**Air Pollution and Investor Gambling Preference: Evidence from Stock Market in China**

1. **Introduction**

*Money won is twice as sweet as money earned.*

-From the movie The Color of The Money

Modern portfolio theory (Markowitz, 1952; Sharpe, 1964) relies on the risk averse assumption. However, instead of diversifying optimally by taking into account the expected returns and correlation of assets, in reality, the speculative needs is so universe and rare people invest based on the principles of portfolio theories. The underneath gambling preference has been linked to personal characteristics, social and economic factors, etc. Many experimental studies (Knutson et al., 2008; Kuhnen and Knutson, 2011) also believe that good mood would encourage people in risk-taking behavior due to the rise in risk tolerance, but there are few empirical evidence. One reason is the difficulty in measuring the variation in emotions, considering the subjectivity. We suppose that, as a salient element of citizens’ daily life, the variation in the purity of each breath they take in could either delight or depress themselves, which consequently alters their investment decisions in the stock market, specifically the propensity to buy risky stocks. With a unique database provided by the Shanghai Stock Exchange, we can examine this conjecture by investigating all the trading records of Chinese nationwide investors during 2013 to 2016.

The major contribution of the project is to introduce an important non-economic variable – air quality and prove the link between mood and investors’ risk-taking behavior. Though experimental evidence on attitude to risk has been accumulated, according to our knowledge, we are the first to empirically test this inference in a real market setting. Besides, most cities suffer air problems and “gray smog” has become a nationwide heated topic in China. The adverse effects in terms of air pollution is gaining attention and we try to explore its economic implications in microeconomics from an original perspective.

Secondly, mood is believed to have an impact on equity returns (Saunders, 1993; Hirshleifer and Shumway, 2003) and by attributing this to deviation in trading behavior, we may explain the anomaly in the market. In light of growing evidence in investors’ irrational behavior, finance has incorporated sentiment-related behavior biases to the classic, traditional pricing model (Barberis, Shleifer, and Vishny, 1998; Baker and Wurgler, 2006), while the underlying mechanism is yet to be explored. Previous research has examined the change in trading characteristics – market turnover and liquidity (Lu and Chou, 2012), and trading volume (Kaustia and Rantapuska, 2016), whereas we choose to focus on behavioral deviation in risk preference. We expect our empirical results would be consistent with our predictions, so that we can provide an explanation for uncanny volatility and weather-related return movements in China stock market.

1. **Prior Literature**

2.1 Mood, Weather and Finance

Psychologists have been documenting correlation between mood and behavior for decades. However, when it comes to the real world, it is still hard to find empirical evidence as the measure of sentiments is a tough problem, considering that they are subjective and difficult to be recorded. While weather, as a source of exogenous variation, is frequently used as a proxy for mood and the correlation among weather and sentiments is grounded in psychology studies. (Sander and Brizzolara, 1982; Denissen, Butalid, Penke, and Van Aken, 2008). Most of them suggest that good weather is associated with positive mood, which could lead to various behavior.

Saunders (1993) shows that the sky cloud cover over New York City has a strong, negative association with New York Stock Exchange (NYSE) index returns. He noticed the significance of cloudiness and weather-induced mood, and their effects on market returns, which was the beginning of research in this specific field. Later on, Hirshleifer and Shumway (2003) employs a larger panel sample of 26 stock exchanges. The findings are consistent with Saunders (2003), but with richer data, they provide more substantial evidence in the negative relation between cloudiness and stock returns, confirming that the relationship is pervasive rather than a result of data mining.

Differing from previous arguments, Loughran and Schultz (2004) find no relation among cloud cover and stock returns. Building on their evidence that trading is localized, they observed nationwide stocks returns and local weather, instead of the weather where stock exchanges are located. However, it seems that trading strategies based on weather condition cannot provide investors enough profitable opportunities. If their inference about localized trading is correct, investors’ behavior may not be heavily influence by local weather, as indicated by Saunders (1993) and HS (2003).

Following studies in weather-related mispricing in stock markets, Goetzmann et al. (2014) choose to focus on the behavior of institutional investors. Despite commonly held assumptions about investor sophistication, there is evidence that institutional investors and other sophisticated market participants are also susceptible to cognitive biases. Cloud cover increases the likelihood of perceived overpricing among institutional investors and the propensity to buy is impaired in cloudy days. Moreover, unlike the former one who posits trading is localized, they adopt a new stock-level proxy for investors’ mood by averaging sky cloud cover above all institutional holders, while the co-movement of the proxy and stock returns is pronounced.

It is widely believed that weather would affect individuals’ mood and lead to varied behavior. Inclined to the notion, Dehaan et al. (2016) examines equity analysts’ responses to weather conditions. Weather-related mood leads to decreased activity - costing analysts’ longer to respond to earnings announcements, and causes analysts’ pessimism - driving down the EPS forecasts. Accordingly, markets can be less efficient due to the inactivity of market participants, represented by equity analysts’.

Although many papers dig into the relation between weather and induced behavior, as an important component of the economy, few touches the study in corporate level. It is understandable that examining the effects of sentiments on corporate decisions are difficult as firms’ day-to-day businesses are normally invisible. Even if they can be traced, it is not easy to evaluate their outcomes without knowing the opportunity cost – namely, the options that were considered rejected. Besides, corporate decisions are made by groups and are generally considered not susceptible to subjective biases.

Cortés et al. (2016) provides evidence on the role of weather on daily corporate decision made by low-level loan officers. Credit approval rates is higher on sunny days and lower on overcast days. The variation in sentiments in response to weather plays a critical part in this phenomenon, which reflects in loan officers’ attitude toward risk or mood projected onto certain tasks (namely, their subjective judgement), while the influence on their productivity is trivial. Their study shows the importance of sentiments to day-to-day firm-level decisions.

2.2 Air pollution, Trading, and Returns

In China, air pollution has become a serious problem that influences people’s daily life. We believe that like other weather variables, the heteroscedasticity of air quality in time and cities could reflect the variation in people’s mood and air quality is well-qualified to be used as a proxy for sentiments. Recent studies (Leport, 2016; Wu, Chen, Guo, and Gao, 2018) also adopt this measure and find the negative effect of air pollution on stock returns.

As aforementioned, now that much evidence support the relation between weather and equity returns, what intrigues us is the underlying mechanism. In the stock market, order flow is driven by both public and private information as well as investor shocks, which may be either rational or irrational. Prices can deviate from fundamental value due to market microstructure, liquidity, and hedging effects, and pricing errors can arise from noise trading and the systematic underreaction or overreaction to information. DeLong et al. (1990) predict that low sentiment will generate downward price pressure and unusually high or low values of sentiment will generate high volume. Chang et al. (2008) observe more selling and higher volatility in cloudy days. Kaustia and Rantapuska (2016) try to prove the impact of weather-induced mood on investors’ behavior – buy ratios, while they cannot conclude this would be the case.

From our perspective, the adoption of impropriate measure might account for Kaustia and Rantapuska (2016)’s failure in identification. According to DeLong et al. (1990), people’s willingness to buy and sell should be aroused simultaneously along with the increase in trading volume. Thus, in order to have a better understanding of this phenomenon, we choose to focus on investors’ preference to risky stocks relative to all stocks.

2.3 Mood and Risk preferences

Evidence shows that mood interacts with risk preferences. Researchers prove that two parts of the brain - the nucleus accumbens and the anterior insula, are very important in decision making under risk. Knutson et al. (2008) found that positive stimulus could activate these areas and encourage risk-taking behavior though the distribution of outcomes is fixed. Kuhnen and Knutson (2011), and Antoniou et al. (2016) provide more evidence about the relationship between emotions and risk preference. Furthermore, Bassi et al. (2013) provide direct experimental evidence that good weather promote risk-taking behavior.

1. **Hypotheses Development**

Chinese stock market is individual-dominated and highly speculative. Individual accounts of A shares has exceeded 160 million[[1]](#footnote-1) by the end of 2016, in contrast, the number of institution accounts is only 583 thousand. In the 1990s, almost all the tradable shares are owned by individual investors. As bans on non-tradable shares start to be lifted since 2005, shares owned by individuals has dropped dramatically (69.8% in 2005 and 23.3% in 2016), however, transaction of individuals still constitute more than 85% of total volume in 2016 and the turnover of stocks is surprisingly high, for example, 389.6% in 2015 and 158.8% in 2016. Investors, especially inexperienced and information-deficient ones who frequently trade in the market, would disrupt the market and make stocks deviate from its prices, supported by the complex unpredictability of stock returns (Ng and Wu, 2007).

Investors, especially individuals, are susceptible to emotion fluctuations to some extent. As investment decisions are products of investors’ volition, changes in exogenous environment interact with subjective will, which, as a result, promote or interfere with advisable judgements. In our specific context, we adopt the quality of atmosphere – an economically significant variable, as air pollution may lead to sentimental variances in a not only mental but also physical way. Thus, following previous studies on the relation between weather and stock market, we posit that air pollution, as a sentiment depressor, would discourage incentives to trade.

Shefrin and Statman (2000) argue that real investors apply mental accounting to organize their investments, which turns out that other than normal investment, investors would also be interested in lottery-like assets, which cater for their speculative needs. Lottery-like stocks refers to those who share lotteries’ features: a very low cost, the possibility of a huge reward and a large probability of a small loss. We assume that poor air depress investors and drive money away from risky assets.

It is natural to extend the reaction in trading to returns. Prior studies has discovered the relation between weather and stock returns. We would like to use air quality as the proxy for mood to explore its negative relation with returns. In our conjecture, lottery stocks should react more dramatic and significant underperform non-lottery stocks.

The following list the hypotheses we would like to test in our analysis:

H1: Bad air condition alter investors’ risk preference, so in higher-polluted area, the propensity to buy stocks is lower.

H2: Comparing with non-lottery stocks, the result should be stronger among lottery stocks.

H3: Cross-sectional hypothesis: the effects is more pronounced among investors who live in less-educated areas, as they are more easily influenced by emotions; on the contrary, institutional investors should be lesser affected because they are relatively not susceptible to cognitive biases.

H4: Unpleasant air lead to the decrease in stock returns and the effect are stronger on lottery stocks.

1. **Data and Statistics**

4.1 Data description

Investor-level data used are two files from Shanghai Stock Exchange (SSE). The first is an order submission (ORDER) file that contains records of order submissions and cancellations for all investors, and tracks the status of each order submitted to the SSE, indicating whether and when the order is executed, modified, or withdrawn. The second is an equity holding (HOLD) file consisting of end-of-day stock holdings for each investor in SSE stocks. Both files contain investors’ Unicode and information about area code of securities business outlets in which securities accounts were opened. The sample covers more than 10 billion trades made by more than 170 investors during 2014-2017 and almost contain no errors. Out of the concern of insufficient computational capability, we gather data at city level for each securities companies (or, brokers).

Weather data is collected from two sources. Firstly, China initiated Air Surveillance Program since 2012, and as of 1 January 2015, air monitor stations have been employed in almost all the municipal cities, providing us with a thorough and proper data. Air Quality Index (AQI) is obtained from China Stock Market and Accounting Research Database (CSMAR), which is a measure of regional air quality based on the density of 6 atmospheric pollutants and is divided into 6 levels according to the readings, from excellent to severely-polluted.

Other weather data is collected from the Integrated Surface Database (ISD), containing weather observations from 20000 weather stations worldwide. We obtain daily variables including TEMP (mean temperature), DEWP (mean dew point), SLP (mean sea level pressure), STP (mean station pressure), VISIB (mean visibility), WDSP (mean wind speed), and PREP (precipitation amount) from 409 stations in China from Jan 1, 2014 to Dec 31, 2017.

Lastly, in order to identify lottery stocks and examine the influence on stock returns, we obtain daily stock close prices and returns from CSMAR during Jan 1, 2014 to Dec 31, 2017, as well as other stock characteristics. Some summary statistics about the sample are presented in the following.

* 1. Variable description
     1. Air pollution measures

China used to use Air Pollution Index (API) to depict regional pollution level, which was considered to be inconsistent with people’s instinct feeling. In order to provide a good measure of new form of pollutants, especially PM2.5, and to be in line with international practice, China drew an all new Air Surveillance Program, which was carried out in three steps. 74 cities including all municipalities, provincial capitals and major cities in the Beijing-Tianjin-Hebei region, the Yangtze River delta region, and the Pearl River delta region were involved in the first stages and at least three monitoring stations were deployed in each before 2013. In the next two consecutive years, more were positioned in 116 and 177 cities. As of 2015, Chinese Ministry of Environmental Protection was able to monitor air conditions in almost all municipal cities.

Air Quality Index (AQI) is obtained from China Stock Market and Accounting Research Database (CSMAR), which is used to portray city-level daily air quality. AQI is computed according to the level of 6 atmospheric pollutants, namely sulfur dioxide (SO2), nitrogen dioxide (NO2), suspended particulates smaller than 10μm in aerodynamic diameter (PM10), suspended particulates smaller than 2.5 μm in aerodynamic diameter (PM2.5), carbon monoxide (CO), and ozone (O3) measured at the monitoring stations throughout each city. Air quality is divided into 6 levels based on the index, which is excellent (0-50), good (51-100), light polluted (101-150), moderately polluted (151-200), heavily polluted (201-250), and severely polluted (300+). Based on AQI, we construct two dummy variables to discover the influence of extreme weather, which are Heavy Pollution – equals one if AQI exceeds 300 and Low Pollution – equals one if AQI does not exceed 100.

Averaging and plotting AQI across all the monitoring stations (seen in Figure 1), like other weather variables – cloud cover, temperature, etc., there is a clear seasonal pattern that air quality begins to aggravate at the end of third quarter and reaches its peak in the coming of next year, and then AQI shows a downward tendency in the following three quarters and the cycle starts anew. A major reason for this feature is china’s heating policy (Huang et al., 2014; Li et al., 2016). Most housing on the north of Huai River and Qinling Mountains is equipped with heating facilities and provided with unlimited heating between November 15 and March 15. In the meantime, tons of pollutants are also carried by wind to the south, so air pollution is particularly severe in most parts of China during winter.

As stated, through airborne transmission, air pollution is diffusible and reciprocal, which accounts for the high correlation of AQI among most cities (normally higher than 0.5). Dismissing the similarity in time trend, the variation in regions is actually quite substantial. We compare the average air quality in 34 major cities during 2014-2017, while they vary from 43.7 to as much as 140.3. Among them, in the most polluted city – Shijiazhuang, 6.8 percent of the days are severe polluted, in contrast with cities like Haikou, Shenzhen, Kunming, where 90% of the days are better than light pollution.

In light of the evident seasonality, to ascertain that the influence of air quality on stock market activity is not only the effects of seasonal fluctuations, we follow Hirshleifer and Shumway (2003)’s method to deseasonalize by subtracting the mean of all the observations in the same week of the year during 2014-2016 from daily records. The deseasonalized variable is called DAQI.

* + 1. Other weather measures

Similarly, other weather variables are also demeaned in the same way and the new variables are shown in the variable list. The environmental factors vector includes TEMP (mean temperature), DEWP (mean dew point), SLP (mean sea level pressure), STP (mean station pressure), VISIB (mean visibility), WDSP (mean wind speed), and PREP (precipitation amount)

* + 1. Stock-level air quality

With nationwide weather and investors’ holding data, we can construct a stock-level proxy in terms of air quality. As stocks are held by diversified investors, we average municipal AQI across locations of all investors and weight their portfolio holdings to get the measure – stock-level air quality index (SKAQI). This index is also updated daily, using the holding data after the stock market close.

* + 1. Lottery stocks

Follow the definition in Kumar (2009) and Boyer, Mitton, and Vorkink (2010): low prices, high idiosyncratic volatility, and high expected idiosyncratic skewness. The meaning contained in this definition accords with features in lottery: the cost is low, but there is still a chance to win a large jackpot, of course, at a small possibility.

To define lottery stocks, we rank and sort stocks on the basis of the dimensions. Specifically, stocks in the lowest Pth price percentile, highest Pth idiosyncratic volatility, and highest Pth idiosyncratic skewness are termed as lottery stocks. Those with high prices, low idiosyncratic volatility, and low idiosyncratic skewness are classified as non-lotteries, which the left are others. In this paper, we choose 50 for the value of P.

Table 2 presents the comparison between lottery stocks, non-lottery stocks, and other stocks. Lottery stocks have relatively lower prices (￥7.57), returns (0.02), and higher book-to-market ratio. The scale is smaller than other firms, showing in shares outstanding (￥12546.49 million), equity (￥8619.68 million), and asset (38614.30), while turnover is noticeably higher.

To give full use of these characteristics, except two dummy variables, we also use an index variable to show the lottery feature of each stock. To construct this index, we assign all stocks from SSE into 20 groups each day by price, idiosyncratic volatility, and idiosyncratic skewness. Group 20 contains stocks from the lowest price group and the highest volatility, and skewness groups. For each stock, the price, volatility, and skewness scores are added to produce a score between 3 and 60. This score is then scaled between 0 and 1 using LIDX=(Score−3)/(60−3). (to be modified)

* + 1. Investor trade measures

Based on the classification of investors, we extract three investor groups – all investors, individual investors, and individual investors of medium and small scale. We compute the logarithm of trading volume and the ratio of purchase to total trading volume for investor groups in each outlets, defined as Trading Volume and Buy Ratio. Similarly, the logarithm of trading in lottery stocks and the ratio of lottery purchase to total purchase are defined as Lottery Volume and Lottery Buy Ratio. The last measure is lottery buy-sell imbalance ratio (LBSI), the difference between total daily values of buy and sell volume with respect to lottery-like stocks across all the securities business outlets, scaled by each outlet’s total trading value in the specific day.

* + 1. Stock market variables

RET is defined as stock daily return. Turnover is the quotient of daily trading volume dividing the shares outstanding for each listed stocks. Volatility is calculated as , where high (low) price is the highest (lowest) price of each stock for the day. The liquidity measure applied in this study is , where is the absolute value of the returns.

1. **Empirical Results**

5.1 AQI and Investor gambling preference

Baseline regression:

The basic regression is to regress the daily trading volume of all the securities outlets on city-level air quality from 2014 to 2017, where X is a vector of control variables and *i, c, t* denote security outlet, city and date. Each volume observation is taking logarithm to mitigate the significant skewness. Control variables include weather variables, e.g. temperature, visibility, wind speed, and precipitation, five-period lagged market returns, calendar dummies, and city, broker, month fixed effects.

We regress trading volume on air quality index. Daily changes in trading activity is very volatile and subject to various impacts. Concerning the effects of other weather conditions, we control for other weather variables, including temperature (Cao and Wei, 2005), wind speed (Cooke et al., 2000), precipitation (Saunders, 1993). High level of pollutants is usually accompanied by low visibility, which is also specifically controlled. Besides, previous studies found evident trading and return patterns relating to the turn of days in a week (Lakonishok and Maberly, 1990), a month (Ogden, 1990), and a year (Keim, 1989). Other important calendar points, like holidays (Ariel, 1990), are also a concern. So in our study, we consider Monday dummy, Friday dummy, pre- and post-holiday dummy, and dummies for the first and last three days of the month and year. We also control lagged equal-weighted market returns due to the high correlation of volume and returns, as well as remove market-wide trading fluctuations, which, may be attributed to macroeconomic shocks, policy enactment, etc. and unrelated to our hypotheses.

Table 3 report the results of an ordinary least squares regression of air quality on the logged market trading, with column 1 include all the trading records, column 2 exclude all the institutions, and column 3 only include medium and small individual investors. Results show that in the market-wide, one unit increase in regional AQI significantly lead to the decrease of trading volume by 0.9 basis point. Comparing with individuals, groups decisions made by institutions are more prudent and less likely subject to cognition biases. Thus, the absolute values of coefficients get larger by adopting smaller samples (1.1 basis point for individuals, 1.2 basis point for medium and small individuals). The effect is significant after controlling visibility, wind speed, precipitation, and temperature, indicating that air quality is not an alternative weather variable, rather an important exogenous variable to financial activities.

The results with respect to the trading of lottery-like stocks are shown in Table 4. Similarly, column 1 reports all investors, column 2 individuals, and column 3 only medium- and small-sized investors. The coefficients of AQI get larger and more significant as we exclude rational institutions and wealthy individuals. The results support the importance of mood in the mechanism. For other variables, PRCP no longer significant but VISIB and TEMP remain.

5.2 Air quality, weather, and stock market

Considering the expanse of China, the variation of weather in different places cannot be ignored. Now that investors are widely dispersed and influenced by local factors, it seems that it is unable to measure the impact of weather on stock trading behavior and returns. Former research is based on dissimilar hypotheses: Saunders (1993) and Hirshleifer and Shumway (2003) use the weather in stock exchange as the proxy, which assumes most orders are from the city that the stock exchange located in. Loughran and Schultz (2004) assume trading is localized and utilize the weather in each investor’s location. Goetzmann et al. (2014) suggest to average nationwide weather, weighted by investor’s holding.

Each method has its strength and weakness and we are intended to examine them separately. Intuitively, trading should reflect weather conditions across investors, not just attaching to one city. However, according to statistics provided by the SSE, the security businesses located in Shanghai are responsible for initiating the majority of transactions on the SSE; indeed, according to the “Monthly Bulletin of Statistics, December 2009” issued by the SSE, the total dollar trading volume on the SSE in 2009 was 34.6511 trillion Yuan, with security businesses located in Shanghai accounting for 32.48% of this total dollar trading volume, and thereby contributing most of all of the major cities in China. Besides, some key variables, like air quality, share a high correlation among areas. As the objection is to explore time-related variance, the adoption of the weather in Shanghai is well-rationalized.

Table 5 presents the results of the panel regression about the effects of air quality on stock returns. With stock returns on the right-hand side, we include AQI, lottery dummy, and their cross term as the independent variable. The coefficients for air quality are negative, which means returns are positively correlated with air quality. This results are expected and consistent with prior literature. The coefficients for the lottery dummy is also significantly negative, showing that lottery stocks are generally underperformed than other stocks. In terms of the cross term, the coefficients show than the returns go down in the times of high pollution. This is consistent with our expectation that weather-induced negative mood would reduce people’s preference in risky stocks, leading to the poor performance in stock market. All the specifications show similar empirical results, after controlling firm characteristics, province macroeconomic variables, as well as city, month, and industry fixed effect.

1. **Conclusion**

China witnessed an explosive economic expansion in the last three decades, while the deterioration of environment is a matter of growing public concern. In 2013, 99.6 percent of China’s population was exposed to PM2.5 air pollution levels exceeding the guidelines of the World Health Organization (Zheng and Kahn, 2017). Not limited to China, emerging markets and poor areas, like Egypt, India, are all suffering similar problems. The vast territory of China is a natural experimental field for conducting air-related research, and conclusions acquired are external valid in heavy-polluted areas.

Air pollution has attracted wide publicity since 1950s. In response to London’s Great Smog of 1952, the parliament of UK passed the Clean Air Act 1956, followed by similar moves in US, Canada, and other developed economies. In the following several decades, these regulations were implemented and revised, accompanied with the improvement of air quality, as well as social and economic benefits. Now, appeals for a better living environment is overwhelming, and Chinese central government starts to reinforce measures to coordinate economic growth and environmental improvement. Therefore, in current China context, the study of this issue is of both theoretical and practical significance.

Along with these regulations, academic studies realize the rapid changes in natural environment and attempt to explore its implications since the middle of last century. Plenty of studies examined the impact of pollution and environmental regulation on health, investment and other economic activities (Chen et al., 2013; Tanaka, 2015; Goetzmann et al., 2015), however, according to our knowledge, there is no such comprehensive evidence of market-wide investors’ responses. Our study is contribute to the enhancement of awareness on stock market structure and investors’ behavioral biases.

In this paper, we explore the impact of air pollution on Chinese stock market. Atmosphere-related mood leads to the variations in the level of investors’ trading activity, also shown in the returns and trading of individual stocks. Specifically, as regional air pollution gets severe, people are less likely to involve trading in the market and their preference for lottery-like stock diminish. The effects are stronger among retail investors as individuals are more subjective to emotion fluctuations. By focusing on investors of smaller investment scale, the coefficients on AQI increase and become more significant. Meanwhile, stock returns generally go down in the time of high pollution and lottery stocks underperform than others. Based on analysis above, we successfully introduce air pollution into the study of financial markets and future studies can keep exploring the impacts of air on markets, investors, and other financial activities.

**References**

Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment. Journal of financial economics, 49(3), 307-343.

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross‐section of stock returns. The Journal of Finance, 61(4), 1645-1680.

Cortés, K., Duchin, R., & Sosyura, D. (2016). Clouded judgment: The role of sentiment in credit origination. Journal of Financial Economics, 121(2), 392-413.

Chen, Y., Ebenstein, A., Greenstone, M., & Li, H., 2013. Evidence on the impact of sustained exposure to air pollution on life expectancy from China’s Huai River policy. Proceedings of the National Academy of Sciences. 110(32), 12936-12941.

Denissen, J. J., Butalid, L., Penke, L., & Van Aken, M. A. (2008). The effects of weather on daily mood: A multilevel approach. Emotion, 8(5), 662.

DeHaan, E., Madsen, J., & Piotroski, J. D. (2017). Do Weather‐Induced Moods Affect the Processing of Earnings News?. Journal of Accounting Research, 55(3), 509-550.

Goetzmann, W. N., Kim, D., Kumar, A., & Wang, Q., 2015. Weather-induced mood, institutional investors, and stock returns. Review of Financial Studies. 28(1), 73-111.

Hirshleifer, D., & Shumway, T. (2003). Good day sunshine: Stock returns and the weather. The Journal of Finance, 58(3), 1009-1032.

Kuhnen, C. M., & Knutson, B. (2011). The influence of affect on beliefs, preferences, and financial decisions. Journal of Financial and Quantitative Analysis, 46(3), 605-626.

Kaustia, M., & Rantapuska, E. (2016). Does mood affect trading behavior?. Journal of Financial Markets, 29, 1-26.

Knutson, B., Wimmer, G. E., Kuhnen, C. M., & Winkielman, P. (2008). Nucleus accumbens activation mediates the influence of reward cues on financial risk taking. NeuroReport, 19(5), 509-513.

Lepori, G. M. (2016). Air pollution and stock returns: Evidence from a natural experiment. Journal of Empirical Finance, 35, 25-42.

Lu, J., & Chou, R. K. (2012). Does the weather have impacts on returns and trading activities in order-driven stock markets? Evidence from China. Journal of Empirical Finance, 19(1), 79-93.

Ng, L., & Wu, F. (2007). The trading behavior of institutions and individuals in Chinese equity markets. Journal of Banking & Finance, 31(9), 2695-2710.

Saunders, E. M. (1993). Stock prices and Wall Street weather. The American Economic Review, 83(5), 1337-1345.

Sanders, J. L., & Brizzolara, M. S. (1982). Relationships between weather and mood. The Journal of General Psychology, 107(1), 155-156.

Shefrin, H., & Statman, M. (2000). Behavioral portfolio theory. Journal of financial and quantitative analysis, 35(2), 127-151.

Tanaka, S., 2015. Environmental regulations on air pollution in China and their impact on infant mortality. Journal of Health Economics. 42, 90-103.

Wu, X., Chen, S., Guo, J., & Gao, G. (2018). Effect of air pollution on the stock yield of heavy pollution enterprises in China's key control cities. Journal of Cleaner Production, 170, 399-406.

Huang, R. J., Zhang, Y., Bozzetti, C., Ho, K. F., Cao, J. J., Han, Y., ... & Zotter, P. (2014). High secondary aerosol contribution to particulate pollution during haze events in China. Nature, 514(7521), 218-222.

Li, H., Yang, S., Zhang, J., & Qian, Y. (2016). Coal-based synthetic natural gas (SNG) for municipal heating in China: analysis of haze pollutants and greenhouse gases (GHGs) emissions. Journal of Cleaner Production, 112, 1350-1359.

Lakonishok, J., & Maberly, E. (1990). The weekend effect: Trading patterns of individual and institutional investors. The Journal of Finance, 45(1), 231-243.

Ogden, J. P. (1990). Turn-of-the month evaluations of liquid profits and stock returns: a common explanation for the monthly and January effects. The Journal of Finance, 45(4), 1259-1272.

Keim, D. B. (1989). Trading patterns, bid-ask spreads, and estimated security returns: The case of common stocks at calendar turning points. Journal of Financial Economics, 25(1), 75-97.

Ariel, R. A. (1990). High stock returns before holidays: Existence and evidence on possible causes. The Journal of Finance, 45(5), 1611-1626.

Figure 1

Table 1

This table reports summary statistics for the air quality in 34 major cities in China during the period of 1 January, 2014 to 31 December, 2017. The first column is the average AQI for the city in the whole interval. Air quality is divided into 6 levels from excellent to severe pollution, and the proportion of each level is shown in the 2rd column to the 8th.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| City | Mean | Excellent | Good | Lightly Polluted | Moderately Polluted | Heavily Polluted | Severely Polluted | Miss |
| Shijiazhuang | 140.3 | 4.5 | 36.9 | 27.9 | 11.8 | 11.7 | 6.8 | 0.5 |
| Zhengzhou | 125.2 | 2.0 | 40.2 | 33.8 | 12.5 | 8.9 | 2.1 | 0.5 |
| Jinan | 122.9 | 1.4 | 37.4 | 40.5 | 12.3 | 6.2 | 1.7 | 0.5 |
| Beijing | 116.5 | 13.8 | 38.6 | 21.6 | 14.2 | 7.9 | 3.1 | 0.8 |
| Xi'an | 112.0 | 4.2 | 52.4 | 25.7 | 8.0 | 7.1 | 1.9 | 0.5 |
| Tianjin | 108.8 | 6.6 | 49.3 | 27.0 | 8.4 | 6.7 | 1.4 | 0.5 |
| Urumqi | 108.3 | 8.5 | 55.3 | 18.5 | 6.0 | 8.3 | 2.9 | 0.5 |
| Taiyuan | 104.8 | 5.6 | 52.2 | 28.3 | 7.5 | 4.7 | 1.2 | 0.5 |
| Chengdu | 102.4 | 7.0 | 53.1 | 26.1 | 7.0 | 5.6 | 0.6 | 0.5 |
| Wuhan | 100.9 | 10.5 | 47.7 | 30.0 | 6.6 | 4.0 | 0.7 | 0.5 |
| Shenyang | 100.4 | 7.7 | 54.3 | 25.2 | 6.8 | 4.7 | 0.8 | 0.5 |
| Lanzhou | 97.3 | 2.7 | 63.6 | 26.4 | 4.7 | 0.8 | 1.4 | 0.5 |
| Hefei | 96.0 | 10.8 | 52.9 | 26.2 | 5.8 | 3.3 | 0.4 | 0.5 |
| Nanjing | 94.9 | 11.2 | 52.1 | 27.4 | 6.1 | 2.4 | 0.2 | 0.5 |
| Harbin | 94.8 | 22.8 | 47.2 | 15.1 | 6.2 | 6.0 | 2.3 | 0.5 |
| Yinchuan | 93.9 | 2.9 | 67.3 | 22.0 | 5.1 | 1.7 | 0.5 | 0.5 |
| Changchun | 91.5 | 11.7 | 59.1 | 19.4 | 5.3 | 3.0 | 1.0 | 0.5 |
| Suzhou | 90.3 | 9.0 | 59.1 | 25.5 | 4.3 | 1.7 | 0.0 | 0.5 |
| Changsha | 89.4 | 17.3 | 51.7 | 21.0 | 5.6 | 3.4 | 0.4 | 0.5 |
| Hangzhou | 88.8 | 11.8 | 56.9 | 25.1 | 4.4 | 1.3 | 0.0 | 0.5 |
| Hohhot | 87.6 | 12.0 | 60.7 | 21.2 | 3.8 | 1.5 | 0.3 | 0.5 |
| Xining | 86.8 | 6.6 | 69.9 | 19.7 | 2.2 | 0.5 | 0.6 | 0.5 |
| Qingdao | 85.5 | 10.2 | 65.4 | 18.1 | 3.7 | 2.0 | 0.2 | 0.5 |
| Chongqing | 84.9 | 16.6 | 58.5 | 16.4 | 5.2 | 2.8 | 0.0 | 0.5 |
| Shanghai | 84.2 | 15.3 | 58.3 | 19.4 | 5.3 | 1.1 | 0.0 | 0.5 |
| Guangzhou | 74.6 | 23.3 | 58.2 | 14.9 | 2.7 | 0.4 | 0.0 | 0.5 |
| Nanchang | 74.2 | 24.0 | 60.0 | 12.6 | 2.0 | 0.8 | 0.1 | 0.5 |
| Lhasa | 64.8 | 23.5 | 70.3 | 5.5 | 0.2 | 0.0 | 0.0 | 0.5 |
| Nanning | 64.2 | 37.9 | 50.7 | 8.6 | 1.7 | 0.5 | 0.0 | 0.5 |
| Guiyang | 61.9 | 35.7 | 56.4 | 6.7 | 0.7 | 0.1 | 0.0 | 0.5 |
| Fuzhou | 59.5 | 34.9 | 60.6 | 3.8 | 0.0 | 0.1 | 0.0 | 0.5 |
| Kunming | 56.6 | 36.5 | 61.3 | 1.6 | 0.0 | 0.0 | 0.0 | 0.6 |
| Shenzhen | 55.6 | 49.1 | 46.3 | 3.8 | 0.2 | 0.0 | 0.0 | 0.5 |
| Haikou | 43.7 | 73.5 | 23.8 | 2.1 | 0.1 | 0.0 | 0.0 | 0.5 |

Table 2 Basic characteristics of Lottery-type stocks

This table reports the mean daily characteristics of lottery-type stocks, measured during 2014-2016 sample period. For comparison, the characteristics of non-lottery-type stocks and stocks that do not belong to either of the two categories (i.e., other stocks) are also reported. The stocks in all three categories are defined at the end of each day using all stocks listed in SSE. The stocks in the lowest kth price percentile, highest kth idiosyncratic volatility percentile, and highest kth idiosyncratic skewness percentile are identified as lottery-type stocks. Similarly, stocks in the highest kth price percentile, lowest kth idiosyncratic volatility percentile, and lowest kth idiosyncratic skewness percentile are identified as non-lottery-type stocks. For the results reported in the table, k = 50. A and all reported measures are defined in

|  |  |  |  |
| --- | --- | --- | --- |
| Type | Lottery | Non-lottery | Others |
| Percentage of observations | 11.72 | 10.82 | 77.46 |
| RET | 0.02 | 0.18 | 0.14 |
| Price | 7.57 | 21.01 | 15.36 |
| Turnover | 2.36 | 1.12 | 1.45 |
| Shares outstanding(in million ￥) | 12546.79 | 31915.43 | 20564.04 |
| Asset (in million ￥) | 38614.30 | 195942.87 | 162087.16 |
| Leverage | 57.15 | 47.61 | 52.81 |
| BM | 675.36 | 568.92 | 662.52 |
| Equity (in million ￥) | 8619.68 | 24244.58 | 20188.09 |
| AGE | 20.47 | 20.63 | 20.04 |
| IPOage | 16.46 | 15.54 | 15.27 |

Table 3

This table presents estimates of the following regression:

The dependent variable is trading volume for broker *i* in city *c* at day *t*. The first specification counts all the trading entries, and we exclude institutional investors in M2 and further large investors in M3. The sample consists of legitimate brokers existed during 2014-2017 and the model is estimated using OLS. AQI is demeaned by subtracting the mean of each week in all three years, which is also the mean variable. Control variables include three types: weather variables (demeaned cloud cover, average temperature, wind speed in Shanghai), calendar effects (dummies of Monday, Friday, first one and three days of the month and year, last one and three days of the month and year), lagged market returns. City fixed effect, month fixed effect, and broker fixed effect are included. The standard deviations are reported in parentheses. \*\*\*, \*\* and \* represent statistical significance at the 1%, 5% and 10% levels, respectively.

|  |  |  |  |
| --- | --- | --- | --- |
|  | (1) | (2) | (3) |
|  | M1 | M2 | M3 |
| VARIABLES | Volume | Volume\_ind | Volume\_sind |
|  |  |  |  |
| AQI | -0.0000945\*\*\* | -0.0001102\*\*\* | -0.0001273\*\*\* |
|  | (0.0000323) | (.0000323) | (0.0000316) |
| VISIB | -0.0026813\*\*\* | -.0028849\*\*\* | -0.0030368\*\*\* |
|  | (0.0003936) | (0.0003933) | (0.0003854) |
| WIND\_SP | 0.0002783 | 0.0004569 | 0.000247 |
|  | (0.0006011) | (0.0006009) | (0.0005889) |
| PRCP | -0.0051136\* | -0.0053879\*\* | -0.0057275\*\* |
|  | (0.0026851) | (0.0026846) | (0.0026313) |
| TEMP | 0.0025903\*\*\* | 0.0026385\*\*\* | 0.0025414\*\*\* |
|  | (0.0002369) | (0.0002368) | (0.000232) |
|  |  |  |  |
| Constant | 16.4188\*\*\* | 17.0236\*\*\* | 16.71644\*\*\* |
|  | (0.019242) | (0.018783) | (0.0184012) |
|  |  |  |  |
| Calendar Effect | YES | YES | YES |
| Market Return | YES | YES | YES |
| City FE | YES | YES | YES |
| Month FE | YES | YES | YES |
| Broker FE | YES | YES | YES |
| Observations | 2,690,599 | 2,681,169 | 2,678,804 |
| R-squared | 0.2323 | 0.2330 | 0.2438 |

Table 4

This table presents estimates of the following regression:

The dependent variable is trading volume of lottery-like stocks for broker *i* in city *c* at day *t*. The first specification counts all the investors, and we exclude institutional investors in M2 and further large investors in M3. The sample consists of legitimate brokers existed during 2014-2017 and the model is estimated using OLS. AQI is demeaned by subtracting the mean of each week in all three years, which is also the mean variable. Control variables include three types: weather variables (demeaned cloud cover, average temperature, wind speed in Shanghai), calendar effects (dummies of Monday, Friday, first one and three days of the month and year, last one and three days of the month and year), lagged market returns. City fixed effect, month fixed effect, and broker fixed effect are included. The standard deviations are reported in parentheses. \*\*\*, \*\* and \* represent statistical significance at the 1%, 5% and 10% levels, respectively.

|  |  |  |  |
| --- | --- | --- | --- |
|  | (1) | (2) | (3) |
|  | M1 | M2 | M3 |
| VARIABLES | Lottery | Lottery\_ind | Lotter\_sind |
|  |  |  |  |
| AQI | -0.0000629\* | -0.0000763\*\* | -0.0000919\*\*\* |
|  | (0.0000346) | (0.0000344) | (0.0000332) |
| VISIB | -0.0026536\*\*\* | -0.0028849\*\*\* | -0.0029248\*\*\* |
|  | (0.0004218) | (0.0004199) | (0.0004042) |
| WIND\_SP | 0.0000768 | 0.000259 | 0.0000796 |
|  | (0.0006441) | (.0006414) | (0.0006174) |
| PRCP | -0.00328 | -0.0038457 | -0.0039749\*\* |
|  | (0 .0028768) | (0.0028654) | (0.0027585) |
| TEMP | 0.0025139\*\*\* | 0.0025432\*\*\* | 0.0024544\*\*\* |
|  | (0.0002538) | (0.0002527) | (0.0002433) |
|  |  |  |  |
| Constant | 16.03829\*\*\* | 17.0236\*\*\* | 16.71644\*\*\* |
|  | (0.0201054) | (0.018783) | (0.0184012) |
|  |  |  |  |
| Calendar Effect | YES | YES | YES |
| Market Return | YES | YES | YES |
| City FE | YES | YES | YES |
| Month FE | YES | YES | YES |
| Broker FE | YES | YES | YES |
| Observations | 2,656,808 | 2,647,653 | 2,642,313 |
| R-squared | 0.2206 | 0.2220 | 0.2327 |

Table 5

This table presents estimates of the following regression:

The dependent variable is stock daily return. The sample consists of all the stocks listed in SEE during 2014-2016 and the model is estimated using OLS. AQI is demeaned by subtracting the mean of each week in all three years. Lottery takes one if the stock fall in the 50th percentile of low price, high idiosyncratic volatility, and high idiosyncratic skewness. The main independent variable is the cross term of AQI and Lottery. Control variables include three types: weather variables (demeaned cloud cover, average temperature, wind speed in Shanghai), firm characteristics (size, book to market ratio, leverage), and macroeconomic variables (province-level GDP, population, unemployment rate, government revenue). Province fixed effect, month fixed effect, and industry fixed effect are included in part specifications except column 1. The standard deviations are reported in parentheses. \*\*\*, \*\* and \* represent statistical significance at the 1%, 5% and 10% levels, respectively.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | (1) | (2) | (3) | (4) |
|  | M1 | M2 | M3 | M4 |
| VARIABLES | dretwd | dretwd | dretwd | dretwd |
|  |  |  |  |  |
| daqi | -7.58e-06\*\*\* | -7.70e-06\*\*\* | -8.53e-06\*\*\* | -4.69e-06\*\*\* |
|  | (1.22e-06) | (1.19e-06) | (1.20e-06) | (1.23e-06) |
| lot | -0.00118\*\*\* | -0.000878\*\*\* | -0.000922\*\*\* | -0.00140\*\*\* |
|  | (0.000115) | (0.000116) | (0.000117) | (0.000117) |
| daqilot | -6.58e-06\*\* | -6.27e-06\*\* | -6.29e-06\*\* | -6.48e-06\*\* |
|  | (3.14e-06) | (3.08e-06) | (3.11e-06) | (3.05e-06) |
| davet | 0.000667\*\*\* | 0.000668\*\*\* | 0.000700\*\*\* | 0.000642\*\*\* |
|  | (1.35e-05) | (1.32e-05) | (1.34e-05) | (1.44e-05) |
| dwind | 0.000376\*\*\* | 0.000373\*\*\* | 0.000363\*\*\* | 0.000371\*\*\* |
|  | (1.29e-05) | (1.26e-05) | (1.28e-05) | (1.30e-05) |
| dcloud | -0.000428\*\*\* | -0.000432\*\*\* | -0.000383\*\*\* | -0.000228\*\*\* |
|  | (1.52e-05) | (1.49e-05) | (1.52e-05) | (1.61e-05) |
| size |  | -0.000232\*\*\* | -0.000199\*\*\* | -0.000245\*\*\* |
|  |  | (2.56e-05) | (2.60e-05) | (2.89e-05) |
| bm |  | -1.54e-07\*\*\* | -2.14e-07\*\*\* | -1.13e-07\*\*\* |
|  |  | (3.30e-08) | (3.31e-08) | (3.28e-08) |
| leverage |  | 0.000162\*\*\* | 0.000132\*\* | 4.83e-05 |
|  |  | (5.25e-05) | (5.27e-05) | (5.19e-05) |
| gdp |  |  | -0.0191\*\*\* | 0.00120 |
|  |  |  | (0.00114) | (0.00135) |
| pop |  |  | -0.0224\*\* | -0.00734 |
|  |  |  | (0.00881) | (0.00952) |
| unemp |  |  | -0.00223\*\*\* | -0.00100\*\* |
|  |  |  | (0.000421) | (0.000418) |
| rev |  |  | 0.00581\*\*\* | -0.000883 |
|  |  |  | (0.000747) | (0.000780) |
|  |  |  |  |  |
| Constant | 0.00164\*\*\* | 0.00688\*\*\* | 0.271\*\*\* | 0.0636 |
|  | (3.98e-05) | (0.000610) | (0.0639) | (0.0737) |
|  |  |  |  |  |
| City FE | NO | YES | YES | YES |
| Month FE | NO | NO | NO | YES |
| Industry FE | NO | NO | NO | YES |
| Observations | 918,065 | 912,656 | 893,624 | 893,624 |
| R-squared | 0.005 | 0.005 | 0.006 | 0.042 |

Table 6

This table presents estimates of the following regression:

The dependent variable is stock daily trading characteristics, including volatility, turnover, and liquidity. The sample consists of all the stocks listed in SEE during 2014-2016 and the model is estimated using OLS. AQI is demeaned by subtracting the mean of each week in all three years. Lottery takes one if the stock fall in the 50th percentile of low price, high idiosyncratic volatility, and high idiosyncratic skewness. The main independent variable is the cross term of AQI and Lottery. Control variables include three types: weather variables (demeaned cloud cover, average temperature, wind speed in Shanghai), firm characteristics (size, book to market ratio, leverage), and macroeconomic variables (province-level GDP, population, unemployment rate, government revenue). Province fixed effect, month fixed effect, and industry fixed effect are included in part specifications except column 1. The t-statistics are reported in parentheses. \*\*\*, \*\* and \* represent statistical significance at the 1%, 5% and 10% levels, respectively.

|  |  |  |  |
| --- | --- | --- | --- |
|  | (1) | (2) | (3) |
|  | M1 | M2 | M3 |
| VARIABLES | Volatility | Turnover | Liquidity |
|  |  |  |  |
| daqi | -2.89e-06\*\*\* | -0.000924\*\*\* | 0.000150\*\* |
|  | (8.50e-07) | (0.000118) | (6.42e-05) |
| lot | 0.00290\*\*\* | 0.0511\*\*\* | -0.0255\*\*\* |
|  | (8.06e-05) | (0.0112) | (0.00609) |
| daqilot | -5.99e-06\*\*\* | 0.000205 | -5.04e-05 |
|  | (2.11e-06) | (0.000292) | (0.000159) |
| davet | 4.28e-05\*\*\* | 0.0106\*\*\* | -0.00172\*\* |
|  | (9.97e-06) | (0.00138) | (0.000753) |
| dwind | -8.65e-05\*\*\* | -0.000869 | -0.000395 |
|  | (8.94e-06) | (0.00124) | (0.000675) |
| dcloud | -0.000108\*\*\* | 0.00121 | 0.00204\*\* |
|  | (1.11e-05) | (0.00154) | (0.000841) |
| size | -0.00215\*\*\* | -0.625\*\*\* | -0.0387\*\*\* |
|  | (2.00e-05) | (0.00277) | (0.00151) |
| bm | -4.72e-07\*\*\* | 0.000272\*\*\* | 2.59e-05\*\*\* |
|  | (2.26e-08) | (3.14e-06) | (1.71e-06) |
| leverage | 6.14e-05\* | -0.0267\*\*\* | 0.00328 |
|  | (3.59e-05) | (0.00497) | (0.00271) |
| gdp | -0.00865\*\*\* | -0.630\*\*\* | 0.359\*\*\* |
|  | (0.000934) | (0.130) | (0.0706) |
| pop | 0.0161\*\* | 1.392 | -0.475 |
|  | (0.00657) | (0.911) | (0.496) |
| unemp | -0.00387\*\*\* | -0.451\*\*\* | 0.0265 |
|  | (0.000289) | (0.0400) | (0.0218) |
| rev | -0.00123\*\* | -0.219\*\*\* | -0.105\*\*\* |
|  | (0.000538) | (0.0746) | (0.0407) |
| Constant | 0.0698 | 14.33\*\* | 2.768 |
|  | (0.0509) | (7.052) | (3.842) |
|  |  |  |  |
| City FE | YES | YES | YES |
| Month FE | YES | YES | YES |
| Industry FE | YES | YES | YES |
| Observations | 893,624 | 893,624 | 893,624 |
| R-squared | 0.357 | 0.216 | 0.004 |

Appendix: variable definitions

|  |  |
| --- | --- |
| Variable Name | Description |
| Weather measures | |
| AQI | Air quality index, which is used to tell how clean or polluted air is based on the density of six pollutants |
| DAQI | Demeaned air quality index, measured by subtracting the daily mean in the same week during 2014-2016 from AQI |
| Heavy Pollution | Set to 1 if AQI > 300 |
| Low Pollution | Set to 1 if AQI <= 100 |
| TEP | Demeaned temperature |
| STEP | Demeaned temperature in Shanghai |
| WSP | Demeaned wind speed |
| WSWP | Demeaned wind speed in Shanghai |
| CLOUD | Cloud cover |
| SCLOUD | Cloud cover in Shanghai |
| Trading measures | |
| LBSI | Lottery buy-sell imbalance ratio, measured by the ratio of excess buy volume (buy volume – sell volume) to total trading volume (buy volume+ sell volume) |
| Stock characteristics | |
| Idiosyncratic volatility | Standard deviation of the residual from a three-factor model |
| Idiosyncratic skewness | Scaled measure of the third moment of the residual obtained by fitting a quadratic excess return (RMRF and RMRF2) model |
| Volatility | The spread of daily stock price, divided by average price. (High price – Low price)/(High price + Low price)\*2 |
| Turnover | The ratio of stock total trading volume and shares outstanding |
| Liquidity | The ratio of absolute returns and daily trading volume |
| Size | Logarithmic year-end firm asset |
| Leverage | Ratio of the liability and the total asset |
| BM | Ratio of the book-value and the market capitalization of the firm |
| Equity | Year-end |
| AGE | Number of years since the foundation of the firm |
| IPOage | Number of years since the firm listed in SSE |
| Macroeconomic variables | |
| GDP | Log of gross domestic product at year end in millions of RMB |
| Population | Log of total population in the region |
| Revenue | Log of government revenue at year end in millions of RMB |
| Unemployment | The rate of unemployed labor among all the labor force |
| North | Equal to one if the region is located north of the Huai River line |

1. All the statistics of trading are quoted from Shanghai Stock Exchange Statistics Annual Book. [↑](#footnote-ref-1)