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Two Essays on Momentum Strategy and Its Sources of Abnormal Returns

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To the Graduate Council:

I am submitting herewith a dissertation written by Yu Zhang entitled "Two Essays on Momentum Strategy and Its Sources of Abnormal Returns." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Business Administration.

George C. Philippatos, Major Professor

We have read this dissertation and recommend its acceptance:

Phillip Daves, Larry Fauver, Jan Rosinski

Accepted for the Council:

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Vice Provost and Dean of the Graduate School

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Two Essays on Momentum Strategy and Its Sources of Abnormal Returns

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ABSTRACT

This dissertation studies the sources of the momentum abnormal returns. The first essay attempts to find the relative role of cross-sectional and time-series variances in generating returns from the momentum strategy. By decomposing the returns from the momentum strategy both theoretically and empirically, the first essay finds that own-stock autocovariance is an important source in generating momentum returns. More interestingly, the own-stock autocovariance comes primarily from the loser portfolio. This finding provides another explanation to the recent finding that the loser portfolio is the driving force of the momentum abnormal returns.

Based on the above discovery from the first essay, the second essay attempts to find out the underlying reason for the important asymmetric own-stock autocovaraince from the loser portfolio. We find that this return predictability comes from the short-selling constraints and risks. Stocks with more severe short-selling constraints prevent pessimistic information from being released into the stock prices more quickly; and thus causes those stocks to be overpriced and auto-correlated in their returns.

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CHAPTER I
INTRODUCTION

Abnormal returns generated from the momentum strategy have puzzled finance researchers for more than twenty years. The underlying sources of abnormal returns from the momentum strategy have provoked heated debate and rethinking about the widely-accepted concept---efficient market hypothesis, which is central to finance. However, momentum strategy---of all the market anomalies, most seriously challenged the efficient market hypothesis even in the weak form.

This dissertation attempts to explain the abnormal returns from the momentum strategy from two different aspects. The first essay develops a theoretical model to decompose the returns generated from the momentum strategy. By utilizing the historical data, the first essay supports the finding of Lehmann (1990) that autocorrelation of own stock returns is one of the driving forces for the expected momentum returns. More importantly to the literature, the first essay finds the own-autocovariance in the winner portfolio is almost negligible compared to that of the loser portfolio. Thus, it provides another underlying reason to the recent finding that the contribution of the winner and loser portfolios to the momentum returns is asymmetric. Therefore, the market may not be as efficient as we previously believed. Furthermore, from the return decomposition, we know the direct link that researchers typically put between the positivity of the momentum abnormal returns and the market inefficiency may not obviously hold. Based on the findings from the first essay, we further investigate the underlying reason for the persistence of the own-stock autocovariance in the loser portfolio, which may lead to its asymmetric contribution to the momentum abnormal returns. In the second essay, we find that the short-selling constraints and risk cause the autocovariance in the loser stock returns, and explain the momentum abnormal returns from the loser portfolio strongly and independently. Stocks which have most short-selling constraints generate the lowest returns. This return prediction in the momentum strategy supports the mispricing explanation that stocks with more severe short-selling constraints prevent pessimistic information from being released into the stock price more quickly; and thus causes those stocks to be more overpriced and auto-correlated in stock returns.

CHAPTER II
UNDERSTANDING THE SOURCES OF ABNORMAL RETURNS FROM THE MOMENTUM STRATEGY

Abstract

In this thesis, we study the sources of the returns from the momentum strategy and attempt to find some hints for the heated debate on the market efficiency hypothesis that has occurred over the past twenty years. By decomposing the momentum returns from a mathematical model, we directly investigated the contributors and their relative importance in generating these momentum returns.

Our empirical results indicated that the autocorrelation of own stock returns is one of the driving forces for the expected momentum returns. The magnitude of the autocorrelation decreased as the ranking period became more remote. The second important source came from the cross-sectional variation of the expected returns in the winner and loser portfolios for a given time. The third important source was the difference of the expected returns between the winner and loser portfolios. To our surprise, the cross-autocovariance did not contribute significantly to the expected momentum returns. Thus, the lead-lag effect can cause momentum returns, but its impact is not as significant as we had anticipated.

More importantly, by changing the weights of the winner and loser portfolios, we found that the own-autocovariance of the winner portfolio was virtually negligible, compared to that of the loser portfolio. The returns of the winners were much more random than those of the losers. This asymmetric own-autocovariance found in the return decomposition provided further support for the recent finding that the contribution of the winner and loser portfolios to the momentum

returns is asymmetric, and it is the losers, rather than the winners, that drive the momentum returns.

Therefore, the market may not be as efficient as we previously believed.

I. Introduction

1.1. Background

In the 1970s the efficient market hypothesis was widely accepted among finance researchers. It has been commonly believed that information spreads in the market very quickly, and hence, the prices of securities can quickly reflect the information with minimal delay. Thus, neither the technical analysis of past stock price behavior nor the fundamental analysis of firm specific information can help investors beat the market and earn returns higher than those of randomly selected portfolios with comparable risk. As stated by Malkiel (2003), in efficient financial markets, no investor can earn above-average returns without accepting above-average risks. This efficient market hypothesis has been engrained in much of the modern theoretical and empirical research in financial economics.

However, two decades ago, researchers found that simple investment strategies based on the past returns of stocks might realize consistently positive abnormal returns. These rejections of the martingale behavior of stock prices have seriously challenged the foundation of even the weakform of the efficient market hypothesis.

Stock return predictability based on past returns alone has attracted considerable attention in finance. The literature has three documented stock trading strategies categorized in terms of time horizons: (a) short-term reversal (Jegadeesh, 1990, Lo and MacKinlay, 1990); (b) intermediate momentum (Jegadeesh and Titman (JT), 1993); and (c) long-term reversal (Debondt and Thaler, 1985, Fama and French, 1988). As evidence opposing the efficient market hypothesis, these stock trading strategies are typical examples of exploiting stock return predictability. The debate on the abnormal returns from the momentum strategy that sells the "losers" and buys the "winners" over a 3 to 12 month horizon is much more diverse and voluminous.

This paper focuses on momentum strategy, which—of all the strategies identified—most seriously challenges the market efficiency hypothesis (Fama, 1998). Unlike either the short-term contrarian strategy that provides too little time and requires too much cost for possible arbitrage or the long-term contrarian strategy, that is not robust to risk adjustment (Fama and French, 1996) and is subject to measurement problems(Ball, Kothari and Shanken, 1995), the intermediate-term momentum strategy shows strong persistence in both the U.S. and international markets (Asness, Liew and Stevens, 1997, Rouwenhorst, 1998), and continues to exist for post 1990 periods (Jegadeesh and Titman, 2001). The persistence of the abnormal momentum returns after the sample period of the original studies diminishes the possibility of data snooping bias and positions it as a more serious anomaly than other well studied anomalies such as "the small firm effect" and "the value/growth stock phenomenon, "both of which disappear after the sample periods in the original studies (Jegadeesh and Titman, 2001).

Many serious attempts have been made to explain the abnormal momentum returns from various market phenomena. Proponents of rational explanations argue that the profitability of momentum strategies is explained by bearing some sort of additional risks; and, therefore, the market is at least weak-form efficient (Conrad and Kaul, 1998, Berk, Green and Naik, 1999, Chordia and Shivakumar, 2002, and Lewellen, 2002). Proponents of behavioral explanations argue that no risk factors can completely absorb the abnormal momentum returns; rather, it is the manner in which irrational investors interpret the information that causes the momentum or pattern of stock returns (Jegadeesh and Titman 1993, 2001, Barberis, Shleiferand Vishny, 1998, Daniel, Hirschleifer and Subrahmanyam, 1998, and Hong and Stein, 1999). Therefore, the abnormal returns from momentum strategies constitute strong evidence that the market is not even weak-form efficient. The middle position between the above two schools of thought focuses on market friction explanations. Proponents of market friction argue that parts or all of the abnormal momentum returns are justified by some kind of transaction costs in the imperfect market (Lesmond, Schilland Zhou, 2004, Korajczyk and Sadka, 2004, Sadka, 2006, and Ali and Trombley, 2006). Nevertheless, the empirical results of the market friction explanations are mixed with respect to market efficiency.

1.2. Motivation

In the literature, there are two ways to address the sources of the returns from the momentum strategy. Some studies attempt to determine the sources of the momentum returns by return decomposition. Expected return decomposition is important because we can determine clearly and directly how the time-series and cross-sectional variations play in generating returns from the momentum strategy. The other line of literature attempts to explain why the aforementioned components can generate abnormal momentum returns. If the researchers believe the cross-sectional variation is the cause of the momentum returns, then they are proponents of the rational explanation. They attempt to discover risk factors that can fully absorb the abnormal returns from the momentum strategy. On the contrary, if the researchers believe the time-series variation is the cause to the momentum returns, then they are advocates of the behavioral finance explanation. As a result, they attempt to use psychological theories to explain the autocorrelation of the stock returns from the momentum strategy.

This essay is an example of the first line of literature and attempts to decompose the momentum returns and determine the major contributors to the momentum strategy. Unlike the rational explanations that reject any possibility of stock return autocorrelation in generating momentum returns or the behavioral explanations that attribute all the momentum returns to the stock return patterns, we hypothesize that both own stock return autocovariances and cross-sectional variances generate the returns from the momentum strategy. However, the focus is determining which component is the main contributor. This thesis first decomposes the momentum expected returns and then uses historical data to calculate the relative weight of each component in the momentum returns.

Lehmann (1990) made the first attempt in literature to decompose the returns from the contrarian strategy. The weight used in Lehmann (1990) is $W_{it-k} = -[R_{it-k} - \bar{R}_{t-k}]$, where $\bar{R}_{t-k} = \frac{1}{N}\sum_{i=1}^{N} R_{it-k}$. Built on Lehmann (1990), Lo and MacKinlay (1990) further advanced the return decomposition. They use the weight $w_{it}(k) = -\frac{1}{N}\,(R_{it-k} - R_{mt-k})\; i = 1, \ldots, N$. All the later studies follow Lo and MacKinlay (1990) return decomposition, including those by Conrad and Kaul (1998) and Lewellen (2002).

Our return decomposition in this thesis is based on that of Lo and MacKinlay (1990). However, unlike the previous studies that include all stocks in the return decomposition, our weighting scheme only picks the top winners and bottom losers in the portfolio. Our model reflects the most common momentum strategy that has been analyzed in the literature, in which only a proportion of stocks ranked as winners or losers are weighted in the strategy. This type of strategy also takes better advantage of potential stock return patterns if any exist. Top winners and bottom losers have more tendency to retain a more stable return pattern. Thus, only including those stocks better reflects the beliefs of investors and avoids potential stock return pattern noises from the intermediate portfolio stocks. Furthermore, this type of momentum strategy reflects the stronger belief of investors in the stock return continuation thus could generate additional abnormal returns and pose a greater challenge to the efficient market hypothesis. More importantly, unlike the previous return decomposition that investigated the component from the whole portfolio, our weighting scheme provides the possibility of further investigating the components from the winner and loser portfolios separately. As the recent literature indicates that the winners and losers are quite different in characteristics and that their contributions to the abnormal momentum returns are asymmetric, our separate investigation of the components in the winner and loser portfolios provides us an opportunity to discover the potential cause of this recent finding in the literature. This is the first study to investigate the components in the winner and loser portfolios in return decomposition.

Our empirical results indicate that both the own stock return autocovariances and cross-sectional variances are the two major contributors to the momentum returns. However, the cross-autocovariances do not play such an important role in explaining the momentum returns as other studies have proposed.

More interestingly, although the own-autocovariances of the winner and loser portfolios bear the same sign, their magnitudes are quite asymmetric. Compared to the winners, the losers have much more stable return patterns and hence much larger own stock autocovariances from the ranking period to the holding period. This provides additional support to the recent finding that the losers, rather than the winners, are the driving force of the abnormal momentum returns.

All of these results indicate that the market may not be as efficient as we previously believed.

II. Literature Review

2.1. Stock Trading Strategies

Three stock trading strategies that utilize only the technical analysis and derive consistent positive profits are short-term contrarian strategy, intermediate-term momentum strategy, and long-term contrarian strategy. Of these three stock trading strategies, returns from the momentum strategy are most robust and therefore are the focus of our study. These three stock trading strategies all consist of a time line of three periods: formation period, holding period and post-holding period. The strategies select stocks on the basis of returns over the past K periods (formation period) and hold them for J periods (holding period).

2.1a Short-term Contrarian Strategy

The short-term contrarian strategy was first documented by Jegadeesh (1990) and Lehmann (1990). It is the strategy that ranks the stocks in the past K periods, which is typically a week or a month. Then construct the portfolio by buying the past worst performing stocks and selling the past best performing stocks, and hold it for another J periods, which is also a week or a month respectively.

2.1b Intermediate Momentum Strategy

First documented by Jegadeesh and Titman (1993), the momentum strategy selects stocks on the basis of returns over the past K periods (formation period) and holds them for J periods (holding period). The typical length for J and K are three to twelve months. Some studies also wait S periods between the formation and holding period to avoid microstructure effects. This is denoted as the skip period. This paper, as many other studies, measures periods in months, so J, K and S are in months. To simplify, all the momentum strategies in this paper will be described as (K, S, J). To increase the testing power, the strategy includes overlapping holding periods. Therefore, in any given month *t*, the strategy holds a series of portfolios that are selected in the current month as well as in the previous K-1 months if there are no skip months.

In the formation period, the securities are ranked in descending order on the basis of their geometric returns over this period. The long portfolio or the "winners" consists of equally weighted top P percent securities. The short portfolio or the "losers" consists of equally weighted bottom P percent securities. In much of the literature, P is 10 percent. Some studies also use value weighted (measured by market capitalization) P percent securities.

This paper will focus on the (6,0,1) equally-weighted rolling strategy and the (6,0,6) equally-weighted nonrolling strategy.

2.1c Long-term Contrarian Strategy

DeBondt and Thaler (1985) first documented profits from the long-term contrarian strategy. Based on the stocks' past three year performance, the portfolio selects the winners and losers, and holds them for another three year period. Since the past losers continuously outperform the past winners, this contrarian strategy of buying the past losers and selling the past winners obtains positive raw returns consistently.

2.2. Literature Review

Voluminous researches try to identify the sources of abnormal returns from the momentum strategy. There are two categories of studies in tackling this issue. The first category of studies tries to discover the sources by decomposing the momentum returns into cross sectional and time series variances. The second category of studies focuses on providing different explanations for the cross-sectional or times-series variances in momentum abnormal returns.

2.2a Return Decomposition

Lehmann (1990) has suggested market inefficiency due to stock price "overreaction". He constructed a contrarian strategy by buying the past k period losers and selling the past k period winners on a weekly basis. However, this zero cost strategy earns positive profits due to the phenomenon that the past winners tend to lose and past losers tend to win in the current period. Lehmann attributes this stock price predictability to stock price "overreaction" in the previous period. For a given set of N securities over a T time periods in the portfolio, at the beginning of period t, buy w_{it-k} dollars of each security i. The weights are given by

$$w_{it-k} = -[R_{it-k} - \bar{R}_{t-k}]; \;\; \bar{R}_{t-k} = \frac{1}{N}\sum_{i=1}^{N} R_{it-k}.$$

The profits for the portfolio in period $t(\pi_{t,k})$ are

$$\pi_{t,k} = \sum_{i=1}^{N} w_{it-k} R_{it} = -\sum_{i=1}^{N}[R_{it-k} - \bar{R}_{t-k}][R_{it} - \bar{R}_{t}],$$

so that the average profit over the T periods on this portfolio strategy is

$$\bar{\pi}_k = \frac{1}{T}\sum_{t=1}^{T}\pi_{t,k} = -\frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N}[R_{it-k} - \bar{R}_{t-k}][R_{it} - \bar{R}_t].$$

Algebraic manipulation of this expression yields

$$\bar{\pi}_k = \frac{N}{T}\sum_{t=1}^{T}[\bar{R}_{t-k} - \bar{\bar{R}}][\bar{R}_t - \bar{\bar{R}}] - \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N}[R_{it-k} - \bar{R}_i][R_{it} - \bar{R}_i] - \sum_{i=1}^{N}[\bar{R}_i - \bar{\bar{R}}]^2,$$

where

$$\bar{\bar{R}} = \frac{1}{T}\sum_{t=1}^{T}\bar{R}_t\ ;\ \bar{R}_i = \frac{1}{T}\sum_{t=1}^{T}R_{it}$$

are the average returns of the equally weighted portfolio and of security *i* overtime, respectively. Therefore, average portfolio profits over the T periods depend on the autocovariances of the returns of an equally weighted portfolio, the autocovariances of the returns of the individual securities, and the cross-sectional variation in the unconditional mean returns of the individual securities.

Jegadeesh (1990) also presents empirical evidence of predictability of individual stock returns on a monthly basis. He first tests serial correlation properties of individual security returns by checking coefficient signs of the following regression: $\tilde{R}_{it} - \bar{R}_{it} = a_{ot} + \sum_{j=1}^{12} a_{jt}R_{it-j} + a_{13t}R_{it-24} + a_{14t}R_{it-36} + \tilde{u}_{it}$ (1), where $\bar{R}_{it}$ is the mean monthly return of security *i in the sample period t+1 to t+60.* This regression estimates show strong serial reversal that the slope coefficients at lag one, a_1 is negative with a significant t-statistic of -18.58. While the coefficients of a_1 and a_2 are negative and demonstrate the return serial reversal in the regression, the rest of the coefficients are positive and indicate return serial momentum. Jegadeesh also examines the return serial correlation from the portfolio perspective. Three different reading strategies are developed. S0 forecasts individual stock raw returns by using the following model: $\hat{R}_{it} = \hat{a}_{0t} + \sum_{j=1}^{12}\hat{a}_{jt}R_{it-j} + \hat{a}_{13t}R_{it-24} + \hat{a}_{14t}R_{it-36}$, where $\hat{a}_{jt}$'s are estimated from a regression model similar to the regression model (1), with the raw return $\tilde{R}_{it}$ as the dependent variable over the period t-60 to t-1, and these estimates are updated every month. Then ten portfolios are formed by descending ranking order of the predicted returns, and they are updated every month too. S1 and S12 strategies also form ten portfolios on the basis of the one-month and twelve-month lagged returns. Finally, the abnormal returns earned by the portfolios formed in the above three strategies are estimated under the market model of $\tilde{R}_{pt} - R_{ft} = \alpha_p + \beta_p(R_{mt} - R_{ft}) + \tilde{u}_{pt}$, where R_{pt} and R_{ft} are the portfolio return and the risk-free rate respectively. The intercept is the abnormal return of the above strategies. The results of the three strategies all demonstrate positive abnormal returns, which provide strong evidence of predictable behavior of security returns.

Lo and Mackinlay (1990) construct a particular weekly contrarian strategy. It is to buy stocks at time t that were losers at time t-k and to sell stocks at time t that were winners at time t-k, where winning and losing is determined with respect to the equal-weighted return on the market. Thus, the weight for security i at time t is,

$$w_{it}(k) = -\frac{1}{N}\,(R_{it-k} - R_{mt-k})\; i = 1, \dots, N$$

where $R_{mt-k} = \sum_{i=1}^{N} \frac{R_{it-k}}{N}$ is the equal-weighted market index. By construction, $w_t(k) = [w_{1t}(k), w_{2t}(k) \dots w_{Nt}(k)]'$ is an arbitrage portfolio because the weights sum to zero. Since the portfolio weights are proportional to the differences between the market index and the returns, securities that deviate more positively from the market at time t-k will have greater negative weight in the time t portfolio and vice versa. Such a strategy is designed to best take advantage of stock market overreactions. The profit $\pi_t(k)$ from such a strategy is

$$\pi_t(k) = \sum_{i=1}^{N} w_{it}\,(k) R_{it},$$

and take the expectation of the above equation,

$$E[\pi_t(k)] = \frac{\iota'\Gamma_k\iota}{N^2} - \frac{1}{N}\, tr(\Gamma_k) - \frac{1}{N}\sum_{i=1}^{N}(\mu_i - \mu_m)^2$$

where $\mu_m = E[R_{mt}] = \frac{\mu'\iota}{N}$, $tr(\cdot)$ denotes the trace operator, and ι is the identity vector with proper dimension.

Therefore, the profit of the contrarian strategy is the summation of three terms: the first term is the k^{th}-order autocovariance of the equal-weighted market index. The second term is the cross-sectional average of the k^{th}-order autocovariances of the individual securities, and the last term is the cross-sectional variance of the mean returns.

In order to separate the effects of cross-autocovariances versus own-autocovariances in generating the expected returns from the contrarian strategy, the above expected return is further rearranged as,

$$E[\pi_t(k)] = \frac{1}{N^2}[\iota'\Gamma_k\iota - tr(\Gamma_k)] - (\frac{N-1}{N^2})tr(\Gamma_k) - \sigma^2(\mu)$$

$$= C_k + O_k - \sigma^2(\mu).$$

C_k is cross-autocovariances of equal-weighted market index returns, O_k is the own-autocovariances of individual stock returns. They found weekly portfolio returns from the contrarian strategy are strongly positively cross-autocorrelated and over 50 percent of the expected profits are attributable to these cross effects. They propose the lead-lag effect as the cause of the strong positive cross-autocorrelation between different stocks in the portfolio. Lead-lag effect occurs when a security' return lags on a common factor. The security with less lags on a common factor leads the security with more lags. Their empirical results show that returns of large stocks almost always lead those of smaller stocks. Therefore, they argue that given individual security returns are generally weakly negatively autocorrelated, the positive contrarian profits are *completely* attributable to cross-effects.

Conrad and Kaul (1998) attempt to determine the sources of the expected profits of the entire class of trading strategies that are based on information contained in past returns of individual securities. They utilize a single framework, which builds on the analyses in Lehmann (1990) and Lo and MacKinlay (1990), to decompose the profits of all strategies, both contrarian and momentum. The expected profit of the momentum strategy is

$$E[\pi_t(k)] = -Cov[R_{mt}(k), R_{mt-1}(k)] + \frac{1}{N}\sum_{i=1}^{N} Cov[R_{it}(k), R_{it-1}(k)] + \frac{1}{N}\sum_{i=1}^{N}[\mu_{it-1}(k) - \mu_{mt-1}(k)]^2$$

$$= -C_1(k) + O_1(k) + \sigma^2[\mu(k)]$$

$$= P(k) + \sigma^2[\mu(k)]$$

where $P(k) = -C_1(k) + O_1(k)$ is the predictability-profitability index, $\mu_{it}(k)$ is the unconditional mean of security *i* for the interval {t-1, t} of length *k*, and $\mu_{mt}(k) = \frac{1}{N}\sum_{i=1}^{N}\mu_i(k)$ is the unconditional single-period mean return of the equal-weighted market portfolio at time *t*.

Under the assumption of mean stationarity of individual security returns, the above decomposition shows that total expected profits of trading strategies result from two distinct sources: time-series predictability in asset returns, measured by *P(k)*, and profits due to cross-sectional dispersion in mean returns of securities, denoted by $\sigma^2[\mu(k)]$. The first term in *P(k)*, i.e. $C_1(k)$, is the average first-order autocovariance of the return on the equal-weighted market portfolio, the second term, i.e., $O_1(k)$, is the average first-order autocovariances of the individual securities in the portfolio. This arrangement of expected returns separates the returns from the time-series predictability entirely from the cross-sectional dispersion, no matter whether the time-series predictability is from own or cross-autocovariances,

The empirical decomposition of the profits from the strategies suggests that the cross-sectional variance of mean returns is both the predominant source of momentum strategy profits, and a major source of losses to long-term contrarian strategy.

However, Jegadeesh and Titman (2002) argue that the Conrad and Kaul (1998) results are subject to small sample biases in their tests and bootstrap experiments. Jegadeesh and Titman's empirical tests indicate that cross-sectional differences in expected returns explain very little, if any, of the momentum profits. Conrad and Kaul use the average realized return of each stock as their measure of the stock expected return. Specifically,$\widehat{\mu_i} = \frac{1}{T_i}\sum_{t=1}^{T_i} R_{i,t}$, where T_i is the number of observations available for stock i. They use the cross-sectional variance of $\widehat{\mu_i}$ as the estimator of σ_μ^2. Jegadeesh and Titman argue that such design ignores the impact of the error in the estimates of $\widehat{\mu_i}$ on the estimate of σ_μ^2. Let $\widehat{\mu_i} = \mu_i + \varepsilon_i$, where ε_i represents estimation error. Since $\widehat{\mu_i}$ is an unbiased estimator of expected returns, $E(\varepsilon_i) = 0$. However, since$\sigma_{\widehat{\mu_i}}^2 = \sigma_{\mu_i}^2 + \sigma_{\varepsilon_i}^2$, the variance of the estimated expected returns overestimates the cross-sectional variance of true expected returns. They argue that the magnitude of this overestimation is exacerbated when use all stocks in the sample period as in Conrad and Kaul, for the calculation of expected returns, regardless of the length of their return history.

2.2b Different Explanations

There are two conflicting schools of explanations for the sources of momentum abnormal returns. The dominant group consists of the behavioral theories, which challenge the market efficiency hypothesis and the classical models of rational pricing. The other group includes the rational theories, which argue that it is premature to reject the rational models and suggest that the profitability of momentum strategies may be compensation for extra risk or macroeconomic factors (Jegadeesh and Titman (2001)). The market friction explanation is the third group that stands in the middle of the above two explanations.

2.2b (1) Behavioral Explanations

The explanations offered by the behavioral theories can be categorized as overreaction and underreaction. DeBondt and Thaler (1985) introduce experimental psychology into the study of finance. They argue that people tend to "overreact" to unexpected and dramatic news events. If stock prices overshoot systematically, then they will have predictable reversals based on the past return data only in the long term. This hypothesis suggests a violation of the weak-form market efficiency. Delong et al. (1990) states that there are rational speculators and liquidity or noise traders. Because the latter buy when prices rise and sell when prices fall, the rational speculators would buy/sell ahead of the noise traders in the hope of selling/buy at a higher/lower price later. But these purchases by rational speculators can make positive feedback traders even more excited and so move prices even further away from fundamental values than they would go in the absence of rational speculators.

More recently, Daniel, Hirshleifer and Subrahmanyam (1998) develop a theory based on investors' overconfidence in their private information signal, rather than the public information signal. This asymmetric confidence results from biased self-attribution of different investment outcomes. Investors tend to attribute the performance of ex post winners to their stock selection skills and that of the ex post losers to bad luck. When an investor receives public confirmation, his confidence rises. But disconfirming public information causes confidence to fall only modestly, if at all. Thus, stock prices overreact to private information signals and underreact to public signals. Even if an individual begins with unbiased beliefs, new public signals on average are viewed as confirming the private signal. This suggests that public information can trigger further overreaction to a preceding private signal. The continuing overreaction causes momentum in security prices, but such momentum is eventually reversed as further public information gradually draws the price back toward fundamentals. This is consistent with the intermediate momentum and long-term reversal in stock returns.

Barberis, Shleifer, and Vishny (1998) and Hong and Stein (1999) both proposed "underreaction", though with a different working mechanism, to explain the intermediate momentum and long-term reversal. BSV (1998) propose two psychological phenomena, "conservatism" and "representativeness heuristic", to construct a parsimonious model of investor sentiment that at the same time, explains underreaction and overreaction as the causes for the momentum and the long-term contrarian abnormal returns. Conservatism is defined as the slow updating of models in the face of new evidence (Edwards, 1968). Representativeness heuristic is a tendency of experimental subjects to view events as typical or representative of some specific behavioral class when a series of such events happen recently. Therefore, investors tend to show underreaction of stock prices to good news such as earnings announcements, but overreaction of stock prices to consistent patterns of good or bad news. They argue that although conservatism alone leads to underreaction and hence to intermediate momentum, the combination of conservatism and representative heuristic can lead to long horizon negative returns for stocks with consistently high returns in the past.

HS (1999) does not apply any behavior biases on the part of investors, but they model a market with two groups of boundedly rational agents: "newswatchers" and "momentum traders". They both act rationally in updating their expectations, but only conditional on their own information sets, or the subset of the available public information. Each newswatcher observes some private information, but ignores information in the past history of prices and failes to extract other newswatchers' information from prices. Therefore, assuming information diffuses gradually across the population, information obtained by the informed newswatchers would be transmitted with a delay and prices undrreact in the short run. This underreaction results in the momentum profit that momentum traders can obtain by trend-chasing. The momentum traders make judgments only by a limited history of prices and do not factor in fundamental information. So the momentum traders tend to extrapolate based on past prices and push prices of past winners above their fundamental values. In the long horizon, prices eventually revert to their fundamentals. This causes long-term reversal.

Hong, Lim and Stein (2000) test the gradual-information-diffusion model of HS (1999) empirically. They found that firm-specific information, especially negative information, diffuses only gradually among the investors. Their findings are: 1) excluding the very small stocks below the 20th NYSE/AMEX percentile, the profitability of the momentum strategies declines sharply with firm size; 2) holding size fixed, stocks with low analyst coverage generates more momentum returns; 3) the effect of analyst coverage is asymmetric, i.e., it is greater for stocks that are past losers than for past winners. They reason this asymmetry as, for low-coverage stocks, when firms get good news; the managers probably have the incentive to push this good news to the investing public as soon as possible. In contrast, when there is bad news, managers are likely to be less forthcoming, and combining with low outside analyst coverage, the stock prices tend to be overpriced more.

In their paper, the analyst coverage is a proxy for the information diffusion speed. Thus, they assume that stocks with lower analyst coverage should, all else being equal, be the ones where firm-specific information diffuse slower across the investing public. However, analyst coverage is strongly related to firm size, and the latter also captures a good portion of the information diffusion effect. In order to investigate the unique role played by the analyst coverage in the rate of information diffusion, they calculate residual analyst coverage, where the residual comes from a regression of log (1+coverage) on log (firm size) and NASDAQ dummy.

2.2b (2) Rational Explanations

On the rational theories side, some financial economists have suggested that cross-sectional variation in expected returns generates the momentum abnormal returns.

Berk, Green, and Naik (1999) develop a theoretical model where the cross-sectional variation in risk and expected return generates profits in short-term reversal and intermediate momentum. They construct a dynamic model that relates changes of a firm's systematic risk through time to firm-specific variables and hence the cross-sectional variation of expected return to explain the abnormal returns from trading strategies. Firm-specific variables refer to book to market ratio, size or past return, which are generally used to explain the cross-sectional variation in expected returns.

Firms in the model have two kinds of assets: (a) in-place assets and (b) growth options. The sum of these types of assets yields the expected returns of firms. In each period, cash flows from in-place assets may die off, and new investment opportunities may emerge to the firm. Because the composition and systematic risk of the firm's assets are persistent, expected returns in a given period are positively related to lagged expected returns (positive time series between expected returns of different periods). However, the expected returns are negatively related to lagged realized returns (negative cross-sectional variation of expected returns) because shocks to the composition of the firm's assets are negatively correlated with changes in systematic risk. Therefore, these lead to momentum effects in the intermediate term and reversal in the short term. At an aggregate level, the time series of portfolio expected returns show positive correlation with book-to-market, which serves as the firm's risk, relative to the scale of its asset base; however, the excess returns are negatively related to interest rates.

Chordia and Shivakumar (2002) show that profits from the momentum strategy can be explained by a set of lagged macroeconomic variables that are related to the business cycle. Payoffs to a six-month/six-month momentum strategy disappear once stock returns are adjusted for their predictability based on these macroeconomic variables. Thus the results provide a possible role for time-varying expected returns, predicted by standard macroeconomic variables, as an explanation for the momentum abnormal returns. The macroeconomic variables used in the study are dividend yield, default spread, yield on three-month T-bills, and term structure spread. Their results suggest that the profitability of momentum payoffs comes from the cross-sectional variation in conditional expected returns. These findings are consistent with the arguments of Berk et al. (1999) that profitability of momentum strategies represents compensation for bearing time-varying risk.

2.2b (3) Market Friction Explanations

Most of above papers have not taken the huge transaction costs into consideration. Neither do empirical studies include the transaction costs when testing the abnormal returns from trading strategies. The work of Korajazyk and Sadka (2004) is one of the few papers that focus on the transactions costs in momentum strategy. They find that momentum strategies remain profitable even after considering market frictions. The price impact models imply that abnormal returns to portfolio strategies decline with portfolio size. In particular, they estimate the size of a momentum-based fund that could be achieved before abnormal returns are either statistically insignificant or driven to zero. They find that the estimated excess returns of some momentum strategies disappear after an initial investment of $4.5 to over $5.0 billion is engaged in such strategies. However, additional costs involved in short sales are not fully captured by their measure of price impact.

III. Decomposition of Momentum Returns

3.1. Theoretical Model

To elucidate the relative role of the cross-sectional and time-series effects in generating momentum returns, we decompose the momentum expected returns first and then discuss their profitability under different return generating processes.

Following Lehmann (1990) and Lo and Mackinlay (1990), we also use a weighted relative strength strategy (WRSS) to decompose the returns from the momentum strategy. However, instead of taking all the stocks with returns higher than the market return as winners and all the stocks with returns lower than market returns as losers, our strategy will follow the typical momentum strategy that only includes top and bottom percentage stocks as winners and losers.

We consider a collection of N securities and denote their period *t* returns R_t a $N \times 1$ vector$[R_{it,} \cdots, R_{Nt}]'$. Following Lo and Mackinlay (1990), in this section, we offer the following assumption:

Assumption 1: R_t follows a jointly covariance-stationary stochastic process with expected value $E[R_t] = \mu \equiv [\mu_1, \mu_2, \cdots \mu_N]'$ and autocovariance matrices$E[(R_{t-1}(k) - \mu)(R_t(k) - \mu)'] = \Gamma(k)$, where $k \geq 0$, since$\Gamma(k) = \Gamma'(-k)$.

Specifically, the momentum strategy buys winners and sells losers at time t based on their performance from time period$\{t-1, t\}$, where *k* is the length of the time interval$\{t-1, t\}$. The winning and losing outcomes are determined with respect to the equal-weighted return on the entire market. Then, we first rank the stocks in descending order by their geometric mean returns over the $\{t-1, t\}$ period, i.e.,$R_1 \geq R_2 \geq \cdots \geq R_{SN} \cdots \geq R_N$, where *S* is the top or bottom percentage of stocks, where $0 < S < \frac{1}{2}$. Hence, top *SN* stocks are winners and bottom *SN* stocks are losers. More formally, we allow $w_{it}\,(k)$ to denote the fraction of the trading strategy portfolio devoted to security *i* at time *t*, that is

$$w_{it}\,(k) = \begin{cases} \frac{\alpha}{SN}[R_{it-1}(k) - R_{mt-1}(k)] & if\ i = 1,2,\dots,SN \\ 0 & if\ i = SN+1,\dots,N-SN \\ \frac{\beta}{SN}[R_{it-1}(k) - R_{mt-1}(k)] & if\ i = N-SN+1,\dots,N \end{cases} \quad (1)$$

where $\alpha > 0, \beta > 0$ are parameters of the weights of the winner and loser portfolios, $R_{it-1}(k)$ is the geometric mean return of security i at time interval $\{t-1, t\}$, $R_{mt-1}(k) = \frac{\sum_{i=1}^{N} R_{it-1}(k)}{N}$ is the return of equal-weighted portfolio of all securities at time interval $\{t-1, t\}$, and k is the length of the time interval $\{t-1, t\}$.

The weighting mechanism reflects the belief of an investor that price has continuations, and the success of this strategy is based solely on the time-series behavior of stock prices. This weighting mechanism permits us to decompose the returns of momentum strategy into time-series and cross-sectional variations. It also permits us to determine the relative importance of these components in predicting momentum returns and answer the frequently argued question of whether the market is efficient or whether the stock prices have memory. More importantly, securities that deviate more positively (negatively) from the market mean at time period $\{t-1, t\}$ will have greater positive (negative) weight in the time t portfolio. Considering only the top and bottom S percentages of stocks in our momentum strategy, rather than all stocks, better represents the belief in stock price continuations, because the strongest winners probably have more momentum to continue winning and the worst losers probably have more momentum to continue losing over an intermediate period.

The returns from such a strategy are simply

$$\pi_t(k) = \sum_{i=1}^{N} w_{it}(k) R_{it}. \tag{2}$$

Plugging the weight function (1) into (2) and taking expectations yields the following:

$$E[\pi_t(k)] = \frac{\alpha}{SN} tr(\Gamma_k^w) + \frac{\beta}{SN} tr\left(\Gamma_k^l\right) + \frac{\alpha}{SN} \sum_{i=1}^{SN} \mu_i^2 + \frac{\beta}{SN} \sum_{i=N-SN+1}^{N} \mu_i^2 - \alpha E[R_{mt-1}(k) R_{wt}]$$
$$-\beta E[R_{mt-1}(k) R_{lt}]. \tag{3}$$

where tr($\cdot$) denotes the trace operator, Γ_k^l represents the autocovariance matrices for the loser portfolio, and Γ_k^w represents the autocovariance matrices for the winner portfolio[1]. $R_{wt} =$

[1] The derivation of Equation (3) is included in Appendix 1.

$\frac{1}{SN}\sum_1^{SN} R_{it}$ is the average return of the winner portfolio at time *t*, $R_{lt} = \frac{1}{SN}\sum_{N-SN+1}^{N} R_{it}$ is the average return of the loser portfolio at time *t*.

$$E[R_{mt-1}(k)R_{wt}] = \frac{\iota'\Gamma_k^w\iota}{SN^2} + S\mu_w^2 + \frac{\iota'\Gamma_k^{\bar{w}w}\iota}{SN^2} + (1-S)\mu_{\bar{w}}\mu_w, \qquad (4)$$

where $\mu_w = \frac{\sum_{i=1}^{SN}\mu_i}{SN}$ is the average expected return of the winner portfolio, $\mu_{\bar{w}} = \frac{\sum_{i=SN+1}^{N}\mu_i}{N-SN}$, is the average expected return of the nonwinner portfolio, $\Gamma_k^{\bar{w}w}$ represents the autocovariance matrices for the interaction of past nonwinners and winners, and ι is the identity of corresponding dimension, for example, $\iota'\Gamma_k^w\iota = \sum \Gamma_{ij}^w$. [2]

Similarly, $E[R_{mt-1}(k)R_{lt}] = \frac{\iota'\Gamma_k^l\iota}{SN^2} + S\mu_l^2 + \frac{\iota'\Gamma_k^{\bar{l}l}\iota}{SN^2} + (1-S)\mu_{\bar{l}}\mu_l \qquad (5)$

where $\mu_l = \frac{\sum_{i=N-SN+1}^{N}\mu_i}{SN}$ is the average expected return of the loser portfolio, $\mu_{\bar{l}} = \frac{\sum_{i=1}^{N-SN}\mu_i}{N-SN}$, is the average expected return of the nonloser portfolio, and $\Gamma_k^{\bar{l}l}$represents the autocovariance matrices for the interaction of past nonlosers and losers.

Combining Equation (3)-(5), we get[3]:

$$E[\pi_t(k)] = \frac{\alpha}{SN}tr(\Gamma_k^w) + \frac{\beta}{SN}tr(\Gamma_k^l) + \frac{\alpha}{SN}\sum_{i=1}^{SN}\mu_i^2 + \frac{\beta}{SN}\sum_{i=N-SN+1}^{N}\mu_i^2 - \alpha[\frac{\iota'\Gamma_k^w\iota}{SN^2} + S\mu_w^2 + \frac{\iota'\Gamma_k^{\bar{w}w}\iota}{SN^2}$$

$$+(1-S)\mu_{\bar{w}}\mu_w] - \beta[\frac{\iota'\Gamma_k^l\iota}{SN^2} + S\mu_l^2 + \frac{\iota'\Gamma_k^{\bar{l}l}\iota}{SN^2} + (1-S)\mu_{\bar{l}}\mu_l]$$

$$= \frac{\alpha}{SN}tr(\Gamma_k^w) + \frac{\beta}{SN}tr(\Gamma_k^l) - \left[\alpha\frac{(\iota'\Gamma_k^w\iota + \iota'\Gamma_k^{\bar{w}w}\iota)}{SN^2} + \beta\frac{(\iota'\Gamma_k^l\iota + \iota'\Gamma_k^{\bar{l}l}\iota)}{SN^2}\right] + \alpha\sigma^2(\mu^w) + \beta\sigma^2(\mu^l)$$

$$+\alpha(1-S)\mu_w^2 + \beta(1-S)\mu_l^2 - (1-S)(\alpha\mu_{\bar{w}}\mu_w + \beta\mu_{\bar{l}}\mu_l) \qquad (6)$$

The first two terms in Equation (6) are the cross-sectional averages of the weighted first-order time-series variance of the individual stock returns in the winner and loser portfolios,

[2] The derivation of Equation (4) is included in Appendix 2.
[3] The derivation of Equation (6) is included in Appendix 3.

respectively. If the market is efficient, then these two terms should equal zero. The third and fourth terms are the average first-order autocovariance between two stocks involving a winner or loser stock and another stock. If the stocks have a lead lag structure, in that the larger firm leads the smaller firm in responding to a specific common factor risk but in the same direction, then the cross-autocovariance is positive. The fifth and sixth terms are cross-sectional variances of the mean returns in the winner and loser portfolios. The size of the fifth and sixth terms increases with increased variation of the mean returns in the winner and loser portfolio. The rest of the terms are the summation of weighted products of expected returns. The fifth to ninth terms are independent of the autocovariances, Γ_k. To measure the role of the own-autocovariances, cross-autocovariances, and cross-sectional variances separately, we further arrange the terms in Equation (6) so that we decompose the expected momentum returns into different parts indicated above:

$$\begin{aligned}
E[\pi_t(k)] = & -\tfrac{\alpha}{SN^2}[\iota'\Gamma_k^w\iota - tr(\Gamma_k^w) + (1-N)tr(\Gamma_k^w) + \iota'\Gamma_k^{\bar{w}w}\iota] - \tfrac{\beta}{SN^2}[\iota'\Gamma_k^l\iota - tr(\Gamma_k^l) \\
& +(1-N)tr(\Gamma_k^l) + \iota'\Gamma_k^{\bar{l}l}\iota] + \alpha\sigma^2(\mu^w) + \beta\sigma^2(\mu^l) + \alpha(1-S)\mu_w^2 + \beta(1-S)\mu_l^2 \\
& -(1-S)(\alpha\mu_{\bar{w}}\mu_w + \beta\mu_{\bar{l}}\mu_l) \\
= & -\tfrac{\alpha}{SN^2}[\iota'\Gamma_k^w\iota - tr(\Gamma_k^w) + \iota'\Gamma_k^{\bar{w}w}\iota] - \tfrac{\beta}{SN^2}[\iota'\Gamma_k^l\iota - tr(\Gamma_k^l) + \iota'\Gamma_k^{\bar{l}l}\iota] \\
& + \tfrac{\alpha}{SN^2}(N-1)tr(\Gamma_k^w) + \tfrac{\beta}{SN^2}(N-1)tr(\Gamma_k^l) + \alpha\sigma^2(\mu^w) + \beta\sigma^2(\mu^l) + \alpha(1-S)\mu_w^2 \\
& +\beta(1-S)\mu_l^2 - (1-S)(\alpha\mu_{\bar{w}}\mu_w + \beta\mu_{\bar{l}}\mu_l)
\end{aligned}$$

We define $C_k = -\frac{\alpha}{SN^2}[\iota'\Gamma_k^w\iota - tr(\Gamma_k^w) + \iota'\Gamma_k^{\bar{w}w}\iota] - \frac{\beta}{SN^2}[\iota'\Gamma_k^l\iota - tr(\Gamma_k^l) + \iota'\Gamma_k^{\bar{l}l}\iota]$, which is the cross-autocovariance of individual stock returns, $O_k = \frac{\alpha}{SN^2}(N-1)tr(\Gamma_k^w) + \frac{\beta}{SN^2}(N-1)tr(\Gamma_k^l)$, is the own-autocovariance of individual stock returns, and $V_k = \alpha\sigma^2(\mu^w) + \beta\sigma^2(\mu^l)$, is the cross-sectional variance of mean returns in the winner and loser portfolios. Thus, the expected returns of the momentum strategy could be written as

$$E[\pi_t(k)] = C_k + O_k + V_k + \alpha(1-S)\mu_w^2 + \beta(1-S)\mu_l^2 - (1-S)(\alpha\mu_{\overline{w}}\mu_w + \beta\mu_{\overline{l}}\mu_l) \quad (7)$$

By deduction[4], we get

$$\alpha(1-S)\mu_w^2 + \beta(1-S)\mu_l^2 - (1-S)(\alpha\mu_{\overline{w}}\mu_w + \beta\mu_{\overline{l}}\mu_l) = \alpha\mu_w(\mu_w - \mu_m) + \beta\mu_l(\mu_l - \mu_m). \quad (8)$$

Let $L_k = \alpha\mu_w(\mu_w - \mu_m) + \beta\mu_l(\mu_l - \mu_m)$. Therefore,

$$\begin{aligned} E[\pi_t(k)] &= C_k + O_k + V_k + \alpha\mu_w(\mu_w - \mu_m) + \beta\mu_l(\mu_l - \mu_m) \\ &= C_k + O_k + V_k + L_k. \end{aligned} \quad (9)$$

Equation (9) shows clearly that the expected momentum returns could be decomposed into four parts: a) C_k is dependent on only off-diagonals of the autocovariance matrixΓ_k, which is the correlation between returns of two different stocks from two different time periods; b) O_k is dependent on only the diagonals of autocovariance matrixΓ_k, which is the correlation of own stock returns from two different time periods; c) V_k is independent of the autocovariance matrix Γ_k, which is the cross-sectional variances of the mean returns in the winner and loser portfolios for a given time period; and d) L_k is also independent of the autocovraiance matrix Γ_k, which is the weighted product of winner portfolio mean return and its deviation from the mean return of the whole portfolio plus the similar weighted product from the loser portfolio.

Equation (9) also indicates the scenarios in which the expected returns from the momentum strategy become positive. Since α, β, S are positive, V_k is always positive. The total number of stocks is greater than 1, so if the summation of the own-autocovariances of the stock returns in the winner and loser portfolios is positive, then O_k is positive. However, the link

[4] The derivation of Equation (8) is included in Appendix 4.

between the sign of O_k and stock return momentum is unclear. According to the definition of own-autocovariance, $O_k = E[(R_{t-1}(k) - \mu)(R_t(k) - \mu)]$, when stock returns at time t and $t - 1$are both greater or smaller than their mean, O_k is positive. Therefore, if O_k is positive, we cannot conclude that there is stock return momentum. For example, assume a past winner's mean return is 15%. Its stock return at time $t - 1$ is 10%, and *decreases* to 5% at time t . Therefore, its own-autocovariance is positive, even though the return of this winner stock declined in the current period. Similarly, if O_k is negative, we cannot conclude that there is return reversal. Stock return momentum is also possible when O_k is negative. For instance, assume a past winner's mean return is still 15%. Its stock return *increases* from 10% to 30% at time t. In this case, O_k is negative, but clearly, there is stock return momentum. To summarize, the sign of O_k cannot clearly indicate stock return momentum or reversal. However, if it is significantly different from zero, it indicates that stock returns are serially correlated, but with stock return pattern undetermined. Furthermore, the profitability of momentum strategy does not require stock return momentum. Of course, if there is return momentum, momentum strategy is more profitable. However, what is required in the momentum strategy is the stable relative ranking of the stocks. If past winners remain winners in the next period, even if their stock returns drop, or past losers stay as losers, even if their stock returns increase, the momentum strategy works. Therefore, the momentum strategy relies on the return predictability belief: winners continue to be winners and losers continue to be losers. The stock return momentum or reversal is not specified. If the correlations of two different stocks from two different times are positive, then C_k is negative. L_k is positive if the expected return of the winner portfolio is positive and higher than the market expected return, and simultaneously, the expected return of the loser portfolio is below zero and lower than the market expected return.

3.2. Circumstance in Generating Positive Momentum Returns

We further investigate a return generating process that can result in a positive return from the momentum strategy.

3.2a Returns follow random walk with starting point $\boldsymbol{\mu}$

Similar to Conrad and Kaul (1998), we allow returns R_{it} to follow a random walk with starting point μ, which was calculated as $R_{it} = \mu + e_{it}$, where e_{it} is white noise or is independently and identically distributed with 0 mean and constant variance. Thus, the stock returns R_{it} are serially independent. Now, we further assume the returns of different stocks are independent between different time periods. Therefore, Γ_k or both C_k and O_k are zero; hence, the momentum return can be written as

$$E[\pi_t(k)] = V_k + L_k = \alpha\sigma^2(\mu^w) + \beta\sigma^2(\mu^l) + \alpha\mu_w(\mu_w - \mu_m) + \beta\mu_l(\mu_l - \mu_m) \qquad (10)$$

V_k is always positive, if L_k is positive. Thus, even though the stock returns do not have cross-sectional or serial dependence, the momentum strategy can still generate positive returns. However, these positive returns do not come from the stock return predictability or stock price momentum. When the expected returns of the winner portfolio are positive and those of the loser portfolio are negative, the momentum strategy generates increasingly large returns as the winners win more and the losers lose more. In this scenario, even though the stock returns follow random walk or the financial market is efficient, the momentum strategy can still generate positive returns. Therefore, even if the returns from the momentum strategy are positive, we cannot directly conclude that they can be attributed to the stock price momentum. Under the above analysis of the return generating process we observe that the momentum returns are determined by the sign and magnitude of the four components. We could not verify the stock return predictability that winners continue to win and losers continue to lose simply from the fact that momentum returns are positive. Furthermore, we could not deny any stock return predictability if the momentum returns are negative. In the literature, both Lo and MacKinlay (1990) and Conrad and Kaul (1998) concluded under the random walk model that the momentum strategy could generate profits equal to the cross-sectional variance in mean returns of individual securities, $\sigma^2(\mu)$, even if stock returns are completely unpredictable. Similarly, zero or negative momentum returns do not imply zero autocovarance automatically. The only method to determining the possibility of stock return predictability is to decompose the momentum returns and empirically measure their component magnitudes directly.

IV. Empirical Results

4.1. An Empirical Appraisal of Momentum Returns

To measure the relative importance of stock price predictability in generating returns from the momentum strategy that we developed in Section III, we empirically decompose the momentum returns into four parts: average cross-autocovariances (C_k), average own-autocovariances (O_k), cross-sectional variances of the expected returns in the winner and loser portfolios (V_k), and the expected returns of the winner and loser portfolios (L_k). By investigating the composition of historical momentum returns directly, we reveal the sources and their relative importance in constituting the momentum returns. All the stocks listed in the NYSE & Amex, and Nasdaq markets are included in the study. The entire dataset includes over 27,000 stocks that have been traded in the U.S. stock market over the past 44-years period, from January 1965 to December 2009. The data on stock returns were collected from the Center for

Research in Security Prices (CRSP) Monthly Stock File for NYSE, Amex, and Nasdaq stocks. Because the trading environments in NYSE and NASDAQ markets are different, stocks in NYSE and Nasdaq markets are also investigated separately to evaluate the influence from market differences.

4.1a Return decomposition

To find a potential pattern between the length of the ranking period *k* and the resulting component weights, different ranking periods *k* equal to 3, 6, 9, and 12 months are examined separately. The default weight parameters for the winner and loser portfolios are set to equal 1 $(\alpha = \beta = 1)$ in Equation (1). In addition, two types of momentum strategies are investigated empirically. One is the rolling strategy, which is very similar to the most frequently investigated momentum strategy. This strategy includes overlapping holding periods. In any given month *t*, the strategy holds a series of portfolios that are selected in the current month as well as in the previous *k* months if there are no skip months. The other strategy has no overlapping holding periods, and it was used in the Lo and Mackinlay (1990) paper.

As the entire time span of 44 years is a rather long time period, four 10-year periods are investigated separately to capture any potential change in the market environment. Before 1995, there were invisibly small amounts of short-selling activities in the U. S. market. Because short sales have been argued as a necessity in correcting overpriced assets, the short-selling level can potentially affect momentum returns from the loser portfolio. It is also well known that in the 2005, to gather data and study thoroughly the effect of the uptick rule on market volatility, price efficiency and liquidity, the SEC implemented a Pilot Program from May 2, 2005 to July 3, 2007.

This Pilot Program suspended the uptick rule[5] on one-third of Russell 3000 Index constituent stocks with high levels of liquidity. On July 3, 2007, the SEC finally abolished Rule 10a-1 and any rule of exchanges, including NASDAQ 3350, which applied a bid test on short sales (Bai, 2007). Therefore, this Pilot Program and the abolition of these price tests may improve the trading environment for short sales, which makes the correction of stock overpricing easier and hence affects the momentum returns from the loser portfolio. Therefore, years 1994 and 2004 were set as two cut-off points for the 10 year sub periods.

Table 1 demonstrates both the magnitudes and weights of the four components in the momentum returns. C_k depends only on cross-autocovariances in which one stock's return may be correlated to another stock's return in the previous period. O_k depends only on own-autocovariances, which is also interpreted as stock price predictability. V_k is the cross-sectional variation of the expected returns in the winner and loser portfolios for a given time. L_k depends on the expected returns in the winner and loser portfolios. Of these four components, only O_k directly challenges the efficient market hypothesis that states that stock price has no memory. In our empirical testing, the expected returns of the stocks are estimated using the average returns over the entire time span. Because it is less likely that the expected stock returns remain the same over the entire 44-year time span, investigating shorter time periods, such as 10 years, becomes very meaningful. Because the momentum returns are time-series, all of the t tests are adjusted for potential autocorrelation and heteroskedasticity by using the method of Kiefer and Bogelsang (2002).

[5] The Securities and Exchange Commission (SEC) had Rule 10a-1 under the Security Exchange Act of 1934, which provided that investors must sell short a listed stock either at a price above the preceding sale price, known as the plus tick or at the last sale price if it was higher than the last different price, known as the zero plus tick. Similarly, NASDAQ Rule 3350 provided that short sales in NASDAQ stocks be either higher or at the best bid when the best bid was below the preceding best bid (Bai, 2007)

Table 1 shows that for rolling momentum strategies, the major determinant of the momentum return is O_k, the autocorrelation of own stock returns. This measure is significant most of the time at the 10 percent level and determines momentum returns to a great extent. In comparison to O_k, two different stocks' correlation between two different times, C_k, constitutes a very small amount in the momentum returns and are much less frequently significant at the 10 percent level. Furthermore, the consistently negative sign of O_k shows that the trace of Γ_k in Equation (28) is negative[6]. As analyzed in the previous section, the negative own stock return autocorrelation does not specify whether the stock returns show a momentum or reversal pattern. However, given the magnitude and significance of O_k, it is an important determinant of returns from the momentum strategy. More interestingly, the magnitude of O_k decreases as the ranking period *k* moves further away for all subperiods and the entire time span in the rolling strategy. This pattern is logical.. Stock return predictability suggesting that winners continue to be winners and losers continue to be losers should weaken as the reference point of time becomes more remote. Such pattern is not observed in the other three components. The second most significant component is V_k, the cross-sectional variance of expected returns in the winner and loser portfolios at a given time. Conrad and Kaul (1998) suggested that cross-sectional variance of expected returns was the main contributor to the momentum returns. However, Jegadeesh and Titman (1999) argue that the large magnitude of V_k in Conrad and Kaul (1998) is due to the measurement error of expected returns. L_k is significant most of the times; however, its weight is much smaller than O_k and V_k. Berk, Green and Naik (1999) argue that L_k is the main

[6] Conrad and Kaul (1998) decompose the expected returns from the momentum strategy. They denote the summation of C_k and O_k as P_k. The empirical results of P_k show that P_k is consistently negative. However, we cannot know the sign of C_k and O_k individually from their paper. So we do not know whether they get negative $O_k$too as we do.

contributor of the momentum returns. They explain that change of a firm's systematic risk causes the change of firm-specific variables and thus the cross-sectional variation of expected return.

The sub-time periods all demonstrate similar patterns. However, the components are more frequently significant and at a higher significant level in recent years. In the second sub-time period from year 1965 to year 1974, none of the components was significant. It should be a volatile market period during which the stock returns had minimal connections. The nonrolling strategy demonstrates similar results, albeit at lower levels of significance. In the nonrolling strategy, both O_k and V_k are the two most important components in terms of their weights in the momentum returns. As observed for the rolling strategy, L_k is significant most of the time, albeit with a much smaller weight. To summarize, the data in Table I indicates that stock returns do have memory to some extent, and taking advantage of this phenomenon can generate profits. This does challenge the market efficiency hypothesis to some extent. In addition, cross-sectional variance of expected returns in the winner and loser portfolios is another important source of momentum returns.

It is often observed in the momentum literature that when Nasdaq stocks are included in the portfolio, the returns of the momentum strategy decrease dramatically. Table 2 decomposes momentum returns for NYSE & AMEX stocks only to take advantage of market differences. Both rolling and nonrolling strategies are investigated for the entire time span from 1965 to 2009 and for different ranking periods k. Similar patterns are observed as those in Table 1. O_k and V_k are the two most important sources for the returns from the momentum strategy and are significant for most of the cases. The magnitude of O_k decreases as the ranking period moves remote. L_k is significant most of times but with a much smaller weight. In the nonrolling strategy, O_k and V_k remain the two most important sources of the momentum returns. However, O_k is not significant at the 10 percent level.

Additionally, a few recent papers noted the following: (1) the proportional contributions of the winner and the loser portfolios to the momentum abnormal returns are indeed asymmetric (Hong, Lim and Stein, 2000, Lesmond, Schill and Zhou, 2004); and (2) the characteristics of the loser firms are quite unique. Unlike the winners, the stocks that generate the bulk of the momentum abnormal returns are the "losers" that can be characterized as small, low-price, high-beta, off-NYSE stocks. Those stocks are typically hard to sell short and involve high trading costs (Lesmond, Schill and Zhou, 2004). To investigate the different influences of the winner and loser portfolios on the momentum returns, we also change the weight parameters α or β for winner and loser portfolios individually to examine their different effects on the sources of momentum returns. Table 3 presents the magnitudes and weights of the four components by increasing the weight of winner or loser portfolio monotonically while keeping the weight of the other portfolio constant. To investigate only the effects from the different weights of the winner and loser portfolios, the ranking period k is fixed at six. Specifically, the rolling momentum strategy (6,0,1) is used in the analysis from January 1965 to December 2009 for NYSE & AMEX stocks only. Panel A shows the results with increasing weights for the loser portfolio from β= 1 to 10 or 50 while keeping the winner portfolio weight constant. The relative contributions of the components to the momentum returns remain in proportion when the weight of the loser portfolio increases. This indicates that the magnitude of the average own-autocovariance of the winner portfolio in the holding period is negligible compared to that of the loser portfolio. Both the own-autocovariances in the winner and loser portfolios took on a negative sign (data not shown). However, the magnitude of the winner portfolio is about 20-fold smaller than that of the loser portfolio. This phenomenon is observed in all the four ranking periods. For example, at k=6, the average own-autocovariances of the winner and loser portfolios are −0.00009765 and −0.0020, respectively. Therefore, the returns of the winner portfolio stocks are much more random than that of the loser portfolio stocks and thus have a much weaker pattern to track over time. In Panel B, the winner portfolio weight is increased while keeping the loser portfolio weight constant. The magnitude of own-autocovariance does not change substantially. Hence, winners' return pattern is much less related over time or is more random than the loser portfolio. Conversely, the loser portfolio has stronger return patterns in terms of own stock autocovariance. These results obtained from the expected return decomposition clearly provide an underlying explanation to the recent finding that the loser rather than the winner portfolio is the major contributor to momentum returns. Therefore, to buy long and take advantage of the return pattern from the winner portfolio is much less reliable than selling short and exploiting the much stronger return predictability in the loser portfolio.

4.1b Empirical comparison of our model and the model in Lo and MacKinlay (1990)

The key difference between our model and the Lo & MacKinlay (1990) model is the weighting scheme. Our momentum strategy includes only the top winners and bottom losers; however, Lo & MacKinlay (1990) included all of the stocks in their portfolio. According to our weighting scheme, our momentum strategy places more weight on the potential stronger stock return patterns because the top winners and bottom losers have a stronger tendency to maintain their return patterns in the next period. Without including the intermediate portfolio stocks, our momentum strategy reduces the noise in the stock return patterns from the middle group stocks.

Table 4 illustrates the empirical decomposition for the Lo & MacKinlay (1990) weighting scheme. Both the rolling and nonrolling momentum strategies with different ranking periods k are attempted for stocks listed in the NYSE & AMEX indices over the 44-year time span from 1965 to 2009. The key difference in the empirical results of the momentum strategy of Lo & MacKinlay (1990) and our momentum strategy is that the average autocorrelation of own stock returns O_k becomes much less important in explaining the momentum returns. Furthermore, it is less frequently significant at the 10 percent level. This phenomenon can be explained by the different weighting schemes. The top winners and bottom losers have a stronger tendency to continue the current return patterns; therefore, by including only those top and bottom performers, the magnitude of average own stock autocorrelation tends to be higher.

V. Conclusions

Momentum strategies that take advantage of potential return predictability have puzzled finance researchers in the past twenty years. Heated dispute about whether the market is efficient makes this topic even more attractive. Instead of trying to identify unknown risk factors or behavioral theories that can fully explain momentum returns, our study attempts to decompose the momentum returns directly and use historical data to discover the sources of the momentum returns and their relative importance in generating the momentum returns.

Lo and MacKinlay (1990) proposed that the positive cross-autocovariance or the lead-lag structure, rather than the small magnitude of the negative autocorrelation, drives the positive contrarian portfolio returns. Conrad and Kaul (1998) further found in their return decomposition that the positive cross-sectional variance in mean returns is responsible for the profitability of the momentum strategy. However, Lehmann (1990) and Jegadeesh (1990) argued that the first-order serial correlation in stock returns is the major contributor to the contrarian returns.

Our empirical results demonstrate that autocorrelation of own stock returns is one of the driving forces for the momentum expected returns. The magnitude of the own-autocorrelation decreases as the ranking period becomes more remote. The second important source comes from the cross-sectional variance of the mean return in the winner and loser portfolios at a given time. The third important source is the difference in the expected returns between the winner and loser portfolios. To our surprise, the cross-autocovariance does not contribute much to the momentum expected returns. Thus, the lead-lag effect can generate momentum returns, but its effect is not as significant as we previously thought.

Furthermore, by changing the weights of the winner and loser portfolios, we find that the return pattern of the winner portfolio is much weaker than that of the loser portfolio. On the contrary, the loser portfolio retains a much stronger return pattern from the ranking period to the holding period. This provides further evidence to explain the recent finding that the loser portfolio is the major contributor to the momentum returns. Therefore, the market may not be as efficient as we previously believed

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Table 1. Return Decomposition with All Stocks in the U.S. Market

Decomposition of monthly returns from momentum strategies with a sample of all stocks in the NYSE, AMEX, and Nasdaq from January 1965 to December 2009. To capture the possible change of expected returns over the whole 44 years and to take into account of the potential change of trading environment, 10 year subperiods are also investigated. Panel A lists the magnitudes and weights of the four components and the size of the expected momentum returns for the rolling momentum strategy. Panel B lists the results for nonrolling momentum strategy. Different ranking periods (k) are examined with k=3, 6, 9, 12 months respectively. The default weight parameters for the winner and loser portfolios are $\alpha = \beta = 1$. The table reports t-statistics in parentheses, adjusted for heteroskedasticity and autocorrelation by using Kiefer and Bogelsang (2002) approach. Significance at the 1%, 5% and 10% levels is indicated by a, b and c, respectively.

Lag(k)	C_k	O_k	V_k	L_k	$E[\pi_k(k)]$	$\%C_k$	$\%O_k$	$\%V_k$	$\%L_k$
Panel A: Rolling strategy with winners and losers scheme									
a)1965~~2009									
3	-0.0001	-0.0053	0.0012	0.0001	-0.0042	2%	126%	-29%	-2%
	(-0.94)	(-6.93)[a]	(5.99)[b]	(9.42)[a]	(-8.72)[a]				
6	0.0002	-0.0038	0.0012	0.0001	-0.0027	-7%	141%	-44%	-4%
	(1.23)	(-4.64)[c]	(5.99)[b]	(14.01)[a]	(-5.14)[b]				
9	0.0004	-0.0034	0.0013	0.0001	-0.0015	-27%	227%	-87%	7%
	(4.28)[c]	(-5.09)[b]	(5.96)[b]	(10.10)[a]	(-4.34)[c]				
12	0.0003	-0.0027	0.0013	0.0001	-0.0010	-30%	270%	-130%	-10%
	(2.12)	(-3.87)	(6.01)[b]	(8.35)[a]	(-2.83)				
b)*1965-1974*									
3	-0.0001	-0.0024	0.0009	0.0005	-0.0011	9%	218%	-82%	-45%
	(-0.27)	(-1.54)	(3.67)	(2.19)	(-1.56)				
6	-0.0002	-0.0012	0.0009	0.0006	0.0001	-200%	-1200%	900%	600%
	(-0.93)	(-1.26)	(3.70)	(2.08)	(0.27)				
9	0.0003	-0.0016	0.0009	0.0007	0.0003	100%	-533%	300%	233%
	(2.08)	(-2.56)	(3.69)	(2.01)	(1.90)				
12	0.0001	-0.0012	0.0009	0.0008	0.0006	5%	-40%	30%	25%
	(1.04)	(-1.97)	(3.79)[c]	(1.98)	(3.61)				
c)1975-1984									
3	0.0001	-0.0071	0.0015	0.0003	-0.0052	-17%	137%	-29%	-6%
	(0.13)	(-4.56)[c]	(4.88)[b]	(3.23)	(-4.29)[c]				
6	0.0005	-0.0045	0.0016	0.0004	-0.0021	-24%	214%	-76%	-19%
	(-0.01)	(-5.18)[b]	(4.59)[b]	(5.85)[b]	(-3.14)				
9	0.0007	-0.0039	0.0016	0.0005	-0.0011	-64%	355%	-145%	-45%
	(1.07)	(-3.18)	(4.90)[b]	(6.11)[a]	(-1.52)				
12	0.0005	-0.0030	0.0016	0.0006	-0.0003	-167%	1000%	-533%	-200%
	(1.43)	(-4.44)[c]	(5.23)[b]	(5.29)[b]	(-0.81)				

Table 1. (continued)

Lag(k)	C_k	O_k	V_k	L_k	$E[\pi_k(k)]$	$\%C_k$	$\%O_k$	$\%V_k$	$\%L_k$
d)1985-1994									
3	-0.0001	-0.0089	0.0023	0.0002	-0.0065	2%	137%	-35%	-3%
	(-1.40)	(-17.81)[a]	(7.63)[a]	(6.69)[a]	(-8.64)[a]				
6	0.0004	-0.0069	0.0024	0.0003	-0.0037	-11%	186%	-65%	-8%
	(4.30)[c]	(-10.40)[a]	(7.87)[a]	(7.94)[a]	(-4.29)[c]				
9	0.0007	-0.0061	0.0024	0.0004	-0.0026	-27%	235%	-92%	-7%
	(5.32)[b]	(-10.80)[a]	(8.28)[a]	(9.21)[a]	(-3.22)				
12	0.0003	-0.0047	0.0024	0.0004	-0.0015	-20%	313%	-160%	-27%
	(2.90)	(-13.43)[a]	(7.68)[a]	(8.70)[a]	(-2.53)				
e)1995-2004									
3	0.0009	-0.0092	0.0028	0.0002	-0.0053	-17%	174%	-53%	-4%
	(2.46)	(-8.14)[a]	(6.98)[a]	(12.10)[a]	(-6.30)[a]				
6	0.0010	-0.0069	0.0029	0.0003	-0.0026	-38%	265%	-112%	-12%
	(4.66)[c]	(-10.99)[a]	(7.33)[a]	(22.19)[a]	(-5.21)[b]				
9	0.0008	-0.0059	0.0029	0.0004	-0.0018	44%	328%	161%	22%
	(5.63)[b]	(-10.92)[a]	(8.00)[a]	(23.88)[a]	(-2.93)				
12	0.0008	-0.0054	0.0029	0.0004	-0.0012	-67%	450%	-242%	-33%
	(6.41)[a]	(-9.03)[a]	(8.88)[a]	(20.31)[a]	(-1.60)				
Panel B: Nonrolling strategy with winners and losers scheme									
a)1965~~2009									
3	-0.0002	-0.0017	0.0011	0.0001	-0.0007	29%	243%	-157%	-14%
	(-1.52)	(-5.52)[b]	(5.83)[b]	(8.06)[a]	(-2.95)				
6	-0.0000	-0.0009	0.0012	0.0001	0.0004	-0%	-225%	300%	25%
	(-0.29)	(-3.77)[c]	(5.51)[b]	(13.69)[a]	(1.93)				
9	-0.0003	-0.0004	0.0013	0.0001	0.0007	-43%	-57%	186%	14%
	(-2.53)	(-0.84)	(6.29)[a]	(15.89)[a]	(3.15)				
12	-0.0001	-0.0016	0.0013	0.0001	-0.0003	33%	533%	-433%	-33%
	(-2.50)	(-2.72)	(5.26)[b]	(9.73)[a]	(-1.00)				
b)*1965-1974*									
3	0.0005	-0.0015	0.0009	0.0004	0.0002	250%	-750%	450%	200%
	(0.87)	(-1.17)	(3.81)[c]	(2.27)	(0.57)				
6	-0.0001	-0.0006	0.0009	0.0004	0.0006	-17%	-100%	150%	67%
	(-0.85)	(-1.42)	(4.13)[a]	(2.18)	(2.58)				
9	-0.0001	-0.0006	0.0011	0.0008	0.0011	-9%	-55%	100%	73%
	(-0.55)	(-0.99)	(3.35)	(1.94)	(4.76)[c]				
12	0.0002	-0.0010	0.0009	0.0005	0.0005	40%	-200%	180%	100%
	(0.54)	(-1.63)	(4.51)[c]	(1.98)	(0.81)				

Table 1. (continued)

Lag(k)	C_k	O_k	V_k	L_k	$E[\pi_k(k)]$	$\%C_k$	$\%O_k$	$\%V_k$	$\%L_k$
c)1975-1984									
3	-0.0001	-0.0031	0.0015	0.0003	-0.0014	7%	221%	-107%	-21%
	(-0.21)	(-1.95)	(5.23)[b]	(2.95)	(-1.31)				
6	0.0007	-0.0026	0.0017	0.0004	0.0002	350%	-1300%	850%	200%
	(0.85)	(-1.98)	(5.73)[b]	(4.28)[c]	(0.42)				
9	-0.0002	-0.0007	0.0016	0.0005	0.0013	-15%	-54%	123%	38%
	(-3.01)	(-2.29)	(3.90)[c]	(6.56)[a]	(5.43)[b]				
12	-0.0001	-0.0014	0.0020	0.0006	0.0010	-10%	-140%	200%	60%
	(-1.10)	(-4.40)[c]	(6.52)[a]	(5.41)[b]	(2.39)				
d)1985-1994									
3	0.0002	-0.0049	0.0024	0.0002	-0.0022	-9%	223%	-109%	-9%
	(-0.21)	(-1.95)	(5.23)[b]	(2.95)	(-1.31)				
6	0.0006	-0.0037	0.0025	0.0003	-0.0003	-200%	1233%	-833%	-100%
	(2.24)	(-4.95)[b]	(5.35)[b]	(6.90)[a]	(-0.23)				
9	-0.0004	-0.0009	0.0026	0.0004	0.0016	-25%	-56%	163%	25%
	(-4.51)[c]	(-0.96)	(5.41)[b]	(10.26)[a]	(1.16)				
12	-0.0002	-0.0029	0.0029	0.0004	0.0002	-100%	-1450%	1450%	200%
	(-1.31)	(-1.76)	(4.04)[c]	(14.04)[a]	(0.10)				
e)1995-2004									
3	0.0004	-0.0034	0.0029	0.0002	0.0001	400%	-3400%	2900%	200%
	(1.91)	(-5.83)[b]	(5.47)[b]	(12.84)[a]	(0.13)				
6	-0.0006	-0.0006	0.0034	0.0003	0.0025	-24%	-24%	136%	12%
	(-2.58)	(-1.10)	(4.38)[c]	(15.66)[a]	(3.10)				
9	-0.0001	-0.0020	0.0037	0.0004	0.0020	-5%	-100%	185%	20%
	(-0.32)	(-2.87)	(3.94)[c]	(18.52)[a]	(1.39)				
12	-0.0002	-0.0038	0.0044	0.0004	0.0008	-25%	-475%	550%	50%
	(-1.28)	(-2.51)	(3.10)	(15.50)[a]	(0.29)				

Table 2. Return Decomposition with NYSE & AMEX Stocks Only
Decomposition of monthly returns from momentum strategies with stocks listed only in NYSE, and AMEX markets from January 1965 to December 2009. Panel A lists the magnitudes and weights of the four components and the size of the expected momentum returns for the rolling momentum strategy. Panel B lists the results for nonrolling momentum strategy. Different ranking periods (k) are examined with k=3, 6, 9, 12 months respectively. The default weight parameters for the winner and loser portfolios are $\alpha = \beta = 1$. The table reports *t*-statistics in parentheses, adjusted for heteroskedasticity and autocorrelation by using Kiefer and Bogelsang (2002) approach. Significance at the 1%, 5% and 10% levels is indicated by a, b and c, respectively.

Lag(k)	C_k	O_k	V_k	L_k	$E[\pi_k(k)]$	$\%C_k$	$\%O_k$	$\%V_k$	$\%L_k$
Panel A: Rolling strategy with winners and losers scheme									
3	-0.0002	-0.0031	0.0006	0.0000	-0.0026	8%	119%	-23%	-0%
	(-2.04)	(-8.63)[a]	(4.31)[c]	(1.94)	(-10.46)[a]				
6	0.0002	-0.0021	0.0007	0.0000	-0.0013	-15%	162%	-54%	-0%
	(1.44)	(-3.98)[c]	(4.23)[c]	(4.92)[b]	(-4.28)[c]				
9	0.0003	-0.0019	0.0007	0.0001	-0.0008	-38%	238%	-88%	-13%
	(6.10)[a]	(-4.08)[c]	(4.22)[c]	(7.19)[a]	(-3.12)				
12	0.0002	-0.0013	0.0007	0.0001	-0.0004	-50%	325%	-175%	-25%
	(1.68)	(-2.45)	(4.21)[c]	(6.95)[a]	(-1.34)				
Panel B: Nonrolling strategy with winners and losers scheme									
3	-0.0001	-0.0009	0.0006	0.0000	-0.0004	25%	225%	-150%	-0%
	(-0.83)	(-3.01)	(4.30)[c]	(1.74)	(-1.40)				
6	0.0001	-0.0004	0.0007	0.0000	0.0004	25%	-100%	175%	0%
	(0.51)	(-2.69)	(4.13)[c]	(4.59)[c]	(2.44)				
9	-0.0001	0.0000	0.0007	0.0001	0.0007	-14%	0%	100%	14%
	(-0.63)	(0.01)	(4.45)[c]	(6.61)[a]	(2.86)				
12	-0.0001	-0.0005	0.0007	0.0001	0.0002	-50%	-250%	350%	50%
	(-1.45)	(-1.85)	(4.29)[c]	(7.35)[a]	(1.52)				

Table 3. Return Decomposition with Change of Weights

Decomposition of monthly returns from rolling momentum strategies with stocks listed only in NYSE, and AMEX markets from January 1965 to December 2009. Different combination of α, β are examined with a fixed ranking period k=6. Panel A lists the magnitudes and weights of the four components and the size of the expected momentum returns for the rolling momentum strategy. Panel B lists the results for nonrolling momentum strategy. The table reports *t*-statistics in parentheses, adjusted for heteroskedasticity and autocorrelation by using Kiefer and Bogelsang (2002) approach. Significance at the 1%, 5% and 10% levels is indicated by a, b and c, respectively.

(α,β)	C_k	O_k	V_k	L_k	$E[\pi_k(k)]$	$\%C_k$	$\%O_k$	$\%V_k$	$\%L_k$
Panel A: Increasing loser portfolio weight with constant winner portfolio weight									
(1, 1)	0.0002	-0.0021	0.0007	0.0000	-0.0013	-15%	162%	-54%	-0%
	(1.44)	(-3.98)[c]	(4.23)[c]	(4.92)[b]	(-4.28)[c]				
(1, 10)	0.0028	-0.0206	0.0050	-0.0001	-0.0129	-22%	160%	-39%	1%
	(2.71)	(-3.94)[c]	(3.84)[c]	(-3.77)[c]	(-4.28)[c]				
(1, 50)	0.0144	-0.0124	0.0242	-0.0008	0.0254	57%	-49%	95%	-3%
	(2.81)	(-3.93)[c]	(3.79)[c]	(-6.08)[a]	(4.26)[c]				
Panel B: Increasing winner portfolio weight with constant loser portfolio weight									
(1, 1)	0.0002	-0.0021	0.0007	0.0000	-0.0013	-15%	162%	-54%	-0%
	(1.44)	(-3.98)[c]	(4.23)[c]	(4.92)[b]	(-4.28)[c]				
(10, 1)	-0.0010	-0.0030	0.0024	0.0006	-0.0011	91%	273%	-218%	-55%
	(-2.36)	(-3.13)	(5.28)[b]	(9.05)[a]	(-1.48)				
(50, 1)	-0.0063	-0.0069	0.0103	0.0028	-0.0001	6300%	6900%	-10300%	-2800%
	(-2.95)	(-1.86)	(5.69)[b]	(9.54)[a]	(-0.03)				

Table 4. Return Decomposition following Lo & MacKinlay (1990)

Decomposition of monthly returns from momentum strategies with stocks listed only in NYSE, and AMEX markets from January 1965 to December 2009. The weighting scheme follows the Lo and MacKinlay (1990) paper with all the stocks included in the portfolio. Panel A lists the magnitudes and weights of the four components and the size of the expected momentum returns for the rolling momentum strategy. Panel B lists the results for nonrolling momentum strategy. Different ranking periods (k) are examined with k=3, 6, 9, 12 months respectively. The default weight parameters for the winner and loser portfolios are $\alpha = \beta = 1$. The table reports *t*-statistics in parentheses, adjusted for heteroskedasticity and autocorrelation by using Kiefer and Bogelsang (2002) approach. Significance at the 1%, 5% and 10% levels is indicated by a, b and c, respectively.

Lag(k)	C_k	O_k	V_k	$E[\pi_k(k)]$	$\%C_k$	$\%O_k$	$\%V_k$
Panel A: Rolling strategy with all stocks included							
3	-0.0001	-0.0002	0.0002	-0.0002	50%	100%	-100%
	(-2.97)	(-4.15)[c]	(5.66)[b]	(-8.49)[a]			
6	-0.0000	-0.0002	0.0002	-0.0001	0%	200%	-200%
	(-0.82)	(-2.59)	(5.55)[b]	(-2.66)			
9	0.0000	-0.0002	0.0002	-0.0000	-0%	2000%	-2000%
	(2.76)	(-4.33)[c]	(5.47)[b]	(-0.62)			
12	0.0001	-0.0001	0.0002	0.0000	1000%	-1000%	2000%
	(0.32)	(-1.58)	(5.41)[b]	(2.03)			
Panel B: Nonrolling strategy with all stocks included							
3	-0.0001	-0.0001	0.0002	0.0000	-1000%	-1000%	2000%
	(-0.72)	(-0.68)	(5.73)[b]	(1.29)			
6	0.0000	-0.0001	0.0002	0.0001	0%	-100%	200%
	(0.68)	(-1.24)	(5.37)[b]	(4.81)[b]			
9	-0.0000	0.0000	0.0002	0.0002	-0%	0%	100%
	(-0.22)	(0.19)	(5.46)[b]	(7.01)[a]			
12	-0.0000	-0.0000	0.0002	0.0001	-0%	-0%	200%
	(-0.69)	(-0.39)	(5.35)[b]	(8.97)[a]			

APPENDIX

Appendix 1: Derivation of Equation (3)

$$E[\pi_t(k)] = \frac{\alpha}{SN}\sum_{i=1}^{SN} E[(R_{it-1}(k) - R_{mt-1}(k))R_{it}] + \frac{\beta}{SN}\sum_{i=N-SN+1}^{N} E[(R_{it-1}(k)$$

$$-R_{mt-1}(k))R_{it}]$$

$$= \frac{\alpha}{SN}\textstyle\sum_{i=1}^{SN} E[R_{it-1}(k)R_{it}] + \frac{\beta}{SN}\sum_{i=N-SN+1}^{N} E[R_{it-1}(k)R_{it}] - \alpha E[R_{mt-1}(k)R_{wt}]$$

$$-\beta E[R_{mt-1}(k)R_{lt}]$$

$$= \frac{\alpha}{SN}\textstyle\sum_{i=1}^{SN}(Cov[R_{it-1}(k), R_{it}] + \mu_i^2) + \frac{\beta}{SN}\sum_{i=N-SN+1}^{N}(Cov[R_{it-1}(k), R_{it}] + \mu_i^2)$$

$$-\alpha E[R_{mt-1}(k)R_{wt}] - \beta E[R_{mt-1}(k)R_{lt}]$$

$$= \frac{\alpha}{SN}tr(\Gamma_k^w) + \frac{\beta}{SN}tr(\Gamma_k^l) + \frac{\alpha}{SN}\textstyle\sum_{i=1}^{SN}\mu_i^2 + \frac{\beta}{SN}\sum_{i=N-SN+1}^{N}\mu_i^2 - \alpha E[R_{mt-1}(k)R_{wt}]$$

$$-\beta E[R_{mt-1}(k)R_{lt}].$$

Appendix 2: Derivation of Equation (4)

$$E[R_{mt-1}(k)R_{wt}] = E[\frac{(\sum_{i=1}^{SN} R_{it-1}(k) + \sum_{i=SN+1}^{N} R_{it-1}(k))\sum_{i=1}^{SN} R_{it}}{N*SN}]$$

$$= SE\left[\frac{\sum_{i=1}^{SN} R_{it-1}(k)\sum_{i=1}^{SN} R_{it}}{S^2N^2}\right] + (1-S)E[\frac{\sum_{i=SN+1}^{N} R_{it-1}(k)\sum_{i=1}^{SN} R_{it}}{(N-NS)*NS}]$$

$$= SE[R_{wt-1}(k)R_{wt}] + (1-S)E[R_{\overline{w}t-1}(k)R_{wt}]$$

$$= S[Cov(R_{wt-1}(k), R_{wt}) + \mu_w^2] + (1-S)[Cov(R_{\overline{w}t-1}(k), R_{wt}) + \mu_{\overline{w}}\mu_w]$$

$$= S\frac{\iota'\Gamma_k^w\iota}{(SN)^2} + S\mu_w^2 + (1-S)\frac{\iota'\Gamma_k^{\overline{w}w}\iota}{(N-SN)SN} + (1-S)\mu_{\overline{w}}\mu_w$$

$$= \frac{\iota'\Gamma_k^w\iota}{SN^2} + S\mu_w^2 + \frac{\iota'\Gamma_k^{\overline{w}w}\iota}{SN^2} + (1-S)\mu_{\overline{w}}\mu_w,$$

Appendix 3: Derivation of Equation (6)

$$E[\pi_t(k)] = \frac{\alpha}{SN}tr(\Gamma_k^w) + \frac{\beta}{SN}tr(\Gamma_k^l) + \frac{\alpha}{SN}\textstyle\sum_{i=1}^{SN}\mu_i^2 + \frac{\beta}{SN}\sum_{i=N-SN+1}^{N}\mu_i^2 - \alpha[\frac{\iota'\Gamma_k^w\iota}{SN^2} + S\mu_w^2 + \frac{\iota'\Gamma_k^{\overline{w}w}\iota}{SN^2}$$

$$+(1-S)\mu_{\bar{w}}\mu_w] - \beta[\tfrac{\iota'\Gamma_k^l\iota}{SN^2} + S\mu_l^2 + \tfrac{\iota'\Gamma_k^{\bar{l}l}\iota}{SN^2} + (1-S)\mu_{\bar{l}}\mu_l]$$

$$= \frac{\alpha}{SN} tr(\Gamma_k^w) + \frac{\beta}{SN} tr\left(\Gamma_k^l\right) - \left[\alpha\frac{\left(\iota\Gamma_k^w\iota + \iota\Gamma_k^{\bar{w}w}\iota\right)}{SN^2} + \beta\frac{\left(\iota\Gamma_k^l\iota + \iota\Gamma_k^{\bar{l}l}\iota\right)}{SN^2}\right] + \frac{\alpha}{SN}\sum_{i=1}^{SN}\mu_i^2$$

$$+ \frac{\beta}{SN}\sum_{i=N-SN+1}^{N}\mu_i^2 - S(\alpha\mu_w^2 + \beta\mu_l^2) - (1-S)(\alpha\mu_{\bar{w}}\mu_w + \beta\mu_{\bar{l}}\mu_l).$$

Since $\frac{\alpha}{SN}\sum_{i=1}^{SN}\mu_i^2 - S\alpha\mu_w^2 = \alpha\left[\frac{\sum_{i=1}^{SN}\mu_i^2}{SN} - \mu_w^2\right] + \alpha\mu_w^2 - \alpha S\mu_w^2$

$$= \alpha\left[\frac{1}{SN}\sum_{i=1}^{SN}(\mu_i - \mu_w)^2\right] + \alpha(1-S)\mu_w^2$$

$$= \alpha\sigma^2(\mu^w) + \alpha(1-S)\mu_w^2$$

Similarly, $\frac{\beta}{SN}\sum_{i=N-SN+1}^{N}\mu_i^2 - S\beta\mu_l^2 = \beta\left[\frac{1}{SN}\sum_{i=N-SN+1}^{N}(\mu_i - \mu_l)^2\right] + \beta(1-S)\mu_l^2$

$$= \beta\sigma^2(\mu^l) + \beta(1-S)\mu_l^2$$

Therefore,

$$E[\pi_t(k)] = \frac{\alpha}{SN}tr(\Gamma_k^w) + \frac{\beta}{SN}tr\left(\Gamma_k^l\right) - \left[\alpha\frac{\left(\iota'\Gamma_k^w\iota + \iota'\Gamma_k^{\bar{w}w}\iota\right)}{SN^2} + \beta\frac{\left(\iota'\Gamma_k^l\iota + \iota'\Gamma_k^{\bar{l}l}\iota\right)}{SN^2}\right] + \alpha\sigma^2(\mu^w) + \beta\sigma^2(\mu^l)$$

$$+\alpha(1-S)\mu_w^2 + \beta(1-S)\mu_l^2 - (1-S)(\alpha\mu_{\bar{w}}\mu_w + \beta\mu_{\bar{l}}\mu_l).$$

Appendix 4: Derivation of Equation (8)

Since $\mu_{\bar{w}} = \frac{\sum_{i=SN+1}^{N}\mu_i}{N-SN} = \frac{E[\sum_{i=1}^{N}R_i] - E[\sum_{i=1}^{SN}R_i]}{N-SN} = \frac{1}{1-S}\mu_m - S\frac{E[\sum_{i=1}^{SN}R_i]}{SN(1-S)} = \frac{1}{1-S}\mu_m - \frac{S}{1-S}\mu_w$,

$$\alpha(1-S)\mu_w^2 - \alpha(1-S)\mu_{\bar{w}}\mu_w = \alpha(1-S)\left[\mu_w^2 - \left(\frac{1}{1-S}\mu_m - \frac{S}{1-S}\mu_w\right)\mu_w\right]$$

$$= \alpha(1-S)(\tfrac{1}{1-S}\mu_w^2 - \tfrac{1}{1-S}\mu_m\mu_w) = \alpha\mu_w(\mu_w - \mu_m)$$

Similarly $\mu_{\bar{l}} = \frac{\sum_{i=N-SN+1}^{N}\mu_i}{N-SN} = \frac{E[\sum_{i=1}^{N}R_i] - E[\sum_{i=N-SN+1}^{N}R_i]}{N-SN} = \frac{1}{1-S}\mu_m - S\frac{E[\sum_{i=N-SN+1}^{N}R_i]}{SN(1-S)} = \frac{1}{1-S}\mu_m$

$-\frac{S}{1-S}\mu_l$, and $\beta(1-S)\mu_l^2 - \beta(1-S)\mu_{\bar{l}}\mu_l = \beta\mu_l(\mu_l - \mu_m)$.

Therefore,

$$\alpha(1-S)\mu_w^2 + \beta(1-S)\mu_l^2 - (1-S)(\alpha\mu_{\bar{w}}\mu_w + \beta\mu_{\bar{l}}\mu_l) = \alpha\mu_w(\mu_w - \mu_m) + \beta\mu_l(\mu_l - \mu_m).$$

CHAPTER III
SHORT-SELLING CONSTRAINTS AND MOMENTUM ABNORMAL RETURNS

Abstract

The winner and loser portfolios of momentum strategies are sensitive to different risks. Short-selling can create a situation in which the loser portfolio is more profoundly affected; this phenomenon may explain the bulk of the momentum abnormal returns that are asymmetrically contributed by the loser portfolio. The short-selling risk also provides a possible explanation for the finding in the first essay that the own-stock autocovariance is much more stable in the loser portfolio and is the major contributor to the momentum abnormal returns. Using a pooled interval regression, this study first estimated the realizable shorting demand by treating the observed short interest data as the lower bound and the institutional ownership as a conservative upper bound. The difference between the estimated realizable shorting demand and the realized shorting demand is our proxy for the short-selling constraints. With this new proxy, we found that the short-selling constraints and risks explained the momentum abnormal returns from the loser portfolio strongly and independently. Stocks that are mostly short-selling constrained generated the lowest returns. This return prediction in the momentum strategy supports the mispricing explanation that stocks with more severe short-selling constraints prevent pessimistic information from quickly being released into the stock price, causing those stocks to be overpriced and autocorrelated in returns. Rather than immediately dropping to the true value, constraints on short-selling cause the stock price to drop in a gradual fashion that is demonstrated as stock return autocorrelation or predictability. We also found that the short-selling constraints

are a key explanation for the well-known puzzle that including NASDAQ stocks in the momentum strategy results in a drastic reduction in the momentum abnormal returns. Our study also derives interesting inferences about the determinants of short-selling demand and lends support to the abortion of the tick and bid tests in NYSE and NASDAQ.

I. Introduction

Recently a few papers have noted the following: (1) the proportional contributions of the winner and the loser portfolios to the momentum abnormal returns are indeed asymmetric (Hong, Lim, and Stein, 2000, Lesmond, Schill, and Zhou, 2004); and (2) the characteristics of the loser firms are quite unique. Unlike winners, the stocks that generate the bulk of the momentum abnormal returns are the "losers" that can be characterized as small, low-price, high-beta, off-NYSE stocks. Those stocks are typically hard to sell short, and involve high trading costs (Lesmond, Schill, and Zhou, 2004).

Due to the different characteristics of winner and loser portfolios, the winner and loser portfolios can be sensitive to different risk exposures. Therefore, in order to understand clearly the sources of the momentum abnormal returns, it is essential to look into the winners and losers separately and investigate the specific risk factors that could affect the winners or losers as a group. Given the overwhelming contribution the loser portfolio makes to the momentum abnormal returns, this study will focus on the losers' side of the phenomenon.

Specifically, this study will investigate the role of short-selling constraints and risk in loser portfolio in order to explain momentum abnormal returns. Among all the risks that could affect winner and loser portfolios, short-selling constraints and risk are the constraints and risk that impact much more on the loser rather than the winner portfolio. Therefore, the short-selling constraints and risk that the losers are more sensitive to may play a very important role in explaining the asymmetric contribution of loser portfolios, and hence the major source of the momentum abnormal returns.

Since the short-selling constraints and risk are much more sensitive to the losers, it may not reflect a significant level of explanatory power if the total momentum abnormal returns are examined. Unlike previous literature that has focused on the explanations of the *total* momentum abnormal returns, one of the contributions of this study is to investigate the short-selling risk on only the *component* momentum returns from the losers' side.

The short-selling constraints and risk this essay investigates are the constraints and risks that, due to economic and cultural reasons, make the investors (1) to bear higher costs or (2) to live with the fact that short-selling is not always feasible due to regulatory restrictions or cultural biases, or (3) to cope with the limited availability of stock to borrow, or (4) to shoulder the costs of the premature short-squeeze repayment[7], or (5) to bear the very high borrowing costs if the stocks are special.

The most challenging impediment that researchers must attempt to overcome in our type of research is the unobservability of the short-selling constraints. There are two major ways to address this issue: (1) with proxy and (2) without proxy. Early research started by using the short-interest ratio to proxy for the short-selling constraints. Later, this proxy was criticized as being uninformative about short-selling constraints and risk because there is an ambiguous

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[7] When stock prices go up, short seller losses get higher, as sellers rush to buy the stock to cover their positions. This rush creates a higher demand for the stock and quickly drives up the price even further. This phenomenon is known as a short-squeeze. Premature short-squeeze repayment is the payments or the losses the short sellers are forced to put in the accounts or to assume in liquidating their position, due to margin call, when short-squeeze happens. Accessed on April 3,2010, at http://www.investopedia.com/university/shortselling/shortselling3.asp

causality between short interest ratio and short-selling constraints. To wit, stocks may have low level of short interest because there is low demand to short or they are subject to severe short-selling constraints. Another stream of proxies was developed under the framework of demand and supply. It is argued that stocks are short-selling-constrained when there is a strong demand to sell short and a limited supply of shares to borrow (Asquith, Pathak and Ritter, 2005). Therefore, two variables are used together to proxy the short-selling constraints. Asquith, Pathak, and Ritter (2005) use short interest ratios as a proxy for short-selling demand, and institutional ownership as a proxy for lendable supply. They define the short-selling-constrained stocks as those with the highest short interest ratios and lowest institutional ownership. However, as mentioned earlier, short interest ratios may not be a good proxy for shorting demand, because the measure is confounded. They argue that short-selling constraints are not common, because only 5% of the stocks on the NYSE, AMEX or NASDAQ have more short interest than their institutional ownership. However, shorting demand is a different concept than realized short interest. That institutional ownership is larger than realized short interest does not clearly imply the shorting demand is fully satisfied, because stock availability is only one type of short-selling constraints. There can be other constraints, for example, uptick rules, which prohibited the short-selling transactions in certain circumstances before July 2005. Cohen, Diether and Malloy (2007) utilize the price-quantity pairs to gauge short-selling risk in stocks. By using a proprietary dataset consisting of loan fees and quantities shorted from a large institutional investor, they employ loan fees as shorting price, and percentage of shares on loan as quantity to gauge the short-selling constraints. They argue that an increase in the loan fee coupled with an increase in the percentage of outstanding shares on the loan correspond to an outward shift of the shorting demand. Similarly, a decrease in loan fees coupled with a decreased loan quantity represents an inward shift of the shorting demand. However, their proprietary dataset includes only one institutional investor within a four-year span[8].

It is well known in the literature that short-selling activities are unreasonably low in the market. The majority of stocks virtually have no short interest outstanding at any given point of time (Chen, Hong, and Stein, 2002). The realizable demand for shorting is probably much larger than the recorded short interest. However, due to some short-selling constraints and risk, the realizable demand is not observable. In this way, instead of serving as a usual proxy for shorting demand, short interest actually represents the *realized* shorting demand. Therefore, if we could find out the realizable demand for short-selling, then the *difference* between the realizable shorting demand and the realized shorting *demand* represents the shares subject to some type of short-selling constraints. This difference can serve as an alternative proxy for short-selling constraints. Through this method, the short-selling constraints and risk are proxied by one variable. This new method not only addresses the confounding problem of short interest ratios, but also avoids establishing another proxy for supply. More importantly, this proxy accounts for all types of short-selling constraints, named or unnamed, that have hindered potential short-selling transactions. Therefore, it is a more complete proxy for short-selling constraints. The measure also complements the study of investigating only one short-selling constraint---stock availability under the framework of demand and supply.

Due to the short-selling constraints, the observed short interest ratio only reflects part of the realizable shorting demand. Therefore, the realizable shorting demand should be always equal to or greater than the recorded short interest ratio, depending on the extent of short-selling constraints. In other words, the observed short interest ratio always gives us the lower bound of

[8] Hence, this sample cannot be representative of the entire shorting market.

the realizable shorting demand. By the same token, theoretically, the shorting supply is a natural upper bound of shorting demand that can be realized. D'Avolio (2002) shows that the main suppliers of stock loans for short sales are institutional investors. Furthermore, Nagel (2005) argues that short sales depend heavily on the existing owners of a stock, because the nonowner investors cannot sell the shares short without borrowing shares from the existing owners in the first place. Based on the research of Asquith, Pathak, and Ritter (2005), institutional ownership is greater than short sales for 95% of stocks among 5,500 domestic operating companies trading on the NYSE and NASDAQ markets over the entire time period of 1980-2002. Therefore, it is reasonable to use institutional ownership as a conservative upper bound for the realizable shorting demand.

In our theoretical design, the realizable shorting demand always falls within an interval, with the censoring values varying for each observation. Therefore, an interval regression can be used to estimate the realizable shorting demand given the suppressed short interest ratio and conservative institutional ownership. The interval regression is a generalization of the censored-normal model and the tobit model. While the tobit model requires one censoring threshold for all the observations, the interval model allows the censoring values to vary across individual observations. Compared to the censored-normal model, which only allows single-sided censoring, i.e., left or right censoring, the interval model permits the data to have double-sided censorings. Specifically, in the interval regression, the dependent variable for each observation can be either point data, where the lower and upper bounds are the same as the observed value, or interval data where the lower and upper bounds are different[9].

[9] For example, it is left-censored data where the lower bound is negative infinity, or right-censored data where the upper bound is positive infinity

After estimating the realizable shorting demand by using the pooled interval regression model, our study will investigate first the direction and magnitude that various factors exert on the realizable shorting demand. These market and individual stock factors are: (a) market to book ratio as in Barberis and Shleifer (2003); (b) institutional ownership, as in Nagel (2005); (c) analyst forecast dispersion as in Diether et al. (2002); (d) trading volume as in Lee and Swaminatham (2000); (e) liquidity as in Sadka (2006); (f) firm level volatility as in Ang et al. (2006); (g) size as in Lewellen (2002); and (h) options, call or put, as in Ofek, Richardson and Whitelaw (2004). Secondly, the study uses the obtained proxy for short-selling constraints from the pooled interval regression model to examine directly whether and how well the short-selling constraints can explain the momentum abnormal returns from the loser portfolio.

The pooled interval regression shows that short sale is a contrarian sign, and investors tend to short more when the current and past returns are high. Similarly if the stock has a potential of price increase as indicated by a high market-to-book ratio, the shorting demand declines. Furthermore, short sellers are rational in taking risks and try to avoid unnecessary risks. When the market has higher past return volatility or higher controversy about stock valuation, the short sellers will short less to avoid potential higher risk. Similarly, if a particular stock is more liquid as indicated by a higher trading volume or by a large but not too large firm size, the shorting demand increases. Therefore, even though in literature trading volume has been treated as proxy for either liquidity or difference of opinions, our study shows that it is more of a proxy for liquidity. We also find that short sellers are informed, rather than noise traders. For example, when the market indicates that it is more likely the information will be permanently embedded in the stock price, the shorting demand becomes higher. Option markets also have complementary rather than substitution effects on short sales.

By double sorting the above control variables and the short-selling constraints, we find strong evidences that short-selling constraints demonstrate an independent and persistent explanatory power in predicting the cross-sectional variation of stock returns, even after holding the control variables constant. More importantly, these cross-sectional variation of stock returns consistently show the same pattern that stocks which are most severely short-selling constrained generate the lowest returns. This is because when stocks are short-selling constrained; the pessimistic information will not be released to the stock price quickly. Thus, those stocks are severely overpriced and the returns are significantly smaller.

To further investigate how strong and important the short-selling constraints in explaining the momentum abnormal returns, we run and compare the Fama-French three factor model and our modified four factor model with the short-selling constraints as the fourth factor on the momentum portfolio returns. It is well known in literature that the Fama-French three factor model is the most efficient model in predicting the cross-sectional stock return variations. However, our four factor model improves the explanatory power of the original Fama-French three factor model significantly on the momentum portfolio returns. More interestingly, the increase of the explanatory power of our modified four factor model comes from the loser portfolio returns, rather than the winner portfolio returns. This asymmetric explanatory power between the loser and winner portfolio returns clearly verifies our previous idea that short-selling constraint is a risk loading that affects losers most. Furthermore, it does capture additional risk loading that the well-established Fama-French three factor model does not pick up.

Our study also provides an answer to the long-puzzled phenomenon that when NASDAQ stocks are added into the portfolio, the returns from the momentum strategy decrease greatly. We find that the decrease of the momentum returns asymmetrically comes from the increase of loser portfolio returns. However, adding in the NASDAQ stocks does not change the returns from the winner portfolio much. The increase in loser portfolio returns can be attributed to the shorting environment in the NASDAQ market. Through two sample t-tests and ordinary least squares regression, we find that the short-selling constraints are significantly less in the NASDAQ market than in the NYSE & AMEX. Therefore, pessimistic information can be reflected into stock price more quickly for the NADSAQ stocks, which leads to less overpricing or higher returns in the losers from the NASDAQ market.

We also use the proxy of short-selling constraints developed in our study to verify whether the price tests are efficient tools in the short sale markets. By utilizing paired t-tests and two-sample t-tests on the difference of difference in the SEC pilot program, we find price tests are not effective tools in controlling short-selling activities. This is mainly because short sellers can avoid the price restrictions by routing their orders to other markets that do not have such rules. This phenomenon is prominent in the NASDAQ market. Thus, it further supports the previous finding that NASDAQ stocks are less short-selling constrained. Based on these findings, we suggest the removal of the tick and bid rules in both markets, under normal market conditions to reduce the regulatory burden that has no significant regulatory benefits. However, this conclusion may not be suitable under abnormal market conditions, such as market crash, when aggressive shorting is more likely to happen.

The contributions of our study to the extant literature are: <u>First</u>, unlike previous studies which use the same risk factors to explain the *total* or the combination of both the winners' and the losers' returns, our study argues that the impact of the risk factors to the long and short sides are different; hence, we investigate the short-selling risk particular to the short side returns, which comprise the bulk of the momentum abnormal returns. <u>Second</u>, our study creates a more complete proxy for short-selling constraints, which includes almost all types of short-selling constraints. This new proxy complements the previous studies that focused on one short-selling constraint, stock availability under the framework of demand and supply. Third, our study also provides an explanation on how shorting demand is determined, and how different market and individual stock characteristics can affect it. Fourth, our study is the first study to solve the long-observed puzzle in momentum literature that when NASDAQ stocks are included in the strategy, the momentum returns drop substantially. Finally, our study also offers collateral evidence to the long debated overpriced-stock question from a different viewpoint, i.e., the momentum strategy perspective.

II. Short-Selling Risks

Short selling is the trading technique used by investors who try to profit from an expected downward trend of stock prices. Short selling is a very risky technique that requires precise timing and runs contrary to the overall movement of the market. Even if the investors correctly identify the overpriced stock, they could lose money as the overpriced stock could have been even more overpriced. Furthermore, the investors who sell short face unlimited downside potential for losses as the stock price can also rise without cap.

2.1. Short-Selling Mechanics

Short-selling mechanics are different and more complicated compared to the long transaction. Short sale involves selling a stock that the seller does not own. Therefore, the seller has to borrow shares from the lender with collateral and simultaneously sell them at the current market price. At this point, the stock borrowers need to pay a fee to the lender as part of the transaction costs. At the same time, since the collateral the seller gives to the lender while borrowing is almost always cash, the lender need to pay an interest rate to the borrower on holding the cash for a period. The difference of the fee that the borrower needs to pay the lender and the interest rate on cash collateral that the lender needs to pay the borrower is called the rebate rate. If the stocks are easy to borrow then the rebate rate is positive, which means the lender needs to pay the rebate rate to the borrower by holding an amount of cash collateral for a period of time. In this situation, the stocks are called general collateral. However, if the stocks are hard to borrow, the fee the borrower needs to pay to the lender could be very high, such that the fee exceeds the interest rate charged on the cash collateral that the lender needs to pay. In this way, the rebate rate reflects a negative number, which indicates that not only the lender can hold the cash for free; the borrower will pay additional money to get a stock loan. In this situation, the stocks are called special. At a specific date in the future, the seller has to return the borrowed shares to the lender. If the stock price drops, the seller can profit from the difference of the beginning and ending price plus the interest rate on cash collateral less the commissions and borrowing costs if the stocks are special.

2.2. Short-Selling Risks

Short selling involves many unique risks, such as regulations, institutional and cultural biases, availability of stocks, high borrowing costs if stocks are special and premature short-squeeze repayment.

The Securities and Exchange Commission (SEC) had Rule 10a-1 under the Security Exchange Act of 1934, which provided that investors must sell short a listed stock either at a price above the preceding sale price, known as the plus tick or at the last sale price if it was higher than the last different price, known as the zero plus tick. Similarly, NASDAQ Rule 3350 provided that short sales in NASDAQ stocks be either higher or at the best bid when the best bid was below the preceding best bid (Bai, 2007). In other words, regulations prohibit selling short the stock if it is already in the downturn. This rule in effect prevents traders from earning large profits by driving down a stock price through heavy short selling first, and then taking a long position. In addition, short selling is margin trading, and the seller must meet the minimum maintenance requirement of 25 percent; otherwise the seller will be subject to a margin call.

Almazan et al. (1999) also points out that 70 percent of mutual funds explicitly state (in Form N-SAR handed to the SEC) that short selling is not permitted, and only 2% actually do sell short due to cultural biases.

Since the lender maintains the right to cancel a loan at any time, the seller faces recall risk of the borrowed securities. Much worse, if a stock starts to rise and a large number of short sellers try to cover their positions at the same time; the sellers will face a short squeeze, which can drive the price even higher.

The short sellers may not able to locate the shares to borrow in the market. When the demand to short a stock exceeds the supply in the market, the stock becomes special and the borrowing costs will rise appreciably.

2.3. SEC Pilot Program

In order to gather data and study thoroughly the effect of the uptick rule on market volatility, price efficiency and liquidity, the SEC implemented a Pilot Program from May 2, 2005 to July 3, 2007. This Pilot Program suspended the uptick rule on one-third of Russell 3000 Index constituent stocks with high levels of liquidity. On July 3, 2007, the SEC finally abolished Rule 10a-1 and any rule of exchanges, including NASDAQ 3350, which applied a bid test on short sales (Bai, 2007).

There were three categories of pilot stocks in the program. Category A securities were not subject to the uptick rule, Category B securities were not subject to the rule from 4:15pm ET until the open of the consolidated tape[10] the next day at 4:00am ET. All other securities were included in Category C and were not subject to the rule from the close of the consolidated tape at 8:00pm ET until the open of the consolidated tape the next day. Since April 2005 the consolidated tape opens at 4:00am and closes at 8:00pm (Bai, 2007).

III. Literature Review

Based on whether or not the argument is in support of the efficient market hypothesis, the sources of momentum abnormal returns can be grouped into two competing explanations: rational and behavioral explanations. In addition to the above two explanations, the market frictions explanation is a newly developed direction to explain the momentum abnormal returns.

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[10] The "consolidated tape" is a high-speed, electronic system that constantly reports the latest price and volume data on sales of exchange-listed stocks. The data reflected on the consolidated tape derive from various market centers, including all securities exchanges, electronic communications networks (ECNs), and third-market broker-dealers. The Nasdaq Stock Market runs a similar tape for its securities. Access at http://www.sec.gov/answers/consolt.htm

Our study of short-selling risk dwells on the market frictions explanation. The investigation of the role of short-selling risk in the momentum strategy is limited in number.

3.1. Market Frictions Explanation

The literature has long recognized the important role of transaction costs in realizing momentum abnormal returns. However, due to data availability problems, and the lack of accurate calculation methods, until recently, only two papers have calculated systematically the transaction costs in executing the momentum strategy.

Lesmond, Schill and Zhou (LSZ) (2004) find that winners and losers traded in the equally-weighted momentum strategy are stocks with disproportionately large transaction costs; especially losers, characterized as small, low price, high beta, off-NYSE stocks, that are hard to sell short and incur the highest trading costs. Furthermore, it is the loser not the winner portfolios that drive the majority of the momentum abnormal returns. As a result, the transaction costs totally erode the illusionary "paper" profit of the equally-weighted momentum strategy. They also tested size-based portfolios as in Hong, Lim, and Stein (2000), and turnover-based portfolios as in Lee and Swaminathan (2000). But they find that strategies with larger paper profits are accompanied by disproportionally larger trading costs. Therefore, they bring up the market frictions explanation that slower price updating is due to larger trading costs, as a competing theory to the slow information diffusion explanation introduced by Hong and Stein (1999).

Unlike LSZ (2004), Korajczyk and Sadka (2004) provide some evidence to support the inefficient market hypothesis. They argue that transaction costs, in the form of spreads and price impacts of trades, do not fully explain the abnormal profits from the value-weighted and liquidity-weighted momentum strategies. However, their calculation of transaction costs is not complete, because short-selling costs for the loser portfolio are not included.

Sadka (2006) decomposes the firm-level liquidity into variable and fixed price effects and estimates liquidity using intraday data for the period 1983-2001. He finds that the unexpected systematic or market-wide variations of the variable components of liquidity are priced in the momentum abnormal returns. As the variable components of liquidity are typically associated with private information, a substantial part of momentum abnormal returns are to compensate for the unexpected variations in the aggregate ratio of informed traders to noise traders. Unlike most of the studies that focus on the level of liquidity as a stock characteristic, Sadka emphasizes the market-wide liquidity as an undiversifiable risk factor. The liquidity measure used in his study is defined as the price-impact induced by trades. Because market liquidity risk affects the short transactions, the systematic liquidity will be included in the short-selling constraints analysis. Our study is probably the first research utilizing this liquidity index to examine the short-selling constraints and momentum strategy.

Sadka and Scherbina (2007) document a close link between stock mispricing and liquidity by investigating stocks with high analyst disagreement about future earnings. They show that heterogeneous beliefs tend to be associated with high transaction costs. Therefore, selling such high-disagreement stocks is considerably less profitable after accounting for the extra transaction costs. They also conjecture that this can be a reason that mispricing has persisted through the years. This observed positive relationship between analyst disagreement and trading costs is consistent with the theoretical models, which predict that trading costs increase with the degree of information asymmetry between the market maker and informed investors, and decrease with the amount of noise trading. Because the higher the analyst disagreement about future earnings, the higher the information asymmetry among the market participants. Therefore, the market makers will raise the cost of trading to protect themselves against potential adverse selection. Sadka and Scherbina find that in the cross-section of high-disagreement stocks, less liquid stocks are more likely to be overpriced, evidenced by their low future returns relative to that of more liquid stocks. In the time series, changes in aggregate liquidity are negatively related to the magnitude of mispricing. Increases in the liquidity reduce the costs of arbitrage and accelerate the convergence of prices to fundamentals.

Ali and Trombley (2006) is the first paper to examine the role of short-selling constraints in preventing the arbitrage of momentum abnormal returns. Loan fees charged by the lenders are direct costs of short selling and are treated as the proxy for the short-selling constraints in this study. However, due to data availability problems, they construct *Prob* as a proxy for a stock being special. *Prob* is estimated by the predicted cumulative distribution function of the Logit model regressed by D' Avolio (2002). Six significant variables in the Logit model are selected to estimate *Prob*, namely, *Size*, *IO* (institutional ownership), *Turn* (turnover ratio), *CF* (cash flow), *IPO*, and *Glam* (indicator variable equal to 1 if the stock is in the lowest three deciles of book-to-market). The coefficients used in D' Avolio (2002) are averages of individual monthly regressions. Ali and Trombley examine the momentum abnormal returns by first sorting *Size*, *IO*, *Turn*, *CF*, *IPO*, *Glam* and *Prob* individually. The results show that portfolios with smaller size, higher turnover, lower cash flow, lower institutional ownership, IPOs, lowest three deciles of book-to-market, and higher short-selling constraints have higher momentum abnormal returns. The notable finding is that for all these sorting criteria, the winners' portfolios do not vary much, and the majority of the momentum abnormal returns are driven from the losers' portfolios. The authors then double sort *Prob*, with size, residual analyst coverage, price, turnover ratio and frequency of zero-return trading days. They find that momentum abnormal returns are significant most of the time and thus *Prob* has an incremental explanatory power for momentum abnormal returns.

Boni and Womack (2006) show that analysts create value in their recommendations mainly through their ability to rank stocks within industries, in which they specialize. They find that the monthly momentum strategy within each industry of buying the firms net upgraded by analysts while selling short net downgraded firms yields 1.23 percent in the next calendar month, which is about 30 percent more than a similar non-industry approach. Furthermore, among the total of 57 industries, 54 industries are nominally positive, and 16 industries are significantly positive. This short-term price momentum may be partly driven by returns of firms with more analyst coverage leading the returns of firms with less coverage in the same industry. However, when analyst information are aggregated across industries, the momentum strategy of buying stocks in net upgraded industries and shorting stocks in net downgraded industries generally does not offer statistically significant returns.

3.2. Proxies for Short-selling Constraints

Because short-selling risk is unobservable, financial researchers have tried many different variables to proxy it. The oldest proxy for short-selling risk is short-interest ratios. Later because of data availability from large institutions, the loan fee, i.e. the rebate on the borrowed stock, is used as a direct proxy to gauge the short-selling risk. Most recently, institutional ownership of stocks has been considered as another proxy for short-selling constraints, because most short transactions are conducted by the institutions.

Figlewski (1981) first uses short interest as a proxy for short-selling constraints. This underlying logic is that the more the shorting demand is, the more likely it is subject to short-selling constraints. Thus, he uses the short interest as a proxy for actual shorting demand, and as a result, a proxy for short-selling constraints. Many papers follow suit, such as Brent et al. (1990), Figlewski and Webb (1993), Wooldridge and Dickinson (1994), Asquith and Meulbroek (1995), and Dechow et al. (2001).

Chen, Hong, and Stein (2002) argue that the use of actual short interest as proxy of short-selling constraints could reduce the test power of the relationship between short-selling constraints and subsequent stock returns. First, because a stock with low or zero short interest could be the one that is hard or costly to sell short, it may hold back more negative information from the market price. Second, tracking the abnormal returns of a portfolio of high-short-interest stocks only potentially reduces the test power and generalizability of the results. Instead, they use breadth of ownership, which is defined as the number of investors with long positions in a particular stock, as a more reliable proxy for how tightly short-selling constraints bind. They argue that when breadth for a stock is lower, fewer investors are trading on the stock and less pessimistic information is released to the market.

Jones and Lamont (2002) study the effect of short-selling constraints on stock returns from 1926 to 1933, when the costs of borrowing stocks are publicly available. They criticize the short interest as a proxy for shorting demand. The quantity of shorting represents the equilibrium of supply and demand, not just demand. Short interest can be negatively correlated with shorting demand, overpricing and shorting costs. They argue that the problematic nature of short interest leads to weak empirical results. Instead, they use the rebate rate as the proxy for short-selling constraints. They find stocks that are expensive to short or enter the borrowing market have high valuations and low subsequent returns, which is consistent with the overpricing hypothesis.

Gene D' Avolio (2002) introduces a supply and demand framework to proxy short-selling constraints the first time in literature. He uses a special 18 month dataset provided by a large institutional lending intermediary on loan supply, loan fees, and loan recalls. He treats loan fees and recalls as short-selling constraints.

Nagel (2005) categorizes the short-selling constraints into indirect and direct constraints. The indirect constraints come from institutional and cultural reasons, which result in a general lack of short-selling in the stock market. If the existing owners are not sophisticated enough, the stock can become overpriced, because other sophisticated investors cannot sell it short. Since institutional investors are likely to be more sophisticated than the general public, indirect constraints are more likely to affect stocks with low institutional ownership. The direct constraints come from the cost of short-selling. Since the main suppliers of stock loans are institutional investors (D' Avolio, 2002), stocks with low institutional ownership are harder to borrow and thus incur higher costs. Therefore, both direct and indirect short-selling constraints indicate that institutional ownership plays an important role in the short transaction, and Nagel uses institutional ownership to proxy short-selling constraints. Because size can also affect market friction and serve as an impediment to arbitrage other than the short-selling mechanism, Nagel uses residual institutional ownership in the empirical tests to purge out the size effects. The residual institutional ownership is obtained as the residual in the cross-sectional regressions where size is the independent variable.

Asquith, Pathak, and Ritter (2005) further develop the supply and demand framework introduced by D' Avolio (2002). They argue that stocks were short-sale-constrained when there is a strong demand to short and a limited supply to borrow. They use both short interest, which proxies for demand and institutional ownership, which proxies for supply to represent the short-selling constraints. However, as mentioned before, short interest is an ambiguous proxy for shorting demand.

Cohen, Diether, and Malloy (2007) use the price-quantity pairs to identify the shift of shorting supply and demand by using a proprietary data on short sale loan fees and quantities from a large institutional investor. They argue that when the shorting demand shifts outward or shorting supply shifts inward, the short-selling constraints are more likely to be severer.

Boehme, Danielsen and Sorescu (2006) use the loan fee rather than the rebate rate in their study to proxy for the short-selling constraints. They argue that loan fee is better because it properly adjusted for changing in interest rate conditions that impact rebate rates. However, because the fee data are available for only a limited time period, they use the data primarily to validate other constraint proxies, like relative short interest and exchange-traded options, and to develop a "portmanteau" constraint metric. This unitary constraint metric is obtained by regressing on relative short interest and the dummy variable, options.

Ali and Trombley (2006) utilize the research by D' Avolio (2002), and create the variable *Prob* to proxy short-selling risk. The *Prob* is constructed as the predicated value of the dependent variable conditional on the six significant determinants of a stock being special in the logit model from D' Avolio (2002).

3.3. Other Factors Influencing Short-Selling Risk

The literature has recognized some additional factors that may directly or indirectly affect the short interest, such as options, differences of opinion, et cetera.

3.3a Options

As early as 1993, Figlewski and Webb (1993) had found empirical evidence that options facilitate short selling. They explain this phenomenon as follows: when a put is purchased from an option market maker, the market maker will normally hedge by shorting the stock, and/or buying a call to reverse the position. This is equivalent to the income effect. However, at the same time, the introduction of options will substitute for part of the short interest, and hence reduce the total short interest. Figlewski and Webb expect this substitution effect as a weaker effect for two reasons. First, compared to a large number of hedging strategy traders, like "protective put" buyers, only a small number of investors are active short sellers. Second, even if former short sellers do switch their trading to options, the options market makers may simply respond by shorting the underlying stock themselves to hedge their positions, thus leaving total short interest unchanged. Therefore, the put buyer's desire to sell the stock is transformed through the options market into an actual short sale by a market professional who faces the lowest cost and fewest constraints. Consequently, they argue that introducing options trading can potentially reduce or even eliminate the informational effect of short-selling constraints, by providing alternative trading strategies for investors with pessimistic information to sell short indirectly. Their empirical results support this argument partially by showing that subsequent underperformance is weakened for optionable stocks. However, the result is not statistically significant at the 5% level.

Sorescu (2000) finds that the effect of option introduction on underlying stock prices switches during 1973-1995. While, before July 1981, the option introduction increased stock prices, the price effect switched to negative after July 1981. Although he does not elaborate on the specific reasons for this astounding shift, he lists possible causes, such as the introduction of index options in 1982, the implementation of regulatory changes in 1981, and the possibility that the options help the dissemination of negative information.

Danielsen and Sorescu (2001) confirm the results in Sorescu (2000) that option listings are followed by negative abnormal returns of the underlying stock during the period of 1981-1995, and with positive abnormal returns during the period of 1973-1981. However, for both sub-periods, option introductions increase the short sales. Their study also finds that the negative abnormal returns in the post-1981 era are driven by a firm's beta and the dispersion of investor expectations. This relationship does not exist for the pre-1981 era.

Ofek, Richardson and Whitelaw (2004) provide an empirical analysis of put-call parity in the context of short-selling constraints. Violations of put-call parity are asymmetric in the direction of the short-selling constraints. In particular, both the probability and magnitude of the violations can be linked directly to the magnitude of the rebate rate, a proxy for short-selling constraints. Moreover, both the size of the violations and the rebate rate predict negative excess stock returns.

3.3b Differences of Opinion

The presence of heterogeneous expectations or differences of investor opinions has been modeled in several analyses within the context of asymmetric information. Many papers have attempted to find out the potential relationship between differences of opinion and subsequent stock prices.

Diether, Malloy and Scherbina (2002) have provided empirical evidence that stocks with higher dispersion in analysts' earnings forecasts have lower future returns than similar stocks. The supporting theoretical framework is proposed by Miller (1977) that prices will reflect a more optimistic valuation if pessimistic investors are kept out of the market by some kind of short-selling constraints. Diether et al. argue that the incentive structure of the analysts, which discourages analysts from voicing pessimistic forecasts, is just another form of short-selling constraint. Therefore, the bigger the disagreement about a stock's value, the higher the market price relative to the intrinsic value of the stock, and the lower the future returns. This effect is also found most pronounced in small stocks and stocks that have performed poorly over the past years. Diether et al. also test the role of dispersion in analysts' earnings per share forecasts as a proxy for measuring risk, instead of differences of opinion. Investors who are not well diversified will demand to be compensated more for bearing the stock's idiosyncratic risks. Therefore, more dispersion in analysts' forecasts may indicate more volatile future returns, and thus, may serve as compensation for idiosyncratic risks. However, the negative relationship between dispersion and future returns rejects this interpretation of dispersion as a measure of risk. They also find the average return differential between the low- and high-dispersion stocks has declined in the period 1992-2000, and becomes insignificant for all but the smallest size quintile.

They attribute this phenomenon to lower short-selling costs, and more availability of firm-related information which lowers the levels of disagreement in analyst opinions.

Lee and Swaminathan (2000) find that the past trading volume predicts both the magnitude and the persistence of future price momentum. Information contained in past trading volume can be useful in reconciling intermediate horizon "underreaction" and long-horizon "overreaction" effects. They further investigate the role of past trading volume for prediction of cross-sectional stock returns. More importantly, they find the trading volume as measured by the turnover ratio, is an unlikely candidate as a liquidity proxy. Trading volume is not highly correlated with firm size or relative bid-ask spread, and the volume effect is independent of the firm size effect. Rather, they argue that the information content of the trading volume is related to market misperceptions of firms' future earnings prospects. This finding indicates that investor expectations affect not only a stock's return but also its trading activity. Furthermore, they find trading volume "fuels" momentum only for losers and helps information "diffusion" only for winners.

Boehme, Danielsen and Sorescu (2006) point out that two necessary and sufficient conditions for Miller's overvaluation are that i) the security is subject to short-selling constraints and ii) investors have heterogeneous expectations. They argue that the reason the previous empirical studies derive mixed results is that only one of the two conditions is tested at a time. Consequently, they reexamine the overvaluation effect in a two-dimensional framework with both conditions binding simultaneously.

Their results suggest that neither the presence of short-selling constraints nor a high dispersion of opinions can independently lead to overpricing of the stocks. However, when these two factors are considered simultaneously, they find Miller's overreaction effects are so severe that the stocks underperform by as much as 21% per year relative to the Fama-French four-factor asset-pricing model[11] over the period of 1988-2002. This level of underperformance is significantly more severe than observed in any previous study. Boehme et al. use three separate proxies for differences of opinion: i) dispersion of analysts' forecasts, ii) idiosyncratic volatility of stock returns (SIGMA) and iii) trading volume as a proportion of shares outstanding. The dispersion of analysts' forecasts is the coefficient of variation for analysts' annual forecasts estimated from IBES data. It is derived by dividing the IBES reported standard deviation of analyst earnings per share forecasts for the current fiscal year-end by the absolute value of the mean earnings per share forecast, as listed in the IBES Summary History file. SIGMA is the standard deviation of the error terms from the Brown and Warner (1985) market model, estimated over the 100 days preceding the first day of the month for which the short interest data are reported.

IV. Theory and Hypotheses

Some recent studies have concluded that the contributions of the winner and loser portfolios to the momentum abnormal returns are asymmetric. Surprisingly, the losers, not the winners, are the dominant driving force of the puzzling abnormal returns from the momentum strategy. Therefore, the unique characteristics the losers possess (and the risk factors that they are more sensitive to) have become a natural focus of the ongoing research. The losers belong to the small, low-price, high-beta, off-NYSE stocks that are typically hard to sell short and involve high trading costs (Lesmond, Schill and Zhou, 2004). Furthermore, unlike the winners, losers

[11] The Fama-French four-factor asset pricing model is $r_{pt} - r_{ft} = \alpha + \beta_m * (r_{mt} - r_{ft}) + \beta_s * smb_t + \beta_h * hml_t + \beta_o * mom_t + \varepsilon_{pt}$

are involved in a different trading activity: short-selling. Therefore, they are impacted uniquely by the short-selling risk that the winners do not face.

Meanwhile, another avenue of research has grown fast and has argued strongly that short-selling constraints can withhold pessimistic opinions from the market and can thus lead to an overpricing of these stocks. The baseline for this argument is that when some stocks are underpriced, the sophisticated investors with full information could always bid a higher price in the market and buy them. However, if some stocks are overpriced, the sophisticated investors cannot sell them if they do not own them in the first place, nor can they borrow them from their current owners who do not have enough information and do not believe the stocks they own are overpriced[12].

If the above logic makes sense in the market, then the phenomenon of losers continuing to perform badly in the momentum strategy may be explained by the short-selling constraints, which hinder pessimistic opinions from influencing the prices quickly enough. However, the mechanism underlying the explanation of the short-selling risk is totally different from that of the behavioral hypotheses. The short-selling risk explanation assumes that the investors are rational, regardless of whether they are pure or adaptive. The main hindrance resides in the market frictions: regulations, cultural biases, stricter requirements and higher transaction costs.

Motivated by the above arguments, our research hypothesizes that the short-selling risk may explain a good part of the momentum returns from the loser portfolio, which consists of the bulk of the abnormal returns from a momentum strategy.

[12] Unless the sophisticated investors are willing to incur higher costs, such as asking for a negative rebate rate from the current owners, as an extreme example.

Hypothesis 1.Stocks that are most constrained by the short-selling risk generate the lowest momentum returns from the loser portfolio.

This hypothesis derives from the argument that the behavior of the stocks with the most severe short-selling constraints will prevent more pessimistic information from quickly being reflected in the price. **Thus, the losers will be more severely overpriced, and the returns will be significantly lower.**

Hypothesis 2.The short-selling risk independently and significantly explains the momentum returns from the loser portfolio.

If the short-selling risk is able to independently and significantly explain the returns of the losers in the momentum strategy, then the continued bad performance of the past losers indicates that the past losers are overpriced due to the limits of short-selling. Otherwise, the prices of the past losers would be lower in the first place because the investors can sell them short and put enough downward pressure on their prices. Alternatively, the momentum abnormal returns can be explained as a compensation of the market frictions, the short-selling risk, for the loser portfolio. These results will also provide additional insight to the long debated conjecture, first raised by Miller (1977), that the short-selling constraints in a market of heterogeneous beliefs will cause stock overpricing.

Hypothesis 3. NASDAQ stocks are less short-selling constrained than are NYSE & AMEX stocks. This difference may explain the long-observed phenomenon that momentum abnormal returns become much smaller when NASDAQ stocks are included.

There is strong empirical evidence that the inclusion of NASDAQ stocks in the momentum strategy leads to a drastic reduction in the momentum abnormal returns. This hypothesis is supported by the argument of some researchers (Bai, 2007) that the short-selling constraints in the NASDAQ are less severe than those in the NYSE and AMEX.

Question 1. Given the proxy for the short-selling constraints, we can directly check the effectiveness of the tick and bid tests in the NYSE and NASDAQ markets.

To gather data and thoroughly study the effect of the tick and bid tests on market volatility, price efficiency and liquidity, the SEC implemented a pilot program from May 2, 2005, to July 3, 2007. This pilot program suspended the uptick rule on one third of the Russell 3000 Index constituent stocks with high levels of liquidity. On July 3, 2007, the SEC finally abolished Rule 10a-1 and any rule of exchanges, including NASDAQ 3350, which applied a bid test on short sales (Bai, 2007). Therefore, the pilot program provides a convenient platform to check whether the tick and bid tests in the NYSE and NASDAQ markets are effective price restrictions.

Several studies, such as Bai (2007) and Reg. SHO Pilot Report (2007), have failed to find any significant difference in the short interests of both markets across the pilot and control stocks, despite the price tests. In addition, neither of the two studies mentioned above found any evidence that the price tests were able to reduce the speed of price decline or overpricing in the pilot program.

V. Data and Methodology

The data on stock returns are collected from the Center for Research in Security Prices (CRSP) Monthly Stock File for NYSE, Amex, and Nasdaq stocks. Throughout the study, closed-end funds, American Depository Receipts (ADR), real estate investment trusts (REIT), and primes and scores[13] are excluded. The short interest data come from two sources. The majority of them are obtained from the Bloomberg database from January 1, 1988 to February 29, 2008. The data were backfilled in June, 2008 to update for ticker changes, delisting, and acquisitions. The rest of them are obtained from the CRSP/Compustat Merged Database. The short interest data contain most of the companies that are listed in the CRSP. The variable of short interest is the total number of shares investors have sold short but have not yet bought back. The short interest ratio (SIR) is the total number of shares an investor has sold short divided by the shares outstanding for a specific month[14].

Data on institutional holdings are extracted from the Thomson Financial Institutional Holdings (13F) database. The quarterly holdings start in the first quarter of 1988 and end in the last quarter of 2007. The shares of institutional ownership are calculated by summing up the stock holdings owned by all reporting institutions for each stock in each quarter. Following Gompers and Metrick (2001), stocks that are on CRSP but without any institutional holdings are assumed to have zero institutional ownership. We also exclude the observations with institutional ownership greater than 100 percent, which are subject to double counting problem. As mentioned in the user's guide of Thomson Financial database, the spectrum's records of late filings reflect stock splits that have occurred between the report date and the filing date, some even reflect stock splits after the filing date. The longest gap between the report date and filing date is two years. This inconsistency makes the data hard to compare among late filers and on-

[13] Americus Trust Components that are created by repackaging certain common stocks into a five-year warrant unit for the underlying stocks (scores) and a five-year holding unit of the stocks but with a covered call (primes).
[14] This paper uses short interest to shares outstanding ratio by following Asquith et al. (2005) paper's argument that short interest to shares outstanding ratio is a better measure in reflecting the information of informed investors than the traditional

time filers. Therefore, following Nagel (2005), the institutional holdings (13F) database is unadjusted for stock splits which occur between the report and filling dates. Institutional ownership (IOS) used in this study is the quotient of the institutional ownership for each company and its corresponding shares outstanding.

Market-to-book ratio (MB), analyst forecast dispersion (ADISP), firm-level volatility (VOL), turnover for current month (TURN) and previous month (lagTURN), Liquidity (LIQ), firm size (logSZ) and its squared form (logSZSQ), stock return for current month (RET) and previous month (lagRET) and option status (CALL and PUT) are also used to estimate the latent shorting demand.

The book value of equity is defined as common equity plus balance sheet deferred taxes and is obtained from the CRSP/Compustat Merged Database. For each month, the market-to-book ratio is calculated as the quotient of the market value of equity at month *t* divided by the most recent fiscal year-end book value of equity that is at least six months ahead of month *t*. If the book value of equity is negative, the market-to-book ratio is set to missing.

As in most studies, analyst forecast dispersion (ADISP) is obtained from the Institutional Brokers Estimates System (I/B/E/S). It is the standard deviation of current fiscal year earnings per share forecasts scaled by the absolute value of mean earnings forecasts, for each month from January 1988 to December 2007. Since the I/B/E/S data have a rounding problem related to stock splits, the unadjusted summary data in I/B/E/S are used.

Firm-level volatility (VOL) is the standard deviation of a firm's monthly stock returns over the last 12 months. Firm size (logSZ) is the log form of market capitalization. We also include the squared logSZ to capture the possibility of a nonlinear relationship.

Turnover (TURN) is the monthly ratio of trading volume divided by the number of shares outstanding from CRSP. LagTURN is the turnover of the previous month. As pointed by Atkins and Dyl (1997), the dealer market, NASDAQ double counts the buys and sells from the dealers. Therefore, to make the stock turnover comparable within all exchanges, we followed Nagel (2005) and divided the stock turnover from NASDAQ by two.

Liquidity (LIQ) is obtained from Liquidity factors in WRDS. This variable is derived by Sadak in his 2006 paper, and is extracted monthly from January 1988 to December 2005. According to Sadak, 2006, firm-level liquidity is decomposed into variable and fixed price effects. Liquidity is the variable or permanent part of price effects. It is a non-traded, market-wide, undiversifiable risk factor that is priced in the momentum portfolio returns.

Call and Put are monthly data obtained from Bloomberg. They are all call or put option contracts (all strike prices and expiration dates) outstanding for a particular security. These two variables are scaled by shares outstanding in units of thousands.

5.1. Summary Statistics

Table 5 presents the summary statistics for the short interest ratio (SIR), institutional ownership (IOS) and predictor variables for the actual shorting demand (SID): MB, ADSIP, VOL, TURN (lagTURN), RET (lagRET), logSZ (logSZSQ), LIQ, CALL and PUT. The sample period for the final dataset ran from January, 1988 to December, 2005.

Panel A indicates the mean and median values of the above variables. It is worth noting that there is a significant difference between the mean and median values of the SIR. Although most of the stocks have very small short interest throughout the period (the 90 percentile of SIR is less than 6.42%), 0.47% of the SIR observations were larger than 1. These observations sharply increased the mean value. From 1988 to 1990, the short interest was so sparse that almost no short interest was observed; this interval was clearly different from the later years in the period. We do not know whether data are missing or whether there were simply no short sales for those three years. The average numbers of firms per month indicate that the sample sizes for the different variables were quite different. In particular, CALL and PUT obtained from the Bloomberg database only have average cross-sectional sample sizes of 1297 and 1284 firms, respectively, which represent approximately one-third of the sample sizes for the other variables. This gap costs a great deduction of data in the later analysis.

All of the correlation coefficients were calculated cross-sectionally for each month and then averaged throughout the whole time period in panel B. Because LIQ is a yearly datum without cross-sectional variation, it is excluded in panel B. TURN, CALL and PUT are strongly correlated with each other, with pairwise correlation coefficients ranging from 0.4055 to 0.8367. This result indicates that when the equity market is trading actively, the option market corresponds. The very high correlation between CALL and PUT may result from divergent opinions in the market or from option trading strategies. The variable SIR is strongly correlated with the variables CALL, PUT, TURN, IOS, and logSZ, with pairwise correlation coefficients ranging from 0.1263 to 0.5697. These correlations indicate that short sales are more active when equity and option markets are more active. As a variable IOS is a proxy for the potential supply of loanable stocks, the positive correlation between SIR and IOS indicates that stocks with greater institutional holdings tend be shorted more easily. This finding is consistent with extant literature that stock supply is a necessary but not sufficient condition for short sales and that institutional holdings are very important source of supply. Similar to the finding of Nagel (2005), the variables IOS and logSZ exhibited a strong positive correlation, at a level of 0.6625.

5.2. Pooled Interval Regression and the True Demand for Shorting

If short-selling constraints do exist in the market, then the short interest ratio we observed was a distorted demand measure with some of the shorting demand suppressed by the short-selling constraints. Therefore, instead of being a proxy for the shorting demand, it only revealed partial demand or realized demand. The more short-selling is constrained, the more shorting demand is suppressed and the less realized shorting demand is reflected. The difference between the realizable demand and the realized demand is the short-selling constraints quantified in the number of shares that could not be shorted by the short-sellers.

Because the observed short interest ratio reflects the constrained demand, it is always the lower bound of the realizable shorting demand. That is, the realizable shorting demand is always equal to or greater than the reflected short interest ratio, depending on the extent of the short-selling constraints. Asquith et al (2005) discovered that, on a firm-by-firm basis over the entire time period of 1980-2002, 95% of their sample stocks in an average month had institutional ownership greater than the short interest. This finding means that, for 95% of the data, the availability of the stock is *not* a constraint that hinders short sales. Therefore, our study used the institutional ownership as a conservative upper bound for the realizable shorting demand. However, the use of this conservative upper bound meant that one short-selling constraint, stock availability from the institutional investors, was ignored. This factor means that the actual short-selling constraints should be equal to (or even higher than) the estimated short-selling constraints, as long as the stock falls in the 5% cases in which the stock availability from institutional investors cannot be satisfied and acts as another short-selling constraint. Using this theoretical design, the realizable shorting demand belongs to the category of interval data with the observed short interest ratio as the lower bound and the institutional ownership as the conservative upper bound.

Interval regression is a generalization of the censored-normal-regression and the tobit models. Unlike the tobit model, which requires one threshold censoring value for all of the observations, the interval regression allows the censoring values to vary from observation to observation. Although the censored-normal-regression provides the varying censoring values, it only allows for three options: not censored (0), right-censored (+1) or left-censored (-1). Therefore, among these three possible models, the interval regression best fits the short-selling data for cases in which the censoring value fluctuates for each observation and, at the same time, the true values are bounded by an interval.

Interval regression can fit models for data in which each observation represents interval data, left-censored data, right-censored data, or point data. Specifically, interval regression fits a model of y = [$depvar_1$, $depvar_2$] on independent variables, where the y for each observation is either point data, interval data, left-censored data, or right-censored data (Stata Reference Book, p. 506). $Depvar_1$ and $depvar_2$ should have the following form:

Type of data		$depvar_1$	$depvar_2$
Point data	a = [a, a]	a	a
Interval data	[a, b]	a	b
Left-censored data	$(-\infty, b]$	.	b
Right-censored data	$[a, +\infty)$	a	.

If we know that the value for J[th] individual is somewhere in the interval [y_{1j}, y_{2j}], then the likelihood contribution from this individual is simply Pr ($y_{1j} \leq Y_j \leq y_{2j}$). For the censored data, their likelihoods contain terms of the form Pr ($Y_j \leq y_j$) for left-censored data and Pr ($Y_j \geq y_j$) for right-censored data, where y_j is the observed censoring value and Y_j denotes the random variable representing the dependent variable in the model.

This study utilized pooled interval regression with cluster robust errors. Pooled interval regression treats the whole sample as a long cross section of size N*T. Cluster robust errors were used to catch the potential correlation of the dependent variable within a cluster (i.e., an individual firm in this study), possibly through unobserved cluster effects.

The linear interval regression model with cluster effects is specified as $y_{it} = x_{it}\beta + u_{it}$, for i=1… N, t=1… T, where u_{it} is the error term. The observed data consist of the couples (y_{1it} ,y_{2it}), such that $y_{1it} \leq y_{it} \leq y_{2it}$. The log likelihood function to estimate the coefficients is $lnL = \sum_i \log[\Phi(\frac{y_{2it} - x_i' * \beta}{\sigma}) - \Phi(\frac{y_{1it} - x_i' * \beta}{\sigma})]$. The advantage of pooled interval regression is that, with T fixed and N approaching infinity, the pooled interval estimator is consistent and $\sqrt{N}$-is asymptotically normal without any assumptions that are required for fixed and random effect panel data regressions, other than identification and standard regularity conditions. For example, the pooled interval estimator is consistent and asymptotically normal even under the following conditions: the error terms are arbitrarily serially correlated, the dynamics are not correctly specified, and the independent variables are not strictly exogenous (Wooldridge, Econometric Analysis of Cross Section and Panel Data). Our data satisfy the conditions for T and N: a large number of clusters N and a relatively small group size T. However, the usual standard errors and test statistics reported from a pooled analysis are not valid, and robust versions should be adopted to make the inferences in the pooled interval regression robust to arbitrary heteroskedasticity and cluster correlation. The following corrected asymptotic covariance matrix is used when the observations occurring in groups may be correlated. $Est.Asy.Var[\hat{\beta}] = V\frac{G}{G-1}[\sum_{i=1}^{G}(\sum_{t=1}^{n_i} g_{ij})(\sum_{t=1}^{n_i} g_{ij})']V$, where V is the estimated asymptotic covariance matrix and g_{ij} is the vector of derivatives of the log likelihood for observation i in cluster j. V = $[\sum_{i=1}^{n}(\frac{\partial^2 logF_i}{\partial\hat{\beta}\partial\hat{\beta}'})]^{-1}[\sum_{i=1}^{n}\left(\frac{\partial logF_i}{\partial\hat{\beta}}\right)\left(\frac{\partial logF_i}{\partial\hat{\beta}'}\right)'][\sum_{i=1}^{n}(\frac{\partial^2 logF_i}{\partial\hat{\beta}\partial\hat{\beta}})]^{-1}$

(Stata Reference Book)

VI. Estimated Realizable Shorting Demand and Short-selling Constraints

This section presents the results of the pooled interval regression, analyzes the determinants of the realizable shorting demand, and derives the short-selling constraints that will be used to explain the abnormal returns from the momentum strategy. Through our research design, we will use institutional ownership as a conservative upper bound to estimate the realizable shorting demand. Therefore, we will only focus on a subset of the database: observations with a short interest ratio less than or equal to the institutional ownership.

6.1. Short Interest Ratio and Institutional Ownership

Figure 1 plots the time series of monthly short interest data and quarterly institutional ownership data with all the observations over the period of January, 1988 to December, 2005. Three ratios are reported in the chart: the median and 95th percentile of the SIR and the median of the IOS. The figure indicates that 1) over the whole period, the level of short interest ratio maintains a very low profile, well below 5%; 2) the 95th percentile of the short interest ratio exhibited a similar pattern to the median of the institutional ownership, indicating that these two ratios are probably connected closely through some mechanism, for example, institutional ownership is an important source of loanable shares for short sales; 3) the median values of institutional ownership are many times larger than those of the short interest ratio throughout the whole time period; and 4) even the 95th percentile of short interest ratio was significantly less than the median of institutional ownership for almost all of the entire period, with the exception of two months: November and December, 1990. This finding implies that, as an important source of loanable stocks for short sales, institutional ownership can satisfy the majority of shorting demand and is a legitimate upper bound for the realizable shorting demand when making conservative assumptions.

Finally, about 4.97% of the data with short-interest ratio larger than the institutional ownership were dropped to estimate the pooled interval regression model. This result confirms the findings of Asquith et al (2005) that only 5% of the institutional ownership was less than the short interest ratio in the whole sample over the entire time span. However, it is still worthwhile to investigate whether the firms being dropped have certain special characteristics that distinguish them from the retained firms. Table 6 compares the summary statistics between the two groups: those with a short interest ratio larger than the corresponding institutional ownership and those with a short interest ratio no larger than the corresponding institutional ownership.

Two-sample t-tests were calculated to identify the differences between the two groups[15]. The results indicate that the two groups have statistically different characteristics at the 1% significance level. Compared to the "SIR≤IOS" group, the "SIR>IOS" group stocks are

[15] Wilcoxon rank-sum tests on medians derive similar results.

glamour stocks with smaller sizes and higher past returns. They have more heterogeneous opinions, as indicated by the higher analyst forecast dispersion, the higher past 12-month return volatility, and the higher turnover. They also have more active secondary option markets, as reflected by the higher call and put open interest. The short interest in the “SIR>IOS” group was higher, which also occurs when the market liquidity risk is lower. For IOS, 52.67% of the observations in the “SIR>IOS” group are the ones with assigned value of 0 when the observations were not available in the Thomson Financial Institutional Holdings (13F) database. Therefore, when there are values for short interest ratio, no matter how large they are, they exceed its corresponding institutional ownership. Those 0 institutional ownership observations (number=16675) pull the median of IOS down to 0 in the “SIR>IOS” group. However, even if those 0 institutional ownership observations are excluded, the IOS median (0.0199)[16] is still significantly smaller than that of the “SIR<IOS” group (0.3468). Given the higher short interest, and lower institutional ownership and the active trading (both in the stock and option markets), those stocks should rely more on individual investors for short sales. Due to the different characteristics of the “SIR>IOS” group, we should be cautious about applying the later results in this category, which was excluded from the regression model in the first place.

6.2. Estimated Interval Regression Model

Stock return, liquidity, dispersion of opinions, and option markets have been well documented in previous research as determinants of shorting demand.

[16] The summary statistics of the subgroup without 0 institutional ownership observations in the “SIR>IOS” category are not shown in the Table II.

RET, lagRET, and MB are return indicators. Short-sellers can only profit when there is a potential overpricing or predicted future price downturn. So they will short more when current or past return indicators are high. Diether et al. (2008) found that short-selling activity was strongly positively related to past returns. D'Avolio (2002) found that glamour stocks, i.e., stocks with high market-to-book ratios, increased the borrowing cost and the likelihood of being special. Therefore, a high market-to-book ratio should decrease the shorting demand.

VOL, TURN and ADSIP are proxies for differences of opinion or valuation dissonance. D'Avolio (2002) found that stocks with high turnover have a higher probability of being special. However, he was unable to find any statistically significant relationship between analyst dispersion and the borrowing cost of the stocks.

Liquidity affects stock returns and, thus, shorting demand. LIQ, TURN, and logSZ are liquidity indicators. Besides the new role of serving as the proxy for differences of opinion, stock turnover has been a traditional proxy for liquidity. Both Datar et al. (1998) and Brennan et al. (1998) documented that stocks with a high trading volume tended to earn lower future returns. Hence, a high trading volume should boost the demand to short if it is a proxy for liquidity rather than for valuation dissonance. LIQ is the market-wide liquidity risk, developed by Sadka (2006), which was found to be priced in the cross-sectional variation of stock returns. Our study is the first to utilize this undiversifiable risk factor for measuring the shorting demand. It is also commonly believed that stocks of large firms are more liquid with less information asymmetry, factors that should facilitate short sales.

Option markets are closely related to the stock markets. Option trading may facilitate or substitute for short sales. Figlewski and Webb (1993) indicated that optioned stocks were more heavily shorted than non-optioned stocks and that option introductions coincide with increased short-selling of the underlying stock.

Specifically, in our study, the pooled interval regression can be expressed as $SID_{it} = Cons_{it} + VOL_{it} * \beta_1 + TURN_{it} * \beta_2 + lagTURN_{it} * \beta_3 + RET_{it} * \beta_4 + lagRET_{it} * \beta_5 + logSZ_{it} * \beta_6 + logSZSQ_{it} * \beta_7 + MB_{it} * \beta_8 + CALL_{it} * \beta_9 + PUT_{it} * \beta_{10} + ADSIP_{it} * \beta_{11}, where\ SIR_{it} \leq SID_{it} \leq IOS_{it}$.

The pooled interval regression was run from January, 1988 to December, 2005. The dependent variable was the latent shorting demand, which is bounded within the interval in which the actual short interest was the lower limit and the institutional ownership was a conservative upper limit. The standard errors were adjusted for the cluster effect. The first column of Table 7 lists all of the independent variables. The likelihood-ratio chi-squared test gauges the difference between the full model (with predictors) and the constant only model. The chi-squared test indicates that the whole model was statistically significant at the 1% level. All of the coefficients were significant at the 1% level. All of the observations in the regression had unequal lower and upper bounds. The McFadden's adjusted R-square was 0.235. Among the total of 135,116 predicted values, 1,787 observations (1.323 percent) were left censored and took on the value of the short interest ratio (i.e., the lower bound) and 4,117 observations (3.047 percent) were right censored and took on the value of the institutional ownership (i.e., the upper bound). The remaining 129,212 observations (95.630 percent) were censored. This result indicates that the majority of stocks are subject to short-selling constraints and that the actual shorting demand is higher than the observed short interest ratio.

Among the return indicators in Table 7, both the return and the past month return were positively related to the shorting demand. Therefore, short-selling is a contrarian sign, and investors sell short to take advantage of potential price downturn or current overpricing. The market-to-book ratio was negatively related to the shorting demand. When the market-to-book ratio is high, the market has a high expectation of the earning power of the firm, which signifies that the stock price will increase in the future. This information decreases the demand for shorting.

The differences of opinion proxies indicated different impacts on the shorting demand. The analyst forecast dispersion variable indicated that, when there is a discrepancy in the security values, the investors become less likely to short. This phenomenon can be associated with higher shorting costs and more trading risks because when the stock value is unclear, the borrowing costs and the probability of premature short squeeze risk are higher. Similarly, the past 12-month return volatility variable displayed a negative coefficient of -0.1743, indicating that the short-sellers were more reluctant to sell short when there was more disagreement about the stock intrinsic value in the recent period. Because short sales are riskier than the long position, a volatile market makes short-sellers cautious.

However, the stock trading volumes in both the current and past periods showed a clearly positive relationship. This positive relationship was exactly opposite from the negative implication given by the other proxies for valuation controversy (i.e., analyst forecast dispersion and the past 12-month return volatility), implying that if investors disagree about the intrinsic value of the stocks, they tend to sell short less. This contradiction can be explained by the proxy role of turnover. Turnover is more of a proxy for liquidity rather than for the valuation controversy among investors. Consequently, the positive relationship between turnover and shorting demand makes sense. More liquid stocks cost less to short and, ceteris paribus, increase the shorting demand. Our results on turnover also matched with the previous finding of both

Datar et al. (1998) and Brennan et al. (1998) that stocks with high trading volume have low future returns. Thus, higher turnover can trigger an increased demand to short. Therefore, even though turnover can reflect both liquidity and differences of opinion, our study indicates that it predominantly plays the former role.

The liquidity factor (LIQ) is a measure that was described in a Sadka (2006) paper. It is defined as the price-impact induced by trades and is separated into fixed (transitory) and variable (permanent) price effects. The permanent change in the stock price is associated with a change in its perceived intrinsic value through the information effect and is dependent on the amounts of both informed and noise trading. LIQ has a positive effect on the shorting demand. When it is more likely that the pessimistic information will be permanently embedded into the stock price, the shorting demand increases. This effect implies that short-sellers are informed traders. They tend to catch the correct timing to short and avoid short squeeze risk. In the risk perspective, when there is less noise trading in the market, short sales are less risky, and the shorting demand increases. Size has a quadratic effect on the shorting demand. The shorting demand increases for the stocks of large firms, as large firm stocks typically attract more attention in the media and reduce the information asymmetry. At the same time, large firm stocks are typically more liquid, as more institutional investors hold them. Consequently, it is easier and less costly for investors to find stock loans for large firm stocks and sell them short. However, when the firm size is very large, the shorting demand decreases. One possible reason for this phenomenon is that a very large firm typically has a high market price, which increases the costs to short (such as the margin requirement).

The option market (both call and put) facilitates short sales. Stocks that are call or put option-enabled are more likely to boost the short sales. This result is also supported by evidence from Figlewski and Webb (1993) that optioned stocks are more heavily shorted than non-optioned stocks. They explain this phenomenon by stating that when a put is purchased from an option maker, the market maker will normally hedge by shorting the stock and/or buying a call to reverse the position. Diether et al. (2008) provided additional evidence for this explanation for the call option. Danielsen and Sorescu (2001) also found that, not only do call-only option listings increase the short interest, but joint put-call listings produce greater increases in short interest. This finding matches the observations from our study. From the liquidity perspective, stocks with an active option market should also have an active stock market; both of these features indicate a more liquid market for trading and an easier environment for shorting.

6.3. Short-selling Constraints

After we estimate the latent shorting demand, the difference between the realizable and the realized shorting demand yield a new proxy for short-selling constraints.

Figure 2 indicates the monthly median values of the short interest ratio (SIR), institutional ownership (IOS), realizable shorting demand (SID), and short-selling constraints (SC). The realizable shorting demand is the censored predicted values from the pooled interval regression model. They are left censored at the short interest ratio when they are smaller than the lower bound, and right censored at the institutional ownership when they are greater than the upper bound. The short-selling constraints (SC) were derived as the difference of the latent shorting demand and the realized shorting demand, in other words, the difference between the predicted realizable shorting demand (SID) and the short interest ratio (SIR). Because the option data were all missing before September, 1995, the predicted shorting demand and the short-selling constraints data start at September, 1995. Over the entire period, the short-selling constraints remained at a stable level, even from 1995 to 2000, when institutional holding fluctuated greatly and after 2000, when the market shares of the institutional investors increased dramatically. This result indicates that the stock supply is only one of the factors that impact short-selling activities and that most of the times it is not binding. The mean and median of the predicted realizable shorting demand with censoring are 0.2333 and 0.2315. The short-selling constraints have a mean of 0.1861 and a median of 0.1982. Clearly, most of the shorting demand was suppressed for some reason, and only a small fraction of the actual shorting demand was realized. This finding matches with the suggestion of the literature that short interest has been unbelievably low over time.

VII. Short-selling Constraints and Momentum Abnormal Returns

After deriving the short-selling constraints (SC), this section presents tests of Hypotheses 1-2, which predict that stocks with more severe short-selling constraints generate lower returns. Hence, short-selling constraints can explain the abnormal returns in the loser portfolio from the momentum strategy, which also constitute the majority of the total momentum abnormal returns.

7.1. Portfolio Sorts on Short-selling Constraints

In Table 8, the stocks are sorted at the end of each month t into three short-selling constraints groups. As indicated by Panel A, strong variation is seen in short-selling constraints across the three groups. The time-series averages of the cross-sectional means and medians of short-selling constraints monotonically increase from a mean of 0.1281 and a median of 0.1438 in the low group to a mean of 0.2329 and a median of 0.2260 in the high group.

In Panels B-H, we double-sort the portfolio by the short-selling constraints (SC), conditional on the independent sort of market-to-book ratio (MB), size (logSZ), past 12-month return volatility (VOL), analyst forecast dispersion (ADISP), turnover (TURN), call open interest (CALL), and put open interest (PUT). At the end of each month, a portfolio is formed based on a double-sorting of the past 6 months' mean values of the above variables, with a holding period of six months. Hence, the holding periods are overlapping and one sixth of the portfolio is rebalanced every month, as in Jegadeesh and Titman (1993). Returns in each portfolio are equally weighted and they are reported in decimal points per month.

Panel B presents the MB results. As the market-to-book ratio increases, the stock returns decrease in all subgroups within the same level of the short-selling constraints. This finding indicates that glamour stocks tend to sell at relatively high price-to-earnings ratios, and thus, they tend to earn smaller returns relative to value stocks. Within each subgroup sorted on the market-to-book ratio, stocks with stronger short-selling constraints tend to be more overpriced and earn smaller returns. For example, in the subgroup with a low market-to-book ratio, the most short-selling constrained group earns a low return of only 1.29% and the much higher return of 1.88% in the least short-selling constrained group. This difference is significant at the 5% level, after controlling for heteroskedasticity and autocorrelation. Hypothesis I predicts that stocks that are most constrained by the short-selling risk generate the smallest returns. As indicated by the table, this prediction is borne out remarkably well. More importantly, the prediction holds when the market-to-book ratio (a factor that is widely believed to affect stock returns) is controlled at different levels. Therefore, the explanatory power of the short-selling constraints is valid and independent of the market-to-book ratio in explaining the cross-sectional stock return predictability.

The strikingly similar pattern we see in the MB results also appears in other predictors. Panel C demonstrates the return patterns based on double-sorting according to the firm size and the short-selling constraints. Even after sorting by the firm size, the stock returns still clearly decrease as the short-selling constraints increase. The stock return in the SC1 group is only 1.15% for the low firm size group, and reaches as high as 1.48% for the least constrained group. This pattern reinforces Hypothesis 1 that the stocks that are most constrained by the short-selling risk generate the lowest returns. Short-selling constraints still show an independent power for explaining the cross-sectional return variations, after controlling for the size effects.

Panel D also displays a very similar pattern as the previous return predictors. When the past 12-month return volatility data are sorted, short-selling constraints still cause the stock returns to decrease across the SC groups. For example, when the past return volatility is high, the stock return drops from 1.17% in the SC3 group (the least constrained group) to 0.37% in the SC1 group (the most constrained group). This drop is statistically significant at the 5% level. This finding further supports Hypothesis 1 that the more short-selling constrained stocks are subject to more overpricing and tend to provide lower returns. Therefore, when the stock market is more volatile or there is more controversy about the intrinsic value of a stock in the past, the short-sellers tend to be more reluctant to sell short to avoid more risk, which translates into more overpriced stocks and lower stock returns. Therefore, past return volatility and short-selling constraints have individual explanatory powers in stock return variations.

Panel E reports the stock return variations after a double-sorting of the analyst forecast dispersion and the short-selling constraints. This panel is important because it directly tests the long-debated hypothesis proposed by Miller (1977) that short-selling constraints in a market of heterogeneous beliefs will cause stock overpricing. However, stocks with the highest degree of heterogeneous beliefs did not display the largest return differences when the short-selling constraints increased from the lowest group to the highest. In the group with the most heterogeneous beliefs (the P1 group), the stock returns showed a clearly increasing pattern as the short-selling constraints decreased. Therefore, stocks with more short-selling constraints were possibly overpriced, even after controlling for the extent of heterogeneous beliefs in the market, which is consistent with Hypothesis 1. Furthermore, this pattern exists in other groups with different levels of valuation controversy.

Panel F indicates that Hypothesis 1 is still very significant when the portfolio is double-sorted by turnover and short-selling constraints. The stock return in SC1 is lower than that in SC3, given the same level of stock turnover. For example, given a low level of turnover, the stock return is 1.08% in the most short-selling constrained group but is as large as 1.53% in the least constrained group.

Panels G and H again indicate the persistent and independent explanatory power of short-selling constraints in predicting cross-sectional stock returns. As predicted by Hypothesis 1, the stocks that are most severely short-selling constrained earn the lowest return in all the subgroups ranked by call (put) open interest. For instance, the stocks with high call or put open interest earned a return of 0.96% in Panel G and 0.95% in Panel H in the most short-selling constrained group. However, they earned as high as 1.70% in Panel G and 1.52% in Panel H when they were in the least short-selling constrained group.

Therefore, the above double-sorting analysis demonstrates a clear and strong pattern that stock returns decrease as short-selling constraints become more severe while holding one of the controlling variables constant. This cross-sectional variation verifies the first hypothesis that the stocks that are most constrained by short-selling risk generate the lowest returns. Short-selling constraints have a strong and independent explanatory power for predicting cross-sectional stock returns.

7.2. Momentum Strategy and Short-selling Constraints

Now we investigate the momentum returns from the loser portfolio and a modified momentum strategy directly.

Table 9 displays monthly returns to a modified momentum strategy based on a single sorting of the past 6 months' short-selling constraints (SC), instead of the past returns in Panel A, and a double-sorting of the short-selling constraints, conditional on the past 6 months' returns in Panel B. Panel A shows a strongly increasing pattern in the stock returns as the short-selling constraints decrease. Therefore, short-selling constraints offer predictability for stock returns. This is consistent with Hypothesis 1 that stocks with more short-selling constraints are more overpriced and thus predict lower returns. The stocks in Panel A in the SC1 group generated a low return of 0.82%, which gradually increased to 1.40% in the least short-selling constrained group. The raw return in this modified momentum strategy was 0.58%.

In Panel B, the momentum strategy first ranks the stocks based on the past 6 months' geometric returns. The stocks with the highest past returns were the winners, and those with the lowest past returns were the losers. According to Hypothesis 1, within the loser portfolio, further sorting on short-selling constraints should still have independent explanatory power in the portfolio returns. Panel B indicates a strong return pattern not only in the loser portfolio but also in the other return groups. The stocks in the most short-selling constrained group provided the lowest returns. In the loser portfolio, the most short-selling constrained stocks only earned an average of 0.77%, which increased to 1.32% when the short-selling constraints were mildest. This finding directly supports Hypothesis 1 that short-selling constraints do cause the return predictability in the momentum strategy, even after controlling for past returns.

7.3. Risk Adjustments

Table 10 provides insights on the sources of abnormal returns from the momentum strategy. Specifically, it explores the importance of short-selling constraints for generating the abnormal returns from the momentum strategy. In this table, four models are compared to explain the momentum abnormal returns: the well-established Fama-French three-factor model, our modified four-factor model with short-selling constraints included as the additional factor, the Carhart four-factor model, and our modified five-factor model with short-selling constraints as the fifth factor. The Fama-French three-factor model is recognized as the most efficient and powerful model for explaining the cross-sectional variation of average stock returns. If our modified four-factor model significantly improves the explanatory power of the three-factor model, then the fourth factor does capture the additional variation of the portfolio returns that is missed by the three-factor model. Similarly, if short-selling constraints (SC) variable is added into the Carhart four-factor model and keeps significant with the presence of momentum factor, then short-selling constraints (SC) does have additional explanatory power that supplements the momentum factor in explaining the returns from the momentum strategy.

First, we run the following time-series regression using the monthly portfolio returns from the momentum strategy, in excess of risk-free rate in Panel A: $r_i - r_f = a_i + b_i * (r_m - r_f) + s_i * SMB + h_i * HML + e_i$. Here, r_i is the monthly average portfolio returns; r_f is the monthly Treasury bill rate (i.e., the risk-free interest rate) obtained from WRDS, $r_m - r_f$ (MKTRF) is the monthly Fama-French excess return on the market, SMB is the monthly Fama-French small firm factor, and HML is the monthly Fama-French book-to-market (value) factor. The momentum strategy is a (6,0,6) strategy, which sorts the portfolio based on the past 6 month returns and holds the portfolio for 6 months without skipping. P0 represent the returns from the winner portfolio, P2 represent the returns from the loser portfolio, and P0-P2 represents the return differences between the winner and loser portfolios (i.e., the total momentum returns).

In all of the return groups, only two of the estimated intercept coefficients from these regressions are significantly different from zero. The explanatory power of the Fama-French three-factor model is highest in the winner portfolio, with an adjusted R-square as high as 91.86%. The explanatory power of the model decrease to 69.41% in the loser portfolio. The total momentum return is least explained by the three-factor model at 10.05%. Clearly the three-factor model explains the winner stocks much better than the loser stocks, probably because it was unable to catch some risk factor that affected the loser stocks predominantly. Two variables were consistently significant in the three-factor model. One was MKTRF, the market excess returns, and the other was SMB, which mimics return for the size factor. These results indicate that the market risk and size difference across firms do capture strong common variation in stock returns.

To investigate the additional explanatory power of short-selling constraints beyond the well-established Fama-French three factors, Panel B runs the same Fama-French three-factor model as above but includes short-selling constraints (SC) as an additional factor. The short-selling constraints (SC) were constructed largely following the Carhart (1997) method for obtaining the momentum factor, which was calculated as the return difference of the 3 equally-weighted portfolios formed by sorting the past six months' short-selling constraints. The portfolios were reformed monthly.

As with the three-factor model, the explanatory power of the four-factor model also decreased from the winner portfolio to the loser portfolio and was lowest in the total momentum return portfolio. It is not surprising that the three-factor model had low explanatory power in the total momentum return portfolio because it was the model for cross-sectional stock returns. However, the most revealing phenomenon was that, while the adjusted R-squares for the winner and intermediate portfolios stay almost unchanged in the four-factor model, the explanatory power of the four-factor model for the loser portfolio increased by 8%, from 69.41% to 77.42%, after the short-selling constraints factor was added in. Furthermore, the short-selling constraints factor was very significant in the loser portfolio at the 1% level but was not significant in the winner and intermediate portfolios. These results clearly verify our previous understanding that the short-selling constraint is a risk factor that predominantly affects the loser portfolio. The modified four-factor model with short-selling constraints does capture additional risk loading that the well-established Fama-French three-factor model was unable to pick up. The four-factor model also greatly increased the explanatory power in the total momentum returns, from 10.05% to 31.78%. These 21% increase of the adjusted R-square strongly indicated again that the short-selling constraints factor in our modified four-factor model captured additional risk loading and better explained the momentum abnormal returns.

The Carhart four-factor model was also compared with our five-factor model with short-selling constraints added in as the fifth explaining factor. The Carhart four-factor model greatly increased the explaining power of the Fama-French three-factor model. It explained the momentum returns much better than the three-factor model and raised the adjusted R-square from 10.05% to as high as 84.90%. The fourth factor, the momentum factor, was also highly significant in all of the regressions. When the short-selling constraints (SC) were added in, the explaining power of the five model still increased; however, the increase was small (approximately 1%). More interestingly, even with the presence of the momentum factor, the short-selling constraint variable was still significant in the loser portfolio regression and the momentum return regression. The significance level of the momentum factor also decreased considerably, which may imply that some of the explanatory power in the momentum factor was absorbed by the short-selling constraints. This result indicates that the short-selling constraints have independent explanatory power and can capture some risk loading that the momentum factor does not capture. Also, the loser portfolio stocks are much more sensitive than the winners in to reflecting such risk loading.

All of these model comparisons indicate that the short-selling constraint has persistent and independent explanatory power for explaining the returns from the momentum strategy.

A new proxy for the short-squeeze risk was also developed and added into the Fama-French three-factor model and the Carhart four-factor model. The short-squeeze risk has proxies in four different measures. SIR/(IOS-SIR) and SIR/(1-SIR) measure the ratio of short interest and available stock loans. When the ratios are small, the availability of the loanable stocks is higher, so the short squeeze risk is lower. The difference in the denominator of these two measures represents the difference between the stock loans available in the whole market and the proportion that is provided by the institutional investors. The results of adding in the short-squeeze risk to the Fama-French three-factor model and the Carhart four-factor model were similar for both of the two measures, indicating that the institutional investors are indeed the major providers of the loanable stocks for short sales. The other group of proxies are (IOS-SIR)/SIR and (1-SIR)/SIR, to include the situation when short interest ratio is larger than or equal to the institutional ownership. These two proxies produce similar results to the previous two proxies. To save space, only the proxy of SIR/(IOS-SIR) results are presented here in Table 11. It should be noted that when IOS is used in the proxy, the explanatory power of the modified Fama-French three-factor model with short squeeze risk included as the fourth factor greatly increases. However, if the total number of shares outstanding was used, no improvement was observed when the short squeeze risk was added in the Fama-French three-factor model. Results for the short-squeeze risk were very similar to the short-selling constraints variable. Both the modified Fama-French three-factor model and the modified Carhart model better explain the momentum returns. The short-squeeze risk also shows independent explanatory power by remaining significant in the presence of the Fama-French three factors and the momentum factor. However, the only difference is that the short-squeeze risk does not show an asymmetric feature in the winner and loser portfolios as the short-selling constraint variable does.

7.4. NASDAQ Effect

Some previous studies have noticed the phenomenon in the momentum strategy that including NASDAQ stocks in the portfolio decreases returns from the momentum strategy. Table 12 compares the returns from the momentum strategies with and without NASDAQ stocks. The momentum strategy in this table was formed based on the past-six-month returns, then held for six months without skip. The portfolio was equally divided into ten groups, with P0 as the winner portfolio with the highest return during the past six months and P10 as the loser portfolio with the lowest return during the past six months.

In Panel A, the stocks in the pooled interval regression model are included. When the NASDAQ stocks are included in the momentum strategy, the loser portfolio return increases from 1.89% to 2.26%. However, the winner portfolio was not affected by the inclusion of NASDAQ stocks, and the return for the winner portfolio only differed by a negligible amount of 0.05%. The returns of P1-P10 in the momentum strategy with only NYSE and AMEX stocks was 0.37%, and this number dropped to 0.05% when the NASDAQ stocks were included. This 0.32% drop in P0-P10 came mostly from the return increase in the loser portfolio. In Panel B, when all of the stocks in the market are included, the above trend is more obvious. In the second column, the loser portfolio obtained a 0.87% return, and this return increased as high as 1.53% when NASDAQ stocks were included. This increase of 0.66% was statistically significant at the 1% level. In addition, the P0-P10 yielded 0.78% in the momentum strategy with only NYSE and AMEX stocks, which was also statistically significant at 1%. However, P0-P10 dropped to only 0.32% when NASDAQ stocks were included, and this drop of 0.46% was very close to being significant at the 10% level. More importantly, this large drop in the momentum returns again was mostly due to the increase of returns from the loser portfolio.

In sum, we find that the decrease of the momentum raw return comes mostly from the increase of the loser portfolio returns, as the winner portfolio returns remained relatively stable. Furthermore, in both panels, the loser portfolio returns increased when the NASDAQ stocks were included. It is not a simple coincidence. Because the stocks in the NASDAQ are subject to less severe short-selling constraints, and thus the pessimistic information can be quickly reflected in the price, the stock returns become higher in the loser portfolio. To verify Hypothesis 3, Table 13 directly investigates the level of short-selling constraints among stocks in the NASDAQ and the NYSE & AMEX.

First, t-tests were calculated on the characteristics of the two groups of stocks according to where they are traded. In Table 13, NASDAQ stocks have a mean of 1.97% short interest ratio, whereas NYSE & AMEX stocks have an average of 2.85% short interest ratio. The short interest ratio difference between the two groups was 0.88%, which is significantly different from zero at the 1% level. Therefore, NASDAQ stocks generally have a lower short interest ratio relative to NYSE & AMEX stocks. However, even though NASDAQ stocks have smaller short interest ratios, they are less short-selling constrained. According to the t-test on the variable SC, an average of 16.48% of shares outstanding are short-selling constrained for NASDAQ stocks, which is 3.78% less than the stocks listed on NYSE & AMEX. This difference is statistically significant at the 1% level. It can be partially explained by the finding in the Reg. SHO Pilot Report (2007) that the bid test in the NASDAQ was less restrictive than the tick test in the NYSE.

An OLS regression was also run in Panel B, with short-selling constraints as a dependent variable and the indicator variable NASDAQ as the only independent variable. NASDAQ is a binary variable which takes the value one when the stocks are traded in the NASDAQ and otherwise takes the value zero. The regression result further verifies our conclusion from the t-tests from Panel A. Comparing to the stocks traded in the NYSE and AMEX, stocks traded in the NASDAQ are subject to 3.74% fewer short-selling constraints. This result is statistically significant at the 1% level.

Therefore, traders in the NASDAQ market encounter fewer constraints on short sales. This factor allows pessimistic information to flow more easily for the NASDAQ stocks than for the NYSE & AMEX stocks, which causes the NASDAQ losers to have higher returns in the momentum strategy relative to the losers in the NYSE & AMEX markets.

7.5. Reg. SHO Pilot Program

In July 2004, the SEC adopted Regulation SHO, which allows the commission to establish a pilot program to examine the efficacy of the tick and bid tests on short sales in the NYSE & AMEX and NASDAQ markets. The pilot program exempted one-third of the stocks in the Russell 3000 Index from all price restrictions at any time, which were named as category A stocks in the July 28, 2004 pilot order and the "pilot" stocks in our study. The control stocks are category B and C stocks in the remainder of the Russell 3000 Index. Category B stocks are exempted from the price tests from 4:15 pm until the open of the consolidated tape the next day only. Category C stocks have no price tests only from the close of the consolidated tape until the open of the consolidated tape the next day. Stocks that exist both in the pre-pilot and pilot period for at least one month, and are in the regression data in Table 14, are included for comparison in the later analysis. Because the NASDAQ market has a more favorable short-selling environment than does the NYSE & AMEX markets from Hypothesis 3, this analysis was conducted separately for both the listed and the NASDAQ stocks. This distinction also helps distinguish the effects of the tick test in the NYSE & AMEX and the bid test in the NASDAQ.

According to the SEC's pilot order, the SEC first excluded 32 stocks that were neither listed in the NYSE & AMEX nor in the NASDAQ, along with IPOs or spin-offs stocks commenced after April 30, 2004 from the 2004 Russell 3000. Category A stocks were then selected by sorting the 2004 Russell 3000 first by the listing market and then by the average daily dollar volume from June, 2003 through May, 2004, and then within each listing market, picking every third company starting with the second (Reg. SHO Pilot Report, 2007).

Table 14 provides the summary statistics of the monthly stock characteristics between the pilot and control samples over the four-month period prior to the start of the pilot program on May 2, 2005. The data are reported separately in the NYSE & AMEX and the NASDAQ markets to capture the market differences. Our sample contains 384 listed pilot stocks and 376 listed control stocks in the NYSE & AMEX markets, and 759 pilot stocks and 826 control stocks in the NASDAQ market. In the listed market, the pilot and control stocks have similar turnover ratios, short-interest ratios, short-selling constraints, and market-to-book ratios from January, 2005 to April, 2005 (before the initiation of the pilot program). In the NASDAQ market, the pilot and control stocks have comparable turnover ratios, short-selling constraints, and market-to-book ratios prior to the pilot program, except for the short interest ratios. According to the two-sample t-test, the pilot group in NASDAQ has a 0.9% greater short-interest ratio than the control group before the start of the pilot program. Overall, at large, the pilot and control stocks were comparable in both markets over the pre-pilot period and support the validity of further comparison over the pilot period.

Two kinds of t-tests were used to determine the efficacy of the price tests. Within both the pilot and control samples, paired t-tests were applied to compare the stock characteristics before and after the pilot program within each sample. The means of the stock characteristics, such as the short interest ratio, short-selling constraints, turnover ratio, and market-to-book ratio were first calculated separately over the pre-pilot and pilot periods in different markets for both samples. Then, paired t-tests on the different stock characteristics in the different markets were calculated to detect changes due to the removal of the price tests. However, this paired t-test method cannot distinguish the effects of market conditions or the time trend over the pre-pilot and pilot periods from the efficacy of the price tests. To address that concern, two-sample t-tests were run on the difference of the differences between the pilot and control samples in both markets. As long as the pilot and control samples are generally well-constructed, this approach can control for changes in the market conditions or the time trend that are unrelated to the removal of price tests.

Table 15 reports the results of the comparison between pilot and control stocks using the above two types of t-tests. In the pilot sample, the listed stocks increase their short-selling constraints by 0.28% from 21.94% to 22.22%, at a significance level of 5%, after the tick test is removed. However, the pilot stocks in the NASDAQ exhibit no significant change of short-selling constraints after the removal of the bid test. This finding once again provides support for our previous finding that the NASDAQ provides a better environment for short transactions and that the bid test does not pose effective hindrance to short sales in the NASDAQ market. Similar results are seen in the control sample. While the listed control stocks indicated an increase in short-selling constraints after the pilot program, the short-selling constraint level of the control sample in the NASDAQ market kept stable. However, an increase in the short-selling constraint level in both samples of the listed market only exhibited a time trend over the one-year study period. The difference of differences shown in the last column of Table 15 indicates that, in both markets, the short-selling constraints of the pilot and control stocks are similar before and after the pilot program, after eliminating the market condition changes over the one-year study period. This result clearly suggests that price tests are not effective measures in posing constraints on short sales. Several reasons can be attributed to this observation. (1) The price restrictions are applied to some markets but not in others, so while trading the same stocks, traders can avoid the price restrictions by choosing a venue where the restrictions are not applied. For example, because not all markets that trade NASDAQ stocks apply the bid test, short-sellers can route their orders to avoid the price restriction (Reg. SHO Pilot Report, 2007). This factor may explain our result that the short interest ratio is negatively impacted by the removal of price tests in both markets. In the NASDAQ market, the short interest of the control stocks increased by 0.53% relative to the pilot stocks (at a significance level of 1%), suggesting that some short-sellers are routing orders to avoid the bid test. A similar negative impact on the short interest is also observed for the NYSE & AMEX markets from the results of the difference in differences. (2) Investors can still sell short after the restricted trading time for control stocks or by converting to limit orders.

In addition, the short interests for the pilot sample in the NASDAQ market, and for the control samples in both markets, increased over the pilot period. This increase in short sales over the one-year period could be a combination of the market conditions and an increase of public awareness through the media.

As a whole, because price restrictions were not effective in controlling short sales, there is no regulation benefits associated with them, but only regulation burdens. Therefore, our study conditionally supports the SEC's decision to abolish the tick and bid rules. However, several papers, such as Bai (2007) and Shkilko et al. (2008) have mentioned that, even if the price tests are not effective under normal market conditions, they may be meaningful under abnormal market conditions (such as the market plunge in the subprime crisis) to prevent predatory shorting.

VIII. Conclusions

The evidence presented in our study suggests that short-selling constraints play a very important role in explaining the source of momentum abnormal returns, which directly challenges the efficiency market hypothesis. We argue that the predictable return from the loser portfolio, which is also the major contributor of the momentum abnormal returns, arises from the short-selling constraints. After constructing a new proxy for short-selling constraints, we found that, consistent with the above argument, stocks that are mostly short-selling constrained generate the lowest returns, even after controlling for the other stock characteristics that are traditionally believed to determine stock returns, such as the market-to-book ratio, turnover ratio, past return volatility, analyst forecast dispersion, call (put) open interest, and firm size. This return prediction in the momentum strategy supports the mispricing explanation that stocks with more severe short-selling constraints prevent pessimistic information from being quickly released into the stock price, causing those stocks to be overpriced. These results also support Miller's (1977) hypothesis that stocks are overpriced in the presence of short-selling constraints and heterogeneous beliefs.

The short-selling constraints also explain the momentum abnormal returns from the loser portfolio strongly and independently. When added into the Fama-French three-factor model, which is well known as one of the best models for explaining cross-sectional stock returns, our modified four-factor model still significantly improved the explanatory power of the three-factor model in the loser portfolio and in the total momentum return portfolio. Therefore, the short-selling constraint is a risk factor that predominantly affects the loser portfolio and captures additional risk loading that the well-established Fama-French three-factor model does not detect.

Our study also explained the long-observed puzzle in the momentum literature that when NASDAQ stocks are included in the momentum strategy, the momentum abnormal returns reduce drastically. We found that the short-selling constraints were the key reason to explain this well-known puzzle. NASDAQ stocks are less severely short-selling constrained relative to stocks in the NYSE & AMEX markets. Therefore, NASDAQ stocks have less of an overpricing problem and generate higher returns in the momentum loser portfolio.

Using the new proxy for short-selling constraints, we also provided more supporting evidence to abolish the price tests in both markets under normal market conditions because they are not effective in controlling short sales. However, the necessity of price tests in an abnormal market, such as a market crisis, should be further explored.

We also derived interesting inferences about the determinants of short-selling demand. We found that short sales are constraint signs. Investors tend to short when the current or past return indicators are high. At the same time, investors are rational and informed traders in short sales. They tend to sell short more when there is less risk and less valuation controversy present in the market. Option market serves as a complement to, rather than a substitution for, short sales.

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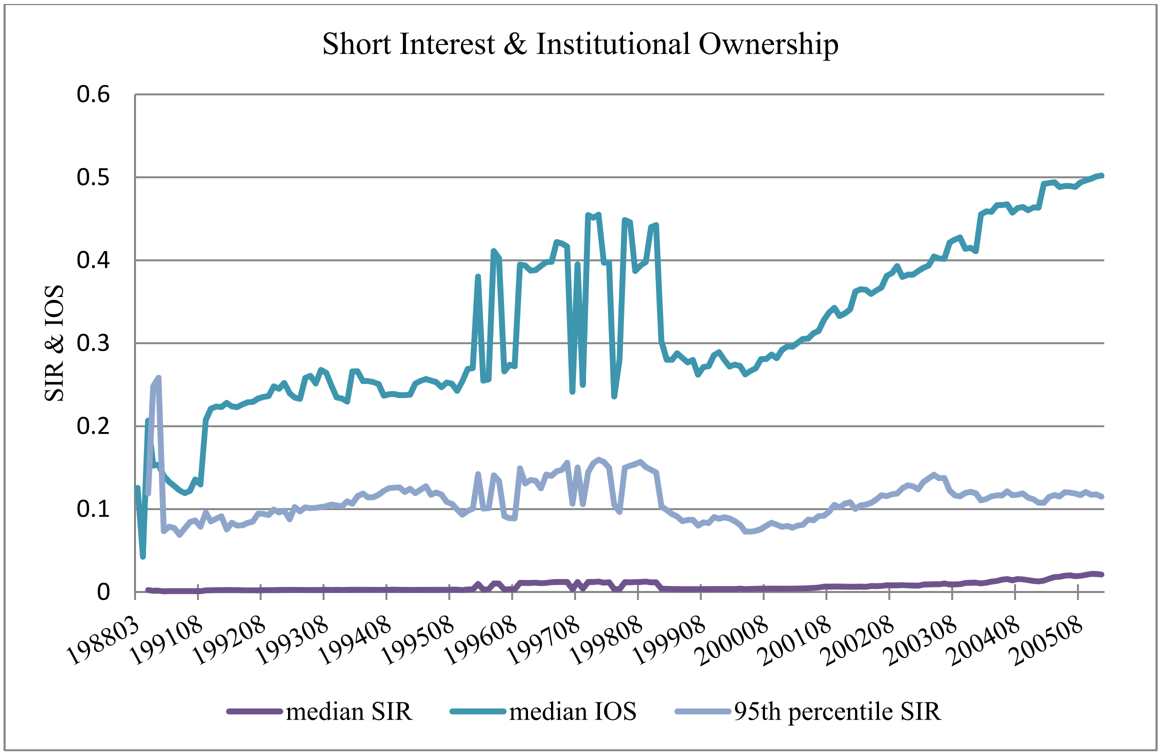

Figure 1. SIR and IOS

Line plots of the median SIR, IOS and the 95th percentile SIR

SIR (short interest ratio) is the monthly short interest ratio, calculated as the number of shares shorted divided by the monthly outstanding shares. IOS (institutional ownership ratio) is the monthly ratio of institutional ownership with stock splits for late filing adjusted, scaled by shares outstanding. The sample period runs from January 1988 to December 2005.

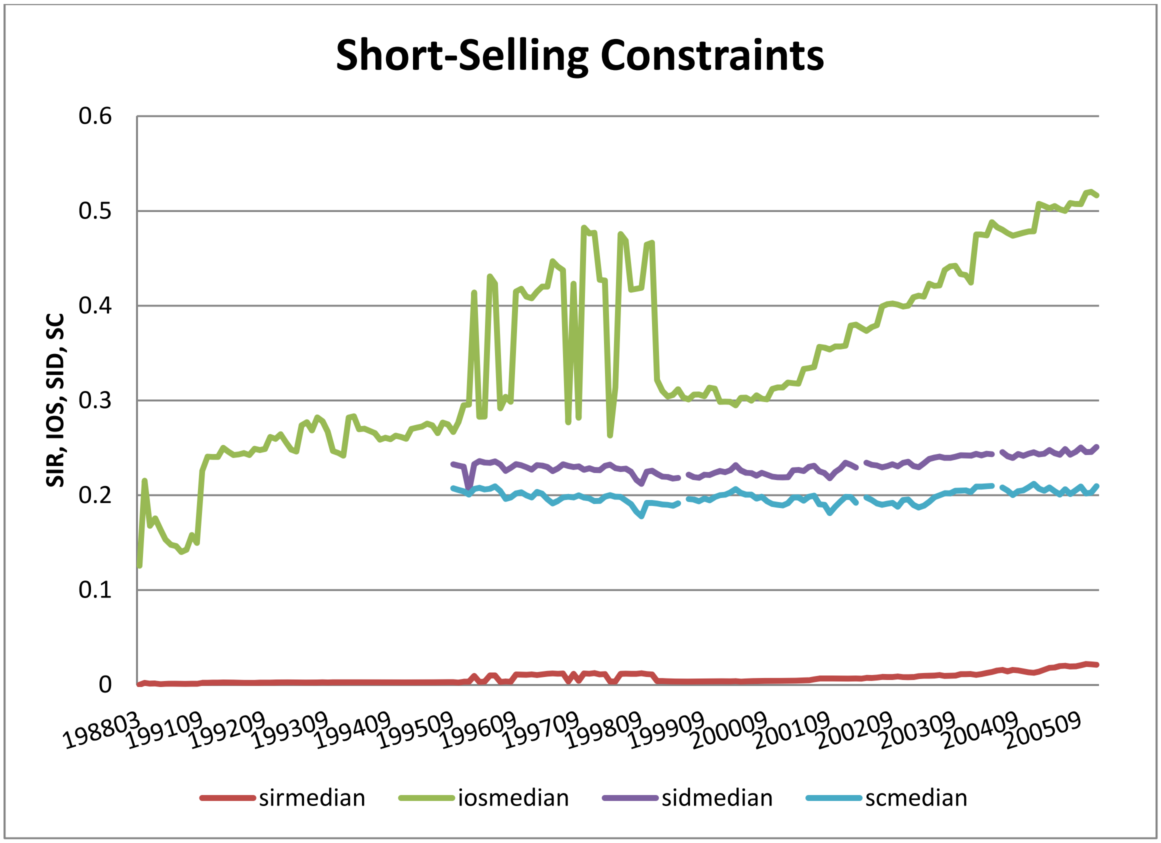

Figure 2. Short-selling Constraints
Line plots of median short interest ratio (SIR), institutional ownership (IOS), predicted realizable shorting demand (SID), and the short selling constraints (SC). SIR is the monthly short interest ratio, calculated as the number of shares shorted divided by the monthly outstanding shares. IOS is the monthly ratio of institutional ownership with stock splits for late filling adjusted scaled by shares outstanding. SID is the predicted realizable shorting demand estimated from the pooled interval regression. SC is calculated as the difference between the realizable shorting demand (SID) and the short interest ratio (SIR). The sample period runs from January 1988 to December 2005.

Table 5. Summary Statistics

Summary statistics of short interest ratio, institutional ownership ratio and firm characteristics

Panel A reports the monthly time-series averages of equally-weighted cross-sectional means and standard deviations of the variables used in the analysis. MB is market to book ratio; ADISP (analyst forecast dispersion) is the standard deviation of analysts' EPS forecasts in I/B/E/S, scaled by the absolute means of forecasts; TURN (turnover) is the monthly trading volume scaled by shares outstanding and divided by two for Nasdaq stocks; IOS (institutional ownership ratio) is the monthly ratio of institutional ownership with stock splits for late filling adjusted scaled by shares outstanding; VOL (volatility) is the standard deviation of monthly individual stock returns for the past 12 months; logSZ is the monthly natural log of market capitalization. CALL (PUT) is the total call (put) option contracts for a particular stock scaled by thousands of shares outstanding. LIQ is the yearly Sadka permanent variable liquidity factor. SIR is the monthly short interest ratio, calculated as the number of shares shorted divided by the monthly outstanding shares. Panel B reports monthly time-series averages of cross-sectional correlations[17]. The sample period runs from January 1988 to December 2005.

	LIQ	MB	ADSIP	VOL	TURN	RET	logSZ	CALL	PUT	SIR	IOS
Panel A: means & standard deviations											
Mean	0.0006	5.3154	0.1668	0.1489	0.0741	0.0179	19.0324	0.1311	0.0813	0.0289	0.3650
Median	0.0008	2.0513	0.0364	0.1191	0.0422	0.0039	18.8862	0.0482	0.0218	0.0059	0.3212
Standard Deviation	0.0037	103.8564	0.9648	0.1183	0.1895	0.1919	2.0707	0.3223	0.2484	0.1583	0.2810
Firms per month (average)	3414	2912	1996	3419	3437	3423	3423	1297	1284	3446	3437
Panel B: cross-sectional correlations											
MB			-0.0051	0.0982	0.1050	0.0249	0.0678	0.0909	0.0864	0.0406	0.0166
ADSIP				0.1039	0.0076	-0.0118	-0.0975	0.0149	0.0128	-0.0006	-0.0592
VOL					0.2267	0.0772	-0.3098	0.1919	0.1236	0.0327	-0.2209
TURN						0.0944	0.1987	0.4454	0.4055	0.2103	0.2455
RET							0.0446	0.0192	0.0241	0.0085	0.0041
logSZ								0.0783	0.1251	0.1263	0.6625
CALL									0.8367	0.5697	0.0000
PUT										0.5487	0.0361
SIR											0.1746

[17] LIQ is not included in Panel B, because it is the same for all the stocks in the market for a given year.

Table 6. Summary Statistics of SIR and IOS

Summary statistics of short interest ratio, institutional ownership ratio and firm characteristics for two groups: SIR ≤ IOS and SIR> IOS. SIR (short interest ratio) is the monthly short interest ratio, calculated as the number of shares shorted divided by the monthly outstanding shares. IOS (institutional ownership ratio) is the monthly ratio of institutional ownership with stock splits for late filing adjusted, scaled by shares outstanding. T-statistics for two-sample t-tests are reported in the parentheses. The sample period runs from January 1988 to December 2005. Significance at the 1%, 5% and 10% level is indicated by a, b and c, respectively.

	SIR ≤ IOS		SIR> IOS		
	Median	Mean	Median	Mean	*(t-statistics)*
SIR	0.0060	0.0229	0.0059	0.1462	(-32.8842)[a]
IOS	0.3468	0.3836	0	0.0496	(393.1767)[a]
MB	2.0535	5.2467	2.1857	7.6906	(-4.7686)[a]
ADSIP	0.0360	0.1653	0.0606	0.2586	(-6.9707)[a]
VOL	0.1169	0.1454	0.1673	0.2120	(-60.6771)[a]
TURN	0.0428	0.0729	0.0342	0.1011	(-7.6866)[a]
RET	0.0044	0.0176	0	0.0234	(-3.4707)[a]
LogSZ	18.9869	19.1389	16.9501	17.2062	(179.2491)[a]
CALL	0.0477	0.1229	0.1242	0.6373	(-16.7423)[a]
PUT	0.0216	0.0763	0.0572	0.3850	(-14.1564)[a]
LIQ	0.0009	0.0006	0.0004	0.0002	(17.3144)[a]

Table 7. Pooled Interval Regression

Pooled interval regression analysis is run to estimate the latent shorting demand from January 1988 to December 2005. Dependent variable (SID) is the monthly realizable shorting demand, which always fall within the interval with the realized short interest ratio as the lower bound and institutional ownership as a conservative upper bound. Explanatory variables are VOL, RET, lagRET, TURN, lagTURN, CALL, PUT, LIQ, logSZ, logSZSQ, MB and ADISP as defined in Table I. The table reports the coefficient estimates with cluster robust error adjusted *t*-statistics.

Variables	Coefficients	Robust Std. Err.	Z	P>|Z|
RET	0.0137	0.0035	3.91	0.0000
lagRET	0.0144	0.0036	4.04	0.0000
MB	-0.00002	5.57e-06	-3.39	0.0000
logSZ	0.2126	0.0206	10.30	0.0000
logSZSQ	-0.0049	0.0005	-10.35	0.0000
TURN	0.1360	0.0187	7.27	0.0000
lagTURN	0.0938	0.0148	6.34	0.0000
ADSIP	-0.0025	0.0007	-3.34	0.0001
VOL	-0.1743	0.0214	-8.13	0.0000
CALL	0.0463	0.0170	2.73	0.0060
PUT	0.0670	0.0170	3.95	0.0000
LIQ	0.5752	0.1588	3.62	0.0000
_CONS	-2.0932	0.2241	-9.34	0.0000
Lnsigma	-2.5400	0.0348	-72.91	0.0000
Sigma	0.0789	0.0027		

Observation summary:	1,787 (1.323%)	left-censored observations
	129212 (95.64%)	uncensored observations
	4,117 (3.047%)	right-censored observations
	135116	interval observations

Measures of Fit for intreg of SIR, IOS			
Log-Lik Intercept Only:	-26515.249	Log-Lik Full Model:	-20263.578
		Prob > LR:	0.000
McFadden's R2:	0.236	McFadden's Adj R2:	0.235

Table 8. Double Sorting

Monthly cross-sectional returns based on the double sorting of short-selling constraints (SC), conditional on market-to-book ratio (MB), size (logSZ), past 12 month's return volatility (VOL), analyst forecast dispersion (ADISP), turnover (TURN), call open interest (CALL), and put open interest (PUT)[18]. At the end of each month *t* from January 1988 to December 2005, stocks are ranked by the past 6 month's mean market-to-book ratio (Panel B), mean size (Panel C), mean past 12 month's return volatility (Panel D), mean analyst forecast dispersion (Panel E), mean turnover (Panel F), mean call open interest (Panel G), and mean put open interest (Panel H). Later the portfolios are further intersected by the independent sorting on the past 6 month's mean short-selling constraints. All the sortings are in 3 groups. Stocks are held in these portfolios for 6 months, i.e., one-sixth of each portfolio is rebalanced each month. The table presents equally-weighted returns on these portfolios with heteroskedasticity-autocorrelation-consistent *t*-statistics shown in parentheses following Kiefer and Bogelsang (2002). Returns are reported in decimal points per month. Significance at the 5% and 10% level is indicated by a and b, respectively. Panel A presents time-series averages of cross-sectional means and medians of short-selling constraints.

		Short-selling Constraints (SC) (High) SC1	SC2	(Low) SC3	SC3-SC1	(t-statistics)
Panel A: firm characteristics by short-selling constraints groups						
Mean SC (percent)		0.2329	0.1972	0.1281		
Median SC (percent)		0.2260	0.1982	0.1438		
Panel B: double sorting on market-to-book (MB)						
P1	(High)	0.0037	0.0046	0.0123	0.0086	(3.3266)
P2		0.0094	0.0101	0.0179	0.0085	(3.2480)
P3	(Low)	0.0129	0.0164	0.0188	0.0059	(5.2035)[a]
P3-P1	Raw	0.0092	0.0118	0.0065	0.0027	(-0.1236)
(*t*-statistics)		(1.9862)	(2.4281)	(2.8464)		
Panel C: double sorting on size (logSZ)						
P1	(High)	0.0086	0.0104	0.0147	0.0061	(2.0475)
P2		0.0089	0.0078	0.0158	0.0069	(3.1632)
P3	(Low)	0.0115	0.0140	0.0148	0.0033	(1.3880)
P3-P1	Raw	0.0029	0.0036	0.0001	-0.0028	(0.0270)
(*t*-statistics)		(0.6638)	(0.5632)	(0.8008)		
Panel D: double sorting on past 12 months' return volatility (VOL)						
P1	(High)	0.0037	0.0096	0.0142	0.0117	(5.3947)[a]
P2		0.0102	0.0104	0.0164	0.0065	(3.6303)
P3	(Low)	0.0102	0.0118	0.0165	0.0064	(3.1211)

[18] LIQ is the market liquid risk and does not vary across firms. Therefore, double sorting based on LIQ and shortcons is not necessary.

Table 8. (continued)

		Short-selling Constraints (SC)				
		(High) SC1	SC2	(Low) SC3	SC3-SC1	(t-statistics)
P3-P1	Raw	0.0065	0.0022	0.0023	0.0042	(4.3199)[b]
(*t*-statistics)		(1.9372)	(1.5289)	(-0.1441)		
Panel E: double sorting on analyst forecast dispersion (ADISP)						
P1	(High)	0.0097	0.0119	0.0160	0.0063	(2.4776)
P2		0.0083	0.0089	0.0134	0.0051	(3.6919)
P3	(Low)	0.0087	0.0109	0.0156	0.0069	(4.4186)[b]
P3-P1	Raw	-0.0010	-0.0010	-0.0004	-0.0006	(1.2695)
(*t*-statistics)		(-0.7214)	(0.6081)	(-1.5217)		
Panel F: double sorting on turnover (TURN)						
P1	(High)	0.0060	0.0064	0.0174	0.0114	(4.0174)[b]
P2		0.0099	0.0119	0.0144	0.0041	(2.3745)
P3	(Low)	0.0108	0.0121	0.0153	0.0059	(3.9604)[b]
P3-P1	Raw	0.0048	0.0057	-0.0021	-0.0054	(1.5371)
(*t*-statistics)		(1.9286)	(2.7553)	(0.3855)		
Panel G: double sorting on call open interest (CALL)						
P1	(High)	0.0096	0.0107	0.0170	0.0074	(3.2170)
P2		0.0077	0.0100	0.0111	0.0034	(3.9165)[b]
P3	(Low)	0.0092	0.0111	0.0138	0.0046	(2.4829)
P3-P1	Raw	-0.0004	0.0004	-0.0032	-0.0028	(1.8872)
(*t*-statistics)		(-0.3591)	(-0.6187)	(-1.7219)		
Panel H: double sorting on put open interest (PUT)						
P1	(High)	0.0095	0.0099	0.0152	0.0057	(2.7121)
P2		0.0079	0.0096	0.0149	0.0070	(4.3777)[b]
P3	(Low)	0.0091	0.0119	0.0158	0.0067	(3.1467)
P3-P1	Raw	-0.0004	0.0020	0.0006	0.0010	(0.5285)
(*t*-statistics)		(-0.4096)	(0.0443)	(-0.6941)		

Table 9. Double Sorting of SC and RET

Monthly returns to momentum strategy based on the double sorting of short-selling constraints (SC), conditional on past 6 months' returns, and single sorting based on the short-selling constraints. At the end of each month *t* from January 1988 to December 2005, stocks are single ranked by the past 6 month's mean short-selling constraints in Panel A. In Panel B, the portfolios are first sorted on the past 6 month's geometric returns, and then are further intersected by the independent sorting on the past 6 month's mean short-selling constraints. All the sortings are in 3 groups. Stocks are held in these portfolios for 6 months, i.e., one-sixth of each portfolio is rebalanced each month. The table presents equally-weighted returns on these portfolios with heteroskedasticity-autocorrelation-consistent *t*-statistics shown in parentheses following Kiefer and Bogelsang (2002). Returns are reported in decimal points per month. Significance at the 5% and 10% level is indicated by a and b, respectively.

		Short-selling Constraints (SC)				
		(High)		(Low)	SC3-SC1	(t-statistics)
		SC1	SC2	SC3		
Panel A: single sorting on short selling constraints (SC)						
		0.0082	0.0118	0.0140	0.0058	(2.3707)
Panel B: double sorting on past 6 months' returns (RET)						
P1	(High)	0.0095	0.0098	0.0188	0.0093	(3.3805)
P2		0.0086	0.0096	0.0142	0.0056	(2.9428)
P3	(Low)	0.0077	0.0120	0.0132	0.0055	(2.4810)
P3-P1	Raw	-0.0087	-0.0022	-0.0056	0.0031	(0.8369)
(*t*-statistics)		(-0.7888)	(0.1262)	(-0.8863)		

Table 10. Factor Models

OLS regressions are run from January 1988 to December 2005 to test the relationship between momentum returns and a measure of short-selling constraints (SC). Dependent variable is the average monthly returns of the portfolios from the momentum strategy in excess of risk free rate. P0 represent the returns from the winner portfolio, P2 represent the returns from the loser portfolio, P0-P2 represents the return differences between the winner and loser portfolios. Panel A shows the coefficient estimates of Fama-French three factor regression: $r_i - r_f = a_i + b_i * (r_m - r_f) + s_i * SMB + h_i * HML + e_i$. r_i is the monthly average portfolio returns; r_f is the monthly Treasury bill rate (i.e. risk-free interest rate), $r_m - r_f$ (MKTRF) is the monthly Fama-French excess return on the market, SMB is the monthly Fama-French small firm factor, HML is the monthly Fama-French book-to-market (value) factor. Panel B shows the coefficient estimates of the four factor model with three Fama-French factors and the short-selling constraints, SC. Panel C shows the coefficient estimates of Carhart four factor model, with three Fama-French factors and momentum factor, MM. Panel D shows the coefficient estimates of the five factor model with three Fama-French factors, momentum factor and the short-selling constraints, SC. The table reports *t*-statistics, adjusted for heteroskedasticity and autocorrelation by using Kiefer and Bogelsang (2002) approach. Significance at the 1%, 5% and 10% level is indicated by a, b and c, respectively.

	P0 (winners)	P1	P2 (losers)	P0-P2
Panel A: Fama-French three factor regressions without short-selling constraints (SC)				
Intercept	0.0018	-0.0020	-0.0020	0.0007
(t-statistics)	(1.4410)	(-1.6855)	(-0.5995)	(0.2228)
SMB	0.6340	0.2610	0.4510	0.1880
(t-statistics)	(20.2499)[a]	(7.2783)[a]	(5.0186)[b]	(1.6695)
HML	0.1320	0.5250	0.2150	-0.0811
(t-statistics)	(2.5964)	(8.6911)[a]	(1.9636)	(-0.5361)
MKTRF	1.0870	1.1550	1.5850	-0.4970
(t-statistics)	(94.9521)[a]	(48.1666)[a]	(18.1756)[a]	(-5.2435)[b]
Adj. R^2	91.86%	88.47%	69.41%	10.05%
Panel B: Fama-French three factor regressions with short-selling constraints (SC) added				
Intercept	0.0028	-0.0030	-0.0096	0.0093
(t-statistics)	(1.7719)	(-2.7022)	(-2.3215)	(2.0388)
SMB	0.7010	0.2010	-0.0489	0.7600
(t-statistics)	(14.2195)[a]	(3.8067)[c]	(-0.3240)	(3.8313)
HML	0.0806	0.5710	0.5930	-0.5130
(t-statistics)	(1.7257)	(10.3678)[a]	(5.3211)[b]	(-3.3698)
MKTRF	1.1180	1.1270	1.3550	-0.2350
(t-statistics)	(83.2145)[a]	(28.8600)[a]	(28.7634)[a]	(-4.4497)[c]
SC	-0.1350	0.1210	0.9980	-1.1420
(t-statistics)	(-3.5589)	(3.0814)	(8.5200)[a]	(-7.5398)[a]
Adj. R^2	92.11%	88.76%	77.42%	31.78%

Table 10. (continued)

	P0 (winners)	P1	P2 (losers)	P0-P2
Panel C: Carhart four factor regressions without short-selling constraints (SC)				
Intercept	-0.0005	0.0004	0.0081	-0.0116
(t-statistics)	(-0.4930)	(0.5662)	(3.4458)	(-6.6942)[a]
SMB	0.5910	0.3080	0.6340	-0.0457
(t-statistics)	(36.8353)[a]	(17.4922)[a]	(16.9791)[a]	(-1.4668)
HML	0.1700	0.4830	0.0400	-0.1330
(t-statistics)	(5.8281)[b]	(11.6113)[a]	(0.9362)	(4.6337)[c]
MKTRF	1.1660	1.0680	1.2290	-0.0634
(t-statistics)	(86.2341)[a]	(32.7398)[a]	(47.3100)[a]	(-2.4275)
MM	0.1800	-0.1990	-0.8150	0.9930
(t-statistics)	(21.4435)[a]	(-14.3461)[a]	(-28.7897)[a]	(36.7326)[a]
Adj. R^2	94.33%	93.03%	93.63%	84.90%
Panel D: Carhart four factor regressions with short-selling constraints (SC) added				
Intercept	-0.0010	0.0014	0.0054	-0.0093
(t-statistics)	(-0.9330)	(1.3775)	(2.3616)	(-5.8003)[b]
SMB	0.5640	0.3580	0.4950	0.0817
(t-statistics)	(36.7031)[a]	(15.6151)[a]	(13.5834)[a]	(1.7953)
HML	0.1920	0.4440	0.1540	0.0344
(t-statistics)	(7.5886)[a]	(12.3264)[a]	(3.4477)	(0.9792)
MKTRF	1.1590	1.1080	1.1930	-0.0324
(t-statistics)	(83.6023)[a]	(32.9764)[a]	(43.3351)[a]	(-1.0367)
MM	0.1910	-0.2180	-0.7560	0.9430
(t-statistics)	(18.3560)[a]	(-13.0905)[a]	(-17.4548)[a]	(24.7925)[a]
SC	-0.0504	0.0903	-0.2670	0.2310
(t-statistics)	(-2.1825)	(2.8571)	(-4.5796)[c]	(4.0658)[c]
Adj. R^2	94.31%	93.14%	94.05%	85.50%

Table 11. Short-squeeze Risk & Factor Models

OLS regressions are run from January 1988 to December 2005 to test the relationship between momentum returns and a measure of short-squeeze risk (SS). Short-squeeze risk is defined as SIR/ (IOS- SIR), where SIR is the short interest ratio, IOS is the institutional ownership scaled by the total number of shares outstanding. Dependent variable is the average monthly returns of the portfolios from the momentum strategy in excess of risk free rate. P0 represent the returns from the winner portfolio, P2 represent the returns from the loser portfolio, P0-P2 represents the return differences between the winner and loser portfolios. Panel A shows the coefficient estimates of Fama-French three factor regression: $r_i - r_f = a_i + b_i * (r_m - r_f) + s_i * SMB + h_i * HML + e_i$. r_i is the monthly average portfolio returns; r_f is the monthly Treasury bill rate (i.e. risk-free interest rate), $r_m - r_f$ (MKTRF) is the monthly Fama-French excess return on the market, SMB is the monthly Fama-French small firm factor, HML is the monthly Fama-French book-to-market (value) factor. Panel B shows the coefficient estimates of the four factor model with three Fama-French factors and the short-squeeze risk, SS. Panel C shows the coefficient estimates of the Carhart four factor model, with three Fama-French factors and the momentum factor, MM. Panel D shows the coefficient estimates of the five factor model with three Fama-French factors, the momentum factor and the short-squeeze risk, SS. The table reports *t*-statistics, adjusted for heteroskedasticity and autocorrelation by using Kiefer and Bogelsang (2002) approach. Significance at the 1%, 5% and 10% level is indicated by a, b and c, respectively.

	P0 (winners)	P1	P2 (losers)	P0-P2
Panel A: Fama-French three factor regressions without short-squeeze risk (SS)				
Intercept	0.0063	0.0031	0.0016	0.0015
(t-statistics)	(8.1594)[a]	(4.9211)b	(1.0860)	(2.0579)
SMB	0.8900	0.5230	0.8370	0.0575
(t-statistics)	(38.9594)[a]	(12.7320)[a]	(6.2838)[a]	(0.4929)
HML	0.1690	0.4470	0.1890	-0.0160
(t-statistics)	(7.0122)[a]	(14.8594)[a]	(1.6197)	(-0.1345)
MKTRF	0.9890	0.9040	1.2770	-0.2890
(t-statistics)	(43.0277)[a]	(50.2886)[a]	(18.0431)[a]	(-3.1690)
Adj. R^2	92.46%	89.16%	67.00%	3.75%
Panel B: Fama-French three factor regressions with short-squeeze risk (SS) added				
Intercept	0.0041	0.0021	-0.0011	-0.0019
(t-statistics)	(6.6934)[a]	(3.6094)	(-0.6815)	(1.5777)
SMB	0.8380	0.5000	0.7750	0.0667
(t-statistics)	(39.7988)[a]	(13.2005)[a]	(6.3866)[a]	(0.6279)
HML	0.1100	0.4200	0.1170	-0.0053
(t-statistics)	(4.4289)[c]	(12.0089)[a]	(1.3078)	(-0.0503)
MKTRF	1.1250	0.9660	1.4420	-0.3130
(t-statistics)	(63.5394)[a]	(53.6645)[a]	(20.0027)[a]	(-5.3927)[b]
SS	-0.3230	-0.1480	-0.3900	0.0577
(t-statistics)	(-6.3342)[a]	(-12.9815)[a]	(-4.9748)[b]	(0.4718)
Adj. R^2	92.55%	89.27%	74.33%	24.93%

Table 11. (continued)

	P0 (winners)	P1	P2 (losers)	P0-P2
Panel C: Carhart four factor regressions without short-squeeze risk (SS)				
Intercept	0.0046	0.0048	0.0095	-0.0081
(t-statistics)	(7.6497)[a]	(9.8513)[a]	(5.1670)[b]	(-6.0275)[a]
SMB	0.8610	0.5520	0.9700	-0.1040
(t-statistics)	(24.5103)[a]	(19.5653)[a]	(12.9767)[a]	(-2.3850)
HML	0.1970	0.4200	0.0613	0.1390
(t-statistics)	(13.2577)[a]	(23.6317)[a]	(0.5402)	(1.2893)
MKTRF	1.0410	0.8520	1.0380	0.0017
(t-statistics)	(87.8889)[a]	(31.3061)[a]	(28.1192)[a]	(-0.0389)
MM	0.1570	-0.1590	-0.7260	0.8820
(t-statistics)	(8.5183)[a]	(-12.1124)[a]	(-17.8082)[a]	(15.6383)[a]
Adj. R^2	94.19%	92.68%	87.40%	74.91%
Panel D: Carhart four factor regressions with short-squeeze risk (SS) added				
Intercept	0.0029	0.0036	0.0057	-0.0062
(t-statistics)	(6.1466)[a]	(7.4953)[a]	(3.4344)	(-4.9807)[b]
SMB	0.8190	0.5230	0.8800	-0.0571
(t-statistics)	(27.1451)[a]	(21.2463)[a]	(12.9215)[a]	(-1.2677)
HML	0.1420	0.3810	-0.0583	0.2010
(t-statistics)	(7.2207)[a]	(14.7557)[a]	(-0.7152)	(2.2322)
MKTRF	1.1540	-0.9300	1.2820	-0.1250
(t-statistics)	(37.7151)[a]	(44.7557)[a]	(50.5027)[a]	(-2.7756)
MM	0.1400	-0.1710	-0.7640	0.9020
(t-statistics)	(9.3347)[a]	(-14.5641)[a]	(-16.7345)[a]	(15.2413)[a]
SS	-0.2830	0.1970	-0.6090	0.3160
(t-statistics)	(-7.0444)[a]	(-13.9530)[a]	(-9.7758)[a]	(3.9802)[c]
Adj. R^2	94.20%	92.80%	88.28%	76.52%

Table 12. Momentum Returns with and without NASDAQ Stocks

This table reports the monthly returns for momentum portfolios (6,0,6) formed based on past-six-month returns and held for six months without skip. P1 (past winners) is the equally-weighted portfolio of 10% of the stocks with the highest returns during the past six months; P10 (past losers) is the equally-weighted portfolio of the 10% of the stocks with lowest returns during the past six months. P0-P10 represents the return difference between the winner and loser portfolios. Difference represents the different returns between the groups of stocks from all markets and stocks without NASDAQ market. Panel A shows the returns from the stocks included this study, and Panel B demonstrates the returns from all the common stocks in the market. Returns are reported in decimal points per month. The table reports *t*-statistics, adjusted for heteroskedasticity and autocorrelation by using Kiefer and Bogelsang (2002) approach. Significance at the 1%, 5% and 10% level is indicated by a, b and c, respectively.

	All Stocks	NYSE+AMEX	Difference
Panel A: Momentum strategy using the data in this study			
P0 (winners)	0.0231	0.0226	0.0005
(t-statistics)	(13.9428)[a]	(17.6230)[a]	(0.4981)
P10 (losers)	0.0226	0.0189	0.0037
(t-statistics)	(8.0942)[a]	(10.0531)[a]	(1.9567)
P0-P10	0.0005	0.0037	-0.0032
(t-statistics)	(0.2644)	(2.4249)	(-1.8155)
Panel B: Momentum strategy using all the firms in the market			
P0 (winners)	0.0185	0.0165	0.0020
(t-statistics)	(8.5929)[a]	(10.6465)[a]	(2.1771)
P10 (losers)	0.0153	0.0087	0.0066
(t-statistics)	(7.3688)[a]	(4.0737)[c]	(6.2740)[a]
P0-P10	0.0032	0.0078	-0.0046
(t-statistics)	(1.6989)	(6.0823)[b]	(-3.7276)

Table 13. NASDAQ Effect

T tests with unequal variances on short interest ratio (SIR) and short-selling constraints (SC) are run between NASDAQ and NYSE & AMEX stocks in Panel A. Panel B runs a linear regression of SC on the indicator variable NASDAQ with heteroskedasticity corrected standard errors. NASDAQ is a binary variable, which takes on value 1 when the stock is listed in NASDAQ and 0 when it is listed on NYSE & AMEX. T-statistics are reported in parentheses. Significance at the 1%, 5% and 10% level is indicated by a, b and c, respectively.

	SIR	SC
Panel A: T test with unequal variances		
NASDAQ	0.0197	0.1648
NYSE & AMEX	0.0285	0.2022
Difference	-0.0088	-0.0378
(t-statistics)	(-65.88)[a]	(-129.98)[a]
Panel B: Regression with robust standard error		
Constants	0.2022	
(*t-statistics*)	(1273.55)[a]	
NASDAQ	-0.0374	
(*t-statistics*)	(-129.98)[a]	
R-square	0.1186	

Table 14. Summary Statistics of Pilot and Control Sample before the Pilot Program

Summary statistics of the Pilot and Control samples in different markets over the four month period prior to the start of the Pilot program on May 2, 2005 are reported. Only stocks that exist both in the pre-pilot and pilot period for at least one month, and in the regression data in Table IV are included in this analysis. The statistical difference between the Pilot and Control samples is tested using two-sample t-tests. N is the average number of firms in the samples, TURN is turnover, SIR is short interest ratio, SC is short-selling constraints, MB is market-to-book ratio. Δ is the difference of the above variables investigated between Pilot and Control samples. T-statistics are reported in parentheses. Significance at the 1%, 5% and 10% level is indicated by a, b and c, respectively.

Variable	NYSE & AMEX				NASDAQ			
	Pilot	Control	Δ	*(t-statistics)*	Pilot	Control	Δ	*(t-statistics)*
N	384	376			759	826		
TURN	0.1422	0.1435	-0.0013	(-0.21)	0.0996	0.1002	-0.0006	(-0.09)
SIR	0.0423	0.0412	0.0011	(0.34)	0.0523	0.0433	0.0090	(2.74)[a]
SC	0.2194	0.2189	0.0004	(0.13)	0.1736	0.1802	-0.0065	(-1.58)
MB	3.5226	4.6555	-1.1330	(-1.46)	4.3041	8.9610	-4.6570	(-1.32)

Table 15. Pilot Program Effect

This table summarizes how stock characteristics change after the tick and bid tests are removed. Paired t-tests are run separately on pilot and control samples for direct comparisons on monthly short interest ratio (SIR), short-selling constraints (SC), turnover (TURN), and market-to-book ratio (MB) before and after the Pilot program which started in May 2, 2005. NYSE & AMEX and NASDAQ are investigated separately for the potential differences between tick and bid tests or different trading environment between the two markets. Pre-Pilot is the four-month period before the starting date of the Pilot program in 2005, Pilot is the eight-month period in 2005 after the program started. Δ is the difference of the variables investigated, between the "Pre-Pilot" and "Pilot" periods within both pilot and control samples. Two-sample t-tests are run on the difference of the differences between the pilot and control samples. T-statistics are reported in parentheses. Significance at the 1%, 5% and 10% level is indicated by a, b and c, respectively.

		Pilot Sample			Control Sample			Pilot Δ-
Variable	Market	Pre-Pilot	Pilot	Δ	Pre-Pilot	Pilot	Δ	Control Δ
SIR	Listed	0.0423	0.0434	0.0011	0.0412	0.0454	0.0043	-0.0032
	(t-statistics)			(0.66)			(5.19)[a]	(-1.72)[c]
	NASDAQ	0.0523	0.0576	0.0052	0.0433	0.0538	0.0105	-0.0053
	(t-statistics)			(4.07)[a]			(11.16)[a]	(-3.32)[a]
SC	Listed	0.2194	0.2222	0.0028	0.2189	0.2216	0.0027	0.0001
	(t-statistics)			(2.13)[b]			(2.25)[b]	(0.06)
	NASDAQ	0.1730	0.1731	0.0001	0.1796	0.1789	-0.0006	0.0007
	(t-statistics)			(0.06)			(-0.42)	(0.30)
TURN	Listed	0.1422	0.1417	-0.0005	0.1435	0.1439	0.0004	-0.0009
	(t-statistics)			(-0.19)			(0.17)	(-0.26)
	NASDAQ	0.0096	0.0981	-0.0015	0.1002	0.0964	-0.0038	0.0023
	(t-statistics)			(-0.45)			(-1.47)	(0.54)
MB	Listed	3.5226	3.4468	-0.0758	4.6555	4.0223	-0.6332	-0.5574
	(t-statistics)			(-0.29)			(1.77)[c]	(1.27)
	NASDAQ	4.2651	4.8204	0.5554	8.9453	4.9418	-4.0034	-4.5588
	(t-statistics)			(0.94)			(-1.14)	(-1.28)

CHAPTER IV
CONCLUSIONS

This dissertation studies the sources of abnormal returns from the momentum strategy. This market anomaly has puzzled researchers in finance for the past two decades.

The first essay decomposes the momentum expected returns from a mathematical model. The empirical results from the historical data show that own-stock autocovariance is an important source in generating momentum returns. More interestingly, the own-stock autocovariance comes primarily from the loser portfolio. Therefore, stock returns are correlated between two consecutive time periods. The market may not be as efficient as we previously believed.

Based on the findings of the first essay, the second essay attempts to find the explanation for the own-stock return autocorrelation, especially from the loser portfolio. The empirical results indicate that short-selling constraints and risks are the key to this asymmetric phenomenon. Stocks with more severe short-selling constraints prevent pessimistic information from being released into the stock prices more quickly; and thus causes those stocks to be overpriced and auto-correlated in their returns.

VITA

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