HONG KONG MONETARY AUTHORITY

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UNVEILING THE DYNAMICS OF HONG KONG PROPERTY MARKET THROUGH TEXTUAL ANALYSIS

Key points:

- *The advance in information and computing technology raises the possibility of using big data to generate more complete, timely and granular information about the property market in Hong Kong. Accordingly, this paper use textual analysis to compile two lexicon-based property market indices, namely a news-based property market sentiment index and an internet search (i.e. Google Trend)-based buyer incentive index.*

- *This paper has several interesting findings. We find that our news-based property market sentiment index can reflect the change in market sentiments following major economic and social events. Another key feature is it can also separately identify the sentiments in the primary and secondary markets, with primary market sentiments tending to lead secondary market sentiments during the low housing supply period. On the other hand, our Google buyer incentive index has value-added in forecasting housing prices, and can become another early warning indicator to identify turning points in the housing cycle.*

- *Our empirical analysis reveals that both market sentiments and buyers' incentives were driven by macro fundamentals. On the transmission channel, rises in market sentiments could stimulate buyers' incentives, which together would then affect housing prices and transaction volumes. Altogether, this paper is novel in using textual analysis to map out the transmission channels of market sentiments and buyers' incentives in the housing market. This paper also illustrates that big data with textual analysis could provide a new toolbox to facilitate the surveillance and research work on the Hong Kong property market.*

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I. INTRODUCTION

The advance in information/computing technology and the growing popularity of digital tools have generated enormous quantities of data, or so-called big data (FSB (2017)). In the field of research and surveillance, it is well recognised that big data has the potential to provide more complete, timely and granular information to supplement "traditional" macroeconomic data (BIS (2019)). Given the importance of the housing market to the Hong Kong economy[1], this paper uses textual data from the web and newspapers, to conduct a series of sentiment and incentive analysis.

In the literature (e.g. Kindleberger (1978), Galbraith (1990), Tetlock (2007) and Shiller (2009)), market sentiments are recognised as one of the key determinants of asset prices, including housing prices. An earlier HKMA study (Wu et al. (2017)) suggested that sentiments could account for about 8% of housing price variations in Hong Kong. For policymaking, it is also important to track market sentiments, as exuberant sentiments could lead to excessive house price valuation, posing financial stability risks down the road. However, in practice, market sentiments are typically unobservable, and are often proxied by other asset market indicators (e.g. volatility index in stock market) which can be noisy and may not be able to reflect events that are specific to the housing market (e.g. new stamp duty on property transactions) [2]. As such, it would be useful if we can directly measure housing market sentiments for our macro-financial surveillance.

This paper uses textual analysis to measure housing market sentiments from mass media, as such technique is becoming popular in sentiments analysis (e.g. Baker et.al (2016), Wong et.al (2017)). In the first step, we use the lexicon approach to set up a news-based property market sentiment index for Hong Kong based on local news articles. Then we examine how market sentiments would influence buyers' incentives

[1] In particular, about 10% of domestic economic activities are directly related to the real estate sector, and nearly half of the household debt is residential mortgage loans. In addition, almost one-third of the Government revenue depends on the property market performance (e.g. stamp duties and land premium).

[2] Previous studies suggest that stock market volatility can be influenced not only by sentiments but also by other factors (Bekaert et al., 2013).

to buy a house. With a rationale that the internet search intensity of housing market-related information can reflect buyers' incentives, we use Google Trend to develop a Google buyer incentive index. In the second step, we map out the transmission channel of market sentiments to the housing market, by estimating a structural vector-autoregressive (SVAR) model and conduct an impulse response analysis.

There are several interesting findings in this paper. First, we find that the news-based property market sentiment index can reflect the change in sentiments during major economic and market specified events. On further distinguishing the market sentiments in the primary market and the secondary market, we find that the primary market sentiments tend to lead the secondary market sentiments during the low housing supply period. For the Google buyer incentive index, we find that it has value-added in forecasting (or nowcasting) the official Rating and Valuation Department (R&VD) housing price index, and the forecasting power is higher than that of the weekly Centa-City Leading Index (CCLI). Regarding the transmission mechanism, we discover that, in line with theories, both market sentiments and buyers' incentives could be driven by the macro environment. In particular, an improvement in market sentiments could stimulate buyers' incentives, which then together would affect housing prices and transaction volumes through the sentiments channel.

The remainder of this paper is structured as follows. Section II describes the methodology that we use to compile the news-based property market sentiments index for Hong Kong, followed by some observations and analysis. Section III describes the methodology of compiling the Google buyer incentive index with some findings. In Section IV, we set out our empirical approach to identify the impacts and transmission channels of market sentiments and buyers' incentives in the Hong Kong housing market. The final section concludes.

II. MEASURING PROPERTY MARKET SENTIMENTS IN HONG KONG

2.1 Methodology

To compile the news-based property market sentiment index for Hong Kong, we follow the lexicon approach of textual analysis (see Soo (2018) and Gao & Zhao (2018)). We first set up a Chinese dictionary of positive or negative sentiment words for the residential property market (Annex 1)[3]. We then count the number of articles in local Chinese newspapers containing the sentiment words. The source of the newspapers is Wisers Information Portal, which is a digital archive containing Chinese news media in Hong Kong since April 1998. To further distinguish the sentiment in different market segments, we build another dictionary (see Annex 1) that is specific to the primary or secondary market. The overall tone of property market sentiments in period t is calculated by

$$S_t = \sum_{i=p,s} \frac{\#pos_{it} - \#neg_{it}}{\#total\_news_t} \tag{1}$$

i.e., the number of the news articles which contain at least one positive sentiments word within a paragraph (*#pos*) from both primary (*p*) and secondary market (*s*) minus the number of the news articles which contain at least one negative sentiments word (*#neg*) and scaled by the number of news articles in real estate section[4] (*#total_news*) in period t. We then standardize the series (S_t) into an overall property market sentiment index. Similarly, a market-specific (i.e. primary and secondary markets) sentiments index (S_{it}) can also be compiled as follows:

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[3] Recent studies (e.g. Loughran and McDonald (2011), Walker (2014)) on textual analysis have argued that general tonal sentiment words could be irrelevant to identify market-specific sentiments and lead to noisy measures. To improve the efficacy of sentiments identification, we follow Soo (2018) method by introducing domain specific vocabulary. In particular, we selected positive or negative tone keywords that are Hong Kong media usually expresses over the property market, and some of them are related to particular market segment only.

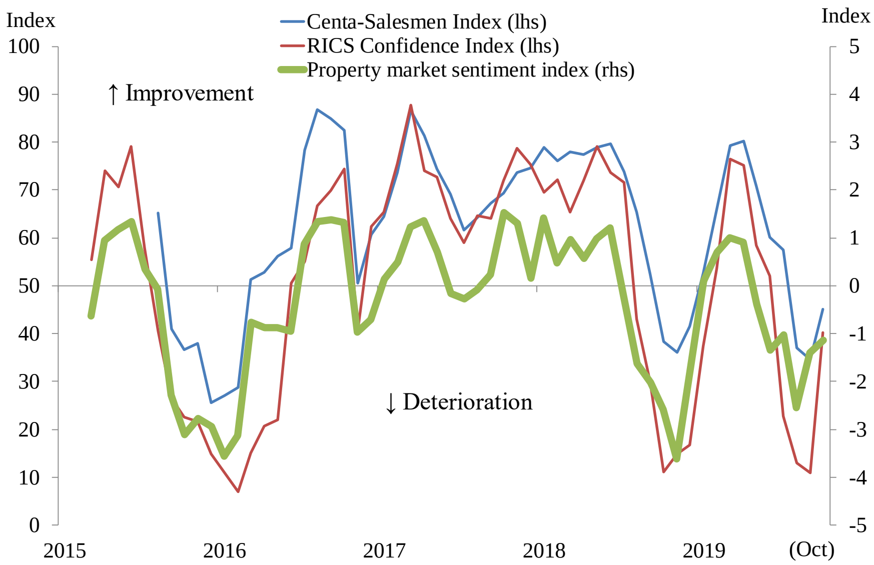
[4] Even though most of the real estate news in Hong Kong newspapers is related to the local property market, they still have some coverage on the regional markets (e.g. Pearl River Delta). To confine our study, we attempt to exclude the non-domestic news articles by filtering the keywords for non-domestic real estate section. The list of keywords is on Annex 2.

$$For\ \ i = p, s \qquad\qquad S_{it} = \frac{\#pos_{it} - \#neg_{it}}{\#total\_news_t} \qquad (2)$$

2.2 Analysis of the news-based property market sentiment index

Chart 1 shows the news-based property market sentiment index (green line) together with other existing survey-based housing sentiment indices, namely the Centa-Salesmen Index (CSI)[5] and the Royal Institution of Chartered Surveyors (RICS) Confidence Index[6]. Positive values mean market sentiments are improving, and vice versa. As shown in the chart, our news-based property market sentiment index fluctuates closely with the existing sentiment indices and is also highly correlated with the timing of domestic and external shocks, such as the start of the US rate hike cycle in 2015, Mainland China stock market turbulence during 2015-2016, escalation of US-China trade tension in the second half of 2018, and the domestic social incidents in 2019. During the periods, housing prices have experienced some corrections between 5 to 11%.

Chart 1: News-based property market sentiment index with other survey-based sentiment indices



Sources: RICS, Centaline property agency and staff estimates.

[5] CSI is compiled from a weekly survey on Centaline property agency's salesman.

[6] RICS Confidence Index is compiled from a sentiments survey that collects and analyses the opinions of professionals in agency.

To verify whether our index can reflect the perception of market participants, we compute the bilateral correlations between our news-based property market sentiment index, CSI and the RICS Confidence Index. The correlation of each pair is very high at around 0.9 (see Table 1). On the one hand, it implies that our index can reflect market sentiments. On the other hand, we may also argue that the mass media could have a strong influence on the people's views on the property market.

Table 1: Correlations between news-based and survey-based sentiment indices between March 2015[7] and October 2019

	Correlation
News-based sentiments index and CSI	0.93
News-based sentiments index and RICS Confidence Index	0.88
CSI and RICS Confidence Index	0.92

Our news-based property market sentiment index has several advantages over the survey-based indicators. Since it is compiled using newspapers, which are the key sources of information to the public[8], our news-based index is more comprehensive in capturing the overall public view on the property market. In contrast, the survey-based indicators are usually based on a small sample of survey interviewees, and the survey responses may be subject to bias or manipulation by interviewees. The second advantage of our news-based index is that it is more timely, and the archived news allow us to backcast the historical series of market sentiments further into the past (i.e. 1998). In contrast, the time series of the current survey-based indicators are relatively short (since 2015), as well as subjecting to a time lag, continuality and comparability issues.

More importantly, our news-based index is more informative as it can distinguish the sentiments in the primary and secondary market, whereas the existing survey-based indicators cannot. This can help fill the information gap in the primary market, which was not transparent until in the recent years[9]. Chart 2 shows a

[7] For CSI, the first observation was August 2015.

[8] See the Yearly Survey of People's Main Source of News conducted by HKU POP https://www.hkupop.hku.hk/chinese/popexpress/press/main/year/datatables.html

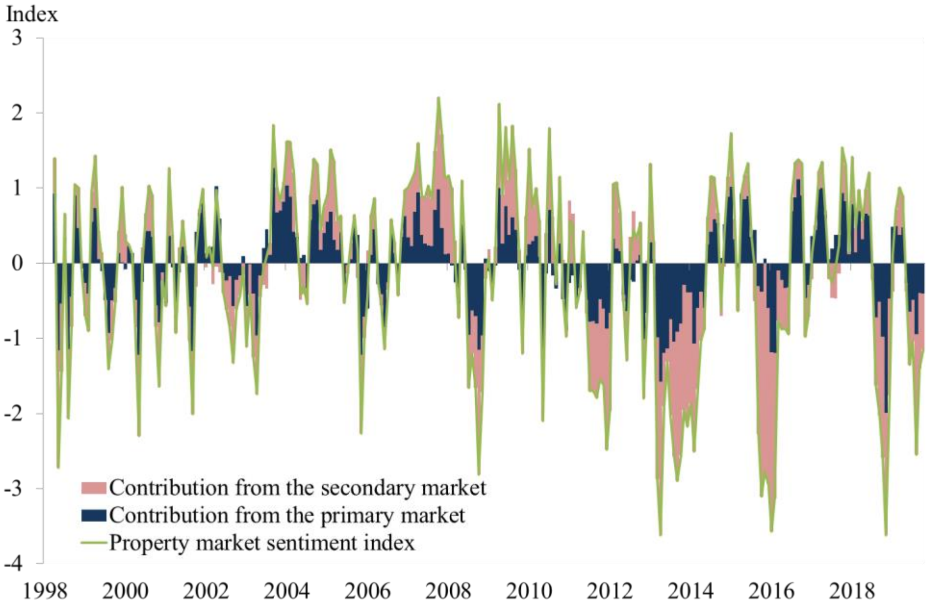
[9] Before the implementation of Residential Properties (First-hand Sales) Ordinance in 2013, there was no standard record of primary market information (e.g. price list, quantity of sales in each launch) provided by property

decomposition of the dynamics of the news-based property market sentiment index into the contribution of the underlying market segments since April 1998. It is interesting to see that in general, the contribution of the primary and secondary markets are roughly the same, even though the secondary market dominates transaction volumes (over 70% during the same period). It is probably because newspapers usually have a disproportionate coverage on the primary market news. For example, they would concentrate on reporting new launches of some large-scale development projects, reflecting the marketing campaigns by property developers.

Another interesting observation is that the contribution of primary and secondary market sentiments is synchronized but asymmetric over the cycles. In particular, primary market sentiments usually contribute more to the up-cycle of the overall market sentiments rather than the down-cycle, such as the recent years since 2014 and the period between 2003 and 2005. One possible explanation is that property developers might adjust their sales pace to search for the best prices according to the market condition. For instance, they would try to raise their unit prices and accelerate the sale pace when the market is booming, while slowing the sale pace when the market is cooling.

developers except the official sale and purchase records in Land Registry after the transactions were completed.

Chart 2: Lexicon-based property market sentiment index with contributions

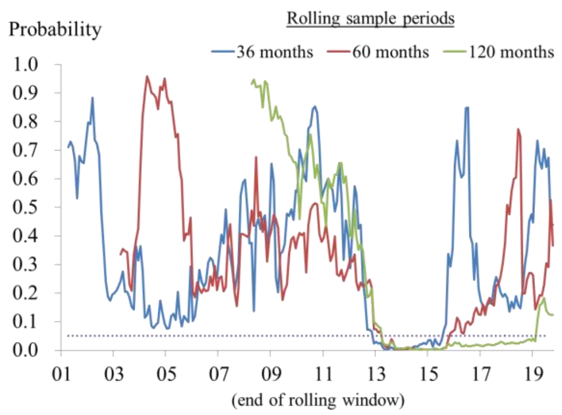


Source: Staff estimates.

Besides the contributions, our market-specific sentiment indices can also help shed some light on the lead-lag relationship between the primary and secondary market sentiments. We run a series of Pairwise Granger Causality tests with different rolling sample windows. Chart 3A illustrates the probabilities of primary market sentiments not granger causing secondary market sentiments. We can see the probabilities went below 5% during 2009-2015 in different sample windows (Table 2). Meanwhile, the Granger Causality tests results of secondary market sentiments on the primary market sentiments were mixed (Chart 3B). These observations suggest that primary market sentiments tend to lead secondary market sentiments during the period of low housing supply (Chart 4). This can be explained by the anchoring effect between the two markets. Given the limited new launches, both buyers and sellers would naturally focus on the primary market condition, and primary market sentiments could be easily spilled over to secondary market sentiments. In recent years, the lead of primary market sentiments has weakened. One of the reasons is that the anchoring effect diminished gradually when the housing supply increased since 2014. Another possible explanation is that the primary market has become more regulated and transparent after the implementation of Residential Properties (First-hand Sales)

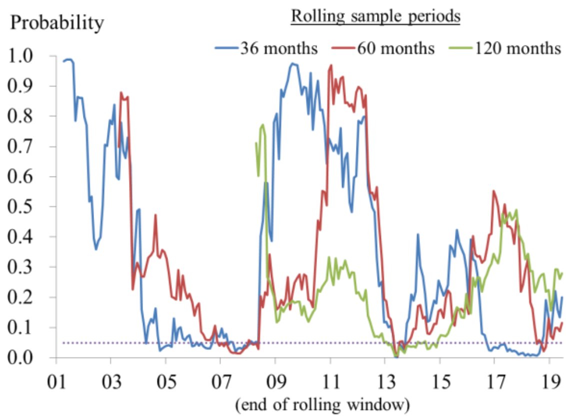
Ordinance in 2013. Before 2013, newspapers were the only source for market participants to understand the primary market and the sentiments reported on the news would weigh heavily on their assessments. Since then, more information (e.g. prices and number of launches) on the primary market has become available, and this weakened the influence of primary market sentiments.

Chart 3A: Probability of primary market sentiments does not have Granger Causality on the secondary market



* Granger Causality tests with the lag of 3 months
Source: Staff estimates.

Chart 3B: Probability of secondary market sentiments does not have Granger Causality on the primary market



* Granger Causality tests with the lag of 3 months
Source: Staff estimates.

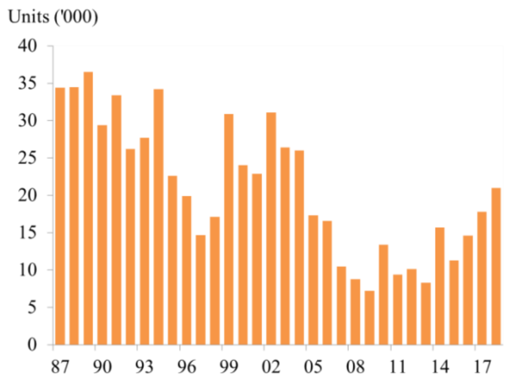
Table 2: Periods of primary market sentiment index significantly leads^ secondary market sentiment index

Rolling window of Granger Causality tests	Periods
36 months	Dec 2009 – Jul 2015
60 months	Apr 2008 – Oct 2015
120 months	Apr 2003 – Feb 2019

^Rejection of no causality at 5% significant level.

*Granger Causality tests with the lag of 3 months.
Source: Staff estimates.

Chart 4: Private housing completions



Source: Transport and Housing Bureau.

While our news-based sentiment index can generate new insights and compare favourably against the existing survey-based indices, our news-based textual analysis also has some limitations. As the word choice of the newspapers may evolve over time, it is possible that some trendy or outdated words are not captured by our dictionaries. Moreover, unlike machine learning, our lexicon-based identification may overlook the information hidden in the sentence structure, which could be essential in interpreting the content (e.g. a double negative statement[10]). Nevertheless, the potential bias is expected to be small, as the volume of our sample news articles is large enough, while local journalists usually prefer to use simple sentence structure in writing their news articles.

III. MEASURING PROSPECTIVE BUYERS' INCENTIVES IN HONG KONG

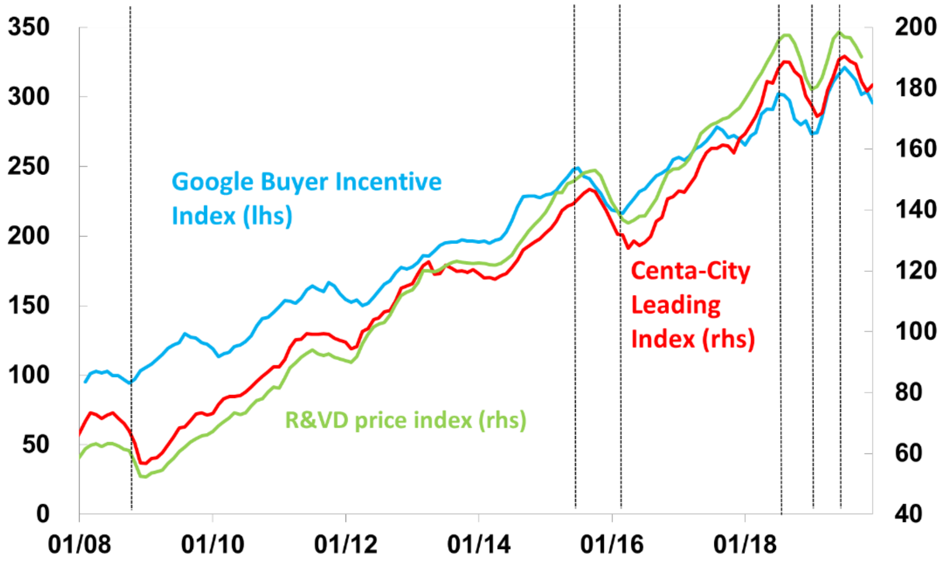
Before analysing the transmission of market sentiments to the housing market, we first need to understand how market sentiments would influence the behaviour of market participants, particularly prospective property buyers. Naturally, buoyant market sentiments would induce more property buyers to search for opportunity. As there is no existing measure of buyers' incentives, we follow the literature (Kulkarni et al. (2009), Dietzel et al. (2014), Wu and Brynjolfsson (2015)) in measuring buyers' incentives using Google Trend.

Our rationale of using Google Trend is that prospective property buyers would naturally search Google for some key Chinese words, such as the name of property agency, for information when they plan for property purchases.[11] Henderson and Cowart (2002) show that visitors of residential real estate agent websites make extensive use of the internet before making a purchase. As such, the intensity of search interests over time on these words could reveal potential buyers' intentions to buy a house.[12] One of the key advantages of Google Trend is that the search volume data is

[10] For example, the word "bad" should be considered as a negative term. But if we add the word "not" before it, then the overall meaning of the sentence would be completely different.
[11] Please refer to Annex 3 for a complete list of the keywords used in our study.
[12] Google Trend data is an unbiased sample of Google search data and is available starting from 2004. Each data point is divided by the total searches of the geography and time range it represents to compare relative popularity. The resulting numbers are then scaled on a range of 0 to 100 based on the topic's proportion to all

available on a real time basis with no publication lag, which enables us to monitor the market more closely.

Chart 5: Google buyer incentive index



Sources: Google Trend, Centaline, Rating and Valuation Department (R&VD), and staff estimates

We conduct a principal component analysis on the Google search volume index of our set of Chinese words, and set the first principal component as the Google buyer incentive index.[13] As shown by the blue line in Chart 5, the Google buyer incentive index tracks closely the CCLI and the R&VD housing price index. In some occasions marked by the vertical lines, the Google buyer incentive index is leading the other two indices. Our granger-causality and forecasting power tests suggest that the Google buyer incentive index has value-added in forecasting the R&VD Index: (i) past values of the Google buyer incentive index can explain future values of CCLI and (ii) the Google buyer incentive index performs better than CCLI in forecasting the one-

searches on all topics. As Google Trend data is a random sample of all searches, the time series could deviate slightly each time it is extracted. To enhance the representativeness of our sample, we perform the data scrapping process repeatedly and use their average values for our analysis. Robustness checks suggest that all of these individual samples yield similar results.

[13] While users can also extract an aggregate search volume index from Google, we consider such approach less desirable for our purpose since certain inherently less-searched (yet indicative) terms would get overshadowed by others in the resultant series. Meanwhile, some previous studies (e.g. Wu and Brynjolfsson (2015)) also make use of the search volume indices of predefined categories (e.g. real estate agencies, real estate listings) to approximate the interest for housing. In the case of Hong Kong, we however note that many of the top search terms under these categories are irrelevant to the domestic property market, rendering the indices ineffective in capturing buyers' incentives.

month-ahead movement of the R&VD Index (see Annex 4). In any case, the merit of the Google buyer incentive index is that it is simple and is available on a real time basis, whereas the R&VD index is released with a month lag. Moreover, CCLI occasionally would also diverge from the R&VD index. So the Google buyer incentive index can help supplement the CCLI in tracking the turning points in Hong Kong housing cycle.

Nevertheless, our Google buyer incentive index is also subject to some caveats arising from using Google Trend. For example, it may not capture a demographically representative sample of prospective property buyers in Hong Kong, as internet usage varies widely across the population. Similar to the news-based sentiment index, the Google buyer incentive index may also not capture some trendy or outdated words, as search requests made by potential buyers would evolve over time.

IV. Transmission Channels of Market Sentiments and Buyers' Incentives to the Hong Kong Housing Market

To analyze the effect of market sentiments and buyers' incentives on Hong Kong's secondary housing market[14], we estimate a structural vector-auto regression (SVAR) model with the following Cholesky ordering of endogenous variables: (1) Volatility Index of Heng Sang Index (*vhsi*); (2) Heng Sang Index (*hsi*); (3) average mortgage rates (*mort*); (4) Purchasing Manager Index (PMI) (*pmi*); (5) unemployment rate (*un*); (6) secondary market sentiments index (*sec*); (7) Google buyer incentive index (*gbii*); (8) transaction volume in the secondary market (*tran*); and, (9) secondary market housing prices (*pp*). To control for the policy impacts from the demand management and macro-prudential measures of the Government and the HKMA, we include a step function of policy variables[15] as exogenous variables in the SVAR. Besides *vhsi*, *mort*, *un*, *pmi* and *sec*, other endogenous variables in first differences.

Regarding the ordering of the endogenous variables, the stock market index

[14] We confine our empirical study to the secondary market as the official housing price index measures the prices of second-hand flats only.

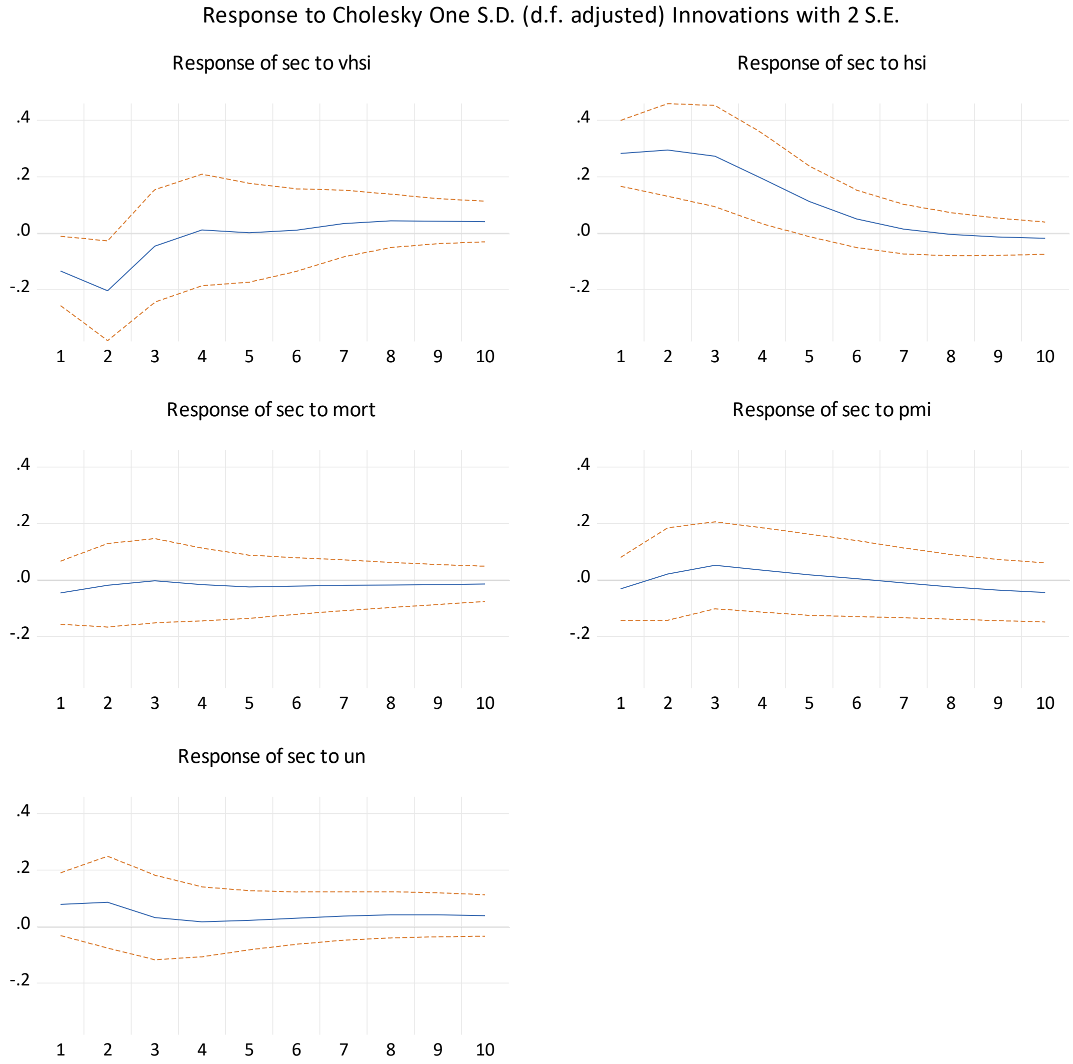
[15] We follow HKMA (2014) and He (2014) to construct a step function of demand management and macro-prudential measures by increasing "count" for each round of new measures.

and the volatility index are ordered first in the SVAR, given its responsiveness to all sorts of news including global financial market shocks. The average mortgage rate is ordered third, as it is determined by both domestic banking liquidity conditions and the US policy rate under the Linked Exchange Rate System. Real economic indicators (PMI and unemployment rate) are ordered next and are included to represent the purchasing power of domestic households. After the macro-financial variables, we include our secondary property market sentiment index and our Google buyer incentive index. Our rationale is that buying incentives are likely affected by property market news updates but not vice versa. Housing prices and transaction volumes are ordered last as they are influenced by the macro-financial conditions, market sentiments and buyers' incentives.

We estimate our SVAR model using monthly data from January 2008 – October 2019. We set the lag length of the SVAR model to two, as suggested by the Akaike Information Criterion. Chart 6 first shows the impulse responses of market sentiments to innovations in different macro-financial variables. In general, market sentiments strengthened when stock prices increased or stock market volatility declined, while market sentiments were not responsive to other shocks[16]. It suggests that the equity market performance is the key driver of property market sentiments. The impulse response also shows that the transmission of equity price shock to property market sentiments was quick and the impact would last for at least one quarter.

[16] The insignificant impulse responses of unemployment rate and average mortgage rate might due to the low volatility of those macro variables after the GFC.

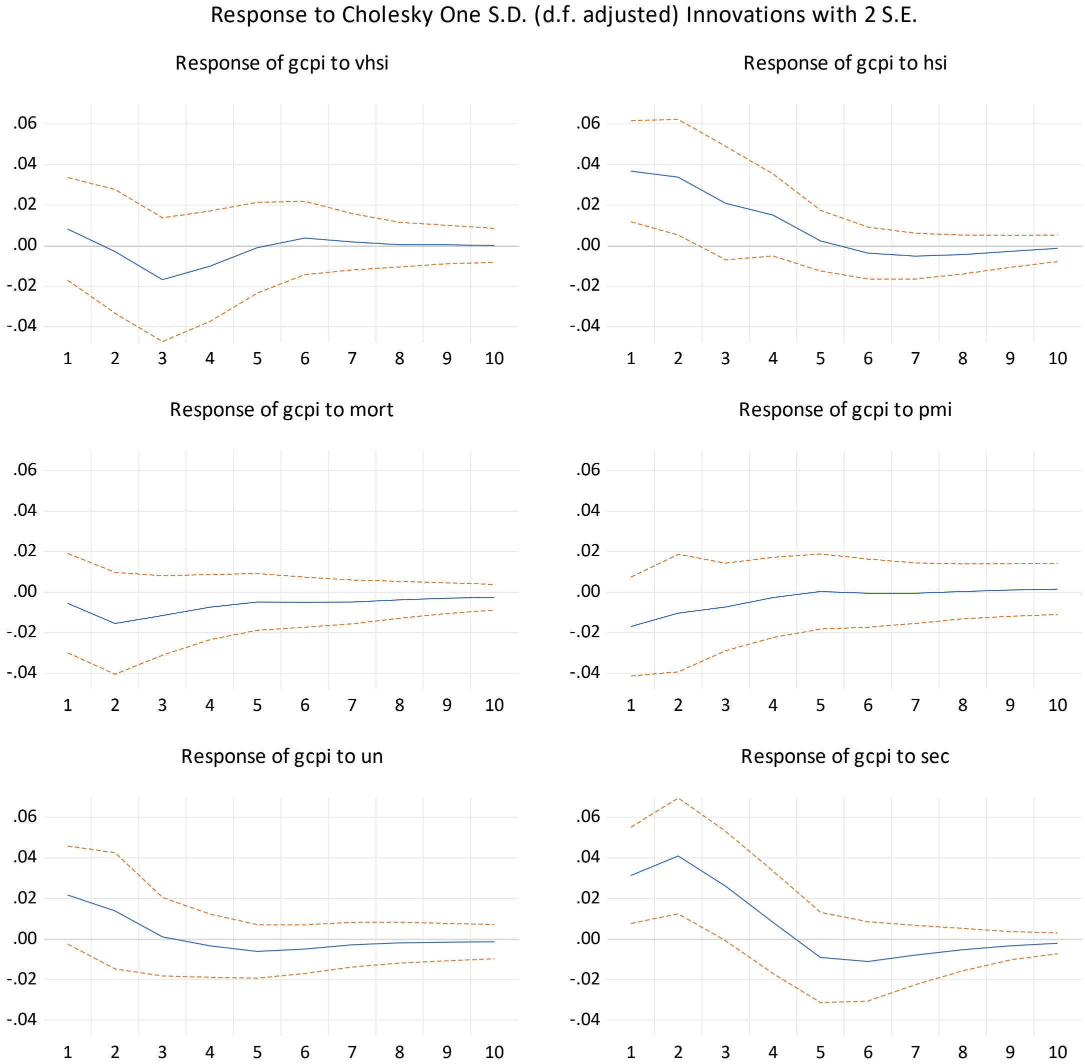
Chart 6: Cholesky impulse responses to one standard deviation innovation to the secondary property market sentiment index



Source: Staff estimates.

Chart 7 shows the impulse responses of buyers' incentives to innovations in macro-financial variables and market sentiments. In line with our expectation, buyers' incentives increased when market sentiments improved, and the impact would last for one quarter. Rises in equity prices would also stimulate buyers' incentives, whereas the other macro-financial variables do not have any significant impact. Similar to the case of market sentiments, the transmission of an equity price shock to buyers' incentives is quick but the duration is relatively short compared with the impact on market sentiments.

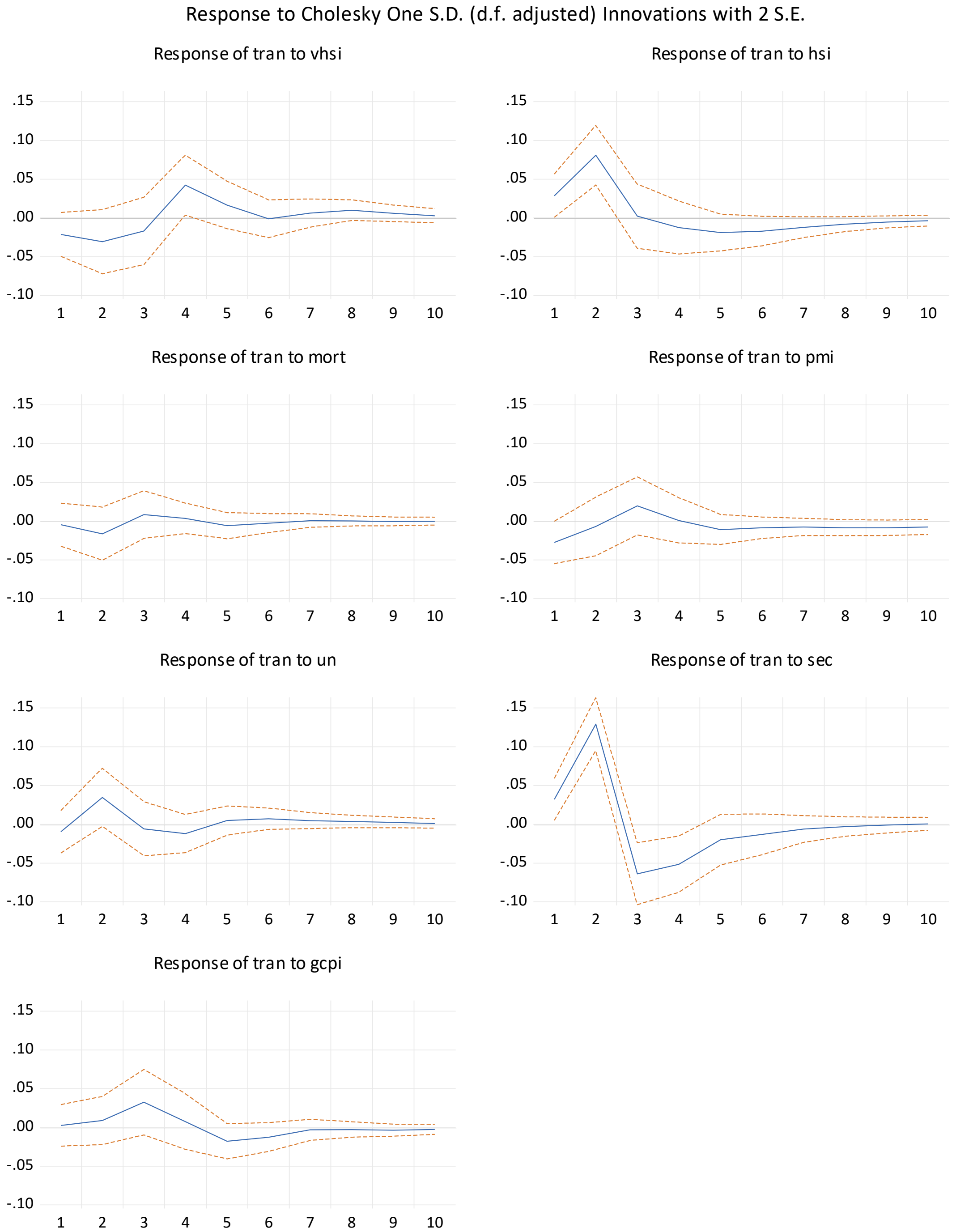
Chart 7: Cholesky impulse responses to one standard deviation innovation to the Google buyer incentive index



Source: Staff estimates.

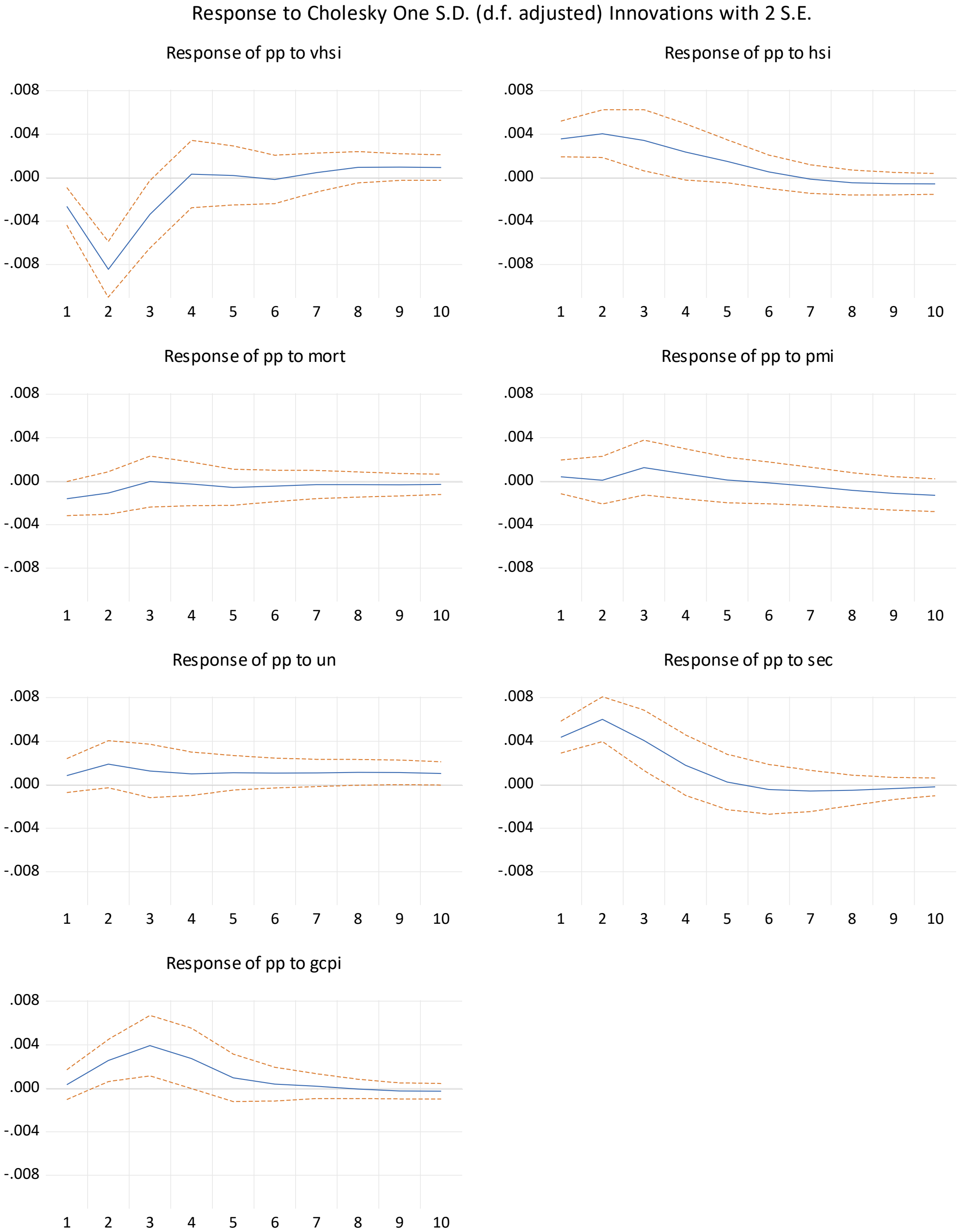
To see the overall impacts of the housing market, Charts 8A and 8B show the impulse responses of transaction volumes and price to innovations in different variables. Similar to the previous studies, an improvement in the equity market would stimulate both housing prices and transactions. The volatility of the equity market could also have a negative impact on housing prices, but the impact was not significant for the transactions. On the other hand, market sentiments have positive impacts on both housing prices and transactions, while rises in buyers' incentives would also stimulate housing prices according to the impulse response in Chart 8B. These suggest that there is a sentiments channel of transmission in the housing market dynamics in Hong Kong, and this channel is additional to the standard macro fundamental channel. The variance decomposition for both housing prices and transactions in Chart 9 indicated that the market sentiments contributed more than 30% of variation in transactions and around 20% of variation in prices.

Chart 8A: Cholesky impulse responses to one standard deviation innovation to the secondary housing transaction volumes



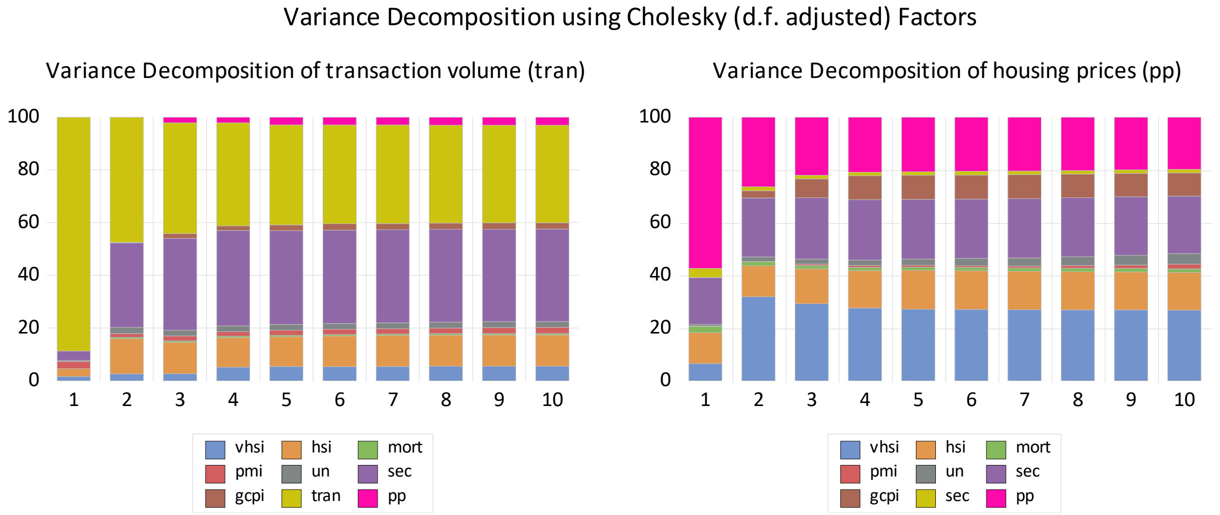
Source: Staff estimates.

Chart 8B: Cholesky impulse responses to one standard deviation innovation to the secondary housing prices



Source: Staff estimates.

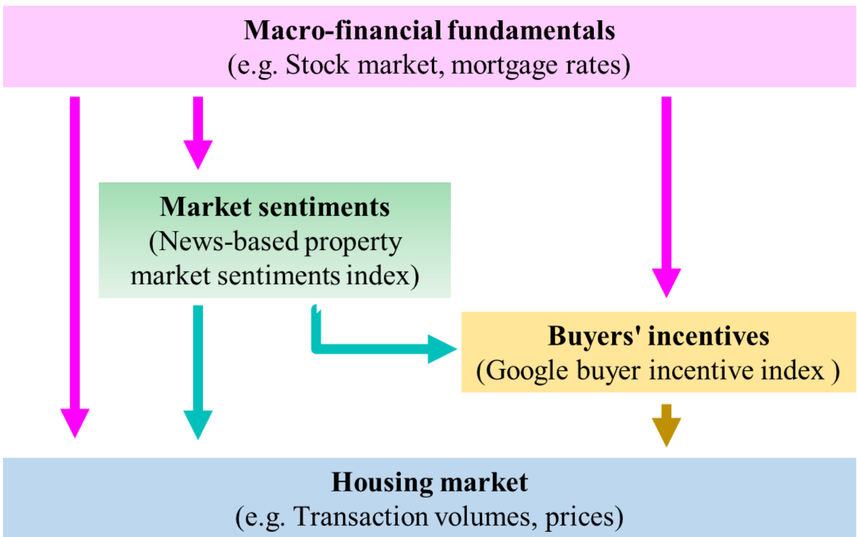
Chart 9: Contributions to the variations in secondary housing transactions and prices (percentage share)



Source: Staff estimates.

Based on our analysis, Chart 10 summarises the transmission mechanism in the Hong Kong housing market into a flow chart. Given the importance of the housing market to the Hong Kong economy, our findings suggest that market sentiments and buyers' incentives, in addition to macro-financial channels, can affect housing prices and transaction volumes through the sentiment channels. Therefore, for macro-financial surveillance purpose, it is important to track both of them closely.

Chart 10: Transmission mechanism with different channels in the housing market



V. CONCLUDING REMARK

Hong Kong's housing market outlook has become more uncertain in recent years amid the rapidly changing economic and social situations. To facilitate our macro-financial surveillance, we use textual analysis to compile the news-based property market sentiment index and the Google buyer incentive index. Our sentiment index is intuitive and is able to differentiate the sentiments in the primary and secondary markets, with primary market sentiments leading secondary market sentiments during the period of low housing supply. In line with theories, we also find that negative property market sentiments would dampen buyers' incentives, which would then affect property prices and transaction volumes. For our Google buyer incentive index, we find that it has value-added in forecasting (or nowcasting) the official housing price index, and the forecasting power is stronger than that of the existing property price indices. Altogether, our paper suggests that market sentiments, as well as buyers' incentives, are useful early warning indicators that can supplement existing property market indicators in identifying turning points in the housing market cycle.

Annex 1: Dictionaries of market segments and corresponding sentiments

Primary market [P]

一手	新盤	發展商	貨尾	餘貨	推盤	成交紀錄冊	認購	推售
價單								

Secondary market [S]

二手	放盤	屋苑	銀主	易手	放售	原業主	易主	承接
轉手								

Positive sentiment [#*pos* $_{p,s}$]

回暖	見底	好轉	轉強	改善	轉旺	復甦	回勇	轉活
理想	熾熱	熱賣	升溫	活躍	報捷	暢旺	造好	不俗
睇好	樂觀	亮麗	大旺	凌厲	看俏	看好	出色	小陽春
旺場	旺市	高漲	踴躍	大熱	佳績	強勁	放心	受歡迎
追捧	熱烈	熱鬧	具信心	正面	百花齊放	如火如荼	向好	發力
白熱	轉好	熱捧	熱搶	好景	良好			

Negative sentiment [#*neg* $_{p,s}$]

見頂	轉差	轉壞	轉弱	轉淡	軟化	回軟	受阻	減弱
平淡	撻定	撻訂	冷清	淡靜	淡風	降溫	睇淡	悲觀
低迷	疲態	萎縮	頹勢	淡市	遜色	受壓	看淡	看差
癱瘓	受挫	劣勢	疲弱	冷卻	慘淡	冰封	冷落	停頓
隱憂	淪陷	薄弱	勢危	爆煲	憂慮	疏落	欠佳	淡勢
黯淡	不景氣	冷淡	脆弱	陰影	倒退	驟減	尋底	擔憂
不利	寒冬	負面	嚴冬	零星	不振	乏力	唱淡	呆滯
陰霾	退卻	每況愈下	困難	乏人問津	急轉直下	停滯	惡化	低谷
白果								

Positive sentiment for primary market only [#*pos* $_p$]

削優惠	爭購	人龍	熱銷	勁銷	打蛇餅	大排長龍

Negative sentiment for primary market only [#*neg* $_p$]

增優惠	加優惠	滯銷	停售	停賣	未有進展	終止買賣合約	自救

Annex 2: Keywords of newspapers section

Real estate section (overall)

地產

Real estate section (non-domestic)

海外	環球	澳門地產	中國地產	中國房地產	內地樓市	內地房地產	珠三角地產

Annex 3: Keywords of Google search in Google Trend

Incentive of buying				
買樓	揾樓			

Affordability assessment			
估價	印花稅	壓力測試	按揭計算機

Property agencies				
中原	美聯	利嘉閣	世紀 21	28hse

Annex 4: Google buyer incentive index (GBII) as a leading indicator of housing price movements

Table A1: Pairwise Granger causality test

Null Hypothesis:	F-Statistic	Prob.
GBII does not Granger Cause CCLI	21.2***	0.00
CCLI does not Granger Cause GBII	0.8	0.44
Null Hypothesis:	F-Statistic	Prob.
GBII does not Granger Cause R&VD Index	6.7***	0.00
R&VD Index does not Granger Cause GBII	6.0***	0.00
Null Hypothesis:	F-Statistic	Prob.
CCLI does not Granger Cause R&VD Index	2.9	0.06
R&VD Index does not Granger Cause CCLI	64.4***	0.00

Note: Significance level: ** p<0.5, *** p<0.01.

Table A2: Comparing the forecasting performances of GBII & CCLI with Ordinary Least Square (OLS) approach

OLS model:

$$D(R\&VD\ \ Index_t) = \ \ c_{11} + c_{12}D(R\&VD\ \ Index_{t-1}) + \ \ c_{13}D(GBII_{t-1})$$
$$D(R\&VD\ \ Index_t) = \ \ c_{21} + c_{22}D(R\&VD\ \ Index_{t-1}) + \ \ c_{23}D(CCLI_{t-1})$$

Independent Variable	RMSE	Adjusted R^2	c_{13} / c_{23}	t-stat of c_{13} / c_{23}
$D(GBII_{t-1})$	0.037	0.55	0.13***	3.18
$D(CCLI_{t-1})$	0.041	0.52	0.01	0.17

Note: Significance level: *** p<0.01.

The smaller the RMSE the better; The higher the adjusted R square the better.

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