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The trading volume trend, investor sentiment, and stock returns

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THE TRADING VOLUME TREND, INVESTOR SENTIMENT, AND STOCK RETURNS

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Abstract

This dissertation relates the information contained in past trading volume to investor sentiment, and investigates its ability in predicting stock returns. Investor sentiment here refers to the enthusiasm of irrational investors on an asset, relative to that of rational investors. Motivated by Baker and Stein (2004) that an increase in trading volume reflects a rise in investor sentiment, I use the change in trading volume per unit of time, referring it as the trading volume trend, as a measure of investor sentiment on individual stocks.

I document a negative and significant cross-sectional relation between the trading volume trend and stock returns, both in the short term and in the long run. This relation is dynamic and holds after controlling for several liquidity measures and other possible determinants of expected returns. It also holds for various volume measures and momentum portfolios. Specifically, both winner and loser portfolios show the effect of the trading volume trend. The effect exists in stocks of small and large firms, and in optioned and non-optioned stocks. These findings suggest that the negative effect of the trading volume trend on stocks returns is robust.

Moreover, a composite trading volume trend, formed on the trading volume trends of individual stocks, can predict both the equally-weighted and the value-weighted market returns in the expected direction, after controlling for other possible determinants of market returns. The composite trading volume trend also explains closed-end fund discounts. Collectively these findings support that the trading volume trend contains information on investor sentiment, and that investor sentiment has a valuation effect on stocks.

Chapter 1. Introduction

Trading volume can contain information on how security prices evolve over time. For instance, Brennan, Chordia, and Subrahmanyam (1998), Datar, Naik, and Radcliffe (1998), and Chordia, Subrahmanyam, and Anshuman (2001) argue that trading volume reflects liquidity. They find that stocks with lower trading volume earn higher expected returns as a liquidity premium. Lee and Swaminathan (2000), on the other hand, argue that trading volume does not measure liquidity. They find that momentum profits depend on the past level of trading volume. Since high- (low-) volume winner (loser) stocks experience faster return reversals, trading volume plays a role in reconciling intermediate-term momentum with long-term reversal on stock returns.

In this dissertation I investigate an alternative explanation for the relation between trading volume and stock returns. Motivated by Baker and Stein (2004) that market liquidity as measured by trading volume can be an indicator of investor sentiment, I apply the framework of Baker and Stein (2004) and devise a volume-based measure of investor sentiment for individual stocks. I investigate the sentiment information contained in trading volume and its relation with stock returns.

In the model of Baker and Stein (2004), there are one class of rational investors and one class of overconfident investors. Both classes of investors have non-negative weights on the pricing function of the underlying security but the overconfident investors outweigh their own information. There are also short-sales constraints on the market and insiders who trade on their private information. The overconfident investors underreact to the information contained in the insiders' trades. As they adjust their beliefs and trade, the price increases gradually. They would trade more as the returns confirming their beliefs, and gain a greater weight on the pricing function. Overconfident investors' transactions drive security prices up and lower the price impact of trades. The elevated prices lead to lower expected returns and the lowered price impact attracts more trading volume. Since there are short-sales constraints on the market, the rational investors cannot counteract the overconfident investors' transactions. To the extreme, when investor sentiment becomes very high, the overconfident investors dominate the market, which is characterized with high liquidity and high trading volume. An increase in trading volume thus reflects the participation of overconfident investors in the market, and indicates an increase in investor sentiment.

Alternatively, extant theories imply a natural link between investor sentiment and trading volume. The sentiment literature suggests that investor sentiment can be measured as the valuation differences between one group of rational investors and one group of irrational investors (Zweig (1973), Lee, Shleifer, Thaler (1991), Baker and Stein (2004), and Brown and Cliff (2005)). Therefore when investor sentiment becomes high, investor heterogeneity would become high as well. On the other hand, the volume literature suggests that investor heterogeneity contributes to trading volume (e.g., Karpoff (1986) and Harris and Raviv (1993)). It is thus conceivable that when investor sentiment becomes high (low), trading volume is likely to increase (decrease).

Nevertheless, researchers also use the level of trading volume as a liquidity measure. First, extant models suggest that trading volume can be one aspect of liquidity (e.g., Stoll (1978a) and Amihud and Mendelson (1986a)). Second, trading volume has negative relations with transaction costs, another aspect of liquidity (e.g., Chordia, Roll, and Subrahmanyam (2000)).To differentiate the information contained in trading volume as either liquidity-related or sentiment-related, I use the trend on the trading volume series of a stock as the sentiment measure on that stock. I call it the trading volume trend. The trading volume trend by definition is the average change on trading volume per unit of time. It shows the propensity of investors to trade. It is a better sentiment measure than the level of trading volume. First, it reflects the movement of overconfident investors on the market in the framework of Baker and Stein (2004). Second, the sentiment literature suggests that investor sentiment is likely formed through a process over time (e.g., Smidt (1968) and Brown and Cliff (2005)). For instance, Brown and Cliff (2005) suggest that "it seems natural to view sentiment as a persistent variable. People become more optimistic as they are reinforced by others joining on the bandwagon." The trading volume trend summarizes the process rather than simply being a snap shot on the process. Third, stocks in the cross section can have the same level of trading volume but very different trading volume trends over a period of time. The trading volume trend thus mitigates the problem of mixing investor sentiment information with liquidity information.

In the next chapter, I review the relevant literature from three aspects: The liquidity literature, the sentiment literature, and the trading volume literature. In each topic I begin with the definitions, then the relations with expected stocks returns, and the measures that are commonly used. I also explain how extant theories can link trading volume and investor sentiment together, and why I use the trading volume trend to measure investor sentiment.

In chapter 3 I employ the framework of Chordia, Subrahmanyam, and Anshuman (2001) and examine the cross-sectional relation between the trading volume trend and expected stock returns. Consistent with earlier work, I find the negative cross-sectional relation between the level of trading volume and expected stock returns. This relation is not as strong as previously documented, however, once I control for the short-term return volatility. The return volatility has a strong negative relation with expected stock returns as documented in Amihud (2002). This finding suggests that both liquidity and non-liquidity reasons may drive the relation between the level of trading volume and expected stock returns. The trading volume trend, on the other hand, has a negative and significant relation with expected stock returns, after controlling for the level and volatility of trading volume, and other possible determinants of return. This finding suggests that investor sentiment as proxied by the trading volume trend is priced in the cross section.

My results also reveal that, for the trading volume trends defined over the past one year, past three years, and past five years, only the one over the past three years has the negative and significant relation with the monthly expected stock returns. These findings can be reconciled with a sentiment explanation. Brown and Cliff (2005) argue that investor sentiment can build up over time. Investor sentiment at its different stages is then likely to exhibit different effects on expected returns. The trading volume trends defined over the different lengths of periods can simply reflect the different stages of investor sentiment and exhibit different effects on stock returns. My results in chapter 4 provide further support to this argument.

In chapter 4 I extend my analyses from the monthly cross-sectional regressions to the portfolio level. I construct stock portfolios based on their trading volume trends and examine the long-run portfolio returns. The results on the trend portfolios suggest that the relations between trading volume trends and stock returns are dynamic and they collaborate with what I find in chapter 3. Consistent with the trading volume trend as a measure of investor sentiment, stocks with higher trading volume trends earn higher contemporaneous returns but earn lower returns in the future.

An examination of momentum portfolios further reveals that, after controlling for past return momentum, stocks with high trading volume trends still earn lower future returns than stocks with low trading volume trends. To distinguish the information contained in the trading volume trend and the past level of trading volume (e.g., Lee and Swaminathan (2000)), I also form my trend portfolios after controlling for the past level of trading volume. The effects of the trading volume trend on stock returns persist after controlling for the trading volume level.

My analyses on the risk profiles of stocks suggest that stocks with extreme trading volume trends perform like stocks of smaller firms. Portfolios formed on them have larger SMB factor loadings than portfolios formed on remaining stocks. This finding supports the hypothesis that investor sentiment is more likely to manifest its effects on stocks of smaller firms (e.g., Lee, Shleifer, Thaler (1991) and Neal and Wheatley (1998)).

Since short-sales constraints play an important role on linking trading volume and expected returns in Baker and Stein (2004), I also investigate whether short-sales constraints as proxied by firm size and whether a stock is optioned or not affect the information of the trading volume trend on stock returns. Unconditionally, stocks of larger firms and optioned stocks are less likely to experience extreme trading volume trends. The effect of trading volume trend on stock returns, however, persists even for those stocks. These results provide only partial support to the model of Baker and Stein (2004), but they are likely to be explained by the findings of Lakonishok, Lee, and Poteshman (2004). Lakonishok, Lee, and Poteshman (2004) find that investors did not increase their purchases on put options during the bubble period of late 1990s. In other words, even without short-sales constraints, rational investors may not trade to counteract the transactions of overconfident investors because they may face the noise trader risk (see De Long, Shleifer, Summers, and Waldman (1990)).

In chapter 5 I construct a market-wide sentiment measure based on the trading volume trends of individual stocks. I call it the composite trading volume trend. If the trading volume trend at the individual stock level measures investor sentiment appropriately, the composite trading volume trend is likely to reflect investor sentiment at the market level and provide information on future market returns. To start my analysis, I examine the time-series relation between the composite trading volume trend and closed-end fund discounts, since closed-end fund discounts are also widely used as a sentiment measure. The results indicate that the composite trading volume trend has a negative and significant near-term relation with a value-weighted index of closed-end fund discounts, suggesting that investor sentiment is one determinant of closed-end fund discounts, and higher investor sentiment leads to lower close-end fund discounts.

Next I examine the time-series relation between the composite trading volume trend and the sentiment index of Baker and Wurgler (2004). Baker and Wurgler (2004) construct their sentiment index as the first principal component of six commonly employed market sentiment measures: The average closed-end fund discounts, the NYSE share turnover, the number and average first-day returns on IPOs, the equity share in new issues, and the dividend premium. The results from the time-series regressions indicate that the composite trading volume trend has a positive and significant near-term relation with the sentiment index. It seems to provide complementary information on the sentiment index of Baker and Wurgler (2004), and it explains an incremental 19% of the variation on the sentiment index, after controlling for the past value of this index.

The composite trading volume trend also explains the market returns. Specifically, a higher composite trading volume trend leads to lower market returns. This result holds for both the equally-weighted market returns and the value-weighted market returns, and after controlling for the sentiment index of Baker and Wurgler (2004) and market liquidity measures such as the price impact measure of Amihud (2002) and the Roll spread. These findings suggest that market sentiment as proxied by the composite trading volume trend affects the market returns.

The results in this dissertation suggest that the trading volume trend provides significant information on stock returns. The results also suggest that the trading volume trend on a stock reflects investor sentiment on that stock. These findings complement several studies that explore the relations between trading volume and expected stock returns, and investor sentiment and expected stock returns. For instance, Lee and Swaminathan (2000) find that past trading volume links intermediate-term momentum and long-term reversal on stock returns. Specifically, high- (low-) volume winners win less (more) than low- (high-) volume winners, and high- (low-) volume losers lose more (less) than low- (high-) volume losers. Further, high- (low-) volume winners (losers) experience faster return reversals than low- (high-) volume winners (losers). My analyses provide the rationale and evidence on why and how past trading volume can carry sentiment information on expected returns.

Baker and Wurgler (2004) argue that stocks in the cross section are subject to different levels of investor sentiment either because of different shocks on sentiment-based demands or because of different arbitrage constraints across stocks. They hypothesize that stocks with certain characteristics, e.g., small stocks, young stocks, distressed stocks, etc., are more vulnerable to investor sentiment. They find that a market-wide index of investor sentiment affects the returns of those stocks in the predicted manner. Unlike Baker and Wurgler (2004), I measure investor sentiment directly at the individual stock level and examine its relation with expected stock returns.

Brown and Cliff (2004) find that a survey measure of investor sentiment does not predict short-term market returns at weekly and monthly intervals, but Brown and Cliff (2005) find that the same investor sentiment measure predicts long-term market returns in the next two to three years. My results suggest that analyses similar to theirs can be performed at the individual stock level by estimating the trading volume trends of individual stocks. Researchers have developed market-wide sentiment measures such as the average close-end fund discount, the number and average first-day returns on IPOs, the equity share in new shares, the dividend premium, indexes based on survey data, or composite measures of the above (e.g., Lee, Shleifer, Thaler (1991), Neal and Wheatley (1998), Baker and Wurgler (2004), Brown and Cliff (2004, 2005), and Qiu and Welch (2004)). None of these measures targets individual stocks, however. Although the level of trading volume may arguably measure investor sentiment at the individual stock level, it is also widely used as a proxy for liquidity. In this regard I fill in the void with the trading volume trend.

The remaining of this dissertation proceeds as follows: In chapter 2 I review the relevant literature and explain my reasons on using the trading volume trend to measure investor sentiment. I explain the construction of the trading volume trend and examine its relations with cross-sectional stock returns in chapter 3. I extend my analyses to the portfolio level in chapter 4. In chapter 5 I link the trading volume trend with the sentiment index of Baker and Wurgler (2004), closed-end fund discounts, and market returns. I summarize and conclude this dissertation in chapter 6.

Chapter 2. Literature Review

What is liquidity? What is investor sentiment? How can we measure them? What are their relations with expected stock returns? What are their relations with trading volume? In the following sections I summarize what we have known and what we may not know from the literature on these issues. Section 2.1 reviews the definitions of liquidity and relates liquidity with expected returns. Section 2.2 reviews the empirical evidence on the relation between liquidity and expected returns. Since trading volume has been widely employed in asset pricing tests as a measure of liquidity, I examine the underlying rationales and corresponding evidence in section 2.3. In section 2.4 I introduce the other liquidity measures that I use as control variables in this dissertation. Section 2.5 reviews the definitions of investor sentiment. The empirical evidence on the relation between investor sentiment and expected returns is reviewed in section 2.6. Section 2.7 introduces the various sentiment measures that researchers have employed. The nature of trading volume is investigated in more details in section 2.8. I also explain in this section how extant theories can link trading volume and investor sentiment together, and why I use the trading volume trend to measure investor sentiment.

2.1 Liquidity: Definition and Rationale

"Because liquidity, like pornography, is easily recognized but not so easily defined…"

Maureen O'Hara, 1995
Market Microstructure Theory
Chapter 8: Liquidity and the Relationships between Markets

It is widely recognized in the literature that liquidity is an elusive concept (e.g., Kyle (1985), Amihud (2002) and Pastor and Stambaugh (2003)). In Demsetz (1968) it is "immediacy of exchange." In Smidt (1968) it is the service that "makes quick exchange possible." Although it generally refers to the speed and ease to convert an asset into cash, liquidity can have several different dimensions. For instance, Kyle (1985) defines liquidity from three aspects: Tightness, depth, and resiliency. Tightness refers to "the *cost* of turning around a position over a short period of time." Depth refers to "the *size* of an order flow innovation required to change prices in a given amount." Resilience refers to "the *speed* with which prices recover from a random, uninformative shock." A liquid market is thus one that is "almost infinitely tight," "not infinitely deep," and "resilient enough so that prices eventually tend to their underlying value" (Kyle (1985). See also Black (1971)).

The above characterization of liquidity is not the only one, nevertheless. Liquidity can also refer to the *time* needed to execute a trade for a certain quantity on the underlying asset. It is thus difficult, if not impossible, to have a comprehensive measure capturing all dimensions of liquidity. This explains the existence of numerous liquidity/illiquidity measures in the finance literature.[1]

Despite the empirical difficulties in measuring liquidity, the concept of liquidity is useful in helping us understand the dynamics of asset prices. For example, since transaction costs are one dimension of liquidity, and it is directly related to an investor's net holding-period return, there should be a link between liquidity and asset prices (Amihud and Mendelson (1986a)).[2] Specifically, a liquid security in terms of lower transaction costs should be favored by investors, and buying pressures from the investors will drive the security price up and lower the expected return on this security. Similarly, an illiquid security in terms of higher transaction costs should subject to selling pressures that will drive its price down and raise its expected returns. Liquidity should therefore have a negative effect on expected returns. This prediction on the

[1] Loosely, a measure of liquidity can also be thought as a measure of illiquidity, and vice versa, because of the inverse relation between liquidity and illiquidity. See also Smidt (1968).

[2] See also Amihud and Mendelson (1986b), Amihud and Mendelson (1988) and Amihud and Mendelson (1991) for discussions on this issue and its implications.

liquidity-expected returns relation is in fact extensively tested over the past decades. I will turn to this relation again in the next section.

Another stream of research that relates to liquidity and expected security returns includes Easley, Hvidkjaer, and O'Hara (2002) and O'Hara (2003). In these studies, asymmetric information between informed and uninformed investors creates the risk of price discovery. Although informed and uninformed investors would hold the same assets, their portfolios are different. In this case the risk of price discovery, though a type of idiosyncratic risk, is priced in the cross sections. Easley, Hvidkjaer, and O'Hara (2002) provide supporting evidence on this argument. With the PIN measure, a measure of the probability of informed trading, Easley, Hvidkjaer, and O'Hara (2002) show that for NYSE stocks in the period from 1983 to 1998, a stock with a higher probability of informed trading in the previous year has a higher expected monthly return in the current year (after controlling for firm size, beta, and the book to market ratio).[3]

However, the probability of informed trading can also be a measure of liquidity because asymmetric information is one major determinant of transaction costs. Further, the PIN measure is positively related to the quoted percentage spread and negatively related to turnover. Although in Easley, Hvidkjaer, and O'Hara (2002) the explanatory power of the PIN measure on expected returns holds even after controlling for the quoted spread or share turnover, it does not eliminate the possibility that the PIN measure still proxies for liquidity. Liquidity has several dimensions. In fact, O'Hara (2003) also recognizes that the transaction costs of liquidity and the risks of price discovery are usually present at the same time. It is thus difficult to disentangle the two.

[3] The PIN measure is first developed by Easley, Kiefer, O'Hara, and Paperman (1996), and extended by Easley, Kiefer, and O'Hara (1997) and Easley, Hvidkjaer, and O'Hara (2002).

2.2 Relation between Liquidity and Expected Stock Returns

2.2.1 Traditional Views

Although the concepts that transaction costs is one dimension of liquidity and that the costs should have a positive relation with expected returns are intuitive, a formal model that links transaction costs and expected returns is not present until Amihud and Mendelson (1986a). Early empirical studies focus mostly on the transaction costs aspect of liquidity. In late 1990s, researchers start to emphasize other dimensions of liquidity and examine their relations with expected returns.

Amihud and Mendelson (1986a) assume an economy with M types of investors and $N+1$ capital assets (asset 0 has zero spread and unlimited supply). Trading is made through competitive markets makers and buy (sell) transactions happen at the ask (bid) prices. The arrivals of investors type-1 to type-M follow different Poisson distributions and their expected holding periods follow exponential distributions. The expected holding period for a type-i investor is longer than the expected holding period for a type $i+1$ investor. Further, investors maximize the expected returns on their portfolios per unit of time. With these assumptions, Amihud and Mendelson (1986a) show an increasing and concave relation between security return and the (quoted) relative spread. They also provide supporting evidence on this relation for NYSE stocks in the period from 1961 to 1980. Even after considering other possible risk factors suggested by Merton (1987), such as security beta, residual risk, firm size, Amihud and Mendelson (1989) find that this relation still holds.

On the other hand, Eleswarapu and Reinganum (1993) document that for NYSE stocks in the period from 1961 to 1990, the positive relation between the relative spread and security return holds only in the months of January, suggesting a seasonal component of the liquidity premium. This finding questions not only the predictions of Amihud and Mendelson (1986a), but also the validity of the quoted spreads as a proxy of transaction costs. Nevertheless, in Amihud and Mendelson (1986a), Amihud and Mendelson (1989), and Eleswarapu and Reinganum (1993), the relative spread for a stock in a given year is defined as the average of its beginning and end-of-year relative spreads. The variation of the relative spreads during the year is not captured by these spread variables.

Rather than using quoted spreads as the estimates of transaction costs/illiquidity, Brennan and Subrahmanyam (1996) employ intraday data in years 1984 and 1988 from the Institute for the Study of Securities Markets (ISSM) database, and decompose the estimated transaction costs into the fixed and variable components. They examine the relation between these cost components and expected monthly stock returns, after controlling for the three Fama and French (1993) factors. For NYSE securities during the period from 1984 to 1991, they find positive and significant relations between these two cost components and expected returns, but a negative and significant relation between the proportional (quoted) spread and expected returns. The latter finding is inconsistent with the notion that the proportional spread serves as a proxy of illiquidity, and Brennan and Subrahmanyam (1996) document that its explanatory power over the expected returns is largely due to the effect of the price level of a stock. In lights of Amihud and Mendelson's (1986a) predictions, Brennan and Subrahmanyam (1996) conclude that the (horizon) clientele effects may not be so important because the predicted concave relation is not observed between the fixed proportional transaction cost and expected returns.

Given that the quoted spread may be a better proxy of transaction costs for NASDAQ stocks than for NYSE stocks (e.g., Petersen and Fialkowski (1994), McInish and Woods (1995), Huang and Stoll (1996), and Bessembinder (2003)), Eleswarapu (1997) reexamines the relation between the relative spreads and security returns on NASDAQ stocks in the period from 1973 to 1990. He finds this relation to be more significant in this sample than in Eleswarapu and Reinganum (1993), where only NYSE stocks are examined. Specifically, Eleswarapu (1997) documents that there is a liquidity premium in both January and non-January months, although the liquidity premium is higher in January.

Aiming at different goals, Brennan, Chordia, and Subrahmanyam (1998) investigate the cross-sectional relations between security characteristics and expected returns, after controlling for possible risk factors. The risk factors they consider include the three Fama and French (1993) factors and the five factors identified through the asymptotic principal components approach suggested by Connor and Korajczyk (1988). They find that for NYSE and NASDAQ stocks in the period from 1966 to 1995, security characteristics such as firm size, book-to-market ratio, dollar trading volume, and past returns have significant explanatory power over cross-sectional stock returns. Furthermore, dollar trading volume has negative and significant coefficient estimates in their cross-sectional regressions, suggesting a liquidity premium in asset prices. Datar, Naik, and Radcliffe (1998) also examine the relation between expected returns and trading volume. Motivated by Amihud and Mendelson (1986a), they use share turnover as their liquidity measure. They find a negative and significant relation between share turnover and expected returns for NYSE non-financial stocks in the period from 1962 to 1991, a result consistent with the predictions of Amihud and Mendelson (1986a).

On the other hand, Rouwenhorst (1999) employs data of 20 emerging markets from 1982 to 1994, and examine the relations between expected returns and possible return factors including beta, size, momentum, and book-to-market ratios. Using share turnover as a proxy for liquidity, he finds no significant relation between share turnover and expected returns, but documents that share turnover is related to the examined return factors in these emerging markets. The insignificance of share turnover in explaining expected returns in emerging markets is also confirmed by Bekaert, Harvey, and Lundblad (2003). Bekaert, Harvey, and Lundblad (2003) employ both share turnover and the proportion of zero returns as proxies of liquidity and examine the relation between liquidity and expected returns in 19 emerging markets for the period from 1987 to 2001. In their VAR analyses, only the proportion of zero returns has a significant effect on expected returns.

Amihud (2002) extends previous studies by examining both the cross-sectional relation between illiquidity and expected returns for individual stocks, and the time-series relation between market illiquidity and expected market returns. Defining the illiquidity measure of a stock as the average ratio of its daily absolute return to its dollar trading volume on the same day over a one-year period, Amihud (2002) finds that for NYSE stocks in the period from 1964 to 1997, a stock's illiquidity has a positive and significant effect on the stock's expected returns, after controlling for the stock's beta, previous returns, size, daily return standard deviation, and dividend yield. For the market as a whole, expected market illiquidity has a positive and significant effect on the market risk premium and unexpected illiquidity shock has a negative and significant effect. These results suggest that investors prefer liquidity and that market liquidity is one of the factors determining market risk premium.

Chordia, Subrahmanyam, and Anshuman (2001) extend previous studies by focusing on the relation between the variability of liquidity and expected returns. In the framework of Brennan, Chordia, and Subrahmanyam (1998), they apply the return-risk concepts to the case of liquidity. Specifically, since investors prefer more liquidity to less, as evident in the literature by the negative relations between the liquidity measures and expected returns, investors should dislike the variability of liquidity. The variability of liquidity should therefore have a positive relation with expected returns in a cross-sectional framework. Chordia, Subrahmanyam, and Anshuman (2001) employ both dollar trading volume and share turnover as their proxies of liquidity, and use the coefficient of variation as the variability measure to control for the level effect. Surprisingly, they find that the variability of liquidity is negatively related to expected returns for NYSE and AMEX securities in the period from 1966 to 1995. The same relation holds for NASDAQ securities in the period from 1984 to 1995. Since this result is unexpected, Chordia, Subrahmanyam, and Anshuman (2001) examine several possible explanations including an alternative GARCH(1,1) specification of conditional volatility, additional macroeconomic variables, nonlinearity in the relation between expected returns and trading volume, and the clientele hypothesis of Merton (1987). However, none of these tests provides an explanation to their finding.

2.2.2 Market Liquidity as a Sentiment Indicator

Other than the traditional view, Baker and Stein (2004) propose another explanation for why liquidity measures would have negative time-series relations with expected returns (e.g., the empirical findings in Amihud (2002)). In their model, there are one class of rational investors and one class of overconfident investors. Both classes of investors have non-negative weights on the pricing function of the underlying security but the overconfident investors outweigh their own information. There are also short-sales constraints on the market and insiders who trade on their private information. When investor sentiment increases, the overconfident investors underreact further to the information contained in the insiders' trades and gain a greater weight on the pricing function. Their transactions drive security prices up and lower the price impact of trades. The elevated prices lead to lower expected returns and the lowered price impact attracts trading volume. Since there are short-sales constraints on the market, the rational investors cannot counteract the overconfident investors' transactions. To the extreme, when investor sentiment becomes very high, the overconfident investors dominate the market. The market is characterized with high liquidity and high trading volume. An increase in trading volume thus reflects the participation of overconfident investors in the market, and indicates an increase in investor sentiment. Since high sentiment leads to lower expected returns, this model provides an alternative explanation for the negative time-series relations between liquidity measures and expected returns.

2.3 Trading Volume as a Measure of Liquidity: Rationale and Empirical Evidence

Trading volume is one of the most widely used proxies of liquidity in asset pricing tests.[4] First, extant models suggest that trading volume can be one aspect of liquidity (e.g., Stoll (1978) and Amihud and Mendelson (1986a)). Second, trading volume has negative relations with transaction costs, another aspect of liquidity (e.g., Chordia, Roll, and Subrahmanyam (2000)). In this section I review three alternative measures of trading volume: 1) turnover, 2) dollar volume, and 3) share volume.[5]

2.3.1 Turnover

Amihud and Mendelson (1986a) provide the rationale for turnover to be a proxy of liquidity. They assume an economy with M types of investors and $N+1$ capital assets (asset 0 has zero spread and unlimited supply). Trading is made through competitive markets makers and buy (sell) transactions happen at the ask (bid) prices. The arrivals of investors type-1 to type-M follow different Poisson distributions and their expected holding periods follow exponential

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[4] Researchers also developed trading volume-based liquidity risk factors. See, for example, Pastor and Stambaugh (2003) and Eckbo and Norli (2004).

[5] Other measures of trading volume include the number of trades and the average trade size defined over a period of time (e.g., within a trading day). See Lo and Wang (2000) for an introduction on those volume measures.

distributions. The expected holding period for a type-*i* investor is longer than the expected holding period for a type *i+1* investor. Further, investors maximize the expected returns on their portfolios per unit of time. With these assumptions, Amihud and Mendelson (1986a) show that "assets with higher spreads are allocated to portfolios with (the same or) longer expected holding periods" (Proposition 1, the clientele effects). Moreover, "in equilibrium, the observed (gross) return is an increasing and concave piecewise-linear function of the (relative) spread" (Proposition II, the spread-return relationship). Since spread is one type of transaction costs and turnover is an aggregated (inverse) measure of investors' holding period, Proposition 1 implies that turnover is positively related to liquidity.

Altogether Proposition 1 and Proposition 2 imply a negative relation between observed returns and turnover. Datar, Naik, and Radcliffe (1998) address this issue and find supporting evidence. They also suggest one more reason for using trading volume as the proxy for liquidity: Trading volume data are relatively easy to obtain, especially over a long period of time.

- **Empirical Evidence**

Using turnover as the liquidity measure, Datar, Naik, and Radcliffe (1998) document a negative and significant relation between share turnover and expected returns for NYSE non-financial stocks in the period from 1962 to 1991, after controlling for firm size, beta, and the book-to-market ratio. For NYSE and AMEX securities in the period from 1966 to 1995 and for NASDAQ securities in the period from 1984 to 1995, Chordia, Subrahmanyam, and Anshuman (2001) also document the same negative relation after controlling for firm size, security price, the book-to-market ratio, the dividend yield, previous returns, and the volatility of turnover. Nevertheless, Chordia, Subrahmanyam, and Anshuman (2001) find the expected returns to be negatively related to the variability of turnover, inconsistent with the hypothesis that investors dislike the variability of liquidity, or the role of turnover as a proxy of liquidity.

Rouwenhorst (1999) and Bekaert, Harvey, and Lundblad (2003) also employ turnover as the proxy of liquidity. In their analyses they find no relation between share turnover and expected returns in emerging markets. Bekaert, Harvey, and Lundblad (2003) further document that the proportion of zero returns, a measure of stock illiquidity, has a positive and significant relation with expected returns even after controlling for turnover. These findings are interesting and point out new research directions: Why does turnover, a measure of trading volume, has its explanatory power over expected security returns in the U.S. but not in emerging markets? Is it because that turnover is too noisy in emerging markets to be a valid proxy of liquidity, or because liquidity is not priced in emerging markets? Bekaert, Harvey, and Lundblad's (2003) results on the proportion of zero returns would suggest the first explanation, but then what are the noises that render turnover but not the proportion of zero returns pale in explaining expected returns?

2.3.2 Dollar Volume

The most frequently cited references for using dollar trading volume as a liquidity measure are Stoll (1978a, 1978b). In Stoll (1978a, 978b), a wealth-constrained market maker provides immediacy to investors and borrows at the risk-free rate to finance his inventory. The market maker maximizes his utility over his terminal wealth. The costs the market maker faces to provide immediacy include the holding cost (inventory cost), the order cost (order processing cost), and the information cost (adverse selection cost). Stoll (1978a) focuses mainly on the holding cost and shows that this component of costs decreases with the probability that the market maker can reverse his position. Since a higher dollar trading volume of a stock implies that its market maker can reverse his position more easily, dollar trading volume is negatively related to the holding cost and positively related to liquidity. Stoll (1978b) finds that the quoted spreads for a sample of NASDAQ stocks are negatively related to dollar trading volume, consistent with his prediction.[6]

- **Empirical Evidence**

Stoll (1978b) uses dollar trading volume as an inverse proxy for the market maker's holding period on a stock. In his analysis for a number of NASDAQ stocks during six trading days in July 1973, the quoted spread is negatively related to dollar trading volume, consistent with the role of dollar trading volume as a proxy of liquidity.

In investigating the cross-sectional relations between security characteristics and expected stock returns, Brennan, Chordia, and Subrahmanyam (1998) find that for NYSE and NASDAQ stocks in the period from 1966 to 1995, dollar trading volume is negatively related to expected returns. They attribute this finding to the existence of a liquidity premium. Chordia, Subrahmanyam, and Anshuman (2001) employ the framework of Brennan, Chordia, and Subrahmanyam (1998) and focus on the relation between the variability of liquidity and expected returns. Dollar trading volume, a proxy of liquidity, has a negative effect on expected returns for NYSE and AMEX stocks in the period from 1966 to 1995 and for NASDAQ stocks in the period from 1984 to 1995. However, the variability of dollar trading volume also has an unexpected negative relation with expected returns, after controlling for firm size, security price, the book-to-market ratio, the dividend yield, previous returns, and the level of dollar trading volume. This finding is inconsistent with the hypothesis that investors dislike the variability of liquidity, or the role of dollar trading volume as a proxy of liquidity.

[6] In Stoll's (1978b) regressions for the determinants of quoted spreads, both dollar trading volume (an inverse proxy for the market maker's holding period on a stock) and turnover (a proxy for informational trading) are included as independent variables and they have opposite signs on their coefficient estimates (see Table V in Stoll (1978b)).

2.3.3 Share Volume

Smidt (1968) suggests that liquidity can be measured by the number of units of property exchanged. In the case of stock transactions, it implies that liquidity can also be measured by share volume. Alternatively, turnover is share volume divided by the number of shares outstanding. Dollar volume is the security price times share volume. Although the uses of turnover and dollar volume as proxies of liquidity come for different reasons, underlying the two proxies is a common component – share volume. Other things being equal, a stock with a larger share volume has a higher turnover and a larger dollar volume. The use of share volume as a proxy of liquidity is therefore not unreasonable.

Empirically share trading volume is not used as frequently as turnover and dollar volume as a proxy of liquidity. This is probably due to the lack of a theoretical model justifying its role. Brennan and Subrahmanyam (1995), nevertheless, employ share volume and examine the relations between analysts following, the adverse selection costs of transaction, and trading volume for NYSE stocks during the year 1988. In their analyses with simultaneous equations, share volume is found to be a major determinant of the adverse selection costs of transaction, consistent with the role of share volume as a proxy of liquidity.

There are still other trading volume measures that may serve as proxies of liquidity. For example, the number of trades and the average trade size defined over a period (e.g., within a trading day). Jones, Kaul, and Lipson (1994) document that the daily return volatility on NASDAQ stocks during the period from 1986 to 1991 is more closely related to the number of trades than to other volume measures. However, this volume measure as well as the average trade size requires the use of intraday data, which are not available for a long period of time.

2.4 Other Liquidity Measures: Rationale and Empirical Evidence

Although trading volume can be a natural proxy of liquidity, the existence of trading volume does not depend on how we interpret it. On the other hand, researchers have proposed several liquidity proxies aiming at one goal – measuring one or more dimensions of liquidity. In the following sections I explicitly consider three of them that I use as control variables in this dissertation: 1) the Roll (1984) spread, 2) the proportion of zero returns by Lesmond, Ogden, and Trzcinka (1999), and 3) the price impact measure of Amihud (2002). The Roll spread and the proportion of zero returns attempt to measure transaction costs. The price impact measure of Amihud (2002), on the other hand, is a measure of market depth and market resilience.

There are still other liquidity measures that either require intraday data or rely heavily on statistical estimation. Examples in the first category include spread-based liquidity measures such as the quoted spread, the effective spread, the relative spread (see Stoll (2000) for definitions of the above), the quoted slope (Hasbrouck and Seppi (2001)), and the amortized spread (Chalmers and Kadlec (1998)). Examples of liquidity measures that rely more heavily on statistical estimation, i.e., more model parameters need to be estimated, include the round-trip proportional transaction costs by Lesmond, Ogden, and Trzcinka (1999), the probability of informed trading by Easley, Kiefer, O’Hara, and Paperman (1996) and Easley, Hvidkjaer, and O’Hara (2002), and the extent to which price changes reverse by Pastor and Stambaugh (2003). Because intraday data are not available for a long period of time and because monthly parameters heavily estimated with daily data can be inaccurate, I do not use those measures to control for liquidity.

2.4.1 Roll Spread

Assuming an informational efficient market with no new information arrival, and that the probability distribution of observed price changes is stationary, Roll (1984) shows that the effective spread (*s*, the Roll spread) of a security is:

$$s = 2\sqrt{-\operatorname{cov}(\Delta p_t, \Delta p_{t+1})},$$

where $\Delta p_t \equiv p_t - p_{t-1}$ is the price change from time *t-1* to time *t*. Specifically, let $Q_t = 1$ be the trade indicator for a buy order and $Q_t = -1$ for a sell order, and ε_t be the unexpected price change from time *t-1* to time *t*. With the assumptions that the effective spread (*s*) is a constant,

$$E[Q_t Q_{t+1}] = 0,$$

$$E[(Q_{t+1} - Q_t)\varepsilon_{t+1}] = 0,$$

$E[(Q_{t+1} - Q_t)\varepsilon_t] = 0$, and

$$E[\varepsilon_t \varepsilon_{t+1}] = 0,$$

it follows that

$$\Delta p_t \equiv p_t - p_{t-1} = \frac{1}{2}(Q_t - Q_{t-1})s + \varepsilon_t,$$

$$\begin{aligned}
\operatorname{cov}(\Delta p_t, \Delta p_{t+1}) &= \frac{1}{4}E\left[(Q_t - Q_{t-1})(Q_{t+1} - Q_t)s^2\right] + \frac{1}{2}E\left[(Q_t - Q_{t-1})s\varepsilon_{t+1}\right] \\
&\quad + \frac{1}{2}E\left[(Q_{t+1} - Q_t)s\varepsilon_t\right] + E[\varepsilon_t \varepsilon_{t+1}] \\
&= \frac{1}{4}E\left[(Q_t - Q_{t-1})(Q_{t+1} - Q_t)s^2\right] \\
&= \frac{1}{4}E\left[Q_t Q_{t+1} s^2\right] - \frac{1}{4}E\left[Q_t^{\,2} s^2\right] - \frac{1}{4}E\left[Q_{t-1} Q_{t+1} s^2\right] + \frac{1}{4}E\left[Q_{t-1} Q_t s^2\right] \\
&= -\frac{1}{4}E\left[Q_t^{\,2} s^2\right]
\end{aligned}$$

$$= -\frac{1}{4}s^2 \text{, and}$$

$$s = 2\sqrt{-\operatorname{cov}(\Delta p_t, \Delta p_{t+1})} .$$

Since the effective spread is one type of transaction costs that an investor incurs, s can be a measure of illiquidity in that a security with a higher s is less liquid.

Nevertheless, the empirical estimates of the covariance defined on daily and weekly price changes are sometimes positive, rendering s inestimable (e.g. Roll (1984) and Harris (1990)). Small sample properties together with noises in observed price series may also bias this estimator (Harris (1990)). To skirt the problem of positive covariance estimates, I redefine s as:

$$s = -2\frac{\operatorname{cov}(\Delta p_t, \Delta p_{t+1})}{\left|\operatorname{cov}(\Delta p_t, \Delta p_{t+1})\right|}\sqrt{\left|\operatorname{cov}(\Delta p_t, \Delta p_{t+1})\right|} ,$$

as do in Roll (1984), Harris (1990), and Lesmond, Ogden, and Trzcinka (1999).[7]

- **Empirical Evidence**

The most important assumption for the Roll spread is that there is no reason other than transaction costs that leads to the serial covariance in price changes, an assumption that can hardly hold empirically. Especially for price changes defined on the daily or weekly interval, the variance of price changes is usually much larger than the serial covariance and the covariance cannot be estimated with high accuracy (Harris (1990), Schultz (2000)). Further, the estimator is downward biased because of Jensen's inequality, i.e.,

$$E(\hat{s}) = E\left[-2\sqrt{\hat{c}}\right] < 2\sqrt{-E(\hat{c})} = s \text{, where } c = \operatorname{cov}(\Delta p_t, \Delta p_{t+1}) .$$

[7] Returns rather than price changes are used in this dissertation to estimate the first-order serial covariance. This yields the proportional effective spread. See also Roll (1984).

Reflecting these concerns, the Roll spread has been modified and estimated with intraday data. For example, with intraday data Schultz (2000) and Bessembinder (2003) employ the following modification of the Roll spread to adjust for the small sample bias:

$$s^* = \frac{\hat{s}}{1 - \frac{7}{8(n-1)}},$$

where n is the number of observations (price changes) used in estimating $\hat{s}$.[8]

Nevertheless, the unadjusted Roll spread estimated with daily data has been found to be negatively related to firm size (Roll (1984)) and positively related to the proportion of zero returns (Lesmond, Ogden, and Trzcinka (1999)), consistent with its role as a measure of transaction costs/illiquidity. Further, the adjustment is unnecessary when the Roll spread of each individual security is estimated with the same number of observations. Specifically, when the Roll spread is used as an independent variable in a cross-sectional expected return regression, the adjustment serves as a scale factor and has no real effects on the coefficient estimate.

2.4.2 Proportion of Zero Returns

Lesmond, Ogden, and Trzcinka (1999) propose using the proportion of zero returns in a stock's return series as a proxy for the stock's illiquidity. This proxy requires only the time series of daily stock returns, which is relatively easy to obtain. In their model, an informed marginal investor will trade only if the value of his private information outweighs his transaction costs. Consequently, a larger proportion of zero returns in a security's return series implies that this security has higher transaction costs[9]. With the additional assumptions that the market model (without the intercept term) is the underlying return generating process and the marginal investor

[8] In Bessembinder (2003) p. 239, n is incorrectly put as the number of *trades*.

[9] Strictly speaking, a cross-sectional comparison of the proportions of zero returns on securities is valid only when the rates of private information arrivals are the same across securities. Otherwise securities with less private information will have more incidents of zero returns and be classified as having higher transaction costs.

uses public information reflected on the market returns to augment his private information, Lesmond, Ogden, and Trzcinka (1999) set up their model as:

$$R_{jt}^* = \beta_j R_{mt} + \varepsilon_{jt},$$

$$R_{jt} = R_{jt}^* - \alpha_{1j} \quad \text{if} \quad R_{jt}^* < \alpha_{1j},$$

$$R_{jt} = 0 \quad \text{if} \quad \alpha_{1j} < R_{jt}^* < \alpha_{2j}, \text{ and}$$

$$R_{jt} = R_{jt}^* - \alpha_{2j} \quad \text{if} \quad R_{jt}^* > \alpha_{2j},$$

where R_{jt} is the observed return at time *t* for security *j* and R_{jt}^* is the true return at time *t* for security *j*. R_{mt} is the market return at time *t* and ε_{jt} is the residual term. $\alpha_{1j} < 0$ is the transaction cost threshold that the value of negative information must exceed (in absolute terms) for the marginal investor to trade. Similarly, $\alpha_{2j} > 0$ is the transaction cost threshold that the value of positive information must exceed for the marginal investor to trade. $\alpha_{2j} - \alpha_{1j}$ is thus the round-trip proportional transaction costs face by the marginal investor.

Lesmond, Ogden, and Trzcinka (1999) notice that the observed return data from CRSP may differ from the *true* return data because of bid-ask bouncing and/or days with zero trading volume. In the case of bid-ask bouncing, a non-zero observed return may in fact arise from trades occurring at the bid (ask) price at the close of the previous day and the ask (bid) price at the close of the current day. In the case of days with zero trading volume, a non-zero observed return will be recorded when the closing price/quote on the previous day differs from the closing quote-mid point on the current day, even when no trades are actually executed. Although the observed proportion of zero returns is only a conservative estimate of the true proportion of zero returns, Lesmond, Ogden, and Trzcinka (1999) find that the observed proportion of zero returns is still a good indicator of the true proportion of zero returns.

- **Empirical Evidence**

Lesmond, Ogden, and Trzcinka (1999) find that the proportion of zero returns for NYSE and AMEX stocks in the period from 1963 to 1990 is negatively related to firm size and positively related to quoted spread and the Roll spread defined on an annual basis, consistent with the role of the proportion of zero returns as a proxy of transaction costs. Lesmond (2002) examines the characteristics of this measure in great detail for 31 emerging markets in the period from 1991 to 2000. In this sample the proportion of zero returns is found to be over 80% correlated with the quoted spread and has significant explanatory power over the proportional bid-ask spreads and spread plus commission, even after controlling for other determinants of liquidity such as price, turnover, and market capitalization (see Stoll (2000) for the possible determinants of liquidity). Bekaert, Harvey, and Lundblad (2003) employ the same measure defined monthly as a proxy of illiquidity and examine the relation between expected returns and liquidity in 19 emerging markets. They also find this measure to be positively correlated with bid-ask spreads and negatively correlated with turnover. Further, in their VAR framework, the monthly proportion of zero returns has significant relations with expected returns but turnover does not.

2.4.3 Price Impact Measure of Amihud (2002)

Amihud (2002) defines for a stock the average ratio of its daily absolute return to its dollar trading volume on the same day as the proxy of its illiquidity. This measure requires only daily returns and dollar volume as its inputs. Specifically, denoting the return on stock *i* on day *t* as R_{it}, and the corresponding dollar volume on the same day as $DVOL_{it}$, this illiquidity measure for stock *i* over a period of *T* days is:

$$RVOL_{iT} = \frac{1}{T}\sum_{t=1}^{T}\frac{|R_{it}|}{DVOL_{it}}.$$

This measure shows the average daily price responses to each one dollar in trading volume for stock *i*. Since stocks with better liquidity should be able to absorb more dollar volume without corresponding price movements, a stock with a higher value on this measure is less liquid in the cross section. This measure thus proxies for the illiquidity of a stock.

- **Empirical Evidence**

Amihud (2002) defines this measure on an annual basis (*T* is the number of trading days in a year). By simply averaging the illiquidity measures across stocks, a market illiquidity measure is constructed. Amihud (2002) examines both the cross-sectional relation between illiquidity and expected returns for individual stocks and the time-series relation between market illiquidity and expected market returns. For NYSE stocks in the period from 1964 to 1997, he finds this measure to be negatively related to firm size and positively related to both the fixed and the variable proportional transaction costs estimated by Brennan and Subrahmanyam (1996), consistent with the role of this measure to be a proxy of illiquidity. Further, a stock's illiquidity defined over the previous year has a positive and significant effect on the stock's monthly returns in the current year, after controlling for the stock's beta, previous returns, size, daily return standard deviation, and dividend yield. For the market as a whole, expected market illiquidity has a positive and significant effect on the annual (equally-weighted) market risk premium and unexpected illiquidity shock has a negative and significant effect. Results for the whole market also hold when the market risk premium and the market illiquidity are defined on a monthly basis. In sum, these findings suggest that investors prefer liquidity and that market liquidity is one of the factors to determine market risk premium. As an application, Acharya and Pedersen (2003) employ this measure and examine the interactions among security returns, security illiquidity, market returns, and market illiquidity for NYSE and AMEX stocks in the period from 1963 to 1999. They find that the expected return of a security is increasing in the sensitivity (covariance) of the security's illiquidity to market illiquidity, but decreasing in the sensitivities of the security's return to market illiquidity and the security's illiquidity to market returns. Among these three sensitivity factors, the sensitivity of a security's illiquidity to market returns has the largest effect on the security's expected returns.

2.5 Investor Sentiment: Definition and Rationale

"The effects of noise on the world, and on our views of the world, are profound."

Fisher Black, 1986
"Noise"
Journal of Finance, Volume 41, pp. 529-543.

Just like liquidity, investor sentiment is also a slippery and elusive concept. In Smidt (1968), it leads to speculative bubbles. In Zweig (1973), it comes from investors' biased expectations on asset values. In Black (1986), it is the noise in financial markets. Generally, investor sentiment refers to investors' propensity to speculate, or investors' optimism/pessimism about stocks (Baker and Wurgler (2004)). Lee, Shleifer, Thaler (1991) define investor sentiment as the component of investors' expectations about asset returns that are not justified by fundamentals. Baker and Stein (2004) define investor sentiment as investors' misvaluation on an asset. Centering in these definitions is that investor sentiment reflects the difference between what an asset price *is* and what an asset price *should be*. In a market with two groups of investors, assuming one holds rational expectations on an asset's value and the other makes biased valuations, it is equivalent to say that investor sentiment reflects the valuation difference between the two groups of investors (Zweig (1973), Lee, Shleifer, Thaler (1991), Baker and Stein (2004), and Brown and Cliff (2005)).[10]

2.6 Relation between Investor Sentiment and Expected Stock Returns

In a frictionless market, there should be no role for investor sentiment on asset prices. Even if investor sentiment could cause asset prices to deviate from their fundamental values, arbitrageurs would have eliminated the discrepancies immediately. In reality, there exist transaction costs and short-sales constraints. Such frictions prevent arbitrage activities (Black (1986) and Shleifer and Vishny (1997)) and investor sentiment can affect asset prices.

Miller (1977) argues that stock prices reflect only the most optimistic opinions among investors when short-sales constraints are present. When investors become more optimistic, i.e., when investor sentiment becomes high, they drive stock prices up. It follows that there should be a contemporaneous positive relation between investor sentiment and stock returns.

Smidt (1968) depicts a distinct feature of the time-series relation between investor sentiment and expected stock returns: A corrective price movement. Zweig (1973) models two types of investors on the market: One non-professionals and the other professionals. Non-professionals use unjustified information to form their expectations and affect security price accordingly. As the security prices deviate more and more and from their intrinsic values, professionals profit from the deviations and bring the security prices back to their fundaments. Similarly, Baker and Stein (2004) and Brown and Cliff (2005) assume the two types of investors and argue that expected stock returns will be lower if the beginning investor sentiment is higher.

On the cross-sectional side, De Long, Shleifer, Summers, and Waldman (1990) model two types of investors on the market: Rational and irrational (noise) investors. Irrational investors,

[10] Barberis, Shleifer, and Vishny (1998) also provide a model of investor sentiment, but in their model there is only one representative investor. They focus on how investor sentiment is formed and corrected by new information.

but not the rational investors, are subject to the influence of sentiment. The trading of irrational investors creates extra risk, i.e., the noise trader risk, and deters the arbitrage activities of rational investors. Since different stocks are subject to different extents of noise trader risk, investor sentiment affects the stocks differently in the cross section. Lee, Shleifer, Thaler (1991) investigate this prediction by examining the relation between closed-end fund discounts and small firm returns, both arguably reflect the sentiment of individual investors.

Baker and Wurgler (2004) also argue that investor sentiment affects asset prices in the cross section. Specifically, a broad sentiment wave on the market can have different effects on stocks either because sentiment-based demand shocks or arbitrage constraints differ across stocks. Therefore, the time-series relations between investor sentiment and expected stocks returns will exhibit most on stocks vulnerable to sentiment waves and/or stocks with difficulties in arbitrage. They hypothesize that those stocks are small, young, unprofitable, non-dividend-paying, distressed, or with high volatility or extreme-growth. Consistent with their predictions, they find that those stocks earn high future returns when their beginning-of-period proxies for investor sentiment are low, and the patterns attenuate or reverse when the beginning sentiment proxies are high.

On the empirical side, Lee, Shleifer, Thaler (1991) find a significant relation between closed-end fund discounts and small firm returns, confirming the prediction of Long, Shleifer, Summers, and Waldman (1990). Neal and Wheatley (1998) also find that closed-end fund discounts predict the size premium. However, Swaminathan (1996) documents that the information contained in closed-end fund discounts is related to expectations on future earnings growth and inflation, which suggests that investor sentiment may not be the sole reason explaining the relation between closed-end fund discounts and small firm returns.

Brown and Cliff (2004) find that investor sentiment does not predict short-term market returns at weekly and monthly intervals, but Brown and Cliff (2005) find that investor sentiment predicts long-term market returns at the next two to three years. They attribute these findings to limited arbitrage in the long-run but not in the short term. Nevertheless, Brown and Cliff (2004) use the Kalman filter and the principal components analysis to construct their composite sentiment measures based on survey data, IPO activities, and other technical indicators. They examine the relations between the composite sentiment measures and market returns by VAR systems. Whether their composite sentiment measures capture the underlying but unobservable investor sentiment is arguable, however. Unless investor sentiment drives the sentiment proxies at the same time or with the same time lag, their composite sentiment measures may end up noisier than a single sentiment proxy.[11]

2.7 Investor Sentiment Measures: Rationale and Empirical Evidence

Since investor sentiment is not directly observable, researchers have employed various measures for investor sentiment. Among them the closed-end fund discount is the most frequently used one, and I introduce it first.

Zweig (1973) uses closed-end fund discounts as the measure of individual investor sentiment, since individual investors are the major traders of closed-end funds. With weekly discount data of 24 closed-end funds in the period from 1966 to 1970, he finds that buy/sell signals generated on the discount data can be used to form trading strategies that lead to superior returns on the Dow Jones Industrial Average. Lee, Shleifer, Thaler (1991) employ monthly discount data in the period from July 1956 to December 1985 and construct a value-weighed index of discounts based on 20 closed-funds. They find that small firm returns are more closely related to the index of discount than large firm returns, and explain their results as supportive to

[11] Baker and Wurgler (2004) address this issue by considering the lags of their sentiment measures.

the model of De Long, Shleifer, Summers, and Waldman (1990). With a valued-weighted index of annual discounts on 74 funds from 1933 to 1993, Neal and Wheatley (1998) find that closed-end fund discounts predict small firm returns and the size premium.

Nevertheless, Chen, Kan, and Miller (1993a, 1993b) argue that the methods in Lee, Shleifer, Thaler (1991) are flawed and the results lack economic significance. With closed-end fund discount data from 1965 to 1990, Swaminathan (1996) confirms the relation between closed-end fund discounts and small firm returns, but he also documents that the information contained in closed-end fund discounts is related to expectations on future earnings growth and inflation. This latter result implies that investor sentiment may not be the sole reason explaining the relation between closed-end fund discounts and small firm returns. Elton, Gruber, and Busse (1998) find that sentiment indexes based on closed-end stock fund discounts from 1969 to 1994 are not priced factors in the return generating processes, suggesting that investors do not care about sentiment.[12]

Other than the closed-end funds discounts, there are still numerous sentiment measures that researchers employ in their studies with various reasons and justifications. For example, Lee, Shleifer, Thaler (1991) relate the net withdraws from open-end funds (the mutual fund redemptions) and the volume of initial public offerings with individual investor sentiment. Neal and Wheatley (1998) use the mutual fund redemptions and the odd-lot sales to purchases ratios, in additional to the closed-end fund discounts, as their sentiment measures. Qiu and Welch (2004) prefer survey data such as the Michigan Consumer Confidence Index, the Conference Board Consumer Confidence Index, and the UBS/GALLUP index of investor Optimism. Brown and Cliff (2004) use survey data from the American Association of individual Investors to measure

[12] To be more precise, the results in Elton, Gruber, and Busse (1998) only suggest that investors may not care about the closed-end fund discounts. For more on the closed-end fund discount debate, see, for example, Palomino (1996), Sias, Starks, and Tinic (2001), Gemmill and Thomas (2002), and Burch, Emery, and Fuerst (2003).

individual investor sentiment and survey data from the Investors Intelligence to measure institutional investor sentiment, of which the latter is also the key sentiment variable in Brown and Cliff (2005).

Brown and Cliff (2004) also use sentiment measures including the ratio of the number of advancing issues to declining issues, the ARMS index, the ratio of new highs to new lows, the change in margin borrowing and short interest, the ratio of short sales to total sales, the ratio of specialists' short sales to total short sales, the ratio of odd-lot sales to purchases, the ratio of CBOE equity put to call volume, the change in the net position in SPX futures by trader type, the expected option volatility to current volatility ratio, the closed-end fund discounts, the proportion of fund assets held in cash, the first day returns on IPOs, and the number of IPOs.

Baker and Stein (2004) argue that market liquidity can by itself serve as a sentiment measure, and they employ turnover as an example. Baker and Wurgler (2004) construct a composite sentiment index based on the principal component of six variables: The closed-end fund discounts, turnover, the number of IPOs, the initial returns of IPOs, the equity shares in new issues, and the dividend premium. Later in chapter 5 I use this composite sentiment index as a control variable in my time-series regressions, and I will go back to the construction of this index later.

To summarize, the enormous number of sentiment measures reflects exactly the elusive nature of investor sentiment. There are some common features among those measures, however. First, it is usually assumed that individual investors are more likely to be affected by their sentiment. Second, most of those measures target the market-wide sentiment rather than the sentiment at the individual stock level.

2.8 The Nature of Trading Volume

“Men willingly believe what they wish.”

Julius Caesar, 100 B.C. – 44 B.C.

There are different views on the validity of trading volume as a liquidity measure. Lee, Mucklow, and Ready (1993) find that intraday spreads widen and depths decrease in responses to abnormal high share volume. Chordia, Subrahmanyam, and Anshuman (2001) recognize that turnover may not be a perfect measure of liquidity because the relation between turnover and expected returns depends on past security returns. Indeed, Lee and Swaminathan (2000) document that momentum profits are largest for past high-volume stocks because low-volume losers significantly outperform high-volume losers in the future. They suggest that “trading volume, as measured by the turnover ratio, is unlikely to be a liquidity proxy.” Chalmers and Kadlec (1998) also find that return volatility can dominate the negative relation between the effective spread and turnover. Specifically, both the effective spread and turnover increase with past return volatility. To provide a better understanding on what is the information contained in trading volume, in the following sections I start by summarizing the literature that suggests specific components of trading volume and their relations with liquidity. I then review the evidence on the time-series properties of trading volume series. Finally I explain how extant theories can link trading volume and investor sentiment together, and why I use the trading volume trend to measure investor sentiment.

2.8.1 Sources of Trading Volume

Several models suggest that trading volume is related to investor heterogeneity in terms of different endowed information or how investors explain common information. For instance, diverse priors and disagreement among investors can both generate trading volume in Karpoff

(1986). Harris and Raviv (1993) analyze how common information can generate trading volume if investors explain the information differently. It is thus both private information and public information that can generate trading volume. If public information dominates, increases in trading volume reflect liquidity trades and should improve liquidity (e.g., Lee, Mucklow, and Ready (1993)). If private information dominates, increases in trading volume should decrease liquidity because private information creates information asymmetry among investors (e.g., Koski and Michaely (2000)). Berry and Howe (1993) provide supports to Harris and Raviv (1993). They find that public information arrivals are associated with increases in trading volume. Further, Blume, Easley, and O'Hara (1994) argue that trading volume reflects the quality of traders' information, while the average level of trader's private information is revealed in security price. Jones, Kaul, and Lipson (1994) hold a similar view that trading volume is positively related to the quality/precision of arrived information.

More recently, Llorente, Michaely, Saar, and Wang (2002) extend Wang (1994), and argue that there are two components in trading volume: One arises from investors' hedging demands while the other is due to investors' speculative needs. In their model, two groups of investors are endowed with different information with respect to the expected returns of traded assets, but within a group the investors are homogeneous. Investors' hedging demands arise from the correlations between the expected returns of traded assets and the payoffs of non-traded assets. Speculative demands reflect the trades of investors with superior information. Since superior information can cause information asymmetry among investors, trading volume reflecting investors' speculative demands can reduce liquidity (e.g., Koski and Michaely (2000)). Chalmers and Kadlec (1998) document that both the effective spread and turnover increase with return volatility. In the arbitrage-free economy of Ross (1989) where there exist martingale measures of asset prices, the variance of price changes equals the rate of information flow.[13] In this regard Chalmers and Kadlec's (1998) evidence is consistent with the view that trading volume reflecting private information reduces liquidity.

On the other hand, high investor sentiment can also generate trading volume. In Baker and Stein (2004), high trading volume reflects the participation of overconfident investors, which is driven by high investor sentiment. High investor sentiment can also cause different opinions between investors with rational expectations on asset prices and investors with distorted asset valuations. If high investor sentiment leads to a higher level of speculative demand, as suggested by Baker and Wurgler (2004), Llorente, Michaely, Saar, and Wang's (2002) model would also suggest a positive relation between investor sentiment and trading volume.

2.8.2 Sources of Trading Volume: An Alternative Framework

Although the notion that there is a market-related component in trading volume has been accepted in the literature, a theoretical model formulating a security's trading volume as a function of the market trading volume is not present until recently.[14] Tkac (1999) assumes two types of investors with different preferences and risk tolerances. They trade solely for their rebalancing needs to hedge against the endogenous uncertainties on asset returns. Two-fund separation holds in this economy and all securities should have the same turnover as the value-weighted market portfolio. Since this model does not explain the apparent deviations of individual security's trading volume from the market turnover, Tkac (1999) further suggests the use of a volume market model to account for firm-specific characteristics and the market volume simultaneously. In this volume market model, trading volume arises from firm-specific characteristics (the regression intercept), the relation between a security's trading volume with

[13] Ross (1989), Theorem II, eq. (25) on p. 8.
[14] See Tkac (1999) for a list of studies that attempt to remove the market component from individual securities' trading volume.

the market volume (the market component), and exogenous information events (the residual). Nevertheless, there is no role for private information to lead to trading volume in the original model of Tkac (1999). The sources of the endogenous uncertainties on asset returns, which lead to investors' rebalance needs, are also unspecified. Judd, Kubler, and Schmedders (2003) further show that in a general equilibrium with heterogeneous agents, portfolio rebalance needs do not generate nontrivial trading volume.

Unlike Tkac (1999), Lo and Wang (2000) assume mutual funds separation (monetary separation) and examine the structure of trading volume in the case of $(K+1)$-fund separation. Their model concludes that turnover satisfies approximately a linear K-factor structure if $(K+1)$-fund separation holds. Their empirical results reject the two-fund separation and suggest that a two-factor linear model (the case of three-fund separation) can reasonably explain the time-series variation in turnover. Nevertheless, the methodology of principal-components decomposition in this study has little to say on what should be the other factor determining trading volume, in addition to the market factor.

In this alternative framework, however, the links between trading volume, liquidity, and investor sentiment become less clear. We have not known yet what a larger sensitivity of a security's trading volume to the market trading volume implies. Neither have we known the meaning of a larger component of market trading volume in the security's trading volume. Future studies aiming at these questions seem promising.

2.8.3 Time-Series Properties of Trading Volume

In contrast to return series, it is widely recognized that trading volume series are likely to be nonstationary. Specifically, trading volume increases over time and may not have a constant mean and a constant variance. Mean and variance alone are not sufficient statistics to characterize a trading volume series.

Lo and Wang (2000) document the evidence that there are secular trends in trading volume measured by weekly turnover for NYSE and AMEX securities in the period from 1962 to 1996. Statistical tests also reject the stationarity of the value-weighted market turnover. However, in attempts to detrend the nonstationary market volume series, Lo and Wang (2000) report that different detrending methods can have substantial impacts on the resulting time series. The detrending methods they experiment include the linear detrending, the log-linear detrending, the first differencing, a four-lag moving average normalization, the linear-quadratic detrending and deseasonalization, and the nonparametric detrending via kernel regression. In face of those problems, Lo and Wang (2000) use raw turnover in their analyses but confine the analyses to 5-year subperiods.

There are still other problems that researchers will encounter in detrending trading volume series. For instance, a detrending method applicable to one trading volume series is not necessarily applicable to another trading volume series. Although statistically it is possible to detrend a time series until further tests do not reject its stationarity, for thousands of stocks over a prolonged period of time, this methodology would suggest numerous specifications and render further analysis infeasible.

2.8.4 The Trend of Trading Volume as a Measure of Investor Sentiment

Trading volume is likely to contain information on investor sentiment. First, Baker and Stein (2004) have explicitly modeled the relation between these two. Second, extant theories imply a natural link between investor sentiment and trading volume.

In the model of Baker and Stein (2004), there are one class of rational investors and one class of overconfident investors. Both classes of investors have non-negative weights on the pricing function of the underlying security but the overconfident investors outweigh their own information. There are also short-sales constraints on the market and insiders who trade on their private information. When investor sentiment increases, the overconfident investors underreact further to the information contained in the insiders' trades and gain a greater weight on the pricing function. Their transactions drive security prices up and lower the price impact of trades. The elevated prices lead to lower expected returns and the lowered price impact attracts trading volume. Since there are short-sales constraints on the market, the rational investors cannot counteract the overconfident investors' transactions. To the extreme, when investor sentiment becomes very high, the overconfident investors dominate the market, which is characterized with high liquidity and high trading volume. An increase in trading volume thus reflects the participation of overconfident investors in the market, and indicates an increase in investor sentiment.

Alternatively, extant theories imply a natural link between investor sentiment and trading volume. The sentiment literature suggests that investor sentiment can be measured as the valuation differences between one group of rational investors and one group of irrational investors (Zweig (1973), Lee, Shleifer, Thaler (1991), Baker and Stein (2004), and Brown and Cliff (2005)). Therefore when investor sentiment becomes high, investor heterogeneity would become high as well. On the other hand, the volume literature suggests that investor heterogeneity contributes to trading volume (e.g., Karpoff (1986) and Harris and Raviv (1993)). It is thus conceivable that when investor sentiment becomes high (low), trading volume is likely to increase (decrease).

Nevertheless, researchers also use the level of trading volume as a liquidity measure. First, extant models suggest that trading volume can be one aspect of liquidity (e.g., Stoll (1978a) and Amihud and Mendelson (1986a)). Second, trading volume has negative relations with transaction costs, another aspect of liquidity (e.g., Chordia, Roll, and Subrahmanyam (2000)).To differentiate the information contained in trading volume as either liquidity-related or sentiment-related, I use the trend on the trading volume series of a stock as the sentiment measure on that stock. I call it the trading volume trend. The trading volume trend by definition is the average change on trading volume per unit of time. It reflects the average propensity of investors to trade. It is a better sentiment measure than the level of trading volume for the following reasons: First, it reflects the movement of overconfident investors on the market in the framework of Baker and Stein (2004). Second, the sentiment literature suggests that the formation of investor sentiment is likely through a process over time (e.g., Smidt ((1968) and Brown and Cliff (2005)). The trading volume trend can summarize the process rather than being a snap shot on the process. Third, stocks in the cross section can have the same level of trading volume but very different trading volume trends over a period of time. The trading volume trend thus mitigates the problem of mixing investor sentiment information with liquidity information. In the next chapter I explain how I construct the trading volume trend for individual stocks.

Chapter 3. Trading Volume: Liquidity or Sentiment?

3.1 Introduction

In this chapter I employ the framework of Chordia, Subrahmanyam, and Anshuman (2001) and examine the cross-sectional relation between the trading volume trend and expected stock returns. Consistent with earlier work, I find the negative cross-sectional relation between the level of trading volume and expected stock returns. This relation is not as strong as previously documented, however, once I control for the short-term return volatility. The return volatility has a strong negative relation with expected stock returns as documented in Amihud (2002). This finding suggests that both liquidity and non-liquidity reasons may drive the relation between the level of trading volume and expected stock returns. The trading volume trend, on the other hand, has a negative and significant relation with expected stock returns, after controlling for the level and volatility of trading volume, and other possible determinants of return. This finding suggests that investor sentiment as proxied by the trading volume trend is priced in the cross section.

My results also reveal that, for the trading volume trends defined over the past one year, past three years, and past five years, only the one over the past three years has the negative and significant relation with the monthly expected stock returns. These findings can be reconciled with a sentiment explanation. Brown and Cliff (2005) argue that investor sentiment can build up over time. Investor sentiment at its different stages is then likely to exhibit different effects on expected returns. The trading volume trends defined over the different lengths of periods can simply reflect the different stages of investor sentiment and exhibit different effects on stock returns. My results in chapter 4 provide further support to this argument.

3.2 Data and Methodology

3.2.1 Data and Variables

My sample includes common stocks listed on the New York Stock Exchange (NYSE) and the American Stock Exchange (AMEX) from July 1962 to December 2002. Only stocks classified as ordinary common shares (with the Center for Research in Security Prices (CRSP) share type codes 10 or 11) enter my sample. I exclude securities such as certificates, American depository receipts, shares of beneficial interest, units, Americus trust components, closed-end funds, real estate investment trusts, and stocks of companies incorporated outside the United States. I do not include stocks listed on Nasdaq because their reported trading volume contains interdealer trades and thus not compatible with those of NYSE and AMEX stocks (e.g., Atkins and Dyl (1997) and Anderson and Dyl (2005)). As in Pastor and Stambaugh (2003), I exclude stocks with prices below $5 and above $1,000 at the end of each month. I also exclude the first and the last month of the time-series data for each stock to avoid missing values.

I obtain monthly stock data from the CRSP monthly stock file and daily data from the CRSP daily stock file. I obtain the book values of equity from the COMPUSTAT database and the three Fama-French factors (Fama and French, 1993) from Kenneth French's data library.[15]

I defined my variables for the cross-sectional regression in month *t* as follows:

RET: the raw return of a stock in month *t*.

RF: the one-month Treasury bill rate in month *t* (from Ibbotson and Associates, Inc), provided by Kenneth French with the three Fama-French factors.

EXRET: the risk-unadjusted excess return in month *t*, defined as *RET* - *RF*.

PRICE: the natural logarithm of the reciprocal of share price, measured in dollars, of a stock at the end of month *t-2*.

[15] I thank Kenneth French for providing the data.

SIZE: the natural logarithm of the market capitalization, measured in millions, of a stock at the end of month *t-2*.

BM: the natural logarithm of the book-to-market ratio for a stock in month *t-2*. As in Fama and French (1992), I calculate the book-to-market ratio for a company at July of year *y* to June of year *y+1* as the sum of its fiscal-yearend accounting figures of book equity and deferred taxes (COMPUSTAT Item 60 and Item 74, respectively) in calendar year *y-1* divided by its market capitalization (from CRSP) at the end of December of calendar year *y-1*.

YIELD: the sum of ordinary dividend amounts of a stock over the period from month *t-12* to month *t-1*, divided by the share price at the end of month *t-2*.

RET2-3: the monthly compounded cumulated return for a stock over the period from month *t-3* to month *t-2*.

RET4-6: the monthly compounded cumulated return for a stock over the period from month *t-6* to month *t-4*.

RET7-12: the monthly compounded cumulated return for a stock over the period from month *t-12* to month *t-7*.

TURN: the natural logarithm of share turnover of a stock in month *t-2*. Turnover in month *t* is defined as the share trading volume of a stock in month *t* divided by the number of shares outstanding for the stock at the end of month *t*.

TURNCV: the natural logarithm of the coefficient of variation of turnover for a stock over the period from month *t-36* to month *t-2*. If any of the turnover of a stock in month *t-36* to month *t-2* is missing, TURNCV(t) is redefined over the remaining observations.

I also define variables parallel to the above for dollar (share) trading volume.

RETSTD: the natural logarithm of the standard deviation of daily returns for a stock in month *t-2*.

As in Chordia, Subrahmanyam, and Anshuman (2001), the sample stocks in month *t* need to satisfy the following criteria to enter the monthly cross-sectional regression:

1) No missing data on stock returns and trading volume from month *t-12* to month *t*;

2) At least 24 observations of return data are available from month *t-60* to month *t-1*;

3) Data on share price and market capitalization in month t-2 are available; and

4) The book-to-market ratio is available in month *t-2*.

3.2.2 Risk-Adjusted Excess Returns

I assume that security returns are generated by a *K*-factor approximate factor model, as in Connor and Korajczyk (1988) and Brennan, Chordia, and Subrahmanyam (1998). That is:

$$R_i(t) = E\left[\tilde{R}_i(t)\right] + \sum_{k=1}^{K} \beta_{ik}\delta_k(t) + \varepsilon_i(t)\,, \tag{1}$$

where $R_i(t)$ is the realized return for stock *i* at time *t*. $E\left[\tilde{R}_i(t)\right]$ is the expected return of stock *i* at time *t*. β_{ik} is the factor loading of the *k*-th risk factor on stock *i*. $\delta_k(t)$ is the unexpected realization of the *k*-th risk factor at time *t*. $\varepsilon_i(t)$ is the return realization of stock *i* due to stock *i*-specific factor at time *t*.

By the equilibrium APT,

$$E\left[\tilde{R}_i(t)\right] = RF(t) + \sum_{k=1}^{K} \beta_{ik} E\left[\lambda_k(t)\right], \tag{2}$$

where $E\left[\lambda_k(t)\right]$ is the expected *k*-th risk factor at time *t*.

Combining (1) and (2),

$$R_i(t) - RF(t) = E\left[\tilde{R}_i(t)\right] + \sum_{k=1}^{K} \beta_{ik}\delta_k(t) + \varepsilon_i(t) - RF(t)$$

$$= \sum_{k=1}^{K} \beta_{ik} E[\lambda_k(t)] + \sum_{k=1}^{K} \beta_{ik} \delta_k(t) + \varepsilon_i(t)$$

$$= \sum_{k=1}^{K} \beta_{ik} F_k(t) + \varepsilon_i(t), \qquad (3)$$

where $F_k(t) = E[\lambda_k(t)] + \delta_k(t)$ is the realization of the *k*-th risk factor at time *t*.

The risk-adjusted excess return for security *i* at time *t* is defined as:

$$\hat{\varepsilon}_i(t) = R_i(t) - RF(t) - \sum_{k=1}^{K} \hat{\beta}_{ik} F_k(t), \qquad (4)$$

where $\hat{\beta}_{ik}$ is the OLS-estimated factor loading of the *k*-th risk factor on stock *i*.

Equation (4) defines the risk-adjusted excess return in this dissertation. The risk factors that I employ are the three Fama-French factors. Their factor realizations are respectively *MKT*, the market risk premium, *SMB*, the size premium, and *HML*, the book-to-market premium. To estimate β_{ik} for a stock in month *t*, I regress the stock's risk-unadjusted excess returns from month *t-60* to month *t-2* on the corresponding factor realizations. I use the Dimson (1979) procedure with one lag to mitigate the effects of thin trading on $\hat{\beta}_{ik}$. I then estimate the following cross-sectional model each month:

$$\hat{\varepsilon}_i = c_i + \sum_{m=1}^{M} c_{mi} C_{mi} + c_{iTREND} TREND_i + e_i, \qquad (5)$$

where $\hat{\varepsilon}_t$ is the estimated risk-adjusted returns of stocks in month *t*. C_{mi} is the *m*-th control variable for stock *i*. M is the number of control variables. $TREND_i$ is the trading volume trend for stock *i* (defined in the next section). c_i, c_{mi}, and c_{iTREND} are the parameters. e_t is the random error term.

Equation (5) defines the model that I use to examine the cross-sectional relation between trading volume trend and expected returns. To be consistent with previous literature, I use the Fama and MacBeth (1973) methodology to make inferences on the coefficient estimates.

3.2.3 The Trading Volume Trend

In contrast to return series, trading volume series are likely to be nonstationary (e.g., Lo and Wang (2000)). Mean and variance alone are therefore not sufficient statistics to characterize a trading volume series. In face of the difficulties on choosing the appropriate detrending method, Lo and Wang (2000) use raw turnover (not detrended) in their analyses but confine the analyses to 5-year subperiods. Baker and Stein (2004) use stochastically detrended turnover as their trading volume measure.

The stationarity of trading volume series for individual stocks cannot be easily achieved, however. In addition to the difficulties on choosing the appropriate detrending method, a detrending method appropriate to the trading volume series of one stock may not be applicable to another stock. Without the existence of a well-articulated model governing the time-series structure of trading volume, researchers must assume the exact specification to analyze a trading volume series. Although statistically it is possible to detrend the trading volume series for each individual stock until further tests do not reject its stationarity, for thousands of stocks over a prolonged period of time, this methodology would suggest numerous specifications and render further analysis infeasible.

Instead of detrending the trading volume series, I use the trend on the trading volume series of a stock to extract the information reflecting investors' propensity of trading contained in that trading volume series. I specify a simple time series model of trading volume as follows:

$$V(t) = \beta_0 + \beta_1 t + \beta_2 t^2 + \varepsilon_t , \qquad (6)$$

where *V(t)* is the trading volume for a stock in month *t*. Explanatory variables *t* is the time indexed in month, and t^2 is the square of *t*. ε_t is the random error term.

The use of indexed time in a time-series model is not new (e.g., Davidson and MacKinnon (1993) and Hamilton (1994)). The coefficients β_1 and β_2 in equation (6) intuitively reflect how trading volume varies with time. I include the second order of the indexed time to allow for a nonlinear relation between trading volume and time. Further, this specification allows the change on trading volume per unit of time to be non-constant, as one would expect the same on investor sentiment. Specifically, taking the first derivative of the trading volume in equation (6) with respect to *t* gives:

$$\frac{dV(t)}{dt} = \beta_1 + 2\beta_2 t, \tag{7}$$

which attributes the change on trading volume per unit of time to a constant component (β_1) and a time-dependent component ($2\beta_2 t$). Empirically I estimate the model over the past one year, the past three years, and the past five years as follows: For each stock in month *t*, I regress its trading volume as measured by turnover, dollar volume, or share volume in the months from month *t-T* to month *t-2* on the index time and its square, with the indexed time 1 in month *t-T*. *T* is 12 for one year, 36 for three years, and 60 for five years. I use the method of ordinary least squares to derive the parameter estimates on β_0, β_1, and β_2 in equation (6). In the cases with one-year and three-year data, I also estimate the model with trading volume defined on the weekly interval to ensure that the number of observations used to estimate the model is not what drives my results. I then define the trading volume trend of a stock in month *t* as $\hat{\beta}_1 + \hat{\beta}_2 T$, and scale it by the stock's average monthly trading volume in the period from month *t-T* to month *t-2*. This definition follows from the expectation of equation (7), since the expected indexed time from month *t-T* to month *t-2* is *T/2*. I scale the trading volume trends to make them comparable in the cross section.

3.3 Empirical Results

On average 1315 stocks enter my sample each month. Table 1 presents the time-series averages of the cross-sectional mean, median, and standard deviation on my variables. In Panel A I show the statistics for the control variables. In Panel B I report the statistics for the trading volume variables including the average, the standard deviation, and the coefficient of variation of trading volume, defined over the past one year, past three years, or past five years. I report the statistics on the trading volume trends later in Table 4.

From Panel A we see that the variables price, market capitalization, book-to-market ratio, turnover, dollar volume, share volume, and return standard deviation are skewed. I employ logarithmic transformations for them as defined in section 3.2. I do not use the same transformation for the variables dividend yield, Roll spread, proportion of zero returns, and the price impact measure of Amihud (2002) because they can have the value of zero. I express all the variables in Table 1 as their deviations from the corresponding cross-sectional means in each month before they enter into the regressions. Since I exclude stocks with prices below $5 at the end of each month, my sample stocks have higher prices and larger market capitalization than in previous studies (e.g., Chordia, Subrahmanyam, and Anshuman (2001)).

From Panel B we see that trading volume increases over time. The average and median trading volume is higher when defined over the past one-year period than over the past three-year or the past five-year period. As expected, the variability of trading volume measured by the standard deviation and the coefficient of variation is larger when variability is defined over a longer period.

Table 1: Sample Characteristics

This table presents the summary statistics on an average of 1315 NYSE and AMEX ordinary common stocks per month from January 1965 to December 2002. The reported numbers are the time-series averages of the cross-sectional mean, median, and standard deviation in each month *t*. All sample stocks have share prices in the range of $5 to $1,000. Additional sample criteria include: 1) No missing data on stock return and trading volume over the previous year; 2) At least 24 observations of return data are available over the previous five years; 3) Data on share price and market capitalization in month t-2 are available; and 4) The book-to-market ratio is available for month *t-2*. In Panel A, the *Book-to-Market (Winsorized)* ratios are winsorized at 0.5% and 99.5% fractiles. *Price*, *Market Capitalization*, and trading volume (*Turnover*, *Dollar Volume*, and *Share Volume*) are measured at the end of month *t-2*. *Return Standard Deviation* is the standard deviation of daily returns in month *t-2*. The illiquidity measures of Roll Spread, the proportion of zero returns, and the price impact measure of Amihud (2002), are estimated with daily data in month *t-2*. In Panel B, the *Average*, *Standard Deviation*, and the *Coefficient of Variation* of trading volume are defined over month *t-T* to month *t-2*, where T is 12 for one year, 36 for three year, and 60 for five years.

Panel A: Control Variables

Variable	Mean	Median	Standard Deviation
Price ($)	27.32	22.50	23.24
Market Capitalization ($ million)	1798.11	327.47	5852.57
Book-to-Market	0.93	0.81	0.69
Book-to-Market (Winsorized)	0.91	0.81	0.59
Dividend Yield (%)	2.92	2.53	4.03
Turnover (%)	4.74	3.35	5.65
Dollar Volume ($ million)	112.34	17.32	303.49
Share Volume (million shares)	2.87	0.77	6.34
Return Standard Deviation (%)	2.17	1.94	1.11
Roll Spread (%)	0.16	0.34	1.98
Proportion of Zero Returns (%)	17.00	14.87	11.91
Price Impact Measure of Amihud (2002) (%/$ million)	0.75	0.16	1.67

Panel B.1: Turnover

Variable	Mean	Median	Standard Deviation
1-Year Average (%)	4.59	3.55	4.34
3-Year Average	4.37	3.50	3.64
5-Year Average	4.21	3.41	3.36
1-Year Standard Deviation (%)	2.19	1.41	3.35
3-Year Standard Deviation	2.61	1.76	3.89
5-Year Standard Deviation	2.75	1.90	4.11
1-Year Coefficient of Variation (%)	47.43	42.59	22.55
3-Year Coefficient of Variation	59.05	53.53	27.02
5-Year Coefficient of Variation	64.48	58.42	29.44

(Table 1 cont.)

Panel B.2: Dollar Volume			
1-Year Average ($ million)	105.18	17.49	276.22
3-Year Average	89.71	15.88	231.70
5-Year Average	76.66	14.49	193.31
1-Year Standard Deviation ($million)	33.96	7.35	85.67
3-Year Standard Deviation	40.29	9.23	98.35
5-Year Standard Deviation	42.20	9.70	102.31
1-Year Coefficient of Variation (%)	52.23	46.52	25.83
3-Year Coefficient of Variation	70.27	62.84	33.95
5-Year Coefficient of Variation	80.23	71.89	38.26
Panel B.3: Share Volume			
1-Year Average (million shares)	2.64	0.76	5.49
3-Year Average	2.22	0.69	4.38
5-Year Average	1.92	0.62	3.61
1-Year Standard Deviation (million shares)	0.90	0.30	1.89
3-Year Standard Deviation	1.02	0.36	2.04
5-Year Standard Deviation	1.05	0.38	2.08
1-Year Coefficient of Variation (%)	47.75	42.98	22.52
3-Year Coefficient of Variation	60.89	55.45	26.78
5-Year Coefficient of Variation	68.16	62.33	29.22

Table 2 presents the monthly average correlation coefficients between the variables that enter into the monthly cross-sectional regressions. From Table 2 we see that the variable *PRICE* (the natural logarithm of the reciprocal of share price) has relatively high negative correlations with market capitalization (*SIZE*), dollar volume (*DVOL*), and share volume (*VOL*), but not with turnover (*TURN*). Unlike dollar volume and share volume, turnover does not have a large correlation with market capitalization (average correlation coefficient = 0.12). Among the trading volume measures, the average correlation coefficient between dollar volume and share volume is 0.95, and the average correlation coefficient between turnover and dollar volume (share volume) is 0.53 (0. 63). Also, the correlations between the volatility measures of trading volume, given the period over which the volatility is estimated, are all large (average correlation coefficients above 0.88).

Table 2: Transformed-Variable Correlations

This table presents the average correlation coefficients between the variables defined over an average of 1315 NYSE and AMEX ordinary common stocks per month from January 1965 to December 2002. The reported numbers are the time-series averages of the cross-sectional correlations in each month *t*. *EXRET* is the raw return of a stock in month *t* minus the corresponding one-month Treasury bill rate. *PRICE* is the natural logarithm of the reciprocal of share price, measured in dollars, of a stock at the end of month *t-2*. *SIZE* is the natural logarithm of the market capitalization, measured in millions, of a stock at the end of month *t-2*. *BM* is the natural logarithm of the book-to-market ratio for a stock in month *t-2*, winsorized at the 0.5% and 0.995% fractiles. *YIELD* is the sum of ordinary dividend amounts of a stock over the period from month *t-12* to month *t-1*, divided by the share price at the end of month *t-2*. *RET2-3*, *RET4-6*, and *RET7-12* are the monthly compounded cumulative return for a stock from month *t-3* to month *t-2*, from month *t-6* to month *t-4*, and from month *t-12* to month *t-7*, respectively. *TURN* is the natural logarithm of turnover of a stock in month *t-2*. *TURNCV1* is the natural logarithm of the coefficient of variation of turnover for a stock from month *t-12* to month *t-2*. TURNCV3 and TURNCV5 are defined similarly but over the periods starting from month *t-36* and *t-60*. *DVOL* (*DVOLCV1*, *DVOLCV3, and DVOLCV5*) and *VOL* (*VOLCV1, VOLCV3, and VOLCV5*) are defined similarly for dollar volume and share volume. *RETSTD* is the natural logarithm of the standard deviation of daily returns of a stock in month *t-2*. *RSPD*, *MZRET*, and *MRVOL* are the Roll spread, the proportion of zero returns, and the price impact measure of Amihud (2002), respectively, estimated with daily return data in month *t-2*. *TTREND1*, *TTREND3*, and *TTREND5* are the trading volume trends defined on turnover over the past one year, past three years, and past five years, respectively. *DTREND1*, *DTREND3*, and *DTREND5* (*STREND1*, *STREND3*, and *STREND5*) are defined similarly on dollar volume (share volume). The variables, except for *EXRET* and the trading volume trends, are expressed as deviations from their respective cross-section means in each month *t*.

(Table 2 cont.)

	EXRET	PRICE	SIZE	BM	YIELD	RET 2-3	RET 4-6	RET 7-12	TURN	TURN CV1
EXRET	1.00									
PRICE	0.00	1.00								
SIZE	-0.01	-0.74	1.00							
BM	0.03	0.30	-0.34	1.00						
YIELD	0.01	-0.09	0.15	0.20	1.00					
RET2-3	0.01	-0.09	0.01	0.05	-0.08	1.00				
RET4-6	0.01	-0.11	0.01	0.06	-0.08	0.00	1.00			
RET7-12	0.03	-0.14	0.02	-0.02	-0.08	0.02	0.02	1.00		
TURN	-0.01	-0.07	0.12	-0.11	-0.22	0.13	0.07	0.09	1.00	
TURNCV1	0.00	0.38	-0.53	0.20	-0.13	0.08	0.08	0.06	0.00	1.00
TURNCV3	0.00	0.43	-0.61	0.19	-0.19	0.06	0.07	0.09	0.00	0.68
TURNCV5	0.00	0.43	-0.61	0.18	-0.19	0.05	0.07	0.09	0.00	0.61
DVOL	-0.01	-0.66	0.89	-0.33	0.02	0.07	0.05	0.07	0.53	-0.44
DVOLCV1	0.00	0.39	-0.54	0.20	-0.18	0.13	0.14	0.10	0.07	0.94
DVOLCV3	0.00	0.42	-0.59	0.16	-0.25	0.09	0.12	0.17	0.10	0.64
DVOLCV5	0.00	0.40	-0.56	0.11	-0.27	0.08	0.11	0.16	0.11	0.56
SVOL	-0.01	-0.40	0.78	-0.28	-0.01	0.05	0.02	0.03	0.63	-0.38
SVOLCV1	0.00	0.36	-0.51	0.18	-0.13	0.09	0.09	0.07	0.01	0.97
SVOLCV3	0.00	0.38	-0.53	0.12	-0.19	0.06	0.08	0.12	0.03	0.66
SVOLCV5	0.00	0.35	-0.48	0.07	-0.19	0.05	0.07	0.11	0.05	0.56
RETSTD	-0.01	0.42	-0.28	-0.04	-0.34	0.11	0.01	0.03	0.48	0.21
RSPD	0.00	0.17	-0.09	0.05	0.02	-0.07	-0.03	-0.05	-0.08	0.02
MZRET	0.01	0.51	-0.46	0.26	0.07	-0.07	-0.07	-0.10	-0.33	0.23
MRVOL	0.01	0.72	-0.93	0.31	-0.11	-0.03	-0.04	-0.06	-0.39	0.49
TTREND1	0.00	-0.05	0.02	0.03	-0.02	0.18	0.22	0.03	0.32	0.12
TTREND3	0.00	-0.08	0.06	-0.02	0.00	0.05	0.11	0.20	0.29	0.16
TTREND5	0.00	-0.06	0.06	-0.03	0.02	-0.02	-0.01	0.04	0.13	-0.01
DTREND1	0.01	-0.13	0.05	0.04	-0.07	0.28	0.41	0.21	0.31	0.12
DTREND3	0.00	-0.22	0.12	-0.17	-0.08	0.06	0.16	0.34	0.29	0.11
DTREND5	-0.01	-0.15	0.11	-0.15	-0.01	-0.04	-0.03	0.05	0.13	-0.05
STREND1	0.00	-0.07	0.06	-0.01	-0.01	0.18	0.23	0.07	0.33	0.11
STREND3	-0.01	-0.12	0.14	-0.15	-0.03	0.04	0.09	0.20	0.31	0.10
STREND5	-0.01	-0.08	0.12	-0.11	0.00	-0.03	-0.02	0.03	0.13	-0.05

(Table 2 cont.)

	TURN CV3	TURN CV5	DVOL	DVOL CV1	DVOL CV3	DVOL CV5	SVOL	SVOL CV1	SVOL CV3	SVOL CV5	RETSTD	RSPD
TURNCV3	1.00											
TURNCV5	0.89	1.00										
DVOL	-0.51	-0.51	1.00									
DVOLCV1	0.68	0.61	-0.42	1.00								
DVOLCV3	0.91	0.82	-0.45	0.69	1.00							
DVOLCV5	0.80	0.88	-0.41	0.60	0.89	1.00						
SVOL	-0.44	-0.44	0.95	-0.35	-0.37	-0.34	1.00					
SVOLCV1	0.66	0.59	-0.42	0.93	0.63	0.55	-0.36	1.00				
SVOLCV3	0.93	0.82	-0.43	0.65	0.90	0.80	-0.36	0.67	1.00			
SVOLCV5	0.81	0.89	-0.37	0.56	0.79	0.88	-0.31	0.56	0.88	1.00		
RETSTD	0.26	0.26	-0.03	0.28	0.35	0.35	0.14	0.22	0.27	0.27	1.00	
RSPD	0.03	0.03	-0.11	0.01	0.02	0.02	-0.07	0.01	0.02	0.02	0.02	1.00
MZRET	0.26	0.26	-0.54	0.21	0.21	0.18	-0.45	0.22	0.21	0.18	-0.16	0.11
MRVOL	0.56	0.55	-0.96	0.48	0.51	0.48	-0.88	0.47	0.48	0.43	0.23	0.11
TTREND1	0.06	0.03	0.16	0.15	0.08	0.05	0.18	0.16	0.08	0.05	0.16	-0.05
TTREND3	0.11	0.09	0.18	0.17	0.17	0.15	0.19	0.16	0.19	0.17	0.11	-0.03
TTREND5	0.03	0.01	0.10	-0.01	0.05	0.06	0.10	-0.02	0.06	0.07	0.02	-0.01
DTREND1	0.07	0.05	0.18	0.18	0.12	0.10	0.18	0.16	0.10	0.07	0.13	-0.07
DTREND3	0.10	0.09	0.24	0.14	0.20	0.21	0.20	0.13	0.20	0.20	0.09	-0.07
DTREND5	0.00	0.00	0.15	-0.05	0.03	0.06	0.12	-0.05	0.05	0.08	0.00	-0.03
STREND1	0.04	0.02	0.20	0.14	0.08	0.07	0.22	0.16	0.10	0.07	0.18	-0.06
STREND3	0.06	0.05	0.26	0.11	0.14	0.15	0.27	0.12	0.20	0.22	0.14	-0.04
STREND5	-0.01	-0.02	0.16	-0.05	0.01	0.04	0.16	-0.06	0.04	0.09	0.03	-0.01

(Table 2 cont.)

	MZRET	MRVOL	T TREND1	T TREND3	T TREND5	D TREND1	D TREND3	D TREND5	S TREND1	S TREND3	S TREND5
MZRET	1.00										
MRVOL	0.46	1.00									
TTREND1	-0.10	-0.10	1.00								
TTREND3	-0.12	-0.14	0.16	1.00							
TTREND5	-0.06	-0.10	-0.10	0.57	1.00						
DTREND1	-0.14	-0.13	0.92	0.18	-0.08	1.00					
DTREND3	-0.20	-0.21	0.14	0.85	0.49	0.23	1.00				
DTREND5	-0.12	-0.15	-0.10	0.48	0.86	-0.09	0.57	1.00			
STREND1	-0.12	-0.13	0.95	0.17	-0.08	0.91	0.20	-0.06	1.00		
STREND3	-0.18	-0.22	0.15	0.88	0.51	0.18	0.86	0.51	0.21	1.00	
STREND5	-0.10	-0.15	-0.10	0.52	0.92	-0.09	0.49	0.88	-0.08	0.58	1.00

The return standard deviation (*RETSTD*), in a univariate framework, does not have large correlations with the volume measures. Its average correlations with *TURN*, *DVOL*, and *VOL* are 0.48, -0.03, and 0.14, respectively. It also has a negative, though small, correlation (-0.01) with the excess return (*EXRET*). Among the liquidity measures *RSPD*, *MZRET*, and *MROVL*, *MRVOL* has large negative correlations with *SIZE*, *DVOL*, and *VOL*, suggesting that smaller firms and firms with low trading volume have low liquidity and high price impact of trades. The trading volume trends (*TTREND1*, *TTREND3*, and *TTREND5* for turnover, *DTREND1*, *DTREND3*, and *DTREND5* for dollar volume, and *STREND1*, *STREND3*, and *STREND5* for share volume) do not have large correlations with the other non-trend variables (the average correlation coefficients are all smaller than 0.41 in absolute value).

Table 3 presents the results from the monthly cross-sectional regressions of risk-adjusted excess returns on firm characteristics. The dependent variable is the risk-adjusted excess return, adjusted for the three Fama-French factors (*MKT*, *SMB*, and *HML*). Model (1) in this table is the base model. I control for return variability (*RETSTD*) in model (2). Results from model (1) confirm the negative relation between trading volume and expected returns, which researchers usually explain as stocks with higher levels of liquidity earn lower expected returns. Specifically, in model (1) turnover has the coefficient estimate of -0.17 (t-value = -4.42), dollar volume has the coefficient estimate of -0.16 (-4.10), and share volume has the coefficient estimate of -0.17 (t = -4.39). The results also confirm the negative but surprising relation between the variability of trading volume and expected returns. The coefficient estimates for the variability of trading volume, i.e., *VOLCV3*, are respectively -0.35 (t = -5.80), -0.39 (t = -5.83), and -0.34 (t = -5.64) for turnover, dollar volume, and share volume. As found in Chordia, Subrahmanyam, and Anshuman (2001), the *PRICE* and *YIELD* variables are not significant, but the SIZE variable is

Table 3: Firm Characteristics and Cross-Sectional Stock Returns

This table presents the coefficient estimates and their corresponding t-statistics (in parentheses) in the Fama-MacBeth type monthly cross-sectional regressions. The dependent variable is the risk-adjusted excess return, adjusted for the three Fama-French factors (*MKT*, *SMB*, and *HML*). In estimating the factor loadings for each stock, I use the Dimson (1979) procedure with one lag to mitigate the effects of thin trading on the estimates. The independent variables are defined in Table 2. I express the variables as deviations from their respective cross-section means in each month *t*. In column Turnover (Dollar Volume; Share Volume), variables *VOL* and *VOLCV3* are the same as *TURN* and *TURNCV3* (*DVOL* and *DVOLCV3*; *SVOL* and *SVOLCV3*). The reported adj. R-square is the time-series average of the adjusted R-squares from the monthly cross-sectional regressions.

	Turnover		Dollar Volume		Share Volume	
Variable	(1)	(2)	(1)	(2)	(1)	(2)
Intercept	0.03	0.03	0.03	0.03	0.03	0.03
	(0.58)	(0.58)	(0.58)	(0.58)	(0.58)	(0.58)
PRICE	-0.10	0.01	-0.09	0.02	0.08	0.12
	(-1.37)	(0.15)	(-1.23)	(0.23)	(1.02)	(1.48)
SIZE	-0.11	-0.10	0.05	-0.01	0.07	0.01
	(-4.47)	(-4.31)	(1.17)	(-0.30)	(1.77)	(0.21)
BM	0.02	-0.01	0.02	-0.01	0.01	-0.02
	(0.42)	(-0.12)	(0.32)	(-0.20)	(0.18)	(-0.35)
YIELD	0.83	0.09	0.50	-0.17	0.84	0.12
	(0.67)	(0.08)	(0.40)	(-0.14)	(0.67)	(0.10)
RET2-3	0.90	1.00	0.93	1.03	0.90	1.00
	(2.54)	(2.83)	(2.64)	(2.90)	(2.55)	(2.82)
RET4-6	0.54	0.55	0.60	0.61	0.55	0.56
	(1.90)	(1.94)	(2.13)	(2.14)	(1.94)	(1.97)
RET7-12	0.69	0.70	0.75	0.75	0.69	0.71
	(3.41)	(3.46)	(3.72)	(3.74)	(3.46)	(3.51)
VOL	-0.17	-0.10	-0.16	-0.09	-0.17	-0.10
	(-4.42)	(-2.67)	(-4.10)	(-2.42)	(-4.39)	(-2.67)
VOLCV3	-0.35	-0.34	-0.39	-0.36	-0.34	-0.33
	(-5.80)	(-5.69)	(-5.83)	(-5.50)	(-5.64)	(-5.42)
RETSTD		-0.32		-0.31		-0.32
		(-5.49)		(-5.30)		(-5.44)
Adj. R-Square	0.0404	0.0412	0.0409	0.0417	0.0405	0.0414

significant in the turnover regression. The momentum control variables (*RET2-3, RET4-6*, and *RET7-12*) also have the expected positive and significant coefficient estimates. Nevertheless, unlike Chordia, Subrahmanyam, and Anshuman (2001), I do not find the book-to-market ratio (BM) to be significant in any of my regressions. This may come from the fact that I exclude stocks below $5 per share and I have a longer sample period.

Results in model (2) are similar to model (1), except that after controlling for return variability, the magnitude and significance of the trading volume measures decrease considerably. The coefficient estimate on *VOL* is now -0.10 (t = -2.67) for turnover, -0.09 (t = -2.42) for dollar volume, and -0.10 (t = -2.67) for share volume. On the other hand, the return variability (*RETSTD*) has negative and highly significant coefficient estimates. This result on the return variability is similar to what Amihud (2002) finds in his cross-sectional regressions. This finding suggests that part of the information contained in the level of trading volume is related to the return volatility.

3.3.1 Characteristics of Trading Volume Trends

In this dissertation I use the trend of trading volume to capture information on investor sentiment. Before I look into its relation with expected stock returns, I examine its relations with firm characteristics. Panel A of Table 4 presents the summary statistics on the trading volume trends. In Panel B, I sort the sample stocks each month into quartiles on their trading volume trends, and report within each quartile the time-series averages of the cross-sectional means on market capitalization, share price, the book-to-market ratio, and the stocks' factor loadings on the three Fama-French factors (*MKT*, *SMB*, and *HML*).

From Panel A of Table 4 we see that the trend measure defined over the past one year has a relatively large cross-section variability when compared to those defined over the past three year and the past five years. This result is not surprising since equation (7) (see section 3.2) is estimated with only 11 observations for the one-year trading volume trend. To address this issue, later I reestimate equation (7) with weekly data for a robust test.

The results in Panel B of Table 4 reveal several interesting patterns. First, across the trend measures and across the estimation periods, stocks in trend quartiles one and four tend to be

Table 4: Trading Volume Trends and Firm Characteristics

This table presents the summary statistics on trading volume trends and their relations with firm characteristics. In Panel A I report the time-series averages of the cross-sectional statistics on trading volume trends (in 1/100). In Panel B, I sort the sample stocks each month into quartiles based on their trading volume trends, and report within each quartile the time-series averages of the cross-sectional means on market capitalization, share price, the book-to-market ratio, and the stocks' factor loadings on the three Fama-French factors (*MKT, SMB*, and *HML*). The trading volume trend is defined as follows: In each month *t* I regress the trading volume of a stock from month *t-T* to month *t-2* on the corresponding indexed month and its square. T is 12 for one year, 36 for three year, and 60 for five year. The coefficient estimate on the indexed month is $\hat{\beta}_1$. The coefficient estimate on the square of the indexed month is $\hat{\beta}_2$. I define the trading volume trend of a stock as $\hat{\beta}_1 + \hat{\beta}_2 T$, scaled by the stock's average monthly trading volume from month *t-T* to month *t-2*.

Panel A: Time-Series Averages of Trading Volume Trends ($\times$1/100)

Trend Measure	Year	Mean	Standard Deviation	Q1	Median	Q3
Turnover	1	0.4410	6.6232	-3.5764	0.2248	4.1701
	3	0.3281	2.4129	-0.9638	0.3342	1.6389
	5	0.1302	3.5603	-0.6235	0.3588	1.3081
Dollar Volume	1	1.1120	7.7049	-3.5670	0.7275	5.3285
	3	1.0044	3.1987	-0.7883	0.9557	2.7929
	5	0.7045	4.4833	-0.3645	0.9995	2.3485
Share Volume	1	1.0831	6.7817	-3.0733	0.7949	4.9468
	3	0.9767	2.5661	-0.4955	0.9217	2.4530
	5	0.7609	3.5083	-0.1576	0.9509	2.0817

Panel B.1: One-Year Trading Volume Trends and Firm Characteristics

Trend Measure	Quartile	Capitalization ($ million)	Price ($)	BM	Beta-MKT	Beta-SMB	Beta-HML
Turnover	1	1097.06	24.32	0.94	1.02	0.79	0.25
	2	2456.82	29.04	0.88	1.02	0.56	0.22
	3	2494.78	29.66	0.89	1.02	0.54	0.23
	4	1143.86	26.26	0.99	1.02	0.76	0.26
Dollar Volume	1	874.20	22.01	0.93	1.02	0.81	0.25
	2	2349.27	28.45	0.88	1.02	0.53	0.23
	3	2566.58	30.50	0.88	1.02	0.51	0.22
	4	1402.89	28.32	1.01	1.02	0.81	0.25
Share Volume	1	965.67	24.40	0.96	1.01	0.79	0.26
	2	2317.12	28.99	0.89	1.02	0.56	0.24
	3	2388.53	29.32	0.90	1.02	0.55	0.23
	4	1521.75	26.56	0.96	1.02	0.75	0.23

(Table 4 cont.)

Panel B.2: Three-Year Trading Volume Trends and Firm Characteristics							
Trend Measure	Quartile	Capitalization ($ million)	Price ($)	BM	Beta-MKT	Beta-SMB	Beta-HML
Turnover	1	1022.63	23.81	0.97	1.03	0.80	0.23
	2	2573.93	29.04	0.90	1.02	0.54	0.22
	3	2463.77	29.79	0.89	1.01	0.51	0.23
	4	1132.30	26.62	0.94	1.02	0.81	0.28
Dollar Volume	1	643.61	20.08	1.10	1.03	0.81	0.26
	2	1967.24	27.97	0.93	1.00	0.49	0.23
	3	2745.99	31.41	0.84	1.01	0.49	0.25
	4	1836.59	29.82	0.83	1.05	0.86	0.22
Share Volume	1	768.40	23.89	1.05	1.01	0.81	0.28
	2	1967.54	28.85	0.94	1.01	0.55	0.25
	3	2285.24	29.13	0.89	1.02	0.54	0.24
	4	2172.62	27.40	0.82	1.04	0.76	0.19

Panel B.3: Five-Year Trading Volume Trends and Firm Characteristics							
Trend Measure	Quartile	Capitalization ($ million)	Price ($)	BM	Beta-MKT	Beta-SMB	Beta-HML
Turnover	1	929.26	23.66	0.99	1.02	0.80	0.20
	2	2712.59	28.92	0.92	1.01	0.55	0.22
	3	2392.21	30.11	0.90	1.01	0.51	0.25
	4	1158.71	26.58	0.89	1.04	0.81	0.29
Dollar Volume	1	538.26	20.19	1.16	1.03	0.84	0.26
	2	1723.58	27.57	0.98	0.99	0.51	0.26
	3	2906.14	31.89	0.84	1.00	0.49	0.24
	4	2025.67	29.63	0.73	1.06	0.83	0.19
Share Volume	1	671.43	23.78	1.08	1.00	0.84	0.27
	2	1701.44	28.81	0.98	1.00	0.57	0.27
	3	2538.05	29.61	0.88	1.03	0.51	0.25
	4	2282.91	27.07	0.75	1.06	0.74	0.16

smaller stocks. For example, with the turnover trend defined over the past three years (Panel B.2), stocks in the lowest and highest trend quartiles have the average market capitalization of $1,022.63 million and $1,132.30 millions, respectively. On the other hand, stocks with their trend measures in the second and the third trend quartiles have the average capitalization of $2573.93 millions and $2463.77 millions. Even more revealing is the results in the column Beta-SMB. Stocks in trend quartiles one and four always have higher SMB loadings than those in trend quartiles two and three. For example, with the share volume trend defined over the past three years (Panel B.2), stocks in the lowest and highest trend quartiles have the SMB loadings of 0.81 and 0.76, respectively. Stocks in the second and third trend quartiles have the SMB loadings of 0.55 and 0.54, respectively. This is especially interesting when we compare the results with those in the column Capitalization. In this case despite that stocks in the highest trend quartile have the average capitalization of $2172.62, larger than the average capitalization of $1967.54 millions for stocks in the second trend quartile, stocks in the highest trend quartile have the SMB loading of 0.76, which is higher than the 0.55 for stocks in the second trend quartile.

Together these results suggest that stocks experiencing extreme trading volume trends behave like stocks of smaller firms, and they tend to be stocks of smaller firms. This finding is consistent with the hypothesis that stocks of smaller firms are more susceptible to investor sentiment (e.g., Lee, Shleifer, Thaler (1991) and Neal and Wheatley (1998)).

Next we look at the column BM and the column Beta-HML. Lee and Swaminathan (2000) document that stocks with higher (lower) levels of turnover tend to have lower (higher) book-to-market ratios (see their Table IX). Here we do not observe the same pattern for stocks classified under the one-year and three-year turnover trends.[16] These findings suggest that the turnover trend may carry information different from what is contained in the level of turnover examined in Lee and Swaminathan (2000), since stocks classified by the turnover trend have very different characteristics and risk profiles when compared to stocks classified by the level of turnover.[17]

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[16] We do, however, observe this pattern when the turnover trend is defined over the past five years. In this case stocks in the trend quartiles one, two, three, and four have the average book-to-market ratios of 0.99, 0.92, 0.90, and 0.89, respectively. On the other hand, the *HML* factor loadings on these stocks (column Beta-HML) suggest that these stocks do not behave accordingly. In fact, stocks in the trend quartile four behave like stocks with high book-to-market ratios rather than stocks with low book-to-market ratios.

[17] In unreported tests I also examine the firm characteristics on portfolios based on the level of trading volume. Specifically, each month I sort my sample stocks based on their average monthly trading volume in the past one year or the past three years, i.e., from month *t-12* or month *t-36* to month *t-2*, and classify stocks with the highest (lowest) 30% average trading volume into the high- (low-) volume portfolio. The middle 40% of stocks are in the

Interestingly, for stocks classified under the three-year and five-year dollar volume and share volume trends, we see the decreasing book-to-market ratios and HML factor loadings as we move from the trend quartile one to the trend quartile four. These results suggest that stocks experiencing high (low) dollar/share volume trends tend to be glamour (value) stocks. As will be shown in the next section, despite that the firm characteristics are different under different trend measures, the effects of trading volume trends based on different volume measures are similar on the cross-sectional stock returns.

3.3.2. Trading Volume Trends and Cross-Sectional Stock Returns

Baker and Wurgler (2004) argue that stocks in the cross section are subject to different levels of investor sentiment either because of different shocks on sentiment-based demands or because of different arbitrage constraints across stocks. To the extent that a higher trading volume trend proxies for a higher level of investor sentiment, I expect that stocks with higher trading volume trends will have lower expected returns in the cross section.

In Table 5 I present the results of the monthly cross-sectional regressions when the trading volume trend enters as an extra independent variable. The dependent variable and the other independent variables are the same as in Table 3. In model (1), the trading volume trend (*TREND1*) and the variability of trading volume (*VOLCV1*) are defined over the past one year. In model (2) and (3), these two variables are defined over the past three years (*TREND3* and *VOLCV3*) and the past five years (*TREND5* and *VOLCV5*). I expect the trading volume trends to have negative coefficient estimates.

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median-volume portfolio. I am able to confirm the negative and monotonic relation between the level of trading volume and the book-to-market ratio (the HML factor loading) across the volume portfolios even with different volume measures. However, although stocks with either low or high turnover tend to be stocks of smaller firms (i.e., low market capitalization), stocks with low turnover has the lowest average SMB loading among the three volume groups. For dollar volume and share volume, I observe a positive (negative) and monotonic relation between firm size (the SMB factor loading) and the level of trading volume across the volume portfolios.

Table 5: Trading Volume Trends and Cross-Sectional Stock Returns

This table presents the coefficient estimates and corresponding t-statistics (in parentheses) in the Fama-MacBeth type monthly cross-sectional regressions. The dependent variable is the risk-adjusted excess return, adjusted for the three Fama-French factors (*MKT*, *SMB*, and *HML*). In estimating the factor loadings for each stock, I use the Dimson (1979) procedure with one lag to mitigate the effects of thin trading on the estimates. The independent variables are defined in Table 2. In column Turnover, the variables *VOL, VOLCV1*, *VOLCV3*, *VOLCV5*, *TREND1*, *TREND3*, and *TREND5* are the same as *TURN*, *TURNCV1*, *TURNCV3*, *TURNCV5*, *TTREND1*, *TTREND3*, and *TTREND5* in Table 2. Similar definitions apply in columns Dollar volume and Share volume. Except for the trend variables, I express the variables as deviations from their respective cross-section means in each month *t*.

	Turnover			Dollar Volume			Share Volume		
Variable	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Intercept	0.03	0.06	0.04	0.01	0.07	0.05	0.02	0.07	0.05
	(0.55)	(1.16)	(0.82)	(0.18)	(1.45)	(1.00)	(0.46)	(1.45)	(0.98)
PRICE	0.02	0.02	0.01	0.03	0.00	0.01	0.14	0.10	0.12
	(0.32)	(0.23)	(0.18)	(0.38)	(-0.01)	(0.10)	(1.71)	(1.30)	(1.50)
SIZE	-0.09	-0.09	-0.09	0.01	-0.02	0.00	0.02	0.00	0.02
	(-3.90)	(-3.85)	(-3.82)	(0.14)	(-0.59)	(-0.05)	(0.50)	(0.03)	(0.43)
BM	0.00	0.00	-0.01	0.00	-0.02	-0.03	-0.00	-0.02	-0.03
	(-0.08)	(-0.06)	(-0.29)	(-0.06)	(-0.33)	(-0.54)	(-0.07)	(-0.52)	(-0.59)
YIELD	0.23	0.47	0.06	0.04	0.17	-0.19	0.18	0.53	0.05
	(0.19)	(0.38)	(0.05)	(0.03)	(0.14)	(-0.16)	(0.15)	(0.44)	(0.04)
RET2-3	1.04	1.00	0.96	1.03	1.02	0.97	1.02	1.00	0.96
	(2.96)	(2.82)	(2.73)	(2.96)	(2.90)	(2.77)	(2.90)	(2.81)	(2.74)
RET4-6	0.58	0.60	0.55	0.55	0.68	0.58	0.55	0.61	0.55
	(2.02)	(2.10)	(1.94)	(1.93)	(2.40)	(2.06)	(1.92)	(2.13)	(1.94)
RET7-12	0.69	0.76	0.69	0.69	0.84	0.73	0.69	0.77	0.69
	(3.43)	(3.77)	(3.41)	(3.44)	(4.18)	(3.64)	(3.44)	(3.83)	(3.44)
VOL	-0.11	-0.07	-0.09	-0.10	-0.07	-0.09	-0.11	-0.08	-0.10
	(-2.66)	(-1.94)	(-2.52)	(-2.63)	(-1.81)	(-2.34)	(-2.84)	(-2.07)	(-2.57)
RETSTD	-0.33	-0.33	-0.32	-0.32	-0.33	-0.31	-0.33	-0.32	-0.32
	(-5.46)	(-5.60)	(-5.48)	(-5.27)	(-5.53)	(-5.34)	(-5.52)	(-5.46)	(-5.41)
VOLCV1	-0.29			-0.34			-0.29		
	(-6.29)			(-7.15)			(-6.22)		
VOLCV3		-0.27			-0.27			-0.25	
		(-4.64)			(-4.34)			(-4.11)	
VOLCV5			-0.24			-0.24			-0.25
			(-3.92)			(-3.44)			(-4.06)
TREND1	0.20			0.44			0.48		
	(0.53)			(1.12)			(1.38)		
TREND3		-3.78			-2.92			-3.30	
		(-3.04)			(-2.21)			(-2.78)	
TREND5			-1.30			-0.92			-1.09
			(-1.87)			(-1.35)			(-1.56)

The results in Table 5 show that the trend variable defined over the past three years, *TREND3* in model (2), has the negative and significant coefficient estimates across the volume measures. For turnover trend, the estimate is -3.78 (t-value = -3.04). For dollar volume trend and share volume trend, the estimates are -2.92 (t = -2.21) and -3.30 (t = -2.78), respectively. On the other hand, the estimates for the trend variable *TREND1*, though positive, are not significantly different from zero. The estimates for the trend variable *TREND5*, though negative, are not significant as well. These findings can be reconciled with a sentiment explanation. Brown and Cliff (2005) argue that investor sentiment can build up over time. Investor sentiment at its different stages is then likely to exhibit different effects on expected returns. The trading volume trends defined over the different lengths of periods can simply reflect the different stages of investor sentiment and exhibit different effects on stock returns. It would become clearer when we discuss the analyses based on trend portfolio returns later on.

3.3.3 Trading Volume Trends, Liquidity Measures, and Cross-Sectional Stock Returns

In Table 5 I provide the evidence that the three-year trading volume trend has a negative and significant relation with expected stock returns. This relation holds across the turnover trend, the dollar volume trend, and the share volume trend. I argue that those findings are consistent with a sentiment explanation but not a liquidity explanation. It is still possible, however, that this relation arises because of the multi-dimensional nature of liquidity. In other words, the variable *VOL* alone may not control for liquidity appropriately.

To shed light on this issue, I employ additional liquidity control variables including the Roll Spread (*RSPD*), the proportion of zero returns (*MZRET*), and the price impact measure of Amihud (2002) (*MRVOL*) in the cross-sectional regressions. These liquidity controls are in fact measures of illiquidity, so they should have positive relations with the dependent variable if they measure illiquidity appropriately. In Panel A of Table 6, I include the extra controls one by one together with the other independent variables. In Panel B of Table 6, I exclude the variable *VOL* from the regressions to avoid its collinearity with the new variables.

From Panel A of Table 6, we see that the coefficient estimates on the three-year trading volume trend (*TREND3*) remain negative and significant across the models and the volume measures, suggesting that the negative relation between trading volume trend and expected returns I document in Table 5 is robust with additional liquidity controls.

On the other hand, among the liquidity control variables, only the coefficient estimates on the Roll spread (*RSPD*) has the significant and expected positive sign. In the case of turnover, the coefficient estimate for *RSPD* is 0.02 (t-value = 2.27). In the cases of dollar volume and share volume, the estimates are both 0.02 (t = 2.18).

For the proportion of zero returns (*MZRET*), although the coefficient estimates are weakly significant, they have the unexpected negative sign. For the price impact measure of Amihud (2002) (*MRVOL*), the coefficient estimates have the expected positive sign but are not significant. Interestingly, the variable *VOL* loses its significance when *MRVOL* is present. This finding corresponds to the results in Table 2 that *MRVOL* has large correlations with dollar volume and share volume (the average correlation coefficients are -0.96 and -0.88, respectively. See Table 2). However, despite that *MRVOL* does not have a large correlation with turnover (average correlation coefficient -0.39), the level of turnover loses its significance as well (variable *VOL* in model (3) under turnover). Altogether these findings suggest that the monthly price impact measure of Amihud (2002) contains information related to the level of trading volume.

Since these liquidity controls may have collinearity problems with the variable *VOL*, I exclude *VOL* in Panel B of Table 6. Again, the coefficient estimates on the three-year trading

Table 6: Trading Volume Trends, Liquidity Measures, and Cross-Sectional Stock Returns

This table presents the coefficient estimates and corresponding t-statistics (in parentheses) in the Fama-MacBeth type monthly cross-sectional regressions. In Panel A, I include the extra liquidity control variables *RSPD*, *MZRET*, and *MRVOL* one by one together with the original liquidity control variable *VOL*. In Panel B, I exclude the variable *VOL* from the regressions. The dependent variable in the regressions is the risk-adjusted excess return, adjusted for the three Fama-French factors (*MKT*, *SMB*, and *HML*). In estimating the factor loadings for each stock, I use the Dimson (1979) procedure with one lag to mitigate the effects of thin trading on the estimates. The independent variables are defined in Table 2. In column Turnover, the variables *VOL*, *VOLCV3*, and *TREND3* are the same as *TURN*, *TURNCV3*, and *TTREND3* in Table 2. Similar definitions apply in columns Dollar volume and Share volume. Except for the trend variables, I express the variables as deviations from their respective cross-section means in each month *t*.

Panel A: Liquidity Measures with the Presence of VOL

	Turnover			Dollar Volume			Share Volume		
Variable	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Intercept	0.06	0.06	0.06	0.07	0.07	0.07	0.07	0.07	0.07
	(1.16)	(1.16)	(1.17)	(1.44)	(1.46)	(1.45)	(1.46)	(1.46)	(1.45)
PRICE	0.00	0.06	0.02	-0.01	0.04	0.00	0.09	0.14	0.04
	(0.04)	(0.82)	(0.26)	(-0.19)	(0.60)	(0.03)	(1.10)	(1.86)	(0.47)
SIZE	-0.09	-0.09	-0.03	-0.03	-0.02	-0.02	0.00	0.00	0.01
	(-3.95)	(-3.92)	(-0.42)	(-0.74)	(-0.61)	(-0.37)	(-0.12)	(0.02)	(0.23)
BM	-0.00	-0.00	-0.00	-0.02	-0.01	-0.01	-0.03	-0.02	-0.02
	(-0.07)	(-0.02)	(-0.03)	(-0.35)	(-0.30)	(-0.30)	(-0.54)	(-0.49)	(-0.49)
YIELD	0.39	0.45	0.48	0.10	0.15	0.18	0.46	0.52	0.55
	(0.32)	(0.36)	(0.39)	(0.08)	(0.12)	(0.15)	(0.38)	(0.43)	(0.45)
RET2-3	1.00	1.02	0.99	1.03	1.04	1.02	1.00	1.01	0.99
	(2.84)	(2.87)	(2.81)	(2.92)	(2.96)	(2.89)	(2.83)	(2.87)	(2.80)
RET4-6	0.60	0.60	0.61	0.68	0.68	0.70	0.60	0.60	0.62
	(2.10)	(2.09)	(2.16)	(2.39)	(2.39)	(2.45)	(2.12)	(2.12)	(2.19)
RET7-12	0.76	0.76	0.75	0.84	0.84	0.84	0.77	0.77	0.77
	(3.79)	(3.79)	(3.77)	(4.20)	(4.20)	(4.17)	(3.84)	(3.84)	(3.83)
VOL	-0.07	-0.08	-0.02	-0.07	-0.07	-0.02	-0.08	-0.08	-0.02
	(-1.84)	(-1.97)	(-0.31)	(-1.73)	(-1.85)	(-0.31)	(-1.97)	(-2.10)	(-0.33)
RETSTD	-0.33	-0.38	-0.38	-0.32	-0.37	-0.37	-0.32	-0.37	-0.38
	(-5.56)	(-6.15)	(-5.11)	(-5.50)	(-6.11)	(-5.01)	(-5.43)	(-6.02)	(-5.04)
VOLCV3	-0.27	-0.27	-0.28	-0.27	-0.27	-0.28	-0.24	-0.24	-0.25
	(-4.58)	(-4.57)	(-4.73)	(-4.29)	(-4.30)	(-4.38)	(-4.00)	(-4.04)	(-4.19)
TREND3	-3.81	-3.80	-3.68	-2.92	-2.95	-2.82	-3.33	-3.33	-3.21
	(-3.06)	(-3.05)	(-2.94)	(-2.21)	(-2.24)	(-2.13)	(-2.81)	(-2.82)	(-2.70)
RSPD	0.02			0.02			0.02		
	(2.27)			(2.18)			(2.18)		
MZRET		-0.35			-0.35			-0.34	
		(-1.80)			(-1.84)			(-1.78)	
MRVOL			0.07			0.06			0.07
			(1.19)			(1.09)			(1.25)

(Table 6 cont.)

Panel B: Liquidity Measures without the Presence of VOL

Variable	Turnover (1)	Turnover (2)	Turnover (3)	Dollar Volume (1)	Dollar Volume (2)	Dollar Volume (3)	Share Volume (1)	Share Volume (2)	Share Volume (3)
Intercept	0.06	0.06	0.06	0.08	0.08	0.08	0.08	0.08	0.07
	(1.28)	(1.28)	(1.22)	(1.60)	(1.63)	(1.51)	(1.64)	(1.65)	(1.50)
PRICE	0.02	0.07	0.02	0.00	0.05	0.00	0.03	0.08	0.03
	(0.30)	(1.04)	(0.28)	(0.01)	(0.75)	(0.05)	(0.41)	(1.14)	(0.37)
SIZE	-0.09	-0.09	-0.01	-0.09	-0.09	-0.02	-0.07	-0.07	0.01
	(-3.79)	(-3.80)	(-0.19)	(-3.90)	(-3.94)	(-0.38)	(-3.23)	(-3.24)	(0.25)
BM	-0.01	0.00	0.00	-0.02	-0.02	-0.01	-0.03	-0.03	-0.02
	(-0.13)	(-0.07)	(-0.03)	(-0.44)	(-0.40)	(-0.31)	(-0.64)	(-0.59)	(-0.49)
YIELD	1.07	1.12	0.57	0.72	0.77	0.27	1.15	1.21	0.65
	(0.87)	(0.91)	(0.47)	(0.59)	(0.63)	(0.23)	(0.94)	(0.98)	(0.53)
RET2-3	0.94	0.95	0.96	0.97	0.98	0.99	0.93	0.95	0.96
	(2.64)	(2.67)	(2.72)	(2.74)	(2.78)	(2.81)	(2.62)	(2.66)	(2.71)
RET4-6	0.56	0.56	0.60	0.64	0.64	0.69	0.57	0.56	0.61
	(1.98)	(1.97)	(2.12)	(2.26)	(2.26)	(2.42)	(1.99)	(1.98)	(2.15)
RET7-12	0.75	0.75	0.76	0.84	0.84	0.84	0.76	0.76	0.77
	(3.74)	(3.74)	(3.79)	(4.18)	(4.19)	(4.20)	(3.80)	(3.80)	(3.85)
RETSTD	-0.40	-0.45	-0.39	-0.39	-0.44	-0.38	-0.40	-0.45	-0.39
	(-5.99)	(-6.73)	(-6.04)	(-5.78)	(-6.53)	(-5.83)	(-5.92)	(-6.63)	(-5.96)
VOLCV3	-0.27	-0.27	-0.28	-0.28	-0.28	-0.28	-0.24	-0.24	-0.25
	(-4.61)	(-4.59)	(-4.75)	(-4.44)	(-4.43)	(-4.43)	(-4.02)	(-4.03)	(-4.25)
TREND3	-4.16	-4.20	-3.74	-3.17	-3.23	-2.91	-3.75	-3.79	-3.26
	(-3.39)	(-3.43)	(-2.98)	(-2.45)	(-2.50)	(-2.19)	(-3.19)	(-3.24)	(-2.73)
RSPD	0.02			0.02			0.02		
	(2.36)			(2.28)			(2.29)		
MZRET		-0.32			-0.33			-0.32	
		(-1.65)			(-1.71)			(-1.64)	
MRVOL			0.08			0.07			0.08
			(2.17)			(2.01)			(2.29)

volume trend (*TREND3*) remain negative and significant across the models and the volume measures. The variable *RSPD* has positive and significant coefficient estimates. The variable *MZRET* has coefficient estimates with the unexpected negative sign. The coefficient estimates on the variable *MRVOL*, on the other hand, are now positive and significant across the volume measures. This result confirms that the monthly price impact measure of Amihud (2002) contains similar information as the level of trading volume at the monthly interval.

3.3.4 Robust Tests

As illustrated in section 3.2.3, I estimate the trading volume trend for each stock by equation (7) with monthly volume data over the past one year, the past three year, or the past five year. For the periods of past one year and past three years, the estimation relies on 11 and 35 monthly observations, respectively. It is thus possible that estimation biases on the trading volume trends arise from the small number of observations. To verify that these biases do not drive my results, I reestimate equation (7) with weekly data for the trading volume trends defined over the past one year and the past three years.

For all stocks that enter into the monthly sample, I construct a weekly dataset that contains their weekly share trading volume and end-of-the-week prices and shares outstanding. I define a week as starting on Tuesday and ending on Monday to avoid the weekend effects document by previous studies (e.g., Lakonishok and Maberly (1990) and Foster and Viswanathan (1993)). Dollar volume for a week is defined as the weekly share trading volume times the end-of-the-week price, and turnover is defined as the weekly share trading volume divided by the end-of-the-week number of shares outstanding.

Defining the first week of month *t* as week 0, I then estimate equation (7) with the weekly trading volume from week -5 to week -51, a total of 47 observations, for the trading volume trend over the past one year. For the trading volume trend over the past three year, I estimate equation (7) with the weekly trading volume from week -5 to week -157, a total of 153 observations. The trading volume trend for a stock is then scaled by its average weekly trading volume over the estimation period and enters the cross-sectional regression in month *t*.

I report the results with the trading volume trends estimated with weekly data over the past three years in model (1) of Table 7. To save space, I do not show the results with the trading volume trends estimated with weekly data over the past one year in the table, but report that the results are similar to the ones when the one-year trading volume trends are estimated with monthly data: The one-year trading volume trend does not have significant coefficient estimates in the cross-sectional regressions even when they are estimated with weekly data. This finding confirms that my results are not driven by estimation biases. On the other hand, the three-year trading volume trend still has negative and significant coefficient estimates as I reported in Panel A of Table 6.

I use coefficient estimates from equation (7) to construct the trading volume trend for each stock. Even though the small numbers of observations do not seem to drive my results (Table 7 Model (1)), the estimates are not without errors. To investigate this issue, I use a resampling technique for the cross-sectional regressions. This technique also avoids the possible effects of extreme values on the coefficient estimates.

For each month during the sample period from January 1965 to December 2002, I resample with replacement the cross-sectional observations with the same size as the original sample. I do this for 100 times to get 100 pseudo samples each month. I then estimate the monthly cross-section regression for each pseudo sample and get 100 sets of coefficient estimates on the independent variables each month. I use the median estimate out of the 100 coefficient estimates for a variable as the true coefficient estimate on that variable, and employ the Fama-MacBeth methodology for inference. The results are shown in model (2) of Table 7.

From model (2) of Table 7 we see that the variables still have the same signs and significance as we see from Panel A of Table 6. Specifically, the trading volume trend (*TREND3*) has the coefficient estimate of -3.75 (t-value = -3.01) for turnover, -2.89 (t = -2.20) for dollar volume, and -3.31 (t = -2.78) for share volume. The negative relation between the trading

Table 7: Alternative Methodologies on the Cross-Sectional Regressions

This table presents the coefficient estimates and corresponding t-statistics (in parentheses) in the Fama-MacBeth type monthly cross-sectional regressions with alternative specifications. The dependent variable is the risk-adjusted excess return, adjusted for the three Fama-French factors (*MKT*, *SMB*, and *HML*). In estimating the factor loadings for each stock, I use the Dimson (1979) procedure with one lag to mitigate the effects of thin trading on the estimates. The independent variables are defined in Table 2 and Table 6. Except for the trend variables, I express the variables as deviations from their respective cross-section means in each month *t*. In model (1), the volume trend variable *TREND3* is estimated with weekly trading volume data over the past three years. In model (2), I use a resampling technique to get the parameter estimates and then apply the Fama-MacBeth methodology to make inference. In model (3), I include the market trading volume on the right-hand side of equation (7) and then estimate the trend measure for each stock. In model (4), I model equation (7) as a GARCH(1,1) process and then estimate the trend measure for each stock. The variable *HVOLA3* in model (4) replaces the variable *VOLCV3*; it is the average of the conditional volatilities obtained over the past three years for a stock, scaled by its average trading volume during the same period.

(Table 7 cont.)

	Turnover				Dollar Volume				Share Volume			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Variable	WEEK	BT	MKT	GARCH	WEEK	BT	MKT	GARCH	WEEK	BT	MKT	GARCH
Intercept	0.05	0.06	0.02	0.06	0.07	0.08	0.02	0.06	0.07	0.08	0.02	0.08
	(1.14)	(1.16)	(0.51)	(1.18)	(1.46)	(1.50)	(0.42)	(1.26)	(1.51)	(1.54)	(0.44)	(1.64)
PRICE	0.00	0.00	-0.00	0.01	-0.01	-0.02	-0.01	-0.02	0.08	0.09	0.09	0.09
	(0.02)	(0.05)	(-0.05)	(0.07)	(-0.20)	(-0.27)	(-0.19)	(-0.22)	(1.08)	(1.11)	(1.09)	(1.14)
SIZE	-0.10	-0.09	-0.10	-0.10	-0.03	-0.03	-0.03	-0.04	-0.01	-0.01	-0.01	-0.01
	(-3.98)	(-3.87)	(-4.17)	(-4.11)	(-0.73)	(-0.69)	(-0.71)	(-0.93)	(-0.12)	(-0.15)	(-0.14)	(-0.21)
BM	-0.00	-0.00	-0.00	-0.01	-0.02	-0.02	-0.01	-0.01	-0.03	-0.03	-0.02	-0.02
	(-0.06)	(-0.06)	(-0.06)	(-0.12)	(-0.39)	(-0.37)	(-0.23)	(-0.32)	(-0.54)	(-0.67)	(-0.51)	(-0.44)
YIELD	0.39	0.36	0.25	0.33	0.09	0.10	0.08	-0.01	0.46	0.46	0.33	0.35
	(0.32)	(0.30)	(0.21)	(0.27)	(0.08)	(0.08)	(0.06)	(-0.01)	(0.38)	(0.38)	(0.28)	(0.29)
RET2-3	1.00	1.01	1.00	0.99	1.02	1.02	1.02	1.01	1.00	0.99	0.98	0.99
	(2.83)	(2.85)	(2.83)	(2.80)	(2.90)	(2.90)	(2.88)	(2.86)	(2.82)	(2.81)	(2.77)	(2.81)
RET4-6	0.59	0.59	0.59	0.59	0.67	0.69	0.67	0.65	0.60	0.62	0.59	0.60
	(2.10)	(2.08)	(2.06)	(2.07)	(2.39)	(2.42)	(2.39)	(2.28)	(2.12)	(2.18)	(2.09)	(2.12)
RET7-12	0.75	0.75	0.74	0.73	0.84	0.84	0.81	0.78	0.77	0.77	0.76	0.75
	(3.76)	(3.73)	(3.66)	(3.64)	(4.17)	(4.21)	(4.03)	(3.87)	(3.81)	(3.82)	(3.77)	(3.72)
VOL	-0.07	-0.07	-0.08	-0.08	-0.07	-0.07	-0.07	-0.08	-0.07	-0.08	-0.08	-0.08
	(-1.87)	(-1.75)	(-2.11)	(-2.07)	(-1.76)	(-1.73)	(-1.97)	(-2.04)	(-1.98)	(-2.00)	(-2.18)	(-2.13)
RETSTD	-0.33	-0.32	-0.33	-0.33	-0.32	-0.33	-0.32	-0.32	-0.32	-0.31	-0.32	-0.32
	(-5.54)	(-5.43)	(-5.52)	(-5.56)	(-5.48)	(-5.60)	(-5.47)	(-5.37)	(-5.42)	(-5.26)	(-5.40)	(-5.38)
VOLCV3	-0.27	-0.27	-0.31		-0.27	-0.27	-0.33		-0.24	-0.25	-0.29	
	(-4.62)	(-4.65)	(-5.26)		(-4.30)	(-4.26)	(-5.06)		(-4.00)	(-4.14)	(-4.84)	
TREND3	-0.16	-3.75	-2.55	-3.28	-0.13	-2.89	-1.71	-2.49	-0.14	-3.31	-2.23	-3.51
	(-3.24)	(-3.01)	(-2.18)	(-2.84)	(-2.39)	(-2.20)	(-1.60)	(-2.09)	(-3.10)	(-2.78)	(-2.26)	(-3.32)
RSPD	0.02	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
	(2.28)	(2.49)	(2.25)	(2.23)	(2.15)	(2.17)	(2.09)	(2.13)	(2.19)	(2.16)	(2.14)	(2.17)
HVOLA3				-0.27				-0.35				-0.26
				(-4.71)				(-6.04)				(-4.53)

volume trend and expected returns still holds after controlling for possible estimation errors and extreme values.

Tkac (1999) and Lo and Wang (2000) suggest that there may be a market component in the trading volume of individual securities. To explicitly take this possibility into account, I include the market trading volume on the right-hand side of equation (7). I use the average trading volume of all sample stocks in month *t* as the proxy for the market trading volume in month *t* and define the trading volume trend the same as before. The results when the market trading volume is controlled for are presented in model (3) of Table 7. From this model we see that the trading volume trend still has negative and significant coefficient estimates from turnover and share volume. The coefficient estimate is still negative, though insignificant, for dollar volume.

Finally, Chordia, Subrahmanyam, and Anshuman (2001) show that their results on the negative relation between the variability of trading volume and expected returns hold even when the trading volume series is fitted as a GRACH(1,1) model with a first-order time trend. In the spirit of their model, I specify the conditional variance of the disturbances in equation (7) to follow an ARMA (1,1) process and reestimate the parameters to construct the trading volume trend for each stock. The resulting specification is equivalent to a GARCH(1,1) model with the first-order and second-order time trend. I report the results based on this specification in model (4) of Table 7. In model (4), I also replace the volatility measure of trading volume (variable *VOLCV3*) with the average of the conditional volatilities obtained over the estimation period, scaled by the respective average trading volume over the same period (variable *HVOLA3*). From model (4) of Table 7, we see that the coefficient estimates on the trading volume trend remain negative and significant across the volume measures. The coefficient estimates on the conditional volatility (*HVOLA3*) are negative and significant as reported by Chordia, Subrahmanyam, and

Anshuman (2001). The results thus suggest that an alternative specification on the error behavior in equation (7) does not affect my results.

Chapter 4. Trading Volume Trend and Investor Sentiment: A Portfolio Framework

4.1 Introduction

In this chapter I extend my analyses from the monthly cross-sectional regressions in chapter 3 to the portfolio level. I construct stock portfolios based on their trading volume trends and examine the long-run portfolio returns. The results on the trend portfolios suggest that the relations between trading volume trends and stock returns are dynamic and they collaborate with what I find in chapter 3. Consistent with the trading volume trend as a measure of investor sentiment, stocks with higher trading volume trends earn higher contemporaneous returns but earn lower returns in the future.

An examination of momentum portfolios further reveals that, after controlling for past return momentum, stocks with high trading volume trends still earn lower future returns than stocks with low trading volume trends. To distinguish the information contained in the trading volume trend and the past level of trading volume (e.g., Lee and Swaminathan (2000)), I also form my trend portfolios after controlling for the past level of trading volume. The effects of the trading volume trend on stock returns persist after controlling for the trading volume level.

My analyses on the risk profiles of stocks suggest that stocks with extreme trading volume trends perform like stocks of smaller firms. Portfolios formed on them have larger SMB factor loadings than portfolios formed on remaining stocks. This finding supports the hypothesis that investor sentiment is more likely to manifest its effects on stocks of smaller firms (e.g., Lee, Shleifer, Thaler (1991) and Neal and Wheatley (1998)).

Since short-sales constraints play an important role on linking trading volume and expected returns in Baker and Stein (2004), I also investigate whether short-sales constraints as proxied by firm size and whether a stock is optioned or not affect the information of the trading volume trend on stock returns. Unconditionally, stocks of larger firms and optioned stocks are less likely to experience extreme trading volume trends. The effect of trading volume trend on stock returns, however, persists even for those stocks. These results provide only partial support to the model of Baker and Stein (2004), but they are likely to be explained by the findings of Lakonishok, Lee, and Poteshman (2004). Lakonishok, Lee, and Poteshman (2004) find that investors do not increase their purchases on put options during the bubble period of late 1990s. In other words, even without short-sales constraints, rational investors may not trade to counteract the transactions of overconfident investors because they may face the noise trader risk (see De Long, Shleifer, Summers, and Waldman (1990)).

4.2 Data and Methodology

4.2.1 Portfolio Formation

I examine the returns of stock portfolios formed on their trading volume trends. I construct the portfolios as follows: I first sort my sample stocks in each month *t* by their trading volume trends into three trend portfolios.[18] Stocks with the highest (lowest) 10% trading volume trends are in the *H* (*L*) portfolio. The remaining stocks are in the *M* portfolio. For each stock I calculate its monthly-compounded cumulative return in the holding periods from one month to five years. The holding-period returns in excess of the corresponding T-bill rate (cumulated for the same holding period) for stocks in a given portfolio are then averaged to give the excess portfolio holding-period return. This excess portfolio holding-period return represents the excess return that an investor could earn if he invests one dollar in every stock in a given portfolio, and holds the stocks for the entire holding period.

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[18] The volume trend measures are estimated with monthly volume data from month *t-T* to month *t-2*, where T is 12 for the past one year, 36 for the past three years, and 60 for the past five years.

For each holding period, I report in the tables the average excess portfolio holding-period return across the sample months. I also report the t-statistics for testing whether the holding-period return differences between the trend portfolios are different from zero. To increase the power of the tests, I perform matched tests in that the portfolio holding-period returns are matched by month. For instance, to test whether the holding-period return difference between the *H* and the *L* portfolios is different from zero, I first subtract the holding-period return of the *L* portfolio in a given month from the holding-period return of the *H* portfolio in the same month, and get a holding-period return difference between the *L* and the *H* portfolios in that month. I then test whether the holding-period return difference (*H-L*) is zero or not across the sample months. This method is a combination of the buy-and-hold approach and the calendar-time portfolio approach in Lyon, Barber, and Tsai (1999).

4.2.2 The CBOE Option Data

Later in this chapter I employ an option dataset provided by the Chicago Board of Exchange (CBOE) to classify whether a stock is optioned or not.[19] This dataset contains the first listing dates, names, and stock symbols for publicly-traded stocks that have options listed on major exchanges including the Chicago Board of Exchange (CBOE), the American Stock Exchange (AMEX), the Pacific Exchange (PCX), and the Philadelphia Stock Exchange (PHLX) in the period from April 1973 to December 2002. I merge the stocks in the option dataset with my sample stocks and classify a sample stock with a corresponding option listed at the beginning of the estimation period for its trading volume trend as an optioned stock.

The option dataset is not perfect, however. It contains a survivorship bias that delisted stocks are not covered in this dataset, even though they are included in my sample. The result is that, although the sample stocks that I identify as optioned are indeed optioned, the sample

[19] I thank Don Chance and William Speth for making this dataset available to me.

stocks that I identify as non-optioned might in fact have corresponding options listed somewhere on the market during certain periods of time. In general, this bias could lead to insignificant difference between optioned and non-optioned stocks.

There are not many stocks with listed options before 1980, and the year 1980 is the first year each month there are at least some optioned stocks in each of the *L*, *M*, and *H* portfolios defined in the previous section. I therefore limit my analyses with the option dataset to the period starting 1980. With the above survivorship bias in mind, during the period from 1980 to 2002 I identify a monthly average (median) of 296 (237) stocks as being optioned and the maximum (minimum) number of optioned stocks each month is 692 (84) in 2002 (1980).

4.3 Empirical Results

4.3.1 Excess Returns on Trend Portfolios

I report the excess returns on the trend portfolios in Table 8. In Panel A (B and C), the trading volume trend is the turnover (dollar volume and share volume) trend. In each Panel, I name the trading volume trend estimated with the volume data over the past one year as trend year one (see the first column). Similar definitions apply to trend year three and trend year five. The numbers under the column M1 are the excess returns (in percentage) on the trend portfolios and the corresponding t-statistics (in parentheses) with the holding period of one month. The numbers under the column Y1 are the excess returns on the trend portfolios and the corresponding t-statistics (in parentheses) with the holding period of one year.

We first look at the returns for trend portfolios defined on the one-year trading volume trend. Across the panels, we see that the *L* portfolios tend to earn the lowest excess return among the trend portfolios for holding periods less than nine months, although the statistical significance differs across the volume measures. For instance, with the six-month holding period (column

Table 8: Excess Returns on Trend Portfolios

This table presents the average excess returns (in percentage) on the trend portfolios with holding periods from one month to five years. In Panel A (B and C), the trading volume trend is the turnover (dollar volume and share volume) trend. The column M1 is for the holding period of one month and the column Y1 is for the holding period of one year. I sort the sample stocks at the beginning of each month *t* by their trading volume trends estimated with volume data from month *t-T* to month *t-2*. T is 12 (36 and 60) for trend year one (three and five). I assign stocks with the highest (lowest) 10% trading volume trends to the *H* (*L*) portfolio. I assign the remaining stocks to the *M* portfolio. Each month I calculate for each stock its monthly-compounded cumulative return for a given holding period. The holding-period returns in excess of the corresponding T-bill rate for stocks in a given portfolio are then averaged to give the excess portfolio holding-period return. I report in this table the average excess portfolio holding-period return across the sample months. I also report the t-statistics (in parentheses) for testing whether the holding-period return differences between the trend portfolios are different from zero. To increase the power of the tests, I perform matched tests in that the portfolio holding-period returns are matched by month.

Panel A: Turnover

Trend Year	Trend Portfolio	M1	M3	M6	M9	Y1	Y2	Y3	Y4	Y5
1	L	0.54	1.74	3.48	5.41	7.68	18.18	27.69	41.57	58.93
	M	0.69	2.05	3.98	6.16	8.29	17.55	27.44	39.71	56.43
	H	0.74	2.13	4.25	6.16	8.07	17.04	26.43	37.91	54.59
	M-L	(1.94)	(2.18)	(2.55)	(2.81)	(1.74)	(-1.08)	(-0.32)	(-1.64)	(-1.63)
	H-M	(0.51)	(0.46)	(1.04)	(0.01)	(-0.55)	(-0.75)	(-1.16)	(-1.52)	(-1.26)
	H-L	(1.70)	(1.84)	(2.42)	(1.73)	(0.74)	(-1.36)	(-1.28)	(-2.42)	(-2.11)
3	L	0.66	2.00	3.87	5.98	7.93	17.48	28.55	40.99	58.93
	M	0.71	2.10	4.10	6.29	8.47	18.02	27.85	40.54	57.59
	H	0.52	1.49	2.85	4.51	6.27	13.96	22.37	32.23	45.29
	M-L	(0.62)	(0.69)	(1.15)	(1.20)	(1.82)	(0.97)	(-0.79)	(-0.33)	(-0.72)
	H-M	(-1.64)	(-2.93)	(-4.23)	(-4.76)	(-4.99)	(-5.35)	(-5.33)	(-6.48)	(-8.36)
	H-L	(-1.02)	(-2.11)	(-3.00)	(-3.49)	(-3.44)	(-4.24)	(-4.78)	(-4.83)	(-5.64)
5	L	0.75	2.38	4.68	7.12	9.48	19.66	29.98	42.90	62.28
	M	0.70	2.06	4.02	6.15	8.30	17.82	27.97	40.74	57.76
	H	0.50	1.43	2.78	4.53	6.18	13.40	19.73	28.06	40.53
	M-L	(-0.60)	(-2.14)	(-2.97)	(-3.35)	(-3.15)	(-2.76)	(-2.13)	(-1.66)	(-3.04)
	H-M	(-1.95)	(-3.24)	(-4.14)	(-4.28)	(-4.99)	(-6.00)	(-8.20)	(-10.82)	(-12.73)
	H-L	(-2.15)	(-4.42)	(-6.06)	(-6.44)	(-7.03)	(-7.92)	(-9.56)	(-9.53)	(-10.51)

(Table 8 cont.)

Panel B: Dollar Volume										
Trend Year	Trend Portfolio	M1	M3	M6	M9	Y1	Y2	Y3	Y4	Y5
1	L	0.45	1.32	2.65	4.59	7.01	17.89	27.01	41.74	59.63
	M	0.69	2.03	3.95	6.09	8.24	17.65	27.55	39.72	56.51
	H	0.90	2.72	5.36	7.59	9.12	16.47	26.08	37.62	53.04
	M-L	(2.28)	(3.97)	(5.42)	(4.82)	(3.09)	(-0.36)	(0.62)	(-1.60)	(-1.86)
	H-M	(1.78)	(3.19)	(4.26)	(3.74)	(1.92)	(-1.53)	(-1.52)	(-1.53)	(-2.23)
	H-L	(2.67)	(4.93)	(6.60)	(5.81)	(3.65)	(-1.49)	(-0.85)	(-2.40)	(-3.01)
3	L	0.69	2.12	4.11	6.47	8.83	20.78	34.08	48.32	66.31
	M	0.69	2.06	4.06	6.25	8.44	17.94	27.77	40.32	57.38
	H	0.62	1.71	3.00	4.34	5.71	11.43	17.57	26.70	39.78
	M-L	(0.06)	(-0.33)	(-0.21)	(-0.65)	(-0.93)	(-3.03)	(-4.42)	(-4.41)	(-3.98)
	H-M	(-0.50)	(-1.39)	(-2.91)	(-4.29)	(-5.27)	(-7.42)	(-8.89)	(-8.84)	(-8.77)
	H-L	(-0.38)	(-1.39)	(-2.80)	(-4.60)	(-5.83))	(-8.76)	(-10.13)	(-9.37)	(-8.21)
5	L	0.91	2.81	5.35	8.05	10.80	22.80	34.77	48.27	68.57
	M	0.70	2.05	4.02	6.20	8.36	17.96	27.92	40.52	57.52
	H	0.37	1.09	2.05	3.24	4.40	9.21	15.61	24.91	36.84
	M-L	(-2.14)	(-4.00)	(-4.74)	(-5.14)	(-5.21)	(-4.92)	(-5.21)	(-4.91)	(-6.24)
	H-M	(-2.50)	(-4.11)	(-5.79)	(-7.17)	(-8.55)	(-10.85)	(-11.13)	(-9.55)	(-9.87)
	H-L	(-3.76)	(-6.79)	(-9.40)	(-11.29)	(-12.67)	(-14.82)	(-14.84)	(-11.19)	(-10.79)

Panel C: Share Volume										
Trend Year	Trend Portfolio	M1	M3	M6	M9	Y1	Y2	Y3	Y4	Y5
1	L	0.54	1.82	3.70	5.78	8.15	19.17	29.13	44.17	62.41
	M	0.70	2.06	3.98	6.14	8.30	17.64	27.52	39.76	56.52
	H	0.72	2.00	4.08	5.89	7.52	15.37	24.36	35.06	50.50
	M-L	(1.91)	(1.70)	(1.40)	(1.34)	(0.44)	(-2.57)	(-2.06)	(-3.92)	(-3.93)
	H-M	(0.26)	(-0.40)	(0.41)	(-0.83)	(-2.08)	(-3.56)	(-4.03)	(-4.42)	(-4.53)
	H-L	(1.46)	(0.85)	(1.21)	(0.25)	(-1.20)	(-4.33)	(-4.74)	(-6.16)	(-6.02)
3	L	0.77	2.36	4.64	7.03	9.28	20.10	32.78	47.20	67.79
	M	0.71	2.12	4.13	6.36	8.59	18.22	28.13	40.77	57.78
	H	0.37	1.00	1.87	2.91	4.10	10.02	16.35	24.90	36.42
	M-L	(-0.77)	(-1.65)	(-2.49)	(-2.46)	(-2.09)	(-2.99)	(-4.75)	(-4.59)	(-5.04)
	H-M	(-2.90)	(-5.62)	(-8.18)	(-10.28)	(-11.12)	(-11.39)	(-12.62)	(-12.91)	(-13.03)
	H-L	(-2.76)	(-5.60)	(-8.43)	(-10.05)	(-10.55)	(-10.77)	(-11.58)	(-11.21)	(-10.52)
5	L	0.87	2.68	5.22	7.96	10.71	22.71	34.93	49.99	72.81
	M	0.70	2.08	4.07	6.23	8.40	17.90	27.97	40.54	57.45
	H	0.36	1.02	1.85	3.04	4.23	9.87	15.27	23.81	34.53
	M-L	(-2.23)	(-4.22)	(-5.36)	(-6.17)	(-6.48)	(-6.22)	(-6.76)	(-7.06)	(-9.79)
	H-M	(-3.23)	(-5.52)	(-7.45)	(-8.23)	(-9.28)	(-10.55)	(-12.69)	(-11.54)	(-13.14)
	H-L	(-4.19)	(-7.62)	(-10.16)	(-11.49)	(-13.01)	(-14.99)	(-16.16)	(-13.35)	(-14.52)

M6), the *L* portfolio defined on the turnover trend (Panel A) earns the average excess return of 3.48%. The *M* portfolio earns the average excess return of 3.98%, and the *H* portfolio earns the average excess return of 4.25%. The *L* portfolio defined on the dollar volume trend (Panel B) has the average excess return of 2.65%, significantly lower than the 3.95% for the *M* portfolio and the 5.36% for the *H* portfolio. The *L* portfolio defined on the share volume trend (Panel C) has the average excess return of 3.70%, lower than the 3.98% for the *M* portfolio and the 4.08% for the *H* portfolio. These results do not support a liquidity explanation on the trading volume trend. If the trading volume trend measures liquidity, we would expect the *L* portfolios to earn the highest returns because of the liquidity premium.

We next look at the returns for trend portfolios defined on the three-year trading volume trend. In Panel A, the *L* portfolios tend to have average excess returns similar to those of the *M* portfolios. The *H* portfolios, on the other hand, have the average excess returns significantly lower than those of the *L* and the *M* portfolios for holding periods of three month or longer. For instance, with the holding period of six months, the *H* portfolios have the average excess return of 2.85%, but the *L* and the *M* portfolios have the average excess returns of 3.87% and 4.10%, respectively. With the holding period of three years, the *H* portfolios have the average excess return of 22.37%, but the *L* and the *M* portfolios have the average excess returns of 28.55% and 27.85%, respectively. From Panel B and Panel C we observe similar patterns: The *H* portfolios earn lower average excess returns than the *L* and the *M* portfolios such that we see the negative and significant t-statistics in the rows H-M and H-L.

We then look at the returns for trend portfolios defined on the five-year trading volume trend. Now we see a monotonic and significant relation between the trading volume trend and the average excess portfolio holding-period return. Specifically, the *L* portfolios have higher returns than the *M* portfolios, and the *M* portfolios have higher returns than the *H* portfolios. This relation holds into 5 years across the volume measures. Together these results across the trend years are consistent with the trading volume trend as a sentiment measure. First, from Baker and Stein (2004) we know that when investor sentiment becomes high, the contemporaneous return should also be high. Second, from Smidt (1968) and Zweig (1973) we know that after high investor sentiment the expected returns should be low. Third, Brown and Cliff (2005) argue that investor sentiment can build up over time. Investor sentiment at its different stages is then likely to exhibit different effects on expected returns. The trading volume trends defined over the different lengths of periods can simply reflect the different stages of investor sentiment and exhibit different effects on stock returns. We now look back to the results in Table 8. For the trend portfolios defined on the one-year volume trend, the *L* portfolios have relatively low returns and the *H* portfolios have relative high returns. For the trend portfolios defined on the three-year volume trend, the *L* portfolios no longer have relatively low returns and the *H* portfolios start to have relatively low returns. For the trend portfolios defined on the five-year volume trend, the *L* portfolios have relatively high returns and the *H* portfolios have relative low returns. These are the patterns that we would expect if we are looking at the expected returns following different stages of investor sentiment. The results in Table 8 therefore are consistent with the trading volume trend as a sentiment measure.

Next I examine the past returns on the trend portfolios. In Baker and Stein (2004), overconfident investors drive security prices up when their sentiment is high. Therefore if we look at the contemporaneous return and investor sentiment, we should see a positive relation between the two. In other words, we should see the *H* portfolios to have relatively high past returns and the *L* portfolios to have relatively low past returns.

I report the results in Table 9. In Panel A (B and C), the trading volume trend is the turnover (dollar volume and share volume) trend. Since in Table 8 I impose a one-month lag between the holding periods and the end of the estimation period for the trading volume trends, I do the same for Table 9. That is, in Table 8 the holding periods start from the beginning of month *t* with the estimation period for the trading volume trends ending at the end of month *t-2*. Now in Table 9 I look backwards to the excess returns on the same trend portfolios from the end of month *t-2*. The numbers under the column M2 are the average past excess returns (in percentage) in month *t-2* on the trend portfolios and the corresponding t-statistics (in parentheses). The numbers under the column Y1 are the average past excess returns (cumulated) from month *t-12* to month *t-2* on the trend portfolios and the corresponding t-statistics.

From Table 9, we see that the results are consistent with our expectations. Stocks with low trading volume trends have relatively low contemporaneous returns, and stocks with high trading volume trends have relatively high contemporaneous returns. The return differences between the portfolios are also large and significant. For instance, with the one-year turnover trend, the *H* portfolio earns an average excess return of 35.09% in the holding period from month *t-12* to month *t-2* (Panel A column Y1). On the other hand, the *M* and the *L* portfolios have the average excess returns of 9.33% and 3.07%, respectively. With the one-year dollar volume trend, the average excess returns are 57.77%, 8.33%, and -11.63% for the *H*, the *M*, and the *L* portfolios, respectively (Panel B column Y1). With the one-year share volume trend, the average excess returns are 38.23%, 9.17%, and 1.22% for the *H*, the *M*, and the *L* portfolios, respectively (Panel C column Y1).

We see similar results for the trend measures defined over the past three years and the past five years. For example, with the three-year turnover trend, the average three-year

Table 9: Past Excess Returns on Trend Portfolios

This table presents the average *past* excess returns (in percentage) on the trend portfolios with holding periods from month *t-2* to month *t-60*, where month *t* corresponds to the one-month holding period that I examine in table 8. In Panel A (B and C), the trading volume trend is the turnover (dollar volume and share volume) trend. The column M2 is for the holding period of month *t-2*, and the column Y1 is for the holding period from month *t-12* to month *t-2*. I sort the sample stocks at the beginning of each month *t* by their trading volume trends estimated with volume data from month *t-T* to month *t-2*. T is 12 (36 and 60) for trend year one (three and five). I assign stocks with the highest (lowest) 10% trading volume trends to the *H* (*L*) portfolio. I assign the remaining stocks to the *M* portfolio. Each month I calculate for each stock its monthly-compounded cumulative return for a given holding period. The holding-period returns in excess of the corresponding T-bill rate for stocks in a given portfolio are then averaged to give the excess portfolio holding-period return. I report in this table the average excess portfolio holding-period return across the sample months. I also report the t-statistics (in parentheses) for testing whether the holding-period return differences between the trend portfolios are different from zero. To increase the power of the tests, I perform matched tests in that the portfolio holding-period returns are matched by month.

Panel A: Turnover

Trend Year	Trend Portfolio	M2	M3	M6	M9	Y1	Y2	Y3	Y4	Y5
1	L	-0.17	-0.50	-1.92	-2.65	3.07	25.11	43.01	60.57	81.17
	M	0.75	1.37	3.42	6.34	9.33	23.27	38.51	56.90	79.86
	H	3.99	8.72	23.01	32.28	35.09	45.53	57.43	71.88	87.95
	M-L	(13.51)	(19.94)	(31.89)	(34.05)	(22.94)	(-2.57)	(-4.34)	(-2.61)	(-0.72)
	H-M	(21.56)	(26.52)	(33.39)	(34.68)	(35.19)	(27.34)	(19.34)	(12.36)	(5.09)
	H-L	(24.89)	(30.07)	(37.84)	(39.83)	(38.73)	(18.15)	(10.39)	(6.32)	(2.88)
3	L	0.82	1.38	2.34	2.79	2.55	1.25	18.50	52.27	78.99
	M	0.89	1.70	4.10	6.57	9.00	21.19	36.23	53.87	76.84
	H	1.87	4.23	13.40	25.04	38.25	86.13	100.04	106.56	117.00
	M-L	(0.89)	(2.94)	(11.10)	(13.63)	(25.59)	(39.98)	(22.07)	(1.05)	(-1.13)
	H-M	(6.88)	(10.96)	(18.35)	(20.23)	(29.55)	(41.88)	(37.98)	(32.40)	(23.18)
	H-L	(6.41)	(11.13)	(20.61)	(22.83)	(33.34)	(48.73)	(46.59)	(30.80)	(18.06)
5	L	1.33	2.55	5.82	8.61	10.55	13.74	11.55	14.80	51.49
	M	0.92	1.78	4.39	7.16	9.88	21.61	34.99	53.02	75.32
	H	1.15	2.44	7.56	14.56	23.25	70.18	122.04	153.35	160.61
	M-L	(-4.76)	(-5.75)	(-5.96)	(-5.82)	(-1.99)	(16.53)	(32.65)	(31.46)	(11.12)
	H-M	(2.01)	(3.64)	(8.44)	(9.80)	(16.02)	(27.69)	(31.49)	(32.26)	(26.38)
	H-L	(-1.35)	(-0.54)	(4.25)	(5.86)	(14.75)	(30.12)	(39.05)	(45.14)	(36.29)

(Table 9 cont.)

Panel B: Dollar Volume										
Trend Year	Trend Portfolio	M2	M3	M6	M9	Y1	Y2	Y3	Y4	Y5
1	L	-0.62	-1.85	-7.35	-13.76	-11.63	6.18	21.82	35.47	52.71
	M	0.65	1.14	2.63	5.39	8.33	22.00	37.12	55.51	78.40
	H	5.20	11.98	34.73	51.00	57.77	74.69	89.91	108.97	128.92
	M-L	(13.69)	(24.96)	(56.56)	(64.35)	(59.16)	(23.52)	(16.27)	(16.12)	(15.64)
	H-M	(24.53)	(33.73)	(48.84)	(51.20)	(49.20)	(45.75)	(35.70)	(28.78)	(20.50)
	H-L	(26.34)	(38.07)	(57.35)	(60.64)	(58.35)	(47.10)	(36.85)	(31.90)	(25.01)
3	L	1.01	1.57	1.94	0.50	-2.57	-22.34	-26.80	-7.27	11.52
	M	0.83	1.58	3.69	5.78	7.76	18.20	32.43	49.77	71.44
	H	2.12	5.01	17.04	33.63	53.23	133.79	174.71	197.66	229.64
	M-L	(-1.58)	(0.04)	(7.21)	(10.30)	(30.56)	(64.56)	(70.38)	(48.23)	(37.18)
	H-M	(7.36)	(12.11)	(21.60)	(24.21)	(36.55)	(52.17)	(52.01)	(46.86)	(39.00)
	H-L	(5.26)	(10.52)	(22.67)	(25.82)	(40.97)	(60.40)	(64.25)	(58.27)	(46.53)
5	L	1.77	3.43	8.01	11.61	13.80	9.10	-14.28	-40.40	-34.59
	M	0.88	1.69	4.08	6.55	8.91	18.97	30.42	45.96	66.20
	H	1.02	2.30	7.84	16.41	27.74	95.91	189.16	273.03	326.19
	M-L	(-8.23)	(-9.96)	(-11.91)	(-12.23)	(-9.56)	(15.15)	(49.13)	(62.10)	(53.28)
	H-M	(1.00)	(2.69)	(8.04)	(9.67)	(17.17)	(35.60)	(48.08)	(54.54)	(48.42)
	H-L	(-4.45)	(-4.29)	(-0.32)	(1.51)	(11.78)	(37.40)	(54.40)	(62.34)	(54.96)
Panel C: Share Volume										
Trend Year	Trend Portfolio	M2	M3	M6	M9	Y1	Y2	Y3	Y4	Y5
1	L	-0.18	-0.58	-2.24	-3.42	1.22	17.79	32.46	47.13	65.18
	M	0.76	1.40	3.46	6.29	9.17	22.61	37.39	55.41	77.58
	H	3.91	8.59	23.02	33.48	38.23	58.15	77.12	97.76	123.44
	M-L	(13.95)	(21.25)	(33.80)	(35.91)	(30.37)	(7.82)	(5.76)	(7.36)	(7.99)
	H-M	(21.03)	(25.78)	(33.55)	(35.19)	(39.64)	(39.81)	(33.79)	(29.10)	(23.14)
	H-L	(23.98)	(29.27)	(37.93)	(40.24)	(43.59)	(34.20)	(29.06)	(26.48)	(21.80)
3	L	0.85	1.45	2.51	2.78	2.29	-2.15	4.09	24.49	43.56
	M	0.93	1.80	4.33	6.91	9.36	20.56	34.05	50.61	71.09
	H	1.48	3.42	11.36	22.36	35.64	94.58	132.13	161.17	202.50
	M-L	(1.00)	(3.26)	(11.89)	(14.82)	(29.62)	(45.88)	(46.72)	(28.74)	(24.25)
	H-M	(4.00)	(7.30)	(14.42)	(16.45)	(26.21)	(43.78)	(51.16)	(51.81)	(41.85)
	H-L	(3.74)	(7.78)	(16.75)	(19.17)	(30.20)	(49.30)	(57.06)	(57.38)	(46.44)
5	L	1.40	2.71	6.30	9.49	11.82	15.55	8.64	1.12	18.63
	M	0.95	1.84	4.59	7.47	10.30	21.88	33.76	49.31	68.46
	H	0.83	1.81	5.52	11.18	18.67	66.17	135.99	202.10	260.11
	M-L	(-5.32)	(-6.57)	(-7.53)	(-7.61)	(-4.59)	(13.70)	(40.21)	(54.10)	(38.24)
	H-M	(-0.99)	(-0.19)	(2.57)	(3.93)	(10.29)	(24.67)	(36.30)	(45.16)	(43.42)
	H-L	(-4.07)	(-4.24)	(-1.97)	(-0.50)	(8.14)	(26.73)	(42.88)	(54.40)	(50.87)

holding-period excess returns are 100.04%, 36.23%, and 18.50% for the *H*, the *M*, and the *L* portfolios, respectively (Panel A column Y3). With the three-year dollar volume trend, the returns are 174.71%, 32.43%, and -26.80% for the *H*, the *M*, and the *L* portfolios, respectively (Panel B column Y3). With the three-year share volume trend, the returns are 132.13%, 34.05%, and 4.09% for the *H*, the *M*, and the *L* portfolios, respectively (Panel C column Y3). Together these evidences are consistent with Baker and Stein (2004) that there is a positive relation between investor sentiment and contemporaneous returns.

We now look a little deeper into the numbers reported in Table 8 and Table 9. Comparing the numbers across the tables, we would notice that the absolute magnitudes of the past return differences between the trend portfolios (Table 9) are much larger than the absolute magnitudes of the future return differences (Table 8). This finding in fact sheds light on the important question of how investor sentiment is formed, and collaborates with results in earlier studies. For instance, Swaminathan (1996) documents that the information contained in closed-end fund discounts is related to expectations on future earnings growth and inflation. Specifically, high closed-end fund discounts predict low real growth rates in gross domestic product, consumption, and after-tax corporate earnings. In the model of Barberis, Shleifer, and Vishny (1998), investor sentiment is driven by news events. The results here also suggest that investor sentiment does not grow on trees. It is driven by real information. Therefore we see only partial rather than full reversals on the returns of the trend portfolios.

4.3.2 Stock Momentum and Trading Volume Trends

- **Excess Returns on Momentum-Trend Portfolios**

The results in the previous section suggest that the relation between trading volume trend and expected returns is dynamic and is unlikely to be explained by liquidity. Instead, this relation is consistent with an investor sentiment explanation on the trading volume trend. Below I examine whether this relation holds for the trend portfolios after controlling for other factors, i.e., the return momentum and the past level of trading volume.

Since Jegadeesh and Titman (1993) first document the existence of return momentum, numerous researchers attempt to explain such continuation in stock returns. For instance, Chan, Jegadeesh, and Lakonishok (1996) suggest that the market adjust gradually to new information and the return momentum reflects underreaction over intermediate horizons. Moskowitz and Grinblatt (1999) argue that the momentum profits in the level of individual stocks come from industries. Hong, Lim, and Stein (2000) argue that momentum profits exist because information diffuses only gradually, a prediction offered in Hong and Stein (1999). Specifically, the short-term underreaction to firm-specific information leads to the momentum profits. Grundy and Martin (2001) find that stock-specific return components are more important than total returns in constructing momentum portfolios. They argue that neither industry effects nor cross-sectional differences in expected returns are the main causes of momentum profits. Jegadeesh and Titman (2001) provide further evidence that momentum profits are due to delayed overreactions, consistent with the implications of Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998) and Hong and Stein (1999).

In a recent study, Lee and Swaminathan (2000) find that the level of past trading volume predicts both the magnitude and persistence of return momentum. Further, the information contained in past trading volume is related to market misperceptions of firms' future earnings prospects. Given the findings in Lee and Swaminathan (2000), it is likely that the momentum profits depend on the trading volume trend. To distinguish the information contained in the trading volume trend and the past level of trading volume, I also form my trend portfolios after controlling for the trading volume level.

I construct the momentum-trend portfolios as follows. In each month *t*, I sort the sample stocks by their past returns from month *t-12* to month *t-2* independent of their three-year trading volume. Stocks with the lowest 10% past return are in the *R1 (Loser)* portfolio and stocks with the highest 10% past return are in the *R10* (*Winner)* portfolio. The remaining stocks are in the *R5* portfolio. As before, stocks with the highest (lowest) 10% trading volume trend are in the *H* (*L*) portfolio. The remaining stocks are in the *M* portfolio. This classification schedule is similar to the one developed in Jegadeesh and Titman (1993), except that I impose a one-month lag between the portfolio formation date and the start of the holding periods. I construct the volume level-trend portfolios in a similar way, except that I define for a stock its past level of trading volume as it average monthly trading volume from month *t-36* to month *t-2*. Stocks with the lowest (highest) 30% past levels of trading volume are in the *Low (High)* portfolio. The remaining stocks are in the *Median* portfolio. The definitions are similar to the ones used by Lee and Swaminathan (2000).

I construct the conditional trend portfolios on their three-year trading volume trends because the results in Table 8 indicate that the three-year trading volume trend, when compared to the one-year trading volume trend and the five-year trading volume trend, may measure investor sentiment at its middle stage. I present the results for the momentum-trend portfolios in Table 10. In Panel A (B and C), the trading volume trend is the turnover (dollar volume and share volume) trend. Across the Panels, we see that the *H* portfolios always have the lowest returns among the trend portfolios, after controlling for the past returns. The *L* portfolios, on the other hand, usually have the returns larger than or indistinguishable from the returns of the *M* portfolios. For

Table 10: Excess Returns on Momentum-Trend Portfolios

This table presents the average excess returns (in percentage) on the momentum-trend portfolios with holding periods from one month to five years. In Panel A (B and C), the trading volume trend is the turnover (dollar volume and share volume) trend. The column M1 is for the holding period of one month and the column Y1 is for the holding period of one year. I sort the sample stocks at the beginning of each month *t* independently by their trading volume trends at the end of month *t-2*, and by their past returns from month *t-12* to month *t-2*. I assign stocks with the highest (lowest) 10% trading volume trends to the *H* (*L*) portfolio. I assign the remaining stocks to the *M* portfolio. For the past return classification, stocks with the lowest (highest) 10% past returns are in the *R1/Loser (R10/Winner)* portfolio. The remaining stocks are in the *R5* portfolio. Each month I calculate for each stock its monthly-compounded cumulative return for a given holding period. The holding-period returns in excess of the corresponding T-bill rate for stocks in a given portfolio are then averaged to give the excess portfolio holding-period return. I report in this table the average excess portfolio holding-period return across the sample months. I also report the t-statistics (in parentheses) for testing whether the holding-period return differences between the momentum-trend portfolios are different from zero. To increase the power of the tests, I perform matched tests in that the portfolio holding-period returns are matched by month.

Panel A: Turnover

Momentum	Trend Portfolio	M1	M3	M6	M9	Y1	Y2	Y3
Loser R1	L	-0.07	0.14	0.38	1.63	3.40	15.75	21.81
	M	0.00	0.01	0.43	1.61	3.73	14.40	23.37
	H	-0.63	-1.79	-2.08	-1.04	0.97	8.85	16.79
	M-L	(0.41)	(-0.41)	(0.12)	(-0.04)	(0.45)	(-0.75)	(0.66)
	H-M	(-3.41)	(-5.62)	(-5.09)	(-4.05)	(-3.15)	(-3.59)	(-3.67)
	H-L	(-2.15)	(-4.34)	(-3.77)	(-2.96)	(-2.03)	(-2.71)	(-1.67)
R5	L	0.75	2.26	4.36	6.68	8.74	18.23	30.53
	M	0.71	2.11	4.14	6.36	8.59	18.18	28.13
	H	0.54	1.64	3.15	4.92	6.88	16.21	25.39
	M-L	(-0.59)	(-0.98)	(-1.03)	(-1.15)	(-0.48)	(-0.08)	(-2.45)
	H-M	(-1.50)	(-2.36)	(-3.09)	(-3.58)	(-3.56)	(-2.18)	(-2.18)
	H-L	(-1.63)	(-2.63)	(-3.27)	(-3.77)	(-3.46)	(-1.96)	(-3.15)
Winner R10	L	1.27	3.82	6.37	8.76	11.96	19.91	27.48
	M	1.53	4.42	8.11	11.07	13.11	21.09	30.80
	H	0.93	2.60	4.13	5.45	6.32	9.25	15.99
	M-L	(0.73)	(1.01)	(2.29)	(2.06)	(0.61)	(0.28)	(1.08)
	H-M	(-3.92)	(-6.59)	(-10.09)	(-10.21)	(-10.09)	(-11.12)	(-10.46)
	H-L	(-1.31)	(-2.22)	(-2.86)	(-3.07)	(-3.91)	(-4.75)	(-3.54)

(Table 10 cont.)

Panel B: Dollar Volume								
Momentum	Trend Portfolio	M1	M3	M6	M9	Y1	Y2	Y3
Loser R1	L	0.10	0.62	1.78	3.63	6.14	21.99	29.57
	M	-0.03	-0.16	0.08	1.11	2.96	12.40	21.31
	H	-1.36	-3.54	-5.18	-4.74	-2.90	2.84	6.04
	M-L	(-0.72)	(-2.43)	(-3.71)	(-4.30)	(-4.30)	(-4.95)	(-3.22)
	H-M	(-5.09)	(-7.75)	(-7.74)	(-6.18)	(-4.49)	(-4.83)	(-5.42)
	H-L	(-4.71)	(-7.61)	(-8.60)	(-7.22)	(-5.86)	(-6.68)	(-6.24)
R5	L	0.81	2.40	4.55	7.04	9.35	20.72	35.22
	M	0.70	2.12	4.18	6.42	8.64	18.12	27.98
	H	0.48	1.31	2.22	3.54	5.09	12.79	20.10
	M-L	(-0.99)	(-1.43)	(-1.31)	(-1.81)	(-1.68)	(-2.98)	(-5.05)
	H-M	(-1.57)	(-3.18)	(-5.07)	(-5.98)	(-6.51)	(-5.32)	(-5.87)
	H-L	(-1.89)	(-3.53)	(-5.22)	(-6.52)	(-6.99)	(-6.49)	(-8.10)
Winner R10	L	1.87	5.17	8.81	12.79	17.40	29.44	38.70
	M	1.52	4.36	8.00	11.29	13.57	23.05	33.86
	H	1.12	3.10	5.34	6.74	7.76	10.32	15.25
	M-L	(-0.94)	(-1.51)	(-1.59)	(-1.57)	(-2.18)	(-1.60)	(-1.01)
	H-M	(-2.94)	(-4.86)	(-6.93)	(-9.63)	(-9.76)	(-13.60)	(-15.23)
	H-L	(-1.86)	(-3.25)	(-4.19)	(-4.38)	(-4.79)	(-4.96)	(-5.12)

Panel C: Share Volume								
Momentum	Trend Portfolio	M1	M3	M6	M9	Y1	Y2	Y3
Loser R1	L	0.03	0.39	1.21	3.01	5.33	18.32	26.57
	M	0.01	0.00	0.42	1.61	3.62	14.24	23.11
	H	-0.77	-2.11	-3.37	-2.91	-1.67	4.39	9.01
	M-L	(-0.11)	(-1.23)	(-1.70)	(-2.33)	(-2.25)	(-2.37)	(-1.59)
	H-M	(-3.91)	(-6.69)	(-7.91)	(-7.16)	(-6.45)	(-7.18)	(-7.79)
	H-L	(-2.90)	(-5.59)	(-6.89)	(-6.59)	(-6.37)	(-5.99)	(-6.53)
R5	L	0.85	2.55	5.01	7.51	9.75	20.37	33.58
	M	0.71	2.13	4.17	6.44	8.70	18.38	28.42
	H	0.37	1.02	1.89	2.94	4.20	11.14	18.28
	M-L	(-1.77)	(-2.84)	(-3.88)	(-3.69)	(-2.97)	(-3.04)	(-4.87)
	H-M	(-3.16)	(-5.96)	(-8.33)	(-10.14)	(-11.01)	(-8.88)	(-9.28)
	H-L	(-3.50)	(-6.42)	(-9.08)	(-10.16)	(-10.35)	(-8.39)	(-9.17)
Winner R10	L	1.55	4.54	7.66	10.38	14.27	24.30	37.71
	M	1.50	4.36	8.00	11.06	13.21	21.35	30.99
	H	0.93	2.52	4.21	5.27	5.90	8.29	13.56
	M-L	(-0.11)	(-0.51)	(-0.10)	(-0.15)	(-1.52)	(-2.01)	(-2.24)
	H-M	(-3.85)	(-6.70)	(-10.09)	(-12.01)	(-12.63)	(-13.49)	(-13.41)
	H-L	(-1.84)	(-3.47)	(-4.67)	(-5.33)	(-6.39)	(-7.64)	(-7.61)

instance, the average three-year excess portfolio return for losers is 21.81% on the *L* portfolio defined over the turnover trend, and it is 23.37% on the *M* portfolio and 16.79% on the *H* portfolio (Panel A column Y3). For winners, it is 27.48% on the *L* portfolio, 30.80% on the *M* portfolio, and 15.99% for the *H* portfolio. We observe similar results in panel B and C. These findings suggest that the relation between the trading volume trend and stocks returns holds even after controlling for past returns. Specifically, with high trading volume trends, past winner tend to win less and past losers tend to lose more in the future. With low trading volume trends, past winner tend to win more and past losers tend to lose less in the future. Therefore a momentum strategy of buying past winners with low trading volume trends and selling past losers with high trading volume trends can possibly provide superior returns than a simple strategy of buying past winners and selling past losers.

The results for the volume level-trend portfolios are presented in Table 11. In Panel A (B and C), the trading volume trend is the turnover (dollar volume and share volume) trend. Across the Panels, we see that the *H* portfolios still tend to have the lowest returns among the trend portfolios, after controlling for the level of trading volume. However, the effects of the trading volume trend on stock returns show up sooner if the stocks are in the *Median* or *High* volume portfolio. For instance, in Panel A, we obtain the statistical significance on the return difference between the *H* and the *L* portfolios for holding periods of one year or longer if the stocks are also in the *Low* portfolio. If the stocks are in the *Median* or *High* volume portfolio, we obtain the statistical significance within months. We see similar patterns in Panel B and Panel C. Together these results indicate that the relation between the trading volume trend and stocks returns holds even after controlling for the level of trading volume.[20]

[20] In unreported results I replicate Table 11 but define the level of trading volume over the past one year, i.e., month *t-12* to month *t-2*. The results do not differ much.

Table 11: Excess Returns on Volume Level-Trend Portfolios

This table presents the average excess returns (in percentage) on the volume level-trend portfolios with holding periods from one month to three years. In Panel A (B and C), the trading volume trend is the turnover (dollar volume and share volume) trend. The column M1 is for the holding period of one month and the column Y1 is for the holding period of one year. I sort the sample stocks at the beginning of each month *t* independently by their trading volume trends at the end of month *t-2*, and by their past levels of trading volume from month *t-36* to month *t-2*. I assign stocks with the highest (lowest) 10% trading volume trends to the *H* (*L*) portfolio. I assign the remaining stocks to the *M* portfolio. For the past level of trading volume classification, stocks with the lowest (highest) 30% past levels of trading volume are in the *Low (High)* portfolio. The remaining stocks are in the *Median* portfolio. Each month I calculate for each stock its monthly-compounded cumulative return for a given holding period. The holding-period returns in excess of the corresponding T-bill rate for stocks in a given portfolio are then averaged to give the excess portfolio holding-period return. I report in this table the average excess portfolio holding-period return across the sample months. I also report the t-statistics (in parentheses) for testing whether the holding-period return differences between the volume level -trend portfolios are different from zero. To increase the power of the tests, I perform matched tests in that the portfolio holding-period returns are matched by month.

Panel A: Turnover

Volume Level	Trend Portfolio	M1	M3	M6	M9	Y1	Y2	Y3
Low	L	0.79	2.17	4.23	6.48	8.56	17.80	30.40
	M	0.71	2.11	4.16	6.30	8.48	17.56	27.32
	H	0.67	2.20	3.91	5.62	7.17	14.45	23.05
	M-L	(-0.69)	(-0.27)	(-0.23)	(-0.48)	(-0.19)	(-0.28)	(-2.38)
	H-M	(-0.52)	(0.16)	(-0.74)	(-1.57)	(-2.59)	(-3.69)	(-3.55)
	H-L	(-0.98)	(-0.08)	(-0.76)	(-1.52)	(-2.07)	(-2.54)	(-3.76)
Median	L	0.68	2.20	4.27	6.66	9.07	21.52	32.13
	M	0.75	2.21	4.35	6.67	9.01	19.27	30.08
	H	0.55	1.64	3.38	5.71	7.70	14.07	24.58
	M-L	(0.70)	(0.08)	(0.27)	(0.03)	(-0.15)	(-3.02)	(-1.94)
	H-M	(-1.72)	(-2.60)	(-2.92)	(-2.05)	(-2.39)	(-6.48)	(-4.54)
	H-L	(-0.85)	(-2.04)	(-2.08)	(-1.61)	(-2.05)	(-7.43)	(-4.97)
High	L	0.68	2.11	3.77	5.71	7.48	15.58	26.65
	M	0.66	1.98	3.79	5.88	7.92	17.14	25.43
	H	0.25	0.72	1.22	2.05	3.19	10.11	15.25
	M-L	(-0.20)	(-0.60)	(0.07)	(0.46)	(0.96)	(1.94)	(-1.09)
	H-M	(-2.91)	(-5.39)	(-7.85)	(-9.99)	(-10.83)	(-9.43)	(-9.10)
	H-L	(-2.39)	(-4.38)	(-5.70)	(-6.93)	(-6.78)	(-4.97)	(-7.22)

(Table 11 cont.)

Volume Level	Trend Portfolio	M1	M3	M6	M9	Y1	Y2	Y3
Panel B: Dollar Volume								
Low	L	0.83	2.56	5.14	8.04	11.18	26.18	42.90
	M	0.92	2.76	5.57	8.69	11.79	24.68	38.66
	H	1.05	3.02	5.33	7.43	9.49	16.99	25.91
	M-L	(0.95)	(1.12)	(1.74)	(2.13)	(1.57)	(-1.50)	(-2.76)
	H-M	(0.87)	(1.00)	(-0.60)	(-2.45)	(-3.96)	(-7.43)	(-9.00)
	H-L	(1.19)	(1.41)	(0.44)	(-1.15)	(-2.91)	(-7.60)	(-9.87)
Median	L	0.68	2.07	3.73	5.72	7.33	16.20	29.27
	M	0.67	1.97	3.80	5.85	7.91	16.88	25.79
	H	0.42	1.24	2.18	3.40	4.59	10.40	16.25
	M-L	(-0.11)	(-0.44)	(0.23)	(0.32)	(1.27)	(0.82)	(-2.60)
	H-M	(-1.51)	(-2.63)	(-3.89)	(-4.77)	(-5.60)	(-7.38)	(-8.63)
	H-L	(-1.31)	(-2.47)	(-3.27)	(-3.99)	(-4.14)	(-5.60)	(-7.54)
High	L	0.43	1.34	3.09	5.19	8.30	22.48	32.47
	M	0.53	1.57	3.08	4.69	6.30	13.80	21.75
	H	0.34	0.63	0.81	1.41	1.83	4.06	6.79
	M-L	(0.45)	(0.58)	(-0.01)	(-0.75)	(-2.43)	(-5.35)	(-5.16)
	H-M	(-0.95)	(-2.89)	(-4.65)	(-5.61)	(-6.48)	(-8.72)	(-10.20)
	H-L	(-0.33)	(-1.57)	(-3.41)	(-4.70)	(-6.58)	(-9.52)	(-10.33)
Panel C: Share Volume								
Volume Level	Trend Portfolio	M1	M3	M6	M9	Y1	Y2	Y3
Low	L	0.82	2.55	5.29	8.13	10.89	24.03	38.69
	M	0.91	2.74	5.39	8.23	11.13	22.94	35.47
	H	0.79	2.21	4.35	6.48	9.01	16.85	23.87
	M-L	(1.04)	(1.28)	(0.43)	(0.35)	(0.64)	(-1.41)	(-3.29)
	H-M	(-0.89)	(-2.29)	(-2.95)	(-4.13)	(-4.08)	(-6.76)	(-9.91)
	H-L	(-0.22)	(-1.22)	(-2.40)	(-3.43)	(-3.15)	(-6.59)	(-9.41)
Median	L	0.81	2.41	4.40	6.21	7.97	17.81	31.05
	M	0.68	2.01	3.92	6.12	8.28	17.88	27.76
	H	0.39	1.04	1.71	2.30	2.90	9.72	18.04
	M-L	(-1.35)	(-2.27)	(-1.88)	(-0.27)	(0.78)	(0.10)	(-3.02)
	H-M	(-2.14)	(-4.02)	(-6.53)	(-9.70)	(-12.30)	(-10.14)	(-8.62)
	H-L	(-2.55)	(-4.76)	(-6.63)	(-7.80)	(-8.93)	(-7.67)	(-8.06)
High	L	0.63	1.90	4.09	6.72	8.80	16.48	26.35
	M	0.57	1.69	3.27	5.00	6.73	14.59	22.50
	H	-0.05	-0.14	-0.01	0.63	1.32	4.36	7.04
	M-L	(-0.36)	(-0.68)	(-1.84)	(-2.99)	(-2.87)	(-1.62)	(-2.44)
	H-M	(-4.15)	(-7.35)	(-8.79)	(-9.25)	(-9.31)	(-11.04)	(-14.17)
	H-L	(-3.27)	(-5.27)	(-7.10)	(-8.62)	(-8.77)	(-8.81)	(-11.09)

- **Risk Profile of Momentum-Trend Portfolios**

The analyses so far show that the trading volume trend predicts stock returns, even after controlling for return momentum or the level of trading volume. However, these analyses focus on excess returns and assume that the portfolios are well diversified. To explicitly take the risk of stocks into account, I construct monthly-rebalanced momentum-trend portfolios and regress their monthly returns on the corresponding three Fama-French factors (*MKT*, *SMB*, and *HML*). Fama and French (1996) find that their three-factor model performs reasonably well in explaining returns of portfolios formed on the earnings-to-price ratio (E/P), the cash flow-to-price ration (C/P), and past sales growth. It also explains the long turn return reversals documented by De Bondt and Thaler (1985). However, it fails to explain the intermediate-horizon return momentum. Given these results, I form the portfolios on return momentum and the trading volume trend first, and then perform the regression.

My methods are as follows: I construct the momentum-trend portfolios as I did in the previous section. The trend portfolios are based on the three-year trading volume trend, and the return momentum is defined over the period from month *t-12* to *t-2*. The intersections of the trend portfolios and the momentum portfolios are the momentum-trend portfolios.

I employ the same portfolio rebalancing technique developed in Jegadeesh and Titman (1993). Specifically, the momentum-trend portfolios are monthly rebalanced by 1/12 of the component stocks, i.e., the portfolio (raw) returns in each month are the equal-weighted average (raw) returns of portfolios initiated in the current month and in the previous 11 months. By doing this I am able to generate a monthly return series for each momentum-trend portfolio. The reason that I choose to rebalance the portfolios by 1/12 of the component stocks is to ensure that the resulting return series contain information on portfolio returns that is revealed only after a period of time.

I subtract from the monthly return series of a rebalanced portfolio the corresponding one-month T-bill rate and regress the monthly excess return series on the three Fama-French factors with an intercept. I report the regression results in Table 12. In Panel A (B and C), the trading volume trend is the turnover (dollar volume and share volume) trend. The rows R1, R5, and R10 correspond to the momentum portfolios with the lowest 10% past returns, the median 80% returns, and the highest 10% returns, respectively. The column L, M, and H correspond to the trend portfolios with the lowest 10% trading volume trends, the median 80% trading volume trends, and the highest 10% trading volume trends, respectively. The column M-L corresponds to the portfolio with its returns the same as the return differences between the rebalanced *M* and the rebalanced *L* portfolios.

We start from Panel A of Table 12. First, the intercepts reveal that the *L* portfolios tend to have larger abnormal returns than the *H* portfolios (column H-L), but the abnormal returns for the *L* portfolios are indistinguishable from those for the *M* portfolios. The abnormal return differences between the *H* and *L* portfolios are especially large when the stocks also experience extreme past returns (row R1 and R10). These results are consistent with the hypothesis that stocks with high trading volume trends (*H*) were subject to high investor sentiment so they earn lower abnormal returns in the future. We next look at the MKT factor loadings (Beta-MKT) on the momentum-trend portfolios. We see a monotonic positive relation between the trading volume trend and the factor loading, as we move from the *L* portfolio to the *H* portfolio. This relation is especially strong for stocks with median past returns (row R5). Together these results

Table 12: Risk Profiles of Momentum-Trend Portfolios

This table presents the coefficient estimates from the regressions of the momentum-trend portfolio excess returns on the three Fama-French factors (*MKT*, *SMB*, and *HML*). The trend portfolios are defined with three-year trading volume trends, and stocks with the highest (lowest) 10% trading volume trends are in the *H* (*L*) portfolio. The remaining stocks are in the *M* portfolio. The momentum portfolios are defined with past one-year returns, and stocks with the lowest (highest) 10% past returns are in the *R1* (*R10*) portfolio. The remaining stocks are in the *R5* portfolio. The intersections of the trend portfolios and the momentum portfolios are the momentum-trend portfolios. A momentum-trend portfolio is then monthly rebalanced by 1/12 to construct a time-series of monthly returns. I subtract from the monthly returns the corresponding one-month T-bill rates and regress the resulting time-series of excess returns on the three Fama-French factors with an intercept, and report the coefficient estimates (t-statistics in parenthesis). In the columns M-L, H-M, and H-L, the dependent variables in the regressions are the monthly return differences between the rebalanced portfolios.

Panel A: Turnover						
	Intercept					
Portfolio	L	M	H	M-L	H-M	H-L
R1	-0.05	-0.04	-0.36	-0.00	-0.32	-0.32
	(-0.26)	(-0.32)	(-2.09)	(0.04)	(-2.62)	(-1.72)
R5	0.47	0.51	0.36	0.04	-0.15	-0.12
	(5.34)	(7.57)	(3.46)	(0.63)	(-1.83)	(-1.04)
R10	0.81	0.89	0.34	0.08	-0.55	-0.47
	(4.69)	(8.35)	(2.33)	(0.54)	(-4.88)	(-2.46)
	Beta_MKT					
R1	1.16	1.21	1.29	0.05	0.08	0.13
	(27.60)	(38.38)	(30.81)	(1.80)	(2.64)	(2.93)
R5	0.98	1.03	1.09	0.05	0.06	0.11
	(45.89)	(63.48)	(43.78)	(3.51)	(2.93)	(4.07)
R10	1.12	1.14	1.18	0.03	0.04	0.07
	(26.89)	(44.72)	(33.51)	(0.79)	(1.46)	(1.47)
	Beta_SMB					
R1	1.13	0.83	0.88	-0.30	0.05	-0.25
	(20.89)	(20.49)	(16.34)	(-8.07)	(1.26)	(-4.38)
R5	0.70	0.40	0.62	-0.31	0.22	-0.08
	(25.49)	(18.89)	(19.32)	(-16.75)	(8.63)	(-2.39)
R10	0.62	0.54	0.83	-0.08	0.29	0.20
	(11.65)	(16.39)	(18.19)	(-1.83)	(8.30)	(3.47)
	Beta_HML					
R1	0.71	0.62	0.65	-0.09	0.03	-0.06
	(11.19)	(13.07)	(10.29)	(-2.01)	(0.60)	(-0.90)
R5	0.53	0.51	0.48	-0.02	-0.03	-0.05
	(16.43)	(20.72)	(12.70)	(-1.04)	(-1.00)	(-1.30)
R10	0.03	0.14	0.13	0.12	-0.01	0.11
	(0.42)	(3.72)	(2.49)	(2.21)	(-0.27)	(1.54)
	Adj. R-square					
R1	0.77	0.84	0.77	0.12	0.02	0.05
R5	0.88	0.92	0.86	0.38	0.21	0.05
R10	0.74	0.87	0.82	0.02	0.16	0.03

(Table 12 cont.)

Panel B: Dollar Volume						
	Intercept					
Portfolio	L	M	H	M-L	H-M	H-L
R1	0.01	0.02	-0.33	0.01	-0.35	-0.34
	(0.05)	(0.15)	(-2.18)	(0.07)	(-2.92)	(-1.94)
R5	0.44	0.52	0.40	0.08	-0.12	-0.04
	(4.59)	(7.79)	(3.51)	(1.06)	(-1.19)	(-0.30)
R10	0.57	0.70	0.40	0.13	-0.30	-0.17
	(4.68)	(9.25)	(3.08)	(1.27)	(-2.96)	(-1.12)
	Beta_MKT					
R1	1.18	1.17	1.28	-0.02	0.12	0.10
	(32.67)	(46.18)	(35.07)	(-0.71)	(4.09)	(2.34)
R5	1.03	1.03	1.16	-0.00	0.14	0.14
	(44.17)	(63.94)	(42.03)	(-0.01)	(5.90)	(4.29)
R10	1.13	1.11	1.18	-0.02	0.07	0.05
	(38.69)	(61.16)	(38.02)	(-0.80)	(2.90)	(1.38)
	Beta_SMB					
R1	1.07	0.69	0.82	-0.38	0.13	-0.25
	(22.91)	(21.09)	(17.41)	(-11.32)	(3.66)	(-4.62)
R5	0.83	0.39	0.62	-0.44	0.23	-0.21
	(27.58)	(18.91)	(17.39)	(-19.51)	(7.61)	(-4.95)
R10	0.96	0.62	0.78	-0.33	0.16	-0.18
	(25.40)	(26.61)	(19.44)	(-10.54)	(4.95)	(-3.74)
	Beta_HML					
R1	0.72	0.54	0.25	-0.18	-0.29	-0.47
	(13.16)	(14.24)	(4.46)	(-4.47)	(-6.89)	(-7.48)
R5	0.64	0.50	0.24	-0.13	-0.26	-0.40
	(18.23)	(20.89)	(5.74)	(-5.12)	(-7.53)	(-8.23)
R10	0.54	0.40	0.08	-0.14	-0.32	-0.47
	(12.33)	(14.62)	(1.61)	(-3.86)	(-8.82)	(-8.41)
	Adj. R-square					
R1	0.82	0.88	0.82	0.23	0.25	0.16
R5	0.88	0.92	0.86	0.46	0.40	0.22
R10	0.86	0.93	0.86	0.20	0.31	0.17

(Table 12 cont.)

Panel C: Share Volume						
	Intercept					
Portfolio	L	M	H	M-L	H-M	H-L
R1	0.15	0.02	-0.38	-0.13	-0.40	-0.53
	(1.06)	(0.19)	(-2.47)	(-1.29)	(-3.72)	(-3.28)
R5	0.53	0.53	0.26	-0.01	-0.26	-0.27
	(5.97)	(7.93)	(2.57)	(-0.10)	(-3.34)	(-2.49)
R10	0.70	0.70	0.24	0.01	-0.46	-0.45
	(5.95)	(9.11)	(1.96)	(0.06)	(-4.82)	(-3.27)
	Beta_MKT					
R1	1.09	1.17	1.30	0.08	0.13	0.21
	(32.88)	(46.69)	(35.10)	(3.28)	(4.90)	(5.31)
R5	0.97	1.03	1.18	0.05	0.15	0.20
	(45.59)	(64.71)	(47.60)	(3.95)	(7.75)	(7.78)
R10	1.06	1.13	1.21	0.07	0.08	0.15
	(37.66)	(60.75)	(40.69)	(2.91)	(3.67)	(4.52)
	Beta_SMB					
R1	1.01	0.72	0.75	-0.29	0.03	-0.26
	(23.56)	(22.13)	(15.68)	(-9.52)	(0.95)	(-5.26)
R5	0.72	0.41	0.52	-0.31	0.11	-0.20
	(26.25)	(19.98)	(16.36)	(-17.51)	(4.58)	(-6.10)
R10	0.88	0.66	0.74	-0.22	0.08	-0.14
	(24.29)	(27.49)	(19.24)	(-7.63)	(2.74)	(-3.33)
	Beta_HML					
R1	0.63	0.54	0.33	-0.10	-0.21	-0.31
	(12.68)	(14.19)	(5.85)	(-2.74)	(-5.40)	(-5.31)
R5	0.58	0.50	0.33	-0.08	-0.17	-0.25
	(18.02)	(20.99)	(8.85)	(-3.70)	(-6.15)	(-6.47)
R10	0.45	0.39	0.16	-0.06	-0.22	-0.29
	(10.60)	(13.83)	(3.62)	(-1.84)	(-6.47)	(-5.71)
	Adj. R-square					
R1	0.82	0.88	0.81	0.17	0.18	0.17
R5	0.88	0.92	0.88	0.40	0.35	0.27
R10	0.85	0.93	0.86	0.11	0.21	0.15

suggest that stocks with high trading volume trends are riskier than stocks with low trading volume trends in the sense that they have higher sensitivities to market movements.

The results on the SMB loadings (Beta-SMB) confirm what we find in chapter 3 (Table 4). Stocks with high trading volume trends and stocks with low trading volume trends both perform like stocks of smaller firms more than do stocks with median trading volume trends. The numbers in the columns M-L and H-M confirms the significance of this observation. Again, this finding is consistent with the hypothesis that stocks of smaller firms are more susceptible to investor sentiment.

The results on the HML loadings (Beta-HML) do not suggest any specific relation between the trading volume trend and the HML factor loading, which is consistent with what we find in Table 4. The numbers in the columns M-L, H-M, and H-L suggest that the HML loadings are usually similar across the trend portfolios.

The results in Panel B and Panel C are very similar to those in Panel A, except that we now find a monotonic positive relation between the trading volume trend and the HML factor loading, as we move from the *L* portfolio to the *H* portfolio. This relation is statistically significant as the HML factor also explains the return differences between the trend portfolios. These results suggest that stocks with high (low) dollar/share volume trends tend to perform like glamour (value) stocks, again consistent with what we find in Table 4.

Overall, the results in Table 11 suggest that trading volume trends explain stock returns even after controlling for the risk of stocks and return momentum. Stocks with high trading volume trends earn lower abnormal returns than stocks with low or median trading volume trends. Further, stock with high trading volume trends and stocks with low trading volume trends both perform like stocks of smaller firms more than do stocks with median trading volume trends. Those findings support the sentiment explanation on the trading volume trend.

4.3.3 Short-Sales Constraints and Returns on Trend Portfolios

- **Distributions of Extreme Trading Volume Trends across Stocks**

In Baker and Stein (2004), short-sales constraints play an important on linking investor sentiment and trading volume. Specifically, when investor sentiment is high, overconfident investors drive security prices up and lowered the price impact of trades. The lowered price impact attracts more aggressive trading and thus generates more trading volume. However, without short-sales constraints, rational investors should be able to counteract the trades of overconfident investors. Consequently, one may expect investor sentiment to have less of an effect on asset valuation.

In this section I investigate the existence of short-sales constraints on the relation between trading volume trend and stocks returns. I employ firm size and whether a stock is optioned or not as the proxies for short-sales constraints. Firm size serves as an inverse proxy for short-sales constraints because as a firm grows larger over time, its stock is more likely to be short-sales eligible on an exchange. If a stock is optioned, investors can write call options or buy put options on the stock to achieve the same effects as short-selling. As implied by Baker and Stein (2004), the relation between the trading volume trend and stocks returns should break down for stocks of larger firms and optioned stocks.

Table 13 shows the distributions of extreme trading volume trends across firm size in Panel A, and across the optioned and non-optioned stocks in Panel B. The numbers in Table 12 represent the time-series averages of the proportions of stocks in a certain trend portfolio each month, given their firm sizes or whether they are optioned or not. As mentioned in section 4.2.2, I limit the optioned-or-not sample in panel B to start from 1980. I do the same in Panel A for comparison. I define the trading volume trend over the past three years and stocks with the highest (lowest) 10% trading volume trends each month are in the *H* (*L*) portfolio. The remaining stocks are in the *M* portfolio. I classify a stock as small (large) if its market capitalization at the beginning of the estimation period for its trading volume trend is in the lowest (largest) 30% tail of the cross-sectional distribution of the sample stocks' market capitalization.[21] Otherwise the

[21] The results based on the market capitalization at the end of the estimation period for the trading volume trend are very similar. Later in Table 14 I use the end-of-period market capitalization as a more relevant risk control.

Table 13: Distributions of Extreme Trading Volume Trends across Stocks

This table presents the time-series averages of the proportions of stocks in a certain trend portfolio each month, given their firm sizes (Panel A) or whether they are optioned or not (Panel B). I define the trading volume trend over the past three years and stocks with the highest (lowest) 10% trading volume trends each month are in the *H* (*L*) portfolio. The remaining stocks are in the *M* portfolio. I classify a stock as small (large) if its market capitalization at the beginning of the estimation period for its trading volume trend is in the lowest (largest) 30% tail of the cross-sectional distribution of the sample stocks' market capitalization. Otherwise the stock is with the median size. I classify a stock with the corresponding option listed at the beginning of the estimation period for its trading volume trend as optioned.

Panel A: Distribution of Extreme Trading Volume Trends Across Firm Size (1980-1990)

	Turnover			Dollar Volume			Share Volume			
Firm Size	L	M	H	L	M	H	L	M	H	Nobs
Small	0.16	0.68	0.16	0.14	0.69	0.17	0.16	0.71	0.13	418.25
Median	0.10	0.81	0.09	0.11	0.80	0.09	0.10	0.80	0.10	556.20
Large	0.04	0.91	0.05	0.05	0.92	0.04	0.04	0.89	0.07	418.25

Panel B: Distribution of Extreme Trading Volume Trends Across Optioned and Non-Optioned Stocks

	Turnover			Dollar Volume			Share Volume			
1980-1989										
Optioned or Not	L	M	H	L	M	H	L	M	H	Nobs
Non-Optioned	0.11	0.79	0.11	0.11	0.79	0.11	0.11	0.79	0.11	1250.37
Optioned	0.02	0.93	0.05	0.03	0.93	0.04	0.02	0.92	0.05	120.90
1990-2002										
Non-Optioned	0.13	0.76	0.12	0.12	0.76	0.12	0.13	0.76	0.11	977.96
Optioned	0.05	0.90	0.05	0.05	0.90	0.05	0.05	0.88	0.07	431.22

stock is with the median size. I classify a stock with the corresponding option listed at the beginning of the estimation period for its trading volume trend as optioned.

Since I define the trend portfolios with the highest and lowest 10% cutoffs, we would expect the proportions of stocks in the *L*, the *M*, and the *H* portfolios to be 10%, 80%, and 10%, if the short-sales constraints have no effects on the occurrence of extreme trading volume trends. The results in Table 12 suggest otherwise, however. From Panel A we see that stocks of smaller firms are more likely to experience extreme trading volume trends than stocks of larger firms. For instance, with the trend portfolios defined over the turnover trend, 16% (16%) of small stocks experience low (high) trading volume trends. On the other hand, only 4% (5%) of large stocks experience low (high) trading volume trends. The statistical significance on rejecting the null hypothesis of equal proportions across firm size is easily obtained with the monthly observations. We observe similar results when the trading volume trend is defined on dollar volume and share volume. The results in Panel A thus suggest that large stocks are less likely to experience extreme trading volume trends.

In Panel B for the optioned-or-not sample I divide the sample period into 1980 to 1989 and 1990 to 2002. In both subperiods we see that optioned stocks are less likely to experience extreme trading volume trends than non-optioned stocks. Altogether these results suggest that extreme sentiment is less likely to occur on stocks of larger firms and optioned stocks.

- **Returns of Trend Portfolios Conditional on Short-Sales Constraints**

The results in Table 13 suggest that whether a stock will experience an extreme trading volume trend depends on the firm size and whether it is optioned or not. Stocks of larger firms and optioned stocks are less likely to experience extreme trading volume trends

I next examine the effects of short-sales constraints on the returns of the trend portfolios. The results conditional on firm size are presented in Table 14. Unlike in Table 13, the firm size-trend portfolios are now constructed for the entire sample period. The methods I use to construct the firm size-trend portfolios are similar to what I use for the momentum-trend portfolios in Table 10, except that now I control for firm size rather than past returns. In Panel A (B and C), the trading volume trend is the turnover (dollar volume and share volume) trend.

From Panel A, we see that the *H* portfolios earn lower future returns than the *L* and the *M* portfolios for stocks of small- and median-size firms. The *L* portfolios earn lower returns than the *M* portfolios across the holding periods. On the other hand, the turnover trend for stocks of larger firms carries virtually no information on future returns, except for the holding period of three years. In Panel B for the dollar volume trend, the *H* portfolios consistently earn the lowest future

Table 14: Excess Returns on Firm Size-Trend Portfolios

This table presents the average excess returns (in percentage) on the momentum-trend portfolios with holding periods from one month to five years. In Panel A (B and C), the trading volume trend is the turnover (dollar volume and share volume) trend. The column M1 is for the holding period of one month and the column Y1 is for the holding period of one year. I sort the sample stocks at the beginning of each month *t* independently by their trading volume trends at the end of month *t-2*, and by their market capitalization at the end of month *t-2*. I assign stocks with the highest (lowest) 10% three-year trading volume trends to the *H* (*L*) portfolio. I assign the remaining stocks to the *M* portfolio. For the market capitalization, stocks with the lowest (highest) 30% capitalization are in the *Small (Large)* portfolio. The remaining stocks are in the *Median* portfolio. Each month I calculate for each stock its monthly-compounded cumulative return for a given holding period. The holding-period returns in excess of the corresponding T-bill rate for stocks in a given portfolio are then averaged to give the excess portfolio holding-period return. I report in this table the average excess portfolio holding-period return across the sample months. I also report the t-statistics (in parentheses) for testing whether the holding-period return differences between the firm size-trend portfolios are different from zero. To increase the power of the tests, I perform matched tests in that the portfolio holding-period returns are matched by month.

Panel A: Turnover

Firm Size	Trend Portfolio	M1	M3	M6	M9	Y1	Y2	Y3
Small	L	0.81	2.41	4.67	7.28	9.89	22.64	36.73
	M	0.90	2.69	5.36	8.31	11.33	24.17	37.40
	H	0.57	1.69	3.24	5.29	7.23	15.65	25.03
	M-L	(1.05)	(1.89)	(3.08)	(3.81)	(4.22)	(2.30)	(0.67)
	H-M	(-2.46)	(-4.42)	(-7.08)	(-7.98)	(-9.21)	(-11.84)	(-11.57)
	H-L	(-1.48)	(-2.62)	(-3.83)	(-4.31)	(-4.86)	(-7.62)	(-8.67)
Median	L	0.60	1.87	3.41	5.28	6.99	15.80	25.57
	M	0.74	2.20	4.22	6.44	8.66	18.17	27.63
	H	0.53	1.50	2.69	4.04	5.30	11.30	19.33
	M-L	(1.55)	(2.08)	(3.77)	(4.15)	(5.15)	(4.42)	(2.42)
	H-M	(-1.56)	(-3.24)	(-4.88)	(-6.29)	(-7.87)	(-10.47)	(-8.09)
	H-L	(-0.43)	(-1.48)	(-2.00)	(-2.79)	(-3.31)	(-5.35)	(-4.56)
Large	L	0.35	1.08	2.65	4.36	5.38	11.59	22.19
	M	0.52	1.52	2.96	4.51	6.04	13.40	21.53
	H	0.33	1.20	2.66	4.19	5.35	12.03	17.87
	M-L	(0.84)	(1.24)	(0.27)	(0.04)	(0.90)	(1.77)	(-0.78)
	H-M	(-1.29)	(-1.34)	(-0.80)	(-0.63)	(-1.05)	(-1.32)	(-2.79)
	H-L	(-0.35)	(-0.29)	(-0.51)	(-0.44)	(-0.17)	(0.23)	(-2.45)

(Table 14 cont.)

Firm Size	Trend Portfolio	M1	M3	M6	M9	Y1	Y2	Y3
Panel B: Dollar Volume								
Small	L	0.81	2.50	4.78	7.50	10.28	24.69	40.05
	M	0.87	2.59	5.25	8.24	11.25	23.66	36.96
	H	0.83	2.25	3.86	5.52	7.35	15.13	22.54
	M-L	(0.55)	(0.52)	(1.93)	(2.56)	(2.63)	(-1.15)	(-2.22)
	H-M	(-0.25)	(-1.37)	(-3.81)	(-5.88)	(-7.64)	(-9.52)	(-11.30)
	H-L	(0.07)	(-0.83)	(-2.18)	(-4.05)	(-5.47)	(-9.16)	(-11.04)
Median	L	0.62	1.90	3.73	5.84	7.87	18.20	31.43
	M	0.72	2.15	4.13	6.33	8.55	18.12	27.46
	H	0.64	1.76	3.06	4.30	5.39	9.68	15.86
	M-L	(0.83)	(1.19)	(1.37)	(1.29)	(1.45)	(-0.10)	(-3.15)
	H-M	(-0.48)	(-1.43)	(-2.71)	(-4.37)	(-5.89)	(-10.41)	(-9.98)
	H-L	(0.09)	(-0.44)	(-1.42)	(-2.71)	(-3.64)	(-7.07)	(-8.45)
Large	L	0.46	1.42	3.45	6.59	9.98	22.99	31.46
	M	0.52	1.54	3.05	4.66	6.24	13.75	22.15
	H	0.37	0.85	1.57	2.35	2.68	5.55	9.01
	M-L	(0.04)	(-0.04)	(-1.35)	(-3.44)	(-5.04)	(-6.84)	(-5.77)
	H-M	(-0.76)	(-2.06)	(-2.76)	(-3.51)	(-4.55)	(-6.25)	(-8.21)
	H-L	(-0.47)	(-1.43)	(-2.85)	(-4.63)	(-6.41)	(-8.72)	(-9.60)

Firm Size	Trend Portfolio	M1	M3	M6	M9	Y1	Y2	Y3
Panel C: Share Volume								
Small	L	0.89	2.66	5.32	8.25	11.15	24.57	39.86
	M	0.88	2.67	5.30	8.27	11.25	23.97	37.17
	H	0.51	1.27	2.39	3.44	5.22	11.90	18.36
	M-L	(-0.13)	(0.09)	(-0.10)	(0.10)	(0.28)	(-0.92)	(-2.96)
	H-M	(-2.37)	(-5.71)	(-8.47)	(-11.81)	(-11.63)	(-15.02)	(-16.67)
	H-L	(-2.09)	(-4.80)	(-7.43)	(-10.28)	(-10.20)	(-13.49)	(-16.19)
Median	L	0.68	2.15	4.13	6.12	7.93	17.42	29.66
	M	0.73	2.17	4.17	6.39	8.62	18.12	27.54
	H	0.49	1.36	2.35	3.47	4.59	10.46	17.15
	M-L	(0.62)	(0.13)	(0.14)	(0.87)	(1.84)	(1.09)	(-2.18)
	H-M	(-1.89)	(-3.57)	(-5.75)	(-7.87)	(-9.80)	(-10.93)	(-10.78)
	H-L	(-1.21)	(-2.94)	(-4.64)	(-5.50)	(-6.00)	(-6.95)	(-9.01)
Large	L	0.53	1.75	3.60	5.84	7.85	16.61	28.73
	M	0.54	1.59	3.13	4.76	6.41	14.07	22.48
	H	0.02	0.00	0.32	0.74	0.88	3.71	8.53
	M-L	(0.10)	(-0.62)	(-1.20)	(-2.36)	(-2.69)	(-2.84)	(-4.61)
	H-M	(-4.08)	(-7.47)	(-8.34)	(-9.32)	(-10.46)	(-12.48)	(-13.25)
	H-L	(-2.41)	(-5.32)	(-6.43)	(-7.96)	(-9.14)	(-10.38)	(-11.39)

returns among the three trend portfolios for holding periods longer than six months. This relation also holds across firm size. The results in Panel C for the share volume trend are similar to what we observe in Panel B.

Overall, the results in Table 14 on the returns of trend portfolios defined on dollar volume trend (Panel B) and share volume trend (Panel C) suggest that sentiment information carried by trading volume is revealed onto stock prices even for stocks of larger firms. However, the results in Panel A suggest that the sentiment information carried by the turnover trend is not revealed on stocks of larger firms. The mixed results on stocks of larger firms provide only partial support to the model of Baker and Stein (2004).

The results conditional on whether a stock is optioned or not are presented in Table 15. Because the option dataset contains the survivorship bias I discuss in section 4.2.2, I examine the returns on the option-trend portfolios in the period from 1980 to 2002 (Panel A.1, Panel B.1, and Panel C.1), and in the later period from 1990 to 2002 (Panel A.2, Panel B.2, and Panel C.2). The survivorship bias should be of less a concern during the latter period. In panel A.1 and A.2, the trading volume trend is the turnover trend. In panel B.1 and B.2 (C.1 and C.2), the trading volume trend is the dollar (share) volume trend.

From Panel A.1 with the turnover trend, we see that for the sample period from 1980 to 2002, the *H* portfolios earn lower future returns than the *L* and the *M* portfolios on non-optioned stocks, a result consistent with the hypothesis that high investor sentiment predicts low future returns. In this case the *L* portfolios also earn lower returns than the *M* portfolios. On the other hand, the turnover trend for optioned stocks carries virtually no return information except for the holding period of two years. From Panel A.2, however, we see that the *L* portfolios tend to earn

Table 15: Excess Returns on Option-Trend Portfolios

This table presents the average excess returns (in percentage) on the option-trend portfolios with holding periods from one month to five years. In Panel A (B and C), the trading volume trend is the turnover (dollar volume and share volume) trend. The column M1 is for the holding period of one month and the column Y1 is for the holding period of one year. I sort the sample stocks at the beginning of each month *t* independently by their trading volume trends at the end of month *t-2*, and by whether a stock is optioned or not at the beginning of the estimation period for its trading volume trend. I assign stocks with the highest (lowest) 10% three-year trading volume trends to the *H* (*L*) portfolio. I assign the remaining stocks to the *M* portfolio. A stock with a corresponding option listed is optioned. Each month I calculate for each stock its monthly-compounded cumulative return for a given holding period. The holding-period returns in excess of the corresponding T-bill rate for stocks in a given portfolio are then averaged to give the excess portfolio holding-period return. I report in this table the average excess portfolio holding-period return across the sample months. I also report the t-statistics (in parentheses) for testing whether the holding-period return differences between the option-trend portfolios are different from zero. To increase the power of the tests, I perform matched tests in that the portfolio holding-period returns are matched by month.

Panel A.1: Turnover (1980-2002)

Optioned or Not	Trend Portfolio	M1	M3	M6	M9	Y1	Y2	Y3
Non-Optioned	L	0.62	1.84	3.78	5.71	7.28	15.27	27.11
	M	0.76	2.27	4.51	6.70	8.85	17.37	29.13
	H	0.43	1.18	2.19	3.14	4.14	8.85	20.02
	M-L	(1.61)	(2.78)	(3.16)	(3.34)	(4.44)	(3.37)	(1.94)
	H-M	(-2.73)	(-5.24)	(-8.32)	(-10.19)	(-11.76)	(-15.61)	(-11.12)
	H-L	(-1.29)	(-2.74)	(-4.69)	(-5.84)	(-6.01)	(-7.11)	(-5.31)
Optioned	L	0.75	2.12	4.48	7.93	11.33	27.25	41.53
	M	0.82	2.43	4.90	7.61	10.47	22.76	38.74
	H	0.87	2.98	5.88	8.14	10.20	21.13	38.26
	M-L	(0.13)	(0.41)	(0.24)	(-0.91)	(-1.56)	(-2.71)	(-1.35)
	H-M	(0.25)	(1.16)	(1.54)	(0.77)	(-0.28)	(-1.31)	(-0.32)
	H-L	(0.30)	(1.19)	(1.37)	(-0.08)	(-1.32)	(-2.97)	(-1.22)

Panel A.2: Turnover (1990-2002)

Optioned or Not	Trend Portfolio	M1	M3	M6	M9	Y1	Y2	Y3
Non-Optioned	L	0.44	1.43	2.92	4.84	7.15	18.77	27.55
	M	0.67	2.11	4.03	6.23	8.99	18.72	28.25
	H	0.35	1.10	2.10	3.22	4.59	9.21	18.81
	M-L	(2.13)	(3.57)	(3.92)	(3.78)	(4.33)	(-0.06)	(0.75)
	H-M	(-1.79)	(-3.30)	(-4.79)	(-5.89)	(-7.36)	(-12.17)	(-9.02)
	H-L	(-0.44)	(-1.05)	(-1.90)	(-2.87)	(-3.87)	(-9.40)	(-7.83)
Optioned	L	0.96	3.34	6.63	10.59	15.48	32.28	46.76
	M	0.81	2.49	4.86	7.83	11.53	26.37	42.47
	H	0.72	2.56	5.37	8.78	12.28	25.63	41.07
	M-L	(-0.65)	(-2.02)	(-3.22)	(-3.96)	(-4.78)	(-3.27)	(-2.01)
	H-M	(-0.34)	(0.14)	(0.65)	(0.94)	(0.59)	(-0.36)	(-0.47)
	H-L	(-0.78)	(-1.23)	(-1.35)	(-1.62)	(-2.46)	(-2.84)	(-1.58)

(Table 15 cont.)

Panel B.1: Dollar Volume (1980-2002)								
Optioned or Not	Trend Portfolio	M1	M3	M6	M9	Y1	Y2	Y3
Non-Optioned	L	0.57	1.78	3.53	5.30	6.94	15.51	28.01
	M	0.75	2.23	4.50	6.76	8.93	17.65	29.59
	H	0.50	1.40	2.32	2.80	3.39	5.65	15.07
	M-L	(1.67)	(2.06)	(3.06)	(3.64)	(4.10)	(2.00)	(0.89)
	H-M	(-1.61)	(-3.21)	(-5.66)	(-8.82)	(-10.97)	(-17.22)	(-16.23)
	H-L	(-0.33)	(-1.15)	(-2.56)	(-4.54)	(-5.54)	(-7.42)	(-5.83)
Optioned	L	1.22	3.74	7.71	11.93	16.67	34.45	51.87
	M	0.82	2.42	4.91	7.61	10.44	22.75	38.79
	H	0.61	2.26	4.20	6.16	7.29	15.84	30.52
	M-L	(-1.23)	(-2.41)	(-3.60)	(-4.34)	(-5.31)	(-5.76)	(-4.28)
	H-M	(-0.83)	(-0.51)	(-1.02)	(-1.74)	(-3.24)	(-4.54)	(-4.15)
	H-L	(-1.51)	(-2.41)	(-3.95)	(-5.39)	(-7.26)	(-7.45)	(-6.61)
Panel B.2: Dollar Volume (1990-2002)								
Optioned or Not	Trend Portfolio	M1	M3	M6	M9	Y1	Y2	Y3
Non-Optioned	L	0.49	1.60	3.09	5.12	7.99	20.92	28.38
	M	0.65	2.05	3.99	6.25	8.95	18.67	28.63
	H	0.41	1.21	1.73	2.08	3.00	5.56	14.29
	M-L	(1.08)	(1.66)	(2.45)	(2.56)	(1.90)	(-2.31)	(0.22)
	H-M	(-1.02)	(-2.22)	(-4.06)	(-6.23)	(-7.75)	(-12.47)	(-12.28)
	H-L	(-0.30)	(-0.91)	(-2.30)	(-4.51)	(-6.55)	(-13.35)	(-9.85)
Optioned	L	1.15	3.98	8.44	14.43	21.71	44.34	63.07
	M	0.80	2.50	4.91	7.85	11.49	26.31	42.02
	H	0.68	2.05	3.89	6.66	9.50	18.88	36.34
	M-L	(-1.23)	(-2.74)	(-4.94)	(-7.47)	(-8.61)	(-8.85)	(-7.94)
	H-M	(-0.36)	(-0.76)	(-1.15)	(-1.06)	(-1.40)	(-3.63)	(-2.31)
	H-L	(-1.26)	(-2.77)	(-4.77)	(-6.33)	(-7.55)	(-9.31)	(-7.50)
Panel C.1: Share Volume (1980-2002)								
Optioned or Not	Trend Portfolio	M1	M3	M6	M9	Y1	Y2	Y3
Non-Optioned	L	0.73	2.23	4.55	6.68	8.43	17.53	31.58
	M	0.76	2.25	4.46	6.70	8.89	17.53	29.43
	H	0.30	0.78	1.59	1.68	2.10	4.48	12.39
	M-L	(0.31)	(0.13)	(-0.35)	(0.09)	(1.11)	(-0.00)	(-1.65)
	H-M	(-3.40)	(-6.63)	(-9.26)	(-14.41)	(-16.76)	(-19.22)	(-20.57)
	H-L	(-2.57)	(-5.30)	(-7.29)	(-9.74)	(-10.40)	(-10.97)	(-10.44)
Optioned	L	0.94	3.31	6.55	10.51	14.59	30.18	47.61
	M	0.83	2.47	5.06	7.86	10.81	23.19	39.10
	H	0.62	1.78	3.27	4.93	6.19	15.83	33.43
	M-L	(-1.55)	(-4.00)	(-4.91)	(-5.49)	(-5.26)	(-5.09)	(-4.32)
	H-M	(-1.09)	(-2.03)	(-3.70)	(-5.62)	(-6.96)	(-6.24)	(-4.24)
	H-L	(-2.00)	(-5.04)	(-6.65)	(-8.17)	(-8.72)	(-7.96)	(-6.31)

(Table 15 cont.)

Panel C.2: Share Volume (1990-2002)								
Optioned or Not	Trend Portfolio	M1	M3	M6	M9	Y1	Y2	Y3
Non-Optioned	L	0.53	1.67	3.42	5.46	7.92	20.16	29.70
	M	0.66	2.07	3.95	6.25	9.04	18.83	28.67
	H	0.28	0.95	1.90	1.75	2.59	5.28	11.57
	M-L	(1.22)	(1.98)	(1.84)	(2.12)	(2.58)	(-1.83)	(-1.00)
	H-M	(-1.91)	(-3.46)	(-4.60)	(-8.96)	(-10.77)	(-15.47)	(-16.50)
	H-L	(-1.05)	(-2.04)	(-3.02)	(-6.05)	(-7.65)	(-15.12)	(-12.47)
Optioned	L	1.15	3.73	7.63	12.06	17.17	36.09	52.17
	M	0.83	2.57	5.09	8.20	12.02	26.96	42.72
	H	0.47	1.64	2.85	4.84	7.29	17.87	36.04
	M-L	(-1.53)	(-3.00)	(-5.29)	(-5.69)	(-6.57)	(-6.08)	(-3.98)
	H-M	(-1.45)	(-2.20)	(-3.75)	(-4.67)	(-5.13)	(-5.55)	(-3.53)
	H-L	(-2.31)	(-3.80)	(-6.94)	(-8.25)	(-9.76)	(-9.45)	(-6.23)

the highest return among the three trend portfolios on optioned stocks, and we obtain the statistical significance for holding periods of one year or longer.

From Panel B.1 with the dollar volume trend, we see that for non-optioned stocks in the period from 1980 to 2002, the *H* portfolios earn lower future returns than the *L* and the *M* portfolios, and the *L* portfolios earn lower returns than the M portfolios. In sharp contrast with non-optioned stocks, for optioned stocks the *L* portfolios earn the highest return among the three trend portfolios for holding periods longer than one month. In this case the *M* portfolios also tend to earn returns indistinguishable from those on the *H* portfolios except for holding periods of one year or longer. The results in Panel B.2 are similar to what we observe in Panel B.1.

From Panel C.1 with the share volume trend, we see that for non-optioned stocks in the period from 1980 to 2002, the *H* portfolios earn lower future returns than the *L* and the *M* portfolios, and the *L* portfolios earn the returns indistinguishable from those on the M portfolios. For optioned stocks, the *L* portfolios earn the highest return among the three trend portfolios for holding periods longer than one month and the *H* portfolios earn the lowest returns. The results in Panel C.2 suggest similar patterns except that, in the period from 1990 to 2002, the *L* portfolios on non-optioned stocks have returns lower than those of the *M* portfolios for holding periods of one year or less.

To summarize the results in Table 15, I focus on the results in Panel A.2, Panel B.2, and Panel C.2. First, the *H* portfolios tend to earn the lowest returns among the trend portfolios whether a stock is optioned or not. Second, the returns on the *L* portfolios relative to the returns of the *M* portfolios depend on whether they are defined on optioned or non-optioned stocks. With optioned stocks, the *L* portfolios tend to earn returns higher than those of the *M* portfolios. With non-optioned stocks, the *L* portfolios tend to earn returns lower than those of the *M* portfolios. These results are not consistent with the prediction that the link between the trading volume trend and stock returns will break down for stocks without short-sales constraints.

Nevertheless, Lakonishok, Lee, and Poteshman (2004) employ a proprietary dataset from the Chicago Board Options Exchange (CBOE) and examine the investor behavior in the period from 1990 to 2001. They find that investors do not increase their purchases on put options during the bubble period of late 1990s. In other words, even without short-sales constraints, investors may not trade to counteract the transactions of overconfident investors because they may face the noise trader risk (see De Long, Shleifer, Summers, and Waldman (1990)). If that is the case, then the short-sales constraints as proxied by firm size and whether a stock is optioned or not may not be binding, and sentiment information can still be reflected onto the trading volume trend.

Chapter 5. Trading Volume Trend and Investor Sentiment: A Time-Series Framework

5.1 Introduction

In this chapter I construct a market-wide sentiment measure based on the trading volume trends of individual stocks. I call it the composite trading volume trend. If the trading volume trend at the individual stock level measures investor sentiment appropriately, the composite trading volume trend is likely to reflect investor sentiment at the market level and provide information on future market returns. To start my analysis, I examine the time-series relation between the composite trading volume trend and closed-end fund discounts, since closed-end fund discounts are also widely used as a sentiment measure. The results indicate that the composite trading volume trend has a negative and significant near-term relation with a value-weighted index of closed-end fund discounts, suggesting that investor sentiment is one determinant of closed-end fund discounts, and higher investor sentiment leads to lower close-end fund discounts.

Next I examine the time-series relation between the composite trading volume trend and the sentiment index of Baker and Wurgler (2004). Baker and Wurgler (2004) construct their sentiment index as the principal component of six commonly employed market sentiment measures: The average closed-end fund discounts, the NYSE share turnover, the number and average first-day returns on IPOs, the equity share in new issues, and the dividend premium. The results from the time-series regressions indicate that the composite trading volume trend has a positive and significant near-term relation with the sentiment index. It seems to provide complement information on the sentiment index of Baker and Wurgler (2004), and it explains an incremental 19% of the variation on the sentiment index, after controlling for the past value of this index.

The composite trading volume trend also explains the market returns. Specifically, a higher composite trading volume trend leads to lower market returns. This result hold for both the equally-weighted market returns and the value-weighted market returns, and after controlling for the sentiment index of Baker and Wurgler (2004) and market liquidity measures such as the price impact measure of Amihud (2002) and the Roll spread. These findings suggest that market sentiment as proxied by the composite trading volume trend affects market returns.

5.2 Data and Methodology

- **The Sentiment Index of Baker and Wurgler (2004)**

Baker and Wurgler (2004) examine the relation between investor sentiment and stock returns in a pooled cross-sectional framework. They employ annual sentiment measures including the average closed-end fund discounts, the NYSE share turnover, the number and average first-day returns on IPOs, the equity share in new issues, and the dividend premium. They also construct a composite sentiment index based on the first principal component of these six measures. I use their sentiment index as a control variable in my time-series regression analysis of market returns.[22]

Baker and Wurgler (2004) define the six sentiment proxies as follows. Except for the series of the average closed-end fund discounts, which lasts from 1962 to 2002, the other data series are from 1962 to 2001.

Average Closed-End Fund Discount (*CEFD*): The value-weighted year-end closed-end stock fund discount. The data are from Neal and Wheatley (1998) for 1962 to 1993, from CDA/Wiesenberger for 1994 to 1998, and from turn-of-the-year issues of the *Wall Street Journal* for 1999 to 2002.

[22] I thank Jeffrey Wurgler for providing the data.

NYSE share turnover (*TURN*): The ratio of reported share volume to average shares listed from the *NYSE Fact Book*.

Number of IPOs (*NIPO*): The number of IPOs each year, provided by Jay Ritter.

Average First-Day Returns on IPO (*RIPO*): The average first-day returns on IPOs each year, provided by Jay Ritter.

Equity Share in New Issues (*S*): The gross equity issuance divided by gross equity plus gross long-term debt issuance using data from the *Federal Reserve Bulletin*.

Dividend Premium ($P^{D\text{-}ND}$): The log difference of the average market-to-book ratios of dividend payers and dividend non-payers.

Baker and Wurgler (2004) regress each of these measures on the growth in the industrial production index, the growth in consumer durables, non-durables, and services, and a dummy variable for NBER recessions. They use the residuals from the regressions as the measures that are independent of major business cycle effects.

The sentiment index (*SI*) is then defined on the purged sentiment measures as:[23]

$$SI_t = -0.358CEFD_t + 0.402TURN_{t-1} + 0.414NIPO_t + 0.464RIPO_{t-1} + 0.371S_t - 0.431P_{t-1}^{D-ND}$$

They reach this specification by a two-stage methodology. In the first stage, they identify the principal component of the six sentiment measures and their lags (a total of 12 variables). In the second stage, each of the proxy's lead or lag that has the higher correlation with the first-stage principal component is used again to form the second-stage principal component. The sentiment index represents the second-stage principal component on six variables.

[23] See Baker and Wurgler (2004), equation (2).

5.3 Empirical Results

5.3.1 Time-Series Relations between Composite Trading Volume Trends and Closed-End Fund Discounts

I define the composite trading volume trend for the market as the equally-weighted trading volume trend of all sample stocks. I begin my analyses by examining the time-series relation between the composite trading volume trend and a value-weighted index of closed-end fund discounts, since closed-end fund discounts are also widely used as a sentiment measure (e.g., Zweig (1973), Lee, Shleifer, Thaler (1991), Neal and Wheatley (1998), and Brown and Cliff (2004)). I obtain the data on the value-weighted index of closed-end fund discounts from Jeffrey Wurgler. It covers the period from 1962 to 2002 (see also section 5.2) and is defined annually. With the limited number of observations, I develop a parsimonious model for the relation between the composite volume trend and the index of discounts. Specifically, I set up the time-series model as:

$$CEFD_t = \beta_0 + \beta_1 CEFD_{t-1} + \beta_2 TREND_t + \varepsilon_t \quad (8)$$

$$TREND_t = \beta_{10} + \beta_{11} TREND_{t-1} + \varepsilon_{1t} \quad (8.1)$$

where $CEFD_t$ is the value-weighted index of closed-end fund discounts at the end of year *t*. $TREND_t$ is the composite trading volume trend in December of year *t*. β_0, β_1, β_2, β_{10}, and β_{10} are the parameters. ε_t and ε_{1t} are the random error terms.

Equation (8) models the year-end index of discounts as a function of its own past value and the near-term composite volume trend. Equation (8.1) models the composite volume trend as a function of its own past value. To get the parameter estimates for inference, I use a bootstrapping technique that is similar to the ones used in Neal and Wheatley (1998), Baker and Stein (2004), and Brown and Cliff (2005). Specifically, I estimate equation (8) and equation (8.1) by OLS first.

I save the residuals ε_t and ε_{1t} and resample with replacement from the residuals to construct a sample of the actual size plus 100. I discard the first 100 observations generated by the resampling procedure and use the remaining residuals to construct the bootstrapping sample of $CEFD_t$ and $TREND_t$ by equation (8) and equation (8.1) with the OLS estimates. I then regress the generated $CEFD_t$ on the generated $CEFD_{t-1}$ and $TREND_t$, and obtain one set of bootstrapping coefficient estimates.

I replicate the above procedure for 5,000 times, and define the average of the coefficient estimates on an independent variable as its true bootstrapping estimate. To get the bootstrapping p-value on one specific independent variable, I replicate the above procedure for another 5,000 times, except that in this case when I generate the bootstrapping sample, the variable in consideration does not appear on the right hand side of equation (8). This procedure imposes the null hypothesis that there is no relation between the independent variable and the dependent variable $CEFD_t$. I then regress for each of the 5,000 bootstrapping samples the generated $CEFD_t$ on the generated $CEFD_{t-1}$ and $TREND_t$, and obtain another 5,000 sets of bootstrapping coefficient estimates. The true bootstrapping estimate that I derive for the variable in the first stage is then positioned into the 5,000 estimates from the second stage, and I obtain the bootstrapping p-value for that specific variable. I report in the table two-tail p-values for the coefficient estimates on the intercept and the lagged index of discounts ($CEFD_{t-1}$). I report the one-tail bootstrapping p-value for β_2 in equation (8) with the alternative hypothesis of a negative coefficient, since if investor sentiment is a determinant of closed-end fund discounts as argued in previous studies, high investor sentiment should lead to lowered closed-end fund discounts. There should be a negative relation between the composite trading volume trend and the index of discounts.

Before we move into the time-series regression results, we first look at the time-series patterns of the composite volume trends. Panel A in Figure 1 shows the composite turnover trend. Panel B and panel C show the composite dollar volume trend and the composite share volume trend, respectively. Across the panels we see that the composite volume trends, although defined on different trading volume measures, exhibit surprisingly similar patterns over time. I present the time-series pattern of the value-weighted index of closed-end fund discounts in Figure 2 for comparison.

Table 16 presents the summary statistics on the independent variables in equation (8) (Panel A) and the time-series regression results (Panel B). In Panel A, the statistics other than the number of observations on the composite trading volume trends (*TTREND, DTREND, and STREND*) are with a multiple of 100. The number of observations is 37 rather than 38 because of the need for a lagged trend variable shown in equation (8.1). In Panel B, the reported numbers include the OLS estimates, the t-statistics from the OLS regressions (in parentheses), the true bootstrapping estimates (in Italics), and the bootstrapping p-values (in brackets). Also reported are the adjusted R^2 from the OLS regressions, and the LM statistics (from Breusch-Godfrey tests) on testing whether the residuals from the OLS regressions are first-order autocorrelated. I set up the base model to have only $CEFD_{t-1}$ on the right-hand side of equation (8) for comparison.

From panel B we see that the composite trading volume trends have the expected negative and significant relations with the value-weighted index of closed-end fund discounts. We also see that in the OLS framework, the composite volume trends explain an incremental 4% to 5% of the variation on the index of discounts, after controlling for the past value of this index. This result suggests that there may exist factors other than investor sentiment that contribute to the closed-end fund discounts (e.g., Swaminathan (1996)). Finally, the LM statistics suggest that

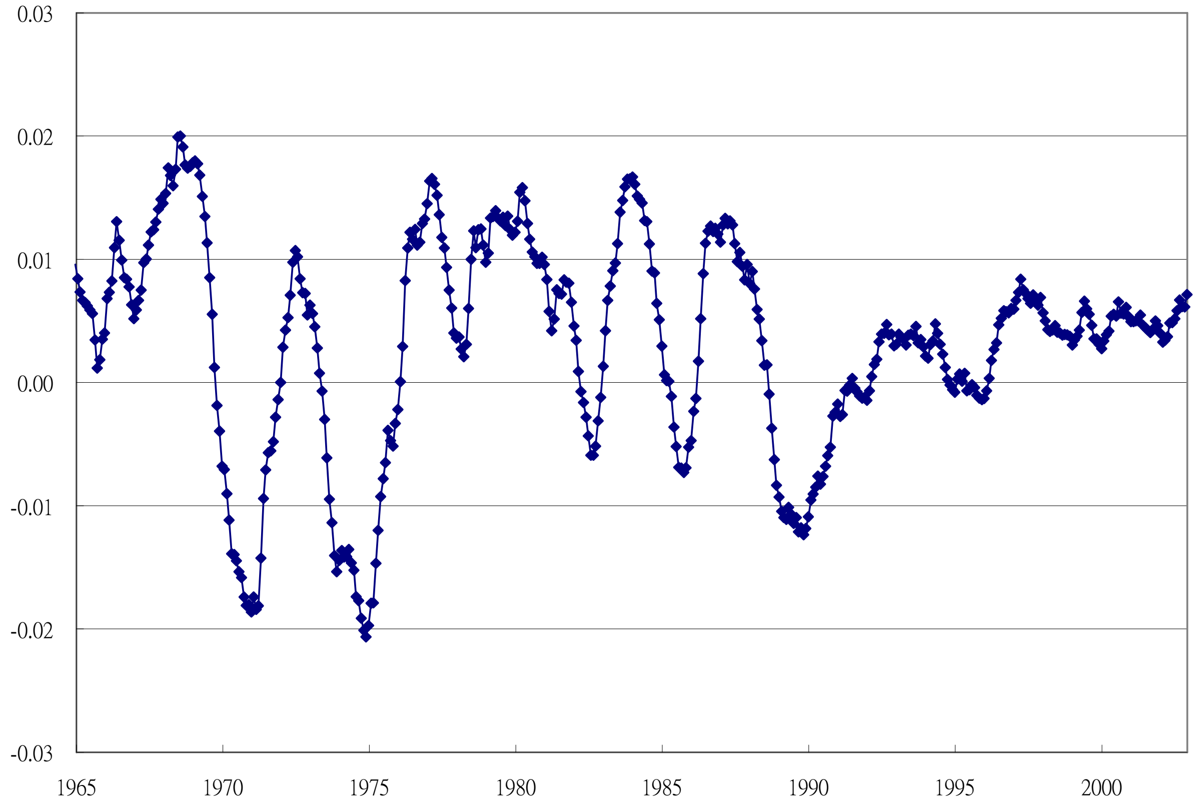
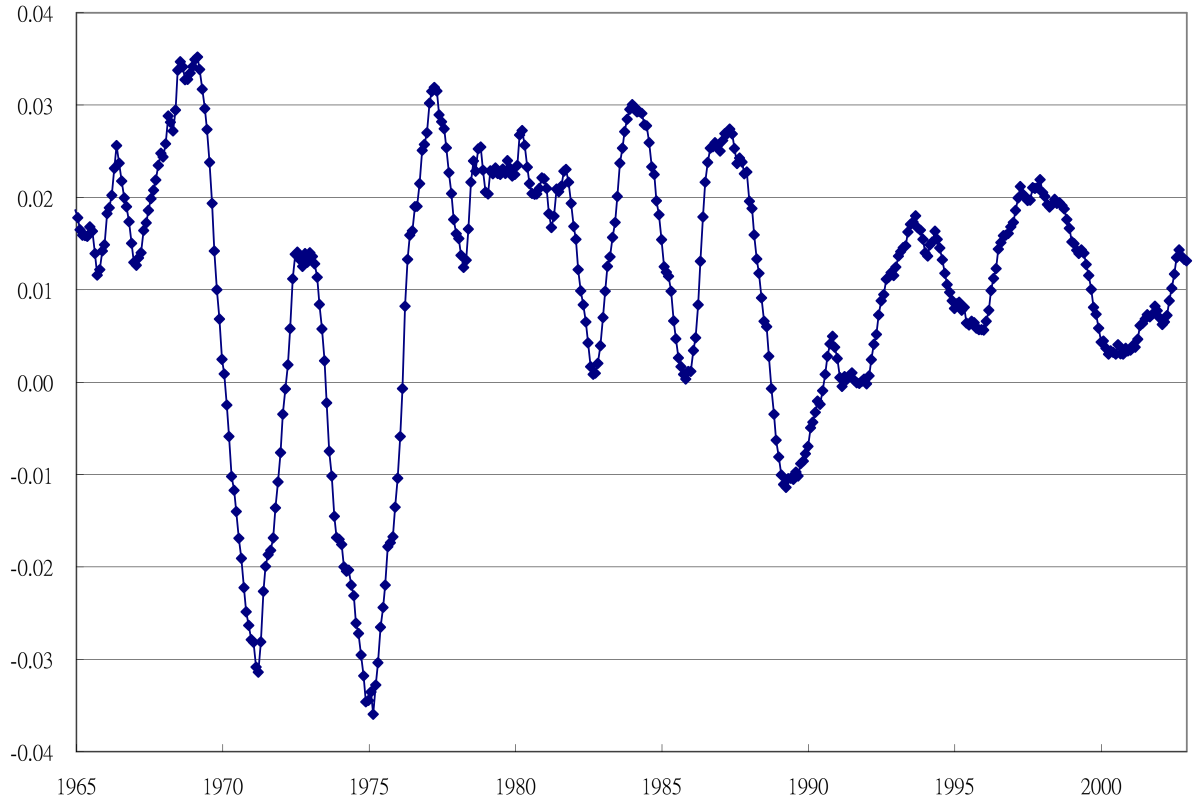
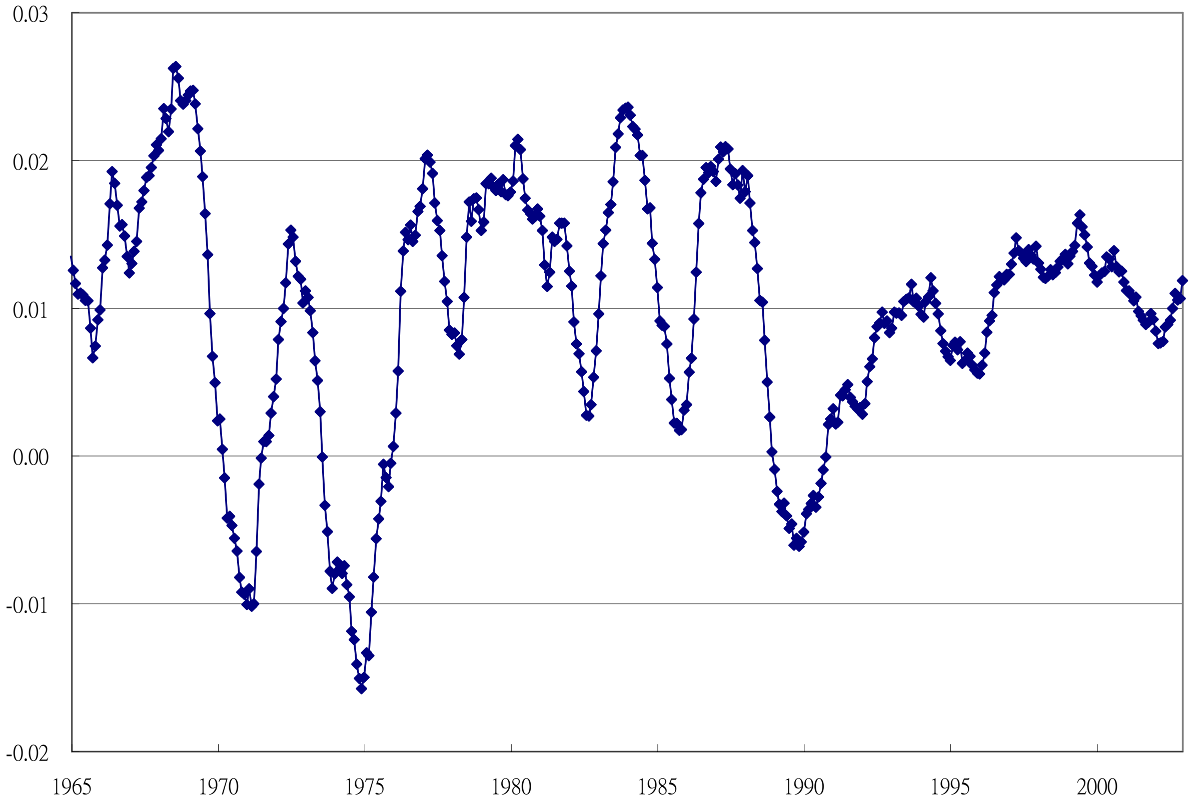


Figure 1: Time-Series Patterns of Composite Trading Volume Trends
Panel A: Composite Turnover Trend

This figure presents the three-year composite trading volume trends during the period from 1965 to 2002. The composite trading volume trend is defined as the equally-weighted monthly average of the trading volume trends on all sample stocks, which include NYSE and AMEX stocks with corresponding three-year trading volume trends. In panel A, the trading volume trend is defined on turnover. In panel B and panel C, the trading volume trend is defined on dollar volume and share volume, respectively.



(Figure 1 cont.)
Panel B: Composite Dollar Volume Trend



(Figure 1 cont.)
Panel C: Composite Share Volume Trend

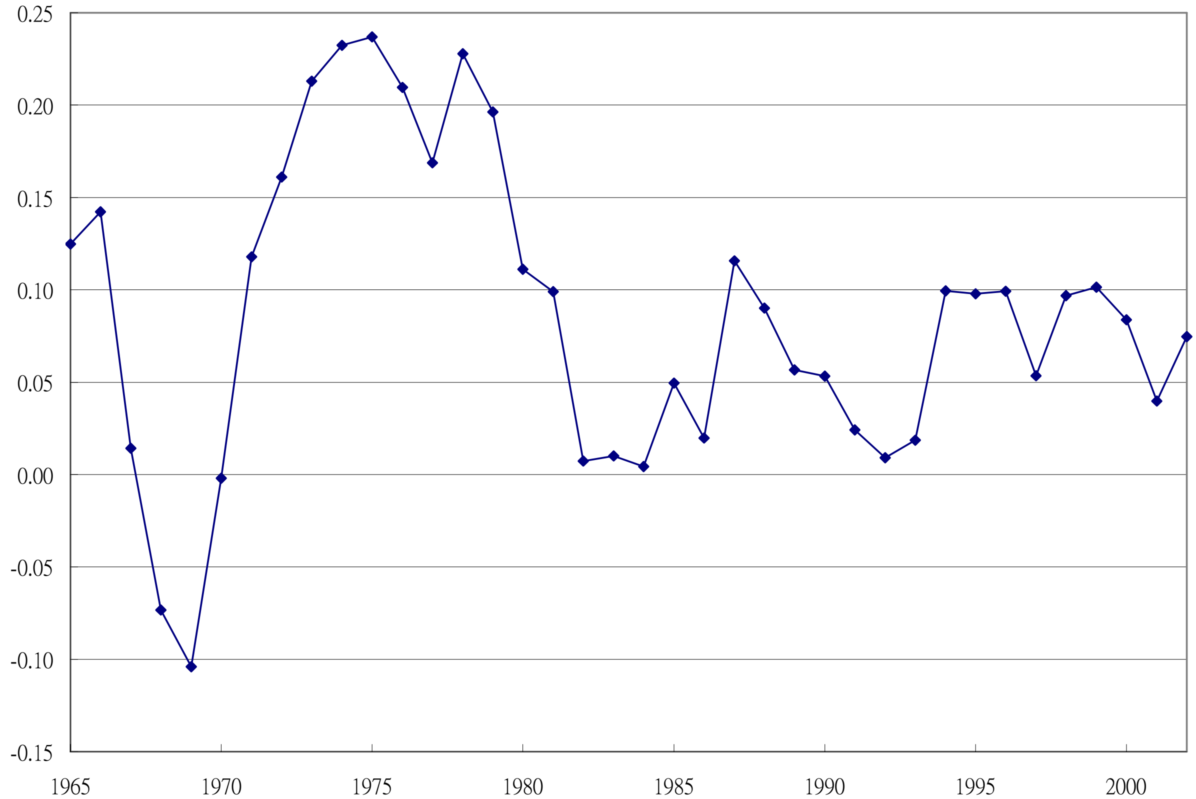


Figure 2: Time-Series Pattern of Closed-End Fund Discounts

This figure presents the value-weighted index of closed-end fund discounts during the period from 1965 to 2002. The index is defined annually at year end and the data are from Neal and Wheatley (1998) for 1965 to 1993, from CDA/Wiesenberger for 1994 to 1998, and from turn-of-the-year issues of the *Wall Street Journal* for 1999 to 2002.

Table 16: Time-Series Regressions of Closed-End Fund Discounts on Composite Trading Volume Trends

This table presents the summary statistics in Panel A on the variables *CEFD*, *TTREND*, *DTREND*, and *STREND* that enter into equation (9) for the time-series regressions of the closed-end fund discounts. *CEFD* is the year-end value-weighted index of closed-end fund discounts. *TTREND* (*DTREND* and *STREND*) is the composite trading volume trend (*TREND)* in equation (9). Panel B presents the results from the time-series regressions of the value-weighted index of discounts on its own lagged value and the composite volume trend. The reported numbers include the OLS estimates, the t-statistics from the OLS regressions (in parentheses), the true bootstrapping estimates (in Italics), and the bootstrapping p-values (in brackets). Also reported are the adjusted R^2 from the OLS regressions, and the LM statistics (from Breusch-Godfrey tests) on testing whether the residuals from the OLS regressions are first-order autocorrelated.

Panel A: Summary Statistics

Variable	Mean	Std	Min	Median	Max	Nobs
CEFD	0.0867	0.0828	-0.1041	0.0969	0.2370	37
TTREND	0.2501	0.9126	-2.0638	0.4015	1.7535	37
DTREND	0.9174	1.5551	-3.4628	1.2984	3.3469	37
STREND	0.9084	0.9178	-1.5734	1.0358	2.4058	37

Panel B: Time-Series Regressions

Variable	Base	Turnover	Dollar Volume	Share Volume
Intercept	0.0177	0.0203	0.0287	0.0347
	(1.41)	(1.70)	(2.30)	(2.41)
		0.0269	*0.0357*	*0.0420*
		[0.05]	[0.01]	[0.01]
CEFD (t-1)	0.7807	0.8053	0.7887	0.7840
	(7.44)	(7.61)	(8.04)	(7.84)
		0.7221	*0.7107*	*0.6968*
		[0.00]	[0.00]	[0.00]
TREND (t)		-1.9264	-1.2851	-1.9073
		(-2.11)	(-2.46)	(-2.11)
		-1.9631	*-1.3338*	*-1.9734*
		[0.03]	[0.02]	[0.03]
N	37	37	37	37
LM	4.82*	0.93	0.77	0.95
Adj-R^2	0.60	0.64	0.65	0.64

*: Significant at the 5% level for rejecting the null hypothesis of no first-order autocorrelation in the regression errors.

with the base model, the residuals from the OLS regression are first-order autocorrelated at the 5% significance level. When the composite volume trend is included into the model, however, the OLS residuals are no longer first-order autocorrelated. This evidence supports the model represented by equation (8).

5.3.2 Time-Series Relations between Composite Trading Volume Trends and the Sentiment Index of Baker and Wurgler (2004)

I next examine the time-series relation between the composite trading volume trend and the sentiment index (*SI*) of Baker and Wurgler (2004). The sentiment index is constructed annually at year end and it covers the period from 1962 to 2001. I set up the time-series model as:

$$SI_t = \beta_0 + \beta_1 SI_{t-1} + \beta_2 TREND_t + \varepsilon_t \tag{9}$$

$$TREND_t = \beta_{10} + \beta_{11} TREND_{t-1} + \varepsilon_{1t} \tag{9.1}$$

where SI_t is the sentiment index of at the end of year *t*. $TREND_t$ is the composite trading volume trend on the market in December of year *t*. Since I impose a one-month lag in constructing the trading volume trends of individual stocks, $TREND_t$ is based on the volume data in the 35-month period ending at the beginning of November in year *t*. β_0, β_1, β_2, β_{10}, and β_{10} are the parameters. ε_t and ε_{1t} are the random error terms.

Equation (9) models the year-end sentiment index as a function of its own past value and the near-term composite trading volume trend. Equation (9.1) models the composite volume trend as a function of its own past value. I use the same bootstrapping technique that I use in the previous section to get the true bootstrapping estimates on the coefficients and the corresponding bootstrapping p-values. I report in the table two-tail p-values for the coefficient estimates on the intercept and the lagged sentiment index (SI_{t-1}). Since both the sentiment index (SI_t) and the composite trading volume trend ($TREND_t$) target investor sentiment, I expect a positive relation between them. I report the one-tail bootstrapping p-value for β_2 in equation (9) with the alternative hypothesis of a positive coefficient.

Figure 3 shows the time-series pattern of the sentiment index of Baker and Wurgler (2004). Unlike what we see in Figure 2 for the value-weighted index of closed-end fund discounts, the time-series pattern of the sentiment index of Baker and Wurgler (2004) closely resembles the patterns of the composite trading volume trends that we see in Figure 1. This observation suggests that the relation between the composite trading volume trend and the sentiment index of Baker and Wurgler (2004) may be stronger than the relation between the composite trading volume trend and the index of discounts (see Table 16).

Table 17 presents the summary statistics on the independent variables in equation (9) (Panel A) and the time-series regression results (Panel B). In Panel A, the statistics other than the number of observations on the composite trading volume trends (*TTREND, DTREND, and STREND*) are with a multiple of 100. *TTREND* (*DTREND* and *STREND*) is the composite trading volume trend (*TREND*) in equation (9) defined on turnover (dollar volume and share volume). The number of observations is 36 rather than 37 because of the need for a lagged trend variable shown in equation (9.1). In Panel B, the reported numbers include the OLS estimates, the t-statistics from the OLS regressions (in parentheses), the true bootstrapping estimates (in Italics), and the bootstrapping p-values (in brackets). Also reported are the adjusted R^2 from the OLS regressions, and the LM statistics (from Breusch-Godfrey tests) on testing whether the residuals from the OLS regressions are first-order autocorrelated. I set up the base model to have only SI_{t-1} on the right-hand side of equation (9) for comparison. From Panel B we see that the composite trading volume trends have the positive and significant relations with the sentiment index of Baker and Wurgler (2004), a result as expected. We also see that in the OLS framework, the composite volume trends explain an incremental 17% to 19% of the variation on the sentiment index, after controlling for the past value of this index. Further, the largest explanatory power does not come from the turnover trend but comes from the dollar volume trend, suggesting that the observed positive relation between the composite trading volume and the

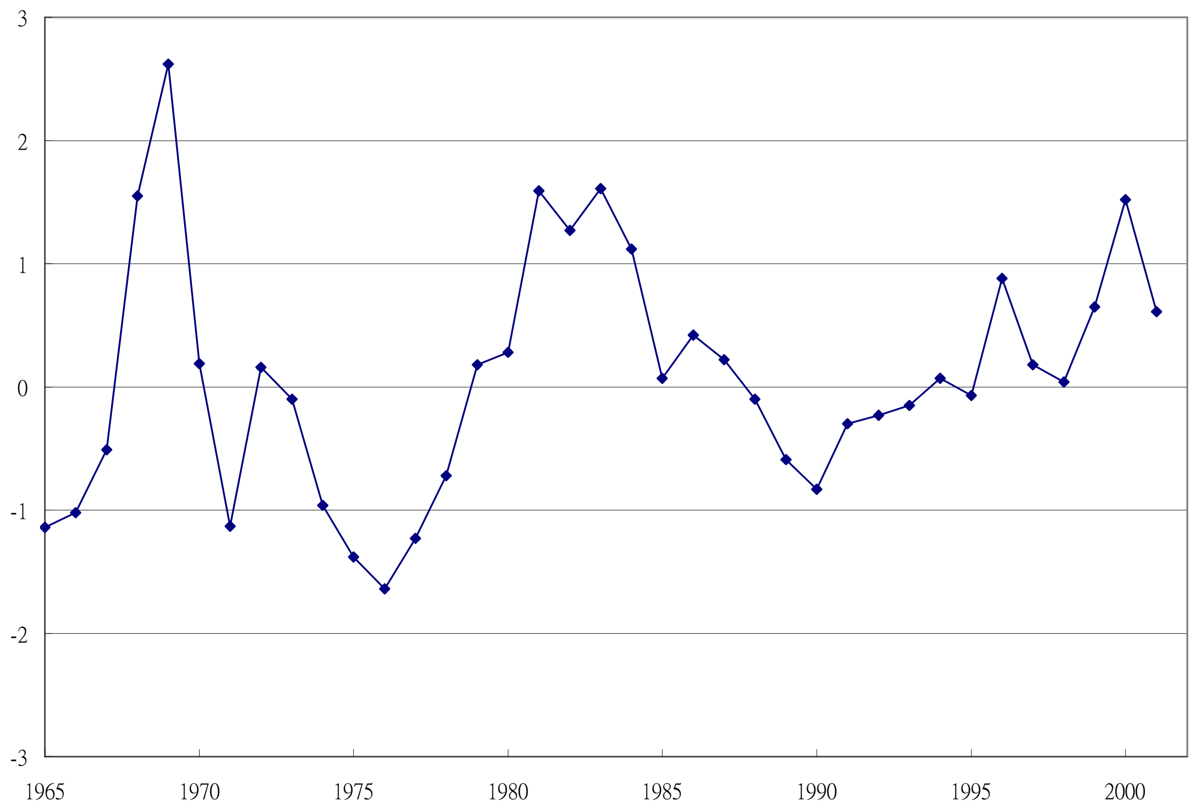


Figure 3: Time-Series Pattern of the Sentiment Index of Baker of Wurgler (2004)

This figure presents the sentiment index of Baker and Wurgler (2004) during the period from 1965 to 2001. The sentiment index is the first principal component of six commonly employed market sentiment measures: The average closed-end fund discounts, the NYSE share turnover, the number and average first-day returns on IPOs, the equity share in new issues, and the dividend premium.

sentiment index is not merely due to the fact that the sentiment index has the component of NYSE turnover. Finally, the LM statistics suggest that with the base model, the residuals from the OLS regression are first-order autocorrelated at the 10% significance level. When the composite volume trend is included, however, the OLS residuals are no longer first-order autocorrelated. This evidence supports the model represented by equation (9).

Now we turn to the OLS coefficient estimates on the sentiment index (SI_{t-1}). Comparing the coefficient estimate in the base model with the estimates in the models where the composite trading volume trend is included, we see that the significance of the estimates improves. This

Table 17: Time-Series Regressions of the Sentiment Index of Baker and Wurgler (2004) on Composite Trading Volume Trends

This table presents the summary statistics in Panel A on the variables *SI*, *TTREND*, *DTREND*, and *STREND* that enter into equation (8) for the time-series regressions of the sentiment index of Baker and Wurgler (2004). *SI* is the year-end sentiment index. *TTREND* (*DTREND* and *STREND*) is the composite trading volume trend (*TREND)* in equation (8). Panel B presents the results from the time-series regressions of the sentiment index on its own lagged value and the composite volume trend. The reported numbers include the OLS estimates, the t-statistics from the OLS regressions (in parentheses), the true bootstrapping estimates (in Italics), and the bootstrapping p-values (in brackets). Also reported are the adjusted R^2 from the OLS regressions, and the LM statistics (from Breusch-Godfrey tests) on testing whether the residuals from the OLS regressions are first-order autocorrelated.

Panel A: Summary Statistics

Variable	Mean	Std	Min	Median	Max	Nobs
SI	0.0700	0.9809	-1.6400	0.0550	2.6200	36
TTREND	0.2372	0.9221	-2.0638	0.3890	1.7535	36
DTREND	0.9064	1.5757	-3.4628	1.2271	3.3469	36
STREND	0.9007	0.9296	-1.5734	1.0249	2.4058	36

Panel B: Time-Series Regressions

Variable	Base	Turnover	Dollar Volume	Share Volume
Intercept	0.0008	-0.0004	-0.0018	-0.0034
	(0.59)	(-0.35)	(-1.47)	*(-2.22)*
		-0.0003	*-0.0018*	*-0.0034*
		[0.50]	[0.03]	[0.00]
SI (t-1)	0.6138	0.7404	0.7238	0.6944
	(4.68)	(6.26)	(6.39)	(6.15)
		0.6810	*0.6649*	*0.6370*
		[0.00]	[0.00]	[0.00]
TREND (t)		0.4521	0.2784	0.4556
		(3.59)	(3.95)	(3.82)
		0.4611	*0.2864*	*0.4688*
		[0.00]	[0.00]	[0.00]
N	36	36	36	36
LM	3.45*	0.19	0.33	0.19
Adj-R^2	0.37	0.54	0.56	0.55

*: Significant at the 10% level for rejecting the null hypothesis of no first-order autocorrelation in the regression errors.

result implies that the composite trading volume trend provides complementary information on the sentiment index in explaining the index values. As will be seen later, the composite trading volume trend also provides complement information on the sentiment index in explaining the equally-weighted market returns.

5.3.3 Time-Series Relations between Composite Trading Volume Trends and Market Returns

Results in the previous sections suggest that the composite trading volume trend is related to the sentiment index of Baker and Wurgler (2004) and closed-end fund discounts. In this section I examine the relations between the composite trading volume trend and market returns. I define the complete time-series model in this section as follows:

$$MRET_{(t,T)} = \beta_0 + \beta_1 DYLD_t + \beta_2 DBM_t + \beta_3 SI_t + \beta_4 RVOL + \beta_5 TREND_t + \varepsilon_t \quad (10)$$

$$DYLD_t = \beta_{10} + \beta_{11} DYLD_{t-1} + + \varepsilon_{1t} \quad (10.1)$$

$$DBM_t = \beta_{20} + \beta_{21} DBM_{t-1} + \varepsilon_{2t} \quad (10.2)$$

$$SI_t = \beta_{30} + \beta_{31} SI_{t-1} + \varepsilon_{3t} \quad (10.3)$$

$$RVOL_t = \beta_{40} + \beta_{41} RVOL_{t-1} + \varepsilon_{4t} \quad (10.4)$$

$$TREND_t = \beta_{50} + \beta_{51} TREND_{t-1} + \varepsilon_{5t} \quad (10.5)$$

where $MRET_{(t,T)}$ is the monthly-compounded cumulated returns on either the equally-weighted CRSP index or the value-weighted CRSP index from time t to time T. t is defined in month for equations (10), (10.1), (10.2), (10.4), and (10.5). t is defined in year for equation (10.3). In equation (10), (t,T) is either one month, three months, six months, 12 months, 24 months, or 36 months. $DYLD_t$ is the first difference of the monthly aggregated dividend yield on the market at time t. The aggregated dividend yield on the market at time t is the value-weighted dividend yield of all sample stocks at time t. DBM_t is the first difference of the monthly aggregated book-to-market ratio on the market at time t. The aggregated book-to-market ratio on the market at time t is the value-weighted book-to-market ratio of all sample stocks at time t. SI_t is sentiment index of Baker and Wurgler (2004). Since the sentiment index is available only annually, I define SI_t as the previous year-end value of SI. $RVOL_t$ is the natural logarithm of the average market price impact measure of Amihud (2002) from month *t-12* to month *t-2*. The market price impact each month is the equally-weighted average of the price impact measures on all sample stocks. Amihud (2002) finds that this price impact measure predicts returns on the equally-weighted CRSP index and favors a liquidity explanation. Later I also use the Roll Spread ($RSPD_t$) as an alternative illiquidity measure. $RSPD_t$ is the average market Roll spread from month *t-12* to month *t-2*. The market Roll spread each month is the equally-weighted average of the Roll Spreads on all sample stocks. Finally, $TREND_t$ is the composite trading volume trend on the market at time *t*. The β 's are the parameters. ε_t, ε_{1t}, ε_{2t}, ε_{3t}, ε_{4t}, and ε_{5t} are the random error terms.

Equation (10) assumes that the market return is explained by the aggregated dividend yield, the aggregated book-to-market ratio, investor sentiment as proxied by the sentiment index of Baker and Wurgler (2004), the market liquidity as proxied by the market price impact measure of Amihud (2002), and investor sentiment as proxied by the composite trading volume trend. Equations (10.1) to (10.5) assume that the explanatory variables are functions of their own past values. Neal and Wheatley (1998), Baker and Stein (2004), and Brown and Cliff (2005) employ similar specifications.

In the specifications *DYLD*, *DBM*, *SI, and RVOL* are my control variables. I do not include additional control variables such as the one-month T-bill rates, the term spreads, and alike because Baker and Wurgler (2000) find that those variables have virtually no explanatory power over the equally-weighted and value weighted CRSP returns. Neal and Wheatley (1998) also document that those variables have virtually no explanatory power over the returns of small firms and the size premium. The reasons that I take the first differences on the aggregated dividend yield and the aggregated book-to-market ratio can be seen from Figure 4. From Panel A and Panel B in Figure 4, it is clear that both the series of the aggregated dividend yield and the aggregated book-to-market ratio are likely to be nonstationary. Since nonstationary variables may lead to spurious regressions in a time-series framework, I take their first differences and present the transformed variables in panel C and Panel D. From panel C and panel D in Figure 4 we now see that those two series no longer have clear time-series patterns.[24] This transformation should therefore mitigate the concern of spurious regressions.[25] On the other hand, I do not transform the variable *RVOL*, despite that it shows a distinct time-series pattern in Figure 5. I choose so to make the specification of *RVOL* similar to the one that Amihud (2002) employs.[26] I also do not transform the variables *SI* and *TREND* because, *ex ante*, investor sentiment should be mean reverting. Further, shocks to investor sentiment should have temporary rather than permanent effects. Baker and Stein (2004) find that detrended or not, the effects of the equity share in new issues, one of the components in the sentiment index, persists on the equally-weighted and the valued-weighted CRSP index returns. To avoid mining the data, I use the levels of these two variables in my regressions.

Empirically I estimate equation (10) and equations (10.1) to (10.5) with the same bootstrapping technique (with 1,000 iterations) as in the previous sections. This method is especially important in this case since the OLS coefficient estimates could be biased because the persistence in the explanatory variables (Neal and Wheatley (1998), Baker and Stein (2004), and Brown and Cliff (2005)). Further, the overlapped dependent variable in equation (10), i.e., the monthly compounded cumulative return, leads to severe autocorrelations in the residuals (Neal

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[24] We see the spikes in Panel D of Figure 4 because I follow the definition of the book-to-market ratio in Fama and French (1992). Each year the book-to-market ratios on the sample stocks are updated only once. The annual updates cause the spikes.

[25] It should be noticed that taking the first difference does not ensure that the resulting series would be stationary. However, this kind of transformation is widely used in the literature, including Baker and Stein (2004), Baker and Wurgler (2004), and Brown and Cliff (2005).

[26] The effects of *RVOL* on the market returns disappear if I take its monthly first differences.

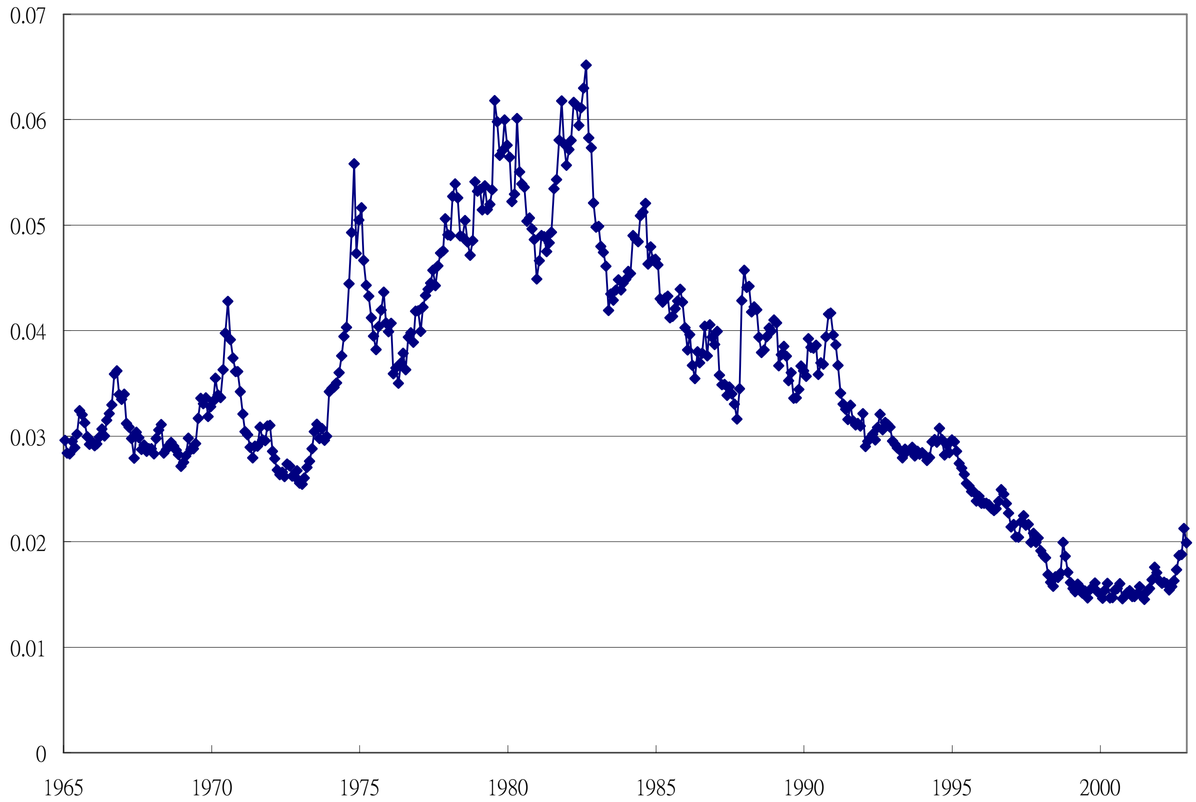
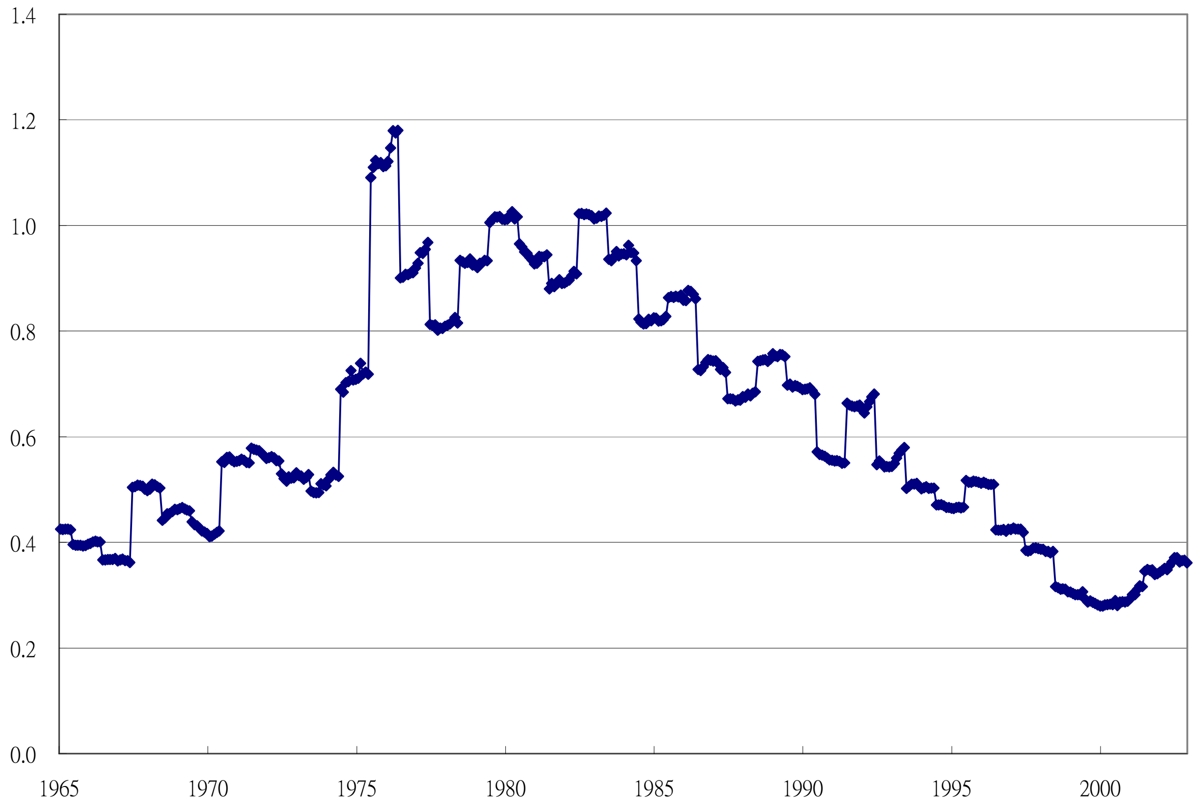
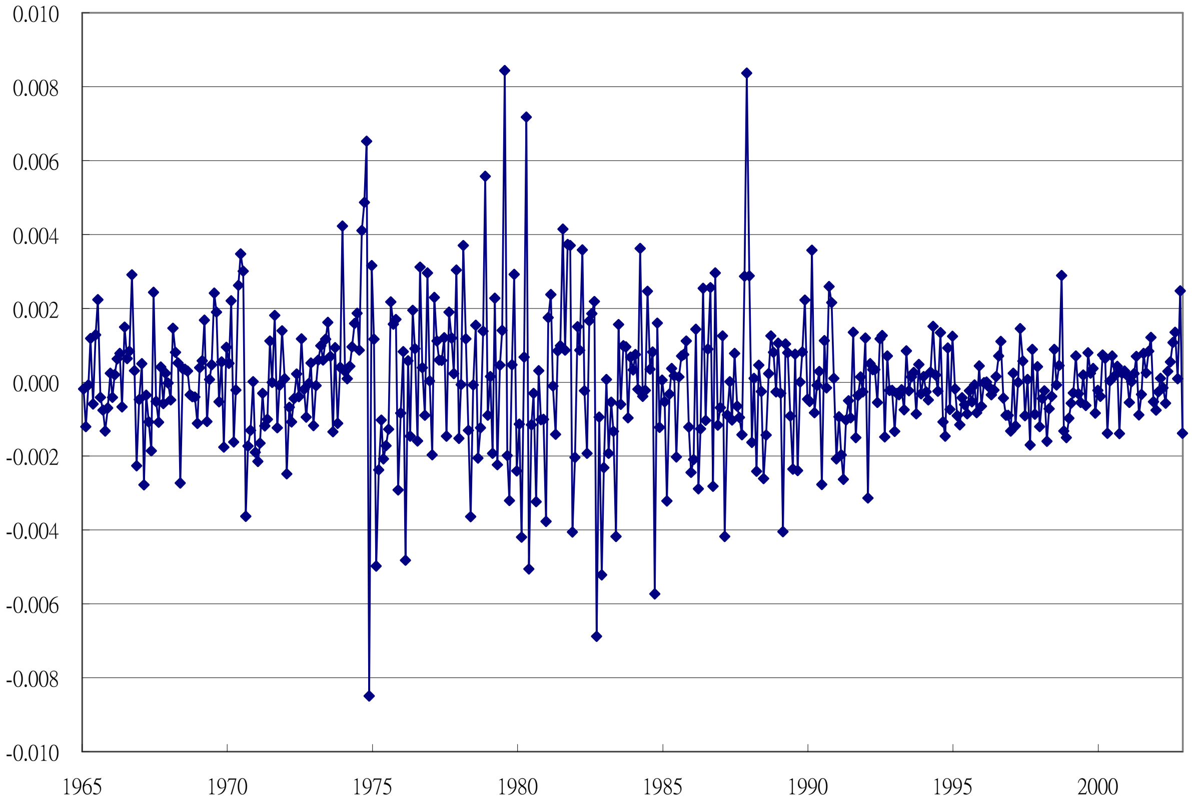


Figure 4: Time-Series Patterns of Dividend Yields and Book-to-Market Ratios
Panel A: Aggregated Dividend Yield

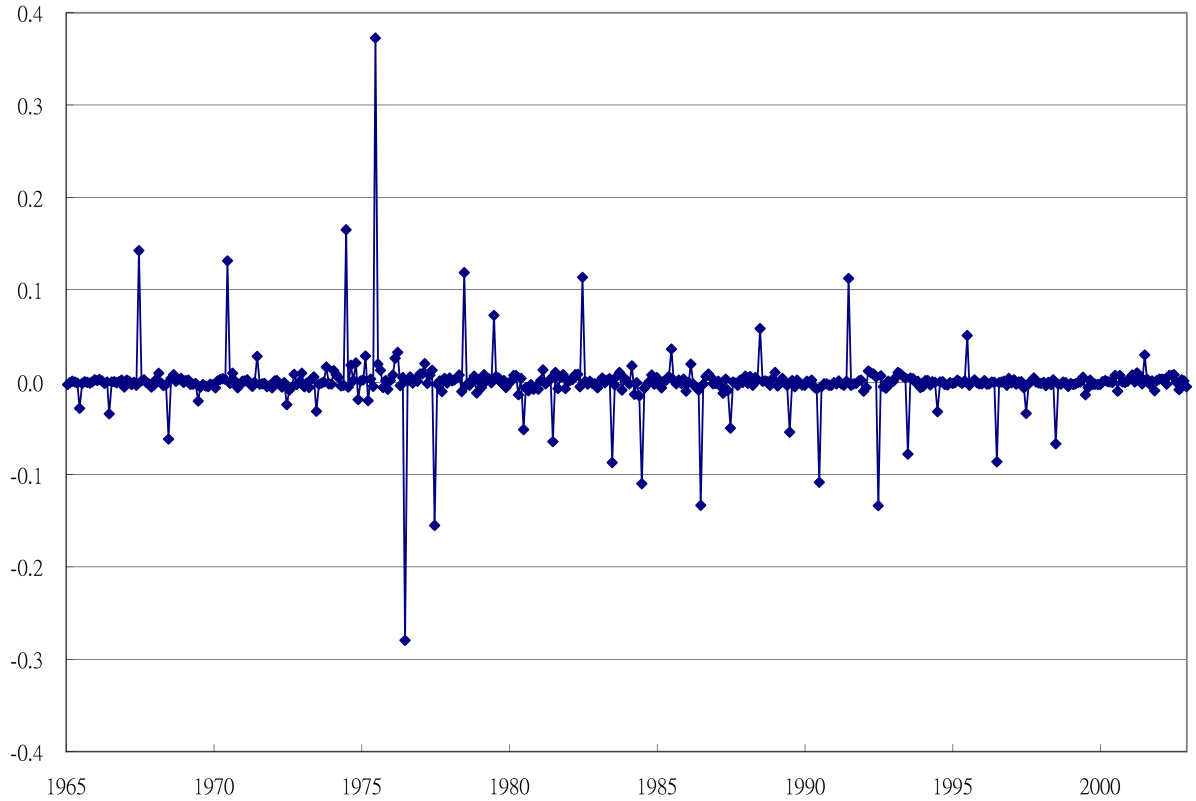
This figure presents the aggregated dividend yield, the aggregated book-to-market ratio, and their first-differenced versions on the market during the period from 1965 to 2002. The aggregated dividend yield (book-to-market ratio) on the market is defined as the value-weighted monthly average of dividend yields (book-to-market ratios) on all sample stocks, which include NYSE and AMEX stocks with corresponding three-year trading volume trends. Panel A shows the aggregated dividend yield. Panel B shows the aggregated book-to-market ratio. Panel C shows the monthly first difference of the aggregated dividend yield. Panel D shows the monthly first difference of the aggregated book-to-market ratio.



(Figure 4 cont.)
Pane B: Aggregated Book-to-Market Ratios



(Figure 4 cont.)
Panel C: First-Differenced Aggregated Dividend Yields



(Figure 4 cont.)
Panel D: First-Differenced Aggregated Book-to-Market Ratios

and Wheatley (1998) and Brown and Cliff (2005)), and the t-statistics obtained through OLS may be problematic.

Table 18 shows the summary statistics on the variables *DYLD*, *DBM*, *RVOL*, *RSPD*, *TTREND*, *DTREND*, *STREND*, and *SI* that enter equation (10). The statistics other than the number of observations on the differenced aggregated dividend yield (*DYLD*), the differenced aggregated book-to-market ratio (*DBM*), and the composite trading volume trends (*TTREND*, *DTREND* and *STREND*) are with a multiple of 100. From Table 18 we see that the differenced aggregated book-to-market ratio (*DBM*) has relatively large maximum and small minimum as

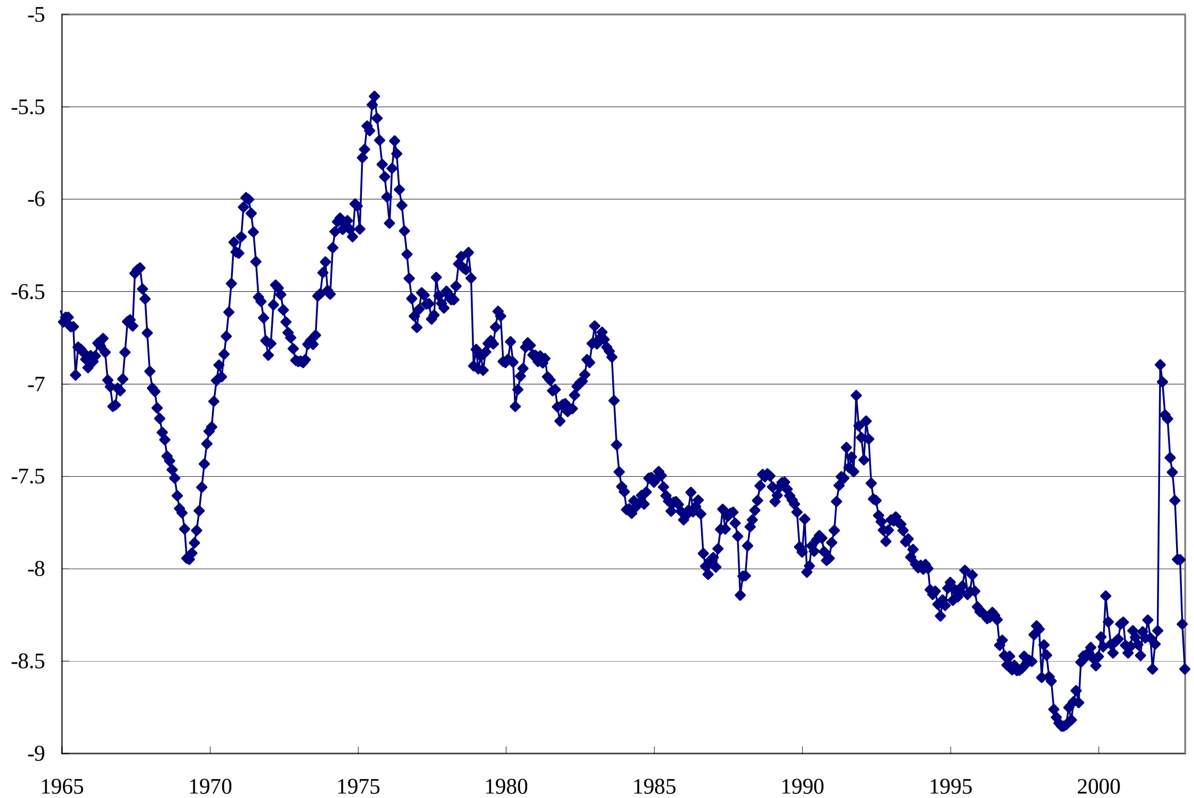


Figure 5: Time-Series Pattern of the Natural Logarithm of the Market Price Impact Measure of Amihud (2002)

This figure presents the natural logarithm of the average market price impact measure of Amihud (2002) during the period from 1965 to 2002. For each month *t*, the average market price impact measure is defined over month *t-12* to month *t-2*. The monthly market price impact measure each month is the simple average of the monthly price impact measures on all sample stocks at that month.

also revealed in Panel D of Figure 4. This occurs because each year the book-to-market ratios on the sample stocks are updated only once (see section 3.2.1).

Table 19 and Table 20 present the time-series regression results of the market returns. The reported numbers include the OLS estimates, the t-statistics from the OLS regressions (in parentheses), the true bootstrapping estimates (in Italics), and the one-tail bootstrapping p-values (in brackets). On average, we should see positive returns on the market. Amihud (2002) suggests

Table 18: Summary Statistics on Time-Series Variables

This table presents the summary statistics on the variables *DYLD*, *DBM*, *RVOL*, *RSPD*, *TTREND*, *DTREND*, *STREND*, and *SI* that enter into equation (10) for the time-series regressions of the market returns. *DYLD* is the monthly first difference on the aggregated dividend yield, defined as the value-weighted monthly average of dividend yields on all sample stocks. *DBM* is the monthly first difference on the aggregated boot-to-market ratio. *RVOL* is the average market price impact measure of Amihud (2002) from month *t-12* to month *t-2*. The market price impact measure each month is the equally-weighted average of the price impact measures on all sample stocks. *RSPD* is the average market Roll spread from month *t-12* to month *t-2*. The market Roll spread each month is the equally-weighted average of the Roll Spreads on all sample stocks. *TTREND* (*DTREND* and *STREND*) is the composite trading volume trend (*TREND*) in equation (10) defined on turnover (dollar volume and share volume). *SI* is the sentiment index of Baker and Wurgler (2004), defined annually. Except for *RVOL*, *RSPD*, and *SI*, the statistics other than the number of observations are with a multiple of 100.

Variable	Mean	Std	Min	Median	Max	Nobs
DYLD	-0.0022	0.1821	-0.8495	-0.0022	0.8439	455
DBM	-0.0145	3.2563	-27.9529	0.0008	37.2669	455
RVOL	-7.3461	0.7729	-8.8524	-7.4734	-5.4426	455
RSPD	0.1746	0.1329	-0.0852	0.1624	0.4887	455
TTREND	0.3267	0.8643	-2.0638	0.4330	2.0027	455
DTREND	1.0025	1.4822	-3.5952	1.3278	3.5199	455
STREND	0.9759	0.8589	-1.5734	1.1024	2.6356	455
SI	0.0542	0.9762	-1.6400	0.0550	2.6200	38

that higher market illiquidity should be followed by higher market returns. Therefore for intercept and *RVOL*, the bootstrapping p-values are for the alternative hypotheses of positive coefficients. For *SI* and *TREND*, the bootstrapping p-values are for the alternative hypotheses of negative coefficients, since high investor sentiment should lead to lowered future market returns. In Table 19, the dependent variable is the returns on the equally-weighted CRSP index. In Table 20, the dependent variable is the returns on the value-weighted CRSP index. I set up the base model in the tables to be without the composite trading volume trend for comparison. In model (1), the independent variables are *DYLD*, *DBM*, and *TREND*. In model (2), the independent variables are *DYLD*, *DBM*, *SI*, *RVOL*, and *TREND* (i.e., the complete model in equation (10)). I skip the coefficient estimates on *DYLD* and *DBM* in these tables to save space.[27]

[27] They usually have insignificant coefficient estimates in the regressions.

Table 19 Time-Series Regressions of Equally-Weighted Market Returns on Composite Trading Volume Trends

This table presents the results from the time-series regressions of the equally-weighted CRSP index returns on the first-differenced aggregated dividend yield (*DYLD*), the first-differenced aggregated book-to-market ratio (*DBM*), the sentiment index of Baker and Wurgler (2004) (*SI*), the market price impact measure of Amihud (2002) (*RVOL*), and the composite trading volume trend (*TREND*). The equally-weighted CRSP index returns are measured as monthly-compounded cumulative returns for the horizons from one month to 36 months in the period from 1965 to 2002. The reported numbers in this table include the OLS estimates, the t-statistics from the OLS regressions (in parentheses), the true bootstrapping estimates (in Italics), and the one-tail bootstrapping p-values (in brackets). For intercept and *RVOL*, the bootstrapping p-values are for the alternative hypotheses of positive coefficients. For *SI* and *TREND*, the bootstrapping p-values are for the alternative hypotheses of negative coefficients. To save space, I do not report the coefficient estimates on the variables *DYLD* and *DBM*.

Panel A: 1-Month Horizon

		Turnover		Dollar Volume		Share Volume	
Variable	Base	(1)	(2)	(1)	(2)	(1)	(2)
Intercept	0.0091	0.0112	0.0058	0.0134	0.0020	0.0127	0.0070
	(0.32)	(4.05)	(0.20)	(3.99)	(0.01)	(3.03)	(0.24)
	0.0101	*0.0121*	*0.0055*	*0.0133*	*0.0007*	*0.0125*	*0.0067*
	[0.38]	[0.00]	[0.40]	[0.01]	[0.51]	[0.01]	[0.43]
SI	-0.0071		-0.0075		-0.0077		-0.0073
	(-2.31)		(-2.38)		(-2.47)		(-2.35)
	-0.0043		*-0.0048*		*-0.0047*		*-0.0045*
	[0.08]		[0.07]		[0.05]		[0.06]
RVOL	-0.0004		-0.0010		-0.0019		-0.0009
	(-0.11)		(-0.24)		(-0.47)		(-0.22)
	-0.0003		*-0.0009*		*-0.0018*		*-0.0009*
	[0.46]		[0.60]		[0.66]		[0.59]
TREND		-0.0489	-0.1918	-0.1547	-0.2146	-0.0934	-0.1404
		(-0.15)	(-0.57)	(-0.82)	(-1.07)	(-0.29)	(-0.42)
		-0.0578	*-0.1767*	*-0.1494*	*-0.2068*	*-0.0710*	*-0.1251*
		[0.40]	[0.35]	[0.29]	[0.23]	[0.44]	[0.40]

(Table 19 cont.)

Panel B: 3-Month Horizon							
		Turnover		Dollar Volume		Share Volume	
Variable	Base	(1)	(2)	(1)	(2)	(1)	(2)
Intercept	0.0634	0.0386	0.0508	0.0423	0.0386	0.0425	0.0547
	(1.12)	(6.55)	(0.88)	(6.34)	(0.66)	(5.08)	(0.95)
	0.0604	*0.0384*	*0.0522*	*0.0423*	*0.0386*	*0.0430*	*0.0487*
	[0.19]	[0.00]	[0.24]	[0.00]	[0.29]	[0.00]	[0.27]
SI	-0.0155		-0.0171		-0.0172		-0.0162
	(-2.54)		(-2.73)		(-2.78)		(-2.63)
	-0.0099		*-0.0106*		*-0.0103*		*-0.0100*
	[0.06]		[0.04]		[0.03]		[0.05]
RVOL	0.0035		0.0014		-0.0007		0.0015
	(0.45)		(0.18)		(-0.09)		(0.19)
	0.032		*0.0017*		*-0.0006*		*0.0008*
	[0.37]		[0.43]		[0.51]		[0.49]
TREND		-0.4587	-0.7322	-0.5183	-0.5960	-0.5537	-0.5798
		(-0.71)	(-1.10)	(-1.38)	(-1.50)	(-0.86)	(-0.87)
		-0.4637	*-0.7102*	*-0.5292*	*-0.5643*	*-0.5953*	*-0.5990*
		[0.26]	[0.20]	[0.18]	[0.15]	[0.22]	[0.25]

Panel C: 6-Month Horizon							
		Turnover		Dollar Volume		Share Volume	
Variable	Base	(1)	(2)	(1)	(2)	(1)	(2)
Intercept	0.2010	0.0803	0.1743	0.0865	0.1597	0.0906	0.1813
	(2.41)	(9.24)	(2.05)	(8.81)	(1.84)	(7.35)	(2.14)
	0.1950	*0.0797*	*0.1678*	*0.0860*	*0.1535*	*0.0906*	*0.1833*
	[0.04]	[0.00]	[0.08]	[0.00]	[0.09]	[0.00]	[0.06]
SI	-0.0180		-0.0214		-0.0209		-0.0196
	(-2.00)		(-2.32)		(-2.29)		(-2.17)
	-0.0112		*-0.0130*		*-0.0132*		*-0.0118*
	[0.11]		[0.05]		[0.05]		[0.10]
RVOL	0.0169		0.0126		0.0099		0.0125
	(1.49)		(1.08)		(0.82)		(1.06)
	0.0163		*0.0119*		*0.0093*		*0.0131*
	[0.15]		[0.22]		[0.27]		[0.19]
TREND		-1.3590	-1.5503	-1.0644	-0.9916	-1.5102	-1.3018
		(-1.44)	(-1.59)	(-1.92)	(-1.69)	(-1.59)	(-1.32)
		-1.2828	*-1.5620*	*-0.9941*	*-0.9955*	*-1.5248*	*-1.2054*
		[0.15]	[0.12]	[0.12]	[0.13]	[0.11]	[0.17]

(Table 19 cont.)

Panel D: 9-Month Horizon							
		Turnover		Dollar Volume		Share Volume	
Variable	Base	(1)	(2)	(1)	(2)	(1)	(2)
Intercept	0.3736	0.1222	0.3436	0.1285	0.3387	0.1359	0.3527
	(3.66)	(11.37)	(3.30)	(10.58)	(3.18)	(8.93)	(3.40)
	0.3736	*0.1220*	*0.3372*	*0.1272*	*0.3361*	*0.1352*	*0.3476*
	[0.01]	[0.00]	[0.02]	[0.00]	[0.01]	[0.00]	[0.02]
SI	-0.0199		-0.0237		-0.0224		-0.0217
	(-1.81)		(-2.10)		(-1.99)		(-1.95)
	-0.0126		*-0.0153*		*-0.0136*		*-0.0136*
	[0.13]		[0.08]		[0.12]		[0.09]
RVOL	0.0349		0.0300		0.0290		0.0302
	(2.51)		(2.10)		(1.96)		(2.09)
	0.0350		*0.0294*		*0.0290*		*0.0297*
	[0.04]		[0.06]		[0.07]		[0.06]
TREND		-1.7508	-1.7368	-1.2022	-0.8393	-1.9836	-1.3830
		(-1.50)	(-1.45)	(-1.76)	(-1.17)	(-1.69)	(-1.15)
		-1.7859	*-1.7182*	*-1.1499*	*-0.7771*	*-1.9963*	*-1.3709*
		[0.12]	[0.14]	[0.12]	[0.24]	[0.10]	[0.19]

Panel E: 12-Month Horizon							
		Turnover		Dollar Volume		Share Volume	
Variable	Base	(1)	(2)	(1)	(2)	(1)	(2)
Intercept	0.4947	0.1644	0.4517	0.1709	0.4557	0.1834	0.4650
	(4.25)	(13.30)	(3.81)	(12.21)	(3.76)	(10.48)	(3.94)
	0.4883	*0.1646*	*0.4466*	*0.1692*	*0.4476*	*0.1834*	*0.4594*
	[0.00]	[0.00]	[0.01]	[0.00]	[0.02]	[0.00]	[0.01]
SI	-0.0337		-0.0392		-0.0365		-0.0362
	(-2.68)		(-3.04)		(-2.85)		(-2.86)
	-0.0210		*-0.0239*		*-0.0233*		*-0.0232*
	[0.04]		[0.03]		[0.03]		[0.04]
RVOL	0.0458		0.0388		0.0392		0.0391
	(2.90)		(2.39)		(2.33)		(2.38)
	0.0454		*0.0387*		*0.0385*		*0.0388*
	[0.03]		[0.05]		[0.06]		[0.06]
TREND		-2.3378	-2.4676	-1.4038	-0.9361	-2.7182	-1.9684
		(-1.75)	(-1.81)	(-1.79)	(-1.14)	(-2.02)	(-1.44)
		-2.3093	*-2.4665*	*-1.3690*	*-0.8956*	*-2.6949*	*-1.8310*
		[0.11]	[0.10]	[0.12]	[0.22]	[0.08]	[0.16]

(Table 19 cont.)

Panel F: 24-Month Horizon							
		Turnover		Dollar Volume		Share Volume	
Variable	Base	(1)	(2)	(1)	(2)	(1)	(2)
Intercept	0.9778	0.3498	0.8847	0.3507	0.9574	0.4000	0.8932
	(5.86)	(18.96)	(5.25)	(16.69)	(5.49)	(15.48)	(5.31)
	0.9642	*0.3473*	*0.8608*	*0.3504*	*0.9362*	*0.3957*	*0.8848*
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
SI	-0.0960		-0.1085		-0.0973		-0.1027
	(-5.30)		(-5.87)		(-5.29)		(-5.67)
	-0.0592		*-0.0669*		*-0.0606*		*-0.0622*
	[0.00]		[0.00]		[0.00]		[0.00]
RVOL	0.0877		0.0726		0.0843		0.0689
	(3.85)		(3.14)		(3.47)		(2.93)
	0.0868		*0.0702*		*0.0824*		*0.0688*
	[0.01]		[0.03]		[0.01]		[0.02]
TREND		-4.4712	-5.4680	-1.5006	-0.4688	-6.6010	-5.4342
		(-2.26)	(-2.85)	(-1.29)	(-0.40)	(-3.34)	(-2.81)
		-4.2472	*-5.2899*	*-1.4230*	*-0.3872*	*-6.2120*	*-5.2880*
		[0.05]	[0.04]	[0.21]	[0.41]	[0.01]	[0.04]

Panel G: 36-Month Horizon							
		Turnover		Dollar Volume		Share Volume	
Variable	Base	(1)	(2)	(1)	(2)	(1)	(2)
Intercept	1.4749	0.5470	1.3661	0.5560	1.4514	0.6284	1.3435
	(6.62)	(21.25)	(6.06)	(18.91)	(6.17)	(17.66)	(6.01)
	1.4515	*0.5462*	*1.3387*	*0.5544*	*1.4332*	*0.6230*	*1.3195*
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
SI	-0.1845		-0.1993		-0.1858		-0.1948
	(-7.74)		(-8.18)		(-7.68)		(-8.21)
	-0.1129		*-0.1220*		*-0.1139*		*-0.1196*
	[0.00]		[0.00]		[0.00]		[0.00]
RVOL	0.1296		0.1119		0.1257		0.1003
	(4.25)		(3.61)		(3.82)		(3.20)
	0.1271		*0.1092*		*0.1244*		*0.0985*
	[0.00]		[0.02]		[0.01]		[0.02]
TREND		-4.1608	-6.4889	-2.1295	-0.4935	-9.7427	-8.4685
		(-1.52)	(-2.57)	(-1.32)	(-0.32)	(-3.59)	(-3.35)
		-3.9241	*-6.3783*	*-2.0188*	*-0.3879*	*-9.3192*	*-8.3732*
		[0.15]	[0.06]	[0.19]	[0.43]	[0.01]	[0.02]

From the base model in Table 19, we see that the sentiment index (*SI*) usually has a negative and significant relation with the equally-weighted CRSP index returns across the return horizons. For example, the true bootstrapping estimate on *SI* is -0.0043 (one-tail p-value of 0.08) for the return horizon of one month. The estimate is -0.1129 (0.00) for the return horizon of 36 months.

These results suggest that high investor sentiment predicts low market returns. On the other hand, the price impact measure of Amihud (2002) has positive and significant coefficient estimates for return horizons of 9 months or longer, which is consistent with the findings in Amihud (2002) that higher market illiquidity is followed by higher market returns.

From model (1), the results suggest that the composite trading volume trend predicts market returns in the expected direction, but this relation also depends on what is the underlying trading volume measure. For instance, we observe the negative and significant relations between the composite share volume trend and market returns in return horizons of 12 months or longer. We observe the same relation with the composite turnover trend in the return horizon of 24 months. However, with the composite dollar volume trend, the negative relation is observed but not significant across the horizons.

From the results in model (2), we see that after controlling for the sentiment index (*SI*) of Baker and Stein (2004) and the price impact measure of Amihud (2002) (*RVOL*), the coefficient estimates on the composite turnover trend and the composite share volume trend are negative and significant for the return horizons of 24 months or longer. More interestingly, the significance on the coefficient estimates of *SI* generally improves across the return horizons but the significance on the coefficient estimates of *RVOL* generally deteriorates. This finding implies that the sentiment index of Baker and Stein (2004) and the composite trading volume trends contain complement information, despite that both the sentiment index and the composite volume trends target measuring investor sentiment. On the other hand, the price impact measure of Amihud (2002) (*RVOL*) may contain similar information as the composite trading volume trends, since it is also a volume-based measure.

We now turn to Table 20, where the dependent variable in the regressions is the value-weighted CRSP index returns. From the results in the base model, we now see that the sentiment index (*SI*) does not have a negative relation with the value-weighted market returns for any of the return horizons. The price impact measure (*RVOL*) does not have a positive relation with the value-weighted market returns for any of the return horizons. Surprisingly, if we look closer at the return horizons of 24 and 36 months, we see the one-tail p-values on *SI* as 0.97 and 0.96, respectively. The one-tail p-value on *RVOL* is 0.99 for the return horizon of 36 months. Since those are one-tail p-values for the alternative hypothesis of a negative coefficient in the case of *SI*, and for the alternative hypothesis of a positive coefficient in the case of *RVOL*, these results translate into positive and significant relations between the sentiment index and the value-weighted market returns, and a negative and significant relation between the price impact measure and the value-weighted market returns.[28] Those results are difficult to reconcile with the roles of *SI* and *RVOL*.

On the other hand, from model (1) we see that the composite turnover trend and the composite share volume trend still have negative and significant relations with the value-weighted market returns for the return horizons from six months to 24 months. For the composite dollar volume trend, we observe the negative relation with market returns for the return horizon of 12 months. From model (2), we see that after controlling for the sentiment index of Baker and Stein (2004) and the price impact measure of Amihud (2002), the composite turnover trend has negative and significant coefficient estimates for the return horizons from three months to 24 months. The composite dollar volume trend now has negative and significant

[28] The negative and significant relation between the price impact measure and the value-weighted market returns is not because the measure for the market is defined as the *equally-weighted* average of the measures on all sample stocks. Even if it is defined as the *value-weighted* average of the measures on all sample stocks, we still observe the negative and significant relation.

Table 20: Time-Series Regressions of Value-Weighted Market Returns on Composite Trading Volume Trends

This table presents the results from the time-series regressions of the value-weighted CRSP index returns on the first-differenced aggregated dividend yield (*DYLD*), the first-differenced aggregated book-to-market ratio (*DBM*), the sentiment index of Baker and Wurgler (2004) (*SI*), the market price impact measure of Amihud (2002) (*RVOL*), and the composite trading volume trend (*TREND*). The value-weighted CRSP index returns are measured as monthly-compounded cumulative returns for the horizons from one month to 36 months in the period from 1965 to 2002. The reported numbers in this table include the OLS estimates, the t-statistics from the OLS regressions (in parentheses), the true bootstrapping estimates (in Italics), and the one-tail bootstrapping p-values (in brackets). For intercept and *RVOL*, the bootstrapping p-values are for the alternative hypotheses of positive coefficients. For *SI* and *TREND*, the bootstrapping p-values are for the alternative hypotheses of negative coefficients. To save space, I do not report the coefficient estimates on the variables *DYLD* and *DBM*.

Panel A: 1-Month Horizon

		Turnover		Dollar Volume		Share Volume	
Variable	Base	(1)	(2)	(1)	(2)	(1)	(2)
Intercept	-0.0102	0.0095	-0.0156	0.0102	-0.0188	0.0103	-0.0137
	(-0.46)	(4.11)	(-0.68)	(3.89)	(-0.81)	(3.13)	(-0.61)
	-0.0097	*0.0094*	*-0.0154*	*0.0102*	*-0.0156*	*0.0103*	*-0.0146*
	[0.64]	[0.01]	[0.28]	[0.01]	[0.74]	[0.01]	[0.72]
SI	-0.0031		-0.0038		-0.0037		-0.0034
	(-1.29)		(-1.52)		(-1.51)		(-1.40)
	-0.0018		*-0.0023*		*-0.0022*		*-0.0020*
	[0.21]		[0.18]		[0.18]		[0.19]
RVOL	-0.0026		-0.0035		-0.0041		-0.0034
	(-0.87)		(-1.12)		(-1.27)		(-1.08)
	-0.0025		*-0.0034*		*-0.0036*		*-0.0035*
	[0.75]		[0.80]		[0.84]		[0.82]
TREND		-0.1913	-0.3066	-0.1287	-0.2066	-0.1442	-0.2340
		(-0.76)	(-1.17)	(-0.87)	(-1.31)	(-0.57)	(-0.89)
		-0.1738	*-0.2792*	*-0.1239*	*-0.1962*	*-0.1501*	*-0.2413*
		[0.28]	[0.23]	[0.26]	[0.19]	[0.33]	[0.26]

(Table 20 cont.)

Panel B: 3-Month Horizon							
		Turnover		Dollar Volume		Share Volume	
Variable	Base	(1)	(2)	(1)	(2)	(1)	(2)
Intercept	-0.0156	0.0293	-0.0318	0.0307	-0.0379	0.0322	-0.0268
	(-0.39)	(7.12)	(-0.78)	(6.57)	(-0.92)	(5.50)	(-0.66)
	-0.0144	*0.0292*	*-0.0317*	*0.0306*	*-0.0388*	*0.0322*	*-0.0281*
	[0.61]	[0.00]	[0.74]	[0.00]	[0.78]	[0.00]	[0.71]
SI	-0.0051		-0.0071		-0.0067		-0.0060
	(-1.18)		(-1.62)		(-1.53)		(-1.39)
	-0.0033		*-0.0042*		*-0.0041*		*-0.0037*
	[0.23]		[0.16]		[0.18]		[0.20]
RVOL	-0.0059		-0.0085		-0.0096		-0.0084
	(-1.08)		(-1.53)		(-1.67)		(-1.48)
	-0.0056		*-0.0084*		*-0.0097*		*-0.0084*
	[0.81]		[0.90]		[0.92]		[0.88]
TREND		-0.6886	-0.9333	-0.3595	-0.5352	-0.5286	-0.7396
		(-1.53)	(-2.00)	(-1.36)	(-1.91)	(-1.17)	(-1.57)
		-0.6433	*-0.9098*	*-0.3748*	*-0.5139*	*-0.5167*	*-0.7026*
		[0.14]	[0.09]	[0.16]	[0.10]	[0.19]	[0.14]

Panel C: 6-Month Horizon							
		Turnover		Dollar Volume		Share Volume	
Variable	Base	(1)	(2)	(1)	(2)	(1)	(2)
Intercept	0.0086	0.0604	-0.0242	0.0623	-0.0301	0.0678	-0.0153
	(0.15)	(10.05)	(-0.41)	(9.12)	(-0.50)	(7.94)	(-0.26)
	0.0102	*0.0607*	*-0.0215*	*0.0623*	*-0.0262*	*0.0677*	*-0.0128*
	[0.45]	[0.00]	[0.63]	[0.00]	[0.65]	[0.00]	[0.55]
SI	-0.0015		-0.0056		-0.0042		-0.0035
	(-0.23)		(-0.87)		(-0.66)		(-0.55)
	-0.0010		*-0.0034*		*-0.0026*		*-0.0026*
	[0.43]		[0.27]		[0.31]		[0.33]
RVOL	-0.0064		-0.0117		-0.0129		-0.0117
	(-0.80)		(-1.44)		(-1.53)		(-1.42)
	-0.0061		*-0.0112*		*-0.0123*		*-0.0112*
	[0.75]		[0.86]		[0.87]		[0.87]
TREND		-1.6360	-1.9003	-0.7126	-0.9296	-1.3026	-1.5797
		(-2.50)	(-2.79)	(-1.85)	(-2.27)	(-1.98)	(-2.30)
		-1.6607	*-1.8591*	*0.7144*	*-0.9519*	*-1.3153*	*-1.5508*
		[0.04]	[0.03]	[0.11]	[0.07]	[0.08]	[0.06]

(Table 20 cont.)

Panel D: 9-Month Horizon							
		Turnover		Dollar Volume		Share Volume	
Variable	Base	(1)	(2)	(1)	(2)	(1)	(2)
Intercept	0.0586	0.0928	0.0131	0.0940	0.0137	0.1038	0.0256
	(0.81)	(12.46)	(0.18)	(11.08)	(0.18)	(9.79)	(0.35)
	0.0612	*0.0922*	*0.0135*	*0.0938*	*0.0117*	*0.1037*	*0.0280*
	[0.25]	[0.00]	[0.42]	[0.00]	[0.46]	[0.00]	[0.40]
SI	0.0034		-0.0024		0.0002		0.0006
	(0.43)		(-0.03)		(0.02)		(0.07)
	0.0021		*-0.0013*		*-0.0001*		*0.0004*
	[0.61]		[0.42]		[0.48]		[0.50]
RVOL	-0.0036		-0.0110		-0.0112		-0.0110
	(-0.36)		(-1.09)		(-1.07)		(-1.07)
	-0.0032		*-0.0109*		*-0.0114*		*-0.0106*
	[0.59]		[0.79]		[0.83]		[0.80]
TREND		-2.4289	-2.6277	-0.9039	-1.0767	-1.9337	-2.1790
		(-3.00)	(-3.12)	(-1.89)	(-2.11)	(-2.37)	(-2.56)
		-2.3824	*-2.5349*	*-0.8564*	*-1.0488*	*-1.9395*	*-2.1231*
		[0.02]	[0.02]	[0.11]	[0.09]	[0.04]	[0.04]

Panel E: 12-Month Horizon							
		Turnover		Dollar Volume		Share Volume	
Variable	Base	(1)	(2)	(1)	(2)	(1)	(2)
Intercept	0.0873	0.1266	0.0240	0.1271	0.0316	0.1422	0.0417
	(1.04)	(14.70)	(0.28)	(12.92)	(0.36)	(11.60)	(0.49)
	0.0897	*0.1265*	*0.0266*	*0.1272*	*0.0271*	*0.1419*	*0.0371*
	[0.22]	[0.00]	[0.43]	[0.00]	[0.43]	[0.00]	[0.39]
SI	0.0031		-0.0049		-0.0008		-0.0007
	(0.34)		(-0.54)		(-0.09)		(-0.08)
	0.0022		*-0.0029*		*-0.0008*		*-0.0004*
	[0.60]		[0.37]		[0.48]		[0.49]
RVOL	-0.0039		-0.0141		-0.0133		-0.0141
	(-0.34)		(-1.22)		(-1.10)		(-1.20)
	-0.0037		*-0.0136*		*-0.0138*		*-0.0147*
	[0.64]		[0.82]		[0.82]		[0.83]
TREND		-3.3393	-3.6272	-1.1257	-1.3353	-2.6976	-3.0178
		(-3.58)	(-3.73)	(-2.04)	(-2.27)	(-2.86)	(-3.07)
		-3.2894	*-3.5479*	*-1.1400*	*-1.3267*	*-2.6343*	*-2.9590*
		[0.01]	[0.01]	[0.09]	[0.08]	[0.03]	[0.02]

(Table 20 cont.)

Panel F: 24-Month Horizon							
		Turnover		Dollar Volume		Share Volume	
Variable	Base	(1)	(2)	(1)	(2)	(1)	(2)
Intercept	0.0947	0.2716	0.0017	0.2591	0.0605	0.3003	0.0091
	(0.78)	(21.58)	(0.01)	(17.82)	(0.48)	(16.83)	(0.07)
	0.0969	*0.2710*	*0.0082*	*0.2583*	*0.0691*	*0.2992*	*0.0064*
	[0.28]	[0.00]	[0.50]	[0.00]	[0.36]	[0.00]	[0.49]
SI	0.0387		0.0263		0.0366		0.0320
	(2.94)		(1.97)		(2.73)		(2.45)
	0.0242		*0.0161*		*0.0230*		*0.0196*
	[0.97]		[0.87]		[0.96]		[0.94]
RVOL	-0.0218		-0.0369		-0.0276		-0.0409
	(-1.32)		(-2.21)		(-1.56)		(-2.41)
	-0.0217		*-0.0362*		*-0.0267*		*-0.0412*
	[0.85]		[0.92]		[0.88]		[0.96]
TREND		-5.4369	-5.4589	-0.4660	-0.7879	-4.7066	-5.5051
		(-4.03)	(-3.94)	(-0.58)	(-0.93)	(-3.45)	(-3.94)
		-5.3579	*-5.1580*	*-0.4060*	*-0.8045*	*-4.6269*	*-5.4036*
		[0.00]	[0.01]	[0.34]	[0.25]	[0.02]	[0.01]

Panel G: 36-Month Horizon							
		Turnover		Dollar Volume		Share Volume	
Variable	Base	(1)	(2)	(1)	(2)	(1)	(2)
Intercept	-0.1408	0.4162	-0.1578	0.3893	-0.0752	0.4215	-0.1786
	(-0.90)	(24.85)	(-0.99)	(20.49)	(-0.46)	(17.99)	(-1.12)
	-0.1276	*0.4162*	*-0.1462*	*0.3889*	*-0.0575*	*0.4214*	*-0.1621*
	[0.74]	[0.00]	[0.76]	[0.00]	[0.61]	[0.00]	[0.81]
SI	0.0498		0.0474		0.0533		0.04678
	(2.97)		(2.75)		(3.14)		(2.77)
	0.0307		*0.0286*		*0.0328*		*0.0289*
	[0.96]		[0.96]		[0.97]		[0.96]
RVOL	-0.0762		-0.0790		-0.0653		-0.0846
	(-3.55)		(-3.59)		(-2.83)		(-3.80)
	-0.0746		*-0.0774*		*-0.0632*		*-0.0826*
	[0.99]		[0.99]		[0.97]		[0.99]
TREND		-0.8940	-1.0147	2.3417	1.3765	-0.8360	-2.4357
		(-0.50)	(-0.57)	(2.25)	(1.26)	(-0.47)	(-1.35)
		-0.9143	*-0.9332*	*2.3456*	*1.3779*	*-0.7835*	*-2.4064*
		[0.35]	[0.35]	[0.93]	[0.81]	[0.37]	[0.17]

coefficient estimates for the return horizons from six months to 12 months. The composite share volume trend still has negative and significant coefficient estimates for the return horizons from six months to 12 months. In general, the significance of the trend variables improves over what we see in model (1), and the unexpected signs on the coefficient estimates of *SI* and *RVOL* still show up for the return horizons of 24 and 36 months.

Collectively the results in Table 19 and Table 20 suggest that the composite trading volume trends predict both the returns on the equally-weighted and the value-weighted CRSP indexes, but their explanatory power depends on what the underlying volume measure is. Specifically, the predicting power of the composite dollar volume trend is weaker than that of the composite turnover trend and the composite share volume trend. On the other hand, the results in Table 20 also suggest that the sentiment index of Baker and Wurgler (2004) and the price impact measure of Amihud (2002) have unexpected relations with the value-weighted market returns. For the sentiment index of Baker and Wurgler (2004), it is possible that it contains information other than investor sentiment since the composite trading volume trends still have the expected negative relations with the value-weighted market returns. For the price impact measure of Amihud (2002), is it possible that it contains information other than illiquidity? My results in Table 2 (see chapter 3) suggest that it contains information similar to that contained in the level of trading volume. To shed lights on this issue, I replace the variable *RVOL* with the Roll spread (*RSPD*) in the regressions and present the results in Table 21.

In Table 21 I report the regression results with either the equally-weighted or the value-weighted CRSP index returns as the dependent variable. To save space, I show the results corresponding to model (2) in previous tables and limit the return horizon from 12 months to 36 months. With the equally-weighted CRSP index returns as the dependent variable, we confirm what we observe in Table 19: The sentiment index (*SI*) has negative and significant coefficient estimates. The illiquidity measure (*RSPD*) has positive and significant coefficient estimate for the return horizon of 36 months. The composite trading volume trends have negative and

Table 21 Time-Series Regressions of Market Returns on Composite Trading Volume Trends and the Roll Spread

This table presents the results from the time-series regressions of the equally- (value-) weighted CRSP index returns on the first-differenced aggregated dividend yield (*DYLD*), the first-differenced aggregated book-to-market ratio (*DBM*), the sentiment index of Baker and Wurgler (2004) (*SI*), the market Roll Spread (*RSPD*), and the composite trading volume trend (*TREND*). The index returns are measured as monthly-compounded cumulative returns for the horizons from one month to 36 months in the period from 1965 to 2002. The reported numbers in this table include the OLS estimates, the t-statistics from the OLS regressions (in parentheses), the true bootstrapping estimates (in Italics), and the one-tail bootstrapping p-values (in brackets). For intercept and *RSPD*, the bootstrapping p-values are for the alternative hypotheses of positive coefficients. For *SI* and *TREND*, the bootstrapping p-values are for the alternative hypotheses of negative coefficients. To save space, I do not report the coefficient estimates on the variables *DYLD* and *DBM*.

Panel A: 12-Month Horizon

	Dependent Variable					
	Returns on CRSP Equally-Weighted Index			Returns on CRSP Value-Weighted Index		
Independent Variable	Turnover	Dollar Volume	Share Volume	Turnover	Dollar Volume	Share Volume
Intercept	0.1537	0.1589	0.1722	0.1280	0.1282	0.1443
	(7.76)	(7.67)	(7.36)	(9.08)	(8.62)	(8.63)
	0.1501	*0.1556*	*0.1670*	*0.1270*	*0.1280*	*0.1442*
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
SI	-0.0478	-0.0446	-0.0443	-0.0007	0.0029	0.0029
	(-3.85)	(-3.62)	(-3.60)	(-0.08)	(0.33)	(0.33)
	-0.0311	*-0.0285*	*-0.0282*	*-0.0000*	*0.0017*	*0.0018*
	[0.01]	[0.01]	[0.01]	[0.49]	[0.58]	[0.60]
RSPD	0.0915	0.0936	0.0857	-0.0080	-0.0079	-0.0138
	(1.02)	(1.04)	(0.95)	(-0.13)	(-0.12)	(-0.21)
	0.0878	*0.0890*	*0.0835*	*-0.0061*	*-0.0059*	*-0.0130*
	[0.17]	[0.19]	[0.20]	[0.52]	[0.53]	[0.57]
TREND	-3.2624	-1.6161	-2.8776	-3.3446	-1.1111	-2.6872
	(-2.46)	(-2.09)	(-2.18)	(-3.54)	(-2.00)	(-2.85)
	-3.1418	*-1.5173*	*-2.7212*	*-3.2319*	*-1.0867*	*-2.6460*
	[0.04]	[0.09]	[0.07]	[0.01]	[0.11]	[0.03]

(Table 21 cont.)

Panel B: 24-Month Horizon						
	Dependent Variable					
	Returns on CRSP Equally-Weighted Index			Returns on CRSP Value-Weighted Index		
Independent Variable	Turnover	Dollar Volume	Share Volume	Turnover	Dollar Volume	Share Volume
Intercept	0.3346	0.3302	0.3822	0.2304	0.2187	0.2598
	(11.64)	(10.94)	(11.35)	(11.22)	(10.12)	(10.78)
	0.3277	*0.3273*	*0.3763*	*0.2350*	*0.2237*	*0.2626*
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
SI	-0.1225	-0.1128	-0.1144	0.0491	0.0564	0.0549
	(-6.53)	(-6.02)	(-6.18)	(3.66)	(4.20)	(4.14)
	-0.0758	*-0.0685*	*-0.0703*	*0.0302*	*0.0340*	*0.0336*
	[0.00]	[0.00]	[0.00]	[0.99]	[0.99]	[0.99]
RSPD	0.1391	0.1530	0.1342	0.2296	0.2342	0.2267
	(1.03)	(1.11)	(0.99)	(2.37)	(2.38)	(2.34)
	0.1416	*0.1311*	*0.1185*	*0.2104*	*0.2135*	*0.2102*
	[0.16]	[0.21]	[0.23]	[0.03]	[0.02]	[0.03]
TREND	-6.8370	-1.9467	-7.0194	-4.7330	-0.4027	-4.4954
	(-3.62)	(-1.76)	(-3.75)	(-3.51)	(-0.51)	(-3.36)
	-6.8692	*-1.9745*	*-6.7971*	*-4.6020*	*-0.3395*	*-4.3457*
	[0.01]	[0.12]	[0.01]	[0.01]	[0.39]	[0.01]

Panel C: 36-Month Horizon						
	Dependent Variable					
	Returns on CRSP Equally-Weighted Index			Returns on CRSP Value-Weighted Index		
Independent Variable	Turnover	Dollar Volume	Share Volume	Turnover	Dollar Volume	Share Volume
Intercept	0.4049	0.4057	0.4811	0.2623	0.2460	0.2660
	(10.88)	(10.48)	(11.12)	(10.26)	(9.37)	(8.87)
	0.4072	*0.4079*	*0.4832*	*0.2724*	*0.2591*	*0.2774*
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
SI	-0.1771	-0.1635	-0.1682	0.1214	0.1206	0.1201
	(-7.16)	(-6.66)	(-6.95)	(7.15)	(7.24)	(7.16)
	-0.1099	*-0.0990*	*-0.1042*	*0.0736*	*0.0738*	*0.0735*
	[0.00]	[0.00]	[0.00]	[1.00]	[1.00]	[1.00]
RSPD	0.9278	0.9691	0.9175	0.9188	0.9005	0.9171
	(5.14)	(5.32)	(5.12)	(7.41)	(7.29)	(7.39)
	0.8760	*0.9119*	*0.8618*	*0.8658*	*0.8446*	*0.8625*
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
TREND	-8.1919	-3.1868	-10.3176	0.7261	2.0881	-0.1252
	(-3.38)	(-2.25)	(-4.33)	(0.44)	(2.17)	(-0.08)
	-8.0624	*--3.0450*	*-10.1150*	*0.8805*	*2.0210*	*-0.0852*
	[0.02]	[0.09]	[0.01]	[0.65]	[0.91]	[0.48]

significant coefficient estimates across the returns horizons, except for the composite dollar volume trend with the return horizon of 24 months. Comparing the results with those for model

(2) in Table 19, we also notice that without the variable *RVOL*, the significance on the trend variables improves. As will be confirmed next, this finding suggests that the price impact measure of Amihud (2002) (*RVOL*) may contain information more than liquidity.

Now we turn to the results with the value-weighted CRSP index returns as the dependent variable. The coefficient estimates on the composite trading volume trends are negative and significant for the return horizons of 12 and 24 months, except in the case of the composite dollar volume trend. These results do not differ much from what we observe in Table 20. However, although the sentiment index (*SI*) still has the unexpected positive sign on its coefficient estimates for the return horizons of 24 and 36 months, the illiquidity measure (*RSPD*) has the expected positive and significant coefficient estimates for the return horizons of 24 and 36 months. These results suggest that the negative relation between the price impact measure of Amihud (2002) (*RVOL*) and the value-weighted market returns in Table 20 does not imply a negative relation between market illiquidity and future market returns. Instead, it implies that the variable *RVOL* contains information more than liquidity, and it is that information contributing to the unexpected relation we observe in Table 20.

Chapter 6. Summary and Conclusion

In this dissertation I relate the information contained in past trading volume to investor sentiment, and investigate its ability on predicting stock returns. I devise a sentiment measure based on the trend of a trading volume series. I call this measure the trading volume trend.

The trading volume trend has a negative and significant relation with expected stock returns, after controlling for the level and volatility of trading volume, and other possible determinants of return. This relation holds for the trading volume trend defined over the past three years, but not for the trading volume defined over the past one year or the past five years. The relation between the three-year trading volume trend and expected returns persists when other liquidity measures are included in the regressions, and when different methodologies are applied to estimate the trading volume trend. These results are consistent with the trading volume trend as a measure of investor sentiment, and investor sentiment affects cross-sectional stock returns.

In a portfolio setting, I find that stocks with higher trading volume trends earn lower future returns than stocks with lower trading volume trends, and this relation persists after controlling for return momentum or the past level of trading volume. The portfolio analyses also suggest that the trading volume trend has a long-term effect on stock returns. Its effect lasts up to several years in the future. Further analyses indicate that stocks with either high or low trading volume trends tend to be stocks of smaller firms. These results support the hypothesis that the victims of investor sentiment are more likely to be small firms (e.g., Lee, Shleifer, Thaler (1991) and Neal and Wheatley (1998)).

I also investigate the effects of short-sales constraints on the returns of the trend portfolios, since in the model of Baker and Stein (2004) short-sales constraints play an important role on linking trading volume and investor sentiment. I use firm size and whether a stock is optioned or not as the proxies for the constraints. Stocks of larger firms and optioned stocks should have less short-sales constraints on them. Unconditionally, stocks of large firms and optioned stocks are less likely to experience extreme trading volume trends. The effect of trading volume trend on stock returns, however, persists even for those stocks. These results provide only partial support to the model of Baker and Stein (2004), but they are likely to be explained by the findings in Lakonishok, Lee, and Poteshman (2004) that (rational) investors do not trade against sentiment.

To examine investor sentiment at the market level, I construct a market-wide sentiment measure based on the trading volume trends of individual stocks. I call it the composite trading volume trend. I examine its relation with a value-weighted index of closed-end fund discounts, the sentiment index of Baker of Wurgler (2004), and the market returns. The results indicate that a higher composite trading volume trend leads to a lower index of discounts, suggesting that investor sentiment is a determinant of closed-end fund discounts. Furthermore, the composite trading volume trend has a positive and significant relation with the sentiment index of Baker of Wurgler (2004), consistent with the composite trading volume trend as a market sentiment measure.

The composite trading volume trend also predicts the market returns. Specifically, a higher composite trading volume trend leads to lower market returns. This result holds for both equally-weighted market returns and value-weighted market returns, and after controlling for the sentiment index of Baker and Wurgler (2004) and market liquidity measures such as the price impact measure of Amihud (2002) and the Roll spread. These findings suggest that market sentiment as proxied by the composite trading volume trend affects market returns.

Overall, in this dissertation I provide the rationale and evidence on why and how past trading volume can carry information on investor sentiment, as measured by the trading volume trend. Most of the earlier studies examining the relation between investor sentiment and stock returns use sentiment measures at the market level. The reason may well be the fact that there is virtually no sentiment measure targeting individual stocks with reasonable justification. In this regard I fill in the void with the trading volume trend, a measure that can be easily estimated for individual stocks.

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Vita

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