PACIFIC RIM PROPERTY RESEARCH JOURNAL
2020, VOL. 26, NO. 3, 223–247
https://doi.org/10.1080/14445921.2021.1946259

Sentiments in the housing market and the effectiveness of government interventions

Calvin W. H. Cheong [a], Lisa L. H. Ngui [b] and Shella Georgina Beatrice [b]

[a]Department of Economics and Finance, Sunway University Business School, Sunway University, Malaysia; [b]Faculty of Business, Design and Arts, Swinburne University of Technology, Sarawak, Malaysia

ABSTRACT
This paper examines the factors that drive the recent growth of house prices in Malaysia. By constructing a housing market sentiment index, we find contemporaneous sentiment to have a strong influence on future housing market returns especially in the short term. Government-introduced cooling measures were ineffective in dampening prices and market sentiment. We also find property developer behaviour to drive sentiments and prices. The study contributes to literature by providing an easily generalizable method of constructing a housing market sentiment index in other countries besides giving clear indication of the drivers of house prices and sentiment for more effective government intervention.

ARTICLE HISTORY
Received 15 January 2021
Accepted 18 June 2021

KEYWORDS
House prices; market sentiments; investor sentiments; government intervention

1. Introduction

Commonly defined as the propensity of investors to behave in a manner that is not justified by the exogenous information at hand, investor sentiments have been shown to have significant influence over asset prices (Baker & Wurgler, 2006, 2007). The effects are no different in the housing market (; Hui, Zheng, & Wang, 2013). In fact, the effects of investor sentiments in the housing market are stronger due to the market's illiquid nature and a lack of short-selling mechanisms thereby restricting the market's ability to correct mispricings (Clayton, MacKinnon, & Peng, 2009b). This creates a vacuum of information especially within the private housing market causing investors to be more susceptible to sentiments.

The past decade has seen persistent house price growth in Malaysia, reigniting fears of the Asian Financial Crisis of 1997 which saw markets tumbling after the bubble burst. In hopes of slowing the growth in prices, the Malaysian government and the central bank – Bank Negara Malaysia (BNM) – had to introduce a range of monetary, fiscal, and legislative measures. Market participants, however, opine that these measures have only succeeded in reducing the number of transactions taking place, and not the price of the house itself (Yeong, 2014). BNM itself has indicated that the growth in house prices are not in line with long-term averages as well as economic fundamentals, attributing the growth to market sentiment and speculation (Hisyam, 2013). In fact, Cheong, Ngui, and Beatrice (2019) established preliminary evidence that house prices in Malaysia were

CONTACT Calvin W. H. Cheong calvinc@sunway.edu.my

largely driven by supply-side market sentiments. That is to say, the property developers played an influential role in (artificially) driving prices up. This study builds upon the findings of Cheong et al. (2019) by investigating the effectiveness of the measures introduced by the government and central bank from the years 2010 to 2019, using an updated dataset.

This study is focused on the West Coast of Peninsular Malaysia because firstly, many economic policies have been focused on this part of the country leading to a disparity in development, pricing, and inflation between Malaysia's 14 states. Various commentators have cited speculation and sentiment as the reason behind this difference providing us with an ideal setting to test for market sentiments. Second, government measures such as the affordable housing project has also been targeted at key urban centres in the country, many of which lie on the West Coast. This again, provides a suitable backdrop to assess their effectiveness in addressing rising house prices and market sentiments.

The study begins in similar fashion to Cheong et al. (2019), Zhou (2017), and Baker and Wurgler (2006) with constructing the housing market sentiment index through the selection of proxies that best represents conditions in the Malaysian housing market. This is followed by a principal component analysis on the selected sentiment proxies to determine the proxies which had the strongest impact on sentiments before regressing each of them against economic fundamentals variables to negate the effects of business and economic cycle variations. This is followed by a partial least squares (PLS) regression to derive a housing market sentiment index. The trends observed in Cheong et al. (2019) persist in this study. Specifically, we find our sentiment index continues to be strongly correlated with Malaysia's consumer and business confidence index, more so the latter than the former. We also found periods of high sentiment to be followed by higher returns, contrary to a few prior studies (Berger & Turtle, 2015; Stambaugh, Yu, & Yuan, 2012; Zhou, 2017).

We then proceed to investigate the effectiveness of government cooling measures in slowing house prices and sentiments. We find most of the measures introduced are not effective in dampening house prices and sentiments in the market. For those measures that were effective in lowering sentiments, we find the effects to only last for a maximum of 3 months after which sentiments rebound. Robustness tests reveal that our results are consistent across all states that were in the dataset graciously provided by National Property Information Centre (NAPIC). We also find the magnitude of effect sentiment has on housing market returns, as well as the effectiveness of cooling measures to differ across states; consistent with our conjecture that concentration of economic activity and development in certain states influences their sensitivity to sentiments and the effectiveness of the cooling measures. Further tests also show that our results remain consistent when we decompose the data into daily instead of monthly observations.

Several contributions arise from this study. First, our approach in measuring housing market sentiments by way of proxies complements that of Soo (2013) who used a textual analysis approach and Hui and Wang (2014). Our approach also complements Zhou (2017) in that we show how the proxy selection process can be adapted in ways that best reflect local market conditions and data availability. The ease of its construction provides a simple guide for the government and other parties interested in monitoring housing market conditions to replicate. Second, our results empirically confirm the opinions of various market commentators on the ineffectiveness of the cooling measures introduced by the government and BNM (Yeong, 2013, 2014). Market sentiments drive house prices and inhibit the effectiveness of these measures. Specifically, our results suggest that sentiments are strongly driven by developer activity among others. Further interventions in the housing market should ideally address this.

The rest of this paper is as follows. Section 2 provides a brief history on the Malaysian housing market and a review of literature on sentiments in the housing market. In Section 3, we detail the process of constructing the sentiment index. In Section 4, we show the results to our tests. Section 5 provides a discussion of results and implications before concluding.

2. Literature review

2.1. A brief history of the Malaysian housing market

From 2001 to 2010, the long-term average annual growth of house prices in Malaysia was approximately 3.2%, in line with the national level of income and economic development (BNM, 2010). This figure tripled to about 9.41% between Q1 2010 and Q3 2014, largely due to the sudden growth in the three largest urban regions of Malaysia – the Klang Valley, Penang, and Johor – where house prices grew at a rate of 11.38%, 10.60%, and 10.36% per year respectively. Fears of a property market crash in 2018 and beyond persisted after the Deputy Finance Minister revealed that the number of unsold residential units rose by 40% (Kaur, 2017). Representatives of developer associations however, rubbished these fears, arguing that market optimism, demand, and buyer expectations will readjust accordingly (Augustin, 2017).

2.2. Government interventions in the housing market

Malaysia housing market history is peppered with various policies and interventions. We summarize a few of the key interventions and policies that were introduced during our 2010 to 2019 sample period.

BNM introduced a 70% limit to the loan-to-value (LTV) on personal third and subsequent mortgages (BNM, 2013; Kamalvacini, 2014) in hopes of discouraging speculators from taking advantage of easy credit. BNM also raised the capital risk-weights on first and second mortgages to 100%, besides requiring LTVs to be calculated based on the net selling price of the property. With effect from 2012, BNM also required debt service ratios to calculated based on the borrower's net (i.e. after statutory deductions such as income taxes, Employee Provident Fund and Social Security contributions) rather gross income (BNM, 2011).

To curb speculative activity, the Malaysian government re-introduced the Real Property Gains Tax (RPGT) in 2010 after a 3-year suspension and has gradually raised the rates over the years. As of writing, the RPGT rates are at 30% for houses sold after 1–3 years of ownership; 20% after 4 years of ownership, 15% after 5 years of ownership, and 5% thereafter. The RPGT was re-introduced in hopes of discouraging speculators from "flipping" – buying a property (often new) without intention of occupying, and then selling it off in a short period of time to (hopefully) earn substantial capital gains.

Besides curbing property speculation, the government also sought to address public concern over housing affordability by establishing Perbadanan PR1MA Malaysia under the PR1MA Act 2012 – a government-owned developer tasked to construct housing projects that are affordable to the middle-income group. These housing projects are located in key urban centres around the country, and are built to compete with the design and build quality of private market developers in the country. Open to only Malaysian citizens, the PR1MA projects are meant to curb speculative activity in the housing market by firstly cutting out the middlemen, and secondly, imposing various restrictions on eligibility of applicants.

Finally, the government in October 2013 abolished the Developer Interest Bearing Scheme (DIBS). Originally intended to make home-ownership easier by allowing developers to bear the interest cost for buyers during the construction phase, many developers abused the DIBS by making inaccurate claims of additional discounts and rebates when in fact, the cost of these benefits were imputed into the price of the property, thereby inflating its price (Chang, 2014) by an additional 20% to 25% (The Star Online, 2013), speculators with the help of investor clubs – loose alliances of high net worth individuals – meanwhile, exploited DIBS by pooling financial resources and buying properties in bulk from developers at a discount prior to the official launch (Mok, 2015). Their speculative purchase distorted actual demand and prices, artificially raising asking prices in the secondary markets (Yeong, 2013).

Various quarters however argue that despite these measures, transacted prices remain high even though there was a fall in the number of transactions (Yeong, 2014). This puts into question the effectiveness of these measures, and what (if any) can be done to curb the rise in prices.

2.3. Sentiments and government intervention in the housing market

Traditionally, the decision-making process behind a property purchase was assumed to be rational, through the use of facts and data that led to an optimal decision. Asymmetric or even deficient information however causes buyers to turn to other sources to justify their decisions and pricing. Gallimore and Gray (2002) found the most common source to be market sentiments. Relying on market sentiments for price information is however, problematic especially in the housing market for a few reasons. Firstly, the large number of individual buyers – all of whom have a unique set of criteria in asset selection and pricing – makes any standard of comparison unequal. Second, the housing market is a market for lemons. The stock market has built-in disclosure and price-discovery mechanisms that help reduce information asymmetry by way of a transparent price market that is updated by the minute, and other regulatory disclosure requirements mandated by the Securities Commission. Property developers, sellers or real estate agents in contrast, are not bound by the same mechanisms and therefore have an incentive to withhold information if it is to their advantage pricewise. Also, without a short-sale mechanism, overvalued assets will remain overvalued until the market corrects itself. It is for these reasons that the housing market is highly vulnerable to sentiment-induced mispricing (Clayton, Ling, & Naranjo, 2009a; Hui & Wang, 2014).

According to the Department of Statistics, Malaysia, as of 2017, total fixed assets in the construction sector was valued at RM27.9 billion. The top four construction and property development companies (by market capitalization as of 18 April 2021) already accounts for more than 50% of this total fixed assets value making the housing market in Malaysia dominated by a handful of large property developers. As a result, a slight shift in optimism on their part would have a huge effect on house prices in the country (Piazessi & Schneider, 2009) even under perfect market conditions (Clayton, 1997; Clayton et al., 2009a). Jin, Soydemir, and Tidwell (2014) similarly found irrational consumer sentiment to be a significant exogenous variable in the pricing of US residential real estate. In fact, the susceptibility of the housing market to sentiments – positive in particular – is so strong that so long as there is uncertainty over the economic outlook of the country, and optimistic agents continue to hold firmer views than others do, the housing boom will continue (Burnside, Eichenbaum, & Rebelo, 2016).

Government intervention in the housing market is nothing new. Whether these interventions are designed to spur the housing market or otherwise does not matter. What matters is whether they are effective at addressing the problem. For example, in an effort to encourage homeownership, the US government provided favourable tax treatment of owner-occupied housing. This however, created an incentive to "over-consume" housing (Cho & Francis, 2011). Chambers, Garriga, and Schlagenhauf (2009) similarly found government interventions to be a double-edged sword. Inherent differences in tax treatments between owned and rented housing could be amplified or mitigated through progressivity of income taxation, with further ramifications on various other aspects of the housing market. A more recent study by Floetotto, Kirker, and Stroebel (2016) also showed that tax incentives encourage homeownership and temporarily raise house prices but adversely affects welfare. Berry, McGreal, Stevenson, and Young (2001) likewise found that government interventions places pressure on owner-occupiers due to investor speculation and are only effective in the short-run as market forces quickly negate them.

The persistent rise in house prices in Malaysia in spite of the measures introduced by the government and central bank provides an ideal setting for us to conduct this study. Due to inherent structural and policy differences between the housing markets of Malaysia and those seen in prior studies, further investigation into the interactions between various housing market factors, government policy, and sentiment is warranted.

3. Methodology

3.1. Data

Our data is from the secondary housing market on the West Coast of Peninsular Malaysia. Collectively, the West Coast contributes to approximately 70% of the national GDP. The data provided by the National Property Information Centre (NAPIC) included the details of 298,038 secondary housing market transactions along the West Coast, over a 10-year sample period from January 2010 to December 2019. We however, chose to focus on four key states namely Kuala Lumpur, Selangor, Johor, and Penang. These four states alone contribute approximately 50% to the national GDP and has been a hotbed of real estate transactions throughout the sample period. The secondary market transactions in these four states alone account for approximately 70% of the total transactions that occurred on the West Coast. The variables in our data include the district, house address, type, number of floors, lot size, valuation date, transacted price, and the identities of the buyer(s) and seller(s).

3.2. Housing market sentiment index proxies

The literature on constructing sentiment indices is typically split into two camps: direct measures, and indirect measures. The direct approach constitutes measures where respondents (i.e. real estate investors, appraisers, and lenders) are surveyed on a variety of issues such as rates of return on equity, rental growth rates, and their expectations of future real estate market conditions (Ling, Naranjo, & Scheick, 2014). Some countries (e.g. the United States) maintain a detailed record of such surveys through dedicated institutions such as the Real Estate Research Corporation (RERC). Malaysia, unfortunately, does not hold such information on the public record. As such, for the purpose of this study, we had to adopt the indirect approach of constructing a sentiment index. The indirect approach to sentiment index construction was made popular by Baker and Wurgler (2006). While seemingly complex, the construction of a sentiment index is an intuitive process. Instead of using a single indicator (e.g. momentum, turnover) as a measure of sentiment, we introduce sentiment proxies that are directly relevant to the housing market in Malaysia by adopting the process of generating proxies provided by Baker and Wurgler (2006). So far, we identified only three other studies that adopted this approach (see Hui & Wang, 2014; Ling et al., 2014; Zhou, 2017).

Ling et al.'s (2014) indirect sentiment index, constructed using real estate investment trust (REIT) data, is arguably comprehensive. There are however, two issues that prevents us from following in their footsteps. First is the availability of data. The proxies used in their construction (e.g. REIT stock price to net asset value; net capital flows to REIT mutual funds) are easily available for a well-established financial market such as the US. The same data however, could not be found for Malaysian REITs from publicly available sources. Second, the Malaysian REITs market is small with only 17 REITs listed (as of 18 April 2021), with a combined market capitalization of MYR20.2 billion, representing a materially insignificant 1% of Bursa Malaysia's Main Market. Furthermore, the distribution of REITs in Malaysia is highly skewed and concentrated. One REIT has a market capitalization of MYR12.5 billion; another has a market capitalization of approximately MYR2 billion, while two have a market capitalization of approximately MYR1 billion. The remaining 13 REITs have a market capitalization that is well below MYR500 million with half of them worth less than MYR10 million. The smallest was worth about MYR1.3 million. With this distribution and sample size, any attempt to remove outliers would result in a sample that is so small as to render it unreliable. Given these considerations, we instead adopt Zhou's (2017) approach of using property market transaction data. We discuss the intuition behind each of our sentiment proxies below.

Malaysia adopts a sale-before-construction system. The system provides a substantial investment incentive to property developers to demand and purchase more land-space as they are able to lock in the profits of the project even before construction begins. As demand for land-space and buy-side investment incentives are major determinants of new housing projects (Tse, Ho, & Ganesan, 1999), it is reasonable to assume that developers are driving and simultaneously sensitive to market sentiments. In Baker and Wurgler (2006), the number of IPOs was a sentiment proxy for the stock market. The greater the number of IPOs, the more optimistic the sentiment. Similarly, we argue that the incoming and completed supply of residential units scaled by the existing stock of residential units in the past quarter reflects sentiments in the housing market. We call this proxy *NewStock* and expect it to be positively correlated with housing market sentiments.

Due to various legal and financial restrictions and requirements, even if they can afford to pay for it in cash, most house buyers in Malaysia prefer to finance the purchase with a mortgage. Some may argue that the distinction between investors and house-consumers (Genesove & Mayer, 2001) may influence the terms and conditions of payment. However, the house-buying process in Malaysia is the same for everyone regardless of intention. As the *NewStock* proxy represents the position of developers, we contend that total residential mortgage divided by total loans in the country represents the position of buyers.[1] We call this proxy *ResMort* and expect it to be positively correlated with housing market sentiments.

Having accounted for the supply and demand drivers in the housing market, we now consider the matter of liquidity. Liquidity has often been regarded as an indicator of sentiment (Baker & Stein, 2004;). Rising liquidity in the housing market is a channel through which a pricing-sentiment spiral in the housing market is amplified (Ling, Ooi, & Le, 2015). Typically, liquidity is measured through turnover. In the housing market, this may be reflected in the length of time the buyer owns the property. In keeping with the literature, we include the natural log of the median holding period of sellers (in months) as a proxy for turnover. We can determine the holding period by identifying the date when the property was bought and sold. Since we are able to identify the buyer(s) and seller(s) for each transaction, we also use the number of sub-sales[2] in a month as a proxy for turnover. While it can be argued that sub-sales are affected by the real property gains tax, they also account for instances where the housing project took longer than 4 years to complete.[3] We call these proxies *HoldPer* and *SubSale* respectively. We expect *HoldPer* to be negatively correlated while expecting *SubSale* to be positively correlated with housing market sentiments.

The final aspect of sentiment we consider here is buyer confidence. The corporate finance literature suggests that overconfident managers are more likely to overinvest or pay a premium on acquisitions when there are surplus funds available (Malmendier & Tate, 2005, 2008). Similarly, a buyer's confidence in the housing market and future property values will have a strong part to play in the price paid for the house. The greater their confidence in future house prices, the more they will be willing to pay for the house now. We feel that simply taking the size of the house (in square meters) transacted would not accurately reflect buyer's confidence in Malaysia as there are many large houses that are cheap and vice versa. Instead, we use the transacted price per square meter (in MYR) as a measure of buyer confidence. It is also not uncommon for sellers to factor various improvements or additions (e.g. renovations, fixtures and fittings, accessibility, security) into their asking prices. The monetary value of these additions however, are subjective and cannot be captured by the price per square meter measure. As an alternative, we also use the number of transactions that are RM1 million[4] and above in a month as a proxy for buyer confidence. We call these proxies *PSQM* and *P1M* respectively. We expect both proxies to be positively correlated with housing market sentiments.

Table 1 provides the annual averages of the six proposed proxies of housing market sentiments from 2010 to 2019. Except for *PSQM* and *P1M*, all other proxies recorded the highest annual average in 2011. The annual averages fell in 2012, presumably after the

Table 1. Annual averages of the sentiment proxies, 2010–2019.

Year	*NewStock*	*ResMort*	*HoldPer*	*SubSale*	*PSQM*	*P1M*
2010	2.541	0.456	6.853	10.578	158.54	5.231
2011	3.289	0.679	6.024	13.911	179.61	5.385
2012	2.132	0.568	6.172	12.118	205.32	6.123
2013	2.291	0.632	6.125	12.654	245.25	6.549
2014	2.875	0.659	7.056	13.271	305.33	7.167
2015	2.116	0.559	7.011	12.513	363.87	7.385
2016	2.758	0.551	6.954	12.245	401.51	8.134
2017	2.811	0.578	6.731	12.355	411.73	8.544
2018	2.859	0.588	6.615	12.521	412.24	8.783
2019	2.979	0.621	6.523	12.489	414.38	8.916

NewStock is the incoming and completed supply of residential units scaled by the existing stock of residential units in the past quarter; *ResMort* is the total residential mortgage divided by total loans in the country; *HoldPer* is the natural log of the median holding period of sellers (in months) as a proxy for turnover; *SubSale* is number of sub-sales in a month; *PSQM* is the average transacted price per square meter in a month; and *P1M* is the number of transactions worth RM1 million and above in a month.

launch of the PR1MA projects at end-2011, before rising again in 2014 – the same year the DIBS was abolished. The numbers slowed in 2015 before climbing in 2016 and has not stopped since. These numbers seem to suggest that the *NewStock*, *ResMort*, *HoldPer*, and *SubSale* metrics are correlated with economic fundamentals and affected by cooling measures. However, throughout the 10-year sample period, both *PSQM* and *P1M* rose regardless, suggesting a persistently high level of confidence in future house prices.

3.3. Constructing the sentiment index

The first step is to negate the effects of business cycle variations and macro-factors from the proxies using an orthogonalization process by regressing each of the standardized sentiment proxies on eight economic fundamental variables (Ling et al., 2014). These variables are the Purchasing Manager's Index (*PMI*), the Industrial Production Index (*IPI*), the profit margin of the real estate industry in the last calendar year (*REP*), the growth of the Consumer Price Index (*CPI*), and the growth of M2 *(M2*). Total loans to the property sector divided by total loans in the country (*TLP*) are included to represent developers' access to credit (Cheong, Lee, & Weissmann, 2020). Risks of loan defaults are accounted for through total non-performing loans to the real estate market divided by the total loans in the country (*NPL*). Finally, *BLR+* defined as the average premium (discount) charged by banks in the country above (below) the base lending rate is included to account for interest rate effects on property loans. The residuals from these regressions should thus contain a measure of housing market sentiment that is orthogonal to business cycle and macro factors. This is followed by a three-month smoothing of the residuals (Huang, Jiang, Tu, & Zhou, 2014).

The next step is a principal component analysis for all sentiment proxies.[5] The daily data for each proxy is aggregated monthly throughout the 10-year sample period (2010–2019; n = 120). The same is repeated for the one-month lagged values to account for the possibility that one proxy may have an impact on another in the future (Baker & Wurgler, 2006). We then compute the correlation between the first principal component (*P1*) and each of the current and lagged proxies. Whichever proxy has the highest

Table 2. Current and lagged sentiment proxy correlation with the first principal component, *P1*.

Current	Correlation with *P1*	Obs.[a]	1-month Lag	Correlation with *P1*	Obs.
NewStock	0.837***	119	*NewStock*	0.767**	119
ResMort	0.791***	119	*ResMort*	0.534***	119
HoldPer	−0.551***	119	*HoldPer*	−0.432**	119
SubSale	0.523***	119	*SubSale*	0.485***	119
PSQM	0.664***	119	*PSQM*	0.781***	119
P1M	0.049	119	*P1M*	0.121	119

[a]At $n - 1$ degrees of freedom

NewStock is the incoming and completed supply of residential units scaled by the existing stock of residential units in the past quarter; *ResMort* is the total residential mortgage divided by total loans in the country; *HoldPer* is the natural log of the median holding period of sellers (in months) as a proxy for turnover; *SubSale* is number of sub-sales in a month; *PSQM* is the average transacted price per square meter in a month; and *P1M* is the number of transactions worth RM1 million and above in a month.

statistically significant correlation magnitude is chosen as a proxy for our housing market sentiment. These values are presented in Table 2.

The principal component analysis suggests the selection of the current value of *NewStock, ResMort, HoldPer, SubSale*, and the lagged value of *PSQM* as our housing market sentiment proxies.[6]

$$Px_{i,t-1} = \beta_{i,0,t} + \beta_{i,1,t}R_t + \beta_{i,2,t}R_{t-1} + e_{i,t-1} \tag{1}$$

$$Px_{i,t} = \alpha_t + S_t\widehat{\beta_{i,1,t}} + \nu_{i,t} \tag{2}$$

The final step is to estimate a partial least squares regression (1) to construct a look-ahead -bias-free sentiment index (Huang et al., 2014). Equation 1 is estimated for each of the chosen proxies, Px_i, where R_t is the housing market return at time t. The series $\beta_{i,1,t}$ captures the time-varying sensitivity of Px_i to the market sentiment instrumented by future housing market returns.[7] Including R_{t-1} on the right side of Equation 1 is intuitive in the Malaysian market since transacted prices are also driven by previous transacted prices in the same locale. It also controls for short-term reversals (Zhou, 2017). Equation 2 is a cross-sectional regression where the independent variable is the loadings estimated from Equation 1. The time series of the slope S represents the sentiment index.

4. Results & discussion

4.1. A simple illustration

Figure 1 illustrates the quarterly cumulative change of our constructed housing market sentiment index, Malaysia's house price index, consumer confidence index, and business confidence index from 2010 to 2019. The sentiment index values have been winsorized at the top and bottom 1% levels and then averaged quarterly before calculating and then cumulating the quarterly changes over time. The computed sentiment index from January 2010 to December 2019 has a mean of 0.501 and a median of 0.548. The index had a maximum value of 0.990, a minimum value of 0.028, and a standard deviation of 0.299. Superimposing our index against the cumulative change in the house price index provides some preliminary evidence of our index's ability to predict house price movement. The correlation coefficient between the sentiment index and house price index is

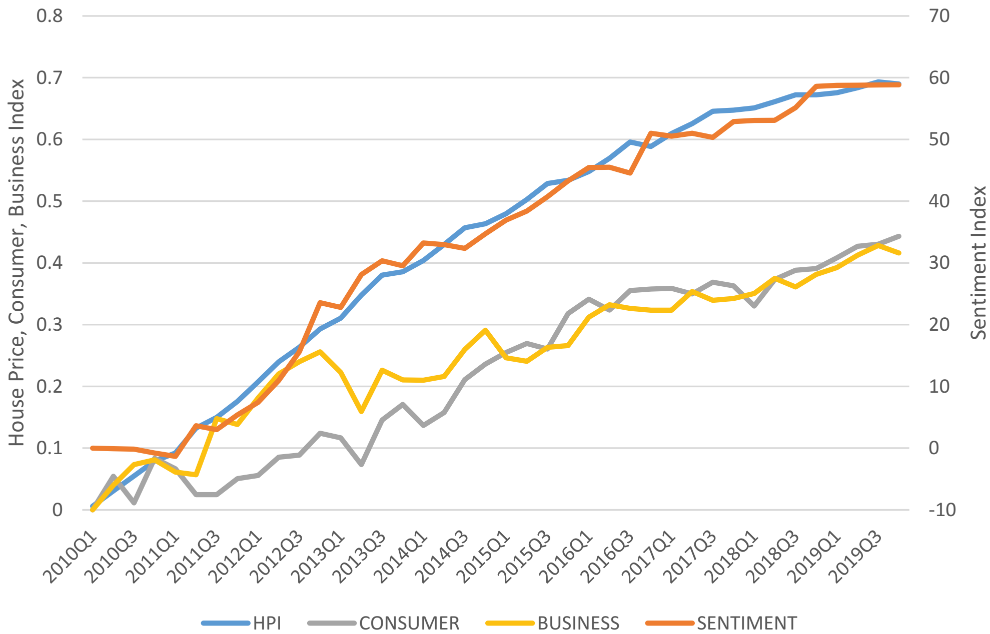

Figure 1. Cumulative Change in the Sentiment Index, House Price Index, Consumer & Business Confidence Index, January 2010 – December 2019 The observation period is from 2010:Q1 to 2019:Q4. Values of each index are averaged quarterly, before calculating and then cumulating the quarterly changes over time. The sentiment index values have been winsorized at the top and bottom 1% levels. Correlation coefficients of the sentiment index against the house price index, consumer confidence index, and business confidence index are 0.8792, 0.7815, and 0.8537, respectively.

0.8792, statistically significant at the 1% level of confidence. Arguably, house prices in Malaysia have been on the cumulative rise despite the various cooling measures introduced since 2010. Figure 1 also suggests that the cooling measures have not been able to curb housing market sentiments. For example, when the PR1MA project launched in Q4 2011, sentiments fell slightly before climbing up again within a few months. Similarly, when the DIBS was abolished in Q4 2013, sentiments fell before climbing up again in the next quarter.

To establish its reliability, we also plot the sentiment index against cumulative change in the consumer confidence and business confidence indices. These indices should suffice for Malaysia since the housing market not only attracts consumers and investors (Han, 2013; Miller & Pandher, 2008) but businesses (i.e. property developers) as well. The consumer confidence index would represent consumer and investor outlook while the business confidence index represents developer outlook. All three indices (sentiment, consumer confidence, business confidence) seem to move in a general upward trend, with their dips and rises seemingly coinciding with the time frame when cooling measures were introduced. The correlation coefficient between our sentiment index and the consumer confidence index is 0.7815 while against the business confidence index, it is 0.8537. Both are statistically significant at the 1% level of confidence. What this seems to suggest is housing market sentiments in Malaysia are more strongly correlated with developer instead of consumer and investor activity.

4.2. The impact of sentiments on housing market returns

Before assessing the effectiveness of government policies in controlling rising house prices, we must first establish the housing market sentiment index's ability to predict future housing market returns. To do so, we estimate the following regression:

$$R_{[t+1,t+b]} = \alpha + \beta_1 S_t + \beta_2 Festival_t + \beta_3 Holiday_t + \beta_4 R_t + \beta_5 M2_t + \beta_6 BLR_t + \varepsilon_t \quad (3)$$

where $R_{[t+1,t+b]}$ is the cumulative housing market return using the Malaysia house price index from month $t+1$ to month $t+b$ where b = 1, 3, 6, 9, and 12; and S is the value of our sentiment index at month t. We account for seasonal effects (Kaplanski & Levy, 2012) in Malaysia's housing market by including the variables $Festival_t$ which is a binary variable that is '1′ if month t or its immediately preceding month has a major festival[8]; and $Holiday_t$ which is a binary variable that is '1′ if month t coincides with the school holidays.[9] The festival and holiday season in Malaysia typically witness a growth in home-related transactions including but not limited to house purchase, moving homes, renovations and modifications to the home. It is also during these periods where developers typically offer various promotions and discounts on their housing projects.[10] We control for current month returns (R_t) to account for current transacted price trends and short-term reversals. We include the growth of M2 $(M2_t)$ to control for effects arising from changing monetary policies over time. We also control for the influence the base lending rate (BLR_t) has on consumer and investor propensity to take up a mortgage. Equation 3 estimates are in Table 3 below.[11]

From Table 3 we can see that S has a positive coefficient across all models. However, the statistical significance of the relationship weakens when we attempt to predict returns farther into the future (i.e. Models (5) – (7)). We can also see that the seasonal effects have no impact on housing market returns in Malaysia. Changes to monetary policy, likewise, has no statistically significant effect on housing market returns. The base lending rate in contrast reduces housing market returns; an effect that is well within expectations since the interest expense on mortgage repayments lowers the returns sellers earn.

In keeping with the literature on market sentiments, Models (3) – (7) in Table 3 are re-estimated but instead of using a single measure of sentiment (S_t), we consider the impact of optimistic and pessimistic sentiments on housing market returns. Here the sentiment index is split into two: $S+$ and $S-$ where $S+$ equals S when S has a positive value while $S-$ equals S when S is negative. Both $S+$ and S- are zero otherwise. The regression estimates are in Table 4.

The results in Table 4 are consistent with those in Table 3; positive sentiments drive housing market returns. Although not statistically significant, we also see that negative sentiments drive housing market returns down. The coefficient signs and statistical significance of all other variables are the same as those in Table 3.

Note that R has the same coefficient sign as S (Table 3) and S+ (Table 4). The statistical significance of S/S+ may be spurious if there is a positive correlation between R and $S/S+$. To address this possibility, Equation 3 is re-estimated without S before regressing the residuals on S, and $S+$ and $S-$. The statistically significant positive relationship between S and $S+$ on housing market returns persist as what we saw in Tables 3 and 4.[12] Thus, it is safe to assume that the predictive power of S/S+ was not the result of its correlation with R.

Table 3. Predicting future housing market returns with current housing market sentiments.

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	0.418*** (0.05)	0.423*** (0.13)	0.325*** (0.11)	0.227** (0.10)	0.641*** (0.21)	0.234*** (0.09)	0.341** (0.11)
S	0.214*** (0.08)	0.241*** (0.05)	0.421*** (0.10)	0.351*** (0.11)	0.552* (0.25)	0.441* (0.25)	0.341* (0.19)
Festival			0.107 (0.21)	0.308 (0.35)	0.244 (0.28)	0.294 (0.25)	0.221 (0.19)
Holiday			0.197 (0.16)	0.251 (0.18)	0.285 (0.19)	0.155 (0.21)	0.136 (0.17)
R	0.231*** (0.05)	0.165*** (0.05)	0.111*** (0.01)	0.137** (0.06)	0.128* (0.07)	0.173* (0.09)	0.159* (0.09)
M2		0.121 (0.34)	0.157 (0.41)	0.174 (0.36)	0.189 (0.35)	0.197 (0.32)	0.253 (0.41)
BLR		−0.215** (0.10)	−0.229* (0.12)	−0.197** (0.10)	−0.172*** (0.05)	−0.188** (0.09)	−0.197* (0.10)
R^2	0.2313	0.2253	0.2398	0.2401	0.2204	0.2353	0.2279
N	119	119	119	119	119	119	119

Model (1) is the basic model; Model (2) includes the control variables *M2* and *BLR*; Model (3) includes all variables and controls for seasonal effects. The dependent variable for Models (1) – (3) is R_{t+1}. The dependent variable for Models (4) – (7) is $R_{t+1,t+3}$; $R_{t+1,t+6}$; $R_{t+1,t+9}$; and $R_{t+1,t+12}$ respectively. ***, **, and * denotes statistical significance at the 1%, 5%, and 10% level respectively. Standard errors are in parentheses. Fixed and time dummies are included but not shown to reduce clutter in the table.

Table 4. The impact of optimistic and pessimistic sentiments on housing market returns.

Model	(1)	(2)	(3)	(4)	(5)
Intercept	0.151*** (0.03)	0.317** (0.05)	0.295*** (0.01)	0.353*** (0.02)	0.351** (0.11)
S+	0.452*** (0.02)	0.368*** (0.04)	0.387* (0.20)	0.349* (0.18)	0.337* (0.17)
S-	−0.083 (0.51)	−0.124 (0.44)	−0.078 (0.27)	−0.065 (0.43)	−0.111 (0.32)
Festival	0.224 (0.35)	0.258 (0.31)	0.201 (0.26)	0.176 (0.31)	0.245 (0.35)
Holiday	0.278 (0.21)	0.242 (0.28)	0.282 (0.20)	0.243 (0.25)	0.193 (0.29)
R	0.185*** (0.05)	0.173** (0.09)	0.175* (0.09)	0.159* (0.08)	0.147* (0.08)
M2	0.169 (0.34)	0.158 (0.31)	0.159 (0.39)	0.166 (0.24)	0.164 (0.34)
BLR	−0.251* (0.13)	−0.227** (0.11)	−0.231*** (0.09)	−0.198** (0.10)	−0.207* (0.11)
R^2	0.2408	0.2355	0.2316	0.2222	0.2358
N	119	119	119	119	119

The dependent variable for Models (1) – (5) is $R_{t+1,t+3}$; $R_{t+1,t+6}$; $R_{t+1,t+9}$; and $R_{t+1,t+12}$ respectively. ***, **, and * denotes statistical significance at the 1%, 5%, and 10% level respectively. Standard errors are in parentheses. Fixed and time dummies are included but not shown to reduce clutter in the table.

4.3. Government interventions

Evidence presented earlier shows that housing market sentiments drive house prices in Malaysia. Now, we need to determine the effectiveness of the government interventions and BNM measures in curbing speculation and cooling the housing market. The interventions and measures examined in this study are: (1) the real property gains tax; (2) abolishing the Developer Interest Bearing Scheme; (3) new PR1MA project launches; (4) the assessment of borrowers on their net instead of gross income; and (5) a stricter loan-to-value ratio policy. Real property gains tax (*RPGT*) is defined as the average tax payable for all transactions occurring in month *t*. The tax payable is calculated by applying the appropriate RPGT rate (based on the duration of the seller's ownership) on the transacted price, and then averaged across all transactions that occurred during month *t*. The abolishment of the Developer Interest Bearing Scheme (*DIBS*) is a binary variable that is '1' if month *t* occurs after the scheme was abolished. The new PR1MA project launch (*PR1MA*) is a binary variable that is '1' if there was a new PR1MA project launched in month *t*. The change from gross to net income (*NI*) is a binary variable that is '1' if one-third of the median net monthly household income for postcode *i*[13] is lower than the monthly repayment of the median transacted house price for postcode *i* in month *t*.[14] The stricter loan-to-value (*LTV*) policy is defined as the average down-payment required for each transaction in postcode *i* in month *t*. To illustrate, a 90% LTV would require a 10% down-payment on the transacted price. We then average this 10% across postcodes and then for the month. Three levels of LTV are considered: 70%, 80%, and 90%. To do so, we estimate the following regression:

$$\begin{aligned} R_{[t+1,t+b]} = {} & a + \beta_1 S_t + \beta_2 RPGT_t + \beta_3 S_t \times RPGT_t + \beta_2 DIBS_t + \beta_5 S_t \times DIBS_t + \beta_6 PR1MA_t \\ & + \beta_7 S_t \times PR1MA_t + \beta_8 NI_{i,t} + \beta_9 S_t \times NI_{i,t} + \beta_{10} LTV_t + \beta_{11} S_t \times LTV_t \\ & + \beta_{12} Festival_t + \beta_{13} Holiday_t + \beta_{14} R_t + \beta_{15} M2_t + \beta_{16} BLR_t + \varepsilon_t \end{aligned} \tag{4}$$

We only use $b = 1$ and $b = 3$ for the dependent variable as the earlier results show a weak relationship from $b = 6$ and onwards. Equation 4 is estimated three times, each time using a different level of LTV. Following these specifications, if the interventions and measures were effective, the coefficient signs of the interaction term with *S* should be negative. The results are in Table 5 below.

Table 5. Effectiveness of cooling measures in dampening house prices.

	$b = 1$			$b = 3$		
	LTV 70%	LTV 80%	LTV 90%	LTV 70%	LTV 80%	LTV 90%
Intercept	0.458*** (0.28)	0.411** (0.21)	0.445*** (0.23)	0.327** (0.44)	0.339*** (0.38)	0.354*** (0.41)
S	0.322*** (0.14)	0.328*** (0.21)	0.337*** (0.17)	0.341*** (0.18)	0.347*** (0.23)	0.358*** (0.25)
RPGT	−0.721 (0.34)	−0.645 (0.41)	−0.723 (0.33)	−0.579 (0.44)	−0.545 (0.29)	−0.551 (0.37)
$S \times RPGT$	0.389 (0.22)	0.511 (0.32)	0.498 (0.29)	0.558 (0.39)	0.472 (0.41)	0.523 (0.35)
DIBS	−0.146 (0.23)	−0.189 (0.28)	−0.194 (0.22)	−0.213 (0.33)	−0.312 (0.41)	−0.363 (0.36)
$S \times DIBS$	0.556 (0.48)	0.534 (0.45)	0.506 (0.41)	0.332 (0.21)	0.368 (0.28)	0.365 (0.36)
PR1MA	−0.835 (0.44)	−0.874 (0.38)	−0.837 (0.39)	−0.713 (0.25)	−0.788 (0.18)	−0.764 (0.22)
$S \times PR1MA$	−0.377* (0.41)	0.399 (0.38)	0.345 (0.32)	−0.315* (0.29)	0.384 (0.28)	0.366 (0.23)
NI	−0.031 (0.11)	−0.038 (0.14)	−0.039 (0.24)	−0.038 (0.33)	−0.036 (0.34)	−0.034 (0.28)
$S \times NI$	0.047 (0.28)	0.046 (0.29)	0.048 (0.33)	0.043 (0.23)	0.041 (0.29)	0.046 (0.31)
LTV	−0.159 (0.47)	−0.164 (0.42)	−0.155 (0.40)	−0.136 (0.39)	−0.132 (0.43)	−0.158 (0.37)
$S \times LTV$	−0.296** (0.51)	−0.256* (0.48)	0.085 (0.45)	−0.268** (0.44)	−0.260* (0.49)	0.077 (0.52)
Festival	0.199 (0.33)	0.152 (0.39)	0.141 (0.28)	0.192 (0.27)	0.185 (0.29)	0.172 (0.33)
Holiday	0.158 (0.23)	0.143 (0.22)	0.146 (0.29)	0.131 (0.19)	0.148 (0.22)	0.139 (0.28)
R	0.187*** (0.51)	0.169*** (0.49)	0.189*** (0.48)	0.173** (0.44)	0.164** (0.39)	0.178** (0.39)
M2	0.121 (0.67)	0.131 (0.61)	0.140 (0.59)	0.123 (0.56)	0.135 (0.51)	0.129 (0.49)
BLR	−0.256* (0.28)	−0.267* (0.23)	−0.271* (0.29)	−0.263** (0.24)	−0.269** (0.21)	−0.275** (0.23)
R^2	0.2371	0.2247	0.2241	0.2195	0.2343	0.2215
N	119	119	119	119	119	119

***, **, and * denotes statistical significance at the 1%, 5%, and 10% level respectively. Standard errors are in parentheses. Fixed and time dummies are included but not shown to reduce clutter in the table.

From Table 5, we can see that apart from $S \times PR1MA$ and $S \times LTV$, all other measures seem to be ineffective in dampening the effects of housing market sentiments. Even so, *PR1MA* is only marginally effective in curtailing sentiments if LTV was at 70%. Likewise, *LTV* is only effective in curtailing sentiments at 70% and 80%. Even if we ignore the effects of sentiments, these measures themselves are ineffective in lowering house prices, judging from the lack of any statistical significance for the non-interaction terms even though their coefficient signs are negative. Collectively, what Table 5 seems to suggest is, while the government and central bank measures may help lower house prices, it does little if anything at all to dampen housing market sentiments which on its own, has a stronger impact on house prices.

Finally, having established that sentiment is the prominent driver of housing market returns in Malaysia, we now investigate the direct impact the cooling measures has on sentiment. Typically, whenever a cooling measure is introduced, house prices should fall. However, with the continued rise in prices, it seems that market players do not regard the cooling measures as a negative, long-term signal (Zhou, 2017). That is to say, if the cooling measures were effective, it should drive sentiments down. An additional test is performed to confirm this argument. The dependent variable here is the difference between the average sentiment after and before a new measure is introduced. In this test, we use a test horizon that ranges from 1 to 6 months after and before the measure is introduced. The regression estimates are in Table 6 below.

The estimates in Table 6 reaffirms the earlier results. The cooling measures introduced seem to have little effect on dampening sentiments except for *PR1MA* and *LTV*. Even so, their effectiveness only lasts up to 3 months before losing significance, suggesting that optimism in the Malaysian housing market persists in spite of extant measures to cool the market; a phenomenon that can be attributed to a protracted housing boom in the country. As a result, the market expects the growth to continue into the future despite contrary measures (Agarwal, Hu, & Huang, 2015). We can also see that the festive and holiday periods in the country contribute to housing market sentiments, reaffirming our earlier argument on seasonal effects in the country.

4.4. Robustness tests

To ensure that our constructed sentiment index accurately reflects sentiments in the housing market of other states, an out-of-sample test is performed using data from the states not included in the earlier estimations[15] by first calculating the monthly sentiment index for the out-of-sample states before estimating Equation 4 using data from these states. As the earlier results show that the strongest statistical significance was at $b = 1$ at an LTV of 70%, the estimation is performed using these parameters. Table 7 provides the regression estimates for every state in our dataset.

The results of the out-of-sample test in Table 7 affirms the earlier findings that housing market sentiments drive Malaysian house prices. There also seems to be a clear difference in the magnitude of the relationship between the former (i.e. Kuala Lumpur, Selangor, Johor, and Penang) and latter (i.e. Kedah, Perak, Negeri Sembilan, and Malacca) states. From Table 7, we can also see that government and central bank measures have been mostly ineffective in dampening sentiments in each state. The exceptions in this case are the effects of *PR1MA* in Kuala Lumpur, Selangor, and Negeri

Table 6. Effectiveness of cooling measures in dampening housing market sentiment.

	1 month	2 months	3 months	4 months	5 months	6 months
Intercept	0.625*** (0.44)	0.610** (0.33)	0.628*** (0.51)	0.667*** (0.43)	0.633*** (0.31)	0.643*** (0.29)
RPGT	−0.078 (0.89)	−0.083 (0.65)	−0.092 (0.55)	0.041 (0.34)	−0.058 (0.27)	0.033 (0.51)
DIBS	−0.024 (0.34)	−0.038 (0.49)	−0.047 (0.20)	−0.033 (0.29)	−0.028 (0.44)	−0.045 (0.22)
PR1MA	−0.249* (0.38)	−0.186* (0.22)	−0.151* (0.19(	0.101 (0.28)	−0.089 (0.35)	0.074 (0.18)
NI	−0.057 (0.45)	−0.081 (0.61)	−0.074 (0.48)	−0.091 (0.55)	−0.083 (0.47)	−0.078 (0.40)
LTV	−0.145** (0.57)	−0.138** (0.49)	−0.123** (0.47)	−0.103 (0.51)	0.099 (0.49)	−0.084 (0.33)
Festival	0.128* (0.48)	0.117* (0.33)	0.105* (0.25)	0.100 (0.33)	0.094 (0.44)	0.089 (0.35)
Holiday	0.118* (0.22)	0.109* (0.19)	0.095 (0.19)	0.088 (0.24)	0.079 (0.28)	0.073 (0.22)
R^2	0.2327	0.2299	0.2462	0.2518	0.2333	0.2128
N	119	119	119	119	119	119

The dependent variable is $S_{[t+1,\ t+n]} - S_{[t-n,\ t-1]}$, where n ranges from 1 to 6 months. *LTV* is at the 70% level. ***, **, and * denotes statistical significance at the 1%, 5%, and 10% level respectively. Standard errors are in parentheses. Fixed and time dummies are included but not shown to reduce clutter in the table.

Table 7. Effectiveness of cooling measures in dampening housing market returns, by state.

	Kuala Lumpur	Selangor	Johor	Penang	Kedah	Perak	Negeri Sembilan	Malacca
Intercept	0.441*** (0.18)	0.456** (0.24)	0.445*** (0.20)	0.507** (0.26)	0.240*** (0.09)	0.278*** (0.11)	0.353*** (0.12)	0.341*** (0.08)
S	0.534*** (0.20)	0.528*** (0.11)	0.537*** (0.08)	0.681*** (0.11)	0.317*** (0.10)	0.289*** (0.05)	0.355*** (0.09)	0.285*** (0.05)
RPGT	−0.811 (0.81)	−0.745 (0.78)	−0.523 (0.63)	−0.779 (0.74)	−0.245 (0.39)	−0.251 (0.37)	−0.314 (0.36)	−0.229 (0.27)
$S \times RPGT$	0.419 (0.42)	0.522 (0.52)	0.387 (0.39)	0.448 (0.39)	0.172 (0.21)	0.123 (0.25)	0.201 (0.28)	0.233 (0.21)
DIBS	−0.461 (0.33)	−0.489 (0.38)	−0.494 (0.43)	−0.413 (0.43)	−0.212 (0.24)	−0.163 (0.33)	−0.233 (0.33)	−0.212 (0.29)
$S \times DIBS$	0.261 (0.31)	0.244 (0.41)	0.216 (0.48)	0.212 (0.26)	0.141 (0.33)	0.132 (0.55)	0.241 (0.40)	0.177 (0.28)
PR1MA	−0.515 (0.38)	−0.574 (0.44)	−0.537 (0.36)	−0.483 (0.49)	−0.188 (0.38)	−0.164 (0.24)	−0.191 (0.37)	−0.194 (0.41)
$S \times PR1MA$	−0.417* (0.23)	−0.499* (0.26)	−0.145 (0.45)	−0.157 (0.30)	−0.184 (0.18)	−0.186 (0.21)	−0.191* (0.10)	−0.148 (0.38)
NI	−0.431 (0.31)	−0.338 (0.34)	−0.139 (0.14)	−0.318 (0.43)	−0.055 (0.34)	−0.032 (0.27)	−0.101 (0.21)	−0.084 (0.18)
$S \times NI$	−0.267 (0.68)	−0.246 (0.79)	−0.148 (0.73)	−0.243 (0.83)	0.051 (0.39)	0.036 (0.21)	−0.114 (0.48)	0.087 (0.33)
LTV	−0.113 (0.37)	−0.121 (0.45)	−0.135 (0.35)	−0.116 (0.40)	−0.122* (0.07)	−0.181** (0.09)	−0.110** (0.06)	−0.107** (0.05)
$S \times LTV$	−0.186* (0.10)	−0.156* (0.08)	−0.111* (0.06)	−0.168** (0.08)	−0.110 (0.43)	−0.067 (0.42)	−0.103* (0.05)	−0.098 (0.41)
Festival	0.135 (0.30)	0.148 (0.43)	0.152 (0.19)	0.160 (0.15)	0.135 (0.24)	0.122 (0.15)	0.153 (0.20)	0.104 (0.14)
Holiday	0.158 (0.34)	0.143 (0.15)	0.163 (0.21)	0.121 (0.25)	0.159 (0.28)	0.153 (0.20)	0.133 (0.23)	0.151 (0.31)
R	0.225*** (0.05)	0.275*** (0.06)	0.189*** (0.03)	0.255*** (0.04)	0.130** (0.03)	0.138** (0.02)	0.155*** (0.03)	0.148** (0.04)
M2	0.133 (0.45)	0.149 (0.31)	0.149 (0.35)	0.122 (0.36)	0.144 (0.25)	0.138 (0.29)	0.148 (0.31)	0.135 (0.24)
BLR	−0.232** (0.10)	−0.235** (0.10)	−0.263** (0.12)	−0.244** (0.12)	−0.151** (0.07)	−0.165** (0.08)	−0.170** (0.08)	−0.145** (0.07)
R^2	0.2553	0.2391	0.2384	0.2411	0.2138	0.2129	0.2165	0.2217
N	119	119	119	119	119	119	119	119

***, **, and * denotes statistical significance at the 1%, 5%, and 10% level respectively. Standard errors are in parentheses.

Sembilan, as well as the effects of *LTV* in Kuala Lumpur, Selangor, Johor, Penang, and Negeri Sembilan.

A possible concern of insufficient degrees of freedom arises from using monthly observations. To address this, Equation 5 is re-estimated using daily observations. After excluding weekends, we have 2,508 observations, which should address this concern. The results are in Table 8 below.

On the whole, the results in Table 8 are qualitatively similar with the earlier findings that housing market sentiment is a strong driver of housing market returns, and that the cooling measures introduced by the government and central bank have so far been ineffective in dampening sentiment.

5. Discussion & conclusion

The results above lead to a few key observations. First, housing market optimism drives house prices in Malaysia. Pessimism meanwhile does not bring prices down. However, as opposed to the literature (Berger & Turtle, 2015; Stambaugh et al., 2012; Zhou, 2017), periods of market optimism are followed by higher rather than lower housing market returns. This may be attributed to the recent trend of seeking rental returns. Property classifieds in the country are flooded with listings citing substantial rental opportunities, largely driven by the advent of crowdsourced accommodation platforms such as Airbnb. Personal correspondence with real estate professionals reveal that a substantial number of recently-concluded deals were the result of optimism in future rental returns. The greater the potential rental return, the higher the price buyers were willing to pay for the house.

Second, the cooling measures introduced by the Malaysian government and the central bank so far has not been able to dampen market sentiments. Even the introduction of government-subsidised affordable housing projects and a stricter loan-to-value policy only curbs market optimism for a short period. We have reason to believe that this because of an extended boom in the housing market, leading to a heightened sense of confidence among consumers, investors, and developers alike. As a result, house prices continue to rise in tandem with market optimism instead of fundamentals, irrespective of the cooling measures introduced by the government.

The results also show a stark contrast in the effects of market optimism in different states. The effects of optimism are much stronger in the states of Kuala Lumpur, Selangor, Johor, and Penang, as compared to Kedah, Perak, Negeri Sembilan, and Malacca. House prices in the former four states are more strongly driven by housing market sentiments as compared to the latter since substantial development take place in the former. The latter in contrast, have a much wider dispersion of population and development. Additionally, agriculture has been the main economic activity in the latter states where infrastructural development progressed at a much slower pace. It is only in recent years that buyers consider Seremban – the capital city of the state of Negeri Sembilan – to be a satellite city to Kuala Lumpur, hence the stronger impact of sentiments in the state.

The findings of this study have a number of policy implications. First, we provide evidence that *NewStock* has the strongest influence on housing market sentiments. This suggests that contrary to popular opinion, developers instead of individual sellers drive

Table 8. Effectiveness of cooling measures in dampening housing market returns, by state, daily.

	Kuala Lumpur	Selangor	Johor	Penang	Kedah	Perak	Negeri Sembilan	Malacca
Intercept	0.383*** (0.04)	0.401*** (0.03)	0.355*** (0.01)	0.502** (0.01)	0.222*** (0.07)	0.251*** (0.03)	0.351*** (0.09)	0.392*** (0.05)
S	0.553*** (0.02)	0.603*** (0.03)	0.453*** (0.03)	0.533*** (0.08)	0.255*** (0.03)	0.248*** (0.05)	0.381*** (0.03)	0.275*** (0.03)
RPGT	−0.633 (0.43)	−0.645 (0.44)	−0.532 (0.41)	−0.649 (0.39)	−0.215 (0.35)	−0.253 (0.23)	−0.324 (0.28)	−0.224 (0.27)
$S \times RPGT$	0.401 (0.31)	0.512 (0.41)	0.377 (0.35)	0.438 (0.37)	0.182 (0.31)	0.133 (0.24)	0.211 (0.19)	0.222 (0.23)
DIBS	−0.441 (0.38)	−0.419 (0.34)	−0.434 (0.42)	−0.313 (0.40)	−0.211 (0.23)	−0.153 (0.23)	−0.222 (0.35)	−0.242 (0.27)
$S \times DIBS$	0.251 (0.32)	0.234 (0.45)	0.266 (0.38)	0.242 (0.20)	0.151 (0.32)	0.133 (0.51)	0.211 (0.45)	0.178 (0.28)
PR1MA	−0.825 (0.58)	−0.984 (0.64)	−0.537 (0.36)	−0.783 (0.59)	−0.178 (0.23)	−0.155 (0.23)	−0.172 (0.34)	−0.164 (0.31)
$S \times PR1MA$	−0.507* (0.26)	−0.489* (0.26)	−0.345 (0.35)	−0.166 (0.28)	−0.148 (0.18)	−0.191 (0.13)	−0.183* (0.09)	−0.138 (0.34)
NI	−0.231 (0.31)	−0.248 (0.17)	−0.149 (0.15)	−0.338 (0.42)	−0.075 (0.31)	−0.042 (0.21)	−0.111 (0.25)	−0.044 (0.19)
$S \times NI$	−0.166 (0.64)	−0.156 (0.49)	−0.137 (0.53)	−0.213 (0.43)	0.081 (0.49)	0.076 (0.31)	−0.104 (0.38)	0.077 (0.34)
LTV	−0.103 (0.31)	−0.111 (0.42)	−0.145 (0.39)	−0.126 (0.44)	−0.123* (0.06)	−0.155** (0.08)	−0.116** (0.06)	−0.117** (0.06)
$S \times LTV$	−0.156* (0.08)	−0.126* (0.07)	−0.104* (0.05)	−0.158** (0.07)	−0.114 (0.42)	−0.077 (0.32)	−0.113* (0.03)	−0.058 (0.31)
Festival	0.155 (0.22)	0.137 (0.43)	0.120 (0.14)	0.161 (0.14)	0.136 (0.19)	0.131 (0.13)	0.133 (0.18)	0.115 (0.29)
Holiday	0.159 (0.27)	0.146 (0.12)	0.128 (0.17)	0.147 (0.39)	0.190 (0.21)	0.128 (0.27)	0.130 (0.30)	0.133 (0.42)
R	0.283*** (0.06)	0.255*** (0.04)	0.188*** (0.01)	0.252*** (0.04)	0.181** (0.09)	0.128** (0.06)	0.125*** (0.04)	0.135** (0.06)
M2	0.111 (0.44)	0.128 (0.37)	0.159 (0.33)	0.113 (0.34)	0.120 (0.28)	0.144 (0.28)	0.133 (0.20)	0.121 (0.33)
BLR	−0.244*** (0.01)	−0.247*** (0.03)	−0.224** (0.10)	−0.257** (0.13)	−0.166** (0.08)	−0.180** (0.09)	−0.189** (0.08)	−0.145** (0.07)
R^2	0.2355	0.2283	0.2258	0.2350	0.2135	0.2338	0.2394	0.2373
N	2,508	2,508	2,508	2,508	2,508	2,508	2,508	2,508

The dependent variable is $R_{[t+1,\, t+b]}$, where $b = 30$. ***, **, and * denotes statistical significance at the 1%, 5%, and 10% level respectively. Standard errors are in parentheses.

housing market sentiments in Malaysia. In fact, homeowners looking to sell have an incentive to set asking prices that match the prices of new developments in the area. When new projects are sold at high prices, there is an incentive for real estate negotiators to keep the seller's asking price high. Driven by the optimism in the initial few transactions, more sellers will follow suit driving sentiments and subsequently prices higher. Second, the populace of an emerging market like Malaysia remains unsophisticated in their investment choices. Many investors still prefer real estate as the "safer" choice compared to financial securities. A lack of attractive investment alternatives in the financial markets also contribute to the demand for real estate investment.

To address the first issue, local governments should limit the number of new projects approved. As of Q3 2017, there are approximately 5.4 million residential units in stock with a further 480,000 units of incoming supply, and a further 427,692 units planned across the country. With an estimated population of 32 million (as of 2017), the number of persons per residential unit will be about 5 when all current projects are completed. Meanwhile, the average household size in Malaysia is 4.31 persons. These simple calculations suggest that the current stock of residential units is sufficient to house the country's population. Measures should thus be taken to ensure that the growth of new housing projects approved should be in tandem with population requirements. Addressing the second issue is a matter of financial education, provision of investment incentives such as tax exemptions, and a reduction in the barriers to entry for new investors. While prudence is always advised, liberalization of the financial markets to allow a wider range of investment alternatives is also required.

Our approach, however, is not without limitations. For instance, even though our dataset provided various information on each property and the transactions, we could not control for property type (e.g. condominium, flat, town house etc.) as there were far too many categories to be considered. Our dataset had 13 distinct property types. Controlling for each of their effects would render the empirical findings unreliable due to overspecification. Another factor we could not account for was the age of the property since this was not included in the dataset provided by NAPIC. For future research, this paper makes a few recommendations. First, further investigation of housing market sentiments with respect to rental returns is required. The costs and restrictions in property purchases can be substantial. As a result, many young adults are looking to renting as opposed to owning as a means to independent living. How then does the prospect of future rental receipts factor into housing market sentiments, especially since there is no guarantee of occupancy given the growing supply of residential units? Second, although Bank Negara's lending policies are considered one of the most prudent, it does not stop the non-performance of housing loans. To develop more holistic measures in addressing housing market sentiments, one can study the bank-specific factors that dampen or drive sentiments. Finally, one may also choose to study the influence of micro-factors (e.g. house characteristics, address, neighbourhood demographics) on housing market sentiments to assist in the development of policies that are more targeted.

Notes

1. The monthly data was sourced from the CEIC database, at the time of writing this manuscript (circa 2019).

2. In Malaysia, a sub-sale is when a buyer buys a house from the developer (under a new project) only to sell it off in the secondary market. A sub-sale also includes a purchase from non-developer sellers.
3. Housing developers in Malaysia are legally allowed to extend the completion date of a housing project up to 48 months. The real property gains tax rate after the 48^{th} month of ownership is 15%. This provides a significant incentive for sellers to hold-off a sub-sale until after that period.
4. A transacted price of RM1 million in our dataset lies in the 90^{th} percentile. In comparison, the average transacted price across all four states is approximately RM600,000. A premium of RM400,000 above the average price would suggest some degree of confidence in the housing market.
5. A correlation matrix between the chosen sentiment proxies is presented in Table A3 of the Appendix. Estimated correlation coefficients are relatively high and statistically significant at the 1% level. Augmented Dickey-Fuller and Durbin-Watson tests do not show any evidence of unit root or serial correlation issues. We did not present the results here to avoid clutter and distracting from the main results.
6. The anonymous reviewer was of the opinion that the proxy *NewStock* does not necessarily capture developer sentiment and suggested the number of newly approved development permits or construction starts as better gauge. We are inclined to agree but this data is only available from the 150 or so local municipal, city, or district council offices. With zero funding and only a small authoring team, obtaining this data within the stipulated time for revising the manuscript was not feasible. Instead, we substituted the *NewStock* proxy with "Value of Construction Work Done" obtained from the Department of Statistics, Malaysia. The rationale is simple. The more optimistic the developer sentiment, the more they are willing to spend on construction work as they are confident in recouping their costs in the future. Similarly, the anonymous reviewer was also of the opinion that *PSQM* and *P1M* does not accurately capture seller sentiments due to various confounding factors. As an alternative, we substituted these two proxies with the "Listed Price per Square Meter", reason being the more optimistic the seller, the higher the price they expect to receive on the sale. The results of these alternative proxies are provided in Tables A1 and A2 of the Appendix. They are fundamentally similar to the original estimates. We thank the reviewer for this suggestion.
7. We assume that the sentiment proxies are related to the expected housing market returns and uncorrelated with unpredictable return shocks.
8. The major festivals in Malaysia are Chinese New Year (January – February); Eid al-Fitr; Diwali (typically October – November); and Christmas.
9. School holidays in Malaysia are typically in the months of March, May, September, and November to December.
10. A casual Google search using the keywords "Chinese New Year; Property; Promo" or "Hari Raya; Property; Promo" (i.e. the two largest festivals / holiday periods in the country) will reveal plenty of these examples from an assortment of property developers.
11. Variables where the source data was recorded on a quarterly basis was disaggregated using a simple fixed-weight dissection .
12. For brevity, these estimates are not presented here but are available upon request.
13. We use the state's monthly median household income to represent the income of all postcodes *i* that fall within its respective state's borders. For example, the income for postcodes starting from 10,000 to 13,800 is represented by the state of Penang's monthly median household income.
14. The intuition behind this variable is simple. BNM's policy to assess borrowers based on their net rather than gross income was to avoid over-leveraging and to dampen demand. Following the typical one-third rule, if one-third of their net income is lower than the monthly repayment of a house, it puts a purchase beyond their reach. This should thus dampen sentiment.
15. The remaining states in our dataset are Kedah, Perak, Negeri Sembilan, and Melaka.

Availability of data and material

Data used in this study are from publicly available sources.

Authors' contributions

All work for this paper was completed equally by all named authors.

Code availability

No proprietary codes or software were used in this study.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

No funding was received for this study

ORCID

Calvin W. H. Cheong http://orcid.org/0000-0001-6206-7954

References

Agarwal, S., Hu, L., & Huang, X. (2015). Rushing into the American dream? House prices growth and the timing of homeownership. *Review of Finance*, *20*(6), 2183–2218.

Augustin, R. (2017, November 15). No, property market won't crash in 2018, say other experts. Free Malaysia Today. Retrieved from http://www.freemalaysiatoday.com/category/nation/2017/11/15/no-property-market-wont-crash-in-2018-say-other-experts/

Baker, M., & Stein, J. C. (2004). Market liquidity as a sentiment indicator. *Journal of Financial Markets*, *7*(3), 271–299.

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *The Journal of Finance*, *61*(4), 1645–1680.

Baker, M., & Wurgler, J. (2007). Investor sentiment in the stock market. *The Journal of Economic Perspectives*, *21*(2), 129–152.

Bank Negara Malaysia. (2010, November 3). Immediate implementation of a maximum loan-to-value (LTV) ratio of 70%. Bank Negara Malaysia Press Statements. Retrieved from http://www.bnm.gov.my/index.php?ch=8&pg=14&ac=2159

Bank Negara Malaysia. (2011, November 18). Measures to promote responsible financing practices. Bank Negara Malaysia Press Statements. Retrieved from http://www.bnm.gov.my/index.php?ch=en_press&pg=en_press_all&ac=2350&lang=en

Bank Negara Malaysia. (2013, July 5). Measures to further promote a sound and sustainable household sector. Bank Negara Malaysia Press Statements. Retrieved from http://www.bnm.gov.my/index.php?ch=en_press&pg=en_press_all&ac=2841

Berger, D., & Turtle, H. (2015). Sentiment bubbles. *Journal of Financial Markets*, *23*, 59–74.

Berry, J., McGreal, S., Stevenson, S., & Young, J. (2001). Government intervention and impact on the housing market in Greater Dublin. *Housing Studies*, *16*(6), 755–769.

Burnside, C., Eichenbaum, M., & Rebelo, S. (2016). Understanding booms and busts in housing markets. *Journal of Political Economy*, *124*(4), 1088–1147.
Chambers, M., Garriga, C., & Schlagenhauf, D. E. (2009). Housing policy and the progressivity of income taxation. *Journal of Monetary Economics*, *56*(8), 1116–1134.
Chang, K. L. (2014, September 20). Why developer interest-bearing schemes should be banned. The Star Online. Retrieved from http://www.thestar.com.my/Business/Business-News/2014/09/20/Saying-no-to-DIBS-It-should-continue-to-be-prohibited-in-the-interest-of-first-time-house-buyers/?style=biz
Cheong, C. W. H., Lee, M. H., & Weissmann, M. A. (2020). Credit access, tax structure, and the performance of Malaysian Manufacturing SMEs. *International Journal of Managerial Finance*, *16*(4), 433–454.
Cheong, C. W. H., Ngui, L. L. H., & Beatrice, S. B. (2019). On Malaysian house price growth: The effects of market sentiments. *Asian Journal of Finance & Accounting*, *10*(2), 167–191.
Cho, S. W. S., & Francis, J. L. (2011). Tax treatment of owner-occupied housing and wealth inequality. *Journal of Macroeconomics*, *33*(1), 42–60.
Clayton, J. (1997). Are housing price cycles driven by irrational expectations? *The Journal of Real Estate Finance and Economics*, *14*(3), 341–363.
Clayton, J., Ling, D. C., & Naranjo, A. (2009a). Commercial real estate valuation: Fundamentals versus investor sentiment. *The Journal of Real Estate Finance and Economics*, *38*(1), 5–37.
Clayton, J., MacKinnon, G., & Peng, L. (2009b). Time variation of liquidity in the private real estate market: An empirical investigation. *Journal of Real Estate Research*, *30*(2), 125–160.
Daily Express. (2015, April 13). Property market in a wait and see mode. Daily Express. Retrieved from http://www.dailyexpress.com.my/news.cfm?NewsID=98912
Floetotto, M., Kirker, M., & Stroebel, J. (2016). Government intervention in the housing market: Who wins, who loses? *Journal of Monetary Economics*, *80*, 106–123.
Gallimore, P., & Gray, A. (2002). The role of investor sentiment in property investment decisions. *Journal of Property Research*, *19*(2), 111–120.
Genesove, D., & Mayer, C. (2001). Loss aversion and seller behavior: Evidence from the housing market. *The Quarterly Journal of Economics*, *116*(4), 1233–1260.
Han, L. (2013). Understanding the puzzling risk-return relationship for housing. *Review of Financial Studies*, *26*(4), 877–928.
Hisyam, K. (2013, July 22). Are we heading towards a property bubble? KiniBiz. Retrieved from http://www.kinibiz.com/story/issues/38574/are-we-heading-towards-a-property-bubble.html
Huang, D., Jiang, F., Tu, J., & Zhou, G. (2014). Investor sentiment aligned: A powerful predictor of stock returns. *Review of Financial Studies*, *28*(3), 791–837.
Hui, E. C., & Wang, Z. (2014). Market sentiment in private housing market. *Habitat International*, *44*, 375–385.
Hui, E. C., Zheng, X., & Wang, H. (2013). Investor sentiment and risk appetite of real estate security market. *Applied Economics*, *45*(19), 2801–2807.
IMF. (2015). 2014 Article IV consultation—staff report; press release; and statement by the executive director for Malaysia (country report no. 15/58). IMF Country Report. Available from http://www.imf.org/external/pubs/ft/scr/2015/cr1558.pdf
Jin, C., Soydemir, G., & Tidwell, A. (2014). The US housing market and the pricing of risk: Fundamental analysis and market sentiment. *Journal of Real Estate Research*, *36*(2), 187–219.
Kamalavacini, R. (2014, September 12). Property players hit by cooling measures. The Malaysian Reserve. Retrieved from http://themalaysianreserve.com/main/news/corporate-malaysia/6455-property-players-hit-by-cooling-measures
Kaplanski, G., & Levy, H. (2012). Real estate prices: An international study of seasonality's sentiment effect. *Journal of Empirical Finance*, *19*(1), 123–146.
Kaur, M. (2017, November 14). Property market will be badly hit in 2018, says expert. Free Malaysia Today. Retrieved from http://www.freemalaysiatoday.com/category/nation/2017/11/14/property-market-will-be-badly-hit-in-2018-says-expert/
Ling, D. C., Naranjo, A., & Scheick, B. (2014). Investor sentiment, limits to arbitrage and private market returns. *Real Estate Economics*, *42*(3), 531–577.

Ling, D. C., Ooi, J. T. L., & Le, T. T. T. (2015). Explaining house price dynamics: Isolating the role of nonfundamentals. *Journal of Money, Credit, and Banking*, *47*(S1), 87–125.
Malmendier, U., & Tate, G. (2005). CEO overconfidence and corporate investment. *The Journal of Finance*, *60*(6), 2661–2700.
Malmendier, U., & Tate, G. (2008). Who makes acquisitions? CEO overconfidence and the market's reaction. *Journal of Financial Economics*, *89*(1), 20–43.
Miller, N., & Pandher, G. (2008). Idiosyncratic volatility and the housing market. *Journal of Housing Research*, *17*(1), 13–32.
Mok, O. (2015, January 2). With promise of real estate boon, property investor clubs boom. The Malaysian Insider. Retrieved from: http://www.themalaysianinsider.com/malaysia/article/with-promise-of-real-estate-boon-property-investor-clubs-boom
Piazessi, M., & Schneider, M. (2009). Momentum traders in the housing market: Survey evidence and a search model. *The American Economic Review*, *99*(2), 406–411.
Soo, C. K. (2013). Quantifying animal spirits: News media and sentiment in the housing market. *The Stephen M. Ross School of Business at the University of Michigan Research Paper Series*.
Stambaugh, R. F., Yu, J., & Yuan, Y. (2012). The short of it: Investor sentiment and anomalies. *Journal of Financial Economics*, *104*(2), 288–302.
The Star Online. (2013, June 27). What is DIBS, plus the pros and cons of this controversial scheme. The Star Online. Retrieved from http://www.starproperty.my/index.php/articles/investment/what-is-dibs-plus-the-pros-and-cons-of-dibs/
Tse, R. Y. C., Ho, C. W., & Ganesan, S. (1999). Matching housing supply and demand: An empirical study of Hong Kong's market. *Construction Management & Economics*, *17*(5), 625–633.
Yeong, E. (2013, October 30). Higher property gains tax, DIBS ban are 'good'. The Sun Daily. Retrieved from http://www.thesundaily.my/news/868889
Yeong, E. (2014, October 9). Housing affordability not addressed in Budget 2014. The Sun Daily. Retrieved from http://www.thesundaily.my/news/1193131
Zhou, Z. (2017). Housing market sentiment and intervention effectiveness: Evidence from China. *Emerging Market Review*. doi:10.1016/j.ememar.2017.12.005

Appendix

VCWD is the value of construction work done from January 2020 to December 2020; *ResMort* is the total residential mortgage divided by total loans in the country; *HoldPer* is the natural log of the median holding period of sellers (in months) as a proxy for turnover; *SubSale* is number of sub-sales in a month; *LPSQM* is the average list price per square meter in a month, sourced from property listing sites. We could not find in-sample data (2010 to 2019) for *LPSQM* as the listings had expired. Web-archived search results for these listings were inconsistent and unreliable.

Table A1 Current and lagged sentiment proxy correlation with the first principal component, *P1*, using alternative proxies.

Current	Correlation with *P1*	Obs.[a]	1-month Lag	Correlation with *P1*	Obs.
VCWD	0.844***	11	*VCWD*	0.727**	11
ResMort	0.781***	11	*ResMort*	0.563***	11
HoldPer	−0.532***	11	*HoldPer*	−0.427**	11
SubSale	0.541***	11	*SubSale*	0.4915***	11
LPSQM	0.614***	11	*LPSQM*	0.761***	11

[a]At $n - 1$ degrees of freedom

Table A2 Predicting future housing market returns with current housing market sentiments, using alternative proxies.

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	0.422***	0.435***	0.355***	0.242**	0.652***	0.251***	0.378**
	(0.02)	(0.06)	(0.03)	(0.12)	(0.01)	(0.04)	(0.11)
S	0.245***	0.215***	0.416***	0.378***	0.412*	0.441*	0.353*
	(0.04)	(0.02)	(0.11)	(0.11)	(0.23)	(0.25)	(0.18)
Festival			0.110	0.245	0.268	0.274	0.233
			(0.31)	(0.35)	(0.24)	(0.26)	(0.21)
Holiday			0.217	0.266	0.305	0.165	0.145
			(0.21)	(0.19)	(0.21)	(0.32)	(0.23)
R	0.245***	0.173***	0.122***	0.141**	0.132*	0.173*	0.145*
	(0.05)	(0.05)	(0.01)	(0.06)	(0.07)	(0.10)	(0.08)
M2		0.131	0.167	0.166	0.129	0.177	0.244
		(0.45)	(0.38)	(0.26)	(0.35)	(0.31)	(0.42)
BLR		−0.224**	−0.231*	−0.202**	−0.183***	−0.193**	−0.175*
		(0.10)	(0.12)	(0.10)	(0.05)	(0.08)	(0.09)
R^2	0.2441	0.2325	0.2376	0.2422	0.2213	0.2418	0.2369
N	118	118	118	118	118	118	118

Model (1) is the basic model; Model (2) includes the control variables *M2* and *BLR*; Model (3) includes all variables and controls for seasonal effects. The dependent variable for Models (1) – (3) is R_{t+1}. The dependent variable for Models (4) – (7) is $R_{t+1,t+3}$; $R_{t+1,t+6}$; $R_{t+1,t+9}$; and $R_{t+1,t+12}$ respectively. ***, **, and * denotes statistical significance at the 1%, 5%, and 10% level respectively. Standard errors are in parentheses.

Table A3 Correlation matrix of sentiment proxies.

	NewStock	ResMort	HoldPer	SubSale	PSQM	P1M
NewStock	1					
ResMort	0.7875	1				
HoldPer	0.7323	0.6858	1			
SubSale	0.7532	0.6826	0.7726	1		
PSQM	0.7964	0.7136	0.7307	0.7101	1	
P1M	0.7270	0.6903	0.7324	0.7860	0.8144	1

NewStock is the incoming and completed supply of residential units scaled by the existing stock of residential units in the past quarter; *ResMort* is the total residential mortgage divided by total loans in the country; *HoldPer* is the natural log of the median holding period of sellers (in months) as a proxy for turnover; *SubSale* is number of sub-sales in a month; *PSQM* is the average transacted price per square meter in a month; and *P1M* is the number of transactions worth RM1 million and above in a month.