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Asymmetric Response of Demand-Supply Mismatch to Investor's Sentiment[1]

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Abstract

We look through both the demand and supply side information to understand dynamics of price determination in the real estate market and examine how accurately investors' attitudes predict the market returns and thereby flagging off extent of any demand-supply mismatch. Our hypothesis is based on the possibility that investors' call for action in terms of their buy/sell decision and adjustment in reservation/offer prices may indicate impending demand-supply imbalances in the market. In the process, we study several real estate sectors to inform our analysis. The timeframe of our analysis (1995-2010) allows us to observe market dynamics over several economic cycles and in various stages of those cycles. Additionally, we also seek to understand how investors' attitude or the sentiment affects the market activity over the cycles through asymmetric responses. We test our hypothesis variously using a number of measures of market activity and attitude indicators within several model specifications. The empirical models are estimated using Vector Error Correction framework. Our analysis suggests that investors' attitude exert strong and statistically significant feedback effects in price determination. Moreover, these effects do reveal heterogeneous responses across the real estate sectors. Interestingly, our results indicate the asymmetric responses during boom, normal and recessionary periods. These results are consistent with the theoretical underpinnings.

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I. Introduction

Understanding the psychology behind investment decision-making is the *sine-qua-non* of issues in behavioural finance. A large number of studies in last couple of decades made numerous attempts to understand what role sentiment of economic agents play in shaping up investment decisions and subsequently, the market situation through collective or individual actions. It is quite obvious that sentiment is the key factor in economic performances. But, it is not as straightforward to understand how exactly that works under various economic environments. An economy is driven by the behaviour of agents and agents' behaviour is shaped by expectations about the market situation.

The theoretical framework, in which related literature has focused on, offers explanation through presence of 'animal spirits', possibility of habit persistence and forward-looking models. While there is no doubt about the existence of this effect, but the extent of the effect is rather unclear despite having been looked at variously. Moreover, the issue is quite under-researched within an important asset class of the economy, real estate. Therefore, we ask a specific question: how precisely the investors' attitude can provide us important clues for the future market imbalances. Since various real estate sectors do behave in quite diverse ways and undergo different dynamics, we seek answer to our question within few different real estate sectors.

Our goal is to understand the relationship between real estate returns, demand-supply mismatch and investors' attitudes as represented by market conditions affecting their behaviour and perceptions they may form about the economic cycle. We therefore study whether these attitudes pre-empt real estate performance or, vice versa, whether returns affect agents' perceptions and attitudes towards investment. However, we acknowledge the indirect relationship existing between returns and investors' attitudes.

In simple economic terms, higher or lower returns over time are determined by imbalances resulted from demand-supply interactions. Hence if excess demand (i.e. demand higher than supply) exists, we should tend to see higher returns. While if supply exceeds demand, returns should drop. In development of such imbalances, behaviours of economic agents (i.e. investors) take various patterns, as the 'mood' of the agents 'swings'.

We have organized the paper as follows. In the second section, relevant literature is discussed in detail and we try to establish our hypotheses within the literature. Then, description of the data used in the study is provided in the third section. Our theoretical hypotheses and empirical framework are outlined in the fourth and fifth sections respectively, followed by in-depth analysis of the empirical evidence in section six. We conclude our discussion with a summary of key findings in the final section.

II. Literature

The finance literature regarding stock market investment and investment psychology revolves around a few strands of theoretical frameworks and empirical tests. The very notion of rationality in asset pricing and assumptions under Capital Asset Pricing Model (CAPM) are frequently challenged in the literature. A brilliant survey of the literature is documented by Hirshleifer (2001). He discussed the theoretical underpinnings at length and in his assessment, he points out that "…although misperceptions are probably most severe when information is sparse and arrives slowly, there is no reason to think that confusion is confined purely to idiosyncratic factors. Market timers trade based on what they perceive to be superior information about the market or about industry plays such as high-tech. Investors (whether wisely or not) purchase macroeconomic forecasts. So if investors sometimes misinterpret information, they will make systematic as well as idiosyncratic errors. Indeed, to the extent that misperceptions are conveyed through social processes, mistakes may be greatest for systematic factors along with a few well-known securities" (p-1537).

Kumar and Lee (2006) examine whether the buy–sell activities of retail investors contain a common directional component. In their clientele-based framework, different investor groups operate within different natural "habitats," i.e. have preference for certain groups of stocks. As a result of such preference-based trading behaviour, the returns may also reflect the sentiment or attitudes. Specifically, authors test the hypothesis that "…if the buy–sell patterns of retail investors do not move in lock-step with overall market movements, assets in market segments dominated by these investors could be characterized by pricing anomalies that are associated with their trading activities".

Outside the investment realm, there exists a sizable literature on consumer sentiment (Katona, 1951; 1960; 1964; and 1975). The studies have used both aggregate and disaggregated data. Using aggregate time series of the Reuters/University of Michigan Index of Consumer Sentiment (ICS), Carroll, Fuhrer and Wilcox (1994) find significant evidence of precautionary motives in consumption data. Acemoglu and Scott (1994) examine whether consumer confidence is consistent with the REPIH (the Rational Expectations Permanent Income Hypothesis by Hall, 1978), which implies strong restrictions on the stochastic behaviour of consumption, given agents' beliefs about the future. Challenging rationality, Souleles (2004) provides evidence of statistically significant boost to forecasting ability using micro database of the ICS. His explanation behind rejection of the PIH is that the systematic demographic heterogeneity contributes largely to the forecast errors.

Within real estate, studies have largely focused on market activity data from the residential sector (Goodman, 1994; Weber and Devaney, 1996; Dua, 2008; Nanda, 2007; Croce and Haurin, 2009; Marcato and Nanda, 2011). On the commercial real estate sector, Baker and Saltes (2005), Clayton, Ling and Naranjo (2009), and Marcato and Nanda (2011) analyse the role of sentiment data in explaining market dynamics. Using the Real Estate Research Corporation (RERC) survey of institutional investors, Ling (2005) finds that the consensus opinions on investment conditions contained in RERC survey are useful in forecasting subsequent return performance. Similarly, using RERC survey and data from Korpacz PriceWaterhouse Coopers to examine the extent to which fundamentals and investor sentiment may explain the time-series variation in national-level cap rates, Clayton et al. (2009) find evidence that investor sentiment impacts pricing, even after controlling for changes in expected rental growth, equity risk premiums, T-bond yields, and lagged adjustments from long run equilibrium.

Marcato and Nanda (2011) evaluate a number of real estate sentiment indices to ascertain current and forward-looking information content. Within a Vector Auto-Regression (VAR) framework, their analysis suggests that sentiment indicators convey important information useful for predicting real estate market returns. Interestingly, authors find improvement in the model performance when an indicator of demand-supply mismatch (RERC percentage of buy recommendations less the percentage of sell recommendations) is incorporated. In this paper, we use detailed RERC data to explore the role of attitude in demand-supply interaction.

III. Data Description

Our analysis includes a set of attitude indicators and 'hard' economic data. Specifically, we analyse a number of indicators from the Real Estate Research Corporation (RERC) survey, along with indicators reflecting financial distress in the real estate markets. Our return or performance variables are based on the MIT/CRE CREDL Transactions-Based Index (TBI) for non-residential real estate sector. From the RERC survey, we use time for marketing, buy-sell recommendations and investment conditions data. The sample period is 1995Q1 through 2010Q4. A detailed definition of the variables is provided in Table 1.

[INSERT TABLE 1]

As there are no direct measures of demand and supply in real estate markets, we have decided to obtain a proxy for demand-supply imbalances using the indices created by CREDL (Centre of Real Estate Data Laboratory) at the MIT.[4] Along with a normal transaction based index for real estate assets, CREDL also publishes a constant-liquidity price index collapsing *"two dimensions of market functionality from the asset owners' perspective, price and expected time-on-the-market, onto a single dimension, liquidity-adjusted price"*. This measure represents price movements holding constant the expected time on the market, i.e. liquidity. Particularly the demand index reflects the buyers' response driving the constant-liquidity values, while the supply index represents the prices required to maintain a constant "ease of selling".

[4] The MIT/CRE CREDL Transactions-Based Index - http://web.mit.edu/cre/research/credl/tbi.html

We then compute a proxy for demand-supply mismatch by taking the differences between the demand and supply indexes relative to the index level at that time. This can be interpreted as the gap between reservation prices of the buyer and seller i.e. Reservation Price Gap (*RPG*):

Reservation Price Gap (RPG) = Return on Demand Index – Return on Supply Index (1)

Figure 1 shows the price indices level, return in price indices and the financial distress indicators. Three price indices (left axis) show demand-supply mismatch or the *RPG*. Clearly, we can notice that *RPG* started to rise towards the end of the crisis at the beginning of the 1990s until 1996. The level then fluctuated for few years, with a slight drop at the beginning of 2000s (i.e. technology dotcom bust), to recover to the highest levels of the end 1990s, starting from 2003 until the beginning of the more recent economic downturn. Interestingly the *RPG* measure shows a peak back in the third quarter of 2005, suggesting that some signals of a possible downturn could have been picked up looking at the fundamentals behind such a price escalation which only ended in the middle of 2007.

[INSERT FIGURE 1 HERE]

RERC tracks investment conditions, marketing time and buy/sell/hold recommendations across nine property types. This historical dataset is aggregated at the national level from RERC's quarterly institutional survey responses, which represent real estate institutional players, such as REITs, pension funds, insurance companies, banks, and opportunity funds.[5]

IV. Theoretical Hypotheses

We test several theoretical hypotheses, which are based on interaction and bargaining behavior of the buyers and sellers in the market. Buyers and sellers in the market shape their behavior based

[5] For details, see Real Estate Research Corporation (RERC) - http://store.rerc.com/collections/historical-research-data

on 'signal processing' of the information set at a given point in time. The 'signal processing' varies from the buyers and sellers and depends on which part of the market cycle they are operating on. Such behaviors will be reflected by the adjustment of buyers' offer prices and sellers' reservation prices. So, the underlying assumption of our theoretical hypotheses is that economic agents' sentiment will be transmitted through their actions, which, in turn, lead to *RPG* or demand-supply mismatch. However, market frictions and asymmetry in 'signal processing' between buyers and sellers would entail violation of this underlying assumption. Below we provide three such cases:

- *Shift in bargaining abilities:* Depending on which part of the cycle the market is moving along, the bargaining power of sellers and buyers changes. Boom time reflects sellers' market, tilting the bargaining power to sellers' side i.e. sellers are price-setters and buyers simply act as price-takers. The recessionary periods are buyers' markets.
- *Long-run investment commitment and maturity mismatch:* Institutional investors cannot sell properties quickly as they are locked in long-term commitment to their past investments. As a result, price rise during boom time will be faster than the normal (given the sellers' market). On the other hand, during the recession, the price correction may not follow the same speed of adjustment (although being the buyers' market) because of long-term commitment i.e. possibility of price stickiness due to maturity mismatch.
- *Presence of 'vulture' investors:* The 'vulture' investors may not follow the market i.e. contrary to typical buyers' and sellers' sentiment, their action of 'picking from the ruins' may be opposite to other typical investors' actions and may further exacerbate the market frictions.

Given these perspectives, we pose two key research questions:

I. Does investors' sentiment indicate market activities as revealed by *RPG* measure?
II. If it does, do the feedback loops follow asymmetric pattern during various stages of the market cycles?

V. Empirical Framework

Our empirical framework builds around the overriding presence of endogenous feedback in the system. The strong assumption of causality is easily violated in most economic relationships. A simple framework for testing causal relationships is Auto-regressive Distributed Lag - *ARDL(p,q)* – which can be specified as follows:

$$y_t = \alpha + \phi_1 y_{t-1} + \phi_2 y_{t-2} + ... + \phi_p y_{t-p} + \beta_1 x_t + \beta_2 x_{t-1} + ... + \beta_q x_{t-q} + v_t \qquad (2)$$

In order to address the endogeneity issue, we formulate a VAR framework around equation 2. In this formulation, causality is not imposed on the data. A simple VAR representation is (see Enders, 2010) as follows:

$$\begin{aligned} y_t &= \alpha_{10} + \beta_{12} x_t + \phi_{11} y_{t-1} + \phi_{12} x_{t-1} + v_{yt} \\ x_t &= \alpha_{20} + \beta_{21} y_t + \phi_{21} y_{t-1} + \phi_{22} x_{t-1} + v_{xt} \end{aligned} \qquad (3)$$

In equation (3), we assume that both $\{y_t\}$ and $\{x_t\}$ are stationary and the error terms are white-noise disturbances. The compact form of the above system is:

$$\begin{bmatrix} 1 & -\beta_{12} \\ -\beta_{21} & 1 \end{bmatrix} \begin{bmatrix} y_t \\ x_t \end{bmatrix} = \begin{bmatrix} \alpha_{10} \\ \alpha_{20} \end{bmatrix} + \begin{bmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{bmatrix} \begin{bmatrix} y_{t-1} \\ x_{t-1} \end{bmatrix} + \begin{bmatrix} v_{yt} \\ v_{xt} \end{bmatrix} \qquad (4)$$

Equation (4) is the first-order VAR. However, we can incorporate multiple lags and variables in the VAR estimation system. We use a multitude of standard tests to choose appropriate lag length (e.g. Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) etc.).

Moreover, assumption of stationarity in equation (4) is easily violated in most economic relationships. Specifically, we use Error Correction approaches to examine long-run relationships, where the short-run change in a variable relates to both the change in another variable and the gap between the variables in the previous period i.e. the lagged disequilibrium.

The relationships among returns and sentiment indicators can be specified using vector error correction models. In order to validate the approach, we conduct detailed tests for time series properties of the variables e.g. standard tests of stationarity and co-integration using Augmented Dickey-Fuller (ADF) and Phillips-Peron tests. Following co-integrating relationships, a Vector Error Correction model can be formulated as follows:

$$\begin{aligned} y_t &= \alpha_0 + \delta_0 x_t + v_{0t} \\ \Delta y_t &= \alpha_1 + \phi_1 \Delta x_t + \beta_1 (y_{t-1} - \theta_1 x_{t-1}) + v_{1t} \\ \Delta x_t &= \alpha_2 + \phi_2 \Delta y_t + \beta_2 (x_{t-1} - \theta_2 y_{t-1}) + v_{2t} \end{aligned} \tag{5}$$

Where ϕ_n is the short-run coefficient; β_n is the speed of adjustment; θ_n is the long-run effect. We estimate all the models using VEC framework. Our model specifications are parsimonious in inclusion of economic and real estate controls.

VI. Results and Analysis

Several model specifications are estimated to explore the relationships. As a first step, we check for stationarity and the direction of causality using standard Granger causality tests. These tests confirm co-integrating relationships. We use four key sentiment variables to test our theoretical hypotheses, namely marketing time, buy-sell recommendations, investment conditions and financial distress level.

The first model simply uses one control variable e.g. marketing time with up to two lags for the overall property sector. The number of lags is decided by Akaike Information Criteria (AIC). The next three models include marketing time interacted with two dummy variables indicating up and down cycles of the market. These dummies are defined in a fashion akin to the National Bureau of Economic Research (NBER) definition of recessions specific to each property sector i.e. down cycle dummy takes a value of 1 when market or sector sees negative return for two consecutive quarters. Similarly, up cycle dummy takes on value equal to 1 when market or sector sees positive rolling annual return over and above 1 standard deviation. This implies that we have also defined time periods of 'normal' market situation. The overall property market model with both interacted variables is then estimated for individual property sub-sectors. We look into three property sub-sectors – industrial, office and retail real estate. Interaction terms invariably bring in multicollinearity into the estimation system. To avoid such severe multicollinearity issues and at the same time, to understand the asymmetric responses, we keep the model specification parsimonious by not including the dummy variable without interaction.

Table 2 presents summary statistics of all variables. The average *RPG* for the overall property sector during 1995Q1-2010Q4 stood at 0.17. Among property sub-sectors, *RPG* in retail real estate was highest - 0.20 - compared with office (0.12) and industrial (0.06). Though we have used four definitions of delinquency variable, these are quite similar in time series patterns. Dummy variables indicating up and down cycles reveal that overall 23 percent of the time periods, market experienced down cycle in the sample period compared with 25 percent for up cycles. Retail real estate sector saw down cycle in 28 percent of the time periods, which is highest compared with office (19 percent) and industrial (18 percent). Office sector experienced up cycle in 28 percent of the time periods, which is highest compared with retail (21 percent) and industrial (18 percent).

[INSERT TABLE 2 AND 3 HERE]

Table 3 provides a detailed correlation matrix of the variables. To remove non-stationarity, we use the variables in changes. The relevant unit root tests (ADF) have been performed on the first differences.

a) Time to market as indicator of demand-supply mismatch

Table 4 reports models that use marketing time as indicator of sentiment. Model 1 is estimated for the overall property sector. Building on model 1, model 2 includes marketing time interacted with a dummy variable indicating up cycle in the market. Similarly, model 3 controls for the marketing time during down cycle by including the marketing time interacted with a dummy variable indicating the down cycle in the market. In model 4, both the up and down market dummy-interacted terms are included. Model 5, takes the cue from model 4, examines the industrial real estate market, while models 6 and 7 analyse the office and retail real estate markets respectively.

We find very robust and consistent results across all these specifications. In general, we find that marketing time exerts negative feedback on the *RPG*. This implies that if marketing time is longer, then the sellers initially will not lower their reservation price, they may instead resort to some non-price discounts to sell off the inventory quicker. Moreover, prices tend to be sticky downwards. While the buyers, looking at such moves by sellers and increased availability of new space, may adjust their offer price downwards. The net effect is thus a negative impact on the price gap, which is corroborated by the robust and statistically significant estimates across all property sectors (models 5, 6 and 7).

Contrarily, when the marketing is shorter (normally in markets with positive returns), the negative coefficient suggests that the price gap increases, with buyers raising their reservation prices faster than sellers because of the eagerness to be invested rather than holding onto cash in a rising market. In fact, as suggested in Lizieri et al (2011), we see that buyers are willing to pay a premium to access the market quickly when returns are positive. When potential buyers cannot execute transactions quickly enough, they face negative effect: there is a loss of income because buyers would not benefit from rising prices if they do not invest available funds in the market (e.g. an increase in marketing time of six months in a market with 12% annual return may lead to 6% loss in return); or, in other words, buyers will have to acquire at a higher price than during normal times if they wait longer, with a consequent reduction of future return expectations (using the same example, the initial acquisition price would be 6% higher than before the increase in marketing time).

However, this response is less pronounced during the down cycle (i.e. the positive coefficient of the down dummy reduces this negative sensitivity of *RPG* to changes in marketing time). In the down cycle, the sellers are not only prepared to offer non-price discounts but also to lower their reservation price. This attitude determines a contraction in the price gap smaller than in normal market conditions because the downward adjustment by the sellers will partly reduce the downward effect on the price gap. This finding is in line with Lizieri et al (2011) who argue that buyers dominate falling markets because sellers are eager to execute their transactions sooner to exit a falling market by achieving the best price (i.e. sellers would otherwise see part of their previous gains shrinking due to the effect on capital growth).

Particularly, with our finding, we shed light upon the fact that, under such circumstances, sellers may need to revise their reservation prices downwards even if they are unwilling to do so, while buyers, aware of the sellers' willingness to sell may decide to reduce their offer prices faster than sellers do. Hence the overall effect in down markets (sum of the general and down dummy coefficients) is still negative, but smaller in absolute terms. Finally, we do not find statistically significant effect during the up cycle, which perhaps reflect the asymmetric responses.

Interestingly, real estate sub-sectors reveal strong heterogeneous effects. Though the direction of the effect is similar, the office sector shows much more pronounced effects (-0.055 compared to -0.025 and -0.044 for industrial and retail real estate sectors respectively) than the industrial and retail real estate sectors. This is perhaps reflection of the office sector's dominance in commercial real estate market. Overall, these models show reasonable explanatory power (49-62% adj. R^2). Main driver of these results is dissimilarity in the adjustment processes of the economic agents i.e. buyers and sellers.

[INSERT TABLE 4 HERE]

b) Buy-sell recommendations as indicator of demand-supply mismatch

Next we turn to analyse the buy-sell recommendations from the RERC survey. Table 5 presents models using the ratio between the percentage of buy and sell recommendations as indicator of market sentiment (i.e. if the ratio is bigger than one there are more buy than sell recommendations, while a ratio less than one indicate prevalence of sell recommendations. Along with buy and sell recommendations, the percentage of hold recommendations is also recorded but not used in our analysis). Model 1 is estimated for the overall property sector. Following up on model 1, model 2 incorporates number of buy recommendations compared with sell recommendations interacted with up cycle dummy variable. Model 3 controls for the down cycle interaction term. In model 4, both the up and down market dummy-interacted terms are included. Model 5, 6 and 7 apply same specification as in model 4 with three separate marker sectors i.e. industrial real estate market, office and retail real estate markets respectively.

The results present robust and consistent effects across all specifications. Across all sectors and overall property market, we find that higher number of buy rather than sell advices affect the *RPG* positively. A possible explanation could be based on variation in 'signal processing' by the buyers and sellers, where buyers are more directly targeted and affected by these recommendations. We find that in general, increases in buy recommendation lead to increase in the *RPG*, implying a much faster upward adjustment in buyers' offer prices than the rise in sellers' reservation prices.

However, during down markets, the effect of buy and sell recommendations disappears. In fact the sum of the general and down dummy coefficients is slightly negative (-0.0070 for model 4) but not significantly different from zero. This result suggests that an improvement of buy versus sell recommendations in down markets may lead to no significant effect on the price gap. This result may be due to, on one hand, buyers resisting any revision in their offer prices when buy-sell recommendations improve, perhaps indicating 'cautious optimism' in their part. On the other hand, the long-term commitment of institutional investors may lead them not to revise their selling reservation price, hence reducing the speed of adjustment (although being in a buyers' market). This result would also corroborate the possibility of price stickiness due to maturity mismatch.

Finally, the up dummy is also negative but not significant, revealing that in normal market conditions there is a positive relationship between buy versus sell recommendations and price gap, while this relationship is reduced in up or down market due to other factors that may play more important roles (e.g. financial distress in down markets and general investment conditions in up markets).

As in Table 4, there exists significant heterogeneity in responses by various real estate sub-sectors. Office sector's effects are generally larger than those for industrial and retail real estate sectors. Overall, these models show reasonably high explanatory power (45-68% adj. R^2).

[INSERT TABLE 5 HERE]

c) Investment conditions as sentiment indicator

Investment conditions as revealed by the RERC survey respondents can serve as an important sentiment indicator. Therefore, we use the measure of investment condition in Table 6. Models 1 through 4 are estimated for the overall property sector with inclusion of dummy-interacted terms. Models 5, 6 and 7 present estimation results with same specification as in model 4 across three separate marker sectors i.e. industrial real estate market, office and retail real estate markets respectively.

We find reasonably robust and consistent results across all these specifications. Across all sectors and overall property market, we find that as investment conditions improve, so does the price gap - *RPG*. As investment conditions improve, liquidity in the market recovers and hence we should find a higher volume of transactions. Increasing transaction volumes may encourage sellers to act as price-setters as they see higher than average number of prospective buyers per sell item or property. This effect gets amplified during boom periods, as we find significantly larger effects (the coefficient of the up dummy is at least two times the one in the general market). Heterogeneous effect across various property sectors is also evident in Table 6. Overall, these models show reasonably high explanatory power (41-64% adj. R^2).

Surprisingly though, we do not find any significantly stronger effect of investment conditions on price gap in down markets. This result could be driven by the fact that during phases of falling prices, the investors' attitude may be influenced by non-institutional agents whose presence and active role may embed signals driving buyers and sellers to move asymmetrically. For this reason, in the next section, we specifically look at the presence of such agents and impact of their investment strategies and actions in distressed market situations.

[INSERT TABLE 6 HERE]

d) Presence of 'vulture' investors during down cycles

Distressed market conditions provide a unique opportunity to investors to accumulate assets and build portfolio at a relatively low prices. Especially, there is ample evidence of 'vulture' investing in real estate market. This is rather fresh in mind as the 'Great Recession of 2008' still hurts. 'Vulture' investors follow a very different strategy than typical investors and thus, they defy the market sentiment. Their strategy of 'picking from the ruins' would be quite contrary to other typical investors' strategies and this may further exacerbate the market frictions. We test such possibility in Table 7, where we use various delinquency measures relevant for the real estate market.

We find that in general market situation, delinquency hits the sellers directly, thus forcing them to lower their reservation prices in order to be able to meet debt obligations. However, this does not necessarily mean any action from the buyers' point of view. As a result, *RPG* may widen. However, during recessionary periods, when we include down-cycle dummy interaction terms, the effect on *RPG* is negative. This is plausible in falling markets if buyers dominate the marketplace by setting more stringent downward price revisions (and 'vulture' investors would be at the forefront in exercising such a power). Sellers, teetering under mounting debt obligations and bankruptcy threats, simply react to such revisions. This implies that the downward revision of buyers' offer price would be much sharper than that of the sellers, leading to shrinkage in *RPG*. This finding suggests the importance of the presence of 'vulture' investors during recessionary time periods, where buyers act as price-setters and sellers as price-takers. Various models using four different delinquency measures show reasonably high explanatory power (57-68%).

[INSERT TABLE 7 HERE]

So far, we have found evidence of bargaining in the market. Such bargaining activities behave differently in recessionary time periods from other times in the property cycle. Empirical results indicated strong evidence of price adjustments and existence of buyers' and sellers' market. In general, office sector seems to show much stronger effects than other real estate sectors. Industrial and retail sectors' dynamics differ considerably from the general market cycles.

These results are consistent with our theoretical hypotheses noted in section-IV. Our analysis suggests that buyers' or sellers' attitude and resultant revisions in reservation/offer prices entail strong and statistically significant feedback effects in price determination. Moreover, these effects do reveal heterogeneous responses across the real estate sectors. Office sector seems to show lot more pronounced effects than retail and industrial sectors. Interestingly, our results support possibility of asymmetric responses during boom, normal and recessionary periods, which is evident in overall property market as well as across all property sectors.

VII. Conclusion

In this study, we examine various indicators of demand-supply imbalances to understand dynamics of price determination in the real estate market. Our theoretical hypothesis is based on the possibility of bargaining and heterogeneous signal processing by buyers and sellers that lead to diverse range of actions in terms of their buy/sell decision and asymmetric adjustment in reservation/offer prices. Several real estate sectors over 1995-2010 are studied to inform our analysis. The timeframe of our analysis allows us to observe market dynamics over past two economic cycles and in various stages of those cycles. Our empirical framework uses various indicators (time to market, buy-sell recommendation, investment conditions, financial distress measures) of market imbalances within a Vector Error Correction approach.

The results suggest strong and statistically significant feedback effect from these indicators in price determination. These effects reveal heterogeneous responses across the real estate sectors like industrial, office and retail sectors indicating diverse dynamics of these market sectors. We find strong evidence of asymmetric responses during boom, normal and recessionary periods.

These demand-supply mismatch and sentiment indicators appear to exert much more pronounced effects during down cycles than the up cycles. These results have important implications for the investment market and forecasting exercises.

The underlying theme of this paper revolves around the shift of bargaining power from buyers to sellers and *vice versa* depending on market situations. Future research may look into cross-sectional multi-country evidence of the findings in this paper, as size and direction of the effects may depend on institutional framework and regulatory constraints in the investment market.

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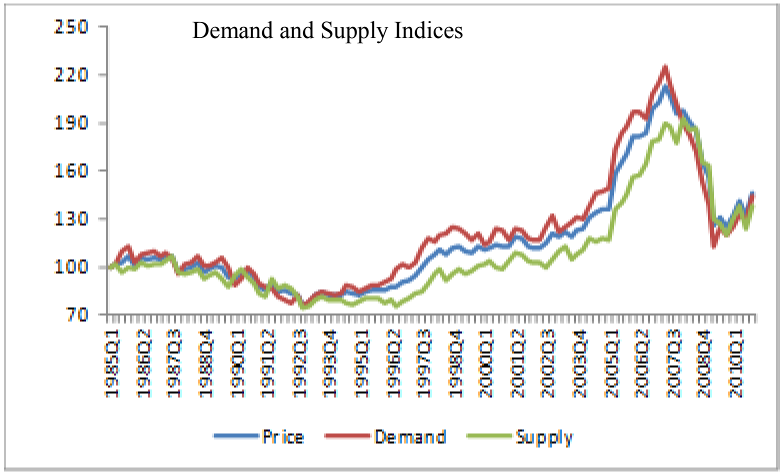
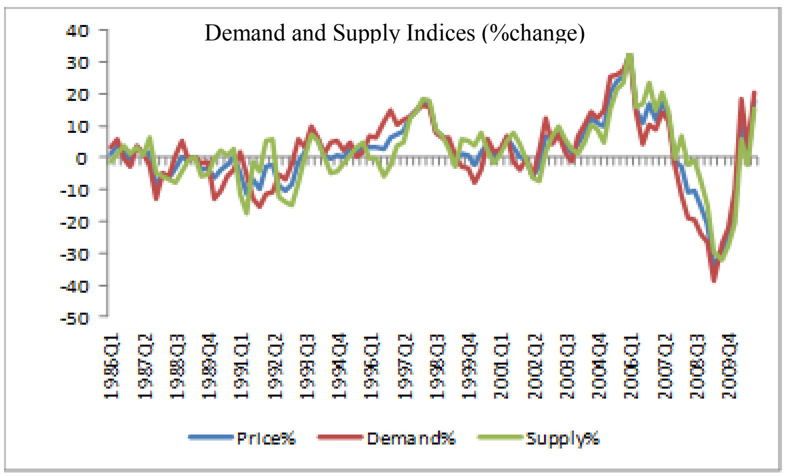
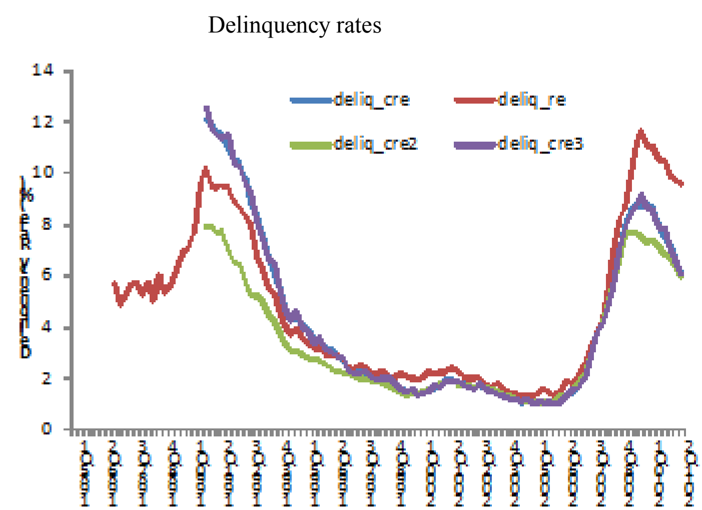
Figure 1: Transaction Based Indices and Price Gap and Delinquency Rate





Source: MIT/CREDL



Source: Federal Reserve Bank, St. Louis

Table 1: Variable Description

ALL_RPG	All property, gap between return on TBI Buy Index and TBI Sell Index
ALL_TMKTG	All property, marketing time index (RERC)
ALL_BUYSELL	All property, buy-sell index (RERC)
ALL_INVCOND	All property, investment condition index (RERC)
DELIQ_CRE	Delinquency Rate On Commercial Real Estate Loans (Excluding Farmland), Booked In Domestic Offices, All Commercial Banks – Seasonally Adjusted;
DELIQ_CRE2	Delinquency Rate On Commercial Real Estate Loans (Excluding Farmland), Booked In Domestic Offices, Banks Not Among The 100 Largest In Size (By Assets);
DELIQ_CRE3	Delinquency Rate On Commercial Real Estate Loans (Excluding Farmland), Booked In Domestic Offices, All Commercial Banks (DRCRELEXFACBN) – Non-Seasonally Adjusted;
DELIQ_RE	Delinquency Rate On Loans Secured By Real Estate, Top 100 Banks Ranked By Assets (DRSRET100N).
IND_RPG	Industrial RE, gap between return on TBI Buy Index and TBI Sell Index
IND_TMKTG	Industrial RE, marketing time index (RERC)
IND_BUYSELL	Industrial RE, buy-sell index (RERC)
IND_INVCOND	Industrial RE, investment condition index (RERC)
OFF_RPG	Office RE, gap between return on TBI Buy Index and TBI Sell Index
OFF_TMKTG	Office RE, marketing time index (RERC)
OFF_BUYSELL	Office RE, buy-sell index (RERC)
OFF_INVCOND	Office RE, investment condition index (RERC)
RET_RPG	Retail RE, gap between return on TBI Buy Index and TBI Sell Index
RET_TMKTG	Retail RE, marketing time index (RERC)
RET_BUYSELL	Retail RE, buy-sell index (RERC)
RET_INVCOND	Retail RE, investment condition index (RERC)
DDALL	Dummy indicating down cycle, all property
DDIND	Dummy indicating down cycle, industrial
DDOFF	Dummy indicating down cycle, office
DDRET	Dummy indicating down cycle, retail
DUALL	Dummy indicating up cycle, all property
DUIND	Dummy indicating up cycle, industrial
DUOFF	Dummy indicating up cycle, office
DURET	Dummy indicating up cycle, retail

Table 2: Descriptive Statistics

	Mean	Std. Dev.	Max	Min	Skewness	Kurtosis	Jarque-Bera	Prob.
ALL_RPG	0.17	0.11	0.30	-0.13	-1.01	3.28	9.87	0.0072
ALL_TMKTG	7.13	0.90	9.40	5.30	0.44	2.90	1.87	0.3921
ALL_BUYSELL	-2.33	12.58	24.00	-30.00	0.25	2.51	1.16	0.5608
ALL_INVCOND	5.57	0.65	6.66	3.86	-0.95	3.60	9.42	0.0090
DELIQ_CRE	2.86	2.47	8.78	1.02	1.57	3.86	25.05	0.0000
DELIQ_CRE2	2.70	2.17	7.67	1.08	1.47	3.50	21.22	0.0000
DELIQ_CRE3	2.86	2.48	9.13	0.99	1.56	3.83	24.73	0.0000
DELIQ_RE	3.51	3.13	11.68	1.35	1.69	4.25	31.01	0.0000
Sectors								
IND_RPG	0.06	0.12	0.23	-0.24	-0.66	2.75	4.27	0.1183
IND_TMKTG	6.61	0.81	8.90	5.00	0.80	3.94	8.16	0.0169
IND_BUYSELL	15.16	19.99	59.00	-67.00	-0.84	6.78	40.50	0.0000
IND_INVCOND	5.92	0.62	7.00	4.50	-0.69	3.18	4.57	0.1019
OFF_RPG	0.12	0.11	0.29	-0.17	-0.66	2.77	4.21	0.1216
OFF_TMKTG	7.09	0.92	9.40	5.30	0.46	2.84	2.05	0.3590
OFF_BUYSELL	25.68	25.17	75.00	-31.00	-0.07	2.35	1.05	0.5906
OFF_INVCOND	5.84	0.81	7.30	3.90	-0.15	2.28	1.46	0.4828
RET_RPG	0.20	0.18	0.51	-0.28	-0.84	3.30	7.00	0.0302
RET_TMKTG	7.72	1.13	10.50	5.80	0.52	2.56	3.04	0.2192
RET_BUYSELL	-29.53	29.14	31.00	-100.00	0.04	2.36	0.98	0.6128
RET_INVCOND	5.08	0.92	6.60	2.70	-0.54	3.24	2.86	0.2390
Dummies								
dummy_down_all	0.23	0.42	1	0	1.30	2.68	16.20	0.0003
dummy_down_ind	0.18	0.38	1	0	1.71	3.91	29.65	0.0000
dummy_down_off	0.19	0.40	1	0	1.56	3.42	23.42	0.0000
dummy_down_ret	0.28	0.45	1	0	0.98	1.95	11.66	0.0029
dummy_up_all	0.25	0.43	1	0	1.18	2.40	14.14	0.0009
dummy_up_ind	0.18	0.38	1	0	1.71	3.91	29.65	0.0000
dummy_up_off	0.28	0.45	1	0	0.98	1.95	11.66	0.0029
dummy_up_ret	0.21	0.41	1	0	1.42	3.02	19.16	0.0001

Table 3: Correlation Matrix

	ALL_RPG	ALL_TMKTG	ALL_BUYSELL	ALL_INVCOND	DELIQ_CRE	DELIQ_CRE2	DELIQ_CRE3	DELIQ_RE
ALL_RPG	1.00							
ALL_TMKTG	-0.01	1.00						
ALL_BUYSELL	0.05	0.23	1.00					
ALL_INVCOND	-0.02	-0.22	0.25	1.00				
DELIQ_CRE	-0.26	0.28	0.18	-0.28	1.00			
DELIQ_CRE2	-0.31	0.16	0.13	-0.28	0.93	1.00		
DELIQ_CRE3	-0.05	0.24	0.11	-0.36	0.88	0.83	1.00	
DELIQ_RE	0.07	0.16	0.07	-0.29	0.76	0.69	0.83	1.00

Table 4: VECM Estimation – All Property and Sectors
(Reservation Price Gap and Marketing Time)

Cointegrating Equation/Long-run Relationship

	All Property Model 1	All Property Model 2	All Property Model 3	All Property Model 4	Industrial Model 5	Office Model 6	Retail Model 7
Intercept	0.0954	0.0908	0.1771	0.1673	0.1656	0.3645	0.3414
Marketing Time	-0.0130	-0.0123	-0.0259	-0.0247	-0.0255	-0.0550	-0.0441
	[-2.67271]	[-2.28337]	[-4.75198]	[-4.29116]	[-3.52628]	[-3.99020]	[-5.17402]
Marketing Time*dummy_UP		0.0000		0.0007	0.0007	0.0003	-0.0031
		[-0.01766]		[0.46991]	[0.36157]	[0.12519]	[-1.07721]
Marketing Time*dummy_ DOWN			0.0053	0.0053	0.0044	0.0159	0.0030
			[3.78147]	[3.70114]	[2.57702]	[4.20612]	[1.19022]
Error Correction							
EC Term	-1.7206	-1.6941	-1.7062	-1.6694	-1.8137	-0.7493	-1.3751
	[-6.03405]	[-5.86687]	[-6.16145]	[-5.97122]	[-5.41668]	[-3.86330]	[-4.86281]
Adj. R-squared	0.60	0.61	0.62	0.62	0.67	0.49	0.52
F-statistic	16.93	12.88	13.21	10.65	12.82	6.61	7.48
Log likelihood	89.92	91.77	92.23	93.70	78.43	85.53	67.39
Akaike AIC	-3.11	-3.10	-3.12	-3.10	-2.53	-2.80	-2.13
Schwarz SC	-2.89	-2.81	-2.82	-2.73	-2.17	-2.43	-1.76

NOTE: The t-stats are reported within parentheses. Sector-specific price gap and marketing time measures are used for sector models.

Table 5: VECM Estimation – All Property and Sectors

(Reservation Price Gap and Buy/Sell Recommendations)

Cointegrating Equation/Long-run Relationship

	All Property Model 1	**All Property Model 2**	**All Property Model 3**	**All Property Model 4**	**Industrial Model 5**	**Office Model 6**	**Retail Model 7**
Intercept	-0.0004	-0.0014	0.0090	0.0099	0.0003	0.0173	-0.0129
Buy-Sell Recommendations	0.0106	0.0111	0.0157	0.0212	0.0058	0.0109	0.0031
	[3.61620]	[2.96108]	[4.27726]	[4.07239]	[3.67861]	[4.53639]	[1.57579]
Buy-Sell Recommendations*dummy_UP		-0.0043		-0.0094	-0.0110	-0.0085	-0.0182
		[-0.70584]		[-1.22519]	[-4.86573]	[-1.76374]	[-4.28222]
Buy-Sell Recommendations*dummy_DOWN			-0.0207	-0.0282	-0.0089	-0.0111	0.0083
			[-2.14245]	[-2.76520]	[-2.16342]	[-2.15233]	[1.88683]
Error Correction							
EC Term	-0.6059	-0.5613	-0.5032	-0.4034	-0.6144	-0.4278	0.0304
	[-3.07769]	[-2.76988]	[-3.15372]	[-2.85734]	[-2.37585]	[-3.28765]	[0.11355]
Adj. R-squared	0.59	0.64	0.63	0.68	0.61	0.45	0.48
F-statistic	9.94	8.83	8.39	7.87	6.25	3.67	3.98
Log likelihood	95.83	102.50	101.45	107.89	83.96	92.09	72.87
Akaike AIC	-3.01	-3.11	-3.07	-3.15	-2.31	-2.60	-1.93
Schwarz SC	-2.65	-2.60	-2.57	-2.51	-1.67	-1.95	-1.28

NOTE: The t-stats are reported within parentheses. Sector-specific price gap and buy-sell recommendations measures are used for sector models.

Table 6: VECM Estimation – All Property and Sectors
(Reservation Price Gap and Investment Conditions)

Cointegrating Equation / Long-run Relationship

	All Property Model 1	All Property Model 2	All Property Model 3	All Property Model 4	Industrial Model 5	Office Model 6	Retail Model 7
Intercept	0.0009	-0.0012	0.0011	-0.0011	-0.0001	0.0048	-0.0012
Investment Conditions	-0.1195	-0.0921	-0.1302	-0.0876	0.0612	-0.0856	-0.1564
	[-4.96439]	[-3.61010]	[-3.78541]	[-2.36660]	[1.40959]	[-3.73689]	[-5.07183]
Investment Conditions*dummy_UP		-0.2305		-0.1935	-0.1721	-0.1131	-0.0963
		[-2.77844]		[-2.52678]	[-2.67360]	[-2.04227]	[-1.83081]
Investment Conditions *dummy_DOWN			0.0310	-0.0185	-0.1195	-0.2455	0.0434
			[0.57762]	[-0.33648]	[-1.65449]	[-3.37390]	[1.20790]
Error Correction							
EC Term	-0.9800	-0.9892	-1.2216	-1.1887	-1.4626	-0.5333	-0.7854
	[-3.16318]	[-3.73177]	[-4.03931]	[-4.26788]	[-4.19350]	[-1.60677]	[-3.06874]
Adj. R-squared	0.52	0.55	0.56	0.58	0.64	0.41	0.44
F-statistic	12.03	9.81	10.12	8.48	9.44	4.32	6.36
Log likelihood	116.78	121.05	121.75	124.88	90.86	95.29	72.90
Akaike AIC	-3.02	-3.06	-3.08	-3.08	-2.48	-2.62	-2.00
Schwarz SC	-2.77	-2.71	-2.73	-2.64	-2.00	-2.14	-1.66

NOTE: The t-stats are reported within parentheses. Sector-specific price gap and investment conditions measures are used for sector models.

Table 7: VECM Estimation – All Property and Sectors
(Reservation Price Gap and Financial Distress)

Cointegrating Equation / Long-run Relationships

	All Property Model 1	**All Property Model 2**	**All Property Model 3**	**All Property Model 4**
Intercept	0.0034	0.0020	0.0026	0.0002
Deliquency Rate	0.0726	0.1210	0.0631	0.0584
	[4.37546]	[3.96523]	[3.82151]	[2.83801]
Deliquency Rate*dummy_DOWN	-0.0601	-0.1219	-0.0530	-0.0468
	[-2.83303]	[-3.26569]	[-2.55302]	[-2.00601]
		Error Correction		
EC Term	-1.5520	-1.2796	-1.5656	-1.7848
	[-5.43974]	[-4.92289]	[-6.23912]	[-6.34049]
Log likelihood	0.60	0.57	0.68	0.57
F-statistic	11.87	10.55	12.06	10.21
Log likelihood	136.34	133.22	136.75	146.91
Akaike AIC	-3.26	-3.18	-3.27	-2.92
Schwarz SC	-2.83	-2.75	-2.84	-2.53

NOTE: The t-stats are reported within parentheses. Model 1 uses ‘Delinquency Rate On Commercial Real Estate Loans (Excluding Farmland), Booked In Domestic Offices, All Commercial Banks – Seasonally Adjusted’; Model 2 uses ‘Delinquency Rate On Commercial Real Estate Loans (Excluding Farmland), Booked In Domestic Offices, Banks Not Among The 100 Largest In Size (By Assets)’; Model 3 uses ‘Delinquency Rate On Commercial Real Estate Loans (Excluding Farmland), Booked In Domestic Offices, All Commercial Banks – Non-Seasonally Adjusted; Model 4 uses ‘Delinquency Rate On Loans Secured By Real Estate, Top 100 Banks Ranked By Assets.