Real Estate & Planning

Working Papers in Real Estate & Planning 14/11

Can Sentiment Surveys Pre-Empt Real Estate Market Activities?[1]

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Draft: August 19, 2011

Abstract

We evaluate a number of real estate sentiment indices to ascertain current and forward-looking information content that may be useful for forecasting the demand and supply activities. Our focus lies on sector-specific surveys targeting the players from the supply-side of both residential and non-residential real estate markets. Analyzing the dynamic relationships within a Vector Auto-Regression (VAR) framework, we test the efficacy of these indices by comparing them with other coincident indicators in predicting real estate returns. Overall, our analysis suggests that sentiment indicators convey important information which should be embedded in the modeling exercise to predict real estate market returns. Generally, sentiment indices show better information content than broad economic indicators. The goodness of fit of our models is higher for the residential market than for the non-residential real estate sector. The impulse responses, in general, conform to our theoretical expectations. Variance decompositions and out-of-sample predictions generally show desired contribution and reasonable improvement respectively, thus upholding our hypothesis. Quite remarkably, consistent with the theory, the predictability swings when we look through different phases of the cycle. This perhaps suggests that, e.g. during recessions, market players' expectations may be more accurate predictor of the future performances, conceivably indicating a 'negative' information processing bias and thus conforming to the precautionary motive of consumer behaviour.

Keywords: Sentiment Data, Predictability, VAR, Impulse Response, Out-of-sample Forecast
JEL Classifications: C53, C82, E37, R31.

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[1] The authors would like to acknowledge financial support from the Royal Institution of Chartered Surveyors (RICS) Education Trust, Real Estate Research Corporation (RERC) and University of Reading, School of Real Estate and Planning, UK. The authors would also like to thank Paul Emrath as well as participants at the 2011 AREUEA Mid Year Meeting for comments. Tumellano Sebehela provided excellent research assistance. All remaining errors are ours.
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I. Introduction

The rational economic agents use market information to form their individual expectations. Such expectations should notionally shape the agents' actual behaviour in the marketplace. A number of sentiment surveys aim to tease out agents' expectations by asking focused questions. Several such surveys concerning both the general economy and the specific sectors are released each month in the United States. Analysts look at these indices to find out clues for weakness/strength in the respective sectors and overall economy. It is of paramount importance to business forecasting to incorporate any information 'gain' from the sentiment surveys. Even a cursory glance through the historical plot of these indices against 'hard' economic data seems to reveal rather interesting patterns of lead/lag relationships.[4] However, the empirical findings around such relationships are somewhat mixed in the literature.

[INSERT FIGURE 1 HERE]

Typically, these surveys ask questions that are comparative (e.g. compared to the previous period) and forward-looking, and try to explore perceptions of the concerned economic agents. For example, the Survey of Consumers conducted by the Reuters/University of Michigan asks whether it is a good time or a bad time to buy a house; the Architecture Billings Index (ABI) obtained from the American Institute of Architects' (AIA) Work-on-the-Boards survey asks respondents (architecture firms) to report firm billings for the just-completed month as compared to the previous month, as well as inquiries for new work over the same period; and the NAHB/Wells Fargo Housing Market Index (HMI) is based on a survey that asks respondents (home builders) to rate three components - current new single-family home sales, expected sales of single-family units over the next six months, and traffic of prospective buyers. These surveys, as constructed, do reveal attitudes of the economic agents and may provide expedient clues about their future behaviour regarding the level of discretionary spending and extent of business expansion.

[4] Refer to Figure 1 and 2.

There is a well-rounded debate around possible channels through which these sentiment indices may provide useful information about the economic activity. A number of studies looked at the information content and predictive power of various indices. However, there is no definitive knowledge about the relationships among indices and whether the information content can be combined in a meaningful way to help predict future economic activities. Most studies use consumer's sentiment indices that are based on survey questions to gauge broader economic attitude. However, we focus on specific sectors: residential and commercial real estate. Moreover, the consumer's sentiment reflects a demand-side 'mood' of the economy. We also analyze survey data that portrays supply-side of the market. Another way to look at the issue is to appreciate the possibility that the quality and quantity of information content and the method of information processing could be quite different between demand-side players (consumers/home buyers) and supply-side players (home builders, architecture firms etc.). Also, it may be plausible that responses from the supply-side players contain information based on the demand-side feedbacks. Therefore, we argue that it may be worthwhile to focus on sector-specific surveys.

The theoretical premise is that consumers and other market agents form their perceptions based on available information and are likely to behave according to their perceptions. Possible explanations include presence of 'animal spirits', habit persistence and forward-looking theories indicating future consumption as they predict variables relevant to the consumers' planning problem (Acemoglu and Scott, 1994). Though we do not engage in the debate on possible channels directly, we try to find out the causal relationships and determinants of the agents' perceptions. We look into few different surveys across the real estate sectors for evidences of such phenomena. These surveys do differ in terms of 'breadth' and 'depth' of the questionnaires and objectives. Several studies looked at the sentiment or attitude data for the residential real estate sector (Goodman, 1994; Nanda, 2007; Dua, 2008; Croce and Haurin, 2009). However, there is very little known about such surveys in the non-residential real estate sector. Therefore, one of our goals in this study is to explore the predictive power of the Architecture Billings Index (ABI) and indices from Real Estate Research Corporation (RERC) on the supply-side.

The focus of our paper is on indicators of both residential and non-residential real estate markets. We analyse the returns or performances in these market segments. Unlike previous studies analysing some sector-specific output (e.g. personal consumption expenditure, level of housing production, etc.) we investigate responses of returns (i.e. pricing information) within respective sectors. We argue that, when looking through the lens of supply-side players who may as well have knowledge and understanding of the demand-side conditions, prices - as determined by demand-supply interactions, may contain significant feedback effects. With these assessments on the topic, we put forward five specific research questions in this study:

a) When forecasting sector performances (for both residential and non-residential sector), what are the information gains from using sentiment indices?
b) Is there any difference between non-residential and residential real estate markets in terms of information gains from respective sentiment indices?
c) What are the causal relationships among real estate and more general business indicators?
d) Do feedbacks from sentiment data differ in the different phases of the cycle?
e) How does the model behave when we include both demand and supply information?

We have organized the paper as follows. In the second section, we review relevant literature and situate our hypotheses within the literature. Then, we proceed to describe the data in the third section. Our methodology is outlined in the fourth section. We discuss the results and present the empirical analysis under section five. We conclude in the final section with a summary of key findings.

II. Literature

A sizable literature exists on various aspects of the consumer sentiment indices. Most studies analyze the Reuters/University of Michigan's Index of Consumer Sentiment and the Conference Board's Consumer Confidence Index. Katona (1951, 1960, 1964, and 1975) analyses the psychology of consumer behaviour in great detail. Both aggregate and disaggregated data have been explored in the literature. Carroll, Fuhrer and Wilcox (1994) use aggregate time series of the Reuters/University of Michigan Index of Consumer Sentiment (ICS) and find significant excess sensitivity of consumption expenditure to sentiment, possibly indicating precautionary motives. They provide evidence that lagged values of the ICS can explain almost 14 percent of the change in real personal consumption expenditure and it contributes almost 3 percent to adj. R^2 of a reduced-form equation for personal consumption expenditure. The authors note that a possible explanation behind this correlation lies on a combination of habit formation and precautionary motives (also supported in a recent study by Kiley, 2010). Their finding, in a simple framework, is quite important as it opens up issues in theoretical and empirical investigations on this subject.

Acemoglu and Scott (1994) look at similar aggregate data from the UK and find some support for predictive power of the sentiment data. They 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. The ability of the consumer confidence indices to predict the future income may indicate that these indices contain consumers' private information. However, the authors dismiss the plausibility of 'animal spirit' and argue that the confidence indicator is also a leading indicator for consumption, contradicting the REPIH and note *"... the REPIH is only rejected because of confidence indicators, and not because of excess sensitivity with respect to income or any other variable"*.

In view of inconclusive results from previous studies, Bram and Ludvigson (1998) investigate consumer attitudes comparing forecasting power of the Reuters/University of Michigan's Index of Consumer Sentiment (ICS) and the Conference Board's Consumer Confidence Index and find that forecasting power varies between these surveys. Vuchelen (2004) presents mixed evidence of information content in the consumer sentiment surveys. There are studies using data from different countries to answer similar questions – Acemoglu and Scott (1994) report results with UK data; Utaka (2003) uses Japanese data; Chua and Tsiaplias (2009) present Australian evidence.

In order to avoid aggregation bias (thus, rejecting rationality), Souleles (2004) uses micro data underlying the ICS and finds that the sentiment index does provide significant boost to the ability to forecast consumption growth. He concludes that rejection of the PIH is due to the systematic demographic heterogeneity (i.e. aggregate shocks may not affect all people uniformly) in forecast errors.

Taking the cue from the existing research on consumer sentiment, we focus on a specific sector – real estate market. There are several studies that look at the residential real estate sector. Some studies explore the housing question from the ICS. Weber and Devaney (1996) use the ICS data on housing market to forecast housing starts. Dua (2008) examines determinants of consumers' buying attitudes for houses using data from the ICS and finds that interest rates have the maximum impact on decisions to purchase houses followed by expectations of real disposable income. Contrary to these studies exploring the demand-side of the market, few articles examine the supply-side, i.e. surveys seeking reactions of the producers. Goodman (1994) evaluates the predictive power of four market indices. Unlike Goodman's paper, Nanda (2007) does not compare various indices. He analyses the NAHB/Wells Fargo Housing Market Index (HMI) based on a survey of home builders. Using monthly data from 1985 to 2006, he finds that HMI significantly increases the explanatory power when the estimation uses housing starts and housing permits. Croce and Haurin (2009) compare the ICS information on housing with the HMI and find that the measure of consumer sentiment performed better than the HMI in predicting housing permits, housing starts and new home sales, confirming the theoretical assumption that supply-side perceptions embed information on demand-side feedbacks.

Compared to the residential sector, there is lot less known about the use of a sentiment survey in predicting activities in the non-residential (or commercial) real estate sector. To our knowledge, Baker and Saltes (2005) and Clayton, Ling and Naranjo (2009) are perhaps the only studies in this sector. Baker and Saltes (2005) examine the Architecture Billings Index (ABI) and suggest that the integration of this leading indicator into more formal structural forecasting models of non-residential construction activity may improve their performance. According to Baker and Saltes (2005), since architecture firms design a majority of commercial buildings in the US and there is a considerable time gap between the award of a design contract and a construction contract, there may be a consistent relationship between architectural design activities and non-residential building construction. However, a detailed study is needed to understand the efficacy of ABI and to separate between demand-side and supply-side effects, which we undertake in this paper.

Finally, Clayton et al. (2009) analyse the RERC survey and data from Korpacz PriceWaterhouse Coopers to evaluate information on investment conditions for nine property types. Using error correction models of the adjustment process, they examine the extent to which fundamentals and investor sentiment may explain the time-series variation in national-level cap rates and authors 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. Therefore, we focus on returns in respective sectors.

III. Data Description

We analyze a set of indicators that include both sentiment indices and indices based on 'hard' economic data from various sectors, thereby capturing the broader economic condition. The list of indices includes the Architecture Billings Index (ABI), the Real Estate Research Corporation (RERC) survey, and the NAHB/Wells Fargo Housing Market Index (HMI) along with other broader market indicators such as the Chicago Fed National Activity Index (CFNAI), Tech Pulse Index (SFTECH), ISM Purchasing Managers Index (PMI), and the Reuters/University of Michigan Consumer Sentiment Index (SENT_CONS). Our return or performance variables are based on the MIT/CRE CREDL Transactions-Based Index (TBI)[5] for non-residential real estate sector and S&P/Case-Shiller Home Price Index (HPI) for the residential real estate sector. Table 1 reports all acronyms used in our estimation output. We try to encompass full history of individual data items. Overall, for the non-residential real estate models, the sample period is 1997Q1 through 2010Q4. For the residential real estate models, the sample period is 1988Q3 until 2010Q4. Our sample period changes across various models depending on the availability of data for the particular set of variables included in individual equations. The frequency of the observations is quarterly.

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

[INSERT TABLE 1 HERE]

ABI is obtained from the American Institute of Architects (AIA) Work-on-the-Boards survey, which is conducted monthly since 1995 across a nation-wide sample of architecture firms. About 300 architecture firms actively participate in this survey. Firms are asked to report whether billings during the month significantly increased (five percent or more), remained about the same, or significantly decreased (five percent or more) compared with the previous month. The ABI is computed as a diffusion index, with the monthly score calculated as the percentage of firms reporting a significant increase plus half the percentage of firms reporting no change – see Baker and Saltes (2005) for details.[6]

RERC tracks investment conditions, marketing time and buy/sell/hold recommendations for nine specific 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.[7]

The National Association of Home Builders (NAHB) and Wells Fargo produce the Housing Market Index (HMI) every month since 1985 to provide an initial reading of the state of the housing market, especially the single-family sector. The survey aims to capture home builders' evaluation of the market – both current and forward looking views. The HMI is a weighted average of three separate indices constructed from three different questions: present sales of new homes, sales of new homes expected in the next 6 months and traffic of prospective buyers in new homes – see Emrath (1995) and Nanda (2007) for details.[8]

The Purchasing Managers Index (PMI) is produced monthly by the Institute for Supply Management (ISM) since 1948. The data for the index comes from a survey of about 400

[6] For details, see American Institute of Architects (AIA) Work-on-the-Boards survey - http://www.aia.org/practicing/economics/AIAS076265.
[7] For details, see Real Estate Research Corporation (RERC) - http://store.rerc.com/collections/historical-research-data
[8] For details, see The NAHB/Wells Fargo Housing Market Index (HMI) - http://www.nahb.org/reference_list.aspx?sectionID=134

purchasing managers in the manufacturing sector. Respondents can report better, same or worse conditions than the previous month.[9]

The Tech Pulse Index, published by the Federal Reserve Bank of San Francisco, is an index of coincident indicators of activity in the U.S. information technology sector. It tracks the health of the tech sector. The indicators used to compute the index are: investment in IT goods, consumption of personal computers and software, employment in the IT sector, as well as industrial production and shipments by the technology sector. We include this series in our analysis so as to capture wider market dynamics.[10]

The monthly Reuters/University of Michigan Surveys of Consumers measure how consumers feel the economic environment will change. The survey's Index of Consumer Expectations is an official component of the US Index of Leading Economic Indicators.[11]

The Chicago Fed National Activity Index (CFNAI), published by the Federal Reserve Bank of Chicago, is a monthly index designed to estimate overall economic activity and related inflationary pressure. The CFNAI is a weighted average of 85 existing monthly indicators of national economic activity. It is constructed to have an average value of zero and a standard deviation of one. Due to mean-reversion in growth rates, a positive CFNAI index reading may indicate growth above trend and a negative reading relates to growth below trend.[12]

[INSERT TABLE 2 HERE]

Table 2 provides descriptive statistics of the variables. We use the variables in changes to address non-stationarity issues. We have performed unit root tests (Augmented Dickey-Fuller,

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[9] For details, see The Purchasing Managers Index (PMI) - http://www.ism.ws/ISMReport/content.cfm?ItemNumber=10752&navItemNumber=12961
[10] For details, see The Tech Pulse Index - http://www.frbsf.org/csip/pulse.php
[11] For details, see The Reuters/University of Michigan Surveys of Consumers - https://customers.reuters.com/community/university/default.aspx?
[12] For details, see The Chicago Fed National Activity Index (CFNAI) - http://www.chicagofed.org/webpages/publications/cfnai/index.cfm

i.e. ADF) on the first differences and found evidence on stationarity.[13] We use changes in real GDP, Term Structure (i.e. difference between 10-year Treasury Bond yield and 3-month Treasury Bill rate), and changes in Producer Price Index as controls for overall economic conditions. We use the change in TBI total return as the dependent variable in our analysis for the non-residential sector and the first difference of the change in HPI (to avoid non-stationarity) for the housing sector.

IV. Empirical Framework

The most important limitation of imposing causal relationships is that feedback effects are quite common among economic variables. It is not clear if the evolution of the so called 'independent' variable is caused by that of the 'dependent' variable. For example, the causality between $\{y_t\}$ and $\{x_t\}$ may be represented in a standard Auto-regressive Distributed Lag - *ARDL(p,q)* - framework as follows:

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

Due to possibility of feedback effects, it is highly likely that two variables may have 'endogenous' relationship, which equation 1 fails to characterize. A VAR framework essentially avoids any *a priori* assumption on causality; rather it treats all variables symmetrically. In the simplest case of two variables and one period, the time path of $\{y_t\}$ is affected by present and past (one period lag) realizations of another sequence $\{x_t\}$ and, simultaneously, $\{x_t\}$ is affected by present and past (one period lag) realizations of $\{y_t\}$. In this case, the VAR representation is (see Enders, 2010):

$$\begin{aligned} y_t &= \alpha_{10} + \beta_{12} x_t + \phi_{11} y_{t-1} + \phi_{12} x_{t-1} + v_{yt} \\ x_t &= \alpha_{20} + \beta_{21} y_t + \phi_{21} y_{t-1} + \phi_{22} x_{t-1} + v_{xt} \end{aligned} \qquad (2)$$

[13] We also perform Phillips-Perron (PP) test for detecting unit roots. We do not find any different outcome than that from the ADF test.

In equation (2), 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:

$$\begin{bmatrix} 1 & \beta_{12} \\ \beta_{21} & 1 \end{bmatrix} \begin{bmatrix} y_t \\ x_t \end{bmatrix} = \begin{bmatrix} \alpha_{10} \\ \alpha_{20} \end{bmatrix} + \begin{bmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{bmatrix} \begin{bmatrix} y_{t-1} \\ x_{t-1} \end{bmatrix} + \begin{bmatrix} \nu_{yt} \\ \nu_{xt} \end{bmatrix} \tag{3}$$

Equation (3) is the first-order VAR. In practice, we use multiple lags and a number of variables in the estimation system. It is evident that the system can accommodate a large number of variables and lags. However, economic theories are useful to select 'relevant' variables. It is also important to determine the appropriate lag length. We use a multitude of standard tests to choose appropriate lag length (e.g. Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) etc.) and report statistics in main tables.

Our empirical strategy is implemented in an error-correction approach to examine the 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. Some studies (e.g. Dua, 2008; Chua and Tsiaplias, 2009) have used a VAR framework to analyze attitude data and sentiment indices could be incorporated in the model as explanatory variables. Before proceeding with the VAR estimation, we perform a multitude of diagnostic tests. First, we use the Augmented Dickey-Fuller (ADF) test to detect non-stationarity in the variables as they may exhibit co-integrating relationship, i.e. non-stationary variables are combined to show stationary long-run equilibrium relationships. In order to test co-integrating relationships, we formulate a Vector Error Correction Model (VECM).

Our particular interest lies in detecting the 'gain' in information when we predict real estate market returns using sentiment indices. Empirically, in a two-equation model with p lags, $\{y_t\}$ does not Granger cause $\{x_t\}$ if and only if all the coefficients are equal to zero. In other words, if $\{y_t\}$ does not improve the forecasting performance of $\{x_t\}$, then $\{y_t\}$ does not Granger cause $\{x_t\}$ (see Granger and Newbold, 1974; Granger, 1988). We test for Granger causality across a set of sentiment and economic variables to ascertain information gains. In our system of equations, we also perform a block-exogeneity test to detect whether incorporating additional variable (i.e. information like sentiment index) improve predictability. After we establish predictability of the variables, we use Impulse Response functions to determine the time length of the diffusion of the effect of a variable. We also present variance decompositions to understand the individual variable's contribution to forecast errors.[14]

V. Results

A. Correlation and Granger Causality

We run several models for both non-residential and residential real estate markets using respectively the ABI and HMI indices as a proxy for real estate specific market sentiment and several business indicators to proxy for more general market conditions. Initially, we investigate the contemporaneous relationship between variables reported in the correlation matrix (Table 3).

[INSERT TABLE 3 HERE]

Of the three economic variables we use, only term spreads are not significantly correlated with real estate returns. Moreover, both real estate specific and more general sentiment indicators do not seem to be linked to the investment returns. However, this finding may be due to the need to account for the inter-temporal nature of their relationship (i.e. we expect current sentiment indices to predict future performances). Furthermore, the HMI measure is correlated to broad economic measures revealing the significant impact the housing market has on the overall economy and vice versa. On the contrary, the ABI measure reveals that there is no contemporaneous relationship between non-residential real estate sentiment and economic conditions, in line with sometimes "irrational" return chasing behaviors of institutional investors (Ling et al., 2009).

The formation of investors' expectations and real estate market behavior requires consideration of the dynamic nature of these relationships. Consequently, we study the inter-temporal

[14] See Enders (2010), Chapter 5 for detailed discussion on the VAR framework.

relationship between each of the explanatory variables and real estate market returns – measured by the MIT Transaction-Based Index (RE_TBI) for the non-residential sector and the S&P/Case-Shiller Index (RE_HPI) for housing. We group variables into three main categories: 'hard' economic variables (Real GDP Growth, Term Structure and Inflation), real estate sentiment index (ABI and HMI) and other economic indicators (Chicago Fed National Activity Index, Reuters/University of Michigan Consumer Sentiment Index, ISM Purchasing Manager's Index and Tech Pulse Index). The fourth and fifth columns in Table 4 report the p-values of the Granger causality test for the first period in which explanatory variables start to become significant in Granger causing real estate total return. Having run the test for lags 1 to 12, we report in columns 2 and 3 of Table 4 the lags at which the Granger causality from explanatory variables to total returns starts and ends being significant (i.e. these dates represent the period where causality persists).

[INSERT TABLE 4 HERE]

Panel A of Table 4 shows the results for the non-residential real estate. First, the only indicator not affecting real estate returns is the Consumer Sentiment Index. This may be due to the fact that consumers are affected by real estate returns and, contemporaneously, returns in real estate markets are affecting consumer sentiment. In fact, in most tests (with different lags), we find both series being significant in explaining each other (hence showing no Granger causality because of the need of a one way relationship). Second, real GDP growth, inflation and the Tech Pulse Index start to affect total returns with a 1 quarter lead, with the effect fading away within two years for the first two variables and immediately for the Tech Pulse indicator. Moreover, other variables show a 3 quarter initial lag, being consistent with their construction methodologies (e.g. the ABI index includes a survey on the performance compared to the previous month), and showing a very resilient causality for both general (CFNAI, 12 quarter ending causality) and sector specific indices (ABI for real estate, 10 quarter ending period).

Panel B of Table 4 reports results for the housing market. The picture is slightly different and we would expect so, considering the different drivers and linkages of the markets. First, we notice that some variables (Real Changes in GDP, Interest Term Spreads, Consumer Sentiment

Index and Tech Pulse Index) do not seem to Granger cause house prices (this result however does not necessarily imply that there is no more general causality between these variables). The fact that some business indicators are less able to explain residential real estate prices is reasonable because one might expect a greater impact of these indicators on real estate markets linked with business activities (i.e. commercial), as well as a feedback effect of real estate prices on agents' expectations and hence business indicators. We also find that two of the more general indices Granger cause house prices, but this result may be due to the 'housing component' of the indicator itself, which – for example – is important in the case of the CFNAI. Second, we do not find reversal of Granger causation happening after the first causation from economic and sentiment indicators to house prices (as in the case of non-residential real estate). However, this reverse causation (from house prices to other variables) happens for real GDP growth, interest rates and one of the business indicators, perhaps signaling more direct linkages of the housing market with the broad economy.

B. VAR models

From the first part of our analysis, the complex nature of the relationships between economic trends, sentiment indicators and real estate markets is evident. Hence, we decided to study these relationships through a VAR system which models a system of potentially endogenous relationships between real estate returns and a series of explanatory variables. Table 5 (non-residential) and Table 6 (residential) report VAR estimation outputs (with 4 lags) across various model specifications, all of which contain main economic indicators among the set of explanatory variables. We introduce variables one after another in models 1 to 6. Finally all types of explanatory variables are included in model 7 (with only one economic indicator chosen among the four available variables, namely the one granting the best result overall). The choice of a 4-period lag structure allows us to consider the information feedback over a period of at least a year and it is derived from both a parsimonious approach (as in previous studies where a 2 quarter lag structure was adopted - Clayton et al. (2009) and our mixed results in lag exclusion tests reported at the bottom of the table. The top part of the table reports the probability of the $\chi 2$ statistic with null hypothesis of no Granger causality within the VAR system for the 4 lags jointly. Finally, the last column shows the maximum weight that each variable has in a variance decomposition using a Cholesky factorization for up to 10 quarters and using four versions of model 7 (i.e. including one business indicator at a time).

[INSERT TABLE 5 HERE]

The main results for commercial real estate returns are reported in Table 5. All models show a goodness of fit (adj. R^2 above 20%) when we use a set of information criteria (i.e. Log-likelihood, AIC and BIC). According to our expectations, adding real estate sentiment indices, we find remarkable improvement in goodness of fit (i.e. adj. R^2 rises to almost 40%).

Furthermore, we find evidence of Granger causality for economic indicators, real estate sentiment and two out of four market indicators (i.e. Chicago Fed National Activity Index and Consumer Sentiment Index), with real GDP growth and inflation showing a weaker predictive power (significance at 10% level). The test of joint significance of all variables in each model also suggests the importance in predictive ability. Finally, variance decomposition figures seem to confirm our results, with market indicators however showing a slightly higher impact than the real estate sentiment.

[INSERT TABLE 6 HERE]

Table 6 reports VAR estimation outputs for the housing market. Similarities with commercial real estate can be clearly seen, with all models showing a better goodness of fit (above 35%). Both real estate sentiment and market indicators improve the modeling exercise, with goodness of fit reaching 46% (and information criteria showing an improvement) and more general market indicators capturing a substantial predictive power.

Looking at the individual variables, we find evidence of Granger causality for real changes in GDP and inflation, but not for the term structure of interest rates, with each of the economic variables showing a maximum of 16% weight in the variance decomposition (24% for non-residential markets). The real estate sentiment index is significant in all models and also shows the largest contribution in the Cholesky decomposition, suggesting a greater importance of real estate specific indicators for housing markets (18%) than for commercial real estate (10%) when compared with more general business indicators (13% vs. 11%), with real GDP growth and inflation showing a weaker predictive power (significance at 10% level).

C. Impulse Responses

Figures 3 and 4 present the impulse responses for the non-residential and residential models respectively. In general, the directions of changes conform to our theoretical expectations. Specifically for the non-residential model, a one standard deviation shock to our variable of interest (ABI) has a positive short-run impact and overall positive net impact. Interest rate and inflation measures exert net negative impact. For the residential model (Figure 4), one standard deviation shock to HMI wields a sharp and immediate positive impact on changes in house prices, although the effect wanes over time and even gets into negative territory resulting in a somewhat flat net impact. The short-run positive impact stays over about two and a half quarters. Response of GDP to shock in house price is positive.

D. Sentiment Indicators, Recessions, Demand-Supply Mismatch

In this part of our analysis we present the feedback process of sentiment indicators during different phases of an economic cycle and introduce an indicator to capture mismatch between demand and supply. As far as the business cycle is concerned, we believe that these expectation measures should work more effectively during recession phases than in a boom or stable periods. During recessionary phases, economic agents may not only provide a gloomy sentiment, but also tend to follow their 'heart' closely by spending reduction (as indicated by Carroll et al., 1994). This hypothesis is also consistent with the precautionary motive argument. Consequently, we include a recession dummy in our model, with 1 for NBER recession dates and 0 otherwise. We interact this dummy with sentiment indices and report results in table 7 and 8 for respectively non-residential and residential real estate markets. The interaction is applied because we believe that different parts of the business cycle may grant different responses and feedbacks to the new release of economic information and/or consumers and suppliers' behavioral attitudes. As we are interested in the interaction with sentiment indicators within a full model, we only report the model incorporating economic variables and real estate sentiment index, and the model including business indicators along with economic variables and real estate sentiment.

[INSERT TABLE 7 HERE]

For non-residential real estate (Table 7), we find that the recession dummy is significant in all models (though 89% confidence level in the last model), suggesting a stronger feedback from sentiment measures during recessions. Particularly in the variance decomposition, we find that the weight of real estate indices reaches a figure of 30% during these periods (i.e. computation as a sum of the weights of real estate sentiment alone and multiplied by the recession dummy). Secondly, general business indicators do not seem to be relevant and recession periods seem to be make a difference only for the CFNAI (though with 84% confidence level), and with a 15% maximum weight reached in the variance decomposition (still bigger than for the models without the recession dummy). Finally, the majority of our models show a goodness of fit at 50% or above, indicating a marked improvement from the models where sentiment indices were assumed to explain returns during recessions and other phases of the market cycle evenly.

[INSERT TABLE 8 HERE]

Table 8 reports the VAR estimation output including a recession dummy for housing markets. Firstly, the goodness of fit is even slightly higher than for non-residential real estate models, with the adj. R^2 above 50% for all models and reaching a maximum of 59%. Real estate sentiment is always significant in both growing/stable markets and recessions. Contrary to the non-residential models, we find that general business indicators become relevant during recessions and should then be incorporated in the modeling exercise. Finally, the weight in the Cholesky variance decomposition reaches 36% for real estate sentiment indices and a maximum of 20% for business indicators during recessionary phases.

Finally, we test for any improvement in the model performance when an indicator of demand-supply mismatch is incorporated. In Table 9, we include one of the RERC indices (i.e. percentage of buy recommendations less the percentage of sell recommendations), possibly flagging off whether it is a buyer's or a seller's market. The results show reassuring development. Compared to the non-residential model in Column 7 of Table 5, Column 5 in Table 9 shows almost a 10 percentage point improvement in adj. R^2 and the RERC buy-sell indicator is also significant at 5% level. This is clearly quite promising, and we intend to explore this case in greater rigour in a follow-up research.

[INSERT TABLE 9 HERE]

E. Out-of-sample Evaluation

One of the drawbacks so far is the fact that we have only performed in-sample testing. As another way to establish the importance of both demand- and supply-side sentiment indices in predicting real estate returns, we have performed simple out-of-sample tests to understand whether our key forecasting models perform better or in desired fashion. Table 10 presents a set of models showing changes in selected forecast evaluation parameters. Theil inequality coefficients show decreases in the value from 0.56 for a model with only 'hard' economic variables to only 0.16 for a model that includes additional controls of sentiment indices and the RERC buy-sell indicator. The improvement is both remarkable and quite desirable. The same is largely corroborated by other parameters e.g. in root mean squared error (RMSE). Though the bias proportion is not in most desirable range (especially for the last model with 0.25), the variance proportion is not particularly large and the covariance proportion nonetheless reveals that the random component comprises more than half of the error. Moreover, in our out-of-sample evaluation exercise, we have perhaps chosen the worst time-period (in terms of economic uncertainties) to roll our models over – 2009-10. Overall, the out-of-sample predictions show quite encouraging evidence of 'gain' in our forecasting ability when we incorporate indices based on attitude data and forward-looking surveys.

[INSERT TABLE 10 HERE]

VI. Conclusion

In this study, we analyze the information content of sentiment indices and their relative importance in modeling real estate returns. After testing for stationarity, contemporaneous and inter-temporal relationships between variables, we estimate a VAR system. Our results seem to suggest that sentiment indices are important in explaining real estate returns, i.e. there are statistically significant information gains from using survey-based indices.

Particularly, the real estate specific sentiment indices show better information content than more general business indicators. However, the latter become more important for housing markets, perhaps suggesting a more substantial feedback effect of housing markets within the broad economy. The goodness of fit of our models is higher for the residential market than for the non-residential real estate sector. In general, impulse responses conform to theoretical expectations and Cholesky variance decompositions show significant contribution of sentiment indices to forecast errors. We also provide an out-of-sample evaluation, which largely supports our results. Quite interestingly, the predictive power fluctuates when we look through different phases of the cycle. This suggests that, e.g. during recessions, market players' expectations may be more accurate predictor of the future performances, possibly indicating a 'negative' information processing bias and thus alluding to the idea of overriding precautionary motives.

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Table 1: Variable Description

	Description	Source
RE_TBITR	Transaction-Based Index - Total Returns	MIT/Credl
DRE_HPI	Differences in Returns for Home Price Index	S&P/Case-Shiller
GDPR2	Real GDP Growth Rate	US Bureau of Economic Analysis (BEA)
INT_TERM	Term Spread (10-year Treasury bond yield minus 3-month T-bill rate)	Federal Reserve
PPIY	Changes in Producer Price Index: Finished Goods Less Food & Energy	U.S. Bureau of Labor Statistics (BLS)
SENTRE_ABI	Changes in Architecture Billings Index	American Institute of Architects (AIA) Work-on-the-Boards survey
SENTRE_HMI	Changes in Housing Market Index	National Association of Home Builders (NAHB) and Wells Fargo
CFNAI	Changes in National Activity Index	Federal Reserve Bank of Chicago
SENT_CONS	Changes in Consumer Sentiment Index	Reuters/University of Michigan Surveys of Consumers
PMI	Changes in Purchasing Managers's Index	Institute for Supply Management
SFTECH	Changes in Tech Pulse Index	Federal Reserve Bank of San Francisco
RECESSION	Dummy variable with 1 for NBER recession dates	NBER Information
RERC_BUYSELL	Ratio of Buy / Sell responses	RERC data

Table 2: Descriptive Statistics

	Statistics					Normality					ADF Test		
	Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis	JB-stat	Prob	Obs	Prob.	Lag	Max Lag
RE_TBITR	2.4%	2.6%	17.4%	-18.3%	5.13%	-0.86	7.09	49.36	0.000	60	0.00	1	12
DRE_HPI	0.0%	0.0%	6.8%	-5.7%	1.50%	0.83	12.07	212.69	0.000	60	0.00	1	12
GDPR	1.1%	1.2%	2.5%	-2.0%	0.73%	-1.68	8.21	96.06	0.000	60	0.00	3	12
INT_TERM	1.6%	1.5%	3.6%	-0.6%	1.26%	0.06	1.69	4.31	0.116	60	0.02	1	12
PPIY	2.3%	2.3%	7.3%	-0.5%	1.62%	0.87	4.05	10.29	0.006	60	0.05	5	12
SENTRE_ABI	0.0%	1.8%	22.5%	-28.7%	10.6%	-0.32	3.16	1.07	0.586	60	0.00	1	1
SENTRE_HMI	-2.0%	0.0%	51.1%	-63.6%	15.4%	-0.65	7.90	64.14	0.000	60	0.00	1	12
CFNAI	0.00	-0.06	1.71	-2.11	69.19%	-0.18	3.42	0.75	0.687	60	0.00	1	12
SENT_CONS	-0.3%	-0.2%	22.0%	-22.2%	8.19%	0.10	4.47	5.48	0.065	60	0.00	1	12
PMI	0.4%	-0.1%	20.0%	-27.4%	7.7%	-0.21	5.15	11.96	0.003	60	0.00	1	12
SFTECH	1.8%	2.3%	12.1%	-13.5%	5.2%	-0.73	3.62	6.31	0.043	60	0.00	1	12

Table 3: Correlation Matrix

Coefficient *Probability*	RE_TBITR	RE_HPI	GDPR	INT_ TERM	PPIY	SENTRE_ ABI	SENTRE_ HMI	CFNAI	SENT_ CONS	PMI	SFTECH
RE_TBITR	1.00										

RE_HPI	0.37	1.00									
	0.004	-----									
GDPR	0.45	0.56	1.00								
	0.000	*0.000*	-----								
INT_TERM	-0.18	0.01	-0.25	1.00							
	0.174	*0.930*	*0.051*	-----							
PPIY	-0.38	-0.56	-0.52	-0.02	1.00						
	0.002	*0.000*	*0.000*	*0.887*	-----						
SENTRE_ABI	0.09	0.07	0.17	0.08	-0.06	1.00					
	0.494	*0.603*	*0.194*	*0.537*	*0.643*	-----					
SENTRE_HMI	0.15	0.37	0.16	0.16	-0.19	0.05	1.00				
	0.254	*0.004*	*0.219*	*0.219*	*0.139*	*0.715*	-----				
CFNAI	-0.11	0.12	0.05	0.19	-0.08	0.10	0.28	1.00			
	0.385	*0.370*	*0.715*	*0.137*	*0.556*	*0.437*	*0.031*	-----			
SENT_CONS	0.09	0.18	0.05	0.14	-0.11	-0.19	0.47	0.29	1.00		
	0.505	*0.159*	*0.731*	*0.296*	*0.403*	*0.138*	*0.000*	*0.026*	-----		
PMI	0.01	0.16	0.19	0.25	-0.11	0.15	0.54	0.39	0.26	1.00	
	0.918	*0.219*	*0.149*	*0.050*	*0.398*	*0.268*	*0.000*	*0.002*	*0.042*	-----	
SFTECH	0.09	0.18	0.52	-0.21	-0.26	0.12	0.18	0.17	0.17	0.15	1.00
	0.513	*0.177*	*0.000*	*0.101*	*0.048*	*0.343*	*0.163*	*0.206*	*0.192*	*0.263*	-----

Table 4: Granger Causality Tests

Panel A: Non-residential Real Estate

	Granger Causality Start	Granger Causality End	P-value* Causing	P-value* Caused	Initial Reversal
GDPR	Q1	Q8	0.0187	0.2850	-
INT_TERM	Q3	Q7	0.0138	0.1928	Q1-Q2
PPIY	Q1	Q7	0.0001	0.6706	-
SENTRE_ABI	Q3	Q10	0.0146	0.9123	-
CFNAI	Q3	Q12	0.0001	0.1301	Q1-Q2
SENT_CONS	Q1	Q1	0.7285	0.0007	Q1
PMI	Q3	Q5	0.0910	0.1387	Q1
SFTECH	Q1	Q1	0.0419	0.7583	-

NOTES: The P-value refers to the starting quarter when the variable granger causes real estate total returns

Panel B: Residential Real Estate

	Granger Causality Start	Granger Causality End	P-value* Causing	P-value* Caused	Initial Reversal
GDPR	-	-	0.2432	0.0001	Q1
INT_TERM	-	-	0.2172	0.0017	Q1-Q3
PPIY	Q4	Q9	0.0034	0.1876	-
SENTRE_HMI	Q1	Q5	0.0283	0.5318	-
CFNAI	Q1	Q6	0.0019	0.9957	-
SENT_CONS	-	-	0.2328	0.8213	-
PMI	Q1	Q6	0.0207	0.6350	-
SFTECH	-	-	0.5049	0.6433	Q5-Q7

NOTES: The P-value refers to the starting quarter when the variable granger causes real estate total returns (or to Q1 if there is no granger causality)

Table 5: VAR Estimation: Non-residential Real Estate

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	Variance Decomposition
GDPR	***0.08***	**0.03**	0.55	0.11	0.69	***0.07***	**0.01**	11%
INT_TERM	**0.01**	***0.08***	0.12	**0.05**	**0.01**	**0.01**	**0.02**	12%
PPIY	***0.07***	0.17	0.52	0.17	0.23	***0.05***	***0.08***	24%
SENTRE_ABI		***0.09***					***0.05***	10%
CFNAI			***0.09***					13%
SENT_CONS				**0.01**				13%
PMI					0.53			3%
SFTECH						0.82	0.28	9%
Joint Probability	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	
Adj. R-squared	0.23	0.40	0.27	0.31	0.22	0.21	0.41	
Log likelihood	1369.87	863.28	1333.86	1530.20	1541.18	1599.44	1006.79	
AIC	-26.30	-27.08	-24.83	-28.79	-29.01	-30.19	-30.60	
SIC	-24.52	-23.28	-22.07	-26.04	-26.26	-27.44	-25.17	
Lag Selection Criteria:								
LR	3	1	3	2	2	2		
FPE	2	1	2	2	2	1		
AIC	2	1	2	2	2	1		
SIC	1	1	1	1	1	1		
HQ	1	1	2	2	1	1		
Lag Exclusion	1	1	3	2	1	1		

NOTE: The p-values from the joint significance across the lags are reported.

Table 6: VAR Estimation: Residential Real Estate

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	Variance Decomposition
GDPR	**0.00**	***0.06***	**0.00**	**0.00**	***0.07***	**0.00**	**0.04**	15%
INT_TERM	0.34	0.36	0.56	0.72	**0.01**	0.30	0.59	6%
PPIY	**0.01**	**0.01**	**0.02**	**0.01**	0.12	**0.00**	**0.01**	16%
SENTRE_HMI		**0.03**					**0.05**	18%
CFNAI			***0.08***				0.10	11%
SENT_CONS				0.21				5%
PMI					**0.00**			7%
SFTECH						0.52		2%
Joint Probability	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	
Adj. R-squared	0.37	0.42	0.40	0.38	0.46	0.36	0.45	
Log likelihood	1379.07	1476.15	1348.79	1511.00	1544.82	1590.90	1453.94	
AIC	-29.13	-30.47	-27.64	-31.24	-32.00	-33.02	-28.98	
SIC	-27.25	-27.55	-24.72	-28.33	-29.08	-30.10	-24.81	
Lag Selection Criteria:								
LR	4	4	4	2	4	4	1	
FPE	2	2	2	2	2	2	1	
AIC	2	2	2	2	2	2	1	
SIC	2	1	1	1	1	1	1	
HQ	2	2	2	2	2	2	1	
Lag Exclusion	4	4	4	4	4	4	1	

NOTE: The p-values from the joint significance across the lags are reported.

Table 7: VAR Estimation and Recession: Non-residential Real Estate

	(1)	(2)	(3)	(4)	(5)	Variance Decomposition
GDPR	**0.00**	**0.04**	0.11	0.11	**0.00**	15%
INT_TERM	**0.02**	***0.07***	***0.07***	**0.01**	**0.05**	9%
PPIY	**0.03**	0.34	0.16	0.34	***0.05***	20%
SENTRE_ABI	**0.01**	**0.02**	0.11	0.14	**0.03**	13%
CFNAI		0.51				6%
SENT_CONS			0.84			7%
PMI				0.48		4%
SFTECH					0.70	6%
RECESSION*SENTRE_ABI	**0.03**	**0.02**	***0.10***	***0.10***	0.11	17%
RECESSION*CFNAI/SENT_ CONS/PMI/SFTECH		0.16	0.96	0.30	0.75	8%
Joint Probability	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	
Adj. R-squared	0.50	0.56	0.41	0.50	0.45	
Log likelihood	1028.65	1167.65	1352.33	1392.07	1463.87	
AIC	-31.38	-32.27	-38.87	-40.29	-42.85	
SIC	-25.96	-22.73	-29.32	-30.74	-33.30	

NOTE: The p-values from the joint significance across the lags are reported.

Table 8: VAR Estimation and Recession: Residential Real Estate

	(1)	(2)	(3)	(4)	(5)	Variance Decomposition
GDPR	0.39	0.32	0.52	0.40	0.56	14%
INT_TERM	0.48	0.63	0.23	**0.04**	0.35	5%
PPIY	**0.01**	**0.01**	**0.01**	**0.04**	**0.03**	16%
SENTRE_HMI	**0.03**	0.64	**0.00**	0.10	***0.08***	27%
CFNAI		0.22				16%
SENT_CONS			0.65			9%
PMI				***0.10***		6%
SFTECH					0.58	4%
RECESSION*SENTRE_HMI	**0.00**	***0.07***	**0.00**	***0.09***	**0.00**	9%
RECESSION*CFNAI/SENT_CONS/PMI/SFTECH		***0.07***	**0.01**	***0.05***	0.55	20%
Joint Probability	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	
Adj. R-squared	0.53	0.57	0.59	0.58	0.51	
Log likelihood	1634.60	1760.18	2064.65	2157.02	2206.01	
AIC	-32.99	-33.25	-40.01	-42.07	-43.16	
SIC	-28.82	-25.92	-32.68	-34.73	-35.82	

NOTE: The p-values from the joint significance across the lags are reported.

Table 9: VAR Estimation: Demand-Supply

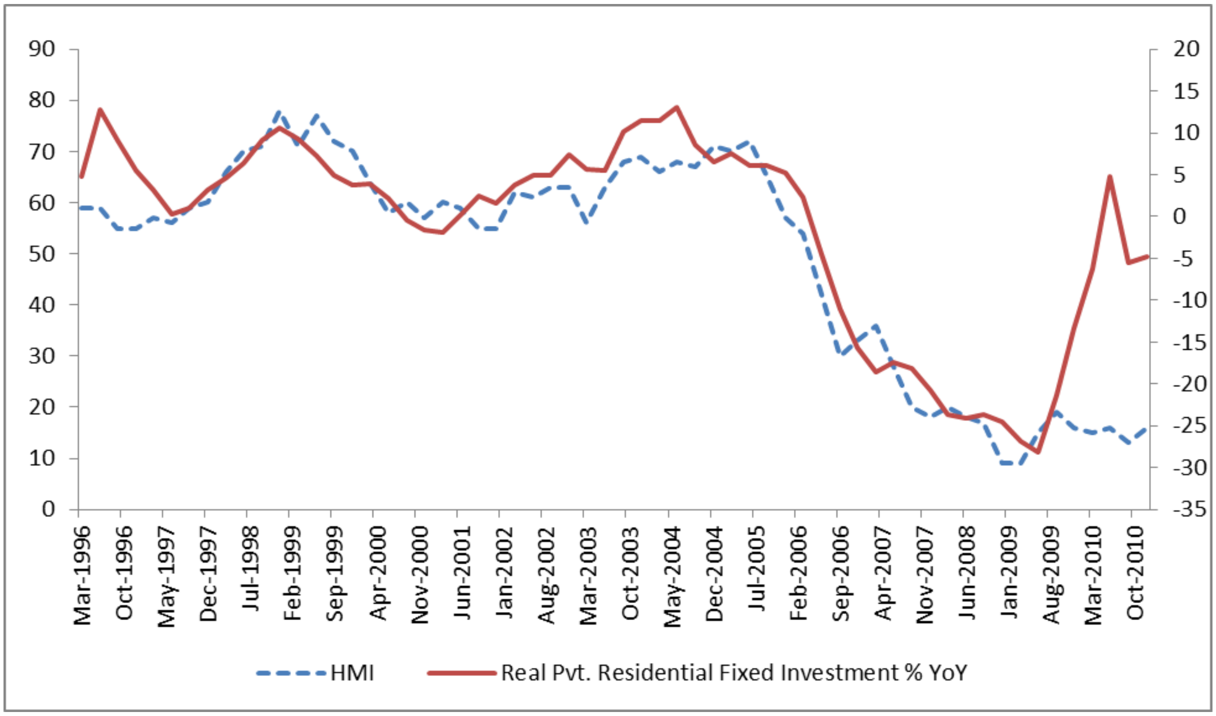
	(1)	(2)	(3)	(4)	(5)	Variance Decomposition
GDPR	**0.01**	0.17	**0.02**	**0.03**	**0.00**	15%
INT_TERM	0.50	0.59	0.50	0.71	0.17	9%
PPIY	0.14	0.76	0.18	0.35	**0.01**	23%
SENTRE_ABI	***0.09***	0.14	0.21	0.14	***0.06***	9%
RERC_BUYSELL	***0.08***	0.28	0.18	0.22	**0.04**	13%
CFNAI		0.79				11%
SENT_CONS			0.69			10%
PMI				0.74		6%
SFTECH					0.12	11%
Joint Probability	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	
Adj. R-squared	0.46	0.42	0.43	0.42	0.51	
Log likelihood	818.90	851.84	935.32	953.36	987.36	
AIC	-23.89	-23.17	-26.15	-26.80	-28.01	
SIC	-18.46	-15.83	-18.81	-19.46	-20.67	

NOTE: The p-values from the joint significance across the lags are reported.

Table 10: Out-of-sample Predictions

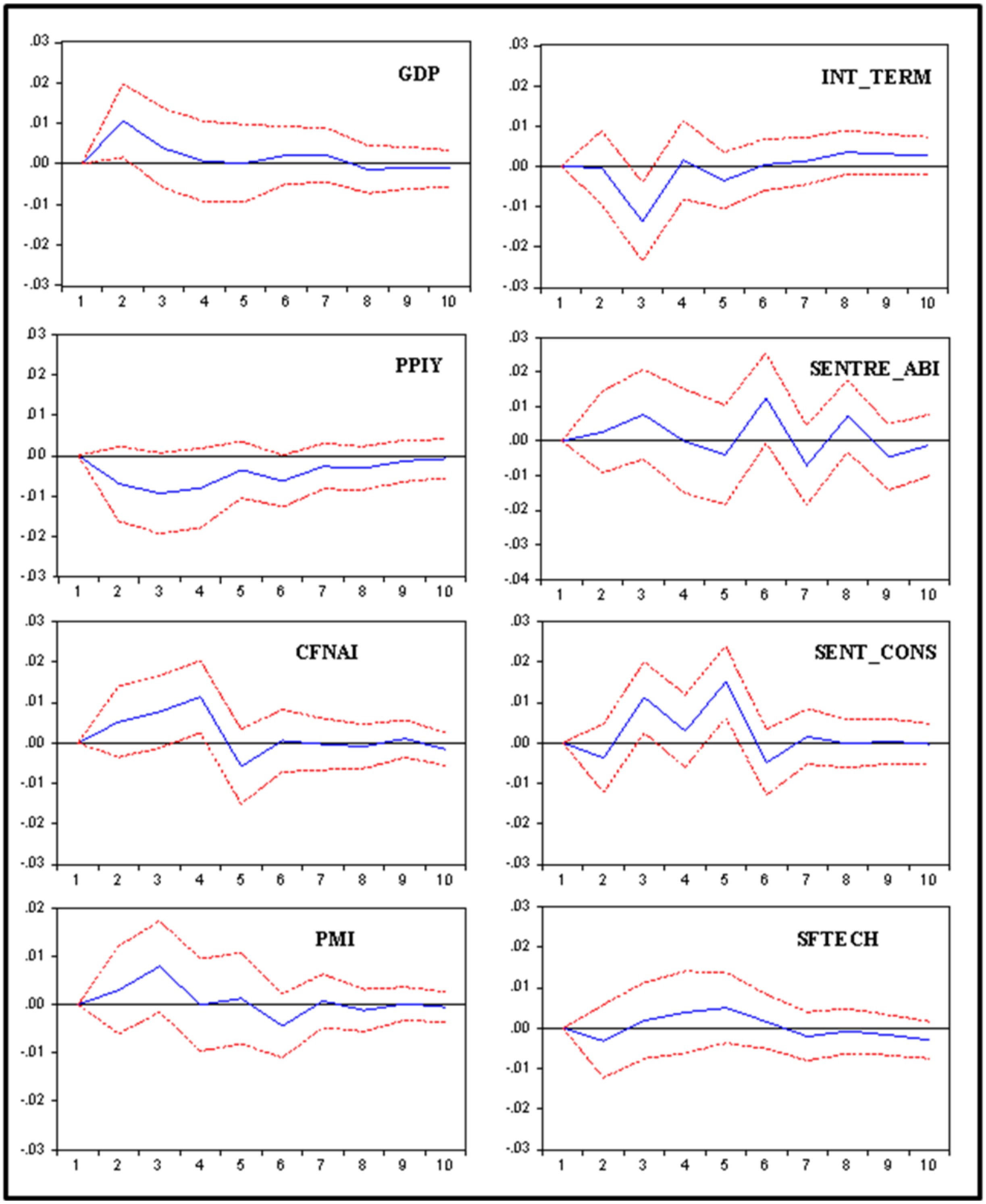
	Model w/ only economic controls	**Model w/ only economic controls and sentiment indices**	**Model w/ only economic controls, sentiment indices and RERC indicator**
Theil Inequality Coefficient	55.99%	37.15%	15.76%
Root Mean Squared Error	10.29%	9.92%	8.77%
Bias Proportion	3.44%	13.91%	25.07%
Variance Proportion	30.05%	35.23%	22.90%
Covariance Proportion	66.51%	50.86%	52.03%

Figure 1: Residential Real Estate Activity



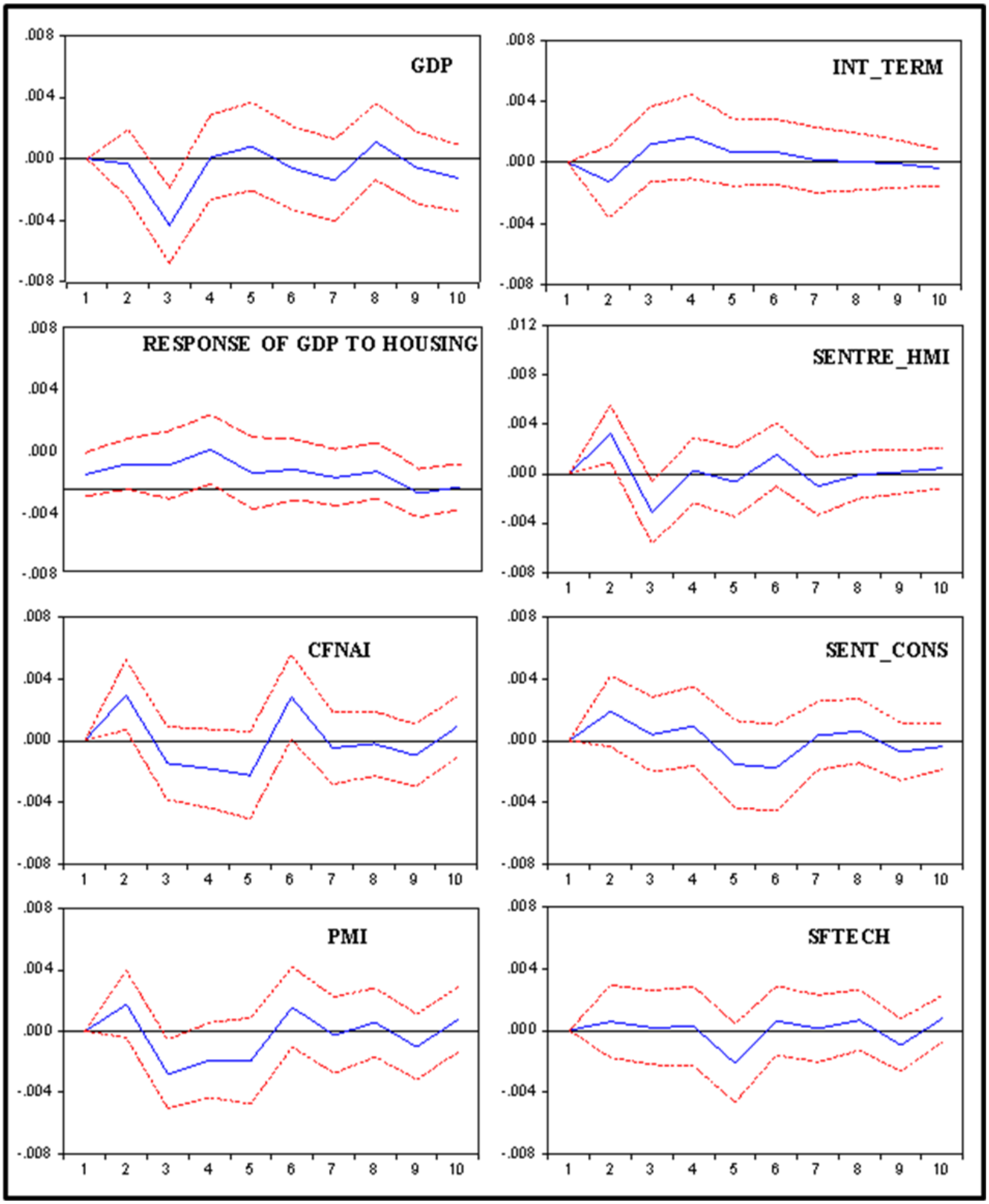
Source: The National Association of Home Builders (NAHB) and Wells Fargo; Bureau of Economic Analysis

Figure 3: Impulse Responses: Non-residential Real Estate



Source: Authors' calculation

Figure 4: Impulse Responses: Residential Real Estate



Source: Authors' calculation