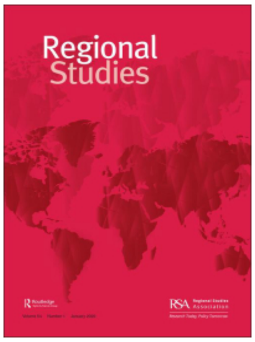

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Developer sentiment, developer's strategy and housing supply: evidence from Hong Kong

Ziyou Wang[a], Eddie Chi-man Hui[b,c] and Cong Liang[d,e]

ABSTRACT
The increasingly important role of sentiment in the housing market has complicated the challenges facing developers during boom-and-bust cycles. This study investigates how developer sentiment affects developers' decision-making and the housing supply at the project level. As the standard evaluation usually overlooks sentiment resulting in suboptimal inferences, we develop a new theoretical model that analyses both sentiment and developers' optimal strategies. Our findings suggest a 'U'-shape relationship between developer sentiment and the expected waiting time to develop. Second, the optimal development density declines when developer sentiment intensifies. The Hong Kong housing market is used as a case for empirical analysis.

KEYWORDS
developer sentiment; developer's strategy; housing supply; real-option analysis; Hong Kong

JEL D21, O18, R31
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1. INTRODUCTION

To mitigate the instability of the housing market, including price turbulence, mortgage default and substantial overbuilding, new housing supply is critical in urban planning and policymaking, while subject to residential developer's strategy, including timing and quantity (Adams et al., 2009; DeCoster & Strange, 2012; Glaeser et al., 2008; Murray, 2020). As development takes time, the strategy-making relies on a forward-looking estimation of future housing demand (Bar-ilan & Strange, 1996). Developers who are deemed to have better information and understanding sometimes deploy improper strategies that cause overbuilding or oversupply (DeCoster & Strange, 2012; Grenadier, 1996).

Market uncertainty alongside housing cycles affect housing demand significantly through channels including house prices, housing stocks and stockholding costs, as well as government and political risks (Cunningham, 2006; Rocha et al., 2007). Uncertainty could delay project development while benefitting developers by price appreciation (Cunningham, 2006). The features of housing development, such as a long time lag and investment irreversibility, complicate the estimation (Holland et al., 2000; Ott et al., 2012). A longer development magnifies the influence of uncertainty as time progresses, and investment irreversibility leads to an enormous capital gap or shrinkage of cash flow.

How to build a reliable model for development evaluation under market uncertainty often concerns authority, industry and academics. The classical theories only consider factors of fundamental risk in project valuation (Holland et al., 2000). Recent studies have highlighted the impacts of non-fundamental factors on housing market and demand (De Stefani, 2021; Wang & Hui, 2017), developers' decision-making (Hui et al., 2017), and their roles in project valuation and investment (e.g., Bulan et al., 2009; Ling et al., 2015). Nevertheless, the channels through which non-fundamental factors affect the total uncertainty are dispersive, which curbs a full understanding of the impact of non-fundamental factors in valuations.

Among the non-fundamental factors, sentiment is identified as a critical indicator for both the financial market (e.g., Baker & Wurgler, 2007) and housing market (e.g., Ling et al., 2015). Sentiment facilitates psychological

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assumptions such as cognitive limitation and imperfect or even lacking information (Baker & Wurgler, 2007; De Stefani, 2021) in the economic theories of decision-making (Barberis et al., 1998). Drawing on the widely accepted definition by Baker and Wurgler (2007), sentiment is defined as people's attitude towards market trend, which cannot be justified by market fundamentals.

Sentiment substantially affects housing markets. First, investors, facing high search costs and transaction expenses, often exhibit herding behaviour due to peer-to-peer social learning. This collective irrationality reflects how sentiment steers people's beliefs in the same direction (Wang & Hui, 2017). Second, behavioural biases (sentiment) intervene in the expectation of future priced formed from historical prices and cause price momentum (De Stefani, 2021). However, short-selling limits and liquidity shortages hinder rational traders from correcting mispricing in the housing market momentum (Piazzesi & Schneider, 2009). Price momentum, in turn, facilitates herding and reinforces the sentiment. Third, turnover rate, as a proxy for housing demand (Berkovec & Goodman, 1996), links sentiment with housing demand. Forward-looking sentiment influences trade timing (Wang & Hui, 2017), making it an informative indicator for housing transactions.

Yet much of the literature focuses only on investor sentiment on the demand side. There is a lack of theoretical or empirical studies of sentiment on the supply side in housing markets. Developers strategically plan their operations to optimise profits (Adams et al., 2009; DeCoster & Strange, 2012; Murray, 2020). In this context, it becomes essential to explore the role of developer sentiment in their project evaluation, and consequently in local housing supply. In this paper, we first develop a theoretical model that yields two key implications on how developer sentiment affects the developer's project strategy. The first implication is that developer sentiment shows a 'U'-shaped non-linear effect on the optimal development timing. Specifically, developer sentiment shortens the developer's waiting time at first and then prolongs it. In a practical sense, developers tend to commence the development when sentiment is low but showing an upward trend. Conversely, developers are less likely to commence the development when sentiment exhibits an upward trend at a high level. The second implication is that optimal density (and housing supply) declines with sentiment. In practical scenarios, this suggests that when developer sentiment is on the rise, developers are more likely to cater to a higher income segment of the housing market. In such cases, they often choose not to build to the maximum permissible density for their projects. This strategy reflects their anticipation of a higher return on investment from these premium segments.

As our theoretical model extended from the classical real-option in real estate development (e.g., Capozza & Li, 2002), the implications are more suitable for developed and free markets where waiting has its own value than developing markets where urban expansion is rapid, or political and institutional factors have significant impacts.

To examine the theoretical implications, an empirical study is conducted which focuses on private housing market in Hong Kong, China. As discussed above, a developed and free market, such as Hong Kong,[1] is an ideal setting for an empirical study to validate the theoretical implications of our model. Hong Kong's economy has experienced constant growth over several decades, leading to significant inflation in house prices and an apparent increase in the housing market volatility (Zheng, 2015) (Figure 1).[2] In the private housing market of Hong Kong, market volatility is influenced by expectations that exceed rational predictions (Zheng, 2015), and house prices and rents are sentiment-driven (Wang & Hui, 2017). Besides, Hong Kong as an important intermediary bridging between mainland China and global markets (Fang et al., 2023) provides a channel for mutual communications and trade between mainland China and oversea markets.

Developers of private property in Hong Kong consist of various developers, including local firms, firms from mainland China and overseas firms, and joint ventures. The Hong Kong government is the monopoly supplier in the primary land market, and land purchases normally follow the public tender route.[3] Developer's strategies differ significantly based on the type or scale of development and business operations.[4] Therefore, Hong Kong presents a typical example to study how developer sentiment affects the developer's strategy on project development.

This study contributes to the knowledge regarding non-fundamental factors in property markets (e.g., Hui et al., 2017; Ling et al., 2014, 2015; Marcato & Nanda, 2016), and housing development and supply (e.g., Cunningham, 2006; Glaeser et al., 2008; Leishman, 2015) mainly in two-fold. First, a theoretical model with a real-option framework is developed to investigate how sentiment influences developers' decision-making and the local housing supply. Our model incorporates two new features, that is, the sentiment shift in developer's house price expectations, and the adaptation of expected return to sentiment. As standard models overlooking the sentiment effect could result in suboptimal or even unreasonable decisions (Baker & Wurgler, 2007), our model implications make a unique contribution by exploring the sentiment effect on optimal timing and supply at the project level, and more broadly, it adds to the discussion on regional dynamics of the housing market through the lens of property development.[5] Second, by addressing the lack of empirical evidence on developer sentiment,[6] our empirical study provides a new framework and unique empirical evidence. Using six sentiment proxies, we construct a developer sentiment index, and an orthogonalised index to eliminate economic cyclical variations and correlations with market fundamentals. Using data from private housing projects in Hong Kong, we verify two main theoretical implications. First, the empirical models with non-linear sentiment variables and different specifications provide robust evidence of a 'U'-shape pattern of developer sentiment effect. Second, findings show developer sentiment decreases housing supply at the project level. In addition, these results offer implications on policy effectiveness regarding housing affordability and supply under different market conditions.

The paper proceeds as follows. The theoretical discussion on developer sentiment via a literature review is presented in section 2. The theoretical model is introduced in section 3 and solved in section 4. Section 5 discusses the developer sentiment effects on the optimal developing strategy. Section 6 presents the empirical analysis. Section 7 concludes and provides the policy implications.

2. THE DEVELOPER SENTIMENT

Are developers who are mainly large, professional entities subject to sentiment? La Porta (1996) found that professional analysts in the stock market are influenced by sentiment: professional analysts are excessively bullish (bearish) about the stocks to which they hold optimistic (pessimistic) attitudes. Berger et al. (2020) showed that managerial professionals incorporate their sentiment in corporate decisions-making. Given a strong link between stock and housing markets (e.g., Bissoondeeal, 2021), developers in property markets show a similar behaviour: they form their sentiment from conducting business over years and use it for reference. In practice, to maximise profits and to cope with the restrictions on land supply and/or project density, developers strategise their development activities including all the way from land hoarding to housing delivery (Adams et al., 2009; Murray, 2020). As discussed in the survey by Adams et al. (2009), developers devise their strategies on future sale prices, based on their own perception about the project, market, competition, product quality, etc. The literature shows that developers foster their own belief and habit in a persistent way from their long-run experience, and tend to form their future expectation by past belief and affected by habit (Antwi & Henneberry, 1995; Atherton et al., 2008).

Due to the informational inefficiency, segmentation and lack of short-sales in the property market (Ling et al., 2014), professionals, including developers are likely to learn from their peers' sentiment, since sentiment works as a source of information (Freybote & Seagraves, 2017). In addition, due to the strong link between public and private real estate markets, institutional sentiment is contagious between the two markets (Freybote & Seagraves, 2017). In that case, sentiment in public real estate markets could serve as a reference for developers in private markets.

Meanwhile, developers take the feedback from the demand side. In practice, there is no doubt that developers always refer to the information in the second-hand market for their development appraisal (Adams et al., 2009). Further, developers have been found to take investor sentiment into consideration (Hui et al., 2017; Ling et al., 2014) in their decision-making. Hence, developers' information processing inevitably incorporates the information of investor sentiment into developer sentiment. Nowadays, as sentiment is found to be able to predict the dynamics of the property market, surveys on developer sentiment emerge (Marcato & Nanda, 2016), because unlike investor sentiment, developer sentiment is difficult to observe.

Furthermore, the supply and demand sides of the housing market may hold different sentiment (Hui et al., 2017; Ling et al., 2015). Unlike the buyers on the demand side where majority of buyers do not trade frequently, the developer forms their own belief from a long-run and rich business experience (Antwi & Henneberry, 1995; Tse et al., 2011). There exist significant difference in information quality and information processing methods between the investor on the demand side and the developer on the supply side (Ling et al., 2014). Besides, developers are involved in both housing and land markets, and thus are likely to collect information from various sources and have more information on which to form their sentiment than do buyers in the housing market (Hui et al., 2017). In addition, evidence shows that developer sentiment is found to lead to changes in investor sentiment in the commercial property market (Freybote & Seagraves, 2017). However, the roles of sentiment in developers' behaviour have not been theoretically analysed in the extant real estate literature. This study explores how developer sentiment affects optimal decision-making in housing projects and eventually the housing supply.

3. THE MODEL

To model developers' decision-making with sentiment in a residential project, our model is extended from the classical real-option framework and its application in real estate development, as the real-option framework has prevailed in project valuation with market uncertainty and decisional flexibility (Rocha et al., 2007). Like a financial option, as the developer has discretion to develop the land at any time, the agreement to develop is deemed as the exercise of the option (Dixit & Pindyck, 1994). This model starts with the basic settings and two channels of developer sentiment effect.

3.1. The basic model

The unique characteristics of property markets, such as illiquidity, highly segmentation and information inefficiency (Clayton et al., 2009), with the inherent heterogeneity of housing due to immobility and location uniqueness, contribute to imperfect competition in local markets. The developer is therefore likely to become a monopoly supplier in local housing markets. In that case, the local house price is a function of housing demand (Ott et al., 2012) as:

$$P = P(Q, X) = XQ^{-\varepsilon}$$

where ε denotes the inverse of elasticity of housing demand.[7] Q denotes the quantity of housing demand in the short-run with $P'_Q < 0$, and also the expected project density. In practice, the maximum density (e.g., plot ratio or height limit) is pre-established by zoning regulations. These prevent developers from exceeding the maximum, but are less constrained when it comes to reducing density. Therefore, Q is assumed to vary under the maximum density $\bar{Q}$, otherwise $Q = \bar{Q}$ when optimal density exceeds the maximum. X denotes the state variable capturing the long-run trend[8] associated with stochastic fluctuations (Bar-ilan & Strange, 1996), and follows a geometric Brownian motion (GBM):

$$dX = \alpha_X X dt + \sigma_X X dw \tag{1}$$

where α_X is the expected growth rate of X, σ_X is the standard deviation of growth rate, and w denotes the increment of a standard Wiener process. The parameters of the process can be observed by developers such that there are two theoretical cases: either developers with perfect foresight if $\sigma = 0$, or with expectations if $\sigma > 0$ (Capozza & Li, 2002).

Typically, the project density Q is required to be determined prior to the project's commencement. Despite fluctuations in market conditions, developers could hardly adjust the supply arbitrarily once the project has started.

The intrinsic value of project at time t is calculated if the developer decides to develop with density Q and development period δ. The houses are delivered at time $t + \delta$. The total development cost $C(Q) = F + cQ$ is determined by the fixed costs ($F > 0$) and variable costs ($c > 0$) with Q. The intrinsic value v_t:

$$\begin{aligned} \mathrm{v}(X_t) &= E_t[e^{-\rho\delta} P_{t+\delta} Q - C_t(Q)] \\ &= e^{-\rho\delta} E_t[X_{t+\delta}] Q^{1-\varepsilon} - C_t(Q) \end{aligned} \tag{2}$$

where ρ denotes the developer's expected return as the discount rate. Equation (2) portrays a classic project valuation under a real-option framework. The developer waits until the optimal time T to develop to maximise the expected project value. At time t, the developer has options in the decision-making process: 'to cease' means to stop waiting and invest instantly, while 'to continue' implies deferring investment decision. Thus, the expected project value (V_t) at any $t < T$ is determined by the expected present value with the optimal timing (T):

$$\mathrm{V}(X_t) = \max_T \{E_t[\mathrm{v}(X_T)] e^{-\rho(T-t)}\} \tag{3}$$

3.2. The channels of sentiment effects

The forward-looking project valuation and development decision are always subject to decision-makers' expectations (Atherton et al., 2008). These expectations being influenced by sentiment are attributed to behaviour biases (Baker & Wurgler, 2007; Barberis et al., 1998). Sentiment evolves unpredictably (DeLong et al., 1990), and should not be confused with rational expectation. Therefore, expectation can be decomposed into two parts, that is, rational expectation, which can be justified by market fundamentals, and irrational expectation, which is formed through self-belief driven by sentiment (Jin et al., 2014). Specifically, irrational expectation adopts non-fundamental information (e.g., sentiment) which introduces systematic behavioural biases into an agent's beliefs (Ling et al., 2015). Sentiment consistently deviates asset prices from their fundamental value in the short run, and such deviation cannot be justified by market fundamentals (Barberis et al., 1998; Ling et al., 2014, 2015). Consequently, sentiment cannot be fully predicted by market fundamentals (Baker & Wurgler, 2007), and is consistently considered as an independent factor from market fundamentals in the literature (Hui et al., 2017; Jin et al., 2014; Ling et al., 2015) and so is in our model.

Different types of investors have varying expectations and sentiment (Barberis et al., 1998), particularly in property markets (Ling et al., 2015). In housing markets, the attitudes of investors and developers are reflected in their sentiments, representing the demand and supply sides, respectively. Although developers' (or real estate professionals') forecasts are highly correlate to subsequent returns, there is a notable discrepancy between developers' forecasts and actual values (McAllister et al., 2008), underscoring the significant role of sentiment in these markets. Evidence suggests that professionals (developers) exhibit habit persistence (Antwi & Henneberry, 1995). Developer sentiment tends to be more consistent than investor sentiment (Tse et al., 2011). In information asymmetry theory, developers form sentiment by monitoring demand feedback, which provides them with more information than individual investors (Marcato & Nanda, 2016). In addition, sentiment plays a crucial role in developers' expectation on future returns of a housing project (Hui et al., 2017). Hence, it is essential to examine how developer sentiment affects their decision-making process.

Assume that developer sentiment can be measured by an index SI,[9] as sentiment usually moves in a 'consensus' direction even when people hold different levels of sentiment (Barberis et al., 1998), and especially developers herd by imitating each other as they assume their peers' decision-making depends on valuable information (DeCoster & Strange, 2012; McAllister et al., 2008). SI is a normally distributed random variable: $SI = 0$ if the developer is neutral, $SI > 0$ if there is positive (bullish) sentiment, and $SI < 0$ if there is negative (bearish) sentiment.

From the sentiment literature, there are two channels by which sentiment affects developers' decision-making in project valuation. First, sentiment intervenes in the investor's expectation of house prices (De Stefani, 2021; Ling et al., 2015; Wang & Hui, 2017). Similarly, developer sentiment influences the developer's estimation of future prices. To demonstrate this, we take an instance of bullish sentiment. With bullish sentiment, the developer believes in a better future where people become more willing to own properties. That is, the demand curve shifts outwards (Figure 1), given that the supplier cannot increase supply in the short run (Leishman, 2015). The future price will then rise from $E1$ to $E2$ in Figure 2.

In that case, the developer incorporates a short-run adjustment of developer sentiment into their estimation at t of the expected house price at $t + \delta$. We follow the theoretical sentiment models of asset pricing (e.g., Yang & Zhang, 2013) to model this short-run adjustment. A typical asset following GBM has the sentiment-expected

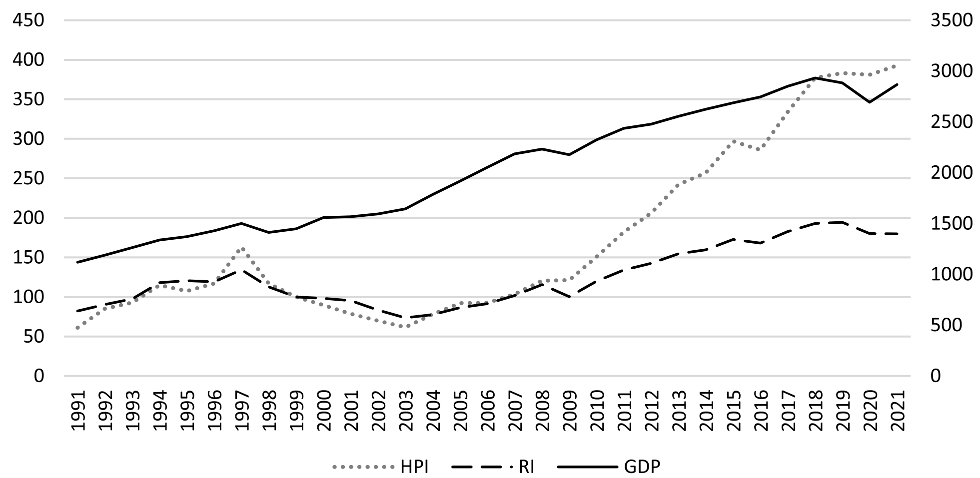

Figure 1. Performance of Hong Kong's economy and private housing market, 1991–2021.
Note: The left *y*-axis measures the two housing indices (HPI, housing price index; RI, rent index); the right *y*-axis measures gross domestic product (GDP) (GDP in chained 2021 price, with a unit of billions of HK$).

asset return $r^s = \alpha + s$, where α is the rational expected return and s is the additive return of sentiment effect. Therefore, the sentiment equilibrium asset price $P^s = P^r + P^r(e^s - 1)$ indicating the sentiment price can be decomposed to rational price P^r driven by α and sentiment term $P^r(e^s - 1)$ driven by s.

In our model, it is assumed that the expected growth of sentiment-driven housing prices becomes $\alpha_X + s$. Then, given project density Q, take sentiment expectation (E_t^s) at t on the future housing price at $t + \delta$:

$$E_t^s[P_{t+\delta}] = X_t \exp(\alpha_X \delta) Q^{-\varepsilon} f(SI_t)$$

where $f(SI_t)$ represents the adjustment of sentiment return, $f(SI) = \exp(kSI_t)$ is a sentiment function and $k > 0$ denotes the developer's sensitivity to sentiment. The sentiment function[10] should be a function with several properties suggested by Yang and Zhang (2013): (a) monotonous increasing, that is, $f'(SI) > 0$; (b) $f(SI) = 1$ when sentiment is neutral ($SI = 0$) and the model reduces to a baseline model without sentiment effect; and (c) $f(SI) > 1$ if a positive sentiment and $0 < f(SI) < 1$ if a negative sentiment, which implies that investors would accept a higher price when sentiment is positive, and vice versa.

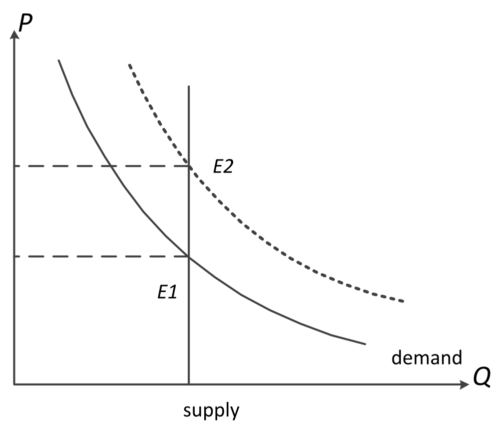

Figure 2. Effect of change in sentiment on the relationship between price and demand in the short run.

The second channel is that sentiment positively affects the developer's expected return. The literature (e.g., Ling et al., 2014; Marcato & Nanda, 2016; Wang & Hui, 2017) shows that sentiment influences the required return and subsequent actual return in property markets. Particularly, a developer sentiment index constructed by Hui et al. (2017) shows the predicting power on the subsequent returns for Chinese housing markets.

Unlike the stock market, the property market would not react immediately to sentiment due to the features of illiquidity and information inefficiency. The sentiment impact on asset values may take place with significant lags due to the lack of continuous price revelation in property markets (Ling et al., 2014). Hence, house prices would not change immediately with sentiment.

Not only does the short-sales constraint impede the opportunity for price adjustments, but also it brings more risk for informed arbitrageurs to counteract mispricing. Thus, the mispricing driven by sentiment usually persists and shows a momentum pattern. This has been clearly observed in property markets (Ling et al., 2014). In addition, information efficiency fades due to the lack of short-sales in a booming market (when positive sentiment is high), and thus over-pricing maintains over long horizons (Ling et al., 2014). Similarly in a downturn market, the short of capital unable rational agents counteracts mispricing. Consequently, under-pricing persists (Shleifer & Vishny, 1997; Ling et al., 2015).

In this model, the developer's required return ρ at t is adjusted by sentiment function $g(SI)$, and sentimental required return ρ^s:

$$\rho^s = \rho g(SI)$$

where g can be different from, but has the same properties as, f, and is not specified so that the variation of function form can capture the developer heterogeneity.

Taking developer sentiment into account, the intrinsic project value at the optimal time $v(X_T)$ is:

$$\begin{aligned} v(X_T) &= E_T^s[e^{-\rho\delta}(P_{T+\delta}Q_T^{-\varepsilon})] - C(Q_T) \\ &= e^{-\rho^s\delta}E_T^s[(X_{T+\delta})]Q_T^{1-\varepsilon} - (F + cQ_T) \\ &= e^{-(g(SI)\rho - \alpha_X)\delta}X_T Q_T^{1-\varepsilon} f(SI_T) - (F + cQ_T) \end{aligned} \quad (4)$$

4. OPTIMAL DECISIONS

The model is solved to obtain the optimal decisions including optimal timing to develop and optimal density in a housing project. For the detailed model solution and relevant discussion, see Appendix A in the supplemental data online.

The analytical solution of optimal timing depends on the state variable. Specifically, the developer will decide to develop when the state variable exceeds the threshold X^*:

$$X^* = \Lambda\left[\frac{(1-\varepsilon)F\Omega}{\varepsilon\left(\Omega - \frac{1}{\varepsilon}\right)}\right]^{\varepsilon} \quad (5)$$

where:

$$\Lambda = \frac{c^{(1-\varepsilon)}\exp((\rho^s - \alpha_X)\delta)}{(1-\varepsilon)f(SI)}$$

$$\Omega = \frac{1}{2} - \frac{\alpha_X}{\sigma_X^2} + \sqrt{\left(\frac{1}{2} - \frac{\alpha_X}{\sigma_X^2}\right)^2 + \frac{2\rho^s}{\sigma_X^2}} > 0.$$

The developer would develop with the optimal density:

$$Q^* = \frac{(1-\varepsilon)F\Omega}{c\varepsilon\left(\Omega - \frac{1}{\varepsilon}\right)} = \frac{(1-\varepsilon)F}{c\varepsilon}\frac{\Omega}{\left(\Omega - \frac{1}{\varepsilon}\right)} \quad (6)$$

and the optimal project value:

$$V^* = F\left[\frac{\Omega}{\left(\Omega - \frac{1}{\varepsilon}\right)} - 1\right] = \frac{F}{\varepsilon}\frac{1}{\left(\Omega - \frac{1}{\varepsilon}\right)} \quad (7)$$

Meanwhile, the expected house price in the valuation as:

$$P^* = X^* Q^{*-\varepsilon} = \frac{c}{(1-\varepsilon)}\frac{\exp((\rho^s - \alpha_X)\delta)}{f(SI)}$$

In real-option valuation, it is of practical significance to discuss the expected waiting time for the state variable to reach a certain threshold, especially within a specified range. In practice, the developer may be subjected to penalties, taxes or even risk losing the land if the land remains idle for a stipulated period by the government after acquisition.[11] Consequently, the optimal waiting time is capped by the land leasing contract. For a detailed discussion, see Appendix D in the supplemental data online. The expected waiting time (WT) to reach the threshold as:

$$WT = E[t; X_0, X^*] = \frac{\ln(X^*/X_0)}{\alpha_X - 0.5\sigma_X^2} \quad (8)$$

where WT positively correlates with X^*, taking all other parameters (X_0, α_X, σ_X) as constants. A lower threshold of the state variable will shorten the waiting time to develop.

5. THE EFFECTS OF DEVELOPER SENTIMENT

To investigate the effects of sentiment on a developer's decision-making and housing supply, we perform a comparative static analysis regarding the expected waiting time, density and project value with respect to developer sentiment, respectively, taking other parameters (X_0, c, F, δ, ρ, α_X, σ_X) as constant. As both timing and density are critical to the housing supply, this analysis offers a theoretical footstone on which to build further studies.

The two sentiment functions f and g offer quantitative sentiment adjustments to the expected house prices and the expected return, respectively. As both functions share the same properties, we assume they are equal ($f = g$) for simplicity and use f only in the sequel.

5.1. The sentiment effect on timing

First, we investigate the impact of developer sentiment (SI) on the expected waiting time (WT) and the threshold of state variable X^*. As WT positively correlates with X^*, developer sentiment influences both in the same direction. Differentiate WT with respect to SI:

$$\frac{\partial WT}{\partial SI} = \frac{\partial E[t; X_0, X^*]}{\partial X^*}\frac{\partial X^*}{\partial SI} = \frac{1}{X^*(\alpha_X - 0.5\sigma_X^2)}\frac{\partial X^*}{\partial SI}$$

$$\frac{\partial X^*}{\partial SI} = \frac{\partial X^*(f, \rho, \Omega)}{\partial SI} = \frac{c^{(1-\varepsilon)}}{(1-\varepsilon)}\left[\frac{F(1-\varepsilon)}{\varepsilon}\right]^{\varepsilon}\frac{\partial M}{\partial SI}$$

where:

$$M = \frac{e^{(\rho^s - \alpha_X)\delta}}{f(SI)}\left[\frac{\Omega}{\left(\Omega - \frac{1}{\varepsilon}\right)}\right]^{\varepsilon}.$$

As:

$$\frac{c^{(1-\varepsilon)}}{(1-\varepsilon)}\left[\frac{F(1-\varepsilon)}{\varepsilon}\right]^{\varepsilon} > 0, \frac{\partial WT}{\partial SI} \text{ and } \frac{\partial X^*}{\partial SI}$$

depend on the sign of $\frac{\partial M}{\partial SI}$. As X^* (or M) involves the elasticity of the project value (Ω), it is of interest to investigate the sentiment effect on Ω first. Differentiate Ω with respect to SI:

$$\frac{\partial\Omega}{\partial SI} = \frac{\rho}{\sigma_X^2}\left(\left(\frac{1}{2} - \frac{\alpha_X}{\sigma_X^2}\right)^2 + \frac{2\rho f}{\sigma_X^2}\right)^{-1/2} f' > 0$$

A positive relationship implies that Ω increases with developer sentiment, which makes the project value more sensitive to the state variable. Thus, sentiment increases a developer's sensitivity to fundamental risks, which determine the state variable X. Besides, a larger Ω as a stochastic discount factor indicates a lower present value of the project and a higher time value of delay.

The following proposition suggests that developer sentiment holds a non-linear impact on the threshold and the expected waiting time, showing a 'U'-shape pattern.

Proposition 1: *There exists a turning point of sentiment (denoted by SI_b), which is defined by $\omega(f(SI_b)) = \delta$, where:*

$$\omega = \frac{1}{\sigma^2\Omega\left(\Omega - \frac{1}{\varepsilon}\right)\left(\Omega - \frac{1}{2} + \frac{\alpha}{\sigma^2}\right)},$$

such that $\frac{\partial X^*}{\partial SI} > 0$ *and* $\frac{\partial WT}{\partial SI} > 0$ *for every* $SI > SI_b$ *and converse.*

For the proof, see Appendix B in the supplemental data online.

Specifically, sentiment negatively affects the threshold and reduces the expected waiting time when $SI < SI_b$. Sentiment positively affects the threshold and delay the investment when $SI > SI_b$. Like $\partial X^*/\partial SI$, the sentiment effect on the expected house price $\partial P^*/\partial SI$ shows a 'U'-shape relationship (see Appendix B online).

To see the intuition, this effect can be decomposed into three parts based on equation (B1) in Appendix B in the supplemental data online. Note that we initially set $f = g$ for simplicity. To offer a clear sight, we redo equation (B1) without this simplification:

$$\frac{\partial M}{\partial SI} = -\frac{e^{(\rho^s - \alpha_X)\delta}}{f^2} f' \left[\frac{\Omega}{\left(\Omega - \frac{1}{\varepsilon}\right)}\right]^{\varepsilon} + \frac{e^{(\rho^s - \alpha_X)\delta}\rho\delta}{f} g' \left[\frac{\Omega}{\left(\Omega - \frac{1}{\varepsilon}\right)}\right]^{\varepsilon} - \frac{e^{(\rho^s - \alpha_X)\delta}}{f} \frac{1}{\Omega\left(\Omega - \frac{1}{\varepsilon}\right)} \left[\frac{\Omega}{\left(\Omega - \frac{1}{\varepsilon}\right)}\right]^{\varepsilon} \frac{\partial \Omega}{\partial g} g'$$

where the right-hand side shows three means by which sentiment affects the threshold. The first term is the sentiment effect through the price channel; the second shows the sentiment effect through the expected return channel; and the third is the sentiment effect indirectly through the expected return channel as it first affects the stochastic discount factor Ω.

The first term is negative, indicating that sentiment lowers the threshold and reduces the waiting time. The second term suggests that a developer with a higher sentiment expects a higher return, which indicates a higher risk. Hence, the developer would wait for a higher threshold to mitigate the potential for adverse outcomes due to future systematic uncertainties (Capozza & Li, 2002). The last term exposes the sentiment effect through the stochastic discount factor Ω. The negative sign indicates that a higher sentiment leading to a larger Ω decreases the threshold. It implies the developer will reduce the waiting time as the benefits from delay decrease with a higher discount factor.

Overall, when sentiment is low, the negative terms dominate and accelerate the development. This finding offers a new explanation for construction booms in the face of decreasing housing demand in Grenadier (1996). When sentiment increases, the second and third terms become decisive determinants of the overall sentiment effect on the threshold. Particularly when sentiment reaches a high level, the second term (the direct sentiment effect through expected return) dominates. The overall effect becomes positive, raising the threshold and delaying development. This theoretical implication contributes to the knowledge of housing development and supply.

Furthermore, investment lag (i.e., the development period) is another critical factor in the decision-making process (Bar-ilan & Strange, 1996). Proposition 2 states how the development period affects the turning point of the 'U'-shape relationship between sentiment and waiting time.

Proposition 2: *The investment lag (development period)* δ *negatively affects the turning point* SI_b*, that is,* $\frac{df_b}{d\delta} < 0$.

For the proof, see Appendix C in the supplemental data online.

A negative relationship implies that SI_b shifts to the left (reduces its value) with δ. A longer δ is more likely to trigger a delay because it widens the 'upward' interval in the 'U'-shape. The reason for this is mainly two-fold.

First, the developer intends to manage the development period within a reasonable range. The longer is the development period, the lower is the net present value of the project, and the developer with a positive sentiment is likely to suspend the project and turn to another project with a shorter development period. Second, a longer development period indicates a larger uncertainty embedded in the project as a longer period enlarges the expected variation in the state variable. This echoes that opportunity cost of waiting rises when construction lag adds into development decision (Bar-ilan & Strange, 1996). Thus, the developer is likely to wait for a higher threshold to hedge against future risk.

5.2. The sentiment effect on density

The second concern in housing supply is the sentiment effect on optimal density. Differentiate Q^* with respect to sentiment, with $\partial\Omega/\partial SI > 0$:

$$\frac{\partial Q^*}{\partial SI} = \frac{\partial Q^*}{\partial \Omega}\frac{\partial \Omega}{\partial SI} = \frac{F}{c\varepsilon\left(\frac{1}{1-\varepsilon} - 1\right)} \frac{-1}{(\Omega - 1/\varepsilon)^2}\frac{\partial \Omega}{\partial SI} < 0$$

The rationale for this negative relationship is as follows. With a positive sentiment, developers anticipate a rise in housing demand. Given the heterogeneous nature of houses, it is challenging to increase supply. Consequently, rising demand compels buyers to pay more. and the developer rationally reacts to this by providing high-end housing products featured by low density and high price. This aligns with the findings of Zhou (2018) that larger houses become popular than smaller ones when sentiment is high. Contrarily, if sentiment declines, bullish enthusiasm and investment needs diminish, and the occupation needs or first-time buyers dominate the market. This shift in demand necessitates more economical houses typically delivered by the high-density projects targeting a lower income segment of the housing market.

To examine the sentiment effect on project value, differentiate V^* with respect to sentiment, with $\partial\Omega/\partial SI > 0$:

$$\frac{\partial V^*}{\partial SI} = \frac{\partial V^*}{\partial \Omega}\frac{\partial \Omega}{\partial SI} = \frac{F}{\varepsilon}\frac{-1}{(\Omega - 1/\varepsilon)^2}\frac{\partial \Omega}{\partial SI} < 0$$

In fact, this negative effect can be decomposed into three parts. To see the intuition, differentiate equation (A3) with respect to sentiment:

$$\frac{\partial V^*}{\partial SI} = \frac{\partial V^*}{\partial \rho^s}\frac{\partial \rho^s}{\partial f}f' + \frac{\partial V^*}{\partial X^*}\frac{\partial X^*}{\partial f}f' + \frac{\partial V^*}{\partial f}f'$$

where on the right-hand side, the first term describes a negative effect as $\partial V^*/\partial \rho^s < 0$. It is because a higher sentimental expected return makes investment lag more costly and suppresses the project's present value. The second term capturing the sentiment effect on project value through the threshold is complicated as $\partial X^*/\partial f$ could be negative or positive. The last term portrays the sentiment effect through the price channel and shows a positive impact of sentiment on the project value.

The overall negative effect indicates that the sentiment effect through the expected return (the first term) dominates. The project value V_t consists of two parts, that is, the value of waiting and the intrinsic project value v_t (Dixit & Pindyck, 1994). The sentiment effect through the expected return significantly influences both parts. First, positive sentiment indicates that the developer expects a high future return, which reduces the value of waiting. Second, sentiment lowers the present value of intrinsic project value by adjusting the expected return. Additionally, as the developer encounters a larger uncertainty due to the investment lag (Bar-ilan & Strange, 1996), the longer is the lag (development period), the lower the project value becomes. Thus, the developer may opt to wait and pursue an investment with a shorter lag.

A numerical analysis is adopted to offer a straightforward illustration of the implications of our theoretical model. For the implementation and graphical demonstration, see Appendix E in the supplemental data online.

6. EMPIRICAL STUDY

To verify the theoretical implications, an empirical analysis is carried out using the data from the private housing sector of Hong Kong. The empirical analysis consists of two parts. First, two sentiment indices are constructed to capture developer sentiment. Second, the regression analysis is employed to verify the 'U'-shape relationship between developer sentiment and waiting time, and the negative sentiment effect on project supply.

6.1. The index of developer sentiment

Constructing a sentiment index involves two main approaches: direct measures from primary surveys with economic agents, and indirect measures using composite indexing (Baker & Wurgler, 2007; Ling et al., 2014; Marcato & Nanda, 2016). Direct surveys capture agents' attitudes toward market trends, and the survey-based index provides indications on agents' future market participation (Marcato & Nanda, 2016). Most surveys focus on demand-side sentiment, but a few explores suppliers' (e.g., home builder) perspectives. Additionally, Da et al. (2015) propose measuring sentiment through internet search behaviour.

For an indirect measure, Baker and Wurgler (2007) propose a composite approach by eliciting the first principal component of sentiment proxies, followed by real estate studies (e.g., Hui et al., 2017; Ling et al., 2014; Zhou, 2018). Empirically, indirect measures tend to correlate highly with direct measures (Zhou, 2018). Due to the data limitation on the supply side,[12] indirect sentiment measurement is adopted in this paper.

As sentiment causes systematic market mispricing, a composite sentiment index can be constructed from common variation among market indicators (Baker & Wurgler, 2007). We follow the established construction of sentiment index such as that in Baker and Wurgler (2007) for financial markets, Ling et al. (2015) for commercial real estate and Zhou (2018) for housing markets. Using principal component analysis (PCA), the index is defined as the first principal component of the correlation matrix of selected sentiment proxies, with zero mean and unit variance. As sentiment is forward-looking we take one lag forward in the index construction, that is, the index SI_t at time t is derived from market information at $t + 1$.

To construct the index, six proxies closely related to housing market are selected from the sentiment literature. The first is housing starts (*start*) representing the number of new residential units under construction. This metric reflects developers' overall perception of market trend (Hui et al., 2017; Zhou, 2018), influenced by sentiment driven by investment incentives. Zhou (2018) suggests that housing start resembles initial public offerings, which serves as a sentiment proxy in the stock market (Baker & Wurgler, 2007). The proxy is expected to have a positive factor loading in PCA as optimistic developers initiate projects once committed to development.

The second proxy housing complete (*comp*) represents the number of residential units with construction completed. This metric reflects developers' response to the housing stock, and reveals the developer's strategy regarding development timing and project progression (Hui et al., 2017). The proxy is expected to have a positive factor loading in PCA as an optimistic developer aim to deliver as many houses as possible for sale.

The third and fourth proxies are transaction volumes in the primary (*vol1*) and second-hand markets (*vol2*), respectively. Transaction volume serves as a direct measure of liquidity, indicating how participants respond in asset markets. It is widely used as a sentiment indicator in both the financial market (Baker & Wurgler, 2007) and the real estate market (e.g., Clayton et al., 2009; Zhou, 2018). Each of the two proxies is expected to have a positive factor loading in PCA as optimism encourages transaction.

The last two proxies relate to market performance, namely, the return rates of the house price index (*rhp*) and the rent index (*rrt*), respectively. Housing price and mispricing directly respond to sentiment (Ling et al., 2015). Rent price is highly correlated with housing price, illustrating the sentiment effect spreading to the rental market. Wang and Hui (2017) emphasise that these two indicators significantly reflect how sentiment influences the dynamics of the housing market. Each of the two proxies is expected to have a positive factor loading in PCA as optimism would encourage over-pricing.

Several other proxies have potential for sentiment proxies. For instance, the median holding period of house sellers suggested by Zhou (2018) is expected to correlate negatively with investor sentiment in the housing market. However, such a proxy primarily reflects sentiment formation on the demand side rather than the supply side. Another emerging method involves leveraging social media and news content for sentiment analysis (e.g., Soo, 2018). However, the accuracy of such textual data and analysis heavily relies on the choice of dictionaries and analytical approaches used to identify the underlying tone of words (Loughran & McDonald, 2011).

The quarterly data of six sentiment proxies are collected and standardised for the period 1994–2018; the data are obtained from the Census and Statistics Department and Land Registry in Hong Kong. For a description of the variable, see Table F1 in Appendix F in the supplemental data online. Table 1 presents the results of PCA. The factor loading of each of the six proxies on *SI* shows the expected sign. The index *SI* explains 62.89% of total variation in the six proxies.

As the above sentiment proxies correlate with fundamentals of economic cycle, it is necessary to eliminate cyclical factors from sentiment proxies, according to the

Table 1. Principal component analysis (PCA) and two sentiment indices.

Variables	*SI* Loadings	SI^O Loadings
Housing start (unit)	0.1153	0.0953
Housing complete (unit)	0.0234	−0.0432
Transaction volume (first hand, unit)	0.2066	0.1830
Transaction volume (second hand, unit)	0.2280	0.1899
Return rate of house prices	0.2417	0.2484
Return rate of rental prices	0.2064	0.2050
Correlation between *SI* and SI^O	0.784	
Total variation explained	62.89%	57.98%
Minimum	−3.9515	−3.8638
Maximum	3.7349	3.9003

Note: Orthogonalised proxies are used to construct SI^O.

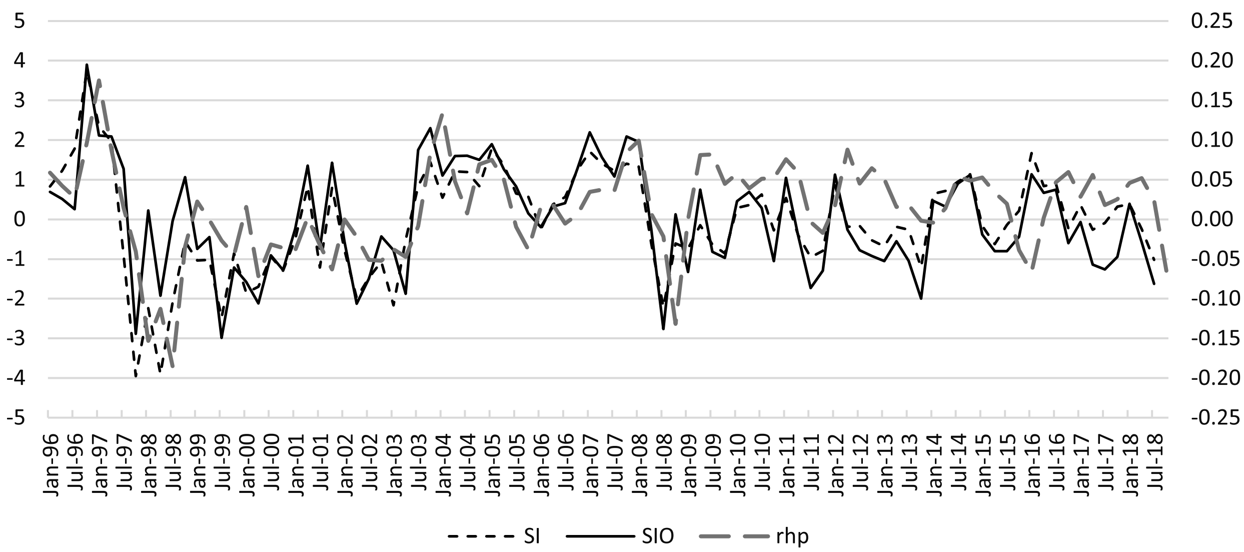

Figure 3. Two proxies of developer sentiment and the return rate of housing price.
Note: The left *y*-axis measures the two sentiment indices *SI* and SI^O; the right *y*-axis measures the return rate of housing price.

Table 2. Estimation results of the regression of waiting time with sentiment index *SI*.

	(I)	(II)	(III)	(IV)	(V)	(VI)
Snt^2	0.081***	0.065***	0.080***	0.065***	0.071***	0.051**
	(0.024)	(0.024)	(0.024)	(0.024)	(0.022)	(0.022)
$Snt \cdot DP$			0.087*	0.086*		
			(0.051)	(0.047)		
DP^2			0.186***	0.164***		
			(0.058)	(0.051)		
Snt	0.050	0.044	−0.040	−0.097		
	(0.058)	(0.055)	(0.109)	(0.099)		
DP			−0.901***	−0.828***		
			(0.284)	(0.265)		
Snt/DP					−0.017	−0.016
					(0.072)	(0.065)
$1/DP^2$					0.322*	0.329*
					(0.170)	(0.177)
MR		0.141		0.105		0.097
		(0.188)		(0.189)		(0.188)
HP		1.866***		1.888***		1.900***
		(0.439)		(0.440)		(0.439)
lgNun		0.020		0.020		0.018
		(0.042)		(0.047)		(0.045)
GovL		0.445*		0.393*		0.417*
		(0.241)		(0.227)		(0.230)
Redev		0.467*		0.407*		0.415*
		(0.249)		(0.235)		(0.239)
Luxury		0.038		0.064		0.015
		(0.130)		(0.128)		(0.129)
Constant	1.773***	−1.888	2.662***	−0.690	1.669***	−1.565
	(0.195)	(1.745)	(0.335)	(1.804)	(0.230)	(1.725)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	494	494	494	494	494	494
R^2	0.080	0.174	0.104	0.198	0.086	0.181

Note: The sentiment variable uses the sentiment index *SI*, that is, $Snt = SI$.
DP, development period; *MR*, lending rate; *HP*, growth in housing price; *lgNum*, logarithm of the number of units developed in a project; *GovL*, whether the land is acquired from government; *Redev*, whether the project is a redevelopment; *Luxury*, whether the project is a luxury housing development.
Figures in parentheses show robust standard errors clustered by year; $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

sentiment literature (e.g., Baker & Wurgler, 2007; Hui et al., 2017; Zhou, 2018). In addition, as the sentiment variable (or index) is derived from the sentiment proxies, it may cause an endogenous issue between the sentiment variable and the dependent variable in the empirical study.

To remove economic cycle variation from the index and to alleviate potential endogeneity, we construct an orthogonalised sentiment index. Following the classical methods (Baker & Wurgler, 2007; Ling et al., 2015; Zhou, 2018), we regress each of the six sentiment proxies onto fundamentals of economic cycle, and maintain the regression residual as a cleaner proxy.[13] Five fundamentals are selected, namely, gross domestic product (GDP), unemployment rate, prime lending rate, consumer price index and Hang Seng stock index.[14] We then adopt the six orthogonalised proxies[15] (i.e., residuals) in PCA to construct the orthogonalised index SI^O; the results of PCA are shown in Table 1. The orthogonalised index SI^O explains 57.98% of total variation in the six orthogonalised proxies.

Figure 2 illustrates two indices of developer sentiment. A positive (negative) index value indicates optimistic (pessimistic) developer sentiment. The two indices are highly correlated (78.4% at a 1% significant level shown in Table 1). This echoes the high correlation between normal and orthogonalised sentiment indices in the literature (Baker & Wurgler, 2007; Ling et al., 2015). Particularly, Figure 3 shows the two sentiment indices leading the return rate of house prices by at least one lag (a quarter) in Hong Kong. This is in line with, and supplementary to, the evidence in Wang and Hui (2017) that investor sentiment index demonstrates

Table 3. Estimation results of the regression of waiting time with sentiment index SI^O.

	(I)	(II)	(III)	(IV)	(V)	(VI)
Snt^2	0.0886***	0.076***	0.090***	0.077***	0.088***	0.073***
	(0.023)	(0.022)	(0.022)	(0.021)	(0.022)	(0.021)
$Snt \cdot DP$			0.085**	0.113**		
			(0.041)	(0.047)		
DP^2			0.184***	0.163***		
			(0.053)	(0.046)		
Snt	−0.041	−0.028	−0.196*	−0.224**		
	(0.048)	(0.045)	(0.110)	(0.097)		
DP			−0.903***	−0.831***		
			(0.266)	(0.247)		
Snt/DP					−0.095*	−0.101*
					(0.054)	(0.059)
$1/DP^2$					0.314*	0.325*
					(0.163)	(0.169)
MR		0.158		0.113		0.114
		(0.187)		(0.187)		(0.186)
HP		1.856***		1.886***		1.891***
		(0.433)		(0.433)		(0.430)
lgNun		0.020		0.017		0.016
		(0.041)		(0.046)		(0.044)
GovL		0.447*		0.404*		0.420*
		(0.239)		(0.235)		(0.236)
Redev		0.481*		0.421*		0.426*
		(0.248)		(0.244)		(0.246)
Luxury		0.034		0.067		0.022
		(0.130)		(0.128)		(0.129)
Constant	1.905***	−1.938	2.812***	−0.654	1.755***	−1.676
	(0.162)	(1.734)	(0.313)	(1.793)	(0.198)	(1.714)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	494	494	494	494	494	494
R^2	0.087	0.180	0.114	0.207	0.097	0.192

Note: The sentiment variable uses sentiment index *SI*, that is, $Snt = SI^O$.
DP, development period; *MR*, lending rate; *HP*, growth in housing price; *lgNum*, logarithm of the number of units developed in a project; *GovL*, whether the land is acquired from government; Redev, whether the project is a redevelopment; *Luxury*, whether the project is a luxury housing development.
Figures in parentheses show robust standard errors clustered by year; $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

a strong predicting power on the growth rate of housing price.

6.2. The empirical design

There are two empirical investigations to examine (1) the 'U'-shape sentiment effect on the expected waiting time to develop (WT), and (2) the negative sentiment effect on housing supply at the project level. In the first investigation, we employ two sentiment indices (SI and SI^O) to provide robust estimation results. Quadratic terms are employed to capture the 'U'-shape pattern, that is, $E[WT] = f\,(SI^2 - 2tp \cdot SI + tp^2)$, where tp is the turning point of the 'U'-shape pattern.

Furthermore, Proposition 2 in the theoretical model suggests that development period (DP) reduces the value of the turning point. Two different specifications are set up to capture a negative relationship: (type 1) $tp = b - aDP$ to capture a linear relationship, and (type 2) $tp = c/DP$ to capture a non-linear relationship,[16] assuming $a, b, c > 0$. Besides, different specifications serve as robustness checks. With the vector of control variables ($\boldsymbol{X}$), the empirical regression models are:

$$WT = \begin{cases} \theta_1 SI^2 + \theta_2 SI \cdot DP + \theta_3 DP^2 + \theta_4 SI + \theta_5 DP + \boldsymbol{X\beta} + c + u & \text{type1} \\ \mu_1 SI^2 + \mu_2 \dfrac{SI}{DP} + \mu_3 \dfrac{1}{DP^2} + \boldsymbol{X\beta} + c + u & \text{type2} \end{cases} \tag{9}$$

where u denotes error terms. From theoretical implications, the coefficients $\theta_1, \theta_2, \theta_3$ are expected to be positive and θ_4, θ_5 to be negative for type 1; the coefficients

μ_1, μ_3 are expected to be positive and μ_2 to be negative for type 2.

Regression analysis utilises the sample of private residential developments in Hong Kong from 1996 to 2016.[17] The data at the project level are collected from the Economic Property Research Centre (EPRC) and Centanet database in Hong Kong, containing the information of land parcel and project development,[18] and then merged. For each development, *WT* is defined as the time between land acquisition and development commencement; *DP* is defined as the time between development commencement and sale (or presale). The sentiment index is then matched to the project by the commencement date of development. The final dataset contains 494 samples.[19]

The control variables include the growth of housing prices during the waiting period (*HP*), the standard lending rate (*MR*), and the logarithm number of units built in the project (*lgNun*). *HP* suggests how housing price evolves over the waiting period. *MR* describes the capital cost and pressure that could prolong *WT*. *WT* is also sensitive to project size *lgNun*. Three dummy variables are employed to identify whether the project is a project on government land (*GovL*), a redevelopment project (*Redev*) or a luxury project (*Lux*). Redevelopment (*Redev*) is usually located in the developed urban area; a luxury project (*Lux*)subjected to constraints and regulations may require a longer *WT* (Chau & Wong, 2014). Besides, time and regional fixed effects are controlled. For a description of the variable, see Table F1 in Appendix F in the supplemental data online.

In the second investigation on the negative sentiment effect on housing supply, different measurements and their logarithm including number of units (*Nun*, *lgNun*), total floor area (*GFA*, *lgGFA*) and average floor area per unit (*avGFA*, *lgavGFA*) are adopted to measure housing supply *HS* at the project level. The regression model is:

$$HS = \gamma SI + \boldsymbol{X\beta} + c + u \tag{10}$$

The coefficient γ is expected to be negative when *HS* is the number of units or total floor area, while it is expected to be positive when *HS* is average floor area per unit. The latter is because when sentiment is high, large houses become more popular than small one (Zhou, 2018), and the developer is willing to supply high-end product (i.e., the unit with a large average floor area). $\boldsymbol{X}$ contains control variables and fixed effects are controlled.

6.3. The empirical results

6.3.1. The sentiment effect on waiting time

The first investigation explores how developer sentiment affects waiting time. Tables 2 and 3 present the estimation results of the regression analysis with two different sentiment indices (SI and SI^O) and different specifications. Models I and II involve linear and quadratic sentiment terms only; models III and IV are configured for type 1, while models V and VI are for type 2 in equation (9). Models II, IV and VI incorporate control variables.

Table 2 reports the estimation using the sentiment index *SI*. Overall, the coefficient signs of sentiment terms and development period in the six models are in line with the theoretical implications. In models I and II, the coefficients of SI^2 are significantly positive, indicating a non-linear relationship between sentiment and *WT*. In models III and IV, the positive coefficients of SI^2, $SI \cdot DP$ and DP^2 suggest the existence of a 'U'-shape pattern of *WT* against sentiment, and the negative coefficients of *SI* and *DP* indicate the negative linear relationship between turning point and development period. In models V and VI, the positive coefficients of SI^2 and $1/DP^2$ suggest the existence of a 'U'-shape pattern, and the negative coefficients of SI/DP show the negative non-linear relationship between turning point and development period.

The significances of non-linear terms are of interest. The coefficients of the quadratic terms are significant, and the results are consistent across six models, especially when including control variables in models. The insignificant SI/DP in either model V or VI may imply that the non-linear relationship between turning point and development period (type 2) may be mis-specified.

Table 3 reports the estimation using the orthogonalised sentiment index SI^O. The coefficient signs of sentiment terms and development period are consistent with those in Table 2, while the coefficient significance is improved. As all the variables of interest are significant, the models in Table 3 provide solid evidence in support of the 'U'-shape relationship between waiting time and sentiment, and a negative relationship between turning point and development period. The model with SI^O performs better than the model with *SI* as the models in Table 3 explain more variation (higher R^2) than those in Table 2. In addition, the magnitude of coefficients in every model with *SI* is slightly lower than that in the model with SI^O, indicating that the results of models with *SI* are biased towards zero, but consistently. This means that the models with *SI* might be biased due to potential endogeneity. However, they are still useful to serve as a valid reference to qualitatively support our theoretical implication.

Several robustness checks are employed to confirm the findings. First, as regional housing markets are significantly influenced by economic crises (Mohino & Ureña, 2020), it is necessary to examine whether the empirical results are sensitive to the crises. The models are re-estimated by using subsamples in which the data for the period of financial crises are left out. There were two financial crises in the sample period, that is, 1997–98 and 2007–08. We re-estimate the models with three different subsamples.[20] The results are robust as the sign and significance of coefficients in models of *SI* and $SI^O$are consistent with those in Tables 2 and 3, respectively.

Second, the development period (*DP*) could be endogenously determined when the decision to develop is made. To alleviate the endogeneity issue, instrumental variable (IV) regression is employed. The days of extreme

Table 4. Estimation results of instrumental variable (IV) regression of waiting time.

	First stage			Main stage			
	WT	***DP***		**(I)**	**(II)**	**(III)**	**(IV)**
D.ew	−0.009	0.147***	Snt^2	0.063***	0.058***	0.074***	0.074***
	(0.028)	(0.013)		(0.024)	(0.022)	(0.022)	(0.022)
			$Snt \cdot DP$	0.077*		0.137*	
				(0.043)		(0.074)	
			DP^2	0.316**		0.321***	
				(0.130)		(0.117)	
			Snt	−0.084		−0.266**	
				(0.143)		(0.135)	
			DP	−1.349**		−1.370***	
				(0.564)		(0.518)	
			Snt/DP		−0.019		−0.082
					(0.073)		(0.065)
			$1/DP^2$		0.345*		0.359*
					(0.186)		(0.183)
MR	0.145	−0.005	*MR*	0.105	0.119	0.110	0.135
	(0.183)	(0.035)		(0.187)	(0.187)	(0.187)	(0.186)
HP	1.940***	0.161	*HP*	1.876***	1.880***	1.885***	1.871***
	(0.428)	(0.109)		(0.441)	(0.441)	(0.437)	(0.435)
lgNun	−0.022	0.121***	*lgNun*	0.022	0.018	0.019	0.017
	(0.046)	(0.022)		(0.047)	(0.045)	(0.046)	(0.044)
GovL	0.454*	−0.040	*GovL*	0.449*	0.444*	0.462**	0.450*
	(0.242)	(0.112)		(0.233)	(0.242)	(0.231)	(0.238)
Redev	0.412	0.013	*Redev*	0.436*	0.455*	0.466*	0.472*
	(0.256)	(0.111)		(0.251)	(0.253)	(0.249)	(0.250)
Luxury	−0.015	0.185***	*Luxury*	0.046	0.036	0.043	0.034
	(0.135)	(0.062)		(0.127)	(0.129)	(0.127)	(0.129)
Constant	−1.599	0.556	Constant	−0.249	−1.671	−0.195	−1.759
	(1.712)	(0.372)		(1.885)	(1.727)	(1.874)	(1.717)
Year fixed effect	Yes	Yes		Yes	Yes	Yes	Yes
District fixed effect	Yes	Yes		Yes	Yes	Yes	Yes
Observations	494	494		494	494	494	494
R^2	0.161	0.614		0.190	0.173	0.200	0.182
F-statistic	4.79***	18.68***	Weak IV test	9.82***	8.66***	8.10***	7.83***

Note: The sentiment variable *Snt* uses two sentiment indices, that is, $Snt = SI$ in models I–II and $Snt = SI^O$ in models III–IV.

DP, development period; *MR*, lending rate; *HP*, growth in housing price; *lgNum*, logarithm of the number of units developed in a project; *GovL*, whether the land is acquired from government; *Redev*, whether the project is a redevelopment; *Luxury*, whether the project is a luxury housing development.

Figures in parentheses show robust standard errors clustered by year; $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

The overidentification test is not necessary as there is one IV for *DP*.

Models I and II echo models IV and VI in Table 2, respectively; models III and IV echo models IV and VI in Table 3, respectively.

weather ($D.ew$) during the development period in Hong Kong is selected as the IV for DP. Extreme weather is defined as weather when the government issues a weather warning that enforces a stoppage on a construction site.[21] Hence, the IV would exogenously affect the construction period but not affect the waiting time.

Table 4 reports the estimation results of the regression on both the first stage and the main stage. In the first stage, the IV ($D.ew$) is insignificant in the regression of WT, indicating that the IV is not directly and statistically correlated with the dependent variable.[22] $D.ew$ is significant and positive in the regression of DP, and all the under-identification tests are significant, confirming the effectiveness of the IV in explaining DP. In the main stage, the first two models are executed with SI while the last two are with SI^O. Models I and III are specified for type 1 non-linear relationship, while models II and IV are for type 2. The results of IV regression suggest the findings of the 'U'-shape relationship between waiting time and sentiment are robust. Specifically, the estimation results of models I and II are consistent with those of models IV and VI in Table 2, respectively. The estimation results of models III and IV are consistent with models IV and VI in Table 3, respectively.

It is worthwhile discussing the economic magnitudes of sentiment effects estimated in the empirical study. Noticeably, the sentiment effect is non-linear, as indicated by the implications of our theoretical model. Such an effect depends on the value of development period. In the following, we assume a typical case where $DP = 2$ years and the sentiment index varies in the interval of $[-3, 3]$. Figure 4 demonstrates the pattern of economic magnitudes of sentiment effects. An increment of 0.1 unit in the sentiment index could cause a change in the waiting time (measured in years) between $[-0.030, 0.045]$ and $[-0.035, 0.034]$ for models I and II in Table 4, respectively. The models with an orthogonalised sentiment index show similar patterns: an increment of 0.01 unit in the sentiment index could cause a change in the waiting time between $[-0.043, 0.046]$ and $[-0.048, 0.041]$ for models III and IV in Table 4, respectively.

Third, there might be endogeneity in the control variables.[23] To alleviate the issue, the two-stage IV

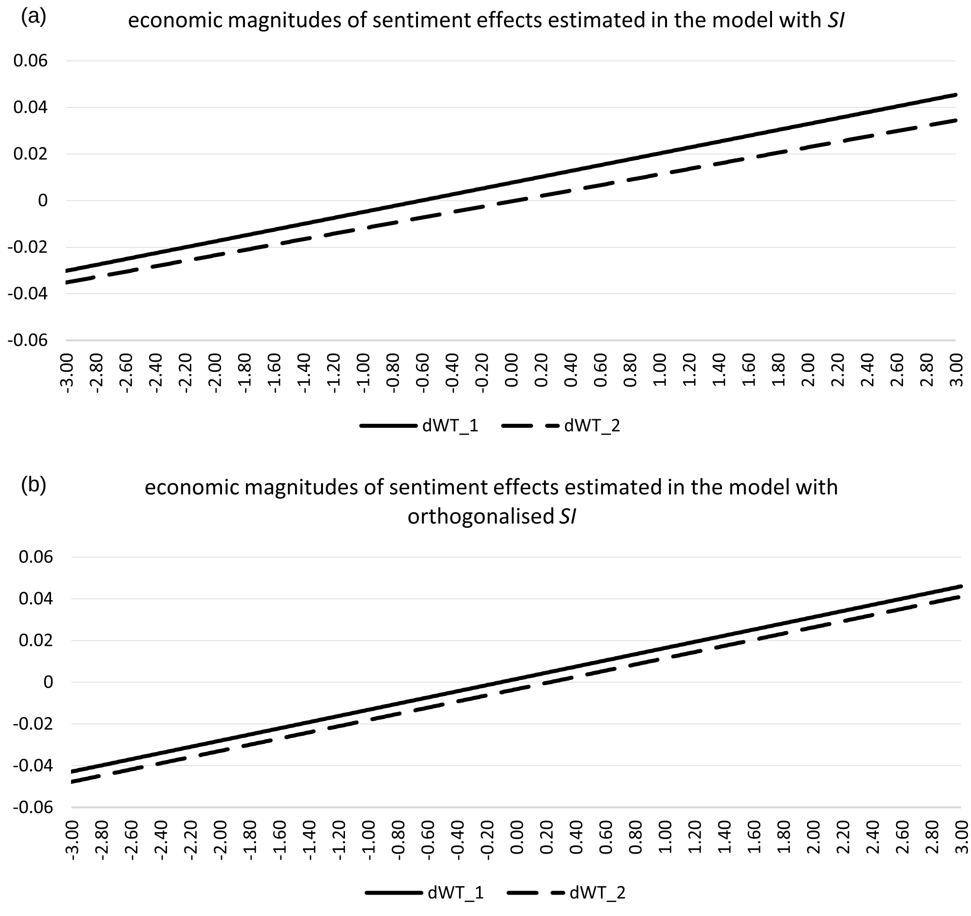

Figure 4. Economic magnitudes of sentiment effects estimated in the model with SI or orthogonalised SI in Table 4: (a) the economic magnitudes of sentiment effects estimated in the model with SI (corresponding to models I and II in Table 4); and (b) the economic magnitudes of sentiment effects estimated in the model with orthogonalised SI (corresponding to models III and IV in Table 4).

Note: The x-axis measures the sentiment index varying between $[-3, 3]$; the y-axis measures the changes in the wating time (years) corresponding to an increment of 0.1 unit in the sentiment index. The development period in all the cases is assumed to be two years.

Table 5. Estimation results of survival regression of waiting time.

	(I)	(II)	(III)	(IV)
Snt^2	−0.057**	−0.044**	−0.074***	−0.071***
	(0.023)	(0.019)	(0.022)	(0.021)
$Snt \cdot DP$	−0.064*		−0.070*	
	(0.036)		(0.040)	
DP^2	−0.091***		−0.090***	
	(0.033)		(0.033)	
Snt	0.048		0.118	
	(0.085)		(0.082)	
DP	0.514**		0.516**	
	(0.204)		(0.200)	
Snt/DP		0.019		0.039
		(0.054)		(0.054)
$1/DP^2$		−0.254*		−0.252*
		(0.150)		(0.145)
MR	−0.073	−0.064	−0.092	−0.091
	(0.133)	(0.130)	(0.133)	(0.130)
HP	−1.364***	−1.353***	−1.339***	−1.317***
	(0.245)	(0.245)	(0.247)	(0.246)
lgNun	0.013	0.021	0.014	0.023
	(0.042)	(0.040)	(0.042)	(0.041)
GovL	−0.408	−0.415*	−0.416	−0.422*
	(0.251)	(0.246)	(0.255)	(0.249)
Redev	−0.379	−0.377	−0.401	−0.404
	(0.256)	(0.251)	(0.261)	(0.254)
Luxury	−0.072	−0.025	−0.069	−0.032
	(0.114)	(0.114)	(0.114)	(0.114)
Year fixed effect	Yes	Yes	Yes	Yes
District fixed effect	Yes	Yes	Yes	Yes
Observations	494	494	494	494
Wald chi^2	65.27***	55.48***	72.31***	64.94***
Proportional hazards (PH) test	16.37	13.48	16.94	14.21

Note: The sentiment variable *Snt* uses two sentiment indices, that is, $Snt = SI$ in models I–II and $Snt = SI^O$ in models III–IV.
DP, development period; *MR*, lending rate; *HP*, growth in housing price; *lgNum*, logarithm of the number of units developed in a project; *GovL*, whether the land is acquired from government; *Redev*, whether the project is a redevelopment; *Luxury*, whether the project is a luxury housing development.
Figures in parentheses show robust standard errors clustered by year; $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.
Models I and II echo models IV and VI in Table 2, respectively; models III and IV echo models IV and VI in Table 3, respectively.

regression is rerun without control variables. The results (see Table F3 in Appendix F in the supplemental data online) are consistent with the findings in Table 4 in terms of the sign and significance of the coefficients.

Fourth, alternative to linear regression analysis in decision-making studies, survival analysis is to analyse the survival duration before event occurrence (Harrell, 2001). In this case, developers survive (wait) until event occurrence (i.e., decide to develop). Besides, survival analysis can help to explore the sentiment effect on the probability of the developer quitting waiting. In this study, the Cox proportional hazards model is adopted for survival analysis. The signs of the coefficients are expected to be opposite to those of coefficients in equation (9). This is because a positive coefficient in survival analysis indicates that the independent variable positively affects the hazard rate. In our case, a positive coefficient suggests that the sentiment variable would increase the probability that the developer decides to develop and decrease the waiting time.

Table 5 reports the estimation results of survival regression. The first two models are executed with SI, while the last two are with SI^O. Models I and III are specified for type 1 non-linear relationship, while models II and IV are for type 2. The estimation results are consistent with our expectation and echo to the results in Tables 2 and 3. The evidence discovered through survival analysis supports our theoretical implication of a 'U'-shape relationship between sentiment and waiting time. The insignificance of proportional hazards (PH) tests indicates that the proportional hazards assumption is met.

In addition, we discuss the economic magnitude of the sentiment effect on the hazard rate instead of the survival period as the regression is built upon the hazard rate. Specifically, this shows how large the impact of an increment in the sentiment index on the hazard rate (or the probability that a developer is willing to quit waiting). The impact is non-linear and depends on the length of the development period. To illustrate, we assume a typical case where $DP = 2$ years and the sentiment index varies within the range of $[-3, 3]$. Figure 5 demonstrates the pattern of economic magnitudes. A 0.1 unit increment in the sentiment index causes a change in the hazard rate between $[-0.041, 0.025]$ and $[-0.026, 0.0027]$ for models I and II in Table 5, respectively. The models with an orthogonalised sentiment index show similar patterns, that is, an increment of 0.01 unit in the sentiment index could cause a change in the waiting time between [−0.044, 0.041] and [−0.040, 0.043] for models III and IV in Table 5, respectively.

6.3.2. The sentiment effect on housing supply

The second investigation is to examine how developer sentiment affects housing supply at the project level. The regression analysis employs three different measurements of housing supply and their logarithm, namely, the number of units (*Nun*, *lgNun*), total floor area (*GFA*, *lgGFA*) and average floor area per unit (*avGFA*, *lgavGFA*).

Table 6 reports the estimation results of the six models with an orthogonalised index SI^O. Models I and II indicate that sentiment significantly suppresses housing supply at the project level. A one unit increase in the sentiment index could cause a decrease of 49.7 housing units (in model I) or a decrease of 9.7% of supply (in model II) at the project level. Models III and IV show a weak negative impact of sentiment on the total area supplied at the project level. A one unit increase in the sentiment index could cause a decrease of 87 m^2 in total GFA (in model III) or a decrease of 1.8% of GFA (in model IV) at the project level. Models V and VI indicate that sentiment significantly increases the average size of each unit in a project. A one unit increase in the sentiment index could lead to an increase of 5.8 m^2 in average GFA (in model V) or an increase of 7.9% of average GFA (in model VI) for each house unit. When sentiment is positive, the developer is willing to supply high-end products (large units). Our

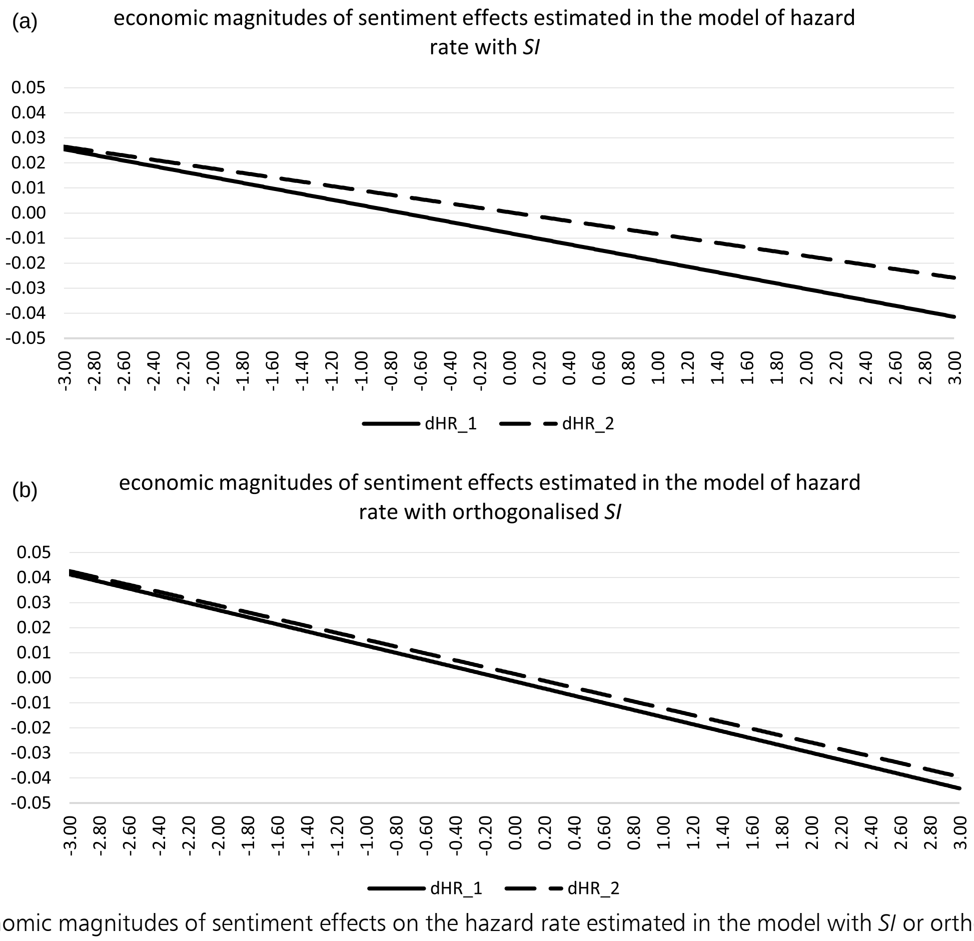

Figure 5. Economic magnitudes of sentiment effects on the hazard rate estimated in the model with *SI* or orthogonalised *SI* in Table 5: (a) the economic magnitudes of sentiment effects estimated in the model with orthogonalised *SI* (corresponding to models I and II in Table 5); and (b) the economic magnitudes of sentiment effects estimated in the model with orthogonalised *SI* (corresponding to models III and IV in Table 5).
Note: The *x*-axis measures the sentiment index varying between [−3, 3]; the *y*-axis measures the changes in the hazard rate corresponding to an increment of 0.1 unit in the sentiment index. The development period in all the cases is assumed to be two years.

Table 6. Estimation results of regression of project supply on sentiment (sentiment index SI^O).

	(I) *Nun*	(II) *lg(Nun)*	(III) *GFA*	(IV) *lg(GFA)*	(V) *avGFA*	(VI) *lg(avGFA)*
Snt	−49.685**	−0.097**	−87.047	−0.018	5.759***	0.079***
	(20.732)	(0.049)	(1257.345)	(0.046)	(2.217)	(0.021)
MR	−12.578	−0.015	−1275.324	0.005	1.168	0.020
	(69.409)	(0.121)	(4257.515)	(0.132)	(4.243)	(0.049)
HP	−78.208	0.025	−4878.493	−0.015	−13.163	−0.040
	(159.300)	(0.231)	(5460.297)	(0.209)	(13.556)	(0.102)
GovL	308.472***	0.384	16,721.020***	0.440*	−1.001	0.056
	(118.752)	(0.276)	(6264.561)	(0.249)	(12.772)	(0.106)
Redev	−286.773***	−1.344***	−17,129.969***	−1.299***	5.681	0.045
	(100.377)	(0.264)	(5609.478)	(0.240)	(12.305)	(0.101)
Luxury	−429.451***	−1.471***	−14,090.233***	−0.425***	124.003***	1.046***
	(83.280)	(0.147)	(2792.297)	(0.120)	(10.145)	(0.065)
Constant	525.194	5.178***	33,051.791	8.956***	56.864	3.778***
	(644.310)	(1.134)	(36,221.304)	(1.201)	(42.681)	(0.451)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	494	494	494	494	494	494
R^2	0.273	0.500	0.314	0.471	0.464	0.488

Note: The sentiment variable uses sentiment index SI^O, that is, $Snt = SI^O$.
DP, development period; *MR*, lending rate; *HP*, growth in housing price; *lgNum*, logarithm of the number of units developed in a project; *GovL*, whether the land is acquired from government; *Redev*, whether the project is a redevelopment; *Luxury*, whether the project is a luxury housing development.
Figures in parentheses show robust standard errors clustered by year; *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

finding regarding developer sentiment echoes that of Zhou (2018) that investor sentiment promotes large houses. Overall, the results from this second investigation confirm that sentiment decreases housing supply at the project level.

7. CONCLUSIONS

Housing supply under uncertainty has predominantly focused on fundamental factors in previous studies. A growing number of studies highlight the critical influence of sentiment, a non-fundamental factor, in property markets. However, the question of how sentiment affects developers' behaviour, and eventually housing supply, has yet to be answered. To address this, our investigation delves into the role of developer sentiment within the decision-making process for housing projects under uncertainty. This study offers insightful implications for relevant authorities when considering policies of housing supply and affordability at different levels of market uncertainty and sentiment.

The theoretical model has several important implications. First, a 'U'-shaped relationship between the expected waiting time for development and sentiment indicates that sentiment accelerates the development process, but then it gradually extends the waiting time. Furthermore, the turning point of the 'U'-shape emerges earlier when the project has a longer development period. Second, sentiment negatively affects optimal density and project value. In practice, a high sentiment induces a lower project density (supply) as the developer with bullish sentiment is willing to produce high-end housing products (featured as low-density).

In the empirical study, we construct two sentiment indices and conduct two investigations using Hong Kong housing market data. The first investigation robustly supports a 'U'-shaped relationship between expected waiting time and developer sentiment, and development period negatively influences the turning point of this 'U'-shaped curve. In the second investigation, we find that developer sentiment is negatively associated with housing supply at the project level.

The limitations of the empirical studies are mainly two-fold. First, the timing of development in practice is influenced by the land and planning system. Unlike Hong Kong where the granting of building permits does not significantly affect development because of its efficient approval process, many developed markets (such as the UK and the US) face situations where obtaining planning permission can be time-consuming. Second, the sample does not include any instances of land flipping (where land is purchased and sold without any development) as this study specifically focuses on the sentiment effect on waiting time in developed projects. However, it is important to note that sentiment can also influence developers to abandon land before initiating development.

The policy implications are worth discussing. During periods of positive sentiment, developers tend to reduce supply by developing low-density projects, or even postponing projects in instances of extremely positive sentiment. This aligns with the fact that new construction may not keep pace with rising house prices in a booming market (e.g., Glaeser et al., 2008). This suggests that policies or interventions aimed at increasing housing supply may have limited effectiveness in such markets. Furthermore, an increase in housing supply may not necessarily improve local affordability (Fingleton et al., 2019). Our findings corroborate this point and suggest that developers with positive sentiment are inclined to provide high-end (low-density) housing, which does not contribute to local affordability.

Government interventions to enhance affordability are more effective during periods of negative sentiment. In such times, developers are likely to reduce the waiting time for high-density projects which are likely to provide economical housing. This presents an opportune moment for local governments to actively promote the supply of economical housing.[24] This implication offers a fresh explanation for construction booms amidst declining housing demand, as discussed by Grenadier (1996). As regional housing markets always exhibit a strong spillover effect (Zhang & Fan, 2019), the sentiment effect could spread across local markets, influencing housing supply in neighbouring areas. Future study may concentrate on identifying the spillover effect of developer sentiment.

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DISCLOSURE STATEMENT

No potential conflict of interest was reported by the authors.

NOTES

1. Hong Kong is continuously ranked as the world leading international market (Fang et al., 2023) and the world's freest economy (https://www.info.gov.hk/gia/general/202209/08/P2022090800841.htm).
2. Figure 1 shows gross domestic product (GDP), housing price and rent in Hong Kong between 1991 and 2021. GDP has grown at 2.9% annually on average over 20 years, while the housing market performance is much more volatile: the price increases with an average annual growth rate of 5.3% and standard deviation of 15%, and rent increases with an average annual growth rate of 2.5% and standard deviation of 9%.
3. In the course of purchasing and developing land, the government announces the annual leasing programme showing the sites available in that financial year, and the zoning of a land parcel is shown in the relevant zoning plan by the Twon Planning Board. The developers then join a public tender for the site while consulting with the authorities (regarding zoning, building and environmental assessment) to obtain building permits approved by the building committee, which typically takes approximately two months. Before construction commencement, the developers need consent from the Buildings Department, which usually takes 28 days. In that case, the grant for building permits would not significantly affect the timing of development in Hong Kong.
4. Generally, developers' land purchase can be categorised into two main types, that is, a classical one, which is to buy and develop land, and flipping, which is to buy, hold and sell the land at a higher price in the future.
5. For a precise summary of dialogues between real estate research and regional studies, see Derudder and Bailey (2021).
6. To our knowledge, there are only two empirical papers about developer sentiment: Hui et al. (2017) examine the effect of developer and investor sentiments on return in the Chinese housing market; and Cheong et al. (2020) state that a developer's behaviour drives sentiments and prices in the Malaysian housing market.
7. Following the common practice, the inverse elasticity of housing demand is assumed to be constant over the development period.
8. The long-run trend with fluctuations is determined by external influence and shocks, such as population and economic growth, regime and institutional changes, political shocks, etc.
9. Assume that *SI* captures developer sentiment appropriately and this theoretical model would not be confounded by index availability.
10. This study focuses on the sentiment effect and thus sentiment function does not need to take developers' idiosyncratic characteristics into account.
11. Such regulations are promulgated in some markets, especially where the government is promoting urbanisation. For instance, developing markets such as India and China and developed markets such as Scotland implement this kind of policy in their land markets. This will affect the developer's strategy on development timing, but marginally. The developer will wait until the optimal timing or the deadline that the government set up at the beginning, whichever comes first.
12. Hong Kong has ongoing surveys of consumers, such as the survey of consumer confidence and the survey of current economic conditions. On the other hand, the Business Tendency Survey (including real estate and construction sectors) involving industry professionals started from 2012, which is insufficient to cover the time period of the data used in this paper. For details about the business survey, see https://www.censtatd.gov.hk/en/scode300.html#section1/.
13. We construct another orthogonalised index SI^{ON} by incorporating additional non-linear terms of economic cycle fundamentals into regression when obtaining orthogonalised proxies. The correlation test shows that SI^{O} and SI^{ON} are an extremely correlated (99.93%). Furthermore, the results of an empirical study with SI^{ON} are considerably consistent with that with SI^{O}

14. We use growth rates of GDP, the consumer price index (CPI) and the Hang Seng index (HSI).
15. For the estimation results of the regression of proxy on cyclical variables, see Table F2 in Appendix F in the supplemental data online.
16. The numerical analysis shows that the negative relationship is convex in shape (see Figure E2 in Appendix E in the supplemental data online). Hence, we use type 2 specification to capture this convexity.
17. The time span of the dataset indicates that all the residential projects acquired the land during the period 1996–2016.
18. The information about the land parcel originally comes from the Lands Department; the information about project development originated from the Buildings Department.
19. To avoid extreme values of *WT* and *DP*, the samples are winsorised at the interval of the 5th and 95th percentiles of *WT* and *DP*.
20. The first subsample excludes the data for the period 1997–98; the second excludes the data for the period 2007–08; while the third excludes the data of both periods 1997–98 and 2007–08.
21. Usually, the extreme weather is caused by typhoons (hurricanes). When Hong Kong observatory (https://www.hko.gov.hk/en/index.html) issues a signal for typhoons of category strengths 8–10 (with 10 being the highest), the government enforces a stoppage in almost all industry, including construction.
22. This is not a formal test for the IV's exogeneity condition. It is to show statistical evidence that the IV is not directly correlated with the dependent variable.
23. We thank a referee for this comment that some of the controls could be endogenous to the dependent variable.
24. For instance, in Hong Kong, the government could increase land supply, or expedite the legal process for building permits and applications to amend project density (especially to increase project density within a regulated range). In other markets, the government or authority could leverage policy tools to incentivise developers, depending on the land, planning and housing system in the market.

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REFERENCES

Adams, D., Leishman, C., & Moore, C. (2009). Why not build faster? Explaining the speed at which British house-builders develop new homes for owner-occupation. *Town Planning Review*, *80*(3), 291–315. https://doi.org/10.3828/tpr.80.3.4

Antwi, A., & Henneberry, J. (1995). Developers, non-linearity and asymmetry in the development cycle. *Journal of Property Research*, *12*(3), 217–239. https://doi.org/10.1080/09599919508724146

Atherton, E., French, N., & Gabrielli, L. (2008). Decision theory and real estate development: a note on uncertainty. *Journal of European Real Estate Research*, *1*(2), 162–182. https://doi.org/10.1108/17539260810918730

Baker, M., & Wurgler, J. (2007). Investor sentiment in the stock market. *Journal of Economic Perspectives*, *21*(2), 129–151. https://doi.org/10.1257/jep.21.2.129

Bar-ilan, A., & Strange, W. C. (1996). Investment Lags. *American Economic Review*, *86*(3), 610–622.

Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment. *Journal of Financial Economics*, *49*(3), 307–343. https://doi.org/10.1016/S0304-405X(98)00027-0

Berger, A. N., Kim, H. H., & Ma, X. F. (2020). Bank management sentiment and liquidity hoarding. SSRN 3586500.

Berkovec, J. A., & Goodman, J. L. (1996). Turnover as a measure of demand for existing homes. *Real Estate Economics*, *24*(4), 421–440. https://doi.org/10.1111/1540-6229.00698

Bissoondeeal, R. K. (2021). The links between regional house prices and share prices in the UK. *Regional Studies*, *55*(2), 256–268. https://doi.org/10.1080/00343404.2020.1795108

Bulan, L., Mayer, C., & Somerville, C. T. (2009). Irreversible investment, real options, and competition: Evidence from real estate development. *Journal of Urban Economics*, *65*(3), 237–251. https://doi.org/10.1016/j.jue.2008.03.003

Capozza, D. R., & Li, Y. (2002). Optimal land development decisions. *Journal of Urban Economics*, *51*(1), 123–142. https://doi.org/10.1006/juec.2001.2240

Chau, K. W., & Wong, S. K. (2014). Externalities of urban renewal: A real option perspective. *The Journal of Real Estate Finance and Economics*, *48*(3), 546–560. https://doi.org/10.1007/s11146-013-9418-z

Cheong, C. W., Ngui, L. L., & Beatrice, S. G. (2020). Sentiments in the housing market and the effectiveness of government interventions. *Pacific Rim Property Research Journal*, *26*(3), 223–247. https://doi.org/10.1080/14445921.2021.1946259

Clayton, J., Ling, D. C., & Naranjo, A. (2009). Commercial real estate valuation: Fundamentals versus investor sentiment. *The Journal of Real Estate Finance and Economics*, *38*(1), 5–37. https://doi.org/10.1007/s11146-008-9130-6

Cunningham, C. R. (2006). House price uncertainty, timing of development, and vacant land prices: Evidence for real options in Seattle. *Journal of Urban Economics*, *59*(1), 1–31. https://doi.org/10.1016/j.jue.2005.08.003

Da, Z., Engelberg, J., & Gao, P. (2015). The sum of all FEARS investor sentiment and asset prices. *Review of Financial Studies*, *28*(1), 1–32. https://doi.org/10.1093/rfs/hhu072

De Stefani, A. (2021). House price history, biased expectations, and credit cycles: The role of housing investors. *Real Estate Economics*, *49*(4), 1238–1266. https://doi.org/10.1111/1540-6229.12328

DeCoster, G. P., & Strange, W. C. (2012). Developers, herding, and overbuilding. *The Journal of Real Estate Finance and Economics*, *44*(1–2), 7–35. https://doi.org/10.1007/s11146-011-9309-0

DeLong, B. J., Shleifer, A., Summers, L. H., & Waldmann, R. (1990). Noise trader risk in financial markets. *Journal of Political Economy*, *98*(4), 703–738. https://doi.org/10.1086/261703

Derudder, B., & Bailey, D. (2021). Real estate and regional studies. *Regional Studies*, *55*(4), 571–574. https://doi.org/10.1080/00343404.2021.1889189

Dixit, A. K., & Pindyck, R. S. (1994). *Investment under uncertainty*. Princeton University Press.

Fang, C., Pan, F., & Lai, K. P. (2023). The brokerage role of Hong Kong in global financial networks: The case of mainland Chinese companies' US listings. *Regional Studies*, *57*(2), 317–329. https://doi.org/10.1080/00343404.2022.2099822

Fingleton, B., Fuerst, F., & Szumilo, N. (2019). Housing affordability: Is new local supply the key? *Environment and Planning A:*

Economy and Space, *51*(1), 25–50. https://doi.org/10.1177/0308518X18798372

Freybote, J., & Seagraves, P. A. (2017). Heterogeneous investor sentiment and institutional real estate investments. *Real Estate Economics*, *45*(1), 154–176. https://doi.org/10.1111/1540-6229.12132

Glaeser, E. L., Gyourko, J., & Saiz, A. (2008). Housing supply and housing bubbles. *Journal of Urban Economics*, *64*(2), 198–217. https://doi.org/10.1016/j.jue.2008.07.007

Grenadier, S. R. (1996). The strategic exercise of options: Development cascades and overbuilding in real estate markets. *The Journal of Finance*, *51*(5), 1653–1679. https://doi.org/10.1111/j.1540-6261.1996.tb05221.x

Harrell, F. E. (2001). *Regression modelling strategies: with applications to linear models, logistic regression, and survival analysis*. Springer.

Holland, A. S., Ott, S. H., & Riddiough, T. J. (2000). The role of uncertainty in investment: An examination of competing investment models using commercial real estate data. *Real Estate Economics*, *28*(1), 33–64. https://doi.org/10.1111/1540-6229.00792

Hui, E. C., Dong, Z., Jia, S., & Lam, C. H. L. (2017). How does sentiment affect returns of urban housing? *Habitat international*, *64*, 71–84. https://doi.org/10.1016/j.habitatint.2017.04.013

Jin, C., Soydemir, G., & Tidwell, A. (2014). The U.S. housing market and the pricing of risk: Fundamental analysis and market sentiment. *Journal of Real Estate Research*, *36*(2), 187–220. https://doi.org/10.1080/10835547.2014.12091390

La Porta, R. (1996). Expectations and the cross-section of stock returns. *Journal of Finance*, *51*(5), 1715–1742.

Leishman, C. (2015). Housing Supply and suppliers: Are the microeconomics of housing developers important? *Housing Studies*, *30*(4), 580–600. https://doi.org/10.1080/02673037.2015.1021767

Ling, D. C., Naranjo, A., & Scheick, B. (2014). Investor Sentiment, limits to arbitrage and private market returns. *Real Estate Economics*, *42*(3), 531–577. https://doi.org/10.1111/1540-6229.12037

Ling, D. C., Ooi, J. T., & Le, T. T. (2015). Explaining house price dynamics: Isolating the role of non-fundamentals. *Journal of Money, Credit and Banking*, *47*(S1), 87–125. https://doi.org/10.1111/jmcb.12194

Loughran, T., & McDonald, B. (2011). When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *The Journal of Finance*, *66*(1), 35–65. https://doi.org/10.1111/j.1540-6261.2010.01625.x

Marcato, G., & Nanda, A. (2016). Information content and forecasting ability of sentiment indicators: case of real estate market. *Journal of Real Estate Research*, *38*(2), 165. https://doi.org/10.1080/10835547.2016.12091442

McAllister, P., Newell, G., & Matysiak, G. (2008). Agreement and accuracy in consensus forecasts of the UK commercial property market. *Journal of Property Research*, *25*(1), 1–22. https://doi.org/10.1080/09599910802397040

Mohino, I., & Ureña, J. M. (2020). Mobility, housing and labour markets in times of economic crises. *Regional Studies*, *54*(4), 443–449. https://doi.org/10.1080/00343404.2020.1711879

Murray, C. K. (2020). Time is money: How landbanking constrains housing supply. *Journal of Housing Economics*, *49*, 101708. https://doi.org/10.1016/j.jhe.2020.101708

Ott, S. H., Hughen, W. K., & Read, D. C. (2012). Optimal phasing and inventory decisions for large-scale residential development projects. *The Journal of Real Estate Finance and Economics*, *45*(4), 888–918. https://doi.org/10.1007/s11146-011-9299-y

Piazzesi, M., & Schneider, M. (2009). Momentum traders in the housing market: Survey evidence and a search model. *American Economic Review*, *99*(2), 406–411. https://doi.org/10.1257/aer.99.2.406

Rocha, K., Salles, L., Garcia, F. A. A., Sardinha, J. A., & Teixeira, J. P. (2007). Real estate and real options – A case study. *Emerging Markets Review*, *8*(1), 67–79. https://doi.org/10.1016/j.ememar.2006.09.008

Shleifer, A., & Vishny, R. W. (1997). The limits of arbitrage. *Journal of Finance*, *52*(1), 35–55.

Soo, C. K. (2018). Quantifying sentiment with news media across local housing markets. *The Review of Financial Studies*, *31*(10), 3689–3719. https://doi.org/10.1093/rfs/hhy036

Tse, M. K. S., Pretorius, F. I., & Chau, K. W. (2011). Market sentiments, winner's curse and bidding outcome in land auctions. *The Journal of Real Estate Finance and Economics*, *42*(3), 247–274. https://doi.org/10.1007/s11146-009-9211-1

Wang, Z., & Hui, E. C. (2017). Fundamentals and Market Sentiment in Housing Market. *Housing, Theory and Society*, *34*(1), 57–78. https://doi.org/10.1080/14036096.2016.1196240

Yang, C., & Zhang, R. (2013). Sentiment asset pricing model with consumption. *Economic Modelling*, *30*, 462–467. https://doi.org/10.1016/j.econmod.2012.11.004

Zhang, D., & Fan, G. Z. (2019). Regional spillover and rising connectedness in China's urban housing prices. *Regional Studies*, *53*(6), 861–873. https://doi.org/10.1080/00343404.2018.1490011

Zheng, X. (2015). Expectation, volatility and liquidity in the housing market. *Applied Economics*, *47*(37), 4020–4035. https://doi.org/10.1080/00036846.2015.1023943

Zhou, Z. (2018). Housing market sentiment and intervention effectiveness: Evidence from China. *Emerging Markets Review*, *35*, 91–110. https://doi.org/10.1016/j.ememar.2017.12.005