Trading for Status

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Abstract

We test the hypothesis that status preference amplifies trading activity in stock markets. This preference leads to demand for local stocks to track neighbors that rises with the stock market and generates trading between status and non-status seekers. We use an empirical design from China, where we measure intensity of status concerns by province based on income and luxury brand internet searches controlling for income. Using large stocks to control for investment sets across provinces, we find higher share turnover and a higher sensitivity of turnover to returns for small relative to big stocks in high-status concern compared to low-status concern provinces. These differences have increased in recent years with a rising middle class in China. Local small stocks in high-status concern provinces also have higher prices.

1. Introduction

What are the determinants of trading volume in financial markets? Innovative research from the last decade exploiting brokerage house trading data from all over the world point to behavioral biases such as overconfidence (see, e.g., Barber and Odean (2001)) and preference for lotteries as being key factors behind this excessive trading (see, e.g., Kumar (2009)). These behavioral biases also appear to be mediated by sociological or peer effects as investor trades are influenced by their neighbors (see, e.g., Hong, Kubik, and Stein (2004) and Grinblatt and Keloharju (2001)). One channel in which social effects might matter for trading volume is status preference. This preference leads households to take excessive risk by holding concentrated portfolios that are tied to their neighbors' or local entrepreneurs' wealth (see, e.g., DeMarzo, Kaniel, and Kremer (2004), Gomez, Priestley, and Zapatero (2009)), thereby naturally generating a strong local bias in portfolios that is confirmed in data from many countries including the U.S., European countries such as Scandinavia and Asian countries such as China. Investors living in a certain city or region are more likely to hold and trade stocks near them.[1]

We show that status effects lead to time-varying demand for local stocks that rise with the stock market and hence generate trading volume in local stocks. We then show that the recent economic boom and the rise of middle class in China provide a compelling empirical design to test this hypothesis and to examine more broadly the influence of status concerns on trading and asset pricing. Economists have long recognized that status is an important component of consumption when households achieve economic security beyond subsistence levels. The role of relative wealth concerns in affecting the marginal utility of leisure has been popularized since Veblen (1934) and is now widely used to think about the demand for luxury goods which convey signalling value (see, e.g., Frank (1985)). There is micro-evidence from panel data and surveys that confirm households have status preferences in that they

[1]That is the original international home bias finding of French and Poterba (1991), which is really part of a deeper local bias among investors.

feel worse when others do better even though their real consumption bundle has improved (Dynan and Ravina (2007), Ravina (2007)). And more recently, interesting work by Ait-Sahalia, Parker, and Yogo (2004) point to preference for luxury goods as being helpful in understanding the equity risk premium puzzle. But the empirical analysis of status concerns on risk taking and trading in asset markets is still relatively sparse in comparison.

We first show in a simple model how status concerns generates trading volume. Non-status investors or market makers have the usual log preferences and status investors have a utility function that is log multiplied by the level of a subset of a benchmark index of stocks in the stock market. As a result, the status investors' marginal utility increases with the value of this benchmark. This benchmark is the subset of stocks that investors want to track so as to compete for status. Higher status in the utility leads to greater investor demand for this risky benchmark, and higher prices for stocks in this benchmark.

This demand also leads to trading between status seekers and market makers. Low market values of the benchmark reduce the need for this status generated risk-demand since there is nothing to catch up to. In contrast, high market values increase the demand for the risky benchmark to Keep-up-with-the-Wangs. We show under some sufficient conditions that share turnover increases with the intensity of the status parameter and so do prices.

The challenge lies in finding an empirical design in which such a shift in the status preference parameter plausibly occurred and then measuring its effect on volume and asset prices. Unfortunately, the U.S., which is the typical venue for most research, does not provide a good setting to measure this comparative static since most U.S. residents are fairly well-off and presumably already have status preferences and trading volume is dominated by institutional investors.

Our empirical strategy to answer this critical question of the comparative static of risk-taking and asset pricing with respect to status centers on a novel empirical design from China. China is an ideal setting to consider status effects and risk-taking for a number of reasons beyond its plentiful data. First, China has a unique geography of status in what the Chinese refer to as Tier 1 (richer, more developed and higher status) compared to Tier 5 (poorer, less developed and lower status) regions. Tier 1 province's GDP per capita has passed over 20,000 Yuan by 2003. So status effects ought to matter more in top tier provinces since status effects are stronger with higher income and wealth. This perspective is in accord with the existing survey evidence that wealthier people are more concerned with their relative position. We expect whatever status induced risk-taking effects to be more prominent in high status than low status areas.

Second, China's economy, its stock market, and income inequality have developed extremely rapidly since the late nineties. This rapid development allows us to not only compare risk-taking from inhabitants across different tier or status places but to compare this difference over time. We expect that status effects to have increased in Tier 1 regions compared to Tier 5 ones over the last ten years. Anecdotal evidence from luxury goods consumption in China, which comes predominantly from Tier 1 areas, backs up this time trend differential approach. In other words, our empirical strategy consists of employing a difference-in-difference approach involving comparing different regions over time.

Third, Chinese markets are still dominated by retail investors. There is virtually no institutional investors to speak off. This stands in contrast to the dramatic role of institutional investors in markets like the U.S.: some 80% of the shares of all U.S. stocks are held by institutional investors and most of the trading volume is generated by them as well. These trends have been ongoing throughout the last thirty years, which makes using our empirical strategy in the U.S. and other developed markets difficult.

Fourth, the Chinese markets are closed over its span as most domestic Chinese residents can only invest in real estate or the stock market and foreigners cannot freely invest in Chinese markets. This means less confounding factors such as globalization that might influence our accounting of status and risk-taking effects due to local residents.

Our predictions are that in Tier 1 areas these status preferences are more intense and hence there is more trading in local stocks there than in lower tier places. Local stocks in top tier places should also as a result have higher prices. Since our empirical strategy in identifying a status effect centers on comparing trading volume and pricing of the stocks of companies located in different places, we naturally need to control for varying investment opportunity sets in these regions. This point is made clearly in Hong, Kubik, and Stein (2008)'s analysis of an only-game-in-town effect in which the lack of stocks located in low density cities or areas results in them having higher prices. We do so by using large local stocks as a control and looking at the share turnover and price gaps between small and large local stocks. This strategy is also well-motivated by theory since the smaller local stocks are likely to track local entrepreneurs in contrast to large stocks which are more likely to be state-owned enterprises and hence not a natural benchmark for status tracking. In short, we use a difference-in-difference estimate by comparing small and large local stock gaps in share turnover and price across low and high status areas.

To further buttress our identification, we consider how this cross region difference in the difference between small and large stock trading and pricing varies over time. Given the extremely rapid development over the last ten years and the closed stock markets being dominated by retail investors, we think of this as a difference-in-difference-in-difference exercise where the third difference is splitting the sample into two-halves, an early period from 1998 to 2003 and a late period of 2004 to 2009.

Our identification strategy boils down to finding that in richer areas with greater status demand recently there is more trading in local small stocks. This strategy can be contrasted with the benchmark findings regarding investor overtrading in Kumar (2009): there is excessive trading in small, local stocks among poorer and less educated households. In other words, the status effects have to be strong enough to overwhelm the baseline effect which is that poor households should trade more small local stocks.

We find that this difference-in-difference is indeed bigger in the 2004-2009 sample than in the early half of the sample. Indeed, we find larger share turnover and price gaps for small stocks relative to big ones in richer places than in poorer places in the latter half of the sample. Moving from Tier 5 provinces to Tier 1 provinces increase the turnover gap for small stocks relative to big ones by 80%, which is 38% of the turnover difference's standard deviation.

We find a large price effect when measured using the market-to-book ratio of companies. The increase in the market-to-book of small relative to big stocks in Tier 1 provinces during the latter half of the sample is about 93% of the market-to-book's difference's standard deviation. But the statistical significance of these estimates are weaker than for share turnover.

We then consider two further identification strategies that speak directly to the status mechanism. The first is that we also provide an alternative measure of which places are most affected using luxury brand searches relative to normal brand searches by provinces using data from Baidu, the main internet search engine in China. While this measure of status is correlated with income, a measure of internet searches residual income also provides independent and confirmatory information of status effects. We find that our residual luxury brand search index controlling for income yields similar results as our income Tier measures.

The second is that the trading volume follows a rise in the stock market as investors are more concerned about status when the market is high. We regress share turnover in a given year on the lagged past returns and a constant for small and for big stocks in different provinces and then calculate the difference in these two regression coefficients on last year's stock return. Consistent with our theory, we find that the turnover-past return sensitivity is higher for small stocks than big stocks in high status provinces in recent years. Our status concern mechanism and finding might be one contributing factor for the well-known strong correlation between price and share turnover in markets (see, e.g., Hong and Stein (2007)).

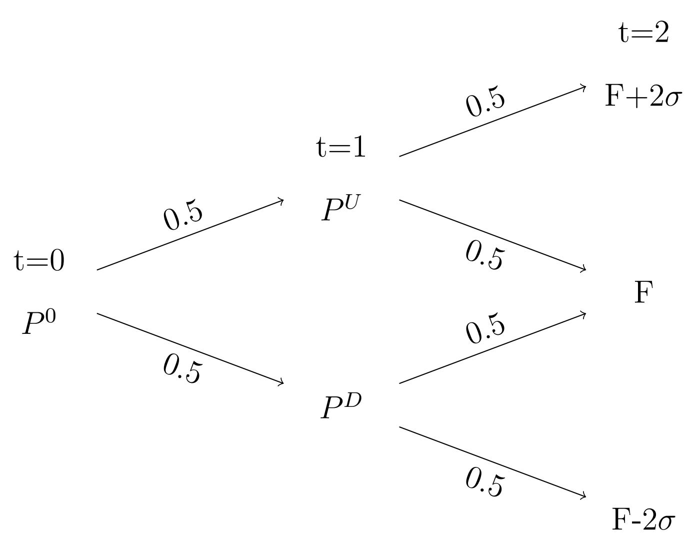
There is a growing literature cited above arguing that status effects matter in financial markets. Much of this work centers on theory arguing how status effects give rise to local bias. The empirical work tries to examine how this might explain the entrepreneurial discounts observed in the U.S. and rationalize some asset pricing patterns associated with the location of stocks. Notably, recent important work by Wei and Zhang (2011) points to a competitive motive for savings in China due to sex ratio imbalances. Their mechanism is consistent with status being important since the savings goes into buying an apartment which serves as a status symbol or signalling device to attract a mate.

Our paper differs in two main ways. First, there is the focus on trading volume. In other words, we look at quantities and not just prices. Second, we provide a number of novel identification strategies. Our model is based on Basak and Pavlova (2011)'s continuous time treatment. Since we want to address stock turnover, we consider a discrete-time binomial tree version of their set-up.

Our paper proceeds as follows. We develop the model in Section 2. We describe the data in Section 3. We make the case for residents in Tier 1 areas having greater relative wealth concerns than those in lower tier places in Section 4. We present the empirical results in Section 5 and conclude in Section 6. All proofs are in the Appendix.

2. Model

We consider a simple model of stock trading in a pure exchange economy with three dates, $t = 0, 1, 2$. The payoff of the stock $\tilde{F}$ follows the following binomial tree.



At $t = 2$, there are three states with payoffs given by $F + 2\sigma$, F, and $F - 2\sigma$. At $t = 1$, investors receive a signal, either U or D, in which the signal equals U with probability 1/2 and equals D with probability 1/2. When the signal equals U, the terminal payoff $\tilde{F}$ equals either $F + 2\sigma$ or F at $t = 2$ with equal probability. When the signal equals D, the terminal payoff is either F or $F - 2\sigma$ with equal probability. There is also a riskless bond with an exogenous interest rate which we set at zero.

There are two types of investors in the population: status (denoted by s) and non-status (denoted by m) investors. We can think of non-status investors as being institutional market makers or speculators. The utility of the s-investors are given by

$$U_s(W_{s,2}) = (1 + b\tilde{F})\log(W_{s,2}), \tag{2.1}$$

and for the m-investors it is given by

$$U_m(W_{m,2}) = \log(W_{m,2}). \tag{2.2}$$

Notice that b is our key parameter of interest and captures the intensity of status in the utility function. When $b = 0$, the status and non-status investors are identical.

The $b\tilde{F}$ term in the utility function of the status investors is a reduced way to capture the Catching-up-with-the-Wangs preferences. $\tilde{F}$, the payoff of the small stocks owned by the local entrepreneurs, keeps track of the status rank of investors living in a place. High payoffs convey higher status. Holding fixed $\tilde{F}$, the utility of the status investor is increasing and concave in wealth. Holding fixed wealth, the utility of the status investor is increasing in $\tilde{F}$ and

$$\frac{\partial U_s^2}{\partial W \partial F} > 0$$

which implies that wealth and status are complements. So marginal utility of wealth rises with status. It is this assumption that is critical for our results. The status investors' preference for the risky asset changes between $t = 0$ and $t = 1$ depending on the signal or the realizations of $\tilde{F}$.

Each type of investor chooses the portfolio weight in the stock of $\phi_{i,t}$ given their initial endowment of wealth, $W_{i,0}$. The dynamics of their wealth evolves for $i \in \{s, m\}$ as

$$W_{i,2} = W_{i,0}(1 + \phi_{i,1}R_1)(1 + \phi_{i,2}R_2) \tag{2.3}$$

where $R_t = \frac{P_t - P_{t-1}}{P_{t-1}}$ is the net-percentage return of the stock in period t. The initial endowment for the s-investors are given by $W_{s,0} = \lambda P^0$ and for the m-investors are given by $W_{m,0} = (1 - \lambda)P^0$.

Our empirical design in China can be mapped in the following way into this model. We assume that only top tier places have status preference while bottom tier places do not, since only top tier places have a significant enough level of wealth to consume status. So in our analysis, we take for Tier 1 and 2 regions to be a non-zero b while lower places have a b close to zero.

All details for the solution of this model are in the Appendix. At the U-state, the demand function for both kinds of investors are given below:

$$\phi_s^U = \frac{P^U(\bar{F} - P^U)}{\sigma^2 - (\bar{F} - P^U)^2} + \frac{P^U}{\sigma^2 - (\bar{F} - P^U)^2}\frac{b\sigma^2}{1 + b\bar{F}} \tag{2.4}$$

$$\phi_m^U = \frac{P^U(\bar{F} - P^U)}{\sigma^2 - (\bar{F} - P^U)^2} \tag{2.5}$$

where $\bar{F} = F + \sigma$ is the expected time 2 payoff of the stock at the U-state.

These demand functions have intuitive interpretations. First, the s-investor will proportionally put more wealth on risky asset. Further, the extra demand for risky asset is increasing in her status preference parameter, b. When $b = 0$, s-investor holds the same portfolio as m-investor does.

By applying the market clearing condition, $\phi_m^U W_m^U + \phi_s^U W_s^U = P^U$, we solve for P^U:

$$P^U = \bar{F} - \frac{\sigma^2}{\bar{F}} + \frac{\bar{k}\sigma^2}{\bar{F}} W_s^U, \text{ where } \bar{k} = \frac{b}{1+b\bar{F}} \tag{2.6}$$

Notice that $\bar{k} \in [0, 1/\bar{F})$ and $\bar{k}$ increases in b. There are three components in P^U: $\bar{F}$ is the expected payoff at the U-state, $\sigma^2/\bar{F}$ is the risk premium when none of the agents have status preference, i.e. $b = 0$, and the last term $\bar{k}\sigma^2 W_s^U/\bar{F}$ is the overpricing component caused by status preference. Also, $\bar{k}\sigma^2 W_s^U/\bar{F}$ increases with b—that is, stronger preference on tracking status pushes the asset price higher.

By using the same method, we solve for the D-state optimal holding and asset price, which deliver identical economic intuitions as those in the U-state. Further, we solve the optimization problem at time 0, obtaining the following optimal portfolio choice:

$$\phi_s^0 = \frac{P^0}{2} \frac{P^U + P^D - 2P^0}{(P^U - P^0)(P^0 - P^D)} + \frac{b\sigma}{1+bF} \frac{P^0}{2} \frac{P^U - P^D}{(P^U - P^0)(P^0 - P^D)} \tag{2.7}$$

$$\phi_m^0 = \frac{P^0}{2} \frac{P^U + P^D - 2P^0}{(P^U - P^0)(P^0 - P^D)} \tag{2.8}$$

The s-investors hold more risky asset at time 0 compared to m-investors, by the amount given in the second term of equation (2.7). This is for exactly the same intuition as in the U-state and the D-state. Also, as b goes up the s-investors tend to bet more on the risky asset.

Proposition 1. *Risk premium decreases as b in U-state, D-state and time 0.*

The intuition of Proposition 1 is identical to that of equation (2.6). Status preferences make investors more willing to bear more risk. Thus, risk premium goes down with more risk-bearing.

In addition to the pricing effect, the share turnover from time 1 to time 0 also varies with the intensity of status preferences. To see this, we denote θ_i^j as the optimal holding in shares for investor $i \in \{s, m\}$ in state $j \in \{U, D, 0\}$. And $\theta_i^j = \phi_i^j W_i^j / P^j$. Then, we define the share turnover as:

$$TURNOVER = \frac{1}{2}(|\theta_m^0 - \theta_m^D| + |\theta_m^0 - \theta_m^U|)$$

Proposition 2. *With moderate λ (more precisely, $\lambda < (F - \sqrt{F^2 - 4\sigma^2})/4k\sigma^2$), share turnover increases with b.*

The intuition of Proposition 2 is the following. First, note that the s-investor will purchase more at the U-state and liquidate some positions at the D-state. This is how trading is generated in this setting; when $b = 0$ the turnover would equal to zero. Thus, the turnover defined above equals to the difference of holding between the D-state and the U-state. Further, note that the risk premium at the D-state is decreasing more quickly than at the U-state. The difference of risk premium at the D- and U-state is thus increasing in b. Also, since the difference of holding is proportional to that of risk premium, it rises as b.

2.1. Empirical Predictions

Moving from our two propositions toward empirical analysis, we use GDP per capita in each province as the proxy for the status preference parameter b in our model. When GDP per capita passes a certain threshold, people start caring about status and being concerned about relative wealth ranks, i.e. b becomes non-zero. Going further, status preference is increasingly stronger (i.e. even higher b) as wealth grows. The other parameter λ, the fraction of status versus non-status investors in the population, we think of as capturing the fraction of retail investors to institutional or market makers or investors who trade in the market for non-status reasons. Thus we consider this being kept fixed across provinces. We could also think of holding fixed b and changing λ which could under certain scenarios accomplish a similar objective. But we prefer b since it speaks to the intensity of status preferences as opposed to heterogeneity of speculators in the population which might confound different economic channels.

We plot average GDP per capita across each tier of provinces for every year in our sample in Figure 1. Several important points stand out. First, Tier 1 provinces have much higher GDP per capita than Tier 5 during the whole sample period from 1998 to 2009. Second, the GDP per capita for Tier 1 and Tier 2 provinces passed the 10,000 Yuan mark around the mid-point of our sample (2003 to 2004). We use this break-point in our identification strategy of status effects mattering more late in the sample.

The geographic difference, as well as the time trend, of status preference naturally motivates us to adopt the difference-in-difference technique. That is, we expect the trading and pricing effects in Propositions 1 and 2 regarding local stocks to be stronger in richer provinces *and* in the later sample period.

To identify the effect of a shift in the status parameter on asset price and trading turnover, our detailed empirical specification is as follows. First, we use local big stocks as a benchmark for regional varying investment opportunity sets and local small stocks as the proxy for local entrepreneurs' wealth that agents are catching up with. Thus the first *difference* is small-minus-big (SMB) of turnover or market-to-book ratio in our baseline model. We also use average local turnover or market-to-book ratio in our robustness check. The second *difference* is the difference of SMB across developed, rich provinces compared to less-developed, poor ones. The third *difference* is these two differences over time, comparing the second half sample, 2004 to 2009, to the first half, 1998 to 2003. The following regression model implements our difference-in-difference-in-difference strategy.

$$SMBGAP_{i,t} = \alpha + \beta_1 GDPPC_{i,t} + \beta_2 LATE_t + \beta_3 GDPPC_{i,t} LATE_t + \boldsymbol{\gamma' YearDummy} + \epsilon_{i,t}, \tag{2.9}$$

where $SMBGAP_{i,t}$ is either the small-minus-big of turnover or market-to-book ratio in province i and year t. $GDPPC_{i,t}$ refers to proxies of GDP per capital in province i and year t and $LATE$ dummy equals to one for sample year of 2004 to 2009. We also include year dummies to control for time-specific factors. The variable of interest is the interaction term of $GDPPC$ and $LATE$.

Based on Propositions 1 and 2, our central predictions lie in β_3 to be positive. The economic agents will start consuming status when their wealth level has passed a certain threshold. Figure 1 suggests that a significant amount of agents in rich provinces in late sample period are status agents. As a result, we expect a strong economic effect for our estimate of β_3.

The mechanism generating the trading volume is that status seeking agents optimally change their hedge portfolio, which depends on the level of the market. When the market is higher, agents buy more shares of the stock, which leads to trading.

When the market falls, agents should also scale back their positions, but this is not likely to happen in reality for a few reasons. First, there are fixed costs to participation which we do not capture. When stocks rise, more status investors participate leading to trading volume. But when stocks fall, status investors do not participate in the market since they do not need to hedge their status risk. Second, there is also the well-documented disposition effect in which investors are unlikely to sell losers.

These two forces imply that we expect to find a stronger effect for positive returns than for negative returns. Hence, we expect to find that in high status provinces, good past returns lead to more trading volume.

2.2. Robustness

What if we modeled the increase in status demand across different regions using the other parameter λ while holding fixed b? Richer areas would have a larger fraction of status investors λ. If we viewed our experiment as all provinces starting out with a low λ close to zero and richer areas experienced a larger increase in λ over the sample, we would naturally get higher turnover and higher asset prices. This is likely to be the realistic way of calibrating the size of λ. But this is a bit of an unappetizing way to model the heterogeneity since when λ gets close to one, there would be no heterogeneity again. But this is assuming that there are no entry of speculators to make the market for the status investors which is an unappetizing way of modeling speculators of market makers. By focusing on b, we are assuming that market making capacity is similar across different provinces which seems more reasonable.

3. Anecdotal Evidence for Recent Status Concerns in Tier 1 versus Lower Tier Provinces

In this section, we make the case that status or relative wealth concerns are greater in richer provinces compared to poorer provinces today. That is, in the verbiage of our model, the status parameter b decreases with the tier number of the location. For example, Tier 1 provinces are Shanghai, Beijing, Guangdong, Tianjin, Zhejiang and Jiangsu, while Tier 5 are those less developed in the deep southwest.

The general points are that residents in Tier 1 areas care about luxury goods much more than residents in lower tier ones, that this reflects concerns about social status and that those in Tier 1 places are not necessarily happier despite the obvious material gains in the last decade because of these Keeping-up-with-the-Wangs effects.

First, we summarize results from an ongoing large study done by a marketing firm Synovate LTD in 2010 entitled "Media Atlas China: Revealing opportunities across upper, middle and lower tiers and rural in today's China". The people sampled are between 15 to 64 years old. Their sample size is an annual rolling sample of 68,000 households/people. Each quarter they obtain 16,000 new interviews. So the results are updated quarterly and we report those in their 2010 edition.

One piece of evidence supporting status concerns is the consumption of brands or status goods. For instance, the most important determinant among respondents regarding the determining factor for a car purchase was the brand in Tier 1 provinces, while price and fuel efficiency were the most important in Tiers 4 and 5 provinces. Tier 2 and 3 provinces ranked price first but brand second.

Second, a similar pattern exists for luxury clothing and jewelry brands according to a recent study by KPMG in conjunction with Monash University on "Luxury Brands in China". For luxury retail in China, an estimated 300,000 millionaires and rising. A middle class of around 250 million people. They spent US$6 billion on luxury goods in 2006, according to Ernst & Young estimates. And are expected by Goldman Sachs to account for 29% of the global luxury goods market worth an estimated US$80 billion a year—second only to Japan. Much of this consumption is driven by residents in Tier 1 provinces. Importantly, surveys on attitudes regarding the role of luxury goods place social status and signalling as being important motivations for residents in Tier 1 and 2 areas. One of the statements most positively agreed upon by respondents in Tier 1 and 2 places was: "Owning luxury goods demonstrates my success and social status." Nearly 70% there agreed with this statement.

A more entertaining cultural evidence of the signalling of status goods is the proliferation of man bags among the young urban professionals in megacities. An LATIMES article on February 7, 2011 entitled "In China, alpha males carry designer purses" reports that many successful business men carry designer purses to signal their status so that they can be distinguished from the others.

Third, happiness surveys in China report that those living in first-tier areas were the least contented, feeling more pressure because of high-price housing and traffic congestion than their counterparts in smaller towns and counties (see, for instance, China.org's online survey of 1,348 individuals in March 2011).

Finally, there is in China the uneven development of Tier 1 status driven provinces and Tier 5 poor under-developed ones. There is still tremendous inequalities and concomitant relative wealth concerns in the Tier 1 areas. According to a World Bank report in 2008, the Gini coefficient for China is now close to 0.5, which points to an unequal distribution of income where 0.4 is considered as the threshold of serious inequality. In contrast to the U.S. experience, where the recent rise in income inequality has been concentrated in the super-rich, China's Gini is driven by a burgeoning upper middle class. Half of the rise of this Gini is driven by within region inequalities and within the top tier areas.

4. Data

Our analysis for different tier locations is done at the province level and we use city level analysis as a robustness check. We obtain province level GDP per capita data from the National Bureau of Statistics of China for each sample year for each province[2]. We get the city GDP per capita data from the Wind database from year 2005 to year 2008 for each city. Monthly stock trading volumes and prices for all Chinese firms listed on Shanghai and Shenzhen Stock Exchange are from CSMAR, then we convert them into annual basis. Annual book value for each company is also from CSMAR. The sample spans from 1998 to 2009. We then merge the province and city GDP per capita data with CSMAR data based on firm's location information given in CSMAR.

In Table 1, Panel A, we report the time series average of the characteristics of stocks located in different provinces. We rank the provinces from 1 to 30 based on their average GDP per capita (GDP PC) over the sample. RANK is the rank of GDP PC for each province in each year, with RANK equals to 1 being the province with the highest GDP PC. Then we break the provinces into five tiers, with 6 provinces in each tier, and TIER 1 being the richest six provinces. RICH is a dummy variable which equals to 1 if the province belongs to the top 2 TIERs and 0 otherwise. It is generally thought that the top two tiers have sufficient income and wealth to care about status effects, especially in the late sample. The provinces are sorted by their average RANK in the table. GDP PC is the time-series average of GDP per capita for each province, quoted in Chinese Yuan.

For each province, we report # OF STOCKS which is the time-series average of number of stocks each year in each province over the sample period. We see that generally the rich provinces have much more stocks located there than in poor provinces. This highlights Hong,

[2] Our sample starts from 1998 when the Chinese stock market is more matured and there are enough firms to execute our study. Also, Tibet is not included in this study because of lack of firms for the analysis.

Kubik, and Stein (2008)'s "only-game-in-town" effect in which the poor provinces do not have many local stocks available for inhabitants in these areas.

TURNOVER is the time-series average of annual turnover of all stocks located in each province. We calculate the annual turnover (defined as the total number of shares traded divided by the number of tradable shares[3]) based on the monthly data available and winsorize them at the top and the bottom 1%. Notice that annual turnover is extremely high in China, nearly 500% per year over this sample period. Moreover, one can see from this turnover measure that turnover is actually slightly higher in the poorer areas than in the richer areas. This reflects the only-game-in-town effect in which poor areas have less stocks or investment opportunities and as a result investors there attract more interest and hence potentially more trading activity. MB[4] is the median of the year-end market-to-book ratio of stocks in each province across sample years. The market-to-book ratio is also winsorized at the top and the bottom 1% as well. There is not as obvious a pattern in the market-to-book ratios across provinces.

In Table 1, Panel B, we report the analogous statistics but for cities rather than provinces. There are a total of 251 cities in our sample. We report the statistics by groups of 10 and by their rank. For each group of ten, we report the time series average for the following variables: # OF STOCKS, GDP PC, TURNOVER, and MB. There is a similar pattern in TURNOVER by city rank though less discernible than for provinces. In robustness checks below, we also conduct our analysis using cities as the geographic entity of interest rather than provinces. The trade-off is that there are far fewer stocks within each city which brings more measurement error. But we find comforting support for the same conclusions no matter whether we use provinces or cities.

Panel C describes the time-series distribution of stocks across industries. INDUSTRY is

[3]Here we use the total number of tradable shares rather than total number of shares outstanding as the denominator because before the reform in 2006 most Chinese stocks have a significant amount of shares outstanding that are not tradable on exchange.

[4]To decrease the noise of market-to-book ratio, we use median as the average for all market-to-book calculations, so we also report the median value here for summary statistics.

the industry classification defined from National Bureau of Statistics of China. IND CODE is the industry code obtained from CSMAR database for each stock, the corresponding INDUSTRY definition of each IND CODE is obtained from National Bureau of Statistics of China. # OF STOCKS is the time-series average of number of stocks in each industry every year. TURNOVER is the time-series average of stock turnover rate in each industry. MB is the time-series average of market-to-book ratios in each industry. Notice that most of the stocks in our sample are in manufacturing industries. These manufacturing industries are scattered throughout the provinces. In contrast, some of the industries such as finance are only in certain provinces.

To see this more clearly, in Panel D, we report the number of stocks from different industries by province. Some provinces are clearly missing some industries. To deal with this heterogeneity in industries across provinces, we also use industry adjusted turnover and market-to-book ratio below which are TURNOVER and MB demeaned by industry as a robustness check.

In Table 2, we report the summary statistics for the difference between turnover and the market-to-book of small compared to big stocks in these different regions. Panel A shows the summary statistics for provinces in China. Stocks are sorted on size (last year market capitalization). Small stocks are the bottom 30% of stocks sorted on size, big stocks are the top 30% of stocks sorted on size. This sort to determine size cut-offs is done using all stocks in China, independent of locations. Last year's market capitalization are used to calculate value-weighted variables. Then for the stocks in each province, we calculate various permutations of turnover. We report value-weighted small-minus-big (VW SMB) and value-weighted small-minus-average (VW SMA). SMA refers to turnover rate of small stocks minus that of all stocks in every province, which we use as an alternative control for locally varying investment opportunity in a robustness check. We also report turnover of equal-weighted small-minus-big (EW SMB) in that province and industry-adjusted value-weighted small-minus-big (IND ADJ VW SMB) which is small stocks' industry adjusted turnover minus big stocks' industry adjusted turnover. We also calculate the analogs for market-to-book. Panel B calculate the same statistics but for cities instead. Locations (both province and city) with less than 3 stocks in either small or big groups (sort on size) each year are deleted from the regression. As a result, the time series average of the number of observations, denoted as # of OBS, is lower than what is reported in Table 1.

Looking at Panel A, notice that value-weighted small-minus-big turnover (VW SMB TURNOVER) has a mean of 1.62 with a standard deviation of 2.08. The corresponding figures for value-weighted small-minus-average (VW SMA) is 1.28 with a standard deviation of 1.65. Not surprisingly there is less of a difference between small and the average stock turnover than there is between small and big stocks. The mean of IND ADJ VW SMB TURNOVER is 1.47 with a standard deviation of 1.91. The equal weighted numbers are 1.46 with a standard deviation of 1.80. Regardless of how we measure this share turnover gap between small and big stocks, we find that small stocks trade much more than big stocks.

Turning to market-to-book, we find that the mean of the difference between the value-weighted market-to-book for small stocks and the value-weighted market-to-book for big stocks is 0.67 with a standard deviation of 2.45. That is, small stocks have a higher market-to-book than big stocks. The same conclusion is drawn when we consider the other metrics. Looking at Panel B, we get very similar results when we cut on cities rather than provinces for both turnover and market-to-book.

In Panel C, we break down these summary statistics by individual provinces. Eyeballing the statistics for turnover and examining their variation by ranks of the provinces, it is easy to see that small stock minus big stock turnover (whether adjusted by industry or equal or value weighted) all point to there appearing to be greater small stock to big stock turnover in richer or top tier provinces. This is very comforting since it appears that our effect can be seen in even these simple statistics. A similar though less obvious pattern exists for the market-to-book of small stocks minus big stocks.

5. Empirical Findings

5.1. Province Status Measure Based on GDP Per Capita

With these comforting summary statistics in mind, we turn to our main results in Tables 3 and 4. In Table 3, we regress turnover on our various measures of income level for provinces. This table reports the coefficients estimated from panel regressions of value-weighted small-minus-big turnover (VW SMB TURNOVER) at the province level. The independent variables in all regressions are GDP PC PROXY, LATE, and the interaction term of GDP PC PROXY and LATE. LATE is a dummy variable that equals to 1 for years from 2004 to 2009, and 0 otherwise. Year dummies are included in regressions, but are not reported. Coefficients on LATE dummy are also not reported. Standard errors are clustered at the province level. T-statistics are reported below the coefficient in parenthesis.

In Panel A, the dependent variable is VW SMB TURNOVER. In specification (1) and (2), the GDP PC PROXY is RANK, where RANK is a number between 1 to 30. From column (1), a one rank move decreases the dependent variable of interest by -0.03 and the t-statistic of the coefficient is -2.17. A move from a province of RANK equals to 20 to one equals to 10 (or a 10 rank move) leads to an economic effect of .3 increase which is around 14% of the dependent variable's standard deviation. All the effect is coming from late in the sample as witnessed in the estimate from column (2). The coefficient on the interaction term of Rank with LATE is -0.074 with a t-statistic of -4.17. This means that the economic effect is around 2.5 times as large late in the sample.

In specification (3) and (4), the GDP PC PROXY is LnGDPPC, which is the natural logarithm of GDP PC. From column (3), the coefficient of interest is 0.515. Moving from a GDP per capita of around 10,000 Yuan (or log (GDP PC) of around 9.21 (which is the average of the poor provinces) to a GDP per capita of 30,000 Yuan (which is the average of the rich provinces or a log (GDP PC) of around 10.31) yields an implied economic move of around 0.57 or roughly 27% of a standard deviation of the left hand side variable. The estimate from column (4) indicates again that the effects are all coming from the latter half of the sample. The economic effect is more than double.

In specifications (5) and (6), the GDP PC PROXY is RICH, where RICH is a dummy variable equals to 1 if the province is in the top two tiers and zero otherwise. In column (5), the coefficient of interest is 0.582 with a t-statistic of 2.78. Being in the top two tiers increases the VW SMB TURNOVER by 0.582. The dependent variable's standard deviation is 2.08. So being in the top two tiers increases VW SMB TURNOVER by around 28% of its standard deviation, which is an economically significant move. In column (6), we see whether this effect is larger later in the sample period as our theory would predict since status effects have become more important in the last ten years as China's top tier residents have moved into middle class living standards. Indeed, almost the entire effect is coming from late in the sample period. The coefficient of interest in front of GDP PC PROXY×LATE is 1.180, which implies that in the second half of our sample, being a RICH province increases the VW SMB TURNOVER more than twice the estimated effect compared to early in the sample period.

In specifications (7) and (8), the GDP PC PROXY is TIER, where TIER takes on the values of 1 (developed) through 5 (less developed). From column (7), a one tier increase in the province's score leads to a change of -0.194 with a t-statistic of -2.36. A comparison of Tier 1 to Tier 5 which is a 4 tier move implies an economic effect of 4 times -0.194 or around a decrease of VW SMB TURNOVER of 80% which is around 38% of the dependent variable's standard deviation. In column (8), when we split this effect up by sample periods, we find that all the effect is from the late period and the coefficient of interest more than doubles.

In Table 4, the dependent variable is the value-weighted measure of the difference of the market-to-book of small firms versus big firms in different provinces. The right hand-side variables are the same as in Table 3. We expect based on our model that small firms' market-to-book to be greater than big firms' during the latter part of the sample. This is indeed what we find. Looking at columns (2), (4), (6) and (8), we find that the market-to-book of small versus big firms is much different during the latter part of the sample compared to the early part. Looking at Rank, the coefficient is -0.096 for the interaction term. So a 10 Rank move implies an economic effect of -0.96 or roughly 39% of a standard deviation of market-to-book. Looking at Rich, the effect is even bigger. The coefficient is 2.082 with a t-statistic of 2.63. This means that being Rich moves the market-to-book by almost 85% of a standard deviation of the left hand side variable. These are sizeable effects.

In Table 5, we repeat the analyses of Table 3 and 4 using a variety of specifications as a robustness check. In Panel A, we use Industry Adjusted VW SMB Turnover and Market-to-Book as the dependent variable. For brevity, we report the results just for Rank and LnGDPPC. Looking at TURNOVER, we observe that the coefficient of interest for Rank from column (2) is -0.055 with a t-statistic of -3.15 and the coefficient of interest for LnGDPPC from column (4) is 0.844 with a t-statistic of 2.73. Both of these coefficients are comparable to their analogs in Table 3. Moreover, the standard deviation of Industry Adjusted VW SMB TURNOVER is comparable to that of VW SMB TURNOVER. As such, the economic significance is comparable using this industry adjusted measure. As such, we can be assured that our effects are not being driven by heterogeneity in industry distributions across provinces. The figures for market-to-book are comparable. Indeed, the coefficients of interest in columns (2) and (4) are almost identical to their analogs in Table 4.

In Panel B, the dependent variable is VW SMA TURNOVER and Market-to-Book, which is simply the difference in the turnover and market-to-book of small stocks relative to the average (or median for market-to-book variables) in that province. Using this alternative measure of the demand for small stocks that presumably most closely track their community, we find similar results. The coefficients of interest for TURNOVER are -.065 with a t-statistic of -4.87 for Rank and 1.06 with a t-statistic of 4.55 for LnGDPPC. These are comparable to those in Panel A. For market-to-book, the coefficients of interest are -0.066 with a t-statistic of -2.55 for Rank and 1.086 with a t-statistic of 2.74 for LnGDPPC. In Panel C, the dependent variable is EW SMB TURNOVER and Market-to-Book. Again, the economic effects are very similar to those obtained in the earlier panels.

Finally, in Panel D, we redo our analysis using cities instead of provinces. Recall that we opt for provinces as our benchmark since there are not many stocks located in any given city per se. This then brings a lot of measurement error which will affect our t-statistics. Also, it is not clear that city is the right geographic unit since it might be too small a unit with which to consider these effects. Since there is not an obvious theory for what unit to take, we consider city level as an additional robustness check. Interestingly, we find similarly significant effects for VW SMB TURNOVER for Rank and LnGDPPC. The economic significance is a bit smaller for Rank but somewhat larger using LnGDPPC. Hence, we conclude that our turnover results are robust regardless of whether we look at provinces or cities. Turning to Market-to-book, we find that the effects are smaller again for Rank but somewhat comparable for LnGDPPC when compared for instance to the coefficients in Panel C. The t-statistics are not large although the point estimates are similar. This is not surprising since market-to-book is likely to be much noisier to measure than turnover and more subject to more variability. In other words, it is likely that averaging of market-to-book for more companies over a larger area would help reduce noise which is what our earlier analysis confirms. Nonetheless, the economic effects are all pointing in the right direction and we take comfort in the robustness along this dimension.

We carry out a similar analysis for the U.S. and use the same sample period for comparison. Our analysis is done on both the state and metropolitan statistical area (MSA) level. Although the results are not significant and the economic magnitudes are smaller than the effects in China, the signs of estimates still suggest that there is a relatively higher status effect in the richer area. The results are not surprising given that the income inequality across regions are not as big in the U.S. as in China. The richest area (either state or MSA)'s GDP per capita is only around twice the number for the poorest area in our sample, however, this number is around 10 times for China. The U.S. results are not reported in the paper but are available upon request.

5.2. Province Status Measure Based on Luxury Brand Searches

We next consider an alternate measure of the status demand intensity of a province by using the ratio or difference of internet searches of luxury brands to non-luxury brands for various goods including clothes, cars, sportswear and watches. We obtain our data from Baidu, which is the main internet search engine in China. We then re-run our analysis above using this luxury search index in addition to GDP per capita.

Table 6 reports the summary statistics of baidu search index across sample provinces in China. Daily Baidu search index from November 2, 2008 to December 31, 2010 are used to calculate the RATIO and DIFFERENCE reported in the table. PROVINCE is the provinces in our sample. RATIO is the average Baidu search index for luxury goods over the average Baidu search index for non-luxury goods. DIFFERENCE is the difference between the average Baidu search index for luxury goods and the average Baidu search index for non-luxury goods. The first 8 columns report the RATIO and DIFFERENCE for four consumption categories: CLOTHES, CARS, SPORTSWEAR, and WATCH. Luxury clothes brands include Chanel, Louise Vuitton, Gucci; non-luxury clothes brands include Only, Jack Jones. Luxury car brands include Audi, BMW, and Porsche; non-luxury car brands include Toyota, Honda, Hyandai, BYD, and Qirui QQ. Luxury sportswear brand includes Nike, non-luxury sportswear brand include Lining. Luxury watch brands include Omega and Rolex; non-luxury watch brands include Swatch and Citizen. The last 2 columns reports the average of the RATIO (or DIFFERENCE) of baidu search index for luxury over non-luxury brands across all four consumption categories for each province.

RATIO and DIFFERENCE of Baidu search index can be used as a measure for status concern. The higher the RATIO or DIFFERENCE of Baidu search index between luxury brands over non-luxury brands, the higher the status concerns in the corresponding province. Guangdong has the highest status concern among all provinces when using Baidu search index RATIO/DIFFERENCE as the measure. Table 6 also suggests that TIER 1 provinces as measured by GDP per capita all have very high Baidu search index RATIO/DIFFERENCE, which coincides with our use of different proxies of GDP per capita as a measure for status concerns.

In order to pin down the impact from the status concern as measured by baidu search index, we also run a horserace between Baidu search index RATIO (or DIFFERENCE) and GDP PER CAPITA in explaining SMB turnover and SMB market-to-book. The results are reported in Table 7. The set-up is the same as in our earlier tables. In Panel A, we report the results for value-weighted SMB turnover. Column (1) shows that the higher the ratio of search for luxury goods over non-luxury goods, the higher the value-weighted SMB turnover. If we move from Qinghai (with RATIO equals to 1.006) to Shanghai (with RATIO equals to 1.785), the value-weighted SMB turnover will increase by 61.3%, which is 29.47% of the left-hand side variable's standard deviation. Panel A, column (2) shows that the result is mainly coming from the late sample period. Moving from Qinghai to Shanghai in the late period of the sample will increase value-weighted SMB TURNOVER by 91.6%, which is 44.04% of the left-hand side variable's standard deviation. Column (3) in Panel A presents the horserace result for Baidu search index and ln GDP per capita. Baidu search index remains economically meaningful and statistically significant after using ln GDP per capita in the analysis. For example, in Panel A, column (3), the interaction term for RATIO and LATE is 0.577, and the interaction term for ln GDP per capita and LATE is 1.001. Moving from Qinghai to Shanghai in the late period of the sample will move baidu search index ratio up by 0.779, which will increase value-weighted SMB turnover by 44.9%, that is 21.6% of the standard deviation of the left-hand side variable. Results using DIFFERENCE are similar and we omit these for brevity.

In Panel B, we report the results for value-weighted SMB market-to-book. In Column (1), the coefficient of interest is 0.177 indicating that high status RATIO areas have higher price ratio but the t-statistic is only 0.51 and not statistically significant. In column (2), we see that the effect is again coming late in the sample. The coefficient on RATIO×LATE is 0.824. So if we moved from Qinghai with RATIO equals to around 1 to Shanghai with RATIO equals to 1.785, we get an implied move in the value-weighted SMB market-to-book of around 0.64, which is around 26.2% of the standard deviation of the left-hand side variable. This is an economically significant effect but the t-statistic is around 1. This result is in line with our earlier findings in which share turnover is more robust economically and statistically than is market-to-book. In column (3), we consider a horserace between RATIO and ln GDP per capita and find that the results are strong using ln GDP per capita. The coefficient for RATIO×LATE is around zero. For market-to-book, it appears that ln GDP per capita does a better job than RATIO in explaining the dispersion in SMB market-to-book.

In Table 8, rather than running a horse race between RATIO and ln GDP per capita, we take the perspective of an instrumental variables estimation in which we project RATIO on ln GDP per capita and a constant and obtain a fitted value for RATIOHAT that is due to ln GDP per capita. In other words, both RATIO and ln GDP per capita appear to contain incremental information from Table 7. If we are interested in how the search results influence the results, we then use this fitted value RATIOHAT as the proxy for status in different provinces.

Panel A, column (2) shows that the higher the ratio of search for luxury goods over non-luxury goods, the higher the value-weighted SMB turnover in the late sample period. If we move the fitted RATIOHAT up by 0.5 in late sample period, the value-weighted SMB turnover will increase by 199%, which is 95.5% of the left-hand side variable's standard deviation. Panel B presents results for value-weighted SMB market-to-book and we find that a higher RATIOHAT leads to a higher value-weighted SMB market-to-book late in the sample. If we move the fitted RATIOHAT up by 0.5 in late sample period, the value-weighted SMB Market-to-Book will increase by 213%, which is 87% of the left-hand side variable's standard deviation. The economic significance is interesting and is also statistical significant.

5.3. Correlation between Turnover and Past Returns

Finally, we test an auxiliary implication of our model as a means to achieve better identification of our mechanism. Status investors will increase their demand for local stocks with a rising market, leading to a stronger correlation of past returns and share turnover in high status compared to low status provinces. The same is not true in a falling market if there are fixed costs to participation or the disposition effect. To see if past good returns indeed lead to more trading volume in high status areas, we run a regression for turnover on last year's return and a constant for small and big stocks respectively. Then we take the difference between these two regression coefficients on last year's return for small and big stocks and run a regression of this difference on the same independent variables as in our earlier analysis.

In Table 9, we report the regression coefficents on last year's stock return for the small stocks, for the big stocks and for the difference in these two coefficients respectively. In Table 10, we then take these regression coefficents on last year's stock return and regress them on our GDP PC PROXY, LATE and GDP PC PROXY×LATE.

Panel A shows that in richer area, the higher the return for small stocks, the higher the turnover for small stocks. Based on the result in column (4), moving from a Tier 5 province into a Tier 1 province, this sensitivity between last year's stock return and current year stock turnover will increase by 366% in the late part of the sample period, which is 67.5% of the left-hand-side variable's standard deviation. Panel B shows that there is not a significant relation between last year's stock return and current year stock turnover for big stocks in different areas. Panel C suggests that the difference of regression coefficients on last year's stock return between small and big stocks varies in different provinces in China. This difference in regression coefficient is higher in the richer areas late in the sample. From column (1), moving from a province 10 ranks up will result in a difference in this regression coefficient of 299%, which is 32.28% of the left-hand-side variable's standard deviation.

The impact is both economically meaningful and statistically significant. These results suggest that the sensitivity of trading volume to past return is much higher in the richer areas than in the poorer areas, which is expected from the conclusion of our model. In Tier 1 provinces, when the entrepreneur's small stocks are performing well, the higher status concern for the residents in Tier 1 area will drive the turnover much higher than at the lower tier places, and this effect is more significant at the late sample period.

6. Conclusion

The topic of income inequality and risk-taking has been an important one for economists over the last several centuries and it appears to be timely again with income inequality rising around the world over the last two decades. There are suggestions that such inequality processes might be important in thinking about many of the big issues in capital markets. With these motivations in mind, we examine in this paper the hypothesis that status preferences lead to excessive risk-taking using a quasi-experiment from China. We develop a simple model of trading to develop a volume metric to gauge such risk-taking and use a difference-in-difference-in-difference estimation strategy to identify the effect of a shift in the status parameter on risk-taking and asset pricing. The first difference is between small and big stocks in trading volume and market-to-book. The second difference is this difference across developed, rich provinces in China compared to poor, less-developed ones. The third difference is these two differences over time, comparing the 2004-2009 sample to the earlier period. We find higher share turnover and larger price ratio gaps for small stocks relative to big ones in developed than in less-developed places which has widened over our sample period. We also develop further identification by looking at internet search indices for luxury goods compared to non-luxury goods and also considering the sensitivity of share turnover to past price increases.

A. Appendix

Solve Optimal Portfolio and Asset Price

At the U-state, the expected time 2 payoff of the stock is $\mathrm{E}[\tilde{F}|U] = \bar{F} = F + \sigma$ and the variance of the payoff is $\mathrm{Var}[\tilde{F}|U] = \sigma^2$. At the D-state the expected payoff is $\mathrm{E}[\tilde{F}|U] = \underline{F} = F - \sigma$ and the variance of the payoff is $\mathrm{Var}[\tilde{F}|D] = \sigma^2$.

First consider demand function of the s-investors at the U-state. The solution for the m-investors follows by setting $b = 0$.

The s-investor chooses the proportion of total wealth invested in the stock, denoted as ϕ_s^U, to maximize the following objective function at time 1 in the U-state with wealth W_s^U given price P^U.

Let θ_s^U be the optimal portfolio in number of shares, and $\theta_s^U = W_s^U \phi_s^U / P^U$.

$$\mathrm{Max}_{\phi_s^U} \mathrm{E}[(1 + b\tilde{F})\log(W_s^U(1 + \phi_s^U \tilde{R^U})|U]$$

The F.O.C. for the investor is

$$\frac{(1 + b(F + 2\sigma))R_+^U}{1 + \phi_s^U R_+^U} + \frac{(1 + bF)R_-^U}{1 + \phi_s^U R_-^U} = 0, \text{ where } R_+^U = \frac{\bar{F} + \sigma - P^U}{P^U} \text{ and } R_-^U = \frac{\bar{F} - \sigma - P^U}{P^U}$$

Solving for ϕ_s^U yields

$$\phi_s^U = -\frac{R_+^U + R_-^U}{2R_+^U R_-^U} - \frac{b\sigma}{1 + b\bar{F}} \frac{R_+^U - R_-^U}{2R_+^U R_-^U}$$

$$\phi_s^U = \frac{P^U(\bar{F} - P^U)}{\sigma^2 - (\bar{F} - P^U)^2} + \frac{P^U}{\sigma^2 - (\bar{F} - P^U)^2} \frac{b\sigma^2}{1 + b\bar{F}} \quad \text{(A.1)}$$

Note that the first part of equation (A.1) has nothing to do with b, while the second part is positive and increasing in b. Let $b = 0$, we have demand function of m-investor,

$$\phi_m^U = -\frac{R_+^U + R_-^U}{2R_+^U R_-^U} = \frac{P^U(\bar{F} - P^U)}{\sigma^2 - (\bar{F} - P^U)^2} \quad \text{(A.2)}$$

Equation (A.1) and (A.2) show that s-investor puts more wealth on risky asset. Further, market clearing condition, $\phi_m^U W_m^U + \phi_s^U W_s^U = P^U$ gives solution for P^U with noting that $W_m^U + W_s^U = W_m^0(1+\phi_m^0 R^U) + W_s^0(1+\phi_s^0 R^U) = P^U$

$$P^U = \bar{F} - \frac{\sigma^2}{\bar{F}} + \frac{\bar{k}\sigma^2}{\bar{F}} W_s^U, \text{ where } \bar{k} = \frac{b}{1+b\bar{F}} \tag{A.3}$$

Based on (A.1) and (A.2), we can transfer the optimal portfolio weights into the number of shares. Let θ_i^j be the optimal holding (in shares) at state $j \in \{0, U, D\}$ for agent $i \in \{s, m\}$.

$$\theta_s^U = \phi_s^U W_s^U / P^U = \frac{\bar{F} - P^U + \bar{k}\sigma^2}{\sigma^2 - (\bar{F} - P^U)^2} W_s^U \tag{A.4}$$

$$\theta_m^U = \phi_m^U W_m^U / P^U = \frac{\bar{F} - P^U}{\sigma^2 - (\bar{F} - P^U)^2} W_m^U \tag{A.5}$$

Applying the same procedure, we obtain the solution in D-state.

$$P^D = \underline{F} - \frac{\sigma^2}{\underline{F}} + \frac{\underline{k}\sigma^2}{\underline{F}} W_s^D, \text{ where } \underline{k} = \frac{b}{1+b\underline{F}} \tag{A.6}$$

$$\theta_s^D = \frac{\underline{F} - P^D + \underline{k}\sigma^2}{\sigma^2 - (\underline{F} - P^D)^2} W_s^D \tag{A.7}$$

$$\theta_m^D = \frac{\underline{F} - P^D}{\sigma^2 - (\underline{F} - P^D)^2} W_m^D \tag{A.8}$$

To calculate the equilibrium at $t = 0$, observe that the value function can be calculated as

$$J_s^U = \mathrm{E}[(1+b\tilde{F})\log(W_s^U(1+\phi_s^U \tilde{R^U}))|U]$$

$$J_s^D = \mathrm{E}[(1+b\tilde{F})\log(W_s^D(1+\phi_s^D \tilde{R^D}))|D]$$

or as

$$\mathrm{E}[(1+b\tilde{F})\{\log(W_s^U) + \log(1+\phi_s^U \tilde{R^U})\}|U]$$

$$\mathrm{E}[(1+b\tilde{F})\{\log(W_s^D) + \log(1+\phi_s^D \tilde{R^D})\}|D]$$

Given that

$$W_s^U = W_s^0(1+\phi_s^0 R_+^0), \text{ where } R_+^0 = \frac{P^U - P^0}{P^0}$$

$$W_s^D = W_s^0(1+\phi_s^0 R_-^0), \text{ where } R_-^0 = \frac{P^D - P^0}{P^0}$$

it is equivalent to solve the following problem,

$$\text{Max } \{\frac{1}{2}(1+b\bar{F})\log(W_s^0(1+\phi_s^0 R_+^0)) + \frac{1}{2}(1+b\underline{F})\log(W_s^0(1+\phi_s^0 R_-^0))\}$$

First order condition with respect to ϕ_s^0 gives,

$$\phi_s^0 = \frac{P^0}{2}\frac{P^U + P^D - 2P^0}{(P^U - P^0)(P^0 - P^D)} + \frac{b\sigma}{1+bF}\frac{P^0}{2}\frac{P^U - P^D}{(P^U - P^0)(P^0 - P^D)} \tag{A.9}$$

When $b = 0$, we have

$$\phi_m^0 = \frac{P^0}{2}\frac{P^U + P^D - 2P^0}{(P^U - P^0)(P^0 - P^D)} \tag{A.10}$$

Using market clearing condition $\phi_s^0 W_s^0 + \phi_m^0 W_m^0 = P^0$, or $\phi_s^0\lambda + \phi_m^0(1-\lambda) = 1$, we solve for P^0,

$$P^0 = \frac{2P^U P^D}{(1-\lambda k\sigma)P^U + (1+\lambda k\sigma)P^D}, \text{ where } k = \frac{b}{1+bF} \tag{A.11}$$

Again, transfer the optimal portfolio weight into the number of shares,

$$\theta_m^0 = (1-\lambda)P^0\frac{P^U + P^D - 2P^0}{2(P^U - P^0)(P^0 - P^D)} \tag{A.12}$$

$$\theta_s^0 = \lambda P^0[\frac{P^U + P^D - 2P^0}{2(P^U - P^0)(P^0 - P^D)} + k\sigma\frac{P^U - P^D}{2(P^U - P^0)(P^0 - P^D)}] \tag{A.13}$$

Plug (A.12) and (A.13) into (A.3), (A.6), then with (A.11) we can solve all equilibrium prices.

$$P^U = \frac{\bar{F}^2 - \sigma^2}{\bar{F} - \lambda\sigma^2\frac{k}{1+\lambda k\sigma}} \tag{A.14}$$

$$P^D = \frac{\underline{F}^2 - \sigma^2}{\underline{F} - \lambda\sigma^2 \frac{k}{1-\lambda k\sigma}} \tag{A.15}$$

$$P^0 = F - \frac{2F\sigma^2 - 2\lambda kF\sigma^2}{F^2 - 2\sigma^2 - 2\lambda kF\sigma^2} \tag{A.16}$$

Proof of Proposition 1

We calculate the risk premium for each state,

$$\bar{F} - P^U = \frac{\sigma^2 - \sigma^2 \bar{F}\bar{t}}{\bar{F} - \sigma^2\bar{t}}, \text{ where } \bar{t} = \frac{\lambda k}{1 + \lambda k\sigma}$$

Notice that $\bar{t}$ is increasing in k, given that k is increasing in b, thus $\bar{t}$ is increasing in b. Then take derivative of risk premium with respect to $\bar{t}$.

$$\frac{\partial(\bar{F} - P^U)}{\partial\bar{t}} = \frac{-\sigma^2\bar{F}(\bar{F} - \sigma^2\bar{t}) - (\sigma^2 - \sigma^2\bar{F}\bar{t})(-\sigma^2)}{(\bar{F} - \sigma^2\bar{t})^2} = \frac{\sigma^2(\sigma^2 - \bar{F}^2)}{(\bar{F} - \sigma^2\bar{t})^2} < 0$$

Thus, the risk premium at the U-state is decreasing in b. Applying the same procedure to the D-state, we have

$$\underline{F} - P^D = \frac{\sigma^2 - \sigma^2 \underline{F}\underline{t}}{\underline{F} - \sigma^2\underline{t}}, \text{ where } \underline{t} = \frac{\lambda k}{1 - \lambda k\sigma}$$

$$\frac{\partial(\underline{F} - P^D)}{\partial\underline{t}} = \frac{\sigma^2(\sigma^2 - \underline{F}^2)}{(\underline{F} - \sigma^2\underline{t})^2} < 0$$

Thus risk premium at the D-state is also decreasing in b.

For the risk premium at time 0, take derivative of $F - P^0$ with respect to k,

$$\frac{\partial(F - P^0)}{\partial k} = -\frac{2F^2\lambda\sigma^2(F^2 - 4\sigma^2)}{(F^2 - 2\sigma^2 - 2Fk\lambda\sigma^2)^2}$$

Since $F > 2\sigma$, we have $F^2 - 4\sigma^2 > 0$. Thus the above derivative is negative. Given that k is increasing in b, $F - P^0$ is decreasing in b.

QED

Proof of Proposition 2

To prove Proposition 2, we fully solve the optimal holdings by market makers at each state by plugging (A.14), (A.15) and (A.16) into (A.5), (A.8) and (A.12).

$$\theta_m^U = \frac{(1-\lambda)(1-\lambda kF)}{1+2\lambda\sigma k} \tag{A.17}$$

$$\theta_m^D = \frac{(1-\lambda)(1-\lambda kF)}{1-2\lambda\sigma k} \tag{A.18}$$

$$\theta_m^0 = \frac{F(1-\lambda)(1-\lambda kF)}{F(1-2\lambda^2\sigma^2 k^2)-2\lambda k\sigma^2} \tag{A.19}$$

To prove that the average turnover rate is increasing in b, we show the following equation is increasing in b.

$$\theta_m^D - \theta_m^U = \frac{4k\sigma\lambda(1-\lambda)(1-\lambda kF)}{1-4\lambda^2k^2\sigma^2}$$

Take the partial derivative with respect to b and we need to show that the derivative is positive when λ is large,

$$\frac{\partial(\theta_m^U - \theta_m^D)}{\partial b} = \frac{4(1-\lambda)\lambda\sigma(1-2\lambda Fk+4\lambda^2k^2\sigma^2)}{(1-4\lambda^2k^2\sigma^2)^2} \tag{A.20}$$

The sufficient condition such that the derivative is positive is

$$4\lambda^2k^2\sigma^2 - 2\lambda Fk + 1 > 0$$

Equivalently,

$$\lambda > \frac{F+\sqrt{F^2-4\sigma^2}}{4k\sigma^2}, \text{or } \lambda < \frac{F-\sqrt{F^2-4\sigma^2}}{4k\sigma^2} \tag{A.21}$$

The first solution never holds. To see this, note that $(F+\sqrt{F^2-4\sigma^2})/(4k\sigma^2)$ is decreasing both in k and σ. Thus we plug in the maximum values of k and σ, which are $1/F$ and $F/2$, respectively, to obtain its lowest bound.

$$\frac{F+\sqrt{F^2-4\sigma^2}}{4k\sigma^2} > \frac{F+\sqrt{F^2-F^2}}{F^2/F} = 1$$

Since $\lambda \in [0,1]$, the first solution never satisfies.

Now, we consider the other solution. We show that its lower bound is 1/2. First, $(F-\sqrt{F^2-4\sigma^2})/(4k\sigma^2)$ is decreasing in k but increasing in σ, to obtain its possibly lowest value, we set $k = 1/F$ and let σ goes to zero.

$$\lim_{\sigma\to 0}\frac{F-\sqrt{F^2-4\sigma^2}}{4\sigma^2/F} = \lim_{\frac{\sigma}{F}\to 0}\frac{1-\sqrt{1-4\frac{\sigma^2}{F^2}}}{4\frac{\sigma^2}{F^2}} = \frac{1}{2}$$

Thus, $\lambda < 1/2$ is one sufficient condition such that equation (A.20) is positive. For necessary condition, we have shown that when $\lambda < (F-\sqrt{F^2-4\sigma^2})/4k\sigma^2$, $\theta_m^D - \theta_m^U$ is increasing in b.

Given $\frac{1}{2}(|\theta_m^0-\theta_m^D| + |\theta_m^0-\theta_m^U|) = \frac{1}{2}(\theta_m^D-\theta_m^0+\theta_m^0-\theta_m^U) = \frac{1}{2}(\theta_m^D-\theta_m^U)$, we have proved that average turnover rate is increasing in b if λ is not too large.

QED

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Table 1. Distribution of Stocks

This table reports the distribution of stocks across provinces and cities in China over the sample year from 1998 to 2009. Panel A reports the time-series average of GDP per capita and annual stock distributions across provinces. # OF STOCKS is the time-series average of number of stocks each year in each province over the sample period. GDP PC is the time-series average of GDP per capita for each province in China in Chinese Yuan. RANK is the average of rank of GDP PC for each province across sample years, with rank equals to 1 being the province with the highest GDP PC in each sample year. TIER is the sample average of tier for each province. All provinces are sorted into 5 tiers based on their GDP PC, with six provinces in each tier, and tier 1 being the six provinces with the highest GDP PC. RICH is the sample average of a dummy variable which equals to 1 if the province belongs to the top 2 tiers and 0 otherwise. TURNOVER is the time-series average of annual turnover of all stocks located in each province. MB is the median year end market-to-book value of all stocks in each province across sample years. Panel B reports the time-series average of annual stock distribution across cities. There are 251 cities in the sample, so we group the cites into 25 groups with 10 cities in each group and report their summary statistics in the same manner as in Panel A. Panel C describes the time-series distribution of stocks across industries. INDUSTRY is the industry classification defined from National Bureau of Statistics of China. IND CODE is the industry code obtained from CSMAR database for each stock, the corresponding INDUSTRY definition of each IND CODE is obtained from National Bureau of Statistics of China. # OF STOCKS is the time-series average of number of stocks located in each industry every year. TURNOVER is the time-series average of stock turnover in each industry. MB is the median market-to-book in each industry across sample years. Panel D describes the time-series average number of stocks across industry-province. RANK is defined in the same manner as in Panel A. IND CODE is defined in the same manner as in Panel C.

Panel A: Time-Series Average of Annual Distributions Across Provinces

PROVINCE	# OF STOCKS	GDP PC	RANK	TIER	RICH	TURNOVER	MB
Shanghai	131.67	47527.08	1.00	1.00	1.00	4.97	3.02
Beijing	77.83	40168.39	2.00	1.00	1.00	4.88	2.80
Tianjin	21.33	32144.85	3.00	1.00	1.00	4.99	2.88
Zhejiang	75.00	24745.31	4.08	1.00	1.00	5.75	2.94
Jiangsu	80.83	22415.83	5.42	1.00	1.00	5.53	2.73
Guangdong	148.17	22196.25	5.50	1.00	1.00	4.94	2.79
Fujian	46.42	18124.07	8.08	2.00	1.00	5.23	2.92
Liaoning	50.92	18271.52	8.17	2.00	1.00	4.64	2.72
Shandong	69.92	18181.62	8.17	2.00	1.00	5.19	2.73
Hebei	31.50	13396.94	11.17	2.00	1.00	4.97	2.56
Heilongjiang	28.92	13292.00	11.25	2.25	0.75	4.56	2.74
Inner Mongolia	18.58	15730.32	11.83	2.42	0.58	5.07	2.42
Jilin	32.17	12972.42	12.58	2.67	0.33	4.87	2.62
Xinjiang	24.42	11863.33	13.83	2.75	0.33	5.51	3.13
Hubei	56.33	11140.33	15.92	3.00	0.00	5.03	2.59
Shanxi	21.00	11053.17	16.33	3.08	0.00	5.01	2.71
Hainan	21.42	10532.33	17.50	3.33	0.00	4.89	3.54
Chongqing	24.75	10487.75	17.58	3.17	0.00	5.15	3.43
Henan	30.17	10423.21	18.83	3.58	0.00	5.19	2.95
Hunan	38.58	9950.17	20.00	4.00	0.00	5.39	3.01
Ningxia	10.17	9965.58	20.25	3.92	0.00	5.31	2.91
Qinghai	8.92	9616.90	22.17	4.00	0.00	4.76	4.32
Shaanxi	24.25	9705.58	22.58	4.08	0.00	5.16	3.21
Sichuan	64.00	8750.67	24.25	4.33	0.00	5.15	3.79
Jiangxi	21.00	8685.58	25.08	4.67	0.00	5.94	2.62
Anhui	37.33	8364.07	26.08	5.00	0.00	5.76	2.20
Guangxi	19.83	8339.39	26.33	4.92	0.00	5.23	2.66
Yunnan	20.67	7519.08	27.00	4.83	0.00	5.84	3.22
Gansu	17.00	6963.54	29.00	5.00	0.00	5.65	2.60
Guizhou	14.17	4894.00	30.00	5.00	0.00	5.78	2.94

Panel B: Time-Series Average of Annual Distributions Across Groups of Cities				
Group	# OF STOCKS	GDP PC	TURNOVER	MB
1-10	277.17	69202.86	4.98	2.93
11-20	177.17	55358.07	5.06	2.82
21-30	77.42	45585.33	5.05	2.62
31-40	66.58	39814.50	5.02	2.94
41-50	93.83	33073.91	5.15	2.74
51-60	76.33	28127.56	5.39	3.14
61-70	55.83	26200.24	5.18	2.35
71-80	57.33	22975.26	4.78	2.99
81-90	55.42	21390.89	5.29	2.79
91-100	36.00	20025.83	5.20	2.94
101-110	36.25	18248.46	5.51	3.01
111-120	19.33	17139.13	4.69	2.86
121-130	22.25	16229.91	5.12	2.75
131-140	46.75	15746.54	5.27	3.22
141-150	26.42	14909.07	5.08	2.80
151-160	14.17	14270.25	5.02	2.53
161-170	20.67	13485.55	5.21	2.63
171-180	20.08	12520.32	5.27	3.49
181-190	20.58	11737.91	5.44	2.81
191-200	12.08	10478.44	5.37	3.92
201-210	11.17	9776.80	5.07	3.27
211-220	14.42	9292.24	5.63	2.53
221-230	14.50	8266.91	5.00	2.71
231-240	15.08	7339.18	5.02	3.29
241-251	7.75	5525.15	5.97	2.82

Panel C: Distribution Across Industries				
INDUSTRY	IND CODE	# OF STOCKS	TURNOVER	MB
Agriculture	A	22.92	6.39	2.88
Mining	B	21.58	5.57	3.00
Manufacturing_Food&Beverage	C0	47.75	5.05	3.11
Manufacturing_Textile, Costume	C1	41.58	5.83	2.51
Manufacturing_Furniture	C2	3.17	5.12	2.42
Manufacturing_Paper&Printing	C3	18.00	5.91	2.46
Manufacturing_Petro, Chemistry	C4	121.42	5.48	2.66
Manufacturing_Electronic	C5	39.92	5.86	2.74
Manufacturing_Metal, Non-metal	C6	96.58	5.43	2.34
Manufacturing_Machine	C7	169.25	5.37	2.88
Manufacturing_Medicine	C8	72.00	4.93	3.32
Manufacturing_Others	C9	7.42	6.06	3.17
Electricity, Gas, Water	D	52.42	4.47	2.41
Construction	E	20.08	5.35	2.48
Transportation, Storage	F	45.67	4.52	2.40
IT	G	65.33	5.25	3.62
Retails	H	85.33	4.47	3.17
Finance, Insurance	I	15.00	4.57	3.53
Real estate	J	85.17	4.67	3.06
Social service	K	34.67	5.22	3.29
Communications, culture	L	10.50	5.32	4.46
Conglomerate	M	66.50	4.83	3.30

Panel D: Number of Stocks Across Provinces and Industries

		IND CODE												
	RANK	A	B	C	D	E	F	G	H	I	J	K	L	M
Shanghai	1.00		1	42	2	2	5	7	11	2	13	5	2	15
Beijing	2.00	3	3	19	3	3	3	8	8	4	4	6	2	1
Tianjin	3.00		2	5	1		3		1		4	2		1
Zhejiang	4.08	1		32	2	4	2	6	8	1	3		1	3
Jiangsu	5.42			39		2	2	7	6	1	3	2	1	4
Guangdong	5.50	1		49	8	3	7	9	8	2	17	4	2	10
Fujian	8.08	2	1	17	1		3	3	3	1	4			6
Liaoning	8.17	1	1	17	5	1	3	3	4	2	4	1	1	2
Shandong	8.17	2	3	36	1	1	1	4	3		2	1		3
Hebei	11.17	1	2	18	2		1		2	1	1			
Heilongjiang	11.25	1		12	2	1		1	1		2	1		3
Inner Mongolia	11.83		1	12	2				1		1			
Jilin	12.58	1	1	14	2		1	1	3	1	3			2
Xinjiang	13.83	4	1	12	1	2			3	1	1			
Hubei	15.92	1		24	4	1	1	2	4		4	1	1	3
Shanxi	16.33		4	11	2		1	1	1					
Hainan	17.50	1	1	5			3		1		3	2	1	3
Chongqing	17.58			10	2	1	2	2	1	1	2	1		
Henan	18.83	1	2	18	2		1	1	1					
Hunan	20.00	3	1	16	1		2	2	2		1	2	1	1
Ningxia	20.25			7					1					
Qinghai	22.17		1	6		1			1					
Shaanxi	22.58		1	12	1	1		3	2	1		2	1	1
Sichuan	24.25	2	1	29	5	3	1	4	1	1	2	1	2	2
Jiangxi	25.08			12	1		2		1		1			
Anhui	26.08	1	2	21	1	2	2	1	1		1	1	1	
Guangxi	26.33			8	1		2	1	1		1	2		2
Yunnan	27.00	1	1	10	1			1	1	1	2	2		1
Gansu	29.00	1	1	9				2	2			1		
Guizhou	30.00		1	10	1						1			1

Table 2. Summary Statistics

This table reports the time-series average of annual cross-sectional statistics over the sample year from 1998 to 2009 of all stocks listed on Shanghai and Shenzhen Stock Exchange in China. Panel A shows the summary statistics for provinces in China. Panel B shows the summary statistics for cities in China. Panel C shows the summary statistics by province in China. TURNOVER equals to the total number of shares traded divided by the number of tradable shares. Market-to-Book is the year-end market-to-book ratio. Stocks are sorted on size (last year market capitalization). Small stocks are the bottom 30% of stocks sorted on size, big stocks are the top 30% of stocks sorted on size. Last year's market capitalizations are used to calculate value-weighted variables. VW is value weighted. SMB is small stocks minus big stocks. SMA is small stocks minus the average of all stocks in that province/city. IND ADJ is industry adjusted. EW is equal weighted. RANK is defined in the same manner as in Table 1. We use median value for all market-to-book calculation.

Panel A: Provinces in China

		MEAN	StDev	25%	MEDIAN	75%	# of OBS
TURNOVER	VW SMB	1.62	2.08	0.16	1.03	2.62	244
	VW SMA	1.28	1.65	0.18	0.66	2.09	244
	IND ADJ VW SMB	1.47	1.91	0.14	0.92	2.46	244
	EW SMB	1.46	1.80	0.25	0.99	2.52	244
Market-to-Book	VW SMB	0.67	2.45	-0.24	0.42	1.42	244
	VW SMA	0.70	2.13	-0.08	0.37	1.22	244
	IND ADJ VW SMB	0.68	2.37	-0.14	0.41	1.25	244
	EW SMB	0.83	1.82	-0.08	0.57	1.45	244

Panel B: Cities in China

		MEAN	StDev	25%	MEDIAN	75%	# of OBS
TURNOVER	VW SMB	1.87	2.51	0.26	1.26	2.90	164
	VW SMA	1.57	2.10	0.25	0.98	2.25	164
	IND ADJ VW SMB	1.64	2.22	0.16	1.12	2.61	164
	EW SMB	1.69	2.08	0.47	1.17	2.62	164
Market-to-Book	VW SMB	0.51	2.18	-0.21	0.43	1.42	164
	VW SMA	0.57	1.61	-0.14	0.41	1.09	164
	IND ADJ VW SMB	0.44	2.09	-0.33	0.41	1.18	164
	EW SMB	0.78	2.04	-0.17	0.63	1.44	164

Panel C: Summary Statistics by Provinces									
PROVINCE	RANK	TURNOVER				Market-to-Book			
		VW SMB	VW SMA	VW IND ADJ SMB	EW SMB	VW SMB	VW SMA	VW IND ADJ SMB	EW SMB
Shanghai	1.00	2.37	2.11	2.02	2.03	1.49	1.33	1.36	1.63
		(1.91)	(1.76)	(1.61)	(1.53)	(0.53)	(0.36)	(0.83)	(0.65)
Beijing	2.00	1.73	1.67	1.29	1.50	1.20	1.16	1.34	0.98
		(2.03)	(1.99)	(1.74)	(1.34)	(0.80)	(0.77)	(1.08)	(1.05)
Tianjin	3.00	2.11	1.99	2.22	1.91	0.39	0.74	0.40	0.42
		(2.27)	(2.14)	(2.26)	(1.98)	(1.60)	(1.28)	(2.33)	(1.49)
Zhejiang	4.08	1.66	1.12	1.60	1.50	0.55	0.62	0.43	0.56
		(2.26)	(1.54)	(2.11)	(2.06)	(1.69)	(1.29)	(1.64)	(1.65)
Jiangsu	5.42	2.05	1.50	1.79	1.73	0.50	0.78	0.63	0.74
		(2.59)	(1.76)	(2.27)	(1.94)	(2.04)	(1.77)	(2.40)	(1.45)
Guangdong	5.50	2.66	2.31	2.23	2.26	1.01	1.01	1.17	1.59
		(2.34)	(2.07)	(1.64)	(1.72)	(1.04)	(1.01)	(1.10)	(1.59)
Fujian	8.08	2.08	1.52	1.75	1.73	0.06	0.48	0.02	0.59
		(2.47)	(1.95)	(1.95)	(1.94)	(1.07)	(0.70)	(0.88)	(1.06)
Liaoning	8.17	1.41	1.18	1.34	1.24	0.58	0.50	0.39	0.23
		(2.30)	(2.01)	(2.22)	(1.98)	(1.18)	(0.88)	(0.90)	(1.06)
Shandong	8.17	1.39	1.13	1.34	1.33	0.89	0.75	0.52	0.98
		(1.50)	(1.19)	(1.41)	(1.34)	(1.19)	(1.03)	(0.89)	(1.29)
Hebei	11.17	2.02	1.61	1.86	1.92	1.31	1.19	1.32	1.03
		(2.22)	(1.88)	(2.07)	(2.35)	(1.23)	(1.22)	(1.22)	(1.27)
Heilongjiang	11.25	1.66	1.06	1.83	1.65	-0.08	-0.16	0.45	-0.01
		(1.33)	(0.86)	(1.43)	(1.38)	(0.46)	(0.32)	(0.88)	(0.53)
Inner Mongolia	11.83	1.35	1.08	1.11	1.06	0.34	0.38	-0.26	0.38
		(1.40)	(1.23)	(1.39)	(1.00)	(0.79)	(0.63)	(0.70)	(0.82)
Jilin	12.58	1.43	1.15	1.43	1.40	1.25	1.44	0.81	1.29
		(2.06)	(1.53)	(2.20)	(1.81)	(1.82)	(1.73)	(1.46)	(1.94)
Xinjiang	13.83	1.02	0.86	0.60	0.87	-2.03	-0.51	-1.20	-1.48
		(1.63)	(1.23)	(1.40)	(1.48)	(1.81)	(1.85)	(1.60)	(1.62)
Hubei	15.92	1.48	1.18	1.39	1.43	0.08	0.07	-0.23	0.15
		(2.02)	(1.59)	(1.97)	(1.71)	(1.32)	(0.95)	(1.20)	(0.98)
Shanxi	16.33	1.80	1.56	1.62	1.51	0.11	-0.11	-0.11	0.57
		(2.75)	(2.62)	(2.31)	(2.45)	(1.68)	(1.47)	(2.27)	(1.42)
Hainan	17.50	1.10	0.70	0.82	1.22	3.94	3.67	3.37	3.07
		(2.44)	(1.35)	(2.09)	(1.76)	(7.00)	(6.88)	(6.63)	(4.52)
Chongqing	17.58	0.63	0.42	0.84	0.56	1.25	0.97	1.25	0.25
		(2.48)	(1.37)	(2.35)	(2.68)	(2.13)	(0.74)	(1.91)	(2.47)
Henan	18.83	1.87	1.44	1.78	1.76	1.75	1.80	1.83	1.23
		(2.11)	(1.57)	(2.03)	(1.97)	(4.13)	(4.08)	(4.11)	(2.17)
Hunan	20.00	2.36	1.72	2.10	2.03	1.35	1.25	1.06	1.67
		(2.52)	(1.90)	(2.31)	(2.06)	(3.63)	(2.67)	(3.22)	(3.08)
Ningxia	20.25	0.30	0.26	0.19	0.23	-1.65	-0.49	-1.60	-1.63
		(1.10)	(0.89)	(1.00)	(1.12)	(2.93)	(0.62)	(2.68)	(3.32)
Qinghai	22.17	1.67	1.08	1.69	1.00	0.41	-0.36	-0.08	1.95
		(2.21)	(1.90)	(2.48)	(1.33)	(2.97)	(2.02)	(2.74)	(2.85)
Shaanxi	22.58	0.72	0.40	0.77	0.63	-1.02	-0.53	-1.13	-1.00
		(2.00)	(1.16)	(1.94)	(2.06)	(2.99)	(1.95)	(2.97)	(2.80)
Sichuan	24.25	2.23	1.57	2.16	1.61	0.46	0.24	0.87	1.78
		(2.13)	(1.78)	(2.02)	(1.70)	(4.07)	(2.64)	(3.44)	(1.52)
Jiangxi	25.08	1.12	0.76	0.86	1.67	0.91	0.53	0.68	1.07
		(1.75)	(1.30)	(1.68)	(2.21)	(1.26)	(0.80)	(1.11)	(1.02)
Anhui	26.08	1.09	0.84	0.89	0.92	0.85	0.35	0.35	0.63
		(2.31)	(1.69)	(2.27)	(1.82)	(0.98)	(0.42)	(0.96)	(0.99)
Guangxi	26.33	1.81	0.70	1.96	1.64	-0.32	0.40	0.14	-0.25
		(2.50)	(1.41)	(2.35)	(2.74)	(3.26)	(1.23)	(3.21)	(2.96)
Yunnan	27.00	1.18	0.73	0.99	1.25	-0.21	-0.27	-0.42	0.18
		(1.61)	(1.25)	(1.51)	(1.47)	(1.81)	(1.59)	(1.78)	(1.70)
Gansu	29.00	0.29	0.35	0.51	0.39	1.05	0.67	0.86	0.86
		(1.13)	(0.55)	(1.37)	(1.08)	(1.00)	(0.84)	(1.24)	(0.84)
Guizhou	30.00	2.76	2.00	2.62	1.55	-3.33	-2.83	-2.94	-0.76
		(3.70)	(3.15)	(3.54)	(2.32)	(8.57)	(8.19)	(7.77)	(4.90)

Table 3. Panel Regressions of Turnover on GDP Per Capita Proxies at Province Level

This table reports the coefficients estimated from panel regressions of value-weighted small-minus-big (VW SMB) turnover at the province level. The dependent variable is VW SMB TURNOVER. The independent variables in all regressions are GDP PC PROXY, LATE, and the interaction term of GDP PC PROXY and LATE. LATE is a dummy variable that equals to 1 for years from 2004 to 2009, and 0 otherwise. The GDP PC PROXY in each specification is defined as the following: in specification (1) and (2), the GDP PC PROXY is RANK, where RANK is as defined in Table 1; in specification (3) and (4), the GDP PC PROXY is LnGDPPC, which is the natural logarithm of GDP PC as defined in Table 1; in specification (5) and (6), the GDP PC PROXY is RICH, where RICH is as defined in Table 1; in specification (7) and (8), the GPD PC PROXY is TIER, where TIER is as defined in Table 1. Year dummies are included in regressions, but are not reported. Coefficients on LATE dummy are also not reported. Standard errors are clustered at the province level. T-statistics are reported below the coefficient in parenthesis.

VW SMB TURNOVER	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	RANK	RANK	LnGDPPC	LnGDPPC	RICH	RICH	TIER	TIER
GDP PC PROXY	-0.030	0.013	0.515	-0.102	0.582	-0.074	-0.194	0.087
	(-2.17)	(1.00)	(2.79)	(-0.47)	(2.78)	(-0.43)	(-2.36)	(1.22)
GDP PC PROXY×LATE		-0.074		1.157		1.180		-0.475
		(-4.17)		(3.59)		(3.91)		(-4.56)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of OBS	244	244	244	244	244	244	244	244

Table 4. Panel Regressions of Market-to-Book on GDP Per Capita Proxies at Province Level

This table reports the coefficients estimated from panel regressions of value-weighted small-minus-big (VW SMB) market-to-book at the province level. The dependent variable is VW SMB Market-to-Book. We use median value for all market-to-book calculation. The independent variables in all regressions are GDP PC PROXY, LATE, and the interaction term of GDP PC PROXY and LATE. LATE is a dummy variable that equals to 1 for years from 2004 to 2009, and 0 otherwise. The GDP PC PROXY in each specification is defined as the following: in specification (1) and (2), the GDP PC PROXY is RANK, where RANK is as defined in Table 1; in specification (3) and (4), the GDP PC PROXY is LnGDPPC, which is the natural logarithm of GDP PC as defined in Table 1; in specification (5) and (6), the GDP PC PROXY is RICH, where RICH is as defined in Table 1; in specification (7) and (8), the GPD PC PROXY is TIER, where TIER is as defined in Table 1. Year dummies are included in regressions, but are not reported. Coefficients on LATE dummy are also not reported. Standard errors are clustered at the province level. T-statistics are reported below the coefficient in parenthesis.

VW SMB MARKET-TO-BOOK	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	RANK	RANK	LnGDPPC	LnGDPPC	RICH	RICH	TIER	TIER
GDP PC PROXY	-0.006	0.049	0.129	-0.630	-0.086	-1.243	-0.030	0.307
	(-0.37)	(1.53)	(0.44)	(-1.27)	(-0.21)	(-1.64)	(-0.28)	(1.56)
GDP PC PROXY×LATE		-0.096		1.424		2.082		-0.569
		(-2.45)		(2.66)		(2.63)		(-2.41)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of OBS	244	244	244	244	244	244	244	244

Table 5. Robustness Check

This table reports the coefficients estimated from panel regressions of robustness check on the analysis for turnover and market-to-book. In Panel A, the dependent variable is Industry Adjusted VW SMB TURNOVER or Market-to-Book. In Panel B, the dependent variable is VW SMA TURNOVER or Market-to-Book. In Panel C, the dependent variable is EW SMB TURNOVER or Market-to-book. In Panel D, the analysis is done at the city level, with the dependent variable equals to VW SMB TURNOVER or Market-to-Book. We use median value for all market-to-book calculation. The independent variables in all regressions are GDP PC PROXY, LATE, and the interaction term of GDP PC PROXY and LATE. LATE is a dummy variable that equals to 1 for years from 2004 to 2009, and 0 otherwise. The GDP PC PROXY in each specification is defined as the following: in specification (1) and (2), the GDP PC PROXY is RANK, where RANK is as defined in Table 1; in specification (3) and (4), the GDP PC PROXY is LnGDPPC, which is the natural logarithm of GDP PC as defined in Table 1. Year dummies are included in regressions, but are not reported. Coefficients on LATE dummy are also not reported. Standard errors are clustered at the province/city level. T-statistics are reported below the coefficient in parenthesis.

Panel A: Industry Adjusted VW SMB								
	TURNOVER				MARKET-TO-BOOK			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Rank	Rank	LnGDPPC	LnGDPPC	Rank	Rank	LnGDPPC	LnGDPPC
GDP PC PROXY	-0.024	0.008	0.389	-0.061	-0.008	0.048	0.144	-0.604
	(-1.80)	(0.67)	(2.03)	(-0.31)	(-0.47)	(1.67)	(0.52)	(-1.31)
GDP PC PROXY×LATE		-0.055		0.844		-0.096		1.402
		(-3.15)		(2.73)		(-2.78)		(2.82)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of OBS	244	244	244	244	244	244	244	244
Panel B: VW SMA								
	TURNOVER				MARKET-TO-BOOK			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Rank	Rank	LnGDPPC	LnGDPPC	Rank	Rank	LnGDPPC	LnGDPPC
GDP PC PROXY	-0.034	0.004	0.575	0.009	-0.014	0.025	0.195	-0.384
	(-3.01)	(0.38)	(4.20)	(0.06)	(-0.89)	(1.03)	(0.79)	(-0.97)
GDP PC PROXY×LATE		-0.065		1.060		-0.066		1.086
		(-4.87)		(4.55)		(-2.55)		(2.74)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of OBS	244	244	244	244	244	244	244	244
Panel C: EW SMB								
	TURNOVER				MARKET-TO-BOOK			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Rank	Rank	LnGDPPC	LnGDPPC	Rank	Rank	LnGDPPC	LnGDPPC
GDP PC PROXY	-0.019	0.009	0.343	-0.051	0.006	0.029	-0.008	-0.343
	(-2.05)	(0.89)	(2.60)	(-0.31)	(0.35)	(1.07)	(-0.03)	(-0.88)
GDP PC PROXY×LATE		-0.048		0.739		-0.039		0.628
		(-3.09)		(2.84)		(-1.60)		(1.96)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of OBS	244	244	244	244	244	244	244	244
Panel D: City VW SMB								
	TURNOVER				MARKET-TO-BOOK			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Rank	Rank	LnGDPPC	LnGDPPC	Rank	Rank	LnGDPPC	LnGDPPC
GDP PC PROXY	-0.012	-0.002	0.879	0.167	-0.002	0.004	0.426	0.088
	(-3.54)	(-0.58)	(3.02)	(0.67)	(-0.18)	(0.41)	(0.78)	(0.13)
GDP PC PROXY×LATE		-0.021		1.311		-0.011		0.621
		(-3.49)		(2.74)		(-1.16)		(0.86)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of OBS	164	164	164	164	164	164	164	164

Table 6. Summary Statistics of Baidu Search Index

This table reports the summary statistics of Baidu search index across sample provinces in China. Daily Baidu search index from November 2, 2008 to December 31, 2010 are used to calculate the RATIO and DIFFERENCE reported in the table. PROVINCE is the provinces in our sample. RATIO is the average Baidu search index for luxury goods over the average Baidu search index for non-luxury goods. DIFFERENCE is difference between the average Baidu search index for luxury goods and the average Baidu search index for non-luxury goods. The first 8 columns report the RATIO and DIFFERENCE for four consumption category: CLOTHES, CARS, SPORTSWEAR, and WATCH. Luxury clothes brands include Chanel, Louise Vuitton, Gucci; non-luxury clothes brands include Only, Jack Jones. Luxury car brands include Audi, BMW, and Porsche; non-luxury car brands include Toyota, Honda, Hyundai, BYD, Qirui QQ. Luxury sportswear brand includes Nike, non-luxury sportswear brand include Lining. Luxury watch brands include Omega and Rolex; non-luxury watch brands include Swatch and Citizen. The last 2 columns reports the average of the RATIO (or DIFFERENCE) of Baidu search index for luxury over non-luxury brands across all four consumption categories for each province.

PROVINCE	CLOTHES		CARS		SPORTSWEAR		WATCH		ALL FOUR CATEGORIES	
	RATIO	DIFFERENCE	RATIO	DIFFERENCE	RATIO	DIFFERENCE	RATIO	DIFFERENCE	RATIO	DIFFERENCE
Guangdong	3.05	418.37	1.19	103.00	6.57	651.41	1.01	3.29	2.96	294.02
Shanghai	2.92	346.63	1.66	140.53	1.71	145.33	0.85	-25.75	1.79	151.68
Zhejiang	2.87	350.63	1.66	231.89	1.00	-0.85	1.18	24.98	1.68	151.66
Jiangsu	2.44	276.97	1.94	238.11	1.11	37.07	0.97	-4.38	1.62	136.94
Beijing	2.24	281.44	1.42	127.29	1.38	147.99	0.90	-19.88	1.48	134.21
Fujian	2.07	112.65	1.43	76.01	1.07	15.25	1.21	17.92	1.45	55.46
Jilin	1.83	72.22	1.09	13.66	0.98	-3.22	1.74	54.89	1.41	34.39
Anhui	1.48	48.71	1.00	1.01	1.96	215.26	1.08	6.35	1.38	67.83
Liaoning	2.03	143.63	1.10	23.76	1.17	33.85	1.21	22.24	1.38	55.87
Guangxi	1.70	55.20	1.66	93.73	0.69	-62.35	1.14	9.98	1.30	24.14
Sichuan	1.57	75.81	1.28	52.76	1.12	22.36	1.06	5.15	1.26	39.02
Tianjin	1.75	75.29	1.13	20.65	1.19	29.88	0.94	-5.34	1.25	30.12
Heilongjiang	1.62	65.14	1.06	10.53	0.97	-5.65	1.32	26.85	1.24	24.22
Guizhou	1.72	49.09	1.11	11.44	1.10	8.73	1.04	2.69	1.24	17.99
Hebei	2.16	94.96	0.98	-4.77	0.69	-91.23	1.15	13.16	1.24	3.03
Yunnan	1.55	39.56	1.16	19.73	1.06	6.96	1.08	5.39	1.21	17.91
Chongqing	1.49	45.25	1.30	34.20	1.04	5.07	1.02	1.60	1.21	21.53
Jiangxi	1.58	47.10	1.14	19.40	0.76	-37.95	1.11	7.63	1.15	9.05
Henan	1.60	78.25	1.11	35.13	0.56	-158.81	1.17	16.11	1.11	-7.33
Hunan	1.37	39.61	1.10	20.43	0.79	-48.91	1.13	10.17	1.10	5.32
Hubei	1.63	86.61	1.22	43.80	0.47	-139.69	1.06	5.76	1.09	-0.88
Inner Mongolia	1.24	19.01	1.10	12.52	0.86	-16.47	1.12	7.88	1.08	5.73
Shanxi	1.44	40.43	0.97	-5.62	0.73	-50.21	1.15	10.67	1.07	-1.18
Ningxia	1.09	5.41	1.10	7.07	1.06	4.28	1.01	0.74	1.07	4.38
Shaanxi	1.38	37.01	0.98	-3.89	0.86	-29.89	1.03	2.73	1.06	1.49
Xinjiang	1.23	15.80	1.01	0.53	0.96	-3.68	1.02	1.31	1.05	3.49
Hainan	1.30	18.55	1.11	8.23	0.98	-1.58	0.80	-16.14	1.05	2.27
Qinghai	1.01	0.37	1.04	2.42	0.99	-0.34	0.99	-0.88	1.01	0.39
Gansu	1.17	11.13	0.95	-4.36	0.84	-14.34	1.01	0.89	1.00	-1.67
Shandong	0.94	-9.85	1.25	96.62	0.57	-205.12	1.05	6.35	0.95	-28.00

Table 7. Panel Regressions of Turnover and Market-to-Book on Baidu Search Index and Ln GDP Per Capita

This table reports the cross sectional results of using RATIO of Baidu search index for luxury over non-luxury goods to analyze VW SMB TURNOVER and Market-to-Book for each year-province observation. In Panel A, the dependent variable is VW SMB TURNOVER. In Panel B, the dependent variable is VW SMB Market-to-Book. The independent variable in column (1) is RATIO; the independent variables in column (2) are RATIO, LATE, and the interaction term between RATIO and LATE; the independent variables in columns (3) are RATIO, LN GDP PC, the interaction term between RATIO and LATE, and the interaction term between LN GDP PC and LATE. RATIO is as defined in Table 6, LATE is as defined in Table 3. Year dummies are included in the regressions and are not reported. Coefficients on LATE dummy are also not reported. Standard errors are clustered at the province level. T-statistics are reported under the coefficient estimate in parentheses.

Panel A: Analysis of VW SMB TURNOVER by Using Baidu Search Index Ratio			
	(1)	(2)	(3)
RATIO	0.787	0.180	0.313
	(5.09)	(1.27)	(3.44)
RATIO×LATE		1.176	0.577
		(2.65)	(2.49)
LN GDP PC			-0.218
			-(0.91)
LN GDP PC×LATE			1.001
			(2.73)
Year Dummies	Yes	Yes	Yes
# of OBS	244	244	244
Panel B: Analysis of VW SMB Market-to-Book by Using Baidu Search Index Ratio			
	(1)	(2)	(3)
RATIO	0.177	-0.249	0.107
	(0.51)	-(0.41)	(0.22)
RATIO×LATE		0.824	0.036
		(1.14)	(0.08)
LN GDP PC			-0.586
			-(1.55)
LN GDP PC×LATE			1.311
			(2.64)
Year Dummies	Yes	Yes	Yes
# of OBS	244	244	244

Table 8. Panel Regressions of Turnover and Market-to-Book on Fitted Baidu Search Index Ratio Hat

This table reports the cross sectional results of using RATIOHAT to analyze VW SMB TURNOVER and VW SMB Market-to-Book. RATIOHAT is the project of RATIO on LN GDP PC and a constant. The dependent variable in Panel A is VW SMB TURNOVER. The dependent variable in Panel B is VW SMB Market-to-Book. The independent variable in column (1) is RATIOHAT; the independent variables in column (2) are RATIOHAT, LATE, and the interaction term between RATIOHAT, and LATE. LATE is as defined in Table 3. Year dummies are included in the regressions and are not reported. Coefficients on LATE dummy are also not reported. Standard errors are clustered at the province level. T-statistics are reported under the coefficient estimate in parentheses.

Panel A: Analysis of VW SMB TURNOVER by Using RATIOHAT		
	(1)	(2)
RATIOHAT	2.152	-0.061
	(4.67)	-(0.12)
RATIOHAT×LATE		3.974
		(4.87)
Year Dummies	Yes	Yes
# of OBS	244	244
Panel B: Analysis of VW SMB Market-to-Book by Using RATIOHAT		
	(1)	(2)
RATIOHAT	0.646	-1.779
	(0.58)	-(0.90)
RATIOHAT×LATE		4.261
		(2.10)
Year Dummies	Yes	Yes
# of OBS	244	244

Table 9. Summary Statistics for Regressing Turnover on Lagged Return

This table lists the summary statistics across provinces for the following variables. The first three columns summarize the coefficient from regressing turnover on lagged return and a constant. SMALL STOCKS summarizes this regression coefficient for small stocks within each province. BIG STOCKS summarizes this regression coefficient for big stocks within each province. SMB summarizes the difference for this regression coefficient between BIG STOCKS and SMALL STOCKS within each province. # of YEARS lists the number of province-year observation in each province. The last two rows give the summary statistics for all provinces in the sample. Mean and standard deviation are reported, standard deviations are in parenthesis under the mean. Province-year with less than 3 small stocks or less than 3 big stocks is deleted from the sample.

PROVINCE	Correlation Between Last Year Return and Current Year Turnover			
	SMALL STOCKS	BIG STOCKS	SMB	# of YEARS
Anhui	-2.975	-1.303	-1.672	7
	(4.791)	(3.150)	(4.101)	
Beijing	0.323	0.125	0.198	12
	(3.623)	(1.782)	(4.260)	
Chongqing	-1.918	-1.758	-0.160	7
	(4.220)	(2.957)	(3.496)	
Fujian	-0.894	0.157	-1.051	12
	(1.925)	(1.779)	(3.163)	
Gansu	-19.878	9.730	-29.608	1
Guangdong	1.382	-0.101	1.484	12
	(2.186)	(1.504)	(2.937)	
Guangxi	-2.444	3.138	-5.582	2
	(0.236)	(1.823)	(1.587)	
Guizhou	-0.683	2.934	-3.617	1
Hainan	-4.432	6.135	-10.567	6
	(6.790)	(9.192)	(8.967)	
Hebei	-2.511	1.168	-3.680	12
	(5.769)	(4.522)	(8.054)	
Heilongjiang	-1.906	0.431	-2.337	11
	(5.837)	(2.800)	(6.559)	
Henan	-3.392	-0.339	-3.053	9
	(11.501)	(1.453)	(11.443)	
Hubei	0.420	0.389	0.031	12
	(2.570)	(2.683)	(4.062)	
Hunan	1.511	-0.797	2.308	11
	(4.454)	(5.557)	(7.250)	
Jiangsu	-0.393	-0.114	-0.279	12
	(2.708)	(1.278)	(3.129)	
Jiangxi	-0.922	-1.285	0.363	8
	(4.883)	(8.041)	(8.546)	
Jilin	-1.064	3.331	-4.395	12
	(2.164)	(8.629)	(8.870)	
Liaoning	-1.011	-0.479	-0.532	12
	(2.805)	(1.520)	(3.757)	
Inner Mongolia	2.202	1.474	0.728	5
	(4.410)	(1.115)	(4.005)	
Qinghai	-40.688	-2.715	-37.974	1
Shaanxi	3.337	-3.084	6.421	4
	(4.506)	(5.283)	(9.666)	
Shandong	0.371	-0.098	0.470	12
	(2.302)	(2.171)	(2.799)	
Shanghai	-0.598	0.407	-1.005	12
	(2.429)	(1.232)	(3.000)	
Shanxi	-2.264	0.251	-2.515	5
	(9.923)	(2.240)	(8.376)	
Sichuan	-1.733	0.702	-2.435	12
	(2.234)	(2.433)	(3.556)	
Tianjin	-0.011	-0.047	0.036	4
	(6.451)	(2.050)	(8.401)	
Xinjiang	2.032	-2.905	4.937	9
	(5.183)	(4.877)	(7.147)	
Yunnan	-0.676	-1.318	0.642	9
	(5.401)	(7.186)	(11.633)	
Zhejiang	0.562	0.962	-0.400	12
	(3.237)	(1.434)	(2.831)	
All Provinces	-0.843	0.204	-1.047	244
	(5.415)	(4.184)	(7.094)	

Table 10. Panel Regressions of Turnover-Return Sensitivity and GDP Per Capita Proxies

This table lists the results for regressing turnover-return sensitivity on different GDP per capita proxies. In Panel A, the dependent variable is the coefficient on lagged return from regressing small stocks' turnover on lagged return and a constant for all province-year observations. In Panel B, the dependent variable is the coefficient on lagged return from regressing big stocks' turnover on lagged return and a constant for all province-year observations. In Panel C, the dependent variable is the difference of the regression coefficient for small stocks and big stocks for all province-year observations. The independent variables are GDP PC PROXY, LATE, and the interaction term between GDP PC PROXY and LATE. In Panel A, B, and C, the GDP PC PROXY in column (1) is RANK, the GDP PC PROXY in column (2) is Ln GDP PC, the GDP PC PROXY in column (3) is RICH, the GDP PC PROXY in column (4) is TIER. Year fixed effects are included and are not reported. Coefficients on LATE dummy are also not reported. Standard errors are clustered at the province level. T-statistics are reported under the coefficient estimate in parentheses.

Panel A: Analysis for Small Stock Turnover and Last Year Stock Return Correlation				
	(1) RANK	(2) LnGDPPC	(3) RICH	(4) TIER
GDP PC PROXY	0.010	-0.088	0.271	0.066
	(0.39)	-(0.23)	(0.53)	(0.40)
GDP PC PROXY×LATE	-0.168	2.408	1.564	-0.914
	-(2.82)	(2.76)	(1.43)	-(2.70)
Year Fixed Effects	Yes	Yes	Yes	Yes
# of OBS	244	244	244	244
Panel B: Analysis for Big Stock Turnover and Last Year Stock Return Correlation				
	(1) RANK	(2) LnGDPPC	(3) RICH	(4) TIER
GDP PC PROXY	-0.044	0.553	0.239	-0.240
	-(1.02)	(0.93)	(0.21)	-(0.82)
GDP PC PROXY×LATE	0.061	-1.062	-0.295	0.256
	(0.79)	-(1.06)	-(0.21)	(0.53)
Year Fixed Effects	Yes	Yes	Yes	Yes
# of OBS	244	244	244	244
Panel C: Analysis for SMB of Correlation of Turnover and Last Year Stock Return				
	(1) RANK	(2) LnGDPPC	(3) RICH	(4) TIER
GDP PC PROXY	0.055	-0.642	0.032	0.306
	(0.93)	-(0.80)	(0.02)	(0.77)
GDP PC PROXY×LATE	-0.229	3.471	1.858	-1.170
	-(2.04)	(2.25)	(0.94)	-(1.71)
Year Fixed Effects	Yes	Yes	Yes	Yes
# of OBS	244	244	244	244

Figure 1. GDP Per Capita across Different Tier Provinces in Sample Period

The horizontal axis denotes year, the vertical axis denotes the GDP per capita (in Chinese Yuan) for provinces in each Tier.