PORTFOLIO TRADING AND INFORMATION TRANSMISSION IN SECURITIES MARKETS: THEORY AND EVIDENCE

DISSERTATION

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ABSTRACT

This dissertation consists of three essays related to stock portfolio trading and information transmission in the security market. The first essay develops a model of trading in the stock and the stock index markets with transaction costs. We study the properties of security prices with cross-market informational trading in the presence of transaction costs and show that introduction of stock index securities improves the dissemination of market-wide information. The model further investigates the causes and consequences of index arbitrage and the bi-directional lead-lag relation between the index and the stock markets. Using S&P 500 index futures data, the essay empirically test one implication of the model that movements in the index basis predict index and stock returns. The empirical evidence is consistent with model predictions.

The second essay applies the model developed in the first essay to examine the implications of closed-end fund trading on the variation and information content of closed-end fund discounts. The model provides a rational expectation explanation for the time series properties of closed-end fund discounts based on information transmission across securities. The model shows that closed-end
fund discounts can predict fund net asset value returns as well as fund price returns, but based on different information. Using weekly data on a sample of U.S. general equity closed-end funds and controlling for the difference between systematic information and security specific information, we find strong evidence supporting the model.

The third essay investigates the trading process and information content in the after-hour index futures market. Using S&P 500 index futures trading data, we study the interaction between the index security market and stock market and the interaction between the regular hour trading session and the after-hour trading session. We find that after-hour trades are associated with significant price discovery. After-hour trading volumes are small, but they process information efficiently and do not distort price movements. The empirical results also support the notion that the index futures market and the stock market are well integrated. The stock market incorporates after-hour index price information very quickly and arbitrage opportunities at the stock market opening are short lived.
To My Family
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CHAPTER 1

OVERVIEW

Portfolio trading has grown tremendously in both scale and scope over the past two decades. The combined dollar trading volumes on S&P 500 index futures and options exceeded the total stock trading volume on the New York Stock Exchange in 2000. New index securities, especially exchange traded funds (ETFs) such as SPDRs, DLMONDS and HOLDRS, have attracted considerable interests from both institutional investors and individual investors. More recently, index security market has led stock market in expanding trading hours and adopting electronic trading systems. Despite considerable policy debates and extensive empirical studies on the effect of index security trading, relatively few models of index security trading have been developed. Interestingly, discounts on closed-end funds, a rather old type of index security, have long puzzled both academics and practitioners. But studies on closed-end fund discounts have largely been separated from studies on index security trading.

The purpose of this dissertation is to study the trading activity in these seemingly redundant securities and its implications. Specifically, the study focuses on stock portfolio trading and information transmission in the security market. To begin with, a general
index trading model is developed to address the following questions: Who trades in the stock index securities? Does the addition of the index securities improve the information transmission in the financial market? And how is the index security market integrated with the stock market? The general model of index security trading is then applied to study the time series properties of closed-end fund discounts. Finally, we provide an empirical analysis on after-hour index security trading and its relation with stock market movements.

This dissertation consists of three essays. The first essay (Chapter 2) develops a general model of trading in the stock and the stock index security markets with transaction costs. We study the properties of security prices with cross-market informational trading in the presence of transaction costs and show that introduction of stock index securities improves the dissemination of market-wide information. The model further investigates the causes and consequences of index arbitrage and the bi-directional lead-lag relation between the index and the stock markets. Using S&P 500 index futures data, the essay empirically test one implication of the model that movements in index basis predict index and stock returns. The empirical evidence is consistent with model predictions.

The second essay (Chapter 3) applies the model developed in Chapter 2 to examine the implications of closed-end fund trading on the variation and information content of closed-end fund discounts. Using the fact that closed-end funds are exchange listed stock portfolios, we provide explanations on the well-documented time series properties
and the predictive power of closed-end fund discounts. This model provides a rational expectation explanation for the movements of closed-end fund discounts based on information transmission across securities. The model results not only provide a new angle for analyzing the behavior of closed-end fund discounts but also provide new testable implications on the relation between fund discounts and various security returns. Specifically, the model yields new predictions that closed-end fund discounts can predict fund net asset value returns as well as fund price returns, but based on different information. Using weekly data on a sample of U.S. general equity closed-end funds and controlling the difference between systematic information and security specific information, we find strong evidence supporting model.

The third essay (chapter 4) investigates the trading process and information content in the after-hour index futures market. After-hour index trading provides an interesting experiment to study the interaction between the index security market and the stock market and the interaction between the regular hour trading session and the after-hour trading session. Using S&P 500 index futures trading data, we find that after-hour trades are associated with significant price discovery. After-hour trading volumes are small, but they process information efficiently and do not distort price movements. The stock market incorporates after-hour index price information very quickly and arbitrage opportunities at the stock market open are short lived. After-hour index futures returns exhibit predictive power over the subsequent regular hour index futures returns, but the predictability is caused by the spillover effect from the pre-open to the market open.
CHAPTER 2

INDEX TRADING AND INFORMATION TRANSMISSION

IN THE SECURITY MARKET

2.1 Introduction

Trading in stock index securities has grown dramatically in both scale and scope in the past two decades.\(^1\) To analyze the trading activity and its implications in these seemingly redundant securities, at least three questions should be addressed: First, who trades in the stock index securities? In other words, does the introduction of the index securities change the liquidity of the existing markets? Second, does the addition of the new securities improve the information transmission in the financial market overall? More specifically, does index trading provide additional price discovery? Third, how is the index security market integrated with the stock market? If security prices in all markets reflect all available information, then what are the mechanisms that facilitate information transmission across security markets?

\(^1\)The daily dollar trading volumes on S&P 500 index futures and options are $25 billion and $9 billion respectively. In contrast, the daily dollar stock trading volume on NYSE is $30 billion. (All data are from exchanges press releases in 2000.) New index securities have been frequently introduced by various exchanges and by investment banks. Some of the more popular contracts include index shares (e.g., SPDRs, DIMONDS), sector index shares, index notes, and HOLDRS. Trading volume in SPDRs is larger than any other individual stocks on AMEX where SPDRs are listed.
Despite considerable policy debates and extensive empirical studies on the effect of index security trading, relatively few models of index security trading have been developed. Exceptions are the work by Subrahmanyam (1991) and Gorton and Pennacchi (1993). Both papers study the function of the stock index as a trading venue for uninformed liquidity traders. They show that when a stock index contract is introduced, uninformed investors will migrate from the stock market to the index market, because adverse selection costs are lower in the stock index market than in the stock market. These models provide an explanation on the popularity of stock index securities. However, they do not study the issue of market integration and changes in the information transmission process when the stock index market is introduced. Because the trading behavior of informed traders is symmetric in the stock index and the stock markets, index trading does not provide additional price discovery beyond the stock market. Furthermore, both papers imply that market integration is achieved through informed traders trading simultaneously in the index and the stock markets. Other mechanisms such as index arbitrage are not studied in these models.

In this chapter we develop a model of stock index trading to examine its implications for price discovery and information transmission in the financial market. Our analysis complements the previous research that have explored the market liquidity implications of stock index trading. To capture features of cross markets trading, we assume that

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2 Mayhew (1999) provides a nice survey on both theoretical models and empirical evidence about the impact of derivative securities on the spot market. As shown in the survey, while existing literature on index security trading covers a broad range of topics, the central theme in these studies is whether the introduction of the index derivative market affects the stability of the stock market.
there exists one type of market friction, transaction costs. We formally derive the trading behavior of informed traders in the presence of transaction costs. Though informed traders are not restricted to trading in a specific market, we show that informed traders with systematic information will trade in the stock index but will not trade in all individual stocks. We also show that the incentive for traders with security specific information to trade in the index market is weak. We then use this basic setup to examine the implications of differently informed traders trading in and across different markets. Particularly, we study the effect of index trading on market liquidity, price informativeness, arbitrage opportunities, and the lead-lag relation between the stock index market and the stock market. Transaction costs have long been advocated as an important reason for stock index trading. In this chapter, we study the impact of transaction costs on informational trading decisions and on market equilibrium conditions.

Including transaction costs in the analysis allows us to examine the effect of index trading on the properties of security prices. The model provides an unified framework in explaining the price discovery and information transmission process in the financial market with index trading. Our analysis provides new insights on market price informativeness, arbitrage opportunities and the lead-lag relation in the stock and the index markets. In particular, we show that the price of the stock index in the index market conveys more systematic information than the price of the stock portfolio in the stock market. Thus, trading in stock index market provides additional information beyond information in the stock market. We further demonstrate that the lead-lag relation be-
tween the index and the stock markets is bi-directional. When systematic information is strong, index market leads stock market. When aggregate security specific information is strong, stock market leads index market. We establish that arbitrage opportunities arise because traders with different information trade in different markets. As a consequence, arbitrage activity not only is a mechanism of achieving market integration but also provides information on the fundamental security value not reflected in the current security prices. Because price differences between the stock index and the stocks (i.e., index basis) are driven by different information flow in the stock index market and the stock market, changes in the index basis have predictive power over subsequent index returns and stock returns. Specifically, changes in the index basis predict index returns with a negative sign, and predict stock returns with a positive sign. We also confirm the major conclusion in Subrahmanyam (1991) and Gorton and Pennacchi (1993) that the stock index market is the preferred venue for liquidity trading.

The theoretical results obtained in this chapter are consistent with a broad range of empirical findings on the relation between index trading and the stock market. The results also present testable implications that have not been previously explored. We specifically test the relation between changes in index basis and the subsequent index and stock returns. Using intraday price data on S&P 500 index futures and S&P 500 stock index, we show that index basis is mean reverting, and is driven by the imbalance of information flow in the index and stock markets. In particular, we find that changes in index basis predict index returns with a negative sign, and predict stock returns with
a positive sign. The evidence is consistent with the model prediction that changes of index basis based on systematic information and security specific information lead index returns and stock returns with opposite directions.

The remainder of this chapter is organized as follows. Section 2.2 summarizes empirical findings on stock index trading that motivate our theoretical analysis in this chapter. Section 2.3 presents the model setup and derives the trading decision of informed traders in the presence of transaction costs. Section 2.4 derives the market equilibrium condition with informed trading and examines its implications for market liquidity, price informativeness, arbitrage opportunities and the lead-lag relations. Section 2.5 describes the empirical test and presents the findings. Section 2.6 concludes the chapter.

**2.2 Empirical Evidence on Index Derivatives Trading**

Since the introduction of index derivative securities, empirical studies have examined the effects of index derivative trading from various angles. In this section, we briefly review some of the results that represent the scope of current empirical studies, and in particular, the results that motivate our theoretical analysis. For simplicity, we classify the empirical studies into four categories: (1) the information content in index trading, (2) the effect of index trading on stock price properties, (3) the lead-lag relation between the stock index market and the stock market, and (4) the causes and consequences of index arbitrage activities.
2.2.1 Information in Index Trading

Many empirical studies have examined the motive for, and the information implications of, index trading. Different interpretations on index trading volume or open interests have been offered. For example, Bessembinder, Chan and Seguin (1996) use stock index futures open interest as a proxy for divergence of traders’ opinions. Chang, Chou and Nelling (2000), however, interpret stock index futures open interest as a proxy for hedging demand caused by past volatility. Bessembinder and Seguin (1992) find evidence that index futures trading represents informed trading. But Chen, Cuny and Haugen (1995) conclude that increasing open interest represents uninformed or liquidity trading. These empirical studies yield no consensus on the information content of index trading. The theoretical literature has provided little guidance on these different interpretations. Aside from the results in Subrahmanyam (1991) and Gorton and Pennacchi (1993) that index market is a preferred venue for liquidity trading, little is known on how the trading activity in the index market may differ from that in the stock market.

2.2.2 Index Trading and Stock Price Properties

Many observers believe that rapid dissemination of market-wide information through index derivative market has fundamentally altered the behavior of the underlying equity market. Consistent with this view, several papers have found strong evidence that properties of stock returns have changed subsequent to the introduction of index derivative securities. Froot and Perold (1995) show that the positive stock index autocorrelation
found in earlier studies was a result of high autocorrelation during the 1960s and 1970s. The positive autocorrelation vanished completely by the later 1980s. After examining several alternative explanations, they attribute this to improved market-wide information dissemination because of index derivative trading. Antoniou, Holmes and Priestley (1998) find that the asymmetric stock return volatility phenomenon migrated from stock market to index futures market after the introduction of index futures trading, suggesting that index markets are more responsive to news arrivals.

### 2.2.3 The Lead-Lag Relation

Another line of research has provided evidence on where informed traders trade by examining the lead-lag relation between index derivative market and the stock market. Kawaller, Koch and Koch (1987), Stoll and Whaley (1990), and Chan (1993) all find that the index futures market lead the stock market. However, the lead-lag relation between the index futures market and the stock market is not constant. Specifically, Chan (1993) shows that when more stocks move together (market-wide information) the index futures leads the cash index to a greater degree. Chan (1993) interprets this as suggesting that the futures market is the main source of market-wide information. More recently, Frino, Walter, and West (2000) find that the index market lead the stock market when there is significant macroeconomic news and the stock market leads the index market around stock-specific information release. These results indicate that in addition to considering how fast one market reflects new information relative to the other market, it's equally
important to investigate what new information one market incorporates relative to the other.

2.2.4 Causes and Consequences of Index Arbitrage

A long standing question in the index derivative literature is the role of index arbitrage. Though there are theoretical models explaining why arbitrage opportunities exists in equilibrium (see, for example, the clientele model of Holden (1995) and Chen, Cuny and Haugen (1995), and the information model of Kumar and Seppi (1994)), these models do not provide specific directions for empirical tests on the effect of index arbitrage trading activities. In particular, while Kumar and Seppi (1994) base their analysis on different information sets in the index and the stock markets, the causes and the nature of such an information differential are not clear. Empirically, the properties of futures prices and “basis” have been examined extensively. For stock index futures, studies by MacKinlay and Ramaswamy (1988) and Brennan and Schwartz (1990) indicate that observed future prices reflect active arbitrage activity. Miller, Muthuswamy and Whaley (1994), however, argue that the widely documented negative autocorrelation of stock index basis changes arises because many stocks in the index portfolio trade infrequently. Many studies have examined the effect of index arbitrage trading on stock market movements, especially whether index arbitrage destabilizes the stock market. Even though most studies conclude that index arbitrage trading does not destabilize the stock market, few have investigated the causes and general implications of index arbitrage activity.
In one study that provides such insights, Harris, Sofianos and Shapiro (1994) find that changes in the index futures prices, and to a less extent, changes in the stock index prices lead arbitrage trading activity, and index arbitrage trades in turn tend to adjust price in one market to information revealed in the other market. Hasbrouck (1996) further finds that index arbitrage trading contains information useful for predicting stock price changes beyond the information already reflected in the index prices.

2.3 A General Index Trading Model With Transaction Costs

In this section, we describe a general index trading model with transaction costs and derive the results that informed traders endogenously determine their trading decision in the presence of transaction costs. Our description of the economy closely follows the discussion in Subrahmanyam (1991) except that we here include transaction costs.

2.3.1 The General Economy

The economy is defined on a discrete time, finite horizon with a sequence of trading rounds at times $t = 1, \ldots, T$. In the current section, we only use a one-period trading framework. We explicitly consider the multi-period trading activity when we examine the arbitrage opportunity and the lead-lag relation between the index market and the stock market. When the context is clear, we will omit the $t$ subscript in the following discussions.
The economy consists of \( N \) risky assets and a stock index contract written on the index composed of the \( N \) risky assets (say, the S&P 500 index). The \( N \) securities are simultaneously traded in the spot market (henceforth the stock market) with their value governed by the following process:

\[
S_{nt} = \bar{S}_{nt} + \beta_n \gamma_t + \epsilon_{nt}, \quad n = 1, \ldots, N
\]  

(1)

This is a “factor model” adopted by Subrahmanyam (1991). \( \bar{S}_{nt} \) is the value of security \( n \) at time \( t - 1 \), which is public information. \( \gamma \) is a vector of systematic factors and is called “factors”. \( \epsilon_{nt} \) is the security specific or idiosyncratic components of the security value innovation. \( \epsilon_{1t}, \epsilon_{2t}, \ldots, \epsilon_{nt} \) and \( \gamma \) are mutually independent and are assumed to be normally distributed with mean zero. The value of a stock index consisting of the \( N \) stocks is expressed as:

\[
S_t = \sum_{n=1}^{N} w_n \bar{S}_{nt} + \sum_{n=1}^{N} w_n \beta_n \gamma_t + \sum_{n=1}^{N} w_n \epsilon_{nt}
\]  

(2)

Where \( w_n \) is the weight of security \( n \) in the index, such that \( 0 \leq w_n < 1 \) and \( \sum_{n=1}^{N} w_n = 1 \). When weight \( w_n \) is zero, stock \( n \) is not included in the index. For simplicity, we assume that \( \beta_n \) and \( w_n \) are constant through the entire trading periods. The stock index is traded as a separate security. There are thus \( N + 1 \) markets for the \( N \) risky assets and the index.
We do not distinguish between the stock index securities and stock index derivative securities. Stock index securities include index shares such as SPDRs, DIAMONDS and various types of Unit Trusts. Stock index derivative securities include mainly index futures, index options and options on index futures. The “value” feature of the index derivative securities are inherently difficult to model (See Back (1993), Biais and Hillion (1994), and Cao (1999) for models on individual stock derivative securities). We adopt the approach in Subrahmanyam (1991), Gorton and Pennacchi (1993) and Kumar and Seppi (1994) to model the “trading” feature of the derivative securities, i.e., the informational, hedging and liquidity trading purposes in the derivative market are different from those in the stock markets. The results derived here should apply to both stock index securities and stock index derivative securities.

2.3.2 Information and Trading

There are two types of investors in the economy whom we broadly refer to as informed and liquidity traders respectively. Informed traders trade to exploit superior information, liquidity traders trade for pure liquidity reasons or to hedge their risk exposures. In addition, there is a risk-neutral market maker for each of the markets. One group of informed traders has information on the common risk factors \( \gamma \).\(^3\) This group of informed traders is referred to as factor informed traders or traders with systematic information. Another group of informed traders has information on the idiosyncratic term \( \epsilon_n \) for

\(^3\)Private information on common factors are difficult to obtain. An alternative interpretation is that factor informed investors are those who are able to process public information faster and more efficiently than others are. See Admati and Pfleiderer (1988) for similar interpretation.
a particular security \( n \). This group of informed traders is termed as security specific informed traders. For simplicity, we also assume that informed traders observe the information perfectly.\(^4\) Private information only lasts one trading period.

For the liquidity traders, we define one type as "index" liquidity traders who trade in the stock index market for portfolio liquidation purposes or to hedge their risk exposures in the stock market. In order to examine the trading decision of liquidity traders, following Subrahmanyam (1991), we further specify index traders as liquidity traders constrained to trade in the index market and liquidity traders who can choose to trade either in the index or in the stock market. The two types of index traders can be interpreted as "non-discretionary" and "discretionary" in the terms of Admati and Pfleiderer (1988) and Subrahmanyam (1991). Another type of liquidity traders is the pure liquidity or noise traders who trade for exogenous reasons in the stock market. All traders are risk neutral.

Before deriving the results on informed traders' trading decision, we briefly discuss the assumption of transaction costs and its implications on trading behavior. One of the most important features of stock index trading is its comparative cost advantage over trading individual stocks. This cost advantage has been the major force behind the introduction of index securities in general, and index shares such as "SPDRs" and "DIAMONDS" in particular. The existence of index arbitrage opportunities has also

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\(^4\)As shown in many earlier studies, adding noise signal may not add too much insight but complicates the exposition considerably. For the purpose of the current paper, the simple perfect information structure is adequate. Results using noisy information are similar and can be requested from the author.
been frequently attributed to the high transaction costs in trading stock portfolios. In this chapter, we explicitly examine the effect of transaction costs on informed trading decisions and its implication on market equilibrium. In the presence of transaction costs, informed traders' decision on whether to trade in one security depends on whether expected profit in trading the security is larger than the transaction costs incurred.

2.3.3 Trading Decisions without Transaction Costs

Without transaction costs, factor informed traders and security specific informed traders will trade in both the index and the stock market. Without cross-market order flow observations, the availability of the stock index market is just an additional trading opportunity for the factor informed traders. For security specific informed traders, possessing information about a stock is equivalent to possessing noisy information about the index if the stock is a component of the index. To examine the effect of transaction costs on informational trading decision, we first present the market equilibrium results with no transaction costs.

For stock $n$, market maker sets the security price equal to the expected value conditional on the aggregate net trading order $\omega_n$ in equilibrium.

$$P_{nt} = E(S_{nt}|\omega_n)$$ (3)
The market maker sets the price by a linear pricing rule:

\[ P_{nt} = \bar{S}_{nt} + \lambda_n \omega_n \]  

(4)

where \( \lambda_n \) is called the "pricing parameter" and the inverse of \( \lambda_n \) is a measure of "liquidity" of the market for security \( n \).

Define the total number of factor informed traders as \( g \). We assume that all the \( g \) factor informed traders perfectly observe the systematic factors \( \gamma \). Similarly, the number of informed traders with security specific information is \( k_n \) for security \( n \), and they also all observe perfectly the security specific information \( \epsilon_n \). The liquidity trading in the index and stock markets is assumed to be fixed in this section. For security \( n \) in the stock market, the following lemma gives the results of market equilibrium with no transaction costs. (Proofs of Lemmas and Propositions are in Appendix A unless otherwise stated.)

**Lemma 1** Without transaction cost, the factor informed trader \( i \) submits order

\[ x_{in} = \frac{\beta_n \gamma}{(g + 1)\lambda_n} , \]

and the security specific informed trader \( j \) submits order

\[ x_{jn} = \frac{\epsilon_n}{(k_n + 1)\lambda_n} , \]
where $\lambda_n$ is given by

$$
\lambda_n = \sqrt{\frac{k_n \text{var}(\epsilon_n)}{(k_n + 1)^2 \text{var}(z_n)} + \frac{g\beta_n^2 \text{var}(\gamma)}{(g + 1)^2 \text{var}(z_n)}},
$$

and $z_n$ is the total liquidity trade for stock $n$ in the stock market.

For the stock index security, we obtain similar results in the following Lemma:

**Lemma 2** The factor informed trader $i$ submits order

$$
x_i = \frac{\sum_{n=1}^{N} w_n \beta_n \gamma}{(g + 1)\lambda},
$$

and the security specific informed trader $j$ submits order

$$
x_j = \frac{w_n \epsilon_n}{(k_n + 1)\lambda},
$$

where $\lambda$ is given by

$$
\lambda = \sqrt{\sum_{n=1}^{N} w_n^2 \frac{k_n \text{var}(\epsilon_n)}{(k_n + 1)^2 \text{var}(z)} + \frac{g(\sum_{n=1}^{N} w_n \beta_n)^2 \text{var}(\gamma)}{(g + 1)^2 \text{var}(z)}},
$$

and $z$ is the total liquidity trade for the index security in the index market.

Without transaction costs, factor informed traders and security specific informed traders will trade in both the index and the stock market. The expected profits before
transaction costs for both the factor informed and security specific informed traders are presented in the following proposition.

**Proposition 1** Without transaction costs, the expected profits for each factor informed trader and each security specific informed trader in trading stock \( n \) are given by:

\[
\pi_{n,g} = \frac{\beta_n^2 \text{var}(\gamma)}{(g + 1)^2 \sqrt{\frac{k_n \text{var}(\epsilon_n)}{(k_n + 1)^2 \text{var}(z_n)} + \frac{g \beta_n^2 \text{var}(\gamma)}{(g + 1)^2 \text{var}(z_n)}}}
\]  

(5)

\[
\pi_{n,k_n} = \frac{\text{var}(\epsilon_n)}{(k_n + 1)^2 \sqrt{\frac{k_n \text{var}(\epsilon_n)}{(k_n + 1)^2 \text{var}(z_n)} + \frac{g \beta_n^2 \text{var}(\gamma)}{(g + 1)^2 \text{var}(z_n)}}}
\]  

(6)

The expected profits for each factor informed trader and each security specific informed trader in the stock index market are given by:

\[
\pi_g = \frac{(\sum_{n=1}^{N} w_n \beta_n)^2 \text{var}(\gamma)}{(g + 1)^2 \sqrt{\sum_{n=1}^{N} w_n^2 \frac{k_n \text{var}(\epsilon_n)}{(k_n + 1)^2 \text{var}(z_n)} + \frac{g (\sum_{n=1}^{N} w_n \beta_n)^2 \text{var}(\gamma)}{(g + 1)^2 \text{var}(z_n)}}}
\]  

(7)

\[
\pi_{k_n} = \frac{w_n^2 \text{var}(\epsilon_n)}{(k_n + 1)^2 \sqrt{\sum_{n=1}^{N} w_n^2 \frac{k_n \text{var}(\epsilon_n)}{(k_n + 1)^2 \text{var}(z_n)} + \frac{g (\sum_{n=1}^{N} w_n \beta_n)^2 \text{var}(\gamma)}{(g + 1)^2 \text{var}(z_n)}}}
\]  

(8)

Note that for factor informed traders, the total trading profit in the stock market is the sum of trading profits in all \( N \) stocks.

The trading profits of the informed traders are a function of the number of both types of informed traders and the payoff structure of the security. Several insights can
be obtained from examining the above profit functions. First, in both the stock and the index market, the profits of security specific informed traders increase with the number of factor informed traders. It nevertheless is lower than with no factor informed trading. For the factor informed traders, higher security specific trading increases factor trading profits. The above result is due to the fact that the systematic factors and security idiosyncratic components are assumed to be independent. An increase in the number of one type of informed traders intensifies the competition between traders of the same type, thus benefiting the other type of informed traders. Second, in the stock market, the trading profits of factor informed traders increase in $\beta_n$, $\text{var}(\gamma)$, and of course the liquidity trading for that particular stock $\text{var}(z_n)$. But the profits decrease with the stock specific information $\text{var}(\epsilon)$. For security specific informed traders, the profits increase with $\text{var}(\epsilon)$ and $\text{var}(z_n)$, and decrease with $\beta_n$ and $\text{var}(\gamma)$.

### 2.3.4 Trading Decisions with Transaction Costs

We now consider the trading decisions of the informed traders in the presence of transaction cost. For simplicity, we assume a symmetric fixed transaction cost structure. Under this structure, transaction costs are the same for all stocks and the stock index. In addition, the transaction costs are constant and do not depend on the trading volumes. Denote the transaction costs as $T_c$ for each stock and the stock index. This definition of transaction cost can be interpreted as representing the set-up cost of trading in each
security.\textsuperscript{5} With transaction costs, the trading decision of informed traders depends on whether the expected trading profit given the information endowment is larger than the transaction costs incurred. Clearly, for all the factor informed traders to trade in stock \( n \) and in the stock index market, the following should hold: \( \pi_g \geq T_c \) and \( \pi_{n,g} \geq T_c \). By contrast, if \( \pi_1 < T_c \) and \( \pi_{n,1} < T_c \), no factor informed traders will trade in the stock index market or in the stock market.\textsuperscript{6} Similarly, for all security specific informed traders to trade both in the stock index and the individual stocks about which they have information, the condition of \( \pi_{kn} \geq T_c \) and \( \pi_{n,kn} \geq T_c \) should be satisfied. Furthermore, if \( \pi_{k1} < T_c \) and \( \pi_{n,k1} < T_c \), no security specific informed trading will occur in the two markets.

The case that all informed traders, both factor informed and security specific informed, trade in the stock market and stock index market simultaneously is discussed in Subrahmanyam (1991). We are more interested in the case where transaction costs play an active role in the trading decision of informed traders. In the following, we examine the possibility that transaction costs are binding for certain types of informed traders in either the stock market or in the stock index market.

\textsuperscript{5}See Cho, Shin and Singh (1999) and Coval and Hirshleifer (2000) for similar discussions on set-up transaction costs. Even though the transaction cost is the same for a single stock and the stock index, trading in a stock portfolio is more expensive than trading in the stock index because stock portfolio trading incurs transaction cost for each stock in the portfolio. Thus the simple fixed cost structure captures the essential difference of transaction costs in trading stock portfolio and the stock index.

\textsuperscript{6}\( \pi_1 \) and \( \pi_{n,1} \) represent expected profits when there is one factor informed trader trading the stock index and stock \( n \). \( \pi_{k1} \) and \( \pi_{n,k1} \) are defined similarly for security specific informed traders.
From factor informed traders' stock trading profit function (equation (5)), the possibility of factor informed traders trading in a stock increases with $\beta_n$ and $\text{var}(z_n)$, but decreases with $\text{var}(\epsilon_n)$. In particular, if $\beta_n \to 0$, $\pi_{n,1} \to 0$, then $\pi_{n,1} < T_c$ holds for a constant $T_c$. Similarly, if the liquidity trading in stock $n$ is low, i.e., $\text{var}(z_n) \to 0$, then $\pi_{n,1} \to 0$, and $\pi_{n,1} < T_c$ holds. In both cases factor informed traders do not trade in this stock. Thus stocks with low factor sensitivity ($\beta_n$), low liquidity trading ($\text{var}(z_n)$), or high security specific information ($\text{var}(\epsilon_n)$) may not attract factor informed trading. In general, certain types of stocks (e.g., stocks with low market capitalization) possess all three properties. This suggests that the factor informed traders do not trade in all stocks.

Further observations can be obtained by comparing factor informed trader's profit function for trading stock $n$ (Equation (5)) and trading the stock index (Equation (7)). Three components are different for the two profit functions: the factor sensitivities $\beta$'s, the security specific components, and liquidity trading. In general, it is a reasonable assumption that the factor sensitivity of the index $\sum_{n=1}^{N} w_n \beta_n$ is fairly strong. Even if the factor sensitivities are the same, it is easy to see that the effect of the stock specific components is much smaller in the stock index because of the diversification effect. Thus, the profit is higher for factor informed traders in the stock index market than in a comparable stock market. The above analysis implies that the possibility of factor informed traders trading in the index market is stronger than the possibility of trading in individual stocks.
Now consider the trading decision by the security specific informed traders to trade in the stock index. The possibility of security specific traders trading in the stock index increases with $w_n$ and $\text{var}(\epsilon_n)$. Assume the security specific innovation has finite variance, i.e., $\text{var}(\epsilon_n)$ is bounded by $\sigma^2$. In a well diversified stock index, when $w_n \to 0$, $\pi_{n,k_1}$ converges to 0. Thus all traders informed with security specific information do not trade in the stock index. This result is intuitive, a well diversified index does not attract security specific informed trading. A weaker result is that, even with a less well diversified stock index, security specific informed traders with information on low $w_n$ stocks do not trade in the stock index. It is possible that when the stock index is not well diversified, security specific informed traders with information on some stocks will trade in the index market if the condition $\pi_{k_1} \geq T_c$ is satisfied. By comparing the two profit functions for security specific informed traders to trade the stock and the stock index, we can see that the possibility of security specific informed traders trading in the stock index is much lower than trading in the individual stocks.

Overall, the results on cross market informational trading decision in the presence of trading costs are clearly dependent upon the parameter values in the security valuation structure and the transaction costs. As discussed above, when $\pi_{n,1} < T_c$ for stock $n$, factor informed traders do not trade in this stock. Further, in a well diversified stock index, $\pi_{k_1} < T_c$ is likely to hold and security specific informed traders do not trade in the stock index. The following lemma summarizes the above discussion.
Lemma 3 Under a constant transaction costs structure, the trading decisions of informed investors trade across markets are determined by their information endowments, the valuation structure of the security and the transaction costs. If the constraint of transaction costs is binding, traders with different information endowments trade in different markets and may not trade across the index and stock markets. Specifically, factor informed traders do not trade stock n if \( \pi_{n,1} < T_c \) and security specific informed traders do not trade the stock index if \( \pi_{k,1} < T_c \).

For the remainder of the paper, we will be concerned with the implications of the above-characterized equilibrium. The above characterization provides a starting point for analyzing the effect of informed trading on market equilibrium and its implications for security price properties in the index and the stock market. In the above analysis we assume that liquidity trading in the index market and the stock market is predetermined. As we show in the next section, index market is the preferred trading place for liquidity traders. In general, this result strengthens the conclusion in this section.

2.4 Market Equilibrium and Implications

Under the assumed simple symmetric transaction costs structure, trading decisions by informed traders are determined endogenously. As a result, differently informed investors trade in different markets and may not trade across the index and the stock

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7Cho, Shin and Singh (1999) provide one example that the number of informed traders in the stock market is endogenously determined given the profit function and fixed transaction costs. Here we adopt a much simpler approach. Note that our no-trading results in one market by one type of informed traders can be viewed as the endogenously determined number of that type of informed traders being zero.
market. In particular, the cross-market trading decisions with transaction costs are drastically different from those without transaction costs. These informational trading decisions affect the market equilibrium conditions and have significant impact on the properties of security prices in the stock and the stock index market. In this section, we study the market equilibrium conditions in the presence of transaction costs, and investigate the implications for market liquidity, security price informativeness, the existence and properties of arbitrage opportunities, and the lead-lag relation between the index market and the stock market.

2.4.1 Market Equilibrium with Cross-Market Trading

To examine the effect of informational trading decisions on the properties of security prices in the index and the stock market, we first present the market equilibrium conditions with cross-market informed trading in the presence of transaction costs.

Motivated by the results from last section, we assume that factor informed traders will not trade in all stocks and security specific informed traders do not trade in the stock index. This simplification enables us to derive easily interpretable results. More specifically, we assume that factor informed traders only trade $M$, with $M < N$, individual stocks. From the properties of the profit functions in the last section, it is easy to see that the $M$ stocks are not a random sample from the individual stock universe.

Whether factor informed traders trade in a specific stock is endogenously determined by

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*A more general assumption is that factor informed traders trade in a subset of individual stocks, and a subset of security specific informed traders, $k_n, n = 1, ..., L, L < N$ trade in the index market. Results using this assumption are qualitatively similar to the current results, but nevertheless more complicated.*
the stock's payoff structure and liquidity trading activity. Compared with the $N - M$ stocks that factor informed traders do not trade, the $M$ stocks have higher $\beta$, higher liquidity trading, and lower security specific value innovation.

When factor informed traders trade in stocks $m$ ($m = 1, 2, ..., M$) in the stock market, the trading order of the factor informed traders and the security specific informed traders will be the same as in Lemma 1. If factor informed traders do not trade stocks $n$ ($n = 1, 2, ..., N - M$), the results are obtained with only security specific informed trading. Also, because only the factor informed traders trade in the index market, the demand function and the equilibrium price schedule for the stock index are different from the results in Lemma 2 with no transaction costs. The following results describe the market equilibrium conditions for both the index and the stock market in the presence of transaction costs.

**Lemma 4** The equilibrium pricing parameter in the stock index is given by

$$
\lambda = \frac{1}{g + 1} \sqrt{g\beta^2 \text{var}(\gamma) \over \text{var}(z)},
$$

The equilibrium pricing parameters in stock $n$ with and without factor informed trading are given by

$$
\lambda_m = \sqrt{\frac{k_m \text{var}(\epsilon_m)}{(k_m + 1)^2 \text{var}(z_m)} + \frac{g\beta_m^2 \text{var}(\gamma)}{(g + 1)^2 \text{var}(z_m)}},
$$

$$
\lambda_n = \frac{1}{k_n + 1} \sqrt{\frac{k_n \text{var}(\epsilon_n)}{\text{var}(z_n)}}.
$$

26
Where \( \lambda_m \) and \( \lambda_n \) are for with and without factor trading respectively. We use \( \beta \equiv \sum_{n=1}^{N} w_n \beta_n \) for notational simplicity.

2.4.2 Market Liquidity

Subrahmanyam (1991) and Gorton and Pennacchi (1993) show that the index market is the preferred trading venue for uninformed liquidity traders because adverse selection costs are lower in the index market than in the stock market. Their models do not consider the effect of transaction costs. With transaction costs, it is obvious that liquidity traders trading in the individual stocks would incur higher transaction costs than trading in the stock index. However, this by itself does not imply that liquidity traders prefer to trade in the stock index market. The reason is that liquidity traders face another type of costs, i.e., the loss to the informed trading in the respective markets. In principle, “discretionary” liquidity traders will trade in either the index market or the stock market to minimize the sum of the transaction costs and the losses to informed trading. Without examining the loss to informed trading, it is unclear whether or not liquidity traders would prefer to trade in the index market.

Given the trading decision by the informed traders, there are, however, disadvantages for discretionary liquidity traders to trade in the stock market. The disadvantage is the presence of both factor informed and security specific informed traders in the stock market. When trading in the index market, they only face factor informed traders. As a consequence, the condition here for discretionary liquidity traders to trade only in the
index market is different from that in Subrahmanyam (1991) even without considering the transaction costs by liquidity traders. We now formally show that the change of informed trading in the presence of transaction costs strengthens the condition under which discretionary liquidity traders only trade in the index market.

Consider the simple case where factor informed traders trade in the index and all the underlying stocks and security specific informed traders only trade in the stock market.\(^9\) Define the demand of discretionary liquidity traders as \(z_h\), and the noise trading in security \(n\) as \(z_n\). Discretionary liquidity traders will trade only in the index market if the loss to informed traders in index market is lower than the sum of losses to informed traders in the stock market. More formally, the following condition holds:

**Proposition 2** When factor informed traders trade in both the stock market and the index market and security specific informed traders only trade in the stock market, discretionary liquidity traders only trade in the index market if the following condition is satisfied:

\[
\sum_{n=1}^{N} \frac{w_n}{\sqrt{\frac{\text{var}(\epsilon_n)}{K_n} + \frac{\beta^2 \text{var}^{(\gamma)}}{G}}} [\text{var}(z_{hn}) + \text{var}(z_n)]^{-1} > \sqrt{\frac{\beta^2 \text{var}^{(\gamma)}}{G}} \left[\text{var}(z)\right]^{-1}
\]  

(9)

In the above equation, we define \(K_n = \frac{(k_n+1)^2}{k_n}\) and \(G = \frac{(g+1)^2}{g}\) to simplify the notation. \(z\) is the total liquidity trading in the index market which includes both discretionary and

\(^9\)Assuming factor informed traders only trade in a subset of stocks does not qualitatively change the results.
tionary and non-discretionary liquidity trading. The above condition is more likely to hold than the condition presented in Proposition 2 in Subrahmanyam (1991). He shows that with all security specific informed traders trading in the index, the tendency for the discretionary liquidity traders to trade in the index is strong. The main reason for his conclusion is that the index provides a diversification benefit for security specific information, hence liquidity trader’s loss to security specific informed traders is minimized in the index market. Because security specific informed investors do not trade in the index in our model, there is no loss to security specific informed traders in the index market. As a result, the tendency for liquidity trading in the index market is more likely to hold.

With our assumed symmetric transaction cost structure, the above condition is more likely to hold. Clearly, discretionary liquidity traders incur higher costs in trading a portfolio of individual stocks. The above result confirms the major conclusion in Subrahmanyam (1991) and Gorton and Pennacchi (1993) that the stock index market is the preferred venue for liquidity trading.

2.4.3 Price Informativeness

What is the effect on price discovery when the stock index is introduced? Does index trading provide additional price discovery in addition to the price discovery taking place in the stock market? The properties of security prices in the index and the stock market are determined by the respective informed trading in the two markets. In this subsection we examine the relative price informativeness in the index and the stock market.
Given the assumed factor structure, it is easy to see that the informativeness of the stock price increases with the addition of factor informed traders trading in the stock market. Define the noisiness of price as the variation of the deviations of prices from their true value, \( Q_n \equiv \text{var}(S_n - P_n) \). Thus, the inverse of \( Q_n \) represents the informativeness of prices. The following gives the noisiness of security \( n \) price with and without factor informed trading.

\[
Q_n = \frac{\text{var}(\epsilon_n)}{k_n + 1} + \frac{\beta_n^2 \text{var}(\gamma)}{(g + 1)}
\]

\[
Q'_n = \frac{\text{var}(\epsilon_n)}{k_n + 1} + \beta_n^2 \text{var}(\gamma)
\]

where \( Q_n \) (when factor informed traders trade in the stock market) is always smaller than \( Q'_n \) (when factor informed traders do not trade in the stock market).

Another measure of informativeness, the reduction in the variance of prices, \( I_n \equiv \text{var}(S_n) - \text{var}(S_n|P_n) \), measures the extent to which prices reveal private information. Not surprisingly, this measure and the noisiness measure are closely related. The measures on the reduction in price variance with and without factor informed trading are given as follows:

\[
I_n = \frac{k_n \text{var}(\epsilon_n)}{k_n + 1} + \frac{g \beta_n^2 \text{var}(\gamma)}{(g + 1)}
\]

\[
I'_n = \frac{k_n \text{var}(\epsilon_n)}{k_n + 1}
\]

Clearly, when price variation reduction is used as an informativeness measure, price with factor informed trading is more informative.
We are more interested in the relative informativeness of the index price and the price of the individual stock portfolio. The noisiness of the index price and the price of the stock portfolio are defined as

\[ Q_I \equiv \text{var}(S - P) \quad \text{and} \quad Q_S \equiv \text{var}(\sum_{n=1}^{N} w_n S_n - \sum_{n=1}^{N} w_n P_n). \]

The values are given in the following proposition:

**Proposition 3** Under the factor structure with cross markets trading, the noisiness of the index price and the price of the stock portfolio

\[
Q_I = \sum_{n=1}^{N} w_n^2 \text{var}(\epsilon_n) + \frac{(\sum_{n=1}^{N} w_n \beta_n)^2 \text{var}(\gamma)}{(g + 1)},
\]

\[
Q_S = \sum_{n=1}^{N} w_n^2 \text{var}(\epsilon_n) + \frac{(\sum_{n=1}^{N} w_n \beta_n)^2 \text{var}(\gamma)}{(g + 1)} + \frac{g \text{var}(\gamma)}{g + 1} \left( \frac{1}{2} \sum_{n=1}^{N} (w_n \beta_n)^2 \right) - \frac{\text{var}(\gamma)}{(g + 1)} \left( \sum_{n=1}^{M} w_n \beta_n^2 \right) + \frac{\text{var}(\gamma)}{(g + 1)^2} \left( \sum_{n=1}^{M} w_n \beta_n^2 - \left( \sum_{n=1}^{M} w_n \beta_n \right)^2 \right).
\]

The above proposition gives the two noisiness measures for the index \((Q_I)\) and the portfolio of individual stocks \((Q_S)\).

Stock index price does not incorporate security specific information. As represented by the first term of both equations, \(Q_I\) contains a larger term on the idiosyncratic components than \(Q_S\). One direct implication is that the price of the stock index is less informative than the price of the stock portfolio on the security specific value innovations, especially when idiosyncratic information components in the stock portfolio are large.
If the sum of the idiosyncratic components approaches zero in a well diversified stock portfolio, it may be justified to obtain $\sum_{n=1}^{N} w_{n}^{2} \text{var}^{2}(\epsilon_{n}) \rightarrow 0$ when $N \rightarrow \infty$ in $Q_{I}$ and $Q_{S}$. In this case, the informativeness of the stock portfolio will converge to the informativeness of the stock index on the security specific components.

The price of the stock portfolio only reflects factor information in $M$ of the $N$ stocks. This is the reason that index price is more informative about the systematic factors than the portfolio of individual stocks. Note that the second term in equation (10) and equation (11) is the same. Price will not reveal all factor information even with factor informed trading. The difference in the informativeness on systematic factors is the third and fourth term in equation (11). From the above noisiness measures, first examine the third term on the right hand side in equation (11). $(\sum_{n=1}^{N} w_{n} \beta_{n})^{2}$ is always larger than $(\sum_{m=1}^{M} w_{m} \beta_{m})^{2}$ when the $\beta$'s are of the same sign. This implies that index price is more informative about the systematic factors. Even if the $\beta$'s are not of the same sign, we would expect this inequality to hold if systematic factors affects most stocks in the same direction. This certainly is a reasonable assumption. The fourth term in equation (11) is of ambiguous sign. Note that, $(\sum_{m=1}^{M} w_{m} \beta_{m})^{2}$ may be larger or smaller than $\sum_{m=1}^{M} w_{m}^{2} \beta_{m}^{2}$, depending on the signs of $\beta$'s. One scenario is that when all the $\beta$'s are of the same sign, the fourth term is negative and the informativeness of the stock index on the systematic factors decreases. However, even in this case, the effect of the fourth term is still dominated by the effect of the third term as the weight on the third term $\frac{\text{var}(\gamma)}{(g+1)^{2}}$ clearly dominates the weight on the fourth term $\frac{\text{var}(\gamma)}{(g+1)^{2}}$. Consequently, the
informativeness on the factor information is likely to be stronger in the index market than in the stock market.

The above result on price informativeness is different from that in Subrahmanyam (1991). He shows that the informativeness of the index price is the same as the price of the stock portfolio on the idiosyncratic components. When the $\beta$'s are of the same sign, the price of the stock portfolio is more informative about the systematic factors than the index price (see Proposition 5 in Subrahmanyam (1991)). The difference stems from the fact that, in Subrahmanyam (1991), factor informed investors are assumed to trade in all individual stocks. When factor information is incorporated in all individual stocks, the informativeness measure on the stock portfolio does not have the third term in equation (11). Consequently, in his result, when all the $\beta$'s are of the same sign, price of stock portfolio is more informative on the systematic factors than the index price because of the diversification effect of noncorrelated liquidity trades in the individual stocks (the fourth term in equation (11) with $N$ instead of $M$). In our results, even when all the $\beta$'s are of the same sign, this diversification effect is always dominated by the third term in equation (11).

2.4.4 Lead-lag Relation

Lead-lag relations between the index market and the stock market have attracted considerable interests from empirical studies. Lead-lag relations between price movements of stock index and the underlying stocks reveal how fast one market reflects new
information relative to the other. More importantly, as we show throughout the chapter, lead-lag relations reveal what new information one market incorporates relative to the other. In this subsection, we investigate the existence and properties of such relations in the framework of cross-market trading.

To analyze the lead-lag relation, we adopt a multi-period framework as presented in equation (1). This framework has essentially the same properties as the one period model. Private information, either systematic or security specific, is useful for only one trading period. All liquidity trades, systematic factors and security specific innovations are serially uncorrelated. In addition, we assume that the variance of systematic factors and the variance of the security specific innovations are constant for all trading periods.

We use the correlation coefficient as the measure for the lead-lag relations. The following two measures represent the lead-lag relation from the index market to the stock market and from the stock market to the index market respectively:

$$\rho_{I,t} \equiv \text{cov} \left( \Delta \sum_{n=1}^{N} w_n P_{n,t}, \Delta P_{t-1} \right) \left[ \text{var} (\Delta P_{t-1}) \right]^{-1/2} \left[ \text{var} \left( \Delta \sum_{n=1}^{N} w_n P_{n,t-1} \right) \right]^{-1/2}$$

$$\rho_{S,t} \equiv \text{cov} \left( \Delta P_{t}, \Delta \sum_{n=1}^{N} w_n P_{n,t-1} \right) \left[ \text{var} (\Delta P_{t-1}) \right]^{-1/2} \left[ \text{var} \left( \Delta \sum_{n=1}^{N} w_n P_{n,t-1} \right) \right]^{-1/2}$$

Where $\Delta$ denotes price changes from the previous period, and $P$, $P_n$ are the price of the stock index and the price for stock $n$ respectively. Because the denominators are the
same in the above expression, we can evaluate the lead-lag relation from one market to
the other by comparing the two covariance measures.

The following Proposition describes the equilibrium implications for the lead-lag
relations in the two markets:

**Proposition 4** The lead-lag relation between the stock index market and the stock mar-
ket can be described by the following measures:

\[
\text{Cov}(\Delta P_t, \Delta \sum_{n=1}^{N} w_n P_{n,t-1}) = \frac{g(\sum_{m=1}^{M} w_m \beta_m)^2 \text{var}(\gamma)}{(g + 1)^2} + \sum_{n=1}^{N} w_n^2 \frac{k_n}{k_n + 1} \text{var}(\epsilon_n) \tag{12}
\]

\[
\text{Cov}(\Delta \sum_{n=1}^{N} w_n P_{n,t}, \Delta P_{t-1}) = \frac{g(\sum_{m=1}^{M} w_m \beta_m)^2 \text{var}(\gamma)}{(g + 1)^2} + \frac{g \text{var}(\gamma)}{g + 1} \left( (\sum_{n=1}^{N} w_n \beta_n)^2 - (\sum_{m=1}^{M} w_m \beta_m)^2 \right) \tag{13}
\]

The above result provides clear predictions on the lead-lag relations between the
two markets. From equation (12), the stock market always leads the index market in
security specific information. For systematic information, in general, \((\sum_{n=1}^{N} w_n \beta_n)^2 >
(\sum_{m=1}^{M} w_m \beta_m)^2\) holds, and the index market leads the stock market. Thus lead-lag
effects exist from both directions. For empirical purposes, which effect dominates depends
on the relative strength of factor innovation and security specific value innovation. When

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systematic information is strong, the index market leads the stock market. When aggregate security specific information is strong, the stock market leads the index market.

This result is consistent with existing empirical findings on lead-lag relations between the stock index market and the stock market. Many studies find that the index derivative market leads the stock market in price innovations (Kawaller, Koch and Koch (1987), Stoll and Whaley (1990), Chan (1993)). However, this lead-lag relation is not constant over time. In particular, Chan (1993) shows that when more stocks move together (market wide information), the index future market leads the stock market to a greater degree. More recently, Frino, Walter, and West (2000) find that the index market leads the stock market when there is significant macroeconomic news, but the stock market leads the index market around stock-specific information releases. Our theoretical results show that the bi-directional lead-lag relation exists because the index market and the stock market incorporate different information at different speeds.

2.4.5 Arbitrage Opportunities and Behavior of Index Basis

Index arbitrage is widely viewed as one major mechanism to achieve market integration between the index derivative market and the stock market. However, empirical studies on the effect of index arbitrage on the stock market movements are inconclusive. Especially, few studies have examined the informational implications of index arbitrage activity. To understand the effect of index arbitrage activity, it is important to examine why arbitrage opportunities exist in the first place. This subsection investigates the
existence and properties of price differentials (i.e., arbitrage opportunities) between the
index market and the stock market. By studying the properties of arbitrage opportuni-
ties, we provide an explanation on the causes and consequences of arbitrage activity in
a unified framework of informed trading.

Our analysis focuses on the existence and the properties of arbitrage opportunities
rather than the activity of the index arbitrageurs. Note that “arbitrage opportunity”
in this chapter refers to the price differentials between the two markets. Because of
the transaction costs, pricing differentials between the two markets do not necessarily
imply “profitable” arbitrage opportunity or generate index arbitrage activity. To make
the model tractable, we in fact do not explicitly model index arbitrageurs throughout
the paper.\textsuperscript{10} Heuristically, the role of index arbitrageurs can be understood in the
same framework as in Kumar and Seppi (1994) where index arbitrageurs do not have
new information but can observe pricing differentials between the index and the stock
market and have access to both markets.\textsuperscript{11}

Because security specific informed traders do not trade in the index market, arbitrage
opportunities exist even when factor informed traders trade in both the stock market

\textsuperscript{10}It’s important to notice that informed traders can not carry out arbitrage activities because the
market clearing prices in all the markets are unknown when they submit their orders. The unconditional
expected price differential is bounded by the transaction costs.

\textsuperscript{11}Kumar and Seppi (1994) use a multi-period framework to examine the information advantage of
arbitrageurs over market makers. In our multi-period framework, private information is useful for only
one period. This assumption effectively rules out the arbitrage activity as defined in Kumar and Seppi
(1994) because index arbitrageurs do not have any advantage over market makers on the arrival of public
information. Nevertheless, in the current framework, trading activity of index arbitrageurs and public
information arrival have similar impact on market equilibrium.
and the index market. As factor informed traders only trade in \( M \) individual stocks, arbitrage opportunities reflect mispricing on both the factor innovations and the security specific value innovations. Define the “basis” \( B \) as the difference between the price of the stock portfolio and the price of the stock index. Let \( B \equiv P - \sum_{n=1}^{N} w_n P_n \) denote the basis, the following proposition gives the value of the “basis”.

**Proposition 5** Under the factor structure with cross markets trading, the difference between index price and the price of stock portfolio, or the index basis, is given by the following:

\[
B = \lambda_\omega - \sum_{n=1}^{N} w_n \lambda_n \omega_n = \lambda_\xi - \sum_{m=1}^{M} w_m^2 \lambda_m \xi_m - \sum_{n=N-M}^{N} w_n^2 \lambda_n \xi_n + \frac{g\gamma}{g+1} \left( \sum_{n=1}^{N} w_n \beta_n - \sum_{m=1}^{M} w_m \beta_m \right) + \sum_{n=1}^{N} w_n \frac{k_n \epsilon_n}{k_n + 1} \tag{14}
\]

The three pricing parameters (\( \lambda \)'s) are from Lemma 4, with \( \lambda \), \( \lambda_m \) and \( \lambda_n \) present the pricing parameters for the stock index, stocks with factor informed trading and stocks without factor informed trading respectively.

The index basis is a measure of market mispricing between the index and the stock market. First, because the stock index does not incorporate stock specific information, arbitrage opportunities exist owning to the existence of security specific innovations. This part is represented by the last term in the above “basis” formula. Second, because the index price is more informative about the systematic information than the
price of the portfolio of stocks, arbitrage opportunities based on systematic information also exist. This is represented by the fourth term in the above formula. Finally, the first three terms in equation (14) consist of liquidity trading components which do not contain fundamental value innovations on either systematic factors or security specific components.

When there exists large imbalance in factor informed trading and security specific informed trading in the index and the stock market, index arbitrage opportunities exist. Specifically, when systematic information is strong, arbitrage opportunities are generated through the imbalance in factor informed trading across the index and the stock market. When aggregate security specific information is strong, arbitrage opportunities are generated through the security informed trading in the stock market.

We now further examine the relation between changes in index basis and the subsequent movements in index price and stock price. Because index basis contains information on the fundamental security value, changes of index basis are correlated with subsequent security price movements. We again use covariance as a measure of such relation. The covariances of changes in the index basis with changes of stock index prices and changes of stock prices are defined respectively as $Cov(\Delta P_t, \Delta B_{t-1})$ and $Cov(\Delta \sum_{n=1}^{N} w_n P_{n,t}, \Delta B_{t-1})$. $\Delta$ denotes price changes from the previous period, and $P$, $P_n$ are the price for the stock index and stock $n$ respectively. $\Delta B_{t-1}$ is changes in the index basis, where $B$ is the index basis as defined in the previous proposition.
Because $\Delta B_{t-1} = \Delta P_{t-1} - \Delta \sum_{n=1}^{N} w_n P_{n,t-1}$, we can use the following covariance measure to represent the relation of changes in index basis with subsequent changes in security prices. The following proposition provides equilibrium solution on such measures.

**Proposition 6** The relation of changes in the index basis with subsequent changes in the index prices and stock prices can be described by the following measures:

$$
\text{Cov}(\Delta P_t, \Delta B_{t-1}) = \text{Cov} \left( \Delta P_t, \Delta P_{t-1} - \Delta \sum_{n=1}^{N} w_n P_{n,t-1} \right) 
$$

$$
= -\frac{g(\sum_{n=1}^{N} w_n \beta_n)^2 \text{var}(\gamma)}{g + 1} - \frac{g(\sum_{m=1}^{M} w_m \beta_m)^2 \text{var}(\gamma)}{(g + 1)^2} - \sum_{n=1}^{N} w_n^2 \frac{k_n}{k_n + 1} \text{var}(\epsilon_n) 
$$

$$
\text{Cov} \left( \Delta \sum_{n=1}^{N} w_n P_{n,t}, \Delta B_{t-1} \right) = \text{Cov} \left( \Delta \sum_{n=1}^{N} w_n P_{n,t}, \Delta P_{t-1} - \Delta \sum_{n=1}^{N} w_n P_{n,t-1} \right) 
$$

$$
= \frac{g(\sum_{n=1}^{N} w_n^2 \beta_n^2) \text{var}(\gamma)}{(g + 1)^2} + \frac{g(\sum_{m=1}^{M} w_m \beta_m)^2 \text{var}(\gamma)}{(g + 1)^2} + \sum_{n=1}^{N} w_n^2 \frac{k_n}{k_n + 1} \text{var}(\epsilon_n) 
$$

$$
+ \frac{g \text{var}(\gamma)}{(g + 1)} \left( (\sum_{n=1}^{N} w_n \beta_n)^2 - (\sum_{m=1}^{M} w_m \beta_m)^2 \right) 
$$

(16)

From the above results, it is easy to see that changes in the index basis can predict both index returns and stock returns, but based on different information. By comparing the above two equations, we can see that the predictions based on systematic information and security specific information have opposite signs. Specifically, the above result shows
that changes in the index basis predict index returns with a negative sign, and predict
stock returns with a positive sign.

Given the definition of index basis, \( B_t \equiv P_t - \sum_{n=1}^{N} w_n P_{n,t} \), the above result becomes
easier to understand by considering the information transmission process across the two
markets. Equation (15) describes the relation between changes in the index basis and
the subsequent stock index returns. When security specific information is incorporated
in the stock price, but has not been incorporated in the index price, index basis and the
subsequent index price move in the opposite direction. For example, a larger increase
in stock price, while decreasing the value of the basis, will lead an increase in the index
price because security specific information is transmitted from the stock market to index
market in the subsequent trading period. In equation (16), where systematic informa-
tion is incorporated in the stock index price, but has not been incorporated in all the
individual stock prices, index basis and the subsequent stock price move in the same
direction.

Clearly, the price difference between the stock index and the stock portfolio does
contain information. This is a result that differently informed investors trade in and
across different markets. Different trading activity has been mentioned in some studies as
a possible reason for market mispricing, thus a possible reason for the existence of index
arbitrage activity (See, for example, MacKinlay and Ramaswamy (1988)). However, no
formal argument has previously been presented. Our results not only provide a rational
explanation for the causes of index arbitrage opportunities, but also provide inferences on the relation between arbitrage opportunity and security price movements. Specifically, the results are consistent with the empirical finding in Harris, Sofianos and Shapiro (1994) that changes in the index futures prices and stock index prices lead arbitrage trading activity, and index arbitrage trades lead to price adjustment in one market to information revealed in the other market. Our results also imply that index arbitrage or program trading activity should contain information not reflected in the current market price, as the empirical results in Hasbrouck (1996) have shown.

Note that the above derived properties of index basis and especially the relation between index basis and security returns are based on different informational trading in the two markets. Such relation can not be obtained from pure pricing errors or noise in liquidity trading. For example, if index basis is a result of pricing errors in the stock index, changes in the index basis do not have any predictive power on subsequent stock returns.

A brief discussion of arbitrage activity is in order. It is possible that even when arbitrage opportunities exist, arbitrage activity may not occur because of transaction costs. This implies that arbitrage activity is carried out by arbitrageurs who can observe the price difference between the two markets and who have low transaction costs. Even with high transaction costs, one-sided arbitrage activity such as buying or selling the index contract is possible if fundamental information will be revealed in later trading
periods. The above discussion on the behavior of the index basis does not rely on the existence of arbitrage activities, as information transmission across securities can clearly be achieved through price observation by market makers.

It is not surprising that lead-lag relations are closely related to arbitrage activities. Because cross-market informational trading generates both arbitrage opportunities and the lead-lag relation. In our analysis, the lead-lag relation is caused by both where informed traders trade (based on the type of information) and what type of information one market incorporates relative to another. Lead-lag relations thus represent cross-market autocorrelation in price changes while arbitrage opportunities represent contemporaneous price differences between the two markets. It is possible that arbitrage trading activity contributes to the lead-lag relation through trading induced information transmission, but other means of information transmission such as price observation can also achieve similar results.

2.5 An Empirical Test on the Relation Between Index Basis and Index Prices

In the last section we presented the main implications of an index trading model. The predictions of the model are broadly consistent with a wide range of empirical findings on index trading, arbitrage activities, and lead-lag relation. Furthermore, the model yields new predictions that have not been explored. In this section, we provide
empirical evidence on one such implication, the relation between the index basis and the movements of index and stock prices.

The model provides a rich structure on the relation between changes in the index basis and the subsequent index returns and stock returns. Even though the properties of the index basis and the relation between index price and stock price have been extensively studied, the relation between changes in the index basis and changes in stock and index prices has not been investigated. The main implications of the model on the relation between the index basis and index and stock prices are summarized as the following hypotheses:

- **Hypothesis 1**: Index basis exists because prices in the index market and the stock market reflect different information. Further, the index basis exhibits mean reverting behavior because of information transmission across securities (either through arbitrage trading activity or through price observation, or both).

- **Hypothesis 2**: Changes in the index basis have predictive power on subsequent index returns and stock returns. Specifically, changes in the index basis predict index returns with a negative sign, and predict stock return with a positive sign.

- **Hypothesis 3**: Index returns and stock returns have predictive power on subsequent movements in index basis.

We should notice that mean reversion in index basis is not a result unique to the current model. Pricing errors in index prices and the eventual correction of price errors
exclude the first half-hour price data from the sample. Regular trading at major U.S. stock exchanges stops at 4:00 p.m. EST, but S&P 500 index futures contracts continue to trade until 4:15 p.m. Since we need data for both market, we delete the index price series after 4:00 p.m. During each trading day we thus have 72 five-minute data points.

Assuming non-stochastic interest rates, forward and future prices are equal. The theoretical or "cost of carry" relation between the price of index futures and the price level of the stock index is given by:

\[ F_t = S_t e^{r(T-t)} - \sum_{i=1}^{N} D_i e^{r(T-t)}, \tag{17} \]

where \( F_t \) is the index futures price at time \( t \) and \( S_t \) is the stock index price level at time \( t \). The interest rate \( r \) and dividend \( D_i \) are assumed to be known. Dividends \( D_i \) are paid at time \( t_i \). \( T \) is the expiration date for the index futures contract. The derived index futures price from this equation when the stock price is known is the implied index futures price \( F_t^i \). In the following calculation, we use the three-month Treasury bill rate and the actual cash dividend on S&P 500 index as inputs for interest rates and dividend payments. After obtaining the implied index futures price \( F_t^i \), we calculate the index basis using \( B_t = F_t - F_t^i \), where \( B_t \) is the index basis and \( F_t \) is the actual index futures price. Change in index basis is thus defined as \( \Delta B_t = B_t - B_{t-1} \). Index futures returns are calculated using \( R_{F,t} = \log(F_t/F_{t-1}) \). Stock price returns \( R_{S,t} \) are defined similarly.
To test the predictive power of the index basis on index futures returns and stock returns, we use the following simple regression

\[ R_t = \alpha + \beta \Delta B_{t-1} + \epsilon_t \quad , \]

(18)

where \( R_t \) refers to either index futures returns \( R_{F,t} \) or stock returns \( R_{S,t} \). To check the robustness of the results, we also use

\[ R_t = \alpha + \sum_{i=1}^{4} \beta_i \Delta B_{t-i} + \epsilon_t \quad . \]

(19)

To isolate the effect of security specific information from systematic information, we then use \( R_t = R_{S,t} - R_{F,t} \) as a measure of security specific value innovation.

2.5.2 Empirical Results

We first provide some preliminary results on the mean reverting behavior of the index basis in our sample. Mean reverting of the index basis may be a result of arbitrage activities (See MacKinlay and Ramaswamy (1988) for more detailed discussions). It may also because information contained in other securities is transmitted to security price either through trading activity or through price observation. From our model, systematic information transmission from the stock index to individual stocks and security specific information transmission from individual stocks to stock index induce the mean reverting behavior in index basis.
Table 1 shows that changes in the index basis exhibit strong mean-reversion behavior. The autocorrelation of changes in the index basis is negative and significant. MacKinlay and Ramaswamy (1988) find strong mean reverting behavior of the index basis using intraday data with 15-minute intervals. Though not reported, we also use intraday data with both ten-minute intervals and 15-minute intervals in the autocorrelation test and the following tests and find similar results.

To investigate the relation between changes in the index basis and subsequent security returns, we now examine the predictive power of the index basis over index futures returns and stock returns using regressions (18) and (19). As discussed in the model, for systematic information, we expect that changes in the index basis predict stock returns with a positive sign. For security specific information, we expect changes in the index basis predict index futures returns with a negative sign. To isolate the effect of security specific information, we further use stock returns in excess of index futures returns.

Table 2 reports the results on the predictive power of the changes in the index basis. Panel A is the result on index futures returns. We can see that the coefficient estimates are negative and significant. Result for stock returns is reported in Panel B. The coefficient estimates are positive and significant. Both results are consistent with the prediction of the model even without controlling the differences between systematic information and security specific information. When we use the difference between stock returns and index futures returns, the coefficient estimates are positive and significant.
as reported in Panel C. The results indicate that changes in the index basis reflect different information flow in the stock index and the stock market. When information is transmitted across securities, changes of index basis forecast individual security returns.

Changes in the index futures price and stock index price may be caused by microstructure effects such as bid-ask bounce. Also, the documented relation between changes in index basis and the subsequent security returns may be driven entirely by the lead-lag relation in the stock index and the stock market we discussed above. We now formally control for such effects in the regressions. We first examine the serial correlation patterns in index futures returns and stock index returns. Consistent with findings in Stoll and Whaley (1990), stock index returns exhibit positive autocorrelation, and index futures returns exhibit negative autocorrelation (see Table 3). The positive autocorrelation of stock index returns may be attributed to infrequent trading in individual stocks in the stock market.\textsuperscript{12} The negative autocorrelation of index futures returns is consistent with the pattern predicted by models of bid/ask effects because index futures is a single security traded in the index market (See discussions in Stoll and Whaley (1990)). To control for such autocorrelation effects in the relation between index basis and security returns, we rerun regressions (18) and (19) by adding lagged security returns as independent variables. As shown in Table 4, the results do not differ qualitatively from the results reported in Table 2. The evidence shows that the relation we find between changes in

\textsuperscript{12}Theoretically, infrequent trading is consistent with rather than contradictory to the results of the model. Simply put, infrequent trading implies that informed traders do not trade in the security and later trading activity incorporates available information.
the index basis and subsequent security returns is not caused by serial autocorrelation effects.

As discussed in the model, the lead-lag relation between the index market and the stock market is closely related to variations in arbitrage opportunities. To investigate the differences between the two effects, we now control for the lead-lag relation in the regressions. Table 5 reports findings on the lead-lag relations between the index market and the stock market. The lead-lag relation is bi-directional: the index market leads the stock market, and the stock market also leads the index market, although the former relation is much stronger. This result is consistent with the model predictions and is also consistent with earlier empirical findings in Stoll and Whaley (1990) and Chan (1993).

Table 6 reports the results on the relation between changes in the index basis and the subsequent security returns after controlling for the lead-lag effects. To control for the lead-lag relations, we include lagged index futures returns (lagged stock returns) in the regressions of stock returns (index futures returns). The relation between changes in the index basis and index futures returns does not change, this is consistent with the weak lead-lag relation from the stock market to the index market. However, we can see that the relation between changes in the index basis and stock index returns is much weaker than the results reported in Table 2. This result is not surprising given the strong lead-lag relation from the index market to the stock market.

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The above results provide an empirical test of the information-based explanations for the index arbitrage opportunities. These findings further provide evidence on the relation between index arbitrage opportunities and the security prices. Overall, the empirical evidence in this section provides strong support on the model's prediction. The documented relation between changes in the index basis and the subsequent security returns is significant, and is robust to various microstructure effects. In results not presented here, we replace S&P 500 index futures with Standard and Poor's Depository Receipts (SPDRs) in the above tests and find similar results.

2.6 Conclusions

This chapter develops a model of trading in the stock and the stock index market with transaction costs. After deriving the trading behavior of informed traders in the presence of transaction costs, we examine the effect of index trading on market liquidity, price informativeness, arbitrage opportunities, and the lead-lag relations. Empirical tests based on the model's predictions are performed.

We study the effect of index trading on price discovery and information transmission in a unified framework. We show that introduction of the stock index securities improves the dissemination of market-wide information. The model generates rich implications on the informativeness of the index price, the causes and consequences of index arbitrage and the bi-directional lead-lag relation between the index and the stock market.
The predictions of the model are broadly consistent with recent empirical findings. The results support the conjecture and empirical results in Chan (1993) and Frino, Walter, and West (2000) on the lead-lag relation between the index and the stock markets. More importantly, the results provide new predictions and/or explanations on both old and new trading practices in the market places. We show that arbitrage opportunities arise because of different informational trading in the two markets. When either factor or security specific informed trading clusters in one market, differences in market prices are created. Furthermore, the current model provides sharper predictions on both arbitrage trading activity and the information content in arbitrage trading than previous models. The model’s prediction on the information implication explains why arbitrage trading is informative as documented in Hasbrouck (1996). We further specifically test the prediction that changes in index arbitrage opportunities are associated with subsequent security returns. These predictions are strongly supported by the data.

The factor structure assumption and the asymmetric trading structure developed in this chapter can be applied to other areas as well. Closed-end funds can be viewed as public traded stock portfolio. In the next chapter, we examine the relation between closed-end funds discounts and both fund returns and net asset value returns. The empirical results on closed-end fund discounts also support the predictions of the current model. In most multi-market trading mechanisms, we often observe “related” securities traded cross markets, rather than the exactly same security traded across markets (a case analyzed in Chowdhry and Nanda (1991) and others). For example, in the pre-hour
trading market, currently only index securities and a number of highly liquid large stocks are actively traded. If a factor structure is assumed for the index and all the stocks, the framework in this chapter can be used to examine the trading decision of the informed traders and the information transmission across trading sessions.
CHAPTER 3

INFORMATION TRANSMISSION AND CLOSED-END FUND DISCOUNT MOVEMENTS

3.1 Introduction

Closed-end equity funds usually are traded at discounts, and the discounts fluctuate over time. U.S. closed-end fund shares typically sell at prices 10 to 20 percent less than the per share market value of assets (NAV) the fund holds. This discount persists and fluctuates according to a mean-reverting pattern. The behavior of closed-end fund discounts represents a challenge to the hypothesis that investors behave rationally and markets function efficiently. Theoretical models based on agency costs and capital gain taxes have attempted to explain the discounts within a rational expectations framework, but they cannot account fully for the behavior of closed-end fund discounts. For example, agency costs, management fees and managerial underperformance may partially explain the existence of the discounts, but they do not explain the magnitude and the fluctuations in fund discounts.
The limited success of standard economic theory to explain the behavior of closed-end fund discounts lead to explanations based on models of limited rationality. In particular, Lee, Shleifer and Thaler (1991) have explored the relation between investor sentiment and the closed-end fund puzzle. In their framework, the irrationality of individual investors, the most prominent holders of closed-end fund shares in the U.S., creates an additional risk for the assets they trade. The misperceptions of these investors translate into optimistic or pessimistic overreactions and result in the fluctuations of closed-end fund discounts. Lee et. al also provide evidence that closed-end fund discounts are correlated with the prices of other securities (such as small stocks), which are affected by the same investor sentiment.

However, the limited rationality theory is inconsistent with empirical evidence for the UK closed-end fund market. UK closed-end funds exhibit similar properties as the U.S. closed-end funds, but the former is largely dominated by institutional investors, thereby less affected by investor sentiment. In a direct test on the role of closed-end fund discounts in the U.S. market, Elton, Gruber and Busse (1998) find that discount on closed-end funds is not a priced risk factor, either in stocks or in closed-end funds. Additionally, the investor sentiment argument is not fully consistent with the evidence that fund discounts not only predict small stock returns, but also predict movements of risk factors (Swaminathan (1996)).

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13See Dimson and Minio-Kozerski (2000) for discussions on empirical evidence of UK closed-end fund market.
In this paper, we develop and test a closed-end fund trading model which emphasizes the information transmission process across different securities. To develop such a model, we use the simple fact that a closed-end fund is a publicly traded stock portfolio. In a trading structure fully consistent with rational expectations, the price of a traded stock portfolio can be different from the aggregate price of the underlying individual stocks. Given endowments of different information and the existence of transaction costs, informed investors trade strategically across securities. Thus, systematic information is quickly incorporated in the closed-end fund prices, but may not be incorporated in the underlying stocks contemporaneously. Similarly, corporate specific information already contained in the underlying stock prices may not be incorporated in fund prices. Because the price differences reflect different informational trading across different securities, closed-end fund discounts will vary over time according to the nature of the information flow. Furthermore, changes of discounts contain information on fundamental value innovations in the underlying securities.

The results obtained from this model are consistent with the well documented time series properties of closed-end fund discounts. For example, the model can explain why closed-end fund discounts vary over time and why closed-end funds discounts predict closed-end funds returns. The empirical evidence on the predictive power of discounts over subsequent closed-end fund returns are investigated in Thompson (1978) and Pontiff (1995). As these authors have noticed, such predictability is not consistent with rational asset pricing models and can only be attributed to mean-reversion in discounts. The
results from the current model, by contrast, provide a rational expectation model for the relation between closed-end fund discounts and subsequent fund returns.

More importantly, the model presents new testable implications and some predictions contrast sharply with earlier empirical findings. Specifically, the model shows that closed-end fund discounts can predict fund net asset value returns as well as fund price returns, but based on different information. Systematic information is incorporated in fund price quicker than in the underlying stock prices, thus discounts predict net asset value returns based on systematic information. Similarly, security specific information contained in underlying stock prices will eventually transmitted into fund price, so discounts can predict fund returns based on flows of security specific information. Furthermore, the predictions based on the two sets of information have opposite signs. Earlier studies using monthly data (Thompson (1978), Pontiff (1995), and Swaminathan (1996)), concluded that closed-end fund discounts cannot predict fund net asset value returns. However, they do not control for the difference between systematic information and security specific information. Using weekly data on a sample of U.S. general equity closed-end funds and controlling for the difference between systematic information and security specific information, we find strong evidence consistent with the predictions of our model.

The model also provides insights into why closed-end fund discounts can predict the returns for small stocks. If systematic information is slower to be incorporated in small stocks than in large stocks, closed-end fund discounts predict small stock returns
based on flows of systematic information. Interestingly, it is stock characteristics such as sensitivity to market-wide information, security specific information and liquidity rather than capitalization per se that produces such a relationship. To test the model predictions, we construct stock portfolios based on the stock characteristics (correlation with market returns, relative importance of security specific information, liquidity, but not capitalization). We find that closed-end fund discounts predict returns of a portfolio of stocks that have low correlation with market, high security specific information, and low liquidity.

Earlier studies on the closed-end fund puzzle have used market frictions as potential explanations for the behavior of closed-end fund discounts. These market frictions include agency costs (Barclay, Holderness and Pontiff (1993)), restricted stocks or investment (Malkiel (1973) and Bosner-Neal, Brauer, Neal and Wheatley (1990)), and taxes (Malkiel (1973) and Brickley, Manaster and Schallheim (1991)). Empirical support for these models to fully explain the behavior of closed-end fund discounts is limited (see Lee, Shleifer, and Thaler (1991) for a review). Nevertheless, these market frictions, along with management fees and managerial performance can partly explain the existence of discounts in closed-end equity fund market. In this model, we consider the effect of one type of market friction - transaction costs on the trading activity of informed traders. Based on the simple fact that the aggregate transaction costs for trading individual stocks are higher than for trading the closed-end funds, we examine the effect of informational trading activity on the time series variation of closed-end fund discounts.
The remainder of the chapter is organized as follows. Section 3.2 derives the implications of closed-end fund discounts based on the index trading model developed in the last chapter. Section 3.3 describes the empirical methodology and data. Section 3.4 presents the empirical results, and Section 3.5 concludes.

3.2 Strategic Informational Trading and Closed-end Fund Discounts

The existence and variations of closed-end fund discounts have been widely documented and studied in the finance literature. However, the time series properties of the discounts and the implications for security market equilibrium have not been fully explained in a rational expectation framework. Using the index trading model developed in the last chapter, we examine the existence and especially the variations of closed-end fund discounts and further investigate the relation between the discounts and security returns.

3.2.1 Existence and Properties of Closed-end Fund Discounts

To apply the results of the index trading model, we use the simple fact that a closed-end fund is a publicly traded stock portfolio. Thus, closed-end fund is just like the stock index security we studied in Chapter 2. Based on the results on informational trading behavior derived in the last chapter, we assume that factor informed traders trade the closed-end fund but do not trade all individual stocks. We also assume that security specific informed traders trade the stocks about which they have information but do not
trade the closed-end fund. In the following discussion, we use the term “discounts” to refer to the price differentials between the fund and the underlying stock portfolio (fund price - net asset value). The price difference may be negative (discount) or positive (premium).\textsuperscript{14}

Because security specific informed traders do not trade in the closed-end fund, and factor informed traders only trade in a subset of all individual stocks, movements in closed-end fund discount reflect mispricing on both the factor innovations and the security specific value innovations. Assume factor informed traders only trade in \( M \) individual stocks, with \( M < N \). Define the “discount” \( D \) as the difference between the price of a portfolio of individual stocks (i.e., the net asset value) and the closed-end fund price. Thus \( D \) is equivalent to “index basis” defined in the last chapter. Let \( D \equiv P - \sum_{n=1}^{N} w_n P_n \) denote the discount, the following proposition gives the value of “discount”.

\textbf{Proposition 7} The value of the closed-end fund discount is given by the following:

\[
D = \lambda \omega - \sum_{n=1}^{N} w_n \lambda_n \omega_n = \lambda z - \sum_{m=1}^{M} w_m^2 \lambda_m z_m - \sum_{n=1}^{N-M} w_n^2 \lambda_n' z_n
\]
\[
+ \frac{g \gamma}{g + 1} \left( \sum_{n=1}^{N} w_n \beta_n - \sum_{m=1}^{M} w_m \beta_m \right) + \sum_{n=1}^{N} \frac{k_n \epsilon_n}{k_n + 1}
\]

\textsuperscript{14}Throughout the chapter we use discount to refer to the difference between fund price and net asset value. A premium is effectively a negative discount.
The three pricing parameters \((\lambda's)\) are from Lemma 1, with \(\lambda, \lambda_m\) and \(\lambda_n\) present the pricing parameters for the closed-end fund, stocks without factor informed trading and stocks with factor informed trading respectively.

Similar to the index basis, closed-end fund discount is a measure of market mispricing between the closed-end fund and individual stocks. Stock specific information is not incorporated in closed-end fund price, so discount as reflected in the last term in the above “discount” formula exists because of security specific value innovations. Further, as closed-end fund price is more informative about the systematic information than the price of the portfolio of stocks, discounts induced by systematic information exist. This is represented by the fourth term in the above formula. Note that the first three terms in the above equation consist of liquidity trading components which do not contain any fundamental value innovations, either on systematic factors or on security specific components.

Closed-end fund discounts vary over time with changes of information flow and with information transmission across securities. Specifically, when systematic information is strong, a discount is generated through the imbalance in factor informed trading across the closed-end fund and the individual stocks. When aggregate security specific information is strong, a discount is generated through security informed trading in individual stocks. When information, either systematic or security specific, is transmitted across
securities through trading activity or price observation, this induces mean reverting behavior in closed-end fund discounts.

3.2.2 Closed-end Fund Discounts and Security Returns

The predictive power of closed-end fund discounts over fund returns, returns for small stocks, and even risk factors have been documented in Thompson (1978), Pontiff (1995) and Swaminathan (1996). However, no formal theoretical argument has previously been presented for why discounts should predict returns. The above result on the value of closed-end discount provides an explanation for why closed-end funds discounts vary across time, why closed-end funds discounts predict closed-end funds returns, and why closed-end funds discounts predict other risk factors. From the above result on the value of closed-end fund discount, the discount, i.e., the price difference between the closed-end fund and the stock portfolio clearly contains information on security fundamental values. Because differently informed investors trade in and across different securities, the discount represents the part of information that has yet to be incorporated in all securities.

We now present the result on the relation between closed-end fund discounts and fund returns and net asset value returns respectively. The following result is identical to the result obtained in the last chapter on the relation between index basis and security returns. For completeness and the exposition of the empirical test hypothesis, we rewrite Proposition 6 using the notation of “discount” instead of “index basis”. Note
the covariances of fund discount changes with fund returns and with net asset returns are defined as \( \text{Cov}(\Delta P_t, \Delta D_{t-1}) \) and \( \text{Cov}(\Delta \sum_{n=1}^{N} w_n P_{n,t}, \Delta D_{t-1}) \) respectively. \( \Delta \) denotes price changes from the previous period, and \( P_t, P_n \) are the closed-end fund price and price for stock \( n \) respectively. \( \Delta D_{t-1} \) is change in closed-end fund discount, where discount \( D \) is defined the same way as in the previous proposition.

**Proposition 8.** The relation of closed-end fund discount changes with fund returns and net asset value returns can be presented using the following measures:

\[
\text{Cov}(\Delta P_t, \Delta D_{t-1}) = \text{Cov}\left(\Delta P_t, \Delta P_{t-1} - \Delta \sum_{n=1}^{N} w_n P_{n,t-1}\right)
\]

\[
= -\frac{g{\sum_{n=1}^{N} w_n \beta_n}^2 \text{var}(\gamma)}{g + 1} - \frac{g{\sum_{m=1}^{M} w_m \beta_m}^2 \text{var}(\gamma)}{(g + 1)^2} - \sum_{n=1}^{N} w_n^2 \frac{k_n}{k_n + 1} \text{var}(\epsilon_n) \tag{21}
\]

\[
\text{Cov}(\Delta \sum_{n=1}^{N} w_n P_{n,t}, \Delta D_{t-1}) = \text{Cov}\left(\Delta \sum_{n=1}^{N} w_n P_{n,t}, \Delta P_{t-1} - \Delta \sum_{n=1}^{N} w_n P_{n,t-1}\right)
\]

\[
= \frac{g{\sum_{n=1}^{N} w_n^2 \beta_n^2} \text{var}(\gamma)}{(g + 1)^2} + \frac{g{\sum_{m=1}^{M} w_m \beta_m}^2 \text{var}(\gamma)}{(g + 1)^2} + \sum_{n=1}^{N} w_n^2 \frac{k_n}{k_n + 1} \text{var}(\epsilon_n)
\]

\[
+ \frac{g \text{var}(\gamma)}{g + 1} \left( \sum_{n=1}^{N} w_n \beta_n \right)^2 - \left( \sum_{m=1}^{M} w_m \beta_m \right)^2 \right) \tag{22}
\]

The above covariance measure presents the relation between closed-end fund discount changes and subsequent fund returns and net asset value returns. First, consider the effect of security specific information. From equation (21), changes in fund net asset value, which contain security specific innovations will lead the fund price when informa-
tion is security specific. This lead relation implies that changes in fund discounts can predict fund price returns. Secondly, for systematic information, equation (22) shows that changes in fund price lead changes in fund net asset value. Thus changes in fund discounts predict net asset value returns based on systematic information.

Given the definition of fund discounts, the relation between discount movements and subsequent security returns is negative for security specific information, and is positive for systematic information. By comparing equation (21) and (22), we can see that the predictions based on systematic information and security specific information have opposite signs.\textsuperscript{15} While changes in discounts predict fund returns based on security specific information (with negative sign), discounts can not predict fund returns based on systematic information. Similarly, discounts only predict net asset value returns based on systematic information (with positive sign), not based on security specific information.

Pontiff (1995) and Swaminathan (1996), using monthly data, both find that fund discounts predict fund returns but not net asset value returns. Those studies do not specify why there is such relation. Our model not only provides a rational explanation for such a relation but also provides sharper inferences than the previous studies. Specifically, the model shows that for systematic information, discounts predict net asset

\textsuperscript{15}Note that $D_t \equiv P_t - \sum_{n=1}^{N} w_n P_{t,n}$, movements in $P_t$, if reflect systematic information, will cause the change in current discounts and the subsequent net asset value movements in the same direction. In contrast, movements in the net asset value, $\sum_{n=1}^{N} w_n P_{t,n}$, if reflects security specific information, will cause the current discounts and the subsequent fund prices move with opposite direction.
value returns, but not fund returns, while for security specific information, discounts can predict fund returns. In addition, the predictions based on different information have opposite signs. We test these predictions by using weekly data and controlling for the difference of systematic information and security specific information.

The model also allows us to explore the predictive power of closed-end fund discounts over stock portfolio returns based on stock characteristics. Swaminathan (1996) documents that closed-end fund discounts predict small stock returns, but not large stock returns. From our model results, it is easy to see why fund discounts can predict small stock returns. The main reason is that fund discounts reflect the flow of systematic information that has not yet been incorporated in prices for small stocks. Because factor informed investors make their stock trading decision based on the valuation structure of stocks, low liquidity, low sensitivity to systematic information and high security specific innovation will decrease the probability of factor informed investors trading in such stocks. So, it is stock characteristics such as sensitivity to factor information, security specific information and liquidity rather than capitalization that determines the relation between closed-end fund discounts and stock portfolio returns. For large stocks, it is more likely that systematic information is incorporated as quickly as in the closed-end funds. Thus closed-end fund discounts do not predict large stock returns.

Note that the above derived properties of closed-end fund discounts and especially the relation between fund discounts and security returns are based on different informational
trading in the closed-end fund and individual stocks. Such relation can not be obtained from pure pricing errors in closed-end funds. Clearly, if the fund discount is a result of pricing errors, changes in fund discounts do not have any predictive power for subsequent net asset value returns. Moreover, pricing errors do not provide any implications on the relation between fund discounts and stock portfolio returns.

The model provides a rich structure on the relation of fund discounts with various security returns. The main results and implications of the model are summarized as follows:

- Closed-end fund discounts exist because a closed-end fund is a publicly traded stock portfolio and it incorporates different information than the simultaneously traded individual stocks. The results are obtained with a factor model (security value is governed by systematic and firm specific value innovations.) where transaction costs affect informational trading decisions.

- Variations of closed-end fund discounts are driven by information flows, either systematic or security specific. Because of information transmission across securities, closed-end fund discounts exhibit mean reverting behavior.

- Closed-end fund discounts have predictive power for subsequent fund returns and net asset value returns, but based on different information. Specifically, for systematic information, discounts predict net asset value returns, but not fund returns. For security specific information, discounts predict fund returns, but not net asset
value returns. In addition, the predictions based on different information have opposite signs.

- Closed-end fund discounts have predictive power over stock portfolio returns. In particular, closed-end fund discounts have predictive power over small stock returns. We conjecture that this happens because small stocks are slower in incorporating systematic information.

3.3 Empirical Methodology and Data

In this section, we describe the methodology and data for testing the predictions of the model. Most empirical studies on closed-end funds have used monthly data. Because our model focuses on informational trading and its implications, weekly data are better suited for the empirical tests.

The closed-end fund discount data for the period of 1996 to 2000 are collected from the Wall Street Journal. We only include the domestic general equity closed-end funds to focus on diversified funds that invest in the U.S. stock market. In order to test the relation between fund discounts and stock portfolio returns, we exclude the specialty funds that invest in specified industry or stocks. We have 19 closed-end funds in the sample period. Most of the funds are large funds that have relatively long history. New funds and delisted funds are not included in the sample because of evidence that
discounts on these funds are affected by price stabilizing and/or arbitrage activities during the listing and delisting periods.\textsuperscript{16}

For each closed-end fund in the sample, we collect weekly fund price, net asset value, and the reported discounts. We also calculate the capitalization of each fund using shares outstanding data from CRSP. We adopt the conventional definition of closed-end fund discount $Disc_{i,t} = (P_{i,t} - NAV_{i,t})/NAV_{i,t}$ to calculate discount for each fund $i$ at time $t$. We then obtain a weekly value weighted closed-end fund discounts index $D_t = \sum_{i=1}^{N} w_n Disc_{i,t}$. The capitalization of each fund at the beginning of each year is used to calculated the weight $w_n$. We define $\Delta D_t = D_t - D_{t-1}$ as changes of the value weighted closed-end fund discounts.\textsuperscript{17} Returns on fund price and fund net asset value are defined as $R_{P,t} = (P_{i,t} - P_{i,t-1})/P_{i,t-1}$, and $R_{A,t} = (NAV_{i,t} - NAV_{i,t-1})/NAV_{i,t-1}$ respectively. We also obtain returns data for closed end funds returns from CRSP. Unlike the above calculated fund returns using prices, $R_{P,t} = (P_{i,t} - P_{i,t-1})/P_{i,t-1}$, fund returns obtained from CRSP include dividends. However, the two return series yield nearly identical results. Returns data for all individual stocks are from CRSP. As explained in details later, we use individual stocks returns to calculate stock portfolio returns based on stock characteristics. We also include size decile stock returns and value weighted market portfolio returns in the tests. Decile 1 portfolio is used as small stocks and decile 10 portfolio as large stock.

\textsuperscript{16}See Dimson and Minio-Kozerski (2000) for related discussions.

\textsuperscript{17}We also use equal weighted discounts for the empirical tests. An alternative value weighted discount measure is using fund net asset value to construct the weight for each fund. Using equal weighted discount and the alternative value weighted discount in the following empirical tests yields similar results.
To test the predictive power of closed-end fund discounts on fund returns and net asset value returns, we use the following regression

$$R_t = \alpha + \beta \Delta D_{t-1} + \epsilon_t$$  \hspace{1cm} (23)

Where $R_t$ refers to either fund price return $R_{P,t}$ or net asset value return $R_{A,t}$. To check the robustness of the results and to compare our results with earlier results using monthly data, we also use

$$R_t = \alpha + \sum_{i=1}^{4} \beta_i \Delta D_{t-i} + \epsilon_t$$  \hspace{1cm} (24)

The predictive power of closed-end fund discounts over fund returns have been widely documented (Thompson (1978), Portiff (1995)). These studies, using monthly data, do not find evidence that closed-end fund discounts predict net asset value returns. To differentiate the effect of systematic information and security specific information, we use both the gross returns on fund price and net asset value, and returns in excess of value weighted market returns. The gross returns should incorporate systematic information as a major component, and the excess returns should specify the effect of aggregate security specific information.

By using weekly data, we test the prediction of the informational trading model that closed-end fund discounts predict fund returns and net asset value returns based
For security specific information, we expect closed-end fund discounts to predict fund returns but not net asset value returns. Also, changes in discounts should predict fund returns with negative a sign. To isolate the effect of security specific information, we use fund returns and net asset value returns in excess of the value weighted market returns in equation (23) and (24). Table 9 reports the results using excess fund returns and excess net asset value returns. Results for net asset value returns are reported in Panel A. Consistent with the model prediction, none of the coefficient estimates are significant. The explanatory power of discounts, measured by the $R^2$, is almost zero. Results for fund returns are reported in Panel B. The coefficient estimates for the first lagged discount are negative and highly significant. The $R^2$ for this regression is 8%. It should be noted that the results on security specific information are much stronger than the results on systematic information. The difference reflects the fact that closed-end funds typically hold large stocks and large stocks incorporated systematic information as quickly as closed-end funds. Nevertheless, both results are consistent with the prediction of the model.

On the surface, the results concerning security specific information are similar to the empirical evidence in Thompson (1978) and Pontiff (1995). Both papers suggest that higher discount (in our definition, lower $\Delta D$) predicts higher fund returns, but do not predict net asset value returns. Thompson (1978) suggests that higher discounts represent certain types of mispricing and as market does not recognize this, it is inefficient. Pontiff (1995) attributes the documented predictability to mean reversion of the
discounts. However, our results in Table 8 show that fund return predictability only reflects one facet of the relation between fund discounts and security returns. Neither paper distinguishes between systematic information and security specific information. More importantly, our findings not only reveal how mispricing may occur but also explain the different implications of the mean version in closed-end discounts. As a whole, our empirical evidence provides strong support for the model. In addition, in both our tests, the predictive power mainly comes from the first lag of discounts. Combined with the mean reverting result for weekly discount changes in Table 7, this further highlights the role of information transmission.

3.4.2 Fund Discounts and Stock Portfolio Returns

We now turn to the question of the predictive power of closed-end fund discounts on stock portfolio returns. Swaminathan (1996) documents evidence that closed-end fund discounts predict small stock returns but not large stock returns. While not providing any specific theoretical arguments, he conjectures that his finding suggests that behavior of closed-end fund discounts may be consistent with rational asset pricing theory. Our model suggests that closed-end fund discounts could predict small stock returns because small stocks are slower in incorporating systematic information. Such predictability is similar to the return predictability of large stock portfolios over small stock portfolios documented in Lo and MacKinlay (1990). Furthermore, if large stocks incorporate
systematic information in a similar manner as closed-end funds, changes in fund discounts do not have predictive power over large stock portfolio returns.

Results from regression (25) and (26) using small (decile 1) and large (decile 10) stock returns provide empirical evidence on the relation between closed-end fund discounts and stock portfolio returns. The results reported in Table 10 show that closed-end fund discounts can predict small stock returns but do not predict large stock returns. The coefficient estimate for small stock is negative, confirming the results in Swaminathan (1996). Results using return difference between small stocks and large stocks (Panel C) provide further evidence on the difference between small and large stocks. This result suggests that larger discounts ($\Delta D_t < 0$) predict higher small stock returns. Note also that this result is different from the finding in Lee et al that larger discounts imply lower small stock returns contemporaneously.

If small stocks move in the same direction as the market, the above results are in fact not consistent with the prediction of the model. However, as the results on fund returns and net asset value returns (Table 8 and 9) suggest, because closed-end fund typically hold large stocks, changes in discounts reflect the imbalance of systematic and security specific information and may not be a good measure of systematic information flow. A more direct test on systematic information can be constructed using lagged fund price returns or market returns as proxy for the market wide information. In Table 11, we report the results with lagged fund returns along with results using both lagged fund

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returns and changes in closed-end fund discounts.\textsuperscript{19} Consistent with our conjecture, fund returns predict subsequent small stock returns while fund returns have virtually no explanatory power for subsequent large stock returns. Even when used together with changes in discounts, the predictive power of fund returns on small stock returns does not change. The consistently negative relation between changes in fund discounts and small stock returns can not be directly explained by our model. However, if the imbalance of systematic information with aggregate security specific information in large stocks affect large stocks and small stocks differently, this result can be consistent with the model.

Why is the predictive power of fund discounts on small stocks different from large stocks? The model suggests that small stocks may also be stocks that are slower in incorporating systematic information. One implication of the model is that stocks with low sensitivity to factor information, with high security specific information and low liquidity do not attract informed trading based on systematic information. We now use the stock portfolios formed on the above characteristics to reexamine the relation of changes in discounts and subsequent stock portfolio returns.

As discussed in the last section, the two stock portfolios (stock portfolio 1 and 2) are formed based on proxies for a stock’s sensitivity to factor information, sensitivity to security specific information and liquidity. Even though the stock portfolios are not formed on market capitalization, the above three criteria may coincide with the size

\textsuperscript{19}The results using lagged market returns are very similar to the results using lagged fund returns and are not reported.
ranking. From the return correlation results in Table 12, it is evident that the returns on portfolio 2 are highly correlated with decile 10 stock returns (0.966). Correlation of stock portfolio 1 returns with decile 1 stock returns is also high (0.842). In addition, the correlation between portfolio 1 return and portfolio 2 return is similar to the correlation between decile 1 return and decile 10 return, at 0.459 and 0.560 respectively. The correlation evidence confirms our conjecture that small stocks possess the same characteristics that are unfavorable to systematic informational trading. In the following test we use the stock portfolio 1 and 2 to examine the relation between changes in closed-end fund discounts and stock portfolio returns. Table (13) and (14) report the results using the returns on the two stock portfolios. Not surprisingly, the results are very similar to the results reported in Table (11) and (12). Changes in closed-end fund discounts predict portfolio 1 returns in the same way as for small stock returns, while fund discounts do not have any predictive power for portfolio 2 returns. Likewise, past fund returns can predict portfolio 1 returns, but not portfolio 2 returns.

Overall, the empirical results in this section provide support for the predictions of the informational trading model. While the methodology is not designed to provide a horse race between our model and models based on “investor sentiment”, the results on the quick mean-reversion of closed-end fund discounts and the relation between changes in the fund discounts and subsequent security returns are not consistent with predictions of the “investor sentiment” model. We also show that it is stock characteristics related to systematic information based trading rather than capitalization that determines the
relation between changes in closed-end fund discounts and stock portfolio returns. The empirical evidence provided here, combined with results in Pontiff (1995) and Swaminathan (1996), provide significant support for a rational explanation of the time series properties of closed-end fund discounts.

3.5 Summary and Conclusion

The basic results and implications obtained in this chapter provide a new angle for analyzing the behavior of closed-end fund discounts. Specifically, we provide a rational explanation for the movements of closed-end fund discounts based on information transmission across securities. The model can explain several important parts of the well documented discount puzzle. More importantly, the model provides new testable implications on the relation between fund discounts and various security returns.

Based on the different transmission patterns for systematic information and security specific information, the model provides specific predictions for the relation of changes of fund discounts to fund returns and net asset value returns. Using weekly data on a sample of U.S. general equity closed-end funds and controlling the difference between systematic information and security specific information, we test the implications of the model and find strong empirical support for the model.

The relation between closed-end fund discounts and small stock returns is further examined. Our model suggests that closed-end fund discounts could predict small stock
returns because small stocks have characteristics that are unfavorable for systematic informational trading and thus are slower in incorporating systematic information. Indeed, we show that stock characteristics related to systematic information based trading rather than capitalization affect the relation between stock portfolio returns and changes in closed-end fund discounts.
CHAPTER 4

AFTER-HOUR INDEX TRADING AND STOCK MARKET MOVEMENTS

4.1 Introduction

Stock index derivative securities such as S&P 500 futures and NASDAQ 100 futures are actively traded outside regular trading hours. Even though overnight trading activity only makes up a small portion of the overall market activity, price changes during the after-hour trading period are substantial. Recently, after-hour index futures prices, trading activity, and especially the basis of the index futures price relative to the U.S. stock market closing price have attracted much attention from the financial press and the investment community alike. While some believe movement in after-hour index prices is an important indicator for the direction of stock market opening, others argue that low liquidity in the after-hour market distorts the overnight price changes.20

The around-the-clock index trading environment raises interesting questions about the interaction between the index futures market and the stock market, and between

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20 These views and other opinions are discussed in “Futures shock: What you see at 6 a.m. isn't what you get at market's opening,” (The Wall Street Journal, 11/02/2000) and “Don't bet the bank on early-hours trading: Conventional wisdom aside, futures aren't crystal balls”, Business Week, 4/2/2001.
the after-hour trading session and the regular hour trading session. Specifically, with its relatively small trading volume, does after-hour index trading contribute to price discovery or merely create noise? Further, if after-hour index trading processes information efficiently, does the stock market incorporate information revealed through index trading? And how quickly do stock prices reflect information in index futures prices?

This chapter attempts to answer the above questions by empirically studying the transaction process in the after-hour index futures market and examining the relation between the after-hour trading session and the regular hour trading session. Empirical results support the notion that after-hour index trading is important for price discovery. After-hour trading volume is small, but the after-hour index futures market incorporates information efficiently and does not "distort" overnight price movements.

We further examine how quickly the stock market incorporates information contained in after-hour index futures prices. The results show that stock prices converge to the index futures implied prices very rapidly when regular trading hour begins. The calculated arbitrage spread at the stock market open disappears in less than five minutes. Taking the evidence of infrequent trading at the stock market opening into account, the evidence suggests that profitable arbitrage opportunities at the market open are short-lived if they exist at all.

Surprisingly, we find that after-hour index futures returns exhibit predictive power for the subsequent regular hour index futures returns. After-hour index returns are
positively correlated with the subsequent regular hour index returns, but are uncorrelated with preceding regular hour index returns. Because the index futures contracts are actively traded both at the close of the after-hour session and at the opening of the regular hour session, this result is not caused by stale prices in index futures. However, further analysis shows that the documented predictive power can be contributed solely to the spillover effect in the first ten minutes during the regular session. In addition, this spillover effect is partly reversed in the remaining twenty minutes of the first half-hour trading period. Overall, after-hour index futures returns do not have any predictive power over regular-hour returns beyond the first half-hour, either in the stock market or in the futures market.

This study is the first to systematically examine after-hour index futures trading activity and its effect on stock market price movement in the U.S. market.\textsuperscript{21} Using daily data, Craig, Dravid, and Richardson (1995) study Nikkei index futures trading in the U.S. and its relation with the Japanese overnight stock price movement. Stoll and Whaley (1988) and Chan (1992) study the lead-lag relation between the index futures market and the stock market in the regular trading hours. For the stock market, Barclay and Hendershott (2000) provide a comprehensive study on the after-hour trading activity in NASDAQ stocks, but they do not examine the effect of after-hour trading on regular hour stock price movements.

\textsuperscript{21}Coppejans and Domowitz (1999) examine the pricing behavior and performance of the electronic GLOBEX and conclude that electronic market performs well in a relatively illiquid setting. Frino and Hill (2000) study the “intraday” patterns in bid-ask spreads, price volatility and trading volume on Sydney Futures Exchange.
The remainder of the chapter is organized as follows. Section 4.2 discusses the data and presents descriptive statistics on after-hour trading activity. Section 4.3 investigates the price discovery process in after-hour index trading. Section 4.4 studies whether and how quickly the stock market incorporates index trading information. Section 4.5 provides evidence on the relation between after-hour index trading and regular hour market price movement. Section 4.6 concludes this chapter.

4.2 Data and Descriptive Statistics

4.2.1 Data

This study uses trade data on S&P 500 index futures and price data on the S&P 500 stock index. S&P 500 index futures are traded on the floor of the Chicago Mercantile Exchange (CME) during regular trading hours and are traded after-hours in the GLOBEX electronic trading system developed by the CME. The S&P 500 index futures contract is one of the most actively traded products on the CME in both the regular hour and the after-hour markets. The total daily dollar trading volume on S&P 500 index futures has exceeded 25 billion dollars in recent years.

The index futures data used in the study are obtained from the CME. The data include both daily data and trade-by-trade data for index futures in the after-hour and the regular hour markets. The sample period for daily index futures trading data covers

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22GLOBEX was established in 1992 for electronic trading. In the fall of 1998 the CME launched GLOBEX2, an updated version of the original system. Currently, major products traded on GLOBEX are futures contracts on currencies, interest rates and equity indexes. These contracts have different trading hours.
from January 1999 to December 2000. This data set contains daily open and close price and the total trading volume for the selected contract. The trade-by-trade data cover the period from March 1, 2000 to December 31, 2000 and contain the time (to the second) and price of every futures contract transaction. S&P 500 index futures contracts follow the March, June, September, and December expiration cycle. Only the data for the most actively traded contracts are used in the analysis. In the sample period, the near term contract is always the most actively traded contract until about two weeks before its expiration date. To examine the relation between after-hour index trading and stock price movements, we use intraday S&P 500 stock index price data. In general, the intraday stock index price data have four price observations in each minute. The stock data are obtained from the Futures Industry Institute over the period January 1999 to December 2000.

The major U.S. stock exchanges have normal trading hours from 9:30 a.m. to 4:00 p.m. Eastern Time. The regular trading hours for equity index futures on the CME are from 8:30 a.m. to 3:15 p.m. Central Time (We use Central Standard Time hereafter in order to be consistent with index futures trading time). So regular hour index futures trading opens at the same time as the stock market opens but closes 15 minutes after the stock market closes. The after-hour index futures trading in GLOBEX begins at 3:45 p.m. and ends at 8:15 a.m. the next day. Strictly speaking, the index futures market is not truly a twenty-four hour trading market because after-hour index futures trading begins 30 minutes after the regular hour session closes and ends 15 minutes before the
regular hour session opens.\textsuperscript{23} Figure 1 provides the timetable for the two trading sessions in the index futures market. For comparison, it also includes the regular hour trading period for the stock market.

\textbf{4.2.2 After-hour Trading Activity}

After-hour trading activity in S&P 500 index futures has grown rapidly since the establishment of the GLOBEX trading system. Still, after-hour trading volume only constitutes a small fraction of total daily trading volume. Table 15 reports S&P 500 index futures trading activities in the regular hour session and after-hour session for the sample period. For comparison, the after-hour trading session is further divided into three sub-periods: the “post-close” period (3:45 p.m. to 6:00 p.m.), the “overnight” period (6:00 p.m. to 6:00 a.m.), and the “pre-open” period (6:00 a.m. to 8:15 a.m.). In the after-hour session S&P 500 index futures trading averages 3,000 contracts per day. This corresponds to about 3\% of total daily trading volume which exceeds 90,000 contracts. After-hour trading in S&P 500 index futures is concentrated prior to the open of the regular trading session. Trading in the two-hour “pre-open” period accounts for more than 50\% of total after-hour trading volume.

Measures of after-hour trading activity are drastically different when evaluated by the number of transactions instead of the number of contracts traded. The after-hour

\textsuperscript{23}E-mini contracts on S&P 500 futures and NASDAQ 100 futures basically trade around clock, beginning at 3:45 p.m. and ending at 3:15 p.m. Central Time. The major difference between S&P 500 index futures and its E-mini version is that E-mini is $50$ times index level and the standard S&P 500 index futures is $250$ times index level.
trading session averages 1000 transactions while the regular hour session averages more than 5000 transactions. Using this measure, after-hour trading represents more than 15% of total daily transactions. This change results from differences in trading size between the two sessions. Trade size in the after-hour session is roughly constant through the three sub-periods, averaging two contracts per transaction. By comparison, the trade size in the regular hour is much larger, averaging eighteen contracts per transaction. The disparity in trade size between the two sessions is consistent with the anecdotal evidence that order size is much lower in the after-hour market and that it is difficult to transact a large number of contracts at a time in CLOBEX.

We further divide the after-hour trading session into thirty-three half-hour intervals. We record both trading volume and number of transactions in each half-hour period. Figure 2 depicts the average trading volume and average number of transactions for each half-hour period from 3:45 p.m. to 8:15 a.m. Trading activity drops dramatically when the after-hour session begins at 3:45 p.m. compared with trading activity that occurred in the close period in the regular hour session. Trading activity remains fairly constant from the beginning of the after-hour session through the overnight periods. Trading activity in the last hour before the regular session open increases significantly. Trading volume in this one-hour period accounts for one third of total after-hour trading volume.

For comparison, we also record the trading volume and the number of transactions for each half-hour period in the regular trading hours. As shown in Figure 3, trading
volume exhibits the familiar "U"-shape in the regular hour session. However, by examining the number of transactions, we find that it is the trading size, not the number of transactions that drives the documented U-shape in the index futures market. The number of transactions stays fairly stable throughout the regular trading hours, ranging from 220 transactions to 400 transactions in each of the half-hour period.

Overall, after-hour trading volume of S&P 500 index futures is relatively small compared with the regular hour trading volume. However, the after-hour index market is very active when measured by the number of transactions.

4.3 After-hour Trading and Price Discovery

A fundamental question about after-hour index futures trading is whether it is related to price discovery. Price movements in the after-hours may be caused by the arrival of public information, by trading of informed traders, or by noise incurred through pure liquidity trading or other pricing errors. The price discovery process involves both the revelation of private information through trading and the incorporation of new public information in security prices. This section investigates the price discovery process in the after-hour index futures market.

It should be noted that public information release and transmission is important in the after-hour trading period. Even though most U.S. macroeconomic news releases occur during the regular trading hours, some important macroeconomic news releases
have been traditionally scheduled in the early morning, before the stock market opens. These news releases include information on CPI, the employment cost index, employment, GDP, housing starts, personal income, PPI, retail sales, the trade balance and Leading Indicators.\textsuperscript{24} Equally important, many company specific announcements such as earning announcements and earning warnings are made primarily after regular trading hours. In particular, corporations tend to make news announcements after the stock market closes if they believe that the news will have a large affect on their stock price. In addition, during the overnight period there is new public information about the returns in foreign stock market, currency exchange rates, and other global economic factors. The recent development of active after-hour trading in stocks and interest rate futures may provide cross-market information about future stock index prices. Therefore, it is likely that public information plays an important role in the price discovery process in the after-hour index futures market.

Similarly, trading based on private information can contribute to the price discovery process in the after hours. As Subrahmanyan (1991) has shown, traders with information on systematic risks can benefit from trading a security basket, such as index futures. Similarly, traders with security specific information can also benefit from trading index securities, because security specific information is equivalent to noisy systematic information. Even though informed trading may be present in the after-hour index futures

\textsuperscript{24}These news releases are scheduled at 7:30 a.m. Two other macroeconomic news releases, Capacity utilization and Industrial production, occur approximately at 8:15 a.m. when the after-hour index futures closes, but still before stock market opens.
market, empirically it is difficult to differentiate price discovery associated with private
information from that associated with the arrival of public information.\textsuperscript{25} Still, given
the nature of S&P 500 index futures contracts, it is reasonable to believe that trading
(hedging) associated with public information is central in the after-hour market. The
reminder of this section will focus on examining whether after-hour trading is associated
with significant price movements and on measuring the speed of price discovery in the
after-hour market.

\textbf{4.3.1 Price Movements in the After-hour Market}

We first present evidence on the price movements in the after-hour trading period
using index returns. After-hour index returns are defined as the after-hour market open-
to-close returns: $\log(\text{after-hour close price}/\text{after-hour open price})$. Figure 4 displays a
time-series plot of the after-hour return series. The average absolute value of the index
futures returns in the after-hour period is 0.39\% in the sample period. For comparison,
Figure 5 provides the daily regular hour index futures returns. The regular hour index
return is defined as $\log(\text{regular-hour close price}/\text{regular-hour open price})$. The average
absolute value of index futures returns in the regular hour session is 0.89\%. As shown by
the two figures, the average price change in the after-hour period is about one half in scale
of the regular hour price change. Results are similar when using half-hour intervals. The
average absolute value of the half-hour index return in the after-hour period is 0.024\%
\textsuperscript{25}See Barclay and Hendershott (2000) for an analysis on private information in the after-hour stock
market.
compared with 0.060% in the regular-hour period. Though the after-hour open-to-close return is considerably smaller in magnitude than the regular hour open-to-close return, it is still a significant component of total returns.

Table 16 provides some summary statistics for the two return series for the sample period. The mean open-to-close return for the after-hour session is 0.08% with a standard deviation of 0.53%. In comparison, the mean open-to-close return for the regular hour session is -0.03% with a standard deviation of 1.18%. The low return and high standard deviation for both return series reflect the tremendous volatility in the stock market during the two year sample period. Even though the two return series both have small skewness coefficients (-0.19 and -0.18) and have kurtosis coefficients close to 3 (2.9 and 1.7), normality is still rejected for both return series.

4.3.2 Price Discovery in the After-hour Market

We now investigate when new information, whether public or private, is reflected in overnight index futures prices. We use the weighted price contribution (WPC) to measure the relative importance of price discovery in the various after-hour trading periods.\textsuperscript{26} Cao, Ghysels, and Hatheway (2000) and Barclay and Hendershott (2000) among others have used this measure to study security price changes during different trading periods.

\textsuperscript{26}The measure of Weighted Price Change (WPC) is superior to other measures such as price change, return or return volatility. The weights in WPC help reduce the heteroskedasticity in the price changes measured and also avoid the difficulties with zero price changes.
For each period $i$, WPC is defined as:

$$\text{WPC}_i = \sum_{t=1}^{T} \left( \frac{|\Delta P_t|}{\sum_{t=1}^{T} |\Delta P_t|} \right) \times \left( \frac{\Delta P_{i,t}}{\Delta P_i} \right) ,$$

where $\Delta P_{i,t}$ is the price change during period $i$ on day $t$ and $\Delta P_i$ is the total price change for day $t$. The first term of WPC is the weighting factor for each day. The second term is the relative contribution of the price change for period $i$ on day $t$ to the total price change on day $t$. The WPC measure normalizes the price discovery per period such that the WPCs of different periods sum to one.

Weighted price contribution (WPC) is first calculated for the three sub-periods in the after-hour market: post-close, overnight and pre-open. In this calculation, the after-hour open-to-close price change is the total price change ($\Delta P_i$ in the above equation). To assess the relative contribution of price discovery of the after-hour trading period in the 24 hour trading environment, we then add three regular trading hour sub-periods: open, noon and close. The “open” period refers to the period from the index futures market open (8:30 a.m.) to before “noon” (10:00 a.m.). The “close” period is defined as from 1:30 p.m. to 3:15 p.m. The trading period between “open” and “close” is defined as the “noon” period. The total daily price change is defined as the regular hour close-to-close price change in this calculation. The fraction of WPC in the after-hour market relative to the regular hour market provides important information on the functioning of the after-hour market. Given the evidence on the substantial price movements in the after
hours, if after-hour trading does not contribute to price discovery (i.e., WPC is low), then after-hour price changes are likely due to noise and pricing errors.

Table 17 presents the results on WPCs. The first row reports the average WPC for the three after-hour sub-periods. Results show that approximately 54% of the overnight price changes occur in the pre-open period. Only 17% occur in the post-close period. The price discovery in the overnight period is fairly large, at 30%, albeit in a span of 12 hours. Row two reports price discovery relative to regular hour close-to-close price changes. When measured relative to the 24-hour trading period, the after-hour trading session accounts for 23% of price discovery. Specifically, the post close, overnight and pre-open periods account for 4%, 7%, and 12% respectively. Not surprisingly, the regular hour trading period is more important for price discovery, with the open, noon and close periods each accounting for more than 20%. Interestingly, the relative significance of WPC in the after-hour and regular hour session is roughly proportional to the fraction of the number of transactions in the two trading periods. In line of the discussions in Jones, Kaul and Lipson (1994), the close relation between price change and trading activity provides additional evidence regarding the price discovery function in the after-hour market.

In sum, significant price discovery takes place during after-hour trading. Though it is difficult to assess the relative importance of private information and public information in the price discovery process, the after-hour WPCs indicate that noise and pricing errors
are not the main reason for overnight price movements. In the next section, we provide further evidence of price discovery in after-hour index trading by examining whether and how quickly stock market prices converge to the index futures implied stock prices.

4.4 After-hour Index Trading and Stock Market Open Prices

This section investigates how the stock market incorporates information contained in the after-hour index futures prices. If price changes during the after-hour trading session are induced by liquidity trading without much fundamental information or simply by pricing errors, the stock market would discard the information in the overnight price changes after the stock market opens and when informed traders begin to trade in the stock market. By contrast, if index price changes contain new fundamental information and the effects are “permanent”, one would expect that the stock market open price converges to the “true” price implied by the index futures after-hour close price.

We use two tests to study the effect of after-hour index futures trading on the stock price formation process. The first test examines whether and how quickly stock market open prices converge to the index futures implied price. In particular, after calculating the stock price implied by the index futures close price, we use a simple average of the arbitrage spread and a weighted average of the arbitrage spread to evaluate the speed with which the stock market price converges to the index futures implied price. The second test investigates how much of the regular-hour close-to-open stock returns are explained by the after-hour index futures returns. Because of its relatively low liquid-
ity, some market participants have argued that after-hour index trading “distort” price movements by “magnifying” them. The second test thus further examines whether the after-hour index futures market processes information efficiently.

4.4.1 Convergence of Stock Price to Index Futures Implied Price

Assuming non-stochastic interest rates, forward price and futures price are equal. The theoretical or “cost of carry” relation between the price of index futures and the price level of the stock index is given by:

$$F_t = S_t e^{r(T-t)} - \sum_{i=1}^{N} D_i e^{r(T-t)}$$,

where $F_t$ is the index futures price at time $t$ and $S_t$ is the stock index price level at time $t$. The interest rate $r$ and dividend $D_i$ are assumed to be known. Dividends $D_i$ are paid at time $t_i$. $T$ is the expiration date for the index futures contract. The derived index futures price from this equation when stock price is called the implied index futures price.

The after-hour index futures closing price is used to calculate the implied index stock price. The three-month Treasury bill rate and the monthly cash dividends on S&P 500 index are the inputs for interest rate and dividend payments in the above calculation.

The arbitrage spread is defined as the absolute value of the difference between the

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27 One popular view on overnight trading is that “the lack of liquidity distorts the price movements by magnifying them”. See related arguments in “Don’t bet the bank on early-hours trading: Conventional wisdom aside, futures aren’t crystal balls”, Business Week, 4/2/2001.
implied stock prices obtained from the above equation and the minute-by-minute stock index prices at stock market open. Note that the implied stock price is calculated using the after-hour index futures close price, not the minute-by-minute regular hour index futures prices. Because the focus of the current analysis is not to examine the “true” index arbitrage opportunities, using the close price can control for the bi-directional lead-lag effect in the two markets and concentrate on investigating how quickly the stock market incorporates information contained in the index futures close price.

Figure 6 plots the average arbitrage spread for each minute during the first half hour after the stock market opens. The average arbitrage spread at market open is about 5.5 index points and falls rapidly during the first five minutes after the stock market opens. From the five minute point to the ten minute point, the arbitrage spread stays at about three index points. Because the arbitrage spread is the absolute value of price differences, the average arbitrage spread in general will not go to zero when nonsynchronous prices are used to calculate the spreads.

The simple average of the arbitrage spread in Figure 6 is affected by heteroskedasticity in price observations. It also does not distinguish between the signs of the differences between the stock price and the index futures implied price. A measure similar to the weighted price contribution (WPC) can be applied to further examine the arbitrage op-
return is just a proxy for the implied stock return. It is essentially a Taylor expansion with all the parameters assumed to be constant. A more serious problem with stock close-to-open return is the "stale" prices of individual stocks at the stock market open. This non-trading problem can be partially resolved by calculating stock market close-to-open returns using various opening prices. To reduce the effect of stale prices, we use five-minute intervals in the stock market opening period to calculate several stock market close-to-open return series. The evidence in Figures 6 and 7 suggest that we do not need to go more than ten minutes after the stock market opens to calculate the close-to-open stock returns. Nevertheless, we set the maximum length for the stock market close-to-open period to be from market close to half an hour after stock market opens (3:00 p.m. - 9:00 a.m.).

Table 18 reports the results of the regression. Because many stocks do not trade immediately at the open (8:30 a.m.), relatively little overnight information is incorporated in the stock prices. The estimate of $\beta$ is low, and the joint test of $\alpha = 0$ and $\beta = 1$ is rejected at the 5% significance level. The R-square for this regression is also low. Five minutes after stock market opens, the $\beta$ estimate increases to 0.83, and the R-square increases to 0.71. The joint test of $\alpha = 0$ and $\beta = 1$ cannot be rejected at conventional significance levels. For all the remaining stock returns using stock prices after 8:40 a.m., the $\beta$ estimates remain close to one and the joint tests of $\alpha = 0$ and $\beta = 1$ are not rejected. The R-squares of the regression begin to decrease after 8:40 a.m., indicating
that more information has been impounded into stock prices and the explanatory power of overnight index futures return decreases.

Combined with the results on arbitrage spreads, the above results show that after-hour index futures returns reflect much of the information during the overnight period. Both results show that the stock market incorporates index trading information within five minutes after the stock market opens. This finding demonstrates that after-hour index trading incorporates information rather efficiently. The empirical evidence does not support the claim that low liquidity in the after-hour index futures market distorts price movements and amplifies pricing errors. The above evidence is also consistent with the conclusion of Coppejans and Domowitz (1999) that the electronic GLOBEX market performs well in a relatively illiquid setting.

4.5 After-hour Trading and Subsequent Regular Hour Price Movement

Studies on security price formation have examined the effect of periodical market closure such as the daily closings on the behavior of security prices. The empirical patterns of stock returns and trading activities associated with market closures are well documented. However, little is known about the stock return properties in a trading environment without such closures. This section studies the time-series properties of stock index returns in an around-the-clock trading environment. In particular, we examine the relation between the two trading sessions by investigating whether after-hour index trading affects the subsequent regular hour index and stock market price move-
ments. Such investigation will help us understand whether and how the introduction of after-hour trading changes the properties of daily index returns.

4.5.1 Correlation of Index Futures Returns with After-hour Trading

We first study the properties of index futures returns with the introduction of after-hour trading. One well-documented property of index futures returns is that, unlike stock index returns, index futures returns do not exhibit positive autocorrelation (see, e.g. Miller, Muthuswamy and Whaley (1994) and Ahn et al. (1999)). By adding the after-hour trading period returns, we study the autocorrelation property of three return series: (1) regular hour open-to-close index futures returns, (2) after-hour open-to-close returns, and (3) regular hour close-to-close returns.

Panel A in Table 19 reports the autocorrelation results. Consistent with earlier studies, autocorrelation in regular hour open-to-close returns is low (0.044), and is not significantly different from zero. Again, the regular hour close-to-close index futures returns do not exhibit any autocorrelation patterns. However, after-hour index futures returns exhibit significant negative autocorrelation (correlation coefficient is -0.15). The results on the open-to-close and close-to-close index futures returns are consistent with the findings of earlier studies.

More interesting is the cross correlation pattern of the after-hour open-to-close index returns and the regular hour open-to-close index returns. Note that we define the after-hour return for day $t$ as from 3:45 p.m. on day $t-1$ to 8:15 a.m. on day $t$, and the regular
hour return is from 8:30 a.m. on day $t$ to 3:15 p.m. on day $t$. These two return series do not overlap. We examine two correlation coefficients. The first one is the correlation between the regular hour return on day $t - 1$ and the after-hour return on day $t$. The second one is the correlation between the after-hour return on day $t$ and the regular hour return on day $t$.

Panel B in Table 19 reports the correlation results. The correlation between the regular hour return on day $t - 1$ and the after-hour return on day $t$ is very low (0.014) and is not significantly different from zero. However, the correlation between the after-hour return on day $t$ and the regular hour return on day $t$ is positive (0.199) and significant. The low correlation of previous daily return with the subsequent after-hour return is consistent with previous empirical evidence on index futures returns. The high correlation of the after-hour return with the subsequent regular hour return is surprising, as it indicates that after-hour index returns have predictive power for the subsequent regular hour returns. This is the question we will address in more detail in the following subsection.

4.5.2 The Predictive Power of the After-hour Index Returns

The result on the positive correlation between the after-hour index futures returns and subsequent regular hour index returns suggests that the after-hour index futures returns have predictive power for subsequent price movements. We now provide further
tests on the predictive power of the after-hour index returns and examine the possible causes of such predictability.

The following simple regression is used to assess the predictive power of after-hour index returns:

\[ R_{i,o-c} = \alpha + \beta R_{f,o-c} + \epsilon \]  \hspace{1cm} (28)

\( R_{f,o-c} \) is the index futures open-to-close return for the after-hour trading period. For \( R_{i,o-c} \), \( i \) represents \( f \) and \( s \) for the index futures and the stock index respectively. \( R_{i,o-c} \) represents the subsequent regular hour open-to-close return immediately following the after-hour trading session. There is no stale price problem for the regular hour index futures opening prices because index futures contracts are actively traded at after-hour market close and at regular-hour market opening. However, measurement of open-to-close stock returns needs more caution because of stale prices at the stock market opening. As discussed earlier, we use several “open” prices to control for this effect.

The regression results are reported in Table 20.\textsuperscript{28} The finding on the regular hour index futures returns is consistent with the correlation results. After-hour index futures returns exhibit predictive power for the subsequent regular hour index futures returns. \( \beta \) is positive and significant, but the \( R \)-square is less than four percent. Evidence on stock market returns does not support the predictability results in the index futures

\textsuperscript{28}We also obtain results after controlling for the day of week, weekends and holiday effects. The results do not change substantially but in general are stronger than the reported results from the above simple regression.
market, however. The regression using the stock market open price (8:30 a.m.) produces significant $\beta$ (0.925) and high $R$-square (0.16), but this is a result caused by the stale stock prices. The seeming predictability disappears when the “open” time is moved forward from 8:30 a.m. Noticeably, after-hour index futures returns do not exhibit any predictability for stock returns calculated using stock open prices later than 8:40 a.m.

How might after-hour index futures returns predict regular hour index futures returns but not stock market returns? One possible explanation is the spillover effect from the after-hour session to the regular hour session in the index futures market. If this spillover effect is short lived, it will not affect the stock market price movements. The spillover effect also implies that predictability is the strongest at the “open” period of the regular hour index futures market and decreases over time. The existence of a spillover effect can be tested using regression (28) with various intraday index futures returns during the regular hour “open” period. Table 21 reports such results using various “open” period returns. After-hour index futures returns have strong predictive power over the first five-minute and ten-minute index futures returns. The $\beta$ estimates are significantly positive and the $R$-squares are in excess of 0.25. For the first half-hour returns, the predictive power is still significant, but moderate with $R$-squares of 0.08. After-hour index futures returns do not have any predictive power over index futures returns from 9:00 a.m. to market close. Not surprisingly, this result is almost identical to the result for the stock index returns for the same period. The decreasing predictability beyond the first ten minutes indicates that the spillover effect in the index futures market is
short lived. Interestingly, as shown in the last row of the table, index futures returns from 8:40 to 9:00 a.m. show a rather strong effect of reversal, partially reducing the spillover effect.

Overall, the documented predictive power of the after-hour index futures returns for the subsequent regular hour index futures returns can be contributed solely to the spillover effect in the first ten minutes after the regular hour session opens. This result may not directly apply to the stock market. Given the problems in measuring stock market open returns, it is difficult to differentiate the spillover effect from the hypothesis that the stock market incorporates information contained in after-hour index prices. But, clearly, after-hour index futures returns do not have any predictive power over index returns beyond the first half-hour, either in the stock market or in the futures market.

4.6 Discussion and Conclusion

This chapter investigates the trading process and information content in the after-hour index futures market. Using S&P 500 index futures trading data, we find that after-hour trades are associated with significant price discovery. After-hour trading volumes are small, but they process information efficiently and do not distort price movements. The empirical results also support the notion that the index futures market and the stock market are well integrated. The after-hour index futures price is an important indicator for the direction of stock market open. We show that stock market incorporates after-
hour index price information very quickly and that the arbitrage opportunities at the stock market open are short lived.

Surprisingly, we find after-hour index futures returns exhibit predictive power for the subsequent regular hour index futures returns. But further analysis shows the documented predictability is caused by the spillover effect from the pre-open to the market open. Overall, after-hour index futures returns do not exhibit any predictive power over returns beyond the first half-hour, either in the stock market or in the futures market.

In the current debate on the role of after-hour index futures trading in the investment community, one side believes that after-hour index futures price provides information on future market movement, while the other side has maintained that index futures price misreads the present market condition. As a closing note, the result in this study does not support the claims of either side. Clearly, after-hour index price incorporates contemporaneous market information efficiently, but as expected, it offers no information on future market movements.
CHAPTER 5

CONCLUSION

This dissertation studies trading activity in stock portfolios and its implication for information transmission in the security market. Chapter 2 develops a general index trading model with transaction costs. The model is then applied in Chapter 3 to study the movements in closed-end fund discounts. Chapter 4 provides an empirical analysis on after-hour index security trading and its relation with stock market movements.

Chapter 2 develops a model of trading in the stock and the stock index security market in the presence of transaction costs. The model shows that introduction of stock index security improves the dissemination of market-wide information and generates rich implications on the informativeness of security prices, the causes and consequences of index arbitrage and the bi-directional lead-lag relation between the index and the stock market.

The results of the model are broadly consistent with existing empirical findings on the relation between the index security market and the stock market. More importantly, the results provide new predictions and/or explanations on both old and new trading
practices in the market places. In the model, arbitrage opportunities arise because of
different informational trading in the two markets. When either factor or security spe-
cific informed trading clusters in one market, differences in market prices are created.
Furthermore, the current model provides sharper predictions on both arbitrage trading
activity and the information content in arbitrage trading. The prediction on the in-
formation implication explains why arbitrage trading is informative as documented in
Hasbrouck (1996). We further test the prediction that changes in index arbitrage oppor-
tunities are associated with subsequent security returns. These predictions are strongly
supported by the data.

Chapter 3 applies the index trading model developed in Chapter 2 to examine the
implications of closed-end fund trading on the variation and information content of
closed-end fund discounts. Different from earlier studies on closed-end funds based on
promises of inefficient market such as pricing errors and irrational investor behavior,
we provide a rational expectation explanation for the movements of closed-end fund
discounts based on information transmission across securities. The model results not
only provide a new angle for analyzing the behavior of closed-end fund discounts but
also provide new testable implications on the relation between fund discounts and various
security returns.

Based on the different transmission patterns in systematic information and security
specific information, the model provides specific implications on the relation of changes
in fund discounts with fund returns and net asset value returns. Using weekly data on a sample of U.S. general equity closed-end funds and controlling the difference between systematic information and security specific information, we test the implications of the model and find strong evidence supporting the model. The relation between closed-end fund discounts and small stock returns are further examined. We show that stock characteristics related to systematic information based trading rather than capitalization determine the relation between stock portfolio returns and changes in closed-end fund discounts.

Chapter 4 investigates the trading process and information content in the after-hour index futures market. Using S&P 500 index futures trading data, we study the interaction between the index security market and stock market and the interaction between the regular hour trading session and the after-hour trading session. We find that after-hour trades are associated with significant price discovery. After-hour trading volumes are small, but they process information efficiently and do not distort price movements. The empirical results also support the notion that the index futures market and the stock market are well integrated. The after-hour index futures price is an important indicator for the direction of stock market opening. We show that stock market incorporates after-hour index price information very quickly and that the arbitrage opportunities at the stock market open are short lived.
Surprisingly, after-hour index futures returns exhibit predictive power for the subsequent regular hour index futures returns. But further analysis shows the documented predictability is caused by the spillover effect from the pre-open to market open. Overall, after-hour index futures returns do not exhibit any predictive power over returns beyond the first half-hour, either in the stock market or in the futures market.
BIBLIOGRAPHY


APPENDIX A: PROOF OR LEMMAS AND PROPOSITIONS

Proof of Lemma 1: See proof of Lemma 1 and 3 in Subrahmanyam (1991). For completeness, we provide the following sketch. Factor informed trader \( i \) observes perfectly the systematic factor \( \gamma \). Security specific informed trader \( j \) observes perfectly the security specific information \( \epsilon_n \) for stock \( n \). \( \gamma \) and \( \epsilon_n \) are independent. For stock \( n \), the informed trader’s objective function is:

\[
E(x_{n,i}(S_n - P_n)|I_l)
\]

Where \( l \) represents \( i \) and \( j \) and \( I_l \) is the information set for trader \( l \).

Let trader \( i \) conjecture that other factor informed traders submit order \( A\beta_n \gamma \). Denoting the order by each security specific informed trader as \( x_{n,j} \). Then the factor informed trader \( i \)'s objective function is:

\[
E(x_{n,i}(\beta_n \gamma + \epsilon_n) - x_{n,i} \lambda_n (x_{n,i} + (g - 1)A\beta_n \gamma + k x_{n,j} + z_n)|\gamma)
\]

This is maximized when:

\[
x_{n,i} = \frac{\beta_n \gamma - (g - 1)A\beta_n \gamma}{2\lambda_n}
\]

Set \( x_{n,i} = A\beta_n \gamma \), we get

\[
x_{n,i} = \frac{\beta_n \gamma}{(g + 1)\lambda_n}
\]

Similarly, for security specific informed trader \( j \), the order flow is:

\[
x_{jn} = \frac{\epsilon_n}{(k_n + 1)\lambda_n}
\]
To get the pricing parameter $\lambda_n$, note that $\lambda_n = \text{Cov}(\epsilon_n, \omega_n)/\text{Var}(\omega_n)$, where $\omega_n$ is the total order flow in the market for stock $n$. Substituting $x_{n,i}$ and $x_{n,j}$ in the above expression, we get:

$$\lambda_n = \sqrt{\frac{k_n \text{var}(\epsilon_n)}{(k_n + 1) \text{var}(z_n)} + \frac{g \beta_n^2 \text{var}(\gamma)}{(g + 1) \text{var}(z_n)}}$$

Where $z_n$ is the total liquidity trading for stock $n$.

**Proof of Lemma 2:** See proof of Lemma 1.

**Proof of Proposition 1:** The profit function for informed trader $l$ for stock $n$ is given by $\pi_{n,l} = E(\lambda_n \omega_n x_l)$. The profit function for informed trader $l$ for the stock index is given by $\pi_l = E(\lambda \omega x_l)$. Substituting the pricing parameters $\lambda_n, \lambda$ and the order flows in the stock and stock index markets in Lemma 1 and 2 gives the results in Lemma 3 and 4.

**Proof of Lemma 4:** See proof of Lemma 1.

**Proof of Proposition 2:** The pricing parameters $\lambda_n, \lambda$ for stock $n$ and the stock index are given in Lemma 1 and 2. Applying the condition $\sum_{n=1}^{N} w_n \lambda_n > \lambda$ yields Equation (10).

**Proof of Proposition 3:** Define $Q = \text{var}(S - P)$ and $Q' = \text{var}(\sum_{n=1}^{N} w_n S_n - \sum_{n=1}^{N} w_n P_n)$ as the noisiness measure for the index and the portfolio of individual stocks. With $P = \bar{S}_t + \lambda \omega$ and $P_{nt} = \bar{S}_{nt} + \lambda_n \omega_n$, substituting the pricing parameters $\lambda_n, \lambda$ and the order flows in the stock and stock index markets gives the result. Because security specific informed traders do not trade in the index market, the pricing parameter $\lambda$ and the order flow in the index market are given in Lemma 5. Factor informed traders trade in $M$ of the $N$ stocks. The pricing parameters $\lambda_n$ and the order flows for the $M$ stocks are given in Lemma 1. The pricing parameters $\lambda_n$ and the order flows for the $N - M$ stocks that factor informed traders do not trade in are given in Lemma 5.
Proof of Proposition 4: The result can be obtained by substituting the pricing parameters \( \lambda_n, \lambda \) and the order flows in the stock and stock index markets in the two covariance measures. See Proof of Proposition 3 for the specifications of pricing parameters and order flows.

Proof of Proposition 5 and 6: The “Basis” is defined as \( B \equiv P - \sum_{n=1}^{N} w_n P_n \). The result can be obtained by substituting the pricing parameters \( \lambda_n, \lambda \) and the order flows in the stock and stock index markets in the above definition. See Proof of Proposition 2 for the specifications of pricing parameters and order flows.
## APPENDIX B: TABLES

<table>
<thead>
<tr>
<th>Dependent Variables</th>
<th>AR (1)</th>
<th>T-Statistics</th>
<th>AR (4)</th>
<th>T-Statistics</th>
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<tr>
<td>ΔB_{t-1}</td>
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Table 1: Mean Reversion in the Index Basis

AR (1) and AR (4) regressions in changes of the index basis:

ΔB_t = \alpha + \beta ΔB_{t-1} + \varepsilon_t \quad \text{and} \quad ΔB_t = \alpha + \beta \sum_{i=1}^{t} ΔB_{t-i} + \varepsilon_t

Where ΔB_t is changes of the index basis as defined in the text.

*** Significant at the 0.01 level.
<table>
<thead>
<tr>
<th>Panel A: Index Futures Returns</th>
<th>β</th>
<th>T-Statistics</th>
<th>β₁</th>
<th>T-Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>ΔBₜ₋₁</td>
<td>-0.402***</td>
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<tr>
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<td>-6.67</td>
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<tr>
<td>R²</td>
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<td>0.120</td>
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<table>
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<th>β₁</th>
<th>T-Statistics</th>
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<tr>
<td>ΔBₜ₋₁</td>
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<td>0.169***</td>
<td>15.80</td>
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<td>11.26</td>
<td></td>
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<td></td>
<td>8.76</td>
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<td>R²</td>
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<td>0.022</td>
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<table>
<thead>
<tr>
<th>Panel C: Stock Return – Futures Return</th>
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<th>T-Statistics</th>
<th>β₁</th>
<th>T-Statistics</th>
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<td>0.775***</td>
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<td>ΔBₜ₋₄</td>
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<td>20.88</td>
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<td>R²</td>
<td>0.243</td>
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Table 2: Predictive Power of the Index Basis for Security Returns

Regressions of security returns on changes in the index basis:

\[ R_t = \alpha + \beta \Delta B_{t-1} + \varepsilon_t \] and \[ R_t = \alpha + \beta \sum_{i=1}^{4} \Delta B_{t-i} + \varepsilon_t \]

Where \( R_t \) represents returns on index futures, stock index and differences between stock index returns and index futures returns. \( \Delta B_t \) is change of the index basis.

*** Significant at the 0.01 level.
<table>
<thead>
<tr>
<th></th>
<th>( \beta )</th>
<th>T-Statistics</th>
<th>( \beta_i )</th>
<th>T-Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Index</strong>&lt;br&gt;Futures Returns</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>( R_{t-1} )</td>
<td>-0.184</td>
<td>-23.10</td>
<td>-0.192***</td>
<td>-23.68</td>
</tr>
<tr>
<td>( R_{t-2} )</td>
<td></td>
<td></td>
<td>-0.043***</td>
<td>-5.22</td>
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<tr>
<td>( R_{t-3} )</td>
<td></td>
<td></td>
<td>-0.007</td>
<td>-0.83</td>
</tr>
<tr>
<td>( R_{t-4} )</td>
<td></td>
<td></td>
<td>-0.012</td>
<td>-1.53</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.033</td>
<td></td>
<td>0.035</td>
<td></td>
</tr>
<tr>
<td><strong>Panel B: Stock Index</strong>&lt;br&gt;Returns</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( R_{t-1} )</td>
<td>0.078***</td>
<td>9.72</td>
<td>0.077***</td>
<td>9.63</td>
</tr>
<tr>
<td>( R_{t-2} )</td>
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<td>-1.32</td>
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<tr>
<td>( R_{t-3} )</td>
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<td></td>
<td>-0.018***</td>
<td>-2.28</td>
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<tr>
<td>( R_{t-4} )</td>
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<td></td>
<td>-0.026***</td>
<td>-3.36</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.006</td>
<td></td>
<td>0.007</td>
<td></td>
</tr>
</tbody>
</table>

Table 3: Autocorrelations in Index Futures and Stock Index Returns

AR (1) and AR (4) regressions of index futures and stock index returns:

\[
R_t = \alpha + \beta R_{t-1} + \epsilon_t, \quad \text{and} \quad R_t = \alpha + \beta \sum_{i=1}^{4} R_{t-i} + \epsilon_t,
\]

Where \( R_t \) is returns on the index futures contract and returns on the stock index respectively.

*** Significant at the 0.01 level.
<table>
<thead>
<tr>
<th>Panel A: Index Futures Returns</th>
<th>β</th>
<th>T-Statistics</th>
<th>β_i</th>
<th>T-Statistics</th>
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<tr>
<td>ΔB_{t,1}</td>
<td>-0.402***</td>
<td>-28.04</td>
<td>-0.644***</td>
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<td>ΔB_{t,2}</td>
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<td>ΔB_{t,4}</td>
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<td></td>
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<tr>
<td>R^2</td>
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<td>0.123</td>
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<table>
<thead>
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<th>Panel B: Stock Index Returns</th>
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<th>β_i</th>
<th>T-Statistics</th>
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<tbody>
<tr>
<td>ΔB_{t,1}</td>
<td>0.106***</td>
<td>12.26</td>
<td>0.168***</td>
<td>15.66</td>
</tr>
<tr>
<td>ΔB_{t,2}</td>
<td>0.129***</td>
<td>9.82</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ΔB_{t,3}</td>
<td>0.098***</td>
<td>7.44</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ΔB_{t,4}</td>
<td>0.069***</td>
<td>6.42</td>
<td></td>
<td></td>
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<tr>
<td>R^2</td>
<td>0.016</td>
<td>0.023</td>
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Table 4: Predictive Power of the Index Basis for Security Returns After Controlling for the Autocorrelation Effects

Regressions of security returns on changes in the index basis after controlling the autocorrelation effect:

\[ R_t = \alpha + \gamma R_{t-1} + \beta \Delta B_{t-1} + \varepsilon, \quad \text{and} \quad R_t = \alpha + \gamma \sum_{i=1}^{4} R_{t-i} + \beta \sum_{i=1}^{4} \Delta B_{t-i} + \varepsilon, \]

Where \( R_t \) represents security returns and \( \Delta B_t \) is change of the index basis as defined in the text.

*** Significant at the 0.01 level.
<table>
<thead>
<tr>
<th></th>
<th>( \beta )</th>
<th>T-Statistics</th>
<th>( \beta_i )</th>
<th>T-Statistics</th>
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<td><strong>Panel A: Index</strong></td>
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<tr>
<td>Futures Returns</td>
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<tr>
<td>( R_{S,t-1} )</td>
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<td>3.08</td>
<td>0.044***</td>
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<td>( R_{S,t-2} )</td>
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<td></td>
</tr>
<tr>
<td>( R_{S,t-3} )</td>
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<td>-1.32</td>
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</tr>
<tr>
<td>( R_{S,t-4} )</td>
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<td>-3.50</td>
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<td></td>
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<tr>
<td>( R^2 )</td>
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<td>0.003</td>
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</tr>
<tr>
<td><strong>Panel B: Stock Index</strong></td>
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</tr>
<tr>
<td>Returns</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( R_{F,t-1} )</td>
<td>0.106***</td>
<td>12.45</td>
<td>0.122***</td>
<td>12.88</td>
</tr>
<tr>
<td>( R_{F,t-2} )</td>
<td>0.030***</td>
<td>3.42</td>
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<td></td>
</tr>
<tr>
<td>( R_{F,t-3} )</td>
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<td>-1.85</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( R_{F,t-4} )</td>
<td>-0.012</td>
<td>-1.39</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.020</td>
<td></td>
<td>0.007</td>
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</tbody>
</table>

Table 5: Lead-lag Relation Between Index Futures and the Stock Index

Regressions of index futures and stock index returns on lagged stock index returns and lagged index futures returns respectively. We estimate the following two regressions:

\[
R_{t} = \alpha + \beta R_{S,t-1} + \varepsilon, \quad \text{and} \quad R_{F,t} = \alpha + \beta \sum_{i=1}^{t} R_{k,t-i} + \varepsilon,
\]

Where \( J = F, S, k = S, F \), and \( R_t \) represents returns on the index futures contract and returns on the stock index respectively.

*** Significant at the 0.01 level.
<table>
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<tr>
<th>Dependent Variables</th>
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<th>AR (4)</th>
<th>T-Statistics</th>
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<tr>
<td>ΔD_{t-1}</td>
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<td>ΔD_{t-3}</td>
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<td>-0.094</td>
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<td>-1.42</td>
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<td>ΔD_{t-4}</td>
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<tr>
<td>R^2</td>
<td>0.077</td>
<td></td>
<td>0.099</td>
<td></td>
</tr>
</tbody>
</table>

Table 7: Mean Reversion in Closed-end Fund Discounts

AR (1) and AR (4) regressions in changes of weekly closed-end fund discounts:

\[ ΔD_t = α + β ΔD_{t-1} + ε, \text{ and } ΔD_t, = α + β \sum_{i=1}^{t} ΔD_{t-i} + ε, \]

Where ΔD_t is change of value weighted closed-end fund discount as defined in the text. *** Significant at the 0.01 level.
<table>
<thead>
<tr>
<th></th>
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<th>$\beta_i$</th>
<th>T-Statistics</th>
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<td><strong>Panel A: Net Asset Value Returns</strong></td>
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<td></td>
<td></td>
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<td>$\Delta D_{t-1}$</td>
<td>0.274*</td>
<td>1.85</td>
<td>0.297*</td>
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<tr>
<td>$\Delta D_{t-2}$</td>
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</tr>
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<td></td>
</tr>
<tr>
<td>$\Delta D_{t-4}$</td>
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</tr>
<tr>
<td>$R^2$</td>
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<td>0.018</td>
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<td><strong>Panel B: Fund Returns</strong></td>
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<td>-0.064</td>
<td>-0.54</td>
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<td>-0.70</td>
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<td>-1.12</td>
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<td></td>
<td>-0.89</td>
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<tr>
<td>$\Delta D_{t-4}$</td>
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<td></td>
<td>-0.16</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.007</td>
<td></td>
<td></td>
<td>0.015</td>
</tr>
</tbody>
</table>

Table 8: Predictive Power of Closed-end Fund Discounts over Fund Returns and Net Asset Value Returns: Systematic Information

Regressions of fund returns and net asset value returns on changes in closed-end fund discounts:

$$ R_i = \alpha + \beta \Delta D_{t-1} + \varepsilon_i, \text{ and } R_i = \alpha + \beta \sum_{t=1}^{4} \Delta D_{t-1} + \varepsilon_i, $$

Where $R_i$ is gross returns on fund price and net asset value. $\Delta D_t$ is change of value weighted closed-end fund discount as defined in the text.

* Significant at the 0.1 level.
<table>
<thead>
<tr>
<th></th>
<th>( \beta )</th>
<th>( T)-Statistics</th>
<th>( \beta_i )</th>
<th>( T)-Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Net Asset Value Returns</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \Delta D_{t-1} )</td>
<td>0.008</td>
<td>0.15</td>
<td>-0.011</td>
<td>-0.19</td>
</tr>
<tr>
<td>( \Delta D_{t-2} )</td>
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<td>-0.066</td>
<td>-1.05</td>
</tr>
<tr>
<td>( \Delta D_{t-3} )</td>
<td></td>
<td></td>
<td>-0.005</td>
<td>-0.09</td>
</tr>
<tr>
<td>( \Delta D_{t-4} )</td>
<td></td>
<td></td>
<td>0.044</td>
<td>0.71</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.000</td>
<td></td>
<td>0.007</td>
<td></td>
</tr>
<tr>
<td><strong>Panel B: Fund Returns</strong></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>( \Delta D_{t-1} )</td>
<td>-0.329***</td>
<td>-4.02</td>
<td>-0.398***</td>
<td>-4.53</td>
</tr>
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<td>( \Delta D_{t-2} )</td>
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<td>-0.147</td>
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<td>-1.48</td>
</tr>
<tr>
<td>( \Delta D_{t-4} )</td>
<td></td>
<td></td>
<td>-0.057</td>
<td>-0.64</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.059</td>
<td></td>
<td>0.081</td>
<td></td>
</tr>
</tbody>
</table>

Table 9: Predictive Power of Closed-end Fund Discounts over Fund Returns and Net Asset Value Returns: Security Specific Information

Regressions of fund returns and net asset value returns on changes in closed-end fund discounts:

\[
R_i = \alpha + \beta \Delta D_{i-1} + \varepsilon_i \quad \text{and} \quad R_i = \alpha + \beta \sum_{i-1}^{t} \Delta D_{i-1} + \varepsilon_i,
\]

Where \( R_i \) is returns on fund price and net asset value in excess of value weighted market returns. \( \Delta D_i \) is change of value weighted closed-end fund discount as defined in the text. *** Significant at the 0.01 level.
<table>
<thead>
<tr>
<th></th>
<th>( \beta )</th>
<th>T-Statistics</th>
<th>( \beta_i )</th>
<th>T-Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Small Stock Returns</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \Delta D_{t-1} )</td>
<td>-0.497***</td>
<td>-3.47</td>
<td>-0.596***</td>
<td>-3.87</td>
</tr>
<tr>
<td>( \Delta D_{t-2} )</td>
<td></td>
<td></td>
<td>-0.302*</td>
<td>-1.87</td>
</tr>
<tr>
<td>( \Delta D_{t-3} )</td>
<td></td>
<td></td>
<td>-0.242</td>
<td>-1.49</td>
</tr>
<tr>
<td>( \Delta D_{t-4} )</td>
<td></td>
<td></td>
<td>0.059</td>
<td>0.38</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.045</td>
<td></td>
<td>0.063</td>
<td></td>
</tr>
<tr>
<td><strong>Panel B: Large Stock Returns</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \Delta D_{t-1} )</td>
<td>0.168</td>
<td>1.08</td>
<td>0.200</td>
<td>1.19</td>
</tr>
<tr>
<td>( \Delta D_{t-2} )</td>
<td></td>
<td></td>
<td>-0.034</td>
<td>-0.19</td>
</tr>
<tr>
<td>( \Delta D_{t-3} )</td>
<td></td>
<td></td>
<td>0.009</td>
<td>0.05</td>
</tr>
<tr>
<td>( \Delta D_{t-4} )</td>
<td></td>
<td></td>
<td>0.047</td>
<td>0.28</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.004</td>
<td></td>
<td>0.007</td>
<td></td>
</tr>
<tr>
<td><strong>Panel C: Small Stock – Large Stock</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \Delta D_{t-1} )</td>
<td>-0.665***</td>
<td>-4.92</td>
<td>-0.796***</td>
<td>-5.22</td>
</tr>
<tr>
<td>( \Delta D_{t-2} )</td>
<td></td>
<td></td>
<td>-0.268*</td>
<td>-1.77</td>
</tr>
<tr>
<td>( \Delta D_{t-3} )</td>
<td></td>
<td></td>
<td>-0.252</td>
<td>-1.65</td>
</tr>
<tr>
<td>( \Delta D_{t-4} )</td>
<td></td>
<td></td>
<td>-0.106</td>
<td>-0.73</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.086</td>
<td></td>
<td>0.114</td>
<td></td>
</tr>
</tbody>
</table>

Table 10: Predictive Power of Closed-end Fund Discounts over Size Sorted Stock Portfolio Returns

Regressions of stock portfolio returns on changes in closed-end fund discounts:

\[
R_t = \alpha + \beta \Delta D_{t-1} + \varepsilon_t \quad \text{and} \quad R_t = \alpha + \beta \sum_{i=1}^{4} \Delta D_{t-i-1} + \varepsilon_t
\]

Where \( R_t \) represents stock portfolio returns and \( \Delta D_t \) is change of value weighted closed-end fund discount as defined in the text.

*** Significant at the 0.01 level. * Significant at the 0.1 level.
<table>
<thead>
<tr>
<th></th>
<th>(1) $\gamma$</th>
<th>$\gamma_i$</th>
<th>(2) $\gamma$</th>
<th>$\beta$</th>
<th>$\gamma_i$</th>
<th>$\beta_i$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Small Stock Returns</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.345***</td>
<td>0.344***</td>
<td>0.309***</td>
<td>-0.393***</td>
<td>0.282***</td>
<td>-0.493***</td>
</tr>
<tr>
<td></td>
<td>(4.67)</td>
<td>(4.57)</td>
<td>(4.17)</td>
<td>(-2.79)</td>
<td>(3.48)</td>
<td>(-3.12)</td>
</tr>
<tr>
<td></td>
<td>0.054</td>
<td>0.094</td>
<td>-0.195</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.72)</td>
<td>(1.12)</td>
<td>(-1.17)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.064</td>
<td>-0.045</td>
<td>-0.197</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.84)</td>
<td>(-0.57)</td>
<td>(-1.19)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.014</td>
<td>0.012</td>
<td>-0.012</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.18)</td>
<td>(0.15)</td>
<td>(-0.08)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.078</td>
<td>0.083</td>
<td>0.105</td>
<td></td>
<td>0.122</td>
<td></td>
</tr>
<tr>
<td><strong>Panel B: Large Stock Returns</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.024</td>
<td>-0.020</td>
<td>-0.008</td>
<td>0.165</td>
<td>0.004</td>
<td>0.194</td>
</tr>
<tr>
<td></td>
<td>(-0.29)</td>
<td>(-0.24)</td>
<td>(-0.10)</td>
<td>(1.05)</td>
<td>(0.05)</td>
<td>(1.09)</td>
</tr>
<tr>
<td></td>
<td>0.046</td>
<td>0.021</td>
<td>-0.002</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.54)</td>
<td>(0.24)</td>
<td>(-0.01)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.015</td>
<td>0.015</td>
<td>0.060</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.18)</td>
<td>(0.17)</td>
<td>(0.32)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.091</td>
<td>-0.094</td>
<td>0.027</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.09)</td>
<td>(-1.06)</td>
<td>(0.06)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.000</td>
<td>0.006</td>
<td>0.011</td>
<td></td>
<td>0.122</td>
<td></td>
</tr>
</tbody>
</table>

Table 11: Predictive Power of Fund Returns and Closed-end Fund Discounts for Size Sorted Stock Portfolio Returns

Regressions of stock portfolio returns ($R_i$) on lagged fund returns ($R_{i-1}^F$) and changes in closed-end fund discounts ($\Delta D_{i-1}$): Regression (1) is for

$$ R_i = \alpha + \gamma R_{i-1}^F + \varepsilon_i, \quad \text{and} \quad R_i = \alpha + \gamma \sum_{t=1}^{4} R_{i-t}^F + \varepsilon_i $$

Regression (2) is for

$$ R_i = \alpha + \gamma R_{i-1}^F + \beta \Delta D_{i-1} + \varepsilon_i, \quad \text{and} \quad R_i = \alpha + \gamma \sum_{t=1}^{4} R_{i-t}^F + \beta \sum_{t=1}^{4} \Delta D_{i-t} + \varepsilon_i $$

*** Significant at the 0.01 level.
<table>
<thead>
<tr>
<th>Return series</th>
<th>Portfolio 1</th>
<th>Portfolio 2</th>
<th>Decile 1</th>
<th>Decile 10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Portfolio 1</td>
<td>0.459</td>
<td>0.842</td>
<td>0.521</td>
<td></td>
</tr>
<tr>
<td>Portfolio 2</td>
<td></td>
<td>0.481</td>
<td>0.966</td>
<td></td>
</tr>
<tr>
<td>Decile 1</td>
<td></td>
<td></td>
<td></td>
<td>0.560</td>
</tr>
<tr>
<td>Decile 10</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 12: Correlations of Stock Portfolio Returns

Portfolio 1 and 2 are stock portfolios formed based on stock characteristics of sensitivity to systematic information, security specific information and liquidity. Decile 1 and Decile 10 stock portfolio are obtained from CRSP for NYSE listed stocks where Decile 1 represent small stocks and Decile 10 represents large stocks. P values for the tests on the correlation coefficients different from zero are all less than 0.001.
<table>
<thead>
<tr>
<th></th>
<th>Panel A: Portfolio 1</th>
<th></th>
<th>Panel B: Portfolio 2</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\beta$</td>
<td>T-Statistics</td>
<td>$\beta_i$</td>
<td>T-Statistics</td>
</tr>
<tr>
<td>$\Delta D_{t-1}$</td>
<td>-0.526***</td>
<td>-3.85</td>
<td>-0.634***</td>
<td>-4.34</td>
</tr>
<tr>
<td>$\Delta D_{t-2}$</td>
<td>-0.348***</td>
<td></td>
<td>-0.333***</td>
<td>-2.27</td>
</tr>
<tr>
<td>$\Delta D_{t-3}$</td>
<td>-0.333***</td>
<td></td>
<td>-0.158</td>
<td>-1.07</td>
</tr>
<tr>
<td>$\Delta D_{t-4}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.054</td>
<td></td>
<td>0.083</td>
<td></td>
</tr>
</tbody>
</table>

Table 13: Predictive Power of Closed-end Fund Discounts for Returns of Characteristics based Stock Portfolios

Regressions of stock portfolio returns on changes in closed-end fund discounts:

$$R_i = \alpha + \beta \Delta D_{t-1} + \varepsilon_i$$

$$R_i = \alpha + \beta \sum_{j=1}^{4} \Delta D_{t-j} + \varepsilon_i$$

Where $R_i$ represents returns of stock portfolio sorted based on stock characteristics as defined in the text and $\Delta D_t$ is change of value weighted closed-end fund discount as defined in the text.

*** Significant at the 0.01 level.
<table>
<thead>
<tr>
<th></th>
<th>(1) $\gamma$</th>
<th>$\gamma_i$</th>
<th>(2) $\gamma$</th>
<th>$\beta$</th>
<th>$\gamma_i$</th>
<th>$\beta_i$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: Portfolio 1</td>
<td>0.411***</td>
<td>0.406***</td>
<td>0.374***</td>
<td>0.337***</td>
<td>-0.400***</td>
<td>-0.537***</td>
</tr>
<tr>
<td></td>
<td>(5.94)</td>
<td>(5.76)</td>
<td>(5.41)</td>
<td>(4.74)</td>
<td>(-3.04)</td>
<td>(-3.66)</td>
</tr>
<tr>
<td></td>
<td>0.077</td>
<td>0.112</td>
<td>-0.259</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.08)</td>
<td>(1.54)</td>
<td>(-1.68)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.011</td>
<td>0.033</td>
<td>-0.254</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.45)</td>
<td>(1.65)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.008</td>
<td>0.019</td>
<td>-0.094</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.26)</td>
<td>(0.26)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.121</td>
<td>0.126</td>
<td>0.151</td>
<td></td>
<td>0.178</td>
<td></td>
</tr>
<tr>
<td>Panel B: Portfolio 2</td>
<td>-0.057</td>
<td>-0.055</td>
<td>-0.040</td>
<td>0.179</td>
<td>-0.032</td>
<td>0.195</td>
</tr>
<tr>
<td></td>
<td>(-0.62)</td>
<td>(-0.59)</td>
<td>(-0.43)</td>
<td>(1.01)</td>
<td>(-0.33)</td>
<td>(0.98)</td>
</tr>
<tr>
<td></td>
<td>0.078</td>
<td>0.052</td>
<td>-0.017</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.82)</td>
<td>(0.52)</td>
<td>(-0.08)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.006</td>
<td>-0.008</td>
<td>0.026</td>
<td></td>
<td></td>
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</tr>
<tr>
<td></td>
<td>(-0.07)</td>
<td>(-0.08)</td>
<td>(0.13)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.096</td>
<td>-0.095</td>
<td>0.021</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.03)</td>
<td>(-0.96)</td>
<td>(0.11)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.002</td>
<td>0.006</td>
<td>0.005</td>
<td></td>
<td>0.012</td>
<td></td>
</tr>
</tbody>
</table>

Table 14: Predictive Power of Fund Returns and Closed-end Fund Discounts for Returns of Characteristics based Stock Portfolios

Regressions of stock portfolio returns ($R_i$) on lagged fund returns ($R_{i-1}$) and changes in closed-end fund discounts ($\Delta D$): Regression (1) is for

$$ R_i = \alpha + \gamma R_{i-1} + \epsilon_i, \quad \text{and} \quad R_{i-1} = \alpha + \gamma \sum_{t=1}^{4} R_{i-t} + \epsilon_i. $$

Regression (2) is for

$$ R_i = \alpha + \gamma R_{i-1} + \beta \Delta D_{i-1} + \epsilon_i, \quad \text{and} \quad R_{i-1} = \alpha + \gamma \sum_{t=1}^{4} R_{i-t} + \beta \sum_{t=1}^{4} \Delta D_{i-t} + \epsilon_i. $$

*** Significant at the 0.01 level.
<table>
<thead>
<tr>
<th>Trading Period</th>
<th>Volume</th>
<th>Trade</th>
<th>Size</th>
<th>% of after-hour volume</th>
</tr>
</thead>
<tbody>
<tr>
<td>Post-close (3:45 pm-6:00 pm)</td>
<td>360</td>
<td>152</td>
<td>2.3</td>
<td>15%</td>
</tr>
<tr>
<td>Over-night (6:00 pm-6:00 am)</td>
<td>790</td>
<td>366</td>
<td>2.1</td>
<td>33%</td>
</tr>
<tr>
<td>Pre-open (6:00 am-8:15 am)</td>
<td>1232</td>
<td>550</td>
<td>2.1</td>
<td>52%</td>
</tr>
<tr>
<td>After-hour Total</td>
<td>3042</td>
<td>1081</td>
<td>2.2</td>
<td></td>
</tr>
<tr>
<td>Regular Hour Total</td>
<td>94380</td>
<td>5530</td>
<td>17.9</td>
<td></td>
</tr>
<tr>
<td>After-hour % of Total</td>
<td>3.1%</td>
<td>16.3%</td>
<td>12.3%</td>
<td></td>
</tr>
</tbody>
</table>

Table 15: Summary of S&P 500 Index Futures Trading Activity

Volume refers to the number of contracts traded and Trade refers to the number of transactions. Size is the average number of contracts per transaction.
<table>
<thead>
<tr>
<th>Trading Period</th>
<th>After Hours Session</th>
<th>Regular Hour Session</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.00081</td>
<td>-0.00032</td>
</tr>
<tr>
<td>Std Deviation</td>
<td>0.00526</td>
<td>0.01178</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.1908</td>
<td>-0.1828</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>2.9203</td>
<td>1.6992</td>
</tr>
<tr>
<td>Shapiro-Wilk Tests</td>
<td>&lt;0.0001</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>for Normality (P Value)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 16: Descriptive Statistics for S&P 500 Index Futures Open-to-close Returns: After Hour Trading Session and Regular Hour Session

<table>
<thead>
<tr>
<th></th>
<th>Post-close</th>
<th>Overnight</th>
<th>Pre-open</th>
<th>Open</th>
<th>Noon</th>
<th>Close</th>
</tr>
</thead>
<tbody>
<tr>
<td>After Hour</td>
<td>0.168</td>
<td>0.296</td>
<td>0.536</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Regular Hour</td>
<td>0.043</td>
<td>0.066</td>
<td>0.124</td>
<td>0.248</td>
<td>0.256</td>
<td>0.202</td>
</tr>
</tbody>
</table>

Table 17: Weighted Price Contribution (WPC) for Various Trading Periods in After Hours and Regular Hours

The definitions of Weighted Price Contribution (WPC) and the trading period are given in the text.
<table>
<thead>
<tr>
<th>Dependent Variables</th>
<th>$\alpha$</th>
<th>$\beta$</th>
<th>P Value</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stock close-to-open return (3:p.m.-8:30 a.m.)</td>
<td>0.0002</td>
<td>0.239</td>
<td>0.001</td>
<td>0.312</td>
</tr>
<tr>
<td>Stock close-to-open return (3:p.m.-8:35 a.m.)</td>
<td>0.0001</td>
<td>0.830</td>
<td>0.246</td>
<td>0.713</td>
</tr>
<tr>
<td>Stock close-to-open return (3:p.m.-8:40 a.m.)</td>
<td>0.0001</td>
<td>0.993</td>
<td>0.742</td>
<td>0.709</td>
</tr>
<tr>
<td>Stock close-to-open return (3:p.m.-8:45 a.m.)</td>
<td>0.0001</td>
<td>0.989</td>
<td>0.816</td>
<td>0.670</td>
</tr>
<tr>
<td>Stock close-to-open return (3:p.m.-8:50 a.m.)</td>
<td>0.0001</td>
<td>0.989</td>
<td>0.933</td>
<td>0.625</td>
</tr>
<tr>
<td>Stock close-to-open return (3:p.m.-8:55 a.m.)</td>
<td>0.0001</td>
<td>0.948</td>
<td>0.357</td>
<td>0.595</td>
</tr>
<tr>
<td>Stock close-to-open return (3:p.m.-9:00 a.m.)</td>
<td>0.0000</td>
<td>0.931</td>
<td>0.185</td>
<td>0.563</td>
</tr>
</tbody>
</table>

Table 18: After-hour Index Returns and the Regular Hour Close-to-open Returns

The results are reported for the following regression in the text.

$$ R_{s.o} = \alpha + \beta R_{f.c.o} + \varepsilon $$

Where $R_{s.o}$ is the regular hour stock index close-to-open return and $R_{f.c.o}$ is after-hour open-to-close index futures return. The t-statistics are in the parenthesis. The P value is for the joint test of $\alpha = 0$ and $\beta = 1$. 

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Panel A: Autocorrelation of three index futures return series

<table>
<thead>
<tr>
<th>Return series</th>
<th>Correlation Coefficient</th>
<th>P Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regular Hour Open-to-close</td>
<td>0.044</td>
<td>0.330</td>
</tr>
<tr>
<td>After-hour Open-to-close</td>
<td>-0.148</td>
<td>0.001</td>
</tr>
<tr>
<td>Regular Hour Close-to-close</td>
<td>0.030</td>
<td>0.512</td>
</tr>
</tbody>
</table>

Panel B: Correlation between after-hour index futures return and regular hour index futures return

<table>
<thead>
<tr>
<th>Return series</th>
<th>Correlation Coefficient</th>
<th>P Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regular hour (t-1), After-hour (t)</td>
<td>0.014</td>
<td>0.757</td>
</tr>
<tr>
<td>After-hour (t), regular hour (t)</td>
<td>0.199</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Table 19: Autocorrelation and Correlation of Index Futures Returns

P value is for the test the correlation coefficient is zero.
<table>
<thead>
<tr>
<th>Dependent Variables</th>
<th>Coefficient Estimate</th>
<th>T-statistics</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Index futures open-to-close return</td>
<td>0.438</td>
<td>4.30</td>
<td>0.038</td>
</tr>
<tr>
<td>Stock open-to-close return (8:30 a.m.-3:00 p.m.)</td>
<td>0.925</td>
<td>9.44</td>
<td>0.159</td>
</tr>
<tr>
<td>Stock open-to-close return (8:35 a.m.-3:00 p.m.)</td>
<td>0.334</td>
<td>3.53</td>
<td>0.026</td>
</tr>
<tr>
<td>Stock open-to-close return (8:40 a.m.-3:00 p.m.)</td>
<td>0.170</td>
<td>1.87</td>
<td>0.007</td>
</tr>
<tr>
<td>Stock open-to-close return (8:50 a.m.-3:00 p.m.)</td>
<td>0.175</td>
<td>1.93</td>
<td>0.007</td>
</tr>
<tr>
<td>Stock open-to-close return (9:00 a.m.-3:00 p.m.)</td>
<td>0.232</td>
<td>2.31</td>
<td>0.014</td>
</tr>
</tbody>
</table>

Table 20: The Predictive Power of After-hour Index Returns over Subsequent Regular Hour Index Futures Returns and Stock Returns

The results are reported for the following regression: \[ R_{i,o-c} = \alpha + \beta R_{f,o-c} + \varepsilon \]
For \( R_{i,o-c} \), \( i \) represents \( f \) for futures and \( s \) for stocks in the regular trading hours. \( R_{f,o-c} \) is the return during the after-hour trading period. Both returns are open-to-close returns.
APPENDIX C: FIGURES

Panel A: Timetable of S&P 500 Index Futures Trading in Regular Hours and After Hours

8:30 am  3:15 pm  3:45 pm  8:15 am  8:30 am  3:15 pm

Regular trading hour (t-1)  After-hour trading period (t)  Regular trading hour (t)

Panel B: Timetable of Stock Market Trading Hours

8:30 am  3:00 pm  8:30 am  3:00 pm

Regular trading hour (t-1)  Regular trading hour (t)

Figure 1: Timetable of S&P 500 Index Futures Trading in Regular Hours and After Hours and Timetable of Stock Market Trading Hours, all in Central Standard Time.
Figure 2: S&P 500 Index Futures Trading Volume and Number of Transactions in the After-hour Trading Period
Figure 3: S&P 500 Index Futures Trading Volume and Number of Transactions in the Regular Hour Trading Period

For the regular hour volumes, the last period is 15 minutes. We normalize it to 30 minutes.
Figure 4: S&P 500 Index Futures After-hour Open-to-close Returns

Figure 5: S&P 500 Index Futures Regular-hour Open-to-close Returns
Figure 6: Average Arbitrage Spread in the First Half-hour after Stock Market Open

Figure 7: Weighted Price Difference in the First Half-hour after Stock Market Open