Charles University in Prague

Faculty of Social Sciences
Institute of Economic Studies

MASTER'S THESIS

Modeling Liquidity Adjusted Value at Risk Using Quantile Regression Analysis

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Declaration of Authorship

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Prague, May 14, 2015

Signature

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Abstract

The master's thesis deals with modeling Value at Risk model adjusted by liquidity. For this purpose we use quantile regression analysis and liquidity proxies. We find out that Garman-Klass volatility estimator can be very useful in period 2000-2008 for the small and mid-size semiconductor companies but not in period 2008-2015. The NASDAQ composite Garman-Klass volatility is useful for all semiconductor companies for period 2008-2015. We might conclude that from the outbreak of the crisis returns of all semiconductor companies might depend on movement of NASDAQ composite index. We use Amihud and Roll measures as the liquidity proxies but the results are not persuasive regardless or size of companies and period we analyzed.

JEL Classification	G11, G14, G17, G18, G32
Keywords	liquidity, value at risk, quantile regression

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Abstrakt

Diplomová práce se zabývá modelováním hodnoty v risku upravenou o likviditu. Pro tuto analýzu jsme použili kvantilovou regresi a proměnné indikující likviditu. Došli jsme k závěru, že Garman-Klass volatility estimator je velmi užitečný pro malé a středně velké firmy operující na trhu s polovodiči a to v období 2000-2007, nikoliv však období 2008-2015. NASDAQ composite Garman-Klass volatility estimator je užitečný pro období 2008-2015 pro všechny firmy bez ohledu na velikost. Předpokladáme, že od začátku krize výnosnost těchto firem můžeme být ovlivněno pohybem NASDAQ composite index. Výsledky u proměnných indikující likviditu nejsou přesvědčivé nehledě na velikost firmy či období, kdy jsme tyto proměnné analyzovali.

Klasifikace JEL	G11, G14, G17, G18, G32
Klíčová slova	likvidita, hodnota v risku, quantilová analýza

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Acronyms

BASI The MarketAxess Bid-Ask Spread Index

CAViAR Conditional Autoregressive Value at Risk

EVT Extreme Value Theory

GARCH Generalized Autoregressive Conditional Heteroskedasticity

GK volatility estimator range-based volatility estimator

LVaR Liquidity Adjusted Value at Risk

NASDAQc NASDAQ Composite

NYSE New York Stock Exchange

POT Peak over Threshold

TSE Tokyo Stock Exchange

VaR Value at Risk

Master Thesis Proposal

Author	Bc. Nguyen Quang Dung, M.A.
Supervisor	PhDr. Jozef Baruník, Ph.D.
Proposed topic	Modeling Liquidity Adjusted Value at Risk Using Quantile Regression Analysis

Topic characteristics The financial crisis unveiled the weakness of many economic models financial institutions have been heavily relied on. One of the most widespread models used in risk management is Value at Risk model (VaR). Fundamentally, it extracts historical values to interfere and compute at certain confidence level the risk of loss. It is the backward-looking model and it is virtually powerless in forecasting the future movement of stock prices. Additionally, the assumption of normality of return is not satisfactorily fulfilled during the upswing and crisis. The classic VaR model captures all risk and defines it as market risk. Therefore, it does not identify multiply dimensions of risk. All weaknesses pose the threat on relevant interference from the model.

There are many reasons why we should consider liquidity as an important parameter in VaR model. Liquidity could affect prices even when fundamental values remain constant (Amihud et al. 1997) Market efficiency goes hand-in-hand with the high liquidity (Amihud et al. 1997). Liquidity is variable that can be priced, e.g. bid-ask spread (Pastor and Stambaugh F. 2003; Acharya and Pedersen 2005; Sadka 2006). During the crisis, we can observe the vanishing liquidity as the harbinger of following crisis (Borio 2004). Therefore, not only liquidity adjusted VaR would solve problems with normality of return but it also would empower to make better prediction.

As great as it seems, we incur a few problems. Even though the liquidity can be price by the bid-price spread, it is not directly observable. Furthermore, both bid and ask prices are not stored and available in financial websites such as Yahoo Finance or Google Finance. Only broker companies store them for their own purposes. The additional problem we may experience lies in the fact that liquidity transmission into price is still unclear. These problems should be taken in mind when modeling liquidity adjusted VaR models.

Hypotheses

1. A small companies encounter higher liquidity risk.
2. NASDAQ composite index is lead by big players such as Apple, Google or Amazon who are focusing on end-users. Therefore, semiconductors firms are dependent on them.
3. Liquidity proxies are good predictors for future returns.
4. At the time of fast moving IT industry, companies listed in NASDAQ composite index entails larger liquidity risk than SP index.

Methodology We use the quantile regression analysis.

Outline

1. Introduction
2. Theoretical Background
3. Related Work
4. The Data and Methodology
5. Empirical Verification
6. Conclusion

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Chapter 1

Introduction

One of the most widespread-used methodologies to measure the risk is the Value at Risk (VaR) concept. During the financial crisis the general methodologies to compute VaR reveal their weaknesses. Fundamentally, they extracts historical values to compute the potential loss at certain confidence level. Hence, it is a backward-looking model and it is not always useful to forecast the future movement of stock prices. Additionally, the assumption of normality of returns is not satisfactorily fulfilled during economic upswings and crises. The general methodologies to compute VaR capture the market risk but they do not identify what particular risk has the largest effect. All weaknesses pose the threat on the inappropriate inference from the models. Hence, we need new methodologies to compute VaR that can identify particular risks and find solutions to mitigate these risks.

There are many reasons why we should consider liquidity as an important parameter used in methodologies to compute VaR. Liquidity could affect share prices even when companies' fundamentals remain constant (Amihud *et al.* 1997). The market efficiency goes hand-in-hand with high liquidity (Amihud *et al.* 1997). Liquidity is a variable that can be priced, e.g. bid–ask spread (Pastor & Stambaugh (2003); Acharya & Pedersen (2005); Sadka (2006)). A period in which we could observe the vanishing liquidity may predict the following crisis (Borio 2004). Hence, methodologies to compute VaR that incorporate liquidity risk would not only give us a better measure of potential loss but help us to detect the liquidity risk and its effect. As a result, the Liquidity Adjusted Value at Risk (LVaR) would be more appropriate and useful than the VaR

However, as useful as LVaR may seem, we face a few problems in constructing an appropriate model. Even though the liquidity proxies could be constructed using various variables, however, not all variables are always available to calculate liquidity proxies. Furthermore, bid and ask prices are not stored and available on financial websites. Only the broker companies store them for their own purposes. The additional problem we might experience lies in the fact that the liquidity transmission into share price is still unclear (Hibbert *et al.* 2009). These problems should be taken into consideration while modeling LVaR. On the contrary, high-frequency trading generates data-sets that give us the great opportunity to analyze the liquidity pattern and its dynamics during a day. The big data-sets might help us to satisfy the assumptions of models where the continuity of time series is required.

The aim of the thesis is to improve the general methodologies to compute VaR by incorporating liquidity risk and obtain more reliable measurement of potential loss. As a subject of the analysis we chose stocks of the semiconductor companies listed on NASDAQ stock exchange market.

The thesis is structured as follows. Section 1 introduces the topic. Section 2 deals with theoretical background for constructing the model for computing LVaR. Section 3 provides a reader with the literature review pertaining to the current models for computing LVaR. Section 4 provides data and suggests the methodology of the model. Section 5 provides the results of the analysis and Section 6 concludes.

Chapter 2

Theoretical Background

2.1 Value at Risk concept

The models built on the VaR concept has been used for a long time in the risk management. They give an answer to the question "How much can I potentially lose in value of a risky asset or portfolio over a specified period for a given level of probability?". For instance, if the VaR on an asset is 100 million EUR at a month, 99 confidence interval, then there is only 1 per cent probability that the asset will drop more than 100 million EUR. The general VaR concept measures only market risk. Although, VaR tells us the potential loss based on market risk, we can not identify which particular risk causes the loss. Hence, the new methodologies to compute VaR should take into consideration various risks that can affect a company in a particular industry. Since the collapse of Long Term Capital Management the risk models built on VaR concept were widely accepted by financial firms and their application in banks reflects the fear of any liquidity crisis (Damodaran). They compute the VaR to compare their available capital and cash reserves with potential losses so that they can protect themselves against market downturn and avoid putting the firms at risk.

2.1.1 Methods of computing VaR

There are five methodologies to compute the VaR:

1 Variance-covariance method

2 Historical simulation

3 Monte Carlo simulation

4 Methodologies built on Extreme value theory

5 Quantile regression analysis

Variance-covariance method

The variance-covariance method does not require many types variables to be calculated. To compute the VaR for an asset or a portfolio we need to define the confidence interval, the probability distribution of risks, the correlation across these risks and the effect of these risks on value. It is easy to compute VaR for an individual asset. However, with an increasing number of assets the model requires more variables to be calculated. For instance, in a portfolio consisting of 100 assets we need variances for each asset, covariances of pairs assets in a portfolio. In total the model requires 49 600 variables to be calculated. Hence, variance-covariance is not appropriate for a large portfolio with shifting asset positions.

Introduction of Risk Metrics The first mathematical approach to compute the VaR was develop by Harry Markowitz in his portfolio theory (Damodaran 2006). From then on, variations of measures of the VaR were developed with different precision. The difficulty of computing variances of many assets causes limited application of risk models or at least the estimated VaR was not correct. In 1995 the investment bank J.P. Morgan provided public access to its variances and covariances across assets they used to assess the risks. The availability of data contributes to the widespread application of variance-covariance method to compute VaR in both financial and non-financial firms.

However, Longerstaey (1996) provide the assumptions to consider when computing the VaR. Firstly, the returns do not have to follow normal distribution but we assume that standardized returns follow normal distribution, i.e. return divided by the forecasted standard deviation. Molnár (2012) argue that unlike low frequency data, high-frequency data we might satisfy this assumption. He also states that it is likely that returns per se do not follow normal distribution but standardized returns might. Secondly, it is not important how large returns are but how large the standardized returns are. They implicitly assume that fat tails are present and occurrence of large negative and positive returns are accompanied by large volatility. However, the difficulty of calculating probability of large returns and their standard deviations constrains applying the variance-covariance method to compute the VaR (Damodaran 2006).

Limitations Since the variances and covariances are based on historical data, they do not have to be correct for computing the VaR. Variances and covariances change over time and non-stationarity of these variables is not uncommon. The history does not have to be a good predictor. Damodaran (2006) argues that the assumption of the normal distribution might not be satisfied resulting in underestimation of the true VaR.

Historical simulation

The historical method is the simplest approach based on historical data. The computation of the VaR is done by taking historical returns in a specific period and predict returns in the future. This approach implicitly assumes that all information we need are included in the price changes. It relies on the repetition of history and take each day with the same weight.

Limitations Despite its popularity the historical approach is sensitive to errors. As stated above, the approach assumes that history repeats itself. This strong assumption is inappropriate when we estimate the VaR during boom or bust periods. The historical approach does not take into consideration the trend in the data. It takes each return with the same weight but (Baruník & Žikeš 2014) state that the negative returns contains more information than positive returns. Consequently, the negative returns should have the larger weight than positive returns. Moreover, the market is constantly changing, stocks are removed and added into exchange markets. The historical approach does not incorporate relevant changes into the model to compute the VaR.

Monte Carlo simulation

The Monte Carlo simulation allows proficient researchers leveraging their expertise and knowledge by using their subjective judgment. The approach focuses rather on probability of losses exceeding a certain value than on the whole distribution. Unlike the other approaches, we specify the probability distribution of returns of an asset in a portfolio and how they move together. After running the simulation, we obtain the histogram with values where we can find out the computed VaR.

Limitations Since Monte Carlo relies on researchers' subjective judgment, the VaR is as good as the researchers' expertise. Hence, to obtain the accurate values we need relevant expertise and knowledge in the specified field. Although, running simulations on individual asset or a small portfolio may not be difficult, for a larger portfolio we need to set the probability distribution for many assets that is not easy.

Extreme value theory

Other statistical model for analyzing the extreme financial events is Extreme Value Theory (EVT). It provides the quantification of the stochastic behavior of a process at unusually large or small level and probability of these events need to be estimated (Singh *et al.* 2011). The parametric models built on EVT capture the extreme tails of the distribution and forecast risks. McNeil & Frey (2000) suggest the dynamic VaR forecasting method built on EVT. They employ Generalized Autoregressive Conditional Heteroskedasticity (GARCH) to model the current market volatility which is further used to compute VaR obtained from the Peak over Threshold (POT) approach. POT approach applies EVT whose extreme value distribution is based on the Generalized Pareto Distribution (Singh *et al.* 2011).

Limitations GARCH often assumes normality. The risk models are as good as the GARCH volatility modeling. **?** oppose that this approach is subject to two difficulties. Firstly, it works only for very low probability quantiles. Secondly, the model is based on the framework of *iid* variables which is not in line with the most financial data-sets.

Quantile regression

Instead of modeling the whole distribution quantile regression models the specific quantile. There are two categories of the quantile regression i) linear quantile regression and ii) non-linear quantile regression.

Baruník & Žikeš (2014) introduce modeling VaR framework that quantile regresses future returns on its volatility that is measured by using high frequency data. They suggest to use realize measure. Moreover, Barndorff-Nielsen & Stehphard (2002) argue that under ideal circumstances the realized volatility consistently estimates the quadratic variation of the price process that the returns are computed from. Baruník & Žikeš (2014) model is stated as follows:

$$q_\alpha(r_{t+1}|\Omega_t) = \beta_0(\alpha) + \beta_v(\alpha)\boldsymbol{v}_{t,M} + \boldsymbol{\beta_z(\alpha)'z_t} \tag{2.1}$$

where
r_t is return and $\boldsymbol{v}_{t,M}$ is realized measure
$\boldsymbol{z_t}$ is a vector of weakly exogenous variables
$\beta_0(\alpha), \beta_1(\alpha), \beta_z(\alpha)$ are coefficients to be estimated.

Engle & Manganelli (2004) propose non-linear quantile regression model called Conditional Autoregressive Value at Risk (CAViAR) as follows:

$$f_t(\beta) = \beta_0 + \sum_{i=1}^{q} \beta_i f_i(\beta) + \sum_{j=1}^{r} \beta_j l(x_{t-j}) \tag{2.2}$$

where
$p = q + r + 1$ is the dimension of β and
l is a function of a finite number of lagged values of observables.

The autoregressive terms $\beta_i f_{t-i}(\beta), i = 1, ..., q$, ensure that the quantile changes smoothly over time. The role of $l(x_{t-j})$ is to link $f_t(\beta)$ to observable variable that belong to the information set. The CAViAR is based on the similar idea of capturing dynamics as GARCH models of Engle & Ng (1993), but in quantile.

While employing the quantile regression we do have to satisfy the strong assumption of normality of returns that other approaches require. Moreover, the quantile regression allows us to focus on the specific quantile and identify the risk more precisely. **?** argues that the quantile regression is more appropriate when extreme values are present and it has two advantage:

1 Quantile regression can be used with various distributions, especially skewed distributions.

2 If the extreme values change, the quantile regression coefficients do not change their value and standard errors.

2.1.2 Market Risk

All approaches have their limitations. Apart from the quantile regression that allows us to add more explanatory variables the common limitation of many methodology to compute VaR is their focus on the market risk. The firms operate in specific industries and they are exposed to different risks such as political risk, regulatory risk, exchange rate risk or liquidity risk. Hence, the researchers have been extending the general methodologies to compute VaR by incorporating different risks into the current risk models. In this thesis we will consider only liquidity risk.

2.2 Liquidity

> *"Liquidity is an elusive notion. It is easier to recognize than to define."* (Crockett 2008)

2.2.1 Types of Liquidity

Global liquidity

We can observe the global liquidity surplus in terms of easily available and cheap credit. It is caused by low short-term interest rate due to post-2000 recession reaction by central banks and *great moderation* period. Asian and Arab countries with global savings surplus transfer capital to the US and cause global imbalances (Gourinchas 2012). As a result of capital inflow to the US, long-term interest rates decrease. The global liquidity surplus has motivates market agents to seek for alternative forms of investment with higher yields.

There are a few indicators how to measure global liquidity. A number of issued credit and money stocks can provide useful information. Before the financial crisis in period 2002-2007 there was a sharp rise in credit and the money stock in many countries (Gourinchas 2012). Another indicator is deviations of the money stock and credit to the private sector as a proportion of the gross domestic product from their long-term trends. According to Merril Lynch, global US dollar liquidity equals the sum of the US monetary base plus reserves held in custody by the Federal Reserve for foreigners, mostly Asian central banks.

Global, market, and funding liquidity are usually positively correlated (Gourinchas 2012). At times of ample global liquidity market and funding liquidity are at a moderate values. During the liquidity squeeze central banks influence liquidity conditions by providing liquidity to the market, mainly money and inter-bank market.

Market/Trading liquidity

Despite of the difficulty to properly define the market liquidity, some researchers attempted to define it so that we can better understand the concept of the market liquidity. Kyle (1985) firstly defines the market liquidity with three dimensions:

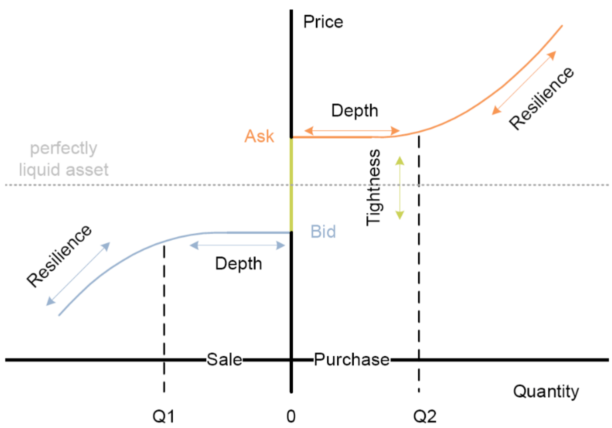
1 *Tightness* refers to low cost to execute a trading position with quoted investor's quoted bid-ask prices. In a liquid market the price at which investors can execute their trading position should not be far from the average market price.

2 *Depth* refers to ability of investors to buy or sell with posted bid-ask spread without affecting the current market prices of an asset.

3 *Resiliency* refers to the time and speed at which price returns to its equilibrium from a random shock.

All three dimensions of market liquidity is depicted in Figure 2.1. The right side represents the buyer's options and left side represents the seller's options.

Figure 2.1: Dimensions of market liquidity



Source: Kerry (2008)

Buhl (2004) suggests other definition of market liquidity with similar three dimensions:

1 *The volume dimension* pertains to the size of position of an investor that can be liquidated or acquired at any time in the market

2 *The price dimension* refers to price concession or markup relating to size of any trading position.

3 *The time dimension* pertains to the speed of liquidation or acquisition of any trading position.

Regardless of the definition we use all dimensions of liquidity are important and can change a share price or be harbinger of the following financial crisis (Borio 2004). We can observe that some dimensions are strongly correlated, e.g. larger positions take longer time to execute. However, from investors' perspective above definitions are rather elusive. What is important for investors is how the liquidity risk is transferred into a share price but Borio (2004) argues that the liquidity transmission into the share price is unclear.

Due to inaccurate measures that approximate market liquidity through relative aggregate measures in the case of a lack of order book data, supplement variables that proxy market liquidity are often used. Based on the first definition, Hasbrouck & Seppi (2001) propose the liquidity proxy as intradaily quote slope as follows:

$$QS_k = \frac{A_k - B_k}{logN_k^A + logN_k^B} \tag{2.3}$$

where

A_k is ask price

B_k is bid price

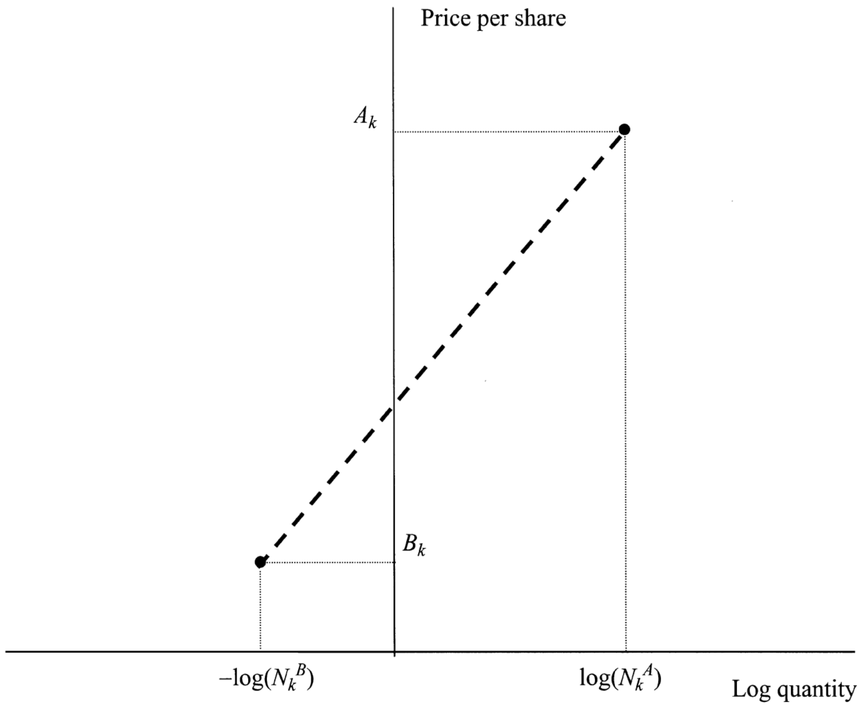
N_k^A is a number of shares sough at ask price

N_k^B is a number of shares sough at bid price

$A_k - B_k$ represents the degree of tightness

$logN_k^A + logN_k^B$ represents the degree of depth

Figure 2.2: The dot line - the quote slope



Source: Hasbrouck & Seppi (2001)

Liquidity premium[1] and the market volatility index[2] are also widely used as proxy for market liquidity. MarketAxess Research developed its own index called The MarketAxess Bid-Ask Spread Index (BASI) and it measures liquidity in the U.S. and European corporate bond markets. BASI demonstrates the relationship between overall market liquidity and transaction costs by tracking the spread differential between buy and sell trades of the most actively traded corporate bonds[3]. Figure 2.3 shows the co-movement of BASI, VIX index and S&P500 index. We can clearly indentify that BASI and VIX are positive cor-

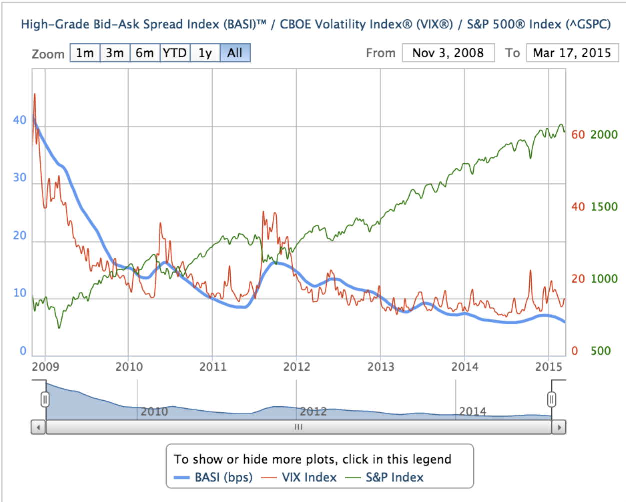
[1]Spreads between alternative assets with different degrees of liquidity

[2]The ticker symbol for the Chicago Board Options Exchange (CBOE) Volatility Index, which shows the market's expectation of 30-day volatility. It is constructed using the implied volatilities of a wide range of SP 500 index options. This volatility is meant to be forward looking and is calculated from both calls and puts. The VIX is a widely used measure of market risk and is often referred to as the "investor fear gauge." There are three variations of volatility indexes: the VIX tracks the SP 500, the VXN tracks the Nasdaq 100 and the VXD tracks the Dow Jones Industrial Average. (Source: Investopedia)

[3]The U.S. index is calculated daily using executed trade data from publicly-disseminated FINRA TRACE data and also incorporates trade data from the MarketAxess trading system. The European index is calculated using quoted price information available through Trax's end-of-day pricing feed, Trax Pricing. The quoted prices from Trax Pricing are also enriched with traded prices as a means of validating the data (www.marketaxess.com)

related with each other and negatively correlated with S&P500 index. Since 2009 both BASI and VIX index have been declining with exception of the end of 2011.

Figure 2.3: BASI/VIX/S&P 500



Source: www.marketaxess.com (accessed April 4, 2015)

Funding Liquidity

Funding liquidity refers to ability of an institution to settle obligations with immediacy (Drehmann & Kleopatra 2009).

2.2.2 Source of liquidity

A study of the micro-structure of financial markets allows us to identify the factors that affect liquidity of assets. Amihud *et al.* (2005) provide the following determinants:

- Exogenous transaction costs
- inventory risk
- private information
- search friction

Exogenous transaction costs

These costs are incurred directly when buyers/sellers buy/purchase an asset. It can be brokerage fees, order processing costs or transaction taxes.

Inventory risk

In case sellers can not find buyers they need to hold assets in inventory. While keeping the assets the prices can change and, hence, a market maker compensates this adverse situation and changes the prices accordingly.

Private information

It is not legal for investors to use insight information prior to its publication for trading and gain advantage over other investors who do not possess them. However, investors can obtain private information and adjust the prices of assets accordingly. Consequently, uninformed traders or noisy traders are in disadvantage. Hence, the uninformed traders may protect themselves by adjusting quoted spreads when trading with the informed traders.

Search friction

Investors can ask prices at which it is difficult to find buyers. They can either keep searching for sellers willing to trade at the ask price or make concession and decrease the ask price. By doing the former they can get higher prices but it takes time to find appropriate buyers. By doing the latter they incur the opportunity cost of finding better buyers but decrease the time they spend searching for buyers.

2.2.3 Liquidity costs

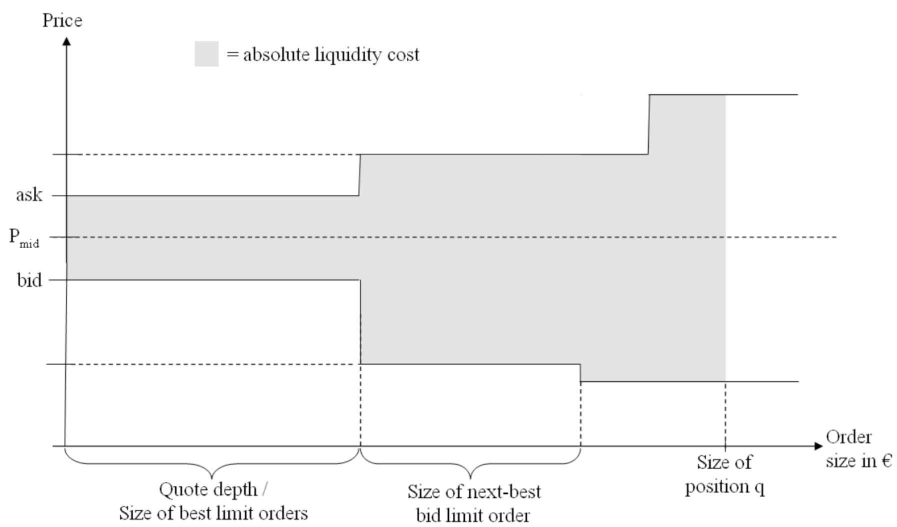
As mentioned above, the theoretical concept of liquidity is useful but elusive. For investors we need the framework that puts the liquidity risk into monetary terms. Stange & Kaserer (2008) propose the following framework that decomposes the total liquidity cost into three components.

$$L_t(x) = T_t(x) + PI_t(x) + D_t(x) \tag{2.4}$$

where
$T_t(x)$ is the direct trading costs for a position x at time t
$PI_t(x)$ is the price impact costs of a position x at time t
$D_t(x)$ is the delay costs of a position x at time t

The liquidity cost is defined as percentage of an asset fair value that is calculated as a midpoint between bid and ask price of the asset, i.e. mid-price. Direct trading costs are deterministic and pertain to transaction taxes, brokerage commissions, and exchange fees. The price impact is calculated as difference between transaction price and mid-price (Stange & Kaserer 2008). Due to imperfect supply and demand at certain time t, the price impact increases with order size (see Figure 2.4).

Figure 2.4: Price impact increases with order size



Source: Stange & Kaserer (2008)

The delay costs incur when a trading position is not immediately executed. Delay can be forced or deliberate. Forced delay is caused by the market condition that does not allow investors to execute their trading positions immediately. Deliberate delay is a part of investors' strategy. For big investors in certain cases it is better to divide a large position into smaller positions in order to mitigate the price impact. Additionally, a small trading position is easier to execute since the searching cost is lower but the sum of direct transaction costs is higher. This proceeding is called the strategic transaction. On the contrary, the non-strategic transaction entails execution of a large trade position at once. Due to difficulty of searching for a counter-party a big position entails the higher searching cost, the price risk, and the larger price impact at time of the trade execution. However, investors should take into consideration that strategic or non-strategic transactions entails the trade-off between the delay costs and the price impact costs. If the additional delay costs exceed the diminished price impact, investors should follow the non-strategic transaction and vice versa.

Since the direct trading costs are deterministic and a proper traceable risk model for measuring the delay costs is lacking the price impact plays a crucial role in determining the liquidity costs (Stange & Kaserer 2008). Hence, for the rest of the thesis we will deal with price impact as the main driver of liquidity costs. We distinguish two types of price impact costs measurement, direct and indirect.

Direct liquidity cost measures

Essentially, the price impact costs are derived indirectly from market data. One of widespread means to indirectly measure the price impact costs is to build the price-volume function based on transaction data. Thanks to availability of data on markets we focus on direct liquidity measures in detail.

Direct liquidity cost measures utilize available data. We have two variables that can provide useful information about the price impact costs, i.e. the bid-ask spread and weighted spread.

The bid-ask spread measures the costs of a round trip transaction, either buy and sell, or sell and buy. For this reason, only the half spread should be attributed to a single transaction (Roy 2004). The bid and ask price for a certain trading position is quoted by the market maker and it is available for all assets. It is rare to observe the constant bid-ask spread for any asset due to the constantly changing market conditions. The bid-ask spread is defined in relative terms as follows:

$$spread_t = \frac{P_t^{ask} - P_t^{bid}}{P_t^{mid}} \tag{2.5}$$

where
P_t^{ask} is ask price
P_t^{bid} is bid price

P_t^{mid} is mid-price $= \frac{P_t^{ask} - P_t^{bid}}{2}$

We distinguish three main drivers of the bid-ask spread:

1 *Costs for order processing*: market makers incur costs and fees associated with paperwork. The costs are fixed and thus the cost per order decreases with increasing transaction volumes.

2 *Costs for the existence of asymmetric information*: market makers protect themselves against more informed traders who possess more information than market makers. Thus, market makers sustain or increase spread.

3 *Costs for inventory carrying*: market makers maintain open positions and face uncertainty in the financial markets. Based on change of certain variables spread may increase or decrease.

The bid and ask prices are quoted for almost all assets. However, since the bid and ask prices are quoted for limited order quantity it is difficult to extrapolate for other order quantities. For this reason, we employ the weighted spread that accounts for the increasing liquidity costs with rising order quantity. The volume weighted spread relative to unit mid price denoted in basis points can be calculated as follows:

$$WS_t(x) = \frac{A_t^v - B_t^v}{P_t^{mid}} * 100 \tag{2.6}$$

where
A_t^v is volume-weighted ask price of trading v shares and is calculated as $A_t^v = \frac{\sum_{i=1}^{n} A_{i,t} v_{i,t}}{v}$, with $A_{i,t}$ being the ask-price and $v_{i,t}$ the ask-volume of individual limit order. An order of size x is executed against several limit order until individual limit order sizes add-up to x, i.e. $\frac{x}{P^{mid}} = v = \sum_{i=1}^{n} A_i v_i$

B_t^v is volume-weighted bid price of trading v shares and is calculated as $B_t^v = \frac{\sum_{i=1}^{n} B_{i,t} v_{i,t}}{v}$, with $B_{i,t}$ being the bid-price and $v_{i,t}$ the ask-volume of individual limit order

P_t^{mid} is mid-price and is calculated as $\frac{P_t^{ask}-P_t^{bid}}{2}$

Similarly, the weighted spread is defined as a round-trip for a trading position x. By the same token, we can interpret the weighted spread as the relative liquidity discount of a round-trip of an order with a transaction volume

$$v = \frac{x}{P^{mid}} \tag{2.7}$$

Stange & Kaserer (2008) assume that the order book is symmetrical on average, which allows calculating relative the liquidity costs of a transaction position x as follows:

$$L_t(x) = \frac{1}{2} * WS_t(x) \tag{2.8}$$

Subsequently, we calculate the absolute liquidity costs for a transaction position x as follows:

$$L_t(x) = \frac{1}{2} * WS_t(x) * x \tag{2.9}$$

The weighted spread is *ex ante* measure of the liquidity costs. The weighted spread is more precise measure of the liquidity costs than the bid-ask spread because it allows calculating liquidity costs beyond the limited volume quoted by a market maker (Stange & Kaserer 2008). However, data for computing the weighted spread are not always available.

The delay costs and the impact costs

As we defined above, liquidity risk entails the direct trading costs, the delay costs and the price impact costs. Unlike the direct trading costs, the delay costs and the price impact costs are uncertain and influence liquidity risk. The most important driver of liquidity risk are the price impact costs because direct trading costs are deterministic and we lack a traceable risk model for delay costs. Therefore we need to distinguish between strategic and non-strategic transaction. Strategic transactions entail cutting a large transaction position into smaller transaction positions

$$x = \sum_{i=1}^{n} x_i \tag{2.10}$$

and each transaction position x_i is executed at a discrete time $t_i^* < t_i$. At each time investors face the different price impact costs and the delay costs since each trading position is executed at different time. Absolute liquidity risk is calculated as difference between a sum of the present values of realized transaction positions x_i at time t_i and the fair value of the trading position x.

$$\tilde{L}_t(x_1, ..., x_n) = \sum_{i=1}^{n} q_i * P_{t_i}^{trans}(q_i) * e^{-r(t_i - t_1)} - q * P_1^{mid} \tag{2.11}$$

where
q_i is order size of a trading position x_i
$P_{t_i}^{trans}$ is the transaction price of a trading position x_i at time t_i
P_1^{mid} is the mid-price of a trading position x_i at time t_1

On the contrary, a non-strategic transaction entails executing one large trading position at once. Thus, the main driver of liquidity risk is price impact cost and absolute liquidity cost at time $t^* < t$ is calculated as

$$\tilde{L}_t(x_i) = q * P_{t^*}^{trans}(q) * e^{-r(t^* - t)} - q * P_t^{mid} \tag{2.12}$$

where
q is order size of trading position x_i
P_t^{trans} is transaction price of trading position x_i at time t
P_t^{mid} is mid-price of trading position x_i at time t

If a trading position is executed immediately, i.e. $t^* = t$, investors may eliminate the delay costs. In both formulas we incorporate market risk. Specifically, at time $t^* < t$ the market risk entails uncertainty about P_t^{mid} at time t.

2.2.4 Liquidity premium

Investors face the liquidity cost when trading. Even though liquidity of assets affect its price, it is difficult to identify absolute value of liquidity premium. Liquidity premium may change over time based on financial market conditions or other fundamentals that more or less affect the price of assets. Hence, investors can use the definition of relative liquidity premium. The relative liquidity premium compares prices of otherwise two identical securities with different liquidity (Hibbert *et al.* 2009). Hence, investors always need to find a benchmark security to calculate the relative liquidity premium.

Based on asset pricing theory in the frictionless market securities with the same cash flow have the same price. Frictionless market is rather the ideal concept and researchers apply this strong assumption to simplify models. However, Amihud *et al.* (2005) analyze many pricing models and conclude that frictional costs in the financial market lead to the downward adjustment of prices and the upward adjustment of returns to compensate investors for bearing illiquidity of assets.

Hibbert *et al.* (2009) carry out extensive literature review on the existence of the liquidity premium. Researchers apply different approaches to identify liquidity premium (microstructure approach, direct approach, structural model approach using the Merton model, and regression-based approach). They conclude that liquidity premium do exist. Hence, the risk managers both in financial or non-financial institutions need new risk models that incorporate liquidity risk.

2.2.5 Liquidity proxies

Hibbert *et al.* (2009) enlists variables that are most used as the liquidity proxies.

- The bid-ask spread
- The unique roundtrip costs
- return-to-volume measures
- a number of zero-return days
- turnover
- volatility

Bid-ask spread

The bid-ask spread is a standard measure of the aggregate liquidity of assets. However, the data are not always available for all assets. (Chung & Zhang 2014) provides a list of liquidity measures using the bid-ask spread

1 The CRSP bid-ask spread

2 The TAQ bid-ask spread

3 Roll (1984) estimator

4 Effective tick

5 Gibbs estimator

6 Holden (2009) estimator

7 Lesmond, Orgen, and Trzcinka (1999) estimator

Unique roundtrip costs

The unique roundtrip costs is the alternative way to measure the bid-ask spread. The concept measures how much does an unique round-trip trade costs. Fundamentally, for a given volume and on a given day investors try to buy and sell asset via one or two dealers. The highest and the lowest prices are collected within a trade then we compute the ratio $\frac{P_{max}-P_{min}}{P_{max}}$. Investors can use Lesmond *et al.* (1999) to calculate the unique round-trip costs.

Return-to-volume measures

The most used return-to-volume measures is the so-called Amihud measure and is calculate as $\frac{|R_t*100|}{v_t}$, where R_t is the return and v_t is the volume of trading at time t. The Amihud measure measures the price impact, i.e. aspects of depth and resilience. During 2009-2013 over one hundred papers published in the Journal of Finance, the Journal of Financial Economics, and the Review of Financial Studies use the Amihud measure (Lou & Shu 2014). Goyenko *et al.* (2009) develop extended Amihud measure by decomposing the Amihud measure into liquidity and non-liquidity components.

Number of zero-return days

This variable measures a number of days on which there is no price change and it measures the trading intensity. Lesmond *et al.* (1999) claim that a number of zero-return days might be a proxy for transaction costs because (1) shares with high trading costs are more likely to have zero volume days and hence zero-return days and (2) shares with high trading costs are more likely have zero-return days even in positive-volume days. However, there might be the significant discrepancies between counts due to different choice of data sources Hibbert *et al.* (2009).

Turnover

Turnover is defined as the total trading volume of an asset over specific period divided by overall volume in circulation in that period. It gives investors information about the percentage of all shares outstanding that are traded. Consequently, investors have both the absolute and percentage values of the total trading volume.

Volatility

We have various forms of volatility measures. Investors can use widely available volatility measures such as VIX index or realized measures calculated from high-frequency data.[4] Investors can calculate other types of estimators such as (Garman & Klass 1980) volatility estimator or (Meilijson 2011) volatility estimator.

The list of the liquidity proxies we provided is extensive but not exhaustive. Researchers use different liquidity proxies, however, they revolve around those we enlist above. They are either extended or slightly changed.

[4]Oxford-Man Institute of Quantitative Finance provides measures only for a few indices. Therefore, its use is limited for our analysis.

Chapter 3

Related Work

Liquidity is arguably present and play a significant role in all financial markets. Bangia *et al.* (1999) first propose a methodology to transfer the liquidity risk into VaR model and it deals only with the exogenous liquidity. Their model was the impetus for further researchers to build more sophisticated models that incorporate both exogenous and endogenous liquidity risk.

Roy (2004) comprehensively divides current approaches into six groups.

1 Ad-hoc approach (lengthening time horizon)

2 Optimal liquidation approach/transaction cost approach

3 Liquidation Discount Approach

4 Exogenous Liquidity Approach and its extensions

5 Market Size Response Approach

6 Intraday Liquidity Risk (based on high frequency data)

3.1 ad-hoc approach (lengthening time horizon)

Liquidity risk is incorporated in VaR models in an ad-hoc way by adjusting time horizon based on the characteristics of liquidity of the considered assets (Roy 2004). Roy (2004) states that if the liquidity risk has an impact on the price then the general VaR model would be insufficient because the period for its calculation does not allow for an orderly liquiditation, and therefore, adjusting the time horizon of the holding period ensures orderly liquidation.

3.2 optimal liquidation approach/Transaction Cost Approach

Lawrence & Robinson (1995) match the VaR time horizon with the time investors believe they could hold and then exit the portfolio. They argue that taking the same period for all positions while ignoring their size, the level of market liquidity and the possible hedging is utterly irrelevant and state that the shorter the holding period the more underestimated the VaR is. They provide a model of VaR by deriving the optimal execution strategy incorporating the market risk using a mean-standard deviation approach.

Almgren & Chriss (1998) consider the problem of portfolio liquidation with the aim of minimizing a combination of volatility risk and transaction costs arising from permanent and temporary market impact. They devise optimal execution strategy using mean-variance approach.

Hisata & Yamai (2000) turn the sales period into an endogenous variable. The model incorporates the mechanism of the market impact caused by the investor's own dealings through adjusting VaR according to the level of market liquidity and the scale of the investor's position. Fundamentally, they devise the optimal execution strategy based on level of market liquidity and the investor's trading position.

Amongst others who derive the optimal execution strategies are Bertisimas & Lo (1998) who derive the optimal trading strategies minimizing the expected cost of execution over an exogenous time horizon

3.3 Liquidation Discount Approach

Jarrow & Subramaniam (1997) measures market impact on liquidity. They suggest integrating the liquidity risk by modeling the price sensibility to the liquidated quantity. They derive the optimal execution strategy and determine the sales schedule to maximize the total sales value but they take sales period as an exogenous variable. However, it is difficult to implement since it requires many parameters to estimate (Roy 2004).

3.4 Exogenous Liquidity Approach and its extensions

Bangia *et al.* (1999) measure exogenous liquidity and take into considaration execution costs and adverse selection costs that are translated into the width of the bid-ask spread. They use a parametric VaR model and incorporate the mean-variance-estimated worst spread to the price risk of an asset. Since the quoted spreads are widely available the model could be easily implemented. However, the market makers are not required to trade positions at the quoted positions above a certain size, the spread depth or normal market size (Stange & Kaserer 2009). Therefore, their model can measure liquidity risk for a small trading position and has problem with measuring liquidity risk for larger trading positions. They also implicitly assume that price and liquidity cost are perfectly correlated in bad times. [1] In case the correlation is not perfect, the model can incorrectly measure the liquidity risk, i.e. it overestimates the liquidity risk.

Saout (2001) find that the exogenous liquidity comprises half of the market liquidity and emphasize that the incorporation of the endogenous liquidity into the liquidity adjusted VaR model is of great importance. To consider the effect of liquidating large size position, he incorporates weighted average spread into Bangia *et al.* (1999) model.

3.5 Market Size Response Approach

Berkowitz (2000) states that unless potential loss arising from the liquidity risk is quantified, the models of VaR would lack of power to explain the market risk. The costs would be more important if the market were illiquid. He argues that elasticity-based measures are most suitable since they incorporate impact of the seller actions on prices.

[1] Specifically they presume that 1 per cent tail event in market and liquidity risk are perfectly correlated.

3.6 Intraday Liquidity Risk (based on high frequency data)

Expansion of the high-frequency trading allows in-depth inspection of market microstrure by using minute-data or even second-data. Prices and volalities in high-frequency data behave somehow differently. It is know that return-to-standard deviation in high frequency might follow the normal distribution unlike return-to-standard deviation in daily data (Molnár 2012).

Due to abundance of data researchers managed to model that incorporate both endogenous and exogenous liquidity into the risk models (Francois-Heude & Wynendaele (2002), Angelidis & Benos (2005) and Saout (2001)). Angelidis & Benos (2005) find that their LVaR follow the U-shaped pattern throughout the day.

Giot & Gramming (2005) model the intraday liqudity risk and generalize Bangia *et al.* (1999) approach and avoid the problem of price-liquidity risk correlation by modeling t-distributed net-returns. They use wighted spread to measure the liquidity cost of a specific order size as the average spread in the limit order book weighted by individual-order size (Stange & Kaserer 2009). They found that liquidity risk follow an L-shape pattern throughout the day.

The above models are applied on data from New York Stock Exchange (NYSE). However, Ahn *et al.* (2002) argues that different stock exchange may be of different microstructure. In Tokyo Stock Exchange (TSE) they argues that adverse selection and order-processing components exhibit U-shape patterns independently which neccessarily implies a U-shape pattern in the implied spread. Unlike TSE, in NYSE the adverse selection component declines and dealer costs increase over the trading day and implied spread exhibits overall U-shape.

Qi & Ng (2009) and Weiss & Supper (2013) are among the recent authors investigating intraday liquidity risk.

Measuring intraday liquidity risk is rather complex topic that is out of scope of this thesis.

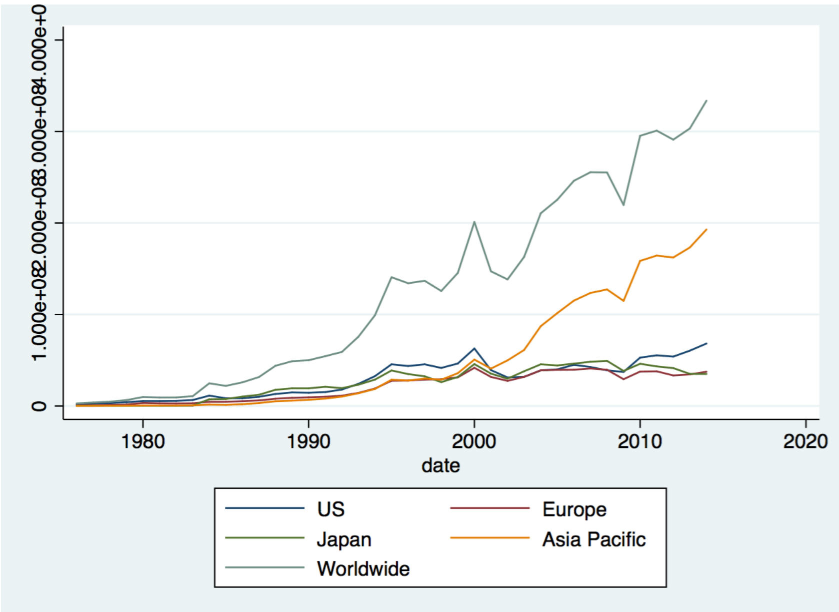
Chapter 4

Empirical Analysis

4.1 Semiconductor industry

The semiconductor industry is an indicator of the technological progress. It positions itself uniquely in the economy and in the global competitive arena. The semiconductor industry plays a significant role as technology enabler for a whole electronics value chain. Hence, it is recognized as a key driver for both electronics industry and for economic growth.[1]

Figure 4.1: Semiconductor Sales in period 1976-2014



Source: Semiconductor Industry Association industry statistics and author's adjustment

[1] http://csanad.hubpages.com/hub/Semiconductor-Industry (accessed on April 15)

Figure 4.1 shows that the semiconductor industry has been continuously growing. During its short history beginning from 1970s it has already experienced 8 major cycles due to loss of competitive advantage, rising costs of fabrication, rising costs of design, consumer price squeeze,limits to Moore's Law, missing technical talents, low returns, high risk or new global competition (Brown & Linden 2009). The semiconductor industry vastly contributes to electronics system growth and services that in total represents 10 percent of the world GDP[2]. Hence, the industry's business cycle is highly cyclical. At times of high incomes, people are willing to purchase more consumer electronics and, hence, spur the growth of the semiconductor industry. Since the semiconductor industry is very capital intensive and the lead-time is long, it is not uncommon that during the boom the companies are not able to produce quickly to meet demand. On the contrary during the bust the downright can be significant.

The fast-paced business environment puts pressure on the semiconductor companies to constantly innovate and come up with new solutions. Even the low sales does not prevent the semiconductor companies from releasing the new innovative products. Nowadays, especially in the mobile industry the products have a short life-cycle. For instance, Samsung changes its flagship mobile almost every year. On the contrary, Apple used to introduce its flagship smartphone every two year. However, the consumers put pressure on the companies to introduce their mobiles every year. Although the semiconductor industry functions as an enabler for the whole electronics value chain, it does not gain significant profit mainly due to the constant price-performance improvement in the semiconductor industry. The industry value chain downstream that manufactures products for end-users may play more significant role in the whole industry. These companies are listed on NASDAQ Composite (NASDAQc) index. Hence, we will empirically test whether NASDAQc index has impact on the semiconductor companies returns.

The semiconductor companies can be divided based on the types of products they produce. The semiconductor companies mainly produces the following devices:

1 standard devices

2 exclusive devices

3 specific devices

[2]http://csanad.hubpages.com/hub/Semiconductor-Industry, accessed on April 1

4 custom devices

5 microprocessors

6 semi-custom devices

4.2 Data

We focus only on the semiconductor companies listed on NASDAQ stock exchange market. There are 106 semiconductor companies with date of initial public offering ranging from 1983 to 2014. Out of 106 companies, there are only 26 companies with small market capitalization[3], 14 companies with mid-size market capitalization, and 11 companies with large market capitalization that have sufficient data for modeling LVaR. We strive to employ the model that use data that are publicly available. Hence, we obtain the data from publicly available source Yahoo Finance.

We use 6 sub-samples for our analysis. In period 2000-2007 we have 3 sub-samples - for the large, mid-size, and small semiconductor companies. In period 2008-2015 we also have 3 sub-samples - for the large, mid-size, and small semiconductor companies.

4.3 Methodology

Fundamentally, computing VaR is equivalent to finding the conditional quantile of r_t as follows:

$$Pr(r_t < V_t|\Omega_{t-1}) = \alpha^* \tag{4.1}$$

where
$\alpha^* \in (0,1)$
Ω_{t-1} is information set at t-1
V_t is α conditional quantile of R_t

[3]The small company has the market capitalization smaller than 2 billion USD, mid-size companies has market capitalization from 2 billion USD to 10 billion USD, and large companies has the market capitalization above 10 billion USD.

We employ model for quantile regression proposed by Baruník & Žikeš (2014). However, instead of the quadratic variation we apply Garman & Klass (1980) volatility estimator since the estimator is constructed by using publicly available data. As the explanatory variables we use the liquidity proxies computed from data publicly available. We suggest the following model for computing LVaR for a particular asset:

$$q_\alpha(r_{t+1}|\Omega_t) = \beta_0(\alpha)+\beta_1(\alpha)\sigma^2_{i,GK}+\beta_2(\alpha)\sigma^2_{N,GK}+\beta_3(\alpha)AM_{t-1}+\beta_4(\alpha)RM_{t-1}+\epsilon_t \tag{4.2}$$

and for NASDAQ composite and S&P500 indices we use the following model:

$$q_\alpha(r_{t+1}|\Omega_t) = \beta_0(\alpha) + \beta_1(\alpha)\sigma^2_{i,GK} + \beta_2(\alpha)AM_{t-1} + \beta_3(\alpha)RM_{t-1} + \epsilon_t \tag{4.3}$$

where
$\sigma^2_{i,GK}$ is Garman & Klass (1980) volatility estimator of an asset i
$\sigma^2_{N,GK}$ is Garman & Klass (1980) volatility estimator of NASDAQ composite
α is α-quantile of future returns
Ω_t is information set at time t
AM_{t-1} is lagged Amihud measure
RM_{t-1} is lagged Roll measure
$\beta_0(\alpha), \beta_1(\alpha), \beta_z(\alpha)$ are coefficients to be estimated

For our purpose, we use Garman & Klass (1980) volatility volatility estimator that is range-based and could be computed from publicly available data. Garman & Klass (1980) volatility estimator with a jump element is defined as follows:

$$\widehat{\sigma^2_{GK}} = 0.5(u_t - d_t)^2 - (2ln2 - 1)c_t^2 + J_t^2 \tag{4.4}$$

where
H_t is the high price at time t
L_t is the low price at time t

C_t is the close price at time t
$u_t = H_t - O_t$
$d_t = L_t - O_t$
$c_t = C_t - O_t$
J is price jump defined as $J_t = O_t - C_{t-1}$

Molnár (2012) tests three range-based volatility estimators and conclude that the Garman & Klass (1980) volatility estimator is the best suited for the daily data. Amihud measure is a price impact measure that captures the daily price response associated with one dollar of trading volume and it represents the aspect of depth and resilience of liquidity. It is defined as follows:

$$AM_{i,t} = \frac{r_{i,t}}{VOL_{i,t}} \tag{4.5}$$

where
$r_{i,t}$ is return of asset i at time t
$VOL_{i,t}$ is trading volume of asset i at time t

The Roll measure is an estimator of the effective spread based on the serial covariance of the change in price and is computed as follows:

$$RM = \begin{cases} 2\sqrt{-Cov(\Delta P_t, \Delta P_{t-1})}, & \text{if } Cov(\Delta P_t, \Delta P_{t-1}) < 0 \\ 0, & \text{otherwise} \end{cases}$$

Typical quantile is set up at 0.01, 0.025 and 0.05. However, there are few theories about guidance of choice of the quantile and it is determined primarily by users of a risk model how they want to interpret the VaR (Linsmeier & Pearson 1999). For instance, RiskMetrics risk model uses 5 percent for modeling VaR and Mobil Oil risk model uses 0.3 percent for its model. It is reasonable for industry where the consequences of risk are severe to precisely quantify the risk. Since we are dealing with returns of securities listed on NASDAQ stock exchange we will apply the same threshold as JP Morgan's RiskMetrics, i.e. 5 percent. We quantile regress future returns on Garman & Klass (1980) volatility and liquidity proxies at 0.05 quantile.

Chapter 5

Result of analysis

In this chapter we provide the reader with the empirical results. In our model we compute the 5 % LVaRs of the S&P500 index, NASDAQc index, and all semiconductor companies estimated by the regression quantiles. The explanatory variables are represented by Garman & Klass (1980) volatility estimator, Amihud measure, and Roll measure. These variables are liquidity proxies that help us to adjust the VaR by liquidity risk. We try to elucidate how the liquidity proxies affect the future returns at 0.05 quantile. The numbers we provide are aggregates.

5.1 Garman & Klass (1980) volatility estimates

Figure A.1, Figure A.2, Figure A.4, and Figure A.6 show volatility dynamics[1] of the two indices and all semiconductor companies for period 2000-2015. We can observe that after the burst of the dot-com bubble the volatility of NASDAQc index and all semiconductor companies were high. Since the dot-com bubble affected mostly technology companies listed on NASDAQ stock exchange, S&P500 index was not severely affected. In Figure A.1 we can clearly see that during this period volatility of S&P500 index did not deviate from its stable level. However, during the financial crisis starting from 2007 we can observe increasing volatility of both two indices and all semiconductor companies. The increase was most noticeable in two indices and the small semiconductor companies.

[1] The volatility is measured by Garman & Klass (1980) volatility estimates

Period 2000-2007

Table A.1, Table A.3, Table A.5, and Table A.7 report the estimated coefficients of the quantile regression for two indices and all semiconductor companies at 0.05 quantile for period 2000-2007. The estimated coefficients $\beta_1(\alpha)$ are highly significant at conventional levels. The estimated coefficient $\beta_1(\alpha)$ for S&P500 is almost 12 times bigger than estimated coefficient for NASDAQc index. In Table A.3 we can see that most of estimated coefficients $\beta_1(\alpha)$ are not statistically significant and, hence it restrains us from using Garman & Klass (1980) volatility estimates for the large semiconductor companies in our model in period 2000-2007. As for the mid-size and small semiconductor companies Table A.5 and Table A.7 show that most of the estimated coefficients are statistically significant at conventional levels. The average of the estimated coefficients $\beta_1(\alpha)$ for the small semiconductor companies is -0.000004 and for the mid-size semiconductor companies is -0.00223. In other words, at 0.05 quantile any change of Garman & Klass (1980) volatility estimates has bigger effect on the mid-size semiconductor companies than on the small semiconductor companies for period 2000-2007.

Period 2008-2015

Table A.2 reports the coefficients the quantile regression for two indices at 0.05 quantile for period 2008-2015. The estimated coefficients $\beta_1(\alpha)$ are still highly significant at conventional levels. Compared to previous period, the magnitude of the estimated coefficients increase by up to 78 percent. It means that the Garman & Klass (1980) volatility estimates have bigger impact in period 2008-2015 than in period 2000-2007. Table A.3, Table A.5, Table A.7 report the coefficients of the quantile regression for all semiconductor companies at 0.05 quantile for period 2008-2015. We can not find any evidence supporting the fact that the Garman & Klass (1980) volatility estimator is a good explanatory variable for this period.

5.2 NASDAQ Composite Garman & Klass (1980) volatility estimates

Period 2000-2007

Table A.4 reports the estimated coefficients the quantile regression for the large semiconductor companies at 0.05 quantile for period 2000-2007. We can see that only 6 out of estimated coefficients $\beta_2(\alpha)$ are significant at conventional levels. The results for the mid-size and small semiconductor companies are different. Table A.5, Table A.7 report the estimated coefficients of the quantile regression for the mid-size and small semiconductor companies at 0.05 quantile for period 2000-2007. We can see that most of estimated coefficients $\beta_2(\alpha)$ are significant at conventional levels. The average of the estimated coefficients $\beta_2(\alpha)$ for the mid-size semiconductor companies is -0.0000018 and for the small semiconductor companies is -0.000004. In other words, at 0.05 quantile any change of NASDAQ composite Garman & Klass (1980) volatility estimates has bigger effect on small semiconductor companies than on mid-size semiconductor companies for period 2000-2007.

Period 2008-2015

Table A.4, Table A.6, and Table A.8 report the estimated coefficients of the quantile regression for all semiconductor companies at 0.05 quantile for period 2008-2015. We can see that almost all estimated coefficients $\beta_2(\alpha)$ are significant at conventional levels. The average of coefficients $\beta_2(\alpha)$ is -0.0000033 for the large semiconductor companies, -0.0000058 for the mid-size semiconductor companies, and -0.0000065 for the small semiconductor companies. In other words, at 0.05 quantile any change of NASDAQ composite Garman & Klass (1980) volatility estimates has bigger effect on the small semiconductor companies than on the mid-size and large semiconductor companies for period 2008-2015.

5.3 Amihud measure

Due to its definition, Amihud measure is a very small number. The larger the volume the smaller the Amihud measure. Hence, the estimated coefficients are very big.

Period 2000-2007

Table A.3, Table A.5, and Table A.7 report the estimated coefficients of the quantile regression for all semiconductor companies at 0.05 quantile for period 2000-2007. The statistical significance of $\beta_3(\alpha)$ low and for this period and we do not find the conclusive evidence that supports Amihud measure as a good explanatory variable in our model.

Period 2008-2015

Table A.4, Table A.6, and Table A.8 report the estimated coefficients of the quantile regression for all semiconductor companies at 0.05 quantile for period 2008-2015. For this period we do not find the conclusive evidence that supports Amihud measure as a good explanatory variable in our model.

5.4 Roll measure

Period 2000-2007

Table A.3, Table A.5, and Table A.7 report the estimated coefficients of the quantile regression for all semiconductor companies at 0.05 quantile for period 2000-2007. Most of the estimated coefficients $\beta_4(\alpha)$ are significant at conventional levels for the large semiconductor companies. The average of the estimated coefficient $\beta_4(\alpha)$ is -0.0167. Hence, we could use Roll measure as a good explanatory variable in our model for the large semiconductor companies. However, most of the estimated coefficients $\beta_4(\alpha)$ in our model for the mid-size and small semiconductor companies are not significant at conventional levels for period 2000-2007.

Period 2008-2015

Table A.4, Table A.6, and Table A.8 report the estimated coefficients of the quantile regression for all semiconductor companies at 0.05 quantile for period 2008-2015. In this period we do not possess enough data to estimate coefficients $\beta_4(\alpha)$ for all semiconductor companies. However, in cases we do have data most of estimated coefficients $\beta_4(\alpha)$ for the large semiconductor companies are significant at conventional levels. Hence, Roll measure is a good explanatory variable for the large semiconductor companies in our model for period period

2008-2015. On the contrary, most of the estimated coefficients $\beta_4(\alpha)$ for the mid-size and small semiconductor companies are not significant at conventional levels. Hence, Roll measure could not be used as a good explanatory variable in our model for the mid-size and small semiconductor companies for period 2008-2015.

Chapter 6

Conclusion

The general methodologies to compute VaR require returns to be normally distributed. Moreover, these methodologies identify overall risk as market risk. To avoid these limitations, researchers have been trying to precisely compute VaR by employing new methodologies such as POT that is built on EVT or quantile regressions. The quantile regression analysis does not require the normality of returns and allows us adding explanatory variables to identify the potential sources of risk.

We employ the model proposed by Baruník & Žikeš (2014) with a little amendment. Instead of realized measure we use range-based Garman & Klass (1980) volatility estimates of the particular stock and NASDAQ composite index. Moreover, we add liquidity proxies to identify risks associated with liquidity. In our model we quantile regress return on Garman & Klass (1980) volatility measures, Amihud measure and Roll measure to compute LVaR.

NASDAQc and S&P500 indices are very important for many investors. We find that Amihud and Roll measures are not good explanatory variable in our model for computing LVaR in period 2000-2007. On the contrary, Garman & Klass (1980) volatility estimator is very good explanatory variable in our model for period 2000-2007 and period 2008-2015.

We observe that both Garman & Klass (1980) volatility estimates of a particular asset and NASDAQc Garman & Klass (1980) volatility estimates are good explanatory variables for mid-size and small semiconductor companies in the period 2000-2007. In period 2008-2015 most of the coefficients of Garman & Klass (1980) volatility estimates of the particular asset for both mid-size and small semiconductor companies are not significant at conventional levels . On the contrary, in period 2008-2015 coefficients of NASDAQc Garman & Klass

(1980) volatility estimates for all semiconductor companies are significant at conventional levels. This fact might lead to the conclusion that in this period the the main source of risk lies in the volatility of the NASDAQc index. In other words, the Garman & Klass (1980) volatility estimates of particular stock is not important as NASDAQc Garman & Klass (1980) volatility estimates. The results of liquidity proxies is not persuasive. In period 2000-2007 Amihud measure do work for partially for all companies regardless of the size. In period 2008-2015 it is applicable mainly for large semiconductor companies. In period 2000-2007 Roll measure is applicable for large semiconductors companies but not for mid-size or small semiconductor companies. In period 2008-2015, if Roll measure is applicable it is the good explanatory variable in our model for all semiconductor companies.

Based on results, the small semiconductors do have larger liquidity risk than the mid-size or larger semiconductor companies.

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Appendix A

Appendix

Figure A.1: Garman & Klass (1980) Estimates of NASDAQ composite and S&P500 indices

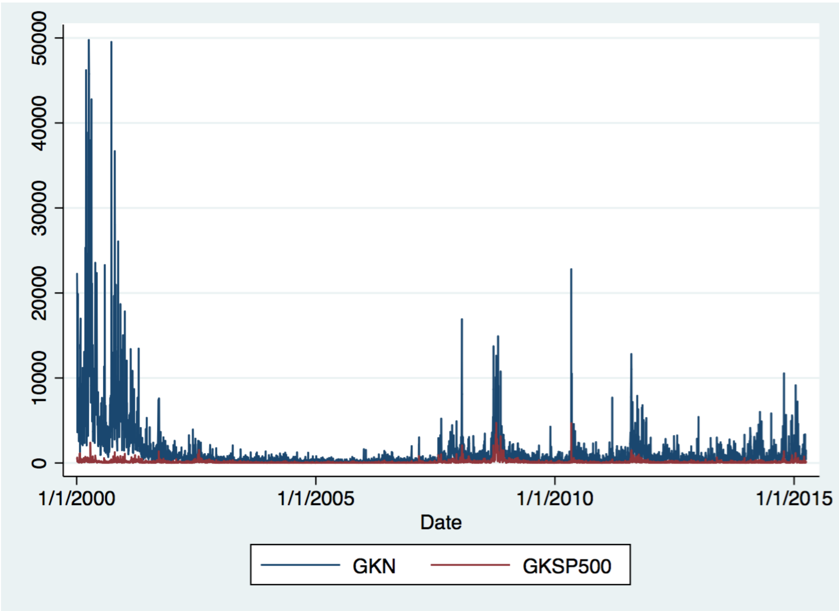

Figure A.2: Garman & Klass (1980) Estimates of all large semiconductor companies

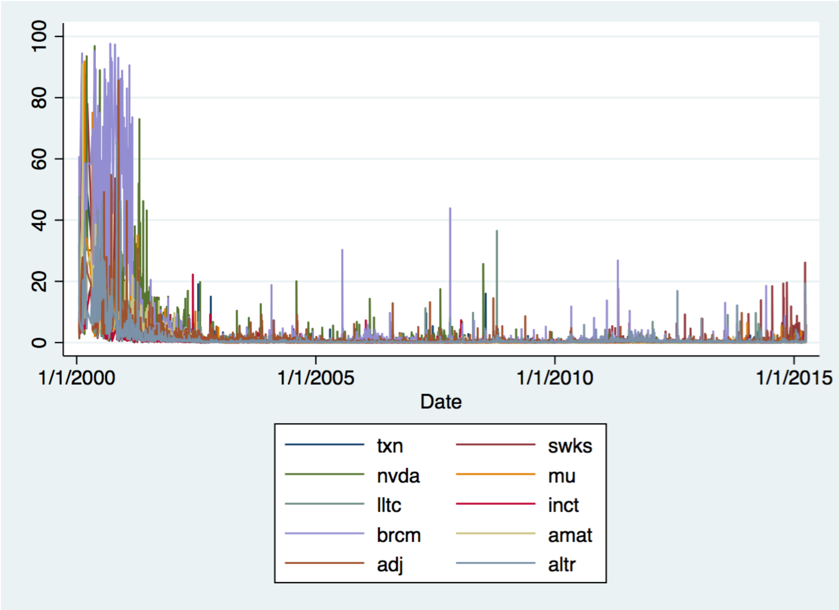

Figure A.3: The average Garman & Klass (1980) Estimates for all large semiconductor companies

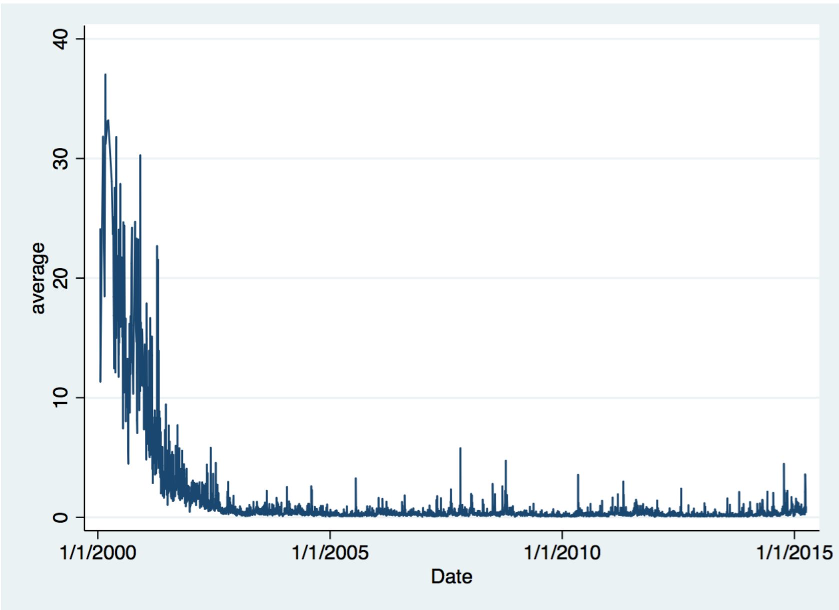

Figure A.4: Garman & Klass (1980) Estimates of all mid-size semiconductor companies

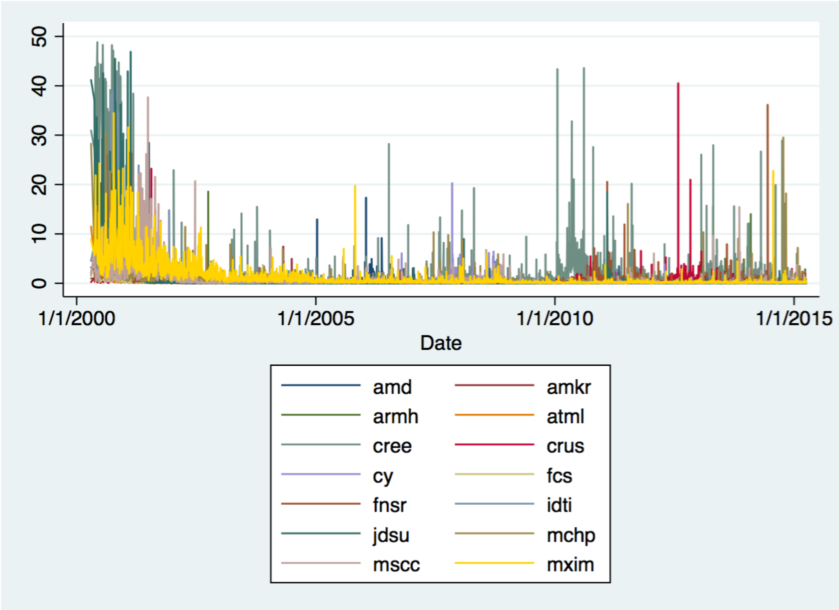

Figure A.5: The average Garman & Klass (1980) Estimates for all mid-size semiconductor companies

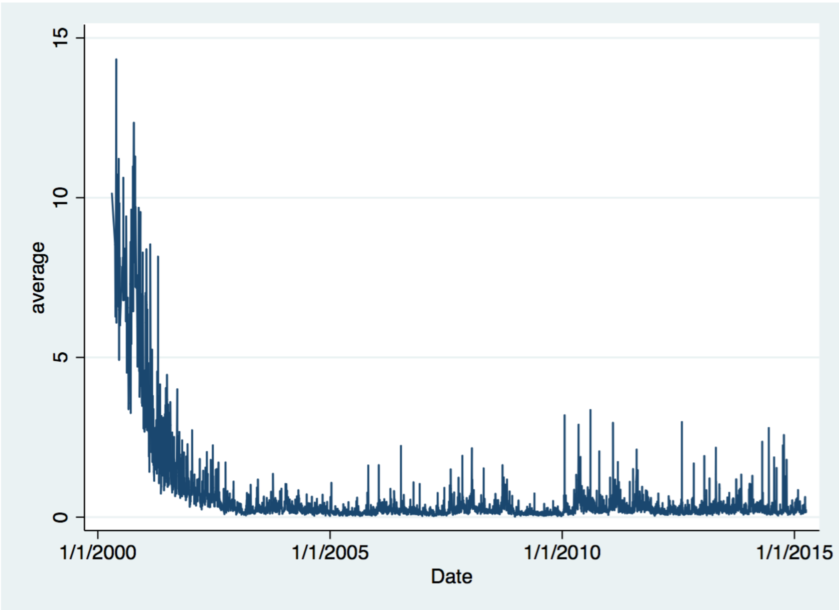

Figure A.6: Garman & Klass (1980) Estimates of all small semiconductor companies

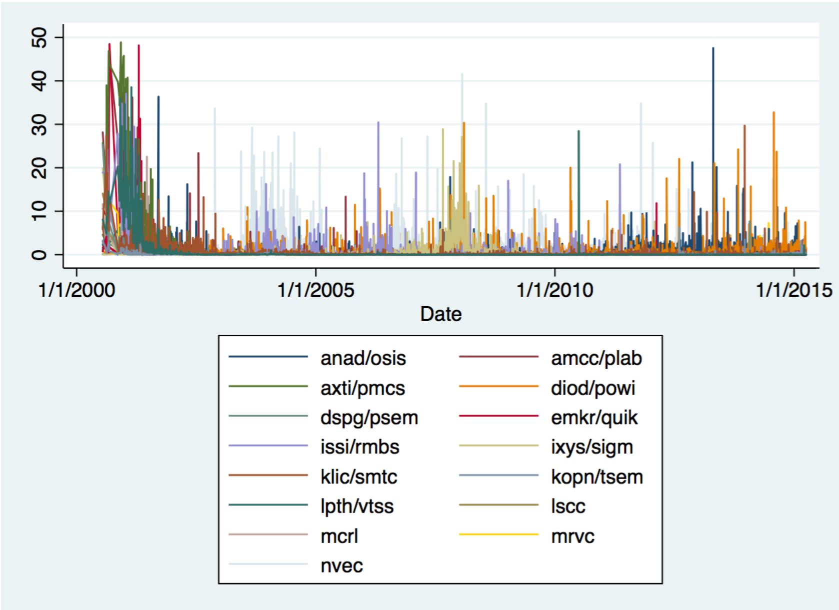

Figure A.7: The average Garman & Klass (1980) Estimates for all small semiconductor companies

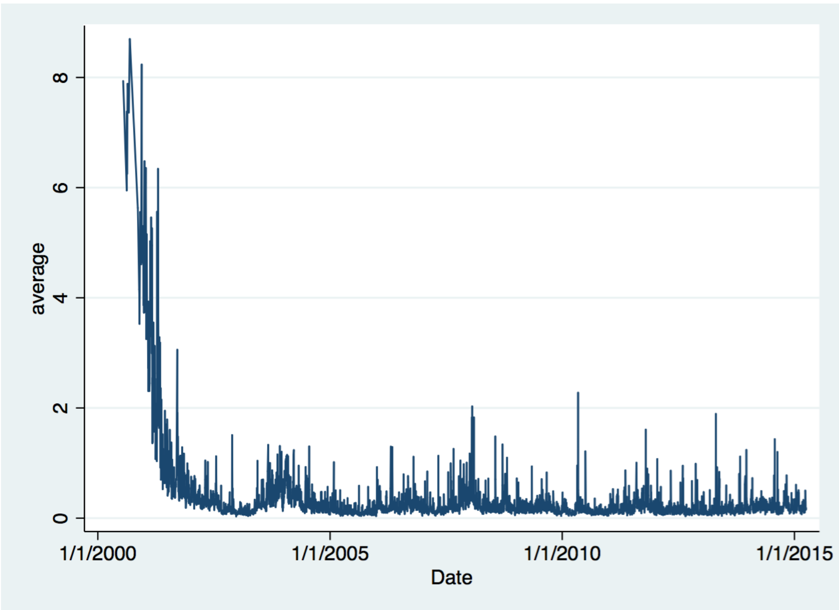

Figure A.8: The estimated coefficient $\beta_1(\alpha)$ (Garman & Klass (1980) Estimates) in period 2000-2007

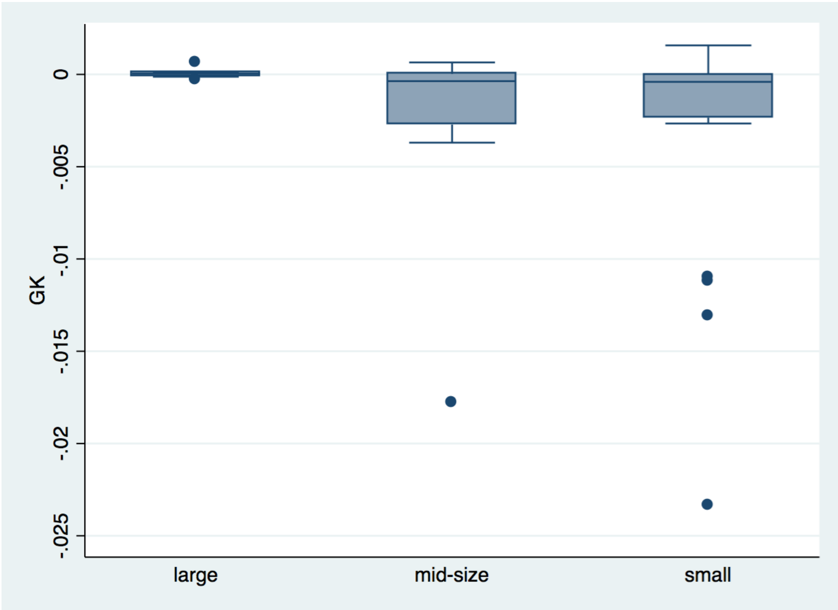

Figure A.9: The estimated coefficient $\beta_1(\alpha)$ (Garman & Klass (1980) Estimates) in period 2008-2015

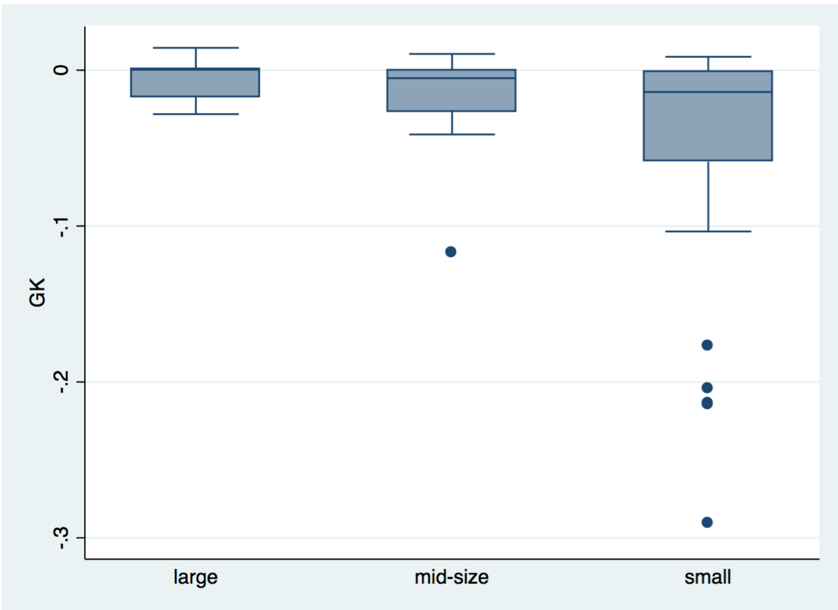

Figure A.10: The estimated coefficient $\beta_2(\alpha)$ (NASDAQ Composite Garman & Klass (1980) Estimates) in period 2000-2007

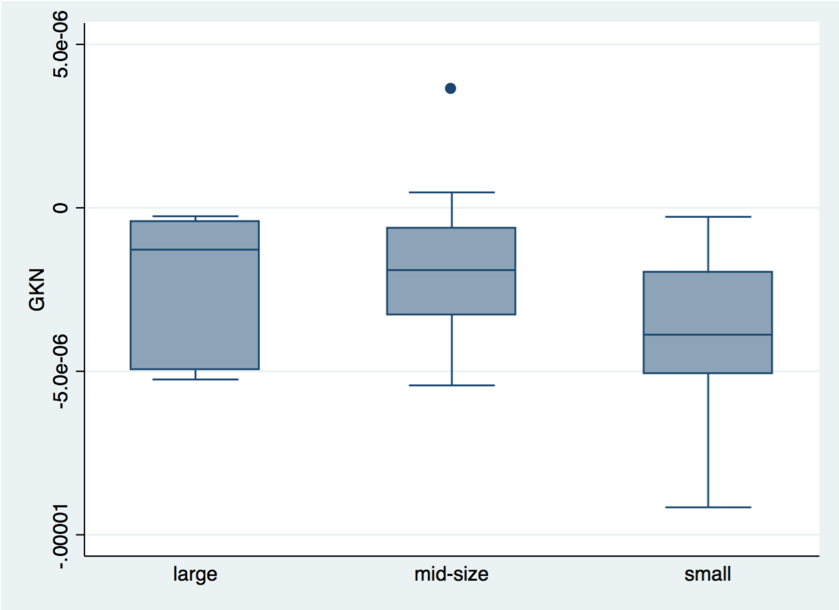

Figure A.11: The estimated coefficient $\beta_2(\alpha)$ (NASDAQ Composite Garman & Klass (1980) Estimates) in period 2008-2015

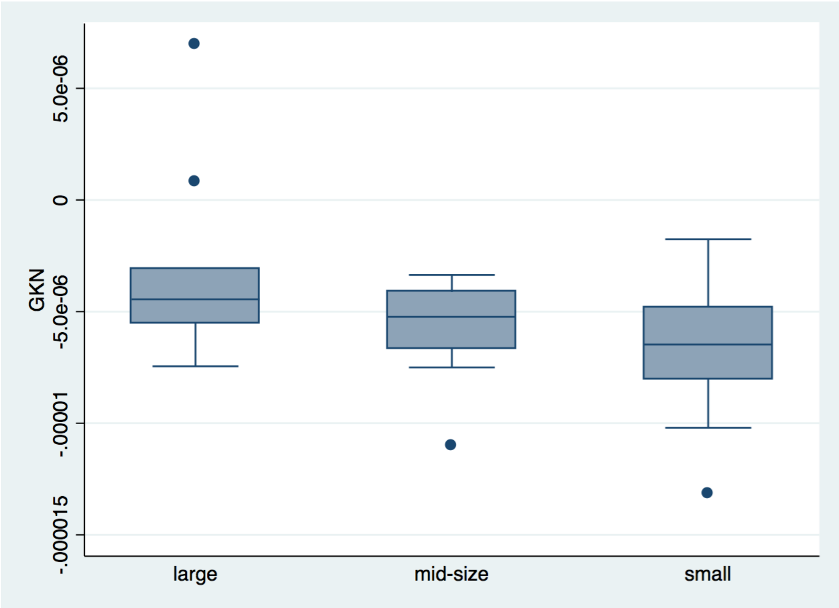

Figure A.12: The estimated coefficient $\beta_3(\alpha)$ (Amihud measure) in period 2000-2007

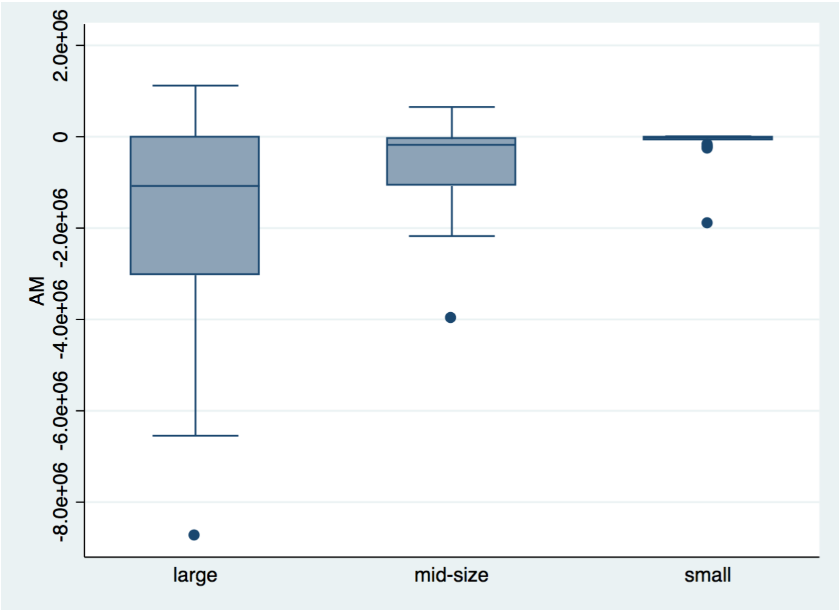

Figure A.13: The estimated coefficient $\beta_4(\alpha)$ (Amihud measure) in period 2008-2015

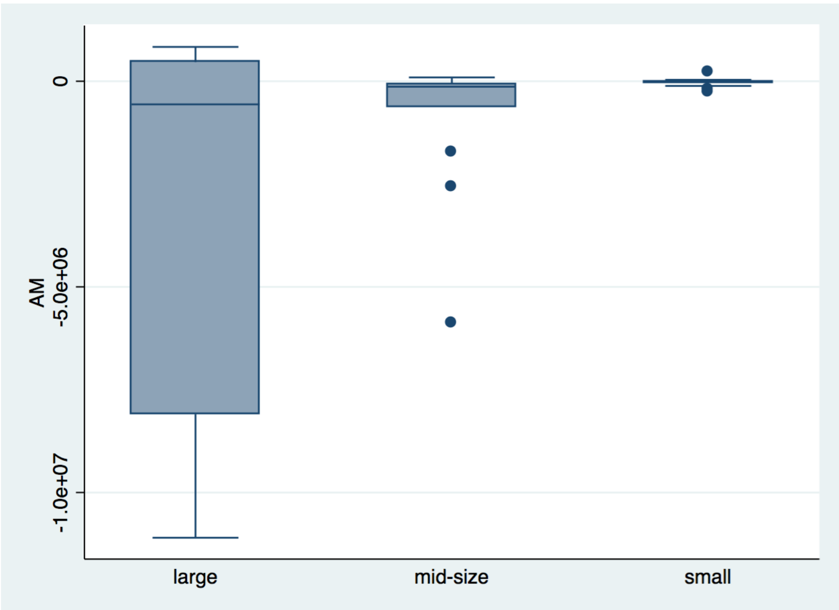

Figure A.14: The estimated coefficient $\beta_4(\alpha)$ (Roll measure) in period 2000-2007

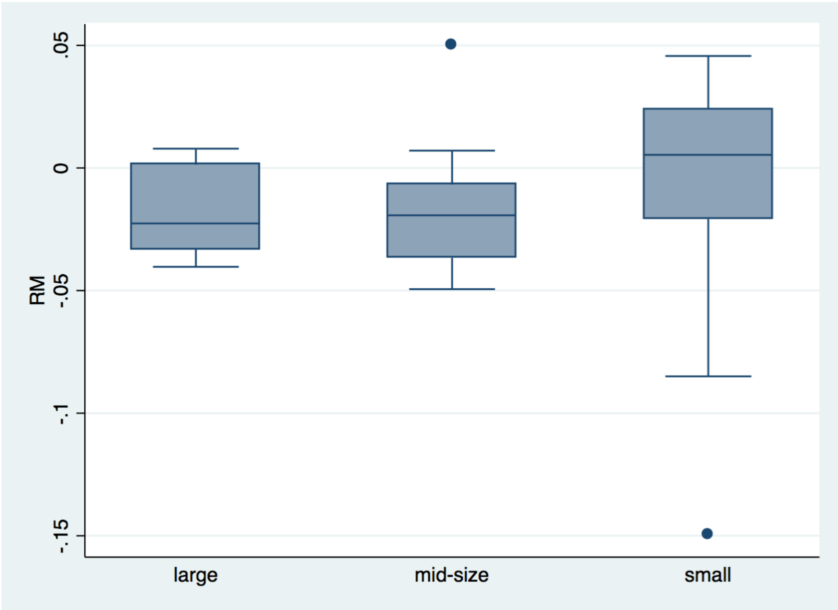

Figure A.15: The estimated coefficient $\beta_4(\alpha)$ (Roll measure) in period 2008-2015

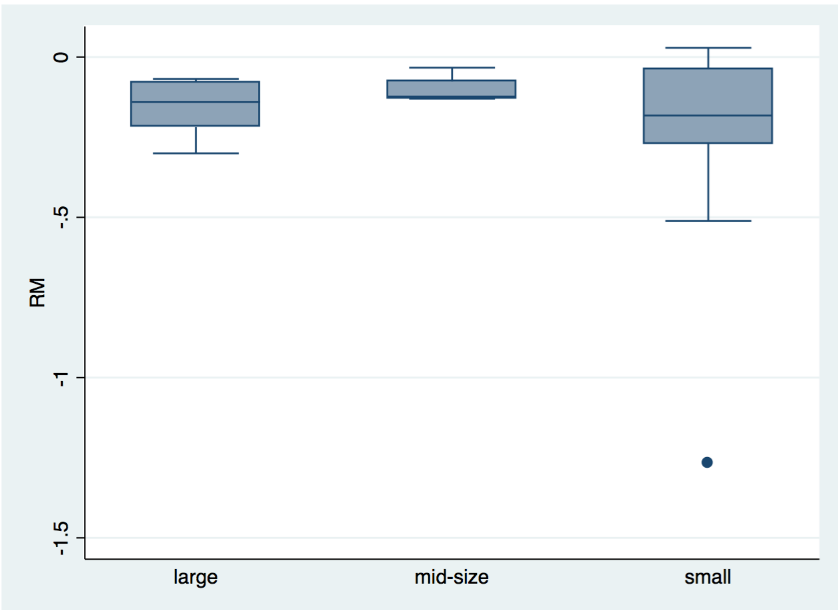

Table A.1: Sub-Sample Estimates of the Equation 4.3 for NASDAQ composite and S&P500 indices in period 2000-2007 at 0.05 quantile

index	$\beta_0(\alpha)$	t	$\beta_1(\alpha)$ (GK)	t	$\beta_2(\alpha)$ (AM)	t	$\beta_3(\alpha)$ (RM)	t
nsdaq	-0.0243263	-21.58	-0.0000032	-17.66	0.0000000	0.07	0.0000292	1.07
sp500	-0.0136523	-18.79	-0.0000383	-12.16	0.0000000	0.44	0.0001067	1.77

Table A.2: Sub-Sample Estimates of the Equation 4.3 for NASDAQ composite and SP500 indices in period 2008-20015 at 0.05 quantile

index	$\beta_0(\alpha)$	t	$\beta_1(\alpha)$ (GK)	t	$\beta_2(\alpha)$ (AM)	t	$\beta_3(\alpha)$ (RM)	t
nsdaq	-0.0179285	-11.95	-0.0000057	-7.1	0.0000000	0.41	0.0000904	2.08
sp500	-0.0143538	-10.88	-0.0000445	-11.18	0.0000000	0.85	0.0001337	1.42

Table A.3: Sub-Sample Estimates of the Equation 4.2 for Large Semiconductor Companies in period 2000-2007 at 0.05 quantile

symbol	$\beta_0(\alpha)$	t	$\beta_1(\alpha)$ (GK)	t	$\beta_2(\alpha)$ (GKN)	t	$\beta_3(\alpha)$ (AM)	t	$\beta_4(\alpha)$ (RM)	t
altr	0.0059281	1.3	0.0000966	2.78	-0.0000004	-1.5	-1077399	-1.93	-0.0246582	-11.95
adi	-0.0439858	-18.66	0.0006353	1.09	-0.0000050	-13.41	-3373.748	-1.45	0.0078758	2.04
amat	0.0118608	3.49	0.0000388	3.44	-0.0000004	-1.4	-8736507	-5.05	-0.0257577	-15.32
brcm	-0.0528232	-8.82	0.0000506	3.36	-0.0000013	-1.74	-6546106	-3.61	0.0015862	0.53
intc	-0.0398619	-23.6	0.0000009	0.05	-0.0000005	-1.69	393385.3	0.53	-0.0013349	-0.67
lltc	-0.0065793	-1.71	0.0000438	1.12	-0.0000029	-9.6	-1316336	-3.56	-0.0341493	-9.18
mu	-0.0262047	-6.08	-0.0000523	-1.35	-0.0000010	-1.98	-3028288	-3.03	-0.022628	-6.15
nvda	-0.0253241	-5.06	-0.000126	-8.55	-0.0000050	-14.27	1119352	1.26	-0.0128343	-7.09
swks	-0.0404301	-7.06	0.0000464	0.63	-0.0000003	-0.35	-28215.96	-0.3	-0.0403243	-7.02
txn	-0.0380193	-14.05	0.0001002	2.91	-0.0000053	-16.63	-2159362	-2.09	0.0013597	0.29
xlnx	0.000797	0.13	-0.000337	-1.15	-0.0000014	-2.85	-258250.4	-0.31	-0.0331211	-7.53

Table A.4: Sub-Sample Estimates of the Equation 4.2 for Large Semiconductor Companies in period 2008-2015 at 0.05 quantile

symbol	$\beta_0(\alpha)$	t	$\beta_1(\alpha)$ (GK)	t	$\beta_2(\alpha)$ (GKN)	t	$\beta_3(\alpha)$ (AM)	t	$\beta_4(\alpha)$ (RM)	t
altr	0.066311	3.35	-0.0005958	-0.29	-0.0000033	-2.93	-562725.9	-0.8	-0.0786124	-4.72
adi	-0.0269008	-14	-0.0169831	-6.36	-0.0000031	-3.17	53435.22	3.87		
amat	0.043163	2.26	-0.0242926	-1.77	-0.0000035	-2.66	-8095309	-3.39	-0.068289	-3.36
brcm	-0.0309764	-8.61	0.0004045	0.21	-0.0000052	-3.67	-2019839	-1.36		
intc	-0.0220498	-7.47	-0.0281961	-4.74	0.0000008	0.61	-11100000	-1.26		
lltc	0.0492442	3.73	0.000438	0.41	-0.0000049	-6.74	466491.5	1.32	-0.1401485	-5.68
mu	0.0681255	2.29	0.0020805	0.22	-0.0000069	-3.56	-9287945	-3.51	-0.3004877	-3.62
nvda	0.2333867	59.58	0.0143369	27.16	0.0000070	28.77	834582.6	2.65	-0.2182802	-75.27
swks	0.0249308	0.94	0.0007136	0.49	-0.0000075	-5.29	-977660.7	-2.25	-0.1607619	-2.22
txn	-0.0243484	-11.85	0.0000252	0.01	-0.0000055	-6.33	635224.6	0.5		
xlnx	0.0770472	5.05	0.0002856	0.32	-0.0000045	-5.2	264093.3	0.46	-0.1308959	-6.83

Table A.5: Sub-Sample Estimates of the Equation 4.2 for Mid-size Semiconductor Companies in period 2000-2007 at 0.05 quantile

symbol	$\beta_0(\alpha)$	t	$\beta_1(\alpha)$ (GK)	t	$\beta_2(\alpha)$ (GKN)	t	$\beta_3(\alpha)$ (AM)	t	$\beta_4(\alpha)$ (RM)	t
amd	-0.0460524	-15.82	-0.0005423	-5.27	0.0000036	9.4	-3998300	-6.36	-0.0065309	-1.47
amkr	-0.0629296	-15.26	-0.0023033	-1.82	-0.0000015	-1.82	-264391.4	-2.77	0.0499072	1.49
armh	-0.0124183	-2.48	0.0000216	2.97	-0.0000054	-13.78	-60787.72	-3.31	-0.0069374	-6.62
atml	-0.0536847	-14.75	0.0006477	1.95	-0.0000033	-7.88	-2174277	-3.53	-0.0145255	-0.83
crus	-0.0569158	-11.62	-0.0177952	-8.32	0.0000005	0.86	-200506.4	-1.94	-0.015721	-0.84
cree	-0.0545123	-11.89	-0.0001835	-2.23	-0.0000039	-6.53	-243197.9	-1.21	0.0070734	1.29
cy	-0.0327048	-7.65	-0.0036978	-4.64	0.0000000	-0.02	651561.2	0.8	-0.0423374	-5.08
fcs	-0.0457728	-16.86	-0.0035213	-1.7	-0.0000021	-5.37	-155571.3	-2.33	-0.0494346	-1.7
fnsr	-0.0738511	-13.93	0.0001442	2.46	-0.0000023	-3.17	-140964.3	-5.78		
idti	-0.041998	-12.55	-0.002717	-7.15	-0.0000006	-1.42	-1079224	-5.43	-0.0229179	-3.38
jdsu	-0.0536959	-19.11	0.0000309	5.55	-0.0000033	-8	-1488389	-12.21		
mxim	0.0028224	0.19	0.0006098	0.94	-0.0000014	-1.45	166126.4	0.15	-0.030732	-3.34
mchp	0.006568	1.48	-0.0001111	-0.79	-0.0000017	-5.24	280138.8	1.26	-0.0404329	-12.32
mscc	-0.0488021	-11.03	-0.0018715	-9.34	-0.0000033	-6.01	-49667.11	-0.75	-0.0328383	-2.65

Table A.6: Sub-Sample Estimates of the Equation 4.2 for Mid-size Semiconductor Companies in period 2008-2015 at 0.05 quantile

symbol	$\beta_0(\alpha)$	t	$\beta_1(\alpha)$ (GK)	t	$\beta_2(\alpha)$ (GKN)	t	$\beta_3(\alpha)$ (AM)	t	$\beta_4(\alpha)$ (RM)	t
amd	-0.0411071	-10.7	-0.117166	-5.8	-0.0000037	-2.16	-5879324	-2.78		
amkr	-0.0416842	-10.62	-0.0263617	-1.27	-0.0000072	-4.35	-139252.5	-0.82		
armh	0.0457391	2.76	-0.0067869	-3.85	-0.0000041	-4.62	-71426.19	-1.69	-0.0331448	-4.59
atml	-0.0346266	-12.08	-0.0412475	-2.27	-0.0000039	-3.19	-1718446	-3.84		
crus	-0.042108	-12.72	-0.0034695	-1.71	-0.0000064	-4.01	-109942.1	-1.68		
cree	-0.0418866	-13.04	-0.0000358	-0.11	-0.0000053	-3.58	-88376.38	-0.46		
cy	-0.0280655	-6.22	0.0003892	0.66	-0.0000110	-6.28	-464969.1	-0.91	-0.1298549	-2.3
fcs	-0.0334158	-8.32	-0.0271207	-1.48	-0.0000052	-2.83	-620044.2	-3.48		
fnsr	-0.0526726	-16.26	0.0001244	0.27	-0.0000075	-4.4	-128068.7	-8.7		
idti	-0.0376956	-12.3	0.0104243	0.78	-0.0000067	-5.08	47554.11	0.21		
jdsu	-0.0344983	-8.1	-0.0203094	-4.67	-0.0000052	-2.81	-2584070	-4.42		
mxim	0.0887449	5.54	0.0000603	0.03	-0.0000051	-5.29	-137553.9	-0.52	-0.1282684	-7.03
mchp	0.0621668	4.65	-0.0001877	-0.16	-0.0000034	-4.15	-8960.324	-0.03	-0.1181078	-6.56
mscc	-0.0344504	-11.25	-0.0105449	-3.26	-0.0000057	-4.44	91937.32	1.17		

Table A.7: Sub-Sample Estimates of the Equation 4.2 for Small Semiconductor Companies in period 2000-2007 at 0.05 quantile

symbol	$\beta_0(\alpha)$	t	$\beta_1(\alpha)$ (GK)	t	$\beta_2(\alpha)$ (GKN)	t	$\beta_3(\alpha)$ (AM)	t	$\beta_4(\alpha)$ (RM)	t
anad	-0.0729379	-14.27	-0.0003588	-3.88	-0.0000043	-6.85	-56325.04	-1.59	0.0332497	0.65
amcc	-0.0347541	-6.69	0.0000189	2.49	-0.0000020	-3.31	-236200.7	-3.79	-0.0144063	-8.63
axti	-0.07075	-14.9	-0.0000187	-0.02	-0.0000039	-5.67	-4530.549	-1.07	0.0334468	0.65
diod	-0.0467343	-24.36	-0.0026587	-10.68	-0.0000039	-13.6	-4664.384	-3.06	0.0143752	0.79
dspg	-0.0108534	-3.09	0.0000887	2.79	-0.0000026	-9.05	-10092.36	-0.63	-0.0146692	-9.42
emkr	-0.0714074	-18.75	-0.0001767	-3.22	-0.0000048	-7.6	-8369.57	-4.32	-0.008272	-0.89
issi	-0.0537927	-12.07	-0.0233576	-6.97	-0.0000006	-0.82	-35173.69	-1.79	0.0050479	0.23
ixys	-0.0482695	-12.02	-0.0025037	-11.48	-0.0000035	-5.68	-16395.96	-3.31	-0.0849776	-1.57
kopn	-0.0367709	-6.85	-0.0001006	-1.06	-0.0000035	-8.67	-35770.32	-0.87	-0.0390156	-8.23
klic	-0.0527549	-15.39	-0.0010893	-4.6	-0.0000016	-3.89	-267300.9	-3.43	0.0158813	1.51
lscc	-0.0315991	-5.71	-0.0016868	-8.11	-0.0000018	-5.31	-70237.54	-0.76	-0.0285072	-4.03
lpth	-0.0926739	-24.66	0.0015753	1.86	-0.0000071	-8.52	0.3744922	0	0.0239755	1.39
mcrl	-0.050851	-15.56	-0.0003379	-6.46	-0.0000034	-8.34	-209762.1	-3.09	0.0060886	1.91
mrvc	-0.0679765	-22.05	0.0000825	0.84	-0.0000092	-20.33	-3823.681	-2.53	0.0055904	1.93
nvec	-0.0712941	-9.35	-0.0023395	-2.36	-0.0000082	-12.98	-85.30188	-7.8	0.0456573	1.74
osis	-0.0073987	-1.46	-0.0110192	-12.27	-0.0000038	-10.36	393.3436	0.56	-0.0533718	-7.02
psem	-0.0502106	-9.37	-0.0004493	-4.09	-0.0000077	-12.68	7590.658	0.46	0.0342276	0.65
plab	-0.0415916	-13.75	-0.0111961	-7.26	-0.0000014	-3.18	-51788.59	-1.35	-0.0207942	-1.79
pmcs	-0.0630734	-10.91	0.0000414	2.87	-0.0000051	-7.86	-1905189	-2.53	0.0146674	1.47
powi	-0.0521595	-15.25	-0.0016607	-5.39	-0.0000043	-9.72	-22196.73	-1.11	0.0356415	2.07
quik	-0.0343314	-5.96	-0.0006729	-1.02	-0.0000046	-8.16	-3132.442	-1.52	-0.1494363	-6.58
rmbs	-0.0593382	-12.51	-0.0000555	-10.05	-0.0000054	-8.84	-193885.6	-1.21	0.0131416	1.26
smtc	-0.0467672	-11.26	0.0000915	1.42	-0.0000051	-9.86	-240357.5	-1.89	0.0051022	1.04
sigm	-0.0626882	-18.1	0.000765	0.54	-0.0000049	-9.97	-4236.939	-9.03	0.0018999	0.05
tsem	-0.0581678	-19.7	-0.0131001	-5.49	-0.0000003	-0.5	-60.95174	-1.16	0.0450945	0.88
vtss	-0.0513577	-6.66	-0.0005292	-1.18	-0.0000018	-1.94	-25505.83	-1.76	-0.0314224	-3.82

Table A.8: Sub-Sample Estimates of the Equation 4.2 for Small Semiconductor Companies in period 2008-2015 at 0.05 quantile

symbol	$\beta_0(\alpha)$	t	$\beta_1(\alpha)$ (GK)	t	$\beta_2(\alpha)$ (GKN)	t	$\beta_3(\alpha)$ (AM)	t	$\beta_4(\alpha)$ (RM)	t
anad	-0.0610306	-12.97	-0.0250735	-1.98	-0.0000050	-2.57	18488.18	0.31		
amcc	-0.0068701	-0.3	0.0027716	0.16	-0.0000051	-3.46	-96599.38	-1.35	-0.0360727	-1.66
axti	-0.0413842	-13.48	-0.1034538	-3.18	-0.0000101	-6.57	-18077.76	-4.35		
diod	-0.0369758	-7.88	0.0003195	0.06	-0.0000102	-5.5	-29579.28	-0.63		
dspg	0.113828	5.81	-0.0587554	-3.74	-0.0000032	-2.71	-5749.95	-1.03	-0.150205	-7.81
emkr	-0.0620141	-11.02	-0.0573895	-4.77	-0.0000080	-3.03	-30340.96	-1.91		
issi	-0.0335431	-11.76	-0.0346404	-3.59	-0.0000063	-4.35	-28858.34	-4.02		
ixys	-0.042078	-9.06	-0.0049514	-0.41	-0.0000065	-3.34	-10406.97	-0.88		
kopn	0.0788128	2.89	-0.2139767	-1.67	-0.0000068	-4.02	-56839.89	-3.48	-0.2686433	-4.29
klic	-0.037035	-11.59	-0.0140686	-0.88	-0.0000055	-3.55	-284327	-7.39		
lscc	0.0426941	1.96	-0.2045744	-6.04	-0.0000041	-3.24	-107516.9	-1.67	-0.2197614	-3.68
lpth	-0.0720019	-14.14	-0.2905618	-2.69	-0.0000082	-3.13	-389.5343	-6.3		
mcrl	-0.0284551	-13.88	-0.0178119	-1.74	-0.0000048	-5.39	-7196.486	-0.24		
mrvc	-0.0504176	-12.36	-0.0014995	-0.4	-0.0000093	-4.37	100.1022	0.32		
nvec	0.0489627	0.93	-0.0021493	-2.51	-0.0000018	-1.36	1707.713	0.71	-0.1824092	-1.57
osis	-0.037163	-3.62	-0.0008262	-4.1	-0.0000063	-5.54	-44752.69	-3.79	0.0288865	1.5
psem	-0.0418438	-13.46	-0.0385715	-4.22	-0.0000031	-2.33	-2101.831	-0.26		
plab	-0.0295798	-7.47	-0.0056656	-0.17	-0.0000132	-7.06	-211605	-9.44		
pmcs	-0.029403	0.0031491	-0.1772395	-6.69	-0.0000076	-5.54	205651.1	0.67		
powi	-0.0342661	-12.53	-0.0001415	-0.56	-0.0000071	-6.35	33429.77	1.26		
quik	0.0678936	2.05	-0.2146005	-3.02	-0.0000076	-3.49	-13478.55	-1.73	-1.269834	-3.53
rmbs	-0.0386178	-10.59	-0.0053549	-3.89	-0.0000083	-5.51	-114655	-0.8		
smtc	-0.030103	-12.67	0.0004456	0.28	-0.0000033	-3.46	-57799.97	-0.97		
sigm	-0.0389361	-1.71	-0.013942	-8.14	-0.0000037	-2.35	14584.47	0.47	-0.0298124	-0.18
tsem	-0.0493569	-14.45	0.0025111	1.42	-0.0000076	-4.21	-1322.585	-3.88		
vtss	0.1329712	4.42	0.0085586	1.73	-0.0000064	-3.73	-5373.751	-1.77	-0.5110169	-5.89