Testing Alternative Theories of the Property Price-Trading Volume Correlation

Authors

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Abstract

This article examines the correlation between the real housing price and trading volume. Contrary to the predictions of standard rational expectation models, a robust positive correlation between the two variables is identified. While no clear lead-lag relationship is found in the raw data, which is more consistent with the downpayment effect model, the medium-run component of the trading volume tends to lead (and Granger cause) the corresponding component of the property price, which is more consistent with the search theoretic model. An explanation for this difference in behavior is suggested and several future research directions are provided.

Introduction

The seemingly increasing volatility in the financial markets motivates the concern of the correlation between the trading volume of an asset and the corresponding price. In a seminal work, Lucas (1978) demonstrates that there will be no correlation if the agents are rational, the capital market is perfect and the market is centralized (the standard rational expectation model henceforth). However, accumulating evidence suggests that the opposite is true in the financial markets. The standard rational expectation model may also be invalid in the property market as well. Apart from the information diffusion aspect emphasized by the finance literature, distinctive features of the property market, such as the downpayment requirement and informational friction, can also generate a positive correlation.

In Stein (1995), a positive correlation between the trading volume and property price (positive correlation hereafter) is generated because of the downpayment. Since the mortgage loan only covers part of the housing price, the remainder of the price, i.e., the downpayment, can only be financed by the equity of the buyers. A rise in the housing price increases the personal wealth of homeowners, and hence enables them to meet the downpayment requirement for new houses. As a result, trading volume increases, and a positive correlation is generated.
While the model receives some empirical support, its static nature prohibits a clear prediction on the lead-lag relationship between the trading volume and the housing price.

While Stein’s (1995) model relies on the downpayment effect, which is a form of capital market imperfection, Berkovec and Goodman (1996) (henceforth BG) focus on the informational friction of the housing market. In their model, the housing market is decentralized and buyers randomly visit sellers. Trade occurs only when the seller’s offer price is equal to, or below, the buyer’s reservation price. Sellers adopt a price reducing policy because sellers are required to sell their houses within a certain period of time. When the market receives a negative demand shock, the number of unsold houses increases and the average transaction price will decrease in the following period. Thus, the BG’s model generates a positive correlation. Notice that the trading volume leads the housing price statistically. This prediction is supported by the aggregated housing data in the United States from 1968 to 1993.5

In sum, convincing explanations exist for the positive correlation.6 However, their relative empirical importance is not clear. Furthermore, some models may not be very clear to whether the trading volume should be contemporaneously correlated to, or leading, or lagging the housing price. The literature has not yet examined this in Asian countries. To complement the previous literature, which tends to employ more aggregate data sets, this article examines the correlation with a Hong Kong disaggregated data set with different frequencies. The Hong Kong property market is chosen for several reasons. It is not uncommon for a family to spend more than 50% of household income in the monthly repayment of the mortgage loan.7 A change in the housing price can generate a significant wealth effect for potential movers (downpayment model). The housing units in Hong Kong also differ significantly (search model). Thus, the Hong Kong property market provides a unique environment to investigate the price-volume correlation.

Employing a disaggregated data set on property may be particularly relevant in Hong Kong. The location of, and views from, different estates8 vary (for example, apartments with spectacular views are typically traded at high prices).9 In addition, the relative shares of different types of estates in the aggregate transaction may change over time. To isolate the potential “aggregation bias,” a micro data set is employed and at least some control of the heterogeneity among different estates is provided.10

Another merit of the current dataset is that it contains information not found in the government publications. They only provide data with quarterly and annual frequency and hence preclude the analysis of housing market changes on a weekly and monthly basis. The current study attempts to take a preliminary step to bridge this gap.

The next section will briefly describe the data set and the methodology. Then the results about price-trading volume will be shown. The last section is the conclusion.
Data Description and Methodology

The data set was purchased from the Economic Property Research Center (EPRC). It traces all sales and purchases records for all individual property during the 1990s. In Hong Kong, all transactions need to be reported to the Land Registry Department of the Hong Kong government. The EPRC, a subsidiary of the Hong Kong Economic Times, purchases all those individual files from the Land Registry Department. The longest time series available covers the transaction dates from June 1991 to November 1998. This research focuses on the most-frequently-traded list of the EPRC, which includes forty-six private residential estates.

Only thirty-five estates are included in this study. Some of the records provided by the EPRC miss the information about the construction area. If the number of such records was greater than 5% of the total records, they were eliminated. For these thirty-five estates, the transaction records were grouped on a weekly and monthly basis. Only seventeen estates had enough transactions to be selected (with about 120,000 transactions) for weekly data analysis. All thirty-five estates are grouped on a monthly basis (with about 160,000 transactions). The treatments of the monthly data parallel those of the weekly data.

Since there is an upward trend in the real housing price in Hong Kong (see Leung, 2001, 2002), the detrended real housing price (price henceforth) variable is used instead, which can be interpreted as the rate of return (ROR) in the current context. For trading volume, the total number of housing units transacted (No.) is used in the empirical tests.

The empirical tools used in this study include the augmented Dickey-Fuller test (ADF test) and the Band-Pass Filter (BP filter) developed by Baxter and King (1995, 1999). The ADF test is used to verify the stationarity of the time series data. The BP filter is employed to isolated different components in the time series data. In practice, raw time series data usually contains components with different periodicities. Obviously, the correlations among the different components of the two time series need not coincide with the correlation of the two raw series.

The BP filter enables researchers to arrange the raw time series into different components, and hence to uncover the correlations in different frequencies. In this article, all raw time series are decomposed into three different components: the noise component, the business cycle component and the trend component. The business cycle component are those components with periodicities between six and thirty-two quarters. Components with periodicity shorter than six quarters are defined as the noise component while those components with periods longer than thirty-two quarters are defined as the trend component. These definitions have been used by the National Bureau of Economic Research for decades (see also Baxter and King, 1995, 1999; and Burnside, 1998).
Empirical Results

After verifying the stationarity of the prices and trading volume by the ADF test, the contemporaneous correlation coefficients for all estates are computed. Exhibit 1 displays the distribution of the correlation coefficients. The correlation coefficients of estate-level trading volumes and property prices are significant in general. The minimum correlation value is above 0.20. Consistent with both the downpayment model and the search theoretic model, positive and statistically significant correlations are found in thirty of the thirty-five estates for monthly data. Hence, the downpayment and search theoretic models receive further support, but the standard rational expectation model is rejected. The results for weekly data are similar and can be found in Lau (2000).

Search theoretic models (such as BG) suggest that the trading volume should be leading the housing price. Limited by the data availability, only eleven cross-periods correlation coefficients are calculated. Neither the weekly nor the monthly data provides any evidence of one variable leading the other. Exhibit 2 displays the distribution of maximum correlation coefficient for different estates. (That is, for each estate, all eleven correlation coefficients were compared and the time lag/lead with the highest correlation coefficient in absolute value term was chosen.) Most of the estates in Hong Kong do not indicate any lead-lag relationships between the trading volume and the property price. It is clear that there is a high concentration at contemporaneous correlation. The Granger causality test is also employed and only in twenty of the thirty-five estates does the trading volume cause the price. Twenty-two of the estates display their maximum correlation coefficients at the contemporaneous period. They range from 0.240 to 0.600. All of the positive correlation coefficients are significant and none of the negative correlation coefficients is significantly different from zero.

Exhibit 1 | Distribution of Correlation Coefficients (Monthly)
Testing Alternative Theories

Exhibit 2 | Distribution of Maximum Correlation Coefficients (Weekly and Monthly Data)

Notice that the (maximum) correlation coefficients in Exhibit 2 are greater in monthly frequency. For example, the weekly contemporaneous correlation coefficient for an estate called Taikoo Shing is 0.175, while its monthly counterpart is 0.530. In general, for estates appearing in both weekly and monthly frequency samples, the monthly correlation coefficients can be up to three times greater (or more) than the weekly counterparts. There might be an explanation for this regularity. It takes time for transactions to complete. And the data series used records only the completion dates. A price rise in this week may lead to a transaction completed and recorded several weeks later. Therefore, lower frequency data may capture the “correlation” between property price and trading volume more accurately. A related point is that the raw time series data may contain some “noises” (such as some discrete events or news), which masks the true relationship. (The terms “noise” and “irregular fluctuations” and “short-run fluctuations” are used interchangeably.) These noises cancel out one another in lower frequency data. Thus, the magnitudes of the monthly correlation coefficients are larger.

To formally extract the short-run fluctuations from the original time series data, the BP filter is employed. This study will focus on the correlation between the business cycle components of the housing price and of the trading volume. As shown in Exhibit 3, the correlation coefficients between the business cycle components of the trading volume and the price are significantly larger than the raw data counterparts, as conjectured. That is, after filtering, the (contemporaneous) correlation coefficients between trading volumes and prices significantly increase. For weekly data, the contemporaneous correlations of
fourteen out of seventeen estates are positive and significant. For monthly data, the contemporaneous correlations of twenty-four of thirty display positive and significant.

The striking feature of the filtered data is found in the cross-period correlation coefficients. In general, the housing price lags the trading volume. The Granger causality test also shows that in general, the trading volume causes the housing price, as predicted by the search theoretic model. For weekly data, the maximum correlation coefficients of sixteen out of seventeen estates are positive and significant. Out of these sixteen estates, the trading volume leads the ROR in eleven estates. For monthly data, the maximum correlation coefficients of twenty-four out of thirty estates are positive and significant. Out of these twenty-four estates, the trading volume leads the ROR in twenty estates. In terms of Granger causality test, the trading volume causes detrended housing price in fourteen estates out of seventeen for weekly data and twenty-eight of thirty for monthly data. Note that while trading volume leads the property price (statistically significant) for most estates, the opposite is true for a few estates (see Lau, 2000). As in the estate-level data, the correlation coefficients for the aggregate data in monthly frequency are higher than the weekly, and the trading volume leads the price (see Exhibit 4). This may indicate some degree of market segmentation, due to spatial separation or property quality difference.

How can we reconcile the two apparently contradicting findings, namely, that the trading volume and the price are only contemporaneously correlated in the raw data, and yet the “medium run” component of the trading volume is leading the medium run counterpart of the price? One possible explanation is that, there are
different kinds of “movers.” Some of them are ready to move yet liquidity constrained. Even if the housing prices only increase temporarily, they realize the “capital gains” by selling the houses and move. Clearly, this type of trading will not be recorded in any (properly filtered) medium run data. On the contrary, some owner-occupants do not move because they have not found the “right buyers” (or they cannot find the right houses to buy). Temporary changes in housing prices have little effect on them. An increase in the trading volume for a long period, however, would significantly reduce the amount of unsold houses in the market and hence increase the (average) trading price, as the search theoretic model predicts. And if the increase in the trading volume lasts long enough (say, more than six quarters), the movement in volume and the consequent change in prices will be recorded in the medium run data and detected by the tests employed in this study. Interestingly, when the data from all the estates was pooled, that while in the pre-filtered “aggregate series,” the correlation between the trading volume and the detrended price is insignificant, the monthly series after filtering display the same pattern that the trading volume leads (and also Granger causing) the property price, as in the disaggregate data (see Hiemstra and Jones, 1994; and Saatcioglu and Starks, 1998).

**Conclusion**

This study employs a disaggregated data set of the Hong Kong property market to examine the correlation between the detrended housing price and the trading volume. Consistent with the prediction of the downpayment model and the search theoretic model, contemporaneous correlation between the two series is found. In
addition, while the raw data does not display any lead-lag relationship, the business cycle component of the trading volume is leading (and also Granger causing) the corresponding counterpart of the detrended price. It may suggest that the downpayment effect dominates in the short-run. As homeowners realize the capital gains and move, its impact is overshadowed by the search effect in the medium run. In other words, different channels emphasized by different models may dominate in different frequencies. However, a panel dataset of households is needed for confirmation. It also takes a panel dataset on household to differentiate different kinds of capital market imperfection theories, namely, the downpayment theory of Stein (1995) versus the loss-aversion theory of Genesove and Mayer (2001). Another potentially interesting question is to understand why while in most of the estates, the correlation coefficients between the trading volume and the corresponding property price are positive and significant, with the former leading the latter, the opposite is true for only a few estates. Again, the owners and tenants of those “minor group of estates” could be systematically different from the “major group.” The current dataset, unfortunately, does not contain any of this information and precluded us from further investigation at this time.

Future research can extend in other directions. First, the sample can be enlarged. This article focuses on the most frequently traded list, which may unintentionally exclude some luxurious housing. Also, the sampling period may not be representative due to many political changes in Hong Kong during the period. Also, it is well known that the results may depend on the very limited length of the data available and the choice of the filter. Therefore, researchers should re-examine the findings here with longer time series and with alternative filters (see Burnside, 1998). Second, it may also extend to a cross-city comparison. Lastly, it would be interesting to investigate whether different types of homeowners (such as company vs. individual investors, old vs. young owners) will trade houses differently (see Leung and Law, 2001).

Endnotes

1 It means that agents are equally informed or equally uninformed. See Wang (1994) for more discussion.

2 The literature is large. For a survey, see Karpoff (1987) or Lo and Wang (2000). Parallel studies in the property market are however, relatively rare.

3 Personal wealth is defined as the value of all belongings plus the market price of the old house minus the outstanding mortgage balance.

4 Similarly, when housing price falls, homeowners are not likely to move as they can only afford a smaller unit now. This leads to a fall in trading volume. Stein finds that a 10% decrease in price reduced volume by over 1.6 millions units with the U.S. housing data from 1968 to 1992 (see also Lamont and Stein, 1999). Follain and Velz (1995) have different empirical findings based on a different data set. However, they believe that the difference is due to the structural changes that occurred during the mid-1980s such as improvements in mortgage instruments and slowdown in the rate of growth in housing price, and is still consistent with Stein’s (1995) model.
Following the work of BG, Hort (1999) estimates a VAR model, using data from Sweden from 1981 to 1996, and shows both monthly and quarterly frequency. Though a positive correlation between price and trading volume is found, the correlation is relatively low. Also, the VAR model does not pass the residual autocorrelation test. However, the simulation results are impressive and are consistent with the search model.

Genesove and Mayer (2001) suggest that when sellers avoid making losses, it may also generate positive price-volume correlation. This study only constructs the housing price series for different estates and cannot identify exactly which individual sellers are making losses. In addition, the authors do not have the listing price data. Therefore, the “loss-aversion” theory will be observationally equivalent to the downpayment theory in this case. The authors are grateful than an anonymous reviewer for bringing this work to their attention.

See the Consumer Council (1996). Also see Lau (2000) and Renaud, Pretorius and Pasadilla (1997) for an overview of the Hong Kong residential property market.

An “estate” in this paper is similar to a “housing development” in the U.S., i.e. a group of buildings built in the same neighborhood, at about the same time, usually by a single developer. In Hong Kong, the population of some large estates is non-negligible. For instance, Taikoo Shing has close to thirty buildings, and each has more than twenty stories.

In Hong Kong, some estates are built on mountains, some have an ocean view and others are built on top of the subway or a train station. Some estates include facilities such as gyms or swimming pools. Others may be close to shopping malls. The demand for estates can therefore be very different.

See Hanushek, Rivkin and Taylor (1996) for a discussion of aggregation bias in empirical works.

One reviewer commented that, “This was Hong Kong during the most tumultuous decade of its modern history, and may not be representative.” Limited by data availability, we acknowledge this limitation.

If the number of zero-transaction weeks was greater than 5% of the total number of weeks, the estate was not used in the weekly data analysis. If the number of zero-transaction weeks was smaller than 5%, the transaction price of the zero-transaction week was set equal to the transaction price of previous week and the number of transaction was recorded as 0.

The details of the data set as well as the results are available from the authors.

The detrended housing price is defined as \( \frac{(p(t) - p(t - 1))/p(t - 1)}{\gamma} \), where \( p(t) \) is the housing price in real terms at time \( t \), which can also be interpreted as the ROR of the housing investment.

Lau (2000) also uses other measures of trading volume and he finds that the results are very similar. However, as observed by an anonymous reviewer, the theories described in the text align well only with No.

A covariance stationary series \( y_t \) fulfills three criteria: (1) \( E(y_t) = E(y_{t-1}) = \mu \), (2) \( E[(y_t - \mu)^2] = E[(y_{t-1} - \mu)^2] = \sigma_y^2 \), and (3) \( E[(y_t - \mu)(y_{t-s} - \mu)] = E[(y_{t-j} - \mu)(y_{t-s-j} - \mu)] = \gamma_s \), where \( \mu \), \( \sigma_y^2 \) and \( \gamma_s \) are constant. A time series that violates any of the above criteria is non-stationary data. A non-stationary series will cause spurious regression and therefore only stationary variables are used for statistical analysis. See Greene (1997) for more details. By definition, if a time series \( y_t \) is stationary, then the change of that variable \( \Delta y_t \) should be uncorrelated to the previous period value \( y_{t-1} \),
after controlling for other factors. In practice, however, the true order of the autoregressive process of the data is unknown, and the result can be affected by the choice of lag length. In this study, Schwartz Bayesian criterion is employed to choose the suitable lag length for its superior large sample properties.


18 It is easy to see why noise component and trend component are not chosen. By definition, the noise components display very irregular fluctuations. As expected, no systematic correlation among the noise components is found. The trend component is discarded for a different reason. The periodicity of the trend component is longer than eight years, which is about the sampling period of this research. Thus, it may not be appropriate to study the trend component in this context. Notice that the number of observations reduces dramatically after the filtering process. Filtered monthly series contain only thirty estates. Series with observations fewer than ten after filtering were discarded. Constrained by data availability, we acknowledge this limitation.

References


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