Bounded Rationality in Real Estate Investment Decisions

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I would like to dedicate this dissertation to my loving parents

Declaration

This dissertation is the result of my own work, and no part of it is the outcome of work done in collaboration, except as declared in the Preface and specified in the text. It is not substantially the same as any other work that I have submitted or is being concurrently submitted for a degree or diploma or other qualification at the University of Cambridge or any other university or similar institution, except as declared in the Preface and specified in the text.

I further state that no substantial part of my dissertation has already been submitted or is being concurrently submitted for any such degree, diploma, or other qualification at the University of Cambridge or any other university or similar institution, except as declared in the Preface and specified in the text. It does not exceed the prescribed word limit for the relevant Degree Committee.

The following parts of the research are collaborative work with other scholars and have been published:

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Abstract

A growing body of literature has shown, again and again, that investors suffer from behavioural biases. They make *cognitive errors* by processing the available information in a selective and biased manner and rely on additional *emotional heuristics* to take mental shortcuts. Instead of making optimal decisions, they seek satisfactory solutions. Overall, they can muster bounded rationality only.

Real estate investors are as human and biased as investors in other financial assets. Previous work has found that the intransparency of markets, low liquidity and the heterogeneity of assets paired with significant emotional involvement of buyers and sellers increase behavioural biases. That is why it is particularly important to understand the behavioural bias of real estate investors in general and owner-occupiers in particular. In this dissertation, I study the bounded rationality of three different types of real estate investors and link these behavioural biases to real estate market dynamics and investment performances.

The first two studies focus on the phenomenon of *anchoring*—a frequently-observed type of cognitive error where investors select reference prices and evaluate offers or market movements relative to existing price points (the *anchors*). In the first study, I reconfirm that prior purchase prices unduly influence sellers in the resale market: Sellers facing nominal losses try to sell at higher prices than those selling at a nominal gain. Evidence of anchoring bias in list and transaction prices has been found in the housing markets. I contribute to the prior literature by showing that the power of the anchors on transaction prices is a function of information availability and general market conditions. The effect is economically significant only when data from comparable transactions are scarce. Second, the effect is relatively weak in a bust period of the market cycle but it grows when markets recover.

The second study sheds light on the anchoring effect in the presale property market. Here, presale homebuyers only pay deposits when signing the purchase contracts and have the option to strategically default in case property values fall sufficiently before the delivery of their units. Effectively, the mental reference points are expected to differ from the anchors used in the resale market if contract holders rationally consider the deposits as option premiums (or sunk costs). I find that presale contract holders still anchor to the full contract prices rather than the outstanding payments. A presale contract is more likely to be rescinded if the property's market price at settlement is lower than its contract price. In contrast, I do not find a sharp increase in the rescission rate when the market price drops further below the outstanding payment at settlement. Moreover, for those presale homebuyers who settle the out-of-money contracts, I find they are more likely to substantially increase their holding periods to recover from the implied losses.

One might think that institutional investors are less prone to suffer from bounded rationality than individual investors. After all, they are well-trained professionals with better access to market information. Nevertheless, earlier papers have shown that institutional investors are still subject to *cognitive errors* like price anchoring. The third segment of this dissertation studies how institutional investors rely on

additional *emotional heuristics* in their decision-making, which are more challenging to correct than *cognitive errors*. I research investment decisions by local and out-of-town investors who have different access to local information and might be subject to *familiarity bias*—an emotional heuristic denoting that investors prefer to over-concentrate on familiar investments. I find that the familiarity bias can dominate the information advantage of local investors when adverse shocks depress the value of home-market assets. Using the public non-REIT firm acquisitions as geography-specific demand shocks, I find equity REITs perform worse if they hold more properties in counties where the acquired non-REIT firms are located. However, due to familiarity bias, institutional home investors are less likely to short the affected REITs than institutional non-home investors despite the continuous decrease in the REITs' rental income up to at least one year after the shocks, which leads to implied investment losses.

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Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction

Grounded in neoclassical economics, traditional finance theories assume that investors are "rational economic men [sic]" (Hollis and Nell, 1975). Specifically, we are believed to be guided by self-interest as we consistently maximise our expected utility under certain budget constraints (Samuelson, 1937). Idealised rational agents can calculate their expected utilities as the sum of the utilitiy under each scenario weighted by the probability of each outcome occuring. They can specify probabilities and outcomes with unbiased precision and update any probabilities whenever new information is released according to Bayes' formula (Bernoulli, 1954). Further, investors are understood to be strictly risk-averse. When presented with options of equivalent expected utilities, rational investors prefer certainty and shy away from risk. After adding unhindered access to information to the set of assumptions, investors may enjoy *perfect rationality* (Arthur, 1994). Without perfectly rational agents, most seminal theories on financial markets lose their foundations, including the "the arbitrage principles of Miller and Modigliani, the portfolio principles of Markowitz, the capital asset pricing theory of Sharpe, Lintner and Black, and the option pricing theory of Black, Scholes and Merton"[1] (Statman, 1999).

In real life, however, humans behave less enlightened. A growing body of empirical studies has, again and again, observed that investors diverge from optimal decision-making. We are "irrational" and not as perfect as traditional finance theorists would like us to be. As an applied economist, I am more interested in understanding investors' actual behaviour and to a lesser degree in elegant theoretical models of financial markets. This is why I hope to contribute to the literature on behavioural finance, which challenges many of the assumptions of rational economic actors. Similar to many recent studies, this dissertation attempts to explore and explain the differences between observed and theoretically optimal investment decisions.

From the perspective of behavioural finance, investors are neither strictly risk-averse nor following the expected utility theory. Instead, cognitive errors and emotional heuristics impact individuals' perceptions towards utility, risk, and probability of occurrence, which result in irrational behaviours. As an alternative to the expected utility theory, the prospect theory introduced by Dr. Daniel Kahneman and Dr. Amos Tversky describes how gains and losses are evaluated differently in different circumstances (Kahneman and Tversky, 1979). According to the prospect theory, people are risk-averse only when facing expected gains. Instead, if a risky choice is expected to bring losses, people will become risk-seeking to order to avoid losses. Also, the perceived value of a loss is larger than an equivalent gain, so people

[1] Partially deviating from the assumptions of perfect rationality, the option pricing theories assume that investors are risk-neutral rather than risk-averse (Black and Scholes, 1973; Merton, 1973).

tend to be loss-averse. Moreover, the perceived gains and losses are not objective either. They are mentally calculated with a subjective reference point, and various behavioural biases can influence the selection of references. Daniel Kahneman was awarded the Nobel Prize in 2002 because of these seminal contributions.

Another prominent critic of *perfect rationality* is the underlying assumption of complete information. It is implausible for investors to access the full market information in real life. Even if all information was accessible, we could not process them completely due to cognitive capacity constraints. In contrast, the concept of *bounded rationality* is introduced as the alternative assumption to *perfection rationality*. Grounded on the prospect theory, this concept further relaxes the requirement that all market information is accessible and processed in an unbiased way (Simon, 1957). It assumes that investors process some available information in a biased manner and rely on emotional heuristics to make mental shortcuts when a comprehensive analysis is not feasible. As a result, rather than reaching the optimal solutions suggested by traditional finance theories, people stop when they arrive at a decision that they are satisfied with.

The assumption of bounded rationality lays the theoretical foundation for explaining the behavioural biases observed in financial markets (Kahneman, 2003). Since then, various types of behavioural biases in financial markets have been documented and investigated, although there is still no conclusive framework systematically categorising different types of observed behavioural biases. One simple but widely accepted classification, introduced by Pompian (2006), distinguishes behavioural biases as *cognitive errors* and *emotional heuristics*. Cognitive errors originate from the incorrect processing of available information due to limitations in cognitive capacity, faulty reasoning, or memory errors. One example of cognitive errors is the *anchoring bias*, which means that people heavily rely on selected reference points (or "anchors") in decision making (Butler, 1986).

In contrast to cognitive errors, emotional heuristics stem from feelings and intuition. Thus, they are usually more difficult to correct than cognitive errors even if the investors have sufficient cognitive capacities. For instance, *familiarity bias* is an important type of emotional heuristics observed in financial markets. It implies that investors prefer to invest in assets they are familiar with because they are overconfident about the familiar investments and excessively fear the risks in the unknown. Although classifying behavioural biases is challenging because some biases may have both cognitive and emotional aspects, most of the documented behavioural deviations from the theoretically optimal decisions can be understood in these two dimensions.[2]

It is essential to notice that, while various types of behavioural biases have been documented in the literature, generalising any behaviours without describing the actual circumstances is not appropriate. Unlike traditional finance that predicts the optimal choice, we learn behaviour biases from the tendencies and statistical patterns observed in various real-life situations. The extent to which an individual presents bounded rationality is a joint function of multiple factors, such as the type of the decision, the knowledge of the person, and the current market condition. For a given type of bias, the actual behaviours vary broadly across markets and investors (e.g., Bailey et al., 2011; Massa and Simonov, 2005; Wei, 2018). Therefore, this dissertation aims to investigate the bounded rationality of different investors in several important but under-researched market scenarios.

[2]Some other examples of cognitive errors include mental accounting (Barberis and Huang, 2001), framing bias (Agnew et al., 2008) and availability bias (Slovic, 1972). Endowment bias (Sprenger, 2015a), status quo bias (Samuelson and Zeckhauser, 1988) and regret aversion bias (Seiler et al., 2008) are other examples of emotional heuristics.

Also, in comparison to other financial assets, understanding the bounded rationality in the real estate market is particularly important because the real estate market is less efficient in price discovery (Barkham and Geltner, 1995; Ong and Sing, 2002; Yavas and Yildirim, 2011). Like many other durable assets, real estate is heterogeneous and less frequently traded (Aubry et al., 2022). Also, an owner-occupied residential property is a joint consumption and investment good (Ioannides and Rosenthal, 1994). These facts either increase the chances of making cognitive errors or result in more emotional judgment from real estate buyers and sellers. As real estate is such a heavy investment for retail buyers (Flavin and Yamashita, 2002) and also an important constituent in the portfolio of institutional investors (Chun et al., 2004), more studies are in need to understand the bounded rationality of investors in real estate investment decisions.

In this dissertation, I study the behavioural biases of three different types of real estate investors and link their bounded rationality to real estate market dynamics and investment performances. The dissertation consists of three independent studies, which constitute one chapter each.

Chapter 2 focuses on the cognitive error of anchoring bias among individual investors in the resale property market. Utilising the data of over a million commercial and residential property transactions in Hong Kong from 1991 to 2015, I reconfirm with the literature in western property markets that individual sellers anchor to their purchase prices in their resale decisions (Bokhari and Geltner, 2011; Genesove and Mayer, 2001). I find that sellers facing expected nominal losses relative to their prior purchase prices intend to sell at higher prices than their counterparts.

However, it remains unexplored whether market condition and efficiency impact the retention of this behavioural bias on actual transactions. I extend the literature by showing that two market factors determine the extent of the anchoring effect on transaction prices. First, the anchoring effect is only prominent when comparable transaction information is not readily accessible, such as in the less frequently transacted commercial property market or the high-end residential property market. Second, my results suggest the relevance of the anchoring effect to the boom-bust property cycle in both the residential and commercial markets. The impact of expected losses on transaction prices is relatively weak in the bust period between 1998 and 2003 when the Hong Kong property market lost almost two-thirds of its value, and it enlarges with the market recovering. Lastly, to complete the study, I show that the anchoring effect is not attenuated at the aggregate market level but is associated with strong reductions in price declines in the bust period and the commercial market. These results have implications for understanding the market adjustment of the anchoring effect in the property market and its association with the aggregate market dynamics in a boom-bust property cycle.

The second study, presented in Chapter 3, sheds light on the anchoring effects of individual buyers in the presale housing market. According to Kahneman (2003), the selection of reference points impacts the formation of satisficing decisions with bounded rationality. Effectively, the reference points are expected to be different in the presale and resale markets. This is because homebuyers only pay deposits when they enter the presale contracts and could strategically default with limited penalties if the property's market value falls sufficiently before the delivery of their units. In fact, over 10% of the presale contracts in the Hong Kong housing market between 1996 and 2014 were rescinded, resulting in a total loss of HKD 436.67 million per year.

In this study, I study presale contracts rescission from a novel perspective of option theory: Rational contract holders should consider the deposits as sunk costs (option premiums) and compare the market price with the outstanding payments (exercise prices) in decision making. However, the results indicate that presale contract holders still anchor to the full contract prices rather than the outstanding payments.

A presale contract is more likely to be rescinded if the property's market price at settlement falls below its full contract price. In contrast, after the market price further drops below the outstanding payment, I do not find a sharp increase in the rescission rate. Moreover, presale homebuyers who settle the out-of-money contracts are more likely to substantially increase their holding periods, probably because they intend to wait for recovery from the implied losses.

Apart from the impact of moneyness on presale contract rescission, the option model also reveals that the rescission rate is higher when presale homebuyers bear more of the price risk (measured by option delta) and time-induced risk (measured by time-to-maturity). Lastly, I find that the rescission rates dropped significantly after the Hong Kong government implemented the macroprudential housing policies to regulate speculation. In summary, this study improves the understanding of the mechanism of presale contracts rescission, homebuyers' strategic default behaviour, and the role of housing market regulation in mitigating rescissions.

Chapter 4 in this dissertation switches to study the institutional investors of real estate. Some empirical studies provide evidence that, although institutional investors may still make cognitive errors like the individuals (Bokhari and Geltner, 2011; Hur and Singh, 2019; Lai et al., 2013), these errors are easier to be monitored and corrected, particularly if the institutions have well-established investment committees and corporate policies (Pompian and Longo, 2005; Rabin and Schrag, 1999; Wei, 2018). After all, institutional investors are well-trained professionals with better access to market information. Nevertheless, institutional investors are still human, and emotional heuristics can play an important role in the decision-making of these professionals (e.g., Cao et al., 2011; Eichholtz and Yönder, 2015; Grinblatt and Keloharju, 2001a; Hau, 2001). Therefore, the third study of this dissertation focuses on the familiarity bias—one important type of emotional heuristic—of institutional investors.

Using data of U.S. REITs from 1993 to 2015 and considering the events of public non-REIT firm acquisitions as geography-specific shocks, this study investigates how institutional investors react to adverse performance signals to their home assets. This novel empirical setting provides a clean identification of familiarity bias, which naturally co-exists with other mechanisms like information advantage in normal market conditions. I find that the irrational familiarity bias can dominate the information advantage of local institutional investors when there are adverse performance shocks to the home assets in their portfolios. Equity REITs perform worse if they hold more properties in counties where the acquired non-REIT firms are located. If the value of properties that a REIT owns in the target county increases by 10 percentage points, its abnormal return decreases by 14.7% in one month after the acquisition announcement. This negative impact is more prominent if the REIT owns more offices than other types of properties in the county or if the acquired firms are larger than other remaining public firms in the county.

More importantly, the REIT's return on asset and dividend yield decrease by 6.4% and 5.4% in the next quarter. The continuous decline in the REIT income lasts till at least one year after the demand shock, implying that rational REIT investors should react to the negative performance signal. However, using a difference-in-differences model, I find that institutional home investors are less likely than institutional non-home investors to lower the holdings of affected REITs after the acquisitions. This familiarity bias is stronger if the investors are closer to the affected properties or implement more active investment strategies. Therefore, this study bears important policy implications for monitoring and regulating the familiarity bias of institutional investors, especially in market downturns.

In summary, this dissertation aims to contribute to the debates on the importance of behavioural finance studies. It shows that bound rationality should not be ignored as in the traditional finance theories due to three main reasons. Firstly, all three studies in this dissertation reveal that the impact of bounded rationality on investment decisions and performances is economically significant. Particularly, real estate investment decision is critical for individual households because it consists of a large share of the household wealth. It is also important for institutional investors who aim to diversify portfolios with real estate investments. Since the real estate market is less efficient in price discovery, the economic impact of bounded rationality in real estate investments is further amplified. Secondly, combining the analyses in the three studies, I show that the impact of bounded rationality broadly applies to both individual and institutional investors in residential and commercial real estate sectors. Not only inexperienced individuals but also professional investors can be significantly influenced by bounded rationality in various types of real estate investments. Thirdly, the formation of bounded rationality in investment decisions is not static; instead, this dissertation aims to show the dynamic nature of bounded rationality, such as the different choices of mental anchors as discussed in Chapters 2 and 3, and the different extent of familiarity bias in normal and negative market conditions as discussed in Chapter 4. Collectively, due to the significant economic impact, broad influence across investors and market sectors, and the dynamic nature, this dissertation emphasises the importance of modelling bounded rationality and behavioural bias in real estate investments.

Chapter 2

The Effect of Expected Losses on the Real Estate Resale Market

2.1 Introduction

This study revisits the importance of expected losses in the property market.[1] Previous literature has revealed that anchored to the initial purchase price, home sellers facing an expected loss tend to set a higher list price and exhibit a lower likelihood of sales (Andersen et al., 2021; Anenberg, 2011; Bokhari and Geltner, 2011; Bracke and Tenreyro, 2021; Einiö et al., 2008; Genesove and Mayer, 2001). This loss effect, or the so-called disposition effect (Barberis, 2013), is also identified in the financial markets where investors are reluctant to sell financial assets at a loss (Chang et al., 2016; Dhar and Zhu, 2006; Grinblatt and Keloharju, 2001b; Odean, 1998; Shefrin and Statman, 1985). Among the efforts to account for the loss effect, loss aversion has gained the most popularity. First demonstrated by Kahneman and Tversky (1979), loss aversion refers to the tendency to consider that a loss is more painful than a gain. Hence, home sellers, due to the psychological aversion to selling their houses for less than what they initially paid, stay longer on the market with higher list prices than their counterparts. The explanation of loss aversion has quickly grown in popularity in the real estate literature with its potential to account for the stylized positive price-volume relationship, a key feature of the property market cycle (Bao and Meng, 2017; Bokhari and Geltner, 2011; Engelhardt, 2003; Genesove and Mayer, 2001; Leung and Tsang, 2013).

The influence of expected losses anchored to purchase prices is not necessarily a reflection of loss aversion. In an efficient market, the loss aversion effect as a psychological bias should be limited to the decision of list prices and weaken or disappear with exposure to market conditions (Anenberg, 2011). For example, Genesove and Mayer (2001) (henceforth, GM) documented no significant effect of loss aversion on transaction prices, and Bokhari and Geltner (2011) (henceforth, BG), Anenberg (2011), and Zhou et al. (2021a) found it to be positive but significantly weaker than that on list prices. Other established explanations to account for changes in transaction prices as a result of expected losses include equity constraints which are binding when the resale price is lower than the buying price (Andersen et al., 2021; Genesove and Mayer, 1997; Stein, 1995) and buyers' informational constraints (Anenberg, 2016;

[1] The study presented in this chapter is a collaborative work with Dr. Ling Li from the University of Cambridge. Materials derived from this chapter have been published in *The Journal of Real Estate Finance and Economics* in 2021. DOI: 10.1007/s11146-021-09851-3. I was in charge of conceptualisation, methodology, software, formal analysis, data curation, validation, and writing original draft.

Ben-David and Hirshleifer, 2012). Recent studies like Bracke and Tenreyro (2021) and Zhou et al. (2021b) generalized the influence of expected losses by focusing on the anchoring behavior, that is, anchoring to the price paid for the asset. They argued that the effect of expected losses on transaction prices is likely a result of insufficient adjustments due to multiple forces such as psychological loss aversion and/or informational and financial constraints.

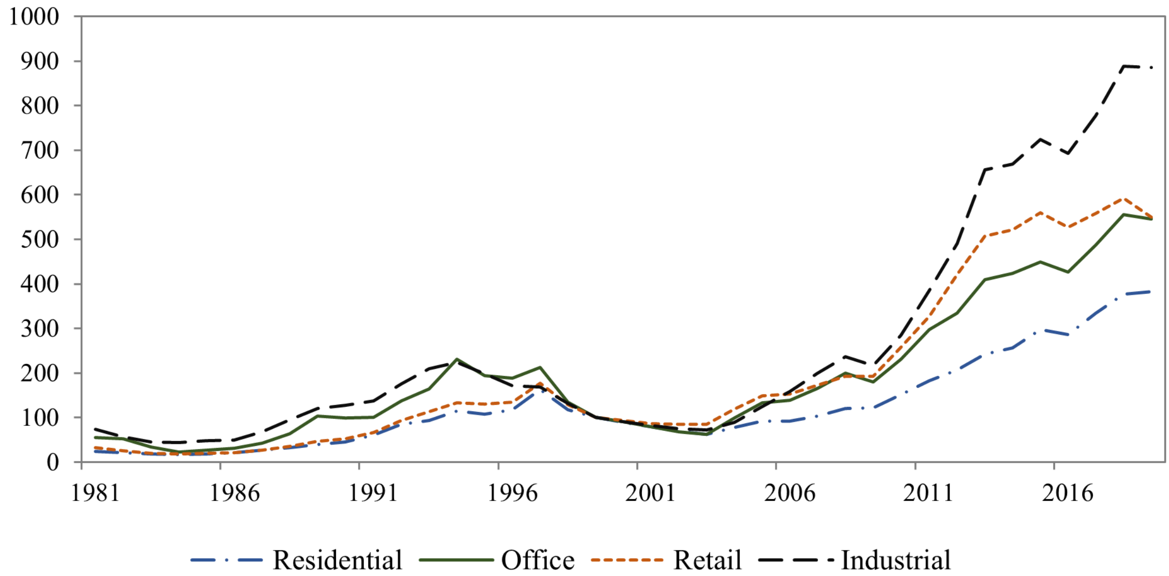
In this study, I follow the strategy of Zhou et al. (2021b) to investigate the pricing effect of expected losses by using the influential empirical model developed by GM, while I extend the literature by considering the role of two market factors in adjusting the loss effect. First, I consider the role of market information. Without perfect information, home sellers subject to expected losses are likely to fish a buyer who will pay more than the market value, though at the cost of staying longer on the market (Anenberg, 2016; Clapp et al., 2020). If the loss effect on transaction prices is due to limited information of the buyer, then I expect a mitigating effect of better market information. Second, I relate the loss effect to the property market cycle. Selling prices may stick to list prices for the sake of psychologically-based anchoring behavior (Ling et al., 2018; Northcraft and Neale, 1987) or signalling for private information (Yavas and Yang, 1995), but they may also deviate from list prices due to rational search and bargain (Carrillo, 2013; Han and Strange, 2016). As a reflection of bargaining between sellers and buyers, the negotiated premiums on expected losses should vary with the boom-bust property cycle. As expected, BG and Zhou et al. (2021b) documented significant cyclicality in the effects of expected losses on transaction prices.

In line with GM, I regard the prior nominal purchase price as the reference point around which sellers are sensitive to gains and losses. In estimating the effect of expected losses on transaction prices, I follow GM's approach to address the entangling of unobserved property characteristics. This concern can be further alleviated by the interaction between the loss effect and the market condition that does not vary the valuation of unobserved quality. I utilize a rich dataset from the Hong Kong property market which consists of over 1 million sales from four major sectors—residential, industrial, office, and retail, with approximately half a million pairs of repeat sales identified. To my knowledge, this is the first study on loss behaviors that encompasses both homeowners of residential properties and professional investors of commercial properties. The sample period spans over two decades, including a large boom-bust market cycle as shown in Figure 2.1.

Overall, my results from reduced-form regressions add to the literature with new evidence on how expected losses anchored to purchase prices affect transaction prices in different sectors of the property market. First of all, my findings suggest a mitigating effect of comparable market information on the influence of expected losses over transaction prices by cross-sector and within-sector comparisons of the loss effects. Close to GM's findings, the residential sector presents a positive loss effect on transaction prices in the upper bound, while it turns insignificant in the lower bound with unobserved quality controlled. In comparison, the three commercial sectors report significantly positive loss effects in the lower bound, consistent with the U.S. evidence provided by BG. Considering that only 10% of the total property transaction volumes are from the three commercial sectors, I ascribe the stronger loss effect on transaction prices of commercial properties to the lack of comparable transaction information. The argument is further supported by a negative crossing effect between the loss effect and a variable of comparable transaction information within each property sector.

Secondly, I find that the loss effect on individual transaction prices decreases with buyers' bargaining power, that is, stronger during market booms than during market downturns. This relationship holds across the four property sectors. In the bust period between 1998 and 2003 when the Hong Kong

Fig. 2.1 Hong Kong Property Price Indices by Sectors: 1981-2019



Notes: Raw data from the Rating and Valuation Department of Hong Kong.

property market lost two thirds of its value, I observe the weakest loss effect, along with the largest presence of sellers subject to potential losses. The loss effect on transaction prices increased when the market recovered and started to boom after 2009, with a small pool of loss-facing sellers. It is also noteworthy that the association between the loss effect and the market cycle is relatively weak in the retail and office sectors. This is possibly caused by the limited number of transactions in these two smaller market sectors, which should be further investigated with better quality of commercial data in future studies.

Lastly, I establish the relevance of the seller loss behavior to the market cycle at the aggregate market levels. I mainly follow the approach of Zhou et al. (2021b) to investigate the effect of expected losses on the aggregate property price indices and several distinct findings were presented. The aggregate loss effect is revealed to be stronger in the retail and office sectors than in the residential sector, and larger in the bust period than in the boom period. That is, the loss effect is associated with reduced price declines in the market trough, particularly in the commercial property market. While existing studies, such as Glaeser and Nathanson (2017) and Bracke and Tenreyro (2021), suggested that anchoring to past transaction prices is associated with excess volatility in the property market, my evidence joins Zhou et al. (2021b) to support the opposite.

Given no asking price information, I rely on the variations in the effects of expected losses on transaction prices to disentangle under what conditions could the loss effect carry through the negotiation process. In addition, the findings on the influence of the seller loss behaviour on the aggregate property market suggest an important channel to understand the price volatility of the boom-bust cycle, particularly in the commercial sector. The rest of the chapter proceeds as follows. The next section develops the estimation strategy, and Section 2.3 describes the unique dataset with summary statistics. Baseline results following GM are presented in Section 2.4. Section 2.5 reports the loss effect across sectors and its interaction with comparable transaction information. Sections 2.6 and 2.7 establish the relevance of the loss effect to the market cycle at the micro and aggregate levels. The last section concludes.

2.2 Empirical Models

I estimate the effect of expected losses on transaction prices following the models proposed by GM and BG, with several specific modifications made to suit the characteristics of my dataset. The estimation can be summarized in two stages. In the first stage, I estimate the expected market selling price of the property using a hedonic pricing model and calculate potential losses that the seller may incur. In the second stage, I estimate the effect of potential losses on the final transaction price, with potential biases from unobserved housing features controlled.

Using the full sample of transaction records in each property sector, the expected selling price of property i in district j at time t is derived from the following hedonic regression model:

$$\log(P_{ijt}) = X_{ij}^{'}\beta + \varphi_{jt} + \epsilon_{ijt}, \tag{2.1}$$

where the dependent variable uses the log form of the transaction price (P_{ijt}). X_{ij} denotes a set of controls for physical housing features, such as building age, unit area, floor, and distances to the closest seacoast, hospital, bus stops, MTR stations, and parks.[2] I include both the first order and the second order terms for these controls to capture the nonlinear relationships. Hong Kong is divided into 57 districts by the Land Registry of Hong Kong. I use φ_{jt} to denote the year times district fixed effects to control spatially and time-varying characteristics that are not easy to observe. Using the coefficients estimated from Equation (2.1), I am able to derive a predicted market value of this property specifically at time t, that is, the expected selling price. I denote this expected selling price in log form as μ_{ijt}. Considering the previous purchase price ($P_{ij,t-1}$) of the property as the reference point to the seller, the expected loss of the seller is therefore defined as the difference between the previous purchase price and expected selling price, truncated below at zero:

$$Loss_{ijt} = \begin{cases} \log(P_{ij,t-1}) - \mu_{ijt} & \text{if } \log(P_{ij,t-1}) - \mu_{ijt} > 0 \\ 0 & \text{otherwise} \end{cases}. \tag{2.2}$$

To estimate the effect of expected losses on the transaction price, I then regress the transaction price in the log form on the expected losses using the following specification:

$$\log(P_{ijt}) = \gamma Loss_{ijt} + \delta\mu_{ijt} + C_{ijt}^{'}\theta + \epsilon_{ijt}. \tag{2.3}$$

Specifically, I add the expected selling price μ_{ijt} at the right-hand side and include a vector of additional controls C_{ijt}, such as the months since the last transaction and the district times year fixed effects. The coefficient estimate of γ thus represents the price difference between the expected selling price and transaction price that is driven by expected losses.

As discussed by GM, two major issues threaten the validity of the estimate of the loss effect on property price. I illustrate how these two issues biased my estimate in Equation (2.3). The first issue is the unobserved housing features that I failed to include in Equation (2.1). I assume these unobservables

[2] For the model of residential properties, I include additional controls such as the housing estate type (i.e., single building or multiple buildings) and the number of total housing units within the estate.

to be fixed over time and denoted as ν_{ij}. Ignoring these factors may bias the estimation of the expected selling price in the hedonic model. Specifically, the real expected selling prices ($\tilde{\mu}_{ijt}$) should be given by:

$$\tilde{\mu}_{ijt} = X_{ij}^{'}\beta + \varphi_{jt} + \nu_{ij}. \tag{2.4}$$

The second potential bias is from the under- or over-payment relative to the expected price when the seller originally purchases the unit, and I denote it as $\omega_{ij,t-1}$. Since the hedonic model of Equation (2.1) also holds for the previous transaction, I have:

$$\log(P_{ij,t-1}) = X_{ij}^{'}\beta + \varphi_{j,t-1} + \nu_{ij} + \omega_{ij,t-1}. \tag{2.5}$$

Combining Equations (2.3)–(2.5), the real expected loss of the seller ($\widetilde{Loss}_{ijt}$) at time t is thus expressed as:

$$\widetilde{Loss}_{ijt} = \log(P_{ij,t-1}) - \tilde{\mu}_{ijt} = \varphi_{j,t-1} - \varphi_{jt} + \omega_{ij,t-1}. \tag{2.6}$$

Substituting Equations (2.4) and (2.6) into Equation (2.3), the unbiased model to estimate the loss effect on property prices is given as:

$$\log(P_{ijt}) = \gamma(\varphi_{j,t-1} - \varphi_{jt} + \omega_{ij,t-1}) + \delta(X_{ij}^{'}\beta + \varphi_{jt} + \nu_{ij}) + C_{ijt}^{'}\theta + \epsilon_{ijt}. \tag{2.7}$$

Since both $\omega_{ij,t-1}$ and ν_{ij} are unobservable, this reflects that my estimate of γ in Equation (2.3) is biased. To address these issues, I follow the adjustment method proposed by GM and BG. Firstly, I still use the noisy measure of the expected loss as in Equation (2.2). Secondly, I include the residuals from Equation (2.1) as an additional control in Equation (2.3). Expanding and rewriting the adjusted Equation (2.3) will end up with an equivalent model to Equation (2.7).[3] This means that the corresponding coefficient of γ in the adjusted model serves as the lower bound for the true effect of expect losses, conditional on the assumption that the first residual captures the unobserved features. If buyers with expected losses are selling at higher prices, then a positive estimate of γ is expected.

2.3 Data

My data comes from EPRC Limited, which covers all transactions of residential properties in Hong Kong from 1993 to 2015, as well as of retail, industrial and office properties from 1991 to 2014. This dataset provides detailed information on repeat transactions, including the transaction prices, dates, and the names of buyers and sellers. It also includes comprehensive information on physical characteristics, including address, unit size, floor, and property type. Using the public geographic data of amenities from ESRI China (Hong Kong) Limited and the tool of ArcGIS, I geocoded the property addresses and calculated the distances between the property and the closest MTR station, bus stop, seacoast, school, university, hospital, and park. The initial dataset contains over 1 million property transactions. To address the potential entry errors in the sample, I filtered the transactions with prices lower than 0.1 million HKD and discarded transactions with incomplete information on the transaction details and physical features. For the commercial properties, the unit sizes are truncated at the top 1% to remove the outliers. The filtered transaction sample is utilized in the hedonic pricing regression of the first stage, i.e., Equation (2.1), to generate estimates of predicted selling price and the results are reported

[3] The details of derivation can be referred to GM and BG.

in Appendix Table A.1. In general, the hedonic models provide a good interpretation of the log of the property sales price. The attributes included can explain 67% of the variations of retail transaction prices, while that number exceeds 80% in the other three sectors.

Since I am interested in the effect of expected nominal losses from the previous purchase price on the subsequent selling price, I further restricted my sample to transactions paired with a previous sale with the same buyer name as the seller name of the target sale. The residential market has the most repeat sales, with 49.6% of the total transactions paired with a previous sale in the secondary market.[4] The percentage is 48.4% in the industrial and office property sectors. The retail properties are the least frequently transacted in terms of repeat sales, with the percentage to be 39%. In the sample of repeat sales, the holding period of the seller is defined as the number of months between consecutive transactions of the same property. To address the impact of property flippers, I excluded transactions with a holding period of less than a year. After filter, the repeat sales sample includes 413,263 residential transactions, 31,374 industrial transactions, 14,566 office transactions, and 6,572 retail transactions.

Table 2.1 provides summary statistics of the repeat sales sample by property sectors. As shown in Panel A, the average subsequent transaction price for a residential property is 3.46 million HKD (equivalent to approximately 0.44 million USD), and the average age is about 18 years old with an average size of 521 square feet. In Hong Kong with extreme density, the average residential property is located at the 15th floor and comes from an estate consisting of over 2,000 housing units that are more or less homogeneous. Panels B to D summarize the repeat sales in the industrial, office, and retail property sectors. The average transaction prices are 2.37 million HKD, 4.63 million HKD, and 4.83 million HKD, respectively, and the average sizes are 16,744 square feet, 999 square feet, and 409 square feet. Compared across sectors, the average holding period of a residential property is 66 months, more than a year shorter than holding a commercial property.

As stated in the empirical strategy, I apply a noisy proxy for the expected nominal loss of the seller, i.e., *Loss*, using the difference between the log of the predicted transaction price and the log of the previous transaction price. Table 2.1 also distinguishes the seller by the variable of *Loss Dummy*, which is equal to 1 if the predicted transaction price is smaller than the previous transaction price and 0 otherwise. I compare the housing features and transaction details between sellers facing expected losses (*Loss Dummy*=1) and expected gains (*Loss Dummy*=0). In the residential sector, approximately one third of the sellers are facing expected losses in the study period, which is much less than the level (50–55%) in the Boston housing market documented by GM. In general, the distributions of physical housing features are balanced between transactions predicted with losses and with gains apart from age. The average holding period of loss-facing sellers is over 11 months longer than that of gain-facing sellers, suggesting that loss-facing sellers have a longer time on the market. In the commercial sectors, the percentage of sellers subject to expected losses are 38.4% for industrial properties, 43.7% for office properties, and 42.7% for retail properties. This is much higher than the 22–25% level identified by BG in the commercial property market of the U.S.

[4]Considering the different pricing mechanisms in the primary and secondary property market, I exclude repeat sales paired with a previous purchase from property developers.

Table 2.1 Summary Statistics

Panel A: Residential Sector

	Total (Obs 413,263)				Loss Dummy = 1 (Obs 143,377)		Loss Dummy = 0 (Obs 269,886)	
	Mean (1)	Std. Dev. (2)	Min (3)	Max (4)	Mean (5)	Std. Dev. (6)	Mean (7)	Std. Dev. (8)
Subsequent Transaction Price (million HKD)	3.455	3.813	0.120	128	2.571	3.073	3.929	4.083
Previous Transaction Price (million HKD)	2.863	2.912	0.110	106.8	3.347	3.368	2.611	2.608
Building Age	18.340	9.501	0	49.99	16.510	8.039	19.35	10.034
Unit Size (100 sq.ft.)	5.210	2.547	1.005	3.290	5.24	2.516	520	256.77
Floor	15.420	10.839	0	89	14.54	9.665	15.89	11.379
Estate units (thousand)	2.560	3.344	0.002	13.149	2.600	3.415	2.542	3.313
Distance to Seacoast (km)	1.180	1.409	0.017	8.060	1.213	1.441	1.163	1.392
Distance to Hospital (km)	1.581	1.427	0.038	8.575	1.627	1.460	1.557	1.41
Distance to Bus Stop (km)	0.368	0.351	0.010	7.636	0.371	0.368	0.366	0.341
Distance to Park (km)	0.960	0.937	0.057	9.536	0.954	0.949	0.964	0.931
Distance to MTR (km)	0.959	1.251	0.003	16.011	1.000	1.333	0.937	1.204
Distance to School (km)	0.146	0.203	0.001	2.992	0.149	0.216	0.145	0.195
Distance to University (km)	3.220	2.743	0.024	21.255	3.269	2.660	3.193	2.787
Holding Period (in months)	65.980	47.041	12.030	269.400	73.452	43.777	62.112	48.279
Sale Year	2007	5.121	1994	2015	2004	3.926	2009	4.879
Purchase Year	2002	5.469	1993	2014	1998	3.472	2004	5.28
Loss Dummy	0.347	0.476	0	1				
Loss	0.129	0.243	0	2.140	0.371	0.284		
Ratio of Predicted Loss to Previous Transaction Price	0.098	0.173	0	0.882	0.284	0.183		
Comparables	64.040	109.884	0	1673	57.250	85.346	67.640	120.757

Table 2.1 Summary Statistics, Continued

Panel B: Industrial Sector

	Total (Obs 31,374)				Loss Dummy = 1 (Obs 12,036)		Loss Dummy = 0 (Obs 19,338)	
	Mean (1)	Std. Dev. (2)	Min (3)	Max (4)	Mean (5)	Std. Dev. (6)	Mean (7)	Std. Dev. (8)
Subsequent Transaction Price (million HKD)	2.372	3.693	0.100	99.800	1.750	2.645	2.760	4.169
Previous Transaction Price (million HKD)	1.732	2.365	0.100	75.936	2.278	2.660	1.393	2.090
Building Age	18.334	8.194	0	50.000	14.242	6.929	20.881	7.882
Unit Size (100 sq.ft.)	16.744	19.571	1.250	503.160	17.109	15.748	16.516	21.609
Floor	10.473	6.263	0	39.000	10.766	6.506	10.291	6.101
Distance to Seacoast (km)	1.211	1.128	0.024	7.797	1.247	1.104	1.190	1.143
Distance to Hospital (km)	1.349	0.588	0.124	5.114	1.324	0.574	1.365	0.596
Distance to Bus Stop (km)	0.322	0.137	0.018	1.728	0.318	0.136	0.325	0.138
Distance to Park (km)	0.888	0.442	0.171	2.969	0.879	0.437	0.894	0.446
Distance to MTR (km)	0.595	0.585	0.030	4.637	0.579	0.543	0.605	0.610
Holding Period (in months)	84.669	63.119	12	278	90.853	53.314	80.820	68.235
Sale Year	2006	5.638	1992	2014	2003	4.500	2008	5.315
Purchase Year	1999	6.468	1991	2013	1995	4.607	2001	6.358
Loss Dummy	0.384	0.486	0	1				
Loss	0.221	0.383	0	4.025	0.575	0.422		
Ratio of Predicted Loss to Previous Transaction Price	0.150	0.235	0	0.982	0.390	0.225		
Comparables	5.414	8.984	0	199	4.198	5.224	6.171	10.605

Table 2.1 Summary Statistics, Continued

Panel C: Office Sector

	Total (Obs 14,566)				Loss Dummy = 1 (Obs 6,360)		Loss Dummy = 0 (Obs 8,206)	
	Mean (1)	Std. Dev. (2)	Min (3)	Max (4)	Mean (5)	Std. Dev. (6)	Mean (7)	Std. Dev. (8)
Subsequent Transaction Price (million HKD)	4.625	8.047	0.100	315.000	4.207	5.793	4.948	9.418
Previous Transaction Price (million HKD)	4.120	6.696	0.120	98.763	5.572	6.781	2.994	6.406
Building Age	17.070	8.826	0	50	15.096	7.791	18.600	9.266
Unit Size (100 sq.ft.)	9.994	11.527	1.050	287.250	10.973	9.544	9.235	12.803
Floor	12.656	7.248	0	47	12.645	7.218	12.665	7.272
Distance to Seacoast (km)	0.596	0.456	0.023	7.918	0.577	0.433	0.612	0.473
Distance to Hospital (km)	0.823	0.562	0.064	2.905	0.841	0.547	0.809	0.573
Distance to Bus Stop (km)	0.318	0.183	0.003	0.828	0.312	0.186	0.323	0.181
Distance to Park (km)	0.745	0.364	0.100	2.237	0.744	0.366	0.745	0.363
Distance to MTR (km)	0.356	0.515	0.004	3.751	0.351	0.497	0.360	0.528
Holding Period (in months)	80.412	62.218	12	280	88.255	54.934	74.332	66.695
Sale Year	2005	5.932	1992	2014	2003	4.605	2007	6.486
Purchase Year	1998	6.266	1991	2013	1996	4.824	2000	6.645
Loss Dummy	0.437	0.496	0	1				
Loss	0.264	0.434	0	6.171	0.604	0.474		
Ratio of Predicted Loss to Previous Transaction Price	0.174	0.252	0	0.998	0.398	0.236		
Comparables	2.986	5.377	0	87	2.395	3.766	3.444	6.312

Table 2.1 Summary Statistics, Continued

Panel D: Retail Sector

	Total (Obs 6,572)				Loss Dummy = 1 (Obs 2,806)		Loss Dummy = 0 (Obs 3,766)	
	Mean (1)	Std. Dev. (2)	Min (3)	Max (4)	Mean (5)	Std. Dev. (6)	Mean (7)	Std. Dev. (8)
Subsequent Transaction Price (million HKD)	4.691	8.143	0.100	98.000	5.581	9.126	4.028	7.256
Previous Transaction Price (million HKD)	3.386	5.602	0.100	92.800	4.975	7.137	2.202	3.679
Building Age	21.473	9.808	0	63.000	19.194	9.568	23.170	9.640
Unit Size (100 sq.ft.)	4.094	4.708	0.270	46.820	3.987	4.531	4.173	4.834
Floor	0.762	1.067	0	19.000	0.739	1.211	0.779	0.945
Distance to Seacoast (km)	0.885	0.834	0.000	8.060	0.875	0.785	0.893	0.869
Distance to Hospital (km)	1.077	0.756	0.088	6.941	1.114	0.792	1.050	0.726
Distance to Bus Stop (km)	0.348	0.298	0.003	7.103	0.358	0.290	0.340	0.304
Distance to Park (km)	0.854	0.495	0.092	7.546	0.872	0.494	0.841	0.496
Distance to MTR (km)	0.514	0.796	0.009	12.290	0.518	0.804	0.511	0.791
Holding Period (in months)	79.278	64.376	12	273	78.807	61.023	79.628	66.771
Sale Year	2007	5.218	1992	2014	2005	4.824	2008	5.269
Purchase Year	2000	6.246	1991	2013	1999	5.913	2001	6.302
Loss Dummy	0.427	0.495	0	1				
Loss	0.254	0.426	0	4.192	0.595	0.471		
Ratio of Predicted Loss to Previous Transaction Price	0.168	0.247	0	0.985	0.394	0.232		
Comparables	2.692	5.758	0	102	2.655	6.418	2.719	5.214

2.4 The Effects of Expected Losses on Subsequent Transaction Prices

Table 2.2 presents the baseline results of discerning the loss effect in the residential sector following GM. As shown in Column (1), the log transaction price is the dependent variable, with the estimated value of the property and holding months since the last sale as the regressors. According to GM, Column (1) registers the upper bound of the loss effect with the assumption of no unobservable characteristics. That is, a one-percent increase in nominal loss is associated with 0.22% increase in the subsequent transaction price. When the variable of residuals from the last sale was included in Column (2) to control for unobserved quality, the coefficient estimate on Loss documents the lower bound on the true loss effect. Consistent with the findings of GM, the lower bound of loss effect is small and insignificant. Column (3) adds a quadratic loss term to test the diminishing effect of large expected losses, as examined by GM. The results show that both the linear loss term and the quadratic loss term are significant, and the estimates imply a positive but decreasing marginal response to the expected loss.

Table 2.2 Baseline Results of the Loss Effect

	Residential			
	(1) log(price)	(2) log(price)	(3) log(price)	(4) log(price)
Loss	0.2238***	0.0029	0.0424***	0.0912***
	(0.0206)	(0.0101)	(0.0122)	(0.0102)
Loss Squared			-0.0463***	
			(0.0135)	
Estimated Value	0.9809***	0.9657***	0.9659***	0.9561***
	(0.0174)	(0.0132)	(0.0132)	(0.0171)
Residuals from Last Sale		0.4518***	0.4504***	
		(0.0138)	(0.0136)	
Adjusted Residuals				0.3710***
				(0.0168)
Holding Period	-0.0004***	-0.0010***	-0.0010***	-0.0002***
	(3.5E-05)	(4.5E-05)	(4.6E-05)	(3.0E-05)
Year * District FEs	Y	Y	Y	Y
Observations	413,263	413,263	413,263	252,474
R-squared	0.918	0.932	0.932	0.928

Notes: Loss is defined as the difference between the log of the predicted transaction price and the log of the previous transaction price, truncated below at zero. *Adjusted Residuals* are the residuals of the previous transaction price from the first-stage hedonic pricing regression by utilizing a subsample with transactions occurred in the boom periods between 1993 and 1997 and between 2009 and 2015. Robust standard errors are clustered at district level. ***, **, * denote for 1%, 5% and 10% significance, respectively.

According to Anenberg (2011), GM's estimation strategy introduces a bias in the measurement of unobservable housing quality because of omitting the loss effect in the first stage hedonic regression. I follow the Anenberg (2011) approach to produce a variable of adjusted residuals as the proxy for unobserved quality. Specifically, I restrict the sample used in the first stage to housing transactions that occurred in boom periods, that is, between 1993 and 1997 and between 2009 and 2015. Given the large price increases during these periods as shown in Figure 2.1, it is reasonable to assume that sellers are less likely to face nominal losses. Because facing losses is rare during these hot markets, the unobserved quality measured by the residual is less likely to contain the loss effect. By utilizing the restricted sample, I generate adjusted residuals by repeating the hedonic pricing regression in the first stage. The period restriction in the first stage further limits the sample in the second stage to housing transactions of which the previous sale occurred between 1993 and 1997 or between 2009 and 2015. Given this requirement on the previous sale, approximately 60% of the repeat sales sample remain in the second stage. In Column (4) of Table 2.2, I repeat Equation (2.7) with the variable of *Adjusted Residuals*, and the coefficient estimate on the Loss variable is positive and significant, falling in the range of the lower and upper bounds following GM's approach. Considering that the Anenberg (2011) approach requires a restrictive repeat sales sample, it may not be applicable to the commercial sectors with relatively limited transactions. Since the revised loss effect is above the GM's lower bound, I can argue that the true loss effect is larger than what was identified by using GM's lower-bound approach.

2.5 The Loss Effects and the Market Information

The property market is characterized by imperfect information due to its uniqueness and high transaction costs associated. Property buyers rely heavily on transaction details of comparable properties to evaluate the pricing of the target property (Anenberg, 2016). More transactions of comparable properties enable ordinary buyers to reduce the mispricing of target properties. That is, sellers facing nominal losses would be less likely to fish a buyer with an irrational high price. In this section, I try to quantify the importance of comparable transaction information in reducing the loss effect.

2.5.1 Across-sector Evidence

I rely on the number of comparable transactions to measure how informative a market is. To begin with, I compare the loss effect across property sectors of different sizes. In Hong Kong, the residential market is the most frequently traded sector. It occupied 90% of the entire property transaction volume with an average of over 80,000 transactions per year between 1995 and 2014 (see Appendix Table A.2). The three commercial sectors—retail, industrial, and office—as a whole only constitute 10% of the total transaction volume over the same period, making it difficult to find comparable transactions for deciding the price of the target commercial property. Therefore, my hypothesis is that the loss effect on list prices should be more likely to carry through to transaction prices in the three commercial sectors than in the residential market.

Also, I further divide the residential market into the mass market (housing units with a saleable floor area of below 1,000 square feet) and the luxury market (housing units with a saleable floor area of above or equal to 1,000 square feet). The mass units are the dominant housing type in Hong Kong, accounting for 95% of the residential transactions that occurred between 1995 and 2014. Likewise, my hypothesis is that fewer comparable transactions should be available for purchasing a luxury unit, thus enabling the loss effect to be realized on transaction prices.

Table 2.3 reports the results of Equation (2.7) by utilizing samples across the five property sectors. To my knowledge, BG is the only exception to examine the loss effect in the commercial property market. Without differentiating the sectors, they documented an overall increase of 2.45% in transaction prices per 10% increase in nominal loss. As shown in the first Column of Panel A, I obtain a similar loss effect in the retail sector. It suggests that a seller facing a nominal loss of 10% receives a 2.57% higher price on average, and the effect is statistically significant at the 1% significance level. The loss effect decreases by around half in the office and industrial sectors where a larger pool of sales is available to search for comparable transactions. In line with the prediction, the loss effect dissipates considerably in the residential sector. In the luxury housing market, the loss effect registers to be positive—10% nominal losses are associated with 0.18% higher transaction prices, whereas it turns negligible for mass housing units.[5]

Table 2.3 Loss Effects Across Four Property Sectors in Hong Kong

	Retail	Office	Industrial	Residential: Luxury	Residential: Mass
	log(price)	log(price)	log(price)	log(price)	log(price)
Panel A	(1)	(2)	(3)	(4)	(5)
Loss	0.2568***	0.1451***	0.1098***	0.0177	-0.0002
	(0.0639)	(0.0380)	(0.0221)	(0.0274)	(0.0097)
Estimated Value	1.0683***	1.0174***	1.0233***	0.9155***	0.9498***
	(0.0222)	(0.0137)	(0.0125)	(0.0257)	(0.0157)
Residuals from Last Sale	0.6994***	0.7444***	0.6770***	0.5241***	0.4459***
	(0.0224)	(0.0117)	(0.0209)	(0.0358)	(0.0141)
Holding Period	-0.0016***	-0.0004***	-0.0003***	-0.0007***	-0.0010***
	(0.0003)	(0.0001)	(0.0001)	(0.0001)	(4.4E-05)
Year * District FEs	Y	Y	Y	Y	Y
Observations	6,572	14,566	31,374	18,711	394,552
R-squared	0.849	0.933	0.915	0.884	0.918
Panel B	(1)	(2)	(3)	(4)	(5)
Loss	0.3952***	0.0670**	0.1525***	0.0382***	0.0141***
	(0.0538)	(0.0282)	(0.0231)	(0.0123)	(0.0023)
Loss * Comparables	-0.0435***	0.0228	-0.0082***	-0.0038***	-0.0002***
	(0.0092)	(0.0136)	(0.0020)	(0.0010)	(2.0E-0.5)
Year * District FEs	Y	Y	Y	Y	Y
Observations	6,572	14,566	31,374	18,711	394,552
R-squared	0.855	0.934	0.915	0.884	0.918

Notes: The subsample of *Residential: Luxury* refers to transactions of housing units with saleable floor area of above or equal to 1,000 square feet; *Residential: Mass* refers to transactions of housing units with saleable floor area of below 1,000 square feet. *Comparables* measures the number of comparable transactions in the same building (estate for residential properties) as the target property in a quarter before the target transaction. Robust standard errors are clustered at district level. ***, **, * denote for 1%, 5% and 10% significance, respectively.

One potential concern is that Hong Kong's residential property market has consistent high demand and insufficient supply (Tang and Leung, 2015), which may also affect the influence of the seller loss behavior on transaction price. Nevertheless, it will not undermine my argument that the loss behavior will have a smaller impact on transaction prices in the residential sector than in the commercial sectors, due to more comparable transactions and higher market efficiency. Particularly, if the homebuyers in

[5] It is possible that the difference in the loss aversion effects between the mass and luxury housing markets may be caused by different compositions of sellers. The results, as shown in Appendix Table A.3, remain robust when I repeat the regressions for mass and luxury housing markets by excluding company sellers, which may behave differently compared with homeowners.

Hong Kong are price takers due to high demand and low supply, it is expected that homebuyers will accept the high listing prices proposed by the loss-facing sellers. In that case, the impact of seller loss behavior on transaction prices in the residential market is expected to become larger. However, even with this potential impact from the supply-side restrictions, I still find that the loss effect is smaller in the residential market than in the other commercial sectors. Thus, it shows that the channel of market information that I identify dominates the potential impact of the supply-side restrictions.

Another potential limitation is that the unobserved variations in property features within districts may potentially bias the loss coefficients I estimate. While my results of residential transactions remain robust if I include the estate and year fixed effects instead (see Appendix Table A.4), this empirical specification could not be implemented for the commercial properties. Therefore, the large coefficients of expected losses in the thinner commercial sectors might be explained by more unobserved features of commercial properties. Nevertheless, my within-sector evidence and cross-cycle evidence, which are presented in following sections, are less likely to be biased due to the unobserved quality.

2.5.2 Within-sector Evidence

I carry out a second step to further explore whether comparable transactions play a role in reducing the loss effect. For each transaction, I calculate the number of comparable transactions (i.e., *Comparables*) in a quarter before the target transaction. A quarter window is allowed for two reasons. First, the pre-determined measurement of *Comparables* mitigates the endogeneity concern. Second, considering the fast changes in the property market, more recent the transactions, more informative they could be. In the residential sector, I select comparable transactions based on two criteria: coming from the same estate with the target transaction and of the same size category (i.e., mass or luxury housing unit). Housing units within the same estate share the same location and neighborhood facilities[6], and they provide the closest substitutes for each other (Wong et al., 2020). Because the format of estates only exists in the residential market, I revise the comparable criteria for commercial properties to transactions in the same building that occurred in the previous quarter. I interact the *Loss* variable with *Comparables* to test the counteraction effect of comparable transaction information. As shown in Panel B of Table 2.3, I obtain a negative and statistically significant interaction estimate between the *Loss* variable and the *Comparables* variable except for the office sector. That is to say, comparable transaction information is useful in mitigating the loss effect in the retail, industrial, and residential sectors.[7]

2.6 The Loss Effects and the Market Cycles

I hypothesize that whether sellers facing nominal losses could fetch a higher price than their counterparts should also depend on the market heat. In hot markets, home sellers have greater bargaining power in the negotiation than buyers and transaction prices tend to stick to sellers' asking price (Carrillo, 2013). That suggests a great possibility for the loss effect to carry through to actual transactions. When the property market experiences continuous declines, buyers gain the bargaining power to set the price (Han and Strange, 2016). Although sellers are more likely to face nominal losses in downward periods, they are limited by their bargaining power to achieve any loss effect in actual sale prices.

[6]However, there are exceptions. Some residential estates in Hong Kong are developed in different phases, which are not located in the exact same location. For such estates, I calculate the comparable transactions by estate phases.

[7]All results remain robust if I use a dummy variable to denote the existence of comparable transactions, as reported in Appendix Table A.5.

2.6.1 Five Distinct Periods of the Market Cycle

To test the relevance of the loss effect to the market heat, I break down the cycle of the Hong Kong property market between 1991 and 2015. As shown in Figure 2.1, the period through 1997 depicted the first stable and increasing property market across the four sectors. The year 1997 is a transition year coincided with the Asian financial crisis and the sovereignty return of Hong Kong to China, followed by a sudden crash of the whole market. The industrial and office sectors started the crash three years before 1997.[8] With the epidemic of SARS in 2003, all sectors reached the bottom with about one third of the price at the last peak. Afterwards, the property market recovered gradually from the bottom and most sectors (except for residential) went back to its pre-crisis level before the global financial crisis (GFC) hit in 2008. Unlike the U.S. and U.K. property markets that lost around 20% of the value in the GFC, the Hong Kong market experienced an approximately 10% price decline which is limited to the industrial and office sectors. Soon the whole market regained the momentum of increase and has begun to shoot new records with rapid increases year by year. At the end of 2015, the residential sector increased by almost 4 times compared with the price at the trough of 2003, while the office and retail sectors witnessed an increase of 6 times and the industrial sector skyrocketed to 10 times of its price in 2003. Therefore, the Hong Kong property market can be divided into five distinct periods: two boom periods (i.e., before 1997[9] and after 2009), two bust periods (between 1998 and 2003 and in the year of 2008) and a recovery period (i.e., between 2004 and 2007).

2.6.2 Descriptive Statistics

I start with descriptive statistics on sales by the market cycle as reported in Table 2.4. In general, sales subject to expected nominal losses or *Loss* sales are closely related to the boom-and-bust cycle. First, the share of *Loss* sales and the magnitude of losses exhibit a negative relationship with the heat of the market. In the residential sector, 90% of repeat sales face expected losses in the bust period between 1998 and 2003. This figure is 56% in the recovery period and 25% in the year of GFC. Given that the residential sector suffered little price decline in the GFC as shown in Figure 2.1, it is not surprising to obtain a relatively small share of *Loss* sales in 2008. The Loss share further declines to 18% and 10% in the two boom periods before 1997 and after 2009, respectively. Likewise, the magnitude of nominal losses (on average) is considerably higher in the bust and recovery periods than in the boom periods. Similar patterns present in the three commercial sectors but in different degrees. The interaction of *Loss* sales and the property cycle in the retail sector is not as strong as in the other sectors. Specifically, the difference in the share of *Loss* sales between the bust period (1998–2003) and the boom period (after 2009) is approximately 40% in the retail sector in comparison with around 80% in the residential and industrial sectors and 74% in the office sector. Through the cycle, the retail sector also presents much flatter variations in the magnitude of expected nominal losses. In addition, because the industrial and retail sectors started the first market crash from 1994 rather than from 1997, they contain an exceptionally large *Loss* share in the boom period before 1997.

[8]Possible reasons for the early decline in the industrial and office sectors include the oversupply of industrial properties due the China's open-door policy in the late 70s and the early retreat of investors in non-residential sectors before the handover (Chau, 1997). Because of the Handover, industrialists moved their production base to Mainland China leaving behind a lot of vacant industrial buildings in Hong Kong, some of which were used illegally as offices, which also depressed office prices. This may explain the co-movements of the industrial and office sectors between 1994 and 1997.

[9]For the purpose of comparison, I define the bust period as between 1997 and 2003 for all sectors. This makes the period before 1997 not entirely a boom period for the industrial and office sectors.

Table 2.4 Key Statistics by the Hong Kong Market Cycle

	Before 1997 Boom	1998-2003 Bust	2004-2007 Recovery	2008 GFC	After 2009 Boom
	Mean	Mean	Mean	Mean	Mean
Residential	(1)	(2)	(3)	(4)	(5)
Share of Loss Sales (Loss>0)	18.28%	89.51%	55.53%	24.90%	9.92%
Loss conditional on Loss>0	0.131	0.466	0.346	0.237	0.125
Holding Period	26.3	48.27	72.77	72.33	73.76
Holding Period of Loss Sales (a)	24.04	49.19	90.46	111.9	101.79
Holding Period of Gain Sales (b)	26.81	40.43	50.68	59.21	70.67
(a)-(b)	-2.77	8.76	39.78	52.69	31.12
Industrial	(1)	(2)	(3)	(4)	(5)
Share of Loss Sales (Loss>0)	47.33%	93.80%	49.40%	20.72%	11.05%
Loss conditional on Loss>0	0.151	0.79	0.26	0.055	0.027
Holding Period	31.97	79.32	94.23	96	95.3
Holding Period of Loss Sales (a)	35.21	78.84	124.92	139.35	92.66
Holding Period of Gain Sales (b)	29.06	38.31	64.28	84.67	95.63
(a)-(b)	6.15	40.53	60.64	54.68	-2.97
Office	(1)	(2)	(3)	(4)	(5)
Share of Loss Sales (Loss>0)	31.77%	92.97%	56.62%	29.68%	19.00%
Loss conditional on Loss>0	0.09	0.856	0.321	0.105	0.051
Holding Period	30.26	72.37	91.29	94.63	97.2
Holding Period of Loss Sales (a)	29.89	73.94	114.55	128.39	100.03
Holding Period of Gain Sales (b)	30.44	51.56	60.93	80.39	96.54
(a)-(b)	-0.55	22.38	53.62	48	3.49
Retail	(1)	(2)	(3)	(4)	(5)
Share of Loss Sales (Loss>0)	40.63%	72.57%	51.91%	41.46%	29.08%
Loss conditional on Loss>0	0.195	0.584	0.333	0.246	0.152
Holding Period	32.58	63.48	80.38	73.87	94.08
Holding Period of Loss Sales (a)	31.55	64.68	88.19	79.92	88.65
Holding Period of Gain Sales (b)	33.29	60.31	71.96	69.59	96.3
(a)-(b)	-1.74	4.37	16.23	10.33	-7.65

Second, I divide the sample conditional on expected losses and gains and find that the holding periods of *Loss* sales are more sensitive to the cycle than those with expected gains or *Gain* sales. When comparing holding periods, I focus on the periods after 1997 that are less biased.[10] Moving from the bust to the boom periods, the average holding period of *Gain* sales increases steadily by around 10 months per period across sectors, while that of *Loss* sales see more radical increases as well as declines. For example, in the industrial sector, the average holding period of *Loss* sales is 79 months in the bust period between 1998 and 2003, and it shot to 125 months in the recovery period and peaked at the GFC period with 139 months, before dropping by over 40 months in the boom period after 2009. Likewise, I find a much weaker sensitivity of the average holding period of Loss sales to the cycle in the retail sector. As a result of different sensitivities of the average holding period between *Loss* sales and *Gain* sales, I observe the holding back behaviour of *Loss* sales to vary with the cycle. Consistent with Zhou et al. (2021b), I find the *Loss* sales to be sold relatively quickly in the boom period compared to the bust and recovery periods in all four property sectors.[11]

Taken together, the descriptive statistics suggest significant cyclicality in the loss behavior in terms of the share of *Loss* sales, the magnitude of losses, and the willingness to sell measured by the holding period.

2.6.3 Regression Results

I verify the aforementioned cyclicality in sellers' loss behavior by regressions. Specifically, I run Equation (2.7) separately by using subsamples of different periods and Table 2.5 presents the results across the four property sectors. In general, I find that the loss effect on transaction prices is larger in the period of market booms than in the period of market downturns. As shown in Panel A of Table 2.5, in the residential sector, the coefficient estimates on Loss are statistically significant and, interestingly, different across the periods. The first boom period between 1993 and 1997 registers the largest loss effect—a seller facing a nominal loss of 10% receives a 2.01% higher price on average (Column (1)), nearly a triple of that in the second boom period after 2009 (Column (5)). When the market started to recover from the bust, 10% of nominal losses are only associated with a higher price of 0.428% (Column (3)). The loss effect in the GFC period (Column (4)) is slightly smaller than the recovery period. However, in the bust period between 1998 and 2003, sellers subject to nominal losses accepted a price lower than the average. Specifically, a one-percent increase in the nominal losses is associated with a higher transaction price of 0.243%.

Similar findings of the loss effects across the periods, according to the results from Panel B and Panel C, are observed in the industrial and office property sectors.[12] Nevertheless, it is worthy to note that the pattern of loss effect increasing with the market heat is less clear in the retail sector as shown in

[10] The lack of early transaction data prevents us from fully identifying repeat sales occurred before 1997. For example, the average holding period of residential sales before 1997 is approximately two years, while that is six years in the next boom period. The concern is not fully alleviated in the following bust period between 1998 and 2003 considering that there remains a discrepancy of one to two years in the average holding periods with the rest periods. In addition, the implementation of the Special Stamp Duty in 2012 that prevents short sales would possibly cause the sample in the boom period after 2009 to be different. Because I have removed repeat sales with a holding period less than a year, the average holding period in the boom period after 2009 is not substantially affected.

[11] In the residential sector, the difference between *Loss* sales and *Gain* sales in the bust period between 1998 and 2003 is only 9 months, while it reaches 53 months during the year of GFC. I attribute it to the exclusion of long-holding Loss sales in the bust period. As comparison, I limit repeat sales within a holding period of 10 years, and the difference between *Loss* sales and *Gain* sales reduces to 16 months in the GFC period and turns negative in the boom period after 2009.

[12] I repeat the tests for the industrial and office sectors by adjusting the cut-off year of market cycle and the results remain. Results are provided in the Appendix Table A.6.

Table 2.5 Loss Effects Across the Hong Kong Market Cycle

	Before 1997 Boom log(price)	1998-2003 Bust log(price)	2004-2007 Recovery log(price)	2008 GFC log(price)	After 2009 Boom log(price)
Panel A: Residential	(1)	(2)	(3)	(4)	(5)
Loss	0.2009***	0.0243**	0.0428***	0.0396**	0.0729*
	(0.0337)	(0.0103)	(0.0076)	(0.0162)	(0.0374)
Estimated Value	1.0131***	0.9941***	1.0697***	0.9938***	0.8940***
	(0.0072)	(0.0106)	(0.0116)	(0.0123)	(0.0166)
Residuals from Last Sale	0.4727***	0.3447***	0.4368***	0.5012***	0.4757***
	(0.0247)	(0.0135)	(0.0176)	(0.0202)	(0.0158)
Holding Period	-0.0015***	-0.0015***	-0.0148***	-0.0012***	-0.0117***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Year * District FEs	Y	Y	Y	Y	Y
Benchmark log(price)	1.080	0.544	0.651	0.810	1.204
Observations	28,883	66,142	95,599	24,795	197,844
R-squared	0.932	0.915	0.934	0.918	0.918
Panel B: Industrial	(1)	(2)	(3)	(4)	(5)
Loss	0.2162**	0.1346***	0.1202***	0.1680	0.3233***
	(0.0801)	(0.0421)	(0.0290)	(0.1098)	(0.0528)
Estimated Value	1.0601***	1.0126***	1.0491***	1.0542***	0.9930***
	(0.0224)	(0.0168)	(0.0192)	(0.0194)	(0.0146)
Residuals from Last Sale	0.6988***	0.6483***	0.7169***	0.6226***	0.6254***
	(0.0512)	(0.0516)	(0.0266)	(0.0453)	(0.0252)
Holding Period	-0.0009	-0.0020***	-0.0010***	-0.0004**	-0.0001
	(0.0006)	(0.0003)	(0.0001)	(0.0002)	(0.0001)
Year * District FEs	Y	Y	Y	Y	Y
Benchmark log(price)	0.407	-0.408	0.001	0.421	0.880
Observations	3,693	4,856	7,987	1,530	13,308
R-squared	0.906	0.859	0.878	0.878	0.892
Panel C: Office	(1)	(2)	(3)	(4)	(5)
Loss	0.0521*	0.2643*	0.1306***	0.1494***	0.2548***
	(0.0299)	(0.1518)	(0.0284)	(0.0498)	(0.0443)
Estimated Value	1.0541***	0.9482***	1.0489***	1.0558***	0.9946***
	(0.0140)	(0.0185)	(0.0232)	(0.0461)	(0.0139)
Residuals from Last Sale	0.8895***	0.5833***	0.7987***	0.7438***	0.6812***
	(0.0252)	(0.1130)	(0.0349)	(0.0329)	(0.0132)
Holding Period	-0.0023**	-0.0024**	-0.0009***	-0.0003***	-0.0001
	(0.0009)	(0.0010)	(0.0002)	(0.0001)	(0.0001)
Year * District FEs	Y	Y	Y	Y	Y
Benchmark log(price)	1.004	0.303	0.651	0.867	1.241
Degrees of Freedom				692	
Observations	2,395	2,418	3,778	721	5,254
R-squared	0.952	0.909	0.919	0.917	0.939

Table 2.5 Loss Effects Across the Hong Kong Market Cycle, Continued

	Before 1997 Boom log(price)	1998-2003 Bust log(price)	2004-2007 Recovery log(price)	2008 GFC log(price)	After 2009 Boom log(price)
Panel D: Retail	(1)	(2)	(3)	(4)	(5)
Loss	0.1974	0.3534***	0.2505***	0.3905***	0.2953**
	(0.1473)	(0.1247)	(0.0890)	(0.0912)	(0.1190)
Estimated Value	1.0185***	0.9906***	1.0544***	1.0608***	1.1114***
	(0.0258)	(0.0525)	(0.0593)	(0.0438)	(0.0238)
Residuals from Last Sale	0.8098***	0.5451***	0.7046***	0.6666***	0.6845***
	(0.0947)	(0.0963)	(0.0504)	(0.0517)	(0.0198)
Holding Period	-0.0015	-0.0041***	-0.0023***	-0.0015**	-0.0013**
	(0.0017)	(0.0012)	(0.0003)	(0.0006)	(0.0005)
Year * District FEs	Y	Y	Y	Y	Y
Benchmark log(price)	0.718	0.432	0.597	0.561	0.934
Degrees of Freedom				330	
Observations	636	920	1,615	369	3,032
R-squared	0.922	0.835	0.822	0.865	0.847

Notes: The benchmark log(price) is the mean of the log(price) for transactions with expected nominal gains. Degrees of freedom for regressions with less than 1,000 samples are reported. Robust standard errors are clustered at district level. ***, **, * denote for 1%, 5% and 10% significance, respectively.

Panel D of Table 2.5. This is consistent with the finding from the descriptive statistics suggesting a weak interaction of the loss behavior and the property cycle in the retail sector.

I consider two robustness tests of the loss effect. First, since my sample period ends in 2015 and I can only observe long-holding sellers in the earlier periods, it is concerned that different loss effects over the cycle may be ascribed to different holding periods of the repeat sales. I alleviate this concern by repeating the tests in Table 2.5 but limiting the holding period within 10 years. The results are reported in Appendix Table A.7. I find that, with the repeat sales sample to be more comparable across the cycle, variations in the loss effects strengthen in the residential and industrial sectors with relatively frequent transactions.

Second, noticing the nonlinear loss effect identified in Column (3) of Table 2.2, I also test the cyclicality of the loss effect by focusing on small losses. Appendix Tables A.8 and A.9 present the results when the ratio of predicted loss to the previous transaction price is limited to be less than 0.2 and 0.1, respectively. In general, with losses being restricted, I find the coefficient estimates of the Loss variable to be large and significant, and the patterns over the cycle remain more stable in the residential and industrial sectors than in the office and retail sectors. The weaker significance of the Loss estimation in the latter two sectors is possibly due to the limited number of observations in each period with the loss restriction.

In summary, my empirical results reveal that, while the magnitude of expected nominal losses decreases with the market heat, the loss effect moves in the opposite direction at the individual transaction level. During booming periods when the pool of potential buyers with high willingness to pay is large, loss-facing sellers with high reservation prices may still find a buyer. However, in the market downturns characterised by low demand, it is difficult for the loss-facing sellers to find buyers that are willing to accept "abnormally" high transaction prices. Consequently, sellers are forced to accept more "rational" prices justifiable by property features and market conditions. It thus implies that the strengths of buyers' bargaining power under different market conditions plausibly exert a channel that influences the extent to which the sellers' loss behavior affects the market transaction prices.

2.7 The Aggregate Loss Effects on Property Price Indices

2.7.1 Construction of the Loss-effect Adjusted Property Price Indices

While there are many loss-facing sellers in the property market, evidence about the aggregate loss effect is mixed. BG took the difference of the impact from losses and gains as the measure of loss aversion behaviour, and they found the aggregate impact negligible: The maximum effect is in the bust period, but it has only increased the market price by approximately 1.2%. Zhou et al. (2021b) adjusted for anchoring to the previous purchase price, including but not limited to loss aversion, and they found that the anchoring effect significantly decreases the market volatility across the property cycle. Still, there are no conclusive evidence explaining the relevance of the aggregate loss effect to the market cycle.

My empirical evidence on the individual-level effect of expected losses across the cycle sheds new insights on the puzzle of the aggregate impact: I find that the individual loss effect on transaction prices in the boom period is stronger than in the bust period, but the total number of sellers facing losses and the average loss per seller are also smaller in the boom period. The aggregate impact is thus influenced by the interaction of both changes in the magnitude of individual impact and the number of loss-facing sellers. I attempt to reveal this by investigating the aggregate loss effect on the price index in the four property sectors in Hong Kong.

I use the repeat sales index derived from the paired repeat transactions in my sample period as the benchmark, which is computed using the widely applied methodology proposed by Case and Shiller (1989).[13] I employ a similar empirical strategy developed by BG and Zhou et al. (2021b) to calculate the loss-effect adjusted property price index. The difference is that, unlike Zhou et al. (2021b) that consider both the effects of gains and losses, my focus is on loss effects and only the coefficients of losses are included in the price index adjustment. Specifically, I decompose the aggregate impact into three components: weight (*%SellerWithLoss*), magnitude (*E(Loss)*), and coefficient (γ):

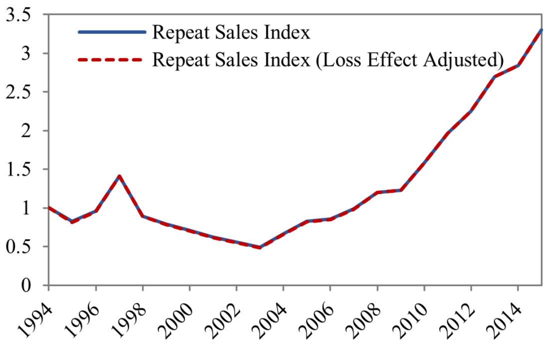
$$AggregateImpact = \%SellerWithLoss * E(Loss) * \gamma. \tag{2.8}$$

In each year, I first calculate the percentage of sellers that are facing an expected loss (i.e., the weight), based on Equation (2.2). Then I calculate the expectation of the loss amount (i.e., the magnitude) given that the seller faces an expected loss. Next, I calculate the individual-level impact of a unit amount of expected loss on the transaction price (i.e., the coefficient), following the specification in Equation (2.3). Due to insufficient data on a yearly basis, I use the coefficient in each period instead, which are reported in Table 2.5. Finally, the aggregate adjustment factor to the property price index is calculated

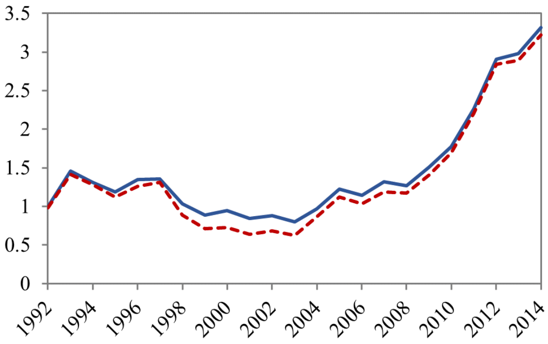
[13] The Rating and Valuation Department (RVD) of Hong Kong also publishes a transaction-based index for all the four major property sectors, which uses the official land registry records and virtually covers all property transactions (Chau et al., 2005). My derived repeat sales index closely follows the trend of this RVD index, which is plotted in Appendix Figure A.1.

as the product of the weight, the magnitude and the coefficient, and the repeat sales index in each year is adjusted accordingly.[14]

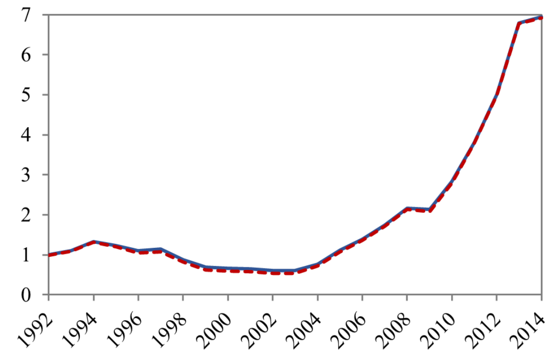
Fig. 2.2 Aggregate Loss Effects on Hong Kong Market Prices Across Four Property Sectors



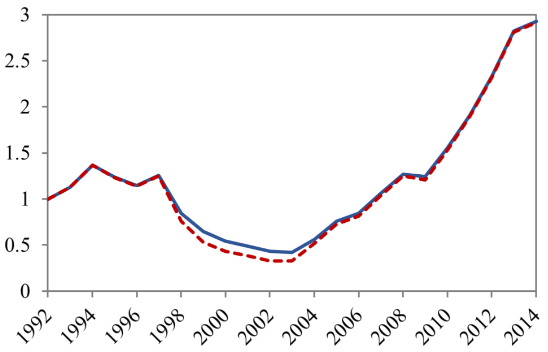
(a) Residential Property Price Index



(b) Retail Property Price Index



(c) Industrial Property Price Index



(d) Office Property Price Index

Unlike the individual-level loss effect of which the magnitude is larger in the boom period, I find the aggregate loss effect is more prominent during the bust period. Figure 2.2 plots the original repeat sales index and the loss-effect adjusted repeat sales index for the four property sectors in Hong Kong. In the year of 2003 during the bust period, the loss behaviour increases the transaction prices (i.e., reduces the price declines) by approximately 1.60% in the residential sector, 11.55% in the industrial sector, 29.07% in the office sector, and 23.01% in the retail sector. However, in 2014 when the market is booming, the loss behaviour only raises the transaction prices by 0.02% in the residential sector, 0.52% in the industrial sector, 0.46% in the office sector, and 2.98% in the retail sector. This implies that the considerable increase in the number of loss-facing sellers mainly drives the loss effect on the aggregate market during the bust period. Appendix Figure A.2 plots changes in the percentage of Loss sales and the magnitude of the Loss sales across the four property sectors. Taking the residential sector for an example, the percentage of loss-facing sellers (i.e., the weight) in the bust period from 1998 to 2003 is 89.51%, which is over 9 times of the percentage in the boom period after 2009 (see Table 2.4). Also, the expected loss of these loss-facing sellers in the bust period is significantly larger than that in the boom period. Although the impact of a unit expected loss on transaction price (i.e., the coefficient) is

[14] Technically, I follow BG and take the log of the repeat sales index first. Then I subtract the loss-aversion adjustment factor, and exponentiate the adjusted index back to the straight levels.

only 0.0243 in the bust period, which is around 1/3 of the coefficient in the boom period, the overall aggregate loss effect is still stronger in the bust period.

The adjusted repeat sales index also reveals that, at the aggregate market level, the loss effect is much stronger in the three commercial sectors than in the residential sector. On the one hand, this can be explained by my findings at the individual level that comparable transaction information impacts the market's adjustment of loss effect on the real transaction prices (Table 2.3). On the other hand, it is also attributable to the larger market volatility of the commercial property markets in Hong Kong. The average percentage of sellers with expected losses is smaller in the residential sector than in the other three sectors. As reported in Table 2.1, the percentage is 34.7% in the residential property market, 38.4% in the industrial property market, 43.7% in the office property market, and 42.7% in the retail property market. Also, the expected loss amount given an expected loss occurs is also smaller in the residential sector than in the other three commercial sectors. The expected loss amount in the logarithmic form is 0.371, 0.575, 0.604 and 0.595 in the residential, industrial, office and retail property market, respectively.

My estimated aggregate loss effect in Hong Kong's residential market is comparable in magnitude to that was estimated in the U.S. by Zhou et al. (2021b).[15] Table 2.6 reports the estimated loss effect on the residential markets in the U.S. and Hong Kong during the bust period (i.e., 2003 in Hong Kong and 2012 in the U.S.), when the aggregate market impacts are found to be larger. Indeed, Zhou et al. (2021b) focused on the overall anchoring effect of purchase prices on the subsequent transaction prices, which include the impact of both nominal losses and gains. It may be concerned that solely extract their estimate of the impact from nominal losses may not be comparable to my estimate of loss effect without considering the gain impact. Therefore, I also calculate the individual loss effect with the gain impact controlled by the inclusion of the variable of *Gain*, defined as the expected loss of the seller being truncated above at zero.

In Table 2.6, the first row reports the coefficient estimates of the *Loss* variable from Table 2.5, while the second row gives the estimates with the impact of gains controlled. I find the individual impact, reflected by the coefficient estimate of loss effect (γ), on Hong Kong's residential transactions (Column (2) of Table 2.6) is smaller than that in the U.S. (Column (1) of Table 2.6) with or without the gain impact controlled. It is because at the individual transaction level, considering that more comparable market information from neighborhood residential units exists in the very dense urban context in Hong Kong, it may be difficult for Hong Kong property sellers with expected losses to earn a higher price. However, the aggregate loss effect on Hong Kong's residential market (0.85%) is very similar to than that in the U.S. (0.90%). This is because, in Hong Kong where the property market is more volatile than that in the U.S., sellers are more likely to face a loss in the bust period, which increases the overall aggregate-level impact despite of the smaller impact at the individual transaction level than in the U.S. For example, 87.8% of the Hong Kong residential property sellers face nominal losses in 2003, while the figure is only 68.6 percent in the U.S. when the burst period ends in 2012. I also document the aggregate loss effect with the impact of gains being controlled in the three commercial sectors and they have larger magnitudes than in the impact in the residential market, as shown in the last three columns of Table 2.6. The findings are consistent with what are observed in Figure 2.2.[16]

[15]For the commercial sectors, BG estimate that in the U.S., the individual-level impact of loss aversion on all commercial properties is 0.380, which lies in the range of my estimates using sub-sectors of commercial properties in Hong Kong. Unfortunately, I cannot compare the aggregate impact of loss aversion on the commercial property market in Hong Kong with that in the U.S, because BG does not report the aggregate impact solely from loss aversion (i.e., excluding the impact from nominal gains) on commercial property market in the U.S.

[16]The aggregate effect of expected gains is much smaller in the bust periods in comparison to the aggregate effect of expect losses: -0.003% for residential, -2.08% for retail, -0.30% for industrial, and -0.54% for office sector in the Hong Kong

Table 2.6 Comparison between the Aggregate Loss Effects in the U.S. and Hong Kong during the Bust Period

	(1) U.S. Residential 2012	(2) HK Residential 2003	(3) HK Retail 2003	(4) HK Industrial 2003	(5) HK Office 2003
Coefficient Estimate of Expected Loss	/	0.024	0.353	0.135	0.264
Coefficient Estimate of Expected Loss (with control of Gain)	0.046	0.013	0.384	0.139	0.269
Loss-facing Sellers (%)	0.686	0.959	0.789	0.898	0.947
log(Expected Loss)	0.290	0.683	0.743	0.905	1.019
Original Price Index	1.079	0.490	0.800	0.602	0.420
Adjusted Price Index	/	0.482	0.651	0.539	0.326
Adjusted Price Index (with control of Gain)	1.069	0.485	0.639	0.537	0.324
Change	/	1.60%	23.01%	11.55%	29.07%
Change (with control of Gain)	0.90%	0.85%	25.22%	11.92%	29.70%

Notes: Statistics in Column (1) are extracted from Table 5 & 7 in Zhou et al. (2021b), which are estimated using the residential transactions in Connecticut. Column (1) include transactions in 2012, which is the last year of the bust period defined by Zhou et al. (2021b). Columns (2)–(5) include transactions in Hong Kong in 2003, which is also the last year of the bust period from 1998 to 2003. *log(Expected Loss)* denotes average loss amount in log form that the sellers face given expected losses occur. *Loss Adjustment Factor* is the product of *Coefficient of Loss Effect*, *Loss-facing Sellers (%)* and *log(Expected Loss)*. Following BG, the *Adjusted Price Index* is calculated by first taking logarithm of the *Original Price Index*, subtracting the *Loss Adjustment Factor*, and finally being converted back to the straight levels.

2.7.2 Limitations

First of all, the accuracy of my loss-effect adjusted index is constrained due to the lack of early transaction data. In generating the loss-effect adjusted index, only the paired repeat transactions are used to calculate the percentage of loss-facing sellers and their expected losses, but a large proportion of transactions in the early years of the sample period do not have information on the prior purchase prices (i.e., these units were initially purchased before the start of my sample period). Specifically, for repeat sales in the bust period from 1997 to 2003, I can only identify the expected losses for the sellers who purchased the units after 1992. Since Hong Kong's property markets had been continuously increasing from 1980 to 1992 (see Figure 2.1), excluding the sellers who purchased in earlier years with lower prices is likely to cause overestimation of loss-facing sellers and the expected losses in the bust periods.

To partially alleviate this concern, I conduct a robustness check by only including the paired repeat transactions with the holding period of less than 10 years (denoted as the truncated sample). Since my sampling period starts from 1992, this allows a more balanced sampling for comparing the by-year loss effect, especially from 2003 onward. The repeat sales index and the adjustment factors for the loss effect are modified accordingly. Appendix Figure A.3 plots the corresponding repeat sales index and the loss-effect adjusted index using the truncated sample. I compare the by-year adjustment factors derived from the full paired samples and from the truncated samples, which are reported in Appendix Table A.10. I find that, for the truncated sample, the aggregate loss effect remains stronger during the bust period, which indicates that my main finding is robust.

Secondly, the estimates of a unit expected loss on transaction price in the office and retail sectors, where fewer transactions occurred, may also be a concern. In accordance with the tests in Section 2.6, the coefficient estimates on expected losses over the property cycle are less stable in the office and retail

property market, respectively. Future studies should explore whether the aggregate effect of expected gains has different dynamics across cycles.

sectors than in the residential and industrial sectors. This may pose a threat to the accuracy of loss effect estimates, thus causing bias in aggregating the loss effect on the overall market.

Thirdly, this study follows GM to take an all-inclusive approach in the first-stage regression in the empirical framework. Specifically, all transaction observations during the entire sample period are included in Equation (2.1) to estimate the transaction price of property i at year t. It leads to a potential concern of the look-ahead bias, because the transaction observations at later periods (e.g., $t + 1$) are used to estimate the market price at time t. The all-inclusive approach is used in the main analysis because GM's empirical model builds on a strong assumption that the impacts of housing features on prices, either observed or unobserved, are fixed over time. Under this assumption, the residuals relative to the expected price at time $t - 1$ can be considered a reliable measurement of the unobservable features at time t. Nevertheless, the actual impact of the look-ahead bias on the findings is yet to be explored. Further analyses that use a series of rolling regressions including only the observations in preceding time windows are recommended for future studies.

2.8 Chapter Summary

Unlike existing studies that estimate an average effect of expected losses on list prices in real estate markets, this paper advances the literature by showing that the power of the loss effect on transaction prices is a function of information availability and market conditions. Built upon the insights of GM, this study first uses a comprehensive dataset of Hong Kong property transactions to empirically demonstrate significant loss effects on transaction prices across the residential, industrial, office, and retail sectors. More importantly, I find the loss effect to be stronger in the commercial market than in the residential market where there is abundant comparable transaction information to help reduce the mispricing of the target property. Combined with the study of BG, I shed light on the importance of sellers' loss behavior in the commercial property market where professional investors occupy.

I also examine variations in the loss effects in a large boom-bust cycle across different property sectors. I find the loss effect on the individual transaction prices to be more prominent in the boom period than in the bust period. But when combining the percentage of sellers facing an expected loss, the expectation of the loss amount, and the impact of a unit amount of expected loss on the transaction price in the aggregate market analysis, the loss effect turns stronger in the bust period than in the boom period. That is, the loss effect reduces aggregate price declines in market downturns, the effect of which is particularly strong in the commercial property sectors. These results suggest a role of loss behaviors in accounting for aggregate property market dynamics.

My effort of examining the interaction between the loss effect and different market conditions also provides fresh insights in understanding why loss behaviors can affect market prices. Based on the reduced-form regression results, I am able to relate it to limited market information and the heat of the market. Admittedly, there exist some limitations of this study, which need further investigation with better quality of data in future studies. In particular, the accuracy of the estimated loss effect is constrained because I do not have the assessed property value like Zhou et al. (2021b,a) to deal with unobserved features but mostly relying on GM's approach combined with the improvement of Anenberg (2011). This might particularly be an issue in the commercial sectors with relatively fewer transactions and inadequate quality control.

Chapter 3

Contract Rescission in the Real Estate Presale Market

3.1 Introduction

This study investigates the contract rescission behaviour in presale residential property market.[1] Real estate developers face substantial risks with new developments. If the market demand for new homes falls unexpectedly at the time of construction completion, developers will be left with vacant buildings to be sold and outstanding construction loans to be paid off. A presale contract serves as an important risk-sharing instrument whereby developers can shift these risks to property buyers (Lai et al., 2004). In a typical presale contract, developers and home buyers agree on the price at the date of the contract, which can be several years before construction completion, and buyers pay their deposit upfront. In this way, property developers lock in prices at the early stage of the development and receive cash flow sooner, which helps to mitigate uncertainty in property sales and improve their financial position.

Although presale contracts are designed by developers for the purpose of risk sharing, property buyers may also benefit from buying homes on the presale market. From their point of view, entering a presale contract locks in a fixed property price and hedges against future price appreciation. In a market boom, presale could reward buyers with lucrative built-in equity when construction is complete. Homebuyers also enjoy more choices in terms of selecting desired features at an early stage. In addition, a presale contract can be used for speculative purposes as the contract can be transferred to another buyer at a higher price before property completion.

Some prior studies model presale contracts as forward contracts between buyers and developers (Wong et al., 2006). However, I argue that it is more appropriate to model these contracts as call options, based on two unique features (Lai et al., 2004). First, when the presale contract is signed, property sellers/developers require a deposit—typically 10% of the sale price—while there is no deposit requirement in a forward contract (Jarrow and Oldfield, 1981). Second, a presale contract gives the buyer the right, but not the obligation[2], to purchase the property at settlement (Chan et al., 2012).

[1]The study presented in this chapter is a collaborative work with Prof. Quan Gan from the University of Sydney and Prof. Maggie Hu from the Chinese University of Hong Kong. Materials derived from this chapter have been published in *Real Estate Economics* in 2021. DOI: 10.1111/1540-6229.12363. I was in charge of methodology, software, formal analysis, data curation, validation, visualisation, and writing original draft.

[2]In most situations, developers will not force the presale buyer to purchase the property if they prefer to rescind.

Buyers can rescind the presale contract and lose the upfront deposit, which corresponds to the loss of a call option premium if the option is not exercised.[3] Therefore, when entering a presale contract, a buyer effectively takes a long position in a call option that expires at settlement.

Newly constructed housing units in Hong Kong are always in high demand, with substantial oversubscription. Given the limited supply, I would expect presale buyers to settle on their units after completion if the property purchased is for owner occupation. It is puzzling, therefore, to find that about 10% of presale contracts from 1996 to 2014 in the Hong Kong housing market were rescinded, which amounts to HKD 436.67 million in forfeited deposits per year (equivalent to approximately USD 56.3 million). The contract rescission rate and associated losses are notably high, which suggests that speculation may play a role in the presale market. Therefore, studying presale contract rescission not only has economic significance, but also carries policy implications for housing market regulations.

To bridge the knowledge gap for this puzzle, I consider the mechanism of presale contract rescission from a novel perspective: option theory. Specifically, I study the impact of three option-related features on the presale contract rescission rate: option moneyness, delta, and time-to-maturity. First, option moneyness measures the intrinsic value of the presale contract. Lower option moneyness at settlement is expected to result in a higher rescission rate, which reflects buyers' strategic default behaviour. Second, I use the call option delta at the time of purchase to measure the buyer's share of the price risk. Option delta is the sensitivity of the option value to the underlying asset's value. In other words, holding one unit of option is approximately equivalent to holding delta units of the underlying asset. In my setting, holding one presale contract is approximately equivalent to holding delta proportion of the to-be-built property in the contract. A higher delta implies a higher risk share for the buyer, which could induce a higher rate of contract rescission. Third, I use the time-to-maturity of the presale call option—the time period between the contract date and settlement—to measure the time-induced risk borne by the homebuyer. In option theory, the call option's value is typically increasing with longer time-to-maturity.[4] However, a long time-to-maturity option may be less valuable to presale buyers if higher time uncertainty is induced, such as information opacity on the building's quality (e.g., Wong and Cheung, 2020). Therefore, I hypothesize that longer time-to-maturity also leads to a higher chance of contract rescission.

I test these hypotheses empirically using a comprehensive dataset on 231,186 presale contracts of residential properties in the Hong Kong housing market from 1996 to 2014. In my baseline results, I find that the moneyness of presale options negatively predicts the rescission rate, controlling for the building's physical features. Specifically, if the market price at the time of settlement becomes 10% higher relative to the presale contract price, the contract rescission rate will drop by 0.46%, which translates to a 4.5% reduction from the average rescission rate. Further, if the market price at settlement is lower than the outstanding payment on the purchase contract, the rescission rate increases significantly by 1.24%, which is equivalent to a 12.2% increase of the average rescission rate. These findings align well with the literature on strategic mortgage default when the market price of the collateral is less than the remaining loan amount (Bradley et al., 2015; Guiso et al., 2013).

Besides option moneyness, I also test the effect of other option metrics, including option delta and time-to-maturity. My result shows that presale contract rescission rate is higher for buyers that have

[3]Note that sellers/developers seldom ask for forfeiture of more than the 10% deposit. See the legal consequences of breaching the sale and purchase agreement at: https://hkclic.org/en/topics/saleAndPurchaseOfProperty/consequences_of_breaching_the_sale_and_purchase_argeement/.

[4]There is an exception for dividend-paying stocks, because the dividend will cause the stock price to decline. In this case, the short-life option could be worth more than the long-life option.

a greater share of price risk (measured by the option delta), and time-induced risk (measured by the time-to-maturity). If buyers' share of price risk, as measured by the call option delta at purchase time of the presale unit, increases by one standard deviation, the contract rescission rate at settlement will increase by 1.06%. In terms of contract timing, I find that entering a presale call option one month earlier (i.e., time-to-maturity increases by one month) will result in a 0.55% higher rescission rate. If the time-to-maturity of the presale call option increases by 10% of the entire presale period of the project, the rescission rate will increase by 0.24%. As the call option delta is an increasing function of option moneyness, I conduct a robustness test by replacing delta with the orthogonalized version of delta, i.e., the residuals from regressing deltas on moneyness measures. I find that the orthogonalized version of delta still has a positive and significant impact on the contract rescission rate, which confirms the robustness of my result.

Next, I compare the explanatory power of the proposed option-related factors with other potential determinants for presale contract rescission. At the regional level, I find that in districts with a 10% higher supply of presale units than the average, the contract rescission rate will go up by 0.21% (in level), or 2.1% of the average rescission rate. Some presale contracts are transferred (i.e., resold) to other buyers before their settlement dates. A higher transfer ratio (defined as the number of transferred contracts prior to the settlement divided by the number of presold units) potentially indicates the popularity of the housing project as it is easy to find the next interested buyers, and hence is expected to reduce presale rescission rate. As expected, I find that at the neighbourhood level, if the transfer ratio of presale contracts in the building increases by 1%, the contract rescission rate will fall by 0.46% (about 5% of the mean, given the mean of rescission rate is 10.2%). In terms of buyer characteristics, I find that buyers involved with multiple presale contracts have a higher rescission rate by 3.31%. On the seller side, I look at developers' sales strategy and find that if the spot market sales proportion increases by 1%, the contract rescission rate falls by 0.15 percentage points. My horse-racing analysis shows that option moneyness and delta together have the highest predictive power for the contract rescission rate, as evidenced by the lowest Akaike information criterion (AIC) and Bayesian information criterion (BIC) scores (Akaike, 1974; Schwarz, 1978), whereas the absolute time-to-maturity has the largest impact on the contract rescission rate in terms of magnitude.

I further conduct heterogeneity analysis with respect to the location and size of the housing unit. The evidence reveals that the impact of moneyness on contract rescission is much weaker for units in the city center (i.e., Hong Kong Island), consistent with buyers' greater confidence in the long-term performance of properties in premium locations (Fan et al., 2019; Gopalan, 2018). In addition, since housing supplies in the city center face greater scarcity, the chance of finding alternative housing options in the same region is lower if buyers rescind, which in turn reduces the rescission rate.

In terms of size, I find that moneyness does not impact the contract rescission rate of units less than 500 square foot (sq. ft.), which are particularly popular among first-home buyers (Wu, 2017). These buyers have inelastic housing demand and are also unlikely to rescind out-of-money contracts. My findings are consistent with the literature, whereby homebuyers do not always rationally default on out-of-the-money contracts as a result of market and personal concerns (Seiler et al., 2012).

I also investigate the impact of the Hong Kong government's housing market macroprudential measures on presale contract rescission. Government regulation plays an important role in curbing housing market speculation and preventing the market from overheating. For example, property tax regulations substantially reduced speculation in the presale market in Singapore, as documented by Fu et al. (2016). Similarly, in 2010 the Hong Kong government introduced a series of policies to cool the overheated housing market. I use the stress test for mortgage loan applicants introduced on May 1, 2010—the first cooling measure to impact the entire housing market since the market recovered from the recession in 2003—as the policy shock date for all cooling measures. One year after the introduction of the stress test, the presale contract rescission rate in the entire market decreases by 8.65%, compared with one year prior to the stress test, because the cooling measure deterred speculation in the presale market. Further, I find that due to the stress test, out-of-the-money contracts have a 5.32% higher chance of rescission than in-the-money contracts within the first year after the policy takes effect. This implies that homebuyers may strategically rescind the contract due to the difficulty of completing a mortgage application after undergoing the stress test (Gerardi et al., 2018). These findings remain robust if I extend the sample period to include a 2-year window before and after the policy shock.

To complete my analysis, I provide an additional discussion on the disposition effect of presale buyers and the impact of option moneyness at settlement on their subsequent holding periods of properties. The disposition effect refers to the phenomenon that investors are usually reluctant to sell at losses and more willing to sell at gains, and the behavioural economics literature (Kahneman and Tversky, 1979; Shefrin and Statman, 1985) attributes it to investors' loss aversion. I examine the impact of moneyness at settlement affect subsequent holding period and find that presale buyers tend to settle an out-of-the-money contract (i.e., take the "implied" loss), and then wait for a prolonged holding period to resell the property. My empirical result shows that if the contract moneyness at settlement decreases by 0.1, the property's holding period after settlement will increase by 5.4%. Compared with presale units that have higher moneyness at settlement, those that are out-of-the-money at settlement hold for 8.9% longer. This result indicates that upon successful settlement, option features embedded in presale contracts continue to impact the buyers' behaviour through the disposition effect.

My study not only contributes to the literature on the presale and housing markets in general, but also offers valuable policy implications for market regulators and industry insights for market participants. First, my study provides a comprehensive analysis of the mechanism behind contract rescission from the perspective of option theory. Prior work mainly focuses on the theoretical analysis of real options embedded in presale contracts (Buttimer et al., 2008; Chan et al., 2012; Edelstein et al., 2012; Lai et al., 2004). Previous empirical studies on the presale market mainly focus on either the developer's behaviours (Chau et al., 2007; Li and Chau, 2019) or the interaction between presale and spot markets (Wong et al., 2006, 2007; Yiu et al., 2009). Empirical evidence on presale contract rescission is scant, with little attention paid to the reasons for presale buyers' rescission. My study, in contrast, closes this knowledge gap.

Second, my analysis of presale contract rescission contributes to the strategic default literature. Previous work mainly focuses on the mechanisms behind strategic defaults on mortgage contracts (Bradley et al., 2015; Guiso et al., 2013; Pennington-Cross and Ho, 2010; Seiler et al., 2012). This study provides unique evidence on homebuyers' strategic defaults in the presale housing market. In addition, I offer explanations on why homebuyers do not always rescind (default on) out-of-the-money presale contracts from demand and the disposition effect, including homebuyers' preference and behavioural reason. I show buyers have a particularly strong demand for small-sized properties in premium locations, and they are also susceptible to loss aversion associated with the disposition effect (Li and Wan, 2021).

Third, I contribute to the literature on speculation in the real estate market. Prior studies focus on speculation in spot primary and secondary markets (Bayer et al., 2020; Chinco and Mayer, 2016; Fu and Qian, 2014). My study suggests that a sizable proportion of speculation occurs in the presale market, in which speculators purchase housing units under construction and transfer the contracts to other homebuyers before construction is complete. Relating to this, my study of presale buyers' contract rescission behaviour offers important policy implications and industry insights. For policymakers and market participants who aim to reduce the presale rescission rate, I identify three dimensions of influential factors: option features, market conditions, and buyer attributes. My findings also offer important policy implications on how macroprudential regulations could play a stabilizing role in the housing market by discouraging market speculation and reducing presale contract rescission rates.

The rest of the chapter is organised as follows. Sections 3.2 and 3.3 discuss the institutional background and call options embedded in presale contracts. Section 3.4 describes my data. Section 3.5 presents my empirical strategy. Section 3.6 presents my main empirical analysis, and Section 3.7 provides additional discussion and analysis. Section 3.8 concludes.

3.2 Institutional Background

3.2.1 Presales of Residential Property

The presale of residential properties was introduced to Hong Kong by a businessman, Dr. Henry Fok, in 1954, with the original intention to improve housing affordability through the sale of properties prior to their completion. In a presale contract, homebuyers pay an upfront deposit on the contract date; the balance would only be paid upon completion of the building. Presale contracts, combined with mortgages, enable buyers to purchase brand-new properties without a large upfront payment. The upfront deposit can be seen as a commitment device, economically. If the homebuyers rescind the contracts and choose not to settle the remaining payments after the completion of construction, they will lose the deposit as a consequence of breaching the contract.[5] Given the clear and standard presale procedures, lawsuit cases filed either by developers to request for the remaining payments, or by presale contract holders to request for returning the deposits, are very rare in Hong Kong.

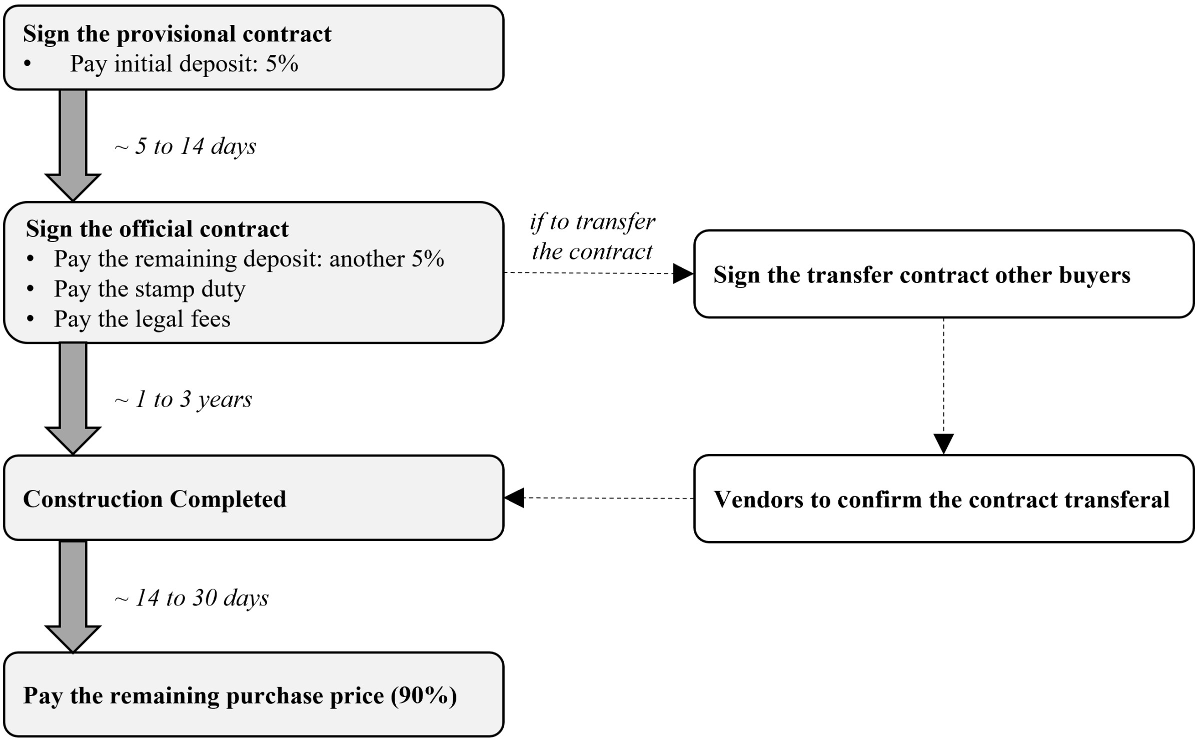
Figure 3.1 is a flow chart for the typical presale process in Hong Kong's residential property market. Once buyers decide to purchase a presale unit, they must sign a provisional contract with the developers and put down an initial deposit, which is normally 5% of the total price.[6] Within about the next 5 to 14 days, buyers must sign an official contract with the developers and pay the remaining upfront deposit and all stamp duty taxes. A total upfront deposit of 10% is typically required when signing the official presale contract, although individual developers could have their own deposit structure and required amount. After construction is complete, buyers pay the remaining 90% of the purchase price. Presale contract holders may also transfer the contract to other homebuyers before construction is complete after negotiating a price with the transferee.

From the developer's perspective, selling units before completion is a way to secure early cash inflows from nonrefundable sales deposits instead of receiving sales proceeds only after construction is complete. Preselling before completion also enables developers to test the water and gauge market demand, which serves as an initial marketing campaign and promotes sales momentum afterwards.

[5]See this link from the Community Legal Information Centre of Hong Kong for more details: https://clic.org.hk/en/topics/saleAndPurchaseOfProperty/consequences_of_breaching_the_sale_and_purchase_argeement.

[6]Based on Section 11.1.15 of the Consent Scheme for the Sale of Units in Uncompleted Private Residential Developments in the Lands Department's Legal Advisory and Conveyancing Office Circular Memorandum No.40A, the preliminary deposit or reservation fee paid to the developer should be approximately 5% of the average purchase price of all units put on sale at any one time.

Fig. 3.1 Flow Chart of the Typical Presale Process in Hong Kong



Notes: This figure illustrates the typical presale process in Hong Kong's residential property market.

In some countries/regions, the construction lenders even require the developers to presale a certain percentage of units in the new development, in order to reduce the risk that the lenders bear.[7]

From homebuyers' perspective, there are several benefits of buying a home using a presale contract, apart from paying a low upfront payment for to-be-built properties. First, by buying in the presale market before other buyers, a buyer can choose from a wider selection of homes in the sales offering, and will be more likely to find a better match in terms of certain physical features, such as locations, floor plans, finishes, etc. Sometimes buyers can also customise certain aspects, such as finishes, according to their own preferences.

Second, using a presale contract, homebuyers could delay the mortgage process until the building construction is completed, and also lock in the home purchase at a predetermined price. This deferment of the payment till building completion allows presale buyers a longer time to save for their down payments and other closing costs while the homes are being built. Thus, property purchases using presale contracts could encourage more efficient budget planning for homebuyers.

Third, it is possible for buyers to build up home equity from the presale contract date to the settlement date. As housing prices rise over the course of the construction period, especially in a booming market, the profit potential from the presale contract can be quite lucrative. By transferring the presale property to another buyer before settlement, initial buyers could reap quick gains from the price appreciation. However, although buying through presale contracts appears to be profitable in a

[7]For instance, in the US, Fannie Mae requires 50% of the new apartment units to be presold (Chan et al., 2014).

rising real estate market, buyers may still face substantial uncertainty due to various risk factors, such as market fluctuations and illiquidity of the housing market.

Since its introduction in 1954 in Hong Kong, presale contracts have been widely used in many countries. For example, most new apartments in China are initially sold on the presale market (Deng and Liu, 2009). Fu et al. (2016) also document that private condominiums in Singapore are typically offered for sale before project completion. In Canada, around 60–70% of new units are presold as of 2008 (Choi et al., 2012). In the UK, US, Australia, New Zealand, and Middle Eastern countries, buying “off-the-plan” properties are equivalent to real estate transactions through presale contracts. During the housing boom before the sub-prime crisis in 2007, presales accounted for a substantial part of residential markets in many cities in the US (Edelstein et al., 2012). Thus, understanding the presale market becomes more important, given that presales have gone mainstream in many countries.

3.2.2 The Hong Kong Housing Market and the Government’s Macroprudential Measures

Hong Kong has topped the list of the world’s most expensive cities to live in for years (Taylor, 2019). According to the Rating and Valuation Department (RVD), Hong Kong’s residential property prices have risen by 242% over the past decade, and the housing price index in 2018 is more than six times the level in 2003. To cool down the overheated residential real estate market, the Hong Kong government has introduced a series of macroprudential policies in recent years. Appendix Table B.1 presents a list of cooling measures in Hong Kong’s housing market. For instance, the government lowered the loan-to-value (LTV) ceiling for residential mortgages on properties valued over HKD 20 million to 50% on Jun 1, 2009. And soon afterwards, the government increased the stamp duty rate on transactions of property valued over HKD 20 million from 3.75% to 4.25% effective from April 1, 2010. However, these policies in earlier years mainly focused on regulating the sub-market of high-end luxury properties (over HKD 20 million), which constitutes fewer than 0.5% of transactions in my sample period.

In contrast, the stress test requirement for mortgage loan applicants introduced on May 1, 2010 was the first cooling measure introduced by the government that has a wide-ranging impact on the entire housing market. As stipulated in the stress test, the debt-servicing ratios (DSRs) of all mortgage applicants are capped at 50%, and banks should also ensure that the DSRs will not exceed 60% after an increase in mortgage interest rates by 3%. Therefore, the stress test imposes financing restrictions on both genuine buyers and speculative buyers.

Also, the Hong Kong government forbade individuals from transferring presale contracts before settlement for all presale contracts signed after August 13, 2010, unless the developers had obtained presale permission for the estate/project before that date. This policy significantly deterred speculators in the presale market as they were no longer able to realize excessive profits by only paying the deposit and transferring the contract at higher prices before settlement.

In addition, over the past decade, the government has introduced three stamp duties to cool the red-hot housing market. The first is the Special Stamp Duty (SSD), which discourages short-term buyers. Specifically, all properties purchased from November 20, 2010 onward will be levied with a tax of 5–15% if buyers sell the unit within two years. The SSD taxable period was extended to 3 years, and the tax rate was increased to 10–20% after October 26, 2012. The second is the Buyer’s Stamp Duty (BSD) which took effect on October 27, 2012. It placed a 15% surcharge on non-permanent residents and corporate buyers. The third is the Double Stamp Duty (DSD), which applies to all non-permanent residents and permanent residents who own more than one residential property. The tax rate for the DSD was 4.25–8.5% when it was introduced on February 22, 2013, and it was further raised to 15% on November 5, 2016.

3.3 The Call Option Embedded in Presale Contracts

The option framework is widely used in studying various aspects of real estate transactions, such as termination, prepayment, and default on mortgages (Ambrose and Buttimer, 2000; Deng et al., 2000; Hilliard et al., 1998); land and property development (Capozza and Li, 2001; Cheng et al., 2021; Grenadier, 1996; Yao and Pretorius, 2014); and presale contract analysis (Buttimer et al., 2008; Chan et al., 2012; Edelstein et al., 2012; Lai et al., 2004). However, option theory is rarely applied to understand market participants' behaviour in the context of the residential real estate presale market. As an exception, Chan et al. (2012) derive a theoretical pricing equation for a presale contract that explicitly accounts for a buyer's default decision. In this study, I incorporate the concepts derived from option pricing theory in my empirical analysis to gain a deeper understanding of the behaviour of presale contract buyers, which contributes to the literature on buyers' behaviour for equity and index options (Boyer and Vorkink, 2014; Byun and Kim, 2016; Lakonishok et al., 2007).

In this section, I explain how to understand presale contracts using option-related concepts. A presale contract of a housing unit can be modeled as a call option in the form of a risk-sharing instrument for developers and homebuyers. The buyer of the presale contract enters a long position in a call option in house price, with an exercise date of the option at the presale contract settlement. The developer, by pre-selling the under-development property, enters a covered call position (i.e., selling the call option and holding the corresponding underlying asset) in house price. Appendix Table B.2 lists the key notations of a call option and the corresponding terms of a presale contract.

Option price C for a presale contract is αH, where H is the sale price of the property on the contract and α (10% in most presales in Hong Kong) is the down payment as a percentage of the house price when the contract is entered. The strike price K is the final payment at settlement $(1-\alpha)H$. Time-to-maturity T is the period from contract date to settlement date. The underlying asset price S is the fair market price of the newly constructed property.

While the 10% deposit rate (α) of presale contracts is typical in the Hong Kong housing market, it varies for presale contracts in many other housing markets around the world and could sometimes be negotiable between buyers and developers. For instance, the deposit to housing price ratio is also typically 10% in Australia,[8] whereas it ranges from 10% to 20% in Singapore (Fu et al., 2016). In Taiwan, the initial deposit can be as low as 5% of the housing price, but homebuyers need to pay an additional 2–3% after each construction stage completes (Chang and Ward, 1993). In mainland China, homebuyers may be required to pay for the entire amount of the housing price at the time of the presales, so the deposit rate in China essentially equals the down payment rate in the mortgage if they choose mortgage financing, which varies between 20% to 70% in different cities (Mak et al., 2007).

Using the option framework to model presale contracts has unique advantages. Option-related concepts, such as moneyness, delta, and time-to-maturity, can be used to analyse the features of presale contracts. A call option is "in-the-money" when the underlying asset price is higher than the strike price ($S > K$), "at-the-money" when $S = K$, and "out-of-the-money" when $S < K$. The concept of

[8] Refer to this webpage for a detailed discussion on presale in the Australian housing market: https://www.realestate.com.au/advice/buying-off-the-plan-is-it-a-good-idea/.

moneyness is related to the intrinsic value of an option. A call option's intrinsic value is max($S-K$, 0), which measures the option value when the exercise decision must be made immediately. The call option's intrinsic value can be rewritten as $K*\max(S/K-1,\,0)$. When $S/K>1$, the intrinsic value is $S-K$; whereas when $S/K\leqslant 1$, the intrinsic value is 0. Also, in a presale contract, the strike price $K=(1-\alpha)H$ is proportional to the property sale price H, so contract moneyness also measures the relative cheapness of the property sale price relative to the fair market price of the property.

The call option delta (Δ) measures the sensitivity of the option price with respect to the underlying asset price movement. Mathematically, $\Delta=\partial C/\partial S$. Risk sharing between the buyer and the developer in the presale market can be mapped on a [0, 1] interval with the risk-share cut-off point delta. The risk share of the buyer is measured by Δ, which represents the risk exposure of a long position in a call option. The risk share of the developer is 1- Δ, which represents the risk exposure of a long position in the underlying asset (the property) and a short position in a call option.

Time-to-maturity measures the time value of an option from the presale contract date to the final settlement. Typically, a call option with longer time-to-maturity is more valuable to option holders. From a presale buyer's perspective, however, time-to-maturity is also a proxy for time-induced risk. The longer the time-to-maturity, the more uncertainty the buyer will face (Wong and Cheung, 2020). The time-to-maturity of a presale contract captures not only the positives but also the negatives of the option time value. If the net time value is negative to buyers holding long positions in call options, then the net time value must be positive to the developer holding short positions in call options. In summary, I focus on using moneyness (intrinsic value), delta (house price sensitivity), and time-to-maturity (time value) to analyse presale contracts.

3.4 Data

3.4.1 Sample Construction

The data used in this study are obtained from the EPRC Limited, a data vendor that tracks all property transaction data from the Hong Kong Land Registry. The raw dataset contains all residential property transactions in Hong Kong from 1992 to 2017.[9] In addition to transaction details such as sale price, names of buyers and sellers, contract dates and settlement dates, the database provides comprehensive information on various physical features of the housing unit, such as size, floor, building age, building type, etc.

I apply the following sample filtration rules to the raw data. First, I exclude presale transactions that have incomplete information on transaction details. Second, I trim the top and the bottom 1% of transaction prices in order to avoid potential data entry errors. Third, I drop observations before 1996 due to incomplete records at the land registry in those early years. Last, I exclude contracts signed between 2015 and 2017, because building construction in these presale contracts may not have been completed during my sample period, which would potentially bias the rescission rate. After data filtration, I have 231,186 presale transactions from 1996 to 2014 as my main sample.

I identify presale contracts as transactions with a contract date earlier than the construction completion date. A presale contract is deemed to be rescinded if the contract is not settled in the end.

[9] The housing units in my sample are mostly apartment units. Note that the majority of the residents in Hong Kong live in the high-density apartment units. Due to the small sizes of these apartment units and the well-developed hotel industry in Hong Kong, these residential apartments are not commonly used for vacation accommodations by tourists, different from the cases in many western cities.

Transfers of presale contracts are identified if the presale contract is resold to other buyers before the settlement date (also called "confirmor sales" in Hong Kong). Once a contract is transferred to a new buyer, I consider it to be a new transaction sample and identify whether it is settled, rescinded, or further transferred.

Next, I calculate several option-related variables for these presale transactions. As explained in Section 3.3, the call option price (C) is the upfront deposit paid when entering the contract, which equals 10% of the presale price in most cases. The strike price (K) of the call option equals the remaining property price to pay at the settlement time. The market price (S) of the property is estimated as the product of unit size and an estimated market price per square foot (psf). Specifically, the market price psf at contract time is calculated as the average price psf of all units in the same building sold within the [-6 months, +6 months] window of the presale contract date. In contrast, as there are few transactions close to the settlement time, I define the market price psf at the settlement time as the average price psf in the same building sold within two years prior to settlement.

In this study, the moneyness of the presale option at settlement time is defined as the fair market price of the property at settlement (S) divided by the original contract price of the property ($K + C$).[10] It is trimmed at the top and bottom 5% level to mitigate the impact of outliers. The delta of the call option at the time of purchase is estimated based on the Black-Scholes model (Black and Scholes, 1973), using the 12-month Hong Kong Interbank Offered Rate (HIBOR) as the risk-free rate.

As time-to-maturity is another important factor of the option value, I calculate the time-to-maturity of a presale contract using the following two approaches. The first is *Absolute Time-to-Settlement*, which equals the months between the presale contract date and the settlement date. For those presale contracts that are ultimately rescinded, their actual settlement dates are not observed in the data[11]; thus, I use the average settlement date of the non-rescinded contracts in the same building as their settlement date. Since the time-to-maturity also highly correlates with the development period of each estate, I also introduce the second measurement, *Relative Time-to-Settlement*, which is calculated as the number of months from the presale contract date to the settlement date divided by the entire presale period of the building.

3.4.2 Summary Statistics

Panel A of Table 3.1 presents the summary statistics of my key variables, and the detailed definition of each variable is presented in Appendix Table B.3. On average, a presale property in Hong Kong has two bedrooms, two living rooms, and is located on the 23rd floor of a high-rise apartment building with about 619 sq. ft. (58 square meters). The average price of a housing unit in my sample is 3.95 million HKD (or 0.51 million USD). Of the total 231,186 presale contracts in the entire sample, 23,561 (10.2%) are rescinded, and 5,969 (2.6%) are transferred to other buyers before settlement. A rescinded contract on average incurs a dollar loss of 0.36 million HKD (45,600 USD). Of all transferred contracts, 5,271 are transferred with gains, with an average gain of 13.85%, and 698 contracts are transferred with losses, with an average loss of 16.47% (including the cost of deposit).

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[10] In most prior literature, the moneyness of a call option is normally defined as the fair market price (S) divided by the option strike price (K). Here, in order to facilitate understanding of how much the market price changes from the original presale contract price, I modify the definition of moneyness as $S/(K + C)$. All my findings are virtually consistent if I use S/K as moneyness; results are available upon request.

[11] Since the actual rescission time is not observed, I cannot employ a hazard model framework to estimate the probability of a rescission over time. Instead, I consider the presale contract as a European option, which limits the execution to its expiration (settlement) time.

Table 3.1 Summary Statistics and Correlation Matrix of Variables

Panel A: Summary Statistics

Variable	Obs.	Count	Mean	Std. Dev.	Min	P25	P50	P75	Max
Transaction Details and House Attributes									
Contract Price (million HKD)	227,683		3.951	3.110	0.410	1.912	2.973	4.825	21.000
Unit Size (thousand sq. ft.)	228,825		0.619	0.228	0.156	0.481	0.559	0.702	5.075
Floor	231,082		22.708	13.944	1	11	20	31	82
Bedrooms	228,188		2.417	0.727	0	2	2	3	6
Living Rooms	228,769		1.787	0.612	0	2	2	2	4
Remaining Lease Years	230,619		68.658	128.395	18	46	48	49	898
Rescission-related Variables									
Rescind (Yes = 1)	231,186	23,561	0.102	0.303	0	0	0	0	1
Loss at Rescission (million HKD)	23,327		0.356	0.293	0.061	0.181	0.259	0.416	2.094
Transfer (Yes = 1)	231,186	5,969	0.026	0.159	0	0	0	0	1
Transfer Gain (million HKD)	5,271		0.454	0.876	0.000	0.029	0.252	0.497	16.68
Transfer Loss (million HKD)	698		0.752	1.220	0.001	0.106	0.328	0.800	14.387
Transfer Ratio to Presales	230,195		0.030	0.068	0	0	0.006	0.027	0.694
Transfer Ratio to Stocks	231,186		0.027	0.064	0	0	0.005	0.024	0.556
Presale Market Supply (thousand)	231,186		1.904	1.392	0.001	0.744	1.714	2.280	6.068
Spot Market Supply (thousand)	231,186		2.704	2.240	0.001	1.087	1.942	4.097	11.048
Multiple Contracts Holder	231,186	18,957	0.082	0.274	0	0	0	0	1
Spot Sale Ratio	231,186		0.132	0.172	0	0.006	0.055	0.210	0.998
Holding Period After Settlement (years)	92,192		4.883	3.772	0.003	1.808	4.110	7.312	18.425
Presale Option Variables									
Call Option Strike Price (million HKD)	227,683		3.556	2.799	0.369	1.721	2.676	4.342	18.900
Call Option Price (million HKD)	227,683		0.395	0.311	0.041	0.191	0.297	0.482	2.100
Market Price at Settlement (million HKD)	221,426		4.051	3.422	0.366	1.961	2.992	4.866	74.300
Moneyness	197,677		1.009	0.071	0.855	0.958	1.007	1.059	1.176
Moneyness [0.95, 1]	197,677	48,192	0.244	0.429	0	0	0	0	1
Moneyness [0.9, 0.95]	197,677	30,035	0.152	0.359	0	0	0	0	1
Moneyness < 0.9	197,677	13,081	0.066	0.249	0	0	0	0	1
Call Option Delta (Black-Scholes)	218,539		0.765	0.098	0.000	0.702	0.750	0.815	1
Absolute Time-to-Settlement (months)	231,186		13.722	6.364	0.033	9.133	13.267	17.567	69.800
Relative Time-to-Settlement	231,186		0.726	0.313	0	0.517	0.877	0.977	1.000
Implied Volatility (monthly)	225,355		0.075	0.021	0.043	0.059	0.069	0.084	0.153

Table 3.1 Summary Statistics and Correlation Matrix of Variables, Continued

Panel B: Correlation Coefficient between the Key Explanatory Variables

	Moneyness	Call Option Delta	Absolute Time-to-Settlement	Relative Time-to-Settlement	Transfer Ratio to Presales	Transfer Ratio to Stocks	log (Presale Market Supply)	log (Spot Market Supply)	Multiple Contracts Holder	Spot Sale Ratio
Moneyness	1.000									
Call Option Delta	0.507	1.000								
Absolute Time-to-Settlement	0.029	-0.137	1.000							
Relative Time-to-Settlement	0.020	0.010	0.384	1.000						
Transfer Ratio to Presales	0.052	-0.113	0.228	0.116	1.000					
Transfer Ratio to Stocks	0.053	-0.111	0.234	0.115	0.991	1.000				
log (Presale Market Supply)	-0.021	0.094	-0.025	0.040	0.061	0.070	1.000			
log (Spot Market Supply)	0.003	-0.101	-0.118	0.042	0.139	0.137	0.282	1.000		
Multiple Contracts Holder	-0.010	-0.055	0.033	0.002	0.038	0.034	-0.032	0.024	1.000	
Spot Sale Ratio	0.005	-0.050	-0.221	-0.090	-0.159	-0.190	-0.198	0.057	-0.020	1.000

The mean value of moneyness is 1.009, with a min-max range of 0.855–1.176. This means that on average, presale buyers enjoy a 0.9% discount on the contract price compared with the fair market price at settlement. This is consistent with the rationale that presale contracts are popular with homebuyers because they may benefit by locking in a lower price before building completion. Approximately 6.6% of presale contracts are out-of-the-money (i.e., moneyness < 0.9) at settlement.

I then examine the option delta, which measures the extent of risk-sharing between property developers and presale buyers. Specifically, a higher delta indicates a higher proportion of the price is shifted from the developers to the presale buyers. The average delta of presale contracts is estimated to be 0.765, which implies that on average, presale buyers take 76.5% of the property price risk by entering a presale contract. Alternatively, from the developer's perspective, presale contracts enable developers to reduce their risk exposure from 100% to 23.5% on average.

Another important option metrics I look at is the time-induced risk, measured using the time-to-maturity of the presale option. The average *Absolute Time-to-Settlement* of a presale contract is 13.7 months. The average *Relative Time-to-Settlement* is 0.726, implying housing units are presold at an early stage during the housing development process (27.4% of the time frame from presale launch to settlement). From the developers' side, this result also suggests that developers tend to reduce their risk exposure early through presales.

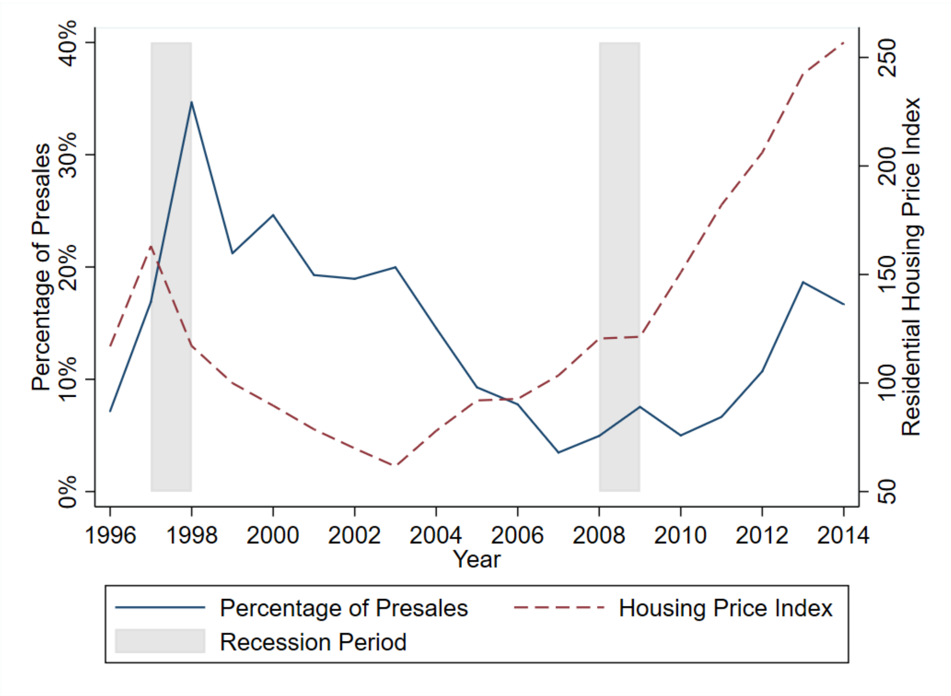
Using the terms of presale contracts, I also calculate the implied volatility (σ) of the forward-looking property price based on the closed-form approximation formula in Brenner and Subrahmanyan (1988). I find that the annualised implied volatility equals 25.98%, which is in line with the annualised Hong Kong real estate market volatility of 23.46% documented by Wong et al. (2006).

In Panel B of Table 3.1, I report the correlation matrix between my key explanatory variables and the contract rescission dummy variable. Apart from a few pairs of alternative measurements of the same factor which naturally have strong positive correlations (e.g., the correlation between *Absolute Time-to-Settlement* and *Relative Time-to-Settlement* is 0.384), the correlation is also quite high (0.507) between the moneyness and the call option delta. Based on option theory, option delta is a nonlinear increasing function of moneyness. In my setting, delta and moneyness each capture different aspects of the call option embedded in a presale contract.

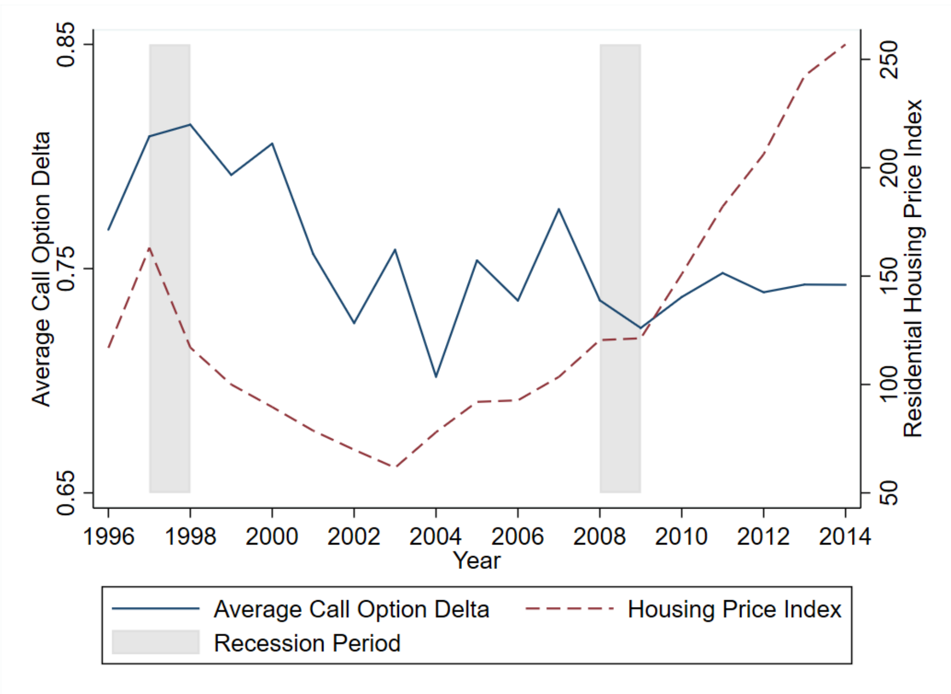
Panel A of Figure 3.2 plots the percentage of presales in Hong Kong's residential real estate market between 1996 and 2014. Presales constitute a significant proportion of housing transactions in Hong Kong, and this proportion varies with housing market conditions. On average, about 13.2% of residential property transactions in this period are presale transactions, which demonstrates the popularity of presale contracts in the Hong Kong housing market. In 1998, one year after Hong Kong's return to China, presale contracts constitute approximately 35% of all housing transactions—the highest number across all sample years. This percentage gradually declines over the next several years, and presales constitute only 3.5% of transactions in 2007, right before the global financial crisis (GFC). After the GFC, the percentage of presales in the Hong Kong residential market climbs and reaches about 17% in 2014. As a general pattern, the share of presale market transaction activity lags behind housing price movement through business cycles. Presale contracts gain more popularity in housing market booms and become less attractive in market downturns. During the two economic recessions in Hong Kong (1997–1998 and 2008–2009), the percentage of presale market transactions increases and then decreases after the recession ends.

I also find that the presale buyers' share of price risk, measured by the call option delta, is positively correlated with the housing price. Panel B of Figure 3.2 plots the average call option delta of presale

Fig. 3.2 Presale Transactions in Hong Kong's Housing Market



(a) Percentage of Presale Transactions



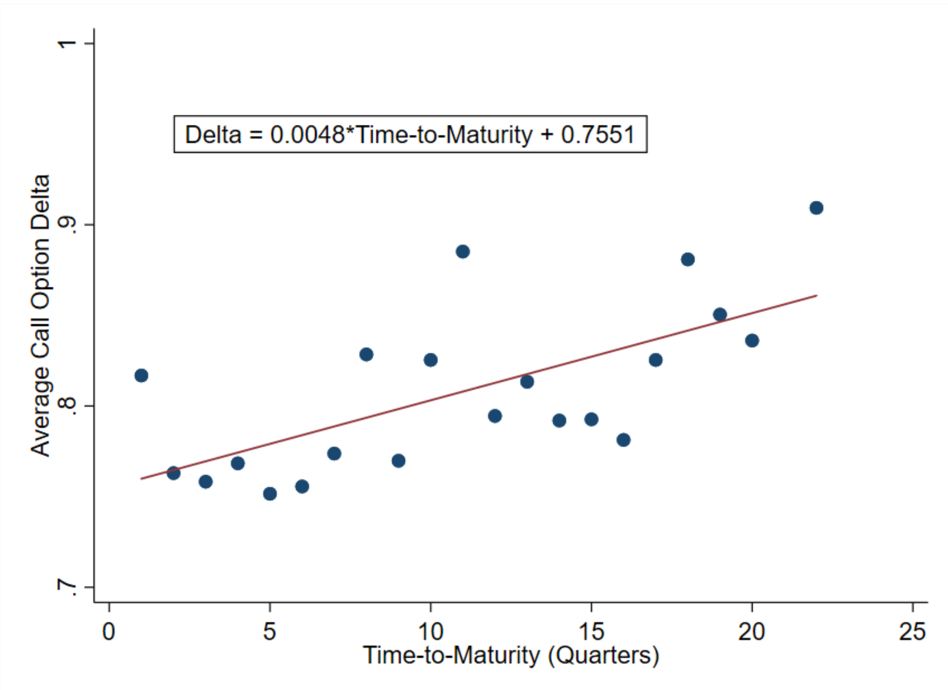
(b) Average Call Option Delta

Notes: Panel A of this figure plots Hong Kong's housing price index and the percentage of presale transactions in Hong Kong's housing market from 1996 to 2014. The housing price index is obtained from the Hong Kong Rating and Valuation Department. Shaded bars indicate two recession periods in Hong Kong, including the Asian Financial Crisis from 1997 to 1998 and the Global Financial Crisis from 2008 to 2009. Panel B of this figure plots Hong Kong's housing price index and the average call option delta of presale contracts. The call option delta is calculated with the Black-Scholes Model.

contracts versus Hong Kong's housing price index from 1996 to 2014. The average option delta of presale contracts lies in the range of 0.7–0.8, suggesting that buyers share around 70–80% of the price risk in the presale contracts. That is to say, developers effectively shift a large portion of price risk to homebuyers using presale contracts. The option delta tends to decline when house prices decline and becomes relatively stable or increase when house prices increase. This finding suggests that presale buyers seek to bear a smaller share of the risk during market downturns, and are willing to bear more risk during market booms.

In addition, I find that presale homebuyers' price risk-sharing is also positively correlated with time-induced risks. Figure 3.3 plots the average delta of the presale call option by the time-to-maturity at the time of purchase; the red line represents the linear fitted function. On average, if the homebuyer enters the presale contract earlier by one quarter, the delta of the presale call option is higher by around 0.005. This shows that if presale homebuyers purchase the unit earlier, they are willing to bear a higher share of the price risk.

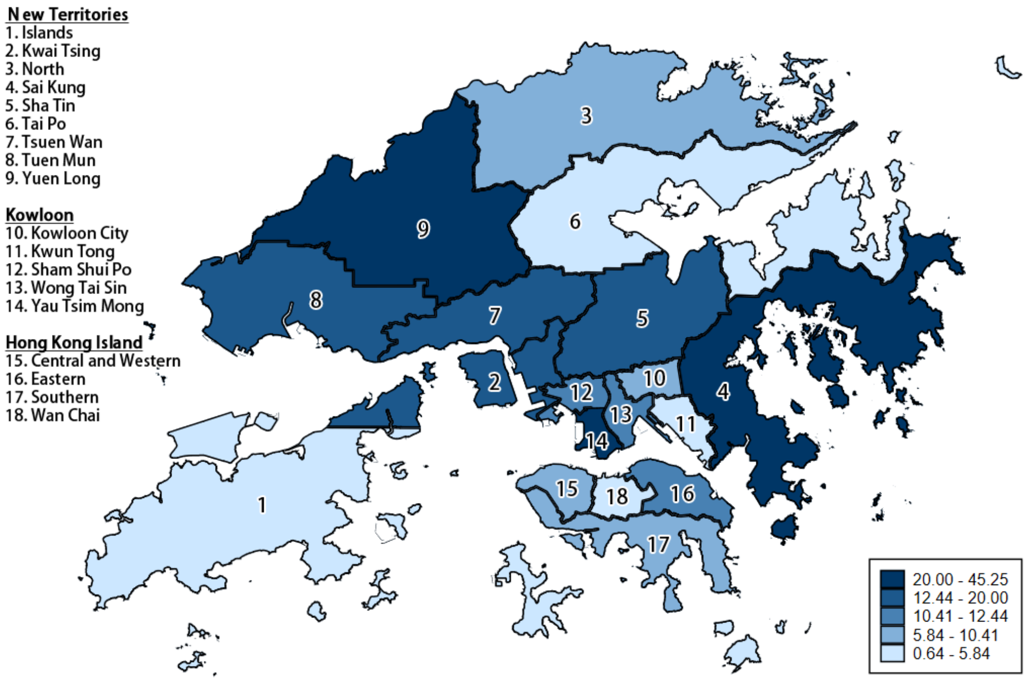
Fig. 3.3 Call Option Delta and Time-to-Maturity at Purchase Time



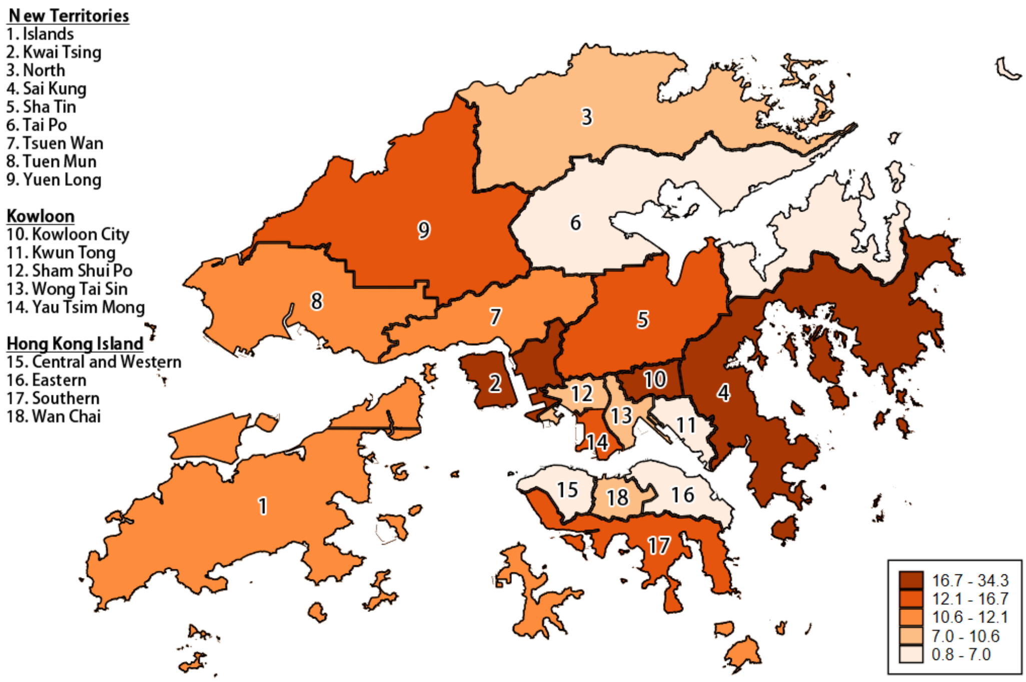
Notes: This figure plots the average delta of the presale call option by the time-to-maturity at the purchase time. The red line represents linear fitted values.

I observe heterogeneity in presale rescission rates across space and time. In the spatial dimension, district-level variations suggest that districts with low housing prices tend to have high presale contract rescission rates. Figure 3.4 shows the number of presales (Panel A) and percentage of presales in total real estate transactions (Panel B) by 18 districts of 3 regions in Hong Kong during 1996-2014, as well as the average presale contract rescission rate (Panel C) and the average unit housing price (Panel D). I find that presale transactions are more concentrated in districts of the New Territories (e.g., districts such as Sai Kung, Sha Tin, and Yuen Long), as shown in Panels A and B. There are fewer presale transactions in Hong Kong Island or Kowloon, especially in the traditional central districts of the city, such as Wan

Fig. 3.4 Rescission Rates and House Prices by District

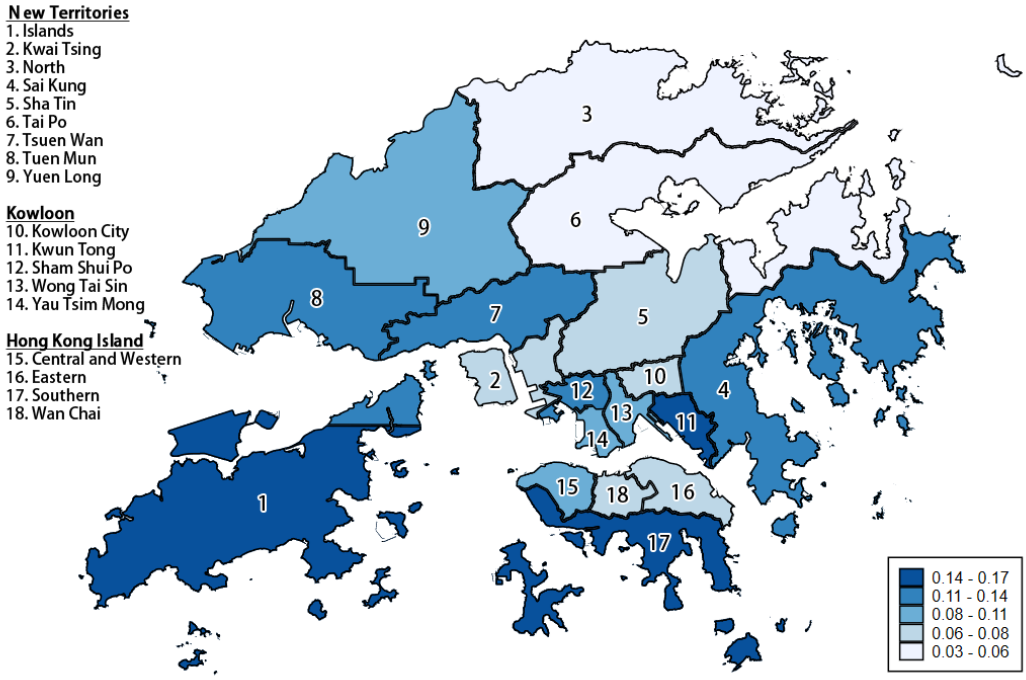


(a) Number of Presales in Each District from 1996 to 2014

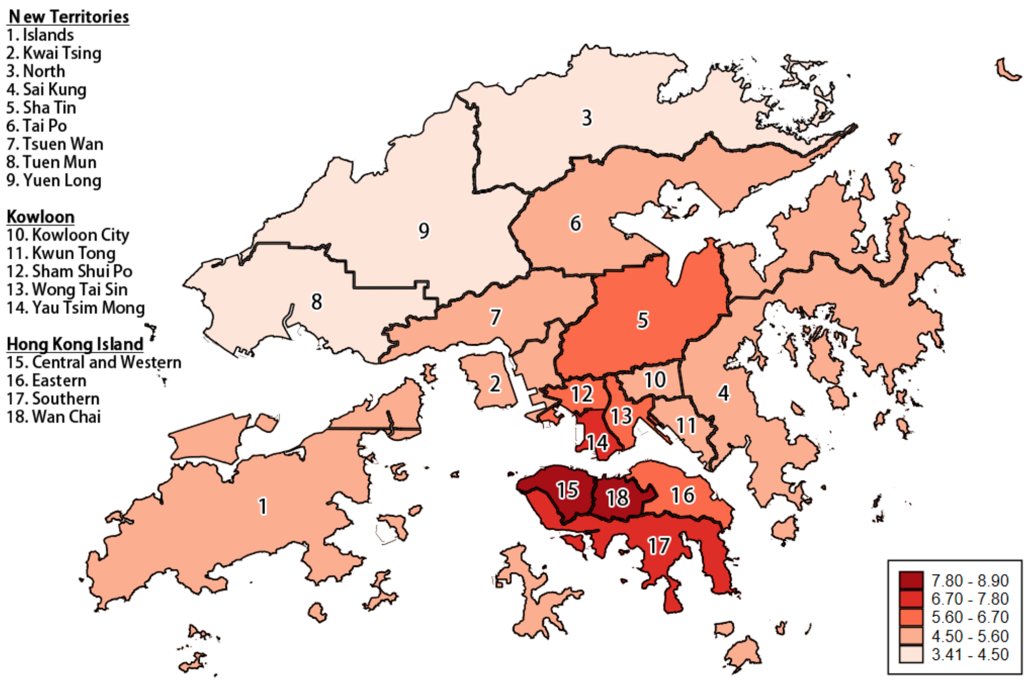


(b) Percentage of Presales in All Transactions from 1996 to 2014

Fig. 3.4 Rescission Rates and House Prices by District, Continued



(c) Rescission Rate of Presale Contracts in Hong Kong from 1996 to 2014



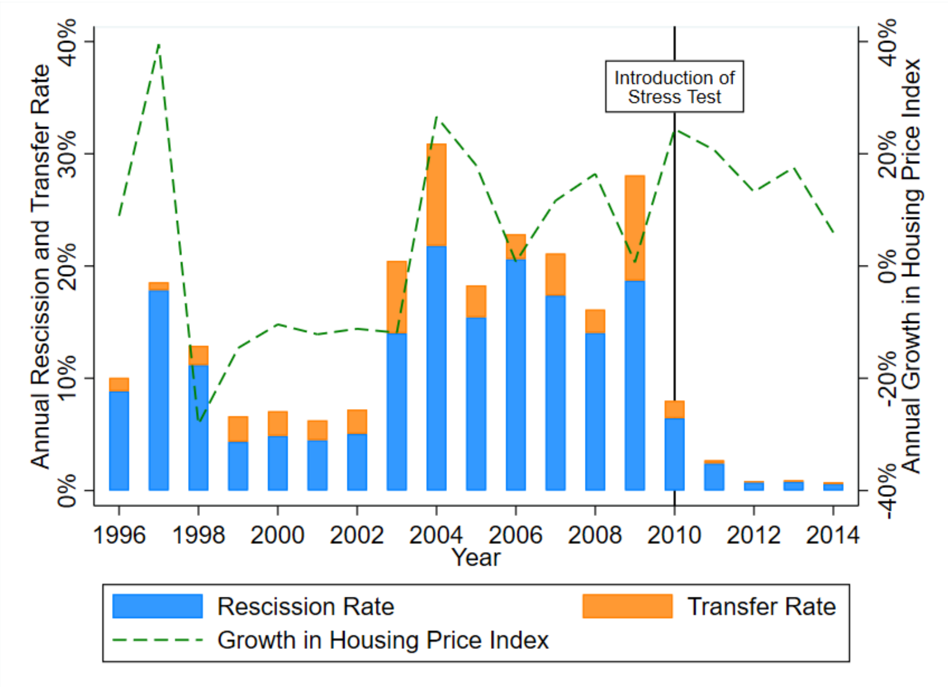
(d) Average Housing Price in Hong Kong from 1996 to 2014

Notes: Panel A plots the number of presale residential units for the 18 administrative districts in Hong Kong from 1996 to 2014, and Panel B plots the density of presale units (i.e., the number of presales divided by the number of all home sales). Panel C presents the average presale contract rescission rate in each district. Panel D presents the average housing price per square foot in each district of Hong Kong from 1996 to 2014.

Chai and Yau Tsim Mong. This is consistent with the fact that there is more land supply—and hence construction of more new housing—in the New Territories, compared with Hong Kong Island or Kowloon. Panel C shows that the rescission rate is generally higher (14–17%) in the Southern and Islands districts, and lower (3–6%) in the North and Tai Po districts. The south-north difference is also evident in the unit housing prices shown in Panel D, in which the Southern and Wan Chai districts have high housing prices and the North, Yuen Long, and Tuen Mun districts have low housing prices.

In the temporal dimension, I find that the rescission rate of presale contracts displays a positive correlation with annual housing price growth before 2010, as shown in Figure 3.5. However, the presale rescission rate significantly dropped from 18.70% in 2009 to 0.63% in 2014, after the Hong Kong government introduced cooling measures to regulate the overheated housing market, and especially after the introduction of the stress test for homebuyers on May 1, 2010. This sharp reduction in response to the cooling policy shows a significant policy response on the presale contract rescission rate, as the policy potentially screens out two main types of higher risk borrowers: (1) speculators who aim to transfer presale contracts before settlement and (2) financially constrained homebuyers who encounter difficulties in applying for a mortgage.

Fig. 3.5 By-year Transfer and Rescission Rates of Presale Contracts from 1996 to 2014



Notes: This figure plots the annual rescission rate (blue bar) and transfer rate (orange bar) of presale contracts in Hong Kong, as well as the annual growth rate of the housing price index (dashed green line), over my sample period from 1996 to 2014. The housing price index is obtained from the Rating and Valuation Department of Hong Kong. I also indicate introduction of the stress test in 2010 with a thick vertical line.

Finally, Table 3.2 further summarizes the characteristics of presale homebuyers, including the number of contracts they hold, their rescission rate, and their holding periods. Panel A presents the average rescission rate in terms of the number of presale contracts that the buyers held concurrently. The results show that units bought by buyers with multiple contracts have a higher rescission rate. Units bought by buyers holding more than one contract have a higher rescission rate than the full sample mean of 10.2%. In general, the more contracts held by the buyer, the higher the rescission rate observed. Contracts with buyers holding five or more contracts have the highest rescission rate (14.57%).

Table 3.2 Summary of Presale Buyers' Characteristics

Panel A: Number of Presale Contracts Buyers Hold and Their Rescission Rates

No. of Presale Contracts Held	No. of Buyers (Count)	No. of Buyers (Freq.)	Rescission Rate
1	213,946	92.54%	9.90%
2	11,496	4.97%	13.94%
3	2,976	1.29%	13.91%
4	1,264	0.55%	11.87%
5	550	0.24%	13.82%
> 5	954	0.41%	14.57%
Total	231,186	100%	10.20%

Panel B: Holding Period of Presale Contract Holders

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
From Presale Contract to Settlement			From Presale Contract to Transfer Before Settlement			From Settlement to Resale in Secondary Market		
Period	Count	Cum. Freq.	Period	Count	Cum. Freq.	Period	Count	Cum. Freq.
0-6 months	20,649	8.93%	0-1 months	1,540	25.80%	0-3 months	5,727	6.21%
6-12 months	78,373	42.83%	1-2 months	529	34.66%	3-6 months	3,959	10.50%
1-1.5 years	78,420	76.75%	2-3 months	403	41.41%	6-9 months	2,729	13.46%
1.5-2 years	42,210	95.01%	3-6 months	945	57.25%	9-12 months	2,433	16.10%
2-2.5 years	8,518	98.70%	6-9 months	966	73.43%	1-2 years	9,982	26.93%
2.5-3 years	1,741	99.45%	9-12 months	754	86.06%	2-3 years	9,745	37.50%
> 3 years	1,275	100%	1-2 years	772	98.99%	3-5 years	18,819	57.92%
			> 2 years	70	100%	5-10 years	27,665	87.92%
						> 10 years	11,133	100%
Total	231,186		Total	5,969		Total	92,192	

Notes: This table presents summary statistics of presale buyers' attributes. Panel A summarizes the number of presale contracts buyers hold and their rescission rates. Panel B summarizes their holding period. Columns (1) to (3) summarize the holding period from presale contracts to settlement for those buyers who settle the presale contract. Columns (4) to (6) summarize the holding period from presale contracts to transfer for those buyers who transfer the contract before settlement. Columns (7) to (9) summarize the holding period from settlement to resales in the secondary market for those buyers who settle the presale contract and resell the unit within my sample period.

Panel B of Table 3.2 presents the holding period of presale homebuyers from presale to settlement (or from presale to transfer if the property is resold before settlement), and from settlement to subsequent resale in the secondary market. I find that 43% of presale contracts are settled within 12 months after signing presale contracts and about 95% are settled within 2 years. A small proportion of presale contracts (0.55%) are settled after 3 years. On average, presale buyers who transfer their contracts hold for only 178 days, and more than half (57.25%) of the transferred contracts are resold within 6 months after the contract date. After presale contracts are settled, around 27% of homeowners resell their units within 2 years.

3.5 Empirical Methodology

In my baseline analysis, I focus on the impact of option-related factors on the presale contract rescission rate using a Probit model as follows:

$$\Pr(Rescind_{it}) = \Phi(\beta Factor_{it} + X_{it}^{'}\lambda + \varphi_i + \omega_t), \tag{3.1}$$

where $Rescind_{it}$ is a dummy variable that equals one if the presold unit i purchased at time t is rescinded at final settlement, and zero otherwise. Φ is the cumulative distribution function of the standard normal distribution. $\Pr(Rescind_{it})$ denotes the probability that unit i purchased at time t is rescinded. The variable of interest, $Factor_{it}$, is a vector of the option-related variables that potentially impact the rescission rate of presale contracts. Specifically, I focus on three factors: moneyness at settlement, call option delta at purchase time, and time-to-maturity at purchase time.

Moneyness is a measure of the call option's intrinsic value, which is a key determinant of the option exercise decision. I estimate the moneyness of the presale option using the following two methods. The first measure is $Moneyness_{it}$, which is a continuous variable equal to the market price at the settlement time divided by the presale contract price. The second measure is a set of dummy variables that indicates whether $Moneyness_{it}$ is between 0.95 and 1, between 0.9 and 0.95, or below 0.9. These dummy variables denote whether the market price at settlement has decreased from the contract price by 0–5%, 5–10%, or over 10%, respectively. In particular, $Moneyness < 0.9$ means that the market price of the property is lower than the remaining payment. Thus, this variable also denotes whether the presale option is out of the money at settlement.

I also estimate the delta of the presale call option at the time of purchase, based on the Black-Scholes formula. For time-to-maturity, I use both *Absolute Time-to-Settlement* in months and *Relative Time-to-Settlement*, which equals the absolute time-to-settlement scaled by the presale period of the project, as explained in Section 3.4.1.

X_{it} is a vector of control variables on property attributes, including the unit's gross sellable area, number of rooms (bedrooms plus living rooms); remaining lease term of building in logarithm of years; and floor and building type (i.e., single building blocks or buildings in an estate). These property characteristics are also commonly used in the literature as control variables when studying the housing market in Hong Kong (e.g., Wong et al., 2012). φ_i denotes district fixed effects and ω_t represents year times quarter fixed effects. Standard errors are clustered at district level.

3.6 Results

3.6.1 Moneyness at Settlement

I first investigate the impact of the moneyness of the presale contract at settlement time on contract rescission rate. A higher moneyness represents a lower price relative to the market price and a higher option intrinsic value. Therefore, contracts with higher moneyness are expected to have a lower probability of rescission. Table 3.3 reports the impact of moneyness on contract rescission rate, estimated from Equation (3.1). I find that if moneyness at settlement increases by 0.1 (i.e., the market price becomes higher than the presale contract price by an additional 10%), the rescission rate will decrease by 0.456%, which is equivalent to a 4.47% increase from the average rescission rate (10.2%). This estimate is statistically significant at the 5% level.

Table 3.3 The Impact of Moneyness at Settlement Time on Rescission Rate

Y: *Rescind*	(1)	(2)
Moneyness	-0.0456**	
	(0.0182)	
Moneyness [0.95, 1]		0.0026
		(0.0024)
Moneyness [0.9, 0.95]		0.0114***
		(0.0028)
Moneyness < 0.9		0.0124***
		(0.0034)
Unit Size	0.0001	-0.0008
	(0.0290)	(0.0293)
Rooms	-0.0025	-0.0024
	(0.0067)	(0.0067)
log(*Lease Years*)	-0.0055	-0.0056
	(0.0078)	(0.0078)
Floor	-0.0004**	-0.0004**
	(0.0002)	(0.0002)
Property Type Fixed Effect	Y	Y
District Fixed Effect	Y	Y
Year*Quarter Fixed Effect	Y	Y
Pseudo R-Squared	0.1399	0.1401
Observations	194,966	194,966

Notes: This table presents Probit regression results of the rescission rate on moneyness at settlement time. The dependent variable is *Rescind*, which equals one if the presale contract is rescinded and zero otherwise. *Moneyness* is defined as the market price at settlement divided by the presale contract price. The market price at settlement is predicted as the size of the unit times the average price psf in the sample building within 2 years before settlement. *Moneyness [0.95, 1]* is a dummy variable equal to one if moneyness is between 0.95 and 1 (zero otherwise). Similarly, *Moneyness [0.9, 0.95]* and *Moneyness<0.9* are dummy variables indicating whether moneyness is between 0.9 and 0.95 or below 0.9, respectively. Definitions of the other independent variables are reported in Variable Definitions. Marginal effects at means are reported. Standard errors are clustered at district level. Robust standard errors are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level.

Based on option theory, the rescission decision for a presale contract should largely be determined by option moneyness, which has a kink point at 0.9 (i.e., when the market price falls by 10% of the contract price and equals the remaining payment at settlement). To test this discontinuity effect, I replace the continuous measure of moneyness with a set of dummy variables that indicate whether the value of moneyness is between 0.95 and 1, between 0.9 and 0.95, or below 0.9. Column (2) in Table 3.3 reports the estimation results, and I find that presale contracts with moneyness between 0.95 and 1 at settlement do not have a statistically significant higher rescission rate than those with moneyness higher than 1. However, if moneyness at settlement is between 0.9 and 0.95, the associated rescission rate will increase by 1.14%, which is 11.2% higher than the average rescission rate. Further, if moneyness is lower than 0.9—that is, when the market price is lower than the remaining payment—the rescission rate increases by 1.24%, which translates to 12.2% of the average rescission rate. All these estimates are statistically significant at the 1% level. These findings align with the strategic default rationale that if the homebuyer considers the down payment to be a sunk cost and the market price of the property falls below the remaining payment, they will strategically default on the presale contracts (Bradley et al., 2015; Guiso et al., 2013).

Interestingly, it is noteworthy that although lower moneyness of the presale contract at settlement leads to a higher rescission rate, I do not observe a very sharp kink when a contract becomes out of the money. In other words, many presale contract holders still pay the remaining balance although the contracts are out of the money. There are several possible explanations for this behaviour bias. First, the literature of the strategic default widely documents that, given sufficient ability to repay, many loan holders do not default on loans when the value of the collateral falls below the value of the remaining liability, for reasons such as a morality concern (e.g., Guiso et al., 2013; Seiler et al., 2012). In the context of presales, it is possible that buyers worry about the credit and reputation risks associated with the rescission, which may impact their future purchases with the developers.

Second, it is possible that the contract holders are reluctant to rescind the out-of-the-money contracts due to loss aversion (Bokhari and Geltner, 2011; Genesove and Mayer, 2001). Instead, they will still settle and hold the property until the market price increases and their losses are recovered. This disposition effect is expected to be stronger when the homebuyers have stronger confidence in the future performance of the market (Chen et al., 2007; Kadous et al., 2014).

Last, it may also be explained by the rigid housing demand of some homebuyers. Rescinding a presale contract and finding a cheaper alternative in the housing market can be a quite risky decision as it involves substantial search cost and market uncertainty and can be time-consuming (i.e., the overall “switching cost” is high), which may not be economically beneficial for homebuyers with urgent housing demand. Moreover, the impact of the switching cost is further exacerbated given the unbalanced supply and demand in the Hong Kong housing market (Leung and Tang, 2015).

I conduct several robustness checks for my result. First, the rescission decision might vary with respect to the actual amount of the deposit paid in the presale, and I expect those contracts involving larger amounts of loss at rescission will be less likely to rescind. To test this effect on loss amount empirically, I conduct an additional test by replacing the rescind dummy with the loss amount at rescission as the dependent variable in Equation (3.1). The rescission loss is defined as equal to the deposit paid if the contract is rescinded, and zero if the contract is settled. The regression results are reported in Appendix Table B.4. I find that call option moneyness is negatively associated with the dollar loss amount at contract rescission, consistent with my baseline Probit regression results using the rescind dummy as the dependent variable.

Second, in my baseline results, the moneyness of the call option embedded in the presale contract at the time of building settlement is estimated using the average price for properties in the same building sold within 2 years prior to settlement. I choose the 2 years window before settlement as there are relatively few transactions close to settlement, and the observation number would be insufficient to provide unbiased estimation if I choose a shorter window such as 1 year before settlement.[12]

One may be concerned that my price estimation based on the [-2, 0] year window around the settlement time may be too broad, making the estimation too coarse. To address the concern, I improve the estimation precision by further applying a time adjustment on the estimated market price. I first

[12]The median number of presale transactions in a newly constructed building within 1 year and 2 years before settlement is 52 and 219, respectively. 13.8% of the buildings do not have any transactions within 1 year before settlement, while only 2.5% of the buildings do not have any transactions within 2 years before settlement.

calculate the average number of months between a presale contract's settlement time and the other transactions in the same building within 2 years prior to settlement. I then calculate the average monthly growth rate of the Hong Kong RVD Housing Price Index during the 2-year period prior to the settlement date of the presale property. Then I construct a time adjustment factor, which is defined as the average monthly growth rate compounded by the average time difference between the settlement time and the prior transactions in the past 2 years. I adjust the average price psf in the same building in 2 years prior to settlement by multiplying it with the time adjustment factor. Using this time-adjusted market price to calculate the contract's moneyness at settlement, I conduct a robustness check for my baseline estimations, and the results are reported in Appendix Table B.5. I obtain similar results as my baseline estimations, which reflects the robustness of my main findings.

Third, I check the robustness of my results using alternative combinations of the fixed effects. I first include the district times year times quarter fixed effects as a robustness check. In this case, the time-variant unobserved features at the district level are also captured by the fixed effects, so the variations I exploited in this empirical model will mainly originate from the estate level. The corresponding estimation results are reported in Columns (1) and (2) of Appendix Table B.6, which is qualitatively similar to my baseline result in Table 3.3.

Moreover, one may be concerned that the contract rescission decisions could be affected by the project developers, besides presale moneyness, property and homebuyer characteristics, and market conditions. As there is no information on developers from the EPRC transaction data, I manually collect information on developer names by searching the name and address of the buildings. I am able to identify the developer names for 31% of the presale transactions, which I can use to create developer fixed effects; and I encode the remaining unidentified samples as a separate group. The corresponding estimations results after including developers' fixed effects are reported in Columns (3) and (4) of Appendix Table B.6. The results are again consistent with my baseline results.

In summary, my findings show that lower moneyness of the presale option results in a higher rescission rate. This effect is stronger when the market price at settlement drops below the remaining payment amount of the presale contract. My findings are consistent with the option theory, whereby out-of-the-money options are more likely to expire unexercised.

As pointed out by Bhutta et al. (2017), many homebuyers may not default immediately on their mortgage contracts when these contracts become underwater with negative home equity. Instead, they will default on mortgage contracts when they are deeply underwater with substantially negative home equity. Along the same vein, there may exist various levels of kink points for the presale option moneyness, which can lead to a different impact on homebuyers' rescission decisions. Note that the minimum value of moneyness is 0.855 for all presale contracts in my sample, with a mean of 1.009. As moneyness is a measure of the market price appreciation of the housing unit from the time of the presale contract, a high minimum moneyness is largely consistent with the upward trend price in the Hong Kong housing market. However, due to this limitation, I could not test other lower rescission trigger points such as 0.8 (when the property value drops by over 20%). I recommend it for future research with other suitable empirical settings.

3.6.2 Delta and Time-to-Maturity at Purchase Time

In the previous section, I investigate the impact of moneyness at settlement on the presale rescission decision. In addition to moneyness, the delta and time-to-maturity of the call option also play important roles in the presale risk-sharing and should impact presale rescission decision.

In this section, I analyse the impact of buyers' risk sharing (measured by delta and time-to-maturity in the call option at purchase time) on the presale contract rescission rate. I measure the buyer's risk along two dimensions. First, I use the call option delta as the explicit measurement for the price-risk exposure of the buyer's long position in a call option. Second, I use the time-to-maturity at purchase time to measure the time-induced risk a buyer will face. In prior research, Gan (2013) shows that time-on-market uncertainty increases property sellers' price risk. By selling properties before completion of development, the developer reduces its time-on-market uncertainty and shifts the time-induced risk to the buyers. Since presale contracts are used as a risk-sharing instrument for developers to shift risk to buyers, I expect that presale buyers who bear higher risk exposure at purchase time will have a higher contract rescission rate.

To test this hypothesis, I include delta and time-to-maturity as the main explanatory variables in Equation (3.1) and report the estimation results in Table 3.4. In Column (1), the independent variable of interest is the call option delta at the purchase time, and I control for physical housing features. I find that if the delta of the call option increases by 0.1, which is approximately a one-standard-deviation increase in the option delta, the contract rescission rate will increase by 1.06%, with statistical significance at the 5% level. This result indicates that a higher delta is associated with a higher probability of rescission, consistent with the economic intuition that as the call option delta increases the buyer's risk exposure also increases, and more price risk is shifted from the developer to the buyer.

I conduct two robustness checks for this result. First, as call option delta is positively correlated with option moneyness (see Panel B of Table 3.1), the positive effect of option delta on rescission rate I document might be driven by moneyness. To mitigate this concern and to show my risk sharing result is not merely driven by moneyness, I conduct a robustness check by first regressing delta on moneyness, and then using the regression residual to replace the delta measure in Table 3.4. I find this orthogonalized delta measure still has a positive and significant effect on contract rescission rate, confirming the unique role of buyer's risk exposure in explaining presale rescission. The results are reported in Panel A of Appendix Table B.7.

Second, to estimate option delta, I define the market price psf at purchase time as the average price psf of all units in the same building sold within the [-6 months, +6 months] window of the presale contract date. I also check the robustness of my findings using a shorter window of [-3 months, +3 months] around the contract date. The result is reported in Panel B of Appendix Table B.7. I continue to observe a positive effect of call option delta at purchase time on contract rescission, and the magnitude of the effect is similar to my baseline estimation results.

Estimation results using time-to-maturity as the key explanatory variable are presented in Columns (2) and (3) in Table 3.4. I use the absolute time-to-settlement in Column (2) and the relative time-to-settlement in Column (3). Full controls for physical housing features are included in both columns. My results reveal that increasing the absolute time-to-settlement by 1 month will increase the rescission rate by 0.55% (Column (3)), which is a 5.4% increase from the average rescission rate. If buyers enter the presale contract earlier by 10% of the entire presale period of the project, the rescission rate will

Table 3.4 The Impacts of Call Option Delta and Time-to-Maturity on Rescission Rate

Y: *Rescind*	(1)	(2)	(3)
Call Option Delta	0.1061**		
	(0.0433)		
Absolute Time-to-Settlement		0.0055***	
		(0.0007)	
Relative Time-to-Settlement			0.0239***
			(0.0057)
Unit Size	0.0419	0.0152	0.0270
	(0.0333)	(0.0221)	(0.0266)
Rooms	-0.0153**	-0.0114**	-0.0142***
	(0.0061)	(0.0047)	(0.0053)
log(*Lease Years*)	-0.0014	-0.0105	0.0002
	(0.0081)	(0.0078)	(0.0080)
Floor	-0.0000	-0.0004**	-0.0003
	(0.0002)	(0.0002)	(0.0002)
Property Type Fixed Effect	Y	Y	Y
District Fixed Effect	Y	Y	Y
Year*Quarter Fixed Effect	Y	Y	Y
Pseudo R-Squared	0.1395	0.1512	0.1401
Observations	215,059	224,918	223,963

Notes: This table presents Probit regression results of the rescission rate on call option delta at purchase time and time-to-maturity at purchase time. The dependent variable is *Rescind*, which equals one if the presale contract is rescinded and zero otherwise. *Call Option Delta* is the delta of the call option at purchase time calculated with the Black-Scholes Model. *Absolute Time-to-Settlement* equals the number of months between contact date and settlement date. *Relative Time-to-Settlement* is defined as the *Absolute Time-to-Settlement* divided by the length of the whole presale period of the building. Definitions of the other independent variables are reported in Variable Definitions. Marginal effects at means are reported. Standard errors are clustered at district level. Robust standard errors are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level.

increase by 0.239% (Column (4)), which translates to a 2.3% increase in the average rescission rate. Both estimates are statistically significant at the 1% level.

In summary, my results support the conjecture that the rescission rate of presale contracts is positively associated with their time-induced risk. In fact, time-to-maturity measures both time-induced risk and the time value of an option. My findings imply that for the call options embedded in presale contracts, the cost of time overtakes the value of time, so the net effect of time-to-maturity is negative. Since the time value to the buyer (the long side) is negative, the time value to the developer (the short side) would be positive, which also reflects the shifting of time-induced risk from the developer to the buyer through presales.

3.6.3 Additional Determinants of Presale Rescission and the Horse-Racing Analysis

In addition to the related variables derived from the call option embedded in presale contracts based on option theory, other determinants may also impact presale buyers' rescission decisions, such as the transfer ratio of comparable contracts, the local housing supply, and the presale buyer's characteristics. In this section, I examine the impact of these additional determinants on the presale rescission decision.

I then conduct a horse-racing analysis to compare the impact of these conventional determinants with those factors derived from option theory.

The first factor I investigate is the percentage of transferred presale contracts in the same building. If more presale contracts in the building are transferred to other buyers before settlement, this indicates that speculative buyers are interested in units in the building. In other words, the ex post percentage of transferred contracts is a proxy for the buyers' ex ante expectation of speculative opportunities. If speculators cannot pass the unit to other interested buyers before presale settlement, they would be more likely to rescind the contract. To test the effects of transfer opportunity, I devise two measures with different scaling factors. The first is calculated as the number of transferred contracts divided by the total number of presale contracts in the same building. The second is the number of transferred contracts divided by the total number of units (i.e., stocks) in the same building.

In addition, a larger local housing supply offers buyers more housing choices, which may encourage them to rescind and choose another unit. Especially when the market price of the presold property drops way below the contract price at settlement, presale contract holders may rescind the contract and choose an alternative housing option. While housing across Hong Kong is generally scarce, variations in the local housing supply at district level could still impact the rescission rate of presale contracts. I use two measures of the local housing supply in my regressions. The first measure, *Presale Market Supply*, is the volume of presale units sold in the same district in the settlement year. The second measure, *Spot Market Supply*, is the number of units sold in the spot market in the same district in the settlement year.

Moreover, the buyers' individual characteristics, especially their speculative motives, should significantly impact their decisions on presale contract rescission. A buyer holding multiple presale contracts is more likely to be a speculator in the property market. Likewise, a short-term buyer who resells quickly after settlement is likely driven by speculative motives. To evaluate this hypothesis on the speculative motive, I check the total number of presale contracts held by a buyer and test its impact on the presale contract rescission rate. Specifically, I use a dummy variable to indicate presale buyers who hold more than one presale contract concurrently.

Last, the proportion of the new units that the developers reserve for sale in the spot market could reflect developers' confidence in the future housing market. I expect presale buyers are less likely to rescind in a strong and booming housing market. As new housing units in Hong Kong are in great demand and are often over-subscribed, the units that the developers offer in the presale market are often sold quickly and are rarely left to the spot market. Therefore, reserving some units to sell in the spot market after the presale launch implies developer's confidence in a strong housing market. I calculate the *Spot Sale Ratio*, which equals the percentage of new units sold in the spot market (i.e., not sold in the presale market) among all new units in a building.

I include these additional variables in Equation (3.1) separately[13] and report the regression results in Table 3.5. I find that if the transfer ratio to presale contracts goes up by 1%, the contract rescission rate will increase by 0.457%, as shown in Column (1). Similarly, a 1% increase in the transfer ratio to unit stocks in the building will lead to a 0.464% increase in the rescission rate, as shown in Column (2).[14] This supports my hypothesis that buildings that attract more speculators are also likely to have more rescissions.

[13] All the results remain robust if I include the additional independent variables sequentially instead.

[14] I also find that buildings with more transfers with losses will have higher rescission rates than buildings with more transfers with gains. The result is presented in Appendix Table B.8. This further supports that speculators tend to rescind the contract if they cannot profit from a transfer before settlement.

Table 3.5 Additional Factors Influencing Rescission Rate

Y: *Rescind*	(1)	(2)	(3)	(4)	(5)	(6)
Transfer Ratio to Presales	0.4574***					
	(0.0542)					
Transfer Ratio to Stocks		0.4643***				
		(0.0578)				
log(*Presale Market Supply*)			0.0214***			
			(0.0044)			
log(*Spot Market Supply*)				0.0054		
				(0.0158)		
Multiple Contracts Holder					0.0331***	
					(0.0037)	
Spot Sale Ratio						-0.1493***
						(0.0275)
Unit Size	0.0346	0.0348	0.0329	0.0276	0.0275	0.0348
	(0.0243)	(0.0242)	(0.0259)	(0.0268)	(0.0271)	(0.0262)
Rooms	-0.0129**	-0.0131**	-0.0143***	-0.0142**	-0.0140**	-0.0154***
	(0.0058)	(0.0058)	(0.0055)	(0.0057)	(0.0058)	(0.0055)
log(*Lease Years*)	0.0074	0.0072	0.0011	0.0006	0.0003	-0.0011
	(0.0059)	(0.0062)	(0.0073)	(0.0080)	(0.0082)	(0.0082)
Floor	-0.0004***	-0.0004***	-0.0003*	-0.0003	-0.0003	-0.0004*
	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Property Type Fixed Effect	Y	Y	Y	Y	Y	Y
District Fixed Effect	Y	Y	Y	Y	Y	Y
Year*Quarter Fixed Effect	Y	Y	Y	Y	Y	Y
Pseudo R-Squared	0.1543	0.1536	0.1407	0.1381	0.1397	0.1447
Observations	224,918	224,918	224,918	224,918	224,918	224,918

Notes: Table presents Probit regression results for the rescission rate on the additional influential factors. The dependent variable is *Rescind*, which equals one if the presale contract is rescinded and zero otherwise. For the independent variables, *Transfer Ratio to Presales* is defined the as number of transferred contracts divided by the number of presale units in the same building. *Transfer Ratio to Stock* is defined as the number of transferred contracts divided by the total number of units in the same building. *Presale Market Supply* denotes the total number of presale units sold in the same district in the settlement year. *Spot Market Supply* denotes the total number of units sold in the spot market in the same district in the settlement year. *Multiple Contracts Holder* is a dummy variable denoting whether the buyer has purchased multiple presale contracts concurrently. *Spot Sale Ratio* is the percentage of spot-sale units among all new units in a building. Definitions of the other independent variables are reported in Variable Definitions. Marginal effects at means are reported. Standard errors are clustered at district level. Robust standard errors are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level.

The result in Column (3) shows that for districts with a 10% higher supply in the presale market, the contract rescission rate is 0.214% higher, whereas I do not observe a statistically significant impact of spot market supply on the presale contract rescission rate (Column (4)). This implies that genuine buyers in the primary housing market may rescind presale contracts and choose alternative presale housing options in the same district if they find that alternative options are better bargains.

Moreover, I find that the rescission rate of multiple contract holders is 3.31% higher compared with single-contract holders, as shown in Column (5). This result again aligns with the rationale that speculators are more likely to rescind the contract if they cannot transfer it to another buyer before settlement. Last, Column (6) shows the result from the perspective of developer's strategy. Specifically, I find that if the share of new units reserved to the spot market increases by 1%, the probability of presale contract rescission will drop by 0.15 percentage points. This is consistent with my expectation that the developer's confidence in the housing market outlook, proxied by their reservation rate of the new units, has a negative impact on the presale contract rescission.

In order to compare the impact of my proposed call option-related factors and these additional influential factors, I further conduct a horse-racing analysis. Specifically, I include all of the identified determinants in Equation (3.1): moneyness at settlement, call option delta, absolute time-to-maturity, transfer ratio to presales, presale market supply, the dummy variable for multiple contract holders, and the spot sale ratio at the building level. I standardize all key explanatory variables for ease of comparison and inference.

Horse-racing analysis results are reported in Table 3.6. In option theory and in my prior empirical analysis, call option moneyness is the main economic driver of the presale contract rescission decision. To assess the relative importance of other determinants of contract rescission, I include moneyness-at-settlement and one additional explanatory variable (delta, absolute time-to-maturity, transfer ratio to presales, presale market supply, multiple contract holder, and spot sale ratio) in Columns (1) to (6), respectively. I find that moneyness at settlement and the call option delta at purchase time best predict the rescission rate, as evidenced by the lowest AIC and BIC scores. To show the full effects of all the determinant factors in one regression, I include the full list of explanatory variables In Column (7). I find that absolute time-to-settlement has the largest impact on the rescission rate compared with other influencing factors, with a one-standard-deviation increase in absolute time-to-settlement leading to a 2.30% increase in the rescission rate. Overall, my horse-racing analysis shows that the list of call option-related variables (moneyness, delta, and time-to-maturity) all exhibit a significant impact on presale contract rescission.

Table 3.6 Horse-Racing Analysis for Factors Influencing Rescission Rate

Y: *Rescind*	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Moneyness	-0.0099***	-0.0047***	-0.0041***	-0.0035***	-0.0032**	-0.0038***	-0.0114***
	(0.0035)	(0.0013)	(0.0011)	(0.0013)	(0.0013)	(0.0013)	(0.0036)
Call Option Delta	0.0130**						0.0125*
	(0.0062)						(0.0065)
Absolute Time to Settlement		0.0348***					0.0230***
		(0.0053)					(0.0030)
Transfer Ratio to Presales			0.0284***				0.0224***
			(0.0038)				(0.0051)
log(*Presale Market Supply*)				0.0166***			0.0048
				(0.0058)			(0.0049)
Multiple Contracts Holder					0.0080***		0.0076***
					(0.0008)		(0.0007)
Spot Sale Ratio						-0.0255***	-0.0124***
						(0.0040)	(0.0044)
Unit Size	0.0013	-0.0012	0.0004	0.0016	-0.0001	0.0007	0.0018
	(0.0067)	(0.0065)	(0.0060)	(0.0065)	(0.0066)	(0.0058)	(0.0057)
Rooms	-0.0035	-0.0032	-0.0014	-0.0036	-0.0024	-0.0035	-0.0037
	(0.0067)	(0.0074)	(0.0068)	(0.0069)	(0.0069)	(0.0058)	(0.0065)
log(*Lease Years*)	-0.0033	-0.0052	0.0028	-0.0017	-0.0023	-0.0033	-0.0011
	(0.0037)	(0.0034)	(0.0030)	(0.0036)	(0.0036)	(0.0035)	(0.0032)
Floor	-0.0046*	-0.0068***	-0.0061***	-0.0055**	-0.0049**	-0.0065***	-0.0080***
	(0.0025)	(0.0020)	(0.0017)	(0.0024)	(0.0024)	(0.0025)	(0.0015)
Property Type Fixed Effect	Y	Y	Y	Y	Y	Y	Y
District Fixed Effect	Y	Y	Y	Y	Y	Y	Y
Year*Quarter Fixed Effect	Y	Y	Y	Y	Y	Y	Y
AIC Score	104,493	105,976	105,371	106,984	106,989	106,313	101,767
BIC Score	104,980	106,475	105,869	107,482	107,488	106,811	102,254
Pseudo R-Squared	0.1404	0.1493	0.1542	0.1412	0.1412	0.1466	0.1628
Observations	188,808	194,966	194,966	194,966	194,966	194.966	188,808

Notes: This table presents the horse-racing analysis results of all factors that influence presale contract rescission, with all of the independent variables being standardized. *Moneyness* is defined as the market price at settlement divided by the presale contract price. The market price at settlement time is predicted as the size of the unit times the average price psf in the sample building within 2 years before settlement. *Call Option Delta* is the delta of the call option at purchase time calculated with the Black-Scholes Model. *Absolute Time-to-Settlement* equals the number of months between the contract date and settlement date. Definitions of the other independent variables are reported in Variable Definitions. Marginal effects at means are reported. Standard errors are clustered at district level. Robust standard errors are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level.

3.7 Discussion

3.7.1 Heterogeneity Analysis

In this section, I analyse the heterogeneous effects of presale option moneyness on the rescission rate. First, I investigate heterogeneity across the space. Specifically, I divide my samples based on the three major regions in Hong Kong—Hong Kong Island, Kowloon, and the New Territories. Among the three regions, Hong Kong Island is the traditional city center where the central business district (CBD) is located. Residents believe that Hong Kong Island is the most premium location in the city, so the housing price in Hong Kong Island increases more in market upturns and is more resilient in market downturns (Fan et al., 2019; Gopalan, 2018). Also, Hong Kong Island has the smallest number of new housing units due to the limited land supply, which is evidenced by having the fewest primary market transactions of the three regions. Because of the high demand and low supply, presale contract holders in Hong Kong Island may be less likely to rescind out-of-the-money contracts based on stronger confidence in this sub-market. In other words, I hypothesize that the impact of moneyness on the contract rescission rate is weaker in Hong Kong Island.

To test this hypothesis, I estimate Equation (3.1) using the subsamples from the three regions. The results are reported in Columns (1) to (3) in Table 3.7. I find that for presales in Kowloon and the New Territories, if the moneyness of the presale option at settlement time increases by 0.1, the contract rescission rates will decrease by 0.81% and 0.46%, respectively. The former estimate is statistically significant at the 5% level and the latter at the 10% level. However, the moneyness of the presale option does not impact the rescission rate in Hong Kong Island, which is evidenced by the statistically insignificant coefficient for moneyness. In addition, I replace the independent variable of interest with a set of dummy variables that indicate the range of moneyness, and estimation results are reported in Columns (4) to (6). Consistent with previous results, I do not observe that out-of-the-money contracts (i.e., $Moneyness < 0.9$) have higher rescission rates in Hong Kong Island. In contrast, out-of-the-money contracts have a higher rescission rate, by 1.74% and 1.33%, in Kowloon and the New Territories, respectively. In sum, this evidence supports my hypothesis that the impact of moneyness on contract rescission is weaker in premium locations such as Hong Kong Island.

Second, I also investigate the heterogeneous effects of moneyness on contract rescission across unit sizes. Due to the extremely unaffordable housing price in Hong Kong, so-called “mini flats” have been a growing trend in recent years, as developers provide more small-size units that target first-time buyers who cannot afford a medium-size or large-size home (Lui, 2016; Wu, 2017; Ye, 2017). Therefore, due to strong housing demand from genuine buyers, I expect that fewer presale contracts for mini flats, compared with presale contracts for larger flats, will be rescinded when the presale options have low moneyness at settlement.

I verify this hypothesis by separating my main sample into three sub-groups according to the sellable unit area. Specifically, based on the definition of Hong Kong’s Rating and Valuation Department (RVD), I classify small-size units (less than 400 sq. ft.), medium-size units (less than 650 sq. ft.), and large-size units (more than 650 sq. ft.). These cut-offs are also very close to the terciles of the unit area, which results in a relatively balanced sample size in each sub-group.

Table 3.8 reports the estimation results of Equation (3.1) using these subsamples. In Columns (1) to (3), I use the continuous variable of *Moneyness* as the independent variable. I find that if the moneyness of the presale contract increases by 0.1, the rescission rate for medium-size and large-size presale units will decrease by 0.997% (Column (2)) and 0.538% (Column (3)), respectively. Both estimates are statistically

Table 3.7 Heterogeneity Effect of Moneyness on Rescission Rate Across Regions

Y: *Rescind*	(1) HKI	(2) KL	(3) NT	(4) HKI	(5) KL	(6) NT
Moneyness	0.0507	-0.0812**	-0.0460*			
	(0.0335)	(0.0359)	(0.0266)			
Moneyness [0.95, 1]				-0.0032	0.0072**	0.0009
				(0.0044)	(0.0035)	(0.0030)
Moneyness [0.9, 0.95]				-0.0057	0.0137***	0.0129***
				(0.0061)	(0.0044)	(0.0030)
Moneyness < 0.9				0.0008	0.0174**	0.0133***
				(0.0080)	(0.0075)	(0.0035)
Unit Size	-0.0237	-0.0338	-0.0587	-0.0241	-0.0336	-0.0609
	(0.0201)	(0.0331)	(0.0466)	(0.0197)	(0.0327)	(0.0466)
Rooms	0.0028	-0.0010	0.0183*	0.0023	-0.0010	0.0186**
	(0.0052)	(0.0055)	(0.0094)	(0.0051)	(0.0055)	(0.0094)
log(*Lease Years*)	-0.0065	0.0074	0.3159	-0.0063	0.0070	0.3133
	(0.0060)	(0.0274)	(0.2444)	(0.0061)	(0.0277)	(0.2439)
Floor	-0.0001	-0.0006***	-0.0003	-0.0001	-0.0006***	-0.0003
	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0001)	(0.0002)
Property Type Fixed Effect	Y	Y	Y	Y	Y	Y
District Fixed Effect	Y	Y	Y	Y	Y	Y
Year*Quarter Fixed Effect	Y	Y	Y	Y	Y	Y
Pseudo R-Squared	0.1915	0.1743	0.1417	0.1913	0.1743	0.1420
Observations	22,935	45,079	126,168	22,935	45,079	126,168

Notes: The table presents heterogeneity analysis results for the impact of option moneyness on presale contract rescission across regions. I separate the samples by the three major regions in Hong Kong: Hong Kong Island (HKI), Kowloon (KL), and the New Territories (NT). *Moneyness* is defined as the market price at settlement divided by the presale contract price. The market price at settlement is predicted as the size of the unit times the average price psf in the sample building within 2 years before settlement. *Moneyness [0.95, 1]* is a dummy variable equal to one if moneyness is between 0.95 and 1 (zero otherwise). Similarly, *Moneyness [0.9, 0.95]* and *Moneyness<0.9* are dummy variables indicating whether moneyness is between 0.9 and 0.95 or below 0.9, respectively. Definitions of the other independent variables are reported in Variable Definitions. Marginal effects at means are reported. Standard errors are clustered at district level. Robust standard errors are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% levels.

significant at the 5% level. However, the moneyness of the presale contract does not impact the rescission rate for small-size units (Column (1)). In Columns (4) to (6), the explanatory variables are the dummy variables that denote the range of moneyness. Column (4) reveals that when the market price decreases by 0–5%, 5–10%, or more than 10% from the initial contract price, there is no statistically significant change in the rescission rate of the small-size presale units. However, consistent with my main results, I find that out-of-the-money presale contracts ($Moneyness < 0.9$) for medium-size units and large-size units have higher rescission rates by 2.86% (Column (5)) and 1.49% (Column (6)), respectively. These estimates are statistically significant at 1% and 5%, respectively. This finding supports my argument that homebuyers of small-size units are less likely to rescind out-of-the-money presale options due to their rigid housing demand.

Third, I investigate the heterogeneous effects of moneyness on contract rescission across different price ranges. For more expensive properties, buyers incur a higher absolute loss amount when the presale options become out-of-the-money. Hence, I expect buyers of more expensive properties are more likely to rescind as the loss-reducing incentive is higher with a higher absolute loss amount. Whereas

Table 3.8 Heterogeneity Effect of Moneyness on Rescission Rate Across Unit Sizes

Y: *Rescind*	(1) Small	(2) Medium	(3) Large	(4) Small	(5) Medium	(6) Large
Moneyness	0.0155	-0.0997**	-0.0538**			
	(0.0416)	(0.0466)	(0.0233)			
Moneyness [0.95, 1]				-0.0031	0.0090*	-0.0010
				(0.0057)	(0.0050)	(0.0045)
Moneyness [0.9, 0.95]				0.0073	0.0185***	0.0086**
				(0.0075)	(0.0071)	(0.0041)
Moneyness < 0.9				0.0004	0.0286***	0.0149**
				(0.0075)	(0.0068)	(0.0058)
Unit Size	0.0562	-0.1006	-0.0088	0.0568	-0.0988	-0.0094
	(0.0919)	(0.2028)	(0.0206)	(0.0916)	(0.2045)	(0.0205)
Rooms	-0.0074	0.0173	-0.0128***	-0.0073	0.0175	-0.0129***
	(0.0061)	(0.0123)	(0.0022)	(0.0062)	(0.0125)	(0.0022)
log(*Lease Years*)	-0.0052	-0.0007	0.0073	-0.0051	-0.0011	0.0071
	(0.0098)	(0.0163)	(0.0120)	(0.0098)	(0.0162)	(0.0120)
Floor	-0.0005*	-0.0003	-0.0004**	-0.0005**	-0.0003	-0.0004**
	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Property Type Fixed Effect	Y	Y	Y	Y	Y	Y
District Fixed Effect	Y	Y	Y	Y	Y	Y
Year*Quarter Fixed Effect	Y	Y	Y	Y	Y	Y
Pseudo R-Squared	0.1550	0.1512	0.1527	0.1552	0.1516	0.1529
Observations	66,280	67,033	60,542	66,280	67,033	60,542

Notes: The table presents heterogeneity analysis results for the impact of option moneyness on presale contract rescission across unit sizes. I separate the samples at the tertiles of the gross sellable area and denote the subsamples as small-size units (smaller than 500 sq. ft.), medium-size units (500 sq. ft. to 650 sq. ft.), and large-size units (larger than 650 sq. ft.). *Moneyness* is defined as the market price at settlement divided by the presale contract price. The market price at settlement is predicted as the size of the unit times the average price psf in the sample building within 2 years before settlement. *Moneyness [0.95, 1]* is a dummy variable equal to one if moneyness is between 0.95 and 1 (zero otherwise). Similarly, *Moneyness [0.9, 0.95]* and *Moneyness<0.9* are dummy variables indicating whether moneyness is between 0.9 and 0.95 or below 0.9, respectively. Definitions of the other independent variables are reported in Variable Definitions. Marginal effects at means are reported. Standard errors are clustered at district level. Robust standard errors are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% levels.

for cheaper units, the absolute loss amount of the out-of-the-money contracts is smaller, and I expect contract holders would be less likely to rescind the contracts. Further, the disposition effect of loss aversion is likely to be stronger when the loss amount is smaller (Genesove and Mayer, 2001; Kahneman and Tversky, 1979), presale buyers with a smaller loss amount are more likely to keep the unit and less likely to rescind. Specifically, I separate my sample into three subsamples based on the price ranges of (1) less than 2.23 million HKD, (2) between 2.23 million HKD and 4.05 million HKD, and (3) more than 4.05 million HKD. The cut-off prices are the terciles of the total transaction price. The corresponding regression results are reported in Table 3.9. The results reveal that the impact of moneyness on contract rescission remains significant for units in medium and expensive price ranges but insignificant for cheaper units, which is consistent with my expectation.

Last, the top-floor units in a building might have more desirable property features (e.g., penthouse units with better interior decorations and higher ceilings) and thus may induce different rescission decisions of their presale contract holders (Gordon et al., 2013). I identify the top floor units by sorting the transaction records in each building by their floor levels and assume the largest floor number in the

Table 3.9 Heterogeneity Effect of Moneyness on Rescission Rate Across Transaction Prices

Y: *Rescind*	(1) Cheap	(2) Medium	(3) Expensive	(4) Cheap	(5) Medium	(6) Expensive
Moneyness	-0.0029	-0.1789***	-0.0778**			
	(0.0801)	(0.0631)	(0.0352)			
Moneyness [0.95, 1]				-0.0034	0.0143**	0.0055
				(0.0064)	(0.0060)	(0.0062)
Moneyness [0.9, 0.95]				0.0101	0.0320***	0.0118*
				(0.0106)	(0.0101)	(0.0066)
Moneyness < *0.9*				0.0104	0.0370***	0.0172**
				(0.0170)	(0.0083)	(0.0080)
Unit Size	0.0848	0.1414***	0.0061	0.0865	0.1416***	0.0062
	(0.1086)	(0.0546)	(0.0155)	(0.1075)	(0.0544)	(0.0156)
Rooms	0.0063	0.0015	-0.0093***	0.0060	0.0017	-0.0095***
	(0.0112)	(0.0094)	(0.0017)	(0.0112)	(0.0094)	(0.0017)
log(*Lease Years*)	-0.0003	-0.0184	-0.0012	-0.0002	-0.0181	-0.0013
	(0.0194)	(0.0131)	(0.0072)	(0.0195)	(0.0131)	(0.0072)
Floor	-0.0003	-0.0007***	-0.0003	-0.0003	-0.0006***	-0.0003
	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0002)
Property Type Fixed Effect	Y	Y	Y	Y	Y	Y
District Fixed Effect	Y	Y	Y	Y	Y	Y
Year*Quarter Fixed Effect	Y	Y	Y	Y	Y	Y
Pseudo R-Squared	0.1736	0.1389	0.1855	0.1736	0.1391	0.1855
Observations	67,105	64,739	62,069	67,105	64,739	62,069

Notes: The table presents heterogeneity analysis results for the impact of option moneyness on presale contract rescission across total transaction prices. I separate the samples into three subsamples at the terciles of the total transaction price and denote the subsamples as cheap units (lower than the first price tercile), medium-price units (between the first and second price tercile), and expensive units (higher than the second price tercile). *Moneyness* is defined as the market price at settlement divided by the presale contract price. The market price at settlement is predicted as the size of the unit times the average price psf in the sample building within 2 years before settlement. *Moneyness [0.95, 1]* is a dummy variable equal to one if moneyness is between 0.95 and 1 (zero otherwise). Similarly, *Moneyness [0.9, 0.95]* and *Moneyness*<*0.9* are dummy variables indicating whether moneyness is between 0.9 and 0.95 or below 0.9, respectively. Definitions of the other independent variables are reported in Variable Definitions. Marginal effects at means are reported. Standard errors are clustered at district level. Robust standard errors are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% levels.

transactions is the top floor. Then I add a dummy variable denoting the top floor units into my baseline model (Equation (3.1)) and interact it with my key explanatory variable of contract moneyness. The results are reported in Appendix Table B.9, and I find moneyness does not have a significantly different effect on top floor units compared to units on other floors.

In summary, the heterogeneity analysis reveals that while the moneyness of presale options impacts the rescission decision in most housing market segments, its effect is weaker for units in premium locations and small-size (or cheaper) units. That is, contract holders are less likely to rescind the out-of-the-money presale options of units in premium locations, potentially due to the housing supply scarcity in Hong Kong and strong confidence in the long-term performance of those units. Presale homebuyers of mini flats are also unlikely to rescind out-of-the-money options due to their strong and inelastic housing demand.

3.7.2 Housing Market Macroprudential Measures by the Hong Kong Government

My baseline analysis mainly focuses on the impact of variables derived from option theory on the presale rescission rate in a cross-sectional manner. On the temporal dimension, it has also been widely documented that speculation in the housing market also contributes to boom and bust cycles in the broader economy (Glaeser, 2013; Malpezzi and Wachter, 2005). Government regulations that aim to curb real estate market speculation are expected to better monitor the housing market and potentially reduce presale rescission. For instance, Fu et al. (2016) show that a transaction tax implemented by the Singapore government effectively curbed speculative trading in the presale market.

In this section, I further investigate whether the housing market interventions by the Hong Kong government play a significant role in affecting the presale rescission rate. Since May 2010,a series of prudential measures have been introduced by the Hong Kong market to curb speculation, reduce bubble risk, and restore market stability, as discussed in more detail in Section 3.2.2. Hence, I use May 1, 2010, as the starting date of the policy shock, on which a stress test policy for mortgage applicants was introduced. I expect that a sizable proportion of speculators will be deterred from the presale market after these macroprudential measures. Also, homebuyers who do not meet the tightened mortgage underwriting standards under the new policy are excluded from the housing market. The remaining homebuyers in the housing market are more financially prudent and less likely to be short-term speculators. As a result, they are less likely to terminate presale contracts. I conjecture the initiation of the macroprudential measures would reduce the contract rescission rate in the overall presale market.

Nevertheless, the impact of the macroprudential measures on decreasing contract rescission rate may be different between the presale contracts that are in-the-money and out-of-money. In my baseline analysis, I find that although the presale contracts out of the money have a significantly high probability of rescission than those contracts in the money, a large number of these out-of-the-money contracts are still settled, probably due to the behavioural bias of contract holders such as overconfidence of the future market performance. After the introduction of the government's macroprudential measures, it is expected that the presale contracts out of the money will have an even higher probability of rescission than those contracts in the money, because more contract holders may rescind the out-of-the-money contracts strategically given the credit restrictions.

In this respect, I can employ an empirical strategy with the following specification:

$$\begin{aligned}\Pr(Rescind_{it}) =&\Phi(\beta_1 Post_{it} + \beta_2(Moneyness < 0.9)_{it} \\ &+ \beta_3 Post_{it} * (Moneyness < 0.9)_{it} + X_{it}^{'}\lambda + \varphi_i + \omega_t).\end{aligned} \tag{3.2}$$

$Post_{it}$ is a dummy variable equal to one if the presale contract of unit i at time t is signed after the introduction of the stress test and zero otherwise. $(Moneyness < 0.9)_{it}$ is a dummy denoting whether the presale contract is out of the money at settlement. It equals 1 if the moneyness at settlement is less than 0.9 (the treatment group) and 0 if the moneyness at settlement is equal to or more than 0.9 (the control group). The rest of the variables are the same as the baseline regression model in Equation (3.1), and I cluster standard errors at the district level.[15]

[15] To avoid collinearity with the dummy variable for the policy shock ($Post_{it}$), I include the month fixed effect in Equation (3.2), instead of using the year times quarter fixed effects as in Equation (3.1). My results remain robust if I omit $Post_{it}$ in the model and include the year times quarter/month fixed effects instead (see detailed discussions in Beck et al. (2010)).

Table 3.10 The Impact of Government Regulations on Rescission Rate

Y: *Rescind*	(1) [-1 year, 1 year] May 2009 – May 2011	(2)	(3) [-2 years, 2 years] May 2008 – May 2012	(4)
Post Stress Test	-0.0865***	-0.0945***	-0.1534***	-0.1989***
	(0.0227)	(0.0251)	(0.0295)	(0.0369)
*Post Stress Test * (Moneyness<0.9)*		0.0532*		0.0749**
		(0.0286)		(0.0310)
Moneyness<0.9		0.0107		-0.0085
		(0.0210)		(0.0114)
Unit Size	-0.0428	-0.1047**	-0.0091	-0.0241
	(0.0405)	(0.0531)	(0.0394)	(0.0555)
Rooms	-0.0102*	-0.0035	-0.0064	-0.0055
	(0.0061)	(0.0080)	(0.0055)	(0.0074)
log(*Lease Years*)	0.0336**	0.0350**	0.0189	0.0138
	(0.0161)	(0.0150)	(0.0184)	(0.0187)
Floor	-0.0004**	-0.0006**	0.0002	0.0001
	(0.0002)	(0.0003)	(0.0004)	(0.0003)
Property Type Fixed Effect	Y	Y	Y	Y
District Fixed Effect	Y	Y	Y	Y
Month Fixed Effect	Y	Y	Y	Y
Pseudo R-Squared	0.1019	0.1057	0.1443	0.1451
Observations	14,827	14,443	24,211	23,189

Notes: This table presents the Probit regression results for the rescission rate on introduction of the stress test policy. $PostStressTest$ is a dummy variable indicating whether the presale contract is purchased after May 1, 2010, the date when the Hong Kong government required all banks to conduct stress tests for loan applicants. In Columns (1) and (2), I include the sample of presale units that are purchased within 1 year before or after the date of introducing the Stress Test. In Columns (3) and (4), I include the sample of presale units purchased within 2 years before or after the date of introducing the Stress Test. $Moneyness < 0.9$ is dummy variable equal to one if moneyness at settlement is below 0.9 (the treatment group). Otherwise, it equals zero (the control group). Definitions of the other independent variables are reported in Variable Definitions. Marginal effects at means are reported. Standard errors are clustered at district level. Robust standard errors are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level.

Table 3.10 reports the corresponding regression results. In Columns (1) and (2), my sample includes presale contracts signed within a 1-year window before and after the policy treatment date on May 1, 2010. In Column (1), I only include $Post_{it}$ in the model to estimate the overall impact of the cooling measures on the rescission rate. I find that there is a significant reduction of 8.65% in the rescission rate after the introduction of the stress test. Given that the average rescission rate is about 10.2%, this indicates that the government's cooling measures play a highly impactful role in curbing speculation and lowering presale rescission. In Column (2), I report regression results of Equation (3.2). I find that before the introduction of the cooling measures, the moneyness of the presale option does not exert a statistically significant impact on the rescission rate, as reflected by the insignificant coefficient of $Moneyness < 0.9$. This is probably because it was easier for contract holders to apply for a mortgage before 2010, and they may have strong confidence in the future growth of the housing price, so many of them still settle the contract even if the market price falls below the remaining payment. After the introduction of the cooling measures, the moneyness of the option becomes more impactful in determining rescission decisions: If the contract becomes out-of-the-money, the probability of rescission will increase by 5.32%. This reflects that more homebuyers strategically rescind contracts that are out of the money, possibly due to stricter mortgage underwriting rules, such as policies on the LTV ratio, that directly restrict the financing of out-of-the-money contract holders. Overall, speculators in the presale market are largely deterred by the cooling measures. Linear combinations of the estimation coefficients reveal that after the cooling measures, rescission rates for presale contracts in the money and out of the money decrease by 9.45% and 4.13%, respectively. In Columns (3) and (4), I further extend my sample period to a 2-year window before and after the policy treatment date, and all of my conclusions remain intact.

To verify the impact of the cooling measures, I conduct a falsification test with a placebo policy shock on May 1, 2008, which is exactly 2 years before the actual policy treatment date. I report falsification test results in Appendix Table B.10. In Columns (1) and (2), the sample period is the 1-year window before and after the placebo policy shock, while in Columns (3) and (4), the sample period extends to the 2-year window before and after the placebo policy shock. In Columns (1) and (3), I only include the dummy variable for the placebo policy shock, and in Columns (2) and (4), I include the full interactions. My results show that the placebo policy shock does not have a statistically significant impact on the rescission rate.

It is noteworthy that soon after the stress test was introduced in May 2010, the Hong Kong government introduced a series of other cooling measures for the residential housing market, such as forbidding presale contract transfers, increasing the mortgage application requirement, further shrinking the maximum LTV and debt-to-income ratios, limiting the maximum mortgage term, and levying stamp duties on flipping transactions. Although I cannot disentangle the impacts from the individual policies as the time intervals between policy shocks are short, these cooling measures—including the stress test itself—are all expected to curb speculative activities and reduce the rescission rate. In other words, what I estimate with the current empirical setting is the aggregate impact of all these cooling measures, beginning with the May 2010 stress test, on presale contract rescission. Therefore, my finding still holds that the government's stricter regulations on loan applications and speculative activities result in a lower rescission rate in the presale market.

3.7.3 The Impact of Moneyness on the Holding Period after Settlement

After presale contract holders settle the remaining payment when the building construction is completed, moneyness at settlement could still influence impact on the property's holding period after settlement. The rationale is that some out-of-the-money presale buyers choose not to rescind despite the loss. Instead, they still honour the presale contracts but wait for a better market timing to sell the properties later. The behaviour can potentially be explained by two reasons, including (1) confidence in housing market outlook; and (2) loss aversion associated with the disposition effect in the housing market (Bokhari and Geltner, 2011; Genesove and Mayer, 2001; Li and Wan, 2021). Homeowners that are more confident about the market outlook tend to keep holding the properties, as they believe the current loss is only temporary. Similarly, loss-averse homeowners are reluctant to rescind and realize the loss. Instead, they prefer to wait for a better market timing to sell at gains in the future.

Given these reasons, I expect that, for those properties settled with out-of-the-money presale contracts, property holders may prolong their holding periods in the secondary market. And I expect the holding period to be longer for those properties with a larger loss at settlement, as it takes longer for property holders to capture a suitable market timing to sell the properties.

To validate this hypothesis, I use the following the empirical specification:

$$\log(HoldPeriod_{it}) = \beta Moneyness_{i,t-1} + X_{it}^{'}\lambda + \varphi_i + \omega_t. \tag{3.3}$$

Specifically, $\log(HoldPeriod_{it})$ is the logarithm of the holding period in months between settlement date of the presold property and its resale date in the secondary market. $Moneyness_{i,t-1}$ is the moneyness of the presale contract at settlement. Definitions for other variables are the same as those in Equation (3.1). Robust standard errors are clustered at the district level.

Table 3.11 reports the estimation results of Equation (3.3). In Column (1), the explanatory variable is the continuous value of moneyness defined as the fair market price divided by the remaining payment. I find that if moneyness at settlement decreases by 0.1, the holding period after settlement will increase by 5.4%. In Column (2), I further replace the explanatory variables with a set of dummy variables that indicate whether the moneyness is between 0.95 and 1, between 0.9 and 0.95, or below 0.9. I find that in comparison with settlements with moneyness over 1, those units that are out of the money at settlement (i.e., $moneyness < 0.9$) are held for 8.9% longer period. All of these estimates are statistically significant at the 1% level.

Table 3.11 The Impact of Moneyness on Holding Period after Settlement

Y: log(*Holding Period After Settlement*)	(1)	(2)
Moneyness	-0.5440***	
	(0.0936)	
Moneyness [0.95, 1]		0.0525***
		(0.0217)
Moneyness [0.9, 0.95]		0.0589***
		(0.0150)
Moneyness < *0.9*		0.0887***
		(0.0224)
Unit Size	-0.0920	-0.0893
	(0.1039)	(0.1039)
Rooms	-0.0237	-0.0232
	(0.0245)	(0.0245)
log(*Lease Years*)	-0.0431	-0.0436
	(0.0534)	(0.0538)
Floor	-0.0017**	-0.0013*
	(0.0007)	(0.0007)
Property Type Fixed Effect	Y	Y
District Fixed Effect	Y	Y
Year*Quarter Fixed Effect	Y	Y
Observations	78,904	78,904
R-Squared	0.184	0.184

Notes: This table presents the OLS regression result for the holding period after settlement on moneyness. The dependent variable is the logarithm of months between settlement and resale date of the property. *Moneyness* is defined as the market price at settlement divided by the presale contract price. The market price at settlement is predicted as the size of the unit times the average price psf in the sample building within 2 years before settlement. *Moneyness [0.95, 1]* is a dummy variable equal to one if moneyness is between 0.95 and 1 (zero otherwise). Similarly, *Moneyness [0.9, 0.95]* and *Moneyness<0.9* are dummy variables indicating whether moneyness is between 0.9 and 0.95 or below 0.9, respectively. Standard errors are clustered at district level. Robust standard errors are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level.

To conclude, my results confirm the negative impact of presale contract moneyness at settlement on the subsequent holding period after successful settlement. It supports the prospect theory that investors tend to value gains more than losses (Kahneman and Tversky, 1979), and they are more reluctant to realize the expected losses due to the disposition effect. Instead, they tend to hold the investment for a longer time until the implied losses are recovered.

3.8 Chapter Summary

Presale contracts are widely used as risk-sharing instruments between property buyers and developers. A presale buyer effectively holds a long position of a call option on the underlying property under construction. There are three exit strategies for a presale buyer: (1) settle the contract at building completion; (2) transfer the contract to another buyer (usually with a gain); and (3) rescind the contract and lose the deposit (option premium). The third exit strategy incurs the highest loss and reflects the buyer's ultimate risk associated with a presale contract. Specifically, in the past two decades, presale contract rescissions in Hong Kong have resulted in substantial losses of HKD 436.67 million per year for homebuyers. Few prior studies have examined the driving factors of the presale contract rescission rate, especially from the perspective of option theory.

In this study, I connect the option theory with empirical analysis by using three call option-related presale contract features to investigate the mechanism behind presale contract rescission: moneyness, option delta, and time-to-maturity. Using a comprehensive housing transaction dataset for the Hong Kong housing market, I document that lower option moneyness (lower intrinsic value with respect to contract price) at settlement leads to a higher presale rescission rate. Out-of-the-money presale contracts with a lower market price than the remaining payment have a higher chance of rescission by 1.2%, which is equivalent to 12.2% of the average rescission rate. Nevertheless, I do not observe a very sharp kink in the rescission rate, which implies that other market frictions such as transaction fees, and behavioural reasons such as disposition effect, may also impact the presale contract rescission.

Also, I find the call option delta (the buyer's share of the housing price risk) and time-to-maturity (time-induced uncertainty) at purchase time positively predict the rescission rate. This confirms that presale contracts are risk-sharing instruments and that higher risk shared by buyers leads to higher rescission rates. Besides, I document another novel finding on option time-to-maturity which offers unique insights for the presale market. Although a longer time-to-maturity typically leads to higher option value based on the option theory, I show that the cost from a longer time-to-maturity dominates its benefit in the context of housing presale market. Presales at a relatively earlier stage of the property development stage are less beneficial to buyers, potentially due to funding pressure and price risk, resulting in higher rescission rates. On the other hand, it brings more benefit to developers as it enables developers to shift a greater amount of the time-induced risk to buyers and to collect property sales proceeds sooner.

These findings offer new insights into the analysis of a homebuyer's strategic default by relating presale contract rescission to contract option features. Compared with other housing market characteristics and individual buyer characteristics (e.g., presale contract transfer rate, local housing supply, multiple contract holders, and spot sale ratio), my proposed call option-related factors improve the prediction of presale rescission. As homebuyers tend to have strong and inelastic demand for those units at premium locations and with small area sizes, I find that option moneyness loses its predictive power on contract rescission for these units, which highlights the heterogeneity in the presale market.

I also provide compelling evidence that the Hong Kong government's cooling measures substantially reduced presale contract rescission. My finding demonstrates that government regulation plays a pivotal role in curbing speculation and reducing the social and financial costs associated with rescission in the presale market. Option moneyness not only impacts the buyer's rescission decision but also the unit holding period conditional on successful settlement. Lower moneyness at settlement leads to longer holding periods after settlement, which indicates that buyers need a longer holding time to make up the implied losses at settlement.

In summary, my study contributes to the literature on presale market dynamics, strategic default, disposition effect, and real estate speculation. My findings have significant policy implications, whereby macroprudential policies, such as a stringent mortgage-lending environment, have a stabilizing effect on the housing market by substantially reducing presale contract rescission rates.

To conclude this chapter, I discuss the limitations in this study and the potential future extensions. First, when I model the presale contracts as call options, I ignore the transaction costs and fees payable right after entering the contracts, mainly because the Black-Scholes model does not consider the transaction costs in option pricing. However, compared to the transaction costs of options, the transaction costs of presale contracts are much higher because they are calculated based on the full prices. For instance, the Ad Valorem Stamp Duty for any property transactions in Hong Kong ranges from 1.5% to 8.5% of the full prices. Thus, contract holders may take the large transaction costs into account when they mentally calculate their profits or losses. The role of transaction costs on contract rescission decisions is yet to be explored.

Second, this study does not consider the potential impact of mortgage markets on presale contract rescissions due to data limitation. In Hong Kong, presale contract holders usually choose to arrange the mortgage only after the contract is settled. Therefore, the higher rescission rates of out-of-money contracts may be driven by the difficulty in mortgage applications for underperformed properties at the settlement time, rather than the contract holders' discretionary choices of strategic default. Also, some presale contract holders may choose to arrange the mortgage payments after entering the contracts but before the settlement, while the developers will provide a small price discount as a reward for the early payments. These contract holders are not affected by the mortgage markets at the settlement time. If the shares of contract holders in the market choosing this early payment option vary over the years, the impact of the government's cooling measures on contract rescission rates might be biased. Since the EPRC data does not have information on mortgage and prepayment choices, this study cannot exclude the impacts of these additional channels.

Lastly, although developers normally provide indicative completion dates to presale homebuyers, the actual time-to-maturity of a presale contract is unknown to the buyers at the contract origination. Instead, the developers have control of the development timeline. Longstaff (1990) discusses the incentives for option writers to extend the out-of-money options. In the same spirit, the positive correlation between time-to-maturity and contract rescission rate may be endogenously driven by developers' project extensions. This mechanism can be further investigated in future studies, using data of presale projects with complete development extension information.

Chapter 4

Blinded by Familiarity? Institutional Investors under Adverse Performance Shocks

4.1 Introduction

Investors tend to over-invest in their home assets, which results in under-diversification and inefficient portfolios. A major strand of literature explains this phenomenon with home investors' information advantage on home assets against the non-home investors (Garmaise and Moskowitz, 2004; Grinblatt and Keloharju, 2001a; Hau, 2001; Ivković et al., 2008; Teo, 2009; Van Nieuwerburgh and Veldkamp, 2009). These studies recognize the information advantage by showing that investors with more home assets have better investment performance (Coval and Moskowitz, 2001; Ivković and Weisbenner, 2005). Other studies argue that home assets do not always outperform non-home assets (Seasholes and Zhu, 2010) and geographic concentration in investments does not bring significant benefit (Ambrose et al., 2000; Milcheva et al., 2020). Instead, the home-asset concentration and portfolio under-diversification can be driven by the irrational familiarity bias of investors (Pool et al., 2012). Home investors tend to overestimate the return and underestimate the risk of their familiar home assets (Agarwal, 2007; Seiler et al., 2013; Solnik and Zuo, 2017; Strong and Xu, 2003). Both information advantage and familiarity bias explain the home-asset concentration concurrently under normal or positive market conditions (Ling et al., 2021a).

Existing evidence for familiarity bias are mainly documented for the individual investors (Cao et al., 2011; Graham et al., 2009; Huberman, 2001; Seasholes and Zhu, 2010), and fewer empirical studies investigate the familiarity bias of institutional investors (Hau and Rey, 2008). In particular, compared with normal or positive market conditions, it remains unexplored whether home and non-home institutional investors will respond differently to potential adverse performance shocks to home assets because of familiarity bias. Familiarity bias under negative performance shocks to the home assets is unique, as it may contradict home investors' information advantage under such conditions. Specifically, when market signals indicate that home assets will perform poorly in future, home investors should decrease their holdings of the home assets more and earlier than non-home investors if their information advantage in the local market has a dominating effect. In contrast, if the familiarity bias dominates the information advantage when there are considerable downside risks in the home assets, home investors should be more reluctant to decrease their holdings of home assets than non-home investors despite the adverse market signals.

To answer this question for the general investors, I use an unique setting of institutional investors of real estate investment trusts (REITs) and the shocks of other non-REIT firm acquisitions near the properties held by the REITs, which addresses two empirical challenges. First, for conventional asset classes, it is challenging to classify the home and non-home assets by the actual geographic footprint of their economic value. Real estate solves this issue as it has a precise location. Many prior studies compare foreign and domestic investors' holding in domestic assets (Choi et al., 2017; French and Poterba, 1991), but it is more difficult to identify home assets among domestic investors. Some studies use the headquarter location of a firm to determine whether the firm is a home asset (Coval and Moskowitz, 1999; Grinblatt and Keloharju, 2001a), as firms may locate their headquarter near their main business for more efficient management (Aarland et al., 2007; Giroud, 2013). Several recent papers emphasize the limitation of this identification because the major economic activities (e.g., sales and operations) of geographically dispersed firms may not happen at or near the headquarter location (Bernile et al., 2015; Garcia and Norli, 2012).

In contrast, the real estate asset has a clean geographic footprint for its economic value, as all property income will be generated at its location only (Hartzell et al., 2014; Ling et al., 2021b). Nevertheless, since the real estate market is illiquid, we cannot obverse the instant changes in investors' direct holding in real estate when there are negative stocks to local real estate performance. Therefore, in this chapter, I study the institutional investors of REITs, instead of the direct real estate investors. Investors can adjust their holdings of REITs quickly in the open market when they predict the properties in the REITs' portfolios will not perform well.

As for the classification of home and non-home investors, I use the business addresses of the investment managers. Past studies measure individual managers' familiarity bias using their home addresses, mother tongues or cultural backgrounds (Grinblatt and Keloharju, 2001a; Hau, 2001; Pool et al., 2012), while business addresses are more commonly used in the fund-level analyses (Hau and Rey, 2008). Since this study focuses on the collective behaviors of institutions instead of individual fund managers, I follow the latter strategy and collect the business addresses of the institutional investors from their SEC 13F filings. The home investors are defined as institutional investors located in the same county as the properties, while the out-of-county investors are denoted as non-home investors. This strategy directly measures the investors' proximity to the properties in REITs, which better identifies the familiarity bias toward the underlying assets than the indirect measurements using the proximity to REIT headquarter (Ling et al., 2021b).

The second challenge is to find geography-specific shocks to the real estate returns that are exogenous to the local property market dynamics. Some studies use natural catastrophes, especially hurricanes, as the exogenous shocks (e.g., Rehse et al., 2019). Still, their impacts may have already been priced effectively in the hurricane-prone areas (Sah et al., 2008). In this study, I propose an identification strategy by investigating the equity REITs' performance after other public non-REIT firm near the properties are acquired and the corresponding responses of the REITs' institutional investors. The rationale is that, after the acquisition, the target firm is likely to dispose of the redundant production lines and employees (Maksimovic et al., 2011; Risberg, 2003), consolidate its research facilities and management team with the acquirer (Brueller et al., 2018; Stiebale, 2016), or even entirely relocate to other locations (Brouwer et al., 2004; Kim, 2022; Voget, 2011). For instance, after purchasing LinkedIn in 2016, Microsoft merged the original sales and client relationship management teams of LinkedIn in California with its own platform in Washington and helped to reduce the labour and operation costs of LinkedIn significantly. Cunningham et al. (2021) document a more severe case of killer acquisitions: Questcor, a US-based pharmaceutical firm, acquired its competitor Synacthen in 2013 to entirely shut down the research center of Synacthen and avoid the competition. Therefore, the commercial real estate in the acquired firm's headquarter is expected to perform worse due to a lower demand after the acquisition. This adverse effect may also spill over to the residential property sector (Chen et al., 2021; Hu et al., 2020). Meanwhile, compared to other shocks like firms' discretionary decisions of headquarter relocation, the acquisitions are less likely to be caused by the dynamics of local property markets.[1]

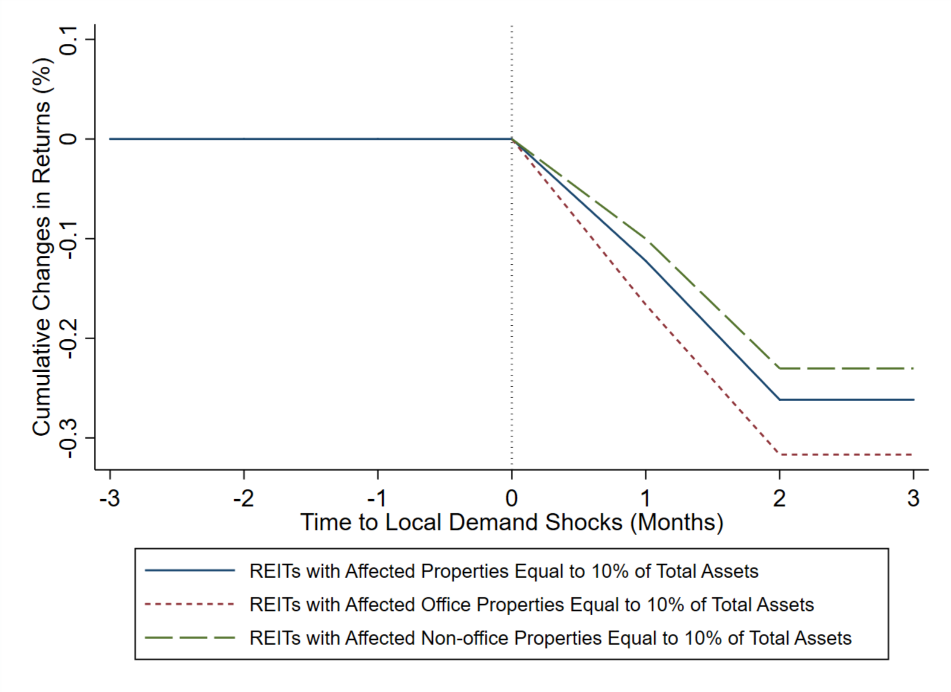
Using the data of all U.S. equity REITs from 1993 to 2015, the events of public firm acquisitions in the U.S. during the same period, and institutional investors of the affected REITs, this study establishes two sets of empirical findings. First, by employing an event study model, I show that firm acquisitions serve as adverse shocks to the REIT performance, if the REITs hold properties in the target county. If the share of a REIT's property value in the target county increases by 10 percentage points, the abnormal return (alpha) of the REIT in one month after acquisition decreases by 0.122 percentage points. Since the average abnormal return of the observations is 0.829%, this translates to a 14.7% decrease in the alpha of REITs. This negative effect is prolonged to the second month after the acquisition, and there is no effect before the announcement. This finding is robust if using the 3-month cumulative abnormal return (i.e., [-1 month, +1 month] around the announcement) as the dependent variable or using the share of property number in the target county as the explanatory variable.

Next, I examine the heterogeneity in the predictive power of local non-REIT firm acquisitions on REIT performance across REIT types and locations. I find the negative impact of local firm acquisitions on REIT return is more prominent in magnitude if the REIT holds more office buildings than other property types in the target county, as shown in Figure 4.1. This finding can be explained as the demand in the office property market is more directly impacted by the acquisition of target firms than the other market sectors. Also, the adverse effect is stronger if the acquired firm is larger than the total size of remaining public firms in the target county. This is because the relative size of the demand shock due to the acquisition will be larger when there are fewer incumbent firms in the target county. Lastly, I find the predictive power of the local firm acquisitions on REIT performances is weak when the REIT is headquartered in the target county but holds no properties there, as the actual economic footprints of the REIT assets are not affected by the acquisitions in this circumstance.

In addition, I document the mechanisms for the REIT market reactions to the local firm acquisitions. I find the firm acquisition events not only negatively impact the short-term stock market performance of REITs, but also decrease the REITs' actual rental income and dividend yield even after taking the stock price changes into account. Since REIT investors mainly look for steady income, the continuous decreases in income yields imply that rational investors should short the underperformed REITs and consider alternatives in the market. In the quarter of the acquisitions, the rental income of REITs with properties in the target counties are not significantly affected, because it takes around three months to complete

[1] Only acquisitions between companies in the non-real estate sectors are used in this study to further reduce the possibility that the acquisitions are driven by falling local property markets. Still, it is noteworthy that the anticipation effect might not be entirely ruled out, as mergers and acquisitions in one industry tend to appear in waves (Jovanovic and Rousseau, 2008; Maksimovic et al., 2013). Nevertheless, the anticipation is not likely to impact the conclusion that the acquisition announcements of incumbent non-REIT firms serve as important market signals to REIT performances. If any, the adjustments in investors' REIT holdings before the announcement could reflect their information advantage towards the underlining real estate assets.

Fig. 4.1 Cumulative Impacts on REIT Total Returns Due to Local Demand Shocks



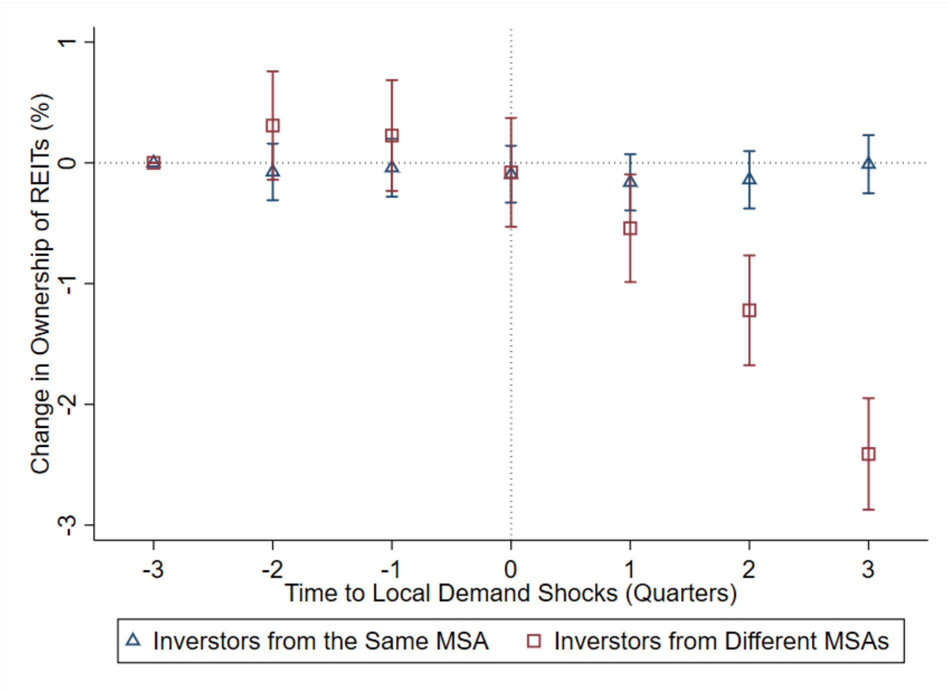
Notes: The figure plots the cumulative changes in REIT total returns (by construction) due to the local demand shocks from firm acquisitions near the REIT properties. The cumulative changes are calculated by compounding the estimated changes in the REIT monthly abnormal returns. The solid line denotes the REITs with any types of properties in the target county that worth 10% of their total assets. The short-dash line denotes the REITs owing office properties in the target county that worth 10% of their total assets. The long-dash line denotes the REITs owning non-office properties in the target county that worth 10% of their total assets.

the merger on average (Luypaert and De Maeseneire, 2015). In one quarter after the announcement, the quarterly return on assets (ROA) of a REIT decreases by 0.051 percentage points if the share of affected property value in its asset base increases by 10 percentage points, equivalent to a 6.4% decrease in the average quarterly ROA. Meanwhile, the quarterly ordinary dividend yield and total dividend yield decrease by 0.093 and 0.232 percentage points. These translate to a 5.4% and a 6.5% decrease in the corresponding average yield levels, respectively. The decreases in ROA and dividend yields continue up to at least one year after the demand shocks, during which period I require the sample REITs do not experience other confounding events. These results indicate that the preceding stock market reactions reflect the expectations for the following decreases in the REIT fundamental performances.

Second, I estimate the changes in home and non-home investors' holding in REITs after the acquisitions using a difference-in-differences (DID) model and find that home investors in the target location are less likely to decrease their holdings in the affected REITs than non-home investors. I obtain the information on institutional holdings from the SEC 13F filings, which are compulsory for investors who manage over $100 million qualified assets. Following Ling et al. (2021b), I define the treatment group as home institutional investors who locate in the same MSA of the affected real estate asset (and also the MSA of the acquired firm). They are expected to be influenced by either information advantage or familiarity bias under the property performance shocks. The control group is the out-of-MSA institutional investors, who are assumed not to be affected by either information advantage or familiarity bias. Therefore, if the effect of information advantage dominates familiarity bias, the home investors are expected to decrease their holdings of affected REITs more and earlier than non-home investors. In contrast, if the effect of familiarity bias dominates information advantage, the home investors are less likely to decrease their holdings of affected REITs than non-home investors.

I find that within one year after the firm acquisitions, the REITs' outstanding common shares held by their existing non-home investors decrease by 1.5 percentage points on average, but the existing home investors do not adjust their holdings. These findings are consistent if using the relative changes in holdings standardized by the pre-treatment holding levels instead. Before the shocks of firm acquisitions, the parallel trends between the treatment and control group are held up to at least one year prior to the treatment, indicating the changes in shareholdings are likely to be caused by the local demand shocks of acquisitions (See Figure 4.2). Also, the empirical finding does not support a dominating effect of information advantage, because the home investors do not sell the affected REITs before the general market responds. This result aligns with the prior literature about individual investors that individual home investors tend to underestimate the downside risk (Seiler et al., 2013) and be overconfident about the future performance of home assets (Agarwal, 2007; Solnik and Zuo, 2017; Strong and Xu, 2003).

Fig. 4.2 Parallel Trend Test between the Existing Home and Non-home Investors' Ownership of Affected REITs



Notes: The figure plots the parallel trend test result for the existing home and non-home Investors' ownership of REITs that are affected by the firm acquisitions. The x-axis denotes the relative time to the local demand shocks, measured in quarter. The y-axis denotes the relative changes in the REIT holdings, after controlling for the REIT fundamentals, time trends and firm fixed effects. Only existing investors with REIT holdings before the treatment are included, and new investors of REITs after the treatment are excluded. The home investors are defined as those located in the same MSA as the firm acquisitions, and the non-home investors are defined as those from different MSAs. The error bars indicate the 95% confidence intervals.

The degree of familiarity bias under negative performance shocks also varies according to distances and investment styles. First, I further separate home investors into three subgroups by their distances to the affected real estate asset: (1) in the same county, (2) in the same MSA but from different counties, and (3) in the same state but from different MSAs. The non-home investors are redefined as those from different states. I find that the farther the investors are from the affected real estate asset, the less they decrease in their REIT holdings after firm acquisitions. This result indicates that the physical proximity to home assets positively correlates to the impact of familiarity bias. Second, I classify the institutional investors into quasi-indexers and active investors, following the methodology introduced in Bushee (1998) and Bushee and Noe (2000). The effect of familiarity bias is stronger for active home investors than quasi-index (passive) home investors, as the active home investors have more discretions in determining their holdings of the affected REITs after the acquisitions than passive home investors. However, the difference in REITs ownership changes between the active and passive non-home investors are small and statistically insignificant. In summary, these findings support that institutional investors' familiarity bias can dominate their information advantage when there are adverse shocks to the home assets in their portfolios.

This study contributes to the thin literature on the familiarity bias of institutional investors (Hau and Rey, 2008). In particular, it introduces a novel identification for institutional investors' reactions to geography-linked adverse market signals, using the shocks of local firm acquisitions to the performance of real estate in the same county. It provides new evidence that the irrational familiarity bias of institutional investors can dominate their local information advantage when there are negative shocks to home assets. As a result, this behavioral bias could potentially lead to investment losses by holding more poorly performing home assets, at least in the short or medium term. Therefore, this study bears important policy implications for institutional investment committees to deal with familiarity bias, especially in bad market conditions.

In addition, this study links the real estate literature with the corporate finance literature and provide new facts on the spatial spillover effects of firm acquisitions on real estate markets. Prior studies investigate how corporate decisions, such as IPOs and headquarter relocations, affect the local housing market and the regional economy (Chen et al., 2021; Hartman-Glaser et al., 2018; Hu et al., 2020). This study extends the knowledge to commercial real estate and provides insights on the property market dynamics when firms are acquired or exit. It has policy implications for preventing negative externalities to real estate markets due to consolidations in other industries.

Moreover, this study adds to the general literature on the stock market responses to the micro-level risks of the REIT counterparts. Past studies document the stock market reactions under situations like REITs losing bank agents due to bank mergers (Hardin and Wu, 2009), increasing common ownership due to mergers of institutional investors (Ling et al., 2021c), decreasing stock market supply due to mergers of other REIT competitors (Chan et al., 2019), or tenants announcing bankruptcies (Liu and Liu, 2013). This study provides new evidences on the stock market responses when the non-REIT firm acquisitions shock the demand for properties in the REIT portfolios.

The remaining parts of the chapter are organized as follows. Section 4.2 reviews the literature. Section 4.3 presents the analysis of the impacts of local firm acquisition on REIT performances, including the methodology, data, and results. Following that, Section 4.4 contains the analysis of REIT institutional investors' responses to the adverse shocks of local firm acquisitions. Finally, Section 4.5 concludes the chapter.

4.2 Literature Review

4.2.1 Firm Acquisition and REIT Performance

Past literature has extensively studied the impact of REITs' mergers and acquisitions (M&As) on their stock market performances. Some studies report positive abnormal returns of the REIT acquirers after the acquisition announcements (Li et al., 2001; Ooi et al., 2011), while other studies document that the post-announcement returns are insignificantly different from zero, or even negative (Booth et al., 1996; Glascock et al., 1991; Pierzak, 2001; Olgun, 2005). Mechanisms driving the differences in the post-announcement returns include market conditions, payment methods and target types (Allen and Sirmans, 1987; Campbell et al., 2001, 2003). The post-announcement effects on abnormal returns can last in the long run till at least five years after the merger (Campbell et al., 2009). The REIT mergers also have a positive spillover effect on the returns of other incumbent REITs in the market (Chan et al., 2019). These findings are generally consistent with the literature on M&As of firms in other conventional industries (e.g., Baker et al., 2012; Bouwman et al., 2009; Chang, 1998; Savor and Lu, 2009).

Apart from the M&As between REITs, a growing strand of literature studies the dynamics of REIT performances due to the M&As between other major counterparties of REIT investments, such as banks and REIT investors. Hardin and Wu (2009) find that bank mergers reduce bank competition for REIT loans, which affects the loan pricing in return. Also, the REITs losing their bank agents due to the bank mergers are more likely to be acquired by other unaffected REITs in the future. Ling et al. (2021c) find that after mergers among institutional investors, REITs with increases in common institutional ownership (i.e., institutional investors who own equity of multiple firms in the same industry) due to the mergers will end up with higher firm value. They explain that it is because institutional investors who hold multiple equity REITs are likely to have better access to the soft information on the properties owned by the REITs, in comparison to other institutional investors.

For the US REITs, it is required that at least 75% of the asset are invested in real estate assets and cash, while at least 75% of the REIT's gross income are derived from real estate related sources.[2] Since REITs primarily invest in real estate assets under these two requirements, the performances of REITs are expected to be affected by the local market shocks to the underlying properties held by the REITs. However, few studies have investigated the spillover effect of general firm acquisitions near the properties owned by REITs on REIT performances, although the evidence from past literature has implied that firm acquisitions influence local real estate markets.

Firm acquisitions impact the demand of local commercial real estate, as they are often associated with relocations of the target firms (Brouwer et al., 2004). Even if the target firm is not entirely relocated, physical integration between the target and acquirer is common: Product lines are integrated, technologies are transferred, and redundant assets are re-deployed (Breinlich, 2008; Jovanovic and Rousseau, 2008; Risberg, 2003). Maksimovic et al. (2011) document that acquirers of entire firms sell 27% and close 19% of the plants of target firms within three years of the acquisition. The innovation activities in the target county also tend to decline after the acquisition, as the R&D investment is usually geographically concentrated within the acquirer (Stiebale, 2016). This, in return, will cause relocation of both facilities and employees of the target firm (Brueller et al., 2018), which negatively affects the demand for local commercial real estate. This impact may spill over from the commercial property

[2] See https://www.sec.gov/files/reits.pdf

market to the residential property market as well. Hu et al. (2020) find firm relocations negatively impact local housing prices due to the exit of employees and decreases in local economic input.

Nevertheless, other researches indicate that the impact of firm acquisitions on the real estate market of the target county can be ambiguous. Some acquirers move their original headquarter to target firms in other counties after cross-border M&As, in order to enjoy the tax benefit in the target countries (Voget, 2011). Cross-state relocations due to state-level corporate income tax advantages are also observed in the U.S. (Chow et al., 2021), while some of these domestic relocations may be completed through firm acquisitions. The local real estate markets of the target counties are more likely to benefit from the acquisitions under such circumstances. In addition, after the acquisition, the market value of the target firm and aggregate economic outcomes may increase (David, 2021), which could positively impact the local real estate market through the wealth effect (Hartman-Glaser et al., 2018). Moreover, to ensure control of the acquired business, the top managers are often transferred from the acquiring to the acquired company (Risberg, 2003), who usually have high wages and may positively affect the high-end housing market in the target county. In summary, the literature is scant and inconclusive for the impact of general (non-REIT) firm acquisitions on the performance of REITs that hold real estate assets in the target county.

4.2.2 Home Bias of Institutional Investors

Over-concentration on home assets is a widely observed phenomenon among institutional investors (Huberman, 2001), which deviates their actual holdings from the Markowitz optimal portfolios (French and Poterba, 1991). Investors are more likely to hold and trade the stocks of firms that are close to the investors, communicating in the investors' mother tongue or having chief executives of the same cultural background (Grinblatt and Keloharju, 2001a; Hau, 2001). Some studies document that, by exploiting informational advantages in selections of nearby stocks, home investors can obtain an excessive risk-adjusted annual return that ranges between 1 and 4 per cent (Coval and Moskowitz, 2001; Ivković and Weisbenner, 2005; Teo, 2009). In the more illiquid real estate market, where information advantage can take a more significant effect in price discovery, Van Nieuwerburgh and Veldkamp (2009) find that market participants also take advantage of information asymmetries by purchasing nearby properties. Garmaise and Moskowitz (2004) argues that the effect of information asymmetry is unlikely to be eliminated by the improvement in global information access, because the learning effort of home investors can further amplify a small endowed home information advantage. This implies that the under-diversification phenomenon due to home bias is persistent.

Some other studies, however, argue that the home bias may stem from simply familiarity instead of information, as concentration on home assets does not always bring excessive returns. Pool et al. (2012) find that mutual fund managers overweight stocks from their managers' home states by 12% compared with their peers, but the home-state stocks do not outperform other holdings, which implies that home-state investments are not informed. Using transaction-level data, Seasholes and Zhu (2010) find that for individual investors, their purchases of local stocks significantly underperform their sales of local stocks, and their portfolios of local holdings do not generate excessive returns. In the real estate market, geographic concentration on home properties does not always bring benefits either (Ambrose et al., 2000). Real estate firms with higher geographic dispersion significantly outperform the market in the post-GFC era (Milcheva et al., 2020).

Apart from the mixed evidence on excess return, literature has also documented the effects of familiarity bias on risk perception. Investors tend to underestimate the risk of home assets due to overconfidence (Graham et al., 2009) and overestimate the risk of non-home assets because of the fear of unknown (Cao et al., 2011). Eichholtz and Yönder (2015) find that overconfident CEOs are less likely to sell assets, and this behavior is not driven by their access to unique private information. Fund managers show a persistent and significant relative optimism towards the home equity, bonds, and currencies they are more familiar with (Solnik and Zuo, 2017; Strong and Xu, 2003). Homeowners are more confident about the future performance of their own houses than other properties in the same neighborhood (Agarwal, 2007), and underestimate the downside risks of their houses (Seiler et al., 2013). Pool et al. (2012) find that overweighting on home assets leads to excessively risky portfolios, compared to the optimal levels.

In summary, the existing literature provides two explanations—familiarity bias and information advantage—for the home-asset concentration observed in the portfolios of global investors (Ling et al., 2021a). Although these two effects concurrently lead to under-diversification under normal market conditions, they may have different effects on investment portfolios when there are adverse performance shocks to the portfolio assets: The irrational familiarity bias is persistent and less likely to be affected by the market shocks (Solnik and Zuo, 2017), while the informed investors are more likely to lower their exposure to affected asset and mitigate the negative shocks (Yuan, 2005). This study attempts to bridge this knowledge gap about how home/non-home investors respond differently to adverse performance shocks. Also, it is noteworthy that most of the findings on familiarity bias are documented at the individual (manager) level, while more evidence is yet to be explored at the firm (fund) level (e.g., Hau and Rey (2008)). In other words, it is not yet conclusive whether institutional investors led by the team of investment committees are still likely to be biased by the home location of their offices.

4.3 Impacts of Firm Acquisitions on REIT Performances

4.3.1 Empirical Methodology

I first investigate whether the shocks of firm acquisitions will negatively impact the stock market performance of REITs that hold properties located in the same districts as the acquired firms. Specifically, the following event-study model is applied to estimate the impact of REIT's exposure to local firm acquisition events on the REIT's stock return:

$$Y_{it} = \beta EXP_{it} + X_{it}^{'}\lambda + \varphi_i + \omega_t + \epsilon_{it}. \quad (4.1)$$

The explanatory variable, EXP_{it}, measures a REIT's exposure to local firm acquisition events, with the subscripts i and t referring to the REIT and the month, respectively. In the baseline estimation, EXP_{it} equals the total value of a REIT i's properties located in the same county of an acquired firm in the announcement month t ($ValueEXP_{it}$), represented as a percentage of the REIT's total assets. If all properties held by the REIT i are not in the same county of any firm acquisitions in month t, then EXP_{it} will equal zero. In the robustness check, I also use the total number of affected properties ($NumEXP_{it}$) as a fraction of the total property number in the REIT to be an alternative measurement of EXP_{it}.

The dependent variable, Y_{it}, is the monthly abnormal return (alpha) of a REIT i in month t. The monthly abnormal return of a REIT is estimated with a Fama-French four-factor model, using the return data of the REIT over the previous 60 months.[3] Therefore, the estimated coefficient β represented the instant effect of firm acquisitions on the REIT's stock return in the month of the acquisition announcement. In a set of parallel models, I replace the dependent variables as the abnormal returns from $t-1$ to $t+2$ in order to estimate the effects in the pre-announcement and post-announcement months, respectively. Lastly, as the robustness checks, I also use the 3-month cumulative abnormal returns over a [-1 month, +1 month] window around each month t as the alternative dependent variables.

X_{it} is a set of control variables for the REIT fundamentals. These controls include the return over asset, the market value (in logarithmic form), the cash holding scaled by the total assets, the leverage of the firm measured as the total debt over the total asset, and the market-to-book ratio. φ_i presents the REIT fixed effects. ω_t denotes the year and month fixed effects. ϵ_{it} is the error term. The standard errors are clustered at the level of firms.

Apart from investigating the impact of firm acquisitions on the stock market performance, I also estimate the impact on the fundamental performance of the affected REITs. In these estimations, I use a REIT's return on asset, the ordinary dividend yield, and the total (ordinary and non-ordinary) dividend yield as the outcome variables in Equation (4.1). Since these fundamental performances are reported by quarters, I update the measurements of EXP_{it} at the quarterly level in the corresponding estimations. In other words, EXP_{it} equals the total value of REIT i's properties located in the same county of an acquired firm announced in quarter t, presented as a share of the REIT's total asset. The same set of control variables (X_{it}) are included in these estimations, except that the return on asset is omitted from the controls because it is used as the dependent variable. The firm and year quarter fixed effects are also included in the corresponding estimations.

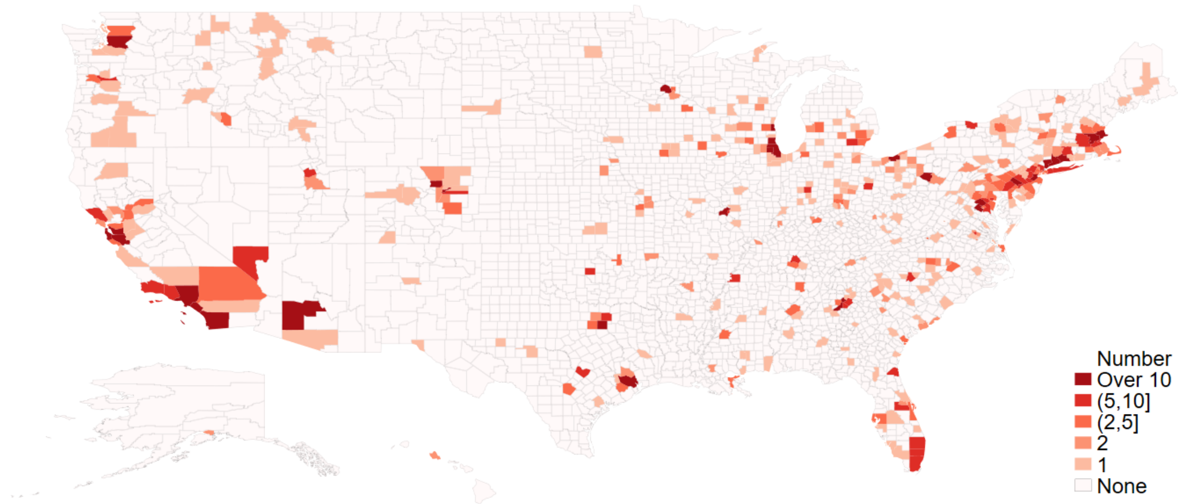
4.3.2 Data

The information of firm acquisitions is obtained from the Thomson ONE Database. The study period is from 1993 to 2015, and I apply the following filtering rules to select the samples further. First, I require the acquiring and target firms to be public firms from non-real estate sectors, with headquarters in the U.S, and listed on the NYSE, AMEX or NASDAQ Exchange. Second, I include only the completed M&A deals with non-missing deal values, and exclude the divestitures and spin-offs. Third, I include only the valid acquisitions if the acquirer's ownership is less than 50% before the event and is more than 50% after the event, as defined by the data vendor. Fourth, the events are dropped if the information on the target firm's headquarter location or total assets in the previous year before the announcement is missing. Lastly, I exclude the events if the target and acquirer are in the same county, or if there are other confounding acquisitions in the target county in the announcement month. This is because these confounding events can potentially bias the overall shocks to the local real estate performance. The county of the firms are defined by the 5-digit FIPS code.

After the filtering processes, it ends up with 1,555 observations of public firm acquisitions, and Figure 4.3 plots the geographic distributions of the target firms by counties of their headquarter. It reveals that a lot of the acquired firms were initially located in areas along the east and west coast, such as California, Massachusetts, and Florida.

[3] The values of the Fama-French factors are provided on the personal website of Professor Kenneth French. See: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Fig. 4.3 Distribution of Firm Acquisitions in the U.S. between 1993 and 2015



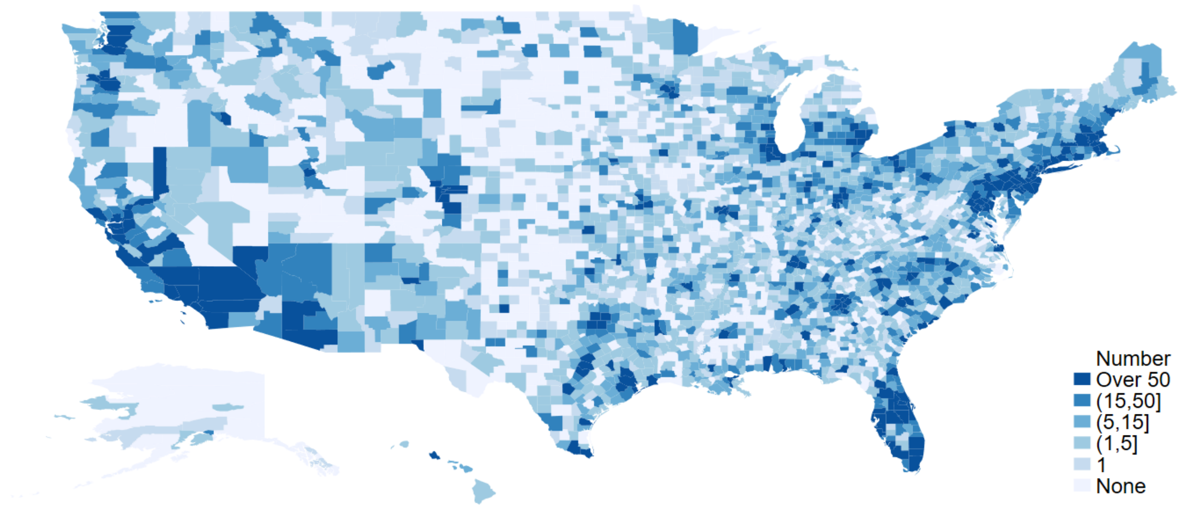
Notes: This figure plots the geographic distribution of headquarter of the public firms in the U.S. that were acquired between 1993 and 2015. This distribution is plotted at the FIPS county level.

The data of REIT stock market performance in this study is obtained from the CRSP-Ziman REIT Database, which provides information on the monthly closing prices and dividends of all REITs listed on the NYSE, AMEX and NASDAQ Exchange. I include only the 408 equity REITs in the study period, because the income of equity REITs are mostly obtained from the rent of properties they hold and are more likely to be affected by acquisitions of local firms than mortgage REITs. Then I match them with the CRSP-Compustat Database to obtain their annual/quarterly fundamental information and drop the 27 unmatched ones. The headquarter locations of the REITs are obtained and cross-checked via multiple sources, including the header of 10-K/Q SEC filings from the Augmented 10-X Header Data (Chow et al., 2021; Hu et al., 2020), the historical snapshot in the Compustat Database, and a manual search on the Internet.

The time-variant information on properties in each REIT's portfolio is collected from the SNL Real Estate Database. For each property that is (ever) held by a REIT, the database provides the annually updated information on its net book value, initial cost, historical cost, property type, county, acquisition date, as well as the sold date if it exists. Following Ling et al. (2021b), I define the adjusted cost of a property as the maximum value among the reported net book value, the initial cost of the property, and the historical cost of the property, including capital expenditures, land improvements and net of writedowns.

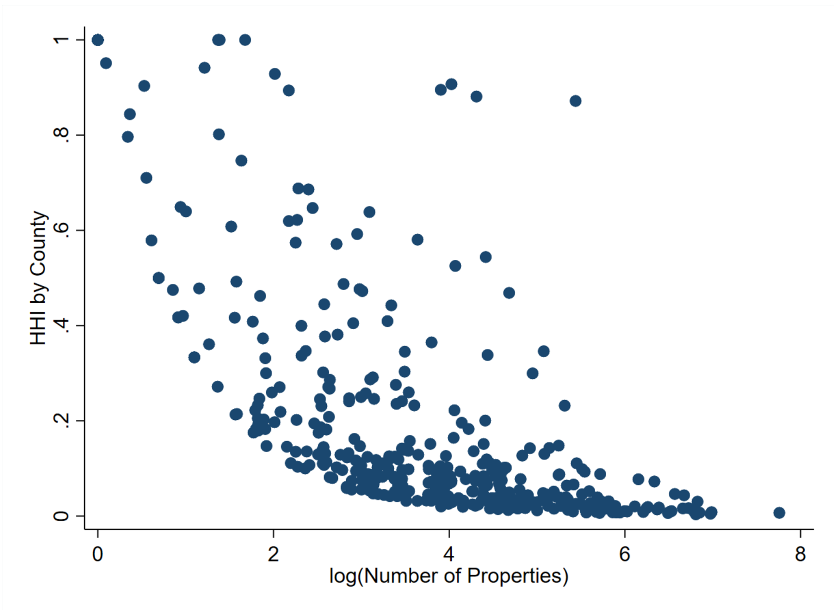
Figure 4.4 plots the geographic distributions of properties held by the REITs, according to the counties of the property location. In comparison with the distribution of acquired firms, the properties held by REITs also tend to concentrate in the major cities, but they are more diversified across the nation. Figure 4.5 further plots the geographic concentration of the REITs' property investments, measured as the Herfindahl Index (HHI) of property numbers by county. It reflects that the REITs owning more properties are generally more diversified in property locations, and the average county-level HHI of the sampled REITs equals 0.218 in the study period.

Fig. 4.4 Distribution of Properties in the U.S. Equity REITs between 1993 and 2015



Notes: This figure plots the geographic distribution of properties held by the equity REITs in the U.S. between 1993 and 2015. This distribution is plotted at the FIPS county level.

Fig. 4.5 Geographic Concentration of REIT Properties: Herfindahl Index (HHI) by County



Notes: This figure presents the geographic concentration of properties held by the equity REITs in the U.S. between 1993 and 2015, measured as the Herfindahl Index (HHI) of each REIT's properties at the county level. The annual HHI of a REIT is calculated as the sum of the squared share of property numbers in each county. The y-axis denotes the average HHI of each REIT over the study period. The x-axis denotes the average number of properties (in logarithmic form) owned by each REIT in the study period.

Table 4.1 Summary Statistics: The Event Study Sample for the Impact of Firm Acquisitions on REIT Performances

	(1) N	(2) Mean	(3) S.D.	(4) P25	(5) P50	(6) P75
Abnormal Return (AR)	37,716	0.829	5.731	-1.086	0.959	3.056
Cumulative Abnormal Return (CAR)	37,716	2.505	11.138	-1.149	2.938	6.744
ValueEXP	37,716	0.017	0.064	0.000	0.000	0.003
ValueEXP_Office	37,716	0.004	0.032	0.000	0.000	0.000
ValueEXP_NonOffice	37,716	0.013	0.055	0.000	0.000	0.000
NumEXP	37,716	0.020	0.061	0.000	0.000	0.015
Return on Assets (ROA)	37,716	0.798	3.430	0.243	0.710	1.187
Log(Market Cap)	37,716	6.273	1.827	5.273	6.485	7.525
Cash Ratio	37,716	0.034	0.070	0.007	0.015	0.035
Leverage	37,716	0.514	0.210	0.416	0.519	0.635
M/B Ratio	37,716	1.987	2.208	1.187	1.602	2.259
Relative Target Size (RelTargetSize)	37,716	0.026	0.102	0.000	0.000	0.004
Ordinary Dividend Yield (ODY)	12,205	1.745	6.589	0.977	1.528	2.012
Total Dividend Yield (TDY)	12,205	3.575	13.772	1.957	3.057	4.027

Notes: This table reports the summary statistics of the event study sample for the impact of firm acquisitions on REIT performances. Definitions of the other variables are represented in Appendix Table C.1.

After merging these three data sources, the final regression sample includes 362 unique equity REITs from 1993 to 2015, expanding to 37,716 firm-month observations and 12,205 firm-quarter observations. Around 36.54% of the firm-month observations (13,781) and 58.09% of the firm-quarter observations (7,090) are affected by the local firm acquisitions. Table 4.1 presents the summary statistics of the regression sample, and the variable definitions are presented in Appendix Table C.1. The monthly abnormal return of the sampled REITs is 0.829%, and the 3-month cumulative abnormal return is 2.505%.[4] On average, the properties affected by a local firm acquisition constitute 1.7% of the REIT's total asset and 2% of the REIT's total property number. Within the subsamples of treated REIT and month only, the affected properties constitute 4.6% of the REIT's total asset and 5.4% of the property number.

4.3.3 Baseline Results

Table 4.2 reports the baseline estimation results for the impact of local firm acquisitions on REITs' stock market performance, using Equation (4.1). In Columns (1) to (4), the dependent variable is the abnormal return of a REIT in month $t-1$ to $t+2$, respectively. The explanatory variable is the REIT's share of property values exposed to the shocks of local firm acquisitions. If the affected property values increase by 10 percentage points relative to a REIT's total asset, the abnormal monthly return of the REIT decreases by 0.122 percentage points in the following month after the announcement of firm acquisitions (Column (3)). Since the average abnormal return of the REITs is 0.829%, this translates to a 14.7% decrease in the average abnormal return.

Similarly, in the second month after the announcement of firm acquisitions, a 10-percentage-point increase in the affected property values leads to a 0.159-percentage-point (or 19.2%) decrease in the

[4]Since the abnormal returns are estimated based on the standard Fama-French momentum four-factor model, the positive average alpha of the observations suggests a positive risk-adjusted excess return of REIT investments against the general equity market.

Table 4.2 The Impact of Firm Acquisitions on REIT Return

	(1) *AR(t-1)*	(2) *AR(t)*	(3) *AR(t+1)*	(4) *AR(t+2)*
ValueEXP	0.1288	0.4201	-1.2230***	-1.5877***
	(0.4173)	(0.3842)	(0.3164)	(0.3591)
ROA	-0.0089	-0.0116	-0.0108	-0.0137
	(0.0074)	(0.0097)	(0.0100)	(0.0107)
Log(Market Cap)	-0.1735*	-0.1913**	-0.2227**	-0.2678***
	(0.0895)	(0.0922)	(0.0912)	(0.0905)
Cash Ratio	1.0300	1.0570	0.7159	0.8845
	(0.9257)	(0.9703)	(1.0052)	(1.0522)
Leverage	-0.6456	-0.6929	-0.6899	-0.6954
	(0.6668)	(0.7408)	(0.7564)	(0.7541)
M/B Ratio	0.0003	0.0003	0.0004	0.0003
	(0.0011)	(0.0009)	(0.0010)	(0.0009)
Constant	2.2594***	2.3700***	2.6018***	2.8888***
	(0.5800)	(0.5807)	(0.5505)	(0.5331)
Year & Month FEs	Y	Y	Y	Y
REIT FEs	Y	Y	Y	Y
Observations	37,683	37,716	37,544	37,372
R-squared	0.118	0.115	0.136	0.170

Notes: This table reports the estimated impact of firm acquisitions at time t on the return of REITs that hold properties in the same county of the acquired firms (i.e., the target county). The dependent variables are the monthly risk-adjusted abnormal returns (alpha) of the REITs at time $t-1$ to $t+2$. The abnormal returns are calculated with a Fama-French four-factor model using return data in the previous 60 months. The explanatory variable, $ValueEXP$, is the total value of properties that a REIT holds in the target county at the acquisition time, as a fraction of the REIT's total asset. Definitions of the other variables are represented in Appendix Table C.1. Robust standard errors are clustered by REITs and are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

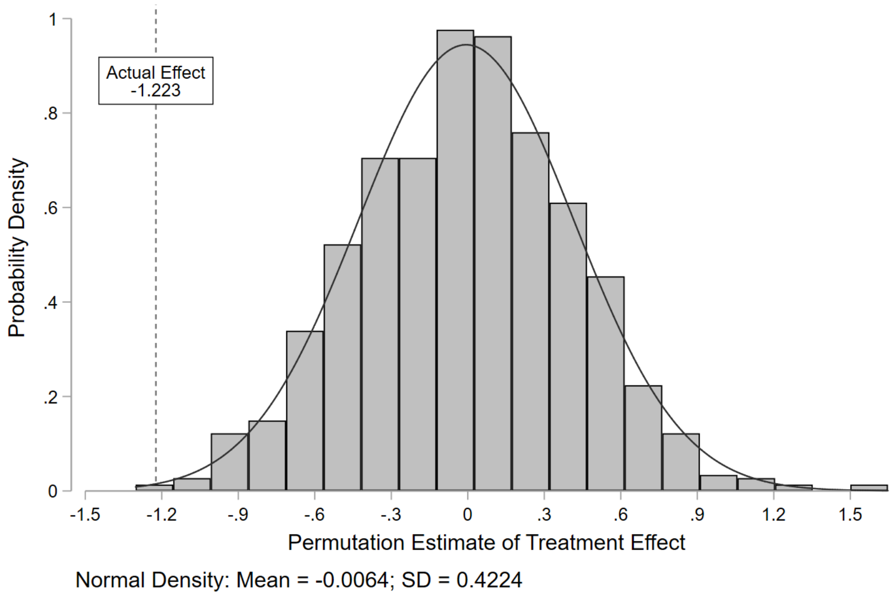
abnormal return (Column (4)). Both of the estimates are statistically significant at the 1% level. However, there is no impact of holding properties in the target countries on a REIT's abnormal return in one month before the official acquisition announcement (Column (1)), or instantly in the month of the announcement (Column (2)), which are revealed by the statistically insignificant estimates for the coefficient of *ValueEXP*.[5]

To verify that the estimated treatment effect of local demand shock on REIT performance is not due to any spurious correlation, I further conduct a permutation test for the effects of placebo shocks on REIT returns in the following month. Specifically, I randomly reassign the values of *ValueEXP* to the REIT-month observations and estimate the pseudo treatment effect on REIT return in the following month using Equation (4.1). I repeat the process for 1,000 times and present the distribution of the permutation estimates in Figure 4.6. The distribution plot reflects that the permutation estimates from random reassignments are centered around zero with a mean of -0.0062 and a standard deviation of 0.4224. The actual relocation effect is -1.223 (Column (3) in Table 4.2), which differs from the mean of

[5]There is no pre-announcement impact from months $t-2$ to $t-3$, or post-announcement impact in month $t+3$, either. These estimation results are available upon request. Figure 4.1 presents the estimated cumulative changes to the REIT total returns given local demand shocks to properties equal to 10% of the REIT assets, compounded by month from $t-3$ to $t+3$.

the permutation distribution at the 1% level (p value = 0.005). The placebo test result supports that the finding is not driven by spurious correlations.

Fig. 4.6 Placebo Test Results for the Impact of Firm Acquisitions on REIT Return



Notes: This figure presents the distribution of the estimates of pseudo treatment effect on REIT return in the following month. The explanatory variable *ValueEXP*, calculated as the total value of properties that a REIT holds in the target county at the acquisition time t divided by the REIT's total asset, is randomly reassigned to the REIT-month observations. The corresponding placebo effect is estimated using Equation (4.1) and the dependent variable is the abnormal return of a REIT in month $t+1$. The process is repeated for 1,000 times and the figure plots the distribution of the coefficients of the reassigned variable *ValueEXP*. The dashed line represents the actual effect as reported in Column (3) of Table 4.2.

Some related studies on home investors of REITs identify home investors and home assets by matching the business address of the investors with the headquarter of the REITs, not with the locations of real estate in the REITs (see Ling et al. (2021b)). While past literature has widely documented that REITs tend to invest more in properties near their headquarter (Milcheva et al., 2020), the connections between the investors' locations and the REITs' headquarter are only likely to have a secondary effect in the setting of this study. When firm acquisitions happen near the headquarter of the REITs, the performances of the REITs are likely to be affected only when the REITs hold properties near the headquarter (i.e., in the target county) as well. If the REITs do not hold any properties near its headquarter, the performances of the REITs are not likely to be affected, as the underlying real estate assets in the portfolio are far from the demand shocks. Aligning with these hypotheses, I find that if firm acquisitions happen in the county of the REITs' headquarter and the REITs also have underlying real estate holdings in that county, the REITs will have a decreasing abnormal return in 1 or 2 months after the acquisition announcement. However, the effect does not exist if the REITs do not hold any properties in that county. The corresponding results are provided in Appendix Table C.2.

Therefore, these results support the hypothesis that if REITs hold properties in locations where a public firm is acquired, the stock market return of the REITs is negatively affected in the subsequent months after the acquisition announcement.

4.3.4 Heterogeneity Analysis

The local firm acquisitions are expected to directly affect the demand for office buildings held by the REITs as the target management is merged with the acquirer out of the county. In contrast, the demand shocks are expected to spill over to other property types as the secondary effect. Therefore, it is hypothesized that firm acquisitions are stronger adverse market signals to REITs with more offices in portfolios. To investigate this heterogeneous effect across property types, I further separate a REIT's share of affected property values into two categories: office and non-office properties. Then I use the shares of affected office and non-office properties as the independent variables of interest in Equation (4.1).

The corresponding estimation results are reported in Table 4.3. Consistent with the baseline estimation results, I find that holding either office or non-office properties in the target counties before or in the month of the acquisition announcement does not impact the return of the REITs (Columns (1) and (2)). It confirms that the firm acquisitions are likely to be unexpected shocks to local real estate performances. One month after the acquisition announcement (Column (3)), a REIT's abnormal return decreases by 0.10% percentage points if the share of its non-office property values in the target county increases by 10 percentage points. In contrast, the abnormal return decreases by 0.17% percentage points if the share of the REIT's office property values in the target county increases by 10 percentage points. The former estimate is statistically significant at the 1% level, and the latter one is statistically significant at the 5% level.

Similarly, as reported in Column (4), the REIT's abnormal return in the second month after the announcement decreases by 0.14 percentage points with a 10-percentage-point increase in the share of affected non-office properties. In contrast, the return will decrease more (0.18% percentage points) conditional on the same 10-percentage-point increase in the share of affected office properties. Both the estimates are statistically significant at the 1% level. These results indicate that, compared with the REITs holding non-office properties in the target county, the returns of REITs holding office properties in the target county are more directly and seriously affects by the exits of the acquired firms.

Apart from the heterogeneity across property types owned by the REITs, the size of the acquired firm relative to the size of local economy in the target county may also impact the magnitude of the shocks on REITs' performances. For instance, compared to the firm acquisitions in the counties with many public firms, an acquisition is expected to have a more significant impact on the demand for commercial real estate in a county if the acquired firm is the only large public firm headquartered there. Since there lacks the data to directly measure the employment bases of each firm in the headquarter, I construct a proxy measurement for the real impact of the acquired firms on the local real estate market. Specifically, I use the the target firm's size (i.e., total asset) as a fraction of the total size of all public firms headquartered in the same county[6], assuming that larger firms will also have more employees and rent more offices in their headquarters. I denote this measurement as *RelTargetSize*. For the REIT-month observations that are not affected by any firm acquisitions, *RelTargetSize* is assigned as zero.

I first add *RelTargetSize* as an additional explanatory variable in Equation (4.1), and the corresponding estimation results are reported in Columns (1) to (4) in Table 4.4. As expected, I find that a larger relative size of the target firm is associated with a larger decrease in the REIT return, and this effect is more pronounced in the month of the announcement (Column (2)) and the following month afterwards (Column (3)). In Columns (5) to (8), I report the estimation results by interacting *ValueEXP* with

[6]Many target firms cease to provide financial reports in the year of the acquisition announcement, so the total asset of the firms in one year before the announcement is used for the calculation.

Table 4.3 Heterogeneity Analysis for the Impact of Firm Acquisitions on REIT Return: Property Type

	(1) *AR(t-1)*	(2) *AR(t)*	(3) *AR(t+1)*	(4) *AR(t+2)*
ValueEXP_Office	-0.6673	-0.4165	-1.6632**	-1.8042***
	(0.6350)	(0.7284)	(0.8057)	(0.6796)
ValueEXP_NonOffice	0.4193	0.7297	-1.0013***	-1.4465***
	(0.4910)	(0.4632)	(0.3350)	(0.4202)
ROA	-0.0090	-0.0117	-0.0108	-0.0137
	(0.0074)	(0.0097)	(0.0100)	(0.0108)
Log(Market Cap)	-0.1726*	-0.1902**	-0.2222**	-0.2678***
	(0.0896)	(0.0923)	(0.0911)	(0.0905)
Cash Ratio	1.0301	1.0571	0.7173	0.8859
	(0.9253)	(0.9699)	(1.0050)	(1.0521)
Leverage	-0.6491	-0.6965	-0.6919	-0.6965
	(0.6666)	(0.7404)	(0.7563)	(0.7542)
M/B Ratio	0.0003	0.0003	0.0004	0.0003
	(0.0011)	(0.0009)	(0.0010)	(0.0009)
Constant	2.2549***	2.3645***	2.5991***	2.8879***
	(0.5807)	(0.5816)	(0.5500)	(0.5332)
Year & Month FEs	Y	Y	Y	Y
REIT FEs	Y	Y	Y	Y
Observations	37,683	37,716	37,544	37,372
R-squared	0.118	0.115	0.136	0.170

Notes: This table reports the estimated impact of firm acquisitions at time t on the return of REITs that hold different types of properties in the same county of the acquired firms (i.e., the target county). The dependent variables are the monthly risk-adjusted abnormal returns (alpha) of the REITs at time $t-1$ to $t+2$. The abnormal returns are calculated with a Fama-French four-factor model using return data in the previous 60 months. The explanatory variables, *ValueEXP_Office* and *ValueEXP_NonOffice*, are the total value of office properties and other properties that a REIT holds in the target county at the acquisition time, as a fraction of the REIT's total asset, respectively. Definitions of the other variables are represented in Appendix Table C.1. Robust standard errors are clustered by REITs and are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

RelTargetSize[7], which essentially represents the value exposure of the REIT to the acquisition, weighted by the relative size of the shock compared to the local economy. I continue to observe an economically and statistically significant effect in the following month after the announcement (Column (7)). Suppose the acquired firm is the only public firm located in the county ($RelTargetSize = 1$), and the share of property values held by the REIT in the county increases by 10 percentage points. In that case, the REIT return will decrease sharply by 2.88 percentage points. This estimate is also statistically significant at the 1% level.

4.3.5 Mechanism Analysis: Fundamental Performance

Lastly, apart from investigating the instant responses to the local demand shocks in the REIT stock market, I further examine the mechanism of the market reactions. Specifically, the stock market reactions may reflect the adverse impact on REITs' future fundamental performances. Alternatively, they could be

[7]Since both *ValueEXP* and *RelTargetSize* will be zero only when the REITs are not affected by any firm acquisition events in a month, the individual terms of the two variables are omitted when their interactions are already included in the model.

Table 4.4 Heterogeneity Analysis for the Impact of Firm Acquisitions on REIT Return: Size of Acquired Firm

	(1) *AR(t-1)*	(2) *AR(t)*	(3) *AR(t+1)*	(4) *AR(t+2)*	(5) *AR(t-1)*	(6) *AR(t)*	(7) *AR(t+1)*	(8) *AR(t+2)*
ValueEXP	0.1367	0.4512	-1.1715***	-1.5866***				
	(0.4179)	(0.3875)	(0.3139)	(0.3601)				
RelTargetSize	-0.1441	-0.5612**	-0.9285***	-0.0196				
	(0.1756)	(0.2171)	(0.2698)	(0.2006)				
*ValueEXP*RelTargetSize*					3.8772	11.4402	-28.7752***	7.7507
					(6.8761)	(8.5339)	(10.0207)	(8.7362)
ROA	-0.0089	-0.0117	-0.0109	-0.0137	-0.0089	-0.0115	-0.0112	-0.0141
	(0.0074)	(0.0097)	(0.0101)	(0.0108)	(0.0074)	(0.0097)	(0.0100)	(0.0107)
Log(Market Cap)	-0.1732*	-0.1899**	-0.2204**	-0.2678***	-0.1743*	-0.1937**	-0.2160**	-0.2617***
	(0.0895)	(0.0921)	(0.0910)	(0.0905)	(0.0891)	(0.0919)	(0.0908)	(0.0902)
Cash Ratio	1.0301	1.0569	0.7154	0.8845	1.0274	1.0485	0.7415	0.9252
	(0.9258)	(0.9708)	(1.0059)	(1.0522)	(0.9253)	(0.9700)	(1.0047)	(1.0534)
Leverage	-0.6436	-0.6849	-0.6767	-0.6951	-0.6477	-0.6995	-0.6716	-0.6796
	(0.6669)	(0.7409)	(0.7564)	(0.7539)	(0.6661)	(0.7406)	(0.7565)	(0.7541)
M/B Ratio	0.0003	0.0003	0.0004	0.0003	0.0003	0.0003	0.0004	0.0003
	(0.0011)	(0.0009)	(0.0010)	(0.0009)	(0.0011)	(0.0009)	(0.0010)	(0.0009)
Constant	2.2599***	2.3720***	2.6050***	2.8889***	2.2650***	2.3884***	2.5476***	2.8111***
	(0.5798)	(0.5801)	(0.5492)	(0.5331)	(0.5742)	(0.5767)	(0.5473)	(0.5307)
Year & Month FEs	Y	Y	Y	Y	Y	Y	Y	Y
REIT FEs	Y	Y	Y	Y	Y	Y	Y	Y
Observations	37,683	37,716	37,544	37,372	37,683	37,716	37,544	37,372
R-squared	0.118	0.115	0.136	0.170	0.118	0.115	0.136	0.170

Notes: This table reports the estimated impact of different firm acquisitions by sizes at time t on the return of REITs that hold properties in the same county of the acquired firms (i.e., the target county). The dependent variables are the monthly risk-adjusted abnormal returns (alpha) of the REITs at time $t-1$ to $t+2$. The abnormal returns are calculated with a Fama-French four-factor model using return data in the previous 60 months. The explanatory variable, *ValueEXP*, is the total value of properties that a REIT holds in the target county at the acquisition time, as a fraction of the REIT's total asset. *RelTargetSize* equals the total asset of the acquired firm as a fraction of the total asset of all public firms in the same county at the acquisition time. Definitions of the other variables are represented in Appendix Table C.1. Robust standard errors are clustered by REITs and are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

transient over-reactions to the imprecise market signals, if the REITs' fundamental performances are not truly affected. Rational investors are expected to adjust their REIT holdings only if the ongoing income yield of the REITs are really affected. Therefore, I study whether the shocks indeed affect the REITs' fundamental performances, including their rental income and dividend yield. Since the fundamental performances are only reported quarterly, I modify the event study model of Equation (4.1) by using the quarterly data accordingly.

The corresponding estimation results are reported in Table 4.5. In Columns (1) to (3), the dependent variables are the REITs' quarterly return on asset (ROA), the ordinary dividend yield (ODY), and the total dividend yield (TDY) in the same quarter of the firm acquisition announcement, respectively. I find that the share of the REIT's property values in the target county does not have a statistically significant impact on the REIT's ROA and dividend yield instantly in the quarter of firm acquisitions. This result can be explained by the fact that the rental demand is not immediately affected right after the announcement of the acquisition, as it takes time for the actual merge to happen.[8]

However, in the next quarter after the announcement, the quarterly ROA of the REIT decreases by 0.051 percentage points with a 10-percentage-point increase in its share of property values in the

[8]For the U.S. listed companies, the mean and median durations between acquisition announcement and completion are 112 days and 93 days, respectively (Luypaert and De Maeseneire, 2015).

target county (Column (4)). Since the average quarterly ROA of the REITs is 0.798%, this impact translates to a 6.4% drop from the average quarterly ROA. Increasing the share of property values in the target county by 10 percentage points is also associated with a decrease in ordinary dividend yield by 0.093 percentage points (Column (5)) and a reduction of total dividend yield by 0.232 percentage points (Column (6)), in the subsequent quarter after the announcement. Given the average ODY and TDY in the sample are 1.745% and 3.575%, these changes are equivalent to decreases from the average ODY and TDY levels by 5.4% and 6.5%, respectively. All these estimates are statistically significant at the level of 5%.

Table 4.5 The Impact of Firm Acquisitions on REIT Fundamental Performance

	(1) *ROA(t)*	(2) *ODY(t)*	(3) *TDY(t)*	(4) *ROA(t+1)*	(5) *ODY(t+1)*	(6) *TDY(t+1)*
ValueEXP	-0.2110	1.1370	1.5954	-0.5118**	-0.9307**	-2.3191**
	(0.1705)	(0.7807)	(1.6568)	(0.2070)	(0.4531)	(0.9517)
Log(Market Cap)	0.1006	-0.5263	-1.2880	-0.0527	-0.5983	-1.4788
	(0.1306)	(0.3473)	(0.7191)	(0.1262)	(0.3651)	(0.7586)
Cash Ratio	3.0353	19.4214*	37.6117	1.4408*	11.7290*	25.5347**
	(4.8804)	(11.6932)	(23.3671)	(0.8644)	(6.3819)	(12.8491)
Leverage	-1.6862***	0.1862	-0.7874	-0.8977**	-0.6132	-2.5260
	(0.5352)	(0.5384)	(1.5251)	(0.4152)	(0.9591)	(2.2468)
M/B Ratio	-0.0034	-0.0017**	-0.0041**	-0.0018	-0.0026**	-0.0058***
	(0.0026)	(0.0009)	(0.0017)	(0.0020)	(0.0011)	(0.0022)
Constant	0.9418	4.2015*	10.6022**	1.7636*	5.4677**	13.4133**
	(1.0899)	(2.2801)	(4.8709)	(0.9690)	(2.6213)	(5.5725)
Year & Quarter FEs	Y	Y	Y	Y	Y	Y
REIT FEs	Y	Y	Y	Y	Y	Y
Observations	12,205	12,205	12,205	11,782	11,782	11,782
R-squared	0.158	0.094	0.094	0.111	0.083	0.089

Notes: This table reports the estimated impact of firm acquisitions at time t on the return on asset and dividend yield of REITs that hold properties in the same county of the acquired firms (i.e., the target county). The dependent variable $ROA(t)$ is the quarterly return on asset of REITs in the quarter of firm acquisitions, and $ROA(t+1)$ is the quarterly return on asset in the following quarter. The dependent variables $ODY(t)$ and $TDY(t)$ are the quarterly ordinary dividend yield and the total dividend yield of REITs in the quarter of firm acquisitions, respectively, while $ODY(t+1)$ and $TDY(t+1)$ denote the quarterly ordinary dividend yield and total dividend yield in the following quarter. *ValueEXP* is the total value of properties that a REIT holds in the target county at the acquisition time, as a fraction of the REIT's total asset. Definitions of the other variables are represented in Appendix Table C.1. Robust standard errors are clustered by REITs and are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

It is noteworthy that the dividend yields of the REITs in subsequent quarters have already taken into account the instant changes in REIT stock prices, which happen in the first two months after the demand shocks only (see Section 4.3.3). Specifically, the denominator of the dividend yield is the post-adjustment stock price. This implies that the ongoing total returns of these REITs are still lowered even if we ignore the losses due to instant price changes around the shocks. In addition, I find the decreases in rental income and dividend yield continue up to at least one year after the demand shock, with the regression results reported in Appendix Table C.3. It reflects that the negative impact on REIT returns are prolonged and therefore rational REIT investors should consider alternative investment opportunities in the market right after the shock.

In summary, the empirical findings support that the local firm acquisitions also negatively affect the fundamental performances of REITs that hold properties in the target county. Also, the stock market responds earlier than the occurrence of actual effects on the REIT fundamentals. The instant decreases in REIT stock market returns reflect the expectations for real adverse impacts on REIT fundamentals, rather than over-reactions to imprecise market signals. Since most of the REIT investors look for high and steady dividend income, the rational existing investors are expected to short the overvalued REITs after the local demand shocks. It lays the empirical foundation for the following analysis on the change in holdings by home and non-home REIT investors.

4.3.6 Robustness Checks

I have conducted a battery of robustness checks for the results. As for the impact of firm acquisitions on REITs' stock market performance, I first use the 3-month cumulative abnormal return (CAR) over a [-1 month, +1 month] window as the alternative outcome variable in Equation (4.1). The corresponding regression results are reported in Appendix Table C.4. It reveals that the share of properties in the target county does not have a statistically significant impact on REIT's CAR in the month of acquisition announcement or one month before that. In contrast, a 10-percentage-point increase in the share of property values in the target county will lead to a 0.24-percentage-point (0.28-percentage-point) drop in the CAR in the first (second) month after the announcement. These are equivalent to decreases in the average CAR by 9.7% and 11.1%, respectively. Both estimates are statistically significant at the 1% level.

Secondly, I construct an alternative measurement for the REIT's asset exposure to the firm acquisitions. Specifically, instead of using the share of property values in the target county as the explanatory variable in Equation (4.1), I use the number of properties in the target county as a fraction of the total property number in the REIT's portfolio. Appendix Table C.5 represents the corresponding estimation results. Consistent with the baseline results, the share of property numbers in the target county does not have a statistically significant impact on the REIT's abnormal return in the month of acquisition announcement or one month before the announcement. However, holding more properties in the target county will result in lower abnormal returns of the REITs in one month or two months after the announcement of local firm acquisitions. If the share of property numbers in the target county increases by 10 percentages points, the REIT's abnormal return in one month and two months after the announcement will decrease by 0.20 percentage points and 0.15 percentage points, respectively. Compared to the average levels, these translate to a lower abnormal return by 23.6% and 18.1%, respectively. Therefore, these robustness test results support the baseline findings that local firm acquisitions have a negative effect on the stock market performance of REITs that hold properties in the target county.

As for the impact of firm acquisitions on REITs' fundamental performance, the results also remain robust if using the share of property numbers in the target county as the alternative explanatory variable. As reported in Internet Appendix Table C.6, REITs with a higher share of property number in the target county by 10 percentage points will have a lower quarterly ROA by 0.07 percentage points in the next quarter after the announcement of firm acquisitions. Meanwhile, the ordinary dividend yield is lowered by 0.17 percentage points, and the total dividend yield reduces by 0.35 percentage points. These are equivalent to decreases from the average level of the corresponding fundamental performances by 9.1%, 9.6%, and 9.7%, respectively. Also, consistent with the baseline result, I find that the share of property numbers in the target county does not have a statistically significant effect on the REIT's fundamental performances in the exact quarter of announcement. Therefore, this result supports that the stock market reacts before the real impacts occur on the REIT's rental income.

Another potential concern for the baseline results on REIT's fundamental performances is the seasonality of the REITs' rental income and dividend payout. Some REITs may not pay dividends at the quarterly level, which potentially bias the estimation results in Equation (4.1). I address this concern by including the REIT times quarter fixed effects in the model, which assumes that for each REIT, the variations in the REIT income across different quarters due to seasonality are relatively consistent. The estimation results using these alternative fixed effects are reported in Appendix Table C.7. The estimates are similar to the baseline results for both the size of the magnitude and the statistical significance level, which indicates that the baseline results are robust.

4.4 Impacts of Firms Acquisitions on Institutional Investors' Holdings of Affected REITs

4.4.1 Empirical Methodology

Next, I investigate how home and non-home institutional investors react differently to the negative performance shocks to the real estate assets. Specifically, I use the subsample of REITs from Section 4.3 that are affected by the shocks of local firm acquisitions. In other words, at least one property in the REIT portfolio is located in the same county as the acquired firms. The home institutional investors are defined as the investment managers with the business addresses located in the same MSA as the affected properties, and the non-home institutional investors are those from different MSAs.[9] The hypothesis is that if the home investors have significant information advantages over the non-home investors about the negative shocks, they are likely to adjust their holdings of the affected REITs earlier and more than the non-home investors. This is because the advantageous knowledge might cover the likelihood of acquisition before the official announcement or the potential impact on local real estate performances. On the contrary, if the familiarity bias towards home assets dominates the information advantages, the home investors may be overconfident about the performance of home assets despite the adverse market signals and are less likely than the non-home investors to adjust their holdings of the affected REITs after the acquisitions.

To test these hypotheses, I apply the following difference-in-differences (DID) model to estimate the changes in REIT holdings by the home and non-home investors due to the impact of firm acquisitions events:

$$Ownership_{ijt} = \beta_1 Post_{ijt} + \beta_2 InMSA_{ijt} * Post_{ijt} + X_{it}^{'}\lambda_X + Event_{it}^{'}\lambda_E + \varphi_{ij} + \omega_t + \epsilon_{ijt}. \quad (4.2)$$

The dependent variable, $Ownership_{ijt}$, denotes the percentage of a REIT's outstanding shares held by the home investors or non-home investors at the end of each quarter, with the subscripts i, j, and t referring to the REITs, the investors and the quarters, respectively. Within each REIT, I calculate the total percentage of shares held by the home or non-home institutional investors, respectively, and use a dummy variable $InMSA_{ijt}$ to indicate the holdings by the home institutional investors (the treatment group). For the non-home investors outside the MSA of the acquired firms (the control group), $InMSA_{ijt}$ is equal to zero. $Post_{ijt}$ is a dummy variable equal to one if the ending date of a holding

[9]Home institutional investors at the MSA level are used in the baseline estimations, as the number of home institutional investors at the county level is relatively small. Different classifications of home institutional investors by counties, MSAs, and states are applied in the heterogeneity analyses to examine the impact of distances to home assets on the degree of familiarity bias.

report is after the announcement of the firm acquisition. Otherwise, $Post_{ijt}$ equals zero.[10] Therefore, the coefficient β_1 represents the changes in REIT holdings by non-home investors after the acquisition events, and $\beta_1 + \beta_2$ represents the corresponding changes for home investors. The coefficient β_2 is the estimate for the impact of familiarity bias on home investors' asset holdings given the adverse market signals, assuming that only the treatment group (home investors) are subject to the familiarity bias toward the home assets, but the control group (non-home investors) are not affected by the familiarity bias.

X_{it} is the same set of control variables for the firm fundamentals as in Equation (4.1), including the return on asset, market capitalization, cash holding, leverage, and market-to-book ratio. In addition, I include a set of acquisition-specific features for each affected REIT, denoted by $Event_{it}$. According to the discussion in Section 4.3, these acquisition-specific controls include the share of property values in the REIT that is affected by the local firm acquisitions and the relative size of the acquired firms in comparison to the total size of all public firms located in the same county. $\varphi_i j$ presents the REIT and investor fixed effects. ω_t denotes the year and quarter fixed effects. ϵ_{ijt} is the error term. The standard errors are clustered by REITs.

4.4.2 Data

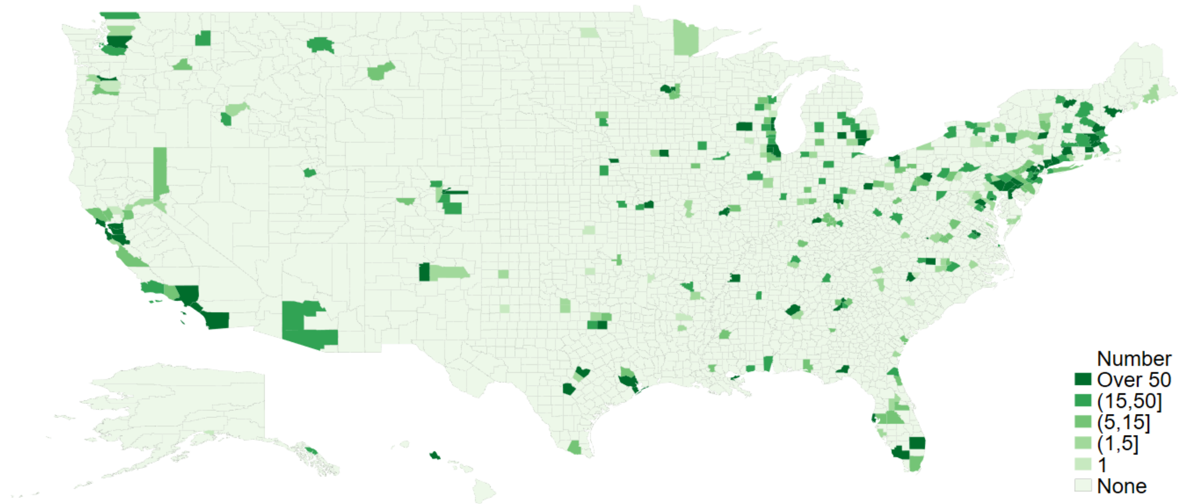
To construct the regression sample for the DID analysis, I start with the subsample of REITs in Section 4.3 that hold properties in the same county as the acquired firms and collect institutional investors' quarterly holdings of these REITs within the [-12 months, +12 months] window around each firm acquisition announcement. The information on institutional investors' holdings of these REITs is obtained from the Thomson Reuters 13F Institutional Holdings Database. It provides quarterly reports on the common stock holdings in the SEC 13F filings, in which the SEC requires all institutional investment managers to report their holdings over $100 million in the qualified assets. Since the database has a reporting issue starting in 2013 (Ben-David et al., 2021), I drop the observations after 2013, and the final study period is between 1993 and 2012.

The historical business addresses of the institutional investors in each quarter are collected from the original 13F filings stored on the SEC DEGAR, using a web-crawling program. The 13F filings of the institutional investors are identified using their company names, and the accuracy of the name matching is also cross-checked with the WRDS SEC 13F Holdings Database. Figure 4.7 presents the geographic distributions of the investment managers' business addresses. It reflects that the investors' business addresses also concentrate in a number of counties, but their distribution is not the same as the distribution of the target firms.

The following filtering rules are further applied to obtain a clean selection of the treatment and control groups. Firstly, I require that the acquired firm is not in the same county as the acquirer, and there are no other firm acquisitions in the same county within the [-12 months, +12 months] window around the announcement. Therefore, the holdings by the institutional investors are not likely to be affected by any confounding firm acquisition events. Secondly, I only keep the REITs that do not sell or purchase any properties within each [-12 months, +12 months] window around the announcement. In other words, any changes in the REIT holdings by the institutional investors are not driven by the property purchases or sales in the REIT portfolios. Lastly, I require the institutional owners of REIT

[10] Note that $InMSA_{ijt}$ is omitted from the model, as the model contains the REIT and investor fixed effects. However, $Post_{ijt}$ is not absorbed by the year quarter fixed effects and is still included in the model, because the pre- and post-treatment samples are identified at the monthly level.

Fig. 4.7 Distribution of Institutional Investors of the Equity REITs Affected by Local Firm Acquisitions



Notes: This figure plots the distribution of business addresses of the institutional investors, which hold equity REITs that are affected by local firm acquisitions. This distribution is plotted at the FIPS county level. If the investors are affected by multiple firm acquisition events at different months, they are considered as different observations. Foreign institutional investors without business addresses in the U.S. are excluded.

in the sample to have non-missing quarterly reporting within the [-12 months, +12 months] window around the announcement. Consequently, within each study window of the REIT by acquisition event sample, the compositions of the home investors in the treatment group and the non-home investors in the control group are consistent in each quarter.

After the filing processes, the final regression sample covers 335 public firm acquisitions in the U.S. from 1993 to 2012, In total, 134 REITs are affected by these events, ending with 2,226 REIT by event observations. Using the [-12 months, +12 months] study window around each treatment, this expands to 15,582 REIT by acquisition event by quarter observations. Further separating the total holdings of these REITs by the home investors and non-home investors, I finally get 31,164 observations of the institutional holding data. Table 4.6 summarizes the total holdings by the home investors and the non-home investors of the REITs in the sample. On average, the groups of home or non-home institutional investors hold 19.3% of the REIT's outstanding shares in the sample.[11] The average value of properties in the target county equals around 3.8% of the sampled REITs' total assets. The average total assets of the acquired firms equal about 18.1% of the total assets of all public firms located in the same county.

[11]In the full sample from the Thomson Reuters 13F Institutional Holdings Database, around 72.8% of the REITs outstanding common shares are held by the institutional investors, which are close to the findings (75.9%) in recent studies like Ling et al. (2021b). After the data filtering process, the remaining sampled institutional investors hold 38.7% of the REITs' outstanding shares. The average total shares held by the groups of home investors and non-home investors are 3.3% and 35.3% in the sampled REITs, respectively. Therefore, after separating the total shares of a REIT held by home investors and non-home investors as different samples in the treatment and control groups, respectively, the average holdings in the regression sample becomes 19.3%. For each REIT, there are on average 4.5 sampled home institutional investors in the same MSA and 62.0 sampled non-home investors from different MSAs. Each home investor holds 0.75% of the REIT's shares on average, and each non-home investor holds 0.57% of the shares, which aligns with the conclusion in prior literature that home investors are more likely to invest in home assets.

Table 4.6 Summary Statistics: The DID Estimation Sample for the Impact of Firm Acquisitions on Institutional Investors' Ownership of REIT

	(1) N	(2) Mean	(3) S.D.	(4) P25	(5) P50	(6) P75
Ownership	31,164	0.193	0.212	0.004	0.111	0.350
SD_Ownership	31,164	0.006	1.004	-0.617	-0.361	0.600
Post	31,164	0.490	0.500	0.000	0.000	1.000
InMSA	31,164	0.500	0.500	0.000	0.500	1.000
ROA	31,164	0.829	1.431	0.398	0.810	1.212
Log(Market Cap)	31,146	6.977	1.230	6.218	6.994	7.755
Cash Ratio	31,164	0.021	0.029	0.005	0.012	0.025
Leverage	30,990	0.544	0.165	0.455	0.538	0.632
M/B Ratio	30,362	2.177	2.493	1.324	1.743	2.394
RelTargetSize	31,164	0.181	0.290	0.007	0.030	0.216
ValueEXP	31,164	0.038	0.071	0.001	0.013	0.044

Notes: This table reports the summary statistics of the DID estimation sample for the impact of firm acquisitions on institutional investors' ownership of REIT. Definitions of the other variables are represented in Appendix Table C.1.

4.4.3 Baseline Results

Table 4.7 reports the baseline estimation results for the impact of local firm acquisitions on institutional investors' holdings of affected REITs, using Equation (4.2). In Columns (1) and (2), the dependent variables are the total percentage of the REIT's outstanding shares held by the home or non-home investors (denoted as *Ownership*). Since the quarterly fundamental control variables from the Compustat Database are missing for a small proportion of the samples, I first report the estimation results without the fundamental controls in Column (1). It reveals that the total holdings by non-home investors for a REIT decreases by 1.52 percentage points within one year after the announcement of acquisitions, as reflected by the coefficient of variable *Post*. In comparison with the non-home investors, the total holdings by home investors increase by 1.64 percentage points after the announcement, as shown by the coefficient of the interaction term between *Post* and *InMSA*. Both these estimates are statistically significant at the 1% level. After the linear combination of *Post* and *Post*InMSA*, the coefficient becomes statistically insignificant, indicating that the home investors did not significantly change their REIT holdings within one year after the announcement.

In Column (2), the quarterly fundamentals of the REITs are included as control variables. As discussed in Section 4.3, I also include the REIT's share of property values in the target county (*ValueEXP*) and the relative size of the target firm in comparison to all public firms in the target county (*RelTargetSize*) as the additional controls for the shock-specific features. I find that non-home investors decrease their holdings in the affected REITs by 1.54 percentage points after the acquisition announcement, but the home investors do not have statistically significant adjustments in their REIT holdings, which leads to a larger difference between the total REIT holdings by non-home and home investors by 1.71 percentages points. The estimates are statistically significant at the 1% level. These baseline estimation results indicate that home investors are more reluctant to adjust their exposure to the home assets than the non-home investors when there are adverse shocks to the performance of the home assets. Therefore, it implies that the home investors' irrational familiarity bias may outweigh their information advantages over the non-home investors under such adverse market shocks.

Table 4.7 The Impact of Firm Acquisitions on Institutional Investors' Ownership of REIT

	(1)	(2)	(3)	(4)
	Base Group: Out-of-MSA Investors			
	Ownership	*Ownership*	*SD_Ownership*	*SD_Ownership*
Post	-0.0152***	-0.0154***	-0.0791***	-0.0802***
	(0.0020)	(0.0021)	(0.0103)	(0.0109)
*Post * InMSA*	0.0164***	0.0171***	0.0866***	0.0912***
	(0.0025)	(0.0025)	(0.0162)	(0.0169)
ROA		0.0005		0.0023
		(0.0007)		(0.0054)
Log(Market Cap)		0.0371***		0.2493***
		(0.0065)		(0.0429)
Cash Ratio		-0.0515		-0.4543
		(0.0646)		(0.5074)
Leverage		0.0093		0.0063
		(0.0207)		(0.1832)
M/B Ratio		-0.0018		0.0016
		(0.0029)		(0.0126)
ValueEXP		-0.0046		-0.0473**
		(0.0132)		(0.0203)
TargetSize		0.0012		0.1028
		(0.0024)		(0.1427)
Constant	0.1968***	-0.0648	0.0175***	-1.6995***
	(0.0005)	(0.0501)	(0.0031)	(0.3481)
Year & Quarter FEs	Y	Y	Y	Y
REIT & Investor FEs	Y	Y	Y	Y
Observations	31,164	30,188	31,164	30,188
R-squared	0.818	0.823	0.473	0.479

Notes: This table reports the estimated impact of firm acquisitions on home and non-home institutional investors' ownership of affected REITs that hold properties in the same county of the acquired firms (i.e., the target county). The home investors (the treatment group) are defined as those investors located in the same MSA as the firm acquisitions, and the non-home investors (the control group) are defined as those investors from different MSAs. For each affected REIT by acquisition event, I calculate the total shares held by all sampled home investors and by all sampled non-home investors. The regression sample includes the quarterly aggregate ownership of the affected REITs by home or non-home investors within a [-3 quarters, +3 quarters] window of each firm acquisition. In Columns (1) to (3), the dependent variable, *Ownership*, is the total shares of a REIT that are held by the sampled home or non-home investors in each quarter, as a fraction of the REIT's total shares outstanding. In Columns (4) to (6), *SD_Ownership* is the standardized value of *Ownership* within groups of home or non-home investors, which measures the relative changes in ownership within the two subgroups. *Post* is a dummy variable equal to one if the sample is after the acquisition, zero otherwise. *InMSA* is a dummy variable denoting the sample of the home investors. Definitions of the other variables are represented in Appendix Table C.1. Robust standard errors are clustered by REITs and are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

The parallel trend between the treatment and control groups before the treatment is a critical assumption for validating the DID model. I test the parallel pre-trend by using a set of dummies to indicate the quarters relative to the treatment time instead of using the *Post* dummy in Equation (4.2). The dummy for three quarters before the acquisition announcement $(t-3)$ is used as the base. Then, I use the subsamples of the home and non-home investors in separate models and re-estimate Equation (4.2) but exclude the interaction term. Therefore, the coefficients for the relative quarter dummies represent how the home and non-investors adjust their holdings of the REITs by quarters, in comparison to their holdings in quarter $t-3$ (i.e., the base).

Figure 4.2 plots the estimated coefficients for the relative quarter dummies. The squared symbols represent point estimates for the non-home investors from different MSAs. It reflects that the non-home investors start to lower their holdings in the affected REITs from the first quarter after the announcement ($t+1$), and their holdings keep decreasing until the quarter $t+3$. However, the holdings by the non-home investors do not have statistically significant changes between quarters $t-2$ and t, in comparison to the holdings in quarter $t-3$. As for the home investors, there are no statistically significant changes in their holdings over the entire window between $t-3$ and $t+3$. The point estimates for the quarter dummies do not statistically differ from zero in the pre-treatment period for both the treatment group (home investors) and the control group (non-home investors). Therefore, it supports that the parallel trend assumption is held for the DID model.

The parallel trends indicate that the acquisition announcement of a public non-REIT firm is likely to be an unexpected shock to both home and non-home investors' holding of REITs. In a semi-strong form market, this might also be explained as the fact that institutional investors are unlikely to trade on material nonpublic information before the M&A incentives are officially announced, and the market primarily reacts in the post-announcement period (Bacon and Von Gersdorff, 2008; Chen et al., 2020; Humphery-Jenner and Powell, 2011; Masulis et al., 2007).

Since the number of home investors for a REIT at the MSA level is smaller than the number of non-home investors of the REIT, the total shares of a REIT held by the non-home investors are also higher than the total shares held by the home investors. Thus, one potential concern for the baseline estimation result is that the absolute changes in the holdings may be biased by the ex ante differences in the holding levels by the home or non-home investors. To address this concern, I standardize the holdings by the home and non-home investors separately, using the pre-treatment mean and standard deviations in the holdings within the treatment and control group, respectively. The standardized holdings are denoted as *SD_Ownership*, which represent the relative changes in the home/non-home investors' holdings in comparison to their ex ante holding levels before the treatment.

Columns (3) and (4) in Table 4.7 report the estimation results of Equation (4.2), using *SD_Ownership* as the dependent variable. In Columns (3), the time and firm fixed effects are included in the model. It reveals that the non-home investors decrease their holdings by 0.079 standard deviations after the announcement, as reflected by the coefficient of variable *Post*. This estimate is statistically significant at the 1% level. However, the relative holdings of affected REITs by the home investors do not have substantial changes after the treatment, as reflected by a statistically insignificant point estimate combining the coefficients of *Post* and *Post*InMSA*. Column (4) further reports the estimation results after including the REIT fundamentals and the treatment-specific features as the control variables. A similar estimate for the coefficient of *Post* is obtained, both for the magnitude and the statistical significance level. The linear combination for the coefficients of *Post* and *Post*InMSA* also remain statistically insignificant. Therefore, these implicate results further support the conclusion that home investors are less likely to lower the holdings in the home assets than the non-home investors, regardless of the negative performance shocks to the home assets.

4.4.4 Heterogeneity Analysis

I further examine the heterogeneities in the home investors' familiarity bias. Firstly, distances to the home assets may impact the degree of home bias under adverse performance shocks, because the physical proximity usually has a positive correlation with familiarity, It is hypothesized that institutional managers with business addresses closer to the real estate affected by local firm acquisitions are more likely to be influenced by the familiarity bias. To test this hypothesis, I classify the institutional investors into four groups and use a set of dummy variables to indicate them: (1) the home investors in the same county of the affected real estate, denoted by the dummy variable *InCty*; (2) the home investors in the same MSA but from different counties of the affected real estate, denoted by the dummy variable *InMSAOutCty*; (3) the home investors in the same state from different MSAs of the affected real estate, denoted by the dummy variable *InStateOutMSA*; and (4) the non-home investors from different states of the affected real estate (the base group in the regression analysis). Then I replace the dummy variable *treat* in Equation (4.2) with these variables denoting the investor subgroups and re-estimate the model using samples of the REITs' ownership by each subgroup of investors.

The corresponding estimation results are reported in Table 4.8. In Columns (1) and (2), *Ownership* is used as the dependent variable, while *SD_Ownership* is the dependent variable in Columns (3) and (4). Time and firm fixed effects are included in all columns, and the firm fundamentals and acquisition-specific features are further controlled for in Columns (2) and (4). In all these estimation models, the magnitudes of the coefficients of the interaction terms are positive and statistically significant, and they decrease by order of *Post*InCty*, *Post*InMSAOutCty*, and *Post*InStateOutMSA*. Therefore, these results support the hypothesis that investors closer to the home assets are more likely to be affected by the familiarity bias given adverse performance shocks to the home assets.

Secondly, the investment strategies of the institutional investors may also affect the extend of their familiarity bias under negative performance shocks to the home assets. Specifically, investors implementing active investment strategies rely more on the management's discretionary analysis, so they are more likely to be affected by the behavioral bias than the passive investors. To test this hypothesis, I classify the institutional investors into passive and active investors, following the methodology introduced by Bushee (1998) and Bushee and Noe (2000). According to the turnover, diversification, and momentum trading patterns in the investors' portfolios, Bushee (1998) classifies the investors as quasi-indexers, transient active investors, and dedicated active investors. I group the transient active and dedicated active investors as the active investors, and consider the quasi-indexers as the passive investors. Then I use a dummy variable to indicate the total holdings by active investors and interact it with the variable denoting home investors.

I report the corresponding results in Table 4.9, using *Ownership* as the dependent variable in Columns (1)–(2) and *SD_Ownership* as the dependent variable in Columns (3)–(4). Same as the baseline analysis, I first include time and firm fixed effects only in Columns (1) and (3), and then add the controls for firm fundamentals and acquisition-specific features in Columns (2) and (4). In all the models, the coefficients of the triple interaction term *Post*InMSA*Active* have the largest positive magnitude among all the interaction terms, which indicate that active home investors have a stronger tendency to hold more shares of the affected REITs after the shocks. In particular, after considering the relative holding changes compared to pre-treatment holding levels by using *SD_Ownership* as the dependent variables (Columns (3) and (4)), I find that both the active and passive non-home investors decrease their holdings after the

Table 4.8 Heterogeneity Analysis for the Impact of Firm Acquisitions on Institutional Investors' Ownership of REIT: Distance to Firm Acquisitions

	(1)	(2)	(3)	(4)
	Base Group: Out-of-State Investors			
	Ownership	*Ownership*	*SD_Ownership*	*SD_Ownership*
Post	-0.0124***	-0.0128***	-0.0703***	-0.0721***
	(0.0022)	(0.0022)	(0.0120)	(0.0127)
*Post * InStateOutMSA*	0.0111***	0.0117***	0.0457**	0.0483**
	(0.0026)	(0.0027)	(0.0186)	(0.0194)
*Post * InMSAOutCty*	0.0129***	0.0136***	0.0715***	0.0756***
	(0.0024)	(0.0024)	(0.0157)	(0.0165)
*Post * InCty*	0.0132***	0.0139***	0.0885***	0.0936***
	(0.0025)	(0.0025)	(0.0193)	(0.0199)
ROA		0.0002		0.0020
		(0.0004)		(0.0046)
Log(Market Cap)		0.0184***		0.1829***
		(0.0033)		(0.0276)
Cash Ratio		-0.0291		-0.2154
		(0.0322)		(0.3930)
Leverage		0.0032		-0.0087
		(0.0110)		(0.1224)
M/B Ratio		-0.0008		-0.0297**
		(0.0014)		(0.0148)
ValueEXP		-0.0006		-0.0263
		(0.0012)		(0.0221)
RelTargetSize		-0.0004		0.0729
		(0.0071)		(0.0989)
Constant	0.0992***	-0.0296	0.0093***	-1.2479***
	(0.0002)	(0.0253)	(0.0022)	(0.2205)
Year & Quarter FEs	Y	Y	Y	Y
REIT & Investor FEs	Y	Y	Y	Y
Observations	62,328	60,376	62,328	60,376
R-squared	0.777	0.781	0.277	0.278

Notes: This table reports the estimated heterogeneous impact of firm acquisitions by distance on home and non-home institutional investors' ownership of affected REITs. The home investors are classified into three groups by their distances to the affected properties: in the same county (*InCty*), in the same MSA but from different counties (*InMSAOutCty*), and in the same state but from different MSAs (*InStateOutMSA*). The base group contains non-home investors from different states. The regression sample includes the quarterly aggregate ownership of the affected REITs by each group of investors within a [-3 quarters, +3 quarters] window of each firm acquisition. Definitions of the other variables are represented in Appendix Table C.1. Robust standard errors are clustered by REITs and are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

treatment. However, there is no statistically significant difference in their post-treatment changes, as shown by the insignificant coefficients of *Post*Active*.

These results imply that, since the non-home investors are not likely to be affected by the familiarity bias toward the home assets, their investment styles will not impact the extent of the familiarity bias either. As for the home investors, the quasi-indexers do not have significant changes in their holdings after the treatment, as indicated by the insignificant coefficient after linearly combining *Post* and

Table 4.9 Heterogeneity Analysis for the Impact of Firm Acquisitions on Institutional Investors' Ownership of REIT: Investment Strategies

	(1)	(2)	(3)	(4)
	Base Group: Out-of-MSA Quasi-index Investors			
	Ownership	*Ownership*	*SD_Ownership*	*SD_Ownership*
Post	-0.0127***	-0.0126***	-0.0649***	-0.0637***
	(0.0011)	(0.0011)	(0.0131)	(0.0134)
*Post * Active*	0.0102***	0.0098***	0.0355	0.0299
	(0.0016)	(0.0016)	(0.0286)	(0.0190)
*Post * InMSA*	0.0127***	0.0129***	0.0597***	0.0617***
	(0.0016)	(0.0016)	(0.0186)	(0.0190)
*Post * InMSA * Active*	0.0139***	0.0141***	0.1011***	0.1018***
	(0.0016)	(0.0016)	(0.0186)	(0.0190)
ROA		0.0002		0.0017
		(0.0002)		(0.0026)
Log(Market Cap)		0.0186***		0.1344***
		(0.0008)		(0.0091)
Cash Ratio		-0.0258**		-0.4067***
		(0.0131)		(0.1544)
Leverage		0.0047		-0.0549
		(0.0032)		(0.0376)
M/B Ratio		-0.0009		0.0042
		(0.0023)		(0.0270)
ValueEXP		0.0006		-0.0399***
		(0.0010)		(0.0120)
RelTargetSize		-0.0023		0.0190
		(0.0047)		(0.0558)
Constant	0.0984***	-0.0324***	0.0078*	-0.8787***
	(0.0004)	(0.0063)	(0.0045)	(0.0737)
Year & Quarter FEs	Y	Y	Y	Y
REIT & Investor FEs	Y	Y	Y	Y
Observations	62,328	60,376	62,328	60,376
R-squared	0.790	0.793	0.386	0.388

Notes: This table reports the estimated heterogeneous impact of firm acquisitions on home and non-home institutional investors' ownership of affected REITs, by the investment strategies of the institutional investors. The home investors are defined as those investors located in the same MSA as the firm acquisitions, and the non-home investors are defined as those investors from different MSAs. The regression sample includes the quarterly aggregate ownership of the affected REITs by each group of investors within a [-3 quarters, +3 quarters] window of each firm acquisition. *InMSA* is a dummy variable denoting the sample of the home investors. *Active* equals one if the investor is "transient" or "dedicated" in active investment and zero if the investor is a passive "quasi-indexer", as defined by Bushee (1998). Definitions of the other variables are represented in Appendix Table C.1. Robust standard errors are clustered by REITs and are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

*Post*InMSA*. Surprisingly, the active home investors even tend to increase their holdings of the affected REITs. The possible explanations include that the home investors tend to underestimate the downside risks (Seiler et al., 2013) and are overconfident about the future performance of home assets (Agarwal, 2007; Solnik and Zuo, 2017; Strong and Xu, 2003). Since the familiarity bias is often associated with overconfidence towards the familiar asset (Graham et al., 2009), these results also complement the findings in Eichholtz and Yönder (2015) that overconfident CEOs of REITs are less likely to sell assets than their counterparts while their access to valuable private information is not the main driver for this behavior.

In summary, the empirical results reveal that the home investors are less likely to lower their holdings of home assets than the non-home investors when there negative signals to home asset performances, at least in the short to medium term. This finding implies that home investors are more likely to be affected by the irrational familiarity bias towards home assets, which could dominate their information advantage over the non-home investors. This effect is more substantial for home investors who are closer to the asset locations and implement a more active investment strategy.

4.4.5 Robustness Checks

The historical business addresses of the institutional investors in the sample are collected from the quarterly13F filings stored on the SEC DEGAR database, which are available since the year 1999 only. In the baseline analysis, I use the earliest business address available in the database for the investors' holdings before 1999, assuming that few investors relocate in the early part of the sample period (i.e., between 1993 and 1999). To mitigate the potential concern for measurement error, I conduct a robustness check by including only the acquisition events and corresponding investors' holdings after 1999. Appendix Table C.8 reports the corresponding estimation results. Our baseline conclusions remain robust, as I find relatively consistent estimates using the subsamples, both in terms of the sizes of coefficient magnitudes and the significance levels.

Another potential concern for the baseline DID analysis is the imbalanced composites of the treatment and control samples. According to the definition of home investors at the MSA level in the baseline estimation, not all affected REITs will simultaneously have home and non-home investors. For instance, if there are no investors located in the same MSA as the target firm, the identified total holdings by home investors will consistently be zero in the entire [-1 year, +1 year] window. Therefore, the decreases in the holdings by home investors in the post-acquisition period may be underestimated. To address this concern, I create a subsample by only including the affected REITs with both the home and non-home investors. This ends with 118 REITs affected by 258 firm acquisition events. I re-estimate Equation (4.2) and report the results in Appendix Table C.9. The results are qualitatively similar to the baseline analysis results, which indicate that the main findings remain robust.

4.5 Chapter Summary

Prior literature has debated over two major reasons why institutional investors concentrate their portfolios in the home assets: The information advantage in the local market which leads to excess returns (Garmaise and Moskowitz, 2004; Grinblatt and Keloharju, 2001a; Hau, 2001; Ivković et al., 2008; Ling et al., 2021a; Teo, 2009; Van Nieuwerburgh and Veldkamp, 2009), and the behavioral bias towards the home assets which they are more familiar with with no significant benefit (Pool et al., 2012; Seasholes and Zhu, 2010). While these two effects can co-exist under normal conditions, they are expected to have differential effects on portfolio diversification when institutional investors face adverse market signals. Using the public firm acquisitions near the properties in REITs as a novel setting to identify the market performance shocks specific at home locations, this study provides new insights that the familiarity bias tend to have a dominating effect over information advantage, given negative market signals.

This study demonstrates that the acquisitions of public firms serve as negative demand shocks and adverse market signals to commercial real estate in the target county. The REITs holding more properties in the target county are likely to have poorer stock market performances and lower rental income after the announcement of acquisitions. This impact is not observed before the announcement, which indicates that the events are likely unexpected by the market. Also, the effect is stronger for the REITs holding more office properties in the target county, as the office properties are under a more direct impact of the acquisitions than the other property types. Last, if the acquired firm is larger in comparison with the other public firms located in the same county, the negative impact on REITs performance is also more substantial, as the relative demand shock to the local real estate market is more remarkable.

However, I find the home investors near the acquired firm, who are expected to have better information on the adverse shocks to the local real estate market, are less likely to decrease their holdings of the affected REITs than the non-home investors despite of the adverse market signals. This tendency of underestimating risks is more evident if the home investors' business addresses are closer to the location of the affected real estate asset, because physical proximity is likely to foster familiarity. Therefore, it implies the dominating effect of irrational familiarity bias under adverse market conditions. I also find this effect is amplified when the investors implement active investment strategies, namely if the managers have a stronger discretionary power to adjust their portfolios.

This study provides implications on how the consolidations of firms in other non-real estate sectors potentially affect the real estate markets. Past literature implies that firm acquisitions can affect the local real estate market, as the target firms tend to dispose of spare facilities and reduce redundant workforce during the post-acquisition integrations (Brueller et al., 2018; Maksimovic et al., 2011; Stiebale, 2016). However, the wealth effect on target firms after acquisitions and the tendency of assigning senior management from the acquirers to the targets may also offset the negative demand shocks to the real estate market (Hartman-Glaser et al., 2018; Risberg, 2003). This study narrows this knowledge gap in literature by showing that, on average, local firm acquisitions serve as negative signals to commercial real estate performance.

Finally, this study contributes to the literature on the home bias of institutional investors (Coval and Moskowitz, 2001; Ivković and Weisbenner, 2005; Pool et al., 2012). It identifies the dominating effects among familiarity bias and information advantage with a novel setting and a clean identification strategy. It also extends the prior findings of the individual investors to the institutional investors (Agarwal, 2007; Seiler et al., 2013; Solnik and Zuo, 2017; Strong and Xu, 2003). The results in this study imply that institutional investors may also underestimate the downside risks and overestimate the future performance of their home assets, although the investment committees rigorously monitor their investments. While this study uses institutional investors of REITs to identify the location-specific performance shocks, the findings in the study are generalizable to the institutional investors of other industries and asset classes. Therefore, this study also bears significant implications for the evaluation and management of the institutional investment committees.

Future developments of this study can be made in the following aspects. First, this study employs a multi-treatment DID model to estimate the correlation between changes in institutional ownership and firm acquisition events. Recent econometric literature demonstrates the importance of investigating the heterogeneous treatment effects across time in such specifications (Callaway and Sant'Anna, 2021; De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021). Therefore, it is worthwhile to ascertain that the estimated effects from the baseline models are not biased due to the heterogeneity across treatments.

Second, the spatial scale of the demand shocks due to firm acquisitions can be further analysed. The current specification assumes that only the properties in the county of the target firm are directly affected by the demand shocks. However, there may exist spillover effects to the surrounding areas outside the county (Butler et al., 2019; Hu et al., 2020; Pope and Pope, 2015). Therefore, if the REITs also hold properties in the surrounding counties, the actual share or number of properties affected by the demand shocks may be underestimated.

Third, the analysis of the demand shocks on REIT stock market performance rests on the calculation of abnormal returns from the Fama-French four-factor model. This model consists of the three major factors (market risk, size, and value) introduced by the seminal work by Fama and French (1993) plus the momentum factor, which has been widely accepted by the academia in the past 20 years (e.g., Ling et al., 2021b). However, it is still under debate whether the multifactor models explain the stock performances well, particularly for REITs. For example, Jackson (2020) finds that the returns of smaller REITs that exist in the market for shorter periods are not well explained by Fama and French's three factors. In more recent years, Hou et al. (2015) introduce an alternative q–factor model, while Fama and French (2015) augment the classic three-factor model with two additional factors of operating profitability and total asset growth. Robustness analyses can be conducted using these alternative methods to calculate the REIT abnormal returns.

Last, by showing that the rental yields of the REITs decrease within at least one year after the demand shock, this study argues that rational REIT investors who seek stable dividend income should sell the underperformed REITs. To further support this argument, future research can conduct a performance race between the portfolios with affected versus unaffected REITs.

Chapter 5

Conclusion

The behavioural finance literature does not limit itself to the concept of a "rational homo economicus" that forms the base of neoclassical economic theory (Hollis and Nell, 1975). Instead, it aims to describe the actions of investors, rational or not, and study market inefficiencies caused by behavioural traits. Unlike the traditional finance theories, behavioural finance studies assume people have bounded rationality only. Specifically, due to the constraints in collecting and processing complete information, investors make mental shortcuts and process the available information in a biased manner. Compared with investors of other financial assets, understanding the bounded rationality and behavioural bias of real estate investors is particularly important because the real estate market has low liquidity, high information barriers, and ineffective price discovery (Barkham and Geltner, 1995; Ong and Sing, 2002; Yavas and Yildirim, 2011). Moreover, due to the complexity of human nature and the heterogeneity across real estate market sectors, investors are subject to very different behavioural biases under various market conditions.

In this dissertation, I study how real estate investors form bounded rationality differently due to cognitive errors (e.g., anchoring bias) or emotional heuristics (e.g., familiarity bias) in three important but under-research scenarios. The three studies cover different investor types (individual versus institutional), property types (residential versus commercial), and market sectors (new sales versus resales). Jointly, the three studies show that bounded rationality leads to deviations from the optimal decisions and thus results in substantial implied losses in real estate investments, indicating the importance of mitigating behavioural bias. The first two studies reveal the impact of bounded rationality on housing investment, which is one of the most critical investment decisions for households. The third study is set in a commercial real estate market where it explores the familiarity bias of investors. Its findings are generalizable beyond property markets: Bounded rationality is not limited to inexperienced retail investors but affects sophisticated financial professionals as well.

Chapter 2 revisits the anchoring bias of individual real estate investors in the resale market. I find that the expected losses anchored to purchase prices can affect actual transactions: Sellers facing nominal losses relative to their prior purchase prices attain higher selling prices than their counterparts, but the premium is much smaller in the Hong Kong housing market than the premium documented in western markets. More importantly, I suggest two market factors to account for the extent of the loss effect on the market transaction prices, including the availability of market information and the boom-bust property cycle. Also, I find that at the aggregate market level, the loss effect mitigates the price declines in the bust period, particularly in the less-liquid commercial market.

Chapter 3 studies the anchoring bias of individual buyers in the presale residential property market. Unlike past literature that considers property presales as forward contracts, I model presale contracts as call options to better understand contract rescission behaviour. I find that the presale contracts with the market price lower than the contract price have an 11.4% higher chance to be rescinded, but there is no sharp increase in the rescission rate after the market price falls below the outstanding payments, implying an irrational selection of mental reference. In addition, presale call option delta and time to maturity at the purchase time positively predict rescission. Moreover, I find the rescission rates drop significantly after the Hong Kong government's housing market macroprudential measures.

Chapter 4 switches to study institutional investors and investigates their familiarity bias given adverse market signals. I first demonstrate that the acquisitions of public firms serve as negative demand shocks and adverse market signals to commercial real estate in the target county. Then, using the non-local investors as the control group, I find the local investors are less likely to sell the overvalued REITs after the demand short despite the continuous decrease in the rental yield until at least one year after the demand shocks. Also, I do not find supporting evidence for significant information advantage of local investors before the demand shocks. Therefore, the results imply that institutional investors' irrational familiarity bias can dominate their information advantage under adverse performance shocks to the home assets in their portfolios.

Overall, this dissertation contributes to behavioural finance literature by showing that the economic impact of bounded rationality in real estate investments is large, and the influence is broad across various types of investors and market sectors. In addition, by showing the different choices of anchors in the resale (Chapter 2) and presale (Chapter 3) property markets and discussing the extent of familiarity bias in normal versus negative market conditions (Chapter 4), the three studies in the dissertation collectively deliver an important message that the formation of bounded rationality is not static. Instead, it depends on multiple factors, like the investment choices, the background of investors, the market conditions, etc. Therefore, the findings in this dissertation respond to a common critique of behavioural finance research that behavioural biases affect things that do not matter and should be simply considered as transaction costs: I do not entirely agree with this opinion because of the large economic impact, board influence, and dynamic nature of bounded rationality. Even if we may consider behavioural bias as a form of transaction cost, it will not be a fixed cost. Instead, the cost varies in difficult conditions and can be economically significant in many investment decisions. Therefore, it is of great importance to understand the impact of bounded rationality on investment decisions, specifically in real estate markets.

While the studies in this dissertation advance the knowledge in a common theme of bounded rationality in the real estate literature, they contribute to this discipline methodology-wise from different aspects, including the use of data, theoretical model, and identification strategy. The first research combines transaction data from different sub-sectors in the same city to reveal the impact of market liquidity and information availability on retention of anchoring bias on actual transactions. In the second study, I propose a new theoretical model that adapts the Black-Scholes-Merton model of stock options to understand the contract rescission behaviour in the presale property market. In the third study, I use a novel institutional setting of adjacent non-REIT firm acquisitions to identify institutional investors' responses caused by geographic-specific shocks to real estate assets.

The findings in this dissertation also have important practical implications. First, for individual homeowners and investors, I demonstrate the importance of understanding cognitive errors because these errors can significantly impact their wealth. Since housing is one of the largest household goods and investments, housing investment performance can substantially affect household wealth accumulation

(Di et al., 2007; Turner and Luea, 2009). It also influences the other financial behaviours of household members, such as consumption and saving (Campbell and Cocco, 2007; Engelhardt, 1996). Although home sellers facing expected losses could list at higher prices and substantially extend their holding periods to wait for a better bargain (Genesove and Mayer, 2001), they may bear more holding costs while waiting and lose the opportunities for more profitable investments. More importantly, Chapter 2 indicates that when the market is more efficient in price recovery with better access to information, the chance of achieving abnormal returns by extending holding periods becomes much smaller. Similarly, presale homebuyers who settle the out-of-money contracts bear the implied losses and tend to hold longer in the resale market until the losses are recovered, as discussed in Chapter 3. This behaviour also increases the opportunity costs in the accumulation of household wealth. These findings reveal the importance of educating homebuyers on correcting their cognitive errors like the anchoring bias.

Second, for institutional investors, this dissertation emphasises the importance of avoiding emotional heuristics in their investment decisions. Chapter 4 uses a unique setting of REIT investors to derive the impact of familiarity bias on investment performances. My findings imply that institutional investors may underestimate the downside risks and overestimate the future performance of their home assets due to bounded rationality. Although REITs may only constitute a relatively small proportion of diversified portfolios, it is noteworthy that these implications apply to institutional investors of other asset classes as well. In fact, compared to the REIT investors, who are commonly believed to be passive (Devos et al., 2013), the active investors in other asset classes could be more easily affected by emotional heuristics. Thus, my study has a significant bearing on the evaluation and management of the institutional investment committees.

Third, for governments and policymakers, it is essential to analyse how bounded rationality could impact the property market dynamics and understand its implications for policymaking. For example, the analysis in Chapter 2 reveals that the impact of anchoring bias on the aggregate market is economically significant in the bust periods. This behavioural bias slows down the drops in housing prices because many loss-facing sellers defer their sales to avoid realising the losses immediately. However, with more advanced information technology implemented in the real estate industry, information barriers are expected to be lower in the future (Viriato, 2019). Better access to market information can alleviate the impact of anchoring bias on transaction prices, as shown in Chapter 2. In that case, we may expect the future property market to be more volatile during the market downturns, and the policymakers are recommended to monitor the associated financial risks closely.

Last, for developers, it is also critical to understand whether the bounded rationality of home buyers will impact the risks in project developments. As introduced in Chapter 3, presale is an important instrument for developers to share the project risks with their customers. Rescissions in presale contracts significantly increase the risks taken by developers because developers cannot receive the payments in time and cannot lock the previous contract prices. Since the presale homebuyers tend to anchor to the (higher) total contract prices instead of the (lower) outstanding payments, this behavioural bias increases the overall chances of presale contract rescissions when the market is weak. Therefore, developers are advised to take the bounded rationality of customers into account when they forecast the risks and evaluate the financial feasibility of their development projects.

To conclude the dissertation, I would like to discuss the challenges and research directions for future work in understanding the bounded rationality of real estate investors. First of all, the studies in this dissertation, like most other literature in this field, are primarily descriptive. As a discipline, we still lack a unifying and systematic theoretical framework to explain the (many) behavioural biases empirically documented so far. Currently, various behavioural biases are often defined and described as observed deviations from the theoretically optimal choices. However, the observations might not be fully replicable in different contexts, and it is still hard to predict investors' behaviours. The explanations for these observed behavioural deviations are sometimes not rigorous enough, which leads to ambiguities in the definitions of some behavioural biases. As the Nobel Prize winner Dr. Richard Thaler mentioned, "traditional economics is precisely wrong", but "behavioural economics is messy" (Morningstar, 2018). This is the general challenge for all behavioural finance researchers and applies to real estate studies as well.

Another important future research area is the relationship between the bounded rationality of market participants and the effectiveness of policies in real estate markets. Literature documents that homeownership rate and real estate market performance can be largely explained by institutional and political developments (Salzman and Zwinkels, 2017). Many governments also use the policy instruments, such as purchase restrictions and stamp duties, to regulate the local property markets. As collectively implied by the three studies in the dissertation, the formation of bounded rationality is not static, and the behaviours of investors may deviate from the rational utility maximisation due to the policy shocks. Nevertheless, the policies are often set based on the assumptions of perfect rationality, and fewer studies have investigated how the bounded rationality of market participants influences the policy outcomes. In one of my ongoing studies beyond this dissertation, I examine the impact of familiarity bias on the effectiveness of macroprudential policies in property markets (Hu et al., 2022). I find that after the Hong Kong government restricted investments in the presale housing market, the investors crowded into the spot housing market, particularly in those districts that they are familiar with. However, although the government had introduced several attractive policies for industrial redevelopment at the same time, the hot money does not flow into that market sector, which the investors are not familiar with.

Finally, an essential progression of this field is to understand more under-researched subjective aspects of emotional heuristics in real estate investment decisions. Existing literature primarily relies on measurable approximations to identify emotional heuristics (e.g., use physical distance as the proxy measurement of familiarity). However, many emotional heuristics, or subjective perceptions, do not have this kind of measurable approximations, so they are more challenging to measure. Thanks to the recent advances in machine learning, a growing strand of literature has started to apply these new tools in measuring personal preferences and associate them with asset pricing (e.g., Aubry et al., 2022). In another ongoing research beyond this dissertation, I apply computer vision techniques to measure the individual subjective assessments of real estate appearances (Lindenthal et al., 2022; Wan and Lindenthal, 2021). I document a strong bias of dynamic inconsistency in personal housing choices (Jackson and Yariv, 2015; Sprenger, 2015b), which means that people's subjective preferences can become inconsistent over time and are easily influenced by external noises. This bias increases the frictions in searching and induces more risks of regret, which have larger economic impacts than the dynamic inconsistency in choosing general consumption goods (Hoch and Loewenstein, 1991).

References

Aarland, K., Davis, J. C., Henderson, J. V., and Ono, Y. (2007). Spatial organization of firms: The decision to split production and administration. *The RAND Journal of Economics*, 38(2):480–494.

Agarwal, S. (2007). The impact of homeowners' housing wealth misestimation on consumption and saving decisions. *Real Estate Economics*, 35(2):135–154.

Agnew, J. R., Anderson, L. R., Gerlach, J. R., and Szykman, L. R. (2008). Who chooses annuities? An experimental investigation of the role of gender, framing, and defaults. *American Economic Review*, 98(2):418–22.

Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, 19(6):716–723.

Allen, P. R. and Sirmans, C. F. (1987). An analysis of gains to acquiring firm's shareholders: The special case of REITs. *Journal of Financial Economics*, 18(1):175–184.

Ambrose, B. W. and Buttimer, R. J. (2000). Embedded options in the mortgage contract. *The Journal of Real Estate Finance and Economics*, 21(2):95–111.

Ambrose, B. W., Ehrlich, S. R., Hughes, W. T., and Wachter, S. M. (2000). REIT economies of scale: Fact or fiction? *The Journal of Real Estate Finance and Economics*, 20(2):211–224.

Andersen, S., Badarinza, C., Liu, L., Marx, J., and Ramadorai, T. (2021). Reference dependence in the housing market. *Available at SSRN 3396506*.

Anenberg, E. (2011). Loss aversion, equity constraints and seller behavior in the real estate market. *Regional Science and Urban Economics*, 41(1):67–76.

Anenberg, E. (2016). Information frictions and housing market dynamics. *International Economic Review*, 57(4):1449–1479.

Arthur, W. B. (1994). Inductive reasoning and bounded rationality. *American Economic Review*, 84(2):406–411.

Aubry, M., Kraeussl, R., Manso, G., and Spaenjers, C. (2022). Biased auctioneers. *The Journal of Finance*.

Bacon, F. and Von Gersdorff, N. (2008). US mergers and acquisitions: A test of market efficiency. *Journal of Finance & Accountancy*, 13(1):69–70.

Bailey, W., Kumar, A., and Ng, D. (2011). Behavioral biases of mutual fund investors. *Journal of Financial Economics*, 102(1):1–27.

Baker, M., Pan, X., and Wurgler, J. (2012). The effect of reference point prices on mergers and acquisitions. *Journal of Financial Economics*, 106(1):49–71.

Bao, H. X. and Meng, C. C. (2017). Loss aversion and housing studies. *Journal of Real Estate Literature*, 25(1):49–75.

Barberis, N. and Huang, M. (2001). Mental accounting, loss aversion, and individual stock returns. *The Journal of Finance*, 56(4):1247–1292.

Barberis, N. C. (2013). Thirty years of prospect theory in economics: A review and assessment. *Journal of Economic Perspectives*, 27(1):173–96.

Barkham, R. and Geltner, D. (1995). Price discovery in American and British property markets. *Real Estate Economics*, 23(1):21–44.

Bayer, P., Geissler, C., Mangum, K., and Roberts, J. W. (2020). Speculators and middlemen: The strategy and performance of investors in the housing market. *The Review of Financial Studies*, 33(11):5212–5247.

Beck, T., Levine, R., and Levkov, A. (2010). Big bad banks? The winners and losers from bank deregulation in the United States. *The Journal of Finance*, 65(5):1637–1667.

Ben-David, I., Franzoni, F., Moussawi, R., and Sedunov, J. (2021). The granular nature of large institutional investors. *Management Science*.

Ben-David, I. and Hirshleifer, D. (2012). Are investors really reluctant to realize their losses? Trading responses to past returns and the disposition effect. *The Review of Financial Studies*, 25(8):2485–2532.

Bernile, G., Kumar, A., and Sulaeman, J. (2015). Home away from home: Geography of information and local investors. *The Review of Financial Studies*, 28(7):2009–2049.

Bernoulli, D. (1954). Exposition of a new theory on the measurement of risk. *Econometrica*, 22(1):23–36.

Bhutta, N., Dokko, J., and Shan, H. (2017). Consumer ruthlessness and mortgage default during the 2007 to 2009 housing bust. *The Journal of Finance*, 72(6):2433–2466.

Black, F. and Scholes, M. (1973). The pricing of options and corporate liabilities. *The Journal of Political Economy*, 81(3):637–654.

Bokhari, S. and Geltner, D. (2011). Loss aversion and anchoring in commercial real estate pricing: Empirical evidence and price index implications. *Real Estate Economics*, 39(4):635–670.

Booth, G. G., Glascock, J. L., and Sarkar, S. K. (1996). A reexamination of corporate sell-offs of real estate assets. *The Journal of Real Estate Finance and Economics*, 12(2):195–202.

Bouwman, C. H., Fuller, K., and Nain, A. S. (2009). Market valuation and acquisition quality: Empirical evidence. *The Review of Financial Studies*, 22(2):633–679.

Boyer, B. H. and Vorkink, K. (2014). Stock options as lotteries. *The Journal of Finance*, 69(4):1485–1527.

Bracke, P. and Tenreyro, S. (2021). History dependence in the housing market. *American Economic Journal: Macroeconomics*, 13(2):420–43.

Bradley, M. G., Cutts, A. C., and Liu, W. (2015). Strategic mortgage default: The effect of neighborhood factors. *Real Estate Economics*, 43(2):271–299.

Breinlich, H. (2008). Trade liberalization and industrial restructuring through mergers and acquisitions. *Journal of International Economics*, 76(2):254–266.

Brenner, M. and Subrahmanyan, M. G. (1988). A simple formula to compute the implied standard deviation. *Financial Analysts Journal*, 44(5):80–83.

Brouwer, A. E., Mariotti, I., and Van Ommeren, J. N. (2004). The firm relocation decision: An empirical investigation. *The Annals of Regional Science*, 38(2):335–347.

Brueller, N. N., Carmeli, A., and Markman, G. D. (2018). Linking merger and acquisition strategies to postmerger integration: A configurational perspective of human resource management. *Journal of Management*, 44(5):1793–1818.

Bushee, B. J. (1998). The influence of institutional investors on myopic R&D investment behavior. *The Accounting Review*, pages 305–333.

Bushee, B. J. and Noe, C. F. (2000). Corporate disclosure practices, institutional investors, and stock return volatility. *Journal of Accounting Research*, pages 171–202.

Butler, A. W., Fauver, L., and Spyridopoulos, I. (2019). Local economic spillover effects of stock market listings. *Journal of Financial and Quantitative Analysis*, 54(3):1025–1050.

Butler, S. A. (1986). Anchoring in the judgmental evaluation of audit samples. *The Accounting Review*, pages 101–111.

Buttimer, R. J., Clark, S. P., and Ott, S. H. (2008). Land development: Risk, return and risk management. *The Journal of Real Estate Finance and Economics*, 36(1):81–102.

Byun, S. J. and Kim, D. H. (2016). Gambling preference and individual equity option returns. *Journal of Financial Economics*, 122(1):155–174.

Callaway, B. and Sant'Anna, P. H. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225(2):200–230.

Campbell, J. Y. and Cocco, J. F. (2007). How do house prices affect consumption? Evidence from micro data. *Journal of Monetary Economics*, 54(3):591–621.

Campbell, R. D., Ghosh, C., and Sirmans, C. (2001). The information content of method of payment in mergers: Evidence from real estate investment trusts (REITs). *Real Estate Economics*, 29(3):361–387.

Campbell, R. D., Giambona, E., and Sirmans, C. (2009). The long-horizon performance of REIT mergers. *The Journal of Real Estate Finance and Economics*, 38(2):105–114.

Campbell, R. D., Petrova, M., and Sirmans, C. (2003). Wealth effects of diversification and financial deal structuring: Evidence from REIT property portfolio acquisitions. *Real Estate Economics*, 31(3):347–366.

Cao, H. H., Han, B., Hirshleifer, D., and Zhang, H. H. (2011). Fear of the unknown: Familiarity and economic decisions. *Review of Finance*, 15(1):173–206.

Capozza, D. R. and Li, Y. (2001). Residential investment and interest rates: An empirical test of land development as a real option. *Real Estate Economics*, 29(3):503–519.

Carrillo, P. E. (2013). To sell or not to sell: Measuring the heat of the housing market. *Real Estate Economics*, 41(2):310–346.

Case, K. E. and Shiller, R. J. (1989). The efficiency of the market for single-family homes. *American Economic Review*, pages 125–137.

Chan, S. H., Chen, J., and Wang, K. (2019). Does a firm's entry or exit affect competitors' value? Evidence from the REIT industry. *Real Estate Economics*, 47(1):214–262.

Chan, S. H., Fang, F., and Yang, J. (2014). Presales, leverage decisions, and risk shifting. *Journal of Real Estate Research*, 36(4):475–510.

Chan, S. H., Wang, K., and Yang, J. (2012). Presale contract and its embedded default and abandonment options. *The Journal of Real Estate Finance and Economics*, 44(1-2):116–152.

Chang, C.-O. and Ward, C. W. (1993). Forward pricing and the housing market: The pre-sales housing system in Taiwan. *Journal of Property Research*, 10(3):217–227.

Chang, S. (1998). Takeovers of privately held targets, methods of payment, and bidder returns. *The Journal of Finance*, 53(2):773–784.

Chang, T. Y., Solomon, D. H., and Westerfield, M. M. (2016). Looking for someone to blame: Delegation, cognitive dissonance, and the disposition effect. *The Journal of Finance*, 71(1):267–302.

Chau, K. (1997). Political uncertainty and the real estate risk premiums in Hong Kong. *Journal of Real Estate Research*, 13(3):297–315.

Chau, K., Wong, S., Yiu, C., and Leung, H. (2005). Real estate price indices in Hong Kong. *Journal of Real Estate Literature*, 13(3):337–356.

Chau, K., Wong, S. K., and Yiu, C. (2007). Housing quality in the forward contracts market. *The Journal of Real Estate Finance and Economics*, 34(3):313–325.

Chen, G., Kim, K. A., Nofsinger, J. R., and Rui, O. M. (2007). Trading performance, disposition effect, overconfidence, representativeness bias, and experience of emerging market investors. *Journal of Behavioral Decision Making*, 20(4):425–451.

Chen, Y., Kelly, B., and Wu, W. (2020). Sophisticated investors and market efficiency: Evidence from a natural experiment. *Journal of Financial Economics*, 138(2):316–341.

Chen, Y., Wilkoff, S., and Yoshida, J. (2021). Amazon is coming to town: Private information and housing market efficiency. *Available at SSRN 3762672*.

Cheng, Y., Clark, S. P., and Womack, K. S. (2021). A real options model of real estate development with entitlement risk. *Real Estate Economics*, 49(1):106–151.

Chinco, A. and Mayer, C. (2016). Misinformed speculators and mispricing in the housing market. *The Review of Financial Studies*, 29(2):486–522.

Choi, J., Rasmussen, H., and Davison, M. (2012). Fair value and risk profile for presale contracts of condominiums. *The Journal of Real Estate Finance and Economics*, 44(4):472–504.

Choi, N., Fedenia, M., Skiba, H., and Sokolyk, T. (2017). Portfolio concentration and performance of institutional investors worldwide. *Journal of Financial Economics*, 123(1):189–208.

Chow, T., Huang, S., Klassen, K. J., and Ng, J. (2021). The influence of corporate income taxes on investment location: Evidence from corporate headquarters relocations. *Management Science*.

Chun, G. H., Sa-Aadu, J., and Shilling, J. D. (2004). The role of real estate in an institutional investor's portfolio revisited. *The Journal of Real Estate Finance and Economics*, 29(3):295–320.

Clapp, J. M., Lu-Andrews, R., and Zhou, T. (2020). Anchoring to purchase price and fundamentals: Application of salience theory to housing cycle diagnosis. *Real Estate Economics*, 48(4):1274–1317.

Coval, J. D. and Moskowitz, T. J. (1999). Home bias at home: Local equity preference in domestic portfolios. *The Journal of Finance*, 54(6):2045–2073.

Coval, J. D. and Moskowitz, T. J. (2001). The geography of investment: Informed trading and asset prices. *Journal of Political Economy*, 109(4):811–841.

Cunningham, C., Ederer, F., and Ma, S. (2021). Killer acquisitions. *Journal of Political Economy*, 129(3):649–702.

David, J. M. (2021). The aggregate implications of mergers and acquisitions. *The Review of Economic Studies*, 88(4):1796–1830.

De Chaisemartin, C. and d'Haultfoeuille, X. (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, 110(9):2964–96.

Deng, Y. and Liu, P. (2009). Mortgage prepayment and default behavior with embedded forward contract risks in China's housing market. *The Journal of Real Estate Finance and Economics*, 38(3):214–240.

Deng, Y., Quigley, J. M., and Van Order, R. (2000). Mortgage terminations, heterogeneity and the exercise of mortgage options. *Econometrica*, 68(2):275–307.

Devos, E., Ong, S.-E., Spieler, A. C., and Tsang, D. (2013). REIT institutional ownership dynamics and the financial crisis. *The Journal of Real Estate Finance and Economics*, 47(2):266–288.

Dhar, R. and Zhu, N. (2006). Up close and personal: Investor sophistication and the disposition effect. *Management Science*, 52(5):726–740.

Di, Z. X., Belsky, E., and Liu, X. (2007). Do homeowners achieve more household wealth in the long run? *Journal of Housing Economics*, 16(3-4):274–290.

Edelstein, R., Liu, P., and Wu, F. (2012). The market for real estate presales: A theoretical approach. *The Journal of Real Estate Finance and Economics*, 45(1):30–48.

Eichholtz, P. and Yönder, E. (2015). CEO overconfidence, REIT investment activity and performance. *Real Estate Economics*, 43(1):139–162.

Einiö, M., Kaustia, M., and Puttonen, V. (2008). Price setting and the reluctance to realize losses in apartment markets. *Journal of Economic Psychology*, 29(1):19–34.

Engelhardt, G. V. (1996). House prices and home owner saving behavior. *Regional Science and Urban Economics*, 26(3-4):313–336.

Engelhardt, G. V. (2003). Nominal loss aversion, housing equity constraints, and household mobility: Evidence from the united states. *Journal of Urban Economics*, 53(1):171–195.

Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3–56.

Fama, E. F. and French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116(1):1–22.

Fan, Y., Hu, M. R., and Wan, W. X. (2019). A tale of two cities: The impact of cross-border migration on the Hong Kong housing market. *Available at SSRN*, 3477421.

Flavin, M. and Yamashita, T. (2002). Owner-occupied housing and the composition of the household portfolio. *American Economic Review*, 92(1):345–362.

French, K. R. and Poterba, J. M. (1991). Investor diversification and international equity markets. *American Economic Review*, 81(2):222–226.

Fu, Y. and Qian, W. (2014). Speculators and price overreaction in the housing market. *Real Estate Economics*, 42(4):977–1007.

Fu, Y., Qian, W., and Yeung, B. (2016). Speculative investors and transactions tax: Evidence from the housing market. *Management Science*, 62(11):3254–3270.

Gan, Q. (2013). Optimal selling mechanism, auction discounts and time on market. *Real Estate Economics*, 41(2):347–383.

Garcia, D. and Norli, Ø. (2012). Geographic dispersion and stock returns. *Journal of Financial Economics*, 106(3):547–565.

Garmaise, M. J. and Moskowitz, T. J. (2004). Confronting information asymmetries: Evidence from real estate markets. *The Review of Financial Studies*, 17(2):405–437.

Genesove, D. and Mayer, C. (2001). Loss aversion and seller behavior: Evidence from the housing market. *The Quarterly Journal of Economics*, 116(4):1233–1260.

Genesove, D. and Mayer, C. J. (1997). Equity and time to sale in the real estate market. *American Economic Review*, 87(3):255–269.

Gerardi, K., Herkenhoff, K. F., Ohanian, L. E., and Willen, P. S. (2018). Can't pay or won't pay? unemployment, negative equity, and strategic default. *The Review of Financial Studies*, 31(3):1098–1131.

Giroud, X. (2013). Proximity and investment: Evidence from plant-level data. *The Quarterly Journal of Economics*, 128(2):861–915.

Glaeser, E. L. (2013). A nation of gamblers: Real estate speculation and american history. *American Economic Review*, 103(3):1–42.

Glaeser, E. L. and Nathanson, C. G. (2017). An extrapolative model of house price dynamics. *Journal of Financial Economics*, 126(1):147–170.

Glascock, J. L., Davidson III, W. N., and Sirmans, C. (1991). The gains from corporate selloffs: The case of real estate assets. *Real Estate Economics*, 19(4):567–582.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, 225(2):254–277.

Gopalan, N. (2018). HK property prices - It's all down to location, size. *The Business Times.*

Gordon, B., Winkler, D., Barrett, D., and Zumpano, L. (2013). The effect of elevation and corner location on oceanfront condominium value. *Journal of Real Estate Research*, 35(3):345–364.

Graham, J. R., Harvey, C. R., and Huang, H. (2009). Investor competence, trading frequency, and home bias. *Management Science*, 55(7):1094–1106.

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.

Grinblatt, M. and Keloharju, M. (2001a). How distance, language, and culture influence stockholdings and trades. *The Journal of Finance*, 56(3):1053–1073.

Grinblatt, M. and Keloharju, M. (2001b). What makes investors trade? *The Journal of Finance*, 56(2):589–616.

Guiso, L., Sapienza, P., and Zingales, L. (2013). The determinants of attitudes toward strategic default on mortgages. *The Journal of Finance*, 68(4):1473–1515.

Han, L. and Strange, W. C. (2016). What is the role of the asking price for a house? *Journal of Urban Economics*, 93:115–130.

Hardin, W. G. and Wu, Z. (2009). Bank mergers, REIT loan pricing and takeover likelihood. *The Journal of Real Estate Finance and Economics*, 38(3):275–301.

Hartman-Glaser, B., Thibodeau, M., and Yoshida, J. (2018). Cash to spend: IPO wealth and house prices. *Available at SSRN 3329651.*

Hartzell, J. C., Sun, L., and Titman, S. (2014). Institutional investors as monitors of corporate diversification decisions: Evidence from real estate investment trusts. *Journal of Corporate Finance*, 25:61–72.

Hau, H. (2001). Location matters: An examination of trading profits. *The Journal of Finance*, 56(5):1959–1983.

Hau, H. and Rey, H. (2008). Home bias at the fund level. *American Economic Review*, 98(2):333–38.

Hilliard, J. E., Kau, J. B., and Slawson Jr, V. C. (1998). Valuing prepayment and default in a fixed-rate mortgage: A bivariate binomial options pricing technique. *Real Estate Economics*, 26(3):431.

Hoch, S. J. and Loewenstein, G. F. (1991). Time-inconsistent preferences and consumer self-control. *Journal of Consumer Research*, 17(4):492–507.

Hollis, M. and Nell, E. (1975). Rational economic man. *Econometrica*, 29:315–35.

Hou, K., Xue, C., and Zhang, L. (2015). Digesting anomalies: An investment approach. *The Review of Financial Studies*, 28(3):650–705.

Hu, M., Tsang, D., and Wan, W. X. (2020). Corporate relocation and housing market spillover. *Available at SSRN 3683630.*

Hu, M. R., Wan, W. X., and Xu, K. (2022). Cross-market spillovers of real estate speculation. *Available at SSRN 4096586.*

Huberman, G. (2001). Familiarity breeds investment. *The Review of Financial Studies*, 14(3):659–680.

Humphery-Jenner, M. L. and Powell, R. G. (2011). Firm size, takeover profitability, and the effectiveness of the market for corporate control: Does the absence of anti-takeover provisions make a difference? *Journal of Corporate Finance*, 17(3):418–437.

Hur, J. and Singh, V. (2019). How do disposition effect and anchoring bias interact to impact momentum in stock returns? *Journal of Empirical Finance*, 53:238–256.

Ioannides, Y. M. and Rosenthal, S. S. (1994). Estimating the consumption and investment demands for housing and their effect on housing tenure status. *The Review of Economics and Statistics*, pages 127–141.

Ivković, Z., Sialm, C., and Weisbenner, S. (2008). Portfolio concentration and the performance of individual investors. *Journal of Financial and Quantitative Analysis*, pages 613–655.

Ivković, Z. and Weisbenner, S. (2005). Local does as local is: Information content of the geography of individual investors' common stock investments. *The Journal of Finance*, 60(1):267–306.

Jackson, L. A. (2020). An application of the Fama–French three-factor model to lodging REITs: A 20-year analysis. *Tourism and Hospitality Research*, 20(1):31–40.

Jackson, M. O. and Yariv, L. (2015). Collective dynamic choice: The necessity of time inconsistency. *American Economic Journal: Microeconomics*, 7(4):150–78.

Jarrow, R. A. and Oldfield, G. S. (1981). Forward contracts and futures contracts. *Journal of Financial Economics*, 9(4):373–382.

Jovanovic, B. and Rousseau, P. L. (2008). Mergers as reallocation. *The Review of Economics and Statistics*, 90(4):765–776.

Kadous, K., Tayler, W. B., Thayer, J. M., and Young, D. (2014). Individual characteristics and the disposition effect: The opposing effects of confidence and self-regard. *Journal of Behavioral Finance*, 15(3):235–250.

Kahneman, D. (2003). Maps of bounded rationality: Psychology for behavioral economics. *American Economic Review*, 93(5):1449–1475.

Kahneman, D. and Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, 47(2):263–292.

Kim, J. D. (2022). Startup acquisitions, relocation, and employee entrepreneurship. *Strategic Management Journal*.

Lai, M. M., Tan, S. H., and Chong, L. L. (2013). The behavior of institutional and retail investors in bursa malaysia during the bulls and bears. *Journal of Behavioral Finance*, 14(2):104–115.

Lai, R. N., Wang, K., and Zhou, Y. (2004). Sale before completion of development: Pricing and strategy. *Real Estate Economics*, 32(2):329–357.

Lakonishok, J., Lee, I., Pearson, N. D., and Poteshman, A. M. (2007). Option market activity. *The Review of Financial Studies*, 20(3):813–857.

Leung, C. K. Y. and Tang, E. C. H. (2015). Availability, affordability and volatility: The case of the Hong Kong housing market. *International Real Estate Review*, 18(3):383–428.

Leung, T. C. and Tsang, K. P. (2013). Anchoring and loss aversion in the housing market: Implications on price dynamics. *China Economic Review*, 24:42–54.

Li, J., Elayan, F. A., and Meyer, T. O. (2001). Acquisitions by real estate investment trusts as a strategy for minimization of investor tax liability. *Journal of Economics and Finance*, 25(1):115–134.

Li, L. and Chau, K. (2019). What motivates a developer to sell before completion? *The Journal of Real Estate Finance and Economics*, 59(2):209–232.

Li, L. and Wan, W. X. (2021). The effect of expected losses on the Hong Kong property market. *The Journal of Real Estate Finance and Economics*, pages 1–30.

Lindenthal, T., Schmidt, C. E., and Wan, W. X. (2022). Aesthetic preferences for residential architecture: Finding ground truth with machine learning approaches. *Working Paper*.

Ling, D. C., Naranjo, A., and Petrova, M. T. (2018). Search costs, behavioral biases, and information intermediary effects. *The Journal of Real Estate Finance and Economics*, 57(1):114–151.

Ling, D. C., Naranjo, A., and Scheick, B. (2021a). There is no place like home: Information asymmetries, local asset concentration, and portfolio returns. *Real Estate Economics*, 49(1):36–74.

Ling, D. C., Wang, C., and Zhou, T. (2021b). The geography of real property information and investment: Firm location, asset location and institutional ownership. *Real Estate Economics*, 49(1):287–331.

Ling, D. C., Wang, C., and Zhou, T. (2021c). Institutional common ownership and firm value: Evidence from real estate investment trusts. *Real Estate Economics*, 49(1):187–223.

Liu, C. and Liu, P. (2013). Is what's bad for the goose (tenant), bad for the gander (landlord)? A retail real estate perspective. *Journal of Real Estate Research*, 35(3):249–282.

Longstaff, F. A. (1990). Pricing options with extendable maturities: Analysis and applications. *The Journal of Finance*, 45(3):935–957.

Lui, K. (2016). Move over, new yorkers: You have no idea how small an apartment can really get. *Time*.

Luypaert, M. and De Maeseneire, W. (2015). Antecedents of time to completion in mergers and acquisitions. *Applied Economics Letters*, 22(4):299–304.

Mak, S. W., Choy, L. H., and Ho, W. K. (2007). Privatization, housing conditions and affordability in the People's Republic of China. *Habitat International*, 31(2):177–192.

Maksimovic, V., Phillips, G., and Prabhala, N. R. (2011). Post-merger restructuring and the boundaries of the firm. *Journal of Financial Economics*, 102(2):317–343.

Maksimovic, V., Phillips, G., and Yang, L. (2013). Private and public merger waves. *The Journal of Finance*, 68(5):2177–2217.

Malpezzi, S. and Wachter, S. (2005). The role of speculation in real estate cycles. *Journal of Real Estate Literature*, 13(2):141–164.

Massa, M. and Simonov, A. (2005). Behavioral biases and investment. *Review of Finance*, 9(4):483–507.

Masulis, R. W., Wang, C., and Xie, F. (2007). Corporate governance and acquirer returns. *The Journal of Finance*, 62(4):1851–1889.

Merton, R. C. (1973). Theory of rational option pricing. *The Bell Journal of Economics and Management Science*, pages 141–183.

Milcheva, S., Yildirim, Y., and Zhu, B. (2020). Distance to headquarter and real estate equity performance. *The Journal of Real Estate Finance and Economics*, pages 1–27.

Morningstar (2018). Why traditional economics is precisely wrong. *Morningstar: Advisor Insights*.

Northcraft, G. B. and Neale, M. A. (1987). Experts, amateurs, and real estate: An anchoring-and-adjustment perspective on property pricing decisions. *Organizational Behavior and Human Decision Processes*, 39(1):84–97.

Odean, T. (1998). Are investors reluctant to realize their losses? *The Journal of Finance*, 53(5):1775–1798.

Olgun, S. (2005). The performance of acquisitions in the real estate investment trust industry. *Journal of Real Estate Research*, 27(3):321–342.

Ong, S.-E. and Sing, T.-F. (2002). Price discovery between private and public housing markets. *Urban Studies*, 39(1):57–67.

Ooi, J. T., Ong, S.-E., and Neo, P.-H. (2011). The wealth effects of property acquisitions: Evidence from Japanese and Singaporean REITs. *Real Estate Economics*, 39(3):487–505.

Pennington-Cross, A. and Ho, G. (2010). The termination of subprime hybrid and fixed-rate mortgages. *Real Estate Economics*, 38(3):399–426.

Pierzak, E. (2001). Payment choice in REIT property acquisitions. *Journal of Real Estate Research*, 21(1-2):105–140.

Pompian, M. M. (2006). *Behavioral Finance and Wealth Management.* New Jersey: John Wiley and Sons, Inc.

Pompian, M. M. and Longo, J. M. (2005). Incorporating behavioral finance into your practice. *Journal of Financial Planning*, 18(3):58.

Pool, V. K., Stoffman, N., and Yonker, S. E. (2012). No place like home: Familiarity in mutual fund manager portfolio choice. *The Review of Financial Studies*, 25(8):2563–2599.

Pope, D. G. and Pope, J. C. (2015). When Walmart comes to town: Always low housing prices? Always? *Journal of Urban Economics*, 87:1–13.

Rabin, M. and Schrag, J. L. (1999). First impressions matter: A model of confirmatory bias. *The Quarterly Journal of Economics*, 114(1):37–82.

Rehse, D., Riordan, R., Rottke, N., and Zietz, J. (2019). The effects of uncertainty on market liquidity: Evidence from hurricane sandy. *Journal of Financial Economics*, 134(2):318–332.

Risberg, A. (2003). The merger and acquisition process. *Journal of International Business Studies*, 34(1):1–34.

Sah, V., Ziobrowski, A., and Ziobrowski, B. (2008). REIT performance during hurricanes. *Journal of Real Estate Portfolio Management*, 14(1):41–48.

Salzman, D. and Zwinkels, R. C. (2017). Behavioral real estate. *Journal of Real Estate Literature*, 25(1):77–106.

Samuelson, P. A. (1937). A note on measurement of utility. *The Review of Economic Studies*, 4(2):155–161.

Samuelson, W. and Zeckhauser, R. (1988). Status quo bias in decision making. *Journal of Risk and Uncertainty*, 1(1):7–59.

Savor, P. G. and Lu, Q. (2009). Do stock mergers create value for acquirers? *The Journal of Finance*, 64(3):1061–1097.

Schwarz, G. (1978). Estimating the dimension of a model. *The Annals of Statistics*, pages 461–464.

Seasholes, M. S. and Zhu, N. (2010). Individual investors and local bias. *The Journal of Finance*, 65(5):1987–2010.

Seiler, M., Seiler, V., Traub, S., and Harrison, D. (2008). Regret aversion and false reference points in residential real estate. *Journal of Real Estate Research*, 30(4):461–474.

Seiler, M. J., Seiler, V. L., Harrison, D. M., and Lane, M. A. (2013). Familiarity bias and perceived future home price movements. *Journal of Behavioral Finance*, 14(1):9–24.

Seiler, M. J., Seiler, V. L., Lane, M. A., and Harrison, D. M. (2012). Fear, shame and guilt: Economic and behavioral motivations for strategic default. *Real Estate Economics*, 40:S199–S233.

Shefrin, H. and Statman, M. (1985). The disposition to sell winners too early and ride losers too long: Theory and evidence. *The Journal of Finance*, 40(3):777–790.

Simon, H. A. (1957). *Models of man, social and rational: Mathematical essays on rational human behavior in society setting.* New York: Wiley.

Slovic, P. (1972). Psychological study of human judgment: Implications for investment decision making. *The Journal of Finance*, 27(4):779–799.

Solnik, B. and Zuo, L. (2017). Relative optimism and the home bias puzzle. *Review of Finance*, 21(5):2045–2074.

Sprenger, C. (2015a). An endowment effect for risk: Experimental tests of stochastic reference points. *Journal of Political Economy*, 123(6):1456–1499.

Sprenger, C. (2015b). Judging experimental evidence on dynamic inconsistency. *American Economic Review*, 105(5):280–85.

Statman, M. (1999). Behaviorial finance: Past battles and future engagements. *Financial Analysts Journal*, 55(6):18–27.

Stein, J. C. (1995). Prices and trading volume in the housing market: A model with down-payment effects. *The Quarterly Journal of Economics*, 110(2):379–406.

Stiebale, J. (2016). Cross-border M&As and innovative activity of acquiring and target firms. *Journal of International Economics*, 99:1–15.

Strong, N. and Xu, X. (2003). Understanding the equity home bias: Evidence from survey data. *Review of Economics and Statistics*, 85(2):307–312.

Tang, E. C. H. and Leung, C. K. Y. (2015). Availability, affordability and volatility: The case of Hong Kong housing market. *International Real Estate Review*.

Taylor, C. (2019). Hong Kong named the most expensive city in the world for expats. *CNBC*.

Teo, M. (2009). The geography of hedge funds. *The Review of Financial Studies*, 22(9):3531–3561.

Turner, T. M. and Luea, H. (2009). Homeownership, wealth accumulation and income status. *Journal of Housing Economics*, 18(2):104–114.

Van Nieuwerburgh, S. and Veldkamp, L. (2009). Information immobility and the home bias puzzle. *The Journal of Finance*, 64(3):1187–1215.

Viriato, J. C. (2019). AI and machine learning in real estate investment. *The Journal of Portfolio Management*, 45(7):43–54.

Voget, J. (2011). Relocation of headquarters and international taxation. *Journal of Public Economics*, 95(9-10):1067–1081.

Wan, W. X. and Lindenthal, T. (2021). Towards accountability in machine learning applications: A system-testing approach. *ZEW-Centre for European Economic Research Discussion Paper*, (22-001).

Wei, J. (2018). Behavioral biases in the corporate bond market. *Journal of Empirical Finance*, 46:34–55.

Wong, S. K., Chau, K. W., and Yiu, C. (2007). Volatility transmission in the real estate spot and forward markets. *The Journal of Real Estate Finance and Economics*, 35(3):281–293.

Wong, S. K. and Cheung, K. S. (2020). Housing price dispersion in the presale market. *Economic and Political Studies*, 8(1):65–81.

Wong, S. K., Li, L., and Monkkonen, P. (2020). Developers' market power: How do developers price new housing in a highly oligopolistic city. *International Real Estate Review*, 22(3):307–332.

Wong, S. K., Yiu, C., Tse, M., and Chau, K. W. (2006). Do the forward sales of real estate stabilize spot prices? *The Journal of Real Estate Finance and Economics*, 32(3):289–304.

Wong, S. K., Yiu, C. Y., and Chau, K. W. (2012). Liquidity and information asymmetry in the real estate market. *The Journal of Real Estate Finance and Economics*, 45(1):49–62.

Wu, V. (2017). Hong Kong "mini" flats boom as government fails to rein in record-high prices. *Reuters*.

Yao, H. and Pretorius, F. (2014). Demand uncertainty, development timing and leasehold land valuation: Empirical testing of real options in residential real estate development. *Real Estate Economics*, 42(4):829–868.

Yavas, A. and Yang, S. (1995). The strategic role of listing price in marketing real estate: Theory and evidence. *Real Estate Economics*, 23(3):347–368.

Yavas, A. and Yildirim, Y. (2011). Price discovery in real estate markets: A dynamic analysis. *The Journal of Real Estate Finance and Economics*, 42(1):1–29.

Ye, J. (2017). A peek into 6 of the smallest flats in Hong Kong. *South China Morning Post*.

Yiu, C., Wong, S. K., and Chau, K. W. (2009). Transaction volume and price dispersion in the presale and spot real estate markets. *The Journal of Real Estate Finance and Economics*, 38(3):241–253.

Yuan, K. (2005). Asymmetric price movements and borrowing constraints: A rational expectations equilibrium model of crises, contagion, and confusion. *The Journal of Finance*, 60(1):379–411.

Zhou, T., Clapp, J. M., and Lu-Andrews, R. (2021a). Examining omitted variable bias in anchoring premium estimates: Evidence based on assessed value. *Real Estate Economics*.

Zhou, T., Clapp, J. M., and Lu-Andrews, R. (2021b). Is the behavior of sellers with expected gains and losses relevant to cycles in house prices? *Journal of Housing Economics*, 52:101750.

Appendix A

Additional Materials for Chapter 2

Supplementary Tables

Table A.1 First Stage Hedonic Estimation

	(1) Residential log(price)	(2) Industrial log(price)	(4) Office log(price)	(3) Retail log(price)
Building Age	-0.0272***	-0.0639***	-0.0255***	-0.0408***
	(0.0022)	(0.0036)	(0.0043)	(0.0064)
Building Age-squared	0.0002***	0.0009***	0.0004***	0.0009***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Unit Size	-0.8560***	0.0366***	0.0799***	0.2361***
	(0.2455)	(0.0017)	(0.0050)	(0.0082)
Unit Size-squared	0.1542***	-0.0001***	-0.0003***	-0.0044***
	(0.0191)	(0.0000)	(0.0000)	(0.0003)
Floor	0.0067***	-0.0127**	0.0014	-0.4986***
	(0.0007)	(0.0050)	(0.0037)	(0.0562)
Floor-squared	-0.0001***	0.0003**	0.0002*	0.0255***
	(1.9E-05)	(0.0001)	(0.0001)	(0.0034)
Single building	-0.1298***			
	(0.0145)			
Estate units	-6.2E-06***			
	(1.2E-05)			
Estate units-squared	1.6E-09***			
	(1.0E-9)			
Distance to Seacoast	-0.0313	-0.0140	-0.5276	-0.3085*
	(0.0273)	(0.0635)	(0.3339)	(0.1699)
Distance to Seacoast-squared	0.0041	0.0064	0.1636	0.0335
	(0.0051)	(0.0129)	(0.1129)	(0.0299)

Distance to Hospital	-0.0301	0.0904	0.7885***	-0.1611
	(0.0216)	(0.1087)	(0.2677)	(0.1653)
Distance to Hospital-squared	0.0070**	0.0049	-0.2249**	0.0871**
	(0.0030)	(0.0312)	(0.0823)	(0.0406)
Distance to Bus Stop	-0.0133	-0.1347	-1.6824***	-0.3735
	(0.0449)	(0.2850)	(0.3088)	(0.2894)
Distance to Bus Stop-squared	0.0128	0.3572	1.5472***	0.1583**
	(0.0142)	(0.2271)	(0.4396)	(0.0763)
Distance to Park	-0.0162	0.1959	0.1188	0.0365
	(0.0283)	(0.2052)	(0.3065)	(0.1345)
Distance to Park-squared	2.4E-05	-0.1265	-0.0027	-0.0450
	(0.0048)	(0.0925)	(0.1653)	(0.0353)
Distance to MTR	-0.0605***	-0.5594**	-0.4063	-0.6061***
	(0.0226)	(0.2353)	(0.2519)	(0.1764)
Distance to MTR-squared	0.0038	0.0805*	-0.0199	0.0293***
	(0.0026)	(0.0420)	(0.2004)	(0.0100)
Distance to University	0.0314***			
	(0.0099)			
Distance to University-squared	-0.0025***			
	(0.0008)			
Distance to School	0.0568			
	(0.1035)			
Distance to School-squared	-0.0655			
	(0.0535)			
Year * District FEs	Y	Y	Y	Y
Observations	1,021,729	95,982	43,146	23,963
R-squared	0.899	0.823	0.836	0.670

Notes: Robust standard errors are clustered at district level. ***, **, * denote for 1%, 5% and 10% significance, respectively.

Table A.2 Transaction Volumes of Hong Kong Property Market by Sectors

Year	Retail	Industrial	Office	Residential
1995	1,270 (1.6%)	3,030 (3.7%)	1,505 (1.9%)	75,437 (92.9%)
1996	2,464 (1.7%)	3,437 (2.4%)	2,625 (1.9%)	133,342 (94.0%)
1997	4,525 (2.8%)	3,881 (2.4%)	2,937 (1.8%)	149,137 (92.9%)
1998	1,730 (2.0%)	2,177 (2.5%)	1,123 (1.3%)	82,443 (94.2%)
1999	1,772 (2.4%)	2,148 (2.9%)	1,496 (2.0%)	69,193 (92.7%)
2000	1,698 (2.6%)	2,575 (4.0%)	1,489 (2.3%)	59,253 (91.1%)
2001	1,922 (2.6%)	2,529 (3.5%)	1,369 (1.9%)	67,136 (92.0%)
2002	1,919 (2.7%)	2,708 (3.8%)	1,213 (1.7%)	65,557 (91.8%)
2003	2,860 (3.8%)	2,856 (3.8%)	1,392 (1.8%)	68,639 (90.6%)
2004	5,533 (5.2%)	4,677 (4.4%)	2,473 (2.3%)	94,191 (88.1%)
2005	5,167 (4.9%)	5,627 (5.3%)	2,854 (2.7%)	92,552 (87.1%)
2006	3,219 (3.6%)	6,487 (7.3%)	2,504 (2.8%)	76,219 (86.2%)
2007	3,902 (2.9%)	7,686 (5.7%)	3,555 (2.6%)	119,433 (88.7%)
2008	2,598 (2.9%)	4,124 (4.6%)	2,045 (2.3%)	81,435 (90.3%)
2009	3,997 (3.3%)	4,997 (4.1%)	2,366 (1.9%)	111,516 (90.8%)
2010	5,368 (3.9%)	7,171 (5.2%)	3,341 (2.4%)	123,259 (88.6%)
2011	3,910 (4.3%)	6,693 (7.4%)	2,877 (3.2%)	76,930 (85.1%)
2012	3,700 (4.0%)	9,354 (10.1%)	3,075 (3.3%)	76,889 (82.7%)
2013	2,865 (5.2%)	3,989 (7.2%)	2,025 (3.7%)	46,538 (84.0%)
2014	1,428 (2.2%)	2,803 (4.2%)	1,301 (2.0%)	60,675 (91.6%)

Notes: Percentages in brackets.

Table A.3 Robustness Tests of the Loss Effect in the Residential Sector by Excluding Company Sellers

	Residential	Residential	Residential	Residential: Luxury	Residential: Mass
	(1) log(price)	(2) log(price)	(3) log(price)	(4) log(price)	(5) log(price)
Loss	0.2150***	0.0012	0.0392***	0.0499	-0.0007
	(0.0187)	(0.0088)	(0.0119)	(0.0316)	(0.0084)
Loss Squared			-0.0461***		
			(0.0140)		
Estimated Value	0.9710***	0.9570***	0.9570***	0.9140***	0.9440***
	(0.0189)	(0.0144)	(0.0143)	(0.0311)	(0.0162)
Residuals from Last Sale		0.4440***	0.4430***	0.4790***	0.4420***
		(0.0135)	(0.0134)	(0.0323)	(0.0141)
Holding Period	-0.0004***	-0.0010***	-0.0010***	-0.0006***	-0.0010***
	(3.4E-05)	(4.4E-05)	(4.5E-05)	(0.0001)	(4.3E-05)
Year * District FEs	Y	Y	Y	Y	Y
Observations	369,318	369,318	369,318	10,804	358,514
R-squared	0.909	0.924	0.924	0.871	0.915

Notes: Loss is defined as the difference between the log of the predicted transaction price and the log of the previous transaction price, truncated below at zero. *Residential: Luxury* refers to transactions of housing units with saleable floor area of above 1,000 square feet; *Residential: Mass* refers to transactions of housing units with saleable floor area of below 1,000 square feet. Robust standard errors are clustered at district level. ***, **, * denote for 1%, 5% and 10% significance, respectively.

Table A.4 Robustness Tests of the Loss Effect in the Residential Sector by Using Estate and Year Fixed Effects

	Residential			
	(1) log(price)	(2) log(price)	(3) log(price)	(4) log(price)
Loss	0.0839***	0.0037	0.0396***	0.0472***
	(0.0107)	(0.0079)	(0.0096)	(0.0077)
Loss Squared			-0.0422***	
			(0.0100)	
Estimated Value	0.9632***	0.9693***	0.9697***	0.9642***
	(0.0109)	(0.0096)	(0.0096)	(0.0120)
Residuals from Last Sale		0.2367***	0.2355***	
		(0.0080)	(0.0080)	
Adjusted Residuals				0.1685***
				(0.0102)
Holding Period	-0.0004***	-0.0007***	-0.0007***	-0.0003***
	(6.77E-06)	(7.01E-06)	(7.08E-06)	(8.27E-06)
Estate Fixed Effects	Y	Y	Y	Y
Year Fixed Effect	Y	Y	Y	Y
Observations	413,263	413,263	413,263	252,474
R-squared	0.942	0.945	0.945	0.944

Notes: *Loss* is defined as the difference between the log of the predicted transaction price and the log of the previous transaction price, truncated below at zero. *Adjusted Residuals* are the residuals of the previous transaction price from the first-stage hedonic pricing regression by utilizing a subsample with transactions occurred in the boom periods between 1993 and 1997 and between 2009 and 2015. Robust standard errors are clustered at district level. ***, **, * denote for 1%, 5% and 10% significance, respectively.

Table A.5 Robustness Tests of the Effect of Comparable Transactions Across Four Property Sectors in Hong Kong

	(1) Retail	(2) Office	(3) Industrial	(4) Residential: Luxury	(5) Residential: Mass
Loss	0.3398***	0.1076**	0.1335***	0.0261	0.0112
	(0.0423)	(0.0179)	(0.0219)	(0.0297)	(0.0164)
Loss * D_Comparables	-0.1624***	0.0553	-0.0277**	-0.0371	-0.0381
	(0.0581)	(0.0333)	(0.0105)	(0.0299)	(0.0225)
Year * District FEs	Y	Y	Y	Y	Y
Observations	6,572	14,566	31,374	18,711	394,552
R-squared	0.850	0.933	0.915	0.884	0.918

Notes: D_Comparables is a dummy variable, which is equal to 1 if it is larger than the mean value of *Comparables* and 0 otherwise. Robust standard errors are clustered at district level. ***, **, * denote for 1%, 5% and 10% significance, respectively.

Table A.6 Adjust the Cut-off Year of Market Cycles for Industrial and Office Sectors of Hong Kong

	Before 1994 Boom log(price)	1995-2003 Bust log(price)
Panel A: Industrial	(1)	(2)
Loss	0.0771	0.1409***
	(0.1771)	(0.0442)
Estimated Value	1.0852***	1.0247***
	(0.0335)	(0.0153)
Residuals from Last Sale	0.7753***	0.6704***
	(0.0641)	(0.0446)
Months since Last Sale	0.0115	-0.0239***
	(0.0406)	(0.0046)
Year * District FEs	Y	Y
Benchmark log(price)	0.557	-0.178
Observations	1,424	7,125
R-squared	0.918	0.892
Panel B: Office	(1)	(2)
Loss	-0.0058	0.1914
	(0.0903)	(0.1157)
Estimated Value	1.0908***	0.9796***
	(0.0156)	(0.0145)
Residuals from Last Sale	0.9647***	0.7060***
	(0.0410)	(0.0676)
Months since Last Sale	0.0326	-0.0250***
	(0.0225)	(0.0082)
Year * District FEs	Y	Y
Benchmark log(price)	0.947	0.870
Degrees of Freedom	945	
Observations	997	3,816
R-squared	0.956	0.929

Notes: Robust standard errors are clustered at district level. Degrees of freedom for regressions with less than 1,000 samples are reported. ***, **, * denote for 1%, 5% and 10% significance, respectively.

Table A.7 Loss Effects Across the Hong Kong Market Cycle: Transactions with A Holding Period<10 Years

	Before 1997 Boom log(price)	1998-2003 Bust log(price)	2004-2007 Recovery log(price)	2008 GFC log(price)	After 2009 Boom log(price)
Panel A: Residential	(1)	(2)	(3)	(4)	(5)
Loss	0.2009***	0.0245**	0.0457***	0.2544**	0.4540***
	(0.0337)	(0.0102)	(0.0084)	(0.0980)	(0.0702)
Benchmark log(price)	1.080	0.544	0.650	0.840	1.223
Year * District FEs	Y	Y	Y	Y	Y
Observations	28,883	65,967	82,697	18,975	154,096
R-squared	0.932	0.915	0.935	0.923	0.926
Panel B: Industrial	(1)	(2)	(3)	(4)	(5)
Loss	0.2162**	0.1454***	0.0635	0.1555	0.4384***
	(0.0814)	(0.0437)	(0.0470)	(0.2285)	(0.0520)
Benchmark log(price)	0.407	-0.387	0.049	0.473	0.887
Year * District FEs	Y	Y	Y	Y	Y
Degrees of Freedom				879	
Observations	3,693	4,480	4,780	906	8,854
R-squared	0.906	0.859	0.882	0.879	0.900
Panel C: Office	(1)	(2)	(3)	(4)	(5)
Loss	0.0521*	0.2972*	0.0902*	0.0679	0.2847***
	(0.0299)	(0.1632)	(0.0469)	(0.1355)	(0.0673)
Benchmark log(price)	1.004	0.340	0.781	0.953	1.295
Year * District FEs	Y	Y	Y	Y	Y
Degrees of Freedom				399	
Observations	2,395	2,249	2,326	427	3,419
R-squared	0.952	0.911	0.924	0.923	0.952
Panel D: Retail	(1)	(2)	(3)	(4)	(5)
Loss	0.1974	0.3662***	0.3727***	0.4566***	0.3465***
	(0.1473)	(0.1084)	(0.0751)	(0.0849)	(0.0450)
Benchmark log(price)	0.718	0.468	0.776	0.678	1.101
Year * District FEs	Y	Y	Y	Y	Y
Degrees of Freedom	522	692		232	
Observations	636	856	1,134	269	2,025
R-squared	0.922	0.852	0.873	0.893	0.904

Notes: Robust standard errors are clustered at district level. Degrees of freedom for regressions with less than 1,000 samples are reported. ***, **, * denote for 1%, 5% and 10% significance, respectively.

Table A.8 Loss Effects Across the Hong Kong Market Cycle: Transactions with A Ratio of Predicted Loss to Previous Transaction Price<0.2

	Before 1997 Boom log(price)	1998-2003 Bust log(price)	2004-2007 Recovery log(price)	2008 GFC log(price)	After 2009 Boom log(price)
Panel A: Residential	(1)	(2)	(3)	(4)	(5)
Loss	0.2886***	0.2147***	0.2495***	0.2636***	0.4237***
	(0.0373)	(0.0352)	(0.0229)	(0.0432)	(0.0355)
Benchmark log(price)	1.098	0.637	0.743	0.837	1.224
Year * District FEs	Y	Y	Y	Y	Y
Observations	27,932	19,309	53,082	22,203	192,109
R-squared	0.933	0.898	0.938	0.920	0.918
Panel B: Industrial	(1)	(2)	(3)	(4)	(5)
Loss	0.3058**	0.4716	0.1760**	0.3556*	0.4546***
	(0.1208)	(0.3686)	(0.0664)	(0.1881)	(0.0672)
Benchmark log(price)	0.317	-0.482	0.020	0.371	0.862
Year * District FEs	Y	Y	Y	Y	Y
Degrees of Freedom		527			
Observations	2,739	622	4,980	1,382	12,702
R-squared	0.923	0.893	0.891	0.880	0.892
Panel C: Office	(1)	(2)	(3)	(4)	(5)
Loss	0.5690***	0.6419**	0.5009***	0.5114*	0.4276***
	(0.1673)	(0.2644)	(0.1711)	(0.2490)	(0.0541)
Benchmark log(price)	0.884	-0.084	0.607	0.788	1.186
Year * District FEs	Y	Y	Y	Y	Y
Degrees of Freedom		256		556	
Observations	2,019	338	2,130	584	4,783
R-squared	0.954	0.951	0.927	0.922	0.938
Panel D: Retail	(1)	(2)	(3)	(4)	(5)
Loss	1.1135	0.8337*	0.6572*	0.7948	0.9402**
	(0.6692)	(0.4400)	(0.3463)	(0.5954)	(0.3949)
Benchmark log(price)	0.541	0.221	0.445	0.392	0.807
Year * District FEs	Y	Y	Y	Y	Y
Degrees of Freedom	364	221	831	214	
Observations	469	329	970	251	2,464
R-squared	0.922	0.857	0.817	0.865	0.842

Notes: Robust standard errors are clustered at district level. Degrees of freedom for regressions with less than 1,000 samples are reported. ***, **, * denote for 1%, 5% and 10% significance, respectively.

Table A.9 Loss Effects Across the Hong Kong Market Cycle: Transactions with A Ratio of Predicted Loss to Previous Transaction Price<0.1

	Before 1997 Boom log(price)	1998-2003 Bust log(price)	2004-2007 Recovery log(price)	2008 GFC log(price)	After 2009 Boom log(price)
Panel A: Residential	(1)	(2)	(3)	(4)	(5)
Loss	0.5324***	0.3719***	0.5240***	0.6892***	0.8146***
	(0.0736)	(0.0938)	(0.0447)	(0.0932)	(0.0517)
Benchmark log(price)	1.080	0.544	0.651	0.810	1.204
Year * District FEs	Y	Y	Y	Y	Y
Observations	26,327	11,946	53,082	20,789	186,931
R-squared	0.933	0.894	0.939	0.921	0.917
Panel B: Industrial	(1)	(2)	(3)	(4)	(5)
Loss	0.6943**	0.8108	0.5860*	0.7529*	0.8059***
	(0.3099)	(0.4766)	(0.2980)	(0.4260)	(0.1711)
Benchmark log(price)	0.286	-0.442	0.026	0.356	0.858
Year * District FEs	Y	Y	Y	Y	Y
Degrees of Freedom		347			
Observations	2,334	432	4,466	1,313	12,340
R-squared	0.927	0.907	0.891	0.882	0.891
Panel C: Office	(1)	(2)	(3)	(4)	(5)
Loss	1.2061***	1.3051	0.8028***	-0.0977	0.5620
	(0.4108)	(0.7626)	(0.2627)	(0.8887)	(0.3376)
Benchmark log(price)	0.824	-0.064	0.590	0.780	1.165
Year * District FEs	Y	Y	Y	Y	Y
Degrees of Freedom		176		517	
Observations	1,830	249	1,858	545	4,534
R-squared	0.954	0.957	0.928	0.921	0.937
Panel D: Retail	(1)	(2)	(3)	(4)	(5)
Loss	1.7319**	-0.1890	0.6133	1.4696	1.7406**
	(0.7995)	(1.6440)	(0.7787)	(3.2278)	(0.8185)
Benchmark log(price)	0.509	0.193	0.410	0.372	0.790
Year * District FEs	Y	Y	Y	Y	Y
Degrees of Freedom	326	160	740	194	
Observations	427	261	876	231	2,325
R-squared	0.925	0.873	0.816	0.862	0.842

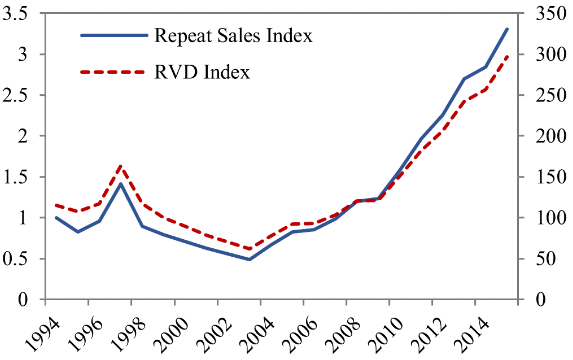
Notes: Robust standard errors are clustered at district level. Degrees of freedom for regressions with less than 1,000 samples are reported. ***, **, * denote for 1%, 5% and 10% significance, respectively.

Table A.10 Comparison between Aggregate Loss Effects with All Repeat Sales and with Repeat Sales Held for Less Than 10 Years

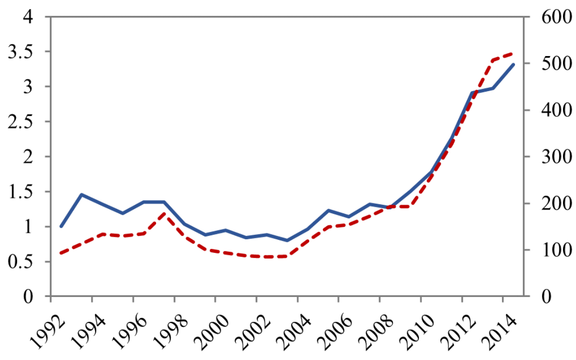
	Increase in Housing Price Index Due to Loss Effect (Adjustment Factor)							
	Repeat Sales Index				Repeat Sales Index (Hold<10 Years)			
Year	Residential	Retail	Industrial	Office	Residential	Retail	Industrial	Office
1992		1.43%	0.32%	0.24%		1.43%	0.32%	0.24%
1993		2.51%	0.68%	0.22%		2.51%	0.68%	0.22%
1994	0.08%	2.23%	1.01%	0.08%	0.08%	2.23%	1.01%	0.08%
1995	1.41%	5.02%	2.68%	0.47%	1.41%	5.02%	2.68%	0.47%
1996	0.98%	5.88%	5.37%	0.78%	0.98%	5.88%	5.37%	0.78%
1997	0.05%	2.86%	6.02%	0.79%	0.05%	2.86%	6.02%	0.79%
1998	0.40%	13.85%	6.77%	11.32%	0.40%	14.39%	7.33%	12.82%
1999	0.75%	19.64%	10.80%	21.79%	0.76%	20.42%	11.71%	24.81%
2000	1.02%	23.42%	11.96%	25.99%	1.03%	24.37%	12.98%	29.67%
2001	1.28%	25.13%	12.00%	27.68%	1.29%	26.33%	13.07%	31.70%
2002	1.43%	23.64%	12.59%	30.38%	1.45%	24.82%	13.66%	35.87%
2003	1.60%	23.01%	11.55%	29.07%	1.63%	21.72%	11.44%	33.61%
2004	1.46%	9.08%	6.82%	8.17%	1.55%	11.66%	2.50%	4.41%
2005	0.85%	7.39%	3.83%	4.42%	0.89%	9.39%	0.86%	1.98%
2006	0.78%	8.62%	2.37%	3.66%	0.81%	10.15%	0.40%	1.60%
2007	0.55%	8.48%	1.33%	2.25%	0.36%	9.90%	0.20%	0.65%
2008	0.23%	10.07%	0.92%	1.58%	0.32%	9.78%	0.35%	0.23%
2009	0.39%	7.04%	2.73%	3.12%	0.79%	8.08%	2.62%	2.42%
2010	0.14%	5.05%	1.11%	1.75%	0.20%	4.25%	1.21%	1.43%
2011	0.06%	2.72%	0.40%	0.82%	0.10%	3.60%	0.50%	0.81%
2012	0.04%	2.33%	0.22%	0.51%	0.11%	3.61%	0.37%	0.64%
2013	0.02%	2.85%	0.20%	0.42%	0.09%	3.84%	0.41%	0.64%
2014	0.02%	2.98%	0.52%	0.46%	0.15%	3.97%	0.91%	0.65%
2015	0.01%				0.06%			

Supplementary Figures

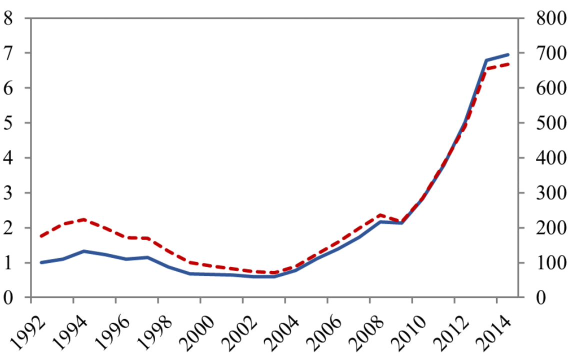
Fig. A.1 Comparison between Repeat Sales Index and RVD Index Across Four Property Sectors in Hong Kong



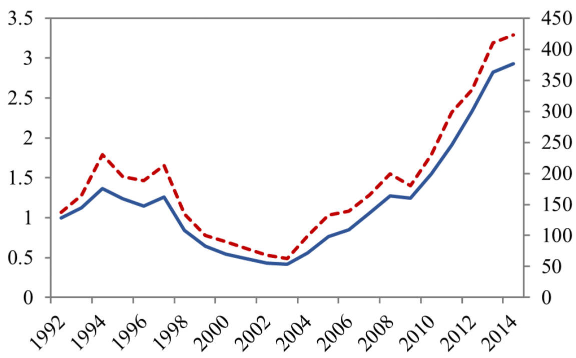
(a) Residential Property Price Index



(b) Retail Property Price Index

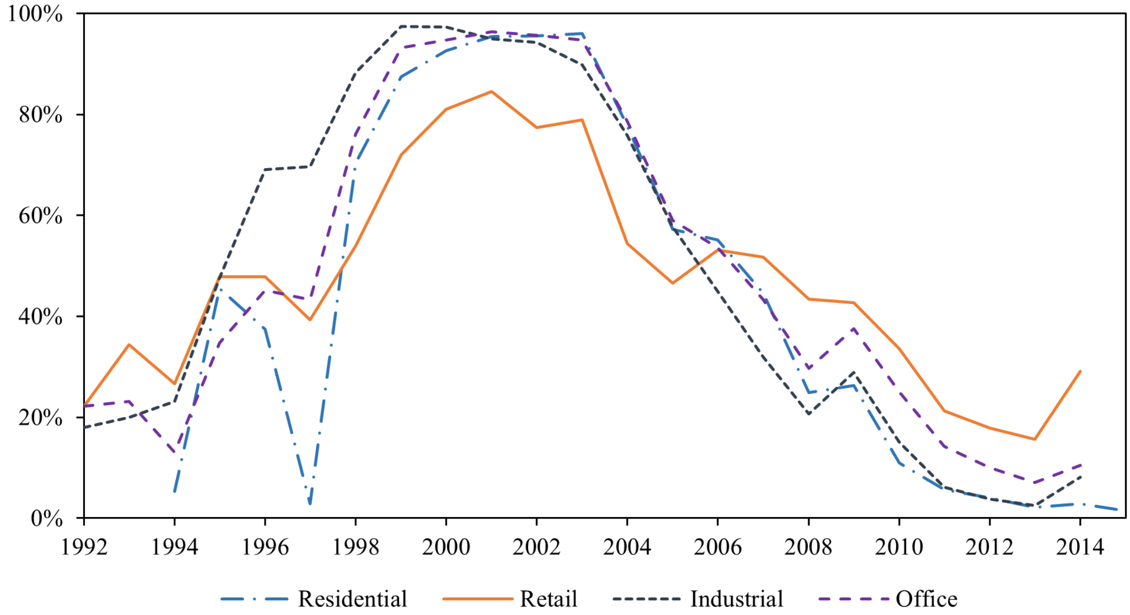


(c) Industrial Property Price Index



(d) Office Property Price Index

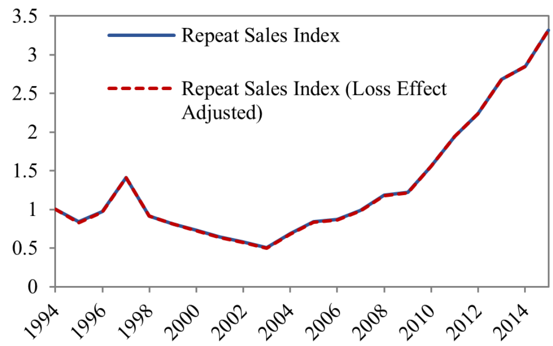
Fig. A.2 Percentage and Magnitude of Loss Sales Across Four Property Sectors in Hong Kong



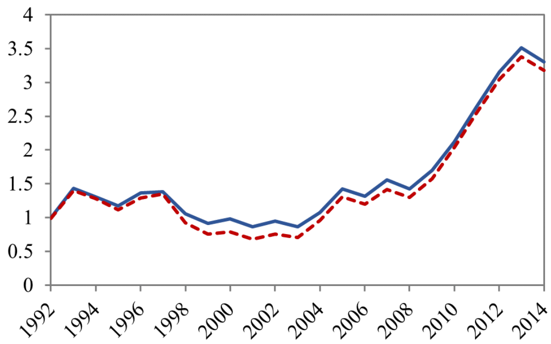
(a) Percentage of Loss Sales

(b) Magnitude of Loss Sales

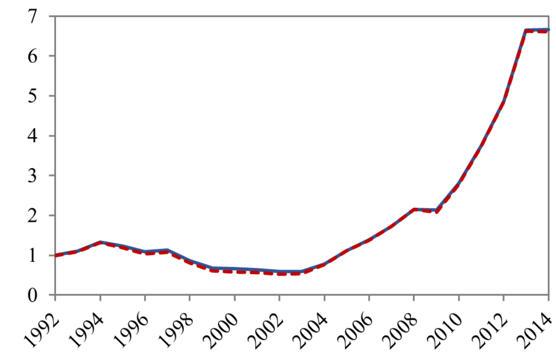
Fig. A.3 Aggregate Loss Effect on Prices of Repeat Sales Held for Less Than 10 Years Across Four Property Sectors in Hong Kong



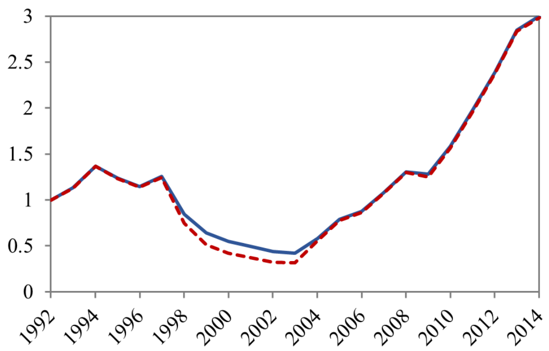
(a) Residential Property Price Index



(b) Retail Property Price Index



(c) Industrial Property Price Index



(d) Office Property Price Index

Appendix B

Additional Materials for Chapter 3

Table B.1 Important Policy Changes in the Hong Kong Housing Market

Date	**Policy Details**
13 Nov 2002	Suen Ming-Yeung announces nine measures to revive the property market
1 Jun 2009	Shrinking the maximum LTV ratio of properties over HK$20 million to 50%
1 Apr 2010	Increasing the stamp duty for property purchases over HK$20 million to 4.25%
1 May 2010	Shrinking the maximum LTV ratio for properties not intended for owner occupation over HK$10 million to 50%
1 May 2010	Introducing the stress test for mortgage applicants
13 Aug 2010	Forbidding transfers of presale contracts before settlement, unless presale permission for the estate/project was obtained before 13 Aug 2010
1 Oct 2010	Introducing the Special Stamp Duty (SSD) for properties resold within 2 years
1 Jun 2011	Shrinking the maximum LTV ratio of properties over HK$10 million to 50%
1 Sep 2012	Shrinking the maximum debt-to-income ratio from 50% to 40% and the maximum mortgage term to 30 years
26 Oct 2012	Extending the Special Stamp Duty (SSD) period to 3 years
26 Oct 2012	Introducing the Buyers Stamp Duty (BSD) for all non-permanent residents and corporate buyers
22 Feb 2013	Introducing the Double Stamp Duty (DSD) for all non-permanent residents and permanent residents who own more than one property
1 Feb 2015	Shrinking the maximum mortgage LTV of properties under HK$7 million from 90% to 60%
5 Nov 2016	Increasing all Double Stamp Duties (DSD) to 15%
12 Apr 2017	Charging the Double Stamp Duty of 15% for "One Contract with Multiple Flats"

Notes: This table presents, in chronological order, a list of important government regulations in the Hong Kong housing market from 2002 to 2017.

Table B.2 Key Variables in Presale Contracts Derived from the Option Notations

Variable Name	Notation	Definition	Calculation
Call option price	C	Deposit paid at the beginning to buy the presale contract	$\alpha * H$ where H is contract housing price and α is the down payment as a percentage of H.
Strike price	K	Payment at settlement	$(1-\alpha) * H$
Time-to-maturity	T	Time period from contract date to settlement date	For rescinded contracts, the settlement date is approximated using the average settlement date in the same building.
Asset price	S	Fair market price of the property	The market price at contract time is estimated as the average price psf in the same building sold within [-6, 6] months of the contract date times the size of the property. The fair market price at the settlement time as a product of the average price psf in the same building sold within 2 years prior to settlement and the size of the property.
Moneyness	M	Value of the underlying asset price relative to the presale contract price	$\frac{S}{K+C}$
Implied volatility	σ	Forward-looking property price volatility implied by the contract terms	This is estimated using the closed-form approximation of Brenner and Subrahmanyan (1988): $\alpha = \sqrt{\frac{2\pi}{T}} * \frac{C}{S}$
Call option delta	Δ	The sensitivity of option price with respect to the underlying asset price movement	Call option delta at the purchase time, which is calculated from Black-Scholes model. Risk-free rate (r) is the 12-month HIBOR rate: $\Delta = \frac{\partial C}{\partial S} = N(d_1)$ $d_1 = \frac{\ln \frac{S}{K} + (r + \frac{\sigma^2}{2})T}{\sigma\sqrt{T}}$

Table B.3 Definition of Variables

Variable Name	**Definition**
Contract Price (million HKD)	Purchase price in the presale contract.
Unit Size (thousand sq. ft.)	Sellable area of the unit in thousand square feet.
Floor	Floor level of the unit.
Bedrooms	Number of bedrooms in the unit.
Living Rooms	Number of living rooms in the unit.
Remaining Lease Years	Remaining lease years of the unit.
Property Type	A dummy variable equal to 1 if the building is a single block building, and 0 if the building is a block in an estate project.
Rescind (Yes = 1)	A dummy variable denoting whether the buyer in the presale contract rescinds. This equals 1 if the presale contract is not transferred to other buyers and the unit is not settled by the original buyer in the end; 0 otherwise.
Loss at Rescission (million HKD)	The loss a buyer suffers when the buyer rescinds on the presale contract. This is equal to 10% of the presale property price.
Transfer (Yes = 1)	A dummy variable denoting whether the buyer transfers the presale contract to another buyer before the settlement date.
Transfer Gain (million HKD)	The gain a buyer realizes from transferring a presale contract to the next buyer.
Transfer Loss (million HKD)	The loss a buyer incurs in transferring a presale contract to the next buyer.
Absolute Time-to-Settlement	Months between the presale contract date and the settlement date. For rescinded contracts, we use the average settlement date in the same building as the settlement date.
Relative Time-to-Settlement	This equals the months to settlement date divided by the length of the whole presale period of the building.

Transfer Ratio to Presales	Number of transferred contracts divided by the number of presold units in the same building.
Transfer Ratio to Stocks	Number of transferred contracts divided by the total number of units in the same building.
Presale Market Supply	Total number (thousands) of presale units sold in the same district in the settlement year.
Spot Market Supply	Total number (thousands) of units sold in the spot market in the same district in the settlement year.
Multiple Contract Holder	A dummy variable denoting whether the buyer purchased multiple presale contracts in our study period.
Spot Sale Ratio	The percentage of new units sold in the spot market among all new units in a building.
Holding Period After Settlement	Number of years between the settlement of the presale contract and the subsequent resales in the secondary market.
Call Option Strike Price (million HKD)	Property price in the presale contracts minus the deposit.
Call Option Price (million HKD)	Upfront deposit paid to acquire the presale in million HKD. 10% of the presale price.
Market Price at Settlement (million HKD)	Predicted spot market price of the unit at settlement time, which equals the size of the unit times the average price psf in the sample building within 2 years before settlement.
Moneyness	Market price divided by the presale contract price at the settlement date, trimmed at the top and bottom 5%.
Moneyness [0.95, 1]	A dummy variable equal to one if moneyness at settlement date is between 0.95 and 1. Otherwise, it equals zero.
Moneyness [0.9, 0.95]	A dummy variable equal to one if moneyness is between 0.9 and 0.95. Otherwise, it equals zero.
Moneyness<0.9	A dummy variable equal to one if moneyness is below 0.9 (i.e., out of the money). Otherwise, it equals zero.

Call Option Delta	Call option delta at the purchase time, which is calculated from the Black-Scholes model. Risk-free rate is the HIBOR (12 months) rate. The market price at purchase time is estimated using the size of the unit times the average price psf in the sample building within 6 months before or after the purchase time.
Implied Volatility	Implied monthly volatility of the housing price at the purchase time, which is estimated using the closed-form estimation from Brenner and Subrahmanyan (1988).
Post Stress Test	A dummy variable indicating whether the presale contract is purchased after May 1, 2010, the date when the HK government requires that all banks conduct stress tests for loan applicants.

Table B.4 Robustness Checks: The Impact of Moneyness on Rescission Loss Amount

Y: *Rescind Loss*	(1)	(2)
Moneyness	-0.0729***	
	(0.0077)	
Moneyness [0.95, 1]		0.0049***
		(0.0010)
Moneyness [0.9, 0.95]		0.0107***
		(0.0014)
Moneyness < 0.9		0.0158***
		(0.0027)
Unit Size	0.0898***	0.0897***
	(0.0182)	(0.0184)
Rooms	-0.0082**	-0.0082**
	(0.0039)	(0.0040)
log(*Lease Years*)	0.0006	0.0006
	(0.0044)	(0.0044)
Floor	-0.0002***	-0.0002***
	(0.0001)	(0.0001)
Property Type Fixed Effect	Y	Y
District Fixed Effect	Y	Y
Year*Quarter Fixed Effect	Y	Y
R-Squared	0.126	0.126
Observations	195,202	195,202

Notes: This table presents the OLS regression results of the rescission loss amount on moneyness at settlement time. The dependent variable is *Rescind Loss*, which equals the loss amount of presale contract deposit if the presale contract is rescinded and zero otherwise. *Moneyness* is defined as the market price at settlement divided by the presale contract price. The market price at settlement is predicted as the size of the unit times the average price psf in the sample building within 2 years before settlement. *Moneyness [0.95, 1]* is a dummy variable equal to one if moneyness is between 0.95 and 1 (zero otherwise). Similarly, *Moneyness [0.9, 0.95]* and *Moneyness<0.9* are dummy variables indicating whether moneyness is between 0.9 and 0.95 or below 0.9, respectively. Definitions of the other independent variables are reported in Variable Definitions. Standard errors are clustered at district level. Robust standard errors are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level.

Table B.5 Robustness Checks: The Impact of Moneyness on Rescission Rate Using Time-Adjusted Market Price at Settlement

Y: *Rescind Loss*	(1)	(2)
Moneyness	-0.0638***	
	(0.0064)	
Moneyness [0.95, 1]		0.0096***
		(0.0019)
Moneyness [0.9, 0.95]		0.0160***
		(0.0024)
Moneyness < 0.9		0.0102***
		(0.0023)
Unit Size	0.0097**	0.0113**
	(0.0047)	(0.0048)
Rooms	-0.0015	-0.0014
	(0.0011)	(0.0011)
log(*Lease Years*)	0.0003	-0.0000
	(0.0024)	(0.0024)
Floor	-0.0003***	-0.0002***
	(0.0000)	(0.0000)
Property Type Fixed Effect	Y	Y
District Fixed Effect	Y	Y
Year*Quarter Fixed Effect	Y	Y
R-Squared	0.151	0.151
Observations	194,966	194,966

Notes: This table presents Probit regression results of the rescission rate on moneyness at settlement time. The dependent variable is *Rescind*, which equals one if the presale contract is rescinded and zero otherwise. *Moneyness* is defined as the market price at settlement divided by the presale contract price. The market price at settlement is predicted as the size of the unit times the average price psf in the sample building within 2 years before settlement, and it is further time-adjusted. The adjustment factor equals the average monthly growth rate of housing price in the prior 2 years compounded by the average months between the settlement time and the transactions in the sample building in the prior 2 years. *Moneyness [0.95, 1]* is a dummy variable equal to one if moneyness is between 0.95 and 1 (zero otherwise). Similarly, *Moneyness [0.9, 0.95]* and *Moneyness*<0.9 are dummy variables indicating whether moneyness is between 0.9 and 0.95 or below 0.9, respectively. Definitions of the other independent variables are reported in Variable Definitions. Marginal effects at means are reported. Standard errors are clustered at district level. Robust standard errors are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level.

Table B.6 Robustness Checks: The Impact of Moneyness on Rescission Rate Using Alternative Fixed Effects

Y: *Rescind*	(1)	(2)	(3)	(4)
Moneyness	-0.0783***		-0.0477***	
	(0.0208)		(0.0183)	
Moneyness [0.95, 1]		0.0035*		0.0024
		(0.0019)		(0.0024)
Moneyness [0.9, 0.95]		0.0161***		0.0118***
		(0.0023)		(0.0027)
Moneyness $<$ *0.9*		0.0205***		0.0138***
		(0.0031)		(0.0034)
Unit Size	-0.0421	-0.0428	0.0038	0.0029
	(0.0259)	(0.0261)	(0.0263)	(0.0265)
Rooms	0.0018	0.0018	-0.0042	-0.0041
	(0.0046)	(0.0047)	(0.0056)	(0.0057)
log(*Lease Years*)	-0.0337	-0.0336	-0.0078	-0.0079
	(0.0282)	(0.0283)	(0.0086)	(0.0085)
Floor	-0.0006***	-0.0006***	-0.0004**	-0.0004***
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Property Type Fixed Effect	Y	Y	Y	Y
District*Year*Quarter Fixed Effect	Y	Y	N	N
District Fixed Effect	N	N	Y	Y
Year*Quarter Fixed Effect	N	N	Y	Y
Developer Fixed Effect	N	N	Y	Y
Pseudo R-Squared	0.1920	0.1921	0.1430	0.1432
Observations	185,078	185,078	194,946	194,946

Notes: This table presents Probit regression results of the rescission rate on moneyness, with alternative sets of fixed effects. In Columns (1) and (2), we replace the district fixed effects and year times quarter fixed effects in the baseline model with the district times year times quarter fixed effects. In Columns (3) and (4), we add the developers fixed effects to our baseline model. The dependent variable is Rescind, which equals one if the presale contract is rescinded and zero otherwise. *Moneyness* is defined as the market price at settlement divided by the presale contract price. The market price at settlement is predicted as the size of the unit times the average price psf in the sample building within 2 years before settlement. *Moneyness [0.95, 1]* is a dummy variable equal to one if moneyness is between 0.95 and 1 (zero otherwise). Similarly, *Moneyness [0.9, 0.95]* and *Moneyness*$<$*0.9* are dummy variables indicating whether moneyness is between 0.9 and 0.95 or below 0.9, respectively. Definitions of the other independent variables are reported in Variable Definitions. Standard errors are clustered at district level. Robust standard errors are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level.

Table B.7 Robustness Checks: The Impact of Call Option Delta on Rescission Rate

Panel A: Call Option Delta Residual

	(1) Y: *Call Option Delta*	(2) Y: *Rescind*
Moneyness	0.6892***	
	(0.0027)	
Call Option Delta Residual		0.1263**
		(0.0593)
Unit Size		0.0085
		(0.0290)
Rooms		-0.0033
		(0.0066)
log(*Lease Years*)		-0.0072
		(0.0080)
Floor		-0.0002
		(0.0002)
Property Type Fixed Effect	N	Y
District Fixed Effect	N	Y
Year*Quarter Fixed Effect	N	Y
Observations	192,080	188,808
R-squared	0.258	0.140

Table B.7 Robustness Checks: The Impact of Call Option Delta on Rescission Rate, Continued

Panel B: Alternative Estimation of Market Price at Purchase Time

Y: *Rescind*	(1)
Call Option Delta	0.0780***
	(0.0068)
Unit Size	0.0496***
	(0.0044)
Rooms	-0.0125***
	(0.0010)
log(*Lease Years*)	0.0044**
	(0.0022)
Floor	0.0001***
	(0.0000)
Property Type Fixed Effect	Y
District Fixed Effect	Y
Year*Quarter Fixed Effect	Y
Pseudo R-Squared	0.153
Observations	214,958

Notes: This table presents robustness check results of the effect of call option delta on rescission rate. The dependent variable is *Rescind*, which equals one if the presale contract is rescinded and zero otherwise. Panel A Column (1) reports the linear regression results of *Call Option Delta* on *Moneyness* of the presale contract. *Moneyness* is defined as the market price at settlement divided by the presale contract price. The market price at settlement is predicted as the size of the unit times the average price psf in the sample building within 2 years before settlement. *Call Option Delta* is the delta of the call option at purchase time calculated with the Black-Scholes Model. Column (2) reports the Probit regression results for impact of the call option delta on rescission rate, after removing the potential colinear impact of moneyness. *Call Option Delta Residual* is the residual of call option delta calculated from the regression in Column (1). In Panel B, the market price at purchase time is predicted as the size of the unit times the average price psf in the sample building using the [-3 months, 3 months] window around the contract date, instead of the [-6 months, 6 months] window in the baseline estimations. Definitions of the other independent variables are reported in Variable Definitions. Marginal effects at means are reported. Standard errors are clustered at district level. Robust standard errors are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level.

Table B.8 The Impacts of Transfer Ratio with Gain and Transfer Ratio with Loss on Rescission Rate

Y: *Rescind*	(1) Trans. No.>0	(2) All Samples	(3) Trans. No.>0	(4) All Samples
*Transfer Ratio to Presales * Transfer Gain Ratio*	-0.4634***	-0.3329**		
	(0.1421)	(0.1456)		
Transfer Ratio to Presales	0.8992***	0.7385***		
	(0.1222)	(0.1197)		
*Transfer Ratio to Stocks * Transfer Gain Ratio*			-0.6293***	-0.4994**
			(0.2197)	(0.2273)
Transfer Ratio to Stocks			1.0582***	0.8973***
			(0.1959)	(0.1988)
Unit Size	-0.0178	0.0344	-0.0151	0.0349
	(0.0156)	(0.0245)	(0.0157)	(0.0246)
Rooms	0.0001	-0.0130**	-0.0009	-0.0133**
	(0.0058)	(0.0058)	(0.0059)	(0.0058)
log(*Lease Years*)	0.0108*	0.0070	0.0124**	0.0082
	(0.0058)	(0.0055)	(0.0055)	(0.0053)
Floor	-0.0007***	-0.0004***	-0.0007***	-0.0004***
	(0.0002)	(0.0001)	(0.0002)	(0.0001)
Property Type Fixed Effect	Y	Y	Y	Y
District Fixed Effect	Y	Y	Y	Y
Year*Quarter Fixed Effect	Y	Y	Y	Y
Pseudo R-Squared	0.1248	0.1550	0.1242	0.1546
Observations	138,147	224,918	138,147	224,918

Notes: This table presents additional analysis results of the effect of the transfer ratio on the rescission rate. *Transfer Ratio to Presales* is defined as the total number of transferred presale contracts divided by the number of presold units in the same building. *Transfer Ratio to Stock* is defined as the total number of transferred presale contracts divided by the total number of units in the same building. *Transfer Gain Ratio* is defined as the number of transferred presale contracts with gains divided by the total number of transferred contracts in the same building. In Columns (1) and (3), we include samples with at least one transferred presale contract in the same building. In Columns (2) and (4), we include the full sample by assigning *Transfer Gain Ratio* to zero for the samples in those buildings without any transferred presale contracts. The dependent variable is *Rescind*, which equals one if the presale contract is rescinded and zero otherwise. Definitions of the other independent variables are reported in Variable Definitions. Marginal effects at means are reported. Standard errors are clustered at district level. Robust standard errors are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level.

Table B.9 Heterogeneity Effect of Moneyness on Rescission Rate Across Top-Floor Units and Other Units

Y: *Rescind*	(1)	(2)	(3)	(4)
Moneyness	-0.0449**		-0.0471**	
	(0.0182)		(0.0187)	
Moneyness [0.95, 1]		0.0026		0.0024
		(0.0024)		(0.0023)
Moneyness [0.9, 0.95]		0.0113***		0.0115***
		(0.0028)		(0.0030)
Moneyness $<$ *0.9*		0.0122***		0.0135***
		(0.0034)		(0.0034)
Top Floor Unit	0.0085	0.0079	-0.0723*	0.0148
	(0.0071)	(0.0074)	(0.0426)	(0.0117)
*Top Floor Unit * Moneyness*			0.1212	
			(0.1094)	
*Top Floor Unit * Moneyness [0.95, 1]*				0.0034
				(0.0110)
*Top Floor Unit * Moneyness [0.9, 0.95]*				-0.0088
				(0.0137)
*Top Floor Unit * Moneyness* $<$ *0.9*				-0.0239
				(0.0153)
Unit Size	-0.0004	-0.0012	-0.0004	-0.0014
	(0.0289)	(0.0291)	(0.0289)	(0.0291)
Rooms	-0.0023	-0.0023	-0.0023	-0.0023
	(0.0066)	(0.0067)	(0.0066)	(0.0067)
log(*Lease Years*)	-0.0054	-0.0056	-0.0055	-0.0056
	(0.0078)	(0.0078)	(0.0078)	(0.0078)
Floor	-0.0004**	-0.0004**	-0.0004**	-0.0004**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Property Type Fixed Effect	Y	Y	Y	Y
District Fixed Effect	Y	Y	Y	Y
Year*Quarter Fixed Effect	Y	Y	Y	Y
Pseudo R-Squared	0.1400	0.1401	0.1400	0.1402
Observations	194,966	194,966	194,966	194,966

Notes: This table presents Probit regression results of the rescission rate on moneyness at settlement time, with additional control for the units on the top floor. The dependent variable is *Rescind*, which equals one if the presale contract is rescinded and zero otherwise. *Moneyness* is defined as the market price at settlement divided by the presale contract price. The market price at settlement is predicted as the size of the unit times the average price psf in the sample building within 2 years before settlement. *Moneyness [0.95, 1]* is a dummy variable equal to one if moneyness is between 0.95 and 1 (zero otherwise). Similarly, *Moneyness [0.9, 0.95]* and *Moneyness*$<$*0.9* are dummy variables indicating whether moneyness is between 0.9 and 0.95 or below 0.9, respectively. Definitions of the other independent variables are reported in Variable Definitions. Marginal effects at means are reported. Standard errors are clustered at district level. Robust standard errors are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level.

Table B.10 The Impact of Government Regulations on Rescission Rate: Falsification Tests

Y: *Rescind*	(1)	(2)	(3)	(4)
	[-1 year, 1 year]		[-2 years, 2 years]	
	May 2007 – May 2009		May 2006 – May 2010	
Post Placebo Shock	0.0417	0.0409	0.0114	0.0107
	(0.0429)	(0.0426)	(0.0437)	(0.0430)
*Post Placebo Shock * (Moneyness<0.9)*		0.0070		0.0111
		(0.0457)		(0.0319)
Moneyness<0.9		0.0359		0.0059
		(0.0420)		(0.0202)
Unit Size	-0.0356	-0.0607	-0.0736	-0.1157
	(0.1302)	(0.1175)	(0.0659)	(0.0802)
Rooms	-0.0102	-0.0103	-0.0077	-0.0019
	(0.0183)	(0.0194)	(0.0121)	(0.0145)
log(*Lease Years*)	-0.0614	-0.0616	-0.0027	-0.0043
	(0.0532)	(0.0544)	(0.0236)	(0.0243)
Floor	-0.0000	-0.0002	-0.0010***	-0.0011***
	(0.0003)	(0.0004)	(0.0003)	(0.0003)
Property Type Fixed Effect	Y	Y	Y	Y
District Fixed Effect	Y	Y	Y	Y
Month Fixed Effect	Y	Y	Y	Y
Pseudo R-Squared	0.1027	0.1033	0.0666	0.0664
Observations	9,478	9,462	24,690	24,414

Notes: This table presents falsification test results for the impact of the stress test policy on the presale contract rescission rate. *Placebo Shock* is a dummy variable indicating whether the presale contract is purchased after May 1, 2008, which is exactly 2 years before the actual effective date of the stress test. In Columns (1) and (2), we include the sample of presale units that are purchased within 1 year before or after the placebo shock date. In Columns (3) and (4), we include the sample of presale units that are purchased within 2 years before or after the placebo shock date. $Moneyness < 0.9$ is dummy variable equal to one if moneyness at settlement is below 0.9 (the treatment group). Otherwise, it equals zero (the control group). Definitions of the other independent variables are reported in Variable Definitions. Marginal effects at means are reported. Standard errors are clustered at district level. Robust standard errors are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level.

Appendix C

Additional Materials for Chapter 4

Table C.1 Definition of Variables

Variable Name	**Definition**
AR	The monthly risk-adjusted abnormal returns (alpha) of the REITs, represented in percentage. It is calculated with a Fama-French four-factor models, using return data of the REIT in the previous 60 months. *AR(t-1)*, *AR(t)*, *AR(t+1)*, and *AR(t+2)* denotes the monthly abnormal return in the previous month, the current month, the next month, and the second next month, respectively.
CAR	The 3-month cumulative abnormal returns of the REITs, calculated as the sum of abnormal returns (AR) within the [−1 month, +1 month] window, represented in percentage. *CAR(t-1)*, *CAR(t)*, *CAR(t+1)*, and *CAR(t+2)* denotes the cumulative abnormal return in the previous month, the current month, the next month, and the second next month, respectively.
ValueEXP	The total value of properties that a REIT holds in the target FIPS county at the firm acquisition time, as a fraction of the REIT's total asset. It equals zero if none of the properties held by the REIT is in the same county of a public firm acquisition.
NumEXP	The total number of properties that a REIT holds in the target FIPS county at the firm acquisition time, as a fraction of the total number of properties held by the REIT. It equals zero if none of the properties held by the REIT is in the same county of a public firm acquisition.

ROA	The quarterly return on asset of a REIT, calculated as the quarterly net income over the total asset, represented in percentage. *ROA(t+1)* denotes the return on asset of the REIT in the following quarter.
Log(Market Cap)	The quarterly market value of a REIT in logarithmic form.
Cash Ratio	The quarterly holding of cash and equivalent by a REIT, as a fraction of the REIT's total asset.
Leverage	The quarterly debt to asset ratio of a REIT.
M/B Ratio	The quarterly market to book value ratio of a REIT.
ValueEXP_Office	The total value of office properties that a REIT holds in the target FIPS county at the firm acquisition time, as a fraction of the REIT's total asset. It equals zero if none of the office properties held by the REIT is in the same county of a public firm acquisition.
ValueEXP_NonOffice	The total value of non-office properties that a REIT holds in the target FIPS county at the firm acquisition time, as a fraction of the REIT's total asset. It equals zero if none of the non-office properties held by the REIT is in the same county of a public firm acquisition.
RelTargetSize	The total asset of the acquired firm in one year before acquisition, as a fraction of the total assets of all public firms in the same county in one year before acquisition.
ODY	The quarterly ordinary dividend yield of a REIT, calculated as the sum of ordinary dividends paid in the quarter divided by the closing price of the REIT, represented in percentage. *ODY(t+1)* denotes the ordinary dividend yield in the following quarter.
TDY	The quarterly total dividend yield of a REIT, calculated as the sum of ordinary and non-ordinary dividends paid in the quarter divided by the closing price of the REIT, represented in percentage. *ODY(t+1)* denotes the ordinary dividend yield in the following quarter.
Ownership	The total shares of a REIT held a group of institutional investors (i.e., the home investors or non-home investors of the REIT) as a fraction of the total shares of the REIT outstanding.

SD_Ownership	The total shares of a REIT held a group of institutional investors (i.e., the home investors or non-home investors of the REIT) as a fraction of the total shares of the REIT outstanding, standardized within each group of investors.
Post	A dummy variable equal to one if the sample is for investor ownership after the firm acquisitions, zero otherwise.
InMSA	A dummy variable equal to one if the group of investors are from the same MSA as the acquired firm, zero otherwise.
InCty	A dummy variable equal to one if the group of investors are from the same FIPS county as the acquired firm, zero otherwise.
InMSAOutCty	A dummy variable equal to one if the group of investors are from the same MSA as the acquired firm but from different FIPS counties, zero otherwise.
InStateOutMSA	A dummy variable equal to one if the group of investors are from the same state as the acquired firm but from different MSAs, zero otherwise.
Active	A dummy variable equal to one if the group of investors are classified as "transient" or "dedicated" active investors, zero otherwise.
TargetInHQ	A dummy variable equal to one if there is a public firm being acquired in the same county as the headquarter of the REIT, zero otherwise.
ValueEXP>0	A dummy variable equal to one if the REIT holds at least one property in the target county (i.e., the share values of the properties in the target county is larger than zero), zero otherwise.
ValueEXP=0	A dummy variable equal to one if the REIT does not hold any properties in the target county (i.e., the share values of the properties in the target county is equal to zero), zero otherwise.

Table C.2 The Impact of Firm Acquisitions in REITs' Headquarter on REIT Return

Panel A: Impact on All REITs Headquartered in Target County				
	(1) *AR(t-1)*	(2) *AR(t)*	(3) *AR(t+1)*	(4) *AR(t+2)*
TargetInHQ	0.1373	-0.1443	-0.1992**	-0.2971***
	(0.1124)	(0.1369)	(0.1006)	(0.1132)
Fundamental Controls	Y	Y	Y	Y
Year & Month FEs	Y	Y	Y	Y
REIT FEs	Y	Y	Y	Y
Observations	37,683	37,716	37,544	37,372
R-squared	0.118	0.115	0.135	0.170
Panel B: Impact on REITs with Property Investment in the Headquarter				
	(1) *AR(t-1)*	(2) *AR(t)*	(3) *AR(t+1)*	(4) *AR(t+2)*
*TargetInHQ * ValueEXP>0*	0.1665	-0.0159	-0.2301*	-0.4330***
	(0.1549)	(0.1467)	(0.1187)	(0.1385)
Fundamental Controls	Y	Y	Y	Y
Year & Month FEs	Y	Y	Y	Y
REIT FEs	Y	Y	Y	Y
Observations	37,683	37,716	37,544	37,372
R-squared	0.118	0.115	0.135	0.170
Panel C: Impact on REITs without Property Investment in the Headquarter				
	(1) *AR(t-1)*	(2) *AR(t)*	(3) *AR(t+1)*	(4) *AR(t+2)*
*TargetInHQ * ValueEXP=0*	0.0827	-0.3176	-0.1365	-0.0739
	(0.1708)	(0.2283)	(0.1666)	(0.1539)
Fundamental Controls	Y	Y	Y	Y
Year & Month FEs	Y	Y	Y	Y
REIT FEs	Y	Y	Y	Y
Observations	37,683	37,716	37,544	37,372
R-squared	0.118	0.115	0.135	0.170

Notes: This table reports the estimated impact of firm acquisitions in the same county as the REITs' headquarter at time t on the return of REITs, using the cumulative abnormal return as the dependent variable. The dependent variables are the monthly risk-adjusted abnormal returns (alpha) of the REITs at time $t-1$ to $t+2$. The abnormal returns are calculated with a Fama-French four-factor model using return data in the previous 60 months. In Panel A, the explanatory variable, *TargetInHQ*, is a dummy variable denoting the target firms in the same county as the REITs' headquarter at time t. In Panel B, the variable $TargetInHQ * ValueEXP > 0$ denotes the situation when the target firms are in the same county as the REITs' headquarter, and the REITs also hold some properties in the same county. In Panel C, the variable $TargetInHQ * ValueEXP = 0$ denotes the situation when the target firms are in the same county as the REITs' headquarter, but the REITs do not hold some properties in the same county. The unreported fundamental controls are the same as the baseline estimations, and their definitions are represented in Appendix Table C.1. Robust standard errors are clustered by REITs and are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table C.3 The Impact of Firm Acquisitions on REIT Fundamental Performance After One Year

	(1) *ROA(t+4)*	(2) *ODY(t+4)*	(3) *TDY(t+4)*	(4) *ROA(t+4)*	(5) *ODY(t+4)*	(6) *TDY(t+4)*
ValueEXP	-0.5445*	-1.4920*	-3.4292**			
	(0.3262)	(0.7709)	(1.6234)			
NumEXP				-0.6590**	-2.2101***	-4.6201***
				(0.3019)	(0.7560)	(1.5626)
Log(Market Cap)	-0.0103	1.1912***	2.2602***	-0.0046	1.2072***	2.2963***
	(0.0670)	(0.4187)	(0.8417)	(0.0788)	(0.4179)	(0.8394)
Cash Ratio	2.1992**	2.2478	4.9243	2.2470*	2.3897	5.2379
	(0.8577)	(3.5181)	(7.3708)	(1.2113)	(3.4974)	(7.3242)
Leverage	0.0159	0.6244	0.5627	0.0218	0.6386	0.5975
	(0.4050)	(1.8071)	(3.6648)	(0.3590)	(1.8037)	(3.6563)
M/B Ratio	-0.0032	-0.0042	-0.0091	-0.0032	-0.0042	-0.0092
	(0.0027)	(0.0069)	(0.0140)	(0.0026)	(0.0070)	(0.0141)
Constant	0.9856**	7.5320***	16.3265***	0.9556	7.4682***	16.1588***
	(0.4956)	(2.7994)	(5.6629)	(0.5839)	(2.7926)	(5.6412)
Year & Quarter FEs	Y	Y	Y	Y	Y	Y
REIT FEs	Y	Y	Y	Y	Y	Y
Observations	10,949	10,949	10,949	10,949	10,949	10,949
R-squared	0.109	0.452	0.437	0.109	0.452	0.437

Notes: This table reports the estimated impact of firm acquisitions at time t on the return on asset and dividend yield of REITs that hold properties in the same county of the acquired firms (i.e., the target county) after one year. The dependent variable $ROA(t+4)$ is the quarterly return on asset in one year (i.e., four quarters) after the acquisition. The dependent variables $ODY(t+4)$ and $TDY(t+4)$ are the quarterly ordinary dividend yield and the total dividend yield of REITs in one year (i.e., four quarters) after the acquisition, respectively. The explanatory variable, *ValueEXP*, is the total value of properties that a REIT holds in the target county at the acquisition time, as a fraction of the REIT's total asset. *NumEXP* is the total number of properties that a REIT holds in the target county at the acquisition time, as a fraction of the total number of properties held by the REIT. Definitions of the other variables are represented in Appendix Table C.1. Robust standard errors are clustered by REITs and are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table C.4 Robustness Check for the Impact of Firm Acquisitions on REIT Return: Cumulative Abnormal Return

	(1) *CAR(t-1)*	(2) *CAR(t)*	(3) *CAR(t+1)*	(4) *CAR(t+2)*
ValueEXP	0.6930	-0.6871	-2.4370***	-2.7734***
	(0.9572)	(0.8570)	(0.6078)	(0.6056)
ROA	-0.0295	-0.0308	-0.0341	-0.0423
	(0.0253)	(0.0267)	(0.0307)	(0.0330)
Log(Market Cap)	-0.5135*	-0.5688**	-0.6097**	-0.7653**
	(0.2655)	(0.2760)	(0.3003)	(0.2956)
Cash Ratio	2.7654	2.7314	2.5847	2.4382
	(2.6633)	(2.9096)	(3.1423)	(3.2075)
Leverage	-2.0836	-2.0744	-2.2788	-2.2975
	(2.0374)	(2.2015)	(2.3928)	(2.4221)
M/B Ratio	0.0008	0.0010	0.0010	0.0005
	(0.0031)	(0.0030)	(0.0028)	(0.0026)
Constant	6.7913***	7.1287***	7.4481***	8.4694***
	(1.7230)	(1.6778)	(1.6729)	(1.6397)
Year & Month FEs	Y	Y	Y	Y
REIT FEs	Y	Y	Y	Y
Observations	37,716	37,716	37,716	37,544
R-squared	0.245	0.276	0.315	0.347

Notes: This table reports the robustness check result for the estimated impact of firm acquisitions at time t on the return of REITs that hold properties in the same county of the acquired firms (i.e., the target county), using the cumulative abnormal return as the dependent variable. The dependent variables are the risk-adjusted 3-month cumulative abnormal returns (CAR) of the REITs at time $t-1$ to $t+2$. The abnormal returns are calculated with a Fama-French four-factor model using return data in the previous 60 months. The cumulative abnormal returns are calculated as the sum of abnormal returns within the [-1 month, +1 month] window. The explanatory variable, *ValueEXP*, is the total value of properties that a REIT holds in the target county at the acquisition time, as a fraction of the REIT's total asset. Definitions of the other variables are represented in Appendix Table C.1. Robust standard errors are clustered by REITs and are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table C.5 Robustness Check for the Impact of Firm Acquisitions on REIT Return: Number of Properties

	(1) *AR(t-1)*	(2) *AR(t)*	(3) *AR(t+1)*	(4) *AR(t+2)*
NumEXP	0.2517	0.5346	-1.9576***	-1.5031***
	(0.4471)	(0.5233)	(0.4881)	(0.5168)
ROA	-0.8881	-1.1525	-1.1098	-1.4099
	(0.7436)	(0.9711)	(0.9998)	(1.0679)
Log(Market Cap)	-0.1742*	-0.1933**	-0.2161**	-0.2601***
	(0.0892)	(0.0919)	(0.0911)	(0.0904)
Cash Ratio	1.0299	1.0523	0.7301	0.9117
	(0.9256)	(0.9698)	(1.0028)	(1.0511)
Leverage	-0.6467	-0.6966	-0.6813	-0.6817
	(0.6662)	(0.7400)	(0.7591)	(0.7564)
M/B Ratio	0.0003	0.0003	0.0004	0.0003
	(0.0011)	(0.0009)	(0.0009)	(0.0009)
Constant	2.4891***	2.6080***	2.8023***	3.0643***
	(0.5743)	(0.5762)	(0.5495)	(0.5318)
Year & Month FEs	Y	Y	Y	Y
REIT FEs	Y	Y	Y	Y
Observations	37,683	37,716	37,544	37,372
R-squared	0.115	0.112	0.134	0.168

Notes: This table reports the robustness check result for the estimated impact of firm acquisitions at time t on the return of REITs that hold properties in the same county of the acquired firms (i.e., the target county), using the share of affected property numbers in the REIT portfolio as the explanatory variable. The dependent variables are the monthly risk-adjusted abnormal returns (alpha) of the REITs at time $t-1$ to $t+2$. The abnormal returns are calculated with a Fama-French four-factor model using return data in the previous 60 months. The explanatory variable, *NumEXP*, is the total number of properties that a REIT holds in the target county at the acquisition time, as a fraction of the total number of properties held by the REIT. Definitions of the other variables are represented in Appendix Table C.1. Robust standard errors are clustered by REITs and are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table C.6 Robustness Check for the Impact of Firm Acquisitions on REIT Fundamental Performance: Number of Properties

	(1) *ROA(t)*	(2) *ODY(t)*	(3) *TDY(t)*	(4) *ROA(t+1)*	(5) *ODY(t+1)*	(6) *TDY(t+1)*
NumEXP	0.2560	0.1812	0.0124	-0.7226**	-1.6779***	-3.4561***
	(0.7430)	(0.9597)	(1.9417)	(0.3477)	(0.6232)	(1.2906)
Log(Market Cap)	0.1025	-0.5383	-1.3044*	-0.0464	-0.5860	-1.4498*
	(0.1295)	(0.3458)	(0.7148)	(0.1249)	(0.3635)	(0.7555)
Cash Ratio	3.0403	19.3568*	37.5268	1.4869*	11.8228*	25.7486**
	(4.8804)	(11.6986)	(23.3757)	(0.8667)	(6.3775)	(12.8411)
Leverage	-1.6821***	0.1700	-0.8110	-0.8933**	-0.6069	-2.5066
	(0.5338)	(0.5423)	(1.5217)	(0.4170)	(0.9573)	(2.2422)
M/B Ratio	-0.0034	-0.0017**	-0.0040**	-0.0019	-0.0026**	-0.0059***
	(0.0026)	(0.0009)	(0.0017)	(0.0020)	(0.0011)	(0.0022)
Constant	0.9055	4.3285*	10.7909**	1.7345*	5.4289**	13.2884**
	(1.0825)	(2.2923)	(4.8741)	(0.9598)	(2.6214)	(5.5653)
Year & Quarter FEs	Y	Y	Y	Y	Y	Y
REIT FEs	Y	Y	Y	Y	Y	Y
Observations	12,205	12,205	12,205	11,782	11,782	11,782
R-squared	0.158	0.094	0.094	0.111	0.084	0.089

Notes: This table reports the robustness check results for the impact of firm acquisitions at time t on the return on asset and dividend yield of REITs that hold properties in the same county of the acquired firms (i.e., the target county), using the share of affected property numbers in the REIT portfolio as the explanatory variable. The dependent variable $ROA(t)$ is the quarterly return on asset of REITs in the quarter of firm acquisitions, and $ROA(t+1)$ is the quarterly return on asset in the following quarter. The dependent variables $ODY(t)$ and $TDY(t)$ are the quarterly ordinary dividend yield and the total dividend yield of REITs in the quarter of firm acquisitions, respectively, while $ODY(t+1)$ and $TDY(t+1)$ denote the quarterly ordinary dividend yield and total dividend yield in the following quarter. *NumEXP* is the total number of properties that a REIT holds in the target county at the acquisition time, as a fraction of the total number of properties held by the REIT. Definitions of the other variables are represented in Appendix Table C.1. Robust standard errors are clustered by REITs and are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table C.7 Robustness Check for the Impact of Firm Acquisitions on REIT Fundamental Performance: Alternative Fixed Effects

	(1) *ROA(t+1)*	(2) *ODY(t+1)*	(3) *TDY(t+1)*	(4) *ROA(t+1)*	(5) *ODY(t+1)*	(6) *TDY(t+1)*
ValueEXP	-0.3328**	-0.4113**	-0.8529*			
	(0.1670)	(0.1960)	(0.4377)			
NumEXP				-0.7002*	-0.9658**	-1.8741*
				(0.3818)	(0.4801)	(0.9850)
Log(Market Cap)	-0.1239	0.1168	-0.0738	-0.1193	0.1226	-0.0619
	(0.0954)	(0.3529)	(0.7253)	(0.0938)	(0.3542)	(0.7277)
Cash Ratio	8.1250***	21.4590*	45.5608*	8.1398***	21.4778*	45.5991*
	(2.7240)	(12.4921)	(24.8657)	(2.7265)	(12.4902)	(24.8622)
Leverage	-1.6505***	1.2732	1.1578	-1.6382***	1.2885	1.1895
	(0.4651)	(1.1270)	(2.5396)	(0.4619)	(1.1313)	(2.5465)
M/B Ratio	-0.0025	0.0019	0.0029	-0.0025	0.0018	0.0029
	(0.0020)	(0.0048)	(0.0094)	(0.0020)	(0.0047)	(0.0093)
Constant	2.3249***	-0.3486	1.9268	2.3103***	-0.3621	1.8931
	(0.7608)	(3.0853)	(6.3593)	(0.7478)	(3.0817)	(6.3518)
Year FEs	Y	Y	Y	Y	Y	Y
REIT*Quarter FEs	Y	Y	Y	Y	Y	Y
Observations	11,782	11,782	11,782	11,782	11,782	11,782
R-squared	0.227	0.150	0.176	0.227	0.150	0.176

Notes: This table reports the robustness check result for the estimated impact of firm acquisitions at time t on the return on asset and dividend yield of REITs that hold properties in the same county of the acquired firms (i.e., the target county). The REIT time quarter fixed effects are included in the regressions to control for the potential REIT-specific seasonal variations in net income and dividend payouts. The dependent variable $ROA(t+1)$ is the quarterly return on asset of REITs in one quarter after firm acquisitions. The dependent variables $ODY(t+1)$ and $TDY(t+1)$ are the quarterly ordinary dividend yield and the total dividend yield of REITs in one quarter after firm acquisitions, respectively. *ValueEXP* is the total value of properties that a REIT holds in the target county at the acquisition time, as a fraction of the REIT's total asset. *NumEXP* is the total number of properties that a REIT holds in the target county at the acquisition time, as a fraction of the total number of properties held by the REIT. Definitions of the other variables are represented in Appendix Table C.1. Robust standard errors are clustered by REITs and are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table C.8 Robustness Check for the Impact of Firm Acquisitions on Institutional Investors' Ownership of REIT: Firm Acquisitions After 1999

	(1)	(2)	(3)	(4)
	Base Group: Out-of-MSA Investors			
	Ownership	*Ownership*	*SD_Ownership*	*SD_Ownership*
Post	-0.0154***	-0.0157***	-0.0784***	-0.0805***
	(0.0025)	(0.0026)	(0.0133)	(0.0141)
*Post * InMSA*	0.0154***	0.0160***	0.0589***	0.0627***
	(0.0032)	(0.0033)	(0.0214)	(0.0225)
ROA		0.0008		0.0054
		(0.0007)		(0.0049)
Log(Market Cap)		0.0379***		0.2672***
		(0.0089)		(0.0559)
Cash Ratio		0.0017		0.0206
		(0.0725)		(0.5731)
Leverage		0.0071		-0.0060
		(0.0276)		(0.1860)
M/B Ratio		-0.0007		0.0057
		(0.0024)		(0.0123)
ValueEXP		0.0034		-0.0471*
		(0.0028)		(0.0248)
RelTargetSize		0.0121		0.2891*
		(0.0138)		(0.1570)
Constant	0.2114***	-0.0619	0.1225***	-1.7667***
	(0.0006)	(0.0717)	(0.0036)	(0.4615)
Year & Quarter FEs	Y	Y	Y	Y
REIT & Investor FEs	Y	Y	Y	Y
Observations	25,746	24,894	25,746	24,894
R-squared	0.822	0.826	0.462	0.464

Notes: This table reports the robustness check result for the estimated impact of firm acquisitions on home and non-home institutional investors' ownership of affected REITs. Only the subsample of firm acquisitions after 1999 are included to address the concern for potentially incomplete investor addresses in earlier years. The home investors (the treatment group) are defined as those investors located in the same MSA as the firm acquisitions, and the non-home investors (the control group) are defined as those investors from different MSAs. The regression sample includes the quarterly aggregate ownership of the affected REITs by home or non-home investors within a [-3 quarters, +3 quarters] window of each firm acquisition. In Columns (1) to (3), the dependent variable, *Ownership*, is the total shares of a REIT that are held by the sampled home or non-home investors in each quarter, as a fraction of the REIT's total shares outstanding. In Columns (4) to (6), *SD_Ownership* is the standardized value of *Ownership* within groups of home or non-home investors, which measures the relative changes in ownership within the two subgroups. *Post* is a dummy variable equal to one if the sample is after the acquisition, zero otherwise. *InMSA* is a dummy variable denoting the sample of the home investors. Definitions of the other variables are represented in Appendix Table C.1. Robust standard errors are clustered by REITs and are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table C.9 Robustness Check for the Impact of Firm Acquisitions on Institutional Investors' Ownership of REIT: Subsample of REITs with Both Home and Non-home Investors

	(1)	(2)	(3)	(4)
	Base Group: Out-of-MSA Investors			
	Ownership	*Ownership*	*SD_Ownership*	*SD_Ownership*
Post	-0.0144***	-0.0145***	-0.0753***	-0.0743***
	(0.0022)	(0.0022)	(0.0112)	(0.0118)
*Post * InMSA*	0.0143***	0.0151***	0.0696***	0.0736***
	(0.0026)	(0.0027)	(0.0186)	(0.0195)
ROA		-0.0003		-0.0006
		(0.0012)		(0.0106)
Log (Market Cap)		0.0350***		0.2384***
		(0.0069)		(0.0494)
Cash Ratio		-0.0641		-0.6820
		(0.0602)		(0.5038)
Leverage		-0.0120		-0.2374
		(0.0207)		(0.1751)
M/B Ratio		-0.0001		-0.0084
		(0.0033)		(0.0137)
ValueEXP		0.0021		0.0036
		(0.0030)		(0.0320)
RelTargetSize		-0.0174		0.2083
		(0.0155)		(0.1622)
Constant	0.2233***	-0.0222	0.2602***	-1.3300***
	(0.0005)	(0.0550)	(0.0044)	(0.4074)
Year & Quarter FEs	Y	Y	Y	Y
REIT & Investor FEs	Y	Y	Y	Y
Observations	21,392	20,944	21,392	20,944
R-squared	0.832	0.835	0.436	0.444

Notes: This table reports the robustness check result for the estimated impact of firm acquisitions on home and non-home institutional investors' ownership of affected REITs. Only the subsample of affected REITs with both home and non-home investors are included. The home investors (the treatment group) are defined as those investors located in the same MSA as the firm acquisitions, and the non-home investors (the control group) are defined as those investors from different MSAs. The regression sample includes the quarterly aggregate ownership of the affected REITs by home or non-home investors within a [-3 quarters, +3 quarters] window of each firm acquisition. In Columns (1) to (3), the dependent variable, *Ownership*, is the total shares of a REIT that are held by the sampled home or non-home investors in each quarter, as a fraction of the REIT's total shares outstanding. In Columns (4) to (6), *SD_Ownership* is the standardized value of *Ownership* within groups of home or non-home investors, which measures the relative changes in ownership within the two subgroups. *Post* is a dummy variable equal to one if the sample is after the acquisition, zero otherwise. *InMSA* is a dummy variable denoting the sample of the home investors. Definitions of the other variables are represented in Appendix Table C.1. Robust standard errors are clustered by REITs and are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.