ABSTRACT

Title of dissertation: EMPIRICAL ESSAYS ON FINANCIAL ECONOMICS

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Using institutional investors' holdings data from Thomson Reuters' 13F filings, the first chapter studies and tests the market microstructure invariance hypothesis proposed by Kyle and Obizhaeva (2016a), and in particular its implied $-2/3$ law on the relationship between investors' bets and stock trading activity, defined by the product of price, volume, and volatility. With the identifying assumption that institutional asset managers' holdings are proportional to their bets, our empirical results support the $-2/3$ law implied by the invariance hypothesis. The $-2/3$ law is robust to a variety of estimation strategies and robustness checks. Then we study whether distributions of bets are invariant and log-normal. Data strongly support the hypothesis before March 1998, and the weak version of the invariance hypothesis (the mean of distributions of bets is invariant) continues to hold in the remaining periods. The strong version failing to hold after March 1998 may be due to adjustment costs and very tiny positions.

The second chapter studies the role of convertible debt on investment. Convertible debt in the capital structure facilitates investment for a firm (especially for a firm with high leverage) since it reduces the firm's interest payments and leverage upon conversion, making it easier for the firm to issue new financial instruments. However, the same property may bring an agency issue: The potential of conversion into equity dilutes existing shareholders' profits, decreasing the firm's motivation to do investment. We hypothesize that the agency issue brought by convertible debt is minimal in very competitive markets since the external pressure is high, so that the facilitation role may outweigh the dilution role, suggesting a positive effect on investment, and that the agency issue brought by convertible debt may outweigh or just offset the facilitation role in less competitive markets since the external pressure is not high, suggesting a negative or insignificant effect on investment. Using data from Compustat, we find that the convertible debt has a positive and quadratic effect on investment rates in competitive industries (industries with very low HHI), a negative and quadratic effect on investment rates in oligopoly industries (intermediate HHI), and an insignificant effect on investment rates in highly monopolistic industries (high HHI). These effects are robust to including different control variables. We also suspect the interaction of warrants and competition has similar effects. These results may have implications on the announcement effects or long term effects of convertible debt issuance under different industry structures.

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by

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Chapter 1: Market Microstructure Invariance: an Empirical Study Using Holdings Data

1.1 Introduction

To study how traders' behavior (e.g, trade size, the number of trades) varies across different time periods and across different assets, Kyle and Obizhaeva (2016a) propose two invariance hypotheses about trading and market microstructure. First, the distribution of bet risk transferred per unit of business time, defined as the product of share prices, the number of shares per bet, and the expected volatility per unit of business time, is the same across different assets and across different time periods. Second, the transaction cost function (price impact) of executing a bet is the same across different assets and across different time periods when the bet size is measured as the dollar risk transferred by a bet per unit of business time. These hypotheses are a potent tool to build a bridge between unobservable microscopic features such as bet sizes and rates and observable macroscopic features such as trading dollar volume and volatility. The purpose of this paper is to empirically study and test the first hypothesis using available public data: in particular, we use Thomson Reuters' 13F quarterly data from 1990 to 2015. There are two advantages of using these data: first, a majority of stock market participants are institutional investors making bets every day; second, as institutional managers whose portfolio value exceeds the 100 million dollar threshold are required to report to the SEC about their holdings at the end of each quarter, their reported holdings are more like independent ideas (bets, a core concept in the invariance hypothesis). We make an identifying assumption that there is a constant linear relationship between an investor's holdings position and the size of a bet, focusing on studying the invariant bet distribution and the invariance hypothesis' prediction of a $-2/3$ law, which means that the logarithm of bet size scaled by expected trading volume should have a $-2/3$ linear relationship with the logarithm of asset trading activity, defined by the product of price, volume, and volatility. A variety of specifications are implemented to study and test the $-2/3$ law and the existence of an invariant distribution.

For the $-2/3$ law, we estimate the relationship quarter by quarter for 75 quarters and find that the mean and the standard deviation of estimated coefficients (or powers) are -0.657 and 0.032 respectively. Before and after the dot-com bubble period, empirical results strongly support the $-2/3$ law. During the dot-com bubble period, the estimated coefficient rides a rollercoaster: the estimated coefficient increases from -0.628 in the 3rd quarter of 1998 to -0.548 in the 2nd quarter of 2000, when the dot-com bubble rose to its peak, then falls from -0.548 to -0.657 in the last quarter of 2003 when the stock market began to recover from the bust. After controlling for lags of trading activity, we, however, find that the sum of coefficients is close to $-2/3$, suggesting that investors' holdings adjustments are relatively sluggish compared with the rocket speed of price changes. We then group observations by stock exchange, and find that estimated coefficients are all similar to $-2/3$. Finally, we estimate 108 quantile regressions, and find 92 estimated coefficients close to -0.667 (absolute value of the difference between an estimated coefficient and -0.667 is less than 0.1). There are 16 estimated coefficients not close to -0.667, most of which are obtained during the bubble period. In sum, while the $-2/3$ law is statistically rejected, our study results are qualitatively consistent and support the $-2/3$ law implied by the invariance hypothesis.

For the bet distribution, pooling observations together, the common mean and variance of bet size before March 1998 are 6.35 and 3.276 respectively. While the variance across 23 quarters displays a slightly upward trend over time due to a rise in the number of managers filling out 13F forms, almost all quarterly variances are close to 3.276, implying that the bet distribution is invariant across different time periods up to a second order. We divide observations before March 1998 into 7 regions based on expected volatility, with thresholds corresponding to the 1st, 10th, 25th, 50th, 75th, and 90th percentiles. Estimated variances of the 7 regions are 3.133, 3.24, 3.276, 3.349, 3.24, 3.168, and 3.24 respectively, indicating that the variance is invariant across different stocks. While variances of the bet distribution increase in the latter quarters (after 1998 Q1), the mean of the bet distribution is stable across different stocks and different quarters, demonstrating that the weak version of the invariance hypothesis continues to hold.

Gabaix et al. (2003, 2009) study shapes of aggregate stock behavior, and find that stock returns and volumes adhere to certain power laws. Rather than focusing only on stocks, the invariance hypothesis proposed by Kyle and Obizhaeva (2016a) explores and emphasizes the relationship between investors' trading strategy and the volatility of stock and other asset returns. Since then, there has been a growing literature testing this hypothesis. Assuming that an order size is proportional to a bet, Kyle and Obizhaeva (2016a) study the invariance hypothesis using portfolio transition orders from 2001 to 2005. Bae, Kyle, Lee, and Obizhaeva (2016) discuss this hypothesis using Korea Stock Exchange trading data from 2008 to 2010. Their tests focus on a different implication (the relationship between the expected bet rates and the expected trading activity) of the invariance hypothesis. Instead of making an identifying assumption on bet size, they assume that the number of switching points is proportional to bet rates. They find that the aggregate number of switching points are related to the 0.675 power of trading activity, which is almost equal to the 2/3 power predicted by the invariance hypothesis. Using Trades and Quotes data from 1993 to 2008, Kyle, Obizhaeva, and Tuzun (2012) assume a TAQ print is proportional to an intended order and hence proportional to a bet. In their work, there are two subperiods: in the first subperiod, they show that the trade arrival rates is related to the 0.69 power of expected trading activity; in the second subperiod, they find that the arrival rate is related to the 0.787 (an average number) power of expected trading activity and that the size of trade orders decreases, suggesting that bets have been shredded into many small orders by investors after 2001. Andersen, Bondarenko, Kyle, and Obizhaeva (2015) study the invariance hypothesis by examing the number and the size of trades per minute using E-mini S&P 500 futures contracts from 2008 to 2011. They show the number of transactions within one minute is related to the 0.671 power of expected trading activity.

In contrast to existing research, we study investors' holding behavior as opposed to trading behavior and use Thomson Reuters' 13F quarterly holdings data, which provides extremely abundant observations with fewer errors and noise. In addition, we make the identifying assumption that holdings are proportional to bet size. This assumption is not without grounds, as Kyle, Obizhaeva, and Wang (2015) suggest that many traders have inventory targets when they trade. In this way, we contribute to this literature by showing that the invariance hypothesis also holds even when we assume the holdings position is part of bet size. Moreover, our study shows that the $-2/3$ law is a good approximation to typical holdings size, which provides the first benchmark for studying styles of certain investment managers (Holdings size is abnormally large or small for a given stock).

In the following, we briefly review market microstructure invariance theory in Section 2. In Section 3, we describe the data and summarize relevant statistics. Various empirical specifications are implemented and reported in Section 4. We perform robustness checks in Section 5. Finally, we draw conclusions in Section 6.

1.2 A Brief Review of Kyle–Obizhaeva Theory

In this section, we review the first hypothesis of market microstructure invariance proposed by Kyle and Obizhaeva (2016a) and show its implications. Readers interested in more details and the second hypothesis may resort to Kyle and Obizhaeva (2016a). For exposition, we use the same mathematical notation as in Kyle and Obizhaeva (2016a).

A bet represents an independent trading idea, which can be implemented by a single order or multiple orders. A buy order is a part of a buy bet while a sell order is a part of a sell bet. We are able to observe order sizes and the number of orders but cannot observe bet sizes or the number of bets since we do not know how many orders form a single bet.[1] When an investor sells a share (a part of a sell bet), the share is bought by an intermediary (a market maker) who in turn will sell this share to another intermediary or a buyer who is implementing a buy bet. Due to the existence of intermediaries, the daily volumes we observe consist of volumes caused by bet arrivals and volumes caused by intermediary trades. Since we don't know how many intermediaries will implement an order, we cannot observe bet volumes. Likewise, the movement of daily volatility of returns can be induced either by the impact of bets or news such as firm earnings reports or macro shocks, so we cannot observe bet volatility (volatility induced by the impact of bets) either.

Denote the size (the number of shares bought or sold) of a bet by $\tilde{Q}_{jt}$ at time t, where j represents a stock. The price of stock j at time t is denoted by P_{jt}. The expected arrival rate of bets per calendar day at time t is denoted by γ_{jt}, so the expected unit of business time at time t is $1/\gamma_{jt}$. Assume the expected bet volatility of stock j's return per calendar day at time t is $\bar{\sigma}_{jt}$ and hence the expected bet volatility per unit of business time is $\bar{\sigma}_{jt}\gamma_{jt}^{-1/2}$. Then the dollar risk transferred by a bet using stock j at time t per unit of business time is given by

$$\tilde{I}_{jt} = P_{jt}\tilde{Q}_{jt}\bar{\sigma}_{jt}\gamma_{jt}^{-1/2}. \tag{1.1}$$

[1] Kyle (1985) built a model in which investors intentionally hide and shred their target amount into many small piece orders, trying to reduce transaction costs.

There are 2 versions of the Kyle-Obizhaeva market microstructure invariance hypothesis on the random variable $\tilde{I}_{jt}$: The strong version says that the distribution of $\tilde{I}_{jt}$ is constant across different assets and across different time periods while the weak version suggests that the mean of $\tilde{I}_{jt}$ is constant across different assets and across different time periods[2]

$$\tilde{I}_{jt} \stackrel{d}{=} \tilde{I}, \tag{1.2}$$

or

$$E\left\{\tilde{I}_{jt}\right\} = E\left\{\tilde{I}\right\} = Cont, \tag{1.3}$$

where $Cont$ represents a constant. When one of P, Q, σ, or γ changes, the other three variables will adjust accordingly in order to keep the risk invariant.

With certain identifying assumptions on relationships between bet volatility and overall daily volatility and between bet volumes and overall daily volumes, either hypothesis can be used to infer microscopic and unobservable trading variables such as traders' bet sizes and the number of bets from macroscopic and observable trading variables such as daily dollar volume (the product of stock price and daily volume) and the daily volatility of returns. Define the expected bet volume per calendar day $\bar{V}$ as

$$\bar{V}_{jt} = \gamma_{jt} E\left\{|\tilde{Q}_{jt}|\right\}. \tag{1.4}$$

Note that a buy bet is positive while a sell bet is negative, but since both bets contribute to bet volume, we use the absolute value of $\tilde{Q}$ to calculate bet volume. Using

[2] Kyle and Obizhaeva (2016b) verify their hypotheses in a dynamic model with adverse selection, under the assumption that the cost of generating a bet and the distribution of a private signal are the same across different assets and across different time periods.

the expected bet volume and expected bet volatility, we are able to get expected bet activity per calendar day as

$$\bar{W}_{jt} = P_{jt}\bar{V}_{jt}\bar{\sigma}_{jt}, \tag{1.5}$$

where expected bet activity is the expected aggregate risk transferred per calendar day. Plug $\tilde{I}_{jt}$ into $\bar{W}_{jt}$ to get

$$\bar{W}_{jt} = P_{jt}\bar{V}_{jt}\bar{\sigma}_{jt} = P_{jt}\gamma_{jt}E\left\{|\tilde{Q}_{jt}|\right\}\bar{\sigma}_{jt} = \gamma_{jt}^{3/2}E\left\{\tilde{I}_{jt}\right\} = \gamma_{jt}^{3/2}E\left\{\tilde{I}\right\}. \tag{1.6}$$

Using this equation, either the strong version or the weak version yields the first implication

$$\gamma_{jt} \propto \bar{W}_{jt}^{2/3}. \tag{1.7}$$

We denote $E\left\{\tilde{I}\right\}$ by C_1 and calculate $\tilde{Q}_{jt}/\bar{V}_{jt}$. The second implication can be derived as follows under the strong version:

$$\frac{\tilde{Q}_{jt}}{\bar{V}_{jt}} = \frac{P_{jt}\tilde{Q}_{jt}\bar{\sigma}_{jt}}{P_{jt}\bar{V}_{jt}\bar{\sigma}_{jt}} = C_1^{-1/3}\bar{W}_{jt}^{-2/3}\tilde{I} \tag{1.8}$$

$$\ln\frac{\tilde{Q}_{jt}}{\bar{V}_{jt}} \propto -2/3\ln\bar{W}_{jt}. \tag{1.9}$$

Stocks with increasing aggregate activity will attract more bets, as shown in equation (1.7), and bets' sizes will increase as well, resulting in higher volumes. As volumes increase more than bets' sizes, increasing aggregate activity leads to lower $\tilde{Q}_{jt}/\bar{V}_{jt}$, as implied by equation (1.9). Similarly, the same procedure yields another implication under the weak version.

$$E\left\{\frac{\tilde{Q}_{jt}}{\bar{V}_{jt}}\right\} = E\left\{\frac{P_{jt}\tilde{Q}_{jt}\bar{\sigma}_{jt}}{P_{jt}\bar{V}_{jt}\bar{\sigma}_{jt}}\right\} = C_1^{2/3}\bar{W}_{jt}^{-2/3} \tag{1.10}$$

$$\ln E\left\{\frac{\tilde{Q}_{jt}}{\bar{V}_{jt}}\right\} \propto -2/3\ln\bar{W}_{jt}. \tag{1.11}$$

Bet volumes V_{jt} are not observable, and neither are expected bet volumes $\bar{V}_{jt}$. Suppose each unit of order transfer from the seller to the buyer passes through ζ_{jt} intermediaries (market makers). Then we have the following relationship between observable daily volume V_{jt}^o and unobservale bet volume V_{jt}:

$$V_{jt}^o = V_{jt}\frac{\zeta_{jt}+1}{2}. \tag{1.12}$$

Here a sell order plus a buy order is counted once in calculating observed volume. To make empirical tests simple, we follow Kyle and Obizhaeva (2016a) to assume ζ_{jt} is constant across different assets and across different time periods. In the next section, we shall discuss how to construct expected bet volume $\bar{V}_{jt}$ from V_{jt}, which in turn is obtained from V_{jt}^o through equation (1.12). We denote $(\zeta_{jt}+1)/2$ by C_2.

Likewise, bet volatility σ_{jt} is not observable, and neither is expected bet volatility $\bar{\sigma}_{jt}$. Naturally, bet-induced volatility σ_{jt} forms only a part of observed volatility:

$$\sigma_{jt} = \eta_{jt}\sigma_{jt}^o. \tag{1.13}$$

To facilitate our tests, η_{jt} is also assumed to be a constant and denoted by C_3. The next section shall discuss how to construct expected bet-induced volatility $\bar{\sigma}_{jt}$ from σ_{jt}, which in turn is obtained from σ^o_{jt} through equation (1.13).

The market microstructure invariance hypothesis implies that the relationship between the bet size scaled by expected volume and the expected trading activity (equations (1.9) and (1.11)) should hold at any time. To test this hypothesis, we choose time periods when we are able to get data. We now go to the next section to discuss our data.

1.3 Data

We use WRDS's (Wharton Research Data Services) CRSP (the Center for Research of Stock Prices) database to get macroscopic variables such as price, volume, and return for individual stocks over time.

In CRSP, there are 2 measures of stock return. The first measure takes into account dividend distributions whereas the second excludes dividend distributions. The values of these two measures of return are very similar. In the empirical analysis, we use the first type of return.

We get institutional investors' holdings data of individual stocks over time from Thompson Reuters' 13F filings. As required by the SEC, institutional investment managers must report their holdings by filling out the 13F form at the end of each quarter if their investment in securities exceeds 100 million dollars.

Our sample covers the period from March 1990 to December 2015. Only common stocks (share codes 10 or 11) listed on NYSE, AMEX, and NASDAQ (exchange codes 1, 2 and 3 respectively) are studied. We employ the following variables from CRSP: *date*, *shrcd* (security type), *exchcd* (exchange code), *cusip*, *prc* (closing price), *vol* (daily volume), and *ret* (return). Cusip and date are combined to make a unique variable used to merge with the 13F database. Observations with incomplete information or non-sensical items such as negative price or negative volume are also dropped.

From the 13F database, the following variables are used: $fdate$ (file date), *cusip*, *mgrno* (manager number), and *shares* (share holdings at the end of a quarter). The $Cusip$ and $fdate$ are combined to merge with the CRSP data file.

After merging, there are 29,729,196 matched observations representing the holdings of a particular stock by a particular manager at the end of a particular quarter. Since the 13F filings only have quarterly data and some of the CRSP Cusip-date observations are dropped due to incomplete or wrong information, there are 31,118,793 unmatched observations from CRSP and 28,235,642 unmatched observations from 13F.

1.3.1 Variable Construction

From CRSP, we get P_{jt}, daily trading volume V^o_{jt}, and daily returns. From 13F filings, we get institution manager i's holding position H_{ijt} on stock j at the end of each quarter.

The expected bet volume $\bar{V}_{jt}$ is calculated as the mean of the bet volume V_{jt} of the previous 20 days. Due to missing data, the 20 days used may not be perfectly continuous. With the previous assumptions on V_{jt} and V_{jt}^o (equation (1.12)), we obtain the following

$$\bar{V}_{jt} = \sum_{m=t}^{m=t-19} \frac{V_{jm}}{20} = \sum_{m=t}^{m=t-19} \frac{V_{jm}^o}{20C_2}. \tag{1.14}$$

We construct observed volatility σ_{jt}^o using the daily returns of the previous 20 days.

$$\sigma_{jt}^o = \left(\sum_{m=t}^{m=t-19} \frac{(r_{jm} - \bar{r})^2}{20} \right)^{1/2}, \tag{1.15}$$

where $\bar{r}$ is the mean of the return over the previous 20 days. With the previous assumptions (equation (1.13)), we have

$$\bar{\sigma}_{jt} = \eta \sigma_{jt}^o = C_3 \left(\sum_{m=t}^{m=t-19} \frac{(r_{jm} - \bar{r})^2}{20} \right)^{1/2}. \tag{1.16}$$

In the section on robustness checks, we shall construct these variables using data from the past 60 days, which approximates the number of working days in a quarter.

1.3.2 Data Statistics

For the 26-year period, there are 75 quarters, 29,729,196 observations (i.e. manager-stock holdings-quarter), 292,409 Cusip-quarter or firm-quarter observations, 14,546 Cusips, and 6,500 institutional managers. As shown in the third and fourth columns of Table A.1 to Table A.3, there is an obvious upward trend over time in the number of managers filling out 13F forms, and there is a clear spike in the number of Cusips as we enter the boom period of the dot-com bubble.

The pertinent summary statistics are shown in Table 1.1. We get asset managers' stock holdings from 13F filings. The maximum holding of a single stock is 752,500,000 shares whereas the minimum is 1 share (e.g., Berkshire Hathaway). Naturally, the standard deviation of the number of stock holdings is substantial. The 25th percentile of stock holdings is 10,891 shares, implying that holdings greater than 10,000 shares are economically important. The key variable in our empirical study is holdings position scaled by expected volume, $H/\bar{V}$. While the mean of this ratio is 1.49, most asset managers' holdings are smaller than the expected volume as the 75th percentile is just 0.454, and only 10 percent of observations have values higher than 2.24. Hence, the distribution of $H/\bar{V}$ is positively skewed with a long but thin right tail.

We get stock prices from CRSP. Without deflating, the mean, maximum and minimum of stock prices are \$154.33, \$226,000 (Berkshire Hathaway) and \$0.016 respectively. The 90th percentile of stock price is \$77.04, making stocks with prices below \$77 economically important. While a very small number of stocks have very high prices, most stocks' prices are below \$100. That is, the distribution of P is also positively skewed with a long but thin right tail. Excluding the outlier Berkshire Hathway, the standard deviation of stock price is \$52.32, which is not so large. Among all matched stocks, the daily dollar volume (the product of price and daily volume) of half of observations is higher than \$22 million. The mean of expected dollar volume in our matched sample is \$120 million. The minimum is \$100 while the maximum is \$11,900 million.

We calculate the ratio of expected volume to outstanding shares. Since the expected volume and outstanding shares are measured in units of shares per day and units of shares respectively, their ratio is measured in units per day. Thereby, whether stocks are active or not can be determined in terms of this ratio. The maximum is 4.8 per day whereas the minimum approximates 0 per day, which means that some stocks are very active and their business time can be expected to be very short, while some stocks are inactive and their business time can be expected to be large. The ratios are 0.000568, 0.001911, 0.003416, 0.006049, 0.010506, and 0.017348 at the 1st, 10th, 25th, 50th, 75th, and 90th percentiles respectively, indicating that, for a majority of stocks, daily trading volume is only a small part of outstanding shares.

As discussed in Section 1.2, in addition to shocks, order imbalances can result in high volatility or big changes in price. Moreover, the square of volatility can also be measured in units per day. Hence, along with the ratio of expected volume to outstanding shares, volatility is an equally important measure as to whether stocks are active or not. The mean of expected daily return volatility is almost 0.02. The minimum approximates 0 whereas the maximum is 1.558. The expected daily return volatility per calendar day is 0.0054, 0.009, 0.0121, 0.0177, 0.027, and 0.04 at the 1st, 10th, 25th, 50th, 75th, and 90th percentiles respectively. The standard deviation of the expected daily return volatility is 0.0176.

In some specifications, we group matched stock observations by stock exchange. Berkshire Hathaway had the highest stock price on the New York Stock Exchange on December 31, 2014. Comparing stock prices at thresholds such as the 1st, 10th, 25th, 50th, 75th and 90th percentiles, most observations on NYSE have higher prices than on AMEX and NASDAQ. Comparing the ratio of expected volume to outstanding shares, stocks on NASDAQ are more active than NYSE, which, in turn, are more active than AMEX. The implications for expected volatility on the three stock exchanges are ambiguous. Since stocks on NASDAQ are more active than NYSE and AMEX and stock prices on NYSE are greater than NASDAQ and AMEX, the dollar volumes of most observations on NYSE and NASDAQ are greater than AMEX.

Having examined the distribution of investors' individuals' holdings, we now study the aggregate holdings at the investor level. Pooling Cusip-quarter observations together, the distribution of each Cusip-quarter's float (the ratio of the sum of shares held by managers with 13F filings, divided by total outstanding shares held by all investors in the market) is shown in Figure 1.1. Among 292,409 observations, there are 65 observations for which this fraction is higher than 2, due to short sales. Excluding these 65 observations in the figure, this fraction is almost uniformly distributed and has a mean of 0.45.

Employing variables such as expected volume relative to outstanding shares and expected daily return volatility, we classify stocks into 7 regions, with the first region consisting of inactive stocks and the last region being composed of active stocks. Dividing $292,409$ observations into 7 regions using the 1st, 10th, 25th, 50th,

	Variables	Mean	Max	Min	Std	1st	10th	25th	50th	75th	90th
13F	H (10^3)	455.832	752500	0.001	3400	0.075	2.5	10.891	42.474	190.046	710.063
	$H/\overline{V}$	1.49	17221	5.92×10^{-9}	17.77	0.00005	0.00186	0.01	0.073	0.454	2.24
CRSP	P	154.329	226000	0.016	3973.23	1.75	8.875	17.875	32.25	52.2	77.37
	$P\overline{V}$ (10^6)	120	11900	0.0001	330	0.0382	0.787	4.2	22	100	300
	$\overline{V}$/Shares (10^{-3})	8.596	4802.2	0.0073	10.382	0.568	1.911	3.416	6.049	10.506	17.348
	$\overline{\sigma}$	0.0223	1.558	0	0.0176	0.0054	0.009	0.0121	0.0177	0.027	0.04
NYSE	P	224.69	226000	0.016	4993.73	3.5	13.74	23.75	38.18	57.99	82.94
	$P\overline{V}$ (10^6)	120	4655	0.0001	240	0.188	2.4	9.4	37	130	340
	$\overline{V}$/Shares (10^{-3})	7.59	393.32	0.01	8.242	0.707	1.95	3.234	5.473	9.136	14.986
	$\overline{\sigma}$	0.0192	1.386	0.0004	0.0142	0.0052	0.0084	0.0111	0.0155	0.0228	0.0332
AMEX	P	34.42	4197.95	0.02	177.066	0.2601	1.56	4.188	11.375	25.05	43.02
	$P\overline{V}$ (10^6)	4.6	257	0.0001	190	0.0044	0.025	0.0791	0.394	1.9	7.1
	$\overline{V}$/Shares (10^{-3})	4.468	615.86	0.02	8.246	0.1956	0.5638	1.0699	2.286	5.068	9.873
	$\overline{\sigma}$	0.0318	1.262	0	0.0285	0.0039	0.0113	0.0161	0.0247	0.038	0.0586
NASDAQ	P	33.09	1274.95	0.0156	52.977	1.219	5.73	11.85	22.75	38.77	62.22
	$P\overline{V}$ (10^6)	110	11900	0.0003	460	0.0226	0.2958	1.4	7.4	43	200
	$\overline{V}$/Shares (10^{-3})	10.609	4802.24	0.0073	13.226	0.528	2.042	4.222	7.693	13.142	21.551
	$\overline{\sigma}$	0.0276	1.558	0	0.021	0.0061	0.0109	0.0151	0.0224	0.0338	0.049

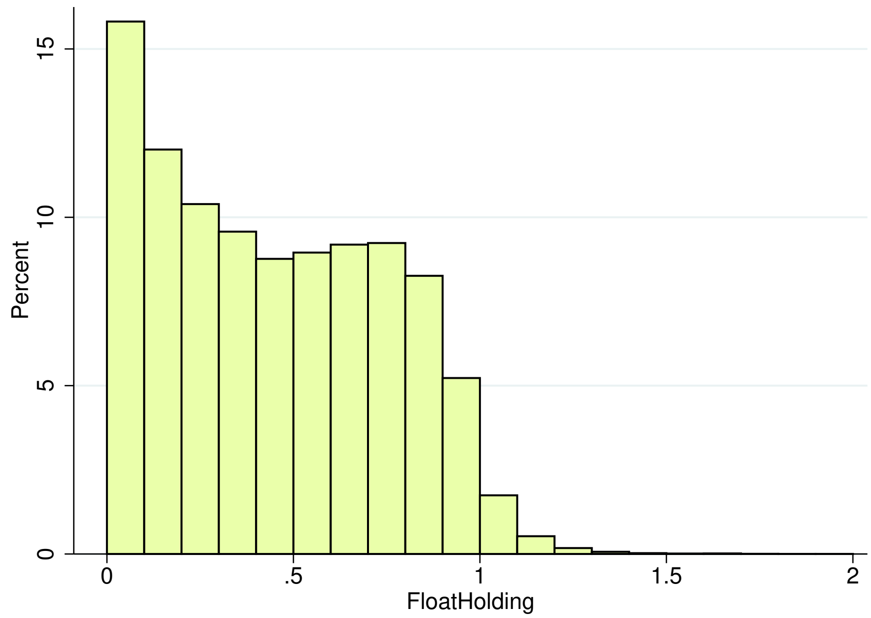
Notes: This table reports the statistics for our matched 29,729,196 observations. The variable H is the holdings position at the end of a particular date (the end of each quarter) and is measured in units of shares. The variable $H/\bar{V}$ is the ratio of holdings position at the end of a date to the expected daily volume and is measured in units of per day. Variables $\bar{V}$ and $\bar{\sigma}$ are constructed as shown in Section 1.3.1. They are measured in units of shares per day and in units of per square root of a day. The variable $P\bar{V}$ is measured in units of dollar shares per day. The panel 13F reports the distributions of variables related to asset managers' holdings. The panel CRSP reports the distributions of variables related to stocks. The panel NYSE has 18,808,120 observations and reports the distributions of variables related to NYSE-listed stocks. The panel AMEX has 497,315 observations and reports the distributions of variables related to AMEX-listed stocks. The panel NASDAQ has 10,423,761 observations and reports the distributions of variables related to NASDAQ-listed stocks.

Table 1.1: Data Statistics for CRSP and 13F Database (1990–2015)

75th, and 90th percentiles of expected volatility, the mean of float held by managers filling out 13F forms are 0.471, 0.541, 0.576, 0.568, 0.511, 0.428, and 0.29. Other than the fact that managers dislike stocks with extremely high volatility (daily return volatility being greater than 0.04), there is no clear trend for their holdings by volatility. Dividing 292,409 observations into 7 regions using the 1st, 10th 25th, 50th, 75th, and 90th percentiles of expected volume over outstanding shares as thresholds, the mean of float held by managers filling out 13F forms are 0.18, 0.272, 0.39, 0.50, 0.592, 0.65, and 0.645. This trend suggests that institutional investors prefer holding stocks with high turnover, consistent with the finding of Gompers and Metrick (2001) using a shorter sample.

The mean of aggregate float across different years is plotted in Figure 1.2. While there are some small blips from 2007 to 2015, the mean of the total float held by managers in the sample almost doubles between 1990 and 2007 as the number of 13F managers grows.

Finally, the distribution of the number of managers per firm-date, shown in Figure 1.3, is right-skewed. Although the mean of this distribution is 102, more than half of firm-date observations have fewer than 50 institutional investors holding that stock.



Notes: Excluding 65 Cusip-date observations with Float Holding being greater than 2 and pooling all other observations together, this figure describes the distribution of float held by asset managers filling 13F. The variable Float Holding is calculated as the ratio of the sum of managers' holdings to outstanding shares.

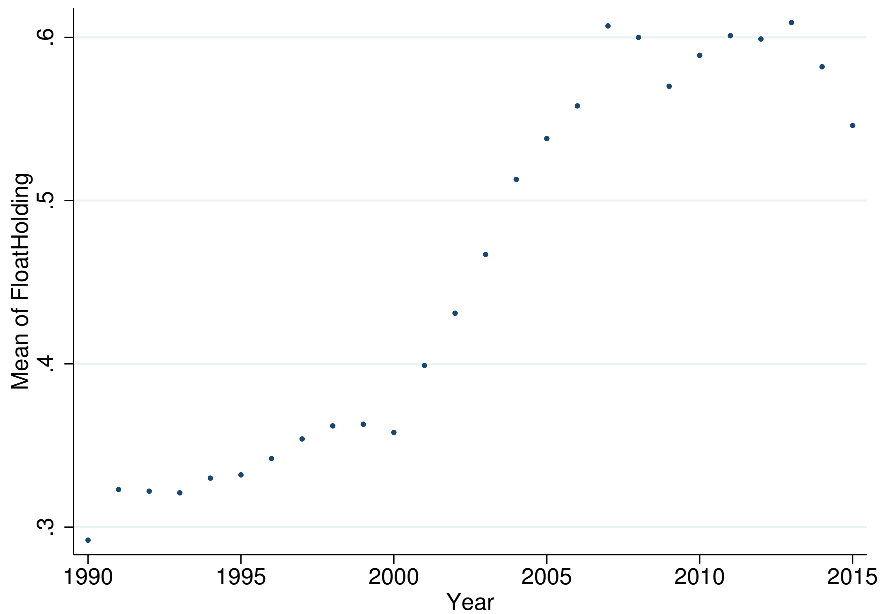
Figure 1.1: The Distribution of Float Held by 13F Filings per Firm

1.4 Empirical Study

In our empirical analysis, we follow Kyle and Obizhaeva (2016a) to assume that stock holdings have a constant linear relationship with bet size:

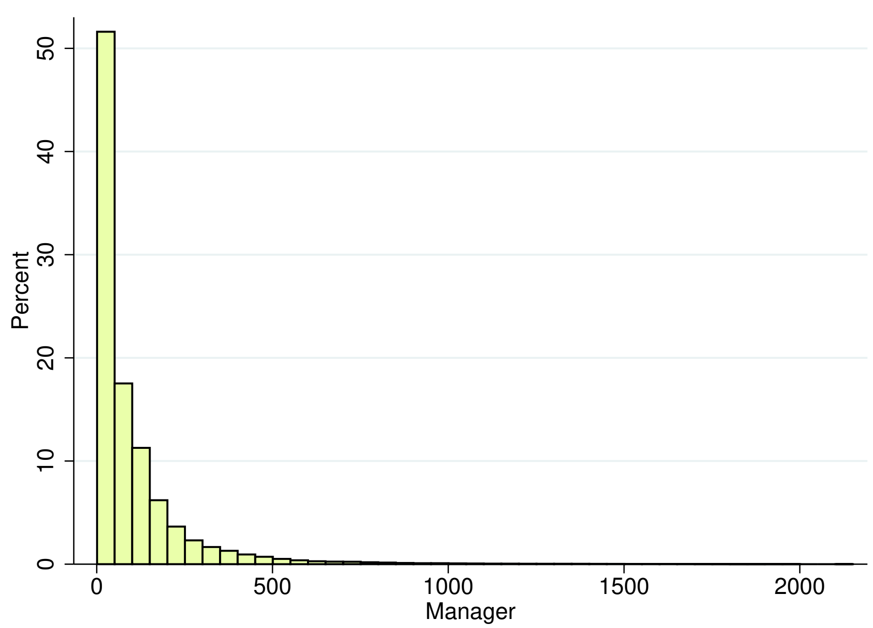
$$\tilde{H}_{i,j,t} = C_4 \tilde{Q}_{i,j,t}, \tag{1.17}$$

where C_4 is a constant and i represents managers, so $H_{i,j,t}$ represents manager i's holdings of stock j at time t. We shall focus on testing the strong version of the invariance hypothesis. As shown in Section 1.2, the strong hypothesis implies the



Notes: This figure plots the mean of float held by asset managers across 26 years.

Figure 1.2: The Mean of Float Holdings across Different Years



Notes: This figure describes the distribution of the number of asset managers for each Cusip-date observation. The $292,409$ Cusip-date observations are pooled together. The variable Manager of each observation is calculated as the number of managers who hold the same stock (Cusip-date).

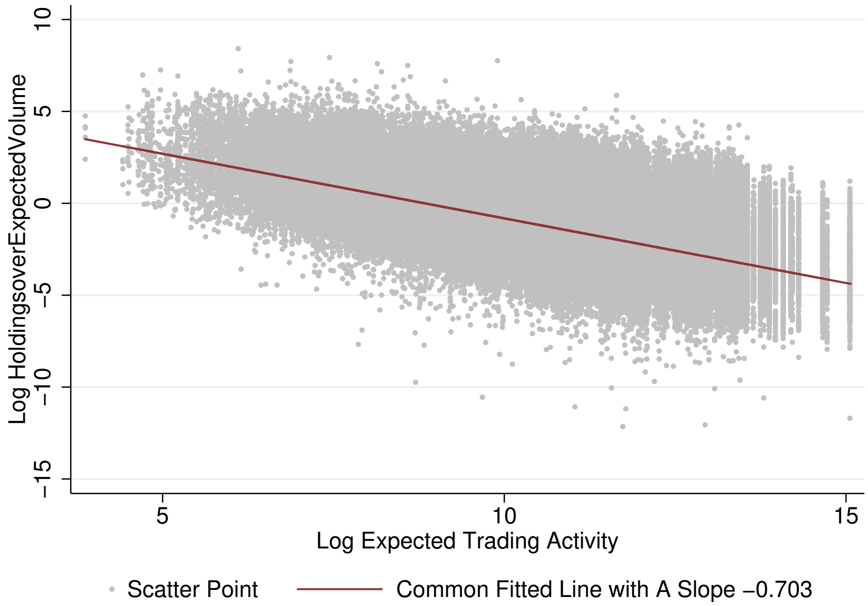
Figure 1.3: The Distribution of the Number of Managers per Firm

following:[3]

$$\frac{H_{i,j,t}}{\bar{V}_{j,t}} = \frac{C_1^{-1/3}}{C_4} \bar{W}_{j,t}^{-2/3} \tilde{I}, \tag{1.18}$$

where $\bar{W}_{j,t}^{-2/3}$ is defined in equation (1.5). To examine whether the $-2/3$ law on the relationship between $H_{i,j,t}/\bar{V}_{j,t}$ and $\bar{W}_{j,t}^{-2/3}$ holds visually, we plot $\ln(H_{i,j,t}/\bar{V}^o_{jt})$ against $\ln(\bar{W}^o_{j,t})$. We have 75 quarters in total. In the interests of space and size, we only present 1 quarter in Figure 1.4. The other quarters are very similar. In the figure, we superimpose a common fitted line with a slope -0.703 and an intercept 6.21 for the super cloud. As shown in Figure 1.4, the super cloud clearly indicate that there is a negative and linear relationship between $\ln(H_{i,j,t}/\bar{V}^o_{jt})$ and $\ln(\bar{W}^o_{j,t})$ and that the shape of these super clouds (only one is presented here) approximates the common fitted line. Finally, almost all scatter points are symmetrically distributed around the fitted line, although the widths of the clouds are not exactly invariant as we increase expected trading activity.

[3]Since the adjustment of holdings positions takes time, this assumption may be violated under extreme market conditions or for very active stocks.



Notes: This figure plots $\ln(H_{i,j,t}/\bar{V}^o_{jt})$ versus $\ln(\bar{W}^o_{j,t})$. The slope -0.703 and intercept 6.21 of the fitted line are estimated using the whole sample.

Figure 1.4: The First Quarter of 1992

1.4.1 Log Linear Regression

The regression model in our study is given as follows:

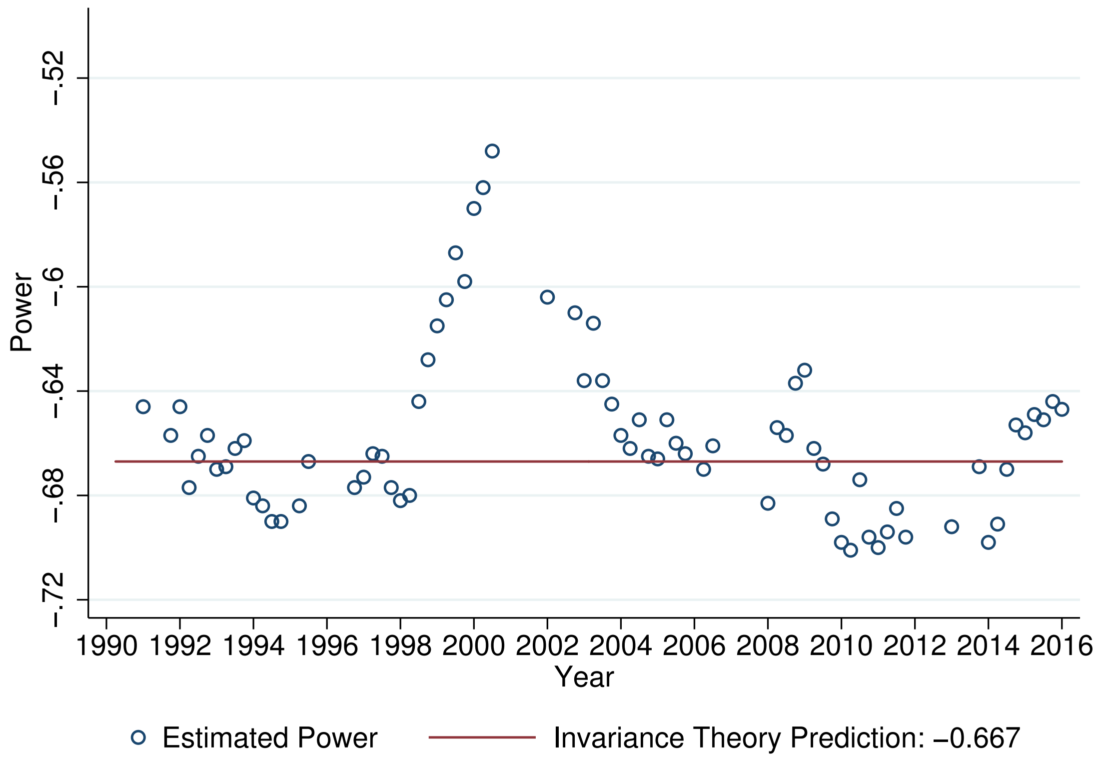
$$\ln\left(\frac{H_{i,j,t}}{\bar{V}^o_{jt}}\right) = C - \alpha\ln(\bar{W}^o_{j,t}) + \epsilon_{i,j,t}, \tag{1.19}$$

where C is a constant. Since we use $\bar{V}^o_{jt}$ and $\ln(\bar{W}^o_{j,t})$ $(\ln P_{j,t}\bar{V}^o_{j,t}\bar{\sigma}^o_{j,t})$ instead of $\bar{V}_{jt}$ and $\ln(\bar{W}_{j,t})$ in the regression, C is a function of C_1, C_2, C_3, C_4, and the mean of $\ln\tilde{I}$. Here $\epsilon_{i,j,t}$ is the difference between the random variable $\ln(\tilde{I})$ and the mean of $\ln(\tilde{I})$, and $-\alpha$ is the estimated coefficient of $\ln\bar{W}^o_{j,t}$ or estimated power of $\bar{W}^o_{j,t}$.

1.4.1.1 Regression across Different Quarters

In this section, we estimate (1.19) using OLS quarter by quarter. Results including the estimated coefficients, estimated constants and R^2 of log linear regressions are reported in Tables A.1–A.3 in the Appendix Section.

The estimated coefficients (or powers) over the 75 sample quarters are plotted in Figure 1.5. Most estimates are close to the prediction of $-2/3$ of the invariance hypothesis, except the period from September 1998 to September 2003. Statistically, the mean and standard deviation of the 75 estimated coefficients are -0.657 and 0.032 respectively while the maximum and minimum estimated coefficients are -0.548 and -0.701 respectively.



Notes: This figure plots 75 estimated powers reported in Tables A.1–A.3. We superimpose a red line, of which the value is -0.667.

Figure 1.5: Estimated Powers for 75 Quarters, 1990–2015

During the period from September 1998 to September 2003, which corresponds to the boom and bust of the dot-com bubble, the estimated coefficient steadily increases to its peak in June 2000, after which the estimated coefficient gradually decreases and goes back to -0.645 in September 2003.[4] Sluggish adjustment caused by transaction costs (price impact costs, see, for example, Kyle (1985)) may account for the gap between the predictions of the invariance hypothesis and the estimated coefficients during the dot-com period. To keep risk invariant (the distribution of $\tilde{I}$), investors in a frictionless model may need to increase their holdings when

[4]This conclusion might be not very precise since we do not have data during the two subperiods: September 2000–September 2001 and March 2002–June 2002. The data during the two subperiods are either missing or discarded due to incomplete information

the price decreases and decrease their holdings when the price increases. However, this adjustment process incurs transaction costs, which may result in a relatively sluggish adjustment during a period of extremely fast price changes such as the bubble period, and hence the bet position ($\tilde{H}_{i,j,t}$) is not able to restore $\tilde{I}$. With this consideration, we re-do the regression including lags of $\bar{W}_{jt}$. Specifically,

$$\ln\left(\frac{H_{i,j,t}}{\bar{V}^o_{jt}}\right) = C - \alpha_{t-t_0}\ln(\bar{W}^o_{j,t}) - ... - \alpha_0\ln(\bar{W}^o_{j,t_0}) + \epsilon_{i,j,t}, \tag{1.20}$$

where t_0 represents the first quarter of 1998. From the 4th quarter of 1998 through the 1st quarter of 2003, the sums of coefficients for each quarter are as follows: -0.64, -0.634, -0.612, -0.63, -0.609, -0.609 -0.59, -0.656, -0.688, -0.660, and -0.661. While choosing the first quarter of 1998 as t_0 is somewhat arbitrary, the results from estimating (1.20) do suggest that adjustment costs may be important to explaining substantial deviations from the invariance hypothesis.

Overall, the invariance hypothesis works well when the stock market is in stable condition. During the bubble period, there is some discrepancy, and we suspect the identifying assumption that the holdings position has a constant linear relationship with the bet size is violated due to the sluggish adjustment process. The results from estimating (1.20) are consistent with the above adjustment arguments.

1.4.1.2 Regression across Different Stock Markets

In this section, we pool all quarters together and estimate log-linear regression (1.19) across different exchange platforms (AMEX, NYSE, and NASDAQ).

	NYSE	AMEX	NASDAQ	All
Number of Cusips	3,605	1,677	10,398	14,546
Number of Managers	6,354	4,392	6,348	6,500
Estimated Coefficient	−0.733	−0.647	−0.673	−0.703
	(0.0003)	(0.0015)	(0.0003)	(0.0002)
Estimated Constant	6.60	5.57	5.86	6.21
	(0.0035)	(0.0139)	(0.0037)	(0.0024)
R^2	0.2734	0.2830	0.3377	0.3173
#Obs	18,808,120	497,315	10,423,761	29,729,196

Notes: Using different exchange codes (the exchange codes of NYSE, AMEX and NASDAQ are 1,2 and 3 respectively), we divide total matched observations into three subsamples. This table reports the estimated results of three subsamples. Value included in the parentheses are White-corrected standard errors

Table 1.2: Log Linear Regression Results across Different Stock Markets

Results are reported in Table 1.2. For the NASDAQ, we have 10,423,761 manager-stock-quarter observations, 10,398 Cusips and 6,348 institutional managers. The estimated coefficient is -0.673. For the AMEX, we have the least number of observations, 497,315, and the estimated coefficient is -0.647. For both exchanges, estimated coefficients are almost equal to the predicted coefficient -0.667. For the New York Stock Exchange, things are a bit complicated. We have the largest number of observations, 18,808,120, and there are 3,605 Cusips and 6,354 managers. The estimated coefficient is -0.733, which is lower than the predicted result -0.667. In the next section, we will study observations in New York Stock Exchange further. Pooling all observations together, the estimated coefficient is -0.703.

1.4.1.3 The First Quarter of Each Year in NYSE

To further study the NYSE, we re-do the log linear regression across different quarters. Here we present only some results in Table 1.3. They are close to the theoretical prediction of $-2/3$ except during the bubble period and the Great Recession. From 1992 to 1998, estimated coefficients are -0.655, -0.64, -0.677, -0.676, -0.645, and -0.675; during the bubble period (1999–2003), estimated coefficients are -0.603, -0.566, and -0.632;[5] after the bubble period, estimated coefficients are -0.667, -0.647, -0.644, -0.646, and -0.678 in years 2004, 2005, 2006, 2008, and 2009 respectively; during the recent period (2010–2014), the estimated coefficients are -0.728, -0.711 and -0.721, which are a bit lower than the prediction of invariance hypothesis; the estimated coefficient goes back to -0.677 in 2015.

These estimated results across different quarters imply that the pooled NYSE coefficient -0.733 may be affected by the period from 2010 to 2014, which needs to be studied further. After dropping observations from 2009 to 2015, the estimated pooled coefficient for the NYSE is -0.694.

[5] Recall we have some missing periods.

Dates	#Obs	Cusips	Managers	Regression Coeff	Constant	R^2
31mar1992	115,690	1007	1111	−0.655	6.136	0.2477
				(0.0033)	(0.0366)	
31mar1994	140,047	1191	1210	−0.677	6.388	0.2634
				(0.0030)	(0.0346)	
31mar1997	175,348	1406	1432	−0.645	6.071	0.2904
				(0.0024)	(0.0285)	
31mar1999	219,946	1472	1722	−0.603	5.374	0.2353
				(0.0023)	(0.0298)	
31mar2003	253,031	1283	2043	−0.632	5.452	0.2286
				(0.0023)	(0.0308)	
31mar2005	296,526	1273	2363	−0.647	5.425	0.1716
				(0.0026)	(0.0346)	
31mar2008	317,407	1232	2972	−0.646	5.397	0.1701
				(0.0025)	(0.0369)	
31mar2010	306,199	1201	2913	−0.728	6.164	0.2121
				(0.0025)	(0.0343)	
31mar2014	389,759	1260	3516	−0.721	6.026	0.1597
				(0.0026)	(0.0361)	

Notes: Only using NYSE observations, this table reports estimated results for the first quarter of some years.

Table 1.3: Log Linear Regression Results for NYSE

1.4.2 Quantile Regression

In previous sections, we estimate coefficients using linear regression. The results are broadly in accordance with the prediction of the invariance hypothesis. However, these estimation results only show how the mean of log holdings divided by expected volume responds to the change of log expected trading activity. We are not sure if managers with different holding positions have the same linear relationship with the log of expected trading activity. In this section, we use quantile regression to study and test the invariance hypothesis. Our results are reported in Tables 1.4 and A.4. Estimated coefficients in the first quarter of years 1992, 1994, 1997, 1999, 2003, and 2005 are plotted in Figure 1.6. For each quarter, we use quantile regression to estimate the linear relationships between the 1st, 10th, 25th, 50th, 75th, and 90th percentiles of the log of holdings divided by expected volume and the log of expected trading activity. As plotted in Figure 1.6, the estimated coefficients in most subfigures fluctuate around the value of $-2/3$ predicted by the invariance hypothesis. Among 108 estimated coefficients shown in Tables 1.4 and $A.4$, there are only 16 coefficients having differences greater than 0.1 from -0.667. All 16 of these coefficients are from quarters after March 1998, and most of them come from the 1st or the 10th quantile regression, suggesting that the invariance hypothesis applies to most holdings but not to very small positions.

1.4.3 Testing the $-2/3$ Law on the Full Sample

Pooling all observations together, we do the following estimation to formally test the invariance hypothesis' prediction of a $-2/3$ law:

$$\ln\left(\frac{H_{i,j,t}}{\bar{V}^o_{jt}}\right) + 2/3\ln(\bar{W}^o_{j,t}) = C + \alpha_0 \ln(\bar{W}^o_{j,t}) + \epsilon_{i,j,t}, \tag{1.21}$$

The null hypothesis that α_0 is zero is statistically rejected. But this rejection may be due to the very large size of our sample. We have millions of observations and hence the standard error (0.0002) is very small, yielding a large t value and making α_0 significant. The estimated coefficient is very small and equal to -0.036. In addition, both the upper support and the lower support of the 95% confidence interval are near zero, suggesting that α_0 is economically close to zero.

In the next section, we directly study whether the distribution $\tilde{I}_{i,j,t}$ is invariant.

Specifically, we study the stronger hypothesis proposed by Kyle and Obizhaeva (2016a) that the distribution $\tilde{I}_{i,j,t}$ is not only invariant but also log-normal. Our empirical results justify the strong version during periods from 1990 to the first quarter in 1998. While the strong version fails to hold during period from the second quarter in 1998 to 2015, the weak version that the mean is invariant continues to hold.

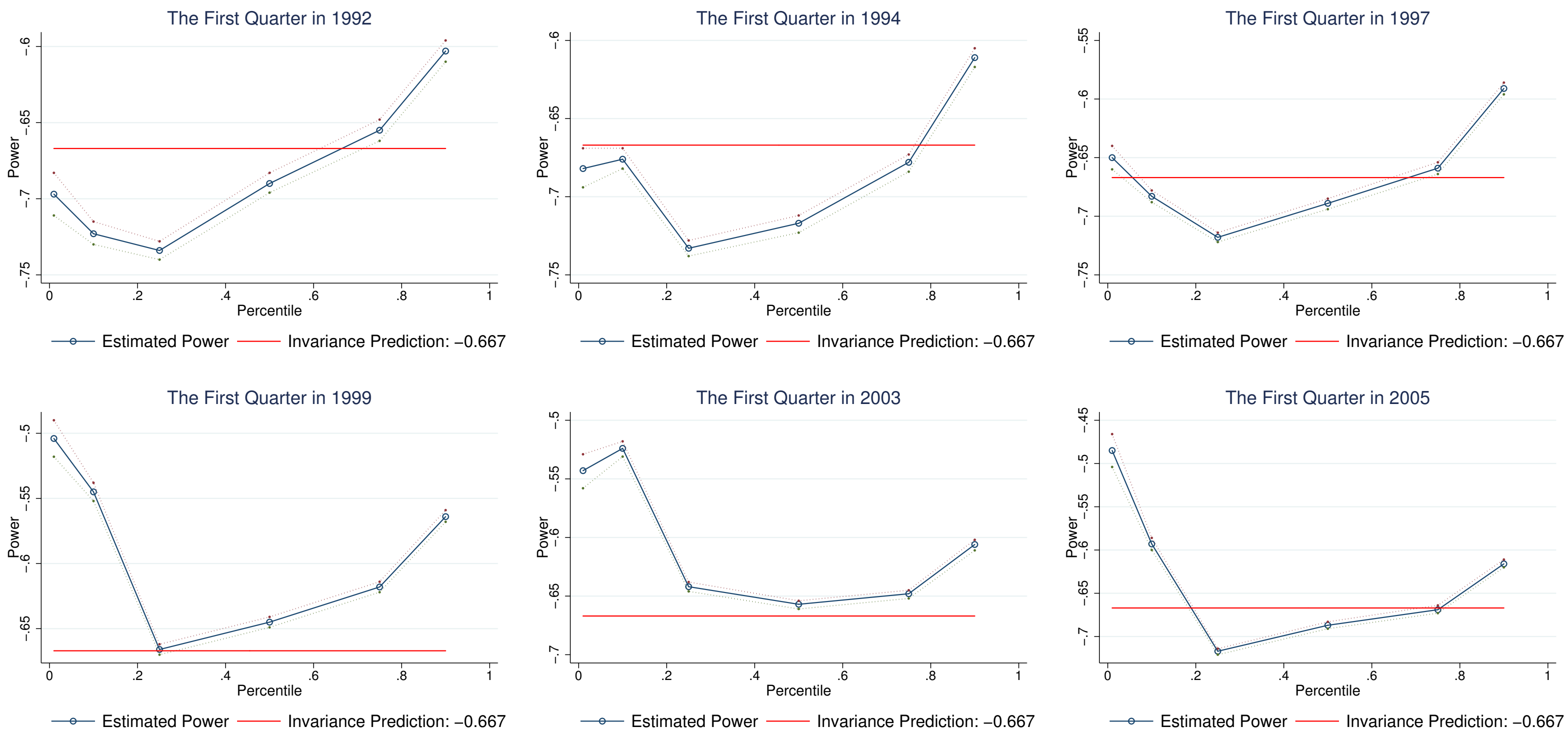
	1st	10th	25th	50th	75th	90th
31mar1992	−0.697	−0.723	−0.734	−0.690	−0.655	−0.603
	(0.0075)	(0.0039)	(0.0028)	(0.0030)	(0.0035)	(0.0034)
31mar1993	−0.677	−0.693	−0.727	−0.685	−0.656	−0.600
	(0.0065)	(0.0035)	(0.0026)	(0.0028)	(0.0031)	(0.0031)
31mar1994	−0.682	−0.676	−0.733	−0.717	−0.678	−0.611
	(0.0065)	(0.0035)	(0.0026)	(0.0027)	(0.0028)	(0.0028)
31mar1995	−0.672	−0.687	−0.738	−0.708	−0.680	−0.616
	(0.0065)	(0.0032)	(0.0026)	(0.0027)	(0.0028)	(0.0027)
31mar1997	−0.650	−0.683	−0.718	−0.689	−0.659	−0.591
	(0.0051)	(0.0026)	(0.0021)	(0.0023)	(0.0024)	(0.0024)
31mar1998	−0.669	−0.730	−0.747	−0.701	−0.662	−0.593
	(0.0049)	(0.0024)	(0.0021)	(0.0022)	(0.0024)	(0.0025)
31mar1999	−0.504	−0.545	−0.666	−0.645	−0.618	−0.564
	(0.0070)	(0.0036)	(0.0021)	(0.0019)	(0.0020)	(0.0022)
31mar2000	−0.457	−0.478	−0.601	−0.603	−0.588	−0.541
	(0.0064)	(0.0032)	(0.0020)	(0.0018)	(0.0019)	(0.0021)
31mar2003	−0.543	−0.524	−0.642	−0.657	−0.648	−0.606
	(0.0075)	(0.0033)	(0.0019)	(0.0018)	(0.0019)	(0.0021)

Notes: Using the regression

$$\ln\left(\frac{H_{i,j,t}}{\bar{V}^o_{jt}}\right) = C - \alpha \ln(\bar{W}^o_{j,t}) + \epsilon_{i,j,t},$$

we estimate how the 1st, 10th, 25th, 50th, 75th and 90th percentiles of $H_{i,j,t}/\bar{V}^o_{jt}$ respond to the change of $\ln(\bar{W}^o_{j,t})$. Estimated coefficients and White-corrected standard errors are reported in the first line and second line respectively. This table reports quantile regression results from March 1992 to March 2003. White-corrected standard errors are included in the parentheses.

Table 1.4: Quantile Regression for the First Quarter of Years (1992–2003)



Notes: This figure plots 1st, 10th, 25th, 50th, 75th and 90th quantitle regression results.

Figure 1.6: Quantile Regression in the First Quarter of Years 1992, 1994, 1997, 1999, 2003, and 2005

1.4.4 The First Subsample: 1990 through 1998 Q1

In this section, we shall study the distribution of the following random variable I^* obtained by transforming equation (1.18):

$$\ln\left(\frac{H_{i,j,t}}{\bar{V}^o_{j,t}}\right) + \ln(\bar{W}^o_{j,t})^{2/3}. \tag{1.22}$$

Pooling data, the common mean and variance are 6.39 and 3.292 respectively. Considering that we have many observations, the variance 3.292 is statistically similar to the 2.58 obtained in Kyle and Obizhaeva (2016a). To check if the distribution of I^* is normal and invariant, two specifications are employed: first, we pool observations together and examine each quarter in each year, where the null hypothesis is that moments of I^* are the same across different quarters and in accordance with the common mean 6.35 and variance 3.29; second, observations are divided into 7 regions in terms of expected volatility $\bar{\sigma}$ or expected volume divided by outstanding shares, with thresholds corresponding to the 1st percentile, 10th percentile, 25th percentile, 50th percentile, 75th percentile, and 90th percentile as shown in Table 1. The null hypothesis is that moments of I^* are the same across different regions and in harmony with common moments.

1.4.4.1 I^* across Different Periods

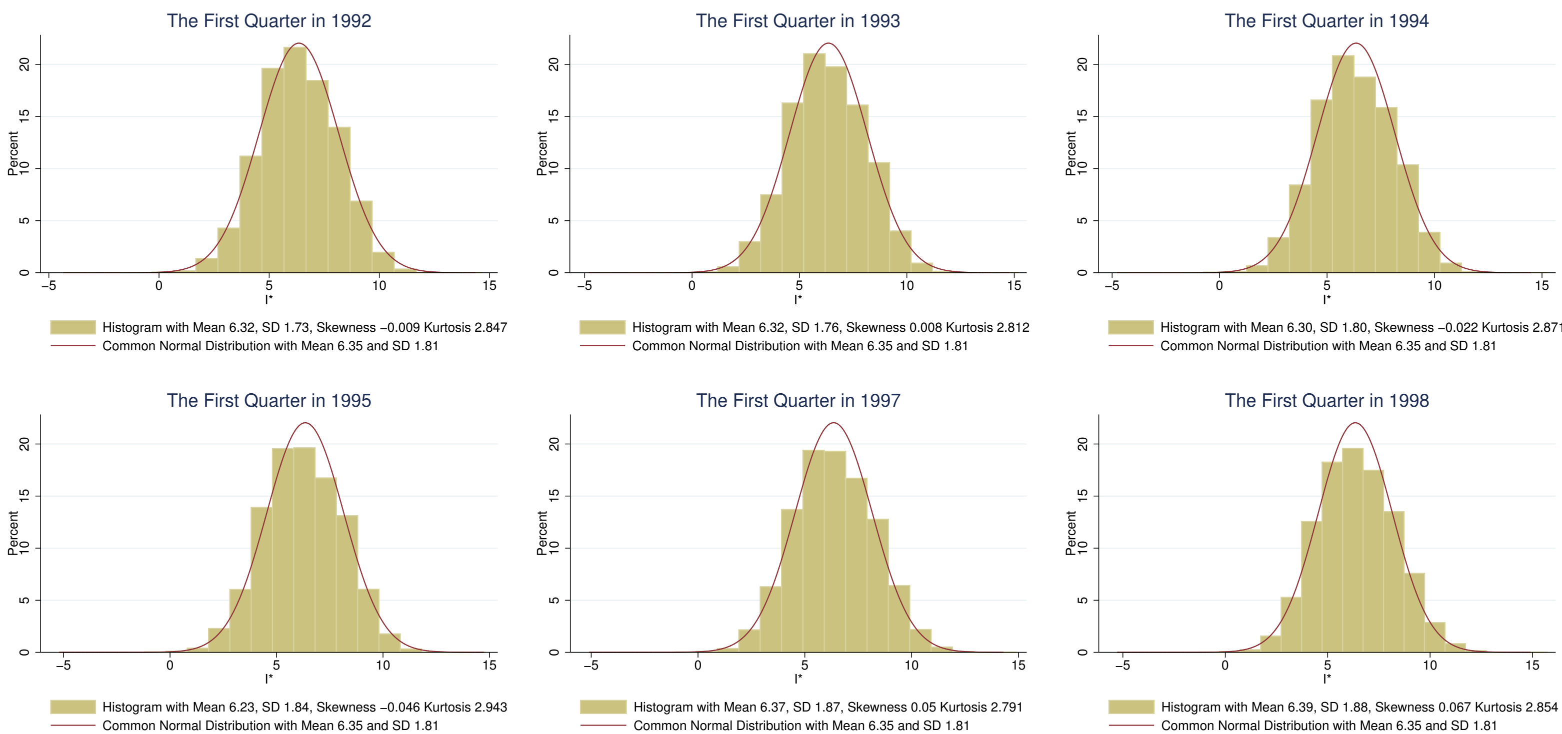
In this section, we compute moments of I^* for the first quarter of each year. The distributions for the six quarters are plotted in Figure 1.7. In each subplot, we superimpose the common normal distribution. There are only small differences between the common mean and the mean of each quarter, as the quarterly means are 6.32, 6.32, 6.30, 6.23, 6.37, and 6.39 respectively. While there is an upward trend of the standard deviation as the number of managers filling out the 13F form increases, all standard deviations are still very close to the common standard deviation 1.81, making the argument that distributions of I^* are invariant across different quarters convincing.[6]

1.4.4.2 I^* across Stocks with Various Levels of Activity

As documented in section 1.3.2, two variables are used to quantify the level of activity in particular stocks, $\bar{\sigma}$ and $\bar{V}/S$, where S is outstanding shares. There are two interesting findings in section 1.2 : investors dislike stocks with extremely high daily volatility (daily volatility greater than or equal to 0.04); and investors favor stocks with high turnover rates. It is interesting to study if the distributions of I^* are invariant across stocks with various levels of volatility or liquidity. In this section, observations are divided into 7 regions in terms of these 2 variables with thresholds corresponding to the 1st, 10th, 25th, 50th, 75th, and 90th percentiles displayed in Table 1.1. All results are plotted in Figures 1.8 and 1.9 respectively. Except for the mean of the first region, all moments are very close to an invariant normal distribution with a mean 6.35, a standard deviation 1.81, a skewness 0, and a kurtosis 3 in Figure 1.8. Results are similar in Figure 1.9, making the argument

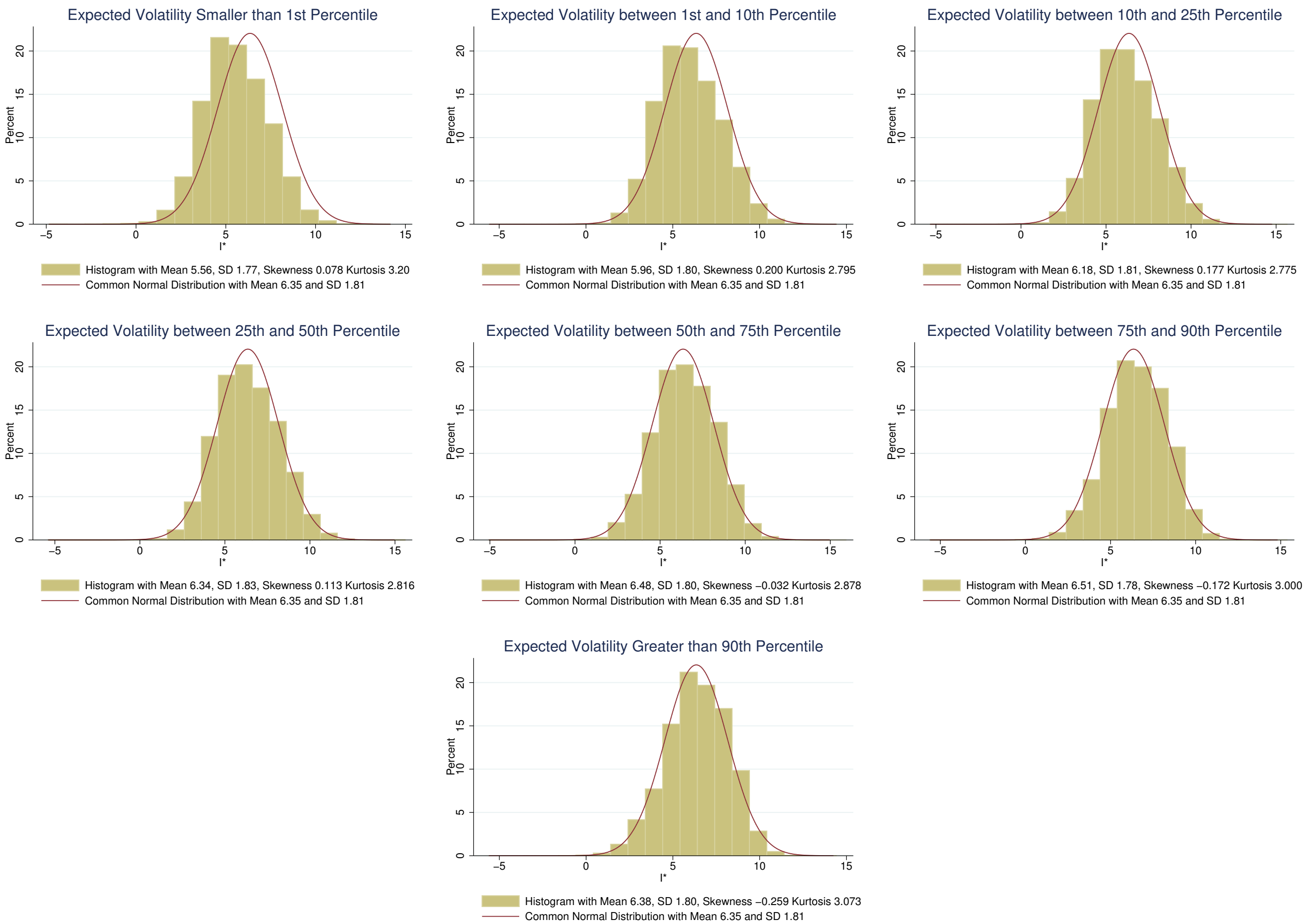
[6] In this paper, we don't present results from the 1980s, but they are almost the same as those presented here.

that distributions of I^* are invariant across stocks with various levels of activity convincing.



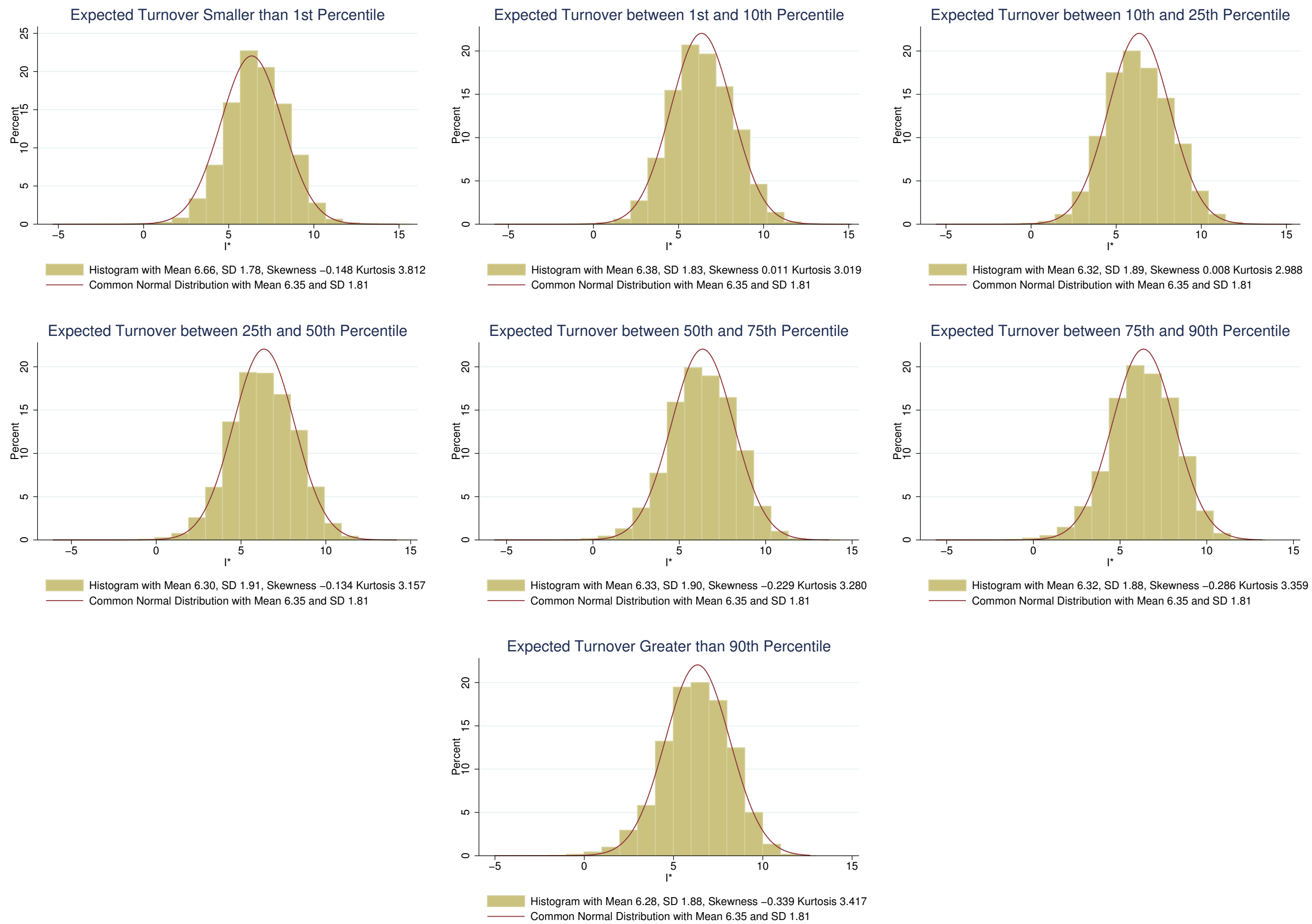
Notes: This figure plots the distribution of I^* defined as $\ln(H_{i,j,t}/\bar{V}^o_{jt}) + 2/3\ln(\bar{W}^o_{j,t})$.

Figure 1.7: The First Quarter of Years 1992, 1993, 1994, 1995, 1997, and 1998



Notes: This figure plots the distribution of I^* for the 7 regions respectively.

Figure 1.8: Distributions of Stocks with Different Expected Volatility



Notes: This figure plots the distribution of I^* for the 7 regions respectively.

Figure 1.9: Distributions of Stocks with Different Expected Turnover Rate

1.4.5 The Second Subsample: 1998 Q2 through 2015

The second subsample rejects the strong version of the invariance hypothesis as the variance of I^* increases over time. We proceed to study the weak version and calculate the following value for each stock in each quarter. The null hypothesis is that the following value should be invariant across different stocks and across different quarters

$$\ln E\left\{\frac{\tilde{H}_{jt}}{\bar{V}^o_{jt}}\right\} + 2/3 \ln \bar{W}^o_{jt}. \tag{1.23}$$

Using the mean of managers' holdings of stock j at time t, results for 23 quarters are shown in Tables A.5 and A.6. To reduce outliers, the 1st percentile and the maximum are not reported. There are two obvious features: first, while there are some small fluctuations, the 10th, 25th, 50th, 75th, and 90th percentiles are almost invariant across different quarters; second, the value of (1.23) ranges between 6 and 8 for more than 80% of stocks, and given there are thousands of stocks in each quarter, this range is small.

In Section 1.3.2, we found that more than half of stocks are held by fewer than 50 managers, suggesting that the sample for each stock might be small. So we also calculate the mean of $\ln E\{\tilde{H}_{jt}/\bar{V}^o_{jt}\} + 2/3 \ln \bar{W}^o_{jt}$ in each quarter. All of these values are found to be close to 7.7.

1.5 Robustness Checks

In this section, we re-examine our regression results by considering various robustness checks.

1.5.1 Winsorize Variables

To reduce the impact of outliers, we winsorize variables such as holdings, prices, expected volumes and expected volatility at 1%. We re-do regressions quarter by quarter. The mean and standard deviation of these 75 newly estimated coefficients or powers are -0.663 and 0.032 respectively. The maximum and minimum are -0.554 and -0.707 respectively. These newly estimated coefficients are not presented but are very similar to Figure 1.3.

We also re-do the regressions for the different stock exchanges. The newly estimated coefficients for NYSE, NASDAQ AND AMEX are -0.734, -0.652 and -0.683 respectively.

1.5.2 Re-Construct $\bar{V}$ and $\bar{\sigma}$

In Section 1.4, we construct $\bar{V}^o$ and $\bar{\sigma}^o$ using data from the previous 20 days. In this section, we use data from the previous 60 days, which approximates the number of working days in a quarter.

We calculate differences between the estimated powers in Section 1.4 and estimated powers in the current section. The maximum, the mean and the minimum of the differences are 0.02, 0.003 and -0.029 respectively. The standard deviation of the differences is about 0.009. So the regressions in this section quantitatively confirm our previous results. Moreover, as was the case in Figure 1.5, the newly estimated coefficients are consistent with the prediction of the market microstructure invariance hypothesis except during the bubble period (1998–2003). The newly estimated power rises to its peak (-0.539) in June 2000 on the exact day the previous estimated power rises to its peak (-0.548). Hence, the regression results in this section also qualitatively confirm our previous results.

1.5.3 Falsification Test

In Section 1.4, the dependent variable is holdings scaled by expected volume, and the econometric setting is implied by the invariance hypothesis. Our empirical tests are consistent with the prediction ($-2/3$ law) of market microstructure invariance. In this section, we test if the $-2/3$ law also applies to relationships not implied by the invariance hypothesis. To this end, we do an alternative empirical test,

$$\ln \frac{H_{i,j,t}}{\bar{V}_{j,t}} = C - \frac{2}{3} \ln(P_{j,t} S_{j,t} \sigma_{j,t}) + \epsilon_{i,j,t}, \tag{1.24}$$

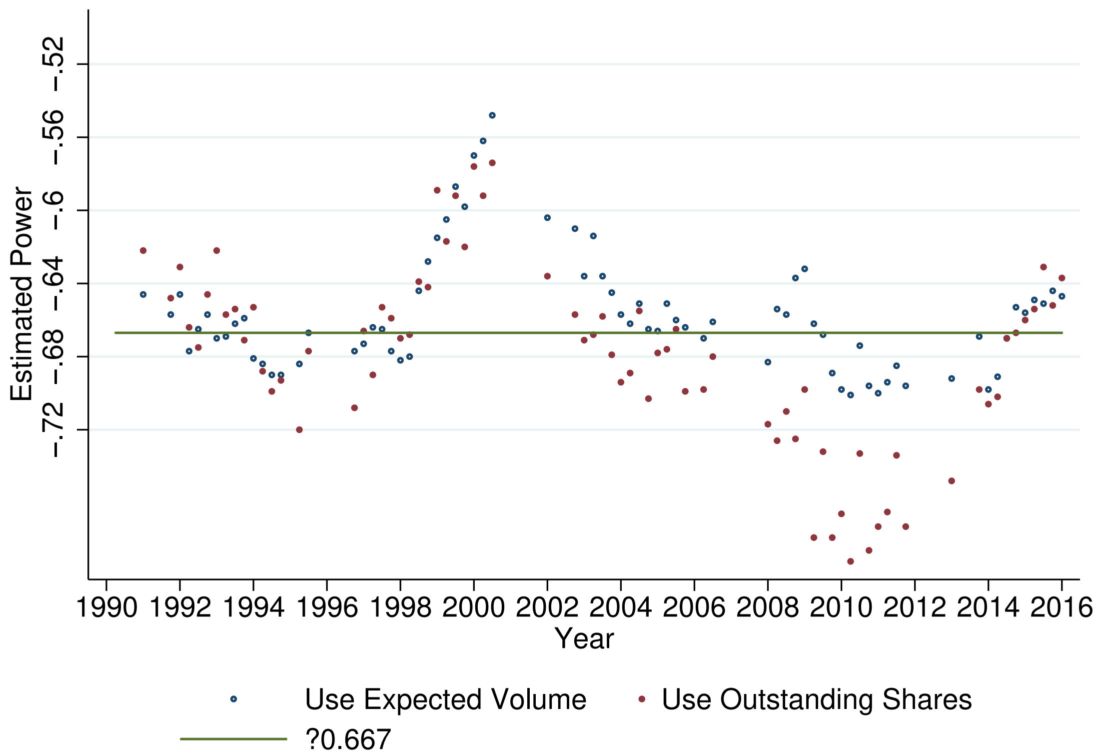
where $S_{j,t}$ is the number of outstanding shares of stock j at time t. There are two reasons why we use outstanding shares to substitute for expected volume on the right side. For one thing, there is a strong correlation between volume and outstanding shares. For another thing, the core definition of market microstructure invariance is a bet. Using the bet rate $\tilde{\gamma}$ and bet size $\tilde{Q}_{i,j,t}$, the market microstructure invariance has implications for expected volume. But the invariance hypothesis doesn't have any implication for outstanding shares. Using outstanding shares to substitute for expected volume in the regression, we should expect that either the R^2 becomes smaller given the validity of the invariance hypothesis, or that the newly estimated coefficients are further away from $-2/3$.

Again, we do this regression quarter by quarter. Our results are shown in Figures 1.10–1.11. The result is visually ambiguous in Figure 1.10.[7] However, Figure 1.11 shows that all R^2 using outstanding shares (red points) are smaller than those using expected volume, suggesting that the invariance hypothesis-implied predictor has more explanatory power.

1.6 Conclusion

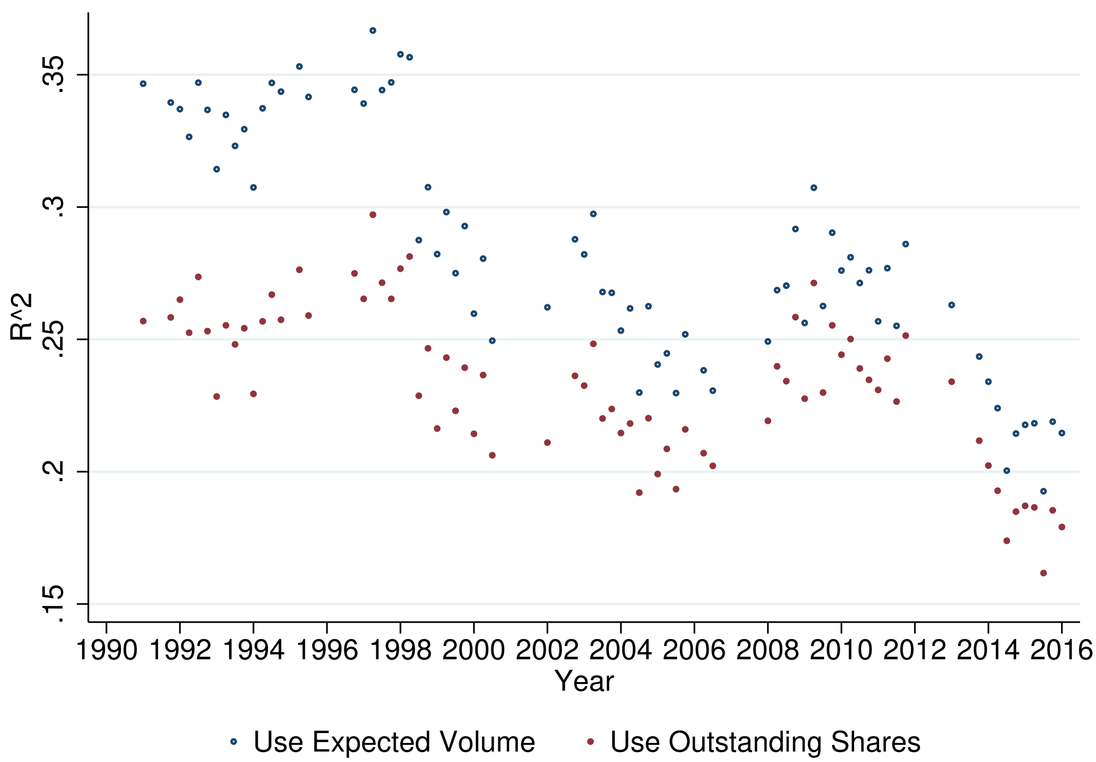
The market microstrucuture invariance hypothesis postulates that the distribution of dollar risk transferred by a bet per unit of business time is the same across different assets and across different time periods. This hypothesis implies that the log of bet size scaled by expected volume has a constant linear relationship with the log of expected trading activity, defined as the product of expected volatility and expected dollar volume. With the identifying assumption that the holding position has a constant linear relationship with the size of a bet, this paper studies and tests this hypothesis. Using various specifications, empirical tests statistically reject but are qualitatively largely consistent with the prediction of the invariance hypothesis.

[7] To be precise, 46 out of 75 newly estimated coefficients using outstanding shares are further away from -0.667 than those using expected volume.



Notes: This figure compare 75 estimated powers using outstanding shares (red points) and estimated powers using expected volume (blue points). We superimpose a red line, of which the value is -0.667.

Figure 1.10: Comparison of Estimated Powers



Notes: This figure compare R^2 of 75 tests using outstanding shares (red points) and tests using expected volume (blue points).

Figure 1.11: Comparison of R^2

Chapter 2: On the Role of Convertible Debt on Investment

2.1 Introduction

According to Calamos (2018),[1] the new issuance of convertible securities in the United States increased by 61% in 2018. A simple calculation suggests that the average issuance of convertible securities over the past 21 years was $51.2 billion per year. As convertible securities become more important for firms, economists have put significant effort into studying different roles of convertible bonds, one of the most important convertible securities.

This paper studies how firms' debt composition, and in particular the ratio of convertible bond value to the total debt value, affects firms' investment under different industry structures. We formulate two empirical hypotheses concerning the interaction effects of debt composition and competition on investment, building a bridge between the literature on the relation between convertible debt and investment and the literature on the relation between competition and investment.

Many researchers have studied how competition or industry structure affects firm investment: Spence (1977), Dixit (1980), and so on. Empirically, Akdogu and Mackay (2008) and Jiang, Kim, Nofsinger and Zhu (2015) find that there is a positive

[1] See page 9 of Calamos (2018), who in turn references Merrill Lynch Global Research.

relation between market competition and investment. Akdogu and Mackay (2008) argue that the sensitivity of investment to Tobin's Q is lower and investment speed is slower in monopolistic industries than competitive industries. Due to firms' strategic incentives to deter entry or induce exit, they find that the investment-Q sensitivity and investment speed are highest in oligopoly industries. In existing empirical work on competition and investment, the only financial instrument hypothesized to affect investment is total debt. We show that investment depends on the composition as well as the level of debt.

While there is a significant literature studying how convertible debt affects firm investment, which will be discussed in the next section, this work has not studied the effect of convertible bonds on investment under different industry structures (as measured by, say, the Hirschmann-Herfindahl Index). We show that convertible debt plays a different (positive or negative or insignificant) role across different industry structures. Convertible debt has a positive and significant effect on investment in very competitive industries, whereas convertible debt has either a negative and significant or insignificant effect in less competitive industries.

To the best of our knowledge, our paper is the first paper studying the interaction effect of convertible debt and industry structure or competitiveness on firms' investment.[2] Our empirical results can be summarized as follows: Pooling observations together, convertible debt doesn't have a significant effect on investment. When observations are divided into three regions using the HHI constructed from

[2]Korkeamaki and Moore (2004a) use the proceeds of convertible debt to study how firms' own characteristics affect their investment speed, but they do not study the effect of debt composition and industry competitiveness.

sales, the results are different in the three regions. Specifically, in the first region, where HHI<0.1, which means the industries in this region are very competitive, convertible debt has a positive, concave, and significant effect on investment, and this effect is especially strong for firms with high leverage. In the second region, where 0.1<HHI<0.18, which means the industries in this region are less competitive, convertible debt has a negative, convex, and significant effect on investment. In the third region, where HHI>0.3, which means the industries in this region are monopolistic, convertible debt has an insignificant effect on investment. Since warrants are similar to convertible bonds, we suspect warrants would have similar interaction effects on investment.

2.2 Literature Review and Hypothesis Development

Many researchers have studied convertible bonds from different perspectives. In this section, we briefly review the literature on convertible bonds and develop our hypotheses. For a detailed review on convertible bonds, see the work of Dutordoir, Lewis, Seward, and Veld (2014).

Convertible debt, a hybrid instrument of equity and straight debt, provides investors with a way of obtaining a relatively safe return on investment while offering an option to take advantage of upward movements of stock prices by converting the straight debt into equity if the issuer performs well. Investors can voluntarily convert their debt into equity. Most convertible bonds have a call provision, which allows the issuer to force the investor to choose between being paid back the straight debt or converting into equity. If there is weak or no call protection, the issuer is able to force conversion whenever they want. Embedding weak or no call protection into convertible debt is costly to the issuer. Since it benefits the issuer, such bonds are cheaper (Korkeamaki and Moore (2004b)). According to their study, weak call protection was more popular before 1988 whereas hard call protection was more popular after 1988. Asquith and Mullins (1991) find that firms' mangers don't want to convert bonds into equities, instead they wait for investors convert voluntarily. An important reason is that firms benefit from paying less in interest than in dividends. When adverse selection make equity issuance less attractive, the existence of convertible debt can make the economy efficient (e.g., investment is efficient and claims are priced fairly), as shown by Stein (1992).

Many researchers have studied how convertible debt solves agency conflicts and hence affects firms' investment. Jensen and Meckling (1976) and Green (1984) suggest that convertible bonds or warrants are able to reduce existing shareholders' risk-shifting incentives. Dorion, Francois, Grass, and Jeanneret (2014) and Eisdorfer (2008) empirically confirm that convertible debt reduces risk-shifting incentives, especially for financially distressed firms. The intuition is as follows: when a firm has high leverage, existing shareholders have incentives to invest in risky projects or invest during periods when volatility is high. If things don't go well, the loss for existing shareholders is not big since their equity is an out-of-the money option with little value. If things do go well, existing shareholders can benefit. However, convertible debt holders can convert their debt into equity when things go well, diluting existing shareholders' profits and reducing their incentive to invest in risky projects. Maksimovic (1988) builds a collusive model, showing that warrants or convertible debt can serve as a contingent tax on existing shareholders if they deviate from a collusive strategy by producing more output. The conversion of warrants or convertible debt into equity dilutes existing shareholders' profit, deterring them from deviating from the collusive strategy. This convertible-bond-dilution literature shows that the potential for dilution ex post deters existing shareholders from doing something ex ante.

Convertible bonds can also facilitate investment. Mayers (1998) argues that convertible bonds in a firm's capital structure facilitate the firm's investment when there is a profitable investment opportunity, since it can reduce interest payments and the firm's leverage upon call conversion, which is helpful for refinancing. Motivated by Mayers' work, Korkeamako and Moore (2004b) study how a firm's investment speed affects the call provision embedded in convertible bonds. More recently, Lyandres and Zhadanov (2014) build a model showing that convertible debt induces firms to invest quickly and that an appropriate composition of convertible debt and straight debt is able to completely solve the under-investment issue induced by straight debt (i.e., the classical debt overhang problem, see Myers (1977)). We simply refer to these works as the convertible-bond-facilitation literature.

It is possible that both facilitation role associated with relaxed financial constraints and the dilution role associated with agency issues interact simultaneously. Although not explicitly assumed in the convertible-bond-dilution literature, the potential of dilution ex post may deter existing shareholders from investing ex ante. This paper tries to rationalize these two (and potentially opposing) roles in a simple framework. We hypothesize that the agency issue associated with dilution is less significant for firms which face significant external competitive pressure and is more significant for firms which do not face significant external competitive pressure. These hypotheses are similar to the conventional wisdom of political economy that external war tends to generate common interests across groups in society whereas internal civil war entails deep conflicting interests across groups (These words are borrowed from Besley and Persson (2008)), and perhaps are more close to the view of Giroud and Mueller (2011) that firms in competitive industries benefit less from good governance than firms in less competitive industries. The theoretical rationale behind the latter study is that CEOs or managers in competitive industries tend to reduce slack and work hard, striving to reach a given target (Hart (1983)) or prevent liquidation (Schmidt (1997)). Consequently, there is not much a role for good governance.

Hypothesis 1: In very competitive industries where firms are facing pressure to survive and have less market power, the issuers' option to force conversion, which turns debt into equity, alleviating firms' debt pressure and reducing interest payments, has a positive effect on investment. Convertible debt encourages investment more in competitive industries than in noncompetitive industries.

Hypothesis 2: In less competitive industries where firms don't face competitive pressure to survive and have more market power, the bondholders' option of voluntary conversion, which turns debt into equity and dilutes existing shareholders' profits, deters firms from investing, including strategically over-investing to deter entry or induce opponents to exit. Convertible debt discourages investment more in noncompetitive industries than in competitive industries.

2.3 Data and Empirical Studies

This paper uses annual data provided by Compustat. Our sample covers the period from January 1985 to December 2005. All observations which report the item *dcvt* (long term convertible debt) are included. The HHI measure for each four-digit industry is constructed from the item *sales* (net). The dependent variable is the investment rate, which is defined as the item *capx* (capital expenditure) divided by the item *at* (total assets). Our key independent variable is debt composition or convertible debt share, which is defined as the item *dcvt* (long term convertible debt) divided by total debt.[3]

Following the investment literature (e.g., Dessaint, Foucault, Fresard, and Matray (2018) and Akdogu and Mackay (2008, 2012), a number of control variables are included. Firm size is the natural log of total asset value. The total debt level is calculated as the sum of two items: *dlc* (debt in current liabilities) and *dltt* (long-term debt). Market value is the product of *csho* (common shares outstanding) and *prcc_c*(price close-annual). Tobin's Q is the ratio of the sum of total assets and market value minus the item *ceq* (common equity) to total assets. Cash flow is

[3]Most research studying convertible debt's effect on firm' performance focuses on the comparison of before and after convertible issuance. For changes in stock returns, see, for example, Lee and Loughran (1998), Spiess and Affleck-Graves (1998), Lewis, Rogalski and Seward (2001). For changes in firms' operating performance, see, for example, Lee and Loughran (1998) and Lewis, Rogalski and Seward (2001). For changes in risk, see, for instance, Lewis, Rogalski, and Seward (2002). These works do not study the effect of firms' debt composition (the ratio of convertible debt to straight debt), which is a key component in the study of Maksimovic (1988) and Lyandres and Zhadanov (2014). The only exception is Dorion, Francois, Grass, and Jeanneret (2014), who use debt composition as a control variable to study the effect of risk shifting incentives on the decision to issue convertible debt.

the sum of the item *ibc* (income before extraordinary items) and the item *dp* (depreciation and amortization). Cash holdings is the item *che* (Cash and Short-Term Investments). Debt level, cash flows, and cash holdings are all scaled by total assets. Firms' riskiness may affect their investment decisions ((Panousi and Papanikolaou (2012)) and their decisions in issuing convertible debt (Dorion, Francois, Grass, and Jeanneret (2014) and a series of works by Lewis). We use stock volatility, which is measured as the standard deviation of the previous 12 monthly returns, as a proxy for a firm's riskiness. Finally, firms' industry peers' characteristics (investment, debt composition, debt level, size, cash holdings, cash flows, and Q) are defined analogously and also included in our study.[4]

2.3.1 Data Statistics

The sample has 377,422 observations over the period from 1985 to 2005. Firms in the Finance ($6000 \leq$ sic ≤ 6999) and Utilities ($4900 \leq$ sic ≤ 4999) industries are excluded due to their regulatory requirements. Observations with negative sales or capital expenditure are excluded. The dependent variable is the investment rate of the next year (capital expenditure in the next year scaled by the total assets of the current year). Thus, we only keep firms with two consecutive years of data on capital expenditure. This leaves us with 16,276 firms and 240,836 observations. By merging with the item volatility, calculated using CRSP's monthly stock returns, 90,274 observations are not matched and we are left with 150,562 observations. Ta-

[4]For each characteristic, we calculate the equally-weighted mean of a firm's peers, defined as other Compustat firms in the same four digit industry.

ble 2.1 presents the relevant summary statistics.[5] The HHI is 0.0634, 0.1050, 0.1782, 0.2883 and 0.4459 at the 10th, 25th, 50th, 75th, and 90th percentiles respectively. We divide HHI into three regions: we refer to industries with HHI<0.1 as very competitive industries; we refer to industries located in the region with 0.1<HHI<0.18 as oligopoly industries; and we refer to industries located in the region HHI>0.18, as monopolistic industries. These cutoffs are the same as in Akdogu and Mackay (2008), who follow the standards of the Department of Justice and Federal Trade Commission. For all three regions, the key variable debt composition is 0 at the 10th, 25th, 50th, and 75th percentiles, respectively. Thus, summary statistics focus on the mean, 90th percentile and standard deviation.

There are 3,992, 4,482 and 7,492 observations with zero overall debt in the lower HHI region, the intermediate HHI region, and the large HHI region respectively. We include these observations in our reported results. Including or excluding these observations doesn't affect our results.

For all three regions, the overall debt level, defined as the ratio of overall debt to total assets, is zero at the 10th percentile. But there are differences in the mean debt levels across the three regions. The mean in the low HHI region is higher than the mean in the intermediate HHI region, which in turn is higher than the mean in the higher HHI region. These means are 0.245, 0.230, and 0.225 respectively. Another notable feature is that the debt level has a much larger standard deviation in the lower HHI region.

The mean of the convertible debt share, defined as the ratio of convertible

[5] These variables frequently appear in previous literature on investment.

debt to overall debt, is a bit lower in the low HHI region than in the intermediate HHI region but higher than in the large HHI region.

In the low HHI region, Tobin's Q is 0.916, 1.133, 1.568, 2.545, 4.333 at the 10th, 25th, 50th, 75th, and 90th percentiles respectively. In the intermediate HHI region, Tobin's Q is 0.900, 1.117, 1.529, 2.409, and 4.117 at the 10th, 25th, 50th, 75th, and 90th percentiles respectively, while in the large HHI region it is 0.872, 1.072, 1.435, 2.177, and 3.624 at the 10th, 25th, 50th, 75th, and 90th percentiles respectively, suggesting that the competitive industries have more growth opportunities than industries in the other two regions. Their means are 2.426, 2.274, and 2.096, respectively.

The investment rate, defined as next year's capital expenditure scaled by this year's total assets, suggests the same trend as Q. Its means across the three regions are 0.103, 0.077, and 0.063 respectively. In the low HHI region, the investment rate is 0.01, 0.025, 0.058, 0.118, and 0.224 at the 10th, 25th, 50th, 75th, and 90th percentiles respectively. In the intermediate HHI region, the investment rate is 0.008, 0.020, 0.043, 0.089, and 0.168 at the 10th, 25th, 50th, 75th, and 90th percentiles respectively. Lastly, the investment rate is 0.009, 0.019, 0.038, 0.072, and 0.128 at the 10th, 25th, 50th, 75th, and 90th percentiles respectively in the high HHI region.

Total assets, expressed as its natural log, has the same trend as Q and investment rate. The means in the three regions are 5.561, 5.198, and 5.081 respectively. At different percentiles, this item is higher in the lower HHI region than the intermediate HHI region. Other than the 90th percentile, it is higher in the intermediate HHI region than the high HHI region at the other 4 percentiles.

The variable volatility, defined as the standard deviation of the previous 12 monthly stock returns, suggests that industries in the lower HHI region are more risky than industries in the other two regions, as its mean is 0.147, which is a bit larger than 0.140 and 0.137, the means in the other regions. The volatility in the lower HHI region at the 10th, 25th, 50th, 75th, 90th percentiles is 0.0548, 0.082, 0.123, 0.184, and 0.262 respectively. The distributions of the volatility in the other two regions are very similar: for the intermediate HHI region, the volatility is 0.054, 0.081, 0.120, 0.173, and 0.244 at those 5 percentiles respectively; for the higher HHI region, the volatility is 0.052, 0.077, 0.115, 0.169, and 0.240 at those 5 percentiles respectively.

Cash flows, defined as its ratio to total assets, do not have a clear trend. While the mean -0.025 in the low HHI region is the smallest, compared to -0.013 in the intermediate HHI region and 0.008 in the high HHI region, the distribution of cash flows tells us a different story: the cash flow ratio is 0.078, 0.133, and 0.183 at the 50th, 75th, and 90th percentiles respectively in the low HHI region, which is higher than in the two other regions. The cash flow ratio is 0.071, 0.121 and 0.174 at the 50th, 75th, and 90th percentiles in the intermediate HHI region, and 0.073, 0.119, and 0.167 in the high HHI region.

The last variable, cash holdings scaled by total assets, has a similar trend as Q. Its mean is 0.219, 0.205, 0.172 in the three regions respectively. Cash holdings in the 10th, 25th, 50th, 75th, and 90th percentiles are largest in the low HHI region, which is counter-intuitive, given their higher debt level. In the low HHI region, holdings are 0.011, 0.037, 0.122, 0.335, and 0.603, compared to 0.008, 0.028, 0.107, 0.308, and 0.578, and 0.008, 0.026, 0.093, 0.245, and 0.469 in the intermediate HHI region and the high HHI region respectively.

2.3.2 Main Results

In this section, we study our two hypotheses regarding the impact of convertible debt on investment.

Given different HHI, our empirical model is formulated as follows:

$$I_{i,j,t} = \alpha_t + \delta_j + ConvertibleShare_{i,j,t-1} + (ConvertibleShare_{i,j,t-1})^2 + Q_{i,j,t-1} + X_{i,j,t-1} \tag{2.1}$$

where $I_{i,j,t}$ is the investment rate, and α_t and δ_j are time and industry effects, respectively, and $X_{i,j,t-1}$ includes a number of control variables, some of which are borrowed from previous work on investment (e.g., Akdogu and Mackay (2008, 2012), Dessaint et al (2018)). We estimate this specification for the pooled sample and for subsamples defined by HHI region. The regression results are reported in Tables 2.2, 2.3, and 2.4. In Table 2.2, the low HHI region, the intermediate HHI region and the high HHI region are HHI<0.09, 0.1<HHI<0.18, and HHI>0.4 respectively. To further study the robustness of these results, we change the cutoffs in Table 2.3 and 2.4. In Table 2.3, we have three regions: HHI<0.08, 0.11<HHI<0.17, and HHI>0.5. In Table 2.4, we have three regions: HHI<0.075, 0.12<HHI<0.16, and HHI>0.6.

	Small HHI			Intermediate HHI			Large HHI		
	Mean	90th	Std	Mean	90th	Std	Mean	90th	Std
Convertible Share$_{t-1}$	0.080	0.277	0.233	0.082	0.318	0.232	0.063	0.181	0.212
Total Leverage$_{t-1}$	0.245	0.542	0.753	0.230	0.512	0.333	0.225	0.500	0.258
Q_{t-1}	2.426	4.333	6.473	2.274	4.117	3.145	2.096	3.624	4.880
Investment Rate$_t$	0.103	0.224	0.424	0.077	0.168	0.159	0.063	0.128	0.149
Firm Size$_{t-1}$	5.561	8.756	2.335	5.198	7.995	2.156	5.081	8.142	2.259
σ_{t-1}	0.147	0.262	0.106	0.140	0.244	0.103	0.137	0.240	0.103
Cash Flow$_{t-1}$	−0.025	0.183	2.053	−0.013	0.174	0.529	0.008	0.167	0.374
Cash Holdings$_{t-1}$	0.219	0.603	0.236	0.205	0.578	0.234	0.172	0.469	0.200

Notes: This table reports summary accounting statistics for 107,664 observations from the period 1985 to 2005 obtained from Compustat and CRSP. There are 25,210, 29,188 and 53,266 observations in the low HHI region (i.e., HHI<0.1), the intermediate HHI region (0.1<HHI<0.18), and the large HHI region (HHI>0.18), respectively.

Table 2.1: Summary Statistics of Firms Reporting Convertible Debt (1985–2005)

	Full	Low HHI	Intermediate HHI	High HHI
$Q_{i,j,t-1}$	0.004^{**}	0.007^{***}	0.007^{***}	0.001^{**}
	(2.02)	(8.20)	(6.31)	(1.98)
Convertible $\text{Share}_{i,j,t-1}$	-0.004	0.031^{*}	-0.063^{***}	-0.013
	(-1.20)	(1.74)	(-5.87)	(-0.88)
Convertible $\text{Share}^2_{i,j,t-1}$	-0.000	-0.030	0.071^{***}	0.019
	(-0.20)	(-1.63)	(5.98)	(1.09)
Total $\text{Leverage}_{i,j,t-1}$	0.001	-0.026^{***}	-0.011^{**}	-0.011^{*}
	(0.10)	(-5.1)	(-2.19)	(-1.66)
$\sigma_{i,j,t-1}$	-0.029^{***}	-0.084^{***}	-0.001	-0.027^{**}
	(-3.28)	(-6.41)	(-0.05)	(-2.30)
Cash $\text{Flow}_{i,j,t-1}$	0.010	0.010^{***}	0.018^{***}	0.010
	(1.46)	(3.94)	(2.94)	(1.58)
Cash $\text{Holdings}_{i,j,t-1}$	0.011^{*}	-0.012^{*}	0.001	0.019^{**}
	(1.92)	(-1.79)	(0.13)	(2.27)
Firm $\text{Size}_{i,j,t-1}$	-0.004^{***}	-0.006^{***}	-0.002^{***}	-0.004^{***}
	(-6.08)	(-6.75)	(-3.72)	(-6.60)
Peers $I_{j,t}$	0.089^{***}	0.164^{***}	0.375^{***}	-0.203^{***}
	(2.20)	(4.72)	(4.13)	(-3.57)
R^2	0.121	0.197	0.129	0.189
#Obs	107,664	21,961	29,188	13,770

Notes: This table reports our main results: the estimated coefficients of independent variables across four samples: full sample, low HHI region (HHI<0.09), intermediate HHI region (0.1<HHI<0.18), and large HHI region (HHI>0.4). t statistics are in parentheses. Firm i's peers' variables are computed by averaging across firms in the same four-digit industry excluding firm i. Most of peers' variables including convertible share, convertible share square, Q, total leverage, $\sigma_{j,t}$, cash holdings, cash flows, and size are not reported in this table. Asterisks $***$, $**$, and $*$ represent 0.01, 0.05, and 0.10 significance levels.

Table 2.2: Linear Regression Results across Different HHI Regions

	Low HHI	Intermediate HHI	High HHI
$Q_{i,j,t-1}$	0.007^{***}	0.008^{***}	0.001
	(8.56)	(6.10)	(1.47)
Convertible $\text{Share}_{i,j,t-1}$	0.041^{**}	-0.054^{***}	-0.013
	(2.42)	(-4.26)	(-0.64)
Convertible $\text{Share}^2_{i,j,t-1}$	-0.047^{***}	0.065^{***}	0.025
	(-2.66)	(4.72)	(1.00)
Total $\text{Leverage}_{i,j,t-1}$	-0.025^{***}	-0.013^{**}	-0.012^{*}
	(-4.61)	(-2.45)	(-1.74)
$\sigma_{i,j,t-1}$	-0.084^{***}	0.019	-0.017
	(-6.62)	(0.69)	(-1.04)
Cash $\text{Flow}_{i,j,t-1}$	0.009^{***}	0.030^{***}	0.018^{**}
	(3.90)	(6.37)	(2.32)
Cash $\text{Holdings}_{i,j,t-1}$	-0.009	-0.005	0.030^{***}
	(-1.41)	(-0.84)	(2.68)
Firm $\text{Size}_{i,j,t-1}$	-0.005^{***}	-0.003^{***}	-0.004^{***}
	(-5.98)	(-4.02)	(-5.76)
Peers $I_{j,t}$	0.107^{***}	-0.000	-0.336^{***}
	(3.33)	(0.00)	(-4.29)
R^2	0.211	0.145	0.199
#Obs	17,884	22,123	7,960

Notes: This table reports the regression results of independent variables across three smaller samples: low HHI region (HHI<0.08), intermediate HHI region (0.11<HHI<0.17), and large HHI region (HHI>0.50). Values in parentheses are t statistics. Most of peers' variables including convertible share, convertible share square, Q, total leverage, $\sigma_{j,t}$, cash holdings, cash flows, and size are not reported in this table. Asterisks $***$, $**$, and $*$ represent 0.01, 0.05, and 0.10 significance levels.

Table 2.3: Linear Regression Results across Different Smaller HHI Regions

As shown in the first column of Table 2.2, which reports pooled results for the full sample, while Q, σ, cash holdings, size, and peers' investment rate all have a significant effect on investment, the effect of debt composition (convertible share in the table) is not significant. However, this result is misleading. When we divide our observations into three regions by the degree of competition, debt composition has a positive and significant effect on investment in the first region (low HHI) while overall debt has a negative and significant effect on investment. In the second region (intermediate HHI), debt composition has a negative and significant effect on

	Low HHI	Intermediate HHI	High HHI
$Q_{i,j,t-1}$	0.007^{***}	0.008^{***}	0.000
	(8.47)	(4.87)	(1.61)
Convertible Share$_{i,j,t-1}$	0.041^{**}	-0.071^{***}	-0.001
	(2.41)	(-5.14)	(-0.03)
Convertible Share$^2_{i,j,t-1}$	-0.047^{***}	0.090^{***}	0.009
	(-2.63)	(5.83)	(0.26)
Total Leverage$_{i,j,t-1}$	-0.026^{***}	-0.010	-0.013^{*}
	(-5.10)	(-1.40)	(-1.87)
$\sigma_{i,j,t-1}$	-0.088^{***}	0.032	-0.009
	(-6.79)	(0.86)	(-0.42)
Cash Flow$_{i,j,t-1}$	0.008^{***}	0.040^{***}	0.017^{*}
	(3.64)	(6.30)	(1.89)
Cash Holdings$_{i,j,t-1}$	-0.013^{*}	-0.006	0.030^{**}
	(-1.93)	(-0.84)	(2.21)
Firm Size$_{i,j,t-1}$	-0.005^{***}	-0.004^{***}	-0.004^{***}
	(-5.94)	(-3.76)	(-3.86)
Peers $I_{j,t}$	0.100^{***}	-0.191	-0.428^{***}
	(3.13)	(-0.98)	(-3.73)
R^2	0.217	0.147	0.212
#Obs	16,451	16,026	4,704

Notes: This table reports the regression results of independent variables across three smaller samples: low HHI region (HHI<0.075), intermediate HHI region (0.12<HHI<0.16), and large HHI region (HHI>0.60). Values in parentheses are t statistics. Most of peers' variables including convertible share, convertible share square, Q, total leverage, $\sigma_{j,t}$, cash holdings, cash flows, and size are not reported in this table. Asterisks $***$, $**$, and $*$ represent 0.01, 0.05, and 0.10 significance levels.

Table 2.4: Linear Regression Results across Different Smaller HHI Regions

	Low HHI	Intermediate HHI	High HHI
$Q_{i,j,t-1}$	0.005^{***}	0.006^{***}	0.010^{***}
	(6.68)	(5.85)	(4.95)
Convertible $\text{Share}_{i,j,t-1}$	0.058^{**}	-0.042^{**}	-0.027
	(2.16)	(-2.53)	(-1.20)
Convertible $\text{Share}^2_{i,j,t-1}$	-0.068^{**}	0.047^{**}	0.033
	(-2.34)	(2.50)	(1.27)
Total $\text{Leverage}_{i,j,t-1}$	-0.056^{**}	-0.005	-0.009
	(-2.44)	(-0.26)	(-0.50)
$\sigma_{i,j,t-1}$	-0.045^{**}	0.001	0.010
	(-2.43)	(0.07)	(0.64)
Cash $\text{Flow}_{i,j,t-1}$	0.027^{***}	0.031^{***}	0.012^{*}
	(4.58)	(4.22)	(1.83)
Cash $\text{Holdings}_{i,j,t-1}$	-0.009	-0.01	-0.006
	(-1.08)	(-1.64)	(-0.52)
Firm $\text{Size}_{i,j,t-1}$	-0.003^{***}	-0.002^{***}	-0.002^{**}
	(-4.01)	(-3.29)	(-2.20)
Peers $I_{j,t}$	0.61^{***}	0.525^{***}	-0.263^{***}
	(3.29)	(3.79)	(-3.38)
R^2	0.276	0.205	0.296
#Obs	10,336	16,975	$8,541$

Notes: This table reports the regression results of independent variables across three regions for firms with low-level leverage (smaller than 0.231): low HHI region (HHI<0.08), intermediate HHI region (0.1<HHI<0.18), and large HHI region (HHI>0.40). Values in parentheses are t statistics. Most of peers' variables including convertible share, convertible share square, Q, total leverage, $\sigma_{j,t}$, cash holdings, cash flows, and size are not reported in this table. Asterisks $***$, $**$, and $*$ represent 0.01, 0.05, and 0.10 significance levels.

Table 2.5: Linear Regression Results across Different HHI Regions for Firms with Lower Leverage

	Low HHI	Intermediate HHI	High HHI
$Q_{i,j,t-1}$	0.011^{***}	0.008^{***}	0.001^{**}
	(4.99)	(3.09)	(2.13)
Convertible $\text{Share}_{i,j,t-1}$	0.041^{*}	-0.044^{***}	-0.011
	(1.81)	(-3.40)	(-0.55)
Convertible $\text{Share}^2_{i,j,t-1}$	-0.060^{**}	0.049^{***}	0.026
	(-2.49)	(3.38)	(1.06)
Total $\text{Leverage}_{i,j,t-1}$	-0.038^{***}	-0.014^{*}	0.007
	(-4.19)	(-1.69)	(0.83)
$\sigma_{i,j,t-1}$	-0.101^{***}	0.009	-0.081^{***}
	(-5.17)	(0.21)	(-4.57)
Cash $\text{Flow}_{i,j,t-1}$	0.017^{***}	0.014^{*}	0.015
	(3.33)	(1.74)	(1.54)
Cash $\text{Holdings}_{i,j,t-1}$	0.006	0.029^{*}	0.018
	(0.42)	(1.69)	(1.27)
Firm $\text{Size}_{i,j,t-1}$	-0.009^{***}	-0.003^{***}	-0.005^{***}
	(-5.73)	(-3.06)	(-5.34)
Peers $I_{j,t}$	0.112^{**}	0.297^{**}	-0.068
	(3.52)	(2.41)	(-0.89)
R^2	0.183	0.105	0.222
#Obs	9,616	12,213	5,229

Notes: This table reports the regression results of independent variables across three regions for firms with high-level leverage (greater than 0.231): low HHI region (HHI<0.09), intermediate HHI region (0.1<HHI<0.18), and large HHI region (HHI>0.40). Values in parentheses are t statistics. Most of peers' variables including convertible share, convertible share square, Q, total leverage, $\sigma_{j,t}$, cash holdings, cash flows, and size are not reported in this table. Asterisks $***$, $**$, and $*$ represent 0.01, 0.05, and 0.10 significance levels.

Table 2.6: Linear Regression Results across Different HHI Regions for Firms with Greater Leverage

	Low HHI	Intermediate HHI	High HHI
$Q_{i,j,t-1} < 1.163$	0.065^{***}	-0.053^{***}	0.040
	(2.95)	(-3.47)	(1.49)
$1.163 < Q_{i,j,t-1} < 2.073$	0.060^{**}	-0.030^{**}	-0.021
	(2.35)	(-2.10)	(-1.37)
$Q_{i,j,t-1} > 2.073$	0.000	-0.081^{**}	-0.084
	(0.01)	(-2.16)	(-1.56)

Notes: This table reports the estimated coefficients of convertible share across three regions for firms with different Q (1.163 and 2.073 are 30th percentile and 70th percentile respectively): low HHI region (HHI<0.09), intermediate HHI region (0.1<HHI<0.18), and large HHI region (HHI>0.40). Values in parentheses are t statistics. Asterisks $* * *$, $**$, and $*$ represent 0.01, 0.05, and 0.10 significance levels.

Table 2.7: Linear Regression Results across Different HHI Regions for Firms with Different Q

investment. The effect is not linear but quadratic, for the coefficient of the quadratic term is positive and significant. Overall debt has a negative and significant effect on investment. In the third region (high HHI), the significance of debt composition disappears. Only overall debt has a negative and significant effect. The effect of debt composition is robust even as we narrow the three regions (see Tables 2.3 and 2.4), further supporting hypothesis 1 and 2. In addition, both the first order effect and the quadratic effects becomes more significant as we narrow the regions. A common result in the three tables is that peers' investment has a positive and significant effect on a firm's own investment rate in competitive industries, suggesting that firms in the first region face very significant external competitive pressure. Another common result shown in these tables, which is consistent with the finding of Akdogu and Mackay (2008), is that the investment-Q sensitivity is highest in oligopoly industries industries and lowest in monopolistic industries.

In our study, there is a gap between region 2 (0.1<HHI<0.18), where the effect of convertible debt is negative, and region 3 (0.4<HHI), where the effect of convertible debt is insignificant. We divide this gap to form a number of subregions using a width of 0.01. We find that the effect of convertible debt is insignificant for a number of subregions, negative and significant for a small number of subregions, and positive and significant for several subregions. Since this gap 0.18<HHI<0.4 is on the boundary of region 2 and region 3, these results are still consistent with our findings. However, for the sake of precision, we don't include this gap in our main regions.

We expect that the facilitation role of convertible debt, which is due to interest payment and leverage reduction (as argued by Mayers (1998)) and has a positive effect on investment, is more significant for firms with greater leverage and less significant for firms with lower leverage. To study this role, the whole sample is divided into two parts using the mean (0.231) debt ratio of all observations. For low leverage firms, neither the positive effect of convertible debt or the negative quadratic term is significant in the first region (HHI<0.09). These results are not reported in Table 2.5. As a comparison, both effects are significant in the first region (HHI<0.09) for high leverage firms, as shown in Table 2.6. When we decrease the cutoff point from 0.09 to 0.08, as shown in Table 5, the positive effect of convertible debt and the negative effect of the quadratic term are significant again even for low leverage firms. Table 2.5 and Table 2.6 report similar results (convertible debt has a positive, negative, and insignificant effect on investment in very competitive industries, oligopoly industries, and monopolistic industries respectively), consistent with our hypothesis and suggesting that our interaction effect is robust for firms with different leverage.

We expect that the dilution role, which has a negative effect on investment, is more significant for firms with high Q and less significant for firms with low Q. To study this role, we divide our sample into three parts using the 30th percentile and 70th percentile of the distribution of Q. Results are reported in Table 2.7. In the first region (HHI<0.09), the estimated coefficient of convertible debt is only significant in the first two subregions. When Q is very large (Q>2.073), the positive effect of convertible debt is no longer significant, even if we narrow the first region. In the second region (0.1<HHI<0.18), all estimated coefficients are negative and significant. In the third region (HHI>0.4), all estimated coefficients are not significant, suggesting that our interaction effect is robust for firms with different levels of Q.

2.3.3 Further Discussion

2.3.3.1 Call Protection

The empirical results presented in this paper suggest that convertible debt has a positive effect, a negative effect, and insignificant effect on investment rates, depending on the degree of competition, supporting our intuition that the facilitation role outweighs the dilution role in competitive industries while the dilution role outweighs or just cancels the facilitation role out in oligopolies and monopolies, respectively. If firms do not expect that they will call convertible debt, then firms will offer hard call protection, since such bonds will be expensive. If firms do expect that they will call convertible debt, then firms will offer weak call protection. Consequently, such bonds will be cheap. We expect that firms with low Q in very competitive industries will offer weak call protection whereas firms in less competitive industries will offer hard call protection. Korkeamaki and Moore (2004*b*) find that the number of years following issuance needed for firms' cumulative capital expenditure to exceed the proceeds has a positive correlation with call protection. The greater the number of years, the harder the call protection. As shown in Table 2.1, the investment rate is the highest in the first region, which may or may not indicate that the call protection offered by firms in the first region will be weak. We leave this question to a future study.

2.3.3.2 Existing Hypotheses

We argue that existing hypotheses cannot explain our empirical finding.

Eisdorfer (2008) and Dorion et al(2014) provide evidence arguing that financially distressed firms have a strong risk shifting incentive. Specifically, Eisdorfer (2008) argues that there is a positive relation between volatility and investment for financially distressed firms. Both find evidence that convertible debt curbs the risk shifting incentive. Using their results, and assuming that investment investment (capital expenditure scaled by total assets) represents risk shifting, convertible debt should have a negative and significant effect on investment for financially distressed firms. We, however, find that convertible debt has a positive and significant effect on investment for financially distressed firms in the first region, as shown in Table 6.

Our hypothesis is similar to Mayers' (1998) sequential investment hypothesis. We extend his work (facilitation role) by considering two opposing roles (facilitation role versus dilution role). If we use Q as a proxy for investment opportunities, using Mayers' results, we should expect that convertible debt has a positive effect on investment for firms with high Q and a negative effect on investment for firms with low Q. However, as reported in Table 7 and depending on region, convertible debt has either a negative and significant or an insignificant effect on investment for firms with high Q. For firms with low Q in the first region, convertible debt has a strong positive and significant effect on investment.

Putting aside Q for a moment, astute readers may still think the negative and significant effect on investment in the second region is due to convertible debt's role of curbing over-investment, which is benefical to existing shareholders. However, many researchers including Spence (1977), Dixit (1980) and Akdogu and Mackay (2012) argue that over-investment is optimal for existing shareholders when there is competition because firms want to induce exit or deter entry. If over-investment is optimal for existing shareholders, then the negative and significant effect might be due to dilution effect.[6]

2.4 Conclusion

This paper analyzes the interaction effect of convertible debt and industry competitiveness on investment. Using data from 1985 to 2005 provided by Compustat, we find interesting results: In very competitive industries, the effect of convertible debt on investment is positive, while in less competitive industries, the effect is negative. These results are consistent with our hypothesis that when firms face serious survival pressure, convertible debt serves as a convenient instrument for funding investment and deleveraging due to its conversion property Conversely, when firms face less survival pressure, the agency issue brought by conversion is more significant, which deters firms from investing.

These results have implications on announcement effects and long term effects of convertible debt issuance. If all investments are value enhancing and the ratio of convertible debt to total debt is small, then we expect that the announcement effect

[6]There might be 2 channels: One is conversion ex post decreasing the investment incentive ex ante. Another is that firms not willing to call convertible debt, which is still due to the dilution effect, have to pay interest and hence have less fund to invest.

of convertible debt is positive for firms with low Q in very competitive industries.

Chapter Appendix:

Dates	#Obs	Cusips	Managers	Regression Coeff	Constant	R^2
31dec1990	147,257	3006	1023	−0.646	6.12	0.3466
30sep1991	155,684	2842	1030	−0.657	6.25	0.3395
31dec1991	165,651	3116	1096	−0.646	6.227	0.3370
31mar1992	170,139	2989	1116	−0.677	6.439	0.3265
30jun1992	172,380	3104	1115	−0.665	6.36	0.3470
30sep1992	175,990	3369	1115	−0.657	6.24	0.3367
31dec1992	186,957	3658	1161	−0.670	6.35	0.3143
31mar1993	191,584	3589	1172	−0.669	6.342	0.3348
30jun1993	196,174	3619	1179	−0.662	6.273	0.3231
30sep1993	202,137	3850	1166	−0.659	6.252	0.3294
31dec1993	209,003	4089	1195	−0.681	6.455	0.3074
31mar1994	214,615	4119	1219	−0.684	6.499	0.3373
30jun1994	213,943	4176	1211	−0.690	6.584	0.3469
30sep1994	215,246	4158	1198	−0.690	6.522	0.3436
31mar1995	219,851	4210	1254	−0.684	6.425	0.3531
30jun1995	227,866	4354	1270	−0.667	6.276	0.3416
30sep1996	254,570	4769	1370	−0.677	6.441	0.3443
31dec1996	265,661	4995	1418	−0.673	6.452	0.3391
31mar1997	270,638	4969	1443	−0.664	6.347	0.3667
30jun1997	276,805	4944	1453	−0.665	6.372	0.3442
30sep1997	286,751	5035	1464	−0.677	6.550	0.3471
31dec1997	297,908	5122	1571	−0.682	6.644	0.3577
31mar1998	307,638	5059	1607	−0.680	6.551	0.3566
30jun1998	322,784	5077	1624	−0.644	5.969	0.2875
30sep1998	316,873	4890	1617	−0.628	5.894	0.3075
31dec1998	328,788	5096	1719	−0.615	5.646	0.2822

Notes: The following regression is implemented:

$$\ln\left(\frac{H_{i,j,t}}{\bar{V}^o_{jt}}\right) = C - \alpha \ln(\bar{W}^o_{j,t}) + \epsilon_{i,j,t}.$$

This table reports estimated results from December 1990 to December 1998. The variable *#Obs* reports the number of matched observations. The variable Cusips reports the number of unique Cusips on that day. The variable Managers report the number of unique asset managers who report their holdings on that day.

Table A.1: Log Linear Regression Results (dec1990–dec1998)

Dates	#Obs	Cusips	Managers	Regression Coeff	Constant	R^2
31mar1999	336,802	4949	1740	−0.605	5.412	0.2981
30jun1999	347,591	4811	1761	−0.587	5.175	0.2750
30sep1999	333,066	4741	1752	−0.598	5.356	0.2928
31dec1999	349,104	4857	1852	−0.570	4.973	0.2597
31mar2000	360,530	4805	1880	−0.562	4.928	0.2805
30jun2000	355,080	4599	1807	−0.548	4.640	0.2495
31dec2001	385,437	4261	1994	−0.604	5.111	0.2621
30sep2002	380,207	4016	2038	−0.610	5.210	0.2878
31dec2002	384,153	4013	2087	−0.636	5.44	0.2821
31mar2003	389,777	3805	2086	−0.614	5.189	0.2974
30jun2003	398,680	3820	2066	−0.636	5.398	0.2679
30sep2003	403,351	3822	2046	−0.645	5.528	0.2676
31dec2003	431,684	3841	2168	−0.657	5.648	0.2533
31mar2004	441,741	3803	2201	−0.662	5.782	0.2617
30jun2004	444,838	3792	2199	−0.651	5.54	0.2299
30sep2004	441,265	3781	2179	−0.665	5.736	0.2625
31dec2004	467,875	3807	2353	−0.666	5.695	0.2405
31mar2005	470,133	3793	2393	−0.651	5.474	0.2447
30jun2005	470,887	3804	2403	−0.660	5.567	0.2297
30sep2005	470,903	3773	2388	−0.664	5.665	0.2519
31mar2006	488,914	3806	2561	−0.670	5.671	0.2383
30jun2006	486,100	3770	2567	−0.661	5.673	0.2306
31dec2007	511,157	3765	3013	−0.683	5.915	0.2492
31mar2008	507,656	3689	3036	−0.654	5.549	0.2686
30jun2008	516,097	3682	3056	−0.657	5.444	0.2703
30sep2008	491,881	3663	2999	−0.637	5.436	0.2917

Notes: This table reports estimated results from March 1996 to September 2008.

Table A.2: Log Linear Regression Results (mar1999–sep2008)

Dates	#Obs	Cusips	Managers	Regression Coeff	Constant	R^2
31dec2008	481,563	3639	3044	-0.632	5.242	0.2562
31mar2009	474,334	3505	3050	-0.662	5.629	0.3073
30jun2009	484,877	3424	3019	-0.668	5.485	0.2626
30sep2009	479,404	3400	2913	-0.689	5.798	0.2903
31dec2009	486,458	3416	2983	-0.698	5.846	0.276
31mar2010	493,145	3361	2985	-0.701	5.828	0.281
30jun2010	485,812	3343	2963	-0.674	5.673	0.2713
30sep2010	487,249	3328	2830	-0.696	5.879	0.2761
31dec2010	503,968	3321	3033	-0.7	5.751	0.2568
31mar2011	516,811	3303	3059	-0.694	5.873	0.2769
30jun2011	512,935	3252	3059	-0.685	5.716	0.2551
30sep2011	496,243	3238	3023	-0.696	6.039	0.286
31dec2012	535,110	3262	3318	-0.692	5.66	0.263
30sep2013	568,495	3296	3273	-0.669	5.411	0.2435
31dec2013	609,084	3343	3584	-0.698	5.767	0.234
31mar2014	628,518	3366	3617	-0.691	5.649	0.224
30jun2014	637,103	3442	3639	-0.67	5.232	0.2004
30sep2014	635,876	3483	3574	-0.653	4.999	0.2144
31dec2014	633,556	3520	3587	-0.656	5.19	0.2177
31mar2015	631,984	3526	3573	-0.649	5.036	0.2183
30jun2015	636,554	3550	3542	-0.651	4.955	0.1926
30sep2015	628,097	3612	3473	-0.644	4.981	0.2189
31dec2015	624,049	3647	3438	-0.647	5.049	0.2146

Notes: This table reports estimated results from December 2008 to December 2015.

Table A.3: Log Linear Regression Results (dec2008–dec2015)

	1st	10th	25th	50th	75th	90th
31mar2004	−0.595	−0.625	−0.712	−0.695	−0.680	−0.623
	(0.0118)	(0.0033)	(0.0020)	(0.0020)	(0.0022)	(0.0024)
31mar2005	−0.485	−0.593	−0.717	−0.687	−0.669	−0.616
	(0.0102)	(0.0037)	(0.0020)	(0.0019)	(0.0022)	(0.0022)
31mar2006	−0.529	−0.624	−0.741	−0.703	−0.679	−0.628
	(0.0090)	(0.0038)	(0.0021)	(0.0019)	(0.0023)	(0.0023)
31mar2008	−0.536	−0.538	−0.703	−0.705	−0.686	−0.632
	(0.0071)	(0.0038)	(0.0020)	(0.0018)	(0.0019)	(0.0022)
31mar2009	−0.571	−0.556	−0.698	−0.705	−0.690	−0.652
	(0.0072)	(0.0037)	(0.0019)	(0.0016)	(0.0018)	(0.0021)
31mar2010	−0.667	−0.598	−0.768	−0.744	−0.701	−0.659
	(0.0082)	(0.0036)	(0.0019)	(0.0018)	(0.0020)	(0.0024)
31mar2011	−0.629	−0.618	−0.765	−0.724	−0.692	−0.659
	(0.0072)	(0.0041)	(0.0018)	(0.0017)	(0.0020)	(0.0024)
31mar2014	−0.546	−0.615	−0.777	−0.732	−0.686	−0.641
	(0.0076)	(0.0045)	(0.0020)	(0.0017)	(0.0021)	(0.0025)
31mar2015	−0.545	−0.516	−0.697	−0.698	−0.676	−0.632
	(0.0070)	(0.0040)	(0.0021)	(0.0017)	(0.0020)	(0.0023)

Notes: This table reports quantitle regression results from march 2004 to march 2015. We report estimated coefficients and White-corrected standard errors in the first and second line respectively for each quarter.

Table A.4: Quantile Regression for the First Quarter of Years (2004–2015)

Dates	Cusips	10th	25th	50th	75th	90th
30jun1998	5077	6.227	7.071	7.640	8.067	8.407
30sep1998	4890	6.351	7.144	7.753	8.203	8.566
31dec1998	5096	6.037	6.934	7.628	8.098	8.466
31mar1999	4949	6.079	6.909	7.527	7.991	8.366
30jun1999	4811	6.126	6.932	7.548	8.016	8.404
30sep1999	4741	6.118	6.936	7.562	8.019	8.417
31dec1999	4857	6.029	6.927	7.585	8.109	8.531
31mar2000	4805	6.071	7.027	7.716	8.224	8.637
30jun2000	4599	6.118	7.011	7.638	8.133	8.577
31dec2001	4261	5.719	6.886	7.497	7.918	8.267
30sep2002	4016	5.966	6.956	7.541	7.921	8.253
31dec2002	4013	6.020	6.933	7.438	7.817	8.164
31mar2003	3805	6.152	6.943	7.443	7.817	8.166
30jun2003	3820	6.182	6.943	7.409	7.770	8.085
30sep2003	3822	6.322	7.002	7.450	7.783	8.097
31dec2003	3841	6.369	7.038	7.485	7.797	8.093
31mar2004	3803	6.403	7.073	7.519	7.841	8.125
30jun2004	3792	6.342	7.010	7.430	7.777	8.069
30sep2004	3781	6.425	7.072	7.488	7.812	8.106
31dec2004	3807	6.331	7.010	7.444	7.775	8.071
31mar2005	3793	6.356	7.009	7.424	7.741	8.060
30jun2005	3804	6.392	7.004	7.418	7.751	8.041
30sep2005	3733	6.419	7.068	7.487	7.816	8.108
31mar2006	3806	6.473	7.083	7.463	7.796	8.099
30jun2006	3770	6.585	7.181	7.583	7.906	8.196
31dec2007	3765	6.669	7.301	7.702	8.027	8.334

Notes: The following calculation is implemented:

$$\ln E\left\{\frac{\tilde{H}_{jt}}{\bar{V}^o_{jt}}\right\} + 2/3 \ln \bar{W}_{jt}.$$

By dropping redundant value for each stock, the 10th, 25th, 50th, 75th and 90th percentile of this value are reported for each quarter ranging from June 1998 to December 2007

Table A.5: Weak Version Study (jun1998–dec2007)

Dates	Cusips	10th	25th	50th	75th	90th
31mar2008	3689	6.755	7.318	7.707	8.047	8.340
30jun2008	3682	6.558	7.120	7.541	7.895	8.207
30sep2008	3663	6.750	7.396	7.808	8.147	8.453
31dec2008	3639	6.443	7.196	7.679	8.025	8.338
31mar2009	3505	6.549	7.228	7.658	7.980	8.261
30jun2009	3424	6.398	6.995	7.391	7.730	8.003
30sep2009	3400	6.450	7.001	7.421	7.756	8.035
31dec2009	3416	6.384	6.990	7.388	7.708	7.993
31mar2010	3361	6.358	6.959	7.371	7.671	7.949
30jun2010	3343	6.368	7.028	7.499	7.832	8.108
30sep2010	3328	6.464	7.057	7.496	7.815	8.082
31dec2010	3321	6.366	6.940	7.367	7.683	7.956
31mar2011	3303	6.476	7.090	7.529	7.860	8.149
30jun2011	3252	6.496	7.049	7.496	7.836	8.109
30sep2011	3238	6.657	7.233	7.674	8.014	8.273
31dec2012	3262	6.384	6.982	7.410	7.758	8.036
30sep2013	3296	6.361	6.995	7.425	7.784	8.116
31dec2013	3343	6.384	7.048	7.485	7.830	8.135
31mar2014	3366	6.406	7.070	7.502	7.840	8.151
30jun2014	3442	6.302	6.926	7.362	7.711	8.013
30sep2014	3483	6.308	6.900	7.355	7.701	8.064
31dec2014	3520	6.398	7.084	7.539	7.898	8.227
31mar2015	3526	6.359	6.998	7.462	7.817	8.172
30jun2015	3550	6.210	6.888	7.375	7.741	8.066
30sep2015	3612	6.341	7.024	7.469	7.873	8.227
31dec2015	3647	6.272	7.028	7.500	7.882	8.235

Notes: This table reports estimated results from December 2008 to December 2015.

Table A.6: Weak Version Study (mar2008–dec2015)

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