On the Strategic Timing of Sales by Real Estate Developers: To Wait or To Presell?

Abstract

In timing property listings, real estate developers can exercise the "option to wait" or "option to presell" to mitigate price uncertainty risk. In this study, we study the effectiveness of both strategies under a unified framework. We test our hypotheses using residential development data from Hong Kong between 1995 and 2015. Empirical evidence shows that when the presale option is unavailable, developers tend to adopt the waiting strategy when facing price uncertainty risk. Conversely, when a presale option is available, developers will accelerate sales when price volatility is high. Moreover, the effectiveness of the presale option depends substantially on government restrictions. Our approach facilitates the identification of the net effect of either tool and provides an opportunity to unify conflicting findings in the literature.

Keywords Real option, Regulation, Planning, Hazard model

JEL Classification D81, R31, R58

1 Introduction

The residential property market is characterized by cyclicality and long development lead-time. Hence, ascertaining the optimal time to sell properties is challenging for developers due to such an immense level of uncertainty. One method to mitigate the risk is to delay the listing of properties, such that the opportunity cost caused by underpricing could be reduced. This "option to wait" can be exercised by holding the completed stocks off the market (Wang et al. 2016)[1]. Alternatively, developers can also sell properties in the early stages of the development to reduce the opportunity cost caused by the long investment lead-time (Bar-Ilan and Strange 1996, Tse 1998). When presale (i.e., selling before completion) is allowed, selling considerably early could even provide financial benefits to the developers with deposits from the agreed buyers. However, once the listed prices are fixed, future price adjustments to market changes are likely to be insufficient because of tacit collusion and the anchor effect (e.g., Bucchianeri and Minson 2013, Leung and Tsang 2013, Wu et al. 2014). Moreover, the cost of "underpricing" may offset the benefits of recovering early expenses. The existing literature analyzes the two tools (i.e., waiting or presale) in isolation and the method of identifying their net effects remains unclear. Accordingly, we investigate the role of both strategies in one unified framework.

Our analysis is based on a well-established line of literature on real option analysis. Such analysis has been applied extensively to model sale decisions by individual sellers in the secondary property market (e.g., Cauley and Pavlov 2002, Qian 2013), and investment decisions by real estate developers (e.g., Titman 1985, McDonald and Siegel 1986, Capozza and Sick 1991, Williams 1993, Cunningham 2006, Schwartz and Torous 2007, Bulan et al. 2009). We focus on price uncertainty because it crucially affects future demand and ultimately determines the success of a project (Holland et al. 2000). In general, high price uncertainty signals considerable risk and subsequently influences developers to delay the listing in an effort to capture the option values attached to future higher prices (Grovenstein et al. 2011). Nevertheless, if developers could hedge the price uncertainty risk with presales, then they may not delay the listing, thereby avoiding the cost of waiting (Lai et al. 2004). For example, Li and Chau (2018) provided empirical evidence for the effectiveness of presale as a hedging tool against future price fluctuations. We extend their analyses to investigate how real estate developers choose between the two tools to mitigate the risk of price uncertainty.

We test our hypotheses using data from Hong Kong for two reasons. First, the unique presale scheme of the Hong Kong property market offers great flexibility for investigating our research question. Presale allows developers to start sales well before the project is completed. This strategy is prevalent in Asia in general and in Hong Kong in particular. The Hong Kong property market is volatile and has relatively restricted financing options for real estate developers. With presale options, Hong Kong developers can finance through prepayment gathered from buyers at early development stages and lock-in buyers to hedge the price uncertainty risk. This unique market setting provides us with the opportunity to investigate how developers choose between waiting and preselling. Second, the Hong Kong property market is characterized with short, but unstable cycles. Our sampling period is between 1995 and 2015, thereby covering a full market cycle (see *Figure 1*). During this time, the Hong Kong

[1] Because we use data from the Hong Kong residential property market, the option to wait by controlling the pace of construction is not considered. Under the leasehold property right system in Hong Kong, the value of delaying development is limited given the short window (i.e., typically four years including the construction time after the acquisition of the land parcel) allowed for development delay in land leases. Developers do not have much room for maneuver in terms of development timing. In comparison, developers enjoy improved flexibility in selecting the timing of listing, particularly when given the option to presell. Considering that the timing of listing is highly important and useful for developers in Hong Kong, our strategy is to focus on the value of delaying listing.

government adjusted its policies on presale schemes in order to regulate the market. This situation provides us with a natural experiment field to study the impact of government regulations on the effectiveness of presales as a hedging tool. In addition, our findings will bridge a gap in the literature because previous studies rarely have the opportunity to cover a full cycle in their sampling periods.

[Insert *Figure 1* here]

Our dataset includes over 500 residential development projects completed between 1995 and 2015. This dataset contains comprehensive information of market conditions, the characteristics of developers, and property attributes. This material enables us to effectively and reliably test our hypotheses. We estimate a fully parametric hazard model to identify the determinants of the listing for sales and consider the endogeneity of the presale choices. The results show that the presale option substantially impacts the developer's sale decision. In particular, developers show considerable inclination to delay the listing in uncertain market conditions when the presale option is unavailable. This outcome confirms the role of the "waiting tool" as verified by Qian (2013). Conversely, if the option to presell is available, then developers are less likely to implement the "waiting tool" but seek to accelerate the sales. The reason for this circumstance is that presale can mitigate the price uncertainty risk and subsequently reduce the necessity to implement the "waiting tool". Moreover, the flexibility of presale schemes is a strong moderator of the aforementioned presale effect. Developers facing limited presale schemes are less likely to presell when the expected future price volatility increases because the "preselling tool" is less effective in hedging the risk. Our results highlight the importance of considering alternative tools (i.e., presale) to hedge the risk of price uncertainty and the role of government regulations in this line of research.

The remainder of this paper is organized as follows. Section 2 provides a brief overview of the property development and presale schemes in Hong Kong. Second 3 introduces the analytical framework and testable hypotheses. Section 4 describes our empirical methods and data to test the predictions. Section 5 discusses the empirical results. The last section concludes.

2 Property Development and Presale Schemes in Hong Kong

In Hong Kong, land is owned by the government and distributed by leases. Under the leasehold system, the scale of the sale flexibility embedded is closely affected by the government through land lease terms and other regulatory arrangements that control the sale. Real estate firms in Hong Kong typically use three methods to obtain land for development: they can acquire land from public auction and tender, draw on their own land bank, or purchase it from the open market (Shen and Pretorious 2013). In the first method, the government decides the amount of land to be released to the market annually and firms must compete to acquire available land. The second method relies on the firm's own land bank collected in its early years with long-term leases. These land lots are often located at the rural-urban fringe at the time of purchase but with prospects to develop profitably in the future. Firms can wait until the market state becomes favourable and pay a premium to the government for conversions, that is, replace the existing leases with new ones with revised development rights for another 30-50 years (Yao and Pretorius 2013). Once the conversion right is granted, such right enables firms to commence development. The third method refers to purchasing the land lot from the market. These land lots have existing residential properties that are often under poor maintenance for years. Developers must work with the majority of the sitting owners of these properties to agree on a redevelopment plan. Redeveloped sites will have improved amenities and high density, such that developers can not only home existing owners but also sell the remaining flats for profit. Given that the residential property market in Hong Kong is dominated by multi-family apartment buildings, negotiation between developers and property owners is often complicated with holdout flats, defective titles, and untraceable owners (Chau and Wong 2014). Therefore, this type of project is limited to small-scale redevelopments.

In Hong Kong, the timing of property sales by developers is regulated by two types of constraints: development and sales time constraints. Development time constraints are imposed by the government in the building covenant clause in land leases, for the first two cases only (i.e., leasing directly from the government or land bank). This clause is a regulatory requirement to complete the land development within a certain period from the date when the (new) lease was granted. The prescribed period is typically 48 months. Development constraints were intended to accelerate the construction, thereby hastening the sales to meet the demand for newly-built housing. The third case (i.e., private redevelopment) is generally unaffected by development time constraints. Developers in this case are only bound by the agreements with existing owners on site and development time can extend beyond the 48 months prescribed in the building covenant clause in land leases (Shen and Pretorious 2013).

Sales time constraints come in the form of the consent scheme, in which the right to presell is granted by the government to eligible developers. This scheme applies to the first two cases only. Moreover, this scheme aims to reduce the consumer's exposure to the developer's default risk because of financial problems. In particular, consent to presale will only be given to a developer if its financial arrangement for the project and the stage of development meet certain criteria[2]. The maximum presale time prior to building completion is limited to 24 months. The third case (i.e., private redevelopment projects) is categorized as the non-consent scheme with no timing limit and consent requirement for presales.

The constraints on the presale scheme mainly arose because of the prevalence of its use in Hong Kong's housing market. Developers presell their new projects to the market considerably before completion to transfer financial risk. Meanwhile, the presale scheme allows homebuyers to secure future ownership of a housing unit with a low deposit or create a geared option with the expectation of reselling it for profit before completion. This condition resulted in the emergence of rampant speculation during previous housing boom periods and subsequently prompted the Hong Kong government to regulate the presale market. For example, in mid-1994, the resale of uncompleted flats was prohibited, while the permitted period of presale on the supply side was reduced to a maximum of 9 months prior to the anticipated completion (Lands Department of HKSAR 1999). These restrictions considerably deterred home buyers and developers from entering into presale contracts. Not until the decline of the property market in late 1997 did the government consider relaxing them. The relaxation measures announced in 1998 include the extension of the permitted presale period to a maximum of 15 months and the suspension of the sub-sales restriction on uncompleted flats.

Presale restrictions substantially affect the flexibility of the use of the presale scheme. For example, developers facing extended presale period could potentially gain extensively by leveraging the presale tool. All else being equal, the earlier they can sell uncompleted properties, the lower the cost of financing the development projects and the greater flexibility for managing future price uncertainty. By contrast, considerably restricted presale conditions provide developers with limited room to time the market, and thereby reducing their effectiveness in mitigating market risk. Although the use of the waiting tool primarily relies on the market, the utilization of the presale tool is significantly affected by government regulations. Therefore, the role of government regulations should be considered when analyzing the

[2] At present, consent can be given if the foundation works of the development have been completed and if approval has been given to commence construction works on the superstructure.

developers' choice between the waiting and the presale tools. In this sense, the changes in the presale constraints sanctioned by the Hong Kong government during our sampling period provide a testing ground for the role of government regulations on the effectiveness of presales to mitigate market risks.

3 Analytical Framework and Testable Hypotheses

Delaying a project has long been recognized as an effective strategy to mitigate the risk of price uncertainty. Titman (1985) explicitly modelled the value of the "option to wait" in real estate investment. He viewed a vacant land as a real option and determined that the option to develop becomes considerably valuable with immense uncertainty regarding the price changes over time. Subsequent studies have focused on analyzing the impact of different types of uncertainty on aggregate real estate development and land values using several different data sources (e.g., Quigg 1993, Holland et al. 2000, Capozza and Li 2001, Cauley and Pavlov 2002, Cunningham 2006, Guthrie 2010, Wang et al. 2016). These empirical evidences consistently proved that uncertainty delays development and increases land value.

This well-tested framework applies to the relationship between the decision of sales timing and the risk of price uncertainty as well. We follow this line of research to develop our analytical framework and testable hypotheses. For simplicity, the impact of the risk of price uncertainty on the developer's decision to sell can be obtained using the following equation:

$$\mathrm{P}(S = 1) = \alpha + \beta VOL + \gamma X + \varepsilon, \tag{1}$$

where S is a dummy variable that equals 1 for a decision to sell and 0 otherwise, $\mathrm{P}(.)$ is the probability function, VOL is the risk of price uncertainty, X is the matrix of the control variables, and ε is the random error.

Titman (1985) proposed the following general prediction of real option theory with respect to the real estate market: uncertainty with future housing prices should reduce the likelihood of current development investment. The same logic applies to the developers' decision about when to list their newly-built properties for sale. When the future market direction is uncertain, developers might risk underpricing the units if listing early. Pricing too low may lead to a quick sale but also a potential loss of profits. Subsequent price adjustments are difficult because of price rigidity: price increases are not easy due to the anchoring effect of the opening prices (Leung and Tsang 2013, Bucchianeri and Minson 2013). Therefore, uncertainty about future housing prices will encourage a developer to delay the listing to minimize the probability of underpricing. We predict a negative effect of price uncertainty on the likelihood of newly-built housing project sale, as expressed in our first hypothesis.

Hypothesis 1: If the uncertainty with future property prices increases, developers are more likely to delay the sale of newly-built housing projects, *ceteris paribus*.

However, delaying listing is not the only tool available to deal with demand uncertainty. The long lead-time between land acquisition and the sales of completed properties generates a great level of uncertainty, particularly in a volatile market. For example, if land was acquired during housing booms, then a profitable development may become unviable should recession hits the market before the project is completed. Developers who are averse to such a risk can share it with prospective buyers through a presale contract (Chang and Ward 1993, Tse 1998, Deng and Liu 2009). Lai et al. (2004) modelled a presale decision in a real-option framework and suggested that the use of presale is primarily for a risk-sharing purpose. By selling uncompleted or even unconstructed properties, developers can reduce the risk of bankruptcy and the cost of holding inventory. Therefore, developers have another option by starting the sale well before the project is completed in order to minimize the impact of demand uncertainty.

The role of presales on the developers' decision to sell has received limited attention in the literature because such an option is not available in all markets. One of the few studies was by Li and Chau (2018), which demonstrated that Hong Kong developers tend to reduce their exposure to the risk of future price fluctuations through presales. We extend the work of Li and Chau (2018) and augment Equation (1) as follows:

$$\mathrm{P}(S = 1) = \alpha + \beta VOL + \theta(VOL \times PRE) + \gamma X + \varepsilon, \qquad (2)$$

where PRE is an indicator of whether a developer exercised the option to sell their properties before completion. When developers sold uncompleted properties and subsequently mitigated the risk of price uncertainty, we expect a reduction of the overall response of the developer to the risk of price uncertainty (VOL). We model this dynamic relationship by introducing an interaction term between VOL and PRE. The coefficient of this interaction term is expected to be positive, thereby generating the second hypothesis to be tested.

Hypothesis 2: Presales can reduce the effect of the price uncertainty risk on the probability to sell, *ceteris paribus*.

The effectiveness of using presales to hedge the risk of price uncertainty is confined by government regulations. The government controls the two most important parameters in presale schemes: who qualifies to presale and when presale can start. Therefore, how government regulations affect the effectiveness of the presale tool should be analysed. We expect that extensively constrained presale schemes have limited effectiveness in reducing the impact of price uncertainty risk on the probability to sell. By introducing a regulation dummy variable REG into Equation (2), we use the interaction term among market risk, presale, and regulation to capture this effect.

$$\mathrm{P}(\mathrm{S} = 1) = \alpha + \beta VOL + \theta(VOL \times PRE) + \delta(VOL \times PRE \times REG) + \gamma X + \varepsilon, \qquad (3)$$

where $\beta < 0$, $\theta > 0$, and $\delta < 0$. X is defined previously. This equation leads to our third hypothesis as follows:

Hypothesis 3: Constrained presale schemes are less effective in reducing the effect of the price uncertainty risk on the probability to sell, *ceteris paribus*.

4 Empirical Implementation

We extract detailed information on transaction data of condominium flats in Hong Kong from the Economic Property Research Centre (EPRC) database. The corresponding land and project information are obtained from the Building Department of HKSAR. The dataset consists of 521 residential housing projects built by listed developers between 1995 and 2015, which are distributed among the 53 districts in Hong Kong as defined by EPRC. We estimate Equation (3) with a parametric hazard model to investigate the determinants of sale timing. This approach enables microdata analysis of the sale timing for each individual project in a duration model. Unlike the common use of aggregated, market-level data in a reduced-form supply equation in the real option literature (e.g., Holland et al. 2000), a hazard model incorporates both the property-level and developer-level characteristics. This feature allows for the investigation of sale decision by individual developers, instead of the joint decision by the real estate development sector.

To implement this empirical strategy, we introduce time into Equation (3) to obtain Equation (4), which is subsequently estimated using the parametric hazard model.

$$h(t) = exp\ (Z'\omega)h_0(t), \quad (4)$$

where $h(t)$ measures the conditional probability of sale occurring at time t, which is routinely called the hazard rate; Z consists of VOL, $VOL \times PRE$, $VOL \times PRE \times REG$, and X as previously defined; ω is a vector of the coefficients to be estimated, and $h_0(t)$ is the baseline hazard[3] that defines the hazard rate when all explanatory variables are equal to 0.

In a fully parameterized hazard model, a start time and an end time must be specified to measure the duration (i.e., the length of waiting). The timeline of typical real estate development in Hong Kong is illustrated in *Figure 2*. T_1, T_2, and T_3 denote the officially recorded date when the land is ready for construction, the date when construction starts, and the date when construction completes, respectively. TE is the end of the waiting duration or the date of the start of listing. Notably, we use dashed lines for symbols corresponding to TE, because the location of TE varies according to the developer's decision to wait or to presell. In *Figure 2* we only provide one possible location of TE for illustration purposes; it is corresponding to a developer's decision to sell after completion. Should a developer decides to exercise the option to presell, the location of TE would be either between T_2 and T_3 (under the consent scheme) or between T_1 and T_3 (under the non-consent scheme). For consent scheme projects, the developers can only start presales once the construction starts. In practice, the start date of the waiting duration (i.e., TS_C) is typically three months[4] after T_2. Therefore, the duration of waiting for consent scheme projects (denoted as WD_C) is the difference between TS_C and TE. The start date of the waiting duration of non-consent scheme projects (i.e., TS_{NC}) can be as early as T_1. However, not all non-consent scheme projects have reliable records of when the land is ready for construction. In our database, the average waiting duration for non-consent scheme projects with available starts is 36 months. Therefore, we use 36 months before listing as the start date for non-consent scheme projects with missing T_1[5]. The duration of waiting for non-consent scheme projects, that is, WD_{NC}, is calculated as the difference between TS_{NC} and TE.

[Insert *Figure 2* here]

Figure 3 depicts the distribution of waiting duration in our sample. The mean duration is approximately 24 months. That is, a developer waits for an average of two years to start selling. The majority of the housing projects are listed for sale within 40 months of waiting. The long wait suggests considerable flexibility for developers to choose the optimal sale timing. In total, the 521 residential projects are transformed into 12,236 observations because the time-span records of a single project are split into monthly records. This method of expansion is necessary

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3 We assume a Weibull baseline hazard with the function form of $h_0(t) = \lambda p(pt)^{p-1}$, where p is the shape parameter to be estimated. The hazard of a new housing project sale should increase with time because retaining the land uncompleted or the completed projects vacant would generate additional costs, such as financing and inventory expenses. Therefore, we expect $h_0(t)$ to increase monotonically with time, that is, $p > 1$.

4 The three-month time for preparation for sales under the consent scheme is identified by surveying the sales pattern in our dataset. When this date occurs before the earliest time allowed for presales (i.e., 24 months before the completion of construction), the later late is chosen as the start date.

5 We performed robustness checks by varying the average waiting time into 42 months and 32 months and the results were similar.

because a few of our covariates (Z) vary with time. *Tables 1* and *2* provide the definition of the variables included in Z and the corresponding summary statistics, respectively.

[Insert *Figure 3* here]

[Insert *Table 1* and *Table 2* here]

4.1. Measurement of the price uncertainty risk

We follow Cunningham (2006) to compute a GARCH (1,1) measure of price uncertainty risk. First, we calculate the annualized housing price return[6] $R_{j,t}$ for district *j* at time *t* as follows:

$$R_{j,t} = 12log\left(\frac{P_{j,t}}{P_{j,t-1}}\right), \quad (5)$$

Thereafter, we specify the following mean equation by regressing $R_{j,t}$ against its six-month-lagged terms:

$$R_{j,t} = \alpha_{0j} + \sum_{\tau=1}^{6} \alpha_{\tau,j} R_{j,t-\tau} + e_{j,t}, \quad (6)$$

where $e_{j,t} \sim N(0, \sigma_{j,t}^2)$. We likewise construct the variable VOL_j, which is the measurement of price uncertainty risk for district j, by regressing $\sigma_{j,t}^2$ on a one-month-lagged squared residual ($e_{j,t-1}^2$) and a one-month-lagged conditional volatility estimate ($\sigma_{j,t-1}^2$) as follows:

$$\sigma_{j,t}^2 = \gamma_{0j} + \gamma_{1j} e_{j,t-1}^2 + \delta_{1j} \sigma_{j,t-1}^2 \quad \text{and} \quad (7)$$

$$VOL_j = \hat{\sigma}_{j,t}^2, \quad (8)$$

We generate 53 price uncertainty risk estimates, one for each of the districts included in our analysis. We plot the average value of VOL_j of all districts to illustrate the overall price uncertainty risk in Hong Kong (see *Figure 4*). Our estimates reliably determine the surge of uncertainty around the time of the Handover and the Asian financial crisis in 1997, the 2008 global financial crisis, and the frequent adjustments of stamp duty charges since 2013.

[Insert *Figure 4* here]

4.2. Measurement of the presales

The definition and measurement of the presale option is essential for testing *Hypothesis 2*. Our observations represent exercised presale options because our dataset contains historical transaction records only. Therefore, we assume that a developer's action of exercising the presale option is consistent with their intention to exercise such option because the developers' intention to presell are unobservable. We define an indicator of presale decision (PRE) equal to 1 when the developer has sold properties before completion. However, development projects with a very small proportion of presales (e.g., less than 10% of all units are sold before completion) are often not a result of developers exercising presale options, but rather consequences of peculiar transactions among related parties. For example, a few units might be sold to designated property agents or relationship customers before the completion. These practices are common in Hong Kong. To exclude these non-presale transactions from our

[6] We used the repeat sales price index from the University of Hong Kong Real Estate Investment Series to estimate the price returns.

sample, we select a 10% presale threshold for the definition of PRE. Specifically, only projects with 10% or more units sold before completion have a value of 1 in PRE[7].

$$PRE = \begin{cases} = 1, & at\ least\ 10\%\ of\ the\ units\ in\ the\ project\ were\ sold\ before\ completion \\ = 0, & otherwise \end{cases}, \quad (9)$$

Table 2 shows that approximately half the projects in our sample are engaged in presales, thereby providing us with sufficient observations to test our hypotheses.

4.3. Measurements of the government regulations

To test *Hypothesis 3*, we adopt two measures of government regulations (REG). The first one (REG_1) focuses on a specific period when presales are strictly regulated, whereas the second one (REG_2) identifies a specific type of properties that are considerably affected by presale regulations. Hong Kong developers faced a restrictive environment for presales between 1994 and 1998. To determine the effect of regulative restrictions during this period, we generate a dummy variable REG_1 as follows:

$$REG_1 = \begin{cases} = 1, & the\ transaction\ was\ completed\ between\ 1994\ and\ 1998 \\ = 0, & otherwise \end{cases}, \quad (10)$$

Note that the presale restrictions in 1994-1998 were mainly imposed on the consent scheme projects. Hence, we generate another dummy variable REG_2 to determine the difference.

$$REG_2 = \begin{cases} = 1, & the\ housing\ project\ is\ under\ the\ Consent\ Scheme \\ = 0, & otherwise \end{cases}, \quad (11)$$

Table 2 shows that approximately 12.4% and 60.6% of our observations are from 1994-1998 and consent scheme projects, respectively.

4.4. Control variables

We include three groups of variables to control for market heterogeneity over time (i.e., market movement), across space (i.e., project characteristics), and among developers.

To determine the market price movement over the sampling period, we use last month's price index as the measurement of the current market price (denoted as CUP). We expect that CUP will have a positive coefficient loading as a lower market price often means that the benefit of an immediate sale is smaller than the opportunity cost, thereby causing developers to delay the sale. Developers often form certain expectations with future market price based on historical trends. These expectations could affect their decision to sell. We construct three control variables to determine these effects: the price index changes in the last 12 and 24 months (expressed as $EXPC_1$ and $EXPC_2$, respectively) and the changes of market rental yield in the last 12 months ($MYDC$). We also consider the change of housing supply over time. In particular, we include the number of units from other developments (SUP) within a 1-km radius of the project that are being sold or about to be placed on sale.

To account for the heterogeneity among developers, we consider two important aspects in property development, namely, financing and scale. Property development is costly because of the long lead time and high capital investment in construction. Developers must often finance

[7] We conducted sensitivity tests by increasing the presale proportion threshold to 20% and 30%. The results are consistent across all three definitions.

their projects at considerable cost, particularly when the credit market is tight. Developers under immense financing pressures tend to sell sooner. To consider the differences of the financial conditions among developers, we use two variables to measure the developer's financing cost: the real interest rate of the market (RIR) and developer's debt-to-equity ratio (DER). RIR is a market-level measurement of financing cost that applies to all developers, while DER quantifies the individual developer's financial constraints. Firms with numerous housing projects in their pipeline and/or with many partners on the same project often prefer to recover their investment early. We include two variables to measure the scale of development firms. Specifically, we calculate the percentage of housing projects completed by each developer in the following year as a measurement of its development scale (SCA) and a dummy variable (JOT) to indicate whether the project is jointly developed with other development firms.

Control variables on the project level include the scale of the development ($SIZE$), land price (LVA), average saleable floor area per flat (SFA), and percentage of flats with sea view (SEA). $SIZE$ is defined as the number of flats in the same project (or the same phase if the project is developed over multiple phases). LVA is derived from the coefficient estimates of the district dummies in a hedonic price model (see Wong et al. 2012). SFA is the average of the saleable floor area of all flats in the same project. SEA is calculated as the percentage of flats with a sea view in each project. These variables are routinely included in studies on the Hong Kong residential property market (e.g., Chau and Wong 2014, Li and Chau 2018) and are sufficient to determine the majority of the variations among the development projects in our sample.

Other than the previously mentioned three groups of control variables, we also include the developer and seasonal fixed effects to determine any developer-specific or temporal factors that may be missing from our models.

4.5. Endogeneity

In our empirical models, the decision to presell (i.e., PRE) enters the estimation as an exogenous variable. Nevertheless, a few of the control variables included in the same model will inevitably affect the decision to presell, as well as the timing of sales (i.e., the dependent variable). Evidently, this condition violates the exogeneity assumptions on the independent variables and could cause serious biases in the coefficient estimations in Equation (4). To address the endogeneity issue, we use the full information maximum likelihood (FIML) estimator for the Weibull durations proposed by Boehmake et al. (2006). This technique is also one of the commonly adopted approach in the literature (see Tang and Wang 2017). That is, FIML simultaneously estimates the selection equation of PRE and the hazard model to yield consistent standard errors.

We use the presale group as an example. For the first step, we model the presale choices as in Equation (12).

$$\Pr(PRE|\,Y) = \exp(Y'\delta)\theta_i, \tag{12}$$

where θ_i is the error term, which follows an exponential distribution; Y refers to the exogenous factors that may affect the presale choices; and δ represents the coefficients to be estimated.

We follow Li and Chau (2018) to estimate Equation (12). The matrix Y includes the majority of the independent variables in the hazard model (i.e., VOL, $EXPC_1$, $EXPC_2$, DER, RIR, SCA, REG_1, REG_2, LVA, SFA, and SEA) and two additional instrumental variables: gross floor area (GFA) and ratio of GFA to the useable floor area (RGU). Chau and Choy (2011) provided empirical justifications for using GFA and RGU as valid instrumental variables in similar studies.

For the second step, we combine Equation (4) and Equation (12) in a maximized likelihood function as follows:

$$\Pr(T, PRE) = \prod_{i=1}^{n}[h(t_i) \times \Pr(PRE_i = 1 | T_i = t_i)]^{PRE_i} \times \Pr(PRE_i = 0)^{1-PRE_i}, \quad (13)$$

where T_i denotes the duration between the start and the end time for project i, where the start and end time are defined previously. The first term on the right-hand side represents the probability density for duration as calculated using Equation (4). PRE_i indicates the binary censoring variable, while the last two terms on the right-hand side represent the probability of presale and non-presale, respectively, which can be derived from Equation (12). By maximizing Equation (13), we can obtain the unbiased coefficients for the hazard model (i.e., Equation (4)), the presales selection model (i.e., Equation (12)), and the error correlation between the two. To obtain the same estimations for the non-presales group, we can simply replace PRE in Equation (13) with $NPRE$, which equals 1 if the project has less than 10% of the units sold before completion and 0 otherwise.

5 Empirical Results

5.1. Main findings

We first estimate Equation (4) using all observations (i.e., with presale and non-presale projects combined). The baseline model results are given in column (1) of *Table 3*. The hazard model is statistically significant, as indicated by the value of the Weibull parameter estimate, p. Specifically, $p > 1$ at all standard significance levels. This outcome suggests a strongly increasing hazard of sales over time that is consistent with theories and empirical observations. The parameter estimates on the control variables also conform well with the predictions. However, the limitation of the baseline model is also evident. For example, the estimated parameter on price volatility (VOL) registers a positive but insignificant sign. This finding suggests that price uncertainty alone is not a deterrent to project sale, thereby providing no support for *Hypothesis 1*. Overlooking the role of the presale option led to significant bias in the estimations. Thereafter, we estimate Equation (4) with presale and non-presale subsamples separately. The results are given in columns (2) and (3) in *Table 3*, respectively. This approach introduced a few improvements over the baseline model because the coefficient estimate for VOL in the presale subsample model is now positive and significant. Nevertheless, the results of the non-presale subsample model remain insignificant. Our final models, which consider the effect of presale options with correction for endogeneity, generated convincing results (see *Table 4*).

[Insert *Table 3* and *Table 4* here]

In panel A of *Table 4*, we display the probit results based on Equation (12) to analyze the determinants of presale choices. We find significant effects from the majority of the variables, including the two instrumental variables. Projects of large scale and high ratio of gross floor area to saleable floor area are associated with a higher probability of presale. This outcome is consistent with the existing literature (Chau and Choy 2011). An increase in price volatility also increases the likelihood of presale relative to non-presale, thereby confirming the role of presale in hedging against future price fluctuations. These results lay the foundation for the correction of endogeneity in the estimation of the hazard model in Equation (13).

Multicollinearity is a concern given the number of interaction terms involved in our final models. To demonstrate the robustness of our empirical estimations, we present the results in three steps in panel B of *Table 4*. Specifically, we start with Equation (13) with VOL and the control variables first. Thereafter, we add the two regulation variables (REG_1 and REG_2) and their interaction terms later. These three models are labelled as Specifications (i), (ii), and (iii), respectively. To facilitate comparison, we list the results of presales and non-presales subsamples using Equation (13) separately in columns (1) and (2). The coefficient estimates of the control variables are not presented for simplicity, but are available from the authors upon request.

First, the error correction parameter *Rho* is significant and positive across the board. This outcome indicates that the effect of presales selection bias is not negligible because *Rho* measures the correlation between the error terms of the presales selection equation and the hazard equation. In addition, the benefit of correcting the endogeneity problem is evident from the coefficient estimates of VOL, which are significantly lower than those in *Table 3*. The statistical significance of these coefficient estimates also improved considerably. That is, the presale selection model separates the net effect of VOL on presale decisions from the net effect of VOL on the hazard ratio of sales. Subsequently, the coefficient estimates of VOL in Panel B are considerably low. Therefore, our strategy of combining Equations (4) and (12) is justified.

Second, the coefficient estimates of VOL and its interaction terms with the regulation variables remain generally consistent across the three specifications. This outcome suggests that our findings are robust to the multicollinearity issue. We then focus on the final model (i.e., Specification (iii)) to test the three hypotheses.

To separate the net effect of the presale options and government regulations, we include three interaction terms between VOL and the regulation dummies. This approach effectively divides our samples into eight categories (see *Table 5*). The overall effect of VOL is calculated by using the coefficient estimates of VOL and its interaction terms (see *Table 5* notes for details). To test *Hypothesis 1*, we use the estimated overall effect in row (1) because the presale option was strictly restricted during this period. This approach reveals the net response of sales timing to price uncertainty risk without the confounding effect of presales. The overall effect of VOL is negative for all four groups of flats in this row. This outcome suggests that when the price uncertainty risk increases, developers are likely to postpone sales in order to mediate the risk. Hence, *Hypothesis 1* is supported.

[Insert *Table 5* here]

When restrictions on presale options were lifted (i.e., during the non-restricted period), the "risk hedging" effect of the presale option was evident. Specifically, row (2) of *Table 5* shows that the coefficient estimates of VOL of the presale group are considerably larger than those of the non-presales group, to the extent that the coefficient changed signs. An increase in the price uncertainty risk encourages developers with presale options to exercise the options early because this method is an effective way to recover investment. The positive, moderating effect of PRE on sales timing is sufficiently strong to offset the negative effect of VOL and results in an overall positive loading of VOL in the two presale subsample models. This outcome offers support for *Hypothesis 2*.

The difference between the results given in rows (1) and (2) in *Table 5* demonstrates the effectiveness of government regulations regarding presale options (i.e., the effect of REG_1). When the Hong Kong government imposed strict presale conditions between 1994 and 1998, the "hedging" effect of presale options was extremely limited, especially in the consent scheme group. By contrast, when the restrictions were removed later, the "hedging" effect was identified consistently in our models. However, with regard to the effect of REG_2, the consent scheme appears to have limited impact on the exercise of presale options among Hong Kong developers. That is, the patterns between the consent scheme and non-consent scheme groups in row (2) in *Table 5* are very similar. One possible reason is that the majority of developments in Hong Kong were completed within two years. Hence, the maximum presale time prior to building completion for consent scheme projects (i.e., 24 months) is an ineffective regulatory tool. The Hong Kong government must have already realized the limitation of the consent scheme because the restrictions imposed in 1994−1998 mainly dealt with the maximum presale time prior to building completion (e.g., it was changed from 24 months to 9 months). The new presale regulations effectively grounded presales to a halt for the majority, if not all, of the consent scheme projects during that period. However, the effect of the presale regulations was substantially limited because the non-consent scheme projects are far less regulated (e.g., they can start preselling flats before the construction commences, which is not allowed for the consent scheme projects). That is, the estimated overall effect of VOL for the presale subgroup under the non-consent scheme is −0.093, which is higher than that of the non-presale subgroup under the same scheme (i.e., −0.756). Therefore, our evidence supports *Hypothesis 3* because the moderating effect from government regulations is significant.

5.2. Cross-sectional effect of VOL

Real estate markets are often characterized with considerable heterogeneity among products and agents. Therefore, developers' responses to price volatility might vary cross-sectionally. For example, large developers might be less likely to exercise presale options to hedge price uncertainty risk because they have different risk preference compared with small developers. In this section we conduct further examination on the cross-sectional effect of VOL by subdividing the whole sample by the size of developers, the size of apartments, and the location of the projects. Specifically, we re-estimate the *Specification (iii)* of *Table 4* by using these subsamples, and the results are given in panels B, C, and D of *Table 6*, respectively. To facilitate comparison, we follow *Table 5* to report the coefficient estimates of VOL and its interaction terms. The corresponding coefficient estimates from the whole sample are also included in panel A of *Table 6*. Because presale regulations (i.e., REG_1) affected consent scheme projects primarily (see the discussions in section 5.1), we show the coefficient estimates of consent scheme groups only in *Table 6*.

[Insert *Table 6* here]

Panel B of *Table 6* gives the results using large- and small- developer subsamples separately. Large developers include Cheung Kong Holdings, Sun Hung Kai Properties, Henderson Land, New World Development, and Sino Land, which together account for over 70% of the market share (Wong et. al. 2018). The results of the subsamples in the restricted and non-restricted periods are largely consistent with what we have found using the whole sample. When comparing the two columns in panel B, we find that small developers are more sensitive to price volatility in exercising the sale option. Specifically, as shown in row (1) of panel B, when the presale option was strictly restricted, small developers are more likely to postpone sales responding to price volatility increases. When presale restrictions were lifted (see row (2) of panel B), they again show stronger willingness to accelerate the sales. Comparing rows (1) and (2) of panel B, presale restrictions have a greater effect on the sale timing of small developers than large developers. One possible reason for such a pattern is that small developers are more financially constrained, and subsequently more likely to exercise presale options to secure funding. However, the financing constraint factor has already been controlled for by including the debt-to-equity ratio (i.e., DER) in the models. A more plausible explanation is that small developers often have shorter planning horizon, which leads them to be more prone to myopic loss aversion, and therefore would be more sensitive to perceived risks.

Second, the effect of VOL may vary among projects with different saleable floor areas. We adopt the classification system of the Rating and Valuation Department of HKSAR to divide our sample into luxury-unit ($SFA \geqslant$1,000 sq.ft.) and mass-unit (SFA<1,000 sq.ft.) subsamples. According to the estimation results given in panel C, the presale options are more valuable for mass-unit projects than for luxury-unit projects in hedging against the price volatility risk. Buyers of mass units are usually more financially constrained than buyers of luxury units. Financially constrained consumers are likely to buy presale properties because they fear that their planned savings would be insufficient to purchase the same property when it is completed (Lai et al. 2004). This situation makes presale a popular option for mass-unit projects when the market is volatile, and developers respond to this demand accordingly. This financial constraint from the demand side is not factored in our models. The submarket analysis in panel C captures this effect indirectly.

Last, we compare the overall effect of VOL between over- and under-developed regions in Hong Kong. Among the three administrative districts in Hong Kong, the older districts, namely, Hong Kong Island and Kowloon districts, have been over-developed with limited sites for new development. By contrast, the New Territory district was only developed in recent decades and thus has more new development supply than the other two older districts. *Figure 5* shows that the volatility of residential property prices in Hong Kong Island and Kowloon is much higher than that in New Territory. Evidently, these two regions should be treated differently. The effects of VOL on these two regions are given in panel D of *Table 6*. During both the presale restricted and non-restricted periods, the influence of price volatility on presale timing is high in the over-developed region of Hong Kong. This finding suggests that the presale option is valuable when the underlying market is volatile.

[Insert *Figure 5* here]

In summary, we identified cross-sectional variations in the effect of VOL between large and small developers, mass and luxury development projects, and over- and under-developed regions in Hong Kong. On one hand, the results presented in this section provide interesting information about the variations of the estimated effect of VOL. On the other hand, the findings should be interpreted with caution as some of the subsample is substantially small (e.g., the sample size of luxury-unit presale subsample is only 952). Therefore, coefficient estimates from smaller samples are sometimes inconsistent with that of the whole sample, and should be further verified when more data are available for future research.

5.3. Robustness check

The measurement of price uncertainty risk is a complex and challenging undertaking. That is, there is no universally agreed theories or models available for such measurement. Meanwhile, the measurement of this construct is central to our analysis; any measurement errors may significantly bias the results. Accordingly, the robustness of our findings should be checked by re-running the models with an alternative measurement of price uncertainty risk. We follow the common practice in the literature by using the near term past information as the alternative measurement (see Cunningham 2006, 2007). In particular, we generate a new variable $HVOL$

based on the moving variance of past returns and re-run the models by replacing VOL with $HVOL$. Alternative rolling window sizes (i.e., 6, 12, and 18 months) are also considered to calculate $HVOL$. For example, the one-year moving variance of annualized price return is calculated by using Equation (14) and Equation (15).

$$\sigma_{j,t}^2 = \sum_{k=1}^{12}(R_{j,t-k} - \overline{R}_{j,t})/11 \quad \text{and} \tag{14}$$

$$HVOL = \hat{\sigma}_{j,t}^2, \tag{15}$$

where: $\overline{R}_{j,t} = \frac{1}{12}\sum_{l=1}^{12} R_{j,t-l}$, while $R_{j,t}$ is defined previously.

Table 7 provides the three sets of new results using $HVOL$. These results are generally consistent with our findings (see *Table 4*). Thus, we conclude that our empirical findings are robust to the alternative measurements of price uncertainty risk.

[Insert *Table 7* here]

6 Conclusions

The risk of price uncertainty is high in real estate development markets. This study deals with the sale strategies of real estate developers to mitigate such risk. Developers have two tools at their disposal in relation to sales timing: to wait or to presell. The existing literature establishes the benefits of both strategies. However, conflicting findings are also common. For example, Bulan et al. (2009) determined that price volatility encouraged developers in Canada to wait, while Wang et al. (2016) reached the opposite conclusion by using data from China. The reason for this disparity is that previous studies tend to investigate these two strategies in isolation, whereas both tools operate in practice. Furthermore, overlooking the intervening relationship between the two tools can bias the estimation of the effect size. Our analytical framework facilitates the holistic investigation of the mechanism of the waiting and presale tools in the real estate development market. The proposed model adds value to the literature by offering alternative explanations for conflicting results in existing studies. For example, Wang et al. (2016) determined that price volatility has a positive effect on development speed when demand is declining. Their explanation for such a counter-intuitive finding involves the 'recession-induced construction booms' (Grenadier 1996). Given that their data were from a rapidly growing Chinese city and that approximately 80% of residential property sales in China are presales, a considerably convincing explanation may be that the effect of presales was overlooked in their investigations. Therefore, our model provides an opportunity to unify conflicting results in prior research.

In this study, we proposed an overarching framework to simultaneously investigate the effects of the two strategies. We also considered the impact of government regulations on the effectiveness of the presale tool because the presale option is regulated closely by planning authorities. Our hypotheses were tested by using data from Hong Kong. Empirical evidence shows that when the presale option is unavailable, developers tend to delay listing when facing price uncertainty risk. If presale option is available, then developers will accelerate sales when price volatility is high. Moreover, the effectiveness of the presale option depends substantially on the restrictions imposed by the government. The findings will fit other countries and cities that share similarities with the Hong Kong property market. For example, in Singapore, Shanghai and Beijing, the presale practice is very common, price volatility is typically high, and the leasehold property right system significantly limits the developers' flexibility to delay development, and subsequently increases the value of timing the listing. Therefore, our analytical framework can be used to study the strategy of sales timing by real estate developers in these cities as well.

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Tables

Table 1■ Variable definitions

Variable	Acronym	Definition	Data source
Price volatility	VOL	annualized variance estimate from Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model	Repeat sales price index are available from University of Hong Kong Real Estate Investment Series; other market information are compiled from Rating and Valuation Department, Building Department of HKSAR, and EPRC
Presale	PRE	1 at least 10% of the units in the project were sold before completion; otherwise, 0	
Regulation period	REG_1	1 the transaction was completed between 1994 and 1998; otherwise, 0	
Consent scheme	REG_2	1 if the housing project is under the consent scheme; otherwise, 0	
#Market variables			
Current price	CUP	repeat sales price index for each sub-district (one-month lag)	
Expected price change	$EXPC_1$	the price change in previous one year using repeat sales price index	
	$EXPC_2$	the price change in previous two years using repeat sales price index	
Market yield change	$MYDC$	the rental yield change of the housing market in previous one year	
Supply	SUP	the number of flats from other developments (who are being sold or about to be placed on sale within 3 months, and located within a 1-km radius from the project)	
#Developer variables			
Debt-to-equity	DER	the ratio of the book value of debt to the book value of the equity of the developer	Developer information are compiled from Building Department of HKSAR, and Datastream
Real interest rate	RIR	the 12-month Hong Kong Interbank Offered Rate minus inflation rate	
Development scale	SCA	the supply of housing flats by each developer as a percentage of total supply in the following year	
Joint development	JOT	1 if the project is developed by more than one developer; otherwise, 0	
#Property variables			
Project size	$SIZE$	the number of flats in the project or phase if it is developed in multiple phases	Property characteristics are collected from Building Department of HKSAR, EPRC, and Google Map
Land price	LVA	average deflated unit sale price by district derived from the coefficients of sub-districts in a hedonic regression	
Average saleable floor area	SFA	average saleable floor area for unit flats in each project	
Sea view	SEA	the percentage of flats with sea view in each project	

Table 2■ Descriptive statistics for explanatory variables

Variables	Mean	Median	S.D.	Min	Max	Obs.
VOL	0.738	0.676	0.304	0.357	5.066	12,236
PRE	0.463	0	0.498	0	1	12,236
REG_1	0.124	0	0.329	0	1	12,236
REG_2	0.626	1	0.486	0	1	12,236
CUP	136.6	108.3	77.81	39.16	636.5	12,236
$EXPC_1$	0.140	0.064	0.360	−0.611	1.823	12,236
$EXPC_2$	0.093	0.108	0.302	−0.599	1.962	12,236
$MYDC$	−0.020	−0.022	0.116	−0.327	0.386	12,236
SUP	247	4	537.1	0	5120	12,236
DER	0.343	0.262	0.252	0.070	4.314	12,236
RIR	0.023	0.025	0.047	−0.118	0.124	12,236
SCA	0.126	0.109	0.108	0.000	0.451	12,236
JOT	0.222	0	0.412	0	1	12,236
$SIZE$	423	144	567.2	4	3334	12,236
LVA	−0.104	−0.114	0.388	−0.670	0.988	12,236
SFA	1125	677	1171	212	8640	12,236
SEA	0.185	0.000	0.324	0.000	1.000	12,236

Table 3■ Hazard models specification: timing of sale

	(1)		**(2)** Subsample: Presale projects		**(3)** Subsample: Non-presale projects	
Weibull hazard function						
Dependent variable: the hazard rate at time t for property i						
VOL	0.183	(1.0)	0.701***	(2.9)	−0.327	(−1.0)
CUP	0.006***	(5.7)	0.004***	(2.6)	0.002	(1.0)
$EXPC_1$	−0.722***	(−4.2)	−0.269	(−1.2)	−0.901***	(−2.8)
$EXPC_2$	−0.036	(−0.2)	0.149	(0.5)	−0.041	(−0.1)
$MYDC$	0.212**	(2.4)	0.162	(1.5)	0.497***	(2.9)
SUP	1.8E-04**	(2.0)	−2.3E-04*	(−1.9)	4.7E-04***	(3.0)
DER	0.749**	(2.4)	1.516***	(3.9)	−0.442	(−0.7)
RIR	−1.445	(−1.0)	−4.325**	(−2.4)	−0.683	(−0.2)
SCA	2.468***	(3.9)	2.214***	(2.8)	−0.006	(−0.1)
JOT	−0.095	(−0.7)	0.294*	(1.9)	0.888***	(3.1)
$SIZE$	4.2E-04***	(4.5)	5.4E-04***	(4.9)	−0.001***	(−4.7)
LVA	−2.154***	(−10.5)	−1.410***	(−5.2)	−2.583***	(−6.6)
SFA	−2.7E-04***	(−4.2)	−4.4E-04**	(−2.4)	1.1E-04	(1.4)
SEA	−0.218	(−1.3)	−0.033	(−0.1)	−0.240	(−0.9)
Firm fixed effects	Yes		Yes		Yes	
Season fixed effects	Yes		Yes		Yes	
Constant	−12.82***	(−19.2)	-19.24***	(−19.0)	−20.93***	(−14.0)
Weibull parameter p [standard error]	2.359 [0.029]		3.627 [0.038]		4.142 [0.049]	
Observation	12,236		5,580		6,656	
No. of Events	521		335		186	
Log likelihood	−1689		−796		−511	

The estimated hazard model is $h(t) = \lambda p(pt)^{p-1} exp\,(Z'\omega)$. Coefficients are reported in real form (ω) and a standard deviation change in Z leads to a $[exp(1 \times \omega \times p) - 1]$ percent change in the hazard rate $h(t)$. Z-statistics are reported in parenthesis (except for where noted).
* Significant at 10%; ** Significant at 5%; *** Significant at 1%

Table 4■ Correction for Endogeneity

Panel A: Presale Choices Selection				
Variables	(1)		(2)	
Dependent variable	PRE		$NPRE$	
$GFA^{\#}$	2.6E-06***	(7.4)	−1.6E-06***	(−4.9)
$RGU^{\#}$	0.394**	(2.3)	−0.343*	(−1.8)
VOL	0.153***	(3.1)	−0.341**	(−6.6)
$EXPC_1$	0.103**	(2.3)	0.016	(0.3)
$EXPC_2$	0.192***	(2.9)	−0.282***	(−4.3)
DER	0.199***	(3.5)	−0.391***	(−6.6)
RIR	−5.096***	(−12.8)	6.359***	(15.5)
SCA	2.241***	(15.3)	−2.524***	(−17.4)
REG_1	0.674***	(13.5)	−0.599***	(−13.8)
REG_2	−0.036	(−1.1)	−0.023	(−0.7)
LVA	0.240***	(4.8)	−0.146***	(−2.7)
SFA	−6.4E-04***	(−31.0)	8.0E-04***	(31.6)
SEA	−0.057	(−1.3)	−0.044	(−0.9)
Constant	0.204*	(1.9)	0.692***	(6.0)
Observations	12,236		12,236	
Panel B: Hazard function (Weibull with correction for endogeneity)				
Specification (i)	(1) Presale projects		(2) Non-presale projects	
VOL	0.138***	(3.5)	−0.044	(−1.3)
Weibull parameter p [standard error]	1.453 [0.018]		1.467 [0.018]	
Rho (Error Correlation)	0.078***		0.013***	
Wald chi^2	1888***		2059***	
Specification (ii)				
VOL	0.226***	(4.9)	−0.080**	(−2.2)
$VOL \times REG_1$	−0.610***	(−7.1)	−0.296**	(3.1)
REG_1	0.733***	(9.2)	0.809***	(8.8)
Weibull parameter p [standard error]	1.502 [0.018]		1.440 [0.019]	
Rho (Error Correlation)	0.020*		0.079***	
Wald chi^2	1877***		2049***	
Specification (iii)				
VOL	0.192***	(2.9)	−0.054	(−0.9)
$VOL \times REG_1$	−0.285**	(−2.2)	−0.702***	(−2.7)
$VOL \times REG_2$	0.094	(1.2)	−0.071	(−1.0)
$VOL \times REG_1 \times REG_2$	−0.503***	(−3.0)	0.427	(1.5)
REG_1	0.355***	(2.9)	1.240***	(5.6)
REG_2	0.237***	(3.9)	0.419***	(7.4)
$REG_1 \times REG_2$	0.544***	(3.5)	−0.492**	(−2.1)
Weibull parameter p [standard error]	1.540 [0.017]		1.481 [0.010]	
Rho (Error Correlation)	0.028*		0.061***	
Wald chi^2	1880***		2044***	
Observations	5,580		6,656	

Panel A regresses the selection model in Equation (12): column (1) presents the results where the binary dependent variable equals 1 for presale projects and 0 otherwise, whilst column (2) presents the results where the binary dependent variable equals 1 for non-presale projects and 0 otherwise. Variables marked with # are instrumental variables that are not included in the hazard model. Panel B estimates the Weibull hazard model with correction using the FLML estimator proposed by Boehmke et al. (2006) as in Equation (13). Only key results in the hazard equation are presented. Coefficients are reported in real form (ω) and Z-statistics are reported in parenthesis (except for where noted).
* Significant at 10%; ** Significant at 5%; *** Significant at 1%

Table 5■ Estimated overall effect of VOL

	Consent Scheme		Non-consent Scheme	
	Presales (1)	Non-presales (2)	Presales (3)	Non-presales (4)
(1) Restricted period	−0.502	−0.400	−0.093	−0.756
(2) Non-restricted period	0.286	−0.125	0.192	−0.054

The effect of VOL for different groups are calculated as follows: (1) consent scheme projects sold during the 1994−1998 restricted period: the summation of coefficient estimates of VOL, $VOL \times REG_1$, $VOL \times REG_2$, and $VOL \times REG_1 \times REG_2$; (2) consent scheme projects sold outside the 1994−1998 restricted period: the summation of coefficient estimates of VOL and $VOL \times REG_2$; (3) non-consent scheme projects sold during the 1994−1998 restricted period: the summation of coefficient estimates of VOL and $VOL \times REG_1$; (4) non-consent scheme projects sold outside the 1994−1998 restricted period: the coefficient estimate of VOL.

Table 6■ Cross-sectional effect of VOL

	Presales (1)	Non-presales (2)	Presales (3)	Non-presales (4)
Panel A:	Whole sample			
(1) Restricted period	−0.502	−0.400		
(2) Non-restricted period	0.286	−0.125		
Observations	5,580	6,656		
Panel B:	Large developer		Small developer	
(1) Restricted period	−0.453	−0.477	−1.334	−0.206
(2) Non-restricted period	0.264	−0.415	0.533	0.187
Observations	4,146	4,398	1,434	2,258
Panel C:	Mass-unit project		Luxury-unit project	
(1) Restricted period	−0.454	−0.544	−0.697	−0.185
(2) Non-restricted period	0.330	−0.052	0.104	0.034
Observations	4,628	3,772	952	2,884
Panel D:	Hong Kong Island & Kowloon		New Territory	
(1) Restricted period	−0.243	−0.118	−0.753	−0.262
(2) Non-restricted period	0.415	−0.227	−0.070	0.046
Observations	3,366	4,042	2,214	2,614

The effect of VOL in rows (1) and (2) in all panels are calculated as follows: (1) consent scheme projects sold during the 1994−1998 restricted period: the summation of coefficient estimates of VOL, $VOL \times REG_1$, $VOL \times REG_2$, and $VOL \times REG_1 \times REG_2$; (2) consent scheme projects sold outside the 1994−1998 restricted period: the summation of coefficient estimates of VOL and $VOL \times REG_2$.

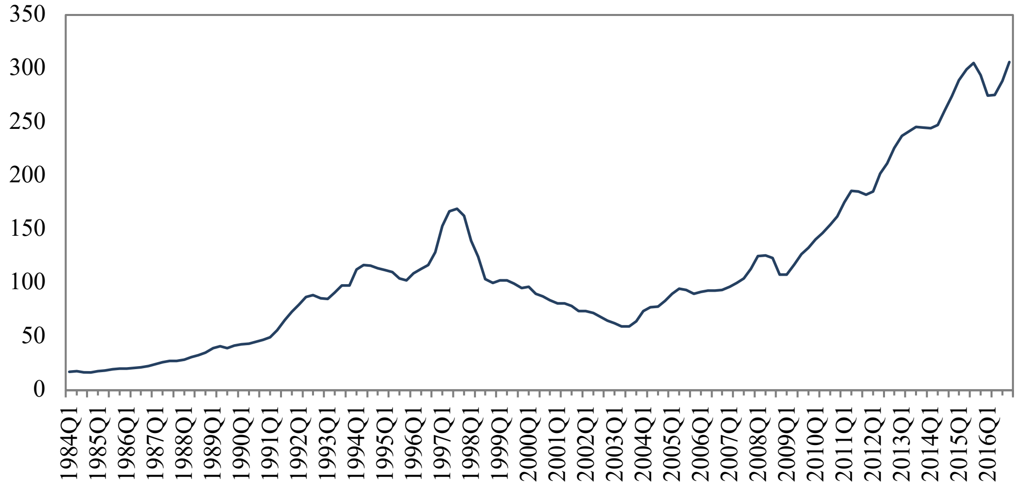
Table 7■ Alternative measures of price uncertainty

Hazard function (Weibull with correction for endogeneity)						
Panel A: Presales	**(6 months)**[a]		**(12 months)**[b]		**(18 months)**[c]	
Specification (i)						
$HVOL$	0.168***	(3.1)	0.296***	(4.3)	0.315***	(3.7)
Rho (Error Correlation)	0.081***		0.027*		0.028*	
Specification (ii)						
$HVOL$	0.299***	(5.2)	0.419***	(6.0)	0.402***	(4.6)
$HVOL \times REG_1$	−1.455***	(−7.9)	−1.983***	(−9.4)	−2.024***	(−8.5)
REG_1	0.760***	(10.3)	0.869***	(9.8)	0.879***	(9.2)
Rho (Error Correlation)	0.017*		0.036**		0.034**	
Specification (iii)						
$HVOL$	0.238***	(2.9)	0.268**	(2.5)	0.294**	(2.3)
$HVOL \times REG_1$	−0.762**	(−2.6)	−1.491***	(−5.0)	−1.324***	(−4.1)
$HVOL \times REG_2$	0.173*	(1.7)	0.245**	(2.0)	0.177	(1.2)
$HVOL \times REG_1 \times REG_2$	−1.010***	(−2.8)	−0.705***	(−2.5)	−0.887***	(−3.3)
REG_1	0.408***	(3.4)	0.695***	(5.8)	0.624***	(4.9)
REG_2	0.246***	(6.3)	0.223***	(5.0)	0.241***	(4.7)
$REG_1 \times REG_2$	0.490***	(3.5)	0.344***	(3.0)	0.426***	(3.8)
Rho (Error Correlation)	0.027*		0.035**		0.034**	
Panel B: Non-presales						
Specification (i)						
$HVOL$	−0.155***	(−3.3)	−0.150**	(−2.5)	−0.078	(−1.1)
Rho (Error Correlation)	0.068***		0.066***		0.066***	
Specification (ii)						
$HVOL$	−0.151**	(−3.1)	−0.120**	(−2.0)	−0.042	(−0.6)
$HVOL \times REG_1$	−0.746***	(−3.6)	−1.116***	(−4.2)	−0.015***	(−5.0)
REG_1	0.820***	(9.8)	1.008***	(9.1)	1.141***	(9.7)
Rho (Error Correlation)	0.081***		0.094***		0.095***	
Specification (iii)						
$HVOL$	−0.237***	(−2.8)	−0.100	(−1.0)	0.080	(0.6)
$HVOL \times REG_1$	−1.196**	(−2.0)	−2.512**	(−3.1)	−1.436**	(−2.7)
$HVOL \times REG_2$	−0.128	(−1.4)	−0.040	(−0.3)	−0.177	(−1.3)
$HVOL \times REG_1 \times REG_2$	0.462	(0.8)	1.590*	(1.9)	0.056	(0.2)
REG_1	1.063***	(5.2)	1.464***	(5.8)	1.120***	(6.1)
REG_2	0.316***	(8.2)	0.370***	(8.1)	0.410***	(8.0)
$REG_1 \times REG_2$	−0.295	(−1.4)	−0.653**	(−2.5)	−0.134	(−0.9)
Rho (Error Correlation)	0.059***		0.092***		0.099***	

[a] Variance of annualized returns over the past 6 months
[b] Variance of annualized returns over the past 12 months
[c] Variance of annualized returns over the past 18 months
* Significant at 10%; ** Significant at 5%; *** Significant at 1%

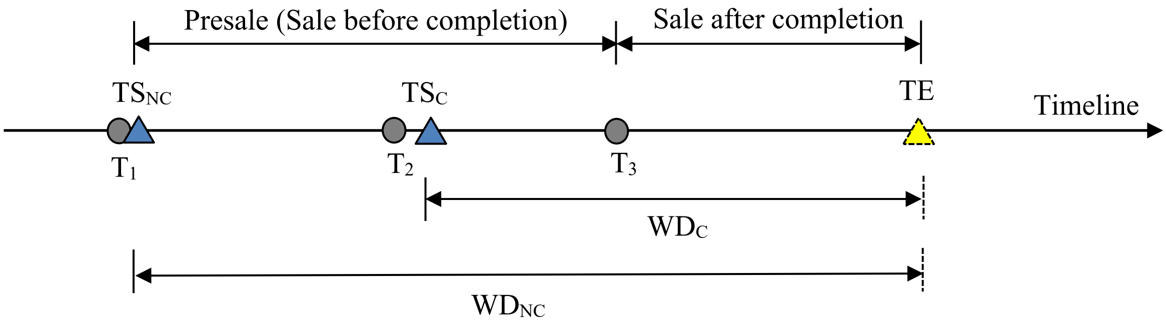
Figures

Figure 1■ Price index in Hong Kong property market (1984-2016)



Source: Raw data from Rating and Valuation Department of HKSAR

Figure 2■ Time line of real estate development in Hong Kong



TS_C: start of the waiting duration for consent scheme projects;
TS_{NC}: start of the waiting duration for non-consent Scheme projects;
TE: end of the waiting duration for both consent and non-consent scheme projects;
T_1: the date when the land is ready for construction;
T_2: the date when construction starts;
T_3: the date when construction completes;
WD_C: the waiting duration for consent scheme projects;
WD_{NC}: the waiting duration for non-consent scheme projects.

Figure 3■ Distribution of the duration (in month) of waiting for sale

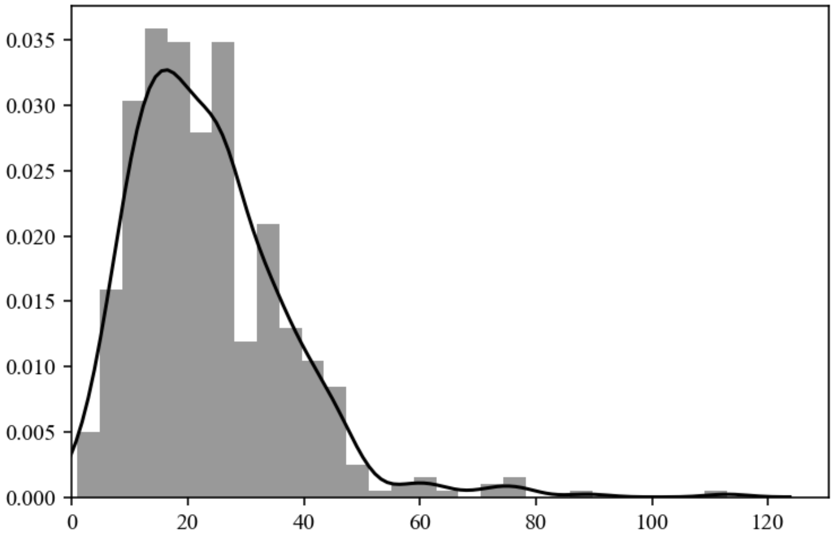
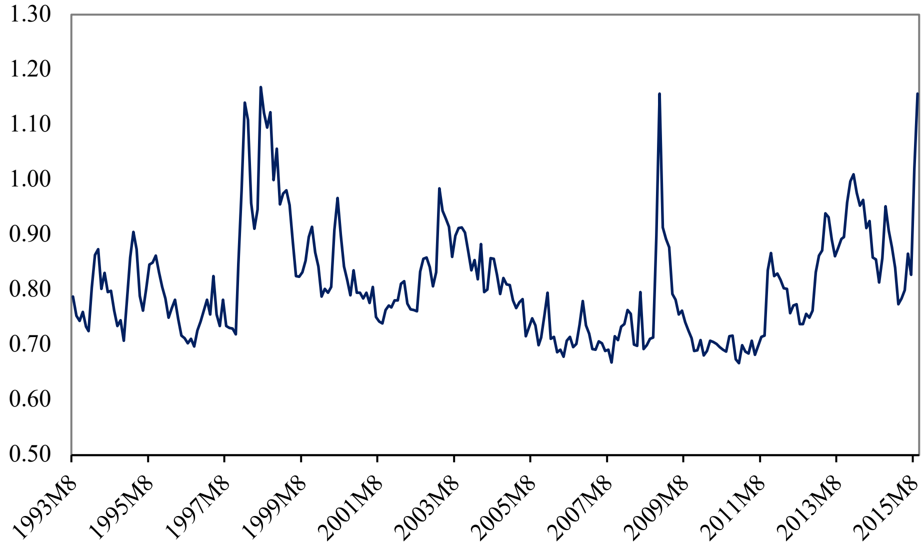
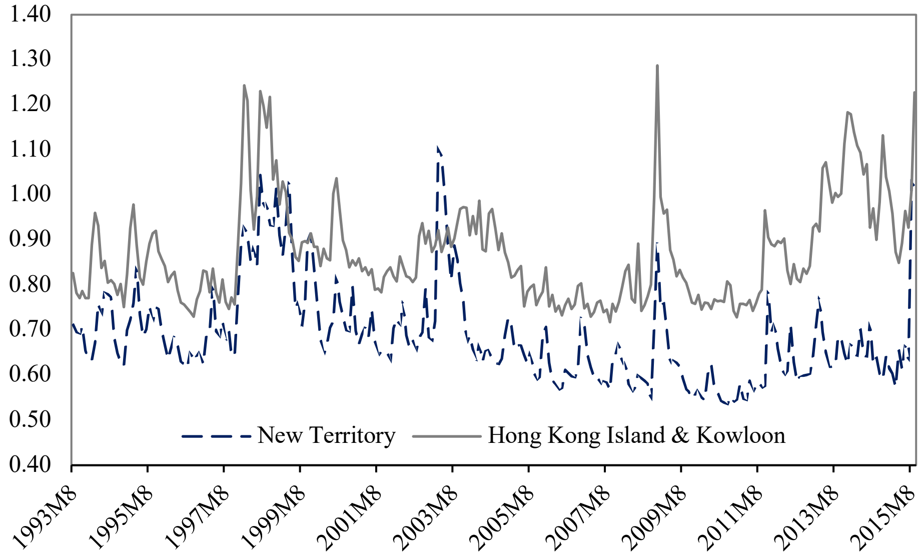


Figure 4■ Movements of *VOL*[a]



[a] Variance estimate from Generalized Autoregressive Conditional Heteroskedasticity model: $\sigma_{jt}^2 = \gamma_{0j} + \gamma_{1j}e_{jt-1}^2 + \delta_1\sigma_{jt-1}^2$

Figure 5■ Residential price volatility across regions in Hong Kong



Source: Raw data from University of Hong Kong, HKSAR