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A field study conducted in Shanghai identified a robust inconsistency between real estate developers' desired sales pattern (selling all apartments in a building at similar rates) and the actual sales pattern (selling good apartments faster). The authors explain this inconsistency using Tversky, Sattath, and Slovic's (1988) prominence principle, according to which buyers, who were in a choice mode, weighed the desirability of floors more heavily than developers, who were in a matching mode when setting prices. This explanation is corroborated by controlled experiments involving potential home buyers and professional real estate price setters. The research relates an intriguing anomaly originally found in paper-and-pencil surveys to a real-world issue in one of the world's most active markets. These findings also have implications for issues beyond real estate markets.

Keywords: real estate, pricing, preference reversal, prominence effect, choice versus matching

The Prominence Effect in Shanghai Apartment Prices

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Leading irregularities due to equations, stacks, etc., will be dealt with in page layout.

Since the new millennium, China has emerged as one of the world's most formidable consumer markets. In 2004, the size of the consumer market was estimated at 36 million urban Chinese, and every year, approximately 20 million Chinese turn 18 years of age (Grant 2006). The impact of this consumer boom has been particularly apparent in the Chinese real estate market, one of the most active real estate markets in the world. During the late 1990s, the Chinese government enacted several radical changes in the regulation of state-provided housing to stimulate economic growth. In 1999, the state lifted a ban on the resale of privatized housing. These measures led to an explosion in the Chinese housing market, which was subsequently estimated as contributing 1.5% of annual growth in gross domestic product (*The Economist* 2001). Rapidly rising housing prices—in Shanghai, prices have nearly doubled between 2000 and 2004 (*The Economist* 2005)—have fueled billions of dollars in housing construction. Since 1996, 67,333 residential properties were sold in Shanghai. In 2000 alone, approximately 7.5 million square meters (80.73 million square feet) of existing houses were sold in Shanghai, with a total transaction value of roughly 65.6 billion renminbi (RMB) (approximately US\$8 billion) (Ye 2004). At a more micro level, real estate developers are increasingly relying on careful pricing practices to avoid missing profitable opportunities in this fast-paced but otherwise relatively young housing market.

In this article, we begin with an interview study (Study 1) that involves real estate professionals who set prices for developers in Shanghai. The study indicates that most of them strategically set their prices to obtain a sales pattern, whereby all their units sell at the same rate over time.

The main empirical part of the article is a field study involving three data sets from Shanghai (Study 2). The study shows that despite developers' efforts to price apartments commensurate with their quality as perceived by consumers, in practice, sellers routinely find that the less desirable units sell at a much slower pace. Specifically, apartments on the lowest floors, the least desirable floors in the Chinese market, are routinely slower to sell.

Note that we do not claim that the good-faster-than-bad sales pattern is necessarily a mistake. Which sales pattern is normatively optimal depends on many additional factors, including the state of the market at the time, developers' budgetary constraints, their rate of time preference, and many other factors that we do not know. In this article, we are interested only in the discrepancy between developers' desired sales pattern and the actual sales pattern.

We explain the discrepancy between the desired and the actual sales patterns using Tversky, Sattath, and Slovic's (1988) prominence principle. According to this principle, different response modes (choice versus matching) lead to different weighting of different attributes. When faced with options involving multiple attributes, people in the matching mode tend to assign less weight to the most important (prominent) attribute than people in the choice mode. In the context of real estate markets, developers are in a matching mode when setting prices, and consumers are in a choice mode when deciding which units to purchase. Survey data suggest that floor is considered a more important attribute than price. Thus, according to the prominence principle, developers underweight the importance of floors relative to

buyers. This explains why good floors sell faster than bad floors.

To rule out confounding variables and test our explanation further, we conducted two controlled experiments (Study 3 and Study 4), in which respondents either set prices for or chose between hypothetical apartments. Study 3 uses participants from the same population (potential home buyers) as price setters and as choosers. Study 4 uses professionals as price setters and potential home buyers as choosers. The results of both experiments were remarkably parallel to the results of the field study, thus reinforcing our belief that the prominence principle is the underlying reason.

To the best of our knowledge, we are the first to make a connection between the prominence effect and real outcomes in the marketplace. Our findings shed light on a peculiar pricing anomaly in one of the world's most turbulent and rapidly growing markets—the Shanghai real estate market. Our findings also yield implications beyond the Shanghai real estate market. We discuss these implications in the “General Discussion” section.

STUDY 1: INTERVIEW OF REALTORS REGARDING THEIR DESIRED SALES PATTERN

The main purpose of this study was to examine the sales patterns that professional price setters who represented developers attempted to achieve. In addition, the study explored why price setters wanted the sales pattern they indicated and how they set prices to achieve it.

Method

We conducted extensive interviews with 47 real estate professionals who collaborated closely with a Web site in the business of apartment trading and financial mortgage. Their qualifications ranged from general managers of real estate companies, to marketing managers responsible for real estate pricing, to employees who had been working for more than two years in the real estate industry with significant pricing experience.

In the interview, we first explained that “sales pattern” was defined as the sales rate of different floors. Then, we explained how price differences shaped sales patterns. Specifically, we told respondents that if the price difference between good floors and bad floors was relatively small, good floors would sell faster than bad floors. If the price difference was sufficiently large, good floors would sell slower than bad floors. Finally, there was an intermediate price difference such that good floors and bad floors would sell roughly at the same rate. These three scenarios corresponded to three sales patterns: good-faster-than-bad pattern, bad-faster-than-good pattern, and flat pattern.

We then asked the interviewees which of these three sales patterns they would attempt to achieve if they were developers setting prices for apartments in a new apartment building. We also asked the interviewees to explain the reasons for their preference for the specific sales pattern they indicated. Finally, we asked them for the pricing methods they used to achieve their desired sales pattern.

Results and Discussion

From the interviews, we learned that, in general, most respondents preferred either a flat or a bad-faster-than-good

sales pattern. Of the 47 interviewees, 26 wanted the flat pattern, 16 wanted the bad-faster-than-good pattern, 3 wanted the good-faster-than-bad pattern, and 2 did not give clear answers. The interview responses provided overwhelming support (89% of interviewees) for a sales pattern in which the bad apartments sell at least as fast as the good apartments.

The respondents also provided several explanations for why they would want apartments on less desirable floors to sell at least at the same rate as good apartments. A common explanation was that good apartments were important for attracting potential consumers who need to expend time and effort to visit a development in the first place. If most of the units on good floors had been sold out, a building had more difficulty attracting potential consumers. Some respondents speculated that if units on good floors were unavailable, consumers would not even bother to come to visit a new building. In general, if there were only bad floors available, developers would need to resort to other means of attracting consumers, such as aggressive price reductions that often lowered the developer's profit.

The interviewees also provided cultural reasons they would prefer not to sell the apartments on the best floors first. In China, it is common for people to live close to their relatives (including parents and children) and friends. Therefore, friends and relatives often buy apartments in the same building. For social reasons, people do not want to purchase apartments on inferior floors. However, a developer would prefer to have early purchasers buy apartments on relatively undesirable floors because it would be much easier subsequently to sell to friends and family on more desirable floors. In contrast, if early buyers purchased on the better floors, it would be much more difficult to sell units subsequently to their friends and family on a less desirable floor.

Each of these reasons implies that selling the more desirable units in a building first hurts the developer financially. Either the time to sell all the units in a building would be increased, or the prices of the less desirable units would need to be decreased. Therefore, developers preferred to sell the less desirable units at least as fast as the more desirable ones.

The interviews also provided accounts of the typical pricing strategy used to achieve the desired sales pattern. To determine the list price, developers first chose an average-quality unit in a building. By dividing the total desired profit from the building by the total square meters, they obtained the base price per square meter for this average unit (i.e., they used cost-plus pricing). They adjusted the prices of the remaining units up or down depending on their quality relative to the average unit. For the floor of an apartment, they typically used a constant price adjustment, assuming that higher floors were more desirable. For example, they might pick an average-quality floor, such as the 5th floor, and set the base price at 6000 RMB per square meter.¹ They would then add 300 RMB per square meter for every floor above the 5th and deduct 300 RMB per square meter for every floor below the 5th. In addition to assigning an upward price adjustment to higher floors, developers might make further adjustments; for example, they might assign a downward adjustment to the price of the top floor because it may get very hot during the sum-

mer. Floor was not the only price differentiator. Developers might also make price adjustments based on other factors, such as exposure and floor plan.

To determine the price adjustment between floors in a building, developers typically took the following steps: First, they surveyed potential consumers with questions such as, “If the 5th floor is worth 6000 RMB per square meter, how much do you think the 6th floor is worth?” These types of stated-preference data generated preliminary estimates of consumer willingness to pay for floors. To gauge the external validity of these estimates, some developers visited buildings in the surrounding area to measure the competitive prices. Developers might also use crude checks, such as comparing results with their own personal views of what they would be willing to pay for a 6th-floor apartment given the availability of a 6000 RMB 5th-floor unit. In general, however, the price adjustment for floors was obtained through a matching strategy, in which floors were priced according to their perceived value relative to a base level. In short, the main finding from Study 1 is that professional price setters preferred to sell apartments on less desirable floors first or to sell all the apartments at the same rate.

STUDY 2: FIELD STUDY

Study 1 revealed developers’ preference to sell the less undesirable units in a building at least as fast as the more desirable units. We now examine the actual pricing of several representative buildings in Shanghai. We examine the corresponding sales patterns of the units in these buildings to determine whether they are consistent with the preferred sales pattern the developers described.

Method

We selectively used developments from three major residential areas in Shanghai to obtain a roughly representative account of the real estate market. The three properties contained both mid-rises and high-rises targeted to consumer groups ranging from middle-income employees to relatively rich people. In each of the properties studied, all units were listed on the market from their launch dates. Thus, developers of these properties did not tactically withhold the good apartments to manipulate the sales rate.

Data Set 1: four 6- or 7-floor mid-rises. Our first data set came from a gated community consisting of two 6-story and two 7-story mid-rises. Each floor in each building had two units with an average unit size of 140 square meters. All the units faced south. The four buildings were initially offered in November 1999. Consistent with our interviews with developers, in general, prices were higher for higher floors except for top floors. Specifically, prices started at 7300 RMB per square meter for the 1st floor and increased by approximately 100 RMB per square meter for each higher floor. However, the price of the 6th floor was the same as that of the 5th floor, and the price of the 7th floor was the same as that of the 3rd floor.

To confirm the relationship between prices and floor, we ran several hedonic price regressions to control for other apartment characteristics. We report the results in Table 1. Approximately 87% of the price variation was explained by the floor on which an apartment was situated. Controlling for the specific building and size of an apartment explained

only an additional 3%. These findings confirm that, consistent with the interviews in Study 1, pricing in our field data was driven primarily by the floor on which an apartment was situated.

Data Set 2: seven 11-floor mid-rises. Our second data set came from seven mid-rises located in a newly developed neighborhood in Shanghai. Each building had 11 floors, with two units on each floor; the average size of each unit was 150 square meters. All seven buildings were initially offered in September 2001. Again, the prices were higher for higher floors, except for top floors. The per-square-meter price was 4459 RMB for the lowest floor, increased by 140–180 RMB for each additional floor, reached the highest level of 5791 RMB for the 10th floor, and dropped to 5605 RMB for the 11th floor. In Table 1, we also report the hedonic price regression results for these data. Again, we found that the floor on which an apartment was situated explained more than 90% of the price variation. Controlling for building and apartment size explained an additional 5%.

Data Set 3: a 30-floor high-rise. In the two previous field data sets, we examined the price pattern of mid-rises. The third data set corresponded to a 30-story high-rise building with 20 units on each floor. With the exception of the 28th and 29th floors, which had larger units, each floor had the same floor plan. The 1st through 3rd floors were for commercial use and not for sale. The unit sizes ranged from 25 square meters to 105 square meters. The per-square-meter price started at 11,000 RMB for the lowest floor and increased by approximately 40 RMB for each additional floor, with two slightly larger jumps for the 5th floor and the 28th floor. Table 1 indicates that 82% of the price variation in these data was explained by the floor on which an apartment was situated. Controlling for building, apartment size, and the specific exposure of the apartment (e.g., North versus Northwest) explained an additional 10%.

Results and Discussion

In this section, we first qualitatively illustrate that bad floors sold more slowly than good floors, we then operationally define good floors and bad floors by surveying consumers, and, from these definitions, we finally quantitatively confirm that bad floors indeed sold more slowly.

Qualitative analysis of the field data. To assess the sales pattern across the four buildings, we report the average number of months for a unit to sell by floor in the Data Sets 1, 2, and 3 in Figures 1, 2, and 3, respectively. As these figures illustrate, contrary to the intentions of most developers, apartments on different floors seemed to sell at different rates. For example, in Figure 1, units on the 4th floor took only 15.1 months to clear the market, but units on the 1st floor took 20.8 months.

Furthermore, the sales pattern across floors did not seem random. On average, apartments on low floors appeared to sell more slowly than apartments on other floors. The observation that low floors sold more slowly was particularly striking in light of the systematic pricing patterns we detected for these same developments. Specifically, apartments on different floors were priced differently. To the extent that such pricing was intended to equalize the selling time of apartments on different floors, as in Study 1, the sales patterns were surprising.

In China, particularly in Shanghai, low floors are considered undesirable because units on low floors usually are damp, have poor views, and are susceptible to mosquitoes. Thus, we hypothesize that, in general, slow-selling units are on undesirable floors, and fast-selling units are on desirable floors.

Note that in the 30-story building (Figure 3), the 13th and 14th floors also sold slowly. We believe that this was because 13 is an unlucky number in China, and 14 sounds similar to “will die” in Chinese. Moreover, the two top floors also sold slowly. This was probably because the floor plans on these floors were different from those on the other floors and also because the top floors in a high-rise can get very hot during the summer. Thus, these results also conform to our speculation that undesirable floors sell more slowly.

Defining good and bad floors. To test this hypothesis, we need a more fine-tuned definition of good and bad floors. We asked potential homebuyers to tell us which floors were good and which floors were bad. We then treated their judgments as the operational definition of good and bad floors and reanalyzed the three data sets.

We conducted a survey on 84 students in an open-enrollment business class in a large university in Shanghai. Their ages ranged from 28 to 55 and were representative of home buyers in Shanghai. Most (93.5%) of them had already purchased homes in the city.

In the questionnaire, participants indicated whether floor or price was more important to them when considering buying an apartment in Shanghai. They were then asked to consider buying an apartment in a hypothetical 7-story building with identical floor plans for each apartment. For this building, participants were asked to indicate which floors they would consider bad floors. Similar exercises were then carried out in the context of a hypothetical 11-story building and then for a 30-story building for which the first 3 floors were not for sale. We chose these three hypothetical buildings to mimic the three types of buildings in our field study.

The results from the survey confirmed the strong role of floor. Of the respondents, 72% indicated that floor was more important than price.

Critically, the survey clarified which floors buyers considered bad. We use 50% as our cutoff point and consider a floor bad if more than 50% of respondents judged it to be bad. In the 7-story building, the 1st and 2nd floors were considered bad. In the 11-story building, the 1st and 2nd floors were considered bad. In the 30-story building, the 4th, the 5th, and the 30th floors were considered bad. (Compared with surrounding floors, the 13th and 14th floors were rated by more respondents as bad, but the percentages did not reach 50%.)

Notably, the relative position of a floor in a building seemed to dictate whether it was perceived as bad or good as opposed to the absolute floor number. For example, in the 30-story building, the relatively low 4th and 5th floors were considered bad even though this was not the case in the smaller 7- and 11-story buildings.

Quantitative analysis of the field data. We now revisit the three field data sets. Recall from Figures 1, 2, and 3 that we observed different selling rates for different floors. Using the survey results to define good and bad floors, we could

empirically test whether bad floors in the field study indeed sold more slowly than good floors.

The results supported our hypothesis that units on bad floors sell slower than units on good floors. In Data Set 1, the bad floors stayed on the market for 21.00 months, whereas the good floors stayed on the market for only 15.00 months ($t = 2.19, p < .05$). In Data Set 2, the bad floors stayed on the market for 36.32 days, whereas the good floors stayed on the market for only 26.10 days ($t = 2.77, p < .01$). In Data Set 3, the bad floors stayed on the market for 10.31 months, whereas the good floors stayed for only 6.40 months ($t = 5.45, p < .0001$).

To confirm that our results were robust to characteristics other than the floor on which an apartment was situated, we conducted the following analysis: For each of the three data sets, we tested for a bad-floor effect on sales time while controlling for other apartment characteristics. We used a Poisson model to address the fact that sales duration data consisted of positive integer values. We specified the mean of this Poisson process as a function of apartment characteristics, including a dummy variable for whether an apartment was on a bad floor. The technical details for the Poisson model appear in the Appendix.

We report the results from the Poisson regression in Table 2. For each of the three data sets, we estimated three specifications. In the first, we conditioned only on the bad-floor dummy. In the second, we also included other observable physical apartment characteristics. In the third, we also conditioned on the price. For each covariate, we report the incidence rate ratios and their standard errors. As the Appendix explains, the reported bad-floor incidence rate ratio can be interpreted as the proportionate difference in time for an apartment to sell on a bad floor versus a good floor, all else being equal. In each of the specifications, we observed a bad-floor effect significantly larger than 1. Thus, even after controlling for apartment characteristics (including price), we found that bad floors took more time to sell than good floors.²

These results provided quantitative support for the apparent empirical puzzle: The actual sales patterns differed from the pattern intended by sellers. Given sellers' intentions, the patterns in prices and sales suggest that sellers were systematically underpricing good floors (or overpricing bad floors).

THEORY: PRICING VERSUS CHOICE

We have now confirmed that consumers indeed consider the floor on which an apartment is situated more important than its price. Apparently, developers were aware of the importance of floor. They attempted to gauge consumer willingness to pay for floors when adjusting prices of units on different floors. The observed inconsistency between the actual sales pattern and the developers' desired sales pattern is perplexing. Developers appeared to be systematically failing to set the relative prices of apartments on good and bad floors to achieve the desired sales pattern.

We consider this inconsistency a manifestation of preference reversals between different evaluation modes—in particular, the prominence effect. When home buyers decide which unit to purchase, they are in a choice mode; they make comparisons between units and choose the one they like most. In the choice mode, a home buyer selects a unit

from an offered set of two or more units after comparing different attributes, such as price and floor. However, when developers set apartment prices, they are in a matching mode; they match the prices of different units so that those units are equally attractive to consumers. Normatively speaking, consumers should be indifferent between apartments that, through matching, have been priced to appear equally attractive.

However, established research in judgment and decision making demonstrates that people do not have well-defined preferences (e.g., Bettman, Luce, and Payne 2006; Hsee, 1996; Lichtenstein and Slovic, 2006; Liu and Soman 2008). Different preference elicitation procedures may highlight different aspects of options, suggest alternative judgment strategies, and reverse or alter preferences.

A classic example of preference reversal is the choice-matching reversal that Slovic (1975) identifies and Tversky, Sattath, and Slovic (1988) extend. Participants in Tversky, Sattath, and Slovic's study were presented with information about two hypothetical job candidates applying for a production engineer position who differed on two attributes, technical knowledge and human relations, as follows:

	<i>Technical Knowledge</i>	<i>Human Relations</i>
Candidate A	86	76
Candidate B	78	91

Both attributes were rated on a scale ranging from 40 ("very weak") to 100 ("superb"). The participants were told that technical knowledge was more important than human relations. One group of participants (the choice condition) was asked to choose between the two candidates. Another group of participants (the matching condition) was presented with the same two alternatives, with one of the four scores missing, and was asked to fill in that missing score so that the two candidates were equally attractive. In the choice condition, most people chose Candidate A (the one with the better technical score), but in the matching condition, the score most people filled in suggested that they would have preferred Candidate B if that score had not been missing and had been the same as presented in the choice condition.

This finding suggests a prominence effect—that the more important attribute in a choice set (e.g., technical knowledge in the study) receives more weight in choice than in matching. This finding has been replicated in various forms by other researchers (e.g., Auh and Johnson 2005; Carmon and Simonson 1998; Chernev 2005; Fischer and Hawkins 1993; Nowlis and Simonson 1997).

Tversky, Sattath, and Slovic (1988) propose the prominence principle to explain the choice-matching reversal (see also Slovic, Griffin, and Tversky 1990). The weight of a stimulus attribute is enhanced by its compatibility with the task. In general, qualitative information about the ordering of the dimensions weighs more in the ordinal method of choice than in the cardinal method of matching, whereas quantitative information weighs more in matching than in choice.

As we mentioned previously, our survey of potential apartment buyers indicated that they considered floors more important than price. Given the prominence principle, in choice mode, we expected the floor of an apartment, the

qualitative attribute, to receive more weight than in matching mode. When developers used matching to determine the price adjustment for apartments on different floors of a building, they assigned relatively less weight to floor. In essence, the developers' use of matching led to a bias in their measure of consumer willingness to pay for floor because the actual demand for apartments was generated by choice.

In the next section, we present two controlled studies to understand better the mechanism that drove the inconsistency between the price setters and the choosers. In the field study, we attributed the observed inconsistency between the developers and the home buyers to difference in response mode—matching versus choice. However, as in most field studies, the result of our field study was susceptible to other explanations. For example, the respondents who participated in our interviews in Study 1 and desired a flat sales pattern were not the same developers who set the prices for the buildings reported in Study 2, which revealed a good-faster-than-bad sales pattern. Thus, we cannot rule out the possibility that the particular developers in Study 2 explicitly attempted to achieve a good-faster-than-bad pattern, in which case the observed sales patterns do not constitute an inconsistency.

Alternatively, developers may not have been from the same population as the home buyers. Thus, the inconsistency between the developers and the home buyers may not have been due to matching versus choice but rather to the developers' lack of understanding of the home buyers' tastes. For example, many developers in Shanghai were not originally from the city, and they may have underestimated Shanghai residents' dislike of low floors.

The purpose of Studies 3 and 4 was to demonstrate that the inconsistency between price setters and choosers as observed in the field data would persist even when we controlled for such confounding variables. These controls allow us to conclude that the inconsistency was indeed due to difference in response mode.

STUDY 3: CONSUMER PRICING VERSUS CONSUMER CHOICE

To control for possible differences between price setters and home buyers other than their different response modes, in Study 3, we used research participants from the same population (consumers) either to set prices or to choose apartments. In the pricing condition, we asked respondents to set the prices of two units in a hypothetical building and explicitly told them to set the prices so that the apartments were equally attractive, which meant a flat sales pattern. In the choice condition, we used the prices generated from the participants in the pricing condition to establish the prices of the same two units, and we asked participants in the choice condition to choose between the two units.

Method

We conducted this study using 140 respondents who were either students in a large business school in Shanghai or employees in two companies in Shanghai who had worked in the city for three to five years. Participants were assigned to either a pricing or a choice condition. In both conditions, participants were asked to imagine that they planned to buy a two-bedroom unit in Shanghai. They were

told that they were interested in a newly built, 15-story building in which only two units were left. The two units had the same 100-square-meter floor plan. The only difference was their floor location: Unit 101 was on the 1st floor, and Unit 801 was on the 8th floor.

In the pricing condition, participants completed two tasks in which they were told the price of one unit and were asked to state the price for the other unit that would make the two units equally attractive to them. In the first task, they were told that Unit 101, on the 1st floor, had a price of 500,000 RMB; then, they were asked to state the indifference price for Unit 801, an identical unit on the 8th floor. The second task was identical except that participants were told that the price of Unit 801 was 500,000 RMB and were asked to price Unit 101. We counterbalanced the order of Unit 101 and Unit 801.

In the choice condition, participants were again asked to perform two tasks. In this case, they were asked to make a choice between units 101 and 801. To be conservative, we designed the choice condition on the basis of the matched prices from the pricing condition to make the choices as “similar” as possible on average. Thus, in the first task, participants were asked to choose between Unit 101 priced at 500,000 RMB and Unit 801 priced at its average stated price from the pricing condition; we rounded the price up to the next highest integer value to make it realistic. In the second task, participants were asked to choose between Unit 101 priced at the average stated price from the pricing condition and Unit 801 priced at 500,000 RMB. Again, we counterbalanced the ordering of these two tasks.

Results and Discussion

In the choice condition, we predicted that the prominent attribute, floor, would weigh more heavily than in the pricing condition. This prominence would make the unit on the 8th floor more attractive to consumers in the choice condition. Thus, we expected to observe a pricing–choice preference reversal, in which the unit on the 8th floor would be more frequently chosen in the choice condition than the unit on the 1st floor, despite their equivalence to consumers in the pricing condition.

To test for a reversal between the choice and the pricing conditions, we proceeded as follows: In the choice condition, we examined the choice frequencies of the two units, and in the pricing condition, we used the matched prices to infer what the participants’ choices would have been had they been in the choice condition. For example, under one of the choice tasks, we presented Unit 101 at 500,000 RMB and Unit 801 at 560,000 RMB. We inferred that any participant in the pricing condition who stated a matched price for Unit 801 greater than 560,000 RMB when Unit 101 was 500,000 RMB would have chosen the former. In the second choice task, Unit 101 was priced at 440,000 RMB, and Unit 801 was priced at 500,000 RMB. We inferred that anyone in the pricing condition who stated a matched price for Unit 101 greater than 440,000 RMB when Unit 801 was 500,000 RMB would have chosen the former.

As we expected, floor played a more prominent role in the choice condition than in the pricing condition. In the choice condition, participants presented with an offer of Unit 101 at 500,000 RMB and Unit 801 at 560,000 RMB chose the latter 85.1% of the time. Participants in the pric-

ing condition were inferred to choose Unit 801 only 30.3% of the time. Similarly, in the choice condition, participants presented with an offer of Unit 101 at 440,000 RMB and Unit 801 at 500,000 RMB chose the latter 78.4% of the time. Participants in the pricing condition were inferred to choose Unit 801 only 33.3% of the time (85.1% versus 30.3%, two-way $\chi^2 = 43.45$, $p < .0001$, and 78.4% versus 33.3%, two-way $\chi^2 = 28.90$, $p < .0001$, respectively). On the basis of the stark difference in choice probabilities under pricing versus choice, we expected that Unit 801 would sell faster than Unit 101 if both units were put on the market simultaneously and priced using the matching policy described by price setters in Study 1.

Study 3 was a controlled experiment. We used price setters and choosers from the same population and asked price setters to set prices to ensure equal attractiveness (flat sales pattern). However, the choice result revealed the same good-faster-than-bad pattern as we found in the field sales data in Study 2. This finding reinforced our belief that the inconsistency was due to the prominence principle.

STUDY 4: DEVELOPER PRICING VERSUS CONSUMER CHOICE

Study 4 extended Study 3 in two ways. First, respondents considered all the units in a hypothetical building instead of only two units. Second, the price setters in this study were professional price setters rather than consumers. The choosers themselves were still consumers. A limitation of this approach was that we could not guarantee consistency between how these professionals perceived consumer tastes and the actual tastes of our choosers (an issue we mentioned previously and controlled for in Study 3). Nevertheless, the use of professional price setters mimicked reality and provided this study with more external validity than Study 3.

Method

As in Study 3, Study 4 had two between-subjects conditions: a pricing condition, in which price setters were asked to set prices for the units in a hypothetical building, and a choice condition, in which consumers were asked to rank the units according to their preference orders. Unlike Study 3, which used only two apartments, Study 4 used an entire building with 10 units to make the price-setting process more realistic for the developers who participated in the study.

In the pricing condition, the respondents were the same 47 professionals surveyed in our field study, who, in general, desired a flat or a bad-before-good sales pattern. Their task was to set unit prices for a hypothetical building before the building was listed on the market. They were asked to imagine that the building was located in a nice residential neighborhood in downtown Shanghai. The building had 10 floors, and each floor had one 100-square-meter unit. Each unit had a living room and two bedrooms; the living room and one bedroom faced south, and the other bedroom faced north. The average per-square-meter cost of the building was 5,000 RMB; thus, the average per-apartment cost was 500,000 RMB.

In the choice condition, the respondents consisted of 43 potential homebuyers recruited from a population of participants in a nondegree executive program in a large uni-

versity in Shanghai. Most of them either already owned an apartment or could afford one in Shanghai. These respondents were told that they were going to buy a unit in a newly developed building in which they were interested. The description of the hypothetical building was the same as in the pricing condition, except that the prices of each unit, instead of the costs, were presented to the participants. We set the price of each apartment in the choice condition at the average recommended price across the developers. As in Study 3, we believed that the use of the average prices from the pricing condition would homogenize the relative attractiveness of apartments to some extent, making the design more conservative. Participants were first asked to assume that all the units were available and to choose the unit they liked the most. They were then asked to assume that the unit they liked the most was no longer available and to choose the one they liked the most among the remaining units. They repeated this procedure until all the floors were exhausted. This method provided us with each consumer's ranking scheme for the 10 apartments. The procedure also mimicked what typically happens during the sales of a building in real life. That is, when more desirable units were already sold, potential buyers could only choose among the remaining units.

Results and Discussion

The results not only replicated the findings of Study 3 but also closely resembled the findings of the field study. As we expected, the prices set by the developers exhibited a near-linear upward adjustment for units on successively higher floors, with a slight downward adjustment for the top floor. The per-square-meter price was 6050 RMB for the 1st floor, 7125 RMB for the 9th floor, and 7000 RMB for the top floor. This pattern was consistent with the price adjustment process described by the respondents in Study 1. Furthermore, the relatively low pricing on lower floors and the downward adjustment on the top floor were consistent with our findings in Studies 1 and 2, in which both consumers and developers rated these floors as less desirable.

As in Study 3, we expected floor to weigh more heavily in the choice condition than in the pricing condition. To construct the test, we used the survey results on the 11-story building in Study 2 to define the first two floors as bad and the remaining floors as good. A participant was deemed to have chosen a good floor (bad floor) if his or her top-ranked floor was a good floor (bad floor). In the choice condition, we used the observed ranks. In the pricing condition, we used each developer's reported price differential between each pair of floors to determine his or her corresponding floor price premium. Thus, if a developer set a 500 RMB price difference between the 3rd and the 6th floors, we concluded that he or she perceived 500 RMB to be the monetary equivalent of the difference in value between those two floors (i.e., we interpreted 500 RMB as the compensating differential for the difference in floor). We then used these differentials to infer each developer's hypothetical ranking scheme had he or she been in the choice condition. For example, in the choice condition, the unit on the 3rd floor was 6280 RMB, and the unit on the 6th floor was 6780 RMB. For any developer who set a price differential between the 3rd and 6th floors of at least 500 RMB, we would infer a higher ranking for the 6th floor. For the few

instances in which a developer would have been indifferent (i.e., actual price difference is equal to his or her matched price difference), we assigned each floor an equal rank.

As we expected, floor played a more prominent role in the choice condition than in the pricing condition. We first compare choosers' and price setters' best choice (rank 1). Choosers assigned the rank of 1 to a good floor 97.7% of the time (only one participant assigned a rank of 1 to a bad floor). In contrast, price setters (developers) were inferred to have assigned a rank of 1 to a good floor only 36.2% of the time (two-way $\chi^2 = 37.62$, $p < .001$). These results replicated the inconsistency between choice and pricing, as in Study 3.

Next, we examine the entire range of ranks. We computed the average rank per floor separately using the observed ranks in the choice condition and the inferred ranks in the pricing condition. In Figure 4, we report a box plot with the mean rank and a 95% confidence interval for each of the 10 floors separately for choice and pricing. If we assume that differences in floor ranks correspond to differences in the expected sales rates, we observe roughly a good-faster-than-bad pattern for participants in the choice condition. In contrast, we observe roughly a bad-faster-than-good pattern for developers in the pricing condition. Recall that the prices in the choice condition were simply the mean prices the developers reported. Thus, the pricing strategies the developers used appear to have generated the same sales pattern among potential consumers as we observed in the field sales data in Study 2. However, the sales pattern we observed among the developers when we used the means of their stated prices mimics the desired sales patterns the price setters described in Study 1.

Study 4 confirmed the potential role of the prominence principle in housing demand in Shanghai. Using actual potential buyers from Shanghai and actual price setters, we show the inconsistency between choice (buyers) and matching (sellers' pricing strategies). Furthermore, the use of a 10-story building enabled us to replicate the inconsistency between the desired bad-faster-than-good pattern of sellers and the actual good-faster-than-bad pattern observed in the field.

GENERAL DISCUSSION

Decades of judgment and decision-making research have generated a vast number of intriguing anomalies. One of the most celebrated anomalies is the preference reversal between choice and matching. Most anomalies in the judgment and decision-making literature are demonstrated using only hypothetical scenarios or real outcomes with low stakes. The current research relates the choice-matching preference reversal to a real-world problem that involves billions of dollars in one of the world's most active real estate markets.

Specifically, we identified an inconsistency between Shanghai real estate developers' desired sales pattern and the actual sales pattern that emerged in the marketplace. Interviews showed that developers wanted to achieve a flat or a bad-faster-than-good sales pattern. Furthermore, developers routinely used stated-preference data to learn consumer willingness to pay for different floors and used this information to price in a way that should have achieved the desired sales pattern. Nevertheless, anecdotal accounts from

developers and actual sales data from selected Shanghai real estate developments demonstrated a good-faster-than-bad sales pattern.

To provide an explanation for this inconsistency based on the prominence principle, we conducted two controlled experiments. The results supported our explanation, indicating that the difference between choice mode and matching mode could generate the inconsistency between the desired and the actual sales patterns of apartments on different floors of a building. That is, the inconsistency could arise from the incompatibility between the matching mode that developers used to measure willingness to pay for floors and the choice mode that consumers used to buy apartments on different floors.

Before concluding the article, we discuss three issues related to this research, one about matching versus anchoring and adjustment, one about ways to reduce the inconsistency between desired and actual sales patterns, and one about the implications of our findings for domains outside the real estate market. First, in setting prices, the matching procedure is also an anchoring-and-adjustment process (Schkade and Johnson 1989; Tversky and Kahneman 1974). Developers anchor on the price of one unit (e.g., a base unit) and adjust the prices of other units to match its attractiveness. Thus, the inconsistency we found between the developers and the consumers could also be attributed to insufficient adjustment by the developers. In our studies, matching always involves anchoring and adjustment. Both the prominence principle and insufficient adjustment could lead to an underweighting of floors in pricing relative to choice. As previous research has demonstrated, insufficient adjustment might be a possible source of pricing-choice reversal (Schkade and Johnson 1989); these two effects cannot be distinguished.

Theoretically, the relative strength of the prominence effect and insufficient adjustment could be tested by asking respondents in the matching condition to match the values on the more prominent attribute rather than the less prominent attribute (e.g., on floor rather than price). Here is an illustration: One group of respondents (matchers) could be told that an apartment on the 1st floor of a building costs \$100,000 and a similar apartment on the x th floor of the same building costs \$120,000. Then, the respondents could be asked to match the floor number x so that the two apartments are equally attractive. Suppose that they say x is 5. Another group of respondents (choosers) could then be asked to choose between the \$100,000 apartment on the 1st floor and the \$120,000 apartment on the 5th floor. If the choosers prefer the \$120,000 apartment on the 5th floor, it reflects the prominence effect, whereby matchers underweight the most prominent attribute (floor) relative to choosers. Conversely, if the choosers prefer the \$100,000 apartment, it is evidence of insufficient adjustment, whereby the matchers insufficiently adjust the target floor (x) from the anchor (1st floor). In real life, however, developers typically set prices when floors are known and rarely match floors when prices are given. Testing the relative strength of the prominence effect and insufficient adjustment is beyond the scope of this article.

Second, the main findings of the current research are the good-faster-than-bad sales pattern revealed in the field study and its inconsistency with price setters' desired flat

sales pattern. As mentioned previously, we do not attempt to prove that the good-faster-than-bad sales pattern is sub-optimal per se from a normative perspective. The theoretically optimal sales pattern would be difficult to derive because it is influenced by numerous factors. For example, from a long-term perspective, if developers underprice good units and overprice bad units (relative to the prices that would produce a flat sales pattern), the good units would not yield as much profit as they otherwise could, and the bad units would prolong the entire sales cycle. Conversely, from a short-term perspective, an impatient developer (i.e., one who heavily discounts the future) might prefer to recover more money in a short time by selling good and expensive units first.

However, to the extent that developers' intended flat sales pattern diverges from the actual sales pattern, they could reduce the inconsistency by simulating the consumer choice condition when setting prices. For example, they could ask potential buyers hypothetically to choose between a unit on a desired floor and one on a less desired floor in repeated iterations, and through these iterations, they could systematically vary the price difference between the two units. For example, they could begin with two extreme cases: "Would you buy Unit 101 on the 1st floor or Unit 801 on the 8th floor if Unit 101 is \$300,000 and Unit 801 is also \$300,000?" and "Would you buy Unit 101 or Unit 801 if Unit 101 is \$100,000 and Unit 801 is \$500,000?" If it is assumed that respondents choose Unit 801 in the first case and Unit 101 in the second, the developers could gradually increase the difference in price from the first scenario and reduce the difference in price from the second. Through this procedure, they could find a point at which consumers are indifferent between the two units. This procedure is a variation of the well-known choice-based conjoint method for estimating consumer demand (e.g., Dolan 1990).

Third, our findings in the context of real estate pricing are notable in their own right, given the sheer magnitude of the Shanghai market. Nevertheless, we do not expect the good-faster-than-bad sales pattern we identified in this research to be limited to the real estate market in Shanghai.

Almost all products involve a trade-off between quality and price; consumers often consider quality more important than price (Simonson and Tversky 1992), and quality may frequently carry more weight than price in consumers' choices (Hardie, Johnson, and Fader 1993). To the extent that sellers of products of different qualities rely on matching to set prices and do not have sufficient relevant past experience from which to learn or do not learn from relevant past experience, we expect to observe similar pricing and sales patterns in domains other than the real estate market. For example, suppose that a person owns two restaurants, one that offers a more popular cuisine than the other or one that is located in a safer neighborhood than the other. Chances are that the owner will not discriminate the prices of the two restaurants enough, and consequently the better restaurant (the one that offers better food or is in a nicer location) will be crowded every night and will need to turn away prospective patrons, whereas the other restaurant (the one that offers less popular food or is in a tougher neighborhood) will tend to have empty seats.

The matching-choice preference reversal is commonly regarded in the judgment and decision-making literature as

a violation of the invariance principle in traditional economic models and as evidence that preferences are unstable and constructed. Our research suggests that the matching-choice preference reversal is not just a topic for academic discourse but has significant real-world correspondence as well.

APPENDIX: THE POISSON REGRESSION MODEL

The sales duration data observed in our three field sales data sets consist of positive, integer-valued outcomes (i.e., counts of units of time). The Poisson model is a standard specification for handling count data. Suppose that the total amount of time (measured in discrete units such as days or months) required for an apartment i to sell, y_i , follows a Poisson distribution with mean λ_i . The probability density function of this Poisson random variable is as follows:

$$(A1) \quad f(y_i|\lambda_i) = \begin{cases} \frac{e^{-\lambda_i} \lambda_i^{y_i}}{y_i!} & \text{for } \lambda_i > 0 \text{ and} \\ & y_i = 0, 1, \dots, \text{ and zero otherwise.} \end{cases}$$

The corresponding joint distribution of the data has the following form:

$$(A2) \quad \Pr(Y|\lambda) = \prod_{i=1}^n \frac{e^{-\lambda_i} \lambda_i^{y_i}}{y_i!}.$$

For estimation purposes, we assume the rate of occurrence, λ_i , depends on observed apartment characteristics, X_i , as follows:

$$(A3) \quad \lambda_i = \exp(X_i\beta),$$

where we use exponentiation to ensure that λ is positive. Model parameters can be estimated by using maximum likelihood based on Equation A2. Because of the exponentiation in Equation A3, it is difficult to interpret the estimates of the parameter vector β . Instead, we report the incidence rate ratios, which effectively exponentiate the parameters. Because our main objective is to test whether the selling time of bad floors exceeds that of good floors, we can use the incidence rate ratios to compute the ratio of time required to sell an apartment on a bad floor versus one on a good floor:

$$(A4) \quad \text{IRR} = \frac{E(Y_i|\text{Bad} = 1) = \lambda_{i|\text{bad}=1} = \exp[\hat{\beta}_o + X\hat{\beta} + (1)\hat{\beta}_{\text{bad}}]}{E(Y_i|\text{Bad} = 0) = \lambda_{i|\text{bad}=0} = \exp[\hat{\beta}_o + X\hat{\beta} + (0)\hat{\beta}_{\text{bad}}]} \\ = \exp(\hat{\beta}_{\text{bad}}).$$

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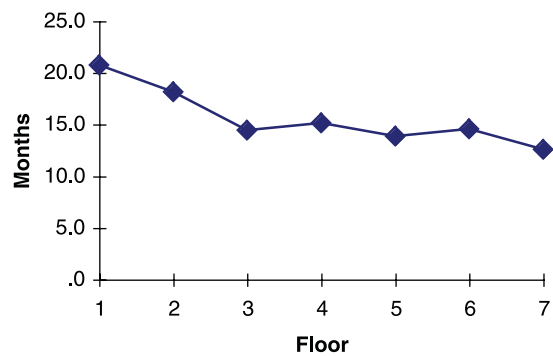
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¹One RMB is approximately US\$.13, and one square meter is approximately 10.76 square feet. For the purposes of this article, and in China in general, the size of an apartment refers to its “construction size.” The construction size of an apartment includes the amortized size of public areas of the building, such as the lobby, elevators, and so on. Typically, a 100-square-meter apartment would have only 72 square meters, or 775 square feet, inside the unit.

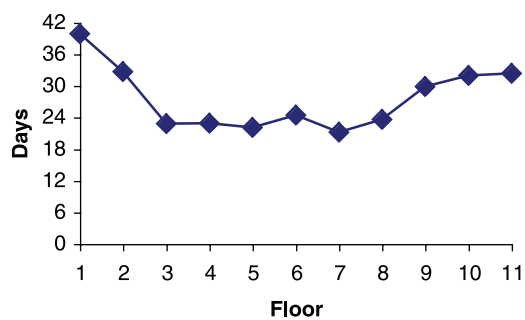
²We also ran the same Poisson regression for each of the three developments using a different definition of “bad floor”; we used the percentage of respondents in the survey who rated the corresponding floor number as bad in the hypothetical building with the same number of floors. When using this variable, we still obtain a statistically significant effect of floor on duration of sales, which suggests that the effect of floor is robust.

Figure 1
MEAN MARKET-CLEARING DURATION OF UNITS ON
DIFFERENT FLOORS IN DATA SET 1 OF STUDY 2



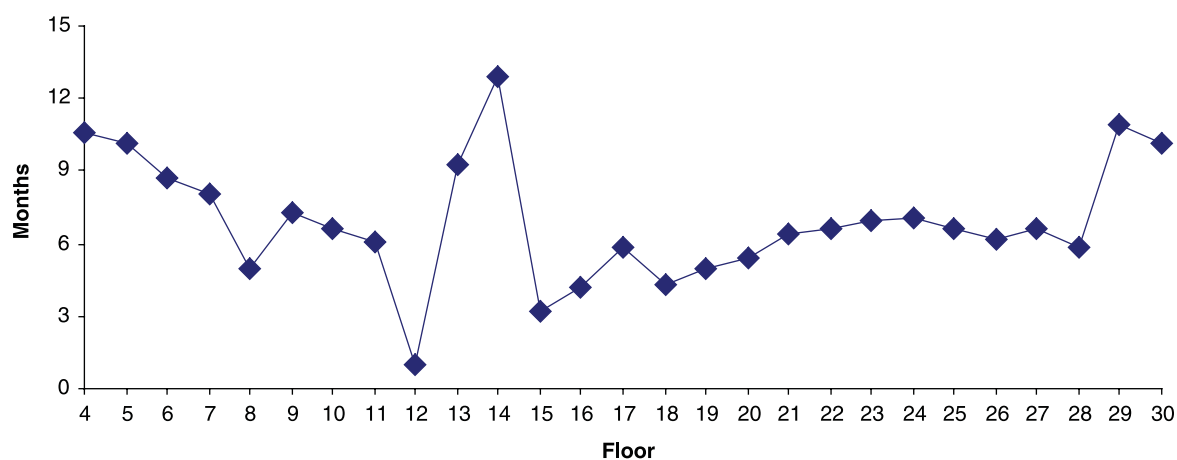
Notes: The results suggest that floors consumers considered bad (low floors) sold more slowly.

Figure 2
MEAN MARKET-CLEARING DURATION OF UNITS ON
DIFFERENT FLOORS IN DATA SET 2 OF STUDY 2



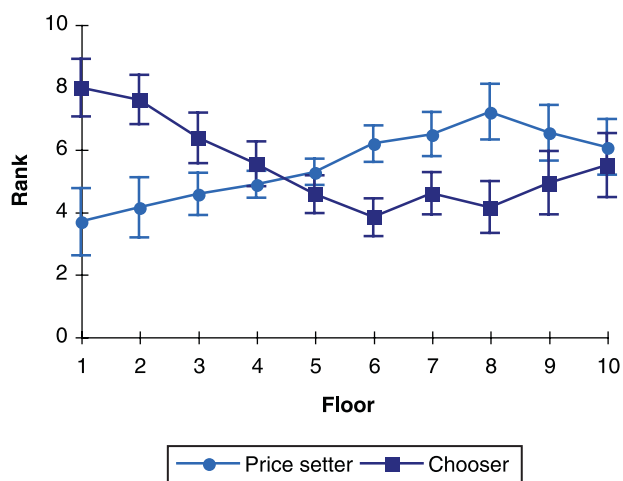
Notes: The results suggest that floors consumers considered bad (low floors) sold more slowly.

Figure 3
MEAN MARKET-CLEARING DURATION OF UNITS ON DIFFERENT FLOORS IN DATA SET 3 OF STUDY 2



Notes: The results suggest that floors consumers considered bad (low and top floors) sold more slowly.

Figure 4
MEAN CHOICE RANK FOR UNITS ON DIFFERENT FLOORS IN THE 10-STORY BUILDING IN STUDY 4



Notes: Higher numbers on the y-axis indicate higher (worse) choice ranks, which imply longer market-clearing duration. The results suggest that price setters want to sell bad (low) floors first, but choosers want to buy bad floors last.

Table 1
HEDONIC PRICE REGRESSION RESULTS ON PRICE IN THE THREE FIELD DATA SETS IN STUDY 2

<i>Covariate</i>	<i>Data Set 1 (Observations = 47)</i>			<i>Data Set 2 (Observations = 148)</i>			<i>Data Set 3 (Observations = 510)</i>		
	<i>1</i>	<i>2</i>	<i>3</i>	<i>1</i>	<i>2</i>	<i>3</i>	<i>1</i>	<i>2</i>	<i>3</i>
Floor	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Building		Yes	Yes		Yes	Yes		Yes	Yes
Size			Yes			Yes			Yes
Exposure									Yes
R ²	.87	.89	.89	.91	.93	.96	.82	.89	.93

Notes: The results reveal a significant effect of floor on price.

Table 2
POISSON REGRESSION RESULTS ON MARKET-CLEARING DURATION IN THE THREE FIELD DATA SETS IN STUDY 2

<i>Data Set 1 (Observations = 47)</i>								
<i>Covariate</i>	<i>1</i>		<i>2</i>		<i>3</i>			
	<i>Coefficient</i>	<i>SE</i>	<i>Coefficient</i>	<i>SE</i>	<i>Coefficient</i>	<i>SE</i>		
Bad floor	1.34	.11	1.40	.11	1.55	.20		
Building			Yes		Yes			
Size			.99	2.38E-03	.99	2.38E-03		
Exposure								
Price					1.00	3.80E-04		
Log-likelihood	-203.53		-186.25		-185.74			
<i>Data Set 2 (Observations = 148)</i>								
<i>Covariate</i>	<i>1</i>		<i>2</i>		<i>3</i>			
	<i>Coefficient</i>	<i>SE</i>	<i>Coefficient</i>	<i>SE</i>	<i>Coefficient</i>	<i>SE</i>		
Bad floor	1.39	.05	1.32	.05	1.99	.10		
Building			Yes		Yes			
Size			1.00	5.73E-04	.99	1.17E-03		
Exposure								
Price					1.00	1.77E-07		
Log-likelihood	-1080.76		-1012.73		-954.30			
<i>Data Set 3 (Observations = 475)</i>								
<i>Covariate</i>	<i>1</i>		<i>2</i>		<i>3</i>			
	<i>Coefficient</i>	<i>SE</i>	<i>Coefficient</i>	<i>SE</i>	<i>Coefficient</i>	<i>SE</i>		
Bad floor	1.61	.08	1.40	.07	1.27	.07		
Building								
Size			1.02	1.72E-03	1.02	1.72E-03		
Exposure			Yes		Yes			
Price					1.00	4.98E-05		
Log-likelihood	-1659.02		-1552.13		-1545.55			

Notes: Effects are reported as incidence rate ratios. The results reveal a significant effect of floor on market-clearing duration.