

Trading for Status*

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Abstract

We test the hypothesis that status preferences lead to excessive risk-taking using a novel empirical design from China. Developed Tier 1 provinces have experienced more income and inequality growth than still-undeveloped Tier 5 ones between 1998 and 2009. This should lead to stronger Keeping-up-with-the-Wangs effects in Tier 1 provinces and hence greater demand for local stocks there to track neighbors than in other areas in more recent years. This demand changes with stock market wealth and generates trading between status and non-status seekers. It also leads to higher price-to-fundamental ratios for local stocks in developed provinces. Using large stocks to control for varying investment opportunities across regions, we find higher share turnover and higher prices for small stocks relative to big ones in developed compared to less-developed provinces; and this difference-in-difference is greater in later years than in earlier ones.

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1. Introduction

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)). Recent theory work in asset pricing on Keeping-up-with-the-Jones effects, for instance, shows that status demand can lead households to take excessive risk by holding concentrated portfolios that are tied to their neighbors' or community's wealth¹. The preference for status, through the risk-taking channel, can also generate unequal income distributions². Indeed, some have proposed income inequality and relative wealth concerns as a potential explanation for the housing bubble of 2003-2007 and subprime mortgage crisis of 2008³. In short, this topic has been an important one for economists over the last century and remains timely with income inequality rising around the world over the last decade, particularly in China.

While the theoretical effects are better understood, empirical work in identifying the economic channels through which inequality and status influence risk-taking and asset prices is only beginning. There is micro-evidence from panel data and surveys that confirm households have status preferences in that they feel worse when others do better even though their real consumption bundle has improved (Dyman and Ravina (2007), Ravina (2007)). There is also suggestive evidence pointing to social status effects in the form of strong local bias of investor portfolios where investors are more likely to buy stocks located near them (see, e.g., French and Poterba (1991)) and in social interaction increasing stock market participation (see, e.g., Hong, Kubik, and Stein (2004)). What is lacking is an identification of how a shift

¹See, e.g., Demarzo, Kaniel, and Kremer (2004), Gomez, Priestley, and Zapatero (2009)

²See Friedman and Savage (1948), Friedman (1953), Robson (1992) and Becker, Murphy, and Werning (2005) for how such status preferences for risk-taking end up in turn generating unequal income distributions.

³See Atkinson and Morelli (2011), Rajan (2010), and Fitoussi and Saraceno (2009) argue that inequality over the last twenty years drove both on the demand and supply side those falling behind to unsustainably try to keep up with leverage.

in the status preference parameter influences portfolio choice and asset 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 portfolio choice 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. So there is not an obvious shock or heterogeneity with which to investigate this question. Indeed, the default of researchers is that status preferences matter and it is routinely used to think about the modeling of portfolio choice and asset prices (see, e.g., Abel (1990)).

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 and most critically, 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. There is limited labor mobility which the government regulates through the "hukou" system: residents are assigned to live in certain areas. Tier 1 regions have developed much more rapidly than Tier 5 over the last decade. So status effects ought to matter more in Tier 1 than Tier 5 places. This then allows for a comparison of risk-taking by residents living in different tiers or status places and the effect on the trading and pricing of local stocks in these different areas.

We expect whatever status induced risk-taking effects to be more prominent in high status than low status areas. This perspective is in accord with the existing survey evidence that wealthier people are more concerned with their relative position. This empirical design, natural to China, is less clear in other countries, such as the U.S., where the successful these days may live anywhere since there is no limits to mobility.

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 com-

pare 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.

Unfortunately, detailed household portfolio data is limited in China as it is in the rest of the world to very short time periods making measuring the impact of status on the demand for risky assets difficult. To overcome this hurdle, we develop a simple equilibrium model of stock trading between status and non-status seekers to derive our predictions. Most importantly, we show that trading volume or share turnover is a measure of demand for risk-taking due to status. In other words, we seek to infer status driven demand for risky assets from share turnover.

Our model features non-status investors who have the usual log preferences and status investors who 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 and non-status seekers. 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.

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.

We find that this difference-in-difference has increased over the 2004-2009 sample as stock market wealth and the wealth of Tier 1 places have grown relative to Tier 5 places. 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 similarly 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.

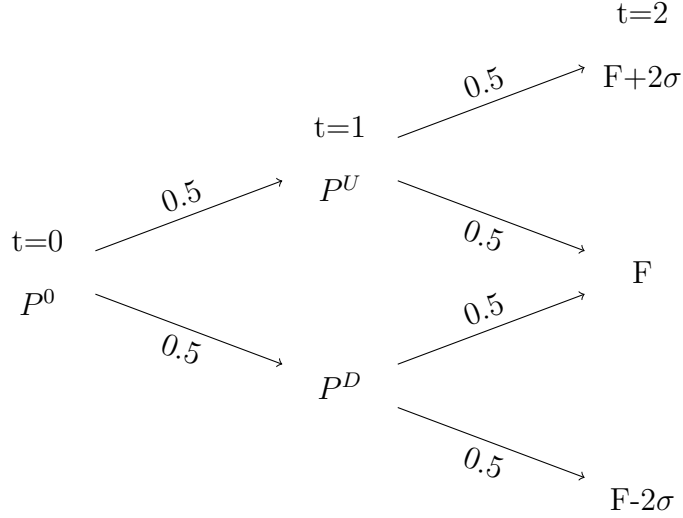
There is a growing literature cited above arguing that status effects matter in financial markets. Much of this work centers on theory arguing how status effects give rise to local bias. The empirical work tries to examine how this might explain the entrepreneurial discounts observed in the U.S. and rationalize some asset pricing patterns associated with the location of stocks.

Our paper differs in two main ways. First, there is the focus on actual risk-taking measures of investors, as epitomized in trading volume. In other words, we look at quantities and not just prices. Second, we try to measure the comparative static of status on trading and pricing of stocks. 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

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

and for the m -investors it is given by

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

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

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

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

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

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:

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

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

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 :

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

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, σ^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:

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

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

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 markets 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 *absolute* difference between the richest and the poorest tier provinces has increased dramatically in the last decade. More precisely, the average GDP per capita of Tier 1 provinces at 1998 is 15,022 Yuan and that for Tier 5 ones is 3,771 Yuan, while the numbers in 2009 are 57,094 and 14,417 Yuan, respectively. The difference of GDP per capita between Tier 1 and Tier 5 places almost quadrupled during the sample period. Note also that the rate of increase begins to diverge around the mid-point of our sample (2003 to 2004). In other words, the growth of income is much higher for the top tier provinces compared to the

bottom tier provinces starting in 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.

$$SMBGAP_{i,t} = \alpha + \beta_1 GDP_{PC_{i,t}} + \beta_2 LATE_t + \beta_3 GDP_{PC_{i,t}} LATE_t + \gamma' Year Dummy + \epsilon_{i,t}, \quad (2.9)$$

where $SMBGAP_{i,t}$ is either the small-minus-big of turnover or market-to-book ratio in province i and year t . $GDP_{PC_{i,t}}$ 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 GDP_{PC} and $LATE$.

Based on Propositions 1 and 2, our central predications 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 .

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 province⁴. 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 equal 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, 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.

⁴Our 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.

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 shares⁵) 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. MB⁶ 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 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

⁵Here 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.

⁶To 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.

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

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 Tier rank 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 later 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 later 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.

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 large 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.

A. Appendix

Solve Optimal Portfolio and Asset Price

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

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 $\theta_s^U = W_s^U \phi_s^U / P^U$.

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

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

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

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 $W_m^U + W_s^U = W_m^0(1 + \phi_m^0 R^U) + W_s^0(1 + \phi_s^0 R^U) = P^U$

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

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 $i \in \{s, m\}$.

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

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

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

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

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

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

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

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

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

or as

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

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

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,

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

First order condition with respect to θ_s^0 gives,

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

When $b = 0$, we have

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

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

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

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

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

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

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

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

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

$$P^0 = F - \frac{2F\sigma^2 - 2\lambda k F\sigma^2}{F^2 - 2\sigma^2 - 2\lambda k F\sigma^2} \quad (\text{A.16})$$

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 plug (A.14), (A.15) and (A.16) into (A.5), (A.8) and (A.12).

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

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

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

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

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

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

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

The sufficient condition such that the derivative is positive is

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

Equivalently,

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

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.

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

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 cities 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. TURNOVER is the time-series average of stock turnover rate in each industry. MB is the median market-to-book in each industry across sample years. # OF STOCKS is the time-series average of number of stocks located in each industry every year. 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.

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

Panel D: Number of Stocks Across Provinces and Industries

	RANK	IND CODE												
		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.

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

<i>VW SMB TURNOVER</i>	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Rank	Rank	LnGDPPC	LnGDPPC	Rich	Rich	Tier	Tier
GDP PC PROXY	-0.030 (-2.17)	0.013 (1.00)	0.515 (2.79)	-0.102 (-0.47)	0.582 (2.78)	-0.074 (-0.43)	-0.194 (-2.36)	0.087 (1.22)
GDP PC PROXY*LATE		-0.074 (-4.17)		1.157 (3.59)		1.180 (3.91)		-0.475 (-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 GDP 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 (-0.37)	0.049 (1.53)	0.129 (0.44)	-0.630 (-1.27)	-0.086 (-0.21)	-1.243 (-1.64)	-0.030 (-0.28)	0.307 (1.56)
GDP PC PROXY*LATE		-0.096 (-2.45)		1.424 (2.66)		2.082 (2.63)		-0.569 (-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.

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

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.

