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Superstition and Financial Decision Making

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In Chinese culture, certain digits are lucky and others unlucky. We test how such numerological superstition affects financial decision in the China IPO market. We find that the frequency of lucky numerical stock listing codes exceeds what would be expected by chance. Also consistent with superstition effects, newly listed firms with lucky listing codes experience inferior post-IPO abnormal returns. Further tests suggest that our conclusions are not driven by endogeneity.

JEL Classifications: G12; G14; G15

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1. Introduction

A rich body of evidence suggests that psychological biases affect financial decision making. These biases are usually modeled as being inherent to the individual, and arising from generic decision-theoretic errors such as overestimating small probabilities or underweighting certain types of information signals. Much less attention has been devoted to the effects of more specific incorrect *ideas about how the world works*, which an individual may or may not choose to adopt. For example, the sometimes-popular theory that "land is the best investment," if adopted, could potentially induce mistaken probability assessments, overinvestment in land, and overpricing. Such effects result from the specific idea rather than some general information-processing error. Indeed, someone with the same inherent cognitive biases might, given exposure to different people and ideas, adopt the opposite conclusion about whether land is a good investment.

In contrast, in most existing behavioral finance models, such as those based upon overconfidence, limited attention, cumulative prospect theory, and the representativeness heuristic, inherent cognitive biases automatically induce errors in assessing probabilities, where these errors depend only on the probability distributions of the gambles investors face and the information signals about these gambles that they receive.[1] Such models do not incorporate the realistic fact that people adopt specific theories about of how the world works. There is surprisingly little direct empirical testing of the proposition that arbitrary ideas (whose specific content is not imposed by either external reality nor, in any direct and single-valued way, by human cognitive bias) affect market behavior.[2]

[1] In overconfidence models, probability errors derive from investors overestimating the precision of an information signal (Kyle and Wang 1997; Daniel, Hirshleifer and Subrahmanyam 1998; Odean 1998). In cumulative prospect theory, individuals overestimate the probabilities of rare events (Barberis and Huang 2008). In models of limited attention, individuals neglect some information signal (Hirshleifer and Teoh 2003; Peng and Xiong 2006).

[2] An exception is the examination of investor beliefs through surveys. Shiller, Kon-Ya and Tsutsui (1996) and Shiller (2000) discuss evidence from surveys of investors about the role popular models about markets during bubble periods. For example, there is no general psychological bias which directly forces people at all times to believe that in the long run California real estate can't go down, but the adoption of this once-popular belief presumably affected how individuals invest. Graham and Harvey (2001) find that many CFOs report using firm risk rather than project risk in evaluating new investments, and that many CFOs at small firms report using the payback criterion as a capital budgeting technique. These reports presumably reflect a mistaken belief about the validity of these procedures. Some theories of security pricing are also based on incorrect adoption by investors of world-views. In Hong, Stein and Yu (2007), investors believe in oversimplified linear models. In Rabin and Vayanos (2010), individuals believe that after a run of successes in independent drawings, a failure becomes more likely. These theories have been used to derive and in some cases test implications about return moments such as autocorrelations and skewness. Our focus on numerological superstition

In this paper, we test whether market participants use a mistaken model of how investment outcomes are generated by focusing on a particular type of mistaken theory, numerological superstitions. We document that firms in China going public have a frequency of lucky listing codes that is greater than would be expected by chance, and that lucky listing codes are associated with lower post-IPO abnormal stock returns.

Superstition is important in its own right, and also provides a valuable testing ground for the idea that mistaken ideas matter in capital markets. Superstitions are arbitrary; their content is not directly implied by general cognitive biases. Where one culture views 8 as lucky, or 13 as unlucky, another does not. A general psychological predisposition to being superstitious does not force individuals or societies to adopt the notion that 13 is unlucky, as contrasted with the opposite belief.

Some heuristics and biases are culture dependent; for example, the tendency to expect reversal of past good or bad outcomes has been found to be stronger in Asian culture. However, heuristics are also not completely arbitrary; they are supposed to be adaptive within their ranges of validity (Gigerenzer, Todd and ABC Research Group 1999). In contrast, a superstitious fear or love of numbers is nonfunctional and can be harmful. As such, tests of the effect of superstition are revealing in showing that people are subject to biases based on the adoption of completely nonfunctional cultural traits.

Furthermore, superstition is an important part of how people make sense of randomness and form strategies for dealing with risk. Throughout history, people have believed that certain rituals, objects, or symbols can be used to influence their luck. For example, Chinese emperors regularly held costly and time-consuming ceremonies to pray for rain. Ancient cultures relied on omens to divine the wills of the Gods.[3] Even in modern times, many people believe in luck and take steps to improve it. Examples include professional athletes and stock traders wearing lucky articles of clothing, keeping lucky objects, or following luck-inducing rituals (Melamed and Tamarkin 1996; Collin 2003; Burger and Lynn 2005).

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allows us to test for implications that are unique to the superstition hypothesis, such as the effects of lucky numbers on decisions.

[3] In ancient Rome, important political decisions, such as the appointment and inauguration of any magistrate and the advancement of any military campaign, required a positive result from taking the auspices. Fortuna, the Goddess of Luck, was worshipped across the Roman Empire.

There is anecdotal evidence that superstition affects financial decisions.[4] However, there has been little systematic empirical work on superstition in finance, perhaps because the testing of some Western superstitious ideas (e.g., unluckiness of Friday the 13th) imposes a small sample size. In this and other respects, numerological superstition in China's stock market provides an appealing venue for testing how superstitious beliefs affect firm behavior and/or market valuations.

Psychological research indicates that beliefs about lucky numbers affect individuals' optimism in everyday life (Darke and Freedman 1997). In cognitive priming experiments, Asian individuals who were exposed to lucky numbers gave higher estimates of their chances of winning a lottery, expressed greater willingness to participate in a lottery, and expressed greater willingness to make risky financial investments (Jiang, Cho and Adaval 2009).

Lucky and unlucky numbers are ubiquitous in Chinese culture. In Chinese numerology, the numbers 6, 8, and 9 are lucky because they sound similar to words that have positive meanings such as 'prosper' and 'longevity', while 4 is unlucky because in Chinese it sounds similar to the word 'death'. For this reason, consumer product advertisements in China disproportionately include 8 and exclude 4 (Simmons and Schindler 2003), and Taiwanese consumers are willing to pay more for a package of 8 tennis balls than 10 (Block and Kramer 2009). Anecdotal evidence abounds that numerological beliefs influence behavior in China. For example, the opening ceremony of the Beijing 2008 Summer Olympic Games officially started at 8:08 p.m. on August 8, 2008, because 8 is a lucky number.[5]

In particular, anecdotal evidence suggests that lucky numbers play a role in investors' decisions in China. One news story (*Wall Street Journal Asia*, 5/24/07) quotes a Mr. Yan, a Chinese investor, as saying "I believe good codes will bring good luck." Mr. Yan attributed the good performance of his stock to the

[4] According to one depression-era report, "One morning, FDR told his group he was thinking of raising the gold price by 21 cents. Why that figure, his entourage asked. 'It's a lucky number,' Roosevelt said, 'because it's three times seven.' As Henry Morgenthau later wrote, `If anybody knew how we really set the gold price through a combination of lucky numbers, etc., I think they would be frightened,'" (Shlaes 2007). One vendor of an astrology-based commodity trading system advertised that it would "put the power of the universe behind your trades." Robert Citron, Orange County Treasurer, consulted astrological charts in making investment decisions, asserting that "They were very accurate" (*San Jose Mercury News*, 7/25/98). Citron's trading created enormous losses for Orange County. The popularity of technical trading systems may come in part from superstitious faith in theories about the power of numerical patterns.

[5] Many more examples can be found in Yardley (2006), Areddy (2007) and an article translated from the May 20, 2006 issue of China Daily, available at http://news.xinhuanet.com/english/2006-05/20/content_4576062.htm.

two 8s in its numerical code (600881).

As this example illustrates, Chinese stock exchanges designate stocks with numerical codes and investors typically refer to those stocks by the codes. For example, The Bank of China's listing code on the Shanghai Exchange is 601988, which contains lucky numbers 6, 8, and 9. We investigate whether Chinese investors resort to this superstitious belief in choosing stocks and thus exhibit preferences for stocks with lucky numbers in their numerical codes.

The market for IPOs is a natural domain for testing for the effects of managerial or investor superstition, because high uncertainty about long-run fundamentals maximizes the space for superstition to play a role, and because individual investors (whom we would expect to be especially prone to superstition) participate heavily in IPOs.[6]

In general, tests of whether managers prefer some stock characteristic, or cater to an investor preference for it, need to distinguish these possibilities from the alternative hypothesis that there is a rational reason why the given characteristic (such as dividends) is rationally valued by investors. However, it is hard to think of a direct rational reason for firms or investors to prefer lucky listing codes (apart from the indirect benefit to firms of catering to investor irrationality).

Our tests are based on a sample of newly listed firms in China from 1991 through 2013. If investors exhibit preferences for IPO firms with lucky numbers in the listing code, we predict that managers will try to obtain lucky numbers in their listing codes either because they share, or cater to, investor superstition; and that the high demand for IPOs with lucky listing codes will result in overpricing of and lower subsequent returns for these IPOs. We therefore predict and test whether (i) IPO firms obtain a higher than expected frequency of lucky listing codes than would be expected to occur randomly; and (ii) the post-IPO stock return performance is lower for firms with lucky listing codes than for those with unlucky listing codes.

[6] IPO firms tend to have much more uncertainty than seasoned firms owing to their earlier stage of development. Several studies offer findings that support greater riskiness of IPOs and proneness to misvaluation. For example, Loughran and Ritter (1995) show that CAPM beta is higher for IPO firms than non-issuers, and Ritter (1991) concludes that imperfect investor rationality affects behavior and pricing in the IPO market. Ljungqvist, Nanda and Singh (2006) suggest that the IPO markets are structured to take advantage of individual investor irrationality. There is also theory proposing and evidence confirming that managerial irrationality affects the decision to go public (Ljungqvist and Wilhelm 2005; Loughran and Ritter 2002).

Our findings are generally consistent with investors preferring firms with lucky numbers, with the managers of IPO firms either sharing this preference, or with managers catering to this preference. We find an abnormally high proportion of firms with lucky listing codes and an abnormally low proportion of firms with unlucky listing codes. For example, on the Shenzhen Stock Exchange, the actual proportion of firms with lucky (unlucky) listing codes is 24% more (27% less) than expected by chance. Furthermore, the actual proportion of firms with at least two consecutive lucky numbers is higher than expected, and that with consecutive unlucky numbers is lower than expected. This evidence is consistent with firms purposefully attempting to obtain numerical codes with lucky numbers during the IPO process.

With regard to (ii), we find that three-year post-IPO abnormal returns are significantly lower for firms with lucky listing codes than for firms with unlucky listing codes, with relative underperformance of about 10.8% per year after appropriate controls. This evidence is consistent with investors overvaluing firms with lucky listing codes. When corrective information arrives, investors undo their mistake, resulting in lower returns for these firms.

To investigate whether superstition-induced mispricing comes from the offer price or from trading on the secondary market, we examine the stock return and the trading volume in a short window around the first trading date. Our results are consistent with mispricing largely taking place on the secondary market, which is dominated by individual investors. Furthermore, in untabulated tests, we show that stock returns are less sensitive to unexpected earnings for firms with lucky listing codes than for firms with unlucky listing codes, consistent with lucky listing codes attracting naïve investors who place less weight upon fundamentals. Taken together, these results imply that the mispricing of lucky listing codes is due to unsophisticated investors relying on superstition to guide their portfolio selection.

There are alternative possible pathways of causality based on the possibility that the firms' assignment of lucky numbers be correlated with misvaluation at the time of issuance. As discussed in the main body of the paper, such a possibility would still imply that numerological superstition affects investors' and/or managers' behaviors. Furthermore, this possibility is not very plausible, as listing codes can be

assigned months before issuance.[7]

Nevertheless, to deal with endogeneity, we use an instrumental variable (IV), based on theory and survey evidence (discussed later) suggesting that low income individuals are more likely to subscribe to superstitious belief. Specifically, we sort provinces into quartiles according to their GNI (Gross National Income) per capita; our IV is the quartile that the firm's headquarter province belongs to. Since we expect investors from low income provinces to be more superstitious, and since there is a well-documented local bias in investment (e.g., Coval and Moskowitz, 1999; Grinblatt and Keloharju, 2001; Ivkovic and Weisbenner, 2005; Massa and Simonov, 2006; Seasholes and Zhu, 2010), we expect firms that are headquartered in low income provinces to have a more superstitious investor base. Furthermore, the managers of such firms may cater to investors' superstitious beliefs or may be influenced by local culture to become superstitious themselves. In addition, there is no reason to expect this IV to affect future returns directly, implying that it satisfies the exclusion restriction. Consistent with the hypothesis that superstition affects behavior, we find that this IV is negatively associated with the probability that a firm has a lucky listing code. The results from this IV approach suggest that our conclusions are robust to possible endogeneity.

Overall, the most plausible explanation for our findings is that lucky listing codes cause overvaluation and subsequent return underperformance.

There has hitherto been little evidence about how the adoption of arbitrary ideas affects market prices. Previous work has provided evidence suggesting that investors' emotions affect stock prices (Hirshleifer and Shumway 2003; Edmans, Garcia and Norli 2007; Goetzmann et al. 2015), but emotion is not necessarily tied to mistaken ideas. Guiso, Sapienza and Zingales (2008) show that trust, a cultural trait, affects stock market participation while Li et al. (2013) find that individualism, uncertainty avoidance and harmony are significantly associated with corporate risk-taking. While our paper is generally consistent

[7] Managers may prefer lucky listing codes, because these codes attract unsophisticated investors, who are presumably less attentive and active in monitoring poor management. We therefore investigate whether lucky listing codes are associated with subsequent corporate governance problems. Since such problems may manifest in earnings manipulations, specifically, we examine the association between the lucky listing code and accounting accruals in the first three years after IPO. We find that the association is insignificant. However, we can't completely rule out this possibility, since there are many possible manifestations of government problems other than earnings management.

with the idea that culture matters in financial market, our focus is on numerological superstition, a different cultural trait based on a specific kind of mistaken belief.

There are several studies on superstition in capital markets. Some focus on Friday the 13th, a day that is viewed by many as unlucky. Kolb and Rodriguez (1987) report that CRSP market returns are lower on Friday the Thirteenth than on other Fridays, but subsequent literature has not confirmed this.[8] Lepori (2009) reports that another low-frequency event that might be interpreted as unlucky, the occurrence of eclipses, is associated with below-average stock returns. In contrast, we consider a sample where good- and bad-luck data are quite frequent. In a recent paper, Agarwal et al. (2014) find that, in Singapore, a country heavily influenced by Chinese culture, lucky-numbered housing units and floors enjoy a price premium. The focus of Agarwal et al. (2014) is the housing market, while ours is the stock market.

Our study also provides new evidence of exploitation of investors by firms. A literature on IPO markets identifies apparent effects of imperfect investor rationality. In the U.S. and many other countries, IPO firms underperform the market in the long run (Ritter 1991; Loughran and Ritter 1995; Henderson, Jegadeesh and Weisbach 2006). Teoh, Welch and Wong (1998) provide evidence that firms manage earnings upwards prior to IPO and that post-IPO stock returns are affected by pre-IPO earnings management. Our study differs in providing a link between superstitious beliefs either by investors and/or managers to post-IPO abnormal performance.

2. Superstition and the Institutional Setting

Magical thinking is reasoning in a way that violates scientific notions of causality. For example, in many cultures luck is viewed as a personal essence that can be acquired or protected by means of prayer or rituals. One kind of magical thinking is treating symbols or arbitrary associations as having direct causal effects on the material world.

[8] Later work reports that the effect vanishes after controlling for the turn of the month effect and does not hold in other countries (Agrawal and Tandon 1994; Chamberlain and Cheung 1991; Dyl and Maberly 1988).

Psychological studies have shown that it is easy to induce magical thinking about everyday matters in the laboratory (Pronin et al. 2006). Nor is superstitious belief limited to the scientific illiterate; indeed, there is no clear relation between education level and paranormal thinking (De Robertis and Delaney 1993; Goode 2002; Mowen and Carlson 2003; Farha and Steward 2006).

2.1 Numerology in China

According to Shu Zhao (as quoted in Yardley 2006), faith in numerological symbolism in China can be traced to Confucius and to Taoism. Chinese numerology reflects at least two deviations from scientific notions of causality. The first is that the similarity in pronunciation of a number to a word has causal import. The second is that having a personal association with a relevant number (and hence indirectly with its associated word) will affect the likelihood that an individual will experience favorable life events.

For example, one news story reports that "Tens of thousands of Chinese rushed to get married on Wednesday, hoping that the 09/09/09 date would bring longevity to their weddings and lives. Besides meaning 'nine, nine', 'jiu, jiu' in Chinese also means 'for a long time,' making Wednesday an auspicious day to get married."[9]

Anecdotally, the Chinese fascination with numbers affects many decisions. The Chinese government auctions license plate numbers for surprisingly high prices (Yardley 2006). One businessman, Mr. Ding, paid 54,000 yuan for plate APY888. "For nearly the same money, which is the equivalent of $6,750, Ding could have afforded two of the Chinese- made roadsters popular in the domestic car market. His bid was almost 20 times what a Chinese farmer earns in a year, and almost seven times the country's per capita annual income." A different license number auction had a high price for AW6666 of 272,000 yuan (US$34,000).[10]

[9] See news reports at http://en.ce.cn/Life/society/200909/09/t20090909_19974517.shtml and http://www.channelnewsasia.com/stories/lifestylenews/view/1003837/1/html.
[10] See news reports at http://news.xinhuanet.com/english/2006-05/20/content_4576062.htm.

2.2 The Institutional Setting

Shares of a Chinese listed company can be classified as tradable shares, state shares and legal person shares. Tradable shares are tradable on the stock exchanges. State shares are held by the government through a designated government agency, while legal person shares are held by separate legal entities, such as other state-owned enterprises (SOEs). Neither state shares nor legal person shares were tradable on stock exchanges until April 2005, when the China Securities Regulatory Commission announced a Split-Share Structure Reform that aimed to make all non-tradable shares publicly tradable, which remained an ongoing process as of November 2013 (Liao, Liu and Wang 2014).

Shares that are tradable on the two stock exchanges in China (the Shanghai Stock Exchange and the Shenzhen Stock Exchange) can be classified as either A-shares or B-shares. A-shares can be traded only by Chinese citizens and selected global institutional investors (QFII), and are quoted in RMB (China's local currency). B-shares were introduced in early 1992, exclusively for foreign investors. Unlike A-shares, B-shares are quoted in foreign currencies, and are dominated by institutional investors from developed countries (Tan et al. 2008). Even after regulators opened the B-share market to domestic investors in 2001, because the government imposes controls on capital flows and the RMB is not fully convertible and freely tradable, domestic investors lack foreign currency and they do not actively trade in the B-share market (Chan, Menkveld and Yang 2008). Hence international institutional investors are the major players in the B-share market, and are unlikely to share Chinese superstitious beliefs. We therefore exclude B-shares in our analysis.

In China the government plays a pivotal role in the IPO process. All IPOs are subject to the approval of Chinese Securities Regulatory Commission (CSRC). After approval from the CSRC, firms typically obtain listing codes from stock exchanges within one or two days. We thoroughly checked all rules on IPOs and were unable to identify any formal rule for the determination of listing codes. Given that there is no official rule and the assignment of listing code is not a simple upward count in order of approval,

there is potentially room for activity on the part of the listing firms' management or the underwriter to influence the choice of code.

IPO firms usually obtain their listing codes prior to conducting road shows. The listing codes are included in the offering documents, and investors typically refer to the stock by their listing codes.[11] For example, ICBC (Industrial Commerce Bank of China) obtained its listing code (601398) before its road shows, when the bank went public in 2006.

We attempt to infer the time lag between the determination of the listing code and the official listing of the IPO shares from the existing literature. Guo and Brooks (2009) show that the average time lag between the approval from CSRC and official listing of the shares is 35 days. In the ICBC IPO example, the time lag was more than two months. Because it takes only one or two days for firms to obtain the listing code after CSRC approval, this indicates that the listing code is typically determined more than one month before the official trading in general.

In sum, IPO firms in our sample conduct road shows after they obtain the listing code. Normally, the time between the determination of the listing code and the official listing of shares is more than one month. This institutional feature makes it less plausible that the firms that are expected to be hot issues are more likely to be assigned lucky listing codes, since the market sentiment towards the particular stock is probably not yet known at the time of assigning listing codes.

3. Sample formation, Variable Definition and Descriptive Statistics

3.1 Sample Formation

The initial sample consists of all firms that issued A shares on either the Shanghai or Shenzhen stock exchange and are covered by the China Securities Market and Accounting Research (CSMAR) Databases

[11] See the description at: http://www.icbc.com.cn/ICBC/%E7%BD%91%E4%B8%8A%E7%90%86%E8%B4%A2/%E7%90%86%E8%B4%A2%E4%B9%A6%E5%90%A7/%E8%A1%8C%E5%AE%B6/06%E5%86%AC%E5%AD%A3%E5%8F%B7/%E4%B8%AD%E5%9B%BD%E5%B7%A5%E5%95%86%E9%93%B6%E8%A1%8C%E8%82%A1%E6%94%B9%E4%B8%8A%E5%B8%82%E5%A4%A7%E4%BA%8B%E8%AE%B0.htm; http://stock.sohu.com/20101129/n277986319.shtml; http://static.sse.com.cn/cs/zhs/scfw/gg/ssgs/2012-05-22/601339_20120522_1.pdf.

between 1990 and 2013. The information on shareholding, financial performance and stock return is directly downloaded from the databases. After deleting firms with missing information on the IPO date, our sample includes 2,194 listed firms, 986 of which are listed on the Shanghai Stock Exchange, and 1,208 of which are listed on the Shenzhen Stock Exchange.

3.2 Variable Definitions

We identify firms with lucky numbers by examining each digit of the listing code. Firms with at least one lucky number (6, 8 and 9) and no unlucky number (4) in the listing code are defined as firms with lucky listing codes, while firms with at least one unlucky number and no lucky numbers are defined as firms with unlucky listing codes. It is hard to gauge the perceived luckiness of the remaining firms' codes, given the co-occurrence of both lucky and unlucky numbers (or the absence of both).[12] All Shanghai-listed firms have numerical codes beginning with 6, and this digit is ignored in our classifications. [13]

3.3 Descriptive Statistics

3.3.1 Distribution of listing codes

We report the distribution of listing codes for our sample firms across the two exchanges in Table 1. Specifically, for each year, Table 1 gives the mean, median, minimum and maximum value of the numerical

[12] It is not clear how to interpret a mix of lucky and unlucky numbers, so we term such a mix "neutral". In particular cases, such numbers may in fact be viewed as either lucky or unlucky. For example, the number '9413' contains both the lucky digit '9' and the unlucky digit '4'. But the Chinese pronunciation of this number is rather ominous, as it sounds like the phrase '90% chance of death and 10% chance of survival'. On November 25, 2012, the *Apple Daily*, an influential newspaper in Hong Kong, reported that a license plate containing 9413 did not receive a single bidding attempt in an open auction before the government took it back (the article is available at http://s.nextmedia.com/apple/a.php?i=20121125&sec_id=4104&a=18079273). This example illustrates that there is no easy way to determine the luckiness/unluckiness of listing codes that contain a mix of lucky and unlucky digits, so we remove such cases from the sample.

[13] Some investors may naively fixate on the lucky number without discounting for the fact that the listing codes of all Shanghai listed stocks begin with 6. However, it seems likely that many or most investors would mentally filter out the initial 6. An investor who compares two Shanghai stocks has no reason to prefer one over the other based on the initial 6 that they share. Also, the psychology of attention suggests that repetitions tend to fade into the background. So investors who have had the chance to screen Shanghai stocks would find digits other than the initial 6 more salient. When we replicate the return tests using an alternative definition which considers the first "6" for Shanghai listed stocks, the untabulated results indicate that the luckiness measure based on our original definition (last four digits) is more negatively correlated with future returns than that based on the alternative definition (based on all six digits). These results suggest that investors ignore the first "6" for Shanghai-listed stocks. Another drawback of considering the first "6" is that Shanghai-listed firms cannot be "unlucky" since all their listing codes have the lucky number of "6". It seems unlikely that investors would perceive that all unlucky firms are listed in Shenzhen. We therefore use the measure which omits the first "6".

codes assigned to firms that were listed in that year separately for the Shanghai Stock Exchange and the Shenzhen Stock Exchange.

Several points emerge. First, the two major stock exchanges differ in the format of the numerical code. Each stock listed on the Shanghai Stock Exchange has a code beginning with 6, and each listed on the Shenzhen Stock Exchange has a code starting with zero.

Second, although the numerical codes have six digits on both exchanges, variations in the numerical codes exist only in the last four digits for the sample period we examine. In defining lucky and unlucky listing codes, we only consider the relevant digits of the code that vary in the sample. Thus, the initial 6 in codes on the Shanghai Stock Exchange is not used in defining lucky codes.

Third, the number of IPOs varies across years. For the Shanghai Stock Exchange, the number of IPOs ranges from 0 in 1991 to 103 in 1996, while for the Shenzhen Stock Exchange, the number of IPOs ranges from 0 in 2003 to 204 in 2010.

Fourth, the assignment of numerical codes is far from sequential. As we can see from both the mean and median values, there is no apparent increasing time-series trend in numerical codes for either exchange (except 2005-2012 in the Shenzhen Stock Exchange).[14] This non-sequential nature of the assignment of the listing codes provides an opening for managerial efforts to obtain lucky numbers.

[Table 1 here]

3.3.2 Summary statistics

Table 2 provides descriptive statistics for firms with lucky and unlucky listing codes within three years after IPO. We have two objectives. First, we investigate whether firms with lucky listing codes experience lower market-adjusted return than firms with unlucky listing codes within three years after IPO. Second, we investigate whether there are differences in firm characteristics between firms with lucky listing codes and firms with unlucky listing codes that might explain the return differentials.

[14] The sequential assignment does not necessarily imply that the assignment of lucky numbers is random, because firms can vie for a position associated with lucky numbers.

We find significant differences in monthly market-adjusted return (*avertn_div*) between firms with lucky versus unlucky listing codes. Specifically, *avertn_div*, the market-adjusted return, averages -0.2% for firms with lucky listing codes and 0.6% for firms with unlucky listing codes, which indicates a 0.8% lower monthly return for firms with lucky listing codes, which is both statistically significant and economically substantial.

The rest of the rows report, separately for lucky and unlucky firms, the mean/median values for the following five variables: *lgBM, lgMV, Top1_state, Top1* and *TAccrual*. *lgBM* is the natural log of the ratio of book value of equity of the year to the sum of the market value of tradable shares and the estimated market value of non-tradable shares at the beginning of the month, assuming an 80% discount relative to tradable shares. The reason for the discount is that during our sample period, a substantial proportion of shares of listed firms in China were in the form of state shares and legal person shares, which could not be traded freely and therefore did not have market prices. To address this issue, we apply the finding of Chen and Xiong (2001) that non-tradable state-owned shares and legal person shares in China are traded on informal markets at a discount of between 70% and 80%. *lgMV* is the natural log of the sum of the market value of tradable shares and the estimated market value of non-tradable shares at the beginning of the month, assuming an 80% discount relative to tradable shares. *Top1_state* is a dummy variable that equals 1 if the firm's largest direct shareholder is a state-owned asset management bureau/company, and zero otherwise. *Top1* is the percentage of shares held by the largest shareholder. *TAccrual* is total accruals, computed as net income minus cash flow from operating activities divided by total assets, in the fiscal year when the firm goes public. [15] Our results show that unlucky firms have higher book-to-market ratios (*lgBM*), they are smaller (*lgMV*), they are less likely to be state-owned firms (*Top1_state*), their ownership is less concentrated (*Top1*), and they report higher accounting accruals in the IPO year (*TAccrual*) than lucky firms. We control for these firm characteristics in our empirical analyses.

[Table 2 here]

[15] Teoh, Welch and Wong (1998) argue that this is a proxy for earnings management related to IPO because this fiscal year includes months prior to IPO, and managers may not want to rewind earnings management immediately after IPO due to concerns over legal and reputational challenges.

We next examine the proportion of firms with lucky/unlucky numbers to see whether managers of the listing firms deliberately attempt to obtain lucky numbers and avoid unlucky numbers in the listing code.

4. Managers Sharing of or Catering to Investor Superstition

If managers are themselves superstitious, they may prefer lucky listing codes. Furthermore, there is evidence that managers cater to imperfectly rational investor perceptions (Baker and Wurgler 2004). If investors are willing to pay more for IPOs with lucky listing codes relative to IPOs with unlucky codes, listing firms should respond accordingly by lobbying the exchanges for lucky listing codes. We therefore test whether the proportion of firms with lucky listing codes is higher, and the proportion of firms with unlucky listing codes is lower, than would be the case under random assignment.

4.1 Frequency of Lucky Numbers

Table 3 reports the actual and expected proportions separately for firms with lucky listing codes, firms with unlucky listing codes and other firms. As a reminder, although the numerical codes have six digits on both exchanges, variations in the numerical codes exist only in the last four digits for stocks listed on both exchanges, for the sample period we examine. In all our empirical tests we consider only these relevant digits in the classifications.

We report our results separately for the two exchanges. The expected proportions are computed assuming a random assignment of four-digit listing codes for the two exchanges.[16] If each relevant digit in the code is determined randomly, it has an equal probability of being any of the digits from 0 to 9.[17]

[16] We exclude firms that were listed in Shenzhen Stock Exchange from 2005 to 2012, because their listing codes were assigned sequentially, which violates the assumption of random assignment.

[17] In many real world data sources, the distribution of digits is not uniform. This is codified in Benford's law, which predicts that the first digit of a number will be 1 almost one third of the time (see, e.g., http://mathworld.wolfram.com/BenfordsLaw.html). However, Benford's law does not apply to listing codes. For example, one listed firm in the Shanghai stock exchange, Shanghai Port Container Co., Ltd, has a listing code of 600018. The relevant portion of the listing code, 018, starts with a zero, which by assumption is precluded in Benford's Law. More generally, since listing codes are arbitrary, a uniform distribution of digits seems a more appropriate benchmark. Listing codes also do not satisfy other conditions for Benford's law, which applies for variables

For example, to compute the expected proportion for a four-digit listing code, we first compute the expected proportion for lucky listing codes where one digit takes on a lucky number and the other three digits take on neutral numbers (numbers that are not deemed as either "lucky" or "unlucky"). Basic probability theory shows that the expected proportion is 25.92%. We then compute the expected proportion for lucky listing codes containing two, three or four lucky digits. The sum of these expected proportions is the expected proportion of four-digit listing codes that contain at least one lucky number and no unlucky number.

Table 3 indicates that among stocks listed on the Shanghai stock exchange, the actual proportion of firms with lucky listing codes is 57.81%, which is 9.80% higher in percentage terms, than 52.65%, the proportion expected by chances. The proportion of firms with unlucky listing codes is 5.68%, which is 48.60% lower in percentage terms, than the expected proportion of 11.05%. For the Shenzhen stock exchange, the proportion of firms with lucky listing codes (65.44%) is higher than the expected proportion (52.65%) by 24.29% in percentage terms; the proportion of firms with unlucky listing codes (8.09%) is lower than the expected proportion (11.05%) by 26.79% in percentage terms. The differences between actual and expected proportions of lucky and unlucky numbers are statistically significant at the 5% level. Overall, these findings support the prediction that lucky listing codes are abnormally prevalent while unlucky listed codes are abnormally rare.

[Table 3 here]

4.2 Sequences of Lucky Digits and End-Lucky Numbers

In Chinese culture, there is a popular belief that a sequence of lucky numbers is luckier than a single lucky number. For example, the listing code of Mr. Yan discussed in the introduction, 600881, was especially pleasing to him as it contained two 8s in immediate succession. We test whether such beliefs affect the frequency of listing codes. Specifically, we report the actual and expected proportions of firms

whose logarithms are distributed uniformly and are distributed across several orders of magnitude. Empirically the listing code frequencies do not obey Benford's law. For example, the frequency of a first digit of 1 is close to 10%, whereas Benford's law predicts a frequency of approximately 1/3.

with at least two consecutive lucky/unlucky numbers in Table 4. We predict that the proportion of firms with at least two consecutive lucky numbers is higher than expected while the proportion of firms with at least two consecutive unlucky numbers is lower than expected.

Table 4 shows that the proportion of firms with at least two consecutive lucky numbers is 18.15% on the Shanghai Stock Exchange and 18.38% on the Shenzhen Stock Exchange, both of which are higher than the expected proportion of 17.01%. When we turn to the proportion of firms with at least two consecutive unlucky numbers, we find the opposite results. The actual proportion on the Shanghai Stock Exchange is 0.2% (0.18% on the Shenzhen Stock Exchange), less than one sixth of the expected proportion of 1.33%, with both differences between the actual and expected proportions being significant at the 5% level. Overall, these results support the hypothesis that investors' preference for a sequence of lucky numbers and distaste for a sequence of unlucky numbers are reflected by firms' listing codes.

A further test for superstition effects is motivated by the idea that the last digit in the listing code is especially salient. In general, we might expect either the first or last digit to be more salient than intermediate digits. However, on the Shanghai Stock Exchange the first digit in the listing code is automatically 6 and on the Shenzhen Stock Exchange the first digit is automatically zero. We therefore focus on testing whether the proportion of firms with a lucky (unlucky) number in the last digit of the listing code is higher (lower) than expected.

Table 4 shows that among Shanghai-listed stocks, the proportion of firms with lucky listing codes ending in a lucky number is 31.44%, which is higher than the expected proportion of 21.87%; the proportion of firms with unlucky listing codes ending in an unlucky number is 1.52%, substantially lower than the expected proportion of 3.43%, and both differences are significant at the 1% level. Results are similar when we turn to Shenzhen-listed stocks. The proportion of firms with lucky listing codes ending in a lucky number is 30.70%, which is significantly higher than the expected proportion of 21.87%. Furthermore, the proportion of firms with unlucky listing codes ending in an unlucky number is 2.76%, which is lower than the expected proportion of 3.43%.

We continue to examine whether one lucky digit in the middle of the listing code is salient enough

to be viewed as lucky by investors. We test whether the likelihood of lucky numbers appearing in the middle is higher or lower than expected. If managers and/or investors perceive middle lucky numbers as lucky we would expect to see them appearing more frequently than expected by chance. [18] Because the first two digits of the listing codes of both Shanghai and Shenzhen listed stocks during our sample period are fixed, the variations in digits only appear in the last four digits (the 3rd to the 6th digit). We examine the likelihood of lucky numbers appearing in the middle (i.e., 4th and 5th digits) and report our results in in the last two rows of Table 4.

We find that, as for the 4th digit, the actual likelihood of having a lucky number is not significantly different from the expected likelihood for Shanghai listed stocks, and it is significantly higher than expected for Shenzhen-listed firms. As for the 5th digit, the actual likelihood is greater than expected for Shanghai listed stocks and lower than expected for Shenzhen-listed firms. Overall, the likelihood of having a lucky number is higher than expected for both the 4th and the 5th digits, and the difference is significant for the 4th digit. In general, our evidence seems to suggest that lucky numbers appearing in the middle are perceived as lucky by managers and investors.

[Table 4 here]

Together, the evidence from the Table 3 and 4 suggests a deliberate attempt by managers or the stock exchange to include lucky rather than unlucky numbers in the listing code.

5. Do Stocks with Lucky Listing Codes Underperform after Listing?

The findings discussed above raise the question of whether managers are successful in inducing market overvaluation by acquiring lucky listing codes. In untabulated tests, we find that during the first three years after IPO, the valuation ratio (Tobin's *q* and the market-to-book ratio) is significantly higher for firms with lucky listing codes than for firms with unlucky listing codes, after controlling for various firm characteristics which affect valuations. The difference in valuation subsequently dissipates. This finding is consistent with lucky listing codes initially being overvalued and the market correcting this mispricing over

[18] We thank the annonymous referee for pointing out this possibility.

time. However, there are many determinants of valuation ratios, so this test is not conclusive. To provide a more refined test, in this section we test the prediction that the post-IPO return is lower for lucky firms than for unlucky firms.

Following previous literature using data from emerging markets (e.g., Chan, Hamao and Lakonishok 1991; Loughran and Ritter 1995; Fan, Wong and Zhang 2007; Peng, Wei and Yang 2011), we run a Fama-MacBeth monthly regression using monthly market-adjusted return, *avretn_div*, as the dependent variable. The independent variables include the natural logarithm of the book-to-market ratio (*lgBM*), the natural logarithm of the market value (*LgMV*) and our test variable, *Lucky*. *Lucky* is a dummy variable which equals 1 if the firm's listing code contains one or more of the lucky digits 6, 8 or 9, but not the unlucky digit 4, and 0 otherwise. We include *LgMV* and *LgBM* to control for the size and book-to-market effects (Fama and French 1993; Fama and French 1997), with the market value for non-tradable shares assumed to be at an 80% discount of that of tradable shares.[19] Our sample consists of firms with lucky listing codes and firms with unlucky listing codes within 3 years after IPO from 1990 through 2013. The coefficient on *Lucky* measures the difference in market-adjusted returns between firms with lucky listing codes and those with unlucky listing codes, after controlling for other firm characteristics. To control for industry effects, we include industry dummies.

The results are reported in Table 5 column (1) for observations within three years after IPO. Firms with lucky listing codes tend to have lower returns than firms with unlucky listing codes for the three years after IPO. This finding is consistent with investors correcting the initial lucky-number premium over time. The coefficient on *Lucky* is −0.009, indicating that on average, the monthly return of firms with lucky listing codes is lower by 0.9% per month relative to firms with unlucky listing codes. Thus, the cost to a trader of investing superstitiously is about 10.8% per year, which is substantial. The coefficient on *lgBM* (*lgMV*) is positive (negative), which is consistent with the literature.

In addition, we control for ownership concentration (*Top1*), state ownership (*Top1_state*) and earnings management (*TAccrual*). Prior literature suggests that these three may potentially affect future

[19] The results are similar if we instead assume that the market value of non-tradable shares is the same as that of tradable shares.

returns (Morck, Shleifer and Vishny 1988; Sun and Tong, 2003; Teoh, Welch and Wong 1998)).

Table 5 column (2) reports results from the return analysis after controlling for the three additional variables. Our findings are the same: firms with lucky listing codes have significantly lower returns than firms with unlucky listing codes. Our previous conclusion, that firms with lucky listing codes have abnormally low returns as compared to unlucky firms, is therefore robust to inclusion of the three additional control variables.

[Table 5 here]

6. Fama-French three-Factor model

Although the Fama-French three-Factor model is popular in studies using U.S. data, its merits in an international setting have been debated. Daniel, Titman and Wei (2001) find that an asset pricing model based on firm characteristics, such as size and the book-to-market ratio, performs better than the Fama-French three-factor model in the Japan setting. Eom and Park (2011) reach a similar conclusion, using data from Korea. Perhaps not surprisingly, most studies on emerging economies rely on characteristics-based models (e.g., Chan, Hamao and Lakonishok 1991; Fan, Wong and Zhang 2007; Loughran and Ritter 1995; Peng, Wei and Yang 2011).

Nevertheless, as a robustness check we consider the Fama-French model. Following Fama and French (1993), we rank all firms listed in Shanghai or Shenzhen Stock Exchanges into two groups, small (S) and big (B), according to their market value (computed as the stock price as of the end of June multiplied by the number of shares outstanding). We also sort them into three groups, Low (L), Medium (M) and High (H), according to the book-to-market ratio (*BM*). *BM* is computed as the book value of equity for the fiscal year divided by the market equity at the end of the fiscal year, which is December 31 for Chinese listed firms. The Low and High groups consist of the bottom and top 30% of the stocks respectively, while the 40% in the middle fall into the Medium group. The intersection of the two size portfolio (S and B) and the three *BM* portfolios (L, M and H) yield six benchmark portfolios: S/L, S/M, S/H, B/L, B/M and B/H.

We form portfolios by shorting firms with lucky listing codes and longing those with unlucky listing codes. Our regression model is specified as

$$R_{pt} - R_{ft} = a + bRMf_t + sSMB_t + hHML_t + \varepsilon_t, \quad (1)$$

where R_{pt} is the month-t equally weighted return of the portfolio of firms that is formed at the end of month $t-1$, and:

R_{ft} is the risk free rate in month t. It is proxied by the short-term rate in China downloaded from the OECD's website (http://stats.oecd.org/Index.aspx). This rate is the annualized rate of either the three month interbank offer rate attaching to loans amongst banks or the rate associated with Treasury bills, Certificates of Deposit or comparable instruments, each of three month maturity;

RMf_t is the excess market return measured by the difference between R_{mt} and R_{ft}, where R_{ft} is the risk free rate in month t defined above. R_{mt} is the market return in month t, computed as the return on the value-weighted portfolio of the stocks in the six benchmark portfolios;

SMB_t is the return on small firms minus the return on large firms in month t, computed as the monthly difference between the simple average of the value-weighted returns on the three small-stock portfolios (S/L, S/M, and S/H) and the simple average of the value-weighted returns on the three big-stock portfolios (B/L, B/M and B/H).

HML_t is the return on high book-to-market stocks minus the return on low book-to-market stocks in month t, measured by the monthly difference between the simple average of the value-weighted returns on the two high-BM portfolios (S/H and B/H) and the simple average of the value-weighted returns on the two low-BM portfolios (S/L and B/L).

If indeed firms with lucky listing codes underperform firms with unlucky listing codes, we expect the intercept term from this model specification to be positive.

The results are reported in Table 6. Regression 1 reports the results where the portfolios consist of firms within three years of their IPOs. We find that the intercept term is 0.5%, significant at the 5% level. This positive alpha of a portfolio that is short on firms with lucky listing codes and is long on those with

unlucky listing codes indicates that firms with lucky listing codes experience poorer returns than firms with unlucky listing codes within the first three years of IPO.

[Table 6 here]

In sum, the results based on the Fama-French three-factor model are consistent with the results based on firm characteristics model, suggesting that our stock return results are robust to the use of alternative asset pricing models.

Short-selling is in general forbidden in China until recently, when investors were allowed to short sell a few large company stocks. This ban on short selling is an important limit to arbitrage of overpricing. This may be an important reason why mispricing is not arbitraged away by the above trading strategy, which includes a short position in lucky IPOs. [20]

7. Return and trading volume analysis around IPO date

If investors are irrationally inclined towards stocks with lucky listing codes, we expect high price run-ups and high trading volumes when they can get their hands on them for the first time. Hence we investigate how the stock return and the trading volume on the first trading date vary with the luckiness of listing codes.

We use a multivariate regression approach and report our results in Table 7. Specifically, we examine market-adjusted returns and daily turnovers over the three windows: the IPO date, the two-day window (0,1) with day 0 being the IPO date, and the three-day window (0,2). Our main independent variable is *Lucky*. We include several controls: *Size* (the natural log of total sales), *OpProfitMargin* (the firm's total operating profit i.e., income from main operations plus income from other operations, divided by its total sales), *Lev* (the firm's total debts, i.e., short-term debts plus long-term liabilities due within one year plus long-term debts, divided by its total assets), *Issue* (the number of shares being issued in millions), *A-share floating % @IPO* (the percentage of tradable shares to total outstanding shares upon IPO), *Over_subscription* (the number of shares subscribed divided by the shares issued), *Top1_State* and *Top1*.

[20] We thank the anonymous referee for pointing this out.

We find that the stock return is higher on the IPO date for firms with lucky numbers. This is consistent with investors exhibiting preferences for firms with lucky listing codes and bidding up their stock price in the secondary market. The difference in the first-trading day return is large, 34.4%. Considering that the stock return differential over the next 36 months is about 32% (0.9% X 36, Table 5), our results suggest that the overvaluation is almost all built up on the first-trading day. This suggests that retail investors who dominate the secondary market in China play a significant role in bidding up the stock price and creating a lucky-number premium on the first trading day.

Trading volume is higher for lucky firms than for unlucky firms for all three windows we examine, and the difference between the two types of firms is statistically significant for the IPO date, (0,1) and (0,2) windows. Specifically, the turnover, measured as the number of shares traded as a fraction of the number of tradable shares offered in the IPO, is 4.6% higher for lucky firms than for unlucky firms. This difference is economically significant. To the extent that trading volume is an indicator of investor enthusiasm, our results suggest that investors are more enthusiastic about firms with lucky listing codes. This finding is consistent with the results based on stock returns.

[Table 7 here]

To illustrate the price run-up and reversal differences between lucky and unlucky IPOs, we plot in Figure 1 the cumulative return differential between lucky and unlucky firms after controlling for various firm characteristics.

[Figure 1 here]

On the horizontal axis, "1" represents the return window starting from the IPO date to the end of the IPO month. We compute the return differential by first cumulating the stock return for the window and then regressing the return on the *Lucky* dummy, *lgBM*, *lgMV* and industry dummies. The value on the vertical axis is the coefficient on *Lucky*, essentially the return differential after controlling for industry, size and book-to-market effects.

A close examination of Figure 1 suggests that in the month of IPO, lucky firms outperform unlucky firms by close to 35%. This is consistent with our tests on the short-window around IPO dates. However, as

time goes on, this lucky number premium gradually dissipates and it enters negative territory towards the end of the third year after IPO. This plot is consistent with that investors initially overpricing lucky numbers and subsequently correcting the mistake over time.

8. The endogeneity problem – 2SLS

An endogeneity problem would occur if firms that acquire lucky listing codes are more likely to be overvalued by the market for reasons unrelated to lucky listing numbers per se. For example, if the market overvalues managerial ability (an unobservable variable) and if more talented managers have a better chance to obtain a lucky listing code, the coefficient estimates in our model will be biased. We note that this alternative explanation requires a positive association between overvaluation and obtaining lucky listing codes. Such an association is supportive of the idea that superstition matters to one or more sets of financial decision makers.

We cannot rule out this possibility completely, but since listing codes are selected prior to IPO road shows which can occur months later, at the time of listing code acquisition the manager will typically not know how under- or overvalued the firm will later be. Furthermore, it is not at all obvious that managers of a firm that will be overvalued will be more eager than managers of later-to-be undervalued firms to obtain lucky listing codes. A firm that will be undervalued may have a strong incentive to obtain a lucky listing code in order to offset the undervaluation. Overall, the most plausible interpretation of our findings is that it is the lucky listing codes themselves that are inducing overvaluation and poor post-IPO return performance.

Nonetheless, to address this endogeneity concern, we provide an instrument for lucky listing codes by exploiting cross-sectional differences in the average income level of the province of the firm's headquarters. This is expected to affect the likelihood that the firm will obtain a lucky listing code, yet is unlikely to affect firm post-IPO return directly.

The instrumental variable is motivated by theory and survey evidence suggesting that personal income affects superstitious belief. In psychology, the deprivation theory suggests that paranormal beliefs provide "spiritual help" to individuals in disadvantaged social and economic status when they face

psychological and physical strains (Glock and Stark 1965; Stark and Bainbridge 1980; Rice 2003; Torgler 2007). As a result, poorer people are more inclined to be superstitious. In addition, Torgler (2007) argues that the opportunity cost of time is higher for wealthier individuals, which prevents them from spending time on superstitious activities.

Consistent with these arguments, Gorer (1955) reports that low-income individuals are more likely to visit fortune-tellers, read horoscopes and believe in lucky mascots. Using survey data, Safiollah, Mousa and Nasrollah (2010) find that higher income is associated with lower superstition. Rice (2003) find that lower-income people are more superstitious and more likely to believe in astrology. Also, superstitious belief in luck or lucky numbers is likely to be a motivation for participating in number-based lotteries. Such lotteries are especially popular among the poor and in poor neighborhoods, to the point that social critics often criticize government run lotteries as a form of regressive taxation (e.g. Blalock, Just and Simon, 2007; Beckert and Lutter, 2009).

We therefore use as IV the ranking of the GNI (Gross National Income) per capita index of the headquarter province from *China National Human Development Report 2013*.[21] As mentioned earlier, evidence that personal income affects superstitiousness, together with evidence on the local bias in investment, implies that the IV will be associated with lucky listing codes.

Specifically, we sort the provinces in which the IPO's headquarter is located into quartiles according to their GNI per capita index. We assign values running from 1 and 4 to the quartiles, with the top quartile having the value of 4. We then shift and rescale this rank by subtracting 1 and then dividing by 3 so that this variable ranges from 0 to 1, with the top quartile having value 1 and the bottom quartile 0. This allows us to interpret the coefficient on the rank variable, which we call *GNI_rank*, as the effect of the difference between the poorest and the richest quartiles.

In our first stage regression, we run a probit model where the dependent variable is the dummy indicating whether the listing code is lucky. The independent variables include *GNI_rank* (the GNI rank of the firm's headquarter province), *Top1_State*, *Top1*, *A-share floating %@IPO*, *Tangibility*,

[21] http://www.cn.undp.org/content/dam/china/docs/Publications/UNDP-CH-HD-Publication-NHDR_2013_EN_final.pdf

OpProfitMargin, *Lev*, *Size*, industry- and year-fixed effects. Our results are reported in Panel A of Table 8. Consistent with the hypothesis that superstition promotes the use of lucky listing codes, the coefficient on *GNI_rank* is -0.303, so that firms based in provinces with higher GNI per capita are less likely to have lucky codes. Marginal analysis shows that that the likelihood of getting a lucky listing code is 5.08% lower for firms from provinces in the richest quartile than for firms from provinces in the poorest quartile, holding all other variables at their mean.

We report our second-stage regression results in Panel B of Table 8. In the second-stage regression, we regress the firm's monthly abnormal return (*avretn_div*) on *Lucky* (predicted probability from the first-stage regression). Column (1) reports the results when we control for *lgBM*, *lgMV* and the industry fixed effects. Column (2) reports the results when we additionally control for *Top1_state*, *Top1* and *TAccrual*. The coefficient on *Lucky* is -0.038, significant at the 1% level in Column (1) and it is -0.026, significant at the 5% level in Column (2). These results show that lucky firms have lower subsequent returns than unlucky firms.

In sum, our results from the 2SLS regression suggest that our earlier findings are not driven by endogeneity.

[Table 8 here]

9. Conclusion

The notion that ideas or ideologies have important effects on political and social behavior is commonplace. It also seems evident that investment ideas, from the specific, such as whether a given firm's strategy for exploiting the cloud is promising, to the general, such as portfolio theory, contrarianism, or the notion that it is good to 'buy on the dips,' affect investor behavior. However, there has been little testing of how popular theories about how the world works (as contrasted with direct general cognitive biases in probability assessments) affect corporate decision making and market prices.

The Chinese IPO market provides an appealing setting for measuring the effects of one kind of

investment idea, superstitious beliefs, on financial outcomes. In Chinese culture, certain digits are lucky and others unlucky, and this superstition affects behavior (such as the scheduling of the opening of the 2008 Olympics). We investigate whether numerological superstition is associated with stock mispricing in the form of overvaluation of firms with lucky listing codes on China's stock exchanges; and whether firms share or cater to investor superstition by obtaining lucky listing codes.

We find that the proportion of firms going public with lucky listing codes is greater than would be expected based on chance, and the proportion of firms with unlucky listing codes is abnormally low. These findings suggest that there is an intentional effort by listing firms to obtain lucky number in their listing codes.

Using both Fama-MacBeth cross-sectional regressions and Fama-French three-factor regressions, we find that, consistent with overvaluation of IPO with lucky listing codes, IPOs with lucky listing codes underperform those with unlucky listing codes. Our untabulated analyses based on the valuation ratio uncover evidence supportive of overvaluation of lucky listing codes.

To investigate whether the mispricing arises from the offer price or from the trading on the secondary market, we examine the stock return and the trading volume in a short window around the first public trading date. Our results are consistent with that mispricing largely takes place on the secondary market, which is dominated by individual investors. In addition, our untabulated tests show that stock returns are less sensitive to unexpected earnings for firms with lucky listing codes than for firms with unlucky listing codes. Taken together, these results imply that the mispricing of lucky listing codes is due to unsophisticated investors relying on superstition to guide their portfolio selection.

We argue that, for several reasons, it is unlikely that the return results are derived from endogenous selection of lucky listing codes by managers who expect their firms to be overvalued for non-superstitious reasons. Using an instrumental variable approach, we show that our conclusions are not driven by endogeneity. In summary, our overall findings are consistent with market prices being biased by superstitious beliefs about lucky numbers.

Our findings suggest further possible directions for testing the effects of superstition. Previous

research has documented that individuals with higher cognitive ability make better financial decisions (Grinblatt, Kelohariju and Linnainmaa 2011; Agarwal and Mazumder 2013). It would be interesting to explore whether the effects of superstition on financial markets are stronger among investors with lower education or cognitive ability.

Arbitrary ideas can cause errors that vary greatly over time and are completely different across cultures. Such differences contrast with the effects of inherent cognitive biases, which should tend to operate fairly consistently across cultures (though of course culture can modulate their effects). This raises the question, for assets that are traded internationally, of whether there is selling by those who find an asset unlucky, at a given time, to those who find it lucky (e.g., stocks with 6's, 8's, or 13's, looking across cultures with different attitudes toward these numbers).

More broadly, such phenomena as the rise of diversified investing over a period of decades, and the occurrence of notable events such as the internet boom are arguably caused by the spread of ideas or 'popular models' about investing (see, e.g., Shiller 2005, Bai, Lu and Tao 2009). Our findings within the more restricted domain of superstition indicate that investor ideas do matter. This suggests that it will be interesting to test in other domains how arbitrary ideas affect capital markets.

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Table 1 Distribution of listing codes

This table shows the summary statistics for listing codes of sample firms that went public from 1990 through 2013 in the Shanghai and Shenzhen Stock Exchange.

	Shenzhen-listed Firms					Shanghai-listed Firms				
Year	**N**	**Mean**	**Median**	**Minimum**	**Maximum**	**N**	**Mean**	**Median**	**Minimum**	**Maximum**
1990	1	000005	000005	000005	000005	7	600638	600652	600601	600656
1991	5	000004	000003	000001	000009	0				
1992	18	000150	000017	000006	000505	22	600615	600614	600603	600655
1993	52	000423	000522	000022	000554	72	600663	600665	600600	600800
1994	42	000373	000552	000021	000.576	69	600846	600835	600801	601607
1995	9	000401	000582	000010	000586	15	600876	600876	600869	600883
1996	100	000559	000610	000055	000689	103	600766	600751	600700	600899
1997	121	000700	000733	000059	001696	85	600195	600093	600051	600799
1998	53	000802	000827	000065	001896	53	600152	600160	600001	600218
1999	52	000906	000922	000090	000959	46	600185	600204	600000	600359
2000	49	000758	000969	000070	000999	87	600274	600278	600008	600500
2001	1	000725	000725	000725	000725	78	600395	600383	600010	600599
2002	1	000875	000875	000875	000875	70	600485	600526	600026	600598
2003	0					67	600401	600446	600004	600900
2004	39	001970	002019	000100	002038	61	600677	600572	600022	600997
2005	12	002045	002045	002039	002050	3	600490	600472	600027	600970
2006	52	002077	002077	002051	002102	14	601195	601366	600017	601991
2007	101	002135	002152	000338	002202	25	601436	601328	601002	601999
2008	71	002238	002238	002203	002274	6	601739	601832	601186	601958
2009	54	002302	002302	002275	002328	9	601499	601618	600999	601989
2010	204	002431	002431	002329	002533	28	601424	601329	600998	601933
2011	115	002591	002591	002534	002648	39	601466	601555	601010	601996
2012	55	002676	002676	002649	002703	26	602413	603001	601012	603993
2013	1	000333	000333	000333	000333	1	600023	600023	600023	600023

Table 2 Summary Statistics

This table presents the mean and median values of variables measuring firm characteristics within three years of IPO for firms with lucky listing codes and firms with unlucky listing codes. An unlucky listing code contains the unlucky digit 4 but not any of the lucky digits 6, 8 or 9; a lucky listing code contains one or more of the lucky digits 6, 8 or 9, but not the unlucky digit 4. *avretn_div* is computed as the firm's monthly return minus value-weighted market return. *lgBM* is the natural log of the ratio of book value of equity of the year to the sum of the market value of tradable shares and the estimated market value of non-tradable shares at the beginning of the month, assuming an 80% discount relative to tradable shares. *lgMV* is the natural log of the sum of the market value of tradable shares and the estimated market value of non-tradable shares at the beginning of the month, assuming an 80% discount relative to tradable shares. *Top1_state* is a dummy variable that equals 1 if the firm's largest direct shareholder is a state-owned asset management bureau/company, and zero otherwise. *Top1* is the percentage of shares held by the largest shareholder. *TAccrual* is total accruals, computed as net income minus cash flow from operating activities divided by total assets, in the fiscal year when the firm goes public. The asterisks ($^{\#}$) indicate the significance level of *t*-statistics (Wilcoxon rank-sum *z* statistics) of the difference between the two subsamples. ***, **, and * ($^{\#\#\#}$, $^{\#\#}$ and $^{\#}$) denote significance at the 1%, 5% and 10% level, respectively.

	Unlucky		Lucky		Differences in			
Variables	Mean	Median	Mean	Median	*Mean*		*Median*	
avretn_div	0.006	-0.007	-0.002	-0.008	0.008	***	0.001	
lgBM	-0.317	-0.309	-0.410	-0.408	0.093	***	0.099	###
lgMV	20.763	20.694	20.900	20.766	-0.138	***	-0.072	###
Top1_state	0.353	0.000	0.561	1.000	-0.207	***	-1.000	###
Top1	40.203	38.850	44.028	43.180	-3.825	***	-4.330	###
TAccrual	0.045	0.035	0.031	0.023	0.013	***	0.012	###

Table 3 Frequency of lucky/unlucky/other listing codes

This table presents the distribution of firms with lucky or unlucky, or mixed/neutral listing codes (labeled "Other"). The sample covers all A-shares firms that were listed in Shanghai or Shenzhen Stock Exchange from 1990 through 2013, except those that were listed in Shenzhen Stock Exchange from 2005 to 2012. These firms are excluded because their listing codes were assigned sequentially, which violates the assumption of random assignment. An unlucky listing code contains the unlucky digit 4 but not any of the lucky digits 6, 8 or 9; a lucky listing code contains one or more of the lucky digits 6, 8 or 9, but not the unlucky digit 4. Mixed/neutral listing codes are those that do not fall into either of these categories. The first digit of all Shanghai-listed firms, which is 6, is not counted when we make the above-mentioned classifications. The last three column reports the actual proportions of firms falling into the above-mentioned categories, while 'expected (%)' reports the expected proportions assuming random assignment of listing codes. ###, ##, and # denote significant difference between actual and expected proportions at the 1%, 5% and 10% level respectively, using a binomial test. ***, **, and * denote significant difference between the actual and the expected overall distribution at the 1%, 5% and 10% level, respectively, using a Chi-squared test.

	Expected (4 digits) (%)	Shanghai A (N = 986) (%)		Shenzhen A (N = 544) (%)		A Shares (N=1,530) (%)	
Unlucky	11.05%	5.68%	***	8.09%	**	6.54%	***
Lucky	52.65%	57.81%	***	65.44%	***	60.52%	***
Other	36.30%	36.51%		26.47%	***	32.94%	***
Total	100%	100%	###	100%	###	100%	###

Table 4 Frequency of (un)lucky number appearing in the listing codes

This table presents the frequency at which (un)lucky numbers appearing at different locations in the listing codes. The sample covers all A-shares firms that were listed in Shanghai or Shenzhen Stock Exchange from 1990 through 2013, except those that were listed in Shenzhen Stock Exchange from 2005 to 2012. These firms are excluded because their listing codes were assigned sequentially, which violates the assumption of random assignment. The last three column reports the actual proportions of firms falling into the above-mentioned categories, while 'expected (%)' reports the expected proportions assuming random assignment of listing codes. ***, **, and * denote significant difference between the actual and the expected overall distribution at the 1%, 5% and 10% level, respectively, using a Chi-squared test.

	Expected (4 digits) (%)	Shanghai A (N=986)		Shenzhen A (N=544)		Combined (N=1,530)	
Lucky code with at least 2 consecutive lucky numbers	17.01%	18.15%		18.38%		18.24%	
Unlucky code with at least 2 consecutive unlucky numbers	1.33%	0.20%	***	0.18%	**	0.20%	***
Lucky code with a lucky end	21.87%	31.44%	***	30.70%	***	31.18%	***
Unlucky code with an unlucky end	3.43%	1.52%	***	2.76%		1.96%	***
The 4th digit is a lucky number	30.00%	28.50%		42.28%	***	33.40%	***
The 5th digit is a lucky number	30.00%	33.67%	**	26.65%	*	31.18%	

Table 5 Stock return analysis – Fama-MacBeth monthly regression

This table reports Fama-MacBeth monthly regression of stock return on lucky listing codes, for the sample consisting of firms with lucky listing codes and firms with unlucky listing codes within 3 years after IPO from 1990 through 2013. The dependent variable of the regressions is the firm's monthly abnormal return, *avretn_div*, computed as the firm's monthly return minus value-weighted market return. *Lucky* is a dummy variable which equals 1 if the firm's listing code contains one or more of the lucky digits 6, 8 or 9, but not the unlucky digit 4, and 0 otherwise. *lgBM* is the natural log of the ratio of book value of equity of the year to the sum of the market value of tradable shares and the estimated market value of non-tradable shares at the beginning of the month, assuming an 80% discount relative to tradable shares. *lgMV* is the natural log of the sum of the market value of tradable shares and the estimated market value of non-tradable shares at the beginning of the month, assuming an 80% discount relative to tradable shares. Industry dummies are included in the regressions to control for the industry fixed effects. *Top1_state* is a dummy variable that equals 1 if the firm's largest direct shareholder is a state-owned asset management bureau/company, and zero otherwise. *Top1* is the percentage of shares held by the largest shareholder. *TAccrual* is total accruals, computed as net income minus cash flow from operating activities divided by total assets, in the fiscal year when the firm goes public. The *t*-statistics are shown in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)
Lucky	-0.009**	-0.003**
	(2.24)	(1.98)
lgBM	0.014***	0.012***
	(4.14)	(4.40)
lgMV	-0.005*	-0.001
	(1.89)	(0.87)
Top1_State		0.002
		(1.05)
Top1		-0.0001
		(1.56)
TAccrual		-0.003
		(0.29)
Industry fixed effects	Yes	Yes
Constant	0.105**	0.036
	(2.09)	(1.00)
N	48,488	30,703
Number of months	276	191
Mean R^2	0.003	0.003

Table 6 Stock return analysis with Fama-French three-factor regressions

This table shows the results based on Fama-French three-factor regressions. The sample covers the portfolio formed monthly by shorting firms with lucky listing codes and longing those with unlucky listing codes within 3 years after IPO. The dependent variable is the portfolio's monthly return minus the risk free rate. The risk free rate is proxied by the short-term rate in China downloaded from ChinaScope. This rate is the annualized rate of either the three month interbank offer rate attaching to loans amongst banks or the rate associated with Treasury bills, Certificates of Deposit or comparable instruments, each of three month maturity. Following Fama and French (1993), we rank all firms listed in Shanghai or Shenzhen Stock Exchanges into two groups, small (S) and big (B), according to their market value (computed as the stock price as of the end of June multiplied by the number of shares outstanding). We also sort the Chinese listed firms into three groups, Low (L), Medium (M), and High (H), according to the book-to-market ratio (BM). BM is computed as the book value of equity for the fiscal year divided by market equity at the end of the fiscal year, which is December 31 for all Chinese listed firms. The Low and High groups consist of the bottom and top 30% of the stocks respectively, while the 40% in the middle fall into the Medium group. The intersection of the two size portfolio (S and B) and the three BM portfolios (L, M and H) yield six benchmark portfolios: S/L, S/M, S/H, B/L, B/M and B/H. *RMf* is the excess market return, computed as the return on the value-weighted portfolio of the stocks in the six benchmark portfolios minus the risk free rate. *SMB* is the monthly difference between the simple average of the value-weighted returns on the three small-stock portfolios (S/L, S/M, and S/H) and the simple average of the value-weighted returns on the three big-stock portfolios (B/L, B/M and B/H). *HML* is the monthly difference between the simple average of the value-weighted returns on the two high-BM portfolios (S/H and B/H) and the simple average of the value-weighted returns on the two low-BM portfolios (S/L and B/L). The *t*-statistics, shown in parentheses, are after allowing clustering by calendar month. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)
RMf	0.011
	(1.16)
SMB	0.071*
	(1.89)
HML	0.029
	(0.94)
Constant	0.005**
	(2.20)
N	217
Adjusted R^2	0.02

Table 7 Return and trading volume analysis around IPO

The table reports multivariate regression results for the return and trading volume around the listing date, for lucky and unlucky A-share firms with available data that went listed in Shanghai or Shenzhen Stock Exchange from 1990 through 2013. The dependent variable for column (1) to (3) is the market-adjusted return, measured as the buy-and-hold rerun on an IPO minus the compounded daily return on value-weighted market index. The IPO day is defined as day 0. Following Ritter and Welch (2002), IPO Day return is measured from the offer price to the first day closing price. (0,1) and (0,2) represent the two and three-day returns after IPO respectively. The dependent variable for column (4) to (6) is the average daily turnover, measured as the number of shares traded as a fraction of the number of tradable shares offered in the IPO. The independent variables are defined as follows: *Lucky* is a dummy variable which equals 1 if the firm's listing code contains one or more of the lucky digits 6, 8 or 9, but not the unlucky digit 4, and 0 otherwise. *Size* is the natural log of total sales. *OpProfitMargin* is the firm's total operating profit (income from main operations plus income from other operations) divided by its total sales. *Lev* is the firm's total debts (short-term debts plus long-term liabilities due within one year plus long-term debts) divided by its total assets. *Issue* is the number of outstanding shares measured in millions and *A-share floating % @IPO* is the percentage of tradable shares to total outstanding shares upon IPO. *Over_subscription* is the number of shares subscribed divided by the number of the shares issued. It measures the relative demand and supply of an IPO issue. When the demand is high, the ratio is high. *Top1_state* is a dummy variable that equals 1 if the firm's largest direct shareholder is a state-owned asset management bureau/company, and zero otherwise. *Top1* is the percentage of shares held by the largest shareholder. Industry and year dummies are included in the regressions to control for industry and year fixed effects. The t-statistics is shown in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Market-adjusted Return			Average Daily Turnover		
	IPO Day	(0,1)	(0,2)	IPO Day	(0,1)	(0,2)
Lucky	0.344*	0.348*	0.354*	0.046*	0.035**	0.030**
	(1.78)	(1.83)	(1.85)	(1.92)	(2.00)	(2.02)
Size	-0.134*	-0.127*	-0.111	-0.039***	-0.034***	-0.029***
	(1.78)	(1.70)	(1.48)	(4.17)	(4.91)	(5.05)
OpProfitMargin	0.229	0.249	0.268	0.082	0.027	0.012
	(0.51)	(0.57)	(0.61)	(1.50)	(0.67)	(0.36)
Lev	2.547***	2.522***	2.415***	0.164**	0.135***	0.114***
	(4.87)	(4.90)	(4.67)	(2.57)	(2.86)	(2.88)
Issue	0.0001	0.0001	0.0000	-0.0001	-0.000**	-0.000**
	(0.16)	(0.12)	(0.04)	(1.54)	(1.98)	(2.09)
A-share floating % @IPO	4.816***	4.687***	4.675***	-0.813***	-0.604***	-0.473***
	(5.22)	(5.16)	(5.12)	(7.21)	(7.23)	(6.80)
Over_subscription	-0.0001	-0.0001	-0.0001	0.0000	0.000**	0.000**
	(0.77)	(0.73)	(0.79)	(1.53)	(1.99)	(2.04)
Top1_State	-0.481***	-0.451***	-0.442***	0.063***	0.049***	0.041***
	(3.17)	(3.01)	(2.94)	(3.39)	(3.57)	(3.57)
Top1	-0.004	-0.004	-0.004	-0.0004	-0.0001	-0.0002
	(1.03)	(1.07)	(1.07)	(0.82)	(0.39)	(0.63)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.674	1.543	1.273	0.924***	0.782***	0.667***
	(0.92)	(0.86)	(0.71)	(3.87)	(4.42)	(4.52)
N	1,408	1,408	1,408	1,412	1,412	1,412
Adjusted R^2	0.22	0.218	0.215	0.156	0.196	0.226

Table 8 2SLS Regression

Panel A: Who gets lucky listing codes?

This table reports results of probit regressions for the prediction of lucky listing codes for A-share firms with lucky listing codes and firms with unlucky listing codes from 1990 through 2013 at their IPO year. The dependent variable is *Lucky*, a dummy variable which equal one if the firm's listing code contains one or more of the lucky digits 6, 8 or 9, but not the unlucky digit 4, and 0 otherwise. *GNI_rank* is the GNI rank of the firm's headquarter province. Specifically, the provinces are sorted into quartiles according to their GNI index and values between 1 and 4 are assigned to the quartiles so that the top quartile has the value of 4. We then transform the value of the rank by subtracting 1 and then dividing it by 3. This transformation renders the value to range between 0 and 1: the top quartile has the value of 1 and the bottom quartile 0. *Top1_state* is a dummy variable that equals 1 if the firm's largest direct shareholder is a state-owned asset management bureau/company, and zero otherwise. *Top1* is the percentage of shares held by the largest shareholder. *A-share floating % @IPO* is the percentage of tradable shares out of total shares outstanding at IPO. *Tangibility* is the book value of the firm's tangible assets (total assets minus intangible assets) divided by its total sales during the period. *OpProfitMargin* is the firm's total operating profit (income from main operations plus income from other operations) divided by its total sales. *Lev* is the firm's total debts (short-term debts plus long-term liabilities due within one year plus long-term debts) divided by its total assets. *Size* is the natural log of total sales. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)
GNI_rank	-0.303**
	(2.20)
Top1_State	0.003
	(0.02)
Top1	-0.001
	(0.20)
A-share floating % @IPO	-1.472***
	(2.58)
Tangibility	-0.014
	(0.68)
OpProfitMargin	1.270***
	(3.65)
Lev	0.241
	(0.62)
Size	0.101**
	(2.36)
Industry fixed effects	Yes
Year fixed effects	Yes
Constant	-0.848
	(0.92)
N	1,412
Pseudo R^2	0.17

Table 8 2SLS Regression (cont'd)

Panel B: Stock return analysis – Fama-MacBeth monthly regression

This table reports Fama-MacBeth monthly regression of stock return on lucky listing codes, for A-share firms with lucky listing codes and firms with unlucky listing codes within 3 years after IPO from 1990 through 2013.The dependent variable of the regressions is the firm's monthly abnormal return, *avretn_div*, computed as the firm's monthly return minus value-weighted market return. *Lucky* is the predicted probability that a firm obtains a lucky listing code, derived from the first-stage regression in Panel A. *lgBM* is the natural log of the ratio of book value of equity of the year to the sum of the market value of tradable shares and the estimated market value of non-tradable shares at the beginning of the month, assuming an 80% discount relative to tradable shares. *lgMV* is the natural log of the sum of the market value of tradable shares and the estimated market value of non-tradable shares at the beginning of the month, assuming an 80% discount relative to tradable shares. *Top1_state* is a dummy variable that equals 1 if the firm's largest direct shareholder is a state-owned asset management bureau/company, and zero otherwise. *Top1* is the percentage of shares held by the largest shareholder. *TAccrual* is total accruals, computed as net income minus cash flow from operating activities divided by total assets, in the fiscal year when the firm goes public. Industry dummies are included in the regressions to control for the industry fixed effects. The t-statistics are shown in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)
Pr(Lucky)	-0.038***	-0.026**
	(3.35)	(2.18)
lgBM	0.007*	0.010***
	(1.79)	(4.07)
lgMV	-0.003	-0.002
	(1.41)	(1.20)
Top1_State		0.002
		(0.85)
Top1		0.000
		(1.20)
TAccrual		-0.006
		(0.55)
Industry fixed effects	Yes	Yes
Constant	0.103**	0.070**
	(2.17)	(2.12)
N	47,793	37,731
Number of groups	276	192
Adjusted R^2	0.003	0.003

Figure 1 Return differences between lucky and unlucky IPOs

We plot the cumulative return differential between lucky and unlucky firms after controlling for various firm characteristics in this figure. On the horizontal axis, "1" represents the return window starting from the IPO date to the end of the IPO month. The return differential is computed by first cumulating the stock return for the window and then regress the return on *Lucky*, *lgBM*, *lgMV* and industry dummies. The value on the y-axis is the coefficient on *Lucky*, essentially the return differential after controlling for industry, size and book-to-market effects.

