This is to certify that the
dissertation entitled

ESSAYS ON ARBITRAGE ACTIVITIES

presented by

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of the requirements for the

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G Geoffrey Booth
Major Professor's Signature

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Date

ESSAYS ON ARBITRAGE ACTIVITIES

By

Umit Gurkan Gurun

A DISSERTATION

Submitted to
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ABSTRACT

ESSAYS ON ARBITRAGE ACTIVITIES

By

Umit Gurkan Gurun

This study contains two chapters. In the first chapter, we provide new insights to the visibility hypothesis of Miller (1977), who argues that increased attention to a given stock should attract and convince more investors to buy the stock. We argue that stocks with low substitutability risk are more likely to experience abnormal trading activity when their prices deviate from fundamentals and postulate that the abnormal trading activities may signal the intentions of the traders, presumably arbitrageurs. Thus, in an economy where short selling is restricted, stocks with close substitutes are more likely to be "visible" when they are underpriced. We present empirical evidence that substitutability risk can explain the high-volume return premium documented by Gervais, Kaniel, and Mingelgrin (2001).

In the second chapter, we show that cross sectional differences of momentum profits across 31 countries can be explained by market intelligence measures such as investor sophistication and earnings management severeness. We present three novel findings: First, momentum is more pronounced in countries that have severe earnings management practices, suggesting that momentum is not due to market under reaction due to earnings related information. Second, momentum strategies appear to be profitable in countries that have more sophisticated investors. And third, the growth rate of momentum

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strategy's volatility (exploitability risk) is positively related to investor sophistication, suggesting that momentum strategies are riskier in markets dominated by sophisticated investors. Overall our empirical evidence is consistent with the notion that exploitability risk is the price of momentum profits, and complements the findings of Lesmond, Schill, and Zhou (2004), who show that stocks that generate momentum profits have higher trading costs.

To my uncle Nevzat Kip (1944-2000)

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Chapter 1

1 Does Fundamental Risk of Arbitrage Explain the High-Volume Return Premium?

1.1 Introduction

Although information content of past trading volume has been intensely scrutinized by both scholars and practitioners in various contexts, there is little consensus about its usefulness in predicting future returns. This article examines the relationship between substitutability risk and trading volume, and proposes a new interpretation of abnormal trading activities.[1]

Our main argument is analogous to the 'substitution hypothesis' of Scholes (1972), who maintains that the availability of close substitutes for individual assets is essential for obtaining efficient prices. When securities have perfect substitutes, deviations from fundamentals provide risk-free profit that can be eliminated by competitive arbitrageurs immediately.[2] On the contrary, when there are no perfect (or close) substitutes, rational investors may be reluctant to trade against mispricing because risk aversion limits their aggressiveness and they therefore have to bear fundamental risk (Shleifer(2000)).

In the first part of this paper, we present a model in which investors are more likely to engage in arbitrage activities when securities have perfect (or close) substitutes. This happens for two reasons. First, return from arbitrage activities of stocks with perfect

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[1] Substitutability risk is also called as arbitrage risk (Wurgler and Zhuravskaya (2002)) or fundamental risk of arbitrage (Shleifer (2000)).

[2] A perfect substitute is an asset (or portfolio) with identical cash flows in all states of the world.

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substitutes is higher than that of with imperfect substitutes. Second, investors take larger positions in these stocks since they are less subject to substitutability risk than the ones with imperfect substitutes. Furthermore, in our model, when assets without perfect substitutes are underpriced, investors can still eliminate deviations from fundamentals even if there are short-selling constraints, but when such assets are overpriced, investors bypass profit opportunities. Methodologically, the model builds on and complements the work of Gromb and Vayanos (2002), who characterize the conditions under which wealth- and margin-constrained arbitrageurs provide liquidity of perfectly substitutable assets in a segmented market. Our model extends their framework to imperfect substitutes.

The empirical evidence presented in the second part of the paper indicates that portfolios that are close substitutes to market portfolio are likely to experience abnormal trading activity. We choose to work with portfolios of assets rather than individual securities for two reasons. First, much research suggests that it is almost impossible to identify perfect (or even close) substitutes for a given stock (Roll(1988), Wurgler and Zhuravskaya (2002)). Second, any method for finding the best substitutes is subject to the criticism of data mining. Whereas individual assets may not have close substitutes, a diversified portfolio may be considered a close substitute for the market portfolio by construction, assuming that the latter is always correctly priced.

The results suggest that the substitutability hypothesis can explain an anomaly documented by Gervais, Kaniel, and Mingelgrin (2001): Stocks that experience abnormally high (low) trading volumes over a day tend to appreciate (depreciate) over the course of the following month. They found that the return premium of high-volume

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stocks over low-volume stocks cannot be explained by information effects (firm announcements), liquidity, momentum and short-term interactions between trading volume and returns. To account for this return premium, they suggest the visibility hypothesis of Miller (1977). That is, when there are short-selling constraints, stock prices will reflect the valuations of optimists but not pessimists, because the latter simply refrain from the market as opposed to selling short, which is what they would do in an unconstrained setting. In other words, investors typically only consider the assets they hold when making their sell decisions. Therefore, the decision about which asset to sell does not convey much information to the market, since it is usually interpreted as liquidity motivated. In buying an asset, however, the selection is limited to the number of assets in the market, so buy orders convey more information than sell orders do. As a result, large buy trading volumes should have a positive price impact.[3]

Although Miller's visibility hypothesis can explain why attention towards a given stock results in a subsequent price increase, it says nothing about why those particular stocks became attractive in the first place. We argue that stocks with close substitutes are more likely to gain investors' attention, because investors believe that those particular stocks are less likely to be mispriced, and even if they are mispriced, mispricing will be eliminated immediately. On the one hand, as our model suggests, the elimination of mispricing should make underpriced stocks especially attractive, since any investor (including current stockholders) can buy them. On the other hand, the elimination of mispricing for overpriced stocks should have limited effect since only the current

[3] Similar arguments are made by Arbel and Strebel (1982), Chan and Lakonishok (1993), and Mayshar (1983).

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stockholders can sell them when the lack of perfect substitutes prevents other investors from shorting these assets.

In other words, all else being equal, stocks with close substitutes are likely to be visible when they are underpriced, so the substitution hypothesis of Scholes (1972) complements Miller's visibility hypothesis, which is the main message of this study. Specifically, we try to answer the following questions: Does substitutability makes it easier to capture deviations from fundamentals or new information, thereby cause unusually high trading activities? Which stocks suddenly become more visible?

Based on empirical tests, we first confirm and then extend the findings of Gervais et al. (2001) (hereafter GKM) by showing that substitutability risk indeed can explain the return premium difference between stocks that experience a positive shock and that of a negative shock in their trading activities. The statistical significance of substitutability risk disappears for the portfolios of large size companies around the tenth trading day, but it remains to be significant for portfolios of small and medium firms. This supports our conjecture that deviations from fundamentals are more likely for stocks without perfect (or close) substitutes. Deviations from fundamentals in large companies are more likely to be identified sooner than an opportunity in stocks of small and medium companies, because large companies are followed by more analysts and by a larger investor (presumably arbitrageur) base. Substitutability of the stocks of large companies increases investors' interest and trading volume (visibility), which will reduce the possibility and duration of mispricing. Because small size firms are less visible to a large number of competitive arbitrageurs in a short period, price corrections take longer time. The relationship between size and substitutability risk also confirms Merton (1987)'s argument ab

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argument about the cost of information gathering. The results are robust to other possible interpretations of trading volume, such as announcement affects (new information releases) and difference of opinion among investors.[4] Therefore, we conclude that **extreme** trading activities are more likely to be explained by substitutability risk than other explanations.

This study mainly contributes to two different streams of the literature: limits to arbitrage and trading volume. First, it provides further empirical evidence that investors care about the fundamental risk of arbitrage (substitutability risk), which means that imperfect substitutes are indeed a limit to arbitrage (Shleifer and Vishny (1997)). The idea that the risk associated with volatility of arbitrage deters arbitrage activity also has implications for other well documented anomalies, such as the book-to-market (B/M) effect (Ali et al. (2003)). We also find that the high-minus-low factor (Fama and French (1992)) can account for part of the high-volume premium, but its explanatory power is not as great as that of substitutability risk. Finally, this research supports the findings of Wurgler and Zhuravskaya (2002), who postulate that demand curves of stocks incorporate substitutability risk. Second, our approach relates extreme trading volumes to the most fundamental motive of trading, arbitrage and its limits. Therefore, the results may shed light on trading activities that cannot be explained by announcement affects, difference of opinion or liquidity.

The rest of paper is organized as follows. The next section reviews recent works on the return-volume relationship and the limits of arbitrage. The following sections introduce the model and present the results of empirical tests. We then discuss the economic

[4] Gervais et al. (2001) rule our liquidity as an explanation for the high-volume premium, so we do not control for that factor explicitly.

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significance of substitutability risk for the high-volume premium puzzle and offer conclusions.

1.2 The Literature

1.2.1 Limited arbitrage

Recent works have raised the issue of limits to arbitrage, such as noise trader risk and transactions costs, and claim that the time it takes to reach fundamental values may be substantially longer than it should be in an efficient market.[5] Shleifer (2000) and Barberis (2003) provide excellent surveys of the limited arbitrage literature.

Obviously, the major risk of arbitrage strategies is substitutability risk (or the fundamental risk of arbitrage), since it is almost impossible to find a perfect substitute. Studies that scrutinize the effects of fundamental risk include Roll (1988), Froot and Dabora (1999) and. Wurgler and Zhravskaya (2002). These works mainly show that assets are far from having a perfect substitute and question the effect of limited arbitrage on the elasticity of demand curves. Kyle (1985) shows that it is not possible to distinguish price effects between private information and supply shocks. Consequently, studies that tests the slope of the demand curve (i.e., effects of substitutability risk) focus on a subset of specific large supply shocks whose source can be identified as uninformed by the market participants. Examples include large block trades (Scholes (1972), Holthausen et

[5] Shleifer and Vishny (1997) show that the agency problem between professional arbitrageurs and investors imposes an indirect wealth constraint that reduces arbitrageurs' ability to exploit opportunities. Theoretical works on short selling restrictions include Littner (1969), Miller (1977), and Jarrow (1980), among others. On the empirical side, Chen, Hong, and Stein (2002), Geczy, Musto, and Reed (2002), Mitchell, Pulvino and Stafford (2002), and Jones and Lamont (2001) provide evidence that short selling restrictions exist in financial markets. In contrast, D'Avolio (2002) shows that short-selling costs may not be economically significant. Noise trader risk is discussed by DeLong et al. (1990).

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In our model, imperfectly substitutable assets that are traded in segmented markets combined with wealth and margin constraints constitute the major frictions that limit arbitrage. Effects of wealth and margin constraints on arbitrageurs' demand for risky assets have been scrutinized in many recent studies including Gromb and Vayanos (2002), Liu and Longstaff (2003), Xiong (2001), and Kyle and Xiong (2001). In these studies, arbitrageurs reduce asset price volatility and provide liquidity by taking risky positions against noise trading. Yet, when an unfavorable shock causes capital losses, they liquidate positions. Furthermore, in combination with wealth constraints, margin constraints prevent arbitrageurs engaging in some of the arbitrage opportunities. Our approach contributes to this literature by adding another dimension, the effect of asset substitutability on the arbitrageur's portfolio choice problem.

1.2.2 Trading volume literature

There is a considerable trading volume literature. Market participants often follow volume data, which presumably convey information about future price movements because it is believed that trading volume shows the degree of disagreement on the fundamental prices.[6] In the finance literature, trading volume not only is used as a proxy for information but also is a sign of the degree of information asymmetry among the investors (divergent opinions).[7]

[6] Earlier works on trading volume is surveyed in Karpoff (1986).
[7] Theoretical work on the relationship between difference of opinion and trading volume includes Harris and Raviv (1993) and Shalen (1993).The major message of these studies is that dispersion can contribute to the positive correlation between volume and absolute

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Volume includes both liquidity-driven trading and information-driven trading. Theoretically speaking, if it is assumed that liquidity trading comes to the market at a constant rate, then the price change of stocks should be caused mainly by new information arriving in the market.[8] If trading volume is linked to the information flow and prices reflect investors' use of this information, then a relationship between price and volume becomes a very convincing argument.[9]

Trading volume plays a minor role in conventional models of asset pricing (e.g., Lucas (1978)). If markets are complete or can be completed through dynamic trading of available securities (as in Kreps (1982)), then asset prices evolve as if there were a single representative agent, even when there are several agents with different tastes and income processes. In this environment, the resulting allocation is optimal, and asset prices are determined purely by the aggregate risk. Trading in the market only reflects the allocation of the aggregate risk and the diversification of individual risks among investors. Volume (i.e. change in demand) provides no additional information about prices, given the characterizations of aggregate risk.

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price changes, and as well as the positive correlation among consecutive absolute price changes.

[8] One recent work related to this study examined the effect of earnings announcements on trading volume. Bamber and Cheon (1995) find that when these announcements are accompanied by large volume but small price changes, they tend to be followed by price increases.

[9] Two branches of literature study the price-volume relationship. The first, which develops rational expectation models with private information flows and noise or liquidity traders (Admati and Pfeiderer (1990); Foster and Viswanathan (1990); Kyle (1985)), suggests a positive relation between information arrival and trading volume. The second branch views information flow as a latent variable that affects trading volume and focuses on the popular mixture of distribution hypothesis (Bollerslev and Jubinski (1999);Clark (1973); Epps and Epps (1976); Harris (1986); Karpoff (1986); Lamoureux and Lastrapes (1990); Smirlock and Starks (1985); Richardson and Smith (1994); Tauchen and Pitts (1983); Tauchen and Pitts (1983))

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In models with an incomplete asset market setting (e.g., Campbell and Kyle (1993); Heaton and Lucas (1993); Wang (1993)), both aggregate and individual risk affect equilibrium prices, and the behavior of prices crucially depends on the nature of investor heterogeneity. In these models, trading volume conveys information about how assets are priced in the market. For example, Wang (1993) maintains that noise traders can affect the risk premium only under asymmetric information, which means that less informed investors will demand additional premium for the risk of trading against better informed investors.

In the trading volume literature, tangential to our study are works by Blume et al. (1994), Campbell et al. (1993), and Wang (1994). Blume et al. (1994) show that when quality of information cannot be deduced from prices, volume can be used to differentiate quality of the information. Therefore volume can be regarded as a learning tool by market participants. Wang (1994) categorizes trading motivation and its relation to price/volume movements into two classes: speculative trades and hedging trades. Speculators' sell (buy) orders reflect negative (positive) private information about future payoffs therefore prices should continue to decrease (increase) after their information revealing process (information content of volume). Hedgers' sell (buy) orders reflect a temporary reduction (increase) in the stock price (noninformational volume).[10] In our context, abnormal trading activity can be regarded as a signal of arbitrage related trades and therefore market participants can use them as learning tools.

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[10] In support of these arguments, Llorente et al. (2002) find that in periods of heavy volume, stocks with a high degree of speculative trading tend to have a positive return autocorrelation and stocks with a low degree of speculative trading tend to exhibit a negative return autocorrelation.

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1.3 The Model

1.3.1 General Setup

Consider an economy in which three different types of investors (investor A, investor B, and an arbitrageur) trade two risky assets (A and B) and a risk-free asset in T+1 periods. Investors can only invest in different subsets of the market due to some market frictions. Examples include institutional constraints, such behavioral biases as familiarity with invested assets, home bias, and information gathering costs (Merton (1987)). The segmented market assumption is required to define a role for the arbitrageur, who acts as a go-between for the segmented investors. With access to both market segments, arbitrageur has better risk sharing opportunities than either investor.

1.3.2 Assets

All agents can invest in the risk-free asset. Investors A and B can invest in only one of the risky assets (A and B, respectively), whereas the arbitrageur can invest in both of the risky assets. Assets A and B are in zero net supply and **pay off only in period T**.[11]

Assets are perfectly substitutable, that is, their payoffs are identical and equal to

$$\sum_{t=0}^{T} \delta_t ,$$

where δ_t is a random variable revealed in period t. It is assumed that the δ_t are independent and identically distributed, and distribution is symmetric around zero on the bounded support $[-\bar{\delta},\bar{\delta}\ ]$. In other words, the payoffs cannot go below or above a certain

[11] The zero net supply assumption means that the market will be cleared at all times, that is any sell by investor i (i=A,B) will be bought by the arbitrageur, or vice versa.

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limit. The bounded support assumption ensures that margin constraints on arbitrageurs become important in certain states of the world.

Price of asset i is denoted by $p_{i,t}$ in period t, and excess return per share of asset i (risk premium), $\phi_{i,t}$, is represented as

$$\phi_{i,t} = E_t\left(\sum_{s=0}^{T}\delta_s\right) - p_{i,t} = \sum_{s=0}^{t}\delta_s - p_{i,t} \quad \text{, (i = A,B).}$$

The risk-free asset has an exogenous return equal to one. Perfect substitutability and zero net supply assumptions ensure that the arbitrageur holds opposite positions in the two risky assets and hedges risks associated with assets' payoffs. Later, we will relax the assumption of perfectly substitutability and focus on the change in the arbitrageur's demand for risky assets.

1.3.3 Investors and Their Investment Opportunity Sets

Investor A can only invest in asset A and the risk-free asset, and investor B can only invest in asset B and the risk-free asset. It is assumed that assets A and B have identical cash flows, so their prices should be the same at all times unless different shocks change propensity of investors to hold the assets.

Both investors and the arbitrageur are competitive and have initial wealth, $w_{i,0}$ and $w_{0,}$ respectively. They all maximize the expected utility of period T wealth,

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In each period t > 1, investors i (i=A,B) receive an endowment that is correlated with the asset payoff (δ_t). We assume that the endowment of investors A (B) in period t is

$u_{t-1}\delta_t$ $(-u_{t-1}\delta_t)$.

The coefficient u_{t-1} measures the extent to which the endowment covaries with δ_t. When u_{t-1} is high, the covariance is high, and thus the willingness of investor i to hold asset i in period t−1 is low. We refer to u_{t-1} as the ''supply shock'' of investor i in period t−1 to emphasize that it negatively affects investor demand in that period.[12] For the base case, the supply shock u_t is deterministic and identical in all periods, that is, $u_t = u_0$ for t= 0, 1, .. ,T−1. All uncertainty is resolved in period 1.

For example, shocks can be interpreted as correlated noise trades caused by herding that lead to deviations from the fundamental price temporarily. Due to different supply shocks, investors A and B will have different propensities to hold the assets. Since they cannot trade with each other because of the segmented market, only the arbitrageur can exploit the price wedge created by these shocks. Intuitively, if the arbitrageur has infinite wealth, she will be able to absorb shocks in all periods and make risk free profit by longing asset A and shorting asset B.

The critical implication of the opposite supply shock assumption for the model is that investors A and B incur different shocks. The arbitrageur does not have any endowment,

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[12] To be consistent with the zero net supply assumption, the endowments can be interpreted as positions in a different but correlated asset. This specification of endowments is quite standard in the literature (Gromb and Vayanos (2002), O'Hara (1995)). As shown in Gromb and Vayanos (2002), the assumption of equal shocks is for simplicity and do not change the conclusions.

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so she is not affected by the supply shock directly. However, the difference of the supply shocks to different segments of the market provides her an indirect endowment. In other words, she exploits price discrepancies between assets A and B, which arise from the circumstances described above. One can think of arbitrageur as a go-between.

The merits of this model can best be understood by an example. Suppose that investor A receives a positive supply shock ($u_0>0$), in which case investor B receives a negative shock. The arbitrageur buys asset A (underpriced asset) from the investor A, who is willing to sell, and sells asset B (overpriced asset) to the investor B, who is willing to buy. Through this transaction the arbitrageur makes a profit and at the same time provides liquidity to the other investors.

1.3.4 Constraints of the Arbitrageur

The arbitrageur is subject to not only a budget constraint but also a margin constraint. The margin accounts can be thought of as collateral to insure possible losses. Collateral in the form of long positions in other assets are risky positions and may create losses for the investment house who acts as custodian for the arbitrageur. Therefore, in practice, investors are often required to keep a cash amount in their margin accounts rather than a long position in another asset. It is assumed that the margin constraint requires arbitrageur to have enough cash (not other stocks) to cover the maximum loss that can occur in the margin account. This implies that her ability to invest is limited by the value of the margin account. In particular, she may be unable to eliminate a price discrepancy in a given period, even if she knows that the discrepancy will disappear in the next period. Late

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period. Later, we will relax this assumption and solve the arbitrageur's problem with and without a margin constraint for perfectly and imperfectly substitutable assets.

Let $x_{i,t}$ denote the number of shares in asset i in period t, and let V_{it} be the value of the margin account for asset i. We have

$$V_{i,t+1} = V_{i,t} + x_{i,t}(p_{i,t+1} - p_{i,t}), \text{ i=A,B.}$$

The requirement that $V_{i,t+1} \geq 0$ implies that

$$w_t = V_{At} + V_{Bt} \geq \max_{p_{A,t+1}}\left(x_{A,t}(p_{A,t} - p_{A,t+1})\right) + \max_{p_{B,t+1}}\left(x_{B,t}(p_{B,t} - p_{B,t+1})\right)$$

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where w_t denotes the arbitrageur's wealth in period t. In other words, imposing the non-negativity constraint on the sum of each margin account ensures that arbitrageurs never default. Notice that the margin constraint is symmetric for both long and short positions. Later, we will change this assumption and completely restrict short sales in certain cases.

Finally, the arbitrageur's problem becomes:

$$\underset{\substack{x_{A,t}, x_{B,t} \\ t=..0,1,..,T-1}}{Max} \quad E_0 U(w_T)$$

subject to the dynamic wealth constraint,

$$w_{t+1} = w_t + \sum_{i=A,B} x_{i,t}(p_{i,t+1} - p_{i,t}) \qquad for \qquad t = 0,1,..,T-1$$

and the margin constraint,

$$w_t \geq \sum_{i=A,B} \max_{p_{i,t+1}} \left(x_{i,t} (p_{i,t} - p_{i,t+1}) \right).$$

1.3.5 Solution of the Arbitrageur's Problem

In this section, the arbitrageur's demand is characterized under different assumptions. Specifically, we focus on four situations: (1) no margin constraints and perfectly substitutable assets, (2) margin constraints and perfectly substitutable assets, (3) no margin constraints and imperfect substitutes, and (4) margin constraints and imperfect substitutes.

The general equilibrium solution for investors A and B and the arbitrageur's portfolio selection problem for perfect substitutes is provided in Gromb and Vayanos (2002). Our interest lies in the relationship between arbitrageurs demand and assets substitutability, therefore we briefly summarize their main results for perfect substitutes and then focus on how substitutability affects the arbitrageur's demand.

Case I: No margin constraints and perfect substitutes

Gromb and Vayanos (2002) show that, in equilibrium, due to the symmetry of the set up and perfect substitution, opposite supply shocks will induce opposite risk premiums:

$$(\phi_{A,t} - \phi_{A,t+1}) = -(\phi_{B,t} - \phi_{B,t+1}) = (\phi_t - \phi_{t+1}),$$

the arbitrageur will buy X_t shares of asset A and sell X_t shares of asset B to satisfy the zero net supply assumption (market clearance). Therefore, in the absence of margin constraint, the arbitrageur's wealth constraint reduces to

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$$w_{t+1} = w_t + x_t(\phi_t - \phi_{t+1} + \delta_{t+1}) - x_t(-\phi_t + \phi_{t+1} + \delta_{t+1}),$$

$$w_{t+1} = w_t + 2x_t(\phi_t - \phi_{t+1})$$

That is, the wealth increase does not involve any risk because the assets are perfect substitutes to each other. The arbitrageur absorbs all the shocks and invests infinite amounts in asset A and B as long as the price wedge is positive. In equilibrium, existence of the arbitrageur keeps prices at their fundamental levels at all times, and no trading take place in the market unless there is mispricing in either assets.

Case II: Margin constraints and perfect substitutes

If assets are perfectly substitutable, the zero net supply assumption ensures that arbitrageur holds opposite positions in the two risky assets $(x_t = x_{At} = -x_{Bt})$ and does not bear any risk. Similar to the previous case, the arbitrageur's wealth constraint implies that

$$w_{t+1} = w_t + 2x_t(\phi_t - \phi_{t+1}).$$

Furthermore, the margin constraint of the arbitrageur implies that

$$w_t \geq \max_{\delta_{t+1}}\left(x_t(-\phi_t + \phi_{t+1} - \delta_{t+1})\right) + \max_{\delta_{t+1}}\left(-x_t(\phi_t - \phi_{t+1} - \delta_{t+1})\right)$$

$$\Rightarrow w_t \geq 2\overline{\delta}\left|x_t\right| + \max\left(x_t(-\phi_t + \phi_{t+1})\right) + \max\left(-x_t(\phi_t - \phi_{t+1})\right)$$

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that is, the margin constraint reduces arbitrageurs ability to exploit opportunities when asset payoffs are more volatile and the arbitrageur has less wealth. Since we assume that all uncertainty is resolved at time 1, the value of the price wedge, $(\phi_t - \phi_{t+1})$, is known to the arbitrageur. As long as $(\phi_t - \phi_{t+1}) > 0$, she invests up to the financial constraint. In other words, if the prices are known to converge to each other over time, the arbitrageur uses all her resources to exploit this opportunity. Due to the margin constraint, however, the price wedge does not converge to 0 at all periods as in Case I.

If the uncertainty is resolved over time rather than at time 1, Gromb and Vayanos (2002) show that the arbitrageur's demand for risky assets depends not only on expected return on the arbitrage opportunity but also the covariance between the arbitrageur's wealth and the profitability of investment opportunities. The interpretation of their result is comparable to the findings of Shleifer and Vishny (1997), Xiong (2001), and Liu and Longstaff (2003)'s findings under different setups: Due to the uncertainty of shocks, the arbitrageur may lose some wealth if the price wedge increases (mispricing becomes larger) and this reduction in wealth prevents her from exploiting more valuable arbitrage opportunities.

When $x_t = \dfrac{w_t}{2\overline{\delta} - 2\ (\phi_t - \phi_{t+1})}$ is used in the wealth constraint, we get

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$w_{t+1} = w_t \dfrac{\overline{\delta}}{\overline{\delta} - (\phi_t - \phi_{t+1})}$, that is, the profit of arbitrageur depends on the evolution of price wedge. As it decreases over time, the arbitrageur's wealth increases, and she invests more in the next period.

Case III: No margin constraints and imperfect substitutes

Assume that asset A does not have a perfect substitute. If a positive shock hits investor A, the price wedge between the new price and the efficient price will become ϕ_t , and the asset will be underpriced by ϕ_t. In the absence of a perfect substitute, the arbitrageur and investor A will have the same investment opportunity set (asset A and the risk-free asset) but they will have different expectations about the value of asset A. The arbitrageur invests in A by using risk-free asset as the other leg of the arbitrage. Her wealth constraint reduces to

$$w_{t+1} = w_t + x_t(\phi_t - \phi_{t+1} + \delta_{t+1}),$$

that is, she is subject to the volatility of asset A's payoff.

The payoff volatility represents the fundamental (substitutability) risk involved in this strategy. In the certainty case, the arbitrageur knows that the price will converge to its efficient price at time T, but due to uncovered fundamental arbitrage risk, she can be considered to be a speculator as opposed to an arbitrageur.

Under these assumptions, the arbitrageur's problem reduces to a mean-variance optimization problem, and the demand of the arbitrageur becomes

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Notice that as arbitrageur's risk aversion (α) increases, the demand for the risky asset decreases. Risk aversion was irrelevant in the previous cases because the arbitrage strategy involved no risk. However, imperfect substitutes cause that strategy to become risky, so the solution incorporates this effect. The arbitrageur is compensated for taking the substitutability risk by the expected return, $(\phi_t - \phi_{t+1})$. Not surprisingly, the variability of cash flows reduces the demand, as it does in case II.

On the one hand, if the uncertainty is resolved in period 1, the return from this strategy will be deterministic and equal to the numerator $(\phi_t - \phi_{t+1})$. On the other hand, if the uncertainty of supply shocks is resolved gradually, further return uncertainty is added to the arbitrageur's strategy and show up in the numerator of the demand expression as $(\phi_t - E(\phi_{t+1}))$.

The intuition is similar to that discussed in case II: The possibility of a larger price wedge in the next period causes the arbitrageur to hedge against this risk and reduce her demand in the current period (DeLong et al. (1990)). The reduction in demand is not caused by a margin requirement as in case II, but by the risk of imperfect substitutes.

These results confirm the findings of Wang (1994), who demonstrates that large trading volume induces positive (negative) return autocorrelations when the primary motive for trading is speculation (liquidity). The arbitrageur that invests in imperfect substitutes is similar to the speculator in Wang (1994). Since the price discrepancy cannot be eliminated i

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eliminated immediately at all periods due to imperfect substitution, the price of asset A (B) will continue to increase (decrease) until time T. In other words, there should be a positive autocorrelation on the returns of assets in which the arbitrageur invests.

Case IV: Margin constraints and imperfect substitutes

If a positive shock occurs for investor A, the price wedge between the new price and the efficient price will become ϕ_t, that is asset A is underpriced by ϕ_t. The wealth constraint of the arbitrageur reduces to

$$w_{t+1} = w_t + x_t(\phi_t - \phi_{t+1} + \delta_{t+1}) \tag{1}$$

In other words, she is subject to the volatility of asset A's payoff and that volatility represents the fundamental risk involved in this arbitrage strategy. Moreover, the margin constraint of the arbitrageur implies that she holds enough funds in her margin account to cover the maximum loss that she can face:

$$w_t \geq \max_{\delta_{t+1}}\left(x_t(-\phi_t + \phi_{t+1} - \delta_{t+1})\right)$$

$$\Rightarrow w_t \geq \overline{\delta}\, x_t - \; x_t(\phi_t - \phi_{t+1})$$

$$\Rightarrow x_t = \frac{w_t}{\overline{\delta} - \phi_t + \phi_{t+1}}, \tag{2}$$

When (1) and (2) are combined, we get

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$$w_{t+1} = w_t \left(1 + \frac{(\delta_{t+1} + (\phi_t - \phi_{t+1}))}{(\overline{\delta} - (\phi_t - \phi_{t+1}))} \right) \tag{3}$$

When a negative shock occurs for investor A, asset A becomes overpriced by ϕ_t. In this case, the wealth constraint and margin constraint imply that

$$w_{t+1} = w_t \left(1 + \frac{(-\delta_{t+1} + (\phi_t - \phi_{t+1}))}{(\overline{\delta} - (\phi_t - \phi_{t+1}))} \right) \tag{4}$$

A comparison of (3) and (4) reveals us the arbitrageur's demand difference, depending on the next period's payoff and the risk premiums. If the next periods payoff is positive (negative), the wealth of the arbitrageur increases more when the asset is underpriced (overpriced) than when it is overpriced (underpriced). Notice that the margin constraint is symmetric for both long and short positions. If the arbitrageur is restricted from shorting the assets, she can only invest in underpriced assets and must bypass the profit opportunities when assets are overpriced. In that case, the equation (2) and (3) give the feasible trading strategy and wealth process respectively.

It may be optimal for the arbitrageur not to execute her strategy if the next period payoff becomes positive (negative) when the asset is overpriced (underpriced). In that case, she demands nothing at all periods and lets the mispricing exist until time T. In fact, this result is not surprising because of the conservative margin requirement.

1.3.6 Empirical Implications of the Solutions

All these cases present the effects of limits to arbitrage and their effects on the trading activities of arbitrageurs. It may not be possible to distinguish case I from case IV, because if a

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because if all mispricing is eliminated instantaneously, there should be no trade in either situations. Therefore, no trade argument becomes equivalent to no arbitrage condition. This is particularly striking since cases I and IV represent the extreme situations in the spectrum of the arbitrageur's ability to absorb shocks.

The similarity between the no-trade result of this model and that of Milgrom and Stokey (1982) is interesting. The latter is often used to argue that in ongoing security markets the arrival of new information cannot generate trade. The usual intuition for this claim is that if traders begin with a Pareto optimal allocation of resources, then any trade is for speculative purposes, so the willingness of one trader to make a trade indicates to others that they should not accept the other side of the trade. In our context, lack of trade happens due to high limits of arbitrage (imperfect substitutes and conservative margin requirements) rather than information asymmetry. Yet, the similarity of predictions mainly originates from the segmented market assumption, which is essentially a by-product of information asymmetry.

Cases II and III produce an observationally equivalent result since the arbitrageur fails to fully absorb the supply shock. The comparison of arbitrageur's demand in these cases depends on the level of financial constraint imposed on the arbitrageur and the risk aversion coefficient. Two propositions can now be stated with respect to arbitrageurs' demand for risky assets.

Proposition 1 (no trade – no arbitrage): If the limits of arbitrage are strong enough, there will be no attempt to eliminate possible mispricing and arbitrageurs will not provide the required liquidity to the market. In a frictionless market, the existence of arbitrageurs ensures no mispricing. In both cases, there will be no arbitrage-related demand for assets.

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Proposition 2 (risky arbitrage): Any mispricing in assets with close substitutes increases the interest among competitive arbitrageurs (increased visibility) and therefore boosts arbitrageurs' demand for risky asset, which is revealed as abnormal trading volume.

We test the second proposition to explain the high-volume premium puzzle documented by GKM (2001). As discussed before, GKM (2001) find that periods of extremely high (low) volume tend to be followed by positive (negative) excess returns, and they postulate that this pattern depends on increased stock visibility or lack of thereof. Their argument can explain increased returns but not the relationship between increased visibility and increased trading activity. Is there any factor that makes some stocks more visible than others? Does substitutability makes it easier to capture mispricings or new information, thereby causing unusually high trading activities?

Investors trade for at least two reasons: portfolio rebalancing and speculation. Portfolio rebalancing trades may be triggered by many factors, such as changes in investment opportunity sets, investment objectives, and liquidity needs. Speculative trades are mainly based on heterogeneity in beliefs or information sets. We argue that neither motive can be the reason for the increased visibility and trading activity that may explain high volume premium **unless** the need for trades due to the above factors is positively correlated among all investors.

Only arbitrage trades, the very basic motivation to trade, can be positively correlated if there is enough competitive arbitrageurs in the market and if they do not face significant limits to arbitrage. This argument is the flip side of the correlated noise trades and associated noise trader risk (DeLong et al. (1990)). One can think of groups of investors

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A and B as noise traders in their segmented markets, which receive correlated supply shocks that make their trades positively correlated. In this sense, it is not possible to distinguish arbitrageurs from noise traders unless the direction of supply shocks is known (Shleifer (2000)). From this perspective, substitutability risk is related to noise trader risk and it is systematic, and therefore should be priced. Arbitrageurs' demand for risky assets depends on the degree of substitutability risk (deviation from the fundamental values), investment horizon, risk aversion, and margin constraints. Therefore, provided that arbitrageurs are competitive, their interest in a certain asset may be strong enough to increase its visibility via abnormal trading activities.

1.4 Empirical Tests

1.4.1 Data and Methodology

We use data from Center for Research in Security Prices (CRSP) on NYSE stocks between August 1963 and January 2001. The sample is constructed by splitting the time interval between August 15, 1963, and Jan 31, 2001, into 188 nonintersecting intervals of 50 trading days.[13] We avoid using the same day of the week as the last day in every trading interval by skipping a day in between each of these intervals.

Each interval is split into a *reference period*, the first 49 days, and a *formation period*, the last day. The reference period is used to determine how unusually large or small trading volume is in the formation period. The number of shares traded is used as the measure of trading volume.[14] In a given trading interval, a stock is classified as a high (low) volume stock if its formation period volume is in the top (low) 10 percentile of 50 daily

[13] We follow GKM's method but our test period is five years longer than theirs.
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volumes.[15] Methods and the terminology we used are illustrated in Figure 1. Descriptive statistics about the sample are summarized in Table 1.1. Overall we end up with 30,832 high volume and 32,148 low volume stocks.

At the end of each formation period (the *formation date)*, we form portfolios based on the trading volume classification of stocks for that interval. We construct zero investment portfolios by shorting low-volume stocks and taking long positions in high-volume stocks. The portfolios are held without any rebalancing over the *test period*, that is, the subsequent 1 to 20 trading days.

All NYSE common stocks are considered in any given trading interval except those for which some data was missing. We also removed (1) any stocks that experienced a merger, a delisting, partial liquidation, or a seasoned equity offering during or within one year prior to the formation period; (2) stocks with less than one year of trading history on the NYSE at the start of an interval; and (3) stocks whose price fell below five dollars at some point in the reference period. Also, we divided the sample in three parts according to company size and calculated the return on high- and low-volume stocks. The firms in market capitalization deciles nine and ten are classified as large, those in deciles six through eight as medium, and those in deciles two to five as small firms. Firms in decile one are excluded from the sample because most do not survive the filters described above.

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[15] GKM uses the highest (lowest) 5 stocks as opposed to top (bottom) 10 percentile. Our approach increases the sample size, which allows us to obtain better substitutability risk estimates of portfolios using the market portfolio as a substitute. The descriptive statistics of our sample is slightly different from those of GKM because of the modified method and the data period.

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1.4.2 Portfolio Formation and Returns

At each formation date, a zero investment portfolio is formed by taking a long position for a total of one dollar in all high-volume stocks in a size group, and a short position for a total of one dollar in all low-volume stocks in that same group. Each stock in the high (low) volume category is given equal weight. The position taken at the end of the formation period in each trading interval *i* is not rebalanced for the whole test period of 1 to 20 days.

The test period returns of the long position are denoted by R_i^h (R_i^l), and the net position by $NR_i = R_i^h - R_i^l$. For the reasons explained later, we use the last 184 periods to test the hypothesis that the average net returns of this strategy over all 184 trading intervals, NR, are positive:

$$\overline{NR} = \frac{1}{184}\sum_{i=1}^{184} NR_i \,.$$

Note that, in any given interval, only stocks that experience a large enough trading volume shock (positive or negative) are included in the zero investment portfolio. In this respect, this portfolio formation approach is similar to Cooper (1999). The zero investment portfolios are also similar to those used by Conrad et al. (1994) in that the high-volume side of the position requires an investment of exactly one dollar, whereas the low-volume side of the position generates exactly one dollar at the outset.

The cumulative returns of high-volume, low-volume and zero investment portfolios are summarized in Table 1.2. Table 1.3 presents descriptive statistics for cumulative returns of the high-volume and low-volume portfolios. Overall, our results confirm the high volume pre

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volume premium documented by GKM (2001) for a longer data period using slightly different methods. The cumulative return differential between high-volume and low-volume stocks is positive and statistically greater than zero. Furthermore, the high-volume return premium is more apparent for small than large companies.

Finally, we replicate the same analysis by skipping one more day after the formation period to control for possible short-term buy/sell pressures that can influence the cumulative returns. Results are not significantly different from the findings in Table 1.2. In the discussion of results, we will compare this buy/sell control sample with the original sample. Also, in order to control for further possible announcement effects (new information), we follow GKM's method and eliminate stocks that experienced a dividend or earnings announcement one day before, the day of, or one day after the formation period. For this purpose, we used I/B/E/S actuals database, which has data available after 1984. Moreover, the five most extreme observations are removed from each trading interval in order to eliminate the effects of outliers. The results are not affected by either of these filters.

Before we attempt to reconcile the high-volume premium documented in Table 1.2, we must define the measures used for certain well-documented risk factors, measures of difference of opinion, and substitutability risk.

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1.4.3 Measure of Substitutability Risk

The substitutability risk of a portfolio (P) is measured at time t as the standard error of the regression and sum of the squared residuals of the following OLS:

$$R_i^P - R_i^f = \beta\ (R_i^m - R_i^f) + \varepsilon_i\ ,$$

where i= t–1, t–2, …, t–k (k determines the estimation window length).

R_i^f corresponds to risk free rate and R_i^m represents to market return at time i. This approach was used by Wurgler and Zhuravskaya (2002), who analyze substitutability effects on demand curve elasticity.[16]

The intuition behind this approach is based on the zero investment portfolio created by arbitrageurs. The implied zero investment strategy is, for every \$1 long in portfolio P: short \$1 in T-bills, short \$ β in market portfolio, and long \$ β in T-bills. In other words, it is assumed that market should be a close substitute for any diversified portfolio, provided that there are enough stocks in the portfolio. On an individual stock basis, finding a perfect substitute is almost impossible as shown by many studies (e.g., Roll (1988), Wurgler and Zhuravskaya (2002)). Yet, the market should be a perfect substitute for any well-diversified portfolio by construction. We interpret the standard deviation of the OLS residuals as the denominator of the Sharpe ratio.

For each high-volume and low-volume portfolios, we calculate the variance of residuals and the standard error of regression by using the previous 150, 200, and 250 days.[17] In

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[16] We also used companies with closest B/M and Size in the same industry as close subsitutes in addition to market portfolio. The results are essentially the same.

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order to compare the effects of measurement changes, we discard the first four periods and focused on the last 184. Descriptive statistics for empirical distributions of substitutability are reported in Table 1.4. A comparison of substitutability risk difference between high-volume and low-volume stocks supports our conjecture that high-volume stocks have lower substitutability risk (Table 1.4 - Panel C), but, the difference becomes less significant as the estimation period decreases.

1.4.4 Measure of Divergence of Opinions

A possible explanation of the observed return premium is that opinions among investors differ more for high-volume portfolios than low-volume portfolios.[18] In order to control for this factor, we employ two measures suggested by Chen et al. (2001), who hypothesize that managers with some discretion over the disclosure of information prefer to announce good news immediately and allow bad news to emerge slowly. In that case, the returns of such companies should reflect asymmetries that can be captured by the positive skewness of the distribution. They also show that positive skewness should be more pronounced for firms that receive attention from fewer analysts. Therefore, they suggest negative skewness of empirical distributions as a measure for difference of opinion:

$$SK_t = \frac{-n(n-1)^{3/2}\sum R_p^3}{(n-1)(n-2)\left(\sum R_p^2\right)^{3/2}},$$

[17] We also calculated substitutability risk using two-day and three-day returns but the results were unaffected.

[18] Analyst coverage and difference between analyst estimates (Diether et al.(2002)) are the two most commonly used measures of difference of opinion. Because of the time interval in our study, we do not use these.

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where R_P represents the sequence of demeaned daily returns of the portfolios for period t, and n represents the number of days before the formation period. They also use the following measure, which is based on the second moments of the empirical distributions:

$$DUVAL_t = \log\left\{\frac{(n_u - 1)\sum_{DOWN} R_p^{\,2}}{(n_d - 1)\sum_{UP} R_p^{\,2}}\right\};$$

n_u represents the number of "up" days, and n_d represents the number of "down" days. The idea of the DUVAL (down-to-up volatility) measure is similar to skewness, but it is less likely to be affected by the extreme returns.[19]

1.4.5 Measure of Other Risk Factors

In order to control for various risk factors suggested in the literature, we use those examined by Fama and French (1992), book-to-market (high minus low, HML) and size (small minus big, SMB).[20] Also, to control for possible momentum effects (Jegadeesh and Titman (1993)), we use an indicator variable that represents whether a portfolio was a winner or loser portfolio with respect to the market for 50,100, and 250 days before the formation period. Using the Trade and Quote (TAQ) database, GKM (2001) show that liquidity (Amihud and Mendelson (1986)) is not a possible explanation for the return differential between high-volume stocks and low-volume stocks. Therefore, we do not control for the liquidity factor.

[19] We report the results for skewness (SK). The results with DUVAL are essentially the same.

[20] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

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1.4.6 Tests

We argue that higher systematic risk requires a higher expected return and that substitutability risk is systematic, so it should be priced when assets deviate from fundamentals. Furthermore, if abnormal trading activity is a proxy for positive shifts in systematic substitutability risk, then a positive trading volume shock should precede large average return. Therefore, the return differential between responsiveness of high- and low-volume portfolios to changes in systematic risk should explain the high-premium puzzle.

In order to test the effect of systematic risk difference on return differential, we use the following equation system. The seemingly unrelated regression method (SURE) allows the disturbance terms for the high- and low-volume portfolios in each trading interval to be correlated.[21]

$$R_{it}{}^{H} = \beta_{HC} + \beta_{HM} R_{it}{}^{m} + \beta_{HS} SMB_{it} + \beta_{HH} HML_{it} + \beta_{HO} M250_t^H + \beta_{HSK} SK_t^H + \beta_{HA} A_t^H + \varepsilon_t{}^H \tag{5}$$

$$R_{it}{}^{L} = \beta_{LC} + \beta_{LM} R_{it}{}^{m} + \beta_{LS} SMB_{it} + \beta_{LH} HML_{it} + \beta_{LO} M250_t^L + \beta_{LSK} SK_t^L + \beta_{LA} A^L{}_t + \varepsilon_t{}^L \tag{6}$$

In these equations, t=5,..,188; i=1..20; and

R_{it}^{H} = cumulative i day return on the equally weighted high volume portfolio;

[21] We also used OLS to estimate the given system, but differences between the methods do not affect the conclusions.

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R^{L}_{it} = cumulative i day return on the equally weighted low volume portfolio;

$A^{H}{}_{t}$ = standard error of the regression in Section 1.4.3 for 250 days before the formation period (substitutability risk measure for high volume portfolio)[22];

$A^{L}{}_{t}$ = standard error of the regression in Section 1.4.3 for 250 days before the formation period (substitutability risk measure for low volume portfolio);

$R_{it}{}^{m}$ = cumulative market return for the corresponding test period;

SMB_t= Fama-French size factor for the corresponding test period;

HML_t = Fama-French book-to-market (B/M) factor for the corresponding test period;

$M250_t{}^{H}$, $M250_t{}^{L}$ = 1 if high (low) volume portfolio outperformed the market for 250 days before the formation period, 0 otherwise (momentum factor); and

$SK_t{}^{H}$, $SK_t{}^{L}$= negative skewness of the high (low) volume portfolio for 250 days before the formation period.

In this setting, the low-volume portfolio is a benchmark for a portfolio of correctly priced securities, and the high-volume portfolio represents a portfolio of possible mispriced securities. Therefore, we expect to estimate a significant β_{HA} and an insignificant β_{LA}. Furthermore, because we are particularly interested in the difference among the coefficients of systematic risks due to other factors, we test the following hypotheses:

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[22] Notice that the substitutability risk is estimated by using the returns before the formation period. This information is available at the formation date.

Hypothesis 1: There is no market risk difference between high-volume and low-volume portfolios, or

$\beta_{HM} - \beta_{LM} = 0.$

Hypothesis 2: Size differences do not explain the return differential of high-volume and low-volume portfolios, or $\beta_{HS} - \beta_{LS} = 0.$

Hypothesis 3: B/M differences do not explain the return differential of high-volume and low-volume portfolios, or $\beta_{HH} - \beta_{LH} = 0.$

Hypothesis 4: Momentum risk differences do not explain the return differential of high-volume and low-volume portfolios, or $\beta_{HO} - \beta_{LO} = 0.$

Hypothesis 5: Difference of opinion differences do not explain the return differential of high-volume and low-volume portfolios, or $\beta_{HSK} - \beta_{LSK} = 0.$

Hypothesis 6: Substitutability risk differences do not explain the return differential of high-volume and low-volume portfolios, or $\beta_{HA} - \beta_{LA} = 0.$

Main results are presented in Table 1.5 and two points should be noted. First, confirming Fama and French (1992), market, size and book-to-market factors are significant for both high- and low-volume portfolios, but difference of opinion is not significant for both. Second, the coefficients for momentum and substitutability risks are significant at the 10% level for high-volume portfolios but are not significant for low-volume portfolios. The results are in line with our conjectures, but the statistical significance of substitutability risk is not as high as for the other systematic risk factors.

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What is more crucial here is that substitutability risk may explain the return premium difference between the portfolios that experienced positive and negative volume shocks. The results for the six hypotheses are presented in Table 1.6.1.[23]

The difference in market betas is not statistically significant for either the original sample or the buy/sell pressure control sample. Therefore, hypothesis 1 cannot be rejected, that is, market risk may not explain the return differential between high- and low-volume portfolios.

Hypothesis 4 also cannot be rejected. The momentum factor difference between high- and low-volume portfolios is zero before the eighth day, but it becomes significant and negative thereafter. In other words, in the short run, return premium is higher for stocks that have performed relatively poorly during the reference period. Therefore, momentum cannot explain the return differential between high- and low-volume stocks.[24]

The difference in the skewness of prior distributions is not statistically significant either for the original or the buy/sell sample. Therefore, hypothesis 5 cannot be rejected, that is, difference of opinion may not account for the return differential between high- and low-volume portfolios.

The substitutability risk coefficients reveal interesting patterns. The arbitrage risk difference is statistically significant at the 1% level for the cumulative returns from days 3 to 14. Comparison of the substitutability risk coefficient differential in part A and B of

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[23] We also estimated the same system by using all possible combinations or explanatory variables. The results and conclusions are unaffected. The results presented in Tables 1.6 to 1.8 include all the variables we considered.

[24] GKM (2001) reach the same conclusion by using both daily and weekly returns.

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Table 1.6.2 shows that temporary buy/sell pressures cannot account for this result.[25] Furthermore, all significant beta differentials are positive, which indicates that substitutability risk is more likely to be priced in high-volume portfolios than low-volume portfolios. The substitutability risk coefficient difference is significant and greater than zero in all cases from days 3 to 14, so hypothesis 6 is rejected.[26]

Interestingly, the p-values of the arbitrage risk coefficient difference reveal a U-shaped significance. During the test period, the standard deviation of arbitrage risk coefficient difference is fairly constant, which suggests that the pattern is indeed caused by a concave arbitrage risk coefficient difference. We will address to this issue later.

1.4.7 Relationship between Size and Substitutability Risk

Hypothesis 2 cannot be rejected on the basis of the overall sample. In order to understand the above pattern of the substitutability risk difference, we separate high- and low-volume portfolios *according to the company size* and test the following systems of equations using seemingly unrelated regression for portfolios of large companies and portfolios of medium and small companies separately.[27]

$$R_{it}^{H} = \beta_{HC} + \beta_{HM} R_{it}^{m} + \beta_{HS} SMB_{it} + \beta_{HH} HML_{it} + \beta_{HO} M250_t^H + \beta_{HSK} SK_t^H + \beta_{HA} A_t^H + \varepsilon_t^H$$

[25] High volume premium documented by GKM (2001) is becomes insignificant around the 15th day.
[26] We tested our hypothesis by using different measures for substitutability risk with different estimation periods and confirm the above results in each case with minor differences.
[27] We combined medium and small size companies to increase the number of stocks in portfolios in order to create a better substitute for the market portfolio.

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$$\beta_{LSK} SK_t^L + \beta_{LA} A^L{}_t + \varepsilon_t{}^L$$

When the same tests are applied to the substitutability risk coefficient differential of large size high- and low-volume portfolios, the differences remain significant at the 5% level until the eleventh day. Most of these effects disappear in the buy/sell control sample, which indicates that immediate returns are more significant for large companies (Table 1.7.1 and Table 1.7.2).

For medium and small companies, the arbitrage risk differential between high- and low-volume portfolios is significant after day three. Furthermore, possible buy/sell pressures do not affect the significance of he high-volume premium for this group (Table 1.8.1 and Table 1.8.2).

These two observations suggest that the pattern observed for the whole sample is created by the combination of arbitrage and company size. This supports the visibility hypothesis: An arbitrage opportunity in large companies is more likely to be identified sooner than an opportunity in stocks of small and medium companies, because large companies are followed by more analysts and a larger investor (presumably arbitrageur) base. Because small size firms are less visible to a large number of competitive arbitrageurs in a short period, price corrections takes longer time.[28] Substitutability of the

[28] Large size can be interpreted as a proxy for less information asymmetry between investors and the companies. In this sense, variables that measures transparency, such as index membership and wide coverage by analysts, are all by-products of size.

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stocks of large companies increases arbitrageurs' interest and trading volume (visibility), which will reduce the possibility and duration of mispricing.

1.4.8 Explanatory Power of the B/M Ratio

Value investors tend to buy high B/M stocks when they become relatively cheap with respect to their fundamental values. Therefore, a high B/M ratio can be viewed as an alternative arbitrage risk measure. Interestingly, the correlation between HML and arbitrage risk is quite small (0.07 for the original sample, 0.11 for the buy/sell sample), which suggests that they capture different aspects of mispricing. For the original sample, we reject the hypothesis 3 after day nine and find that the short-term return difference between high- and low-volume portfolios may also be associated with value investing strategies due to higher factor loadings on the HML factor. Although the significance of that factor is not as strong as the substitutability risk factor, it shows effects in the latter parts of the test period. Therefore, HML may be a viable explanation for high-volume premium puzzle but its significance is not as strong as the substitutability risk.

1.5 Economic Significance of Arbitrageur's Profits and High-Volume Investing as a Hedge Fund Strategy

If it is assumed that the possibility of getting positive or negative information on a particular asset is equally likely in the long run, then the returns due to information received during abnormal trading period should eventually be canceled (diversification of unsystematic risk).

Yet, returns obtained from deviations from fundamentals exhibit an asymmetry. Assume that fundamental prices of two perfect substitutes (A and B) are \$100. For some reason,

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asset A is underpriced by 10% and sold at $90. In this case, the arbitrageur's strategy is to long 10/9 shares of asset A and short 1 share of asset B (zero investment), and wait. When asset A reverts to its true price ($100), its price will increase by 11.11%, and the arbitrageur makes $11.11.

Now consider another pair of substitutes (C and D) and assume asset C is overpriced by 10% and sold at $110. The arbitrageur shorts 10/11 shares of asset C and longs 1 asset D. Once the prices converge to $100, arbitrageur makes $9.09, and the price of C declines by 9.09%. For an equally weighted portfolio of A, B, C and D, longing all of them will yield a return of 0.505%. This represents the return on the portfolio that contains assets with abnormally high trading activities. Although deviations from fundamental values is symmetric (i.e., a security can be under priced or overpriced equal likelihood), the observed return on an equally weighted portfolio of mispriced securities is asymmetric and skewed to positive values, as presented above.

The strategy of arbitrageurs includes selling overpriced stocks and/or buying underpriced stocks, and presumably their trading activities are signaled as increased trading volumes. Therefore, their profit depends on the price movements of the stocks that are more likely to be traded in high-volume portfolio. We should reemphasize that the situation that is described above does not distinguish which stocks are overpriced or underpriced, but it shows the relationship between average mispricing in an equally weighted portfolio and the magnitude of mispricing.

If it is assumed that high-volume portfolios include all the mispriced securities in the market, then the level of correction for mispricing can be estimated. Based on the parameter estimates obtained for the risk factors for 15-day cumulative returns

(β_{HC}=0.0031, β_{HM} =1.0295, β_{HS} =0.3828, and β_{HH} =0.3707) given in Table 1.5 and the values of the average of observations (R_H=1.2%, R_M = 0.45%, HML= 0.54%, and SMB=0.03%), the return captured by the substitutability risk is 0.23%. In a market where short selling is not constrained, this premium corresponds to a mispricing of 6.75%. As the selling constraints become binding, however, the return from substitutability risk drops down to 0.23% per 15 days.[29] Therefore, as a hedge fund strategy, identification of mispricing via "positive" volume shocks may produce positive returns, depending on the level of short-selling constraints.

1.6 Conclusion

In this paper, we provide new insights to the visibility hypothesis of Miller (1977), who argues that increased attention to a given stock (such as heavy trading) should attract and convince more investors to buy the stock. Therefore, abnormal trading activities should signal price increases in a market where short selling is restricted. Miller's argument can explain the relationship between abnormal trading activity and subsequent price increases, but it falls short to explain why particular stocks experience high trading volume in the first place. We argue that stocks with low substitutability risk are more likely to experience abnormal trading activity when their price deviates from fundamentals and we postulate that the abnormal trading activities may signal the intentions of the traders, presumably arbitrageurs. Thus, in an economy where short sales are restricted, stocks with substitutes are more likely to be "visible" when they are underpriced. We have presented empirical evidence that substitutability risk can explain

[29] Conrad, Gultekin, and Kaul (1997) estimate that one-week return of less than 1 percent on zero investment portfolios would be wiped out by one-way transaction costs of 0.2 percent.

the premium between high- and low-volume stocks (Gervais, Kaniel, and Mingelgrin (2001)).

The arbitrage interpretation of the visibility hypothesis complements Chan and Lakonishok (1993), who suggest that investors typically only consider the assets they hold when making their sell decisions and all assets in the market when making buy decisions. They postulate that the decision about which asset to buy conveys more information to the market than the decision to sell, because sell orders usually are interpreted as liquidity motivated. We maintain that the information effect on trading volume is only one side of the story. In the model presented here, the trading strategies of investors who have access to all assets in a segmented market may not be driven only by information. Investors, who provide the liquidity to other investors with limited investment opportunity sets and who profit from any price discrepancy between markets segments, care about the availability of perfect substitutes (substitutability risk). Their demand for such assets increases the visibility of those assets and forces other investors to consider them. When assets with low substitutability risk are underpriced, increased visibility causes prices to appreciate and expected returns to depreciate.

Finally, our approach relates extreme trading volume to the most fundamental motive of trading: arbitrage and its limits and it may shed light to trading activities that cannot be explained by announcement affects, difference of opinion, or liquidity.

APPENDIX 1

TABLES AND FIGURES FOR CHAPTER 1

Table 1.1

Descriptive Statistics for the Daily CRSP Sample

The daily CRSP sample is comprised of 188 nonoverlapping trading intervals of 50 days. For each interval, a stock is classified in one of three size groups according to its market capitalization deciles at the end of the year preceding the formation period. Firms in market capitalization deciles nine and ten are assigned to the large-firm group, firms in deciles six through eight are assigned to the medium-firm group, and those in deciles two to five are assigned to the small-firm group. Volume represents the number of shares traded every day in each stock. Panel A shows statistics on the averages and medians taken over all the trading days of all trading intervals. Those in Panels B and C are taken over the trading days of these 5th and last trading intervals. Panel D shows statistics on the number of stocks that are classified as high or low volume stocks in each trading interval. High and Low Volume classification is defined in section 1.4.1. Panel E shows number of stocks that are classified as high or low volume stocks in selected trading intervals.

Panel A: Overall Sample - 188 Trading Intervals

	Large Firms	Medium Firms	Small Firms
Average Volume	164322	36320	14234
Median Volume	44200	8430	4520
Panel B: 5th Trading Interval (Formation Period 08/12/1964)			
Average Volume	6461	2717	1623
Median Volume	3500	1400	700
Panel C: 188th Trading Interval (Formation Period 12/12/2000)			
Average Volume	1067714	108151	30229
Median Volume	414300	51200	11800

Table 1.1 (Continued)

Table 1.1 (Continued)

Panel D: Descriptive statistics of number of stocks with respect to volume and size classification

	High Volume	Low Volume	High Volume	Low Volume	High Volume	Low Volume
Average	87.0	91.3	61.7	65.6	16.2	15.3
Median	80.5	78.0	54.0	56.0	11.0	8.5
Std dev	42.8	58.5	29.2	32.7	14.9	15.7
Minimum	17	7	19	9	0	0
Maximum	320	372	235	235	71	80

Panel E: Number of Low and High Volume Stocks with respect to firm size for selected periods

		Large Firms		Medium Firms		Small Firms	
Period	Formation period	High Volume	Low Volume	High Volume	Low Volume	High Volume	Low Volume
1	10/24/1963	68	32	69	32	28	8
10	8/10/1965	29	68	76	49	19	26
20	8/3/1967	73	15	101	13	45	5
40	8/31/1971	24	65	34	62	22	24
60	8/18/1975	35	235	24	122	1	4
80	8/2/1979	125	51	84	46	11	8
100	7/18/1983	59	144	36	78	1	13
120	7/1/1987	87	119	36	51	1	4
140	6/14/1991	87	97	50	68	1	1
160	5/30/1995	80	184	68	97	20	28
180	5/14/1999	58	169	86	140	34	26

Table 1.2

Zero Investment Portfolio Formation Strategy for the Daily CRSP Sample

In each trading interval, stocks are classified according to size and trading volume. The size groups are based on the firms' market capitalization deciles at the close of the year prior to each formation period: The firms in market capitalization deciles nine and ten are assigned to the large-firm group, the firms in deciles six through eight are assigned to the medium-firm group, and those in deciles two to five are assigned to the small-firm group. The volume classification is based on whether the stock's trading volume during the formation period (last day of each trading interval) is among the top (high volume) or bottom (low volume) 10% percentile of the 50 daily volumes in the whole trading interval.

Test Period (in days)	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Panel A.Small Firms								
High Volume	0.0046	0.0072	0.0082	0.0096	0.0099	0.0106	0.0118	0.0117
Low Volume	-0.0026	-0.0036	-0.0021	-0.0001	0.0004	0.0005	-0.0005	0.0000
NR	0.0072	0.0108	0.0103	0.0097	0.0096	0.0101	0.0124	0.0117
Panel B: Medium Firms								
High Volume	0.0023	0.0035	0.0042	0.0057	0.0063	0.0068	0.0073	0.0081
Low Volume	-0.0012	-0.0021	-0.0024	-0.0013	-0.0016	-0.0019	-0.0016	-0.0010
NR	0.0035	0.0056	0.0066	0.0070	0.0078	0.0087	0.0089	0.0091
Panel C: Large Firms								
High Volume	0.0013	0.0018	0.0023	0.0037	0.0038	0.0044	0.0053	0.0060
Low Volume	-0.0006	-0.0012	-0.0017	-0.0011	-0.0015	-0.0019	-0.0013	-0.0010
NR	0.0020	0.0030	0.0040	0.0048	0.0053	0.0064	0.0066	0.0071
Panel D: All Firms								
High Volume	0.0020	0.0028	0.0035	0.0049	0.0052	0.0057	0.0065	0.0072
Low Volume	-0.0010	-0.0016	-0.0020	-0.0011	-0.0014	-0.0017	-0.0014	-0.0010
NR	0.0029	0.0044	0.0054	0.0060	0.0066	0.0075	0.0079	0.0082
t-stat	**4.31**	**4.10**	**3.85**	**3.58**	**3.18**	**3.09**	**2.91**	**2.63**

Table 1.2 (Continued)

Test Period (in days)	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
Panel A.Small Firms								
High Volume	0.0129	0.0141	0.0156	0.0152	0.0150	0.0165	0.0162	0.0180
Low Volume	0.0013	0.0022	0.0025	0.0029	0.0037	0.0037	0.0042	0.0046
NR	0.0116	0.0118	0.0131	0.0123	0.0113	0.0127	0.0120	0.0135
Panel B: Medium Firms								
High Volume	0.0088	0.0100	0.0111	0.0114	0.0124	0.0128	0.0133	0.0147
Low Volume	-0.0005	0.0005	0.0015	0.0018	0.0018	0.0020	0.0025	0.0035
NR	0.0093	0.0095	0.0097	0.0097	0.0106	0.0108	0.0108	0.0112
Panel C: Large Firms								
High Volume	0.0067	0.0083	0.0091	0.0095	0.0101	0.0103	0.0108	0.0122
Low Volume	-0.0005	0.0007	0.0012	0.0014	0.0017	0.0020	0.0027	0.0037
NR	0.0072	0.0076	0.0079	0.0081	0.0084	0.0083	0.0081	0.0086
Panel D: All Firms								
High Volume	0.0077	0.0091	0.0102	0.0106	0.0113	0.0117	0.0122	0.0136
Low Volume	-0.0005	0.0006	0.0012	0.0014	0.0017	0.0020	0.0025	0.0034
NR	0.0083	0.0085	0.0091	0.0092	0.0096	0.0097	0.0097	0.0103
t-stat	**2.49**	**2.48**	**2.51**	**2.45**	**2.46**	**2.33**	**2.15**	**2.24**

Table 1.3

Empirical Distribution and Sample Statistics for the 20-day Net Returns of the High Volume and Low Volume and Market Portfolios Using the Daily CRSP Sample

In each trading interval, stocks are classified according to size and daily trading volume as described in section 1.4.1. The empirical distribution and sample statistics of the following table are then obtained from the 20-day returns for each of the 188 trading intervals of the high volume and low.

Days	1	2	3	4	5	6	7	8	9
High Volume									
Mean	0.002	0.003	0.004	0.005	0.005	0.006	0.006	0.007	0.007
Median	0.002	0.003	0.003	0.006	0.005	0.005	0.006	0.009	0.008
Std. Dev.	0.007	0.011	0.014	0.016	0.020	0.023	0.026	0.030	0.032
Skewness	0.148	0.152	-0.219	-0.014	0.374	0.494	0.376	0.219	0.058
Kurtosis	3.830	4.058	3.679	3.960	4.687	4.986	5.380	5.743	5.338
Low Volume									
Mean	-0.001	-0.001	-0.002	-0.001	-0.001	-0.002	-0.002	-0.001	-0.001
Median	-0.001	0.000	0.000	0.000	0.000	-0.001	0.000	0.001	0.001
Std. Dev.	0.006	0.010	0.014	0.016	0.019	0.023	0.026	0.030	0.032
Skewness	-0.329	-0.588	-0.529	-0.447	-0.320	-0.129	-0.112	-0.024	-0.220
Kurtosis	3.239	4.328	3.871	3.676	3.601	4.113	4.158	4.706	4.629
Market Portfolio									
Mean	0.000	0.000	0.001	0.001	0.000	0.000	0.001	0.001	0.001
Median	0.000	0.001	0.002	0.003	0.000	0.002	0.003	0.004	0.005
Std. Dev.	0.008	0.012	0.015	0.017	0.021	0.025	0.027	0.029	0.030
Skewness	0.315	0.117	-0.033	0.121	0.298	0.268	0.151	0.152	0.060
Kurtosis	3.561	4.558	3.695	3.966	4.771	5.483	5.058	5.154	4.715
Observations	184	184	184	184	184	184	184	184	184

Table 1.3 (continued)

Days	11	12	13	14	15	16	17	18	19	20
High Volume										
Mean	0.010	0.011	0.011	0.012	0.012	0.014	0.015	0.016	0.016	0.017
Median	0.013	0.011	0.013	0.013	0.014	0.016	0.017	0.017	0.017	0.017
Std. Dev.	0.035	0.037	0.038	0.041	0.044	0.045	0.047	0.048	0.050	0.052
Skewness	0.227	0.151	0.145	0.052	-0.093	-0.058	0.049	-0.001	-0.111	-0.151
Kurtosis	4.901	4.615	4.584	4.875	5.065	4.854	4.655	4.683	4.944	5.168
Mean	0.001	0.001	0.002	0.002	0.003	0.003	0.004	0.005	0.006	0.007
Low Volume										
Median	0.005	0.005	0.005	0.005	0.006	0.009	0.011	0.011	0.013	0.010
Std. Dev.	0.035	0.036	0.038	0.040	0.043	0.044	0.045	0.047	0.050	0.051
Skewness	-0.146	-0.159	-0.145	-0.278	-0.395	-0.421	-0.310	-0.293	-0.391	-0.445
Kurtosis	4.788	4.676	4.967	5.419	5.483	4.763	4.383	4.512	4.693	4.745
Market Portfolio										
Mean	0.003	0.003	0.004	0.005	0.005	0.006	0.007	0.008	0.008	0.008
Median	0.005	0.003	0.005	0.005	0.008	0.010	0.010	0.011	0.012	0.013
Std. Dev.	0.032	0.034	0.035	0.037	0.039	0.041	0.043	0.044	0.045	0.046
Skewness	0.300	0.200	0.196	0.132	-0.044	-0.030	0.079	0.050	0.004	-0.039
Kurtosis	4.819	4.457	4.599	4.934	4.889	4.460	4.152	4.192	4.352	4.672
Observations	184	184	184	184	184	184	184	184	184	184

Table 1.4

Descriptive Statistics of Substitutability Risk Estimates

In each trading interval, stocks are classified as high volume and low volume according to the methodology described in section 4.1. Arbitrage risk measure in Panel A is obtained from the standard error of the regression in Section 1.4.3 for each high volume and low volume portfolio: where i= T-1, T-2, ..., T-k; k=150,200 and 250. R^f_t corresponds to risk free rate and R^m_t corresponds to market return at time t. Values in Panel B represents the sum of squares of the heteroscedastocity robust residuals of the above regression (ε_i). Entries in Panel C shows the t-values of the tests of equality of means obtained by using substitutability risk measures of for k=150,200 and 250.

Panel A: Substitutability risk measure based on the standard error of the regression (SER)

	HIGH VOLUME			LOW VOLUME		
Estimation Period	150	200	250	150	200	250
Mean	0.0029	0.0029	0.0029	0.0031	0.0031	0.0031
Median	0.0027	0.0027	0.0027	0.0028	0.0029	0.0029
Maximum	0.0066	0.0064	0.0058	0.0087	0.0077	0.0081
Minimum	0.0015	0.0015	0.0016	0.0017	0.0017	0.0017
Std. Dev.	0.0009	0.0009	0.0008	0.0011	0.0011	0.0011
Skewness	1.3716	1.3877	1.2209	1.7538	1.5021	1.5272
Kurtosis	5.23	5.36	4.41	7.52	5.82	6.01
Jarque-Bera	96	102	61	251	130	141
Observations	184	184	184	184	184	184

Table 1.4 (Continued)

Table 1.4 (Continued)

Panel B: Substitutability risk measure based on the sum of the squared residuals (SSR)

Estimation Period	150	200	250	150	200	250
Mean	0.0014	0.0019	0.0023	0.0016	0.0022	0.0028
Median	0.0011	0.0014	0.0019	0.0012	0.0016	0.0021
Maximum	0.0065	0.0081	0.0084	0.0113	0.0120	0.0164
Minimum	0.0003	0.0004	0.0006	0.0004	0.0006	0.0007
Std. Dev.	0.0010	0.0012	0.0014	0.0014	0.0017	0.0022
Skewness	2.3089	2.3240	1.9272	3.3549	2.6532	2.7600
Kurtosis	9.76	9.80	7.19	18.70	12.13	13.44
Jarque-Bera	514	520	248	2235	855	1070
Observations	184	184	184	184	184	184

Panel C. Testing equality of substitutability risk estimates' means

Estimation Period	150	200	250
Based on Standard error of the regression (SER)	1.68	1.94	2.17
Based on Sum of the squared residuals (SSR)	1.83	2.08	2.40

Table 1.5

All companies

All companies - SURE Model of High- and Low-volume Portions of the Zero Investment Portfolios

Table 1.5

Using the Daily CRSP Sample.

Using the 184 zero investment portfolios, we estimate the following SURE model, where t=5, . . . ,188, which indexes the trading periods:

$$R_{it}^{H} = \beta_{HC} + \beta_{HM} R_{it}^{m} + \beta_{HS} SMB_{it} + \beta_{HH} HML_{it} + \beta_{HO} M250_t^H + \beta_{HSK} SK_t^H + \beta_{HA} A_t^H + \varepsilon_t^H$$

$$R_{it}^{L} = \beta_{LC} + \beta_{LM} R_{it}^{m} + \beta_{LS} SMB_{it} + \beta_{LH} HML_{it} + \beta_{LO} M250_t^L + \beta_{LSK} SK_t^L + \beta_{LA} A_t^L + \varepsilon_t^L$$

The two equations for this model describe the two portions of the zero investment portfolios, R^{H}_{it} and R^{L}_{it}, as defined in Section 1.4.2. R_{it}^{m} , SMB_{it}, and HML_{it} represent the corresponding returns on the market and the Fama-French (1992) factors in the i–day test period (i=5,10,15,20). $M250^{H}_{t}$ ($M250^{L}_{t}$) is the 0-1 momentum indicator that shows if the high-(low-) volume portfolios outperformed the market in the 250 days before the formation period t. SK^{H}_{t} (SK^{L}_{t}) is the skewness of the high- (low-) volume portfolio's returns before the formation period t. A^{H}_{t} and A^{L}_{t} denote the substitutability risk of high- and low-volume portfolios respectively and calculated by the method described in section 4.3 for the 250-day period before the formation date t. In all cases, the model is estimated for 4 different test periods (i=5,10,15,20 cumulative trading days). For each such regression we show the parameter estimates and the p-values (in parenthesis).

Table 1.5 (continued)

Table 1.5 (continued)

	β_{HC}	β_{HM}	β_{HS}	β_{HH}	β_{HO}	β_{HSK}	β_{HA}	β_{LC}	β_{LM}	β_{LS}	β_{LH}	β_{LO}	β_{LSK}	β_{LA}
5-day cumulative	0.0012	0.9856	0.4080	0.4041	-0.0018	0.0002	1.2484	-0.0003	0.8949	0.4707	0.2742	0.0000	0.0003	-0.7466
returns	(0.53)	(0.00)	(0.00)	(0.00)	(0.08)	(0.76)	(0.05)	(0.84)	(0.00)	(0.00)	(0.00)	(0.98)	(0.64)	(0.13)
10-day cumulative	0.0030	1.0262	0.4364	0.3908	-0.0030	-0.0011	1.4590	-0.0010	0.9620	0.4235	0.2822	0.0006	0.0003	-0.8162
returns	(0.21)	(0.00)	(0.00)	(0.00)	(0.02)	(0.16)	(0.07)	(0.67)	(0.00)	(0.00)	(0.00)	(0.70)	(0.72)	(0.22)
15-day cumulative	0.0031	1.0295	0.3828	0.3707	-0.0033	-0.0019	1.7042	-0.0045	0.9893	0.4098	0.2770	0.0012	0.0002	-0.0391
returns	(0.31)	(0.00)	(0.00)	(0.00)	(0.06)	(0.07)	(0.09)	(0.10)	(0.00)	(0.00)	(0.00)	(0.47)	(0.84)	(0.96)
20-day cumulative	0.0025	1.0251	0.4167	0.3399	-0.0030	-0.0023	2.2318	-0.0048	1.0031	0.4329	0.2886	0.0021	0.0006	-0.0888
returns	(0.50)	(0.00)	(0.00)	(0.00)	(0.15)	(0.06)	(0.07)	(0.14)	(0.00)	(0.00)	(0.00)	(0.29)	(0.61)	(0.92)

Table 1.6.1
Original Sample, All companies
Wald test results of the SURE Model that Regresses High- and Low-volume Portions of the Zero Investment Portfolios Using the Daily CRSP Sample.

Using the 184 zero investment portfolios, we estimate the following SURE model, where t=5, . . ,188, which indexes the trading periods:

$$R_{it}^{H} = \beta_{HC} + \beta_{HM} R_{it}^{m} + \beta_{HS} SMB_{it} + \beta_{HH} HML_{it} + \beta_{HO} M250_t^H + \beta_{HSK} SK_t^H + \beta_{HA} A_t^H + \varepsilon_t^H$$

$$R_{it}^{L} = \beta_{LC} + \beta_{LM} R_{it}^{m} + \beta_{LS} SMB_{it} + \beta_{LH} HML_{it} + \beta_{LO} M250_t^L + \beta_{LSK} SK_t^L + \beta_{LA} A^L{}_t + \varepsilon_t^L$$

The two equations for this model describe the two portions of the zero investment portfolios, $R^H{}_{it}$ and $R^L{}_{it}$, as defined in Section 1.4.2. R_{it}^m , SMB_{it}, and HML_{it} represent the corresponding returns on the market and the Fama-French (1992) factors in the i–day test period (i =1..20). $M250^H{}_t$ ($M250^L{}_t$) is the 0-1 momentum indicator that shows if the high-(low-) volume portfolios outperformed the market in the 250 days before the formation period t. $SK^H{}_t$ ($SK^L{}_t$) is the skewness of the high- (low-) volume portfolio's returns before the formation period t. $A^H{}_t$ and $A^L{}_t$ denotes the substitutability risk of high and low volume portfolios, respectively, and calculated by the method described in section 4.3 for the 250 day period **before** the formation date t. In all cases, the model is estimated for 20 different test periods (i=1,..., 20 cumulative trading days). For each such regression we show the difference between estimated slopes, as well as their differences. The values in Panel A show the estimated slope differences. The values in Panel B show the corresponding Wald test p-values for the null hypothesis indicated in the column heading.

Table 1.6.1 (Continued)
Panel A: Estimated Slope Differences.

i	$\beta_{HC}-\beta_{LC}$	$\beta_{HM}-\beta_{LM}$	$\beta_{HS}-\beta_{LS}$	$\beta_{HH}-\beta_{LH}$	$\beta_{HO}-\beta_{LO}$	$\beta_{HSK}-\beta_{LSK}$	$\beta_{HA}-\beta_{LA}$
1	0.001	0.090	0.011	-0.008	0.001	0.000	0.517
2	0.003	0.035	-0.010	0.014	0.000	-0.001	0.648
3	0.002	0.043	-0.051	0.139	0.000	-0.001	1.310
4	0.002	0.049	-0.059	0.124	-0.001	-0.001	1.639
5	0.002	0.091	-0.063	0.130	-0.002	0.000	1.995
6	0.002	0.064	-0.085	0.092	-0.002	0.000	2.092
7	0.002	0.041	-0.004	0.080	-0.001	0.000	1.968
8	0.002	0.037	0.024	0.095	-0.002	0.000	2.189
9	0.004	0.052	0.044	0.119	-0.003	-0.001	1.976
10	0.004	0.064	0.013	0.109	-0.004	-0.001	2.275
11	0.003	0.041	0.016	0.131	-0.003	-0.001	2.676
12	0.003	0.048	-0.003	0.127	-0.003	-0.002	2.786
13	0.004	0.038	-0.009	0.130	-0.004	-0.002	2.679
14	0.005	0.037	0.013	0.132	-0.005	-0.002	2.458
15	0.008	0.040	-0.027	0.094	-0.005	-0.002	1.743
16	0.006	0.055	-0.035	0.092	-0.005	-0.002	2.629
17	0.006	0.060	-0.051	0.074	-0.005	-0.002	2.704
18	0.006	0.041	-0.040	0.074	-0.005	-0.002	2.689
19	0.007	0.031	-0.035	0.067	-0.005	-0.003	2.358
20	0.007	0.022	-0.016	0.051	-0.005	-0.003	2.321

Table 1.6.1 (Continued)
Panel B: Wald Test *P*-values for the Null Hypothesis Indicated in the Column Heading.

	Constant	Market	SMB	HML	Momentum	Skewness	Sub. Risk
i	$\beta_{HC}-\beta_{LC}=0$	$\beta_{HM}-\beta_{LM}=0$	$\beta_{HS}-\beta_{LS}=0$	$\beta_{HH}-\beta_{LH}=0$	$\beta_{HO}-\beta_{LO}=0$	$\beta_{HSK}-\beta_{LSK}=0$	$\beta_{HA}-\beta_{LA}=0$
1	0.24	0.03	0.85	0.92	0.28	0.38	0.06
2	0.06	0.43	0.89	0.86	0.68	0.06	0.13
3	0.24	0.25	0.37	0.04	0.75	0.09	0.01
4	0.34	0.16	0.27	0.03	0.38	0.33	0.01
5	0.51	0.10	0.26	0.02	0.19	0.88	0.01
6	0.43	0.07	0.15	0.10	0.31	0.94	0.01
7	0.41	0.24	0.95	0.15	0.62	0.84	0.03
8	0.41	0.26	0.66	0.08	0.31	0.91	0.02
9	0.17	0.10	0.38	0.02	0.12	0.40	0.03
10	0.17	0.04	0.79	0.03	0.05	0.16	0.01
11	0.29	0.16	0.72	0.01	0.06	0.19	0.00
12	0.34	0.09	0.94	0.01	0.08	0.14	0.01
13	0.21	0.17	0.84	0.01	0.07	0.07	0.01
14	0.11	0.17	0.77	0.01	0.03	0.08	0.02
15	0.04	0.15	0.53	0.05	0.04	0.10	0.12
16	0.11	0.05	0.42	0.05	0.02	0.13	0.02
17	0.15	0.03	0.24	0.11	0.03	0.10	0.03
18	0.16	0.15	0.36	0.12	0.06	0.08	0.03
19	0.08	0.29	0.43	0.17	0.03	0.06	0.07
20	0.09	0.46	0.71	0.31	0.06	0.05	0.09

Table 1.6.2
Buying/Selling Pressure Control Sample, All companies
Wald Test Results of the SURE Model That Regresses High- and Low-volume Portions of the Zero Investment Portfolios Using the Daily CRSP Sample.
Panel A: Estimated Slope Differences.

i	β_{HC}-β_{LC}	β_{HM}-β_{LM}	β_{HS}-β_{LS}	β_{HH}-β_{LH}	β_{HO}-β_{LO}	β_{HSK}-β_{LSK}	β_{HA}-β_{LA}
1	0.001	0.094	0.003	0.197	0.000	-0.001	0.215
2	0.001	0.066	-0.046	0.186	-0.001	-0.001	0.767
3	0.001	0.044	-0.047	0.128	-0.001	0.000	0.995
4	0.001	0.053	-0.039	0.123	-0.002	0.000	1.417
5	0.001	0.032	-0.093	0.088	-0.002	0.000	1.555
6	0.002	0.015	-0.008	0.077	-0.002	0.000	1.369
7	0.002	0.007	0.027	0.101	-0.003	0.000	1.624
8	0.003	0.024	0.048	0.121	-0.004	-0.001	1.385
9	0.003	0.043	0.009	0.104	-0.004	-0.001	1.720
10	0.003	0.027	-0.008	0.127	-0.004	-0.001	2.142
11	0.002	0.034	-0.031	0.121	-0.004	-0.002	2.204
12	0.003	0.025	-0.034	0.121	-0.004	-0.002	2.118
13	0.005	0.021	-0.002	0.133	-0.005	-0.002	1.862
14	0.007	0.027	-0.040	0.089	-0.005	-0.002	1.080
15	0.005	0.042	-0.048	0.077	-0.006	-0.002	2.035
16	0.005	0.045	-0.060	0.059	-0.005	-0.002	2.081
17	0.005	0.025	-0.047	0.060	-0.005	-0.002	2.113
18	0.006	0.017	-0.046	0.055	-0.006	-0.003	1.843
19	0.006	0.008	-0.027	0.042	-0.005	-0.003	1.796
20	0.006	-0.003	-0.016	0.038	-0.005	-0.002	1.669

Table 1.6.2 (Continued)

Panel B: Wald Test *P*-values for the Null Hypothesis Indicated in the Column Heading.

i	Constant $\beta_{HC}-\beta_{LC}=0$	Market $\beta_{HM}-\beta_{LM}=0$	SMB $\beta_{HS}-\beta_{LS}=0$	HML $\beta_{HH}-\beta_{LH}=0$	Momentum $\beta_{HO}-\beta_{LO}=0$	Skewness $\beta_{HSK}-\beta_{LSK}=0$	Sub. Risk $\beta_{HA}-\beta_{LA}=0$
1	0.23	0.05	0.97	0.01	0.93	0.07	0.45
2	0.53	0.10	0.45	0.01	0.44	0.10	0.07
3	0.53	0.24	0.42	0.02	0.16	0.45	0.05
4	0.77	0.15	0.52	0.02	0.06	0.95	0.02
5	0.66	0.38	0.13	0.10	0.13	0.91	0.03
6	0.51	0.68	0.89	0.14	0.31	0.94	0.08
7	0.52	0.83	0.61	0.06	0.11	0.97	0.05
8	0.20	0.46	0.33	0.02	0.02	0.38	0.10
9	0.21	0.18	0.86	0.03	0.01	0.15	0.04
10	0.37	0.35	0.86	0.01	0.01	0.17	0.01
11	0.42	0.22	0.46	0.01	0.02	0.14	0.02
12	0.28	0.37	0.42	0.01	0.02	0.06	0.03
13	0.13	0.43	0.97	0.00	0.01	0.07	0.06
14	0.04	0.33	0.33	0.06	0.01	0.10	0.30
15	0.14	0.12	0.25	0.09	0.01	0.14	0.06
16	0.19	0.11	0.15	0.19	0.01	0.11	0.07
17	0.20	0.37	0.26	0.19	0.03	0.08	0.07
18	0.11	0.56	0.28	0.24	0.01	0.06	0.12
19	0.12	0.77	0.51	0.39	0.03	0.05	0.15
20	0.14	0.93	0.70	0.44	0.06	0.14	0.20

Table 1.7.1
Original Sample, Large Size Companies
Wald Test Results of the SURE Model That Regresses High- and Low-volume Portions of the Zero Investment Portfolios Using the Daily CRSP Sample
Panel A: Estimated Slope Differences.

i	β_{HC}-β_{LC}	β_{HM}-β_{LM}	β_{HS}-β_{LS}	β_{HH}-β_{LH}	β_{HO}-β_{LO}	β_{HSK}-β_{LSK}	β_{HA}-β_{LA}
1	0.000	0.083	-0.042	0.051	0.000	0.000	0.725
2	0.000	0.088	-0.004	0.131	0.000	0.000	1.115
3	0.001	0.030	0.004	0.190	-0.001	-0.001	1.388
4	0.002	0.033	-0.025	0.090	-0.002	-0.001	1.614
5	0.002	0.065	-0.008	0.117	-0.003	-0.001	1.733
6	0.001	0.050	-0.059	0.067	-0.002	0.000	2.630
7	0.002	0.042	-0.015	0.070	-0.002	-0.001	2.363
8	0.001	0.013	0.019	0.090	-0.003	0.000	2.723
9	0.003	0.009	0.027	0.107	-0.003	-0.001	2.131
10	0.004	0.024	-0.011	0.092	-0.003	-0.001	2.255
11	0.004	0.028	-0.035	0.124	-0.003	-0.001	2.142
12	0.005	0.045	-0.059	0.130	-0.004	-0.001	1.867
13	0.005	0.047	-0.073	0.113	-0.004	-0.002	2.069
14	0.008	0.046	-0.059	0.104	-0.004	-0.002	1.199
15	0.011	0.037	-0.082	0.056	-0.005	-0.002	0.338
16	0.007	0.050	-0.088	0.060	-0.005	-0.002	1.830
17	0.007	0.058	-0.102	0.053	-0.004	-0.003	1.858
18	0.007	0.052	-0.096	0.053	-0.003	-0.002	1.660
19	0.008	0.046	-0.103	0.067	-0.005	-0.003	1.617
20	0.007	0.053	-0.096	0.066	-0.004	-0.003	1.543

Table 1.7.1 (Continued)
Panel B: Wald Test *P*-values for the Null Hypothesis Indicated in the Column Heading.

i	Constant $\beta_{HC}-\beta_{LC}=0$	Market $\beta_{HM}-\beta_{LM}=0$	SMB $\beta_{HS}-\beta_{LS}=0$	HML $\beta_{HH}-\beta_{LH}=0$	Momentum $\beta_{HO}-\beta_{LO}=0$	Skewness $\beta_{HSK}-\beta_{LSK}=0$	Sub. Risk $\beta_{HA}-\beta_{LA}=0$
1	0.73	0.11	0.56	0.59	0.55	0.39	0.03
2	0.97	0.08	0.96	0.14	0.82	0.55	0.02
3	0.54	0.48	0.95	0.01	0.20	0.14	0.02
4	0.37	0.43	0.70	0.19	0.08	0.16	0.02
5	0.48	0.13	0.91	0.07	0.13	0.60	0.03
6	0.87	0.22	0.38	0.30	0.19	0.69	0.00
7	0.64	0.28	0.82	0.27	0.25	0.52	0.02
8	0.68	0.73	0.76	0.15	0.12	0.72	0.01
9	0.32	0.82	0.65	0.08	0.13	0.57	0.04
10	0.30	0.51	0.85	0.11	0.16	0.30	0.03
11	0.24	0.43	0.51	0.03	0.14	0.32	0.05
12	0.16	0.18	0.25	0.02	0.13	0.28	0.11
13	0.16	0.16	0.16	0.04	0.12	0.16	0.08
14	0.05	0.17	0.27	0.07	0.08	0.23	0.33
15	0.01	0.26	0.11	0.33	0.04	0.21	0.79
16	0.08	0.13	0.08	0.26	0.05	0.20	0.16
17	0.11	0.07	0.04	0.32	0.11	0.07	0.17
18	0.12	0.10	0.05	0.31	0.24	0.14	0.23
19	0.09	0.17	0.04	0.22	0.12	0.09	0.25
20	0.14	0.11	0.05	0.24	0.26	0.05	0.30

Table 1.7.2
Buying/Selling Pressure Control Sample, Large Size Companies
Wald Test Results of the SURE Model That Regresses High- and Low-volume Portions of the Zero Investment Portfolios
Using the Daily CRSP Sample
Panel A: Estimated Slope Differences.

i	$\beta_{HC}-\beta_{LC}$	$\beta_{HM}-\beta_{LM}$	$\beta_{HS}-\beta_{LS}$	$\beta_{HH}-\beta_{LH}$	$\beta_{HO}-\beta_{LO}$	$\beta_{HSK}-\beta_{LSK}$	$\beta_{HA}-\beta_{LA}$
1	0.000	0.123	-0.034	0.237	0.000	-0.001	0.454
2	0.002	0.054	-0.007	0.151	-0.002	-0.001	0.597
3	0.003	0.024	-0.019	0.040	-0.003	-0.002	0.713
4	0.003	0.024	0.000	0.085	-0.003	-0.001	0.710
5	0.002	0.009	-0.084	0.026	-0.003	-0.001	1.608
6	0.003	0.006	-0.030	0.032	-0.003	-0.001	1.264
7	0.003	-0.021	0.015	0.074	-0.004	-0.001	1.705
8	0.006	-0.021	0.017	0.093	-0.004	-0.001	1.008
9	0.005	0.004	-0.029	0.069	-0.004	-0.002	1.261
10	0.006	0.019	-0.071	0.105	-0.004	-0.002	1.072
11	0.007	0.039	-0.103	0.105	-0.005	-0.002	0.749
12	0.007	0.040	-0.113	0.088	-0.004	-0.002	1.007
13	0.010	0.036	-0.091	0.090	-0.005	-0.002	0.127
14	0.013	0.029	-0.109	0.046	-0.006	-0.002	-0.758
15	0.009	0.044	-0.118	0.042	-0.006	-0.002	0.701
16	0.009	0.046	-0.124	0.034	-0.005	-0.003	0.745
17	0.008	0.041	-0.117	0.034	-0.004	-0.003	0.671
18	0.009	0.036	-0.129	0.050	-0.005	-0.003	0.765
19	0.008	0.045	-0.122	0.051	-0.004	-0.004	0.676
20	0.008	0.040	-0.108	0.052	-0.003	-0.003	0.496

Table 1.7.2 (Continued)
Panel B: Wald Test *P*-values for the Null Hypothesis Indicated in the Column Heading.

	Constant	Market	SML	HML	Momentum	Skewness	Sub. Risk
i	$\beta_{HC}-\beta_{LC}=0$	$\beta_{HM}-\beta_{LM}=0$	$\beta_{HS}-\beta_{LS}=0$	$\beta_{HH}-\beta_{LH}=0$	$\beta_{HO}-\beta_{LO}=0$	$\beta_{HSK}-\beta_{LSK}=0$	$\beta_{HA}-\beta_{LA}=0$
1	0.90	0.03	0.70	0.01	0.49	0.13	0.15
2	0.30	0.25	0.92	0.06	0.09	0.01	0.20
3	0.14	0.61	0.79	0.57	0.02	0.04	0.22
4	0.16	0.59	1.00	0.19	0.03	0.30	0.31
5	0.44	0.83	0.25	0.68	0.05	0.36	0.05
6	0.24	0.88	0.67	0.60	0.07	0.24	0.15
7	0.29	0.59	0.81	0.24	0.02	0.37	0.07
8	0.08	0.58	0.77	0.12	0.03	0.28	0.29
9	0.09	0.92	0.60	0.23	0.04	0.12	0.19
10	0.07	0.59	0.17	0.07	0.03	0.14	0.29
11	0.04	0.24	0.04	0.06	0.03	0.12	0.49
12	0.05	0.22	0.03	0.11	0.05	0.07	0.35
13	0.01	0.28	0.08	0.12	0.02	0.10	0.91
14	0.00	0.39	0.03	0.42	0.01	0.11	0.52
15	0.03	0.18	0.02	0.43	0.02	0.12	0.56
16	0.04	0.15	0.01	0.52	0.06	0.04	0.55
17	0.05	0.21	0.02	0.52	0.16	0.08	0.60
18	0.05	0.28	0.01	0.35	0.08	0.05	0.56
19	0.08	0.18	0.01	0.36	0.18	0.02	0.62
20	0.10	0.21	0.02	0.34	0.30	0.08	0.72

Table 1.8.1
Original Sample, Small and Medium Size Companies
Wald Test Results of the SURE Model That Regresses High- and Low-volume Portions of the Zero Investment Portfolios Using the Daily CRSP Sample
Panel A: Estimated Slope Differences.

i	β_{HC}-β_{LC}	β_{HM}-β_{LM}	β_{HS}-β_{LS}	β_{HH}-β_{LH}	β_{HO}-β_{LO}	β_{HSK}-β_{LSK}	β_{HA}-β_{LA}
1	0.002	0.085	0.110	-0.066	0.000	-0.001	0.420
2	0.003	-0.020	0.022	-0.067	0.000	-0.002	0.730
3	0.001	0.050	-0.030	0.069	0.001	-0.001	1.249
4	0.000	0.052	-0.019	0.140	0.000	0.000	1.640
5	0.000	0.087	-0.058	0.121	-0.001	0.000	1.680
6	0.002	0.053	-0.058	0.087	0.000	0.000	1.426
7	0.002	0.010	0.045	0.055	0.000	0.000	1.574
8	0.003	0.024	0.074	0.075	-0.001	0.000	1.560
9	0.005	0.072	0.110	0.131	-0.003	-0.001	1.284
10	0.004	0.070	0.087	0.135	-0.004	-0.002	1.712
11	0.001	0.010	0.083	0.138	-0.004	-0.002	2.534
12	0.002	-0.002	0.076	0.127	-0.005	-0.002	2.313
13	0.003	-0.010	0.057	0.139	-0.005	-0.002	2.328
14	0.003	-0.010	0.079	0.159	-0.007	-0.002	2.666
15	0.003	0.007	0.033	0.132	-0.008	-0.002	2.773
16	0.002	0.018	0.029	0.106	-0.010	-0.002	3.278
17	0.001	0.024	-0.001	0.079	-0.010	-0.002	3.581
18	0.002	-0.011	0.020	0.082	-0.010	-0.002	3.501
19	0.003	-0.021	0.029	0.060	-0.010	-0.003	3.247
20	0.003	-0.050	0.065	0.039	-0.010	-0.002	3.328

Table 1.8.1 (Continued)
Panel B: Wald Test *P*-values for the Null Hypothesis Indicated in the Column Heading.

	Constant	Market	SMB	HML	Momentum	Skewness	Sub. Risk
i	$\beta_{HC}-\beta_{LC}=0$	$\beta_{HM}-\beta_{LM}=0$	$\beta_{HS}-\beta_{LS}=0$	$\beta_{HH}-\beta_{LH}=0$	$\beta_{HO}-\beta_{LO}=0$	$\beta_{HSK}-\beta_{LSK}=0$	$\beta_{HA}-\beta_{LA}=0$
1	0.13	0.21	0.24	0.60	0.58	0.08	0.13
2	0.09	0.75	0.82	0.55	0.86	0.02	0.07
3	0.55	0.35	0.71	0.48	0.57	0.21	0.01
4	0.99	0.28	0.80	0.08	0.99	0.64	0.00
5	0.90	0.06	0.42	0.09	0.73	0.80	0.00
6	0.50	0.23	0.43	0.21	0.94	0.91	0.03
7	0.57	0.83	0.54	0.43	0.92	0.88	0.03
8	0.43	0.57	0.28	0.27	0.57	0.89	0.03
9	0.15	0.08	0.09	0.04	0.20	0.35	0.09
10	0.25	0.09	0.17	0.03	0.07	0.18	0.03
11	0.86	0.78	0.14	0.02	0.08	0.28	0.00
12	0.58	0.96	0.18	0.04	0.05	0.24	0.00
13	0.42	0.79	0.33	0.03	0.03	0.18	0.01
14	0.44	0.78	0.18	0.01	0.01	0.13	0.00
15	0.44	0.84	0.54	0.03	0.00	0.17	0.00
16	0.56	0.60	0.58	0.06	0.00	0.27	0.00
17	0.83	0.50	0.99	0.17	0.00	0.39	0.00
18	0.69	0.76	0.72	0.18	0.00	0.21	0.00
19	0.47	0.57	0.61	0.33	0.00	0.16	0.00
20	0.48	0.17	0.23	0.53	0.00	0.25	0.00

Table 1.8.2
Buying/Selling Pressure Control Sample, Small and Medium Size Companies
Wald Test Results of the SURE Model That Regresses High- and Low-volume Portions of the Zero Investment Portfolios Using the Daily CRSP Sample
Panel A: Estimated Slope Differences.

i	$\beta_{HC}-\beta_{LC}$	$\beta_{HM}-\beta_{LM}$	$\beta_{HS}-\beta_{LS}$	$\beta_{HH}-\beta_{LH}$	$\beta_{HO}-\beta_{LO}$	$\beta_{HSK}-\beta_{LSK}$	$\beta_{HA}-\beta_{LA}$
1	0.001	0.036	0.047	0.161	0.000	-0.001	0.416
2	-0.001	0.054	-0.018	0.162	0.000	0.000	0.870
3	-0.002	0.033	-0.010	0.175	0.000	0.000	1.181
4	-0.001	0.035	-0.039	0.121	-0.001	0.001	1.204
5	0.000	0.013	-0.078	0.095	-0.001	0.001	0.986
6	0.000	-0.017	0.022	0.063	0.000	0.000	1.140
7	0.001	-0.008	0.064	0.086	-0.002	0.000	1.115
8	0.003	0.044	0.103	0.134	-0.003	-0.001	0.857
9	0.002	0.047	0.076	0.138	-0.005	-0.001	1.283
10	-0.001	-0.013	0.047	0.148	-0.004	-0.001	2.133
11	0.000	-0.024	0.040	0.136	-0.005	-0.001	1.911
12	0.001	-0.032	0.027	0.148	-0.006	-0.002	1.975
13	0.001	-0.035	0.062	0.175	-0.008	-0.002	2.292
14	0.001	-0.013	0.016	0.131	-0.009	-0.002	2.396
15	0.001	-0.004	0.020	0.095	-0.010	-0.001	2.910
16	-0.001	0.004	-0.006	0.067	-0.011	-0.001	3.205
17	0.000	-0.034	0.018	0.073	-0.010	-0.002	3.122
18	0.001	-0.039	0.022	0.051	-0.011	-0.002	2.893
19	0.001	-0.069	0.056	0.036	-0.011	-0.002	2.972
20	0.002	-0.085	0.059	0.033	-0.010	-0.001	2.781

Table 1.8.2 (Continued)

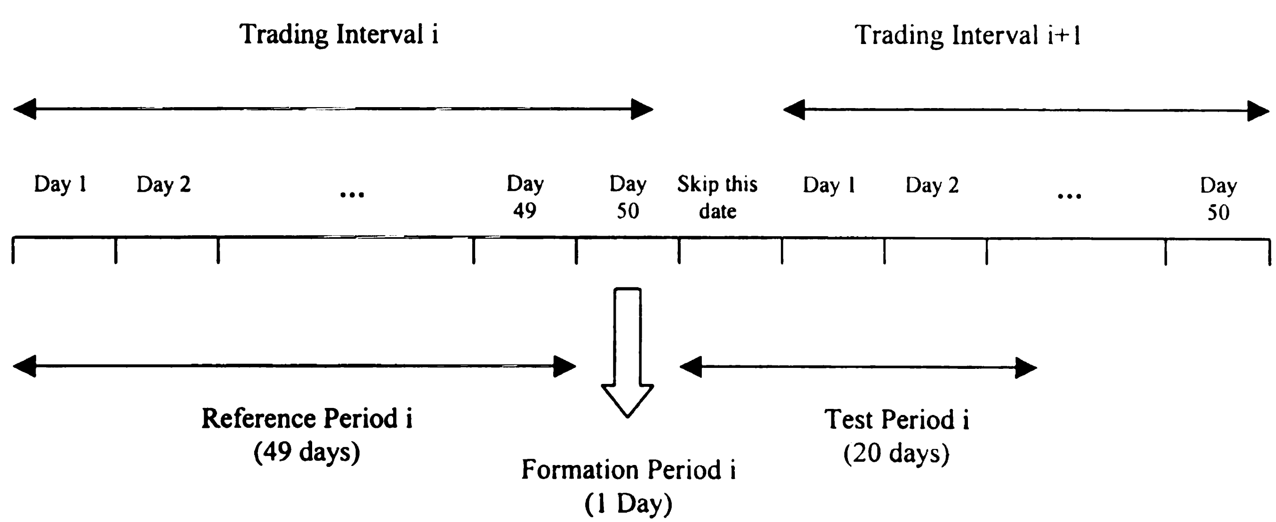
Panel B: Wald Test *P*-values for the Null Hypothesis Indicated in the Column Heading.

i	Constant β_{HC}-β_{LC}=0	Market β_{HM}-β_{LM}=0	SMB β_{HS}-β_{LS}=0	HML β_{HH}-β_{LH}=0	Momentum β_{HO}-β_{LO}=0	Skewness β_{HSK}-β_{LSK}=0	Sub. Risk β_{HA}-β_{LA}=0
1	0.54	0.60	0.65	0.13	0.65	0.06	0.12
2	0.65	0.34	0.83	0.09	0.80	0.62	0.02
3	0.39	0.50	0.90	0.02	0.74	0.78	0.01
4	0.61	0.45	0.61	0.08	0.45	0.32	0.02
5	0.93	0.78	0.31	0.15	0.71	0.48	0.09
6	1.00	0.71	0.77	0.34	0.95	0.73	0.08
7	0.75	0.85	0.35	0.20	0.38	0.78	0.11
8	0.32	0.29	0.11	0.04	0.11	0.58	0.24
9	0.49	0.26	0.23	0.03	0.03	0.34	0.08
10	0.71	0.72	0.39	0.01	0.04	0.45	0.00
11	0.96	0.52	0.48	0.03	0.03	0.40	0.02
12	0.74	0.39	0.64	0.02	0.01	0.28	0.02
13	0.75	0.33	0.28	0.01	0.00	0.21	0.01
14	0.72	0.72	0.77	0.03	0.00	0.28	0.01
15	0.86	0.90	0.71	0.09	0.00	0.41	0.00
16	0.85	0.92	0.91	0.25	0.00	0.56	0.00
17	0.98	0.36	0.75	0.22	0.00	0.31	0.00
18	0.74	0.29	0.68	0.40	0.00	0.25	0.00
19	0.77	0.06	0.29	0.57	0.00	0.37	0.00
20	0.72	0.02	0.26	0.60	0.00	0.49	0.01

Figure 1.1
Time Sequence for Sample Selection.

Each of the 188 trading intervals consists of 50 trading days. In each trading interval, the first 49 days are used to measure whether trading volume during the last day is unusually large (top 10 percentile of daily volumes) during the trading interval or small (bottom 10 percentile). Based on this measure, portfolios are formed at the end of the last day, and their performance is evaluated over the subsequent 1 to 20 days. For the first sample, we followed Gervais et al. (2001) and started the test period after the formation period i. In order to control for temporary buy/sell pressures, we created another sample by starting the test period after skipping another day after the formation period i.

Figure 1.1 (Continued)



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Chapter 2

2 Tests of Competing Theories of Momentum: Market Intelligence and Statistical Arbitrage

2.1 Introduction

The simple investing strategy of buying prior winners and selling prior losers, now dubbed momentum, appears significantly profitable both statistically and economically in both US (Jegadeesh and Titman (1993)) and other major markets (Rouwenhorst (1998, 1999) and Griffin, Ji, and Martin (2003)). As an example, in the US, from 1965 to 2000, stocks in the top six-month return decile beat stocks in the bottom decile by 5.59% (p-value = 0.00), on average, during the subsequent six months. This finding is interesting because it suggests that prices are not weak form efficient.

In general, we can summarize the momentum literature in terms of their interpretation of the sorting procedure that is employed in the empirical setup. Let us assume that realized returns can be decomposed into a sum of unconditional expected return and unexpected return,

$$r_{i,t} = \mu_i + \varepsilon_{i,t} .$$

Explanations based on rational expectations (such as Conrad and Kaul (1998) and Johnson (2002)) argue that the sorting procedure classifies securities with respect to their expected returns (μ_i); Therefore momentum profits reflect the risk that is inherit in expected returns. On the other hand, explanations based on behavioral explanations argue that sorting on realized return is mainly dominated by the effect of unexpected return (ε_{it}), hence firm specific risk should be the driving factor behind momentum profits (Jegadeesh and Titman(1993), Barberis, Shleifer and Vishny (1998)). Although many studies empirically compare the relative explanatory power of these two explanations, none test these two competing hypothesis using out-of-sample data.

In this study, we fill this void in the literature. Our first hypothesis is that, if momentum profits are due to the idiosyncratic risk of securities, as argued by behavioral models of momentum such as Hong and Stein (1999) and Daniel, Hirshleifer, and Subrahmanyam (1998), then countries that have high asset price comovements should not exhibit momentum profits. In our tests, we show evidence consistent with this hypothesis, suggesting that momentum strategies rely on firm-specific rather than well-known systematic risks. This evidence is also consistent with other studies such as Liew and Vassalou (2002), who show that the growth rate of GDP cannot be captured by momentum strategy profitability, and Griffin, Ji, and Martin (2003), who show that macroeconomic risk cannot capture the difference between momentum profitability in an international context.

Exploiting the relation between asset price comovements and country-specific factors, we develop empirical tests to study determinants of momentum profitability. We present three novel findings. First, momentum is more pronounced in countries that have severe earnings management practices, suggesting that momentum is not due to market underreaction that is related to earnings-related information. This finding is not consistent with Chan, Jegadeesh, and Lakonishok (1996) who show that, in the US, past return and earnings surprise predict large drifts in future returns after controlling one another.

Moreover, in some countries where momentum strategies are more profitable, winners and losers subsequently experience reversals in their stock prices, which suggests that profitability of momentum strategies may be due to overreaction induced positive feedback strategies of the sort discussed by DeLong, Shleifer, Summer, and Waldman (1990). However, this pattern is not common to all markets analyzed in this study.

Second, momentum strategies appear to be profitable in countries that have more sophisticated investors. Findings indicate that in sophisticated markets, firm-specific information can be used to infer more informative prices; hence investors make better decisions. This is consistent with Roll (1988)'s predictions: higher firm-specific return variation as a fraction of total variation signals more information-laden stock prices. High stock price synchronicity represents a failure to incorporate firm-specific information into market prices, as discussed in Morck, Yeung and Yu (2000) and Durnev, Morck, Yeung, and Zarowin (2003), and momentum profits are more pervasive in markets where firm-specific information can be incorporated into prices.

Third, after decomposing momentum profits into two parts as suggested by Hogan, Jarrow, Teo, and Warachka (2004), trading profit per unit of time and the growth rate of a trading strategy's volatility (exploitability risk), we document that investor sophistication is positively related to exploitability risk, suggesting that momentum strategies are riskier in markets dominated by sophisticated investors. In other words, exploitability risk is the price of momentum profits.

Thus, we conclude that momentum explanations based on rational expectations are capable of explaining differences in momentum profitability across countries. Our results indicate that a combination of earnings management and investor sophistication explain about 40% of the cross-sectional differences of momentum profitability in 31 countries. Findings are robust after controlling for country-specific factors including investor protection, market size, and industry concentration.

The rest of the paper is organized in four sections. In the following section, we briefly review the related literature in momentum and asset price comovements. In the third section, we present a simple economy where momentum profits are generated with the idiosyncratic risks of individual stocks. In the fourth section, we describe our data and tests, and report the results of the hypotheses in three parts: (1) momentum profits and asset price comovement, (2) determinants of momentum profitability, and (3) risk of momentum strategy arbitrage and investor sophistication. The fifth section offers conclusions and directions for future research.

2.2 Related Literature

Our study is related to two different streams of finance literature: asset price synchronicity and momentum. Morck, Yeung, and Yu (2000) show that two factor model R^2 (with U.S. and local market factors) and other measures of stock market synchronicity are higher in countries with relatively low per-capita GDP and less-developed financial systems. These results imply that the stocks markets in emerging economies may be less useful in terms of processing information and guiding capital towards its best economic use. Moreover, they imply that stocks markets in underdeveloped countries act as 'side shows' in the sense that stock market performance does not influence managers' investment decisions (Morck, Shleifer and Vishny (1990)).

Durnev, Morck, Yeung and Zarowin (2003) and Campbell, Lettau, Malkiel, and Xu (2001) document a radical decline in the R^2s in the US over the last century, which indicates that we may be able to learn about profitability of certain trading strategies not only from the level of stock prices but also from second or higher moments of stock returns. Jin and Myers (2004) argue that these findings are mainly driven by the risk-bearing division between inside managers and outside investors. Our study distinguishes itself from this strand of literature by showing the relationship between investor sophistication and asset price comovement. In other words, we focus on the effects of the investment environment on exploitability of momentum strategies, rather than investigating the reasons why particular countries end up with current investment environment.

Most studies agree on the existence of momentum profits. An exception is Lesmond, Schill, and Zhou (2004), who present evidence that profits from momentum strategies may not be large enough to cover transaction costs. Despite the near unanimity with regard to the existence of momentum profits, there are diverging opinions on why it exists.

Some argue that momentum profits can be attributed to firm-specific returns. For instance, Lo and MacKinlay (1990) show that momentum could be caused by autocorrelation in returns, lead-lag relations among stocks (cross-serial correlation), or cross-sectional dispersion in unconditional means.[1] Jegadeesh and Titman (1993) show

[1] Intuitively a stock that outperformed other stocks in the past might continue to do so for three reasons: (1) the stock return is positively autocorrelated, so its own past return predicts high future returns; (2) the stock return is negatively correlated with the lagged

that momentum is not driven by market risk. Fama and French (1996) demonstrate that Fama and French (1992) unconditional three-factor model cannot explain momentum. Conrad and Kaul (1998) argue that cross-sectional differences in expected returns explain the profitability of momentum returns, whereas Grundy and Martin (2001) measure conditional exposure to three-factor risk and show that neither industry effects nor cross-sectional differences in expected returns are the primary cause of the momentum. Jegadeesh and Titman (2002) argue that cross-sectional differences in expected returns explain very little, if any, of the momentum profits. Johnson (2002) shows that a highly persistent shock to the dividend growth rate can produce momentum patterns in a rational expectations setting. His model predicts momentum profits which can decline rapidly (as observed empirically), but remain positive at longer horizons.

Berk, Green and Naik (1999) offer a model based on economic risk factors that affect firm investment life cycles and growth rates. In their model, a firm's value depends on interest rates as well as the number and systematic risk of its existing projects. Slow turnover in the firm's project portfolio leads to persistence in both the firm's asset base and its systematic risk, all of which makes expected returns positively correlated with lagged expected returns. Simulations results of this model produce momentum profits that are roughly equal to the magnitude observed in the U.S. at slightly longer horizons.

Behavioral approaches such as Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999) argue that imperfect formation and revisions of investor expectations in response to new information causes momentum

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returns on other stocks, so their poor performance predicts high future returns; and (3) the stock simply has a high unconditional mean relative to other stocks.

patterns in stock data. Chordia and Shivakumar (2002) investigate the one-step-ahead forecasts obtained by projecting momentum profits onto lagged macroeconomic variables and conclude that U.S. momentum profits are completely explainable using these forecasts.

Momentum profits are also associated with several characteristics not typically associated with priced risk in standard models of expected returns. For example, Chan, Jegadeesh, and Lakonishok (1996) show that return momentum coexists with earnings momentum. Lee and Swaminathan (2000) document that momentum is more prevalent in stocks with high turnover. Hong, Lim, and Stein (2000) show that small firms with low analyst coverage have more momentum. Moskowitz and Grinblatt (1999) demonstrate that industry momentum is large. Grinblatt and Moskowitz (2004) present evidence that momentum is more prevalent for small firms with few institutional owners, growth firms, and firms with high volume. Jegadeesh and Titman (2001) show that U.S. momentum returns quickly dissipate after the investment period, a finding difficult to reconcile with standard notions of priced financial risk. Lewellen (2002) shows that behavioral models based on firm-specific returns cannot explain a significant component of momentum. Momentum shows up in stocks and many types of portfolios, suggesting that momentum cannot be attributed solely to firm-specific returns. He suggests that a coherent story should explain why momentum shows up in, say, individual stocks and size quintiles, but vanishes at the market level. Griffin, Ji, and Martin (2003) study the relation between stock returns and macro-economic risk through the use of the unconditional approach of Chen, Roll, and Ross (1986) and examine if the conditional macroeconomic risk argument of Chordia and Shivakumar (2002) is robust. Their evidence shows that international momentum profits extinguish slowly, as predicted by many risk-based explanations, or reverse sign completely, consistent with several behavioral explanations. In this sense, our study confirms and complements the findings of Griffin, Ji, and Martin (2003). They argue that macroeconomic risks cannot explain momentum profits whereas we demonstrate that firm-specific risk mainly drives the profitability of momentum strategies. Moreover, we show that exploitability of momentum profits depends on certain market characteristics such as investor sophistication and earnings management. These factors need to be related to factors controlled in Griffin, Ji, and Martin (2003).

2.3 Model

In this section, we present a simple model that shows the relation between the idiosyncratic risk of individual stocks and momentum profitability. We choose to focus on the effect of idiosyncratic risk on momentum profitability because of the previous empirical evidence that suggests macroeconomic risk cannot account for momentum profitability. Similar models have been offered by Lo and MacKinlay (1990), Jegadeesh and Titman (1993, 2002) and Chen and Hong (2002).

Our main objective in this setup is to demonstrate that in a simple economy where systematic risk cannot account for the expected returns by design, idiosyncratic risk can drive momentum profitability.

Consider a one-factor world in which the only source of momentum is investor under-reaction to shocks. Assume there are N stocks each with the following one-factor structure:

$$f_t = \rho f_t + e_{i,t}$$

$$r_{i,t} = \mu_i + \beta_i f_t + \varepsilon_{i,t} \qquad (1)$$

where e_t is a mean-zero, serially uncorrelated shock to the factor f_t and $\varepsilon_{i,t}$ is a mean-zero, positively serially correlated idiosyncratic shock with variance σ^2_ε and $E[\varepsilon_{i,t}, \varepsilon_{i,t-1}] = \sigma^2_\varepsilon$.

The unconditional variance of factor f_t is σ^2_f. The parameter ρ is the serial correlation of the factor. All other correlations are assumed to be zero. Also, for simplicity, assume that every asset has the same mean and beta, $\mu_i = \mu$ and $\beta_i = \beta = 1$. The only source of momentum in this setting is the positive serial autocorrelation of the idiosyncratic shock, which one can think of as due to some under reaction mechanism along the lines of recent behavioral models. The momentum strategy relies on buying stocks based on their returns in period t-1 and holds it in period t. With this strategy, the portfolio weight assigned to stock i is

$$w_{i,t} = \frac{1}{N}\left(r_{i,t-1} - r_{t-1}\right) \qquad (2)$$

where

$$r_t = \frac{1}{N}\sum_{i=1}^{N} r_{i,t}$$

is the equally weighted index return. Note that if a return is less than the equally weighted return, then its weight will be a negative number indicating a short position.

The time t profit of this momentum strategy at time t is

$$\pi_t = \sum_{t=1}^{N} w_{i,t} r_{i,t} \, .$$

Given the one-factor structure in equation (1), the momentum strategy in equation (2) is given by the weights of each asset of

$$w_{i,t} = \frac{N-1}{N^2}\varepsilon_{i,t-1} - \frac{1}{N^2}\sum_{j\neq i}^{N}\varepsilon_{j,t-1} \, . \tag{3}$$

Therefore, the momentum profit in equation (3) is simply

$$\pi_t = \sum_{t=1}^{N}\left[\frac{N-1}{N^2}\varepsilon_{i,\, t-1} - \frac{1}{N^2}\sum_{j\neq i}^{N}\varepsilon_{j,\, t-1}\right] r_{i,t}$$

The expected momentum profit is

$$E(\pi_t) = \frac{N-1}{N}\sigma_{\varepsilon}^2 \, .$$

There are two properties of these results. First, by construction, expected momentum profits only depend on the positive autocovariance of the idiosyncratic shocks since the unconditional means and stock betas are assumed to be identical. Second, as idiosyncratic shocks increase, expected momentum profits increase. In the following section, we focus on this relationship between expected momentum returns and idiosyncratic risk.

2.4 Empirical Setup

2.4.1 Data

In this section, we describe our sample selection procedure and calculations. We used data from 31 countries. U.S. monthly stock return data include common shares of all NYSE, Amex and NASDAQ listed firms available from CRSP between January 1965 and December 2000.[2] In order to mitigate from possible microstructure effects, we eliminated observations if stock price is less than $5.

For non-U.S. data, we follow Griffin, Ji, and Martin (2003) and select countries from TSF Datastream International which have at least 50 stocks after Janauary 1982. This yielded an additional 30 countries.[3]

Table 2.1 displays sample starting dates for each country and some market statistics. The sample of non-US data ends in December 2003. We also eliminated real estate trusts and investment companies from our international sample. We did not employ any price-

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[2] ADRs, SBIs, certificates, REITs, closed-end funds, companies incorporated outside the U.S., and Americus Trust Components are excluded from the sample to maintain consistency with the existing momentum literature.

[3] Some countries (Egypt, Argentina, Brazil, Peru, China, Taiwan, Thailand) are excluded from our sample due to lack of data on reliable risk free rate note.

related filtering for non-US data.[4] Table 2.1 also reports the number of firms available at the beginning of 1982 (or the first available month for countries when they are included in the sample). Our sample contains all of the major markets (US, UK, Canada, France, Germany and Japan) and some of the emerging markets that have enough data to calculate momentum profits.

2.4.2 Variables

Returns to the momentum strategy

In order to calculate the returns to the momentum strategy, we employed the procedure used in previous studies. Any momentum strategy consists of a ranking period over which winners and losers are determined, and an investment period over which winners are held and losers sold short. We use an N-month ranking and investment period (N=3,6,9 and 12) and created portfolios with equal weights. This investment rule is followed every month.

Our international strategies examine the top (winner) and bottom (loser) 20 percent of stock returns as some countries do not have enough stocks to allow for use of the more common top and bottom decile classification. For the US, we use the top and bottom 10 percent of stock returns.[5] To avoid microstructure distortions, we skip a month between portfolio ranking and investment periods. Thus, for each month *t*, the portfolio (Winner

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[4] Ince and Porter (2004) discuss the reliability of Thomson Datastream individual equity return data. In this study, we followed their suggestions about data cleaning procedures. We also excluded monthly returns above 500% and less than -99% since such observations are unlikely unless there is a recording error. Our results are not sensitive to such filtering procedures.

[5] Using the top and bottom 20% in the U.S. does not materially alter the results.

minus Loser (WML)) held during the investment period months t to $t+(N-1)$, is determined by performance over the ranking period, months $t-(N+1)$ to t - 2. We denote such a strategy by "N/1/N". Table 2.2 presents the sample statistics of *cumulative* momentum profits for the corresponding investment period in 31 countries.[6]

A close inspection of Table 2.2 reveals two important patterns that we exploit in later parts of the study. First of all, momentum strategies are profitable in most of the major markets, such as Australia, Belgium, Canada, Denmark, Finland, France, Spain, Sweden, Germany, UK and US, whereas it is rarely profitable in emerging countries. Second, 3/1/3 and 6/1/6 strategies seem to produce the highest cumulative profits in some countries. However, this pattern disappears as we increase the ranking and investment periods. These reversals in winners and losers suggest that the profitability of momentum strategies may be due to overreaction induced positive feedback strategies of DeLong, Shleifer, Summer, and Waldman (1990). It is important to note that some countries (such as Japan, Korea, Philippines, Portugal, and Turkey) never present momentum profitability in any ranking or investment periods.

In order to test our hypotheses, measures for asset price comovement, investor sophistication, earnings management severeness, and the risk of statistical arbitrage need to be defined.

[6] We should note that these statistics represent the profitability of zero investment portfolios, therefore they do not represent returns. Hence, the cumulative profitability of a certain strategy may be less than -100% in extreme cases. Of course, such positions may not be attainable in financial markets due to constraints against short selling. We replicated the study after excluding such cases, the results are essentially the same, if not stronger. We choose to report the results with all the cases in order to mitigate from survival bias arguments.

Asset price comovement measure

We follow the procedure used in Morck, Yeung and Yu (2000) to calculate a measure that captures the asset price comovement in a given market. In their study, Morck, Yeung and Yu (2000) follow French and Roll (1986) and Roll (1988), and suggest using R^2s of regressions of the below specification to measure asset price comovement:

$$r_{i,t} = \alpha_i + \beta_{i,\ t} r_{m,jt} + \beta_{2,\ i}[r_{US,t} + e_{jt}] + \varepsilon_{it}\ . \qquad (4)$$

where i is a firm index, j is a country index, t is a two-week time period index, $r_{m,jt}$ is a domestic market index, $r_{US,t}$ is the U.S. market return, and e_{jt} is the rate of change in the exchange rate per U.S. dollar. They include the U.S. stock market return in equation 4 because most economies are partially open to foreign capital. The expression $r_{US,t} + e_{jt}$ translates U.S. stock market returns into local currency units. In order to overcome thin trading problems, biweekly returns are used. Returns are compounded from daily total returns. For stock markets in the Far East, U.S. market returns are lagged by one day to account for time zone differences. Therefore, if the biweekly stock return in Japan used data from June 7, 1995 to June 21, 1995, the contemporaneous U.S. market return uses data from June 6, 1995 to June 20, 1995. When equation 4 is used for U.S. data, $\beta_{2,i}$ is set to zero. A high R^2 indicates a high level of asset price comovement. Morck, Yeung, and Yu (2000) show that this measure has high correlations with other comovement measures.[7] R^2 is shown in Table 2.3 for each country.

[7] We also used other measures that are suggested in Morck, Yeung and Yu (2000), such as "% of stock moving in the same direction" and obtained similar results.

Investor sophistication measure

For investor sophistication, we used four proxies. The first measure, education enrollment rate, shows the total enrollment in tertiary education regardless of age, expressed as a percentage of the population in the five-year age group following on from the secondary-school leaving age. The second measure, education life, shows the average education level of population, which is proxied by school life expectancy, in each country from 1988 through 1996. The other two measures we use are the number of domestic firms per capita and education expense per capita. All investor sophistication data are summarized in Table 2.3-2.[8]

Earnings management severeness measure

For earnings management severeness, we use the aggregate earnings management severeness index of Leuz, Nanda, and Wysocki (2004) who show that firms in countries with developed equity markets, dispersed ownership structures, strong investor rights, and legal enforcement engage in less earnings management. Their aggregate earnings management measure relies on four different aspects of earnings management: (1) smoothing reported operating earnings using accruals, (2) the correlation between changes in accounting accruals and operating cash flows, (3) the magnitude of accruals,

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[8] The existing literature on investor sophistication generally uses institutional ownership as a measure (e.g., Hand (1990), Walther (1997) and El-Gazzer (1998) and Bartov, Radhakrishnan, and Krinsky (2000)). Due to a lack of international data on this measure, we are unfortunately not able to use this measure. Some critics argue that institutional ownership data is a noisy measure of investor sophistication as institutions tend to be more passive (index) investors.

and (4) small loss avoidance.[9] They rank countries with respect to each of these four earnings management measures, and calculate an aggregate earnings management score by averaging the country rankings. A high value in the ranking represents severeness of earnings management. A detailed discussion of this measure is provided in Table 2.9. Table 2.3 reports the rankings of counties with respect to the aggregate earnings management severeness index.

Risk of momentum strategies: Statistical arbitrage approach

To calculate the risk of momentum strategies, we followed the methodology developed in Hogan, Jarrow, Teo, and Warachka (2004) who introduce the concept of statistical arbitrage, a long horizon trading opportunity that generates a riskless profit and is designed to exploit persistent anomalies. Following their methodology, which is briefly summarized in Table 2.10, we decompose momentum profits of 31 countries into two parts: momentum profit per month (μ) and the growth rate of volatility of momentum profits (λ), and classify countries with respect to these two measures. The idea of this decomposition is similar to that of the intercept (α) test of classical asset pricing models, except decomposition of the intercept term (WML profits in our case) allows us to study its time series behavior. In this framework, momentum profit per month (μ) represents the true risk free profit, provided that the volatility of the trading strategy declines fast. The decline is governed by the second parameter (λ), which is the growth rate of volatility.

[9] We used the first three components of the aggregate earnings management severness index separately and found essentially similar results.

Of these two measures, we focus on the second one (λ), volatility growth rate of a given zero investment trading strategy, since it defines the **exploitability** of a given momentum strategy. A lower (higher) volatility growth rate (λ) means that the momentum portfolio's profit is less (more) likely to be wiped out by the fluctuations in the long and short parts of the portfolio. In our sample, most λ estimates are below 0, indicating that risks associated with particular momentum strategies are declining over time.[10]

With the use of momentum profit per month (μ) and exploitability risk of momentum profits (λ), we can also test whether a particular momentum strategy presents any statistical arbitrage opportunity in a given country. For statistical arbitrage opportunities to be present, momentum profits per month should be greater than zero ($\mu>0$) and growth rate of volatility should be less than zero ($\lambda<0$).[11] Results of the momentum strategy statistical arbitrage tests are summarized in Table 2.4 and Figure 2.2.

In Figure 2.2, the third quadrants ($\mu>0$, $\lambda<0$) show the countries that presented statistical arbitrage opportunities. For the 6/1/6 strategy, 15 countries allow statistical arbitrage. However, μ and λ estimates are statistically significant at a 10% level only for 8 countries (US, UK, Denmark, Finland, India, Italy, New Zealand and Spain). Other countries do not seem to present any statistical arbitrage opportunities.

Two things should be noted. First, even though some countries present momentum profitability with respect to simple t-tests on the mean of the WML profits, they do not

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[10] The link between exploitability risk (λ) and momentum profits depends on the specification of incremental momentum profits. Please see Table 2.10 for the specification we employed in this study.

[11] Table 2.10 describes the estimation procedure for μ and λ.

necessarily offer statistical arbitrage (e.g., Belgium, Switzerland). Second, as we increase the ranking and investment horizons (from Figure 2.2.1 to Figure 2.2.4), the patterns change slightly, but not dramatically. What is important for our study is, the volatility growth rate of the zero investment portfolios determines most of these patterns. Therefore, the determinants of this factor may give us insights about the riskiness of momentum strategies.

Other variables

Risk-sharing and hedging opportunities offered by markets may be different because of many reasons. First of all, some markets may be dominated by few industries; therefore an industry related shock may force asset prices to comove more frequently than it does in other markets. Second, in order to maintain a viable market, the volume of trade must be large enough to ensure sufficient market depth and liquidity to avoid excessive price volatility. In this sense, indirect and direct transactions costs also may affect the profitability of trading strategies. In this paper, we use several measures to control for liquidity-related transactions costs. Third, uncertainty about how the legal system will treat the introduction of new securities may be a barrier for risk arbitrageurs (Allen and Gale(2001)). Consequently, issues that are linked to the legal system, such as corruption and investor protection, may matter in the exploitability of certain momentum strategies (La Porta, Lopez-de-Silanes, Shleifer, and Vishny (1997, 1998, 1999, 2000, 2002)).

In order to control for such effects, we employed industry concentration, the size of the market, legal origin, a corruption perception index, the relative size of the equity markets (CAP/GDP(%)), ratio of value traded to GDP (Trading), and an index of state owned enterprises in the economy as our control variables. Descriptions of each of these measures and their data sources are reported in Table 2.9 and summarized in Table 2.3. Correlations between these variables are disclosed in Table 2.5.

2.4.3 Hypotheses , Tests, and Results:

(1) Momentum profits and asset price comovement

Our first hypothesis is that, if momentum profits are due to asset price comovement, then momentum profits should decrease in asset price comovement. Formally, we test the following specification:

$$MOM = \beta_0 + \beta_1 R^2$$

where MOM is the momentum profits with x month ranking and investment period, and R^2 is the measure of asset price comovement.

Hypothesis (H_0) 1: If momentum profits are due to the idiosyncratic risk of securities, then there should not be a negative relationship between asset price comovement and momentum profits; that is $\beta_1 \geq 0$.

We should note that the independent variable, R^2, can be represented as a function of various country specific factors, including investor protection (Morck, Yeung and Yu (2000)), industry concentration, choice of organization (conglomerate vs. focused firms) (Campbell, Lettau, Malkiel, and Xu (2001), Gertner, Scharfstein, and Stein (1994)), and power of outside investors (Jin and Myers (2004)). We break up R^2 into such factors in the next section.

The results in Table 2.6 show that hypothesis 1 is rejected at 5% level (one sided test) for 3/1/3 and 6/1/6 strategies. The coefficient signs for 9/1/9 and 12/1/12 are also negative as predicted; however, the coefficient estimates are statistically significant at a 10% level.[12] The momentum literature mostly reports significant profits for medium term (3-6 months), therefore the decrease in the significance of the p-values for longer periods is consistent with existing research.

This evidence complements the findings of Liew and Vassalou (2002) and Griffin, Ji, and Martin (2004). In their study, these authors show that momentum is not a compensation for macroeconomic risk. Consistent with the predictions of the simple model presented in Section 3 and some behavioral models in the literature (Hong and Stein (1999) and Chen and Hong (2002)), the results show a positive relation with idiosyncratic risk. Our findings also support the conjectures of Hong, Lim and Stein (1998), who find that momentum profitability declines with firm size and analyst coverage. In other words, they argue that firm-specific information, especially negative information, diffuses gradually across investing public, and small firms and low analyst coverage are the factors capture the information dissemination process.

The consistency of our results and the behavioral models should not be overemphasized. Because, as we will demonstrate, if asset prices are more informative when idiosyncratic risk is higher, then momentum profits may have rational components that can be explained by risk measures based on idiosyncratic risk. Using these results, at this stage

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[12] We employed both Newey-West and White heteroscedasticity robust standard errors to test our hypothesis. Results are essentially the same. The tables report White heteroscedasticity robust p-values.

we can only conjecture that R^2 captures some of these factors. In the next section, we disentangle the comovement measure to test for the determinants of momentum profitability (or lack of thereof) and get a deeper look at the validity of such behavioral models' predictions.

(2) Determinants of momentum profitability

If momentum profits present systematic differences across countries with respect to idiosyncratic risk, then we may find the determinants of momentum profits by investigating the attributes of economies that lead to idiosyncratic risk. In this section, we test two different but related hypotheses. The intent of these two hypotheses is to assess the effectiveness of the information flow from companies to the investment audience. In a perfect market, managers reveal firm-specific information to the market instantaneously, and the investors instantaneously capitalize this information in stock prices. Any distortion of this process affects the informativeness of stock prices and trading strategies. We break up distortions to information flow into two parts: (1) distortions due to the ability of the investment audience to comprehend the value of firm-specific information and, (2) information flow distortions due to managers' activities, such as earnings management practices. Obviously, these two types of distortions need not be independent of each other.[13] However, the combined effects of these two factors define

[13] For instance, proponents of earnings management argue that information distortion via earnings smoothing helps investors evaluate companies in a less volatile environment. This does not necessarily imply that investors base their decisions on wrong information, but less informative earnings, provided that they know that managers are allowed to engage in such activities. In fact, investors in certain markets, such as Germany, know that companies smooth their earnings legally. In short, the market for firm-specific information is determined by suppliers of information (managers) and the demand of information users (investors) under several frictions. In this paper, we are only concerned

the efficiency of information flow from companies to investors, and therefore determine a given market's information (intelligence) environment. Nevertheless, the important issue for our case is that any distortion to information flow can influence on the profitability of momentum strategies.

First, we investigate the effect of investor sophistication. Our hypothesis is that in economies that are dominated by sophisticated investors, firm-specific information can be incorporated into asset prices easily and quickly and such economies should present less asset price comovement. Therefore, there should be a positive relation between momentum profits and investor sophistication. The foundation of this idea goes back to Grossman (1980), who argues that the existence of informed traders (sophisticated investors) ensures correctly priced securities, so that firm-specific information is more likely to be incorporated into prices in such economies.

Roll (1988) also has similar predictions, that higher firm-specific return variation as a fraction of total variation signals more informed stock prices. Because high stock price synchronicity represents a failure to incorporate firm-specific information into market prices, as discussed in Morck, Yeung and Yu (2000) and Durnev, Morck, Yeung, and Zarowin (2003), momentum profits should be more pronounced in markets where firm-specific information can be incorporated into prices.

On the other hand, if firm-specific information drives momentum profitability and this information diffuses gradually across the investing public as in Hong, Lim and Stein

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with certain attributes of markets that may help us evaluate the effectiveness of information flow, namely investor sophistication and earnings management.

(1998) and Hong and Stein (1999), then there should be a positive medium-term autocorrelation in stock returns that are owned by less sophisticated investor groups. This type of "underreaction" based behavioral model assumes that prices adjust slowly to news. Therefore, momentum profits should be decreasing in investor sophistication. The key underlying assumption of this *competing* hypothesis is that, in economies dominated by sophisticated investors, information is disseminated immediately rather than gradually.

Second, we test if earnings management, information flow distortions due to managers' activities, is related to the profitability of momentum strategies. A number of studies in the momentum literature argue that profitability of momentum strategies should be due to the component of medium-horizon returns that is related to earnings-relevant news; therefore, momentum strategies should not be profitable after accounting for past innovations in earnings and earnings forecasts (Bernard and Thomas (1990), Chan, Jegadeesh, and Lakonishok (1996)). Use of international data gives us an opportunity to test the validity of such arguments. If momentum is due to market underreaction due to earnings related information, then countries that have severe earnings management practices should not present momentum profitability because investors can easily forecast the future direction of returns by using past earnings.

We summarize the above conjectures in the following specification and hypotheses:

$$MOM = \beta_0 + \beta_1 InvestorSophistication + \beta_2 EarningMan,$$

where *MOM* represents the profits to the WML portfolio for x month ranking and investment period, *InvestorSophistication* represents one of the four proxies we described in Section 2.4.2, and *EarningMan* represents the severeness of earnings management practices as described in Table 2.9.

Hypothesis (H_0) 2: Assume that momentum profits are more pronounced in markets with low asset price comovement. Firm specific information cannot be incorporated into asset prices easily and quickly in economies that are not dominated by sophisticated investors; therefore such markets allow more asset price comovement. Consequently, there should not be a positive relation between momentum profits and investor sophistication (i.e., $\beta_1 \leq 0$).

Hypothesis (H_0) 3: Assume that earnings surprises are less likely to occur in markets with severe earnings management practices. In that case, if momentum profits are caused by under-reaction to earnings related information (earnings surprises), then there should not be a positive relationship between momentum profits and earnings management severeness (i.e., $\beta_2 \leq 0$).[14]

As discussed before, markets may portray different characteristics and these characteristics may affect the results. For example, some countries are more concentrated

[14] We should note that hypothesis 3 is based on the assumption that earnings surprises are less likely to occur in markets with a severe earnings management environment. We are not aware of any study that contradicts this assumption. Of course, the validity of this assumption is based on the continuation of earnings management; if companies are likely to smooth their earnings indefinitely, which means truth will never reach the market and earnings surprises are less likely to occur, then investors may be reluctant to take positions by using the difference between their expected earnings and realized smoothed earnings.

in certain industries than others; therefore a shock to these industries may comove the asset prices. We use the Herfindahl index to control for industry concentration.

Market size, transactions costs and liquidity also effect the execution of momentum strategies. We use three proxies to capture such effects: (1) the relative size of the equity market (CAP/GDP), (2) the ratio of value traded to GDP (Trading), (3) the per capita number of domestic firms listed in an exchange (Domestic).

Factors such as an economy's legal origin and corruption index capture certain market characteristics related to investor protection, and information dissemination process of firms is closely related to investor protection (Jin and Myers (2004)). In order to isolate the effects of investor protection, we use origin of law (LAW), corruption, and an index for state-owned enterprises (SEO). Table 2.9 and Table 2.3 discloses a detailed description and values of these variables.[15]

After controlling for these factors, we formally test the below specification:

$$MOM = \beta_0 + \beta_1 LAW + \beta_2 Corruption + \beta_3 Herfindahl + \beta_4 CAP/GDP$$

$$+\beta_5 Trading + \beta_6 EarningMan + \beta_7 SOE + \beta_8 EduEn + \beta_9 EduLife + \beta_{10} Domestic$$

[15] We assume that the variables we use to control for investor protection implicitly control for outside shareholder rights. Recent research shows that better legal protection of outside shareholders is associated with more valuable stock markets (La Porta, Lopez-de-Silanes, Shleifer, and Vishny (1997)), a higher number of listed firms (La Porta, Lopez-de-Silanes, Shleifer, and Vishny (1997), larger listed firms in terms of their sales or assets (Kumar, Rajan, and Zingales (1999)), higher valuation of listed firms relative to their assets (La Porta, Lopez-de-Silanes, Shleifer, and Vishny (2002)), greater dividend payouts (La Porta, Lopez-de-Silanes, Shleifer, and Vishny (2000)) and lower concentration of ownership and control (La Porta, Lopez-de-Silanes, Shleifer, and Vishny (1999)).

In this specification, we are interested in the coefficients of EduEn (β_8), EduLife (β_9), Domestic (β_{10}) and EarningsMan (β_6). In Table 2.7.1 to Table 2.7.4, we examine the cross-sectional determinants of various momentum strategies.

Hypothesis 3 is rejected at a 5% level for the 3/1/3, 6/1/6 and 9/1/9 strategies, suggesting that the profitability of momentum strategies is not due to the component of medium-horizon returns that is related to earnings-related news.

This finding is not consistent with the findings of Chan, Jegadeesh, and Lakonishok (1996)), who show that, in the US, past return and earnings surprise predict large drifts in future returns after controlling one another. In other words, momentum is not created by market underreaction due to earnings-related information. Had it been related to earnings surprises, countries with severe earnings management practices would not have presented momentum profitability. One possible explanation for this finding is that, in countries that have severe earnings management practices, investors' can predict the future returns better because earnings smoothing will help stock returns to present positive autocorrelations.

Overall, the results in Table 2.7 suggest that **hypothesis 2** is rejected at 1% in medium-term momentum strategies, i.e., 3/1/3 and 6/1/6 WMLs. However, the effect of investor sophistication is positive but statistically insignificant for longer ranking and investment periods.[16]

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[16] The results are robust to all proxies used for investor sophistication and earnings management severeness index constituents. For instance, in Table 7-5, we used "principal component of private enforcement and anti-director rights" measure of La Porta, Lopez-de-Silanes, Shleifer, and Vishny (1999) as a control variable in the 6/1/6 WML

These findings support the notion that when sophisticated investors' trades incorporate firm-specific information into stock prices, asset prices comove less. Therefore, momentum strategies become profitable. However, predictions of "prices adjust too slowly to news" type behavioral models, such as Hong and Stein (1999) and Daniel, Hirshleifer, and Subrahmanyan (1998), are not supported by these results. Moreover, the dependence of momentum profitability on investment horizon indicates that firm-specific information is more likely to be incorporated in short- to medium-term rather than longer horizons. If positive feedback traders are less likely to exist in markets with more sophisticated investors, then this finding is also inconsistent with the positive feedback trader model of DeLong, Shleifer, Summers, and Waldman (1990). In their study, authors argue that prices initially overreact to news about fundamentals, than overreact further for a period of time.

Finally, although the correlation between earnings management severeness and investor sophistication is strongly negative (-0.45), their combined effect on momentum profits is positive for all momentum strategies. Furthermore, a combination of these two factors explains about 40% of the cross-sectional variation in momentum profitability across countries.

We believe that these findings are thought-provoking for three reasons. First, we know that momentum is not related to systematic risk or the risk factors of Fama and French

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regression. The correlation between earnings management and investor protection is negative (-0.50); therefore, when we test the relationship between earnings management and momentum strategies, we excluded the "investor protection" variable in order to mitigate possible multicollinearity problems.

(1993) (see also Liew and Vassalou (2002), Griffin, Ji, and Martin (2004), and Fama and French (1996)). Second, we established that idiosyncratic risk is positively related to momentum profitability in hypothesis 1, a finding that is compatible with predictions of some behavioral models of momentum mentioned above. Third, neither "underreaction to news" nor "continuing overreaction to news" types of behavioral models explain the relationship between momentum profitability and investor sophistication. In sum, existing behavioral models fall short in explaining the three observations we summarized above. On the other hand, our second hypothesis posits a link between a relationship between momentum profits and firm specific risk based on immediate information incorporation, and is capable to explain the crossectional differences of momentum profits across countries. Up to this point, we only analyzed the returns to momentum strategies and have not commented on the riskiness of such strategies. In the next section, we will revisit this issue and investigate the relation between the risk of momentum strategies and investor sophistication.

(3) Risk of momentum strategies

Rational expectation models of momentum argue that momentum profits have a risk-based explanation. Examples of this approach include Conrad and Kaul (1998) and Johnson (2002). Since we have already established a positive link between investor sophistication and momentum profitability, that is inconsistent with some behavioral models, the next logical step is to test the relation between the risk of momentum strategies and investor sophistication.

In contrast to previous studies of rational momentum effects, our main focus is the exploitability of momentum strategies, rather than cross-sectional differences in the expected returns as in Conrad and Kaul (1998) or growth rate risk as in Johnson (2002). Our argument is as follows. Competitive momentum traders accumulate firm-specific information until the marginal cost of gathering an additional unit of information exceeds its risk-adjusted marginal return. In such an environment, the exploitability of such strategies constitutes the major risk of momentum strategies. Therefore, assuming that investor sophistication is a proxy for the intensity of *competitive* risk arbitrage activities, momentum strategies should be less likely to be exploitable in markets dominated by sophisticated investors. In other words, exploitability risk is the price of momentum profitability. It is important to emphasize that we built on the notion that the greater the number of the sophisticated investors, the more they influence the stock price, because they are expected to quickly correct the mispricing that arises from the trades of unsophisticated investors.

We employ the statistical arbitrage framework of Hogan, Jarrow, Teo, and Warachka (2004) to estimate the exploitability risk of momentum strategies. As discussed in Section 4.2, we decompose momentum profits of the 31 counties into two parts: momentum profit per month (μ) and growth rate of volatility of momentum profits (λ), i.e., exploitability risk of momentum strategies. A high volatility growth rate (λ) means that a given WML's profit is more likely to be wiped out because of the increases in volatility; therefore the exploitability risk of such a strategy is high. On the contrary, a low volatility growth rate (λ) means that a given WML's profit is less likely to be wiped out; hence exploitability risk of such strategy is low.[17]

To isolate the effects of country-specific characteristics, we control for industry concentration, size, liquidity, origin of law (LAW) and corruption. Motivations for these control variables were explained in the previous section.[18]

Formally, we test the below specification:

$$\lambda_{MOM} = \beta_0 + \beta_1 LAW + \beta_2 Corruption + \beta_3 Herfindahl$$

$$+\beta_4 CAP/GDP + \beta_5 Trading + \beta_6 Domestic + \beta_7 EduEn$$

where λ represents the growth rate of volatility, i.e. exploitability risk, which is estimated by using the methodology described in Table 2.10 and reported in Table 4. We state the above arguments in the following hypothesis:

Hypothesis (H_0) 4: If momentum profits are not explained by the exploitability risk, then there should not be a positive relationship between investor sophistication and the exploitability risk of momentum strategies, i.e., $\beta_7 \leq 0$.

Results are reported in Table 2.8. Consistent with the risk explanation based momentum models, coefficient of investor sophistication is positive, i.e., hypothesis 4 is rejected, and

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[17] One can think of exploitability risk along the lines of Shleifer and Vishny (1997) limits of arbitrage framework. In this sense, exploitability risk is a measure of limits to arbitrage that captures the risk of a zero investment portfolio.

[18] Results are not sensitive to various proxies of investor sophistication, liquidity, and investor protection.

statistically significant mostly at a 1% level for all momentum strategies. The coefficients of all control variables are not statistically significant for 3/1/3, 6/1/6 and 9/1/9 strategies.

Combined with the results of the hypothesis 2, these results suggest that, markets with sophisticated investors may offer momentum profits, however the exploitability of these profits increases in investor sophistication. In other words, exploitability risk can explain the momentum profits.

Can we reconcile these findings with the prediction of behavioral models? One finding that is prevalent in US markets is that small stocks and stocks with few analysts present more momentum profits, consistent with the predictions of the "prices adjust too slowly to news" behavioral models of Hong and Stein (1999) and Daniel, Hirshleifer, and Subrahmanyan (1998). If exploitability risk is indeed the price of momentum profit as the international evidence suggests, then we should also argue that small stocks and stocks followed by few analysts should be owned by more sophisticated investors. Clearly, this argument is not warranted. However, investor sophistication is only one of the determinants of the exploitability risk that explains the cross-sectional differences of momentum profitability across countries. Other measures of limits to arbitrage, such as substitutability risk or transactions cost, a factor that comes up insignificant in our tests, may be significant in certain segments of the market.[19] In this sense, our findings are compatible with evidence provided in Lesmond, Schill, and Zhou (2004), who show that

[19] Transactions costs involve direct costs (such as brokerage fees, etc.) and indirect costs (such as liquidity cost). In this sense, our "trading" and "size" variables partly control for transactions costs.

momentum profits are not exploitable because of high transactions costs required to implement momentum strategies for small size companies in U.S.

2.5 Conclusion

We show that momentum strategies are less profitable in markets where stock price synchronicity is higher. Empirical evidence suggests that momentum profits are largely due to firm-specific risks, consistent with behavioral models of momentum. However, after controlling for investor protection, market size, liquidity and high industry concentration, we find that factors that proxy the information flow process from companies to investors (i.e., investor sophistication and earnings management) explain about 40% of the cross-sectional difference in momentum profitability.

Our results suggest that the profitability of momentum strategies is not due to the component of medium-horizon returns that is related to earnings-related news, which means that momentum is not created by market under-reaction due to earnings-related information. We conclude that in countries that have severe earnings management practices, investors can predict future returns better because earnings smoothing forces stock returns to exhibit positive autocorrelations.

We also document a positive and statistically significant relation between the profitability of momentum strategies and investor sophistication. Furthermore, the relation between investor sophistication and exploitability risk is also positive, suggesting that exploitability risk is the price of momentum profitability. Overall, we conclude that our evidence is more consistent with risk-based rational expectation models than behavioral models of momentum. In this sense, our results complement the findings of Lesmond, Schill, and Zhou (2004).

Our findings provide new research directions. First of all, what are the other determinants of exploitability risk other than competition between arbitrageurs (sophisticated investors)? The relation between other limits of arbitrage (such as substitutability risk and transactions cost) and exploitability risk also may provide additional insight to the cross-sectional differences of momentum profitability across countries. Second, can we use exploitability risk as a measure of "limits to arbitrage" to provide rational expectations explanations for other persistent anomalies? And finally, and more importantly, we only point out the explanatory power of exploitability risk without any theoretical model that shows that exploitability risk is the price of momentum strategies. Such a model should answer why exploitability risk, probably a function of idiosyncratic risk, is systematic. Future research needs to be done in this area.

APPENDIX 2

TABLES AND FIGURES FOR CHAPTER 2

Table 2.1

Sample Dates and Number of Companies and Descriptive Country Specific Information

This table summarizes sample beginning and ending dates and number of stocks for the first portfolio available at the beginning of the sample for each country. All samples end in November 15, 2003 except for US. US data includes common shares of all N.Y.S.E., Amex and NYSE listed firms available from C.R.S.P between January 1965 and December 2000. Columns 5 to 8 show country specific market information. Definitions are provided in Table 2.9.

	Country	Date	Number of Companies	GDP 2001 (in 1995 USD)	Stock market capitalization to GDP	Stock market total value traded to GDP	Stock market turnover ratio
1	Australia	11/15/1982 – 11/15/2003	164	468,042,400,000	0.867	0.653	0.753
2	Belgium	11/15/1982– 11/15/2003	70	319,128,300,000	0.649	0.179	0.276
3	Canada	11/15/1982– 11/15/2003	485	717,385,800,000	0.950	0.665	0.699
4	Chile	8/15/1989– 11/15/2003	78	82,946,800,000	0.746	0.064	0.086
5	Denmark	11/15/1982– 11/15/2003	50	208,830,100,000	0.537	0.437	0.814
6	Finland	5/15/1988– 11/15/2003	69	165,154,500,000	1.716	1.482	0.863
7	France	11/15/1982– 11/15/2003	157	1,809,676,000,000	0.857	0.823	0.960
8	Germany	11/15/1982– 11/15/2003	201	2,703,244,000,000	0.543	0.769	1.416
9	Greece	2/15/1988– 11/15/2003	74	144,831,600,000	0.721	0.319	0.442

Table 2.1 (Continued)

	Country	Date	Number of Companies	GDP 2001 (in 1995 USD)	Stock market capitalization to GDP	Stock market total value traded to GDP	Stock market turnover ratio
10	Hong Kong	11/15/1982– 11/15/2003	73	168,948,200,000	2.986	1.213	0.406
11	India	2/15/1990– 11/15/2003	423	494,543,000,000	0.208	0.510	2.450
12	Ireland	6/15/1987– 11/15/2003	51	112,010,900,000	0.651	0.218	0.335
13	Italy	11/15/1982– 11/15/2003	84	1,229,741,000,000	0.510	0.507	0.995
14	Japan	11/15/1982– 11/15/2003	886	5,707,028,000,000	0.559	0.441	0.788
15	Korea	8/15/1984– 11/15/2003	291	639,698,400,000	0.425	1.645	3.867
16	Malaysia	2/15/1986– 11/15/2003	175	112,219,400,000	1.320	0.236	0.179
17	Mexico	4/15/1988– 11/15/2003	50	371,373,000,000	0.092	0.064	0.691
18	Netherlands	11/15/1982– 11/15/2003	199	503,865,100,000	1.238	2.719	2.197
19	New Zealand	3/15/1993– 11/15/2003	50	71,523,030,000	0.311	0.167	0.538
20	Norway	11/15/1982– 11/15/2003	66	180,003,300,000	0.345	0.315	0.913
21	Pakistan	9/15/1992– 11/15/2003	118	73,038,780,000	0.079	0.224	2.854

Table 2.1 (Continued)

	Country	Date	Number of Companies	GDP 2001 (in 1995 USD)	Stock market capitalization to GDP	Stock market total value traded to GDP	Stock market turnover ratio
22	Philippines	1/15/1990– 11/15/2003	81	92,551,230,000	0.506	0.044	0.087
23	Portugal	2/15/1988– 11/15/2003	64	132,068,300,000	0.417	0.248	0.595
24	Singapore	2/15/1983– 11/15/2003	158	110,992,500,000	1.350	0.740	0.548
25	South Africa	11/15/1982– 11/15/2003	61	177,012,100,000	1.313	0.614	0.468
26	Spain	4/15/1987– 11/15/2003	67	724,008,400,000	0.715	1.441	2.016
27	Sweden	11/15/1982– 11/15/2003	93	294,847,100,000	1.145	1.437	1.256
28	Switzerland	11/15/1982– 11/15/2003	167	339,097,100,000	2.277	1.218	0.535
29	Turkey	3/15/1988– 11/15/2003	60	190,074,100,000	0.016	0.522	1.558
30	UK	11/15/1982– 11/15/2003	2161	1,336,697,000,000	1.441	1.314	0.912
31	US	1/1/1965– 12/31/2000	2119	8,977,800,000,000	1.229	2.885	2.348

Table 2.2.1

Momentum Profits for Some Countries: Australia-India

Momentum strategy consists of a ranking period, over which winners and losers are determined, and an investment period, over which winners are held and losers sold short. We use N-month ranking and investment period (N=3,6,9 and 12) and give equal weights to stocks in order to form the winner and loser portfolios. The investment rule is followed every month. Non-US momentum strategies examine the top (winner) and bottom (loser) 20 percent of stock returns. For US, we use top and bottom 10 percent of stock returns. To avoid microstructure distortions, we skip a month between portfolio ranking and investment periods. Thus, for each month *t*, the portfolio held during the investment period months t to $t+(N-1)$, is determined by performance over the ranking period, months $t-(N+1)$ to $t - 2$. We report the descriptive statistics of "cumulative" return of winner minus loser (WML) portfolio for each investment period. The t-statistics (which assume iid momentum profits) in table 4a-2, 4b-2, 4c-2, and 4d-2 report the statistical significance of the momentum profits for 3/1/3, 6/1/6, 9/1/9 and 12/1/12 strategies, respectively.

	Australia	Belgium	Canada	Chile	Denmark	Finland	France	Germany	Greece	Hong Kong	India
Strategy : 3/1/3											
Mean	0.025	0.033	-0.004	0.034	0.016	0.011	0.016	0.024	0.021	0.004	-0.001
Median	0.034	0.030	-0.001	0.028	0.016	0.006	0.027	0.023	0.018	0.026	0.020
Maximum	0.434	0.984	0.256	1.254	0.322	0.357	0.329	0.482	0.839	0.323	0.546
Minimum	-0.297	-0.956	-0.470	-0.382	-0.362	-0.562	-0.806	-0.373	-0.927	-1.076	-0.488
Std. Dev.	0.101	0.171	0.121	0.151	0.089	0.119	0.108	0.087	0.197	0.150	0.152
Skewness	-0.141	0.330	-0.565	2.968	-0.545	-0.979	-2.558	0.329	0.247	-2.608	-0.418
Kurtosis	4.749	16.272	4.302	28.357	5.611	7.152	17.825	9.938	8.592	17.170	5.379
Observations	244	246	244	165	246	180	246	246	182	246	159

Table 2.2.1 (Continued)

	Australia	Belgium	Canada	Chile	Denmark	Finland	France	Germany	Greece	Hong Kong	India
Strategy : 6/1/6											
Mean	0.040	0.106	0.007	0.113	0.029	0.059	0.050	0.065	0.125	0.034	0.044
Median	0.045	0.084	0.016	0.067	0.049	0.058	0.060	0.068	0.065	0.066	0.059
Maximum	0.494	2.176	0.445	2.316	0.361	0.593	0.358	0.455	2.323	0.527	0.809
Minimum	-0.670	-0.959	-0.812	-0.641	-0.574	-0.636	-0.670	-0.755	-1.154	-1.277	-0.512
Std. Dev.	0.170	0.315	0.180	0.431	0.137	0.180	0.136	0.138	0.385	0.224	0.220
Skewness	-0.438	1.933	-0.683	3.351	-0.936	-0.289	-1.101	-1.355	1.719	-1.824	-0.217
Kurtosis	4.233	16.682	5.284	16 .608	5.239	4.531	7.025	11.285	12.644	10.202	3.659
Observations	238	240	238	159	240	174	240	240	176	240	153
Strategy : 9/1/9											
Mean	-0.031	0.202	-0.036	0.122	0.017	0.053	0.084	0.111	0.005	-0.052	0.053
Median	0.022	0.121	-0.021	0.061	0.022	0.056	0.089	0.117	0.072	0.024	0.059
Maximum	0.859	3.383	0.648	3.013	0.556	0.601	0.573	0.576	3.070	0.687	1.252
Minimum	-1.324	-1.168	-1.151	-0.613	-0.563	-0.634	-0.744	-0.716	-7.903	-2.993	-1.000
Std. Dev.	0.279	0.524	0.236	0.511	0.187	0.231	0.191	0.164	1.053	0.414	0.315
Skewness	-1.207	2.894	-0.668	3.673	-0.148	-0.254	-0.588	-0.391	-4.051	-3.346	-0.041
Kurtosis	6.314	16.822	5.011	19.205	3.341	3.215	4.772	5.910	29.096	19.541	4.775
Observations	232	234	232	153	234	168	234	234	170	234	147
Strategy : 12/1/12											
Mean	-0.123	0.317	-0.172	0.040	-0.009	-0.019	0.080	0.127	-0.292	-0.138	0.073
Median	-0.013	0.119	-0.132	0.007	-0.002	0.032	0.083	0.131	0.026	-0.051	0.089
Maximum	0.486	4.377	0.593	2.351	0.525	0.588	0.611	0.564	2.082	0.943	1.377
Minimum	-1.823	-1.267	-2.257	-1.571	-0.531	-1.398	-0.931	-0.573	-10.422	-5.659	-0.655
Std. Dev.	0.394	0.741	0.333	0.491	0.221	0.324	0.234	0.183	1.742	0.603	0.353
Skewness	-1.706	2.354	-1.626	2.337	0.036	-1.223	-0.450	-0.389	-3.993	-5.004	0.607
Kurtosis	6.699	10.270	9.613	12.750	2.714	6.074	4.233	3.367	20.218	40.137	4.410
Observations	226	228	226	147	228	162	228	228	164	228	141

Table 2.2.2
Momentum Profits for Some Countries: Ireland-Norway

	Ireland	Italy	Japan	Korea	Malaysia	Mexico	Netherlands	New Zealand	Norway
Strategy : 3/1/3									
Mean	0.006	0.030	-0.002	-0.015	-0.013	0.036	0.015	0.044	0.046
Median	0.035	0.025	0.002	-0.011	-0.006	0.019	0.038	0.042	0.058
Maximum	0.279	0.772	0.245	0.587	0.652	1.383	0.426	0.834	0.833
Minimum	-1.888	-0.310	-0.434	-0.621	-1.194	-0.392	-2.931	-0.847	-0.907
Std. Dev.	0.203	0.122	0.089	0.149	0.170	0.172	0.239	0.173	0.170
Skewness	-4.967	1.656	-0.777	-0.212	-2.776	3.234	-8.370	-0.489	-0.543
Kurtosis	42.975	12.664	6.135	6.009	23.214	24.348	97.710	11.817	12.019
Observations	191	246	246	225	207	181	246	122	246
Strategy : 6/1/6									
Mean	0.039	0.092	-0.008	-0.077	0.008	0.021	0.044	0.090	0.085
Median	0.082	0.059	0.005	0.004	0.018	0.028	0.079	0.078	0.084
Maximum	0.904	1.909	0.549	0.869	0.789	1.426	1.185	1.193	4.014
Minimum	-1.008	-0.262	-0.533	-2.387	-0.892	-1.276	-4.764	-0.969	-1.255
Std. Dev.	0.253	0.223	0.140	0.404	0.187	0.298	0.380	0.284	0.455
Skewness	-0.814	4.187	-0.373	-2.841	-0.706	-0.100	-8.769	0.203	3.793
Kurtosis	5.631	30.078	4.883	14.409	8.071	9.289	108.881	7.261	33.032
Observations	185	240	240	219	201	175	240	116	240

Table 2.2.2 (Continued)

	Ireland	Italy	Japan	Korea	Malaysia	Mexico	Netherlands	New Zealand	Norway
Strategy : 9/1/9									
Mean	0.011	0.134	-0.005	-0.181	-0.015	0.036	0.072	0.040	0.080
Median	0.069	0.094	0.003	-0.020	0.026	0.076	0.144	0.108	0.051
Maximum	0.875	1.662	0.618	0.658	0.440	1.510	0.634	0.737	4.450
Minimum	-2.343	-0.509	-0.845	-4.911	-1.324	-2.508	-5.340	-1.340	-1.827
Std. Dev.	0.403	0.245	0.181	0.617	0.235	0.493	0.423	0.332	0.595
Skewness	-1.833	1.858	-0.264	-3.914	-2.102	-2.067	-9.208	-1.560	2.635
Kurtosis	10.245	11.099	6.328	23.418	11.044	12.769	116.247	6.875	21.507
Observations	179	234	234	213	195	169	234	110	234
Strategy : 12/1/12									
Mean	-0.044	0.110	-0.036	-0.301	-0.078	0.025	0.069	-0.020	0.019
Median	0.057	0.075	-0.008	-0.090	-0.013	0.086	0.150	0.099	-0.003
Maximum	0.855	1.544	0.550	0.385	0.414	1.728	0.569	0.765	4.636
Minimum	-1.650	-0.564	-0.743	-4.727	-1.945	-2.569	-5.618	-2.092	-1.698
Std. Dev.	0.426	0.269	0.195	0.710	0.361	0.644	0.458	0.463	0.663
Skewness	-1.196	1.281	-0.047	-2.842	-2.588	-2.079	-8.565	-1.988	3.064
Kurtosis	4.792	7.382	4.466	13.026	11.696	9.531	105.760	7.900	22.578
Observations	173	228	228	207	189	163	228	104	228

Table 2.2.3
Momentum Profits for Some Countries: Pakistan - US

	Pakistan	Philippines	Portugal	Singapore	Spain	South Africa	Sweden	Switzerland	Turkey	UK	US
Strategy : 3/1/3											
Mean	-0.017	-0.035	-0.015	-0.011	0.018	0.018	0.028	0.008	-0.050	0.026	-0.003
Median	-0.009	0.012	-0.003	0.001	0.029	0.017	0.017	0.013	-0.013	0.031	0.000
Maximum	0.256	0.465	1.423	0.390	0.773	0.365	0.924	0.417	0.606	0.424	0.118
Minimum	-0.437	-1.321	-1.473	-0.840	-0.494	-0.388	-0.503	-0.477	-1.048	-0.401	-0.193
Std. Dev.	0.116	0.241	0.193	0.142	0.148	0.120	0.137	0.102	0.217	0.084	0.030
Skewness	-0.500	-2.020	-0.309	-1.449	0.849	-0.168	0.923	-0.674	-1.563	-0.487	-1.282
Kurtosis	4.133	9.804	35.574	8.930	10.132	3.733	12.101	8.266	8.438	8.062	10.144
Observations	128	160	183	242	193	246	246	246	182	244	427
Strategy : 6/1/6											
Mean	-0.020	-0.062	-0.010	0.011	0.027	0.066	0.027	0.041	-0.124	0.076	0.004
Median	-0.007	0.004	-0.004	0.025	0.031	0.081	0.028	0.046	-0.049	0.093	0.006
Maximum	0.631	1.802	1.287	0.702	0.997	0.576	0.520	0.597	0.905	0.387	0.052
Minimum	-0.901	-2.696	-0.560	-1.061	-0.985	-0.686	-0.932	-0.641	-2.125	-0.498	-0.099
Std. Dev.	0.212	0.447	0.194	0.194	0.222	0.203	0.196	0.137	0.435	0.124	0.020
Skewness	-0.698	-1.444	1.223	-1.362	0.019	-0.616	-1.171	-0.351	-1.691	-1.284	-0.878
Kurtosis	6.549	12.536	13.505	9.330	9.119	3.881	7.744	7.406	8.055	6.186	5.335
Observations	122	154	177	236	187	240	240	240	176	238	421

Table 2.2.3 (Continued)

	Pakistan	Philippines	Portugal	Singapore	Spain	South Africa	Sweden	Switzerland	Turkey	UK	US
Strategy : 9/1/9											
Mean	-0.014	-0.152	-0.053	-0.003	0.036	0.059	-0.001	0.069	-0.238	0.089	0.005
Median	-0.028	0.029	0.002	0.028	0.063	0.066	0.054	0.077	-0.069	0.129	0.006
Maximum	0.364	2.325	0.565	0.523	0.942	0.788	0.580	0.493	2.177	0.442	0.054
Minimum	-0.560	-4.599	-6.341	-1.827	-1.301	-0.994	-2.325	-0.369	-4.704	-0.614	-0.061
Std. Dev.	0.173	0.687	0.547	0.261	0.293	0.277	0.364	0.159	0.803	0.171	0.016
Skewness	-0.274	-2.636	-9.065	-3.110	-0.825	-0.636	-2.687	0.037	-1.879	-1.328	-0.431
Kurtosis	3.463	16.716	103.754	21.411	6.488	4.426	14.200	3.088	10.354	5.587	4.739
Observations	116	148	171	230	181	234	234	234	170	232	415
Strategy : 12/1/12											
Mean	0.001	-0.201	-0.053	-0.049	-0.031	-0.025	-0.027	0.064	-0.454	0.062	0.002
Median	-0.014	-0.043	0.013	-0.023	0.048	-0.008	0.029	0.066	-0.202	0.101	0.002
Maximum	0.385	2.306	0.642	0.637	0.807	0.827	0.788	0.621	1.443	0.457	0.031
Minimum	-0.667	-3.574	-6.332	-1.971	-1.591	-1.464	-2.253	-0.491	-5.025	-0.645	-0.033
Std. Dev.	0.175	0.714	0.607	0.330	0.441	0.395	0.401	0.204	0.981	0.206	0.010
Skewness	-0.403	-1.338	-7.293	-2.658	-1.610	-0.822	-2.136	0.038	-1.749	-0.914	-0.109
Kurtosis	4.491	9.060	72.459	15.400	5.979	4.758	10.869	2.817	7.681	3.908	3.281
Observations	110	142	165	224	175	228	228	228	164	226	409

Table 2.3.1
Variables

This table summarizes the data used in the empirical tests. All data except the first column are defined in Table 2.9. The first column, R^2, shows the asset price comovement that is calculated by the specification given in equation 4. R^2 data is obtained from Morck, Yeung, and Yu (2000). UK_LAW, FR_LAW, SC_LAW and GE_LAW shows the legal origins of the countries. Corruption shows the corruption index. Herfindahl shows the industry concentration. CAP/GDP (%) shows market capitalization as a percentage of total gross domestic product. Trading shows the ratio traded asset value to gross domestic product. SEO shows state owned enterprises in the economy. Domestic shows logarithm of the average ratio of the number of domestic firms listed in a given country to its population. Education Enroll and Education life represents the investor sophistication levels. Finally, earnings management index shows the severeness of earnings managements and is obtained from Leuz, Nanda, and Wysocki (2004).

Country	Rsq	UK_LAW	FR_LAW	SC_LAW	GE_LAW	Corruption	Investor Protection	Education per capita
Australia	0.06	1	0	0	0	8.3	6.86	966
Belgium	0.15	0	1	0	0	6.1	0.48	1,299
Canada	0.06	1	0	0	0	9.2	9.72	1,272
Chile	0.21	0	1	0	0	7.4	6.29	199
Denmark	0.08	0	0	1	0	9.8	4.44	2,497
Finland	0.14	0	0	1	0	10	4.89	1,471
France	0.08	0	1	0	0	6.7	4.24	1,270
Germany	0.11	0	0	0	1	7.6	0.10	1,048
Greece	0.19	0	1	0	0	4.9	2.44	393
Hong Kong	0.15	1	0	0	0	7.7	8.56	975
India	0.19	1	0	0	0	2.8	8.56	19
Ireland	0.06	1	0	0	0	7.2	6.20	1,296
Italy	0.18	0	1	0	0	4.6	1.71	880
Japan	0.23	0	0	0	1	6.4	6.86	1,319
Korea	0.17	0	0	0	1	4	4.61	

Table 2.3.1 (Continued)

Country	Rsq	UK_LAW	FR_LAW	SC_LAW	GE_LAW	Corruption	Investor Protection	Education per capita
Malaysia	0.43	1	0	0	0	4.8	7.43	261
Mexico	0.29	0	1	0	0	3.3	1.05	261
Netherlands	0.10	0	1	0	0	8.9	4.92	1,542
New Zealand	0.06	1	0	0	0	9.4	5.83	864
Norway	0.12	0	0	1	0	9.1	5.54	2,492
Pakistan	0.18	1	0	0	0		6.67	8
Philippines	0.16	0	1	0	0	2.8	7.18	31
Portugal	0.07	0	1	0	0	6.4	4.60	628
Singapore	0.19	1	0	0	0	9.1	7.72	807
South Africa	0.20	1	0	0	0	5	8.27	169
Spain	0.19	0	1	0	0	9.1	6.01	651
Sweden	0.14	0	0	1	0	9.4	4.05	2,023
Switzerland	0.14	0	0	0	1	8.6	3.58	1,730
Turkey	0.39	0	1	0	0	3.8	2.26	103
UK	0.06	1	0	0	0	8.7	8.27	1,052
US	0.02	1	0	0	0	7.8	10.00	1,752

Table 2.3.2 (Continued)

Country	Herfindahl	CAP/GDP	Trading	Earnings Management	SOE	Education Enroll	Education Life	Domestic
Australia	0.25	73.04	0.28	4.80	6.00	63.00	14.60	4.17
Belgium	0.19	39.55	0.06	19.50	6.00	57.00	15.40	2.75
Canada	0.15	58.90	0.33	5.30	6.00	60.00	16.70	4.35
Chile	0.21	80.94	0.17		7.60	38.00	12.10	2.95
Denmark	0.23	34.03	0.15	16.00	4.00	56.00	14.30	3.79
Finland	0.18	30.96	0.15	12.00	6.00		15.50	3.19
France	0.13	33.63	0.24	13.50	4.80	53.00	14.80	2.58
Germany	0.19	25.65	0.24	21.50	6.00	46.00	15.30	2.30
Greece	0.34	13.54	0.05	28.30	2.00	55.00	13.20	3.21
Hong Kong	0.29	195.61	0.77	19.50	10.00			4.64
India	0.29	195.61	0.04	19.10	0.40	10.00		1.80
Ireland	0.27	26.27	0.21	5.10	4.00	46.00	13.20	3.07
Italy	0.33	17.58	0.08	24.80	2.00	47.00		1.50
Japan	0.14	88.12	0.24	20.50	8.00	46.00	13.30	2.96
Korea	0.18		0.41		6.00		13.60	3.02
Malaysia	0.14	184.95	0.88	14.80	5.20	25.00		3.48
Mexico	0.26	28.32	0.12		3.20	20.00	10.80	0.69
Netherlands	0.23	70.64	0.63	16.50	6.00	52.00	15.30	2.62

Table 2.3.2 (Continued)

Country	Herfindahl	CAP/GDP	Trading	Earnings Management	SOE	Education Enroll	Education Life	Domestic
New Zealand	0.18	51.88	0.14		6.40	66.00	15.20	3.60
Norway	0.28	25.90	0.17	5.80	2.00	68.00	14.60	3.76
Pakistan	0.28	25.90	0.05	17.80	2.80		14.60	1.77
Philippines	0.27	47.67	0.20	8.80	4.00	29.00	11.00	1.10
Portugal	0.30	18.15	0.06	25.10	2.00	47.00	14.10	2.61
Singapore	0.30	137.40	0.71	21.60	8.00			4.42
South Africa	0.47	156.51	0.13		4.00	15.00	13.70	2.74
Spain	0.22	31.51	0.11	18.60	4.00	58.00		2.71
Sweden	0.27	65.26	0.40	6.80	4.00	66.00	13.80	3.38
Switzerland	0.34	112.19	1.01	22.00	8.00	40.00	10.90	3.48
Turkey	0.16	13.52	0.30		4.00	15.00	8.80	1.46
UK	0.15	113.77	0.93	7.00	5.20	58.00	15.30	3.55
US	0.11	83.80	0.70	2.00	8.00	72.00	15.80	3.40

Table 2.4.1.1

Statistical Arbitrage Tests for 3/1/3 Momentum Strategies

This table summarizes the statistical arbitrage parameter estimates of 3/1/3 momentum strategy as described in Table 2.10. Sample periods are reported in Table 1. Statistical arbitrage profits are calculated for a formation period of 3 months and a holding period of 3 months. Every month, stocks are sorted based on past 3 months of returns into decile portfolios. The portfolio 3/1/3 longs the top two deciles and shorts the bottom two deciles (except US, where we used top deciles) and holds that spread for 3 months as in Jegadeesh and Titman (1993). The risk free asset is used to finance the portfolio. p1 and p2 denote the p values from statistical arbitrage tests which test whether the portfolio's mean monthly incremental profit is positive and whether its time-averaged variance is declining over time. The sum of the p1 and p2 columns is the p value for the statistical arbitrage test. Note that the sum may exceed one because of the Bonferonni inequality.

Country	mu	sigma	lambda	se(mu)	se(sigma)	se(lambda)	p1	p2	p1+p2
Australia	0.000	0.218	-0.651	0.001	0.056	0.056	0.22	0.00	0.22
Belgium	0.004	0.004	0.304	0.001	0.001	0.040	0.00	1.00	1.00
Canada	-0.001	0.045	-0.219	0.001	0.013	0.061	0.76	0.00	0.76
Chile	0.001	0.986	-1.000	0.001	0.450	0.112	0.20	0.00	0.20
Denmark	0.001	0.110	-0.548	0.000	0.027	0.054	0.05	0.00	0.05
Finland	0.001	0.024	-0.041	0.001	0.007	0.073	0.20	0.29	0.49
France	0.000	0.033	-0.193	0.001	0.007	0.048	0.61	0.00	0.61
Germany	0.003	0.010	0.076	0.001	0.002	0.043	0.00	0.96	0.96
Greece	0.000	0.121	-0.424	0.001	0.036	0.070	0.36	0.00	0.36
Hong Kong	0.000	0.074	-0.228	0.002	0.013	0.038	0.48	0.00	0.48
India	0.000	0.088	-0.342	0.002	0.024	0.065	0.57	0.00	0.57
Ireland	0.001	0.034	-0.008	0.002	0.009	0.058	0.35	0.45	0.80
Italy	0.001	0.181	-0.590	0.001	0.050	0.060	0.08	0.00	0.08
Japan	0.000	0.060	-0.242	0.001	0.016	0.060	0.39	0.00	0.39
Korea	0.001	0.583	-0.792	0.001	0.185	0.071	0.04	0.00	0.04

Table 2.4.1.1 (Continued)

Country	mu	sigma	lambda	se(mu)	se(sigma)	se(lambda)	p1	p2	p1+p2
Malaysia	-0.002	0.042	-0.043	0.002	0.011	0.059	0.77	0.23	1.00
Mexico	-0.002	0.733	-1.000	0.001	0.320	0.110	1.00	0.00	1.00
Netherlands	0.006	0.014	0.226	0.003	0.004	0.067	0.01	1.00	1.01
New Zealand	0.008	0.143	-0.341	0.003	0.040	0.072	0.01	0.00	0.01
Norway	-0.002	0.509	-0.703	0.001	0.178	0.077	0.97	0.00	0.97
Pakistan	-0.003	0.073	-0.336	0.002	0.022	0.077	0.97	0.00	0.97
Philippines	-0.003	0.105	-0.308	0.002	0.030	0.068	0.92	0.00	0.92
Portugal	-0.001	0.016	0.102	0.002	0.003	0.047	0.63	0.99	1.61
Singapore	-0.001	0.022	0.085	0.002	0.005	0.048	0.76	0.96	1.72
South Africa	0.000	0.691	-0.932	0.000	0.230	0.073	0.56	0.00	0.56
Spain	0.003	0.071	-0.281	0.001	0.017	0.056	0.02	0.00	0.02
Sweden	0.002	0.027	-0.142	0.001	0.005	0.042	0.04	0.00	0.04
Switzerland	0.001	0.007	0.210	0.001	0.002	0.045	0.14	1.00	1.14
Turkey	0.000	0.335	-1.000	0.000	0.116	0.106	0.14	0.00	0.14
UK	0.001	0.018	-0.142	0.001	0.004	0.052	0.01	0.00	0.01
US	-0.003	0.033	-0.017	0.001	0.006	0.034	0.97	0.31	1.27

Table 2.4.1.2

Summary Statistics for 3/1/3 Momentum Portfolios

Sample periods are reported in Table 1. Portfolio MOM 3/1/3 denotes a momentum portfolio with a formation period of 3 months and a holding period of 3 months. Every month, stocks are sorted based on past 3 months of returns into decile portfolios. The portfolio MOM 3/1/3 longs the top 20% and shorts the bottom 20 % for non-US and holds that spread for 3 months as in Jegadeesh and Titman (1993). The risk free asset is used to finance the portfolios. The t-statistic on the mean monthly trading profit is provided for comparison. T-statistics are calculated under the assumption that observations are independent.

Country	N	mean	median	stdev	max	min	t-stat
Australia	243	0.002	0.002	0.016	0.100	-0.081	1.539
Belgium	245	0.003	0.004	0.019	0.092	-0.098	2.453
Canada	243	0.000	0.000	0.017	0.064	-0.051	-0.249
Chile	164	0.002	0.000	0.024	0.177	-0.087	0.907
Denmark	245	0.001	0.001	0.013	0.062	-0.045	1.061
Finland	179	0.001	0.000	0.020	0.066	-0.078	0.854
France	245	0.001	0.001	0.015	0.050	-0.074	1.340
Germany	245	0.003	0.004	0.014	0.063	-0.049	3.418
Greece	181	0.001	0.001	0.023	0.116	-0.100	0.466
Hong Kong	245	0.000	0.004	0.029	0.100	-0.165	0.175
India	158	0.000	0.002	0.024	0.077	-0.108	-0.092
Ireland	190	0.001	0.006	0.033	0.079	-0.279	0.376
Italy	245	0.001	0.001	0.016	0.120	-0.069	1.486
Japan	245	0.000	0.001	0.021	0.065	-0.117	-0.246
Korea	224	0.000	0.001	0.024	0.103	-0.116	-0.251

Table 2.4.1.2 (Continued)

Country	N	mean	median	stdev	max	min	t-stat
Malaysia	206	-0.002	-0.002	0.035	0.147	-0.193	-0.682
Mexico	180	0.000	-0.002	0.019	0.136	-0.038	0.101
Netherlands	245	0.002	0.003	0.039	0.096	-0.475	0.685
New Zealand	121	0.008	0.006	0.044	0.177	-0.192	2.038
Norway	245	0.002	0.000	0.027	0.138	-0.102	1.446
Pakistan	127	-0.002	-0.002	0.022	0.066	-0.071	-0.954
Philippines	159	-0.002	0.003	0.033	0.090	-0.162	-0.838
Portugal	182	-0.001	-0.001	0.024	0.161	-0.165	-0.808
Singapore	241	-0.002	0.000	0.032	0.088	-0.173	-1.026
South Africa	245	0.000	0.000	0.017	0.086	-0.065	0.385
Spain	192	0.001	0.004	0.023	0.078	-0.089	0.662
Sweden	245	0.002	0.001	0.015	0.067	-0.060	1.626
Switzerland	245	0.001	0.002	0.020	0.089	-0.083	0.938
Turkey	181	0.000	0.000	0.018	0.075	-0.103	0.204
UK	243	0.002	0.003	0.010	0.035	-0.033	2.809
US	427	-0.003	0.000	0.030	0.118	-0.193	-1.785

Table 2.4.2.1 Statistical Arbitrage Tests for 6/1/6 Momentum Strategies

Country	mu	sigma	lambda	Se(mu)	se(sigma)	se(lambda)	p1	p2	p1+p2
Australia	0.000	0.182	-0.643	0.001	0.055	0.067	0.82	0.00	0.82
Belgium	0.005	0.004	0.299	0.001	0.001	0.038	0.00	1.00	1.00
Canada	0.000	0.031	-0.197	0.001	0.009	0.061	0.61	0.00	0.61
Chile	-0.002	1.407	-1.000	0.001	0.864	0.161	0.90	0.00	0.90
Denmark	0.001	0.094	-0.560	0.000	0.030	0.071	0.00	0.00	0.00
Finland	0.004	0.032	-0.170	0.001	0.012	0.088	0.00	0.03	0.03
France	0.000	0.104	-0.518	0.001	0.026	0.056	0.36	0.00	0.36
Germany	0.004	0.013	-0.026	0.001	0.003	0.046	0.00	0.28	0.28
Greece	-0.001	0.204	-0.550	0.001	0.051	0.059	0.83	0.00	0.83
Hong Kong	0.000	0.049	-0.191	0.001	0.010	0.042	0.44	0.00	0.44
India	0.002	0.085	-0.401	0.001	0.026	0.076	0.05	0.00	0.05
Ireland	0.001	0.059	-0.232	0.002	0.016	0.061	0.20	0.00	0.20
Italy	0.001	0.060	-0.384	0.001	0.014	0.051	0.01	0.00	0.01
Japan	-0.001	0.020	-0.056	0.001	0.004	0.047	0.85	0.11	0.97
Korea	-0.001	0.074	-0.320	0.001	0.018	0.054	0.78	0.00	0.78
Malaysia	0.000	0.041	-0.163	0.001	0.011	0.062	0.46	0.00	0.47
Mexico	-0.001	0.532	-1.000	0.000	0.157	0.079	0.96	0.00	0.96
Netherlands	0.003	0.025	0.054	0.002	0.007	0.059	0.08	0.82	0.90
New Zealand	0.004	0.132	-0.391	0.003	0.034	0.065	0.08	0.00	0.08
Norway	-0.003	2.529	-1.000	0.001	0.954	0.086	0.99	0.00	0.99
Pakistan	-0.001	0.170	-0.572	0.001	0.064	0.097	0.76	0.00	0.76
Philippines	-0.003	0.069	-0.226	0.002	0.021	0.073	0.93	0.00	0.93
Portugal	-0.001	0.019	-0.079	0.001	0.004	0.051	0.77	0.06	0.83
Singapore	0.002	0.014	0.095	0.001	0.003	0.051	0.13	0.97	1.10
South Africa	-0.001	0.403	-0.828	0.000	0.171	0.094	0.98	0.00	0.98
Spain	0.001	0.034	-0.172	0.001	0.009	0.060	0.11	0.00	0.11
Sweden	0.001	0.015	-0.066	0.001	0.003	0.050	0.12	0.10	0.21
Switzerland	0.004	0.010	0.079	0.001	0.002	0.054	0.00	0.93	0.93
Turkey	0.000	0.404	-1.000	0.000	0.112	0.096	0.14	0.00	0.14
UK	0.002	0.027	-0.280	0.000	0.007	0.055	0.00	0.00	0.00
US	0.004	0.037	-0.125	0.001	0.007	0.037	0.00	0.00	0.00

Table 2.4.2.2
Summary Statistics for 6/1/6 Momentum Portfolios

Country	N	mean	median	stdev	max	min	t-stat
Australia	238	0.001	0.000	0.013	0.059	-0.036	1.374
Belgium	239	0.005	0.005	0.018	0.105	-0.071	4.251
Canada	237	0.000	0.001	0.013	0.046	-0.055	0.273
Chile	158	0.003	-0.002	0.036	0.179	-0.080	1.138
Denmark	239	0.001	0.002	0.009	0.032	-0.036	1.454
Finland	173	0.004	0.005	0.016	0.058	-0.065	3.059
France	239	0.002	0.002	0.012	0.043	-0.075	2.609
Germany	239	0.004	0.004	0.012	0.033	-0.050	5.273
Greece	175	0.003	-0.002	0.027	0.137	-0.054	1.552
Hong Kong	239	0.002	0.004	0.022	0.077	-0.094	1.515
India	152	0.002	0.004	0.019	0.058	-0.064	1.196
Ireland	184	0.002	0.005	0.023	0.068	-0.083	1.322
Italy	239	0.002	0.000	0.012	0.076	-0.023	2.986
Japan	239	-0.001	0.000	0.016	0.052	-0.056	-0.807
Korea	218	-0.002	0.003	0.020	0.064	-0.119	-1.214

Table 2.4.2.2 (Continued)

Country	N	mean	median	stdev	max	min	t-stat
Malaysia	200	0.000	0.001	0.021	0.089	-0.079	0.261
Mexico	174	0.000	0.000	0.022	0.140	-0.078	0.110
Netherlands	239	0.002	0.003	0.033	0.139	-0.398	1.165
New Zealand	115	0.008	0.006	0.039	0.197	-0.113	2.269
Norway	239	0.003	-0.001	0.041	0.381	-0.127	0.952
Pakistan	121	-0.001	0.000	0.024	0.081	-0.099	-0.476
Philippines	153	-0.002	-0.001	0.029	0.113	-0.125	-0.962
Portugal	176	-0.001	0.000	0.014	0.079	-0.042	-0.617
Singapore	235	0.001	0.003	0.022	0.080	-0.105	0.755
South Africa	239	0.001	0.000	0.012	0.052	-0.051	0.686
Spain	186	0.001	0.002	0.017	0.051	-0.065	1.171
Sweden	239	0.001	0.001	0.011	0.031	-0.056	1.310
Switzerland	239	0.003	0.003	0.014	0.064	-0.051	3.655
Turkey	175	0.000	0.000	0.030	0.097	-0.205	0.008
UK	237	0.003	0.003	0.008	0.027	-0.027	4.931
US	421	0.004	0.005	0.020	0.052	-0.099	4.447

Table 2.4.3.1 Statistical Arbitrage Tests for 9/1/9 Momentum Strategies

Country	mu	sigma	lambda	se(mu)	se(sigma)	se(lambda)	p1	p2	p1+p2
Australia	-0.001	0.134	-0.558	0.001	0.045	0.075	0.99	0.00	0.99
Belgium	0.005	0.002	0.425	0.001	0.000	0.040	0.00	1.00	1.00
Canada	-0.001	0.078	-0.419	0.001	0.025	0.071	0.86	0.00	0.86
Chile	-0.002	1.112	-1.000	0.001	0.640	0.153	0.99	0.00	0.99
Denmark	0.001	0.053	-0.457	0.000	0.015	0.063	0.00	0.00	0.00
Finland	0.002	0.022	-0.114	0.001	0.007	0.073	0.01	0.06	0.07
France	0.001	0.122	-0.566	0.001	0.031	0.056	0.05	0.00	0.05
Germany	0.004	0.020	-0.147	0.001	0.004	0.048	0.00	0.00	0.00
Greece	-0.005	0.097	-0.262	0.002	0.021	0.050	0.97	0.00	0.97
Hong Kong	-0.003	0.031	-0.058	0.002	0.006	0.043	0.97	0.09	1.06
India	0.003	0.077	-0.392	0.001	0.020	0.063	0.00	0.00	0.00
Ireland	0.000	0.052	-0.180	0.002	0.017	0.077	0.57	0.01	0.58
Italy	0.001	0.122	-0.584	0.000	0.028	0.050	0.08	0.00	0.08
Japan	-0.001	0.029	-0.164	0.001	0.007	0.055	0.73	0.00	0.73
Korea	-0.003	0.038	-0.181	0.001	0.008	0.050	0.99	0.00	0.99
Malaysia	-0.002	0.042	-0.202	0.001	0.014	0.078	0.92	0.00	0.93
Mexico	0.000	0.652	-1.000	0.001	0.284	0.123	0.75	0.00	0.75
Netherlands	0.002	0.030	-0.038	0.002	0.009	0.064	0.10	0.28	0.37
New Zealand	0.000	0.044	-0.145	0.002	0.011	0.067	0.53	0.01	0.54
Norway	-0.002	2.197	-1.000	0.001	0.790	0.082	0.96	0.00	0.96
Pakistan	0.000	0.044	-0.367	0.001	0.017	0.103	0.62	0.00	0.62
Philippines	-0.003	0.023	0.053	0.002	0.008	0.084	0.91	0.74	1.64
Portugal	0.000	0.011	0.182	0.002	0.002	0.046	0.54	1.00	1.54
Singapore	0.003	0.005	0.305	0.001	0.001	0.055	0.01	1.00	1.01
South Africa	-0.001	0.349	-0.814	0.000	0.148	0.094	0.90	0.00	0.90
Spain	0.001	0.032	-0.175	0.001	0.011	0.080	0.27	0.01	0.28
Sweden	0.001	0.006	0.169	0.001	0.001	0.048	0.24	1.00	1.24
Switzerland	0.003	0.017	-0.086	0.001	0.004	0.049	0.00	0.04	0.04
Turkey	0.000	0.436	-1.000	0.000	0.085	0.065	0.16	0.00	0.16
UK	0.001	0.023	-0.262	0.000	0.005	0.049	0.02	0.00	0.02
US	0.005	0.021	-0.055	0.001	0.004	0.036	0.00	0.06	0.06

Table 2.4.3.2
Summary Statistics for 9/1/9 Momentum Portfolios

Country	N	mean	median	stdev	max	Min	t-stat
Australia	231	-0.001	0.001	0.013	0.067	-0.053	-0.667
Belgium	233	0.006	0.005	0.019	0.112	-0.054	5.145
Canada	231	-0.001	0.000	0.013	0.044	-0.059	-1.205
Chile	152	0.002	-0.002	0.031	0.171	-0.058	0.940
Denmark	233	0.000	0.001	0.008	0.024	-0.036	0.476
Finland	167	0.002	0.003	0.014	0.036	-0.058	2.161
France	233	0.002	0.002	0.012	0.042	-0.058	2.880
Germany	233	0.005	0.005	0.010	0.035	-0.033	6.947
Greece	169	0.000	-0.003	0.036	0.145	-0.186	-0.026
Hong Kong	233	-0.002	0.000	0.024	0.071	-0.144	-1.452
India	146	0.002	0.004	0.019	0.047	-0.077	1.033
Ireland	178	0.000	0.003	0.025	0.045	-0.121	0.147
Italy	233	0.002	0.000	0.012	0.076	-0.022	2.934
Japan	233	0.000	0.000	0.014	0.055	-0.056	-0.352
Korea	212	-0.003	0.001	0.018	0.060	-0.092	-2.205

Table 2.4.3.2 (Continued)

Country	N	mean	median	stdev	max	min	t-stat
Malaysia	194	-0.001	0.002	0.018	0.041	-0.109	-0.679
Mexico	168	0.001	0.000	0.027	0.109	-0.124	0.287
Netherlands	233	0.003	0.006	0.026	0.051	-0.307	1.574
New Zealand	109	0.002	0.006	0.026	0.081	-0.101	0.678
Norway	233	0.002	-0.001	0.037	0.283	-0.082	0.785
Pakistan	115	0.000	-0.001	0.012	0.030	-0.039	-0.307
Philippines	147	-0.004	0.001	0.028	0.110	-0.154	-1.520
Portugal	170	-0.002	-0.001	0.024	0.028	-0.256	-1.076
Singapore	229	0.000	0.002	0.020	0.040	-0.130	-0.123
South Africa	233	0.000	0.000	0.011	0.034	-0.055	0.535
Spain	180	0.001	0.002	0.016	0.033	-0.082	1.120
Sweden	233	0.000	0.002	0.012	0.024	-0.068	-0.007
Switzerland	233	0.004	0.004	0.011	0.040	-0.027	4.975
Turkey	169	0.000	0.000	0.043	0.176	-0.266	0.126
UK	231	0.002	0.002	0.008	0.023	-0.028	4.132
US	415	0.005	0.006	0.016	0.054	-0.061	6.930

Table 2.4.4.1 Statistical Arbitrage Tests for 12/1/12 Momentum Strategies

Country	mu	sigma	lambda	se(mu)	Se(sigma)	Se(lambda)	p1	p2	p1+p2
Australia	-0.002	0.075	-0.416	0.001	0.024	0.071	1.00	0.00	1.00
Belgium	0.006	0.003	0.382	0.001	0.001	0.037	0.00	1.00	1.00
Canada	-0.003	0.089	-0.433	0.001	0.031	0.078	1.00	0.00	1.00
Chile	0.000	0.781	-1.000	0.001	0.373	0.128	0.56	0.00	0.56
Denmark	0.001	0.062	-0.518	0.000	0.017	0.061	0.00	0.00	0.00
Finland	0.000	0.025	-0.134	0.001	0.008	0.074	0.51	0.03	0.54
France	0.001	0.089	-0.515	0.001	0.022	0.054	0.13	0.00	0.13
Germany	0.003	0.030	-0.275	0.001	0.006	0.046	0.00	0.00	0.00
Greece	-0.009	0.084	-0.186	0.003	0.016	0.043	1.00	0.00	1.00
Hong Kong	-0.004	0.025	0.009	0.002	0.005	0.041	0.99	0.59	1.58
India	0.003	0.045	-0.302	0.001	0.011	0.060	0.00	0.00	0.00
Ireland	-0.001	0.080	-0.332	0.001	0.031	0.091	0.82	0.00	0.82
Italy	0.000	0.109	-0.605	0.000	0.023	0.046	0.69	0.00	0.69
Japan	-0.002	0.056	-0.361	0.001	0.014	0.055	1.00	0.00	1.00
Korea	-0.002	0.090	-0.387	0.001	0.020	0.050	0.96	0.00	0.96
Malaysia	-0.003	0.020	-0.008	0.001	0.006	0.069	0.98	0.45	1.44
Mexico	0.001	0.639	-1.000	0.001	0.244	0.108	0.16	0.00	0.16
Netherlands	0.001	0.046	-0.172	0.001	0.014	0.068	0.22	0.01	0.23
New Zealand	0.002	0.012	0.220	0.003	0.005	0.111	0.26	0.98	1.23
Norway	-0.001	1.781	-1.000	0.001	0.586	0.075	0.92	0.00	0.92
Pakistan	0.000	0.018	-0.207	0.001	0.008	0.121	0.53	0.04	0.58
Philippines	-0.004	0.048	-0.158	0.002	0.016	0.082	0.95	0.03	0.98
Portugal	0.001	0.005	0.322	0.001	0.001	0.054	0.27	1.00	1.27
Singapore	-0.001	0.008	0.191	0.001	0.002	0.054	0.74	1.00	1.74
South Africa	0.000	0.145	-0.600	0.001	0.064	0.098	0.55	0.00	0.55
Spain	-0.001	0.047	-0.227	0.001	0.022	0.112	0.77	0.02	0.79
Sweden	-0.001	0.008	0.077	0.001	0.002	0.059	0.75	0.90	1.66
Switzerland	0.001	0.030	-0.230	0.001	0.006	0.044	0.05	0.00	0.05
Turkey	0.000	0.288	-1.000	0.000	0.078	0.076	0.24	0.00	0.24
UK	0.000	0.022	-0.275	0.000	0.005	0.046	0.18	0.00	0.18
US	0.002	0.010	0.000	0.001	0.002	0.036	0.00	0.50	0.50

Table 2.4.4.2
Summary Statistics for 12/1/12 Momentum Portfolios

Country	N	mean	median	stdev	max	min	t-stat
Australia	225	-0.002	0.000	0.013	0.031	-0.057	-2.256
Belgium	227	0.008	0.004	0.020	0.113	-0.049	5.775
Canada	225	-0.004	-0.001	0.014	0.033	-0.083	-4.076
Chile	146	0.001	0.000	0.025	0.115	-0.111	0.276
Denmark	227	0.000	0.001	0.008	0.025	-0.035	-0.299
Finland	161	-0.001	0.003	0.015	0.024	-0.073	-0.536
France	227	0.002	0.001	0.011	0.043	-0.055	2.351
Germany	227	0.004	0.004	0.010	0.032	-0.024	6.381
Greece	163	-0.005	-0.001	0.042	0.166	-0.195	-1.541
Hong Kong	227	-0.004	-0.001	0.026	0.072	-0.210	-2.629
India	140	0.002	0.003	0.015	0.042	-0.049	1.590
Ireland	172	-0.001	0.003	0.021	0.032	-0.085	-0.880
Italy	227	0.002	-0.001	0.012	0.055	-0.014	1.945
Japan	227	-0.002	0.000	0.012	0.040	-0.053	-2.170
Korea	206	-0.003	0.003	0.020	0.025	-0.118	-2.468

Table 2.4.4.2 (Continued)

Country	N	mean	median	stdev	max	min	t-stat
Malaysia	188	-0.003	0.001	0.020	0.027	-0.112	-2.125
Mexico	162	0.001	0.000	0.031	0.130	-0.169	0.342
Netherlands	227	0.002	0.005	0.022	0.040	-0.250	1.317
New Zealand	103	-0.002	0.005	0.027	0.042	-0.119	-0.584
Norway	227	0.000	-0.001	0.033	0.241	-0.098	0.185
Pakistan	109	0.000	-0.001	0.009	0.025	-0.028	0.290
Philippines	141	-0.004	0.000	0.026	0.093	-0.097	-1.784
Portugal	164	-0.001	0.001	0.020	0.021	-0.199	-0.907
Singapore	223	-0.003	-0.002	0.019	0.039	-0.106	-1.961
South Africa	227	0.000	0.000	0.011	0.032	-0.043	-0.102
Spain	174	-0.001	0.002	0.019	0.025	-0.073	-0.585
Sweden	227	0.000	0.001	0.012	0.023	-0.069	-0.642
Switzerland	227	0.003	0.001	0.012	0.049	-0.023	3.357
Turkey	163	0.000	0.000	0.022	0.090	-0.142	0.058
UK	225	0.001	0.002	0.007	0.027	-0.021	2.265
US	409	0.002	0.002	0.010	0.031	-0.033	2.999

Table 2.5

Correlation Matrix for the Variables Described in Table 2.9 and Reported in Table 2.3

Corruption shows the corruption index. Herfindahl shows the industry concentration. CAP/GDP (%) shows market capitalization as a percentage of total gross domestic product. Trading shows the ratio traded asset value to gross domestic product. SEO shows state owned enterprises in the economy. Domestic shows logarithm of the average ratio of the number of domestic firms listed in a given country to its population. Education Enroll and Education life represents the investor sophistication levels. Earnings management index shows the severeness of earnings managements.

	Corruption	Herfindahl	CAP/GDP	Trading	Earnings Management	Domestic	SOE	Eduction Enroll	Education Life
Corruption	1.000								
Herfindahl	0.289	1.000							
CAP/GDP	-0.019	-0.284	1.000						
Trading	0.029	-0.147	0.866	1.000					
Earnings Management	-0.150	0.349	-0.267	-0.238	1.000				
Domestic	0.459	-0.060	0.270	0.222	-0.322	1.000			
SOE	-0.030	-0.537	0.729	0.575	-0.106	0.108	1.000		
Eduction Enroll	0.249	-0.304	0.064	0.068	-0.453	0.704	-0.023	1.000	
Education Life	0.070	-0.633	-0.093	-0.074	-0.254	0.404	0.077	0.668	1.000

Table 2.6

Momentum Profits and Asset Price Comovement

This table summarizes the results of the equation, $MOM_{x/1/x} = \beta_0 + \beta_1 R^2$, where $MOM_{x/1/x}$ is the momentum profits with x month ranking and investment period and R^2 is the asset price comovement (x=3,6,9 or 12). Details of these measures are explained in Table 2.9. p- values of estimates are provided below the estimated values. R^2 shows the goodness of fit of the regressions. The p-value for β_1 represents the one-sided test statistics, whereas that of for β_0 represents the two-sided test statistics.

Dependent Variable	β_0	β_1	R2
$MOM_{3/1/3}$	0.026	-0.098	0.159
	0.001	0.022	
$MOM_{6/1/6}$	0.068	-0.219	0.136
	0.000	0.038	
$MOM_{9/1/9}$	0.065	-0.305	0.097
	0.036	0.070	
$MOM_{12/1/12}$	0.045	-0.509	0.106
	0.367	0.069	

Table 2.7.1

Momentum Profits of 3/1/3 Strategy and Its Determinants

This table reports the regression results of the below specification to investigate the determinants of 3/1/3 momentum strategy. In this regression, the dependent variable, $MOM_{3/1/3}$, is the momentum profits with 3 month ranking and investment period. Details of independent variables are summarized in Table 2.9. LAW is the legal origin. Corruption shows the corruption index. Herfindahl is the industry concentration. CAP/GDP (%) shows market capitalization as a percentage of total gross domestic product. Trading shows the ratio traded asset value to gross domestic product. Earnings management index shows the severeness of earnings managements as defined in Leuz, Nanda, and Wysocki (2004). SEO shows state owned enterprises in the economy. Education Enroll and Education life represent the investor sophistication levels. Finally, Domestic shows logarithm of the average ratio of the number of domestic firms listed in a given country to its population. p- values of estimates are provided below the estimated values. R^2 shows the goodness of fit statistics of the regressions. White heteroscedasticity consistent coefficient covariances are used to calculate the p-values. The p-values for investor sophistication variables (Education Enroll, Education Life) and Earnings Management represent the one-sided test statistics, whereas the others show the two sided values.

Table 2.7.1 (Continued)

Eq #	C	UK_LAW	FR_LAW	SC_LAW	GE_LAW	Corruption	Herfindahl	CAP/GDP	Trading	Earnings Management	SOE	Education Enroll	Education Life	Domestic	R2
1	-0.076					0.000	0.028	0.000	-0.005	0.001	-0.002	0.001			0.587
	0.024					0.849	0.510	0.173	0.717	0.130	0.418	0.003			
2	-0.113					0.003	0.070	0.000	0.010	0.000	0.000		0.006		0.355
	0.316					0.442	0.485	0.970	0.637	0.500	0.922		0.086		
3	-0.080					0.002	0.035	0.000	-0.007	0.001	-0.002	0.002		-0.007	0.623
	0.035					0.400	0.427	0.092	0.576	0.167	0.467	0.003		0.194	
4	-0.075	-0.002				0.000	0.027	0.000	-0.005	0.001	-0.002	0.001			0.588
	0.039	0.876				0.885	0.521	0.252	0.727	0.228	0.416	0.006			
5	-0.064		-0.009			-0.001	0.018	0.000	-0.001	0.001	-0.002	0.001			0.608
	0.072		0.405			0.774	0.706	0.412	0.964	0.086	0.360	0.002			
6	-0.074			0.004		0.000	0.025	0.000	-0.004	0.001	-0.002	0.001			0.590
	0.038			0.732		0.992	0.562	0.217	0.783	0.128	0.571	0.005			
7	-0.064				0.017	-0.001	0.009	0.000	-0.001	0.000	-0.004	0.002			0.624
	0.072				0.318	0.804	0.836	0.149	0.952	0.273	0.211	0.001			

Table 2.7.2
Momentum Profits of 6/1/6 Strategy and Its Determinants

Eq #	C	UK_LAW	FR_LAW	SC_LAW	GE_LAW	Corruption	Herfindahl	CAP/GDP	Trading	Earnings Management	SOE	Education Enroll	Education Life	Domestic	R2
1	-0.116					-0.007	0.037	0.000	0.023	0.003	-0.007	0.003			0.446
	0.251					0.238	0.740	0.406	0.576	0.074	0.317	0.011			
2	-0.318					-0.002	0.246	-0.001	0.083	0.001	0.002		0.021		0.355
	0.216					0.779	0.305	0.196	0.082	0.257	0.813		0.087		
3	-0.115					-0.007	0.035	0.000	0.024	0.003	-0.007	0.003		0.002	0.446
	0.273					0.246	0.768	0.492	0.594	0.080	0.340	0.019		0.883	
4	-0.141	0.031				-0.006	0.057	0.000	0.024	0.004	-0.006	0.003			0.492
	0.107	0.288				0.307	0.622	0.684	0.555	0.036	0.384	0.007			
5	-0.083		-0.024			-0.010	0.007	0.000	0.035	0.003	-0.008	0.003			0.479
	0.415		0.372			0.056	0.952	0.683	0.468	0.041	0.284	0.005			
6	-0.125			-0.018		-0.005	0.050	0.000	0.019	0.003	-0.008	0.003			0.457
	0.199			0.580		0.527	0.633	0.349	0.630	0.079	0.333	0.010			
7	-0.102				0.020	-0.008	0.015	0.000	0.028	0.002	-0.009	0.003			0.455
	0.345				0.666	0.151	0.906	0.411	0.546	0.118	0.296	0.009			

Table 2.7.3
Momentum Profits of 9/1/9 Strategy and Its Determinants

Eq #	C	UK_LAW	FR_LAW	SC_LAW	GE_LAW	Corruption	Herfindahl	CAP/GDP	Trading	Earnings Management	SOE	Eduction Enroll	Education Life	Domestic	R2
1	-0.148					0.001	-0.217	0.000	0.015	0.005	-0.005	0.003			0.255
	0.421					0.937	0.385	0.573	0.882	0.061	0.739	0.151			
2	-0.343					0.005	-0.088	-0.001	0.167	0.003	0.011		0.020		0.456
	0.478					0.750	0.842	0.088	0.084	0.070	0.515		0.254		
3	-0.174					0.010	-0.170	0.001	0.001	0.005	-0.004	0.004		-0.048	0.353
	0.395					0.433	0.465	0.283	0.988	0.088	0.782	0.073		0.093	
4	-0.149	0.002				0.001	-0.216	0.000	0.015	0.005	-0.005	0.003			0.255
	0.453	0.975				0.938	0.412	0.635	0.887	0.107	0.746	0.162			
5	-0.136		-0.009			0.000	-0.227	0.000	0.019	0.006	-0.005	0.003			0.257
	0.508		0.872			0.998	0.401	0.684	0.868	0.074	0.744	0.151			
6	-0.152			-0.010		0.002	-0.209	0.000	0.013	0.005	-0.005	0.003			0.256
	0.425			0.867		0.902	0.426	0.570	0.902	0.069	0.741	0.156			
7	-0.126				0.030	-0.001	-0.250	0.000	0.021	0.005	-0.009	0.003			0.262
	0.539				0.752	0.966	0.357	0.574	0.849	0.111	0.682	0.119			

Table 2.7.4
Momentum Profits of 12/1/12 Strategy and Its Determinants

Eq #	C	UK_LAW	FR_LAW	SC_LAW	GE_LAW	Corruption	Herfindahl	CAP/GDP	Trading	Earnings Management	SOE	Education Enroll	Education Life	Domestic	R2
1	**-0.117**					**0.014**	**-0.406**	0.000	-0.041	0.005	0.004	0.000			**0.131**
	0.689					**0.662**	**0.376**	0.693	0.832	0.178	0.882	0.499			
2	-0.201					0.012	-0.535	-0.002	0.195	0.005	0.019		0.006		**0.310**
	0.831					0.712	0.575	0.271	0.329	0.121	0.528		0.458		
3	**-0.192**					**0.039**	**-0.276**	0.002	-0.079	0.005	0.006	0.004		-0.135	**0.388**
	0.521					**0.213**	**0.432**	0.140	0.633	0.198	0.791	0.196		0.031	
4	**-0.053**	**-0.080**				**0.011**	**-0.458**	0.001	-0.044	0.003	0.002	0.000			**0.165**
	0.878	**0.437**				**0.731**	**0.307**	0.525	0.828	0.351	0.948	0.482			
5	**-0.168**		**0.036**			**0.018**	**-0.362**	0.001	-0.059	0.005	0.006	0.000			**0.139**
	0.630		**0.713**			**0.598**	**0.457**	0.649	0.793	0.254	0.841	0.484			
6	-0.098			**0.041**		0.010	-0.437	0.000	-0.032	0.006	0.006	0.000			**0.137**
	0.757			**0.667**		0.786	0.370	0.758	0.875	0.179	0.819	0.491			
7	**-0.105**				**0.018**	**0.013**	**-0.426**	0.000	-0.037	0.005	0.001	0.000			**0.132**
	0.766				**0.917**	**0.682**	**0.396**	0.695	0.867	0.233	0.980	0.486			

Table 2.7.5
Momentum Profits of 6/1/6 Strategy and Its Determinants (with Investor Protection)

Eq #	C	UK_LAW	FR_LAW	SC_LAW	GE_LAW	Investor Protection	Herfindahl	CAP/GDP	Trading	Earnings Management	SOE	Education Enroll	Education Life	Domestic	R2
1	-0.021					-0.010	-0.043	0.001	0.005	0.001	-0.009	0.002			**0.570**
	0.771					0.081	0.651	0.145	0.876	0.380	0.053	0.015			
2	-0.092					-0.012	0.029	0.000	0.070	-0.001	-0.003		0.014		**0.486**
	0.589					0.057	0.845	0.891	0.176	0.324	0.689		0.056		
3	-0.023					-0.010	-0.040	0.001	0.005	0.001	-0.009	0.003		-0.002	**0.571**
	0.774					0.090	0.704	0.215	0.876	0.385	0.070	0.049		0.906	
4	-0.039	0.055				-0.013	-0.018	0.000	0.007	0.002	-0.008	0.002			**0.709**
	0.525	0.028				0.007	0.870	0.290	0.812	0.186	0.121	0.001			
5	-0.019		-0.002			-0.010	-0.046	0.001	0.005	0.001	-0.009	0.002			**0.571**
	0.810		0.899			0.100	0.647	0.201	0.870	0.375	0.069	0.019			
6	-0.016			-0.058		-0.014	-0.003	0.001	-0.002	-0.001	-0.013	0.003			**0.701**
	0.796			0.045		0.005	0.979	0.026	0.951	0.372	0.005	0.001			
7	-0.024				-0.005	-0.010	-0.037	0.001	0.004	0.001	-0.008	0.002			**0.571**
	0.753				0.805	0.085	0.704	0.159	0.898	0.378	0.158	0.023			

Table 2.8.1

Risk of 3/1/3 Momentum Strategy and Its Determinants

This table reports the regression results of the below specification which links growth rate of incremental profits obtained from 3/1/3 momentum strategy to various factors. In this regression, the dependent variable, λ, is the growth rate of incremental profits of 3/1/3 momentum strategy. The procedure to estimate λ is discussed in Table 2.10. λ values for 3/1/3 momentum strategy is reported in Table 4a-1. LAW is the legal origin. Corruption shows the corruption index. Herfindahl is the industry concentration. CAP/GDP (%) shows market capitalization as a percentage of total gross domestic product. Trading shows the ratio traded asset value to gross domestic product. Domestic shows logarithm of the average ratio of the number of domestic firms listed in a given country to its population. Education Enroll represents the investor sophistication levels. p- values of estimates are provided below the estimated values. R^2 shows the goodness of fit statistics of the regressions. White heteroscedasticity consistent coefficient covariances are used to calculate the p-values. The p-values for investor sophistication variables (Education Enroll, Education Life) represent the one-sided test statistics, whereas the others show the two sided values.

Eq #	C	UK_LAW	FR_LAW	SC_LAW	GE_LAW	Corruption	Herfindahl	CAP/GDP	Trading	Domestic	Education Enroll	R2
1	-0.773					-0.013	-0.252	0.002	0.476	-0.093	0.014	0.315
	0.090					0.808	0.770	0.508	0.138	0.494	0.073	
2	-0.784	-0.072				-0.018	-0.304	0.002	0.463	-0.073	0.014	0.319
	0.092	0.768				0.732	0.735	0.532	0.162	0.601	0.077	
3	-0.812		0.025			-0.012	-0.251	0.002	0.475	-0.087	0.014	0.315
	0.205		0.931			0.838	0.777	0.571	0.158	0.579	0.080	
4	-0.939			-0.321		0.010	-0.006	0.001	0.418	-0.088	0.014	0.366
	0.042			0.120		0.868	0.994	0.523	0.207	0.511	0.069	
5	-0.805				0.332	-0.032	-0.249	0.002	0.378	-0.079	0.016	0.381
	0.046				0.083	0.563	0.752	0.435	0.188	0.585	0.040	

Table 2.8.2
Risk of 6/1/6 Momentum Strategy and Its Determinants

Eq #	C	UK_LAW	FR_LAW	SC_LAW	GE_LAW	Corruption	Herfindahl	CAP/GDP	Trading	Domestic	Education Enroll	R2
1	-0.795					-0.004	-0.189	0.002	0.317	-0.151	0.015	0.266
	0.069					0.932	0.828	0.163	0.293	0.237	0.043	
2	-0.810	-0.098				-0.012	-0.259	0.003	0.299	-0.124	0.015	0.274
	0.068	0.675				0.820	0.768	0.230	0.328	0.372	0.045	
3	-0.805		0.006			-0.004	-0.188	0.002	0.316	-0.149	0.015	0.266
	0.154		0.981			0.942	0.833	0.287	0.316	0.310	0.049	
4	-0.971			-0.339		0.019	0.070	0.002	0.256	-0.146	0.015	0.330
	0.021			0.215		0.724	0.931	0.158	0.406	0.245	0.043	
5	-0.834				0.403	-0.027	-0.185	0.003	0.197	-0.134	0.017	0.374
	0.026				0.002	0.600	0.798	0.094	0.393	0.337	0.017	

Table 2.8.3
Risk of 9/1/9 Momentum Strategy and Its Determinants

Eq #	C	UK_LAW	FR_LAW	SC_LAW	GE_LAW	Corruption	Herfindahl	CAP/GDP	Trading	Domestic	Education Enroll	R2
1	-0.822					-0.043	-0.005	0.002	0.200	-0.088	0.018	0.242
	0.065					0.401	0.995	0.195	0.447	0.503	0.022	
2	-0.832	-0.059				-0.048	-0.048	0.002	0.190	-0.072	0.018	0.244
	0.070	0.792				0.369	0.959	0.276	0.499	0.618	0.024	
3	-0.876		0.034			-0.041	-0.004	0.002	0.198	-0.080	0.018	0.242
	0.097		0.899			0.454	0.996	0.299	0.478	0.597	0.028	
4	-0.962			-0.269		-0.024	0.200	0.002	0.152	-0.085	0.018	0.277
	0.024			0.444		0.669	0.814	0.203	0.580	0.535	0.026	
5	-0.848				0.260	-0.058	-0.003	0.002	0.123	-0.077	0.020	0.281
	0.045				0.035	0.289	0.997	0.154	0.593	0.582	0.014	

Table 2.8.4
Risk of 12/1/12 Momentum Strategy and Its Determinants

Eq #	C	UK_LAW	FR_LAW	SC_LAW	GE_LAW	Corruption	Herfindahl	CAP/GDP	Trading	Domestic	Education Enroll	R2
1	-0.901					-0.067	-0.060	0.003	0.031	-0.005	0.019	0.281
	0.017					0.171	0.943	0.047	0.902	0.966	0.008	
2	-0.889	0.074				-0.061	-0.007	0.003	0.044	-0.025	0.019	0.285
	0.025	0.713				0.243	0.993	0.129	0.872	0.856	0.012	
3	-1.034		0.084			-0.063	-0.058	0.003	0.026	0.016	0.018	0.286
	0.022		0.758			0.246	0.947	0.091	0.924	0.907	0.014	
4	-1.086			-0.357		-0.042	0.212	0.003	-0.033	0.000	0.019	0.346
	0.002			0.297		0.447	0.783	0.046	0.898	1.000	0.011	
5	-0.911				0.101	-0.073	-0.059	0.003	0.001	-0.001	0.019	0.287
	0.016				0.519	0.164	0.945	0.049	0.998	0.996	0.008	

Table 2.9

Data description and sources

- **Investor sophistication variables**

Education Enrollment:

This measure shows the total enrolment in tertiary education regardless of age, expressed as a percentage of the population in the five-year age group following on from the secondary-school leaving age. Source: UNESCO Institute for statistics: http://www.uis.unesco.org

Education Life

This measure summarizes the average education level of investors, which is proxied by school life expectancy, in each country from 1988 through 1996. Source: UNESCO Institute for statistics: http://www.uis.unesco.org

Domestic

Logarithm of the average ratio of the number of domestic firms listed in a given country to its population (in millions) for the period 1996-2000. Source: La Porta, Lopez-de-Silanes, and Shleifer, (2002)

Per capita education expense

This measure reports the ratio of education expense allocated in GDP to total population in 2000. Source: UNESCO Institute for statistics: http://www.uis.unesco.org

- **Earnings management index**

Leuz, Nanda, and Wysocki (2004)'s aggregate earnings management measure relies on four different aspects of earnings management: (1) smoothing reported operating earnings using accruals, (2) correlation between changes in accounting accruals and operating cash flows, (3) the magnitude of accruals, and (4) small loss avoidance. Countries with respect to each of these four earnings management measures, and an aggregate earnings management score is calculated by averaging the country rankings. A high value in the ranking represents severeness of earnings management. The details of this measure is discussed in Leuz, Nanda, and Wysocki (2004, p.509);

> *Smoothing reported operating earnings using accruals*
>
> Insiders can conceal changes in their firm's economic performance using both real operating decisions and financial reporting choices. Focusing on insiders' reporting choices, this measure captures the degree to which insiders "smooth", i.e., reduce the variability of reported earnings by altering the accounting component of earnings, namely accruals. The measure is a country's median ratio of the firm-level standard deviation of operating earnings divided by the firm-level standard deviation of cash flow from operations. Scaling by the cash flow from operations controls for differences in the variability of economic performance across firms. Low values of this measure indicate that, ceteris paribus, insiders exercise accounting discretion to smooth reported earnings.
>
> *Smoothing and the correlation between changes in accounting accruals and operating cash flows*
>
> Insiders can also use their accounting discretion to conceal economic shocks to the firm's operating cash flow. For example, they may accelerate the reporting of future revenues or delay the reporting of current costs to hide poor current performance. Conversely, insiders underreport

strong current performance to create reserves for the future. In either case, accounting accruals buffer cash flow shocks and result in a negative correlation between changes in accruals and operating cash flows. A negative correlation is a natural result of accrual accounting (Dechow (1994)). However, larger magnitudes of this correlation indicate, ceteris paribus, smoothing of reported earnings that does not reflect a firm's underlying economic performance. Consequently, the contemporaneous correlation between changes in accounting accruals and changes in operating cash flows is the second measure of earnings smoothing.

Discretion in reported earnings: The magnitude of accruals

Apart from dampening fluctuations in firm performance, insiders can use their reporting discretion to misstate their firm's economic performance. For instance, insiders can overstate reported earnings to achieve certain earnings targets or report extraordinary performance in specific instances, such as an equity issuance (Dechow and Skinner(2000)). Accordingly, this earnings management measure uses the magnitude of accruals as a proxy for the extent to which insiders exercise discretion in reporting earnings. It is computed as a country's median of the absolute value of firms' accruals scaled by the absolute value of firms' cash flow from operations. The scaling controls for differences in firm size and performance.

Discretion in reported earnings: Small loss avoidance

Small losses are more likely to lie within the bounds of insiders' reporting discretion. Thus, in each country, the ratio of small reported profits to small reported losses reflects the extent to which insiders manage earnings to avoid reporting losses. Following Burgstahler and Dichev (1997), the ratio of "small profits" to "small losses" is computed, for each country, using after-tax earnings scaled by total assets. Small losses are defined to be in the range [_0.01, 0.00) and small profits are defined to be in the range [0.00, 0.01].

- **Origin of Law**

UK_LAW: 1 if English legal origin.

FR_LAW: 1 if French legal origin.

SC_LAW: 1 if Scandinavian legal origin.

GE_LAW: 1 if German legal origin.

- **Corruption**

Corruption Perception Index. Source: Transparency International (2000).

- **Investor Protection:**

Principal component of private enforcement and anti-director rights. Scale from 0 to 10. Source: La Porta, Lopez-de-Silanes, Shleifer, Vishny (1999).

- **Industry Concentration: (Herfindahl)**

Time-series mean of weekly industry concentration in each market. The industry concentration of each market is measured by a Herfindahl variable. For each week, Herfindahl industry concentration measure is calculated as

$$IND_i = \sum_{j=1}^{n} \left(\frac{MVIND_{ij}}{CAP_i} \right)^2 ,$$

where IND_i is the industry concentration measure for country i, $MVIND_{ij}$ is the market value of industry j in country i, and CAP_i is country i's total market capitalization. The yearly market industry concentration is then approximated by the mean of weekly industry concentration values in a year. Source: Xing (2004).

- **CAP/GDP (%)**

The Relative Size of the Equity Market - the time-series mean of the yearly relative size of the equity market in each country from 1988 to 1997. The relative market size in a year is computed by dividing the the total market capitalization of all listed firms in a market (CAP) to the gross domestic production (GDP) of that particular country. Both *CAP* and *GDP* are from the World Development Indicator database of the World. Source: Xing (2004).

- **Trading**

Ratio of value traded to GDP in 1995. Source: Beck, Levine, and Loayza (2000)

- **State owned enterprises in the economy (SOE)**

Index of State owned enterprises in the economy. Scale from 0 to 10. Higher values given to countries with fewer government-owned enterprises. Source: La Porta, Lopez-de-Silanes, Shleifer, (2002).

- **Descriptive aggregate statistics on countries**

  Stock market capitalization to GDP: Value of listed shares to GDP in 2001.

  Stock market total value traded to GDP: Total shares traded on the stock market exchange to GDP in 2001.

  Stock market turnover ratio: Ratio of the value of total shares traded to market capitalization in 2001.

Source: World Bank's Financial Structure and Economic Development Database

(http://www.worldbank.org/research/projects/finstructure/database.htm)

Table 2.10

Statistical Arbitrage

In this table, we summarize the methodology developed in Hogan, Jarrow, Teo and Warachka (2003) that tests the existence of statistical arbitrage for a given zero investment trading strategy (such as long 1$ worth of the top decile of B/M stocks and short 1$ worth of bottom decile of B/M).

To test for statistical arbitrage, a time series of dollar denominated discounted cumulative trading profits $v(t_1)$, $v(t_2)$, . . . , $v(t_n)$ generated by a trading strategy are analyzed.

For a given trading strategy, let $\Delta v_i = v(t_i) - v(t_{i-1})$ denote increments of the discounted cumulative trading profit measured at equidistant time points $t_i - t_{i1} = \Delta$ with $t_i = i\,\Delta$.

Let the discounted incremental trading profits satisfy

$$\Delta v_i = \mu\, i^\theta + \sigma\, i^\lambda z_i$$

For i=1,2,…,n where z_i are i.i.d. N(0,1) random variables.

In this case discounted cumulative trading profits generated by the trading strategy are

$$v(t_n) = \sum_{i=1}^{n} \Delta v_i \sim N(\mu \sum_{i=1}^{n} i^\theta, \sigma^2 \sum_{i=1}^{n} i^{2\lambda})$$

and the log likelihood function for the increments is

$$LogL(\mu,\sigma^2,\lambda,\theta|\Delta v) = -\frac{1}{2}\sum_{i=1}^{n}\log(\sigma^2 i^{2\lambda}) - \frac{1}{2\sigma^2}\sum_{i=1}^{n}\frac{1}{i^{2\lambda}}(\Delta v_i - \mu i^{\theta})^2$$

The parameters to be estimated are μ, σ^2, λ are θ. We primarily focus on the estimates of μ, and λ since a statistical arbitrage by definition of Hogan, Jarrow, Teo, and Warachka (2004) should have

(i) Initial investment is zero

(ii) Positive payoff (μ)

(iii) Time averaged variance converging to zero (λ)

A trading strategy generates a statistical arbitrage with 1-α percent confidence if the following conditions are satisfied:

H1: $\mu > 0$

H2: $\lambda < 0$

H3: $\theta > \max(\lambda - ½, -1)$

In Table 2.4 and Figure 1, we summarize the estimates of μ, σ^2 for 31 countries for momentum strategies with N-month ranking and investment horizon. We employed unconditional mean estimates, i.e. $\theta=0$, in order to compare our results with that of Hogan, Jarrow, Teo, and Warachka (2004). We obtained monthly risk free rate data from Global Finance Database (www.globalfindata.com).

Figure 2.1.1
Statistical Arbitrage Tests of 3/1/3 Momentum Strategy

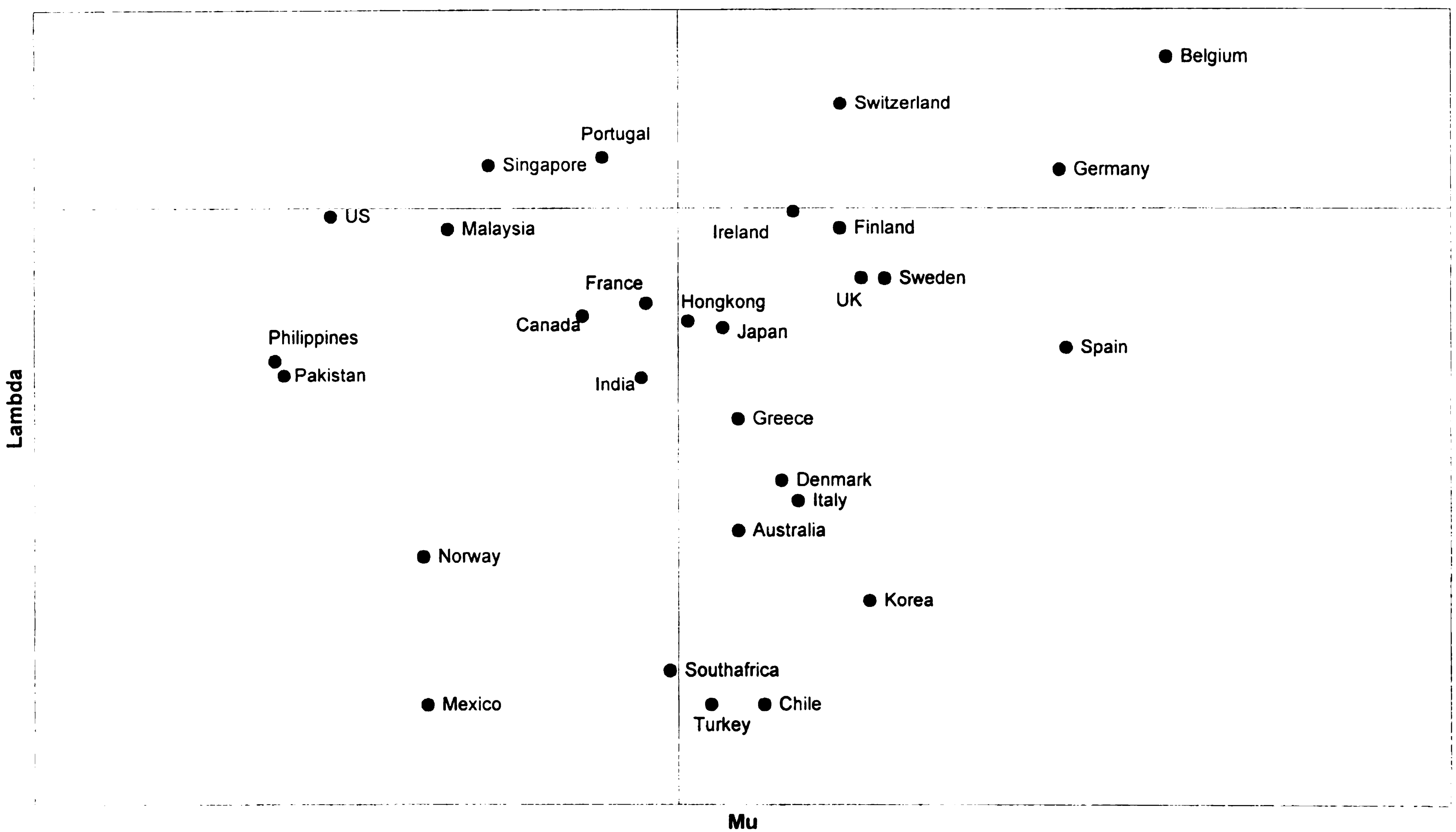


Figure 2.1.2
Statistical Arbitrage Tests of 6/1/6 Momentum Strategy

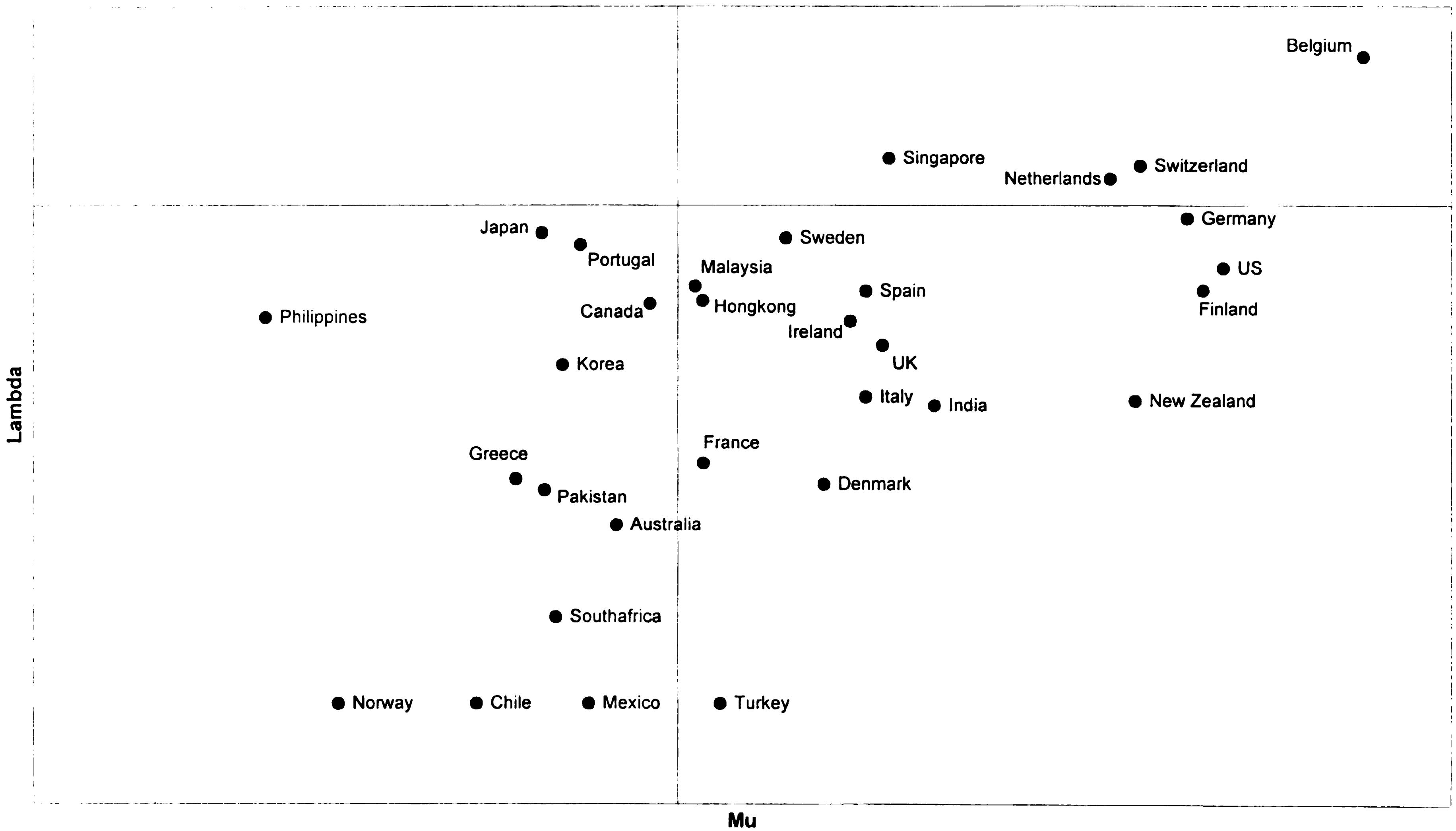


Figure 2.1.3
Statistical Arbitrage Tests of 9/1/9 Momentum Strategy

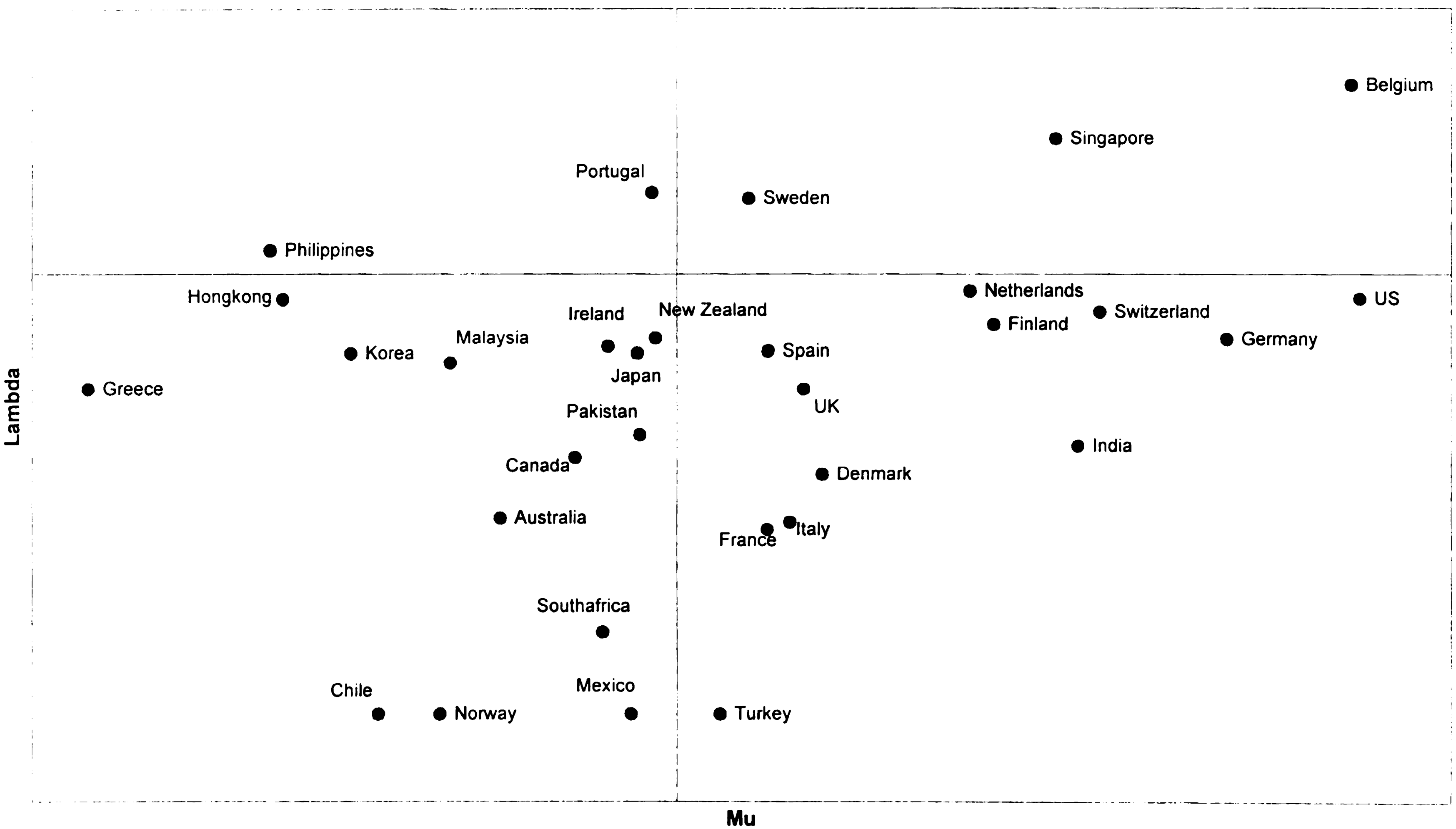
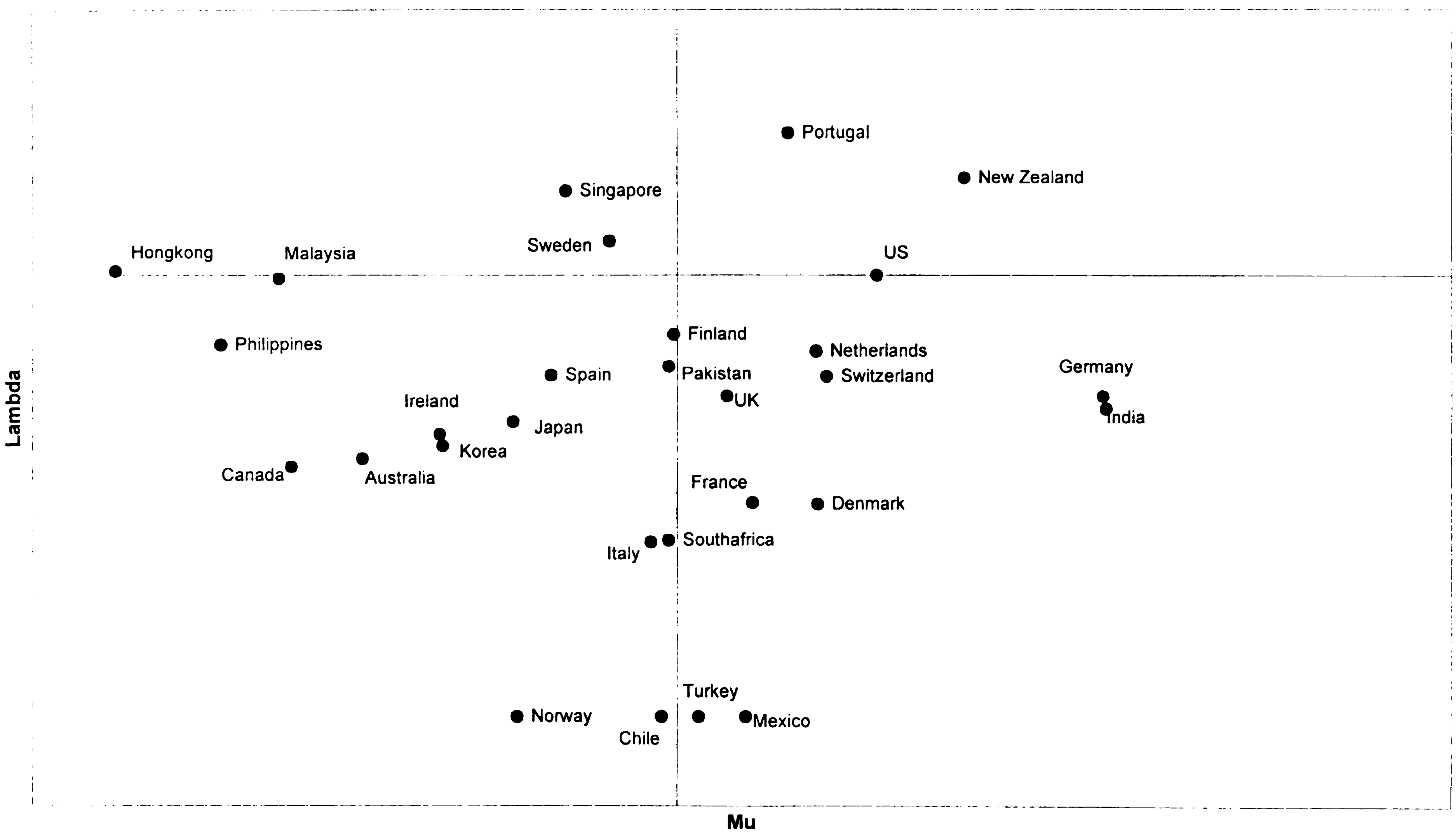


Figure 2.1.4
Statistical Arbitrage Tests of 12/1/12 Momentum Strategy



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