints than ordinary households because large firms, which represent a significant portion of office property consumers, can raise funds through not only mortgages but also debt and equity issues (Leung, Cheung and Ding, 2008). Therefore, the results for the housing market should not be generalized directly to office markets without further empirical investigation. In the short run, co-movements of different-quality property prices, however, might be caused by non-fundamental forces and behave differently in the long run; for example, representative heuristics (Oikarinen, 2004; Lee, Lee, & Lin, 2014).

Data Description

This empirical study obtained office property price data from the Hong Kong Rating and Valuation Department. These data are the quarterly price indices for Class A, Class B, and Class C for the whole Hong Kong territory from the second quarter of 2000 to the first quarter of 2015.[2] All price indices are log-transformed before analysis. Class A office properties are modern with high-quality finishes, flexible layouts, large floor plates, spacious and well-decorated lobbies and circulation areas, effective central air conditioning, good elevator services zoned for passengers and goods deliveries, professional management, and included parking facilities. Class B office properties have ordinary designs with good-quality finishes, flexible layouts, average-sized floor plans, adequate lobbies, central or free-standing air conditioning, adequate elevator services, good management, and optional parking facilities. Class C office properties are plain with basic finishes, less flexible layouts, small floor plans, basic lobbies, a general lack of central air conditioning, barely adequate or inadequate elevator services, minimal to average management, and no parking facilities.

Trend Properties, Unit Root, and Stationarity Tests

Figure 1 reveals the potential trending in office property price indices. To check for deterministic trends in the logarithmic indices, this study follows Lee et al. (2014) and applies the Vogelsang (1998) t-PS_T^1 test. It is not necessary to have a priori knowledge of office property price innovations or test whether they are I(0) or I(1). The t-PS_T^1 test is based on Equation (1):

Figure 1. Office property price indices for quality classes.

$$LOP_t = \beta_0 + \beta_1 t + \varepsilon_t \qquad (1)$$

where LOP_t is the logged office property price index level in one studied class, β_0 is the initial level of LOP_t, β_1 is the average slope of the time trend in LOP_t, and ε_t is a serially correlated random process. Testing for a time trend in the office property price index is essentially a test of whether the parameter β_1 is different from zero.

The t-PS_T^1 test statistic is specified as Equation (2):

$$\text{t-PS}_\text{T}^1 = T^{-1/2} t_p e^{-kJ_T^1} \qquad (2)$$

where T is the sample size, t_p is the set of t-statistics for testing whether the individual parameters in the partial-sum regression in Equation (1) are zero, k is a constant, and J_T^1 is the Park and Choi (1988) and Park (1990) unit root statistic. When the stationarity of innovations is not clear, k is chosen so that the critical values of the t-PS_T^1 test statistics are the same regardless of whether ε_t is I(0) or I(1). For this reason, different values for k are associated with different levels of statistical significance. Because of the asymptotic non-normal distribution of the t-PS_T^1 statistic, Vogelsang (1998) tabulated the critical values.

For the 10%, 5%, and 1% levels of significance, the values of k should be specified as 0.494, 0.716, and 1.501, respectively. Table 1 presents the resulting t-PS_T^1 test statistics for the logarithmic office property prices of three quality classes. The test statistics are all very low and not statistically significant, providing clear evidence that there are no deterministic trends in logarithmic office property prices in Hong Kong. This evidence contrasts Chaudhry et al. (1999), who found deterministic trends in commercial property prices. However, the evidence found here is logical because deterministic trends imply that office property prices are constrained to increase forever. This finding provides valuable information for stationarity testing and VEC modeling, which are well known to be sensitive to the inclusion or exclusion of deterministic time trends (Ahking, 2002).

Next, the stationarity of the logarithms of office property prices is checked. Based on evidence from the t-PS_T^1 test, the unit root and stationarity tests do not include deterministic time trends in their specifications. This study begins univariate testing with the ADF (augmented Dickey-Fuller) unit root test (Dickey & Fuller, 1979), the PP (Phillip-Perron) test (Phillips & Perron, 1988) and the KPSS (Kwiatkowski–Phillips–Schmidt–Shin) test (Kwiatkowski, Phillips, Schmidt, & Shin, 1992). Panel A of Table 2 presents the results for logarithms of office property prices. The results of the ADF and PP tests cannot reject the unit-root null hypothesis. The KPSS result, in contrast, rejects the stationarity null hypothesis at the 1% significance level. Panel B of Table 2 reports the results of the tests on logarithmic housing price changes. The ADF and PP tests clearly reject the unit-root null hypothesis at the 1% significance level. The KPSS result, in contrast, cannot reject the stationarity null hypothesis. The

Table 1. *Deterministic Trend Tests*

	LOPA	**LOPB**	**LOPC**
10% significance level			
t-PS_T^1	0.000 (1.331)	0.000 (1.331)	0.000 (1.331)
5% significance level			
t-PS_T^1	0.000 (1.720)	0.000 (1.720)	0.000 (1.720)
1% significance level			
t-PS_T^1	0.000 (2.647)	0.000 (2.647)	0.000 (2.647)

Notes: 1. LOPA is the logarithm of the Class A office property price index. LOPB is the logarithm of the Class B office property price index. LOPC is the logarithm of the Class C office property price index. 2. The critical values are in parentheses.

Table 2. *Univariate Unit Root and Stationary Tests*

	ADF	PP	KPSS
Panel A: Level Series			
LOPA	-0.755	-0.339	0.895***
LOPB	-0.260	0.255	0.907***
LOPC	0.167	0.538	0.913***
Panel B: Differenced Series			
DLOPA	-4.430***	-4.609***	0.103
DLOPB	-4.604***	-4.456***	0.190
DLOPC	-4.951***	-4.889***	0.290

*Notes: 1. LOPA is the logarithm of the Class A office property price index. LOPB is the logarithm of the Class B office property price index. LOPC is the logarithm of the Class C office property price index. 2. DLOPA is the first difference of LOPA. DLOPB is the first-difference of LOPB. DLOPC is the first-difference of LOPC. 3. ADF, PP, and KPSS are the augmented Dickey-Fuller test, Phillip-Perron test, and Kwiatkowski–Phillips–Schmidt–Shin) test, respectively. 4. ***, **, and * indicates significance at the 1%, 5%, and 10% levels, respectively.*

Table 3. *Panel Unit Root and Stationary Tests*

Method	Level Series	Differenced Series
LLC	0.775	-7.342***
IPS	2.439	-6.247***
Fisher-ADF	0.610	48.471***
Fisher-PP	0.264	47.775***
Hadri	8.590***	0.177

*Notes: 1. LLC and IPS are the panel unit root tests of Levin et al. (2002) and Im et al. (2003), respectively. Fisher-ADF and Fisher-PP are the panel unit root tests of Maddala and Wu (1999) and Choi (2001), respectively. Hadri is the panel stationarity tests of Hadri (2000). 2. ***, **, and * indicates significance at the 1%, 5%, and 10% levels, respectively.*

results shown in Table 2 indicate that Class A, B, and C office property prices are integrated of order one, or I(1).

To provide additional evidence about the stationarity of the logarithms of office property prices, this study next conducted panel data testing with LLC (Levin-Lin-Chu) (Levin, Lin, & Chu, 2002), IPS (Im, Pesaran, & Shin, 2003), Fisher-ADF (Maddala & Wu, 1999), and Fisher-PP (Choi, 2001) panel unit root tests, as well as a Hadri panel stationarity test (Hadri, 2000). The results of the panel unit-roots tests in Table 3 clearly support the univariate tests and show that office property prices are I(1) series. Therefore, the trends appearing in Figure 1 are stochastic trends, implying that identifying sources of trend shocks are crucial for evaluating office property price trends in Hong Kong (Murray & Nelson, 2000; Naoussi & Tripier, 2013; Amdur & Kiziler, 2014).

The VEC Model

Building the VEC Model

To build the VEC model, this study first constructed the VAR (vector autoregression) model, which is then reformatted into a VEC model for logarithmic office property prices. The five selection criteria used to select the optimal lag length in the VAR model are the final prediction error (FPE) method (Akaike, 1969), Akaike's information criterion (AIC; Akaike, 1974), the Schwarz information criterion (SC; Schwarz, 1978), the Hannan-Quinn criterion (HQ; Hannan & Quinn, 1979), and the sequential modified likelihood

Table 4. *VAR Lag Selection*

Lag	FPE	AIC	SC	HQ	LR
1	0.000	-15.128	-14.690	-14.959	368.318
2	3.54e-11**	-15.555**	-14.789**	-15.259**	36.199**
3	0.000	-15.338	-14.243	-14.915	4.963
4	0.000	-15.242	-13.819	-14.691	9.709

Notes: 1. **indicates lag order selected by the criterion. 2. FPE is final prediction error; AIC is Akaike's information criterion; SC is Schwarz's information criterion; HQ is Hannan-Quinn's information criterion; LR is the sequential modified likelihood ratio test statistic.

Table 5. *Johansen's Cointegration Test Results*

Hypothesized No. of CE(s)	Trace Statistic	5% Critical value	Max-Eigen Statistic	5% Critical value
None	60.976**	35.193	41.941**	22.300
At most 1	19.034	20.262	15.690	15.892
At most 2	3.344	9.165	3.344	9.165

*Notes: 1. No. of CE(s) denotes the number of cointegration vectors. 2. **denotes rejection of the hypothesis at the 5% level.*

Table 6. ***VEC Residual Portmanteau Tests for Autocorrelations***

Order of Correlation	Q-Stat	Adj Q-Stat
1	2.259	2.298
2	11.101	11.457
3	19.722	20.548

ratio (LR) test. As shown in Table 4, all five criteria selected two lags to include in the VAR model.

Since the previous section indicates the office property prices are I(1) processes, the VAR(2) is reformulated into a VEC model with one lag in differenced office property prices. Based on the t-PS_T^1 test statistics in the previous section, the VEC model contained only intercepts and no deterministic trends. To explore the long- and short-run relationships between Class A, B, and C office property prices and to check for the existence of common trends, this study employed the Johansen (1988) multivariate maximum likelihood cointegration test.

For Johansen's cointegration rank test, this study computed the trace and maximum eigenvalue test statistics and their 5% critical values. As shown in Table 5, both test statistics clearly reject the null of no cointegrating vector and, thus, support the convergence of office property prices in the long run. In other words, the evidence shows that office property prices can ripple out across quality tiers in the long run. The two tests, however, cannot reject the nulls of, at most, one cointegrating vector and, at most, two vectors. Therefore, the two tests showed that there is only one cointegrating vector driving the office property prices, which share a common stochastic trend. The cointegration test result contrasts the housing study of Ho et al. (2008), who showed that housing prices in the various quality tiers are not cointegrated in Hong Kong. The different results highlight the importance of researching office property markets.

Residual Autocorrelation and Stability checks

To check whether the VEC model suffers from residual autocorrelation, this study performed portmanteau tests. Table 6 exhibits the Box-Pierce/

Table 7. *Roots of Characteristic Autoregressive Polynomial*

	Root 1	Root 2	Root 3	Root 4	Root 5	Root 6
Root	1.000	1.000	0.830	0.563	-0.386	-0.119
Modulus	1.000	1.000	0.830	0.563	0.386	0.119

Table 8. *Speed of Adjustment Coefficients*

	LOPA	LOPB	LOPC
Coeff.	-0.239	0.190	0.254
LR	3.255**	2.575*	5.621

*Notes: 1. LOPA is the logarithm of the Class A office property price index. LOPB is the logarithm of the Class B office property price index. LOPC is the logarithm of the Class C office property price index. 2. Coeff. denotes the coefficient, and LR denotes the likelihood ratio statistics. 3. ** and * indicate significance at one-sided significance levels of 5% and 10%, respectively.*

Ljung-Box Q-statistics and the sample-size-adjusted Q-statistics (Lütkepohl, 1991) up to lag 3. None of the statistics is statistically significant. Thus, the VEC model is free from material autocorrelation and acceptable in this respect.

To check the stability of the VEC model, this study examined roots of characteristic autoregressive polynomials for the model. If the VEC model is stable, none of the roots should be outside the unit disk. Moreover, the number of unit roots should be equal to the number of I(1) series minus the number of cointegrating vectors; that is, there should be two unit roots in the current study. Table 7 shows that two of the roots of characteristic autoregressive polynomials are equal to the unit disk, while the rest are inside the unit disk. Therefore, Table 7 provides evidence that the VEC model is stable.

Lead-lag Relationships

To explore long-run price lead-lag relationships across quality classes in Hong Kong's office property market, this study estimated their speeds of adjustment to the long-run equilibrium and tests whether the prices error-correct their deviations from the long-run equilibrium. Constrained by the cointegrating vector, the speed of adjustment coefficients for Classes A and C office properties should be negative, and those of Class B office properties should be positive to restore equilibrium. As shown in Table 8, the signs of the coefficients for Class A and Class B indicate convergence toward long-run equilibrium. By contrast, the sign of the coefficient for Class C does not indicate error-correction towards the equilibrium. In other words, this finding implies that Class C office property prices do not error-correct their deviations and, thus, lead the office property price trend in the long run. The log-likelihood ratio statistics for Classes A and B are statistically significant. This finding indicates that with respect to long-run office property price movements, Classes A and B are followers.

The above results indicate unidirectional Granger causality from Class C office properties to Classes A and B in the long run. In other words, confirming the cointegration test results in the previous section, the finding here once again shows that Hong Kong office property prices ripple up across quality classes in the long run. Moreover, that Class C takes the lead on the office property price trend is consistent with the trading-up theory. The lead-lag pattern indicates that credit constraints are a significant hurdle for office property owners to filter up the property ladder (Stein, 1995; Ortalo-Magné & Rady, 2004, 2006). The magnitudes of the speed of adjustment coefficients indicate that Class A responds more quickly than Class B to deviations from long-run equilibriums. In particular, Class A corrects 23.9% of its resulting deviation within a quarter, and Class B corrects only 19.0% of its resulting deviation within the same length of time. The results, therefore, provide support for the trading-up theory in the office market.

In the short run, lead-lag patterns may be caused by non-fundamental forces, such as representative heuristics (Meen, 1999; Oikarinen, 2004; Füss, Zhu, & Zietz, 2011). As a result, causality associated with short-run disturbances might move in different directions from causality associated with adjustments to long-run relationships (Andersson, 1999). Therefore, this study also investigated short-run

Table 9. *Short-Run Granger Causality Test Results*

	Dependent Variable		
	DLOPA	**DLOPB**	**DLOPC**
Lagged DLOPA		4.293**	1.742
Lagged DLOPB	0.616		0.994
Lagged DLOPC	2.90*	0.109	
Lagged DALL	9.686***	4.300	5.083*

*Notes: 1. DLOPA is the first-differenced logarithm of the Class A office property price index. DLOPB is the first-differenced logarithm of the Class B office property price index. DLOPC is the first-differenced logarithm of the Class C office property price index. DALL denotes the first-differenced logarithm of all office property price indices in the same column. 2. The figures reported are Chi-square statistic values. 3. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively.*

lead-lag relationships in price changes for various quality classes of office properties. Table 9 reports short-run block Granger causality tests on these changes in the VEC model. Each column of this table has at least one significant Chi-square statistic value at the 10% level. Therefore, Table 9 indicates significant lead-lag interdependence among office property classes. The joint test for short-run causality from Classes B and C to Class A is significant at the 1% level. Moreover, Class C leads Class A at the 10% significant level. These test statistics reveal that price changes can ripple up in the short run and the long run. The tests for short-run causality indicate that Class B is led by Class A in the short run, likely because of heuristics, in addition to other information factors as the Class A market tends to be more heavily covered by news media, including magazines for international commercial real estate agencies. The same explanation could also apply to the significance of the joint test for short-run causality from the Classes A and B to Class C.

Impulse Response Analysis

To determine the extent and the persistence of the response of office property prices of one quality class to unanticipated price changes in another quality class, this study applied impulse response analysis. Following Coulson and McMillen (2007), this study employed Choleski decomposition to identify the impulse responses. Because the previous section suggests that Class C office property prices are most exogenous, followed by Class B and Class A, the prices are therefore placed in the same order in Choleski decomposition.

Figures 2 to 4 show the mutual impacts of shocks on the prices of office properties in the three quality classes. The horizontal axes present the quarters past the sudden and unanticipated office property price changes. The vertical axes are the extent of the responses of office property prices, scaled so that 1.00 equals one standard deviation. The 95% confidence intervals are computed with the responses ±2 standard errors. The confidence bands are constructed with a Monte Carlo simulation procedure with 1,000 replications. Wherever the confidence bands are above the horizontal line at zero, the impulse responses are deemed to be significantly different from zero at the 5% significance level.

The impulse responses show how long and to what extent each class's office property price reacts to unanticipated shocks in the prices of another class. The responses are presented up to 12 quarters since the initial shocks. Figure 2 exhibits the responses to an initial shock from Class C property prices. A price shock from Class C properties has significantly positive impacts on all three classes' office property prices. The impacts remain significant up to nine, 10, and 11 quarters for Classes A, B, and C, respectively. The point estimates show that the impact effects rise gradually and reach a plateau of approximately 4.5% standard deviation after about three quarters. The responses of Class A and B property prices decline slightly starting in about the sixth quarter after the initial shock. The patterns reveal that the price shock from Class C properties can last over two years for all classes of office properties.

Figure 3 presents the responses to an initial shock from Class B property prices. A price shock from Class B properties has significant and positive impacts only on the prices of Classes A and B office properties. The impacts remain significant only within four quarters. The point estimates show that the impact effects are

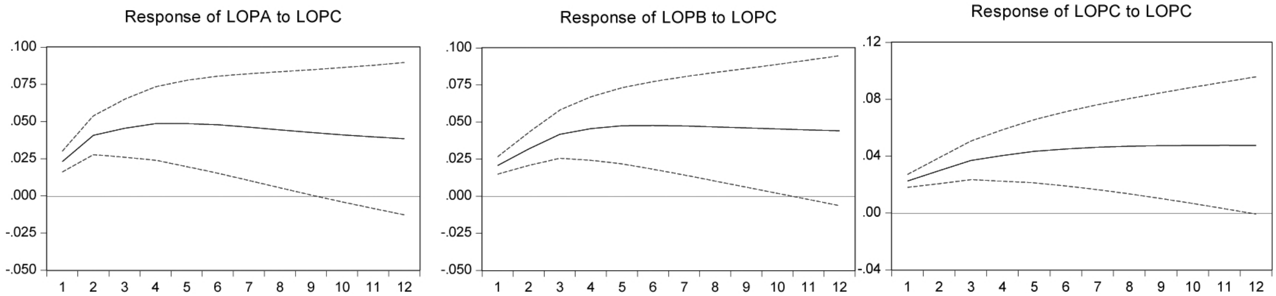

Figure 2. Impulse responses to shocks from Class C.

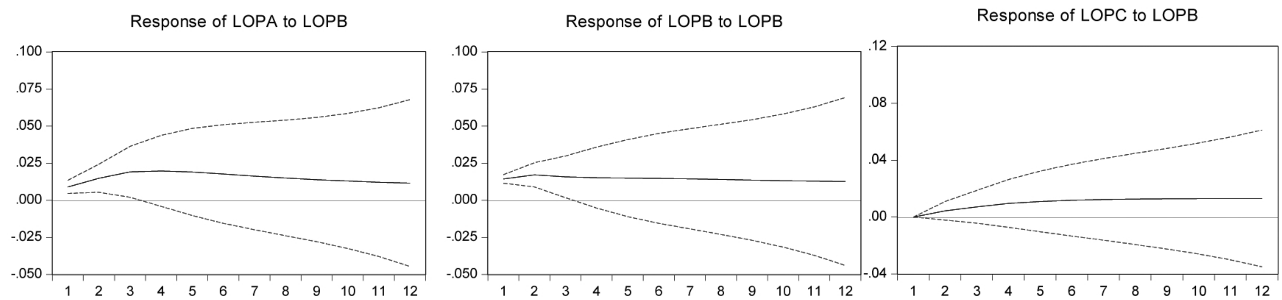

Figure 3. Impulse responses to shocks from Class B.

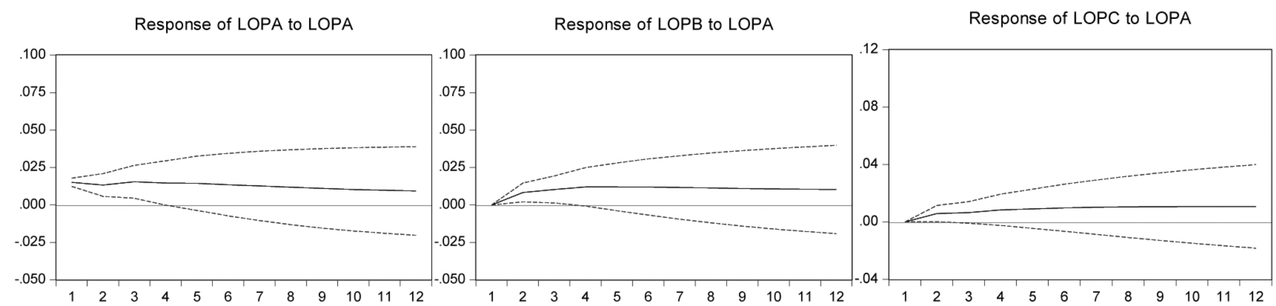

Figure 4. Impulse responses to shocks from Class A.

within a standard deviation of less than 2%. As shown in Figure 4, the responses to an initial shock from Class A property prices also lose their significance quickly, within four quarters. The impact effects are only approximately 1.5% or less for Class B and Class A. In contrast to Class B, the shock from Class A has significant impacts on Class C. However, the impacts become insignificant very quickly, within two quarters. These patterns reveal that the price shocks from Class A and B properties have only relatively temporary impacts. The impulse response results again support the domination of the trading-up theory over the filtering-down theory in terms of the ability to explain the diffusion of office property prices.

Robustness Checks

Several procedures are implemented to check for the extent of robustness of this study's empirical findings. The Engle and Granger (1987) approach tests for the cointegration and lead-lag relationship of the office property prices. As shown in Table 10, no matter which class's property price is used as the dependent variable, both the tau-statistic and z-statistic values are statistically significant. The results clearly confirm that office property prices of Classes A, B, and C are cointegrated, as shown by the Johansen (1988) approach. The speed of adjustment coefficients in Table 11 again shows that Class C is the leader and Classes A and B are followers in the long run. Moreover, Class A

Table 10. *Engle-Granger Cointegration Test Results*

Dependent Variable	Tau-statistic	z-statistic
LOPA	-4.111**	-27.810**
LOPB	-4.444**	-30.704***
LOPC	-3.800*	-23.570**

*Note: 1. The number of lags is selected based on Schwarz's information criterion. 2. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively.*

Table 11. *Speed of Adjustment Coefficients of Engle-Granger Approach*

	LOPA	LOPB	LOPC
Coeff.	-0.320	0.262	0.101
t-statistic	1.785**	1.752**	0.728

*Notes: 1. LOPA is the logarithm of the Class A office property price index. LOPB is the logarithm of the Class B office property price index. LOPC is the logarithm of the Class C office property price index. The cointegrating regression is estimated with fully modified ordinary least squares. 2. Coeff. denotes the coefficient. 3. ** and * indicate significance at one-sided significance levels of 5% and 10%, respectively.*

Table 12. *Short-Run Granger Causality Test Results of the Engle-Granger Approach*

	Dependent Variable		
	DLOPA	DLOPB	DLOPC
Lagged DLOPA		1.830*	1.607
Lagged DLOPB	0.250		0.630
Lagged DLOPC	1.442	-0.704	
Lagged DALL	2.857*	1.878	2.945*

*Notes: 1. DLOPA is the first-differenced logarithm of the Class A office property price index. DLOPB is the first-differenced logarithm of the Class B office property price index. DLOPC is the first-differenced logarithm of the Class C office property price index. DALL denotes the first-differenced logarithm of all office property price indices in the same column. 2. The figures reported are t-statistic values for lagged DLOPA, DLOPB, and DLOPC and F-statistic values for lagged DALL. 3. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively.*

Table 13. *Specification Test Results of Error-Correction Regressions*

	Dependent Variable		
	DLOPA	DLOPB	DLOPC
Ramsey RESET test	2.043	0.183	0.616
Chow breakpoint test	1.254	1.254	1.370
Chow forecast test	0.595	0.595	1.008
No. of breaks selected by LWZ	0	0	0

*Notes: 1. DLOPA is the first-differenced logarithm of the Class A office property price index. DLOPB is the first-differenced logarithm of the Class B office property price index. DLOPC is the first-differenced logarithm of the Class C office property price index. 2. The figures reported for the first three tests are F-statistic values. 3. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively. 4. LWZ is the modified Schwarz criterion proposed by Liu et al. (1997).*

adjusts back to the long-run equilibrium more quickly than Class B when deviating from equilibrium.

Table 12 exhibits the short-run Granger causality test results of the Engle-Granger approach. This table suggests short-run lead-lag patterns similar to those revealed in Table 9. In other words, significant lead-lag interdependence among office property classes is confirmed. Table 13 presents the specification test results of error-correction regressions. The reset test statistics are not significant and show that the regressions are not misspecified. Chow breakpoint and forecast test statistics are also not significant and suggest no structural breaks due to the recent global financial crisis.[3] In addition, the Bai and Perron approach (1998, 2003) was adapted to detect potential multiple structural breaks at unknown dates and the modified Schwarz criterion proposed by Liu, Wu, and Zidek (1997) indicates no structural breaks. Moreover, incorporated into the long-run and short-run relationships, quarterly dummies do not have statistically significant coefficients and, thus, confirms no bias due to seasonality.

To check the robustness of the previous impulse response findings, the ordering of the price series in the Choleski decomposition changes to Class C, followed by Class A, and then Class B (Lee & Chiang, 2004). Figures 5 and 7 present the responses to an initial shock from Class C, B, and A property prices with the new ordering of the Choleski decomposition. The overall response patterns are quite similar to those in Figures 2 to 4. The significant impacts from Class C still last up to nine, 10, and 11 quarters for Classes A, B, and C, respectively. Shocks from Classes A and B lose their significance within five quarters. The magnitudes of impacts from Class C are still approximately 4.5% when reaching a plateau. The impacts from Classes A and B are still much smaller in magnitude. Moreover, the unreported impulse response analyses also show that the previous impulse response findings of both orderings of the price series are robust when a global financial crisis dummy is included in the VAR model. Moreover, the patterns remain qualitatively similar when the real gross domestic product is included as an exogenous variable in the model.

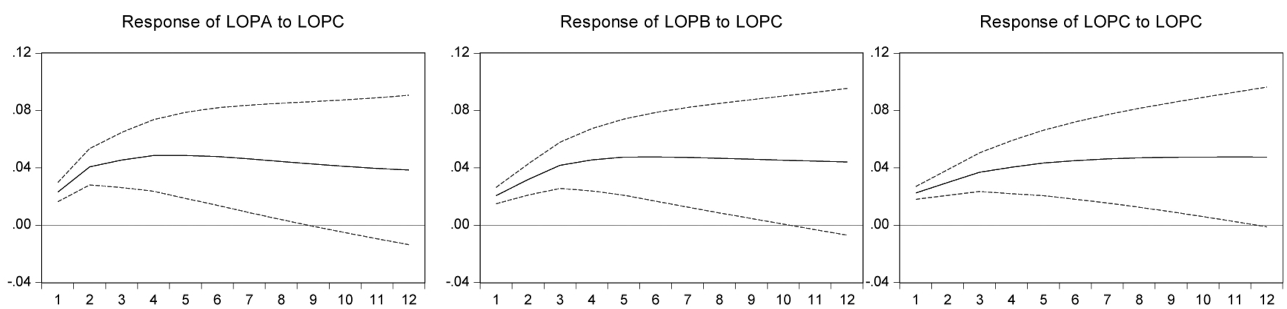

Figure 5. Impulse responses to shocks from Class C with different ordering.

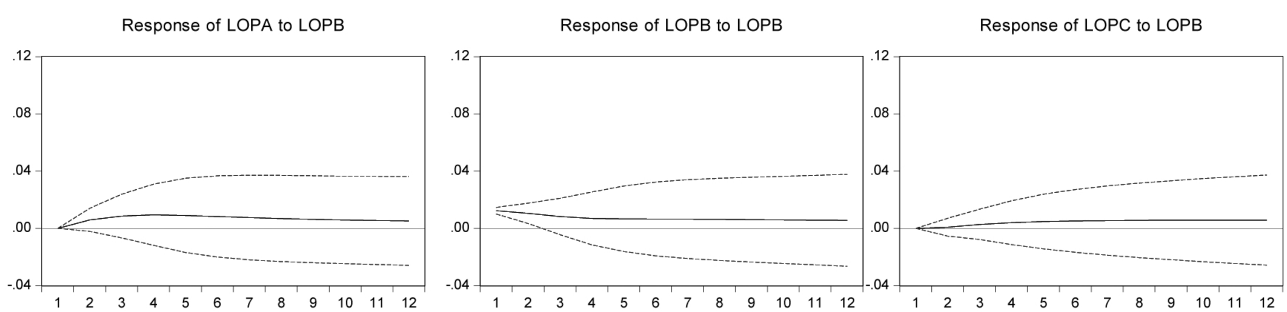

Figure 6. Impulse responses to shocks from Class B with different ordering.

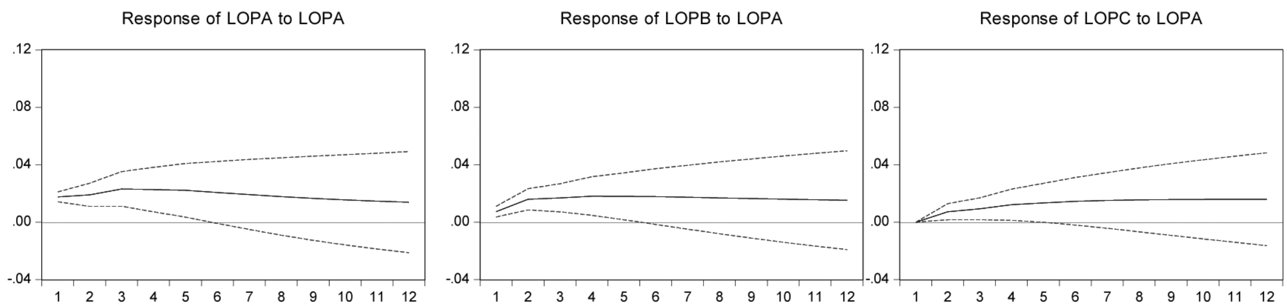

Figure 7. Impulse responses to shocks from Class A with different ordering.

Conclusion

This paper examined the trend properties, cointegration, and diffusion of prices of Hong Kong office properties in three quality classes: Classes A, B, and C. This study first applied the Vogelsang (1998) $t\text{-}PS_T^1$ test to re-examine previous studies on trend specification in the unit-root tests of office property prices in Hong Kong. The study further employed cointegration tests to inspect whether prices of office properties in different quality classes share a long-run equilibrium relationship, constructed Granger causality tests to investigate how they lead-lag one another, and then performed impulse response analysis to explore the impacts of unexpected shocks. Overall, the empirical results indicate that prices of Class C office properties can ripple out to other classes both in the long run and the short run and, given that it receives the most media attention, Class A's prices can have ripple effects in the short run. However, shocks from Class C have more prominent and lasting impacts than those from Classes A and B. The study's main findings and implications are as follows.

First, the trends in office property prices in Hong Kong are stochastic. This finding has implications for management and assessment of the policies related to the affordability of office space. More specifically, the Hong Kong government must identify trend shocks to effectively curb its soaring office property prices, thereby helping businesses.

Second, the results support office property price cointegration, which involves all quality classes. Therefore, seeking diversification across quality classes may be difficult. In contrast, the presence of cointegration may provide investors with cross-hedging opportunities (Chaudhry et al., 1999).

Third, Class C office properties are leaders in terms of long-run office property price movements. Therefore, investors who missed a boom in the Class C market might still have an opportunity to enter the market by investing in Class A and B markets.

Fourth, there is a strong lead-lag interdependence among office property price changes across quality classes in Hong Kong. Due to the lead-lag relations, static quarterly correlations are likely to exaggerate diversification opportunities. Therefore, when diversifying their office property-related portfolios, financial institutions and investors should be aware of this finding and adapt conditional investment strategies.

Fifth, shocks from Class C have the most prominent and lasting impacts on office property prices in Hong Kong. Therefore, government authorities and investors may benefit from paying more attention to the Class C office property sectors in terms of forming policies and discerning trends in the Hong Kong office market.

Notes

1 When the information set contains more than just the variables of direct interest, Granger-Causality may not illustrate the complete story (Lütkepohl, 2005).

2 The Hong Kong Rating and Valuation Department altered the definitions of office property classes in April 2000.

3 Given that the recent global financial crisis had an impact on office markets, Figure 1 suggests that the structural break should be around Q3 2008, which is the date checked by the Chow tests in Table 13. This study also conducted the Chow tests for Q2 2008. The unreported results also revealed no structural breaks.

Acknowledgments

The authors would like to thank an anonymous reviewer for valuable comments and suggestions. Grant support from Taiwanese Ministry of Science and Technology (MOST 103-2410-H-259 -006 -) is gratefully acknowledged.

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