

Herding Behavior among Residential Developers

SeungHan Ro¹ · Paul Gallimore² · Sherwood Clements³ · Gang-Zhi Fan⁴

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Abstract

We investigate whether US real estate developers display herding in their building permit seeking behavior. We measure herding over the period 1988 through 2011 by applying to permit issuances measures previously used in studies of stock herding. We find evidence of herding at levels comparable to those found in studies involving common-stock trading. Developer herding is also stronger in up markets, than in down markets. This is consistent with up market buoyancy constraining the availability of reliable, independent information, which reinforces the tendency to follow the behavior of others.

Keywords Herding · Building permit · Residential development

Sherwood Clements jsclements@cba.ua.edu

> SeungHan Ro shro@konkuk.ac.kr

Paul Gallimore p.gallimore@reading.ac.uk

Gang-Zhi Fan fangz@gzhu.edu.cn

- ¹ Department of Real Estate Studies, Konkuk University, 120 Neungdong-ro, Gwangjin-gu, Seoul 05029, South Korea
- ² School of Real Estate & Planning, Henley Business School, University of Reading, Whiteknights, Reading RG6 6UB, UK
- ³ Department of Economics, Finance and Legal Studies, Culverhouse College of Business, University of Alabama, Tuscaloosa, AL 35487, USA
- ⁴ School of Management, Guangzhou Higher Education Mega Center, Guangzhou University, 230 Wai Huanxi Road, Guangzhou 510006, China

Introduction

The conventional view of developer decision-making is that their most important reference point is the profit target of a development project (Baerwald 1981; Somerville 1999); and consequently that what drives decisions are fundamentals such as price expectations, material costs and changes in short-term interest rates. On the other hand there is anecdotal evidence that developers focus insufficiently on future fundamentals on the delivery of their projects, but are instead unduly prone to follow other developers' decisions. This tendency to mimic is attributed to both existing participants and new entrants to the development market. More formally, Simon (1979) argues that residential developers are widely characterized as having 'satisficing' behavior, in which they aspire to meet suboptimal goals when developing new real estate projects. This satisficing behavior in real estate developers has been aligned with bounded rationality, via which people use decision rules to simplify processes and find answers to complex problems (Simon 1957; Hepner 1983; Leung 1987; Mohamed 2006). Kenney (1972) finds that developers avoid risks and use recent choices to determine their prospects, including the motivation to begin a similar project in the near future.

The possibility that developers may deviate from the conventional model leads us to the conjecture that they may be prone to herding, a phenomenon that is accepted as sometimes present elsewhere in financial decision-making. We treat herding as correlated behaviors by individuals that can lead to systematic sub-optimal decisions across a population (Devanow and Welch 1996). In this paper, we investigate whether herding behavior is present among residential developers in the US. In essence, we frame our expectations as the following hypotheses: (i) residential developers herd, (ii) this herding occurs in both up-markets and down-markets, (iii) it occurs both into and out of permits, and (iv) herding into permits dominates in up markets and herding out of permits dominates in down markets.

The rest of the paper is organized as follows. We review the literature on herding behavior as it relates to real estate and follow this with a theoretical exposition to support our conjectures. We then describe our data, followed by a description of our methods. We report our findings and finish by reflecting upon these in the conclusion.

Relevant Literature

Early studies in the financial literature vary in the extent that that investment decisionmakers are found to exhibit herding behavior. Lakonishok et al. (1992) created the seminal herding measure used in financial studies although they found little evidence of it in pension fund investing. Conversely, Grinblatt et al. (1995) and Wermers (1999) discover that mutual fund managers do exhibit this behavior. More recently, Choi and Sias (2009) find strong evidence that institutional investors follow each other into and out of the same industry sectors, and that this form of herding impacts prices.

There are few studies of herding in the real estate literature, and none to date that empirically examine this behavior in real estate developers. For example, Pierdzioch et al. (2010) show that housing forecasters "anti-herd", whereby they scatter forecasts around the given consensus.¹ Their results are taken from survey data in Canada, Japan and the United States. Seiler et al. (2014) investigate herding in the context of whether borrowers are willing to strategically default on their residential loans. They create a hypothetical experimental scenario and, by this means, conclude that homeowners 'are easily persuaded to follow the herd'. Using an empirical approach, Hott (2012) considers whether herding has been present over the preceding 30 years or so across a range housing markets in 10 developed countries. He observes differences in these markets between his calculation of the prices that would be justified by fundamentals, and actual prices; and using a model developed by Lux (1995), investigates these with a herding measure based on contagious investor sentiment. He finds that the herding measure helps to some extent, although its success is variable across markets.

Ro and Gallimore (2014) test for evidence of herding in the trading of US real estate mutual funds (REMF). They report that herding does occur in stocks traded by REMFs, although this is present in the selling of past winners rather than past losers (suggesting the presence of a disposition effect). Zhou and Lai (2008) investigate herding in real estate related securities versus non-real estate securities in the Hong Kong stock market. They find the level of herding to be lower in real estate securities. Due to limitations in their data, however, they do not distinguish institutional investors from individual investors, nor utilize REITs. Zhou and Anderson (2013) study investor herding in US REITs, although they similarly do not differentiate between investor types. They contend that the tendency of REIT investors to herd is positively associated with market turbulence, which inclines them to suppress their own beliefs. They conclude that herding is stronger and more likely in down markets than up markets, but do not offer an interpretation for this.

In the only study to date to focus on real estate development, DeCoster and Strange (2012) examine developer herding from a theoretical perspective, examining rational overbuilding by this sector in times of uncertainty.² They argue that builders learn from each other and tend to copy when starting new development projects. They also contend that builders' herding is reputation-based, discouraging innovative schemes because of the risk of stigma. They do not, however, pursue their conjectures through analysis of actual data.

Herding behavior has been found in studies of various aspects of financial decisionmaking in general, and to a lesser extent in respect in decisions concerning real estate. No studies, however, have yet investigated empirically whether these behaviors are displayed by real estate developers. In our study, we test aspects of herding theory empirically, using building permits, which supply the earliest evidence of the intent by developers to build (Somerville 2001). We investigate this by focusing on monthly changes in permit issuance for residential development in the US.

¹ "Anti-herding" is also reported in the financial literature. For example, Bernhardt et al. (2006) find that financial analysts issue contrarian forecasts that overshoot the consensus in the direction of private information.

 $^{^{2}}$ Lai and Van Order (2010) are among those who document the speculative real estate bubble that occurred in the 2000s and was accompanied by overbuilding in many US regions.

Theoretical Considerations

This section develops a theoretical framework for analyzing herding behavior by extending the previous research such as Bikhchandani et al. (1992), and DeCoster and Strange (2012).³ In marked contrast to these studies, we attempt to distinguish between herding both into and out of real estate development. We reason that not only may a potential developer imitate earlier developers with the commencement of the development project, but they may also imitate the actions of other developers in abandoning the development option. Furthermore, since real estate markets can be characterized as having long construction periods, our model also takes sequential development into consideration. We posit that sequential development should be a remarkable feature of herding behavior in real estate market.

Our reasoning is as follows. Suppose that there are two real estate developers, *A* and *B*, who possess the same characteristics except for their signal qualities and location choices.⁴ For simplicity, we only take account of two periods of time: periods 1 and 2. For these two periods, we allow for two possible states: a good state and a bad state. At the time of development, the two developers do not know which state will occur. If a good state emerges, this increases the probability of the development being successful, and vice versa. Let*p*denote the probability of the good state ensues, the value of the real estate project, *V*, will be 1. However, if the bad state ensues, *V* will be 0. These two developers are also assumed to incur the same development cost in their investment, *C*. For expositional convenience, *C* can be set to 1/2 in our discussion as in Bikhchandani et al. (1992).

We also assume that before their decision in each period to develop, the two developers can observe two possible private market signals: $S_{ij} = 1 \text{ and } S_{ij} = 0$, for $i \in \{1, 2\}$ and $j \in \{A, B\}$, where $S_{ij} = 1$ denotes the signal, for developer j, that a good state will occur at time i, while $S_{ij} = 0$ represents the signal of a bad state. The conditional probability of receiving a signal can be written as the following form:

$$\Pr(S_{ii} = 1 | V = 1) = \phi_i$$

and

$$\Pr(S_{ij} = 0 | V = 0) = \phi_i \tag{1}$$

³ Scheinkman and Xiong (2003) attempt to explain the occurrence of asset price bubbles from a perspective of heterogeneous beliefs and highlight that overconfidence might lead to these beliefs and in turn cause the bubbles. Xiong (2013) further addresses the important implication of heterogeneous beliefs for excessive financial leverage and investment. However, our study pays special attention to herding behavior, which can be viewed as a form of learning process and therefore is in opposition to overconfident behavior. Investors' learning from each other actually might mitigate their heterogeneous beliefs in some cases. Xiong (2013) also notices and discusses similar behavioral effects.

⁴ Similar to DeCoster and Strange (2012), we assume that the two developers are homogenous, while they might receive informational signals with different qualities and choose differentiated development locations. The previous studies, such as Bikhchandani et al. (1992) and DeCoster and Strange (2012), emphasize that informational asymmetry and management's reputation might matter in interpreting the behavior of herding or information cascade, which can be driven by investors' rational, optimal investment decisions. This assumption facilitates identifying this class of mutual mimicking investment behavior.

These two categories of signals are assumed to be conditionally independent of each other as in previous studies. We also specify $\phi_i > 1/2$ and $\phi_1 < \phi_2$. Of them, $\phi_i > 1/2$ implies that if a good-state (bad-state) signal is received, the good (bad) state is more possible to happen in period $i.\phi_1 < \phi_2$ can be interpreted as the signal in period 2 having "better" quality than that in period 1. That is, the signal in period 2 is more informative compared with that in period 1 such that a developer can more "certainly" judge the state of nature in period 2. This suggests that a later developer who makes an investment decision in period 2 will make use of his own signal observed in this period instead of that observed by himself in the preceding period in addition to the inferences concerning the preceding behavior of his competitor.

We also assume that it is only in later period that a developer can incorporate into his development decision the information from observation of the first developer's decision. This is because there are multiple review activities associated with local land use regulations, such as environmental impact assessment, subdivision and re-zoning approvals, which lead to regulatory delay in the development process before construction can start (Mayer and Somerville 2000). These activities are usually unobservable to the later developer and it is their culmination in a construction start that sends the signal of the first developer's decision.

In period 1, without loss of generality, we assume that if developer A observes a good signal, he will make a property investment immediately. In this case, its expected development profit can be written as:

$$R_{1A}\left(S_{1A}|_{S_{1A}=1}\right) = E(V|S_{1A}=1) - C = \Pr(V=1|S_{1A}=1) - C$$
(2)

We can further show that:

$$R_{1A}\left(S_{1A}|_{S_{1A}=1}\right) = \frac{\phi_1 p}{\phi_1 p + (1-\phi_1)(1-p)} - C.$$
(3)

See Appendix 1 for this derivation. This suggests that when $\frac{\phi_1 p}{\phi_1 p + (1-\phi_1)(1-p)} > C$, developer *A* will expect to earn a positive development profit. In eq. (3), there are three main parameters, namely *C*, ϕ_1 and *p*. When C = 1/2, $\phi_1 = 1/2$, and p = 1/2, it can be shown that the developer is indifferent between developing and rejecting this project because $R_{1A}(S_{1A}|_{S_{1A}=1}) = 0$. However, if $\phi_1 > 1/2$ and all else is unchanged, the developer will have a greater likelihood of earning a positive profit, because:

$$\frac{\phi_1 p}{\phi_1 p + (1 - \phi_1)(1 - p)} = \frac{\phi_1 p}{\phi_1 p + 1 - \phi_1 - p + \phi_1 p} > \frac{\phi_1 p}{\phi_1 p + \phi_1 p} = \frac{1}{2}.$$
 (4)

On the other hand, if developer *A* receives a bad signal in period 1, according to Bayes' Rule the expected profit can be written as:

,

$$R_{1A}(S_{1A}|_{S_{1A}=0}) = E(V|S_{1A}=0)-C = \Pr(V=1|S_{1A}=0)-C$$

= $Pr(S_{1A}=0\cap V=1)/Pr(S_{1A}=0)-C$
= $\frac{Pr(S_{1A}=0|V=1)Pr(V=1)}{Pr(S_{1A}=0|V=1)Pr(V=1) + \Pr(S_{1A}=0|V=0)Pr(V=0)}-C$ (5)
= $\frac{p(1-\phi_1)}{p(1-\phi_1) + (1-p)\phi_1}-C.$

Developer *A* will give up this development opportunity in period 1, because it is more likely to incur an investment loss in this case. For example, it can be shown that if C = 1/2, $p \le 1/2$, $\phi_1 > 1/2$, then $R_{1A}(S_{1A}|_{S_{1A}=0}) < 0$ usually holds.

Based on developer A's investment decision, we can further analyze developer B's investment choices. Developer B can infer developer A's private signal by observing her behavior. This information is valuable to developer B in making his investment decision. Specifically, if developer B receives a bad signal in period 1, its expected profit can be written as:

$$R_{1B}\left(S_{1B}|_{S_{1B}=0}\right) = E(V|S_{1B}=0) - C = \frac{p(1-\phi_1)}{p(1-\phi_1) + \phi_1(1-p)} - C.$$
 (6)

When $R_{1B}(S_{1B}|_{S_{1B}=0}) < 0$, this implies that developer *B* will choose to give up the development opportunity during period 1 due to receiving the bad signal. However, this developer might choose to undertake development in period 2, since developer *B* can observe and infer developer *A*'s preceding decision in the period due to the multiple regulatory reviews we note earlier.

When developer B observes the action of developer A and infers the good signal he has received in period 1, he can undertake a development activity in period 2 as a response to inferring the good signal developer A has received in period 1.

We can show that:

$$R_{2B}\left(S_{1A}, S_{2B}|_{S_{1A}=1\cap S_{2B}=0}\right) = \frac{\rho\phi_1(1-\phi_2)p}{\phi_1(1-\phi_2)p + \phi_2(1-\phi_1)(1-p)} - \rho C.$$
(7)

where ρ denotes the positive discounting factor (See Appendix 2).

This suggests that if:

$$R_{1B}\Big(S_{1B}|_{S_{1B}=0}\Big) < 0$$

and

$$R_{2B}\left(S_{1A}, S_{2B}|_{S_{1A}=1\cap S_{2B}=0}\right) > 0, \tag{8}$$

that is, when

$$\frac{p(1-\phi_1)}{p(1-\phi_1)+\phi_1(1-p)} < C < \frac{\phi_1(1-\phi_2)p}{\phi_1(1-\phi_2)p+\phi_2(1-\phi_1)(1-p)},\tag{9}$$

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developer B will develop a property project in period 2. While developer B gives up his investment chance in period 1 and observes a bad signal in period 2, he can imitate developer A to exercises his development option in period 2 when inequality (9) is satisfied. This implies that developer B's investment decision may be affected by the previous action of developer A. In other words, when inequality (9) holds, herd behavior may occur.

In contrast to the previous studies, however, inequality (9) suggests that in addition to development costs and state signals, the probability of a good or bad state occurring also plays an importance role in determining the occurrence of herding behavior. This is because p is also an important factor in inequality (9). When p > 1/2, the market is more likely to go up; vice versa, it has a greater likelihood to move down. As a result, whether a market goes up or down is material to the likely occurrence of herding behavior.

Also, we can calculate partial derivative for $R_{2B}(S_{1A}, S_{2B}|_{S_{1A}=1\cap S_{2B}=0})$ with respect to *p*. We have

$$\frac{\partial R_{2B} \left(S_{1A}, S_{2B} |_{S_{1A}=1 \cap S_{2B}=0} \right)}{\partial p} = \frac{\rho \phi_1 (1-\phi_2) \left[(\phi_1 (1-\phi_2)p + \phi_2 (1-\phi_1) (1-p)) - p(\phi_1 - \phi_2) \right]}{(\phi_1 (1-\phi_2)p + \phi_2 (1-\phi_1) (1-p))^2}.$$
(10)

Since we have specified $\phi_1 < \phi_2$, we can find that:

$$\frac{\partial R_{2B}\left(S_{1A}, S_{2B}|_{S_{1A}=1\cap S_{2B}=0}\right)}{\partial p} > 0 \tag{11}$$

always holds. This suggests that developer *B*'s period 2 expected profit $R_{2B}(S_{1A}, S_{2B}|_{S_{1A}=1\cap S_{2B}=0})$ driven by his imitation is positively associated with *p*. In other words, an increase in the probability of a good state occurring can enhance the expected profit. This implies that an upward market increases the likelihood of herd behavior associated with real estate development.

To illustrate this kind of herding behavior, we consider a simplified example in which developer *A* receives the signal of a good state at the beginning of period 1, while developer *B* obtains the signal of a bad state at this time. Suppose that $\phi_1 = 0.7$, $\phi_2 = 0.75$, p = 0.6, C = 1/2, and $\rho = 1$. By Eq. (3), we know that because developer *A* expects to earn a positive profit of 0.28 at the end of period 1, he chooses to undertake a property development within period 1. In contrast, since developer *B* receives a bad signal at the beginning of period 1 and his expected profit is -0.11 by Eq. (6), he chooses to give up the development opportunity during period 1. However, because developer *B* observes the development action of developer *A*, he can infer that developer *A* has received the good signal in period 1. As result, even though developer *B* continues to receive a bad signal at the beginning of period 2, he can choose to undertake a similar property development. This is because his expected profit is 0.04 under the situation according to Eq. (7).

If developer B receives a good signal in period 1, his expected profit can be expressed as:

$$R_{1B}\left(S_{1B}|_{S_{1B}=1}\right) = E(V_1|S_{1B}=1) - C = \frac{\phi_1 p}{\phi_1 p + (1-\phi_1)(1-p)} - C.$$
(12)

If he receives the good signal during period 1 and $R_{1B}(S_{1B}|_{S_{1B}=1}) > 0$, developer *B* is very likely to choose to develop immediately in period 1. However, if his expected profit is negative, that $isR_{1B}(S_{1B}|_{S_{1B}=1}) < 0$, this developer will likely wait, in which case he can observe developer *A*'s period 1 investment decision and receive a new signal in period 2. In this case, even if developer *B* receives a bad signal in period 2, he may still undertake a property project in this period based on inferring that developer *A* has received a good signal.

As a result, because

$$R_{1B}\left(S_{1B}|_{S_{1B}=1}\right) = \frac{\phi_1 p}{\phi_1 p + (1-\phi_1)(1-p)} - C < 0, \tag{13}$$

we can write inequality (9) as

$$\frac{\phi_1 p}{\phi_1 p + (1 - \phi_1)(1 - p)} < C < \frac{\phi_1(1 - \phi_2)p}{\phi_1(1 - \phi_2)p + \phi_2(1 - \phi_1)(1 - p)}.$$
(14)

This indicates that when inequality (14) is satisfied, developer B can imitate developer A to undertake a property project. Similar to (9), inequality (14) suggests that in addition to the factors identified above, the development delay also affects herd behavior, in that the information on developer A's investment decision is incorporated into developer B's development decisions in a later period (as discussed earlier).

Our reasoning can be applied equally to show that developer B may imitate the action of developer A so as to give up his development opportunity in period 2.

We know that if:

$$R_{1B}\Big(S_{1B}|_{S_{1B}=0}\Big) < 0, \tag{15}$$

developer B will choose not to exercise his development option in period 1. If developer A does not exercise his development option in period 1, developer B can infer in period 2 that developer A has received a bad signal in period 1. Under this situation, it can be shown that if developer B receives a good signal in period 2, his expected profit can be written as

$$R_{2B}\left(S_{1A}, S_{2B}|_{S_{1A}=0\cap S_{2B}=1}\right) = \frac{\rho(1-\phi_1)\phi_2 p}{(1-\phi_1)\phi_2 p + \phi_1(1-\phi_2)(1-p)} - \rho C.$$
(16)

See Appendix 3 for the derivation of this formula.

It can then be found that if

$$R_{2B}\left(S_{1A}, S_{2B}|_{S_{1A}=0\cap S_{2B}=1}\right) = \frac{\rho(1-\phi_1)\phi_2 p}{(1-\phi_1)\phi_2 p + \phi_1(1-\phi_2)(1-p)} - \rho C < 0, \quad (17)$$

$$R_{1B}\left(S_{1B}|_{S_{1B}=0}\right) = \frac{p(1-\phi_1)}{p(1-\phi_1) + \phi_1(1-p)} - C < 0$$
(18)

can also be satisfied due to $\frac{p(1-\phi_1)}{p(1-\phi_1)+\phi_1(1-p)} < \frac{p(1-\phi_1)}{p(1-\phi_1)\phi_2p+\phi_1(1-p)}$. That is, if inequality (17) holds, developer *B* will not exercise his investment

That is, if inequality (17) holds, developer *B* will not exercise his investment option in periods 1 and 2. In other words, even though developer *B* receives a good signal in period 2, he may imitate developer *A*'s period 1 actions and not proceed to develop.

Similarly, we can also find

$$\frac{\partial R_{2B} \left(S_{1A}, S_{2B} |_{S_{1A}=0 \cap S_{2B}=1} \right)}{\partial p} = \frac{\rho \phi_1 \phi_2 (1-\phi_1) (1-\phi_2)}{\left((1-\phi_1) \phi_2 p + \phi_1 (1-\phi_2) (1-p) \right)^2} > 0.$$
(19)

This suggests that a fall in the probability of a good state happening can reduce developer *B*'s expected development profit. In other words, an increase in the probability of a bad state occurring can enhance the likelihood of herd behavior associated with the abandonment of real estate development.

Furthermore, we also notice that if developer *B* receives a good signal in period 1 but his expected profit is negative, that $is_{R_{1B}}(S_{1B}|_{S_{1B}=1}) < 0$, he will not exercise his development option in period 1. He will observe the action of developer *A* and further wait for a new signal in period 2. Thus, when

$$R_{1B}\left(S_{1B}|_{S_{1B}=1}\right) = \frac{\phi_{1}p}{\phi_{1}p + (1-\phi_{1})(1-p)} - C < 0$$

and

$$R_{2B}\left(S_{1A}, S_{2B}|_{S_{1A}=0\cap S_{2B}=1}\right) = \frac{\rho(1-\phi_1)\phi_2 p}{(1-\phi_1)\phi_2 p + \phi_1(1-\phi_2)(1-p)} - \rho C < 0, \quad (20)$$

developer B can also mimic developer A not to exercise his development option in period 2 even though he receives a good signal during period 2. These results suggest that the factors, identified earlier, are of importance to interpreting herd behavior associated with real estate development action and are likewise important in driving herd behavior related to the abandonment of real estate development. This therefore implies that up-market or down-market conditions are not the only determinant which might drive herding behavior associated with real estate development decisions.

Data and Methodology

Data Description

The time period for our study is from 1988 to 2011. To track the differing phases of real estate development, we use data for this period from the United States Census Bureau. Building permits, indicating local government's approval of the anticipated project, are the first sign of the intent by the developer. The permits show the developer's behavior towards moving into a given market as the issuance must occur prior to the actual beginning of the construction. We considered using housing starts, but delays may occur prior to the initial construction due to zoning changes, environmental assessments and other factors. Carliner (1986) notes that the two measures appear to be reasonably correlated. He observes a small time lag between permits and starts. For example, in 1985 roughly 60% of starts occurred in the same month as the permit being issued and close to 26% ensued in the following month. Additionally, he observes that only approximately 2% of the latter do not occur after the former for a variety of reasons such as abandonment or expiration. Building permits are collected on a national, regional, and state level as well as from metropolitan statistical areas, and after being seasonally adjusted are shown as an annual rate by the Census Bureau.

Summary Statistics on the data are presented in Table 1. On average, 79,243 building permits are granted monthly (on an annualized basis) in the sample period with 76,153 of these being for one-unit single-family homes. Most of the remainder is five plus unit and two-to-four unit structures averaging less than 2000 permits issued a month.⁵ In addition, this data presented confirms higher levels of residential construction during 'up' markets regardless of the type of new residential construction. Figure 1 shows the trends of regional residential building permit issuance overall sample periods. It indicates higher levels of residential development in the southern and western regions, a characteristic accentuated in the post-2000 housing boom. The southern region's peak month totaled 1,090,000 permits on an annualized basis. By comparison, construction expansion in the western region hit its monthly apex with the pulling of 661,000 permits. The south had the highest average per month at approximately 617,000 permits issued.

Herding Measurement

To test for the presence of herding, we develop a herding measurement for residential developer activity by modifying that devised by Lakonishok et al. (1992), which was originally designed to measure investors' herding in the stock market. We replace herding around a stock with herding around a locality, since we contend that the type of herding most likely to be exhibited by developers is that triggered by observation of the behavior of other developers in proximate locations.⁶ Effectively, we seek to detect herding in MSA permit-issuance within States. We calculate the herding measure based

⁵ Two-to-four unit residential homes are commonly known as duplexes, triplexes and quadriplexes. The larger units are generally considered to be multi-family residential (aka. apartments).

⁶ This type of behavior can be modeled through the device of an 'information cascade' (Banerjee 1992; Bikhchandani et al. 1992).

		All Units	1 Unit-Bldg	2 Unit- Bldg	3–4 Unit- Bldg	5+ Unit- Bldg
Panel A. Summary statistics for	or residen	tial developmen	t permits by per	iods		
Overall (1988 ~ 2011)	Mean	79,243	76,153	1020	628	1441
	(Sum)	(22,029,447)	(21,170,666)	(283,683)	(174,562)	(400,536)
1st period (1988 ~ 1993)	Mean	75,210	71,923	1057	630	1599
	(Sum)	(5,415,089)	(5,178,489)	(76,108)	(45,358)	(115,134)
2nd period (1994 ~ 1999)	Mean	91,988	88,347	1165	679	1797
	(Sum)	(6,623,124)	(6,360,965)	(83,885)	(48,889)	(129,385)
3rd period (2000 ~ 2005)	Mean	101,964	98,332	1261	805	1566
	(Sum)	(7,341,437)	(7,079,898)	(90,827)	(57,991)	(112,721)
4th period (2006 ~ 2011)	Mean	42,739	41,150	530	360	698
	(Sum)	(2,649,797)	(2,551,314)	(32,863)	(22,324)	(43,296)
Panel B. Summary statistics for	or residen	tial developmen	t permits by ma	rkets		
Up Market	Mean	88,421	84,971	1139	704	1607
	(Sum)	(19,717,950)	(18,948,612)	(253,963)	(156,943)	(358,432)
Down Market	Mean	42,027	40,401	540	320	766
	(Sum)	(2,311,497)	(2,222,054)	(29,720)	(17,619)	(42,104)

Table 1 Summary statistics: January 1988 - December 2011

Residential development permits indicate the number of new housing units authorized by the acquisition of building permits. Data are available on a monthly, year- to- date, and annual basis at the national, state, and selected metropolitan area levels as provided by the US Census Bureau. 1 unit-buildings include all new privately-owned detached and attached single-family houses, which includes town houses and/or row houses. 2 unit-buildings indicate all new privately-owned residential buildings that contain two housing units and are known commonly as duplexes. 3–4 unit-buildings include all new privately-owned residential buildings that contain two housing units and are known commonly as triplexes and quadriplexes. 5 or more unit buildings specify all new privately-owned residential buildings that contain five or more housing units and are commonly known as multi-family housing

on the difference, in each month, between two ratios. The first ratio is that of (21) the number of MSAs within a State whose monthly change in permit issuance is higher than the corresponding average monthly change for all US MSAs, as a proportion of (22) the number of MSAs issuing permits within the State. This ratio, $P_{s,t}$, is represented formally as:

$$Ps, t = Ht/(Ht + Lt) \tag{21}$$

where Ht is the number of MSAs having a housing permit change rate higher than that in the US overall at month *t* within a States while *Lt* is the number of MSA lower than or equal to the overall. The second ratio replicates the first ratio but with the expectation of no inter-State herding. This expectation is captured by the ratio of the total number of MSAs nationally having higher than-US-average permit change rate as a proportion of all US MSAs issuing housing permits. At this stage, the herding measure, HM_{s,t}, is represented as:

$$HMs, t = | Ps, t - E[Ps, t] |$$
(22)

1978

U n

> i t s

> > 0 1974



Notes: This figure shows the trends in the annualized monthly building permit issuance on a regional basis. The United States Census Bureau classifies the four regions as the Northeast (NE), Midwest (MW), South and West.

- South BP

1990

Year

1994

1998

-West BP

2002

2006

2010

1986

Fig. 1 ■ Regional Residential Building Permit Issuance: (1973–2010)

MW BP

1982

The measure is calculated as the absolute value of the difference in the ratios, because herding within a State may be positive, indicating herding into housing permits, or negative, indicating herding out of permits.

We must, however, expect some distribution of this measure around zero, even if no herding is occurring. This is because, even assuming no herding, the permit issuance pattern is not expected to mirror the national average in every State. Consequently, the absolute value of the measure will tend towards being positive. To adjust for this we need to make an assumption of how we expect issuances to be distributed around this overall level - i.e. what we expect the measure to be, given our assumptions about the distribution. Following Lakonishok et al. (1992), we adopt the assumption that the number of MSAs displaying higher than average issuances in the ratio $p_{s,t}$ follows a binomial distribution. We therefore modify Eq. (22) by deducting its expected value, which is calculated based on the binomial assumption.

$$HMs, t = |Ps, t - E[Ps, t]| - E |Ps, t - E[Ps, t]|$$
(23)

This resulting measure is a percentage. This percentage indicates the extent within a State by which permit issuance in the overall direction of the market exceeds that under the null hypothesis of no herding in permits. In addition, we employ the constituent

components of measure (22) respectively to capture herding towards an increase in permit issuance (or herding into permits - HIP) and towards a decrease in issuance (herding out of permits - HOP). So:

$$HIP = HMs, t|Ps, t > E[Ps, t]|$$

HOP = HMs, t|Ps, t < E[Ps, t]| (24)

These conditional measures are used to test for herding behavior in up-market and down-market conditions.

One may question the similarity of stock market investors to residential developers, but we believe they have similar actions. The simple answer is that both are looking at an investment project in which they expect to make a positive return. A stock investor herds into a given stock as they believe that the stock should appreciate in price over the holding period and provide a dividend in some cases. A developer herds into a given location (MSA in our case) looking to make the return from the sale of the home at the end of the holding period (construction term) in most cases and rent it over time extending the holding period in others.

Empirical Results

Table 2 shows the overall mean and various component means of the herding measure (HMs,t – Eq. 3), for the period 1988/01 to 2011/02, averaged over all months for all US States. The columns represent a series of thresholds for the minimum number of MSAs in a State for it to be included in the calculation. These are applied to reflect the argument that below a particular number it is debatable that a "herd" can form. The rows in the two Panels provide further information on the herding measure by reference to time and to the condition of the market. The herding measure over our whole sample period (1988–2011), shown in Panel A, is 1.93% at the lowest threshold MSA level. This measure progressively increases to 3.87%, as the MSA threshold increases. These measures, like all those displayed in Table 2, are statistically significant (due to the large sample size).

The levels of herding found in Table 2 can be viewed against those found using the same methodology in prior studies, although these studies have all had stock trading as the herding signal rather than permit issuance. The comparators in common stock trading are 2.7% (Lakonishok et al. 1992), 3.4% (Wermers 1999) and 4.32% (Grinblatt et al. 1995); and in trading of REIT stock by real estate mutual funds, 1.73% (Ro and Gallimore 2014). Our herding levels are sufficient to conclude that developers do herd, in line with our first hypothesis.

In Table 2 Panel A, we also examine the herding statistics over time by dividing the sample into four successive six-year periods. These boundaries of these periods are arbitrary, and are not intended to proxy for different market conditions. What they do suggest, however, is that herding is time-varying. Therefore, to investigate more formally, we explore in Table 2 Panel B the mean herding statistics by reference to 'up' and 'down' markets. To allocate the periods to these market states we employ US Business Cycle Expansions and Contractions data provided by the National Bureau of Economics Research

Number of MSA	≥ 5	≥ 10	≥ 15	≥ 20
Panel A. Mean Herding Statistic				
Overall (1988 ~ 2011)	1.93%	2.70%	3.88%	3.87%
(# of state - month)	(7277)	(3574)	(957)	(792)
t - statistics	10.67***	12.84***	11.15***	10.63***
1st period (1988 ~ 1993)	2.74%	3.72%	3.97%	4.34%
(# of state - month)	(1728)	(940)	(340)	(212)
t - statistics	7.77***	8.21***	6.07***	5.65***
2nd period (1994 ~ 1999)	2.71%	3.49%	6.11%	6.11%
(# of state - month)	(1802)	(860)	(216)	(216)
t - statistics	6.62***	7.47***	7.37***	7.37***
3rd period (2000 ~ 2005)	1.68%	2.37%	3.14%	2.82%
(# of state - month)	(1949)	(906)	(215)	(192)
t - statistics	5.09***	6.94***	5.20***	4.84***
4th period (2006 ~ 2011)	0.39%	1.00%	2.05%	1.94%
(# of state - month)	(1798)	(868)	(186)	(172)
t - statistics	1.58*	3.33***	3.72***	3.36***
Panel B. Up and Down Markets				
Up Market	2.11%	3.03%	4.20%	4.22%
(# of State - Month)	(5732)	(2820)	(776)	(628)
t - Statistics	10.13***	12.68***	10.34***	9.97***
Down Market	1.21%	1.39%	2.61%	2.43%
(# of State - Month)	(1545)	(754)	(181)	(164)
t - Statistics	3.56***	3.50***	4.35***	3.86***
Difference t-test				
t-statistics	2.27**	3.53***	2.20**	2.36**
t critical two-tail	1.98	1.98	1.98	1.98

 Table 2
 Herding statistics in residential development in MSA level

Residential development permits indicate the number of new housing units authorized by the acquisition of building permits. Data are available on a monthly, year- to- date, and annual basis at the national, state, and selected metropolitan area levels as provided by the US Census Bureau. We employ US Business Cycle Expansions and Contractions provided by the National Bureau of Economics Research (NBER) to define the market cycle (up- and down-market).***, **, * are the 1%, 5 and 10% significance levels respectively

(NBER). Regardless of minimum threshold number of MSAs, the means in both 'up' and 'down' market conditions are sufficiently large to confirm the presence of herding. This is consistent with our second hypothesis. When compared, the herding statistics in 'up' market conditions are higher than that in 'down' markets. The application of t-tests (assuming unequal variance) to these differences shows that they are statistically significant. The finding that developer herding in permits is significantly higher in up-markets than downmarkets aligns with Welch's (2000) conclusions regarding security analysts' consensus herding. He attributes this to less information aggregation in "good times", which in turn induces greater likelihood of mutual imitation.

Table 3 presents the results for herding into permits (HIP) and herding out-of permits (HOP), both across the sample and for up- and down-markets. We include in Table 3 the results for only the two lower values of the minimum MSA-within-state thresholds. Table 3 Panel A (where the lower bound is five MSAs) reveals that both forms of herding are present, as predicted in our third hypothesis. Setting aside the market state, the HIP measure (2.38%) is significantly higher than the HOP measure (1.79%). The difference persists in the down-market sub-periods (HIP = 2.01% vs HOP = 0.65%),

Herding Statistics	HIP	НОР	Difference t-test (High vs. Low)
			t-statistics
Panel A. Mean Herding Statisti	c (Number of MSA \geq 5)		
Total Market	2.38%	1.79%	
(# of MSA - Month)	(3721)	(3556)	
t-statistics	10.60***	8.32***	1.89**
Up Market	2.47%	2.07%	
(# of MSA - Month)	(2945)	(2787)	
t-statistics	9.55***	8.42***	1.11
Down Market	2.01%	0.65%	
(# of MSA - Month)	(776)	(769)	
t-statistics	4.62***	1.63*	2.3**
Difference t-test (Up vs. Down Market)			
t-statistics	0.90	3.03***	
Herding Type	HIP	HOP	Difference t-test (High vs. Low)
			t-statistics
Panel A. Mean Herding Statisti	c (Number of MSA \geq 10)		
Total Market	2.99%	2.95%	
(# of MSA - Month)	(1793)	(1781)	
t-statistics	10.68***	11.13***	0.11
Up Market	3.25%	3.40%	
(# of MSA - Month)	(1436)	(1384)	
t-statistics	10.08***	11.28***	-0.35
Down Market	1.97%	1.13%	
(# of MSA - Month)	(357)	(397)	
t-statistics	3.69***	2.36**	1.16
Difference t-test (Up vs. Down Market)			
t-statistics	2.06**	3.99***	

Table 3 Mean herding statistics, segregated by herding into (HIP) and out-of permits (HOP)

Residential development permits indicate the number of new housing units authorized by the acquisition of building permits. Data are available on a monthly, year- to- date, and annual basis at the national, state, and selected metropolitan area levels as provided by the US Census Bureau. We employ US Business Cycle Expansions and Contractions provided by the National Bureau of Economics Research (NBER) to define the market cycle (up- and down-market).***, **, * are the 1%, 5 and 10% significance levels respectively

but fades in up-market periods, as its statistical significance declines (HIP = 2.47% vs HOP = 2.07%). With the higher threshold of 10 MSAs (Table 3 Panel B), we find no significant differences in herding directions (HIP vs HOP) regardless of the market conditions. These results do not support the fourth of our hypotheses.

Generally, the results show that overall herding occurs irrespective of the state of the market, but is higher in up markets. This difference between overall herding in up markets and down markets tends to disappear when herding is further analyzed by direction. It persists only for down markets with the lower, and arguably less robust, MSA threshold. While intuition might suggest that herding into permits (HIP) might be stronger in up markets, and vice versa, the definition of the herding measure means this need not be so. Specifically, it is possible that even with permit issuance high and/or increasing in a State, developers' uncertainty about personal information still inclines them to mimic the behavior of those developers whose actions they observe - not all of whom may be increasing their permit seeking. Conversely, in down markets, developers may still exhibit a tendency to mimic the behavior of developers who are increasing their permit seeking, because they lack sufficient information to arrive at the more 'expected' response. It is important to note that we are describing neither the behavior of all developers nor the impact of market conditions on their overall level of permit seeking behavior, but rather one dimension of that behavior. Recognition of this accommodates the possibility that differences such as we observe in down markets using our less robust filter (sampling all states with MSAs of 5 or more), where herding into permits exceeds herding out of permits, are possible. Taken as whole, however, the results indicate that herding, both in its presence and in its duality of direction, persists irrespective of market condition.

Herding and House Prices

Herding into (out-of) permits increases (decreases) the supply of residential units. We therefore expect that herding into (out-of) permits will be associated with decreased (increased) house prices at the time when corresponding supply reaches the market. We assume that construction of residential homes takes on average 6 months to complete (Coulson 1999) and can typically take a minimum of a further 30 days to close (due to such issues as surveys, real estate appraisals, county inspections, attorney deed preparation and loan closing). Therefore, we use six and 7 month time lags between the herding behavior associated with residential development permit issuance and its reflection in housing prices. For example, if residential developers herd toward an increase in permit issuance (HIP), this increases the supply of residential space which other things equal results in a decrease in housing price. And, vice versa.

We test these hypotheses, using vector autoregressive (VAR) models.⁷ The dependent variable, our proxy for national home prices, is the House Price Index (HPI)

⁷ The Akaike information criterion (AIC) and the Final prediction error (FPE) criterion specify 6 lags to be included in the regressions. We verify these findings with the post-estimation Lagrange-multiplier Test (LM). The LM test conveys the condition of no serial correlation in the residuals with a larger lag order for some models. We report only 3 lags for the sake of brevity.

able 4 Phillips and I	Perion (PP)	Unit Root Tests				
	Bandwidth	Test Statistic Intercept Only	Critical Value	Bandwidth	Test Statistic Intercept and Trend	Critical Value
Δ HPI	7	-5.986	-3.457	7	-6.519	-3.996
Δ BP (6)	7	-15.826	-3.457	6	-16.123	-3.996
Δ BP (7)	7	-15.800	-3.457	6	-16.101	-3.996
HIP5 (6)	4	-13.065	-3.457	3	-13.764	-3.996
HIP5 (7)	4	-13.175	-3.457	3	-13.845	-3.996
HOP5 (6)	4	-12.408	-3.457	5	-13.341	-3.996
HOP5 (7)	4	-12.411	-3.457	5	-13.350	-3.996
HIP5 Interaction (6)	6	-12.163	-3.457	2	-13.234	-3.996
HIP5 Interaction (7)	6	-12.143	-3.457	2	-13.158	-3.996
HOP5 Interaction (6)	5	-12.191	-3.457	3	-13.236	-3.996
HOP5 Interaction (7)	5	-12.188	-3.457	3	-13.184	-3.996

Table 4 Phillips and Perron (PP) Unit Root Tests

HPI is the monthly home price index as published by Federal Housing Finance Agency (FHFA) and is the dependent variable. Building permits are the total monthly building permits issued in the US as collected by the Census Bureau. The HIP5 and HOP5 variables are an increase and corresponding decrease in building permit issuance in states with 5 or more metropolitan statistical areas (MSA). (6) and (7) are the corresponding months that each variable is lagged for the model. Δ is the first difference operator. MacKinnon asymptotic critical values are shown at the 1% level. The Phillips-Perron test bandwidth is determined by the Newey West procedure with a Bartlett kernel

provided by the Federal Housing Finance Agency (FHFA).⁸ Initially, we test each variable to see its order of integration using the Phillips and Perron (1988) (PP) test. The home price index and building permits, transformed by first differencing from their original price levels as is proper for VAR models, are stationary as expected. Additionally, our HIP and HOP variables and their interactions are I(0) following a random walk process. The results are presented in Table 4. We report results only for the lowest of our MSA thresholds (i.e. for States with five or more MSAs) for the sake of brevity-

Our VAR model results are provided in Table 5. Overall, the first four models (1 through 4) have 6 months lagged variables while the second four models (5 through 8) are where the variables are lagged 7 months. Table 5 shows national home prices (HPI) have significantly positive coefficients, which provide evidence that current home prices are highly dependent on past home prices. In terms of building permit issuance variable, the first lag of monthly building permit issuance with models 5~8 has a statistically positive relationship with home prices. In Models 1~4 the second lag has a similar relationship. These findings imply that building permit issuance approximately 8 months prior positively affects current national home prices, which is consistent with our expectation.

⁸ This is a repeat sales index taken from mortgage data provided by the Federal National Mortgage Association (FNMA) and the Federal Home Loan Mortgage Corporation (FHLMC). It was first published in 1995 by the Office of Federal Housing Enterprise Oversight (OFHEO), but is updated and released currently by FHFA.

Table 5 Housing price vector	-autoregressive (VA	AR) model and here	ling behavior					
Variables	1 HPI	2 HPI	3 HPI	4 HPI	5 HPI	6 6	7 HPI	8 HPI
Constant	-0.000	-0.000	0.000	0.000	-0.000	000.0-	0.001	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(00)	(000)	(0.00)	(000)
HPI (-1)	0.248 * * *	0.245***	0.253***	0.294^{***}	0.222^{***}	0.221^{***}	0.222***	0.281^{***}
	(0.06)	(0.06)	(0.07)	(0.07)	(0.06)	(0.07)	(0.07)	(0.07)
HPI (-2)	0.179^{**}	0.154^{**}	0.183^{**}	0.099	0.162^{**}	0.148^{**}	0.190^{**}	0.089
	(0.07)	(0.07)	(0.08)	(0.08)	(0.07)	(0.07)	(0.07)	(0.08)
HPI (-3)	0.111	0.119*	0.129	0.146*	0.114	0.119*	0.123	0.155*
	(0.07)	(0.07)	(0.08)	(0.08)	(0.07)	(0.07)	(0.08)	(0.08)
BP (-1)	0.004	0.003	0.003	0.004	0.013^{***}	0.013^{***}	0.011^{**}	0.013**
	(0.00)	(00.0)	(00.0)	(0.00)	(00.0)	(000)	(0.00)	(0.00)
BP (-2)	0.014^{***}	0.014^{***}	0.012**	0.015^{***}	0.005	0.004	0.007	0.008^{*}
	(0.00)	(00.0)	(00.0)	(0.00)	(0.00)	(000)	(0.00)	(0.00)
BP (-3)	0.004	0.003	0.007	0.006	-0.004	-0.005	-0.001	0.002
	(0.00)	(000)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
HIP5 (-1)	0.004		-0.010		-0.000		-0.043^{***}	
	(0.00)		(0.01)		(00.0)		(0.01)	
HIP5 (-2)	-0.000		-0.037^{**}		-0.001		-0.041^{***}	
	(0.00)		(0.01)		(0.00)		(0.01)	
HIP5 (-3)	-0.002		-0.042**		0.007		0.042***	
	(0.00)		(0.01)		(0.00)		(0.01)	
HOP5 (-1)		0.002		0.002		0.011*		0.039**
		(00.0)		(0.01)		(0.00)		(0.01)

Table 5 (continued)								
Variables	1 HPI	2 HPI	3 HPI	4 HPI	5 HPI	6 HPI	7 HPI	8 HPI
(<i>-</i> -) HOP5		0.010*		0.036**		0000		-0.054***
		(0.00)		(0.01)		(0.00)		(0.01)
HOP5 (-3)		-0.000		-0.049***		0.002		-0.038**
		(0.00)		(0.01)		(0.00)		(0.01)
Herding Interaction (-1)			0.012	-0.000			0.046^{***}	-0.033*
			(0.01)	(0.01)			(0.01)	(0.01)
Herding Interaction (-2)			0.040 **	-0.032*			0.041 **	0.059***
			(0.01)	(0.01)			(0.01)	(0.01)
Herding Interaction (-3)			0.044^{**}	0.052***			-0.043**	-0.031
			(0.01)	(0.01)			(0.01)	(0.01)
Updown Dummy	0.000	0.001	0.000	0.000	0.000	0.000	-0.000	0.000
	(0.00)	(00.0)	(0.00)	(0.00)	(00.0)	(0.00)	(000)	(000)
Adjusted R ²	0.64	0.65	0.66	0.68	0.64	0.65	0.67	0.68
We examine the following ve variable. Building permits an corresponding decrease in bui denoting expansions and con significance levels respective	ctor autoregressiv e the total monthly lding permit issua tractions as provi ly	e models (VAR). HI y building permits i nce in states with 5 ded by the Nationa	PI is the monthly h issued in the United or more metropolita I Bureau of Econo	ome price index as pu 1 States as collected 1 In statistical areas (MS mics Research (NBE	blished by Federal by the Census Bure SA). The Up down I R). Standard errors	Housing Finance / au. The HIP5 and Dummy is a 0 (dow are in parentheses	Agency (FHFA) and HOP5 variables are m-market) and 1 (up- s, ***, **, * are the	s the dependent an increase and market) variable 1%, 5 and 10%

With regard to linkages between the herding behavior of an individual developer to the totality of building permits across the United States, we posit that individual developers herd into permits during "up" periods in the market and herd out of permits during "down" periods. As a result, the aggregate total of permits should increase during expansionary cycles, while decreasing during recessionary cycles. We include an "updown" dummy and the corresponding HIP and HOP interaction terms in our VAR models in order to properly control for real estate market conditions. The HIP and HOP variables provide additional evidence of an approximate 8 months' time lag between herding behavior and the ensuing change in housing prices. As the coefficients of HIP shows, herding toward an increase in development issuance has a negative relationship with home prices in almost all cases. This result supports our expectation: HIP raises the supply of residential space, which results in a decrease in housing prices. In particular, the interaction between the up-market dummy and the HIP variable increases the statistical significance, magnitude and coefficient of the herding variable. This is not surprising as we find the mean herding statistics in up market conditions show higher herding behavior rather than in down markets.

We also find the consistent evidence with HOP. As the coefficients of HOP show, herding toward decrease in development issuance has a positive relationship with home prices; HOP causes a decrease in supply, with raises in housing prices after approximately 8 months. As a form of robustness check, we modeled a VAR equation including the returns of the HPI and BP variables. These confirm our previous results in the first difference model shown here as the findings are quite similar. These are not shown to save space, but can be provided upon request.

Conclusion

We investigate herding by residential real estate developers, using building permit issuances as our indicator for this and adopting measures that have been widely adopted in studies of the same phenomena is financial markets. We find evidence of herding in building permits, which occurs in up markets and in down-markets. The overall level of this herding is comparable to that found in other studies involving common-stock trading, and higher than found by Ro and Gallimore (2014) for trading by real estate mutual funds. The herding is stronger in up markets than in down markets. This finding is consistent with the assumption that in the buoyancy of up markets there is relatively less reliable, independent information, and that this reinforces the tendency to follow the behavior of others (i.e. herd). We also find that herding can be present when permit issuance is both rising and falling. Although our expectation that the former will be stronger in up-markets, and vice versa, is not reflected in our results. When we turn to the relationship between herding and house prices we find that after a lag, herding feeds through into price changes in the expected direction, making discovery of the phenomenon revealing from both theoretical and practical perspectives.

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Appendix 1

By Bayes' Rule, since

$$\begin{aligned} ⪻(V = 1|S_{1A} = 1) = Pr(S_{1A} = 1 \cap V = 1)/Pr(S_{1A} = 1) \\ &= \frac{Pr(S_{1A} = 1|V = 1)Pr(V = 1)}{Pr(S_{1A} = 1|V = 1)Pr(V = 1) + \Pr(S_{1A} = 1|V = 0)Pr(V = 0)} \\ &= \frac{\phi_1 p}{\phi_1 p + (1 - \phi_1)(1 - p)}, \end{aligned}$$

we have

$$R_{1A}\left(S_{1A}|_{S_{1A}=1}\right) = E(V|S_{1A}=1) - C$$

= $\Pr(V = 1|S_{1A} = 1) - C$
= $\frac{\phi_{1P}}{\phi_{1P} + (1 - \phi_{1})(1 - p)} - C.$

Appendix 2

By Bayes' Rule, because

$$Pr(S_{1A} = 1 \cap S_{2B} = 0)$$

= Pr(S_{1A} = 1 \cap S_{2B} = 0 | V = 1)Pr(V = 1)
+ Pr(S_{1A} = 1 \cap S_{2B} = 0 | V = 0)Pr(V = 0)
= \phi_1(1-\phi_2)p + \phi_2(1-\phi_1)(1-p),

we have

$$\begin{aligned} R_{2B}\Big(S_{1A}, S_{2B}|_{S_{1A}=1\cap S_{2B}=0}\Big) &= \rho[E(V|S_{1A}=1\cap S_{2B}=0)-C] \\ &= \rho\Big[\frac{Pr(S_{1A}=1\cap S_{2B}=0|V=1)Pr(V=1)}{Pr(S_{1A}=1\cap S_{2B}=0)}-C\Big] \\ &= \frac{\rho\phi_1(1-\phi_2)p}{\phi_1(1-\phi_2)p+\phi_2(1-\phi_1)(1-p)}-\rho C. \end{aligned}$$

Appendix 3

By Bayes' Rule, because

$$Pr(S_{1A} = 0 \cap S_{2B} = 1)$$

= Pr(S_{1A} = 0 \cap S_{2B} = 1 | V = 1)Pr(V = 1)
+ Pr(S_{1A} = 0 \cap S_{2B} = 1 | V = 0)Pr(V = 0)
= (1-\phi_1)\phi_2p + \phi_1(1-\phi_2)(1-p),

we can obtain

$$\begin{split} R_{2B}\Big(S_{1A}, S_{2B}|_{S_{1A}=0\cap S_{2B}=1}\Big) &= \rho[E(V|S_{1A}=0\cap S_{2B}=1)-C] \\ &= \rho\Big[\frac{Pr(S_{1A}=0\cap S_{2B}=1|V=1)Pr(V=1)}{Pr(S_{1A}=0\cap S_{2B}=1)}-C\Big] \\ &= \frac{\rho(1-\phi_1)\phi_2p}{(1-\phi_1)\phi_2p+\phi_1(1-\phi_2)(1-p)}-\rho C. \end{split}$$

References

- Baerwald, T. (1981). The site selection process of suburban residential builders. Urban Geography., 2(4), 339– 357.
- Banerjee, A. V. (1992). A simple model of herd behavior. *Quarterly Journal of Economics.*, 107(3), 797-817.
- Bernhardt, D., Campello, M., & Kutsoati, E. (2006). Who herds? Journal of Financial Economics, 80(3), 657–675.
- Bikhchandani, S., Hirshleifer, D., & Welch, I. (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of Political Economy.*, 100(5), 992–1026.
- Carliner, M. (1986). Lags and leakages in housing data. Housing Economics. September, 7-8.
- Choi, N., & Sias, R. (2009). Institutional industry herding. Journal of Financial Economics, 94(3), 469-491.
- Coulson, N. E. (1999). Housing inventory and completion. Journal of Real Estate Finance and Economics., 18(1), 89–105.
- DeCoster, G. P., & Strange, W. C. (2012). Developers, herding and overbuilding. Journal of Real Estate Finance and Economics., 44(1–2), 7–35.
- Devanow, A., & Welch, I. (1996). Rational herding in financial economics. European Economic Review, 40(3–5), 603–615.
- Grinblatt, M., Titman, S., & Wermers, R. (1995). Momentum investment strategies, portfolio performance, and herding: a study of mutual fund behavior. *American Economic Review*, 85(5), 1088–1105.
- Hepner, G. (1983). An analysis of residential developer location factors in a fast growth urban region. Urban Geography, 4(4), 355–363.
- Hott, C. (2012). The influence of herding behaviour on house prices. Journal of European Real Estate Research, 5(3), 177–198.
- Kenney, K. (1972). The residential land developer and his land purchase decision. PhD Dissertation. University of North Carolina: Chapel Hill, North Carolina.
- Lai, R. N., & Van Order, R. A. (2010). Momentum and house price growth in the United States: Anatomy of a bubble. *Real Estate Economics*, 38(4), 753–773.
- Lakonishok, J., Shleifer, A., & Vishny, R. W. (1992). The impact of institutional trading on stock prices. *Journal of Financial Economics*, 32(1), 23–43.
- Leung, L. (1987). Developer behavior and development control. Land Development Studies., 4(1), 17-34.
- Lux, T. (1995). Herd behaviour, bubbles and crashes. *The Economic Journal*, 105(431), 881–896.
- Mayer, C., & Somerville, T. (2000). Land use regulation and new construction. *Regional Science and Urban Economics*, 30(6), 639–662.

Mohamed, R. (2006). The psychology of residential developers: lessons from behavioral economics and additional explanations for satisficing. *Journal of Planning Education and Research*, 26, 28–37.

Phillips, P. C. B., & Perron, P. (1988). Testing for unit roots in time series regression. *Biometrika*, *71*, 335–346. Pierdzioch, C., Rulke, J., & Stadtmann, G. (2010). Housing starts in Canada, Japan and the United States: do

- forecasters herd? Journal of Real Estate Finance and Economics, 45(3), 754–773.
 Ro, S., & Gallimore, P. (2014). Real estate mutual funds: herding, momentum-trading and performance. Real Estate Economics, 42(1), 190–222.
- Scheinkman, J. A., & Xiong, W. (2003). Overconfidence and speculative bubbles. *Journal of Political Economy*, 111(6), 1183–1219.
- Seiler, M. J., Lane, M. A., & Harrison, D. M. (2014). Mimetic herding behavior and the decision to strategically default. *Journal of Real Estate Finance and Economics*, 49(4), 621–653.
- Simon, H. (1957). Models of man: Social and rational; mathematical essays on rational human behavior in a social setting. In *Wiley* (Vol. 24, p. 382). New York: New York.
- Simon, H. (1979). Rational decision making in business organizations. American Economic Review, 69(4), 493–513.
- Somerville, C. T. (1999). The industrial organization of housing supply: market activity, land supply and the size of homebuilder firms. *Real Estate Economics*, 27(4), 669–694.
- Somerville, C. T. (2001). Permits, starts, and completions: structural relationships versus real options. *Real Estate Economics*, 29(1), 161–190.
- Welch, I. (2000). Herding among security analysts. Journal of Financial Economics, 58(3), 369–396.
- Wermers, R. (1999). Mutual fund herding and the impact on stock prices. Journal of Finance, 54(2), 581-622.
- Xiong, W. (2013). Bubbles, crises, and heterogeneous beliefs. In J.-P. Fouque & J. Langsam (Eds.), Handbook of system risk. Cambridge University Press: New York.
- Zhou, J. Q., & Anderson, R. (2013). An empirical investigation of herding behavior in the US REIT market. Journal of Real Estate Finance and Economics, 47(1), 83–108.
- Zhou, R. T., & Lai, R. N. (2008). Herding and positive feedback trading on property stocks. Journal of Property Investment & Finance, 26(2), 110–131.