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 are initially traded at a premium after controlling for known determinants of valuation multiples, the lucky number premium dissipates within three years after IPO, and lucky number firms experience inferior post-IPO abnormal returns.

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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 overweighting 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 mistaken idea instead of 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 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 adoption of specific theories about of how the world works. Furthermore, 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 (Daniel, Hirshleifer and Subrahmanyam (1998); Kyle and Wang (1997); 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

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, that there is an initial valuation premium associated with lucky listing codes, 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.

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 often wear lucky articles of clothing, keep lucky objects, or follow luck-inducing rituals (Burger and Lynn (2005); Collin (2003); Melamed and Tamarkin (1996)).

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estate can't go down, but the adoption of this once-popular belief presumably affected how individuals invest. Some theories of security pricing are also based on incorrect adoption by investors of world-views. In Barberis, Shleifer and Vishny (1998), investors incorrectly believe that there are two possible earnings regimes (trend and reversal), when in fact there is only one. 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 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 also abounds that numerological beliefs are influential 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]

Anecdotal evidence suggests that lucky numbers play a role in investors' decisions in

[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 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.

China. For example, 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 two 8s in its numerical code (600881).

As this story 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 2005. 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; that the high demand for IPOs with lucky listing codes will be associated with a price premium; and that as subsequent performance information arrives, there

[6] Evidence from U.S. IPO markets suggests that imperfect investor rationality affects behavior and pricing (Ritter (1991)). Theoretical work suggests that U.S. IPO markets are structured to take advantage of individual investor irrationality (Ljungqvist, Nanda and Singh (2006)). There is also theory proposing and evidence confirming that managerial irrationality affects corporate IPO behavior (Ljungqvist and Wilhelm (2005); Loughran and Ritter (2002)) .

will be a price reversal to eliminate the lucky number premium. We therefore predict and test whether (i) there is a higher than expected frequency of lucky listing codes; (ii) there is an initial high price premium, as measured by Tobin's q (henceforth q) and by the market-to-book ratio, for firms with lucky listing codes; and (iii) the post-IPO abnormal stock returns are lower for firms with lucky listing codes than for firms with unlucky listing codes.

Our findings are generally consistent with investors preferring firms with lucky numbers, and/or with the managers of IPO firms either sharing or 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; large firms are more likely to obtain lucky numbers. For example, on the Shenzhen Stock Exchange, the actual proportion of firms with lucky (unlucky) listing codes is 22% more (17% less) than expected by chance. This evidence is consistent with firms purposefully attempting to obtain numerical codes with lucky numbers during the IPO process.

To test whether the high frequency of lucky listing codes is driven by managers being superstitious themselves or managers catering to investors' superstition, we examine whether firms acquire other lucky numbers that are less visible to IPO investors. If managerial superstition drives the acquisition of lucky listing codes we would expect the probability of having a lucky telephone/fax number to be higher for firms with lucky listing codes than for firms with unlucky listing codes. Contrary to this implication, the probability is insignificantly lower for firms with lucky listing codes. This result seems to suggest that managerial superstition is not the main driver of the acquisition of lucky listing codes.

With regard to (ii), we find that both q and the equity market-to-book ratio are significantly higher for newly listed firms with lucky numbers than for those with unlucky numbers, after controlling for known determinants of firms' valuation ratios. Specifically, q is 23% higher for firms with lucky listing codes than for firms with unlucky listing codes, a

difference that is both statistically and economically significant.

Moreover, with regard to (iii), 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 6% per year after appropriate controls. This is consistent with corrective information arriving and eliminating the premium that is correlated with lucky numbers. This may be a correction of mispricing caused by lucky numbers, or (under a less plausible interpretation) of preexisting mispricing that is correlated with lucky numbers. Either way, it is consistent with superstitious behavior on the part of economic decision makers. In sum, this evidence suggests either that superstition affects stock prices, and/or that firms either share or cater to investor superstition, and that the overvaluation associated with lucky numbers tends to be corrected over time.

There are alternative possible pathways of causality that imply predictions (ii) and (iii) 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 require that numerological superstition play a role in the IPO market. Furthermore, this possibility is not very plausible, as listing codes can be assigned months before issuance.

To further test whether managers are more likely to obtain lucky listing codes for overvalued firms, we examine whether obtaining a lucky listing codes is correlated with the level of accruals. Past literature suggests that high accruals prior to the IPO are associated with greater overvaluation (e.g., Teoh, Wong and Rao (1998)). Inconsistent with the argument that overvalued firms acquire lucky numbers, we find that accruals are not significantly related to the probability of firms having lucky listing codes (with a negative point estimate for the relationship).

Overall, the most plausible explanation for our findings is that firms obtain lucky listing

codes to cater to investor superstition, and that lucky listing codes cause overvaluation and subsequent return underperformance. Furthermore, the alternative pathways of causality discussed above are also based upon superstition affecting investors' and/or managers' behaviors.

There has heretofore 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 (Edmans, Garcia and Norli (2007); Hirshleifer and Shumway (2003)), but emotion is not necessarily tied to mistaken ideas. Several studies 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.[7] 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.

Our study also has implications for the exploitation of investors by firms. A literature on IPO markets identifies apparent effects of imperfect investor rationality. Ritter (1991) and Loughran and Ritter (1995) document that IPO firms underperform the market in the long run. Henderson, Jegadeesh and Weisbach (2006) find that this phenomenon exists in many countries. Teoh, Welch and Wong (1998) provide evidence that firms manage earnings upwards prior to IPO and that post-IPO stock returns are related to pre-IPO earnings manipulations. Our study differs in providing a link between superstitious beliefs either by investors and/or managers to post-IPO abnormal performance.

[7]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)).

1. 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.

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); Farha and Steward (2006); Goode (2002); Mowen and Carlson (2003)).

1.1 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 a double deviation 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 being associated with the number (and hence indirectly with the word) will affect the likelihood of 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."[8]

Anecdotally, the Chinese fascination with numbers affects many decisions. The

[8] The related news stories can be retrieved at http://en.ce.cn/Life/society/200909/09/t20090909_19974517.shtml and http://www.channelnewsasia.com/stories/lifestylenews/view/1003837/1/.html.)

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).[9]

1.2 The Institutional Setting

Shares of a Chinese listed company can be classified as tradable shares, state shares and legal person shares. Tradable shares are shares that 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 share restructure reform that aimed to make all non-tradable shares publicly tradable. By the end of 2007, 1,254 firms had completed this reform, representing over 97% of the market capitalization at the time.

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.[10] A-shares can be traded only by Chinese citizens 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 domestic investors were not initially permitted to trade B shares. This restriction was later lifted in March 2001. Although A- and B-shares have the same shareholder rights, B-shares are traded at a discount relative to A-shares. Chan, Menkveld and Yang (2008) provide evidence that information asymmetry

[9] The news story can be retrieved at http://news.xinhuanet.com/english/2006-05/20/content_4576062.htm.

measures explain the cross-sectional variation in B-share discounts.

Listing shares on China's stock markets requires approval from the China Securities Regulatory Commission (CSRC) and other relevant regional and national authorities, whose decisions are affected by political considerations, such as social development, regional balance, etc. After approvals are granted, the firm to be listed is examined by the listing committees of the stock exchanges before the formal IPO announcement. In China, stock exchanges generally assign numerical listing codes to IPOs, although the Shenzhen Stock Exchange allows listing companies to apply for specific listing codes.[11] Those listing codes serve as identifiers in stock transactions, and investors commonly refer to stocks by their numerical codes. There is no explicit rule specifying how numerical codes are assigned, and it seems plausible that the assignment of numerical codes on both exchanges could be influenced by lobbying efforts on the part of the management of the listing companies. Since the listing code is important for identifying the security to be issued, it is usually obtained prior to the road show.

After listing, the first three years mark an important period for investors' assessment of the newly listed firms owing to two Chinese regulations that are based on firms' three-year performance. The first regulation addresses rights issues. In China, the central government sets a national annual dollar quota of IPOs and allocates the quota to various industry ministries as well as provincial and municipal governments. Many firms are in competition for the limited IPO quota, and local governments tend to 'play fair' by spreading the quota widely. This results in an insufficient allocation to those firms approved for IPO. To make up the shortfall, many newly listed firms need to raise additional capital through rights offered to their existing shareholders. In order to do so, firms must demonstrate that their financial performance for the past three years meets certain criteria. For example, the regulation issued in 2001 by the China

[11] For relevant stock exchange rules, please go to http://www.szse.cn/main/nssqyfwzq/wtjd/fxyss/2007060510726.shtml for the Shenzhen Stock Exchange, and http://www.sse.com.cn/cs/zhs/xxfw/flgz/rules/sserules/sseruler20060601.htm for the Shanghai Stock Exchange. Both are in Chinese; we are unable to find English versions.

Securities Regulatory Commission (CSRC) stipulates that listed firms are not allowed to offer rights if the three-year average ROE before rights issue is lower than 6%.[12] Investors of newly listed firms are thus likely to pay close attention to the firms' accounting performance in the first three years after the offering.

The second regulation is related to stock trading. Both the Shanghai and Shenzhen Stock Exchanges require that firms reporting losses for the past three consecutive years be designated as "Particular Transfer" firms (PT firms). The liquidity of stocks of PT firms is severely constrained. For example, those stocks can be traded only on Friday, and their daily price fluctuations cannot exceed 5%. The illiquidity of PT firms gives investors a reason to monitor the IPO firms' performance in the first three years.

In sum, investors are likely to pay close attention to the IPO firms' performance during the first three years after IPO. Investors' scrutiny of subsequent fundamental firm performance offers opportunities for them to correct any misperceptions that they may have.

2. Sample formation, Variable Definition and Descriptive Statistics

3.1. Sample Formation

Our 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 (2005 version) between 1990 and 2005.[13] The information on shareholding, financial performance and stock return is directly downloaded from the databases. After we delete firms with missing information on the IPO date, our final sample includes 1,384 listed firms, 832 of which are listed on the Shanghai Stock Exchange, and 552 of which are listed on the Shenzhen Stock Exchange.

[12] Chen and Yuan (2004) provide evidence that listed firms in China engage in earnings management in order to exceed the financial performance thresholds for rights issuance.
[13] We find results that are similar to those reported in the paper when our sample is extended to include B-shares.

3.2. Variable Definitions

This section provides 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). All Shanghai-listed firms have numerical codes beginning with 6, and this digit is ignored in our classifications.

To investigate whether firms with lucky listing codes are initially priced at a premium, we use *q* and the equity market-to-book ratio to measure firms' valuations. Tobin's *q* is defined as the ratio of the market value of a firm to the replacement cost of its assets. We estimate the replacement cost by using the book value of total assets.

We use two measures of *q*. (As a robustness check, we examine other measures in Subsection 9.3.) *TQ0* is the firm's price per share multiplied by the total number of shares, plus its book value of long-term debt, inventory, and current liabilities, minus its book value of current assets; divided by its book value of total assets. *TQ0* assumes that the market price of non-tradable shares is the same as that of tradable shares.

Our second proxy for *q*, *TQ80*, is calculated by applying an 80% discount to the market price of the firm's tradable shares to estimate the market value of non-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%.

In addition, we use the equity market-to-book ratio as an alternative valuation measure. *MB* is computed as the firm's price per share multiplied by the total number of shares at the end of the month divided by the book value of equity at the beginning of the year.

We obtain measures of firms' size, performance, leverage, growth and the relative magnitude of firms' tangible assets, which previous literature has shown help explain valuation multiples (for example, La Porta, et al. (2002); Morck, Shleifer and Vishny (1988)). *Size* is proxied by the natural logarithm of total sales.[14]We have two measures for firms' operating performance. One is operating profit margin (*OpProfitMargin*), computed as profits from operations divided by sales; and the other is cash return on assets (*Cash ROA*), computed as operating cash flows scaled by total assets. We use a cash-based operating performance measure because previous literature provides evidence that IPO firms tend to manipulate earnings upward (Aharony, Lee and Wong (2000); Teoh, Welch and Wong (1998)), which makes accrual-based accounting earnings noisy measures of actual operating performance for IPO firms. Leverage (*Lev*) is computed as total debt (short term plus long term liabilities due within one year plus long-term debt) divided by total assets. *Growth* is defined as growth in sales in the current year. The relative magnitude of the firm's tangible assets (*Tangibility*) is defined as the book value of the firm's tangible assets (total assets minus intangible assets) divided by its total sales.

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, we provide the mean, median, minimum and

[14] We do not use the market value as the proxy for size because the market value of non-tradable shares is difficult to estimate. Our use of sales as a proxy for size is consistent with many academic studies related to China (for example, Ding, Zhang and Zhang (2007)) and other emerging markets (for example, Friedman, Johnson and Mitton (2003)).

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

Several points are illustrated in Table 1. 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 three digits for stocks listed on the Shanghai Stock Exchange and in the last four digits for stocks listed on the Shenzhen Stock Exchange, 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 121 in 1997.

Fourth, the assignment of numerical codes is far from perfectly 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. This imperfectly sequential nature of the assignment of the listing codes provides room for managerial efforts to obtain lucky numbers.

[Table 1 here]

3.3.2. Time-series trends in q

To investigate whether firms with lucky numbers are priced at a premium, we first examine visually the time-series trend of q. Figure 1 depicts the mean value of *TQ80* for firms with lucky listing codes and those with unlucky listing codes. Since the calculation of *TQ80*

requires information from financial statements, such as book value of long-term debt and inventory, which are not immediately available at IPO, we start from the 12th month after IPO, with a sufficient time lag to allow such information to be disclosed to investors. As is evident from the graph, firms with lucky listing codes enjoy a premium over firms with unlucky listing codes, and this premium lasts until the 36th month after IPO. This evidence is consistent with investors paying a premium for firms with lucky listing codes initially, and that this premium gradually dissipates over the three years after IPO. Alternatively, it is also consistent with managers of overvalued firms selecting lucky numbers (perhaps to cater to investor sentiment), and that this overvaluation results in high *q* and low subsequent abnormal returns.

[Figure 1 here]

The disappearance of the lucky-number premium about three years after IPO is probably not a coincidence. Due to regulations, discussed in Section 2.2, which are arbitrarily based upon three-year performance, investors of newly listed firms are likely to pay special attention to firms' performance during the first three years. Figure 1 suggests that when investors realize that firms with lucky listing codes do not achieve superior performance during that period, they adversely revise their valuations of such firms.

3.3.3. Summary statistics

Table 2 provides descriptive statistics for valuation measures and firms' fundamentals, such as profitability and growth, for firms with lucky and unlucky listing codes within three years after IPO. We have two objectives. First, we investigate whether, as suggested by Figure 1, the lucky-number premium exists for the valuation measures we consider. Second, we investigate whether there are differences in firms' fundamentals between firms with lucky listing codes and firms with unlucky listing codes that might explain the lucky-number premium.

We find significant differences in valuation multiples between firms with lucky versus unlucky listing codes. For both measures of *q*, and for the market-to-book ratio, newly listed firms with lucky listing codes trade at a premium relative to those with unlucky listing codes. Specifically, *TQ80*, a relatively precise measure of *q*, averages 1.142 for firms with lucky listing codes and 0.928 for firms with unlucky listing codes, suggesting that firms with lucky listing codes are priced at a 23% premium relative to firms with unlucky listing codes. This lucky-number premium is both statistically significant and economically substantial.

In contrast, there are no significant differences between the two groups of firms in operating profit margin (*OpProfitMargin*), cash return on assets (*Cash ROA*), leverage (*Lev*), growth (*Growth*) or the relative magnitude of tangible assets (*Tangibility*). However, firms with lucky codes are significantly larger in *Size* than those with unlucky codes. The differences in both the mean and the median are significant at the 10% level. This is consistent with large firms having greater bargaining power to obtain lucky listing codes from the stock exchanges.

[Table 2 here]

The descriptive statistics in Table 2 generally corroborate the findings in Figure 1, and suggest a premium for newly listed firms with lucky listing codes. This premium seems unjustified by fundamentals, as there is no difference in profitability, leverage or growth between firms with lucky numbers and firms with unlucky numbers. This suggests either that lucky numbers cause overvaluation, or that overvalued firms are more likely to obtain lucky numbers (perhaps in order to cater to investor perceptions).

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.

3. Managers Sharing 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 and avoid IPOs with unlucky listing 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 three digits for stocks listed on the Shanghai Stock Exchange and in the last four digits for stocks listed on the Shenzhen Stock Exchange, for the sample period we examine. In all our empirical tests we consider only these 'relevant' digits in the classifications.

Since the number of digits that vary differs across the two exchanges, the expected distribution for the lucky/unlucky listing codes is different. Consequently, we report our results separately for the two exchanges. The expected proportions are computed assuming a random assignment of three-digit listing codes for firms listed on the Shanghai Stock Exchange and a random assignment of four-digit listing codes for those on the Shenzhen Stock Exchange. 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.[15]

[15] A possible objection is that 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 whose logarithms are distributed uniformly and are

For example, to compute the expected proportion for a three-digit listing code, we first compute the expected proportion for lucky listing codes where one digit takes on a lucky number and the other two digits take on neutral numbers (numbers that are not deemed as either "lucky" or "unlucky"). Basic probability theory shows that the expected proportion is 28.8%. We then compute the expected proportion for lucky listing codes containing two or three lucky digits. The sum of these expected proportions is the expected proportion of three-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 52.2%, which is much higher than the expected proportion, 51.4%. The proportion of firms with unlucky listing codes is 6.7%, which is lower than the expected proportion of 12.7%. Similar evidence applies to stocks listed on the Shenzhen stock exchange: the proportion of firms with lucky listing codes, 64%, is higher than the expected proportion, 52.7%; the proportion of firms with unlucky listing codes, 9.2%, is lower than the expected proportion of 11.1%. In percentage terms, the actual proportion of firms with lucky (unlucky) listing codes is 22% more (17% less) than expected by chance. The differences between actual and expected proportions of lucky and unlucky numbers are statistically significant at the 5% level, except for the proportion of unlucky numbers among Shenzhen-listed firms. 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 Numbers 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

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.

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 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 Panel A shows that the proportion of firms with at least two consecutive lucky numbers is 15.6% on the Shanghai Stock Exchange, which is significantly higher than the expected proportion of 13.5%, while it is 18.1%, higher than expected (17.0%), on the Shenzhen Stock Exchange. 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%, less than one sixth of the expected proportion of 1.3% while it is 0.4% on the Shenzhen Stock Exchange, less than one third of the expected proportion of 1.3%. The differences between actual and expected proportions are 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. Our results are reported in Table 4 Panel B.

Panel B shows that among Shanghai-listed stocks, the proportion of firms with listing codes ending in a lucky number is 26.4%, which is higher than the expected proportion, of

24.3%; the proportion of firms with listing codes ending in an unlucky number is 1.8%, substantially lower than the expected proportion of 4.9%, and the difference is significant at the 1% level. Results are similar when we turn to Shenzhen-listed stocks. The proportion of firms with listing codes ending in a lucky number is 30.4%, which is significantly higher than the expected proportion of 21.9%. Furthermore, the proportion of firms with listing codes ending in an unlucky number is 2.9%, which is lower than the expected proportion of 3.4%. Overall, results in Panel B are consistent with investors' preference for lucky numbers in the last digit of the listing code.

[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.

4.3 Managerial Superstition or Catering to Investors' Superstition?

The abnormally high frequency of lucky listing codes is consistent with two possible explanations. The first is that managers are superstitious themselves, incorrectly believing that lucky listing codes bring good fortune. The second is that managers cater to investors' preference for lucky numbers.

If this finding is driven by managerial superstition, then managers of firms with lucky listing codes will be more superstitious, and thus will be more likely than managers of firms with unlucky listing codes to obtain lucky telephone/fax numbers. To test this prediction, we obtain firms' telephone/fax numbers in the IPO year from the ORIANA database. There are 498 firms with lucky listing codes and 59 firms with unlucky listing codes that have non-missing telephone/fax numbers. We examine the last four digits of these numbers, because the managers have more flexibility in choosing these digits. The firm is deemed as having a

lucky telephone number/fax number if the last four digits of the firm's telephone number/fax number contain one or more of the lucky numbers 6, 8 and 9, but not the unlucky number 4. We report the likelihood of having lucky telephone/fax numbers separately for firms with lucky listing codes and firms with unlucky listing codes in Panel C of Table 4.

Panel C reports that, contrary to our prediction, the probability of having lucky telephone number is lower for firms with lucky listing codes than for firms with unlucky listing codes (0.761 versus 0.814), although the difference is not statistically significant. A similar finding emerges when we examine the likelihood of lucky fax number (0.741 versus 0.814).

In sum, Panel C of Table 4 suggests that the abnormally high frequency of lucky listing codes is not mainly driven by managers subscribing to the numerology belief themselves. This leaves managerial catering to investors' superstition as the more plausible explanation.

4. Which Firms Get Lucky Listing Codes?

In this section we examine what determines the likelihood of a firm receiving a lucky listing code. Specially, we run a logit regression with the sample of firms with lucky listing codes and those with unlucky listing codes. The dependent variable, *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.

The independent variables include various firm characteristics: the magnitude of tangible assets (*Tangibility*), operating profit margin (*OpProfitMargin*), leverage (*Lev*), growth (*Growth*) and size (*Size*). In addition, we examine whether the likelihood of having lucky listing codes is affected by concentration and state ownership. For example, greater concentration of ownership could increase the incentive for the firm to obtain lucky listing codes to attract investors to the IPO and later rights issues. Ownership concentration is measured by *Top1*, which is the percentage of shares held by the largest shareholder. It is also

possible that firms controlled by a state-owned enterprises or state-owned asset management agent would, through political influence, be more likely to get a lucky listing code. We measure state ownership through *Top1_state*, a dummy variable that equals 1 if the firm's largest direct shareholder is a state-owned asset management bureau/company, and zero otherwise. Firms may also manipulate earnings to increase their bargaining power in obtaining lucky listing codes. We therefore control for total accruals (*TAccrual*), computed as net income minus cash flow from operations, (both scaled by total assets), in the fiscal year when the firm goes public.

The regression results are reported in Table 5. Model 1 does not include industry dummies while Model 2 does. In both regressions, the only independent variable that is significant in the regression is *Size* which indicates that larger firms are more likely to get lucky listing codes. Following the results in model 1, when *Size* increases from its 5th percentile to the 95th percentile and all other independent variables are kept at their median values, the probability of having an unlucky instead of a lucky listing code declines from 13% to 6%, i.e., it is roughly cut in half. These findings are consistent with the notion that larger firms have more bargaining power and hence are more likely to obtain lucky numbers and avoid unlucky numbers in their listing codes.

[Table 5 here]

5. Are Lucky Firms Valued More Highly than Unlucky Firms at Listing?

We next perform multivariate tests to examine whether the premium associated with lucky listing codes remains after controlling for known determinants of firms' valuation multiples. The descriptive statistics in Table 2 provide preliminary evidence that within three years after IPO, newly listed firms with lucky listing codes are traded at a premium without justification from fundamentals, such as profitability and growth. However, it is important to control for other possible determinants of *q*. To the extent that there are differences between

firms with lucky and unlucky listing codes in other fundamental measures such as *Size*, a multivariate test is necessary to determine whether the premium is actually associated with lucky listing codes *per se*.

We therefore regress *q* and the equity market-to-book ratio on leverage (*Lev*), size (*Size*), growth (*Growth*), the relative magnitude of tangible assets (*Tangibility*), and current operating performance (proxied by *Cash ROA*). We use cash return on assets due to the concern that accrual-based earnings are manipulated upwards at IPO (Teoh, Welch and Wong (1998)). In addition, we include year and industry dummies to control for the year and industry fixed effects. The sample consists of firms with lucky listing codes and firms with unlucky listing codes. We run the regression separately for observations within three years after IPO and those more than three years after IPO, since our graphical evidence suggests that the lucky-number premium seems to disappear three years after IPO.

The results are reported in Table 6. We do not report the coefficients on year and industry dummies. Our inferences are based on *t*-statistics with clustering by firm (Petersen (2009)). The first three columns, under "≤ 3 Years after IPO", report the results for observations three years after IPO. These results are largely consistent with previous literature. The coefficient on leverage (*Lev*) is reliably negative (except when the market-to-book ratio is the dependent variable), while the coefficient on *Growth* is reliably positive. This finding is consistent with prior evidence that firms with high leverage tend to be traded at a discount, while firms with high growth tend to be valued at a premium (La Porta, et al. (2002); Lang, Ofek and Stulz (1996)). The coefficient on *Size* is negative, indicating that larger firms are traded at a lower valuation multiple. The coefficient on *Tangibility* is negative, which is consistent with the notion that firms with more intangible assets tend to have higher valuations (Morck, Shleifer and Vishny (1988)).

[Table 6 here]

We focus on the coefficient on the dummy (*Lucky*), which is equal to 1 for firms with lucky listing codes, and 0 for firms with unlucky listing codes. It is positive and significant at the 5% level, regardless of which valuation measure we examine. This evidence suggests that firms with lucky listing codes are traded at a premium within three years after IPO, and this premium cannot be explained by other determinants of valuation multiples. The coefficient on *TQ80* is equal to 0.108, indicating that on average, q is higher by 0.108 for firms with lucky listing codes. Compared to the average q of 0.928 for firms with unlucky listing codes as reported in Table 2, 0.108 represents a premium of 11.6%. This indicates that the lucky-number premium is economically substantial as well as statistically significant.

If the lucky-number premium results from superstitious beliefs, we expect correction over time as uncertainty about the firm diminishes and expectations are forced toward more rational levels. To investigate whether the superstition premium dissipates in the long run, we examine the premium more than three years after IPO. The results are reported in columns 4 to 6 of Table 6, under "> 3 Years after IPO". We find that the premium greatly diminishes. Among the three regressions with different valuation measures, only one yield positive and significant coefficients for the dummy representing firms with lucky numbers (*Lucky*), and it is significant only at the 10% level.

Firms with lucky listing codes may differ from firms with unlucky listing codes, potentially creating an endogeneity problem. For example, our q tests would be biased if growth firms or overvalued firms were more likely to obtain lucky listing codes. We cannot entirely rule out this explanation. However, in the tests of Section 5, only size is a significant predictor of a firm receiving a lucky listing code. So it does not seem to be the case that having a lucky listing code is a proxy for growth opportunities.

Furthermore, the endogeneity explanation (both here, and for the abnormal return tests of Section 7) is based on the probability that a firm obtain a lucky listing code be higher for

high-valuation firms. It is not obvious why this would occur unless managers share or cater to perceived investor superstition. Thus, the endogeneity explanation still implies accepting one of the primary conclusions of this paper, that firm behavior is influenced by superstition.

To summarize, this evidence based on *q* suggests that superstitious beliefs cause Chinese investors to overvalue IPO firms with lucky numbers relative to those with unlucky numbers. By the end of the 3rd year after the IPO, as more information about the firm is revealed and uncertainty diminishes, the superstition premium dissipates.

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

The previous section provides evidence that the premium associated with IPOs with lucky listing codes dissipates over time, consistent with eventual correction of the numerology-driven mispricing of IPOs. Given such reversal, we expect relatively low returns for IPOs with lucky listing codes. We now examine this issue explicitly and with controls for other return predictors.

We regress monthly market-adjusted returns, *avretn_div*, on the natural logarithm of the market value (*LgMV*), the natural logarithm of the book-to-market ratio (*LgBM*) and our test variable, *Lucky*. 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.[16] The coefficient on *Lucky* measures the difference in market-adjusted returns between newly listed 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. Our inferences are based on *t*-statistics with clustering by calendar month. According to Petersen (2009), such *t*-statistics are robust with respect to cross-sectional correlation in residuals.

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

The results are reported in Table 7 separately for observations within three years after IPO and those more than 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 -0.005, indicating that on average, the monthly return of firms with lucky listing codes is lower by 0.5% per month relative to firms with unlucky listing codes. Thus, the cost to a trader of investing superstitiously is about 6% per year. The lucky listing code premium is therefore a substantial economic effect.

For observations more than three years after IPO, we find no evidence of different returns between those with lucky listing codes and those with unlucky listing codes. This evidence seems to indicate that investors correct their initial mispricing of IPOs with lucky listing codes within the first three years after IPO.

An endogeneity problem, either for the tests here or for the valuation ratio tests, 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*. This would induce both high valuations and low subsequent abnormal returns.

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.

Furthermore, the evidence from Section 5 that the level of accruals is not a predictor of the firm receiving a lucky listing code does not support the hypothesis that managers who

expect their firms to be overvalued are more likely to obtain lucky numbers. Previous literature on U.S. firms finds that high accruals are associated with overvaluation both among general firms (Sloan (1996)) and among IPO firms in particular (Teoh, Welch and Wong (1998)). There is evidence of earnings management prior to China IPOs, and that higher accruals in China IPOs are associated with lower subsequent operating performance (Aharony, Lee and Wong (2000); Chen and Yuan (2004)).[17] If managers of firms that are later -to-be overvalued (for reasons other than superstition) were prone to obtaining lucky codes, we would have expected high accruals to be associated with receiving lucky codes.

In consequence, 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.

[Table 7 here]

7. Robustness Checks

This section provides robustness checks for the valuation and return findings of Tables 6 and 7. In our earlier analyses, the choice of control variables was mainly motivated by previous findings about return predictors using U.S. data. We now add additional controls to take into account the institutional settings peculiar to emerging markets, especially China.

8.1. Ownership Concentration, State Ownership and Earnings Management

We consider three variables that potentially affect inferences: ownership concentration, state ownership and earnings management. We first discuss ownership concentration. Previous literature (Bai, et al. (2004)) argues that the relationship between ownership concentration and

[17] Table 8 shows that high accruals are associated with higher *q;* Table 9 reports a negative relation between accruals and post-IPO returns after controlling for other predictors, though the association is not statistically significant.

firm valuation depends upon the current level of ownership concentration. If current ownership concentration is low, an increase in ownership concentration is likely to increase firm valuation by mitigating the free-rider problem among shareholders attempting to monitor the managers (Shleifer and Vishny (1986)). However, if current ownership concentration is high, a further increase is likely to lower firm valuation because it reduces constraints on tunneling from other shareholders.

As ownership concentration of firms listed in China is normally high, Bai et al. (2004) predict and find a negative relation between ownership concentration and q in China. Following Bai et al. (2004), we add *Top1*, a measure of ownership concentration, to our multivariate regressions.*Top1* is the percentage of shares held by the largest shareholder.[18]

We next turn to state ownership. Sun and Tong (2003) find that the state ownership has a negative effect on post-IPO performance. We therefore control for state ownership by including *Top1_state*, a dummy that equals 1 if the firm's largest direct shareholder is a state-owned asset management bureau/company and zero otherwise, in the regression.

Lastly, we control for pre-IPO earnings management, which potentially affects firms' valuations and returns (Teoh, Welch and Wong (1998)). Our measure of pre-IPO earnings management is total accruals (*TAccrual*), computed as net income minus cash flow from operating activities, both scaled by total assets, in the fiscal year when the firm goes public.[19]

Table 8 reports the valuation analysis, and Table 9 reports the post-IPO return analysis that includes the three additional control variables. In the valuation analysis, we also control for the operating profit margin, following Bai et al. (2004). The first three columns of Table 8 are based on observations within three years after IPO.

[Table 8 here]

[18] However, our results could be driven by ownership concentration only if concentration were correlated with the assignment of lucky listing codes. That in itself would be consistent with exchanges' or managers' belief in lucky numbers. Moreover, results in Table 5 show that ownership concentration is not statistically associated with the likelihood of having lucky numbers.
[19] 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.

Consistent with previous literature, firm valuations are higher for smaller firms, firms with higher sales growth and firms with higher current operating profit margin. *Tangibility* takes a negative coefficient, suggesting that firms with more intangible assets are valued at a higher multiple.

A higher value of *Top1* indicates more concentrated ownership. The negative coefficient indicates that the lower the ownership concentration, the higher the firm's valuation, which is consistent with Bai et al. (2004).

The coefficient on *TAccrual* is positive and significant, which indicates that firms that manage earnings upwards are valued more highly. This finding is consistent with the findings for U.S. firms of Teoh, Welch and Wong (1998).

More importantly, we find that inclusion of the additional variables does not affect our inferences. The coefficient on the dummy associated with lucky numbers (*Lucky*) is positive and statistically significant in all regressions. This evidence is consistent with investors paying a premium for newly listed firms with lucky listing codes, and this premium is not explained by ownership concentration, state ownership, or earnings management.

Columns 4 through 6 report results based on observations more than three years after IPO. Consistent with our earlier findings, we find that firms are valued more highly if they are smaller, have higher growth, lower state ownership, lower tangibility and higher current operating profit margin. As in Table 6, among the three measures of stock valuation, only one yields a positive and significant coefficient on *Lucky*, at the 10% level. These findings confirm that the premium associated with lucky listing codes largely dissipates by the end of the 3rd year after IPO.

Table 9 reports results from the return analysis. The first regression is based on observations within three years after IPO. After controlling for the three additional variables, firms with lucky listing codes have significantly lower returns than firms with unlucky listing

codes. The second regression shows that there is no significant difference in stock returns between firms with lucky listing codes and those with unlucky listing codes, when we look beyond the first three years after IPO. In sum, our previous conclusions, that the lucky-number-premium unwinds within the first three years after IPO, resulting in abnormally low returns over this period, are robust to inclusion of the three additional control variables.

[Table 9 here]

8.2 The Share Conversion Program

Our tests might also be affected by the non-tradable share conversion program started in April 2005. As mentioned in Section 2.2, the China Securities Regulatory Commission announced a share restructure reform that aimed to convert all non-tradable shares to publicly tradable shares. During the reform the compensation plan to tradable shareholders varied across companies, in the form of cash, warrants, additional shares and asset restructuring (Li, et al. (2011)). In our study, stock returns are based on dividends and changes in the share price of publicly tradable shares and thus exclude such compensations paid by holders of non-tradable shares, which should be included from the perspective of holders of tradable shares. This raises the concern that some of our returns and valuation multiples are measured with error.

It is not obvious why such error would be correlated with lucky listing codes (even after controlling for several firm characteristics). Nevertheless, as an additional robustness check we replicate our analysis using observations not affected by the share conversion program. Specifically, for the analysis related to observations within three years after IPO, we obtain a subsample of IPOs that were listed before or in year 2002 so that the valuation multiples and stock returns within three years after IPO are not affected by the share conversion program. Similarly, for the analysis related to observations more than three years after IPO, we eliminate all observations in and after 2005. Using this refined sample, we repeated the analyses reported

in Tables 8 and 9. The results are qualitatively similar to those reported in the paper.

8.3 Alternative Measures of *q* and Equity Market-to-Book

Instead of *TQ0* and *TQ80*, we considered alternative measures of *q* in the valuation analysis, which we call *TQ1*, *TQ2* and *TQ70*. *TQ1* is the firm's stock price per share multiplied by its total number of shares, plus its book value of total liabilities, divided by its book value of total assets. As mentioned earlier, 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. *TQ1* thus assumes that the market price of non-tradable shares is the same as that of tradable shares. *TQ2* is the firm's stock price per share multiplied by its total number of tradable shares, plus book value of its non-tradable shares and book value of total liabilities, divided by its book value of total assets. *TQ2* implicitly assumes that non-tradable shares' market value equals their book value. *TQ70* is computed in the same way as *TQ0*, except that, following Chen and Xiong (2001), we apply a 70% discount to the market price of tradable shares to estimate the market value of non-tradable shares. The regression results using the above alternative valuation measures are qualitatively similar to those reported in Tables 6 and 7.

8. 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. Large firms are more likely than small firms to have lucky listing codes. These findings suggest that there is an intentional effort by listing firms to obtain lucky number in their listing codes.

Furthermore, newly listed firms with lucky listing codes are traded at a premium relative to those with unlucky listing codes, after controlling for various characteristics that can affect valuation multiples, including leverage, size, growth and operating performance. Consistent with overvaluation of stocks with lucky listing codes, firms with lucky listing codes underperform those with unlucky listing codes by about 6% per year after appropriate controls.

We argue that, for several reasons, it is unlikely that the valuation and return results derive from endogenous selection of lucky listing codes by managers who expect their firms to be overvalued for non-superstitious reasons. For example, past literature suggest that high accruals induce overvaluation, but we do not find high-accrual firms disproportionately selecting lucky listing codes.

There is also suggestive evidence that the effects we find are not driven by managerial superstition. Superstitious managers who like lucky listing codes would presumably also like

to obtain other lucky numbers for their firms. Using a smaller sample, we find no evidence that firms with lucky listing codes are more likely to have lucky telephone/fax number than firms with unlucky listing codes.

In summary, overall our findings are consistent with firms seeking lucky numbers (either because managers share or cater to investor superstition), with market prices being biased by superstitious beliefs about lucky numbers, and with investors correcting their expectations over time as uncertainty about the new firms are resolved.

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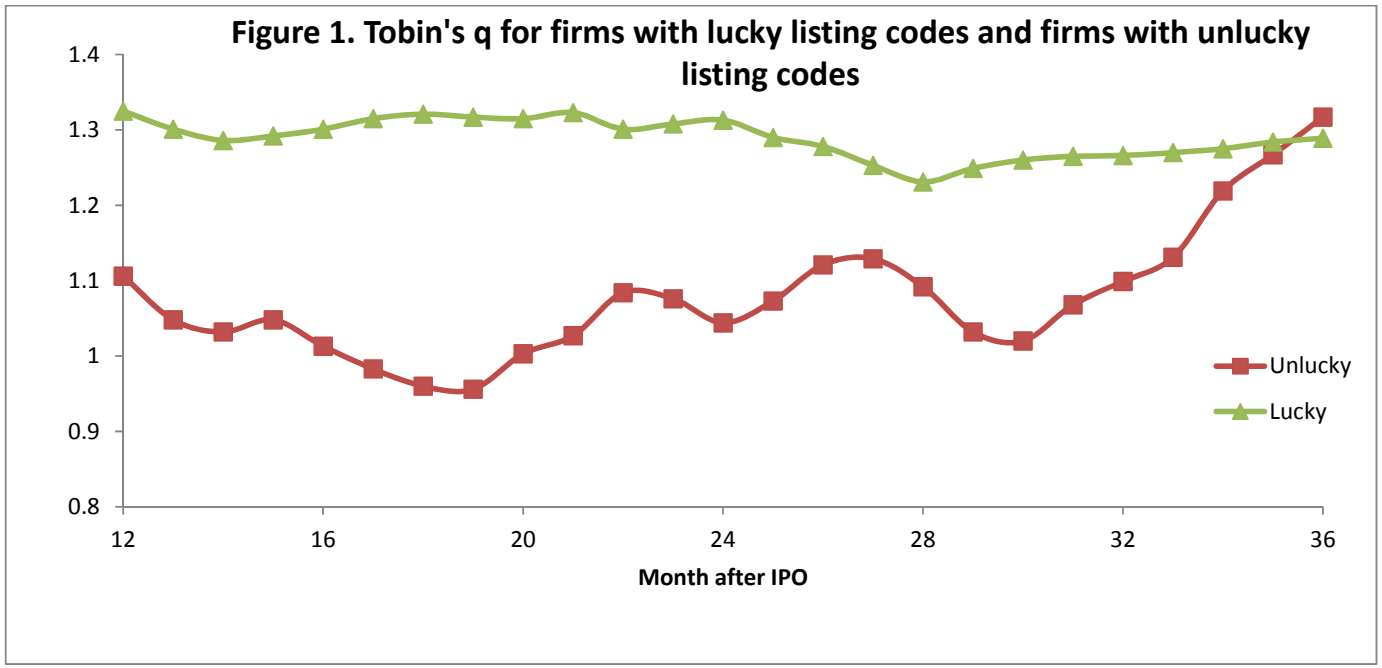

Figure 1: Tobin's q for firms with lucky listing codes and firms with unlucky listing codes. Figure 1 shows the mean value of TQ80 for firms with lucky listing codes and firms with unlucky listing codes. The former represented by "Lucky" and the latter "Unlucky". The time period covered is from the 12th month to the 36th month after IPO.

T**able 1: Distribution of listing codes**

This table shows the summary statistics for listing codes of sample firms that went public from 1990 through 2005 in the Shanghai and Shenzhen Stock Exchange.

	Shanghai-Listed Firms					Shenzhen-Listed Firms				
Year	**N**	**Mean**	**Median**	**Min**	**Max**	**N**	**Mean**	**Median**	**Min**	**Max**
1990	7	600638	600652	600601	600656	NA				
1991	0					5	000005	000004	000002	000009
1992	22	600615	600614	600603	600655	18	000150	000017	000006	000505
1993	72	600663	600665	600600	600800	52	000423	000522	000022	000554
1994	67	600835	600835	600801	600868	40	000363	000546	000021	000576
1995	15	600876	600876	600869	600883	9	000401	000582	000010	000586
1996	103	600766	600751	600700	600899	100	000559	000610	000055	000689
1997	85	600195	600093	600051	600799	121	000700	000733	000059	001696
1998	53	600152	600160	600001	600218	53	000802	000827	000065	001896
1999	45	600189	600205	600003	600359	52	000906	000922	000090	000959
2000	87	600274	600278	600008	600500	49	000758	000969	000070	000999
2001	78	600395	600383	600010	600599	1	000725	000725	000725	000725
2002	69	600492	600526	600026	600598	1	000875	000875	000875	000875
2003	65	600413	600449	600004	600900	0				
2004	61	600677	600572	600022	600997	39	001970	002019	000100	002038
2005	3	600490	600472	600027	600970	12	002045	002045	002039	002050
Total	832	600487	600504	600001	600997	552	000748	000699	000002	002050

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. *TQ0* is firm's price per share multiplied by the total number of shares, plus its book value of long-term debt, inventory, and current liabilities, minus its book value of current assets, divided by book value of total assets. *TQ80* is similar to *TQ0*, except that we apply an 80% discount to the market price of tradable shares to compute the market value of non-tradable shares. *MB* is the firm's price per share multiplied by the total number of shares at the end of the month divided by the book value of equity at the beginning of the year. *OpProfitMargin* is the firm's total operating profit (income from main operations plus income from other operations) divided by its total sales. *Cash ROA* is the firm's cash flow from operating activities divided by its total assets at the beginning of the year. *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. *Tangibility* is the book value of the firm's tangible assets (total assets minus intangible assets) divided by its total sales during the period. *Growth* represents the firm's current year sales growth ratio. *Size* is the natural log of total sales.

	Unlucky		Lucky					
Variables	Mean	Median	Mean	Median	*t*		*z*	
TQ0	2.233	1.941	2.692	2.297	-13.67	***	-14.45	***
TQ80	0.928	0.833	1.142	0.958	-13.36	***	-12.58	***
MB	4.085	3.608	4.658	3.962	-9.79	***	-10.58	***
OpProfitMargin	0.223	0.198	0.227	0.199	-0.31		-0.32	
Cash ROA	0.095	0.075	0.093	0.061	0.31		0.57	
Lev	0.201	0.193	0.204	0.192	-0.35		0.33	
Tangibility	2.714	2.265	2.722	2.124	-0.12		0.74	
Growth	0.229	0.167	0.226	0.131	0.12		0.51	
Size	19.677	19.638	19.806	19.742	-1.90	*	-1.78	*

Note: The asterisks following *t* (*z*) indicate the significance level of *t*-statistics (Wilcoxon rank-sum *z* statistics) of the difference between the two subsamples. ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

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"). 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. 'Actual (%)' reports the actual proportions of firms falling into the above-mentioned categories, while 'expected (%)' reports the expected proportions assuming random assignment of listing codes.

	Shanghai (N = 832)			Shenzhen (N = 552)		
	Actual (%)	Expected (3 digits) (%)		Actual (%)	Expected (4 digits) (%)	
Unlucky	6.7%	12.7%	###	9.2%	11.1%	
Lucky	55.2%	51.4%	##	64.3%	52.7%	###
Other	38.1%	35.9%		26.4%	36.3%	###
Total	100%	100%	***	100%	100%	***

Note: #, ##, 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.

Table 4 Frequency of listing codes with a sequence of (un)lucky numbers and (un)lucky-end number and frequency of lucky telephone/fax numbers

Panel A and B present the distributions of listing codes with a sequence of (un)lucky numbers or a(n) (un)lucky-end number respectively. 'Actual (%)' reports the actual proportions of firms falling into the above-mentioned categories, while 'expected (%)' reports the expected proportions assuming random assignment of listing codes. Panel C reports the frequency of having a lucky telephone/fax number separately for firms with lucky listing codes and firms with unlucky listing codes in the IPO year. Lucky telephone/fax numbers are defined in the same way as lucky listing codes. Specifically, the firm is deemed to have a lucky telephone number/fax number if the last four digits of the firm's telephone number/fax number contain one or more of the lucky numbers 6, 8 and 9, but not the unlucky number 4.

Panel A Proportion of listing codes with at least two consecutive (un)lucky numbers

	Shanghai (N = 832)			Shenzhen (N = 552)		
	Actual (%)	Expected (3 digits) (%)		Actual (%)	Expected (4 digits) (%)	
At least 2 consecutive lucky numbers	15.6%	13.5%	#	18.1%	17.0%	
At least 2 consecutive unlucky numbers	0.2%	1.3%	###	0.4%	1.3%	##

Panel B Proportion of firms with (un)lucky numbers in the last digit of the listing code

	Shanghai (N = 832)			Shenzhen (N = 552)		
	Actual (%)	Expected (3 digits) (%)		Actual (%)	Expected (4 digits) (%)	
Lucky end	26.4%	24.3%		30.4%	21.9%	###
Unlucky end	1.8%	4.9%	###	2.9%	3.4%	

Panel C: Probability of obtaining lucky telephone/fax numbers for firms with lucky listing codes and firms with unlucky listing codes

Listing code	Pr(*Lucky Tel*)	Pr(*Lucky Fax*)	N
Lucky	0.761	0.741	498
Unlucky	0.814	0.814	59
Lucky - Unlucky	-0.053	-0.073	
p value of the difference	0.3681	0.2249	

Note: #, ##, and ### denote significant difference between actual and expected proportions at the 1%, 5% and 10% level respectively, using a binomial test.

Table 5 Who gets lucky listing codes?

This table reports results of logit regressions for the prediction of lucky listing codes. The dependent variable, *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. *Top1* is the percentage of shares held by the largest shareholder. *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. *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. Other control variables are as defined in Table 2.

	Model 1	Model 2
Top1	0.006	0.007
	(*0.83*)	(*0.84*)
Top1_state	-0.163	-0.265
	(*0.59*)	(*0.83*)
Tangibility	0.055	0.077
	(*0.76*)	(*1.20*)
OpProfitMargin	0.563	0.459
	(*0.67*)	(*0.40*)
Lev	-0.131	-0.218
	(*0.13*)	(*0.22*)
Growth	-0.104	-0.076
	(*0.49*)	(*0.34*)
Size	0.219**	0.221***
	(*2.03*)	(*2.59*)
TAccrual	-0.411	-0.995
	(*0.31*)	(*0.84*)
Industry dummies	No	Yes
N	847	801
Pseudo R^2	0.01	0.05

Table 6 Valuation analysis – fixed effect regression

This table reports multivariate regression results for the sample consisting of firms with lucky listing codes and firms with unlucky listing codes. Results based on observations within 3 years after IPO are presented in Panel A, while those based on observations more than 3 years after IPO are presented in Panel B. The dependent variable of the regressions is the firm's market valuation, measured by *TQ0*, *TQ80* and *MB*, as defined in Table 2. 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. Other control variables are as defined in Table 2.

	≤ 3 Years after IPO			> 3 Years after IPO		
	TQ0	TQ80	MB	*TQ0*	TQ80	MB
Lucky	0.254**	0.108**	0.286*	0.210*	0.049	-0.040
	(*2.54*)	(*2.40*)	(*1.81*)	(*1.93*)	(*0.80*)	(*0.13*)
Lev	-1.799***	-0.283**	0.583	-0.998***	0.010	1.406**
	(*7.41*)	(*2.37*)	(*1.32*)	(*4.15*)	(*0.07*)	(*2.56*)
Growth	0.328***	0.165***	0.537***	0.300***	0.165***	0.513***
	(*4.67*)	(*4.73*)	(*3.83*)	(*5.98*)	(*6.71*)	(*3.95*)
Tangibility	-0.133***	-0.066***	-0.197***	-0.119***	-0.062***	-0.224***
	(*7.74*)	(*7.80*)	(*5.96*)	(*8.86*)	(*8.69*)	(*6.86*)
Cash ROA	-0.677*	-0.269	-0.205	-0.093	-0.016	1.327
	(*1.86*)	(*1.44*)	(*0.30*)	(*0.24*)	(*0.08*)	(*1.44*)
Size	-0.444***	-0.234***	-0.587***	-0.600***	-0.316***	-1.059***
	(*11.02*)	(*11.99*)	(*7.73*)	(*15.17*)	(*15.72*)	(*11.27*)
N	25,645	25,645	25,645	43,702	43,702	43,702
Adjusted R^2	0.361	0.344	0.315	0.394	0.391	0.283

Notes: Year and industry dummies are included in the regressions to control for year and industry fixed effects. The *t*-statistics, shown in parentheses, are after allowing clustering by firm. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 7 Stock return analysis – fixed effect regression

This table reports multivariate regression results for the sample consisting of firms with lucky listing codes and firms with unlucky listing codes. Results based on observations within 3 years after IPO are presented in Column 1, while those based on observations more than 3 years after IPO are presented in Column 2. 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 at the end of the year to the sum of the market value of tradable shares and the estimated market value of non-tradable shares at the end 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 end of the month, assuming an 80% discount relative to tradable shares.

	≤ 3 Years aft IPO	> 3 Years after IPO
Lucky	-0.005**	0.000
	(*2.52*)	(*0.10*)
LgBM	-0.019***	-0.009***
	(*7.58*)	(*3.63*)
LgMV	0.006**	0.010***
	(*2.59*)	(*2.87*)
N	31,649	52,174
Adjusted R^2	0.019	0.015

Notes: Industry dummies are included in the regressions to control for the industry fixed effect. 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.

Table 8 Robustness check – valuation analysis

This table reports multivariate regression results for the sample consisting of firms with lucky listing codes and firms with unlucky listing codes. Results based on observations within 3 years after IPO are presented in Panel A, while those based on observations more than 3 years after IPO are presented in Panel B.

	≤ 3 Years after IPO			> 3 Years after IPO		
	(1)	(2)	(3)	(4)	(5)	(6)
	TQ0	TQ80	MB	*TQ0*	TQ80	MB
Lucky	0.285***	0.123***	0.334**	0.190*	0.056	-0.086
	(*2.94*)	(*2.80*)	(*2.14*)	(*1.72*)	(*0.94*)	(*0.28*)
Lev	-1.077***	-0.025	1.392***	-0.854***	-0.022	1.424**
	(*4.43*)	(*0.20*)	(*2.90*)	(*3.41*)	(*0.16*)	(*2.57*)
Growth	0.301***	0.155***	0.506***	0.286***	0.161***	0.486***
	(*4.50*)	(*4.50*)	(*3.81*)	(*5.58*)	(*6.44*)	(*3.76*)
Top1	-0.004*	-0.004***	-0.005	0.003	-0.005***	0.006
	(*1.74*)	(*3.84*)	(*1.27*)	(*1.32*)	(*4.29*)	(*1.50*)
Top1_state	-0.103	-0.013	-0.018	-0.298***	-0.088**	-0.508**
	(*1.26*)	(*0.35*)	(*0.13*)	(*3.73*)	(*2.22*)	(*2.48*)
Tangibility	-0.143***	-0.068***	-0.208***	-0.121***	-0.060***	-0.220***
	(*7.37*)	(*6.90*)	(*5.14*)	(*8.77*)	(*8.22*)	(*6.71*)
OpProfitMargin	2.137***	0.767***	2.894***	0.873***	0.478***	0.463
	(*7.88*)	(*5.82*)	(*5.12*)	(*3.38*)	(*4.04*)	(*0.80*)
Cash ROA	0.190	0.075	0.561	-0.028	-0.058	1.057
	(*0.53*)	(*0.39*)	(*0.76*)	(*0.07*)	(*0.28*)	(*1.14*)
Size	-0.427***	-0.218***	-0.545***	-0.594***	-0.288***	-1.052***
	(*11.09*)	(*11.76*)	(*7.30*)	(*14.82*)	(*14.09*)	(*11.22*)
TAccrual	2.495***	1.137***	2.135**	-0.156	-0.370	-2.287***
	(*5.13*)	(*4.14*)	(*2.33*)	(*0.38*)	(*1.28*)	(*2.64*)
N	25,621	25,621	25,621	43,702	43,702	43,702
Adjusted R^2	0.408	0.38	0.338	0.403	0.408	0.29

Notes: The dependent variable of the regressions is the firm's market valuation, measured by *TQ0*, *TQ80* and *MB*, as defined in Table 2. 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. *Top1* is the percentage of shares held by the largest shareholder. *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. *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. Other control variables are as defined in Table 2. Year and industry dummies are included in the regressions to control for the year and industry fixed effects. The *t*-statistics, shown in parentheses, are after allowing clustering by firm. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 9 Robustness check – stock return analysis

This table reports multivariate regression results for the sample consisting of firms with lucky listing codes and firms with unlucky listing codes. Results based on observations within 3 years after IPO are presented in Column 1, while those based on observations more than 3 years after IPO are presented in Column 2. The dependent variable of the regressions is the firm 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 at the end of the year to the sum of the market value of tradable shares and the estimated market value of non-tradable shares at the end 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 end of the month, assuming an 80% discount relative to tradable shares. Other control variables are as defined in Table 2. *Top1* is the percentage of shares held by the largest shareholder. *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. *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.

	≤ 3 Years after IPO	> 3 Years after IPO
Lucky	-0.005**	-0.001
	(*2.16*)	(*0.42*)
LgBM	-0.020***	-0.009***
	(*7.82*)	(*3.80*)
LgMV	0.007***	0.010***
	(*3.00*)	(*2.78*)
Top1	0.000	0.000***
	(*0.64*)	(*3.97*)
Top1_state	0.004***	-0.002
	(*2.70*)	(*1.34*)
TAccrual	-0.011	-0.002
	(*1.37*)	(*0.45*)
N	30,506	52,166
Adjusted R^2	0.019	0.015

Notes: Industry dummies are included in the regressions to control for the industry fixed effect. 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.