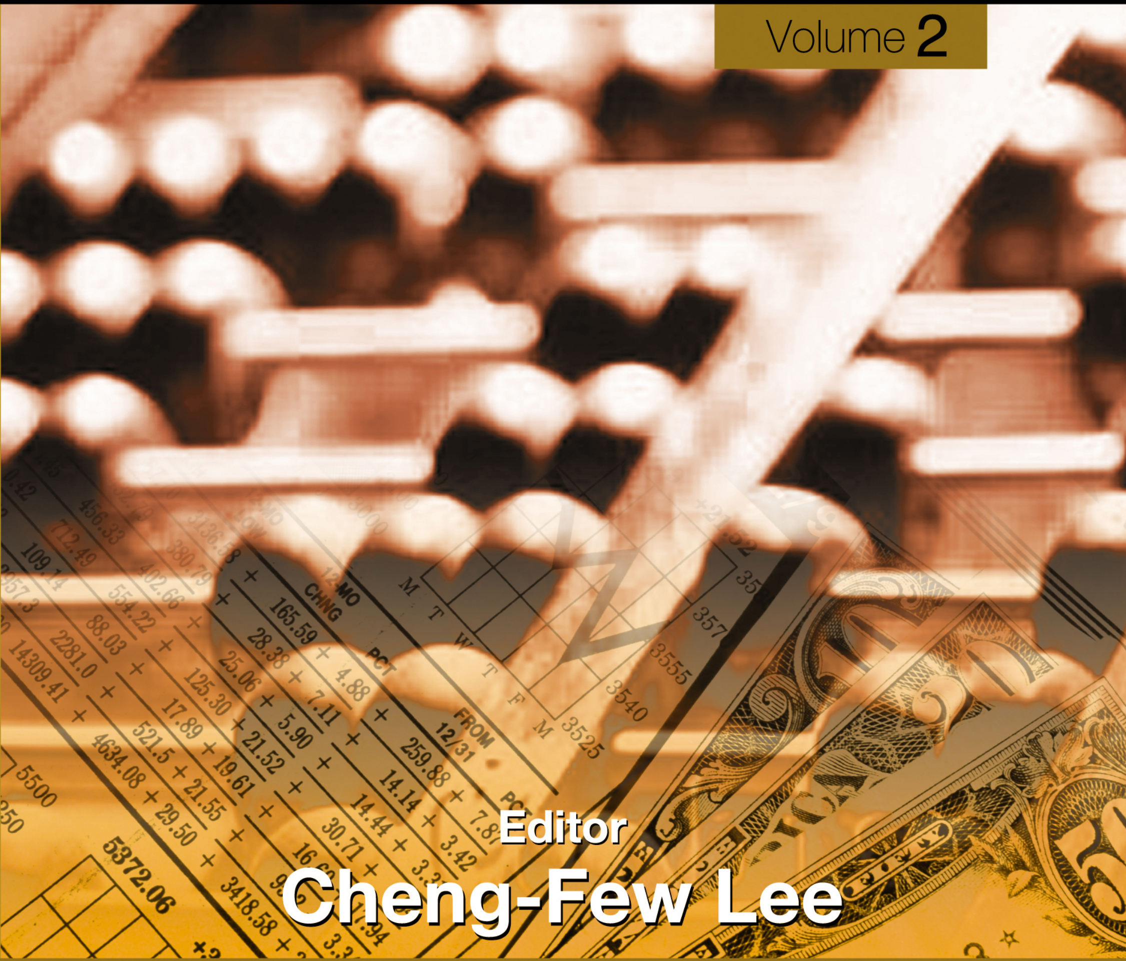
ADVANCES IN QUANTITATIVE ANALYSIS OF

# FINANCE AND ACCOUNTING

New Series

Volume 2



Editor

**Cheng-Few Lee**

World Scientific

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Cheng-Few Lee

Rutgers University, USA

World Scientific

NEW JERSEY • LONDON • SINGAPORE • BEIJING • SHANGHAI • HONG KONG • TAIPEI • CHENNAI

*Published by*

World Scientific Publishing Co. Pte. Ltd.
5 Toh Tuck Link, Singapore 596224
*USA office:* 27 Warren Street, Suite 401-402, Hackensack, NJ 07601
*UK office:* 57 Shelton Street, Covent Garden, London WC2H 9HE

**British Library Cataloguing-in-Publication Data**
A catalogue record for this book is available from the British Library.

**ADVANCES IN QUANTITATIVE ANALYSIS OF FINANCE AND ACCOUNTING (NEW SERIES) VOLUME 2**



ISBN 981-256-164-1

Typeset by Stallion Press
Email: enquiries@stallionpress.com

Printed in Singapore.

## Preface to Volume 2

*Advances in Quantitative Analysis of Finance and Accounting (New Series)* is an annual publication designed to disseminate developments in the quantitative analysis of finance and accounting. It is a forum for statistical and quantitative analyses of issues in finance and accounting, as well as applications of quantitative methods to problems in financial management, financial accounting and business management. The objective is to promote interaction between academic research in finance and accounting, applied research in the financial community, and the accounting profession.

The chapters in this volume cover a wide range of topics including derivatives pricing, hedging, index securities, asset pricing, different exchange trading, knowledge spillovers and analyst performance and voluntary disclosure.

In this volume, there are 12 chapters. Five of them are related to stock exchange trading, index securities and hedging: 1. *Intraday Trading of Island (As Reported to the Cincinnati Stock Exchange) and NASDAQ*; 2. *The Impact of the Introduction of Index Securities on the Underlying Stocks: The Case of the Diamonds and the Dow 30*; 3. *Hedging with Foreign-Listed Single Stock Futures*; 4. *Listing Switches from NASDAQ to the NYSE/AMEX: Is New York Issuance a Motive*? 5. *Using Path Analysis to Integrate Accounting and Non-Financial Information: The Case for Revenue Drives of Internet Stocks*.

Two of the 12 chapters are related to derivatives securities. 1. *Multinomial Lattices and Derivatives Pricing*; 2. *Is Covered Call Investing Wise? Evaluating the Strategy Using Risk-Adjusted Performance Measures*

The other two of the 12 chapters are related to analysts' earnings forecast: 1. *Voluntary Disclosure of Strategic Operating Information and the Accuracy of Analysts' Earnings Forecast*; 2. *CFA Designation, Geographical Location and Analyst Performance.* Finally, the other three papers are 1: *Value-Relevance of Knowledge Spillovers: Evidence from Three High-Tech Industries*; 2. *A Teaching Note on the Effective Interest Rate, Periodic Interest Rate and Compounding Frequency*; 3. *Asset Pricing with Higher Moments: Empirical Evidence from the Taiwan Stock Market.*

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Chapter 1

# Multinomial Lattices and Derivatives Pricing

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This article elaborates an $n$-order multinomial lattice approach to value derivative instruments on asset prices characterized by a lognormal distribution. Nonlinear optimization is employed, specified moments are matched, and $n$-order multinomial trees are developed. The proposed methodology represents an alternative specification to models of jump processes of order greater than three developed by other researchers. The main contribution of this work is pedagogical. Its strength is in its straightforward explanation of the underlying tree building procedure for which numerical efficiency is a motivation for actual implementation.

**Keywords:** Lattice; multinomial; derivatives; moment matching; numerical efficiency.

## 1. Introduction

Since the seminal article by Black and Scholes (BS, 1973), numerous methods for valuing derivative securities have been proposed. Merton (1973) extended the BS model to include valuing an option on a stock or index that pays continuous dividends. From this framework, the BS model was easily extended to currency options. In the case of exotic contracts where there is no closed form solution, various techniques have been elaborated including Monte-Carlo simulation, numerical integration, analytical and series approximation, jump

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The views expressed in this article are those of the authors and do not necessarily reflect the position of Fannie Mae, Santel or Wachovia Securities.

processes, and finite difference methods. Parkinson (1977) applied a three-jump model via numerical integration to the valuation of American put options. Brennan and Schwartz (1978) demonstrated that the probabilities of a jump process approximation to the underlying diffusion process correspond to the coefficients of the difference equation approximation of the BS partial differential equation. Further, they demonstrated that the trinomial tree is equivalent to the explicit finite difference method and that a generalized multinomial jump process is equivalent to a complex implicit finite difference approximation. Courtadon (1982) suggested an alternative finite difference approximation.

Cox, Ross and Rubinstein (CRR, 1979) and Rendleman and Bartter (RB, 1979) introduced the two-state lattice approach, which proved to be a powerful tool that can be used to value a wide variety of contingent claims. Jabbour, Kramin and Young (2001) generalized the standard binomial approach and incorporate the main existing models as particular cases of an alternative approach to the specification of these lattices. Geske and Shastri (1985) compared a variety of approximation methods for contingent claims valuation, including the efficiency of the binomial lattice approach and finite difference method for option valuation. A number of alternative analytical approximations for continuous time valuation were suggested by Johnson (1983), Geske and Johnson (1984), Blomeyer (1986), Macmillan (1986), Whaley (1986), Barone-Adesi and Whaley (1987), and Omberg (1987). Boyle (1986) introduced a three-jump process as a modification of the CRR model in the case of a single state variable.

Boyle (1988) extended the lattice approach to option valuation in the case of two underlying state variables. Boyle's trinomial model was based on a moment matching methodology. The mean and variance of the discrete distribution were equated to those of the continuous lognormal distribution. By introducing a numerically optimized parameter, Boyle ensured non-negativity of the risk-neutral probabilities. Further, Boyle introduced a two-dimensional five-jump process for pricing options on two underlying assets that follow a bivariate lognormal distribution. This left the three or more state variable question unanswered. The difficulties associated with the practical implementation of Boyle's model to three or more state variables were connected with ensuring non-negative risk-neutral probabilities. Boyle, Evnine and Gibbs (1989) overcame this problem by equating the moment generating function of the approximating distribution to the true normal moment generating function. This technique can be easily generalized to $k$ state variables. Kamrad and

Ritchken (1991) developed a multinomial lattice approximating method for valuing claims on several state variables that included many existing models as special cases. For example, the Kamrad and Ritchken (1991) model extended the model proposed by Boyle, Evnine and Gibbs (1989) offered some computational advantages by incorporating horizontal jump. Hull and White (1988) suggested a generalized version of the lattice approach to option pricing using a control variate technique and introduced a multivariate multinomial extension of the CRR model. Further, Hull and White (1994a, 1994b) proposed a robust two-stage procedure for one- and two-factor trinomial lattice models. Madan, Milne and Shefrin (1989) generalized the CRR model to the multinomial case to approximate a multi-dimensional lognormal process. They showed that the distribution of the discrete-time process converged to that of a one-dimensional lognormal process for a number of underlying assets, but they failed to specify the correlation structure among assets and establish convergence for general multivariate contingent claims prices. Hua (1990) solved this problem by using an alternative multinomial multivariate model.

Omberg (1988) derived a number of multinomial jump processes via pure Gauss-Hermite quadrature. The drawback to this method is that the nodes of the corresponding multinomial tree of order greater than three are not uniformly spaced (i.e., the tree is not recombining and the number of possible states increases geometrically with the number of time steps). To overcome this problem, Omberg (1988) suggested a modified Gauss-Hermite quadrature technique with uniform jumps and a lower degree of precision using Lagrangian polynomial interpolation to determine the value of the function at the Gaussian points.

Heston and Zhou (2000) investigated the rate of convergence of multinomial trees. They showed that the highest possible convergence rate for the lattice that ensures matching the first $K$ central moments of the underlying stochastic process probability distribution, $\left(\frac{1}{(\sqrt{n})^{K-1}}\right)$, can be achieved with certainty only when the payoff of the derivative valued is continuously differentiable up to order $2K$ $(C^{(2K)})$. This condition is rarely satisfied. To overcome these difficulties, Heston and Zhou (2000) proposed a smoothing and adjustment approach and implemented them on trinomial and pentanomial lattices. Alford and Webber (2001) considered numerous techniques related to convergence and processing time improvement: smoothing, and Richardson extrapolation and truncation for multinomial lattices of order $(4m-1)$, where $m$ is an integer, to achieve higher convergence rates for payoff functions with a finite set of critical points. This approach allowed one to match up to $(4m + 1)$ central moments of the underlying log-normal distribution. They concluded that the heptanomial lattice is the fastest and most accurate higher-order lattice. The focus of the last two papers was the application of multinomial trees to improve the rate of convergence of lattice methods. This was why Heston and Zhou (2000) and Alford and Webber (2001) considered numerous techniques for convergence improvement. Focusing on convergence, they considered only the lattices of orders 2, 3 and 5, and the latter — 3, 7, 11, 15, 19 etc. Working in a Black-Scholes world, they initially imposed a symmetry condition (the odd central moments are zero) on their systems and solved to match the even central moments consistent with a normal distribution. This is similar to the methodology specified in this paper.

In the Heston and Zhou (2000) and Alford and Webber (2001) papers, the methodology is not the focus and is therefore not as fully developed as in this paper. The purpose of this paper is pedagogical. It provides a step-by-step description of the moment matching technique, which is applied to develop $n$-order multinomial lattice parameterizations for a single-state option-pricing model. Thus, the underlying methodology is the focus. The remaining format of this paper is as follows. Section 2 provides a general description of $n$-order multinomial lattices. Section 3 defines the procedure when the underlying asset is described by a Geometric Brownian Motion process. Section 4 discusses practical implementation and provides numerical results. Section 5 gives conclusions.

## 2. A General Description of $n$-Order Multinomial Lattices

Consider a stochastic variable $Q$ that follows an Ito process:

$$dQ = a(Q, t)\, dt + b(Q, t)\, dz, \tag{1}$$

where $dt$ is an infinitely small increment of time, $dz$ is a Wiener process, $a(Q, t)$, $b(Q, t)$ are some functions of $Q$ and $t$ is time. In a multinomial model of order $n$, for a short period of time $\Delta t$, the variable $Q$ can move from $Q_0$ (the value at time zero) to $Q_0 + q_j$, with $j = \overline{1, n}$, where $q_j$ is a change in the value of $Q$ for time $\Delta t$ and $n$ is the number of possible jumps. The change of $Q$ for time $\Delta t$ has the following discrete distribution:

$$\{q_j \text{ with risk-neutral probability } p_j\}.$$

For a lattice approach, the first moment ($M_1$) of the distribution of the variable $Q$ is given by the following:

$$M_1 = \sum_{j=1}^{n} p_j \cdot q_j. \tag{2}$$

To apply a moment matching technique and develop an $n$-order multinomial framework, one has to equate the first $n$ central moments of the discrete lattice distribution to those of the specified continuous distribution. In order to match the first moment of the lattice approach for variable $Q$ with the first moment consistent with the underlying process, one has to set:

$$M_1 = \sum_{j=1}^{n} p_j \cdot q_j = E(Q_{\Delta t}) = m.$$

The $k$th order central moment of the lattice approach for variable $Q$ can be given as follows:

$$\tilde{m}_k = \sum_{j=1}^{n} p_j \cdot (q_j - m)^k = \sum_{j=1}^{n} p_j \cdot z_j^k,$$

where $z_j = q_j - m$. The first central moment $\tilde{m}_1$ is zero by construction, and the second central moment $\tilde{m}_2$ is set equal to the variance of the variable $Q$. To match the remaining central moments, it is necessary to specify the set of central moments of the variable $Q$ determined by the moment generating function (MGF) $M(t)$ of the underlying distribution. The central moments of the distribution can be obtained by applying a Taylor series expansion to the MGF as follows:

$$M(t) = \sum_{j=0}^{\infty} M^{(j)}(0) \frac{t^j}{(j!)},$$

where $M^{(j)}(0)$ (the derivative of $j$ order at time zero) represents the $j$ order central moment. In order to set the lattice probability distribution consistent with a specified underlying distribution, one can apply a moment matching approach by solving the following nonlinear system with respect to the unknown parameters $p_j$ and $z_j$, $j = \overline{1, n}$:

$$\tilde{m}_k = \sum_{j=1}^{n} p_j \cdot z_j^k = m_k^Q, \quad k = \overline{0,L}, \tag{3}$$

where $m_k^Q$ is the central moment of order $k$ of the continuous distribution and $L$ is the number of moments matched. In order to specify the $n$-order multinomial lattice, it is sufficient to set $n+1$ equations, that is, $L=n$. The first equation is the condition that the probabilities sum to one. The remaining $n$ equations match the first $n$ central moments of the discrete distribution to those of the continuous underlying distribution. Solution vectors $[P]=\{p_j\}_{j=1}^n$ and $[Z]=\{z_j\}_{j=1}^n$ in this case are not unique because for $2n$ unknowns there are only $n+1$ nonlinear equations. In order to determine the unique solution $\{[P],\ [Z]\}$, one has to impose additional constraints. These constraints, if feasible, will affect only the convergence speed of the lattice model.

## 3. Multinomial Lattices and Lognormally Distributed Asset Prices

In a risk-neutral world, if one assumes that the stock price $S$ follows a Geometric Brownian Motion process (GBM), then:

$$dS = rS\,dt + \sigma S\,dz, \tag{4}$$

where $r$ is the instantaneous risk-free interest rate, and $\sigma$ is the instantaneous volatility of the stock price. By using Ito's Lemma, one can show:

$$dX = \alpha\,dt + \sigma\,dz, \tag{5}$$

where $X=\ln(S)$ and $\alpha=\left(r-\frac{\sigma^2}{2}\right)$. As a result, $\ln(S)$ follows a generalized Wiener process for the time period $(0,t)$, where $t$ is a point in time. The variable $\hat{X}=X_t-X_0=\ln\left(\frac{S_t}{S_0}\right)$ is distributed with a mean of $\alpha\cdot t$, a variance of $\sigma^2 t$ and $S_0$ and $S_t$ represent the stock price at time 0 and $t$ respectively. In a multinomial model of order $n$, the stock price can move from $S_0$ to $u_j\cdot S_0$, $j=\overline{1,n}$, where $u_j$ is a proportional change in stock price for time $t$ and $n$ is the number of possible jumps. The variable $\hat{X}$ has the following discrete distribution:

$$\{q_j \text{ with risk-neutral probability } p_j\},$$

where $q_j=\ln(u_j)$. The first moment of the continuous underlying process for variable $\hat{X}$ is $E(\hat{X})=\alpha\cdot t=m$. The second moment $\tilde{m}_2$ is set equal to $\sigma^2\cdot\Delta t$. The moment generating function for a variable $R$ that is normally distributed $R\sim N(\mu,\delta)$ is given by the following:

$$M(t)=e^{\mu\cdot t+\frac{1}{2}\cdot\delta^2\cdot t^2}.$$

Because the normal distribution is symmetrical, all odd central moments are zero. For the standard normal distribution $W$,

$$M(t) = e^{\frac{1}{2}\cdot t^2} = \sum_{j=0}^{\infty} \frac{t^{2j}}{(j!)\cdot 2^j}.$$

The (central) moment of order $k$ represents the coefficient before $t^k$ in the series above multiplied by $k!$ and can be given by the following formula:

$$m_k^W = \begin{cases} 0 & \text{if } k \text{ is odd} \\ \prod_{i=1}^{k/2}(2\cdot i - 1) & \text{if } k \text{ is even} \end{cases}.$$

For example,

$$\begin{cases} m_1^W = 0;\ m_3^W = 0;\ m_5^W = 0;\ m_7^W = 0;\ m_9^W = 0;\ \text{etc.} \\ m_2^W = 1;\ m_4^W = 3;\ m_6^W = 15;\ m_8^W = 105;\ m_{10}^W = 945;\ \text{etc.} \end{cases}$$

Analogously, for the variable $R$, it can easily be shown that the central moments are given by the following:

$$m_k^R = \begin{cases} 0 & \text{if } k \text{ is odd} \\ \prod_{i=1}^{k/2}(2\cdot i - 1)\delta^k & \text{if } k \text{ is even} \end{cases},$$

and:

$$\begin{cases} m_1^R = 0;\ m_3^R = 0;\ m_5^R = 0;\ m_7^R = 0;\ m_9^R = 0;\ \text{etc.} \\ m_2^R = \delta^2;\ m_4^R = 3\delta^4;\ m_6^R = 15\delta^6;\ m_8^R = 105\delta^8;\ m_{10}^R = 945\delta^{10};\ \text{etc.} \end{cases}$$

The lattice probability distribution consistent with a normal distribution can be obtained by solving the system (3), where $m_k^Q = m_k^W$, $z_j = \frac{q_j - m}{\delta}$, $\delta = \sigma\sqrt{t}$, $j = \overline{1,n}$, $k = \overline{0,L}$.

To illustrate the moment matching methodology, consider the binomial and trinomial models. In the first case, $n = 2$, thus the first two moments should be matched. In a binomial (two jump process) model, the stock price can either move up from $S_0$ to $u \cdot S_0$ or down to $d \cdot S_0$, where $u$ and $d$ are two parameters such that $u$ is greater than one — to avoid arbitrage it is actually greater than $e^{rt}$ — and $d$ is less than one. Since the stock price follows a binomial process, the variable $\hat{X}$ has the following discrete distribution:

$$\begin{cases} \text{U with risk-neutral probability } p \\ \text{D with risk-neutral probability } (1-p) \end{cases},$$

where $U = \ln(u)$ and $D = \ln(d)$. For the binomial lattice, the system is given by the following:

$$p \cdot U + (1-p) \cdot D = \alpha \cdot \Delta t,$$
$$p(1-p)(U-D)^2 = \sigma^2 \Delta t.$$

This system of two equations and three unknowns $U$, $D$, and $p$ can be further specified as follows:

$$\begin{aligned} p_1 + p_2 &= 1, \\ p_1 w_1 + p_2 w_2 &= 0, \\ p_1 (w_1)^2 + p_2 (w_2)^2 &= 1, \end{aligned} \tag{6}$$

where $p_1 = p$; $p_2 = 1 - p$; $w_1 = \frac{(U - \alpha \Delta t)}{\sigma \sqrt{\Delta t}}$; and $w_2 = \frac{(D - \alpha \Delta t)}{\sigma \sqrt{\Delta t}}$. It should be noted that a properly specified binomial lattice always results in a recombining tree. If one imposes the additional constraint that the third central moment is zero (this is consistent with normally distributed returns and may improve the convergence of the lattice approach but is not critical for the binomial model), then

$$p_1 (w_1)^3 + p_2 (w_2)^3 = 0. \tag{7}$$

The system (6) and (7) has four equations and four unknowns $(p_1, w_1, p_2, w_2)$ and is complete. With constraint (7) the solution is trivial and unique: $p_1 = p_2 = \frac{1}{2}$, and $w_1 = -1$, $w_2 = 1$. This solution is equivalent to the specification of RB (1979) and Jarrow-Rudd (1983). As is well known, the standard binomial framework affords numerous specifications, which are fully discussed in Jabbour, Kramin and Young (2001).

For a trinomial (three-jump process) model, the system of the moment matching methodology is given by the following:

$$\begin{aligned} p_1 + p_2 + p_3 &= 1, \\ p_1 w_1 + p_2 w_2 + p_3 w_3 &= 0, \\ p_1 (w_1)^2 + p_2 (w_2)^2 + p_3 (w_3)^2 &= 1, \\ p_1 (w_1)^3 + p_2 (w_2)^3 + p_3 (w_3)^3 &= 0. \end{aligned} \tag{8}$$

The additional constraints can be imposed on the fourth and fifth moments as follows:

$$p_1 (w_1)^4 + p_2 (w_2)^4 + p_3 (w_3)^4 = C, \tag{9}$$
$$p_1 (w_1)^5 + p_2 (w_2)^5 + p_3 (w_3)^5 = 0. \tag{10}$$

In this case the complete system (8), (9) and (10) has a simple and unique analytical solution that can be obtained using pure Gauss-Hermite quadrature. The following is the parameterization of the system:

$$p_1 = p_3 = \frac{1}{2C}, \;\; p_2 = \frac{C-1}{C}, \;\; w_1 = -\sqrt{C}, \;\; w_2 = 0, \;\; w_3 = \sqrt{C}. \quad (11)$$

When one specifies the fourth moment of the lattice distribution corresponding to the fourth moment of the standard normal distribution (the kurtosis is equal to three, $C = 3$), the parameterization simplifies to the following as demonstrated by Omberg (1988):

$$p_1 = p_3 = \frac{1}{6}, \quad p_2 = \frac{2}{3}, \quad w_1 = -\sqrt{3}, \quad w_2 = 0, \quad w_3 = \sqrt{3}. \quad (12)$$

While there is no need to set the particular restrictions given by (9) and (10), which are consistent with the fourth and fifth moments of the normal distribution, these constraints should improve the convergence of the lattice approach in the case when payoff smoothness conditions (Heston and Zhou, 2000) are satisfied. For this case, the recombining condition is given by the following:

$$w_3 - w_2 = \Delta_2 = \Delta_1 = w_2 - w_1. \quad (13)$$

Therefore, the lattice consistent with the parameterization (11) recombines. Equation (10) can be considered a constraint that ensures a symmetrical lattice distribution. Parameter $C$ represents a degree of freedom. The value of this parameter will not affect convergence to the correct value but rather the rate of convergence (Heston and Zhou, 2000). It is worth noting that multinomial trees of order higher than three obtained via pure Gauss-Hermite quadrature are not recombining. This does not diminish the theoretical importance of the technique but limits it as a practical method to applying $n$-order multinomial trees.

In general, the system for the moment matching approach can be mathematically represented as follows:

$$[P]^T[W^k] = m_k^W, \quad k = \overline{0, L}, \quad (14)$$

where $[W^k] = \{w_j^k\}_{j=1}^n$, $[W^0] = \{w_j^0\}_{j=1}^n = \{1\}_{j=1}^n = [J]$ and $[J]$ is a unit vector. Analogous to (13), in order to make the $n$-order multinomial tree recombine, one may impose the following constraints:

$$\Delta_{j+1} = \Delta_j, \quad j = \overline{1, n-2}, \quad (15)$$

where $\Delta_i \equiv w_{i+1} - w_i$, $i = \overline{1, n-1}$.[1] The nonlinear system (14) and (15) can be solved with respect to $[P]$ and $[W]$ numerically.[2]

Given a proper specification of an $n$-order multinomial lattice, the value of an option can be obtained through the usual backward recursion procedure:

$$f = e^{-r\Delta t} \sum_{k=1}^{n} p_k f_k = e^{-r\Delta t} \cdot [P]^T [F],$$

where $\Delta t$ is the length of a time step, and $[F] = \{f_j\}_{j=1}^{n}$ represents the value of the option along a number of appropriate nodes of the $n$-order multinomial lattice.

## 4. Practical Implementation and Numerical Results

In this section, the practical implementation of $n$-order multinomial lattices is outlined and numerical results are provided. The first step of the approach is to determine the set of risk-neutral probabilities $[P]$ and jump parameters $[W]$. While a number of methods exist to implement this task one may minimize the following function:

$$\min_{[W],[P]} \left| [P]^T [W^K] - m_K^W \right|, \tag{16}$$

subject to constraints (14) and (15) where $K$ is the minimum even number that is greater than $n$.This nonlinear optimization procedure ensures a minimum difference between the $K$th central moment of the discrete distribution and that of the continuous distribution for the $n$-order multinomial model. While one does not have to specify this procedure to obtain the unknown tree parameters $[P]$ and $[W]$ (the satisfaction of constraints (14) and (15) and, perhaps, risk-neutral probability non-negativity constraints would be enough), the procedure (16) can accelerate convergence of the lattice approach via the output parameters. It

[1]While multinomial trees of order higher than two obtained via pure Gauss-Hermite quadrature do not recombine for the discrete-time GBM parameterization, a moment matching technique implemented through nonlinear optimization with constraints analogous to (15) does produce trees that recombine.

[2]Negative probabilities can easily be avoided by directly imposing the appropriate additional constraints: $0 \le p_i \le 1$.

is worth noting that the equality $[P]^T[W^K] = m_K^W$ cannot be always satisfied. Moreover, imposing an additional constraint:

$$[P]^T[W^I] = m_I^W, \tag{17}$$

where $I$ is the minimum odd number that is greater than $n$, causes all remaining odd central moments to be equal to zero and thus ensures a symmetrical discrete distribution.

As discussed earlier, specifications of lattices with jump processes of order greater than three obtained using pure Gauss-Hermite quadrature do not recombine. Interestingly, a four-jump process lattice developed using the numerical procedure outlined above is degenerative and reduces to a trinomial tree. Thus the four-jump process lattice is redundant. All other $n$-order lattice parameterizations examined have a unique representation in terms of this algorithm. Below, in Table 1, are the risk-neutral probabilities, $[P]$, jump parameters, $[W]$, based on a lognormally distributed asset price, and thus normally distributed returns for lattices of order two through seven.[3]

**Table 1.** Risk-neutral probabilities $[P]$ and jump parameters $[W]$.

| $[P]$ | p1 | p2 | p3 | p4 | p5 | p6 | p7 |
|---|---|---|---|---|---|---|---|
| n = 2 | 0.500000 | 0.500000 | | | | | |
| n = 3 | 0.166667 | 0.666667 | 0.166667 | | | | |
| n = 4 | 0.000000 | 0.166667 | 0.666667 | 0.166667 | | | |
| n = 5 | 0.013333 | 0.213334 | 0.546666 | 0.213334 | 0.013333 | | |
| n = 6 | 0.003316 | 0.081193 | 0.415492 | 0.415492 | 0.081193 | 0.003316 | |
| n = 7 | 0.000802 | 0.026810 | 0.233813 | 0.477150 | 0.233813 | 0.026810 | 0.000802 |
| $[W]$ | w1 | w2 | w3 | w4 | w5 | w6 | w7 |
| n = 2 | −1.000000 | 1.000000 | | | | | |
| n = 3 | −1.732051 | 0.000000 | 1.732051 | | | | |
| n = 4 | −3.464102 | −1.732051 | 0.000000 | 1.732051 | | | |
| n = 5 | −2.738608 | −1.369304 | 0.000000 | 1.369304 | 2.738608 | | |
| n = 6 | −3.189031 | −1.913419 | −0.637806 | 0.637806 | 1.913419 | 3.189031 | |
| n = 7 | −3.594559 | −2.396373 | −1.198186 | 0.000000 | 1.198186 | 2.396373 | 3.594559 |

The above table presents the risk-neutral probabilities $[P]$ and jump parameters $[W]$ for jump processes of the order two through seven. These results are based on a lognormally distributed asset price with normally distributed returns.

[3]For the pentanomial and heptanomial trees, the probabilities $[P]$ and parameters $[W]$ are slightly different from those provided by Heston and Zhou (2000) and Alford and Webber (2001) respectively because the solution of underlying system is not unique.

Once the parameters of the discrete distributions $[P]$ and $[W]$ are specified, the tree building procedure for any $n$-order multinomial lattice is analogous to that of the binomial and trinomial trees. Option values are obtained through a recursive procedure.

In Table 2, $n$-order multinomial lattices are used to price European put options on a non-dividend paying stock. The underlying stock price distribution is assumed lognormal and thus the asset returns are normally distributed. The models considered are based upon two, three, five, six and seven-jump processes respectively. The stock price is set equal to 100. The three exercise prices considered are 90, 100 and 110. The time to expiration is one-year, the risk-free rate is 5% per annum and the volatility is 30%. The numbers of time steps considered include 25, 50 and 100. Lastly, the corresponding BS values and percentage errors — with respect to BS — are provided. As seen from the

**Table 2.** European put values for jump processes of order two, three, five, six and seven.

| $X$ | Time Steps ($N$) | | 2 | 3 | 5 | 6 | 7 | Black-Scholes |
|---|---|---|---|---|---|---|---|---|
| 90 | 25 | Value | 5.3943 | 5.2432 | 5.3280 | 5.2738 | 5.3309 | 5.3081 |
| | | Error | 0.0162 | −0.0122 | 0.0038 | −0.0065 | 0.0043 | |
| | 50 | Value | 5.3378 | 5.3321 | 5.2948 | 5.2878 | 5.3043 | |
| | | Error | 0.0056 | 0.0045 | −0.0025 | −0.0038 | −0.0007 | |
| | 100 | Value | 5.3098 | 5.2994 | 5.3126 | 5.3032 | 5.3010 | |
| | | Error | 0.0003 | −0.0016 | 0.0009 | −0.0009 | −0.0013 | |
| 100 | 25 | Value | 9.4651 | 9.2700 | 9.3068 | 9.3838 | 9.3205 | 9.3542 |
| | | Error | 0.0119 | −0.0090 | −0.0051 | 0.0032 | −0.0036 | |
| | 50 | Value | 9.3211 | 9.3184 | 9.3352 | 9.3387 | 9.3413 | |
| | | Error | −0.0035 | −0.0038 | −0.0020 | −0.0017 | −0.0014 | |
| | 100 | Value | 9.3424 | 9.3404 | 9.3477 | 9.3492 | 9.3503 | |
| | | Error | −0.0013 | −0.0015 | −0.0007 | −0.0005 | −0.0004 | |
| 110 | 25 | Value | 14.7054 | 14.6176 | 14.6199 | 14.6756 | 14.6632 | 14.6553 |
| | | Error | 0.0034 | −0.0026 | −0.0024 | 0.0014 | 0.0005 | |
| | 50 | Value | 14.6192 | 14.6583 | 14.6734 | 14.6662 | 14.6566 | |
| | | Error | −0.0025 | 0.0002 | 0.0012 | 0.0007 | 0.0001 | |
| | 100 | Value | 14.6829 | 14.6602 | 14.6544 | 14.6615 | 14.6625 | |
| | | Error | 0.0019 | 0.0003 | −0.0001 | 0.0004 | 0.0005 | |

The above table presents European put values for jump processes of order two, three, five, six and seven. The steps utilized include 25, 50 and 100. Option parameters are given by the following: $S = 100$; $X = 90$, 100, 110; $r = 5\%$; $\nu = 30\%$ p.a.; $T = 1$ year. BS values and percentage errors are reported.

results in Table 2, while there is no significant improvement in convergence with increase of the order of the multinomial lattice, the option values for all considered orders converge to the benchmark (BS) prices under decreasing step size.

While it was shown by Heston and Zhou (2000) that the convergence rate for the multinomial lattice is determined by the order of differentiability of the payoff function, and that, in general, numerical efficiency of the $n$-order multinomial lattice increases with $n$, it is the processing time that is the key measure, which defines computational efficiency among models of different orders or specifications. Numerical efficiency is not the focus of this work but may be considered using the techniques delineated by Kamrad and Ritchken (1991), Heston and Zhou (2000), and Alford and Webber (2001). Thus computational burden should be the subject of future efforts.

## 5. Conclusions

This article develops an $n$-order multinomial lattice approach to price options on assets that are characterized by a lognormal distribution with normally distributed returns. In order to determine an $n$-order multinomial lattice parameterization, a moment matching technique is implemented through nonlinear optimization. The focus of the paper is pedagogical and numerical results are provided for practical implementation purposes. While the numerical results are limited to asset with prices that are lognormally distributed, future research should focus on alternative moment generating functions. This is of crucial importance as alternative return distributions may provide a rich framework for reconciling theoretical option values with actual prices.

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Chapter 2

# Value-Relevance of Knowledge Spillovers: Evidence from Three High-Tech Industries

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The objective of this study is to examine an important aspect of R&D capital — knowledge spillovers — as an explanation for the observed inconsistency between market values and book values. By tracing the linkages between inventions across time as established by patent citations, knowledge spillovers are decomposed into intraindustry, internal, and interindustry spillovers. The empirical findings from this study conclude that the intensity of knowledge spillovers is value-relevant. The results also suggest that, among the three components of spillovers, intraindustry spillovers have the strongest impact on market-to-book ratios. These results have implications on strategic R&D activities aiming to increase market values.

**Keywords:** Knowledge spillovers; intangible capital; valuation; patent.

## 1. Introduction

Publicly traded corporations are bundles of assets, both tangible and intangible, whose values are determined every day in financial markets. As such, under the efficient market hypothesis, market values of firms efficiently capitalize all the expected future benefits generated by the currently held assets. A central question in both financial and accounting research is why market values differ so dramatically across firms having similar book values reported in their balance sheets. Early efforts to account for such variations in market values across firms (and industries) focused upon market power explanations for excess profits, collusion, entry barriers (Porter, 1974; Weiss, 1974; Mueller, 1986), and efficiency differences (Carter, 1978; Mueller, 1986). However, most of the past studies on this track failed to produce conclusive evidence. Another plausible explanation is that the values of intangible capital, such as R&D, are not properly accounted for under the current accounting standards.[1] This explanation is the focus of this article.

[1] In the US, FASB requires the full expensing of R&D outlays in financial reports of public corporations. Similarly, the UK SSAP 13 and the Canadian Standard require that expenditures on pure and applied research should be written off as incurred.

Stock market valuations reflect a forward-looking viewpoint on the value of firms' future cash flows. In contrast, accounting information reflects the value of firms based on historical book values. Where intangible assets are not purchased in the market, their costs are taken to be zero. As such, the true values of these assets are not properly accounted for in both accounting statements and financial data. Not surprisingly, a decline in the value-relevance of information from financial statements is expected (Brown, Lo and Lys, 1999). Intangible assets, by definition, are nonphysical rights that are able to generate a future stream of benefits for the owner. By their very nature, they are difficult to value. In high-tech industries, such as computer, chemical and electronic/electrical, intangible assets are a major component of a firm's assets with much of them generated from R&D activities.

Based on the framework established by economists (see, for example, Griliches, 1981, 1990; Cockburn and Griliches, 1991; Megna and Klock, 1993; Hall, 1999), a few attempts have been made recently in accounting research to study how R&D capital affects the market values of firms (such as Shane and Klock, 1997; Hirschey *et al.*, 2001). Patent counts weighted by *forward* citations are a common measure of R&D output in those studies. As Trajtenberg (1990) suggests, the number of times a patent is cited by subsequent patents as measured by forward citations can reflect technological significance for both legal and economic reasons.

Most of the related studies in past literature were managed to find a positive relationship between R&D expenses and market values. The objective of this study is to examine another important component — knowledge spillovers — that may contribute to the observed inconsistency between market values and book values. In practice, spending on R&D is not the only way (even not the most important way in a fast-changing market environment) to make technological progress. Firms improve their know-how both by producing new knowledge — innovations — and by learning from others — knowledge spillovers. It is the non-rival nature of knowledge as a productive asset that creates the possibility of knowledge spillovers, whereby investment in innovations by one party produces external benefits by facilitating innovations by other parties (Jaffe *et al.*, 2000). Jovanovic and MacDonald (1994) suggest that innovations and imitations tend to be substitutes. A firm may benefit from its competitors' research efforts because extensive spillovers of knowledge facilitate intellectual exchanges between research teams (Spence, 1984; Reinganum, 1989; Cockburn and Henderson, 1994). The disclosure of new technologies in patents also allows competitors to lower the costs of research by "working around" past patents [see Nadiri (1993) for a detailed discussion].

With due reference to three global industries, namely, chemical (CHEM), computer (COMP), and electrical/electronic (ELEC), the impacts of knowledge spillovers, among other factors, on market values are examined. Akin to the idea of Jaffe *et al.* (1993) and Fung and Chow (2002), a few measures for knowledge spillovers are constructed from *backward* citations in patent statistics. Backward citations are made in the reference section of a patent to cite patents granted previously. It is important to note that backward citations are different from forward citations as the latter represent the citations received by a patent from subsequent patents. While forward citations are a common proxy in past literature for the quality of innovations, backward citations measure knowledge spillovers by forming "paper trails" of past innovations. In this study, knowledge spillovers are decomposed into intraindustry, internal, and interindustry spillovers. The impacts of these spillovers on firms' market values are examined.

The rest of this article is organized as follows. A few measures for knowledge spillovers are devised in Section 2. Section 3 then describes the data. In Section 4, a regression based on the Ohlson model is set up and the major hypotheses are specified. This is followed by Section 5 presenting the results of estimation. Finally, conclusions are drawn in Section 6.

## 2. Measuring Knowledge Spillovers

Economists have long used patent data to answer questions about the relations between technological progress and economic growth, market structures, productivity, and the like. The practice of measuring innovations by number of patents has been widely adopted. For instance, the intensity of forward citations has been used to measure the significance of innovations, and the flow of backward citations used to proxy knowledge spillovers across technological, organizational and geographical boundaries. Griliches (1990) provides a comprehensive survey for the use of patent statistics in economic research.

There have been a number of studies in economic research conducted to validate the use of patents. For example, Lanjouw and Schankerman (1999) find that the number of citations received by a patent is pertinent to the quality of the invention associated with that patent. Hall *et al.* (2000) find that the market values of firms increase with the number of citations received per patent. Validating the use of patent data is beyond the scope of this study. Indeed, the attempt is to operationalize the concept of knowledge spillovers in measuring R&D capital.

Knowledge spillovers are induced benefits that an inventor receives from innovations of others. One possible solution to measure inter-firm knowledge spillovers is to trace the linkage between two inventions across time as established by references or citations. Jaffe *et al.* (1993) offers a brief discussion on how patents are examined and relevant citations manifested. Although these citation flows come in handy when measuring knowledge spillovers, they should be used with caution. A recent survey conducted by Jaffe *et al.* (2000) shows that only about half of the patent citations truly represent the knowledge flows perceived by citing inventors themselves. In other words, only half of the total backward citations can really generate knowledge flows that are useful to the citing innovators, with the rest purely based on the judgements of patent examiners. In addition, they find a significant difference in spillover scores between actual citations and "placebo" citations.[2] Therefore, they conclude that aggregate citation flows could be used as proxies for knowledge spillovers, but the "noise" embed in those data have to be filtered out before meaningful interpretations can be made. Another way to capture knowledge flows among firms and industries is to classify firms into different technological clusters according to the technological classifications of their patents. Jaffe (1988), for instance, relies on the US Patent and Trademark Office's (USPTO) classification system to identify the proximity of firms in the technology space. Proximity between two firms measures the degree of overlap or duplication in their research interests. Hence, a relevant spillover pool pertinent to a firm can be constructed by summing up the R&D efforts of all the other firms weighted by their proximity.

[2]In the survey asking inventors about the degree of intellectual communication they have with the inventors of three previous patents. Two of these previous patents were actually cited by the surveyed inventors before. The third previous patent was a "placebo" patent that was actually *not* cited by the surveyed inventor, but which was granted in the same patent class and year as one of the actually cited patents. This placebo was not distinguished from the others in the survey questionnaire. As such, the difference in spillover scores between "actual citations" and "placebo citations" reflects the reliability of the former as a measure of knowledge spillovers.

Following the work of Fung and Chow (2002), the approach employed in this study is to look at potential knowledge pools at industry level. This is equivalent to grouping firms into different technological clusters according to the types of product they produce. A similar study has been conducted by Scherer (1981) in which he constructs an "inter-industry technology flows matrix" to examine the knowledge flows between different industries.[3] In this study, knowledge spillovers measured by backward citations are further decomposed into three separate components — intraindustry, internal and interindustry spillovers.

Intraindustry spillovers to firm $i$ in industry $j$ at time $t$ is denoted by $\mathrm{TRA}(i, j, t)$, which is the number of backward citations made by firm $i$ to the patents held by other firms in the same industry.[4] Note that firm $i$ must belong to industry $j$ in calculating $\mathrm{TRA}(i, j, t)$. Thus, $\mathrm{TRA}(i, j, t)$ measures the intensity of knowledge flows between firms within industry $j$.

Internal knowledge spillovers within firm $i$ at time $t$ is denoted by $\mathrm{INT}(i, j, t)$, which is the number of backward citations made by firm $i$ to the patents owned by itself (so-called "self-citations"). Internal spillovers could originate from the citing inventor's past research or current research in different areas. The internal spillovers measured by $\mathrm{INT}(i, j, t)$ can also be interpreted as spillovers initiated by an internal knowledge base. An internal knowledge base is the stock of firm-specific knowledge accumulated in the course of research activities. A firm retrieves past experience from its knowledge base by making citations to its past patents. Therefore, the intensity of internal knowledge spillovers also implies a firm's capability of internalizing the values of its knowledge and past experience in future research.

Finally, interindustry knowledge spillovers to firm $i$ can be derived from $\mathrm{TRA}(i, j, t)$ and $\mathrm{INT}(i, j, t)$, which is $\mathrm{TER}(i, j, t) = \mathrm{TBC}(i, j, t) - \mathrm{TRA}(i, j, t) - \mathrm{INT}(i, j, t)$, where $\mathrm{TBC}(i, j, t)$ is the total number of backward citations made by firm $i$. $\mathrm{TER}(i, j, t)$ is essentially the number of backward citations made by firm $i$ to the patents held by firms outside industry $j$, which measures the spillovers to firm $i$ from sources that are external to industry $j$. These external sources could be upstream industries that supply intermediate goods to industry $j$, or industries that produce totally unrelated products.

[3]Instead of backward citations, he uses R&D expenditures adjusted by a certain measure of technological proximity.

[4]Following the suggestion of Griliches (1990), $t$ is the year of application for firm $i$'s patents.

## 3. Data

### 3.1. *Knowledge spillovers*

Measures for knowledge spillovers are constructed by patent statistics obtained from USPTO to identify those attributes in three distinct industries: chemical (CHEM), computer (COMP), and electrical/electronic (ELEC). These industries are chosen because they are among the ones with the largest number of patents granted in the US. The list of firms in the sample is obtained from *Hoover's Online* (http://www.hoovers.com/). The NBER patent data file is not used in this study because it provides no information on specific linkages between patents and citations (see Hall *et al.*, 2001). Therefore, another data set is compiled by tracing the trails of each backward citation. Some thoughts were given to the issue of striking a balance between enlisting a reasonable representation of those industries and maintaining a manageable sample size. It is decided to confine the study to the following sub-sectors:

- CHEM: diversified chemical products,
- COMP: personal computers, large scale computers, data storage devices, computer software,
- ELEC: consumer electronics, durable electrical appliances.

The sample is composed of 224 firms: 70 in CHEM, 77 in COMP, and 77 in ELEC. The sampling period for the computation of TRA($i$, $j$, $t$), INT($i$, $j$, $t$) and TER($i$, $j$, $t$) runs from 1976 to 1997. Including non-US firms in the sample is crucial because the inventors with US origin and foreign origin respectively accounted for 58% and 42% of the total patents granted in 1997. Moreover, in the same year, the top 400 patenting firms alone accounted for 60% of the patents granted that year, while the patents obtained by the 224 firms in our sample is 19% of the total. Judging from this figure, the breadth of the sample should be large enough to generate reliable results.

Since the computation involves tracing each backward citation throughout the entire pool of patents granted to the three industries, effort is focused on the backward citations made by a subset of firms in each industry. The selection of this subset is based on Fortune 500 (1997) that ranks firms according to their revenues. As a result, 22 firms are selected from CHEM, 24 from COMP and 18 from ELEC.[5] To simplify the task further, only those backward citations

[5] They are also the most active patenting firms in the industries. The focusing on large firms may introduce selection bias in the sample, but it avoids the problematic differences in propensity to

made within the period 1983 to 1997 are searched. In order to compute TRA$(i, j, t)$, INT$(i, j, t)$ and TER$(i, j, t)$, the entire record of patents granted to industry $j$ throughout the period 1976–1997 for each backward citation made by firm $i$ from 1983–1997 are screened. The number of backward citations made within the period 1983–1997 by the 64 selected firms is 1,229,079, while the number of patents granted to the three industries (which have a total of 224 firms within the period 1976–1997) is 73,228. The screening and identification were processed with MATLAB.

Table 1 presents summary statistics of TRA$(i, j, t)$, INT$(i, j, t)$ and TER$(i, j, t)$. To allow comparison across industries, the three measures are

**Table 1.** Descriptive statistics of knowledge spillovers.

| | CHEM | | |
|---|---|---|---|
| | TRA*$(i, j, t)$ | INT*$(i, j, t)$ | TER*$(i, j, t)$ |
| Mean | 0.148 | 0.161 | 0.694 |
| Stdev | 0.092 | 0.075 | 0.116 |
| Max | 0.527 | 0.492 | 1.003 |
| Min | 0.000 | 0.000 | 0.000 |
| | COMP | | |
| | TRA*$(i, j, t)$ | INT*$(i, j, t)$ | TER*$(i, j, t)$ |
| Mean | 0.173 | 0.099 | 0.632 |
| Stdev | 0.112 | 0.111 | 0.244 |
| Max | 0.664 | 0.366 | 1.001 |
| Min | 0.000 | 0.000 | 0.000 |
| | ELEC | | |
| | TRA*$(i, j, t)$ | INT*$(i, j, t)$ | TER*$(i, j, t)$ |
| Mean | 0.113 | 0.113 | 0.783 |
| Stdev | 0.055 | 0.067 | 0.073 |
| Max | 0.214 | 0.358 | 0.901 |
| Min | 0.000 | 0.000 | 0.604 |

TRA$(i, j, t)$, TER$(i, j, t)$ and INT$(i, j, t)$ are intraindustry, interindustry and internal spillovers received by firm $i$ (which belongs to industry $j$). The sampling period runs from 1983–1997. The total number of firms is 64. For comparison purpose, these spillovers are all normalized by total spillovers [TBC$(i, j, t)$] such that TRA*$(i, j, t)$ + TER*$(i, j, t)$ + INT*$(i, j, t) = 1$. The means of TRA*$(i, j, t)$, TER*$(i, j, t)$ and INT*$(i, j, t)$ reported by the table are average values calculated across all firms and years. Standard deviations (stdev), maximum (max) and min (minimum) are defined similarly.

patent between large and small firms. Therefore, the results of estimation from this study can be interpreted as a behavioral outcome of firms in the upper hierarchy of the industries.

normalized by TBC($i$, $j$, $t$) before generating the summary statistics. Each of the normalized measures is marked with an asterisk (*).

In Table 1, all the key variables appear with a substantial amount of variations. COMP has the highest level of intra-industry knowledge spillovers, ELEC has the lowest and CHEM somewhere in between. In general, the share of knowledge spillovers that is attributable to each of the three industries' R&D activities varies from 11% to 17%. A peculiar observation in Table 1 is the large values of inter-industry knowledge spillovers, which account for over 50% of the total spillovers in each of the three industries. It is possible that these values are upwardly biased due to the limited amount of manufacturing industries in this sample. The inter-industry knowledge pool is supposedly larger for a narrow definition of industrial categories. For instance, the computer industry is narrowly defined as comprising personal computers, large-scale computers, software, and storage devices. Thus, a fairly large proportion of the knowledge spillovers shown in Table 1 is supposed to come from other closely related industries, such as semiconductors and computer electronics.

### 3.2. *Firm-specific financial data*

Market values, MV($i$, $j$, $t$), for each firm in the sample are taken from DataStream (the item code is MV). Market values of both US and non-US firms are in US dollars. Book values of common equity, BV($i$, $j$, $t$), are obtained from Compustat (item A#60). Earnings, ERN($i$, $j$, $t$), are measured by annual net sales (item A#172 in Compustat). Expenditures on R&D, RND($i$, $j$, $t$), are taken from annual income statements (item A#46 in Compustat). The whole cross-section contains the 64 firms selected in Section 3.1 for the calculations of TRA($i$, $j$, $t$), INT($i$, $j$, $t$) and TER($i$, $j$, $t$). The sampling period runs from 1983 to 1997. The panel data set is unbalanced because records of some firms in early 1980s are incomplete in either DataStream or Compustat. Some missing data, especially for many of the non-US firms, were filled up by information taken from the EXTEL database of financial statements. The total number of

**Table 2.** Descriptive statistics of financial data.

| | MV($i$, $j$, $t$) | BV($i$, $j$, $t$) | ERN($i$, $j$, $t$) | RND($i$, $j$, $t$) |
|---|---|---|---|---|
| Mean | 9703.9 | 4759.8 | 12273.5 | 663.2 |
| Median | 3282.7 | 1756.0 | 4308.6 | 189.3 |
| Standard deviation | 17154.3 | 7241.3 | 17112.6 | 1039.1 |

observations finally available for regression analyses is 668. Table 2 describes the financial data. The figures shown in Table 2 suggest that, on average, the market value of a firm is more than 100% larger than its book value. This is a typical characteristic of firms operating in high-tech industries. This inconsistency between market values and book values is also revealed by the fact that the standard deviation of $\mathrm{MV}(i, j, t)$ is about 136% larger than that of $\mathrm{BV}(i, j, t)$. That is to say, any two firms that are similar in book values could be very different in terms of market values.

## 4. Empirical Formulation — The Ohlson Model

The main hypothesis proposed in this study is that knowledge spillovers are a value-relevant intangible R&D capital. Among other factors, knowledge spillovers are able to explain the observed divergence between book values and market values. To be more specific, the excess of market values over book values is expected to be positively related to the three measures of knowledge spillovers, namely, $\mathrm{TRA}(i, j, t)$, $\mathrm{INT}(i, j, t)$ and $\mathrm{TER}(i, j, t)$. Ohlson (1995) and Feltham and Ohlson (1995) suggest that a linear model could capture the relation between market values and value-relevant events (i.e., book values, earnings and intangible capital). Therefore, a linear regression equation is constructed as follows.

$$\begin{aligned}\frac{\mathrm{MV}(i, j, t)}{\mathrm{BV}(i, j, t)} &= \Lambda + \phi\frac{1}{\mathrm{BV}(i, j, t)} + \gamma_1\frac{\mathrm{RND}(i, j, t)}{\mathrm{BV}(i, j, t)} + \gamma_2\frac{\mathrm{PAT}(i, j, t)}{\mathrm{BV}(i, j, t)}\\ &\quad + \gamma_3\frac{\mathrm{ERN}(i, j, t)}{\mathrm{BV}(i, j, t)} + \beta_1\frac{\mathrm{TRA}(i, j, t)}{\mathrm{BV}(i, j, t)} + \beta_2\frac{\mathrm{INT}(i, j, t)}{\mathrm{BV}(i, j, t)}\\ &\quad + \beta_3\frac{\mathrm{TER}(i, j, t)}{\mathrm{BV}(i, j, t)} + \varepsilon(i, j, t), \qquad (1)\end{aligned}$$

where $\varepsilon(i, j, t)$ is a white noise, $\Lambda$ is a vector of constant and industry dummies and $\mathrm{PAT}(i, j, t)$ is the total number of *successful* patent applications made by firm $i$ at time $t$. Following the suggestion of Lo and Lys (2000), all variables are normalized by $\mathrm{BV}(i, j, t)$ to control for scale effect in the valuation equation. $\mathrm{TRA}(i, j, t)$, $\mathrm{INT}(i, j, t)$ and $\mathrm{TER}(i, j, t)$ are the three measures of knowledge spillovers, namely, intraindustry, internal and interindustry spillovers. The coefficients for these three variables are all expected to be positive.

The inclusion of $\mathrm{PAT}(i, j, t)$ in the regression is necessary because bigger firms, which produce more patents per year, are more likely to cite a larger number of other patents. Moreover, both RND($i$, $j$, $t$) and PAT($i$, $j$, $t$) are included because most of the past studies find that these two variables have a modest explanatory power on market values (see, for example, Griliches, 1981; Cockburn and Griliches, 1991; Megna and Klock, 1993; Shane and Klock, 1997; Hirschiey *et al.*, 2001). In fact, they are commonly considered as the input and output measures of R&D capital, respectively. Including both of them in the regression would reveal whether investors have different perceptions for these two variables.

## 5. Results

Equation (1) is estimated by ordinary least square. The results of estimation are presented in Table 3.

Model 1 as specified in the table is the benchmark model in which book values and earnings are the only explanatory variables. In addition to the

**Table 3.** Estimation of the Ohlson model with knowledge spillovers (1983–1997, dependent variable = MV($i$, $j$, $t$), sample size = 668).

| Independent Variable | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| Time trend | 0.062** | 0.062** | 0.071** |
| | (3.975) | (3.972) | (4.441) |
| 1/BV($i$, $j$, $t$) | −57.391** | −49.664* | −46.960* |
| | (−4.011) | (−1.702) | (−1.758) |
| ERN($i$, $j$, $t$)/BV($i$, $j$, $t$) | 0.431** | 0.434** | 0.499** |
| | (25.388) | (21.982) | (23.306) |
| PAT($i$, $j$, $t$)/BV($i$, $j$, $t$) | — | 1.724** | 0.628** |
| | | (3.223) | (2.843) |
| RND($i$, $j$, $t$)/BV($i$, $j$, $t$) | — | −0.103 | −0.364 |
| | | (−0.304) | (1.051) |
| TRA($i$, $j$, $t$)/BV($i$, $j$, $t$) | — | — | 4.502** |
| | | | (2.569) |
| TER($i$, $j$, $t$)/BV($i$, $j$, $t$) | — | — | 0.830** |
| | | | (3.688) |
| INT($i$, $j$, $t$)/BV($i$, $j$, $t$) | — | — | −1.785 |
| | | | (1.351) |
| Adjusted R-square | 0.773 | 0.874 | 0.889 |
| $F$-statistic | 1146.214 | 1530.353 | 704.922 |
| Durbin-Watson | 1.987 | 1.986 | 2.041 |

Coefficients for constant and industry dummies are not reported.
Values in parentheses are $t$-statistics.
∗ significant at 5% level.
∗∗ significant at 1% level.

basic financial variables included in Model 1, patent counts and R&D expenditures enter the regression in Model 2. In Model 3, the three measures of knowledge spillovers, namely, intraindustry, internal and interindustry spillovers, are included to test for their value-relevance. One can see that the positive coefficient for earnings (ERN) is robust across the three models.

Model 2 conditions on R&D capital by including patent counts [PAT($i$, $j$, $t$)] and R&D spending [RND($i$, $j$, $t$)]. The estimated coefficient is positive and significant for PAT($i$, $j$, $t$), but insignificant for RND($i$, $j$, $t$). In other words, in the presence of an output measure, the input measure appears to be insignificant in determining market-to-book ratios. In Model 3 where the estimated coefficient of PAT($i$, $j$, $t$) remains positive, RND($i$, $j$, $t$) remains insignificant. The insignificance of RND($i$, $j$, $t$) here is not compatible with the findings in past literature, such as Chan *et al.* (1990), Lev and Sougiannis (1996) and Sundaram *et al.* (1996). There are two possible explanations. First, large firms that invest more heavily in R&D activities tend to obtain a larger number of patents. Therefore, the correlation between PAT($i$, $j$, $t$) and RND($i$, $j$, $t$) may be high enough to pose the problem of multicollinearity.[6] Second, output is considered by investors as more important than input in assessing the future profitability of R&D due to the typically low rates of success for innovative activities. The second explanation is supported by Hirschiey *et al.* (2001) who find that the valuation effects tied to R&D expenditures diminish when technologies are changing rapidly. In addition, as the Generally Accepted Accounting Principles (GAAP) requires the full-expense-as-incurred treatment of R&D expenditures in financial statements, an increase in these expenditures means a lower profit reported in the same period.

Model 3 demonstrates the importance of knowledge spillovers in determining the market values of firms. The estimated coefficients for intra- and inter-industry spillovers are positive and significant. In particular, the face values of the estimates suggest that interindustry spillovers have a stronger impact than intraindustry spillovers on market-to-book ratios. In other words, intraindustry spillovers coming from other firms conducting similar (or even competing) research inside the industry are valued higher by investors than those coming from firms outside the industry. This finding is reasonable

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[6] If both ERN($i$, $j$, $t$) and PAT($i$, $j$, $t$) are discarded from Model 2, the estimated coefficient for RND($i$, $j$, $t$)/BV($i$, $j$, $t$) becomes 1.236 ($t$-statistic = 2.741).

because intraindustry spillovers are presumably more direct and visible to investors than interindustry spillovers. The insignificance of internal spillovers is also interesting, since it implies that “self-learning” or the development of stand-alone technologies is not an effective way to attract investors in high-tech industries. This is particularly true for firms operating in high-tech industries characterized by fast-changing technologies and short product life cycles. In addition, the unstable hierarchy of technology leaders (as suggested by Malerba and Orsenigo, 1995) and frequent technological shocks in these industries imply that technology laggards can survive better by standing on rivals’ shoulders than by relying on their own internal knowledge base. In the personal computer industry, for instance, Intel’s microprocessors and Microsoft’s operating systems coordinate with one another to optimize the performance of IBM’s platform. On the contrary, Apple’s Macintosh is a “closed system”. Apart from the programming of the operating system, Apple also produces the hardware architecture in-house. This closed system employed by Apple is relatively slow in turning out hardware and software improvements.

The magnitude of the impact of knowledge spillovers on market-to-book ratio as indicated by the estimated coefficients are rather conservative because a large number of backward citations are purely due to the judgements of patent examiners that have nothing to do with knowledge spillovers. A survey conducted by Jaffe *et al.* (2000) finds that only about half of the backward citations truly represent knowledge flows perceived by citing inventors. Based on the results of their survey, the valuation impact tied to the “true” knowledge spillovers could be at most 100% larger than that as indicated by the estimated coefficients.[7]

From the empirical findings of this study, it is clear that scientific information concerning knowledge spillovers could sharpen investors’ perception about the on-going values created by firms’ innovative activities. Consequently, strategic R&D activities, such as technology transfers, research collaborations, licensing agreements, and the like, would be effective ways to increase the market values of high-tech firms. To this end, the measures for knowledge spillovers devised in this study, when used in conjunction with other measures

[7] For instance, let $\mathrm{TRA}^{\mathrm{R}}(i, j, t)$ be the “true” amount of intraindustry spillovers. If only half of the backward citations can truly represent knowledge spillovers perceived by the citing firms, then $\mathrm{TRA}^{\mathrm{R}}(i, j, t) = \mathrm{TRA}(i, j, t)/2$. Thus, $\beta_1 \mathrm{TRA}(i, j, t) = 2\beta_1 \mathrm{TRA}^{\mathrm{R}}(i, j, t)$.

of R&D capital, would allow investors to judge more comprehensively the economic merits of firms' R&D efforts.

## 6. Conclusions

The objective of this study is to examine an important aspect of intangible R&D capital — knowledge spillovers — as an explanation for the observed inconsistency between market values and book values of firms. Knowledge spillovers are induced benefits that an inventor receives from innovations of others. The solution adopted in this study to measure knowledge spillovers is to trace the linkages between inventions across time as established by backward citations. As such, knowledge spillovers are decomposed into intraindusry, internal, and interindustry spillovers. The empirical findings from this study conclude that the intensity of knowledge spillovers and market values are positively related. Among the three components of knowledge spillovers, the results also suggest that intraindustry spillovers have the strongest impact on market-to-book ratios.

This study demonstrates possible ways to make the concept of knowledge spillovers operational in measuring R&D capital. Knowledge spillovers are tremendously important to high-tech firms operating in a dynamic, fast-changing market environment. In such an environment with relatively short product life cycles, efficient spillovers of knowledge between firms allow them to make timely deliveries of innovations. Most of the related studies in past literature are focused on measuring the input and output components of R&D capital with the use of R&D expenditures and patent counts. Apart from these two components, this study shows that the extent of knowledge spillovers is another important one. Further research may reveal other important components that also have an influence upon market values, such as scope of research and inter-firm research overlap. Information contained in patent statistics may be useful in identifying these components.

## Acknowledgments

Work described in this article was supported by the Departmental Research Grant (G-T266) at Hong Kong Polytechnic University. The author is indebted to colleagues at the Department of Economics, Hong Kong University of Science and Technology, for their helpful technical supports and comments.

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Chapter 3

# Using Path Analysis to Integrate Accounting and Non-Financial Information: The Case for Revenue Drivers of Internet Stocks

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This paper utilizes path analysis, an approach common in behavioral and natural science literatures but relatively unseen in finance and accounting, to improve inferences drawn from a combined database of financial and non-financial information. Focusing on the revenue generating activities of Internet firms, this paper extends the literature on Internet valuation while addressing the potentially endogenous and multicollinear nature of the Internet activity measures applied in their tests. Results suggest that both SG&A and R&D have significant explanatory power over the web activity measures, suggestive that these expenditures represent investments in product quality. Evidence from the path analysis also indicates that both accounting and non-financial measures, in particular SG&A and pageviews, are significantly associated with firm revenues. Finally, this paper suggests other areas of accounting research which could benefit from a path analysis approach.

**Keywords:** Path analysis; Internet; simultaneous equations; accounting; marketing; R&D spending.

## 1. Introduction

Prior academic literature on the relevance of accounting and non-financial statement measures for Internet firms has generally focused on explaining their stock valuations. In the absence of clear relationships between earnings and these valuations, analysts, corporate insiders and researchers have concentrated their attention on other measures for explaining their valuations. These include focusing on earnings components, such as revenues and gross margin, and non-financial proxies for market share and potential future growth opportunities, such as unique audience and pageviews. With the exception of an examination of revenue forecast errors by Trueman, Wong and Zhang (2001b), however, there has been little research attempting to explain how these activity measures are generated or into their effect on firm revenues, which is addressed in this paper.

Kozberg (2001) discusses how a better understanding of the relationships among accounting and non-financial measures for Internet firms should help improve the identification of value drivers and the means by which they are specified. Figure 1 (replicated herein) provides a conceptual path diagram from initial management decisions on the levels of SG&A and R&D expenditures through to revenue realization for firms which rely upon website activity. This paper refines the path diagram and uses it to test whether firm expenditures on SG&A and R&D translate into measures reflecting increased consumer activity and whether said activity results in improved revenue opportunities for the firm.

In addition, Kozberg (2001) illustrates the hazards of testing a sample of heterogeneous firms involved in the Internet (distinguished by their business models) as one collective sample. Heterogeneity is only one of several statistical issues that can arise regarding current methodologies for testing these or other developing firms, however. For instance, little attention has been paid by the existing literature to the likely relationships among the accounting and non-financial variables used to explain firm valuations. Finally, Kozberg (2001) shows evidence of high multicollinearity among the internet activity measures for Internet firms in general and for distinct types of Internet firms. One method employed in that paper and in Demers and Lev (2001) is factor analysis, which replaces raw or deflated Internet usage measures with a smaller set of orthogonal factors. This approach, however, allows the data to determine the factors and is inevitably followed by a researcher's ad hoc attempt to interpret the factors. In addition, the choice of factors is highly sensitive to the combination of variables chosen and the approach taken in calculating them.[1]

While high degrees of correlation and endogeneity are not the same thing, this relationship suggests that some or all of these variables could be endogenous, violating an assumption made in OLS estimation. Treating these variables as exogenous when they are in fact endogenous could result in a number of statistical problems including measurement error and bias. Ideally, these factors should be specified *ex ante*, while still providing the researcher with the ability to control for variable endogeneity.

The methodology employed in this paper is based upon a path analysis estimation technique first used by Wright (1921). Commonly employed in the behavioral and natural sciences literatures, this approach allows a researcher to address issues of factor identification and endogeneity simultaneously. In addition, it permits separate testing of the direct and indirect (through intermediate

[1] For instance, Demers and Lev (2001) choose the almost perfectly correlated reach and unique audience as factor components in their model. This choice influences their first factor to load predominately on these two variables.

variables) effects of the selected independent variables on the dependent(s). Path analysis is based upon a diagram of the hypothesized relationships among the independent and dependent variables. In the analysis, the variables examined are classified into two types, exogenous or endogenous, based upon whether or not they appear as dependent variables in any of the system of equations. Among the variables employed in this study, expenditures on R&D and SG&A are treated as exogenous while website activity measures and revenues are endogenous.[2] The path diagram is presented in Figure 2, an expanded version of Figure 1, which specifies empirically testable relationships among the data. In Figure 2, single arrows indicate the predicted direction of causation from the exogenous to the endogenous variables.

Empirical testing of this path diagram provides several interesting results regarding the use of non-financial data in the analyses of Internet firms. Consistent with findings in Kozberg (2001), accounting data on firm expenditures in SG&A and R&D have explanatory power over both website activity measures and firm revenues. R&D, a proxy for investments made to develop website quality, reduces the amount of time an individual needs to spend visiting a firm's website. SG&A, which should proxy for efforts to increase website activity levels, is positively and significantly related to the average time spent and number of visits per person for financial services and online retailing firms. It is also positively and significantly related to time spent per person for portal and content-community firms.[3] Consistent with expectations, both SG&A and R&D are positively and significantly related to the number of unique audience members visiting the site within a month. Finally, SG&A is positively and R&D is negatively and significantly associated with firm revenues, with the latter relationship appearing to be driven by financial services and online retailing firms. These results indicate that at least some portion of firm expenditures on SG&A and R&D are directed towards improving website quality and visitor activity.

[2]The path analysis methodology presented in this paper could be easily adapted to other areas of accounting research. In particular, it could be used to improve measurement of other variables by decomposing components or effects of accounting and non-financial data. For instance, evidence from this and other papers suggests that expenditures on SG&A and R&D might be regarded as investments and should therefore be capitalized. Path analysis could help address issues like how best to capitalize these investments.

[3]Portals and content-community firms, often regarded as only one segment of the Internet, are those sites which focus on providing news and other information, searching services, and/or a place to interact with others online. For a more detailed explanation of the types of firms involved in the Internet, I refer the reader to Kozberg (2001).

Internet activity measures are systematically related to firm revenues as well. As unique audience and time spent per person increase, so do pageviews. Pageviews have the direct effect of increasing firm revenues in addition to increasing the amount of advertising shown. This direct effect on revenues is most likely the result of the ability of pageviews to proxy for other, non-advertising, revenue opportunities which are associated with greater site activity (e.g., the use of mailing lists and user profiling for portal and content-community firms and increased transactions for financial services or online retailing firms). Finally, while initial results for advertising data do not show explanatory power over revenues, alternative tests provide evidence that click-through rates on advertisements shown are positively and significantly associated with firm revenues.

This paper includes seven sections. Section 2 provides a brief review of the relevant literature. Section 3 details the data collection process and provides summary statistics for the variables. Section 4 describes the path analysis methodology employed. Sections 5 and 6 give the initial and expanded results from empirical testing, respectively. Section 7 summarizes the findings and provides suggestions for future testing.

## 2. Literature Review

A number of recent papers have attempted to value Internet firms using a combination of accounting and non-financial measures. Hand (2000a, b), Trueman, Wong and Zhang (TWZ, 2001a), Rajgopal, Kotha and Venkatachalam (RKV, 2000) and Demers and Lev (2001) provide evidence that Internet firms' earnings are generally not priced (or in some cases negatively priced). In the absence of positive and significant results for net income, several of these earlier papers attempt to use earnings components such as revenues to explain firm valuations. The evidence from those studies is generally mixed, with revenues, marketing expenses (a component of SG&A) and R&D all showing some signs of being positively and significantly valued. Results from Kozberg (2001), which includes more recent data than prior studies, provides evidence that net income has become positively priced for Internet firms in general and for most business models over time. In addition, SG&A and R&D both show stronger evidence of being positively and significantly priced for the overall sample as well as most individual business models. Finally, non-financial measures such as reach, pageviews and advertisements are shown to be priced for Internet firms in general. None of these papers, however, make any attempt at directly examining the determinants of activity and the ability of firms to convert that activity into revenues.

Trueman, Wong and Zhang (TWZ, 2001b) utilize current financial and non-financial data in the prediction of Internet firm revenues, which it suggests are a key driver in the valuation of these firms.[4] It focuses on the types of firms for which one would *ex ante* expect web activity measures to have relevance: portal, content-community and online retailing. TWZ (2001b) examines how well different accounting and Internet usage variables correlate with analysts' forecast errors (measured in percentages). It finds that analysts systematically underestimate revenue growth from 1999 to early 2000. Growth rates in historical revenues and Internet usage seem to have power in explaining these errors for portal and content-community firms, while growth in Internet usage is significant in explaining errors for online retailers. While TWZ (2001b) examines the relationship between revenue estimates and their realized values, it does not examine the usefulness of accounting or non-financial information in explaining either analysts forecasts or realized revenues directly. If the influences of the web activity measures are already accurately impounded into the revenue estimates made by analysts, then these measures should have little or no ability to explain errors.

Given the availability of Internet activity data from several sources (Nielsen//NetRatings, Media Metrix and PC Data) on a monthly or even weekly basis, it is not surprising that the explanatory ability of the tests conducted in TWZ (2001b) are somewhat low ($R^2$s of 0.15 or less). In addition, given the emphasis placed on the importance of revenue growth for Internet firms, these firms may attempt to influence their reported numbers through such activities as the inclusion of "grossed-up" and/or barter revenues as discussed in Bowen, Davis and Rajgopal (2001). Over a long enough time horizon, such adjustments would naturally reverse and/or lead to a higher denominator used for the calculation of revenue growth (implying a negative correlation between past growth and the error). However, over the shorter time horizon examined in TWZ (2001b), it may be possible for management to continue to manipulate revenues in this fashion. These management actions could result in the systematic underestimating of revenues that TWZ (2001b) document.

[4]Justification for their usage of audience measurement data comes from the suppositions that: (1) higher usage reflects greater demand for products and services; (2) increased traffic leads to greater advertising revenues; and (3) higher usage brings in more advertisers and, at least indirectly, higher advertising rates.

With the exception of TWZ (2001b), no previous research has examined the ability of either financial or non-financial data to explain other fundamental economic data than Internet firm valuations. This paper extends upon the previous literature by examining the financial and non-financial determinants of firm revenue, while addressing the endogenous and multicollinear nature of these measures.

## 3. Data Collection

Table 1 provides a breakdown of the number of firms and observations in the samples studied in this paper. Unlike Kozberg (2001) but consistent with most other papers in the Internet literature, this paper restricts its focus to firms with positive levels of Internet activity. This is done in order to restrict the sample to firms that are dependent on web activity for revenues, for which the hypothesized path diagram is more likely to be a reasonable description. Accounting data for these firms comes from Compustat for quarters ending in 1999 through March 2001.

The top rows of Table 2 provide descriptive financial statistics for these Internet firms. The average (median) market value of these companies is \$3.21 billion (\$464 million) and average (median) revenues are about the same at \$80 million (\$17.1 million). Mean (median) net income is −\$66.9 million (−\$14.9 million) and the market-to-book ratio is 8.48 (2.99).[5] These descriptive statistics are consistent with the larger sample examined in Kozberg (2001).

**Table 1.** Sample breakdown.

| | |
|---|---|
| Firms in initial sample | 332 |
| Firms (observations) with complete accounting data | 317 (2049) |
| Firms (observations) also with data reported in the NNR audience database | 129 (583) |
| Firms (observations) with advertising data as well | 86 (373) |

[5]Market values and net income are presented for descriptive purposes only and are not used in any tests in this paper. Similarly, book value is not used, therefore the constraint that firms have a book value over 0 is not necessary (leading the market-to-book ratio to be negative for some observations and biasing the ratio lower relative to the full sample in Kozberg, 2001).

**Table 2.** Descriptive statistics.

| Variable | N | Mean | Median | Std Dev | Min. | Max. |
|---|---|---|---|---|---|---|
| Market value | 583 | 3215.90 | 464.38 | 12651.94 | 0.40 | 17140.2 |
| Market-book | 582 | 8.48 | 2.99 | 41.36 | −45.64 | 900.01 |
| Net Income | 583 | −66.86 | −14.90 | 330.49 | −5426.3 | 1178.0 |
| Sales | 583 | 80.01 | 17.10 | 406.06 | 0.00 | 6830.0 |
| SG&A | 583 | 38.06 | 21.38 | 54.63 | 0.00 | 425.00 |
| R&D | 583 | 4.86 | 1.50 | 12.06 | 0.00 | 159.72 |
| Unique audience | 583 | 3.03 | 0.96 | 5.14 | 0.10 | 44.56 |
| Reach | 583 | 2.36 | 0.78 | 4.24 | 0.07 | 37.38 |
| Pageviews | 583 | 69.89 | 13.87 | 177.91 | 0.27 | 1698.13 |
| Time spent per person | 583 | 0.19 | 0.15 | 0.13 | 0.02 | 0.86 |
| Visits per person | 516 | 2.04 | 1.75 | 0.99 | 1.03 | 6.24 |
| Ad impressions | 377 | 85.71 | 16.52 | 191.37 | 0.14 | 1821.05 |
| Click-throughs | 377 | 0.15 | 0.02 | 0.47 | 0.00 | 7.12 |

The Internet activity data for this study are taken form Nielsen// NetRatings "Audience Measurement" and Bannertrack™ databases from February 1999 through May 2001. The data employed include:[6]

- Unique Audience (UNQAUD) — Defined as the number of different individuals visiting a website within the month. In practice, this measure can only detect the number of unique web browsers rather than unique visitors.
- Reach (REACH) — This figure represents the percentage of Internet users that visit a particular web property within a month.
- Pageviews (PAGEVIEW) — In the NNR database, pageviews refers to the total number of pages seen by all users in the sample, regardless of the means by which they are viewed.
- Visits per person (VISITSPP) — Indicates the number of different times an average audience member visits a particular property within a month. NNR does not begin reporting this statistic until August 1999.
- Time spent per person (TIMEPP) — Indicates the total amount of time an audience member spends at a property over the month.
- Advertisements served (ADSEEN) — The total number of *delivered* ad impressions each month across all reported domains for a given property. NNR does not begin reporting this statistic until May 1999.

[6]In tests conducted using advertising data, the time period examined begins in May 1999 rather than February 1999. For a more detailed explanation of the databases and a longer description of terms, I refer the reader to Kozberg (2001).

- Click-throughs (CLICKS) — The number of advertisements shown that are clicked upon by the browser. NNR does not begin reporting this statistic until May 1999.

Descriptive audience statistics for these variables are provided in the lower rows of Table 2.[7] The average firm reaches about 2.36% of the estimated population of internet users in the US while the median firm enjoys an audience only one-third as large. These data suggest that there are a small number of firms which dominate the internet in terms of their market share of unique browsers. The average (median) user makes 2.04 (1.75) trips to a given property each month spending a total of 0.19 (0.15) hours.[8] These firms show an average (median) of 69.9 (13.9) million pages carrying 85.7 (16.5) million ads but only 0.15 (0.02) million of these ads were clicked upon. As a result, firms that are able to deliver a high volume of click-throughs could command a premium in the marketplace. On the other hand, if advertising dollars on the net are more focused upon enhancing brand value (similar to more traditional media), click-throughs may have a negligible impact on firm revenues.

## 4. Methodology

This section presents an alternative approach for examining the interrelated nature of the accounting and non-financial variables used in the valuation of Internet firms. Figure 1, recreated from Kozberg (2001), specifies a hypothetical path for web-activity-dependent firms from start-up to revenue generation. This paper expands upon Figure 1 to develop a more detailed, empirically testable, path diagram.

Conceptually, management initiates expenditures on R&D, intending to establish (or enhance) a website's quality. The potential effects of this spending may offset one another, however. Increased site quality should improve a

[7] The differences in the number of observations in this sample and those in the "web sample" in Kozberg (2001) result from slight differences in the matching and truncation criterion employed in this study. Observations are matched based upon the final month of the firm quarter in question rather than the month a firm announces earnings. Observations more than three standard deviations from the mean are removed.

[8] Kozberg (2001) showed an almost order of magnitude difference between the means and medians for time spent online as well as considerably larger means than medians for other activity measures as well. Due to the greater need to control for outliers using a path analysis framework this relationship has been considerably mitigated.

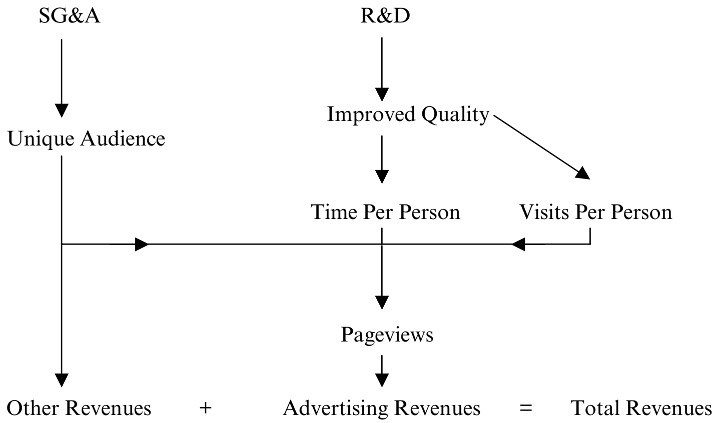


**Figure 1.**

firm's ability to retain viewers, which can be proxied for by the amount of time spent and the number of visits made per person to its websites. On the other hand, website R&D expenditures could be focused upon aspects of quality such as improved delivery times (lowering the average time spent online) rather than on adding further content (potentially increasing time online). Regardless of the means by which quality improves, however, the websites should generate larger audiences as the result of improved brand recognition and from reputation effects.

In addition to spending on R&D, firms may choose to engage in major advertising campaigns and other promotions (SG&A) designed to attract new visitors to their websites. These increases in audience should improve the quantity of user-generated content. It should also allow more opportunities for members to develop into communities with those possessing similar interests. As a result, increased SG&A could have the secondary effect of encouraging existing members to use their websites more frequently. Overall, expenditures on SG&A should enhance the "network effects" from having more users online with whom to interact and share information.[9]

As audience increases so does the total number of pages viewed, increasing advertising revenue opportunities for the firms. In addition, pageviews should

[9]Noe and Parker (2000) show analytically that two Internet firms, competing in a two-period, winner take all model, will advertise aggressively and make large investments in site quality in order to capture market share. Under this model, any variables that are (linearly) related to pageviews should be explained, although not necessarily in a linear fashion.

increase as individual audience members visit and/or spend more time at a website. Increased pageviews translates into more opportunities for firms to deliver advertisements or other forms of sponsored content to their viewers. Naturally, increases in the number of delivered advertisements leads to additional chances for browsers to click-through to the website of an advertiser. On the other hand, as time spent per person increases, browsers are more likely to have seen the same advertisements previously or already viewed those advertised sites reducing their likelihood of clicking-through.

Apart from their impact on the quantity of advertisements shown, increased audience and pageviews could also generate an improved ability to target content and promotions to their viewers which could further increase advertising revenues. Additionally, audience, pageviews, SG&A and R&D could all influence firm revenues directly, proxying for other revenue opportunities such as: (1) online or offline sales of goods and services; (2) the creation and use of mailing lists; (3) alliances; and/or (4) services rendered and content delivered for other sites.

Building upon the logic contained in Figure 1, the methodology used for estimation in this paper focuses on path analysis, a statistical technique based upon a linear equation system that was first developed by Wright (1921). While uncommon in the financial accounting literature,[10] it has been utilized frequently in the behavioral and natural sciences literatures. Path analysis' popularity in those literatures results from its explicit recognition of possible causal relationships among variables. In so doing, it enables the researcher to decompose the correlations between each pair of variables into the different effects that flow from the causal variable(s) to the dependent variable. These effects may be either direct (e.g., increased audience should lead directly to more individuals seeing a site's webpages) or channeled indirectly through other variables (increased audience directly leads to increased pageviews and indirectly causes more advertisements to be seen). Thus one may examine both the direct and various indirect effects of firm expenditures and activity generation measures and assess the impact of each.

This focus on intermediate pathways along which these effects travel makes the application of this technique particularly appealing for Internet firms.

[10]An example of the application of path analysis in the accounting literature is Amit and Livnat (1988), which examines the direct and indirect effects of diversification, operating risk and leverage on a firm's systematic risk.

As discussed previously, understanding the path from firm expenditures to revenue creation provides a clearer understanding of what may be driving the value of Internet firms. The analysis begins with a path model that diagrams the expected relationships among the independent and dependent variables. It should be noted, however, that the pathways in these models represent the hypotheses of researchers, and cannot be statistically tested for the direction of causality. Figure 2 provides a more developed version of Figure 1 expressed as a path diagram. In path analysis, the variables examined are broken into two types, exogenous or endogenous, based upon whether or not they appear as dependent variables in any of the system of equations. Among the variables employed in this study, expenditures on R&D and SG&A are treated as exogenous while site activity and revenues are endogenous.

In the main model tested there are four exogenous variables, SG&A and R&D deflated by *both* total firm assets and unique audience (per-person). In any particular equation tested, however, only one of the two deflated sets of variables is used. The decision as to which set to use is based primarily, but not

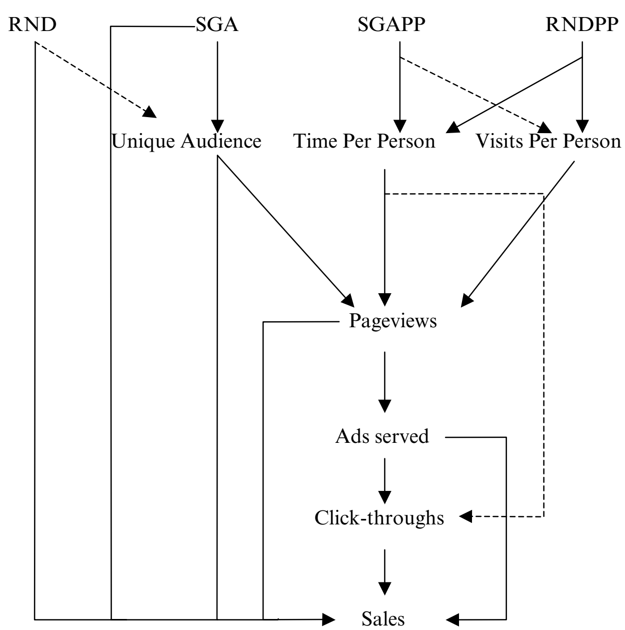


**Figure 2.** Path analysis diagram. Solid and dashed arrows both indicate the predicted direction of causality between any two variables. Please see the Appendix for an explanation of these variables.

exclusively, upon which deflator is employed for the dependent variable. The choice of this specification is also intended to avoid unnecessary transformation of the data from its reported format, to allow easier interpretability of the results and to avoid introducing competing effects into the data. In Figure 2, single arrows indicate the predicted direction of causation from the exogenous to the endogenous variables that is suggested from the earlier discussion in this section.

The coefficients generated in a path analysis are standardized regression coefficients (betas), showing the direct effect of an independent variable on its dependent variable in the path diagram. Thus, when the model has two or more causal variables, path coefficients are partial regression coefficients that measure the extent of the effect of a causal variable and its dependent in the path model controlling for other prior variables. The path analysis typically uses standardized data or a correlation matrix as an input. In terms of its practical application, the path analysis amounts to the following system of simultaneous equations, processed iteratively.[11]

$$\text{UNQAUD} = \beta_{11}\text{SGA} + \beta_{13}\text{RND} + \varepsilon_1, \tag{1a}$$

$$\text{TIMEPP} = \beta_{22}\text{SGAPP} + \beta_{24}\text{RNDPP} + \varepsilon_2, \tag{1b}$$

$$\text{VISITSPP} = \beta_{32}\text{SGAPP} + \beta_{34}\text{RNDPP} + \varepsilon_3, \tag{1c}$$

$$\text{PAGEVIEW} = \beta_{45}\text{TIMEPP} + \beta_{46}\text{VISITSPP} + \beta_{47}\text{UNQAUD} + \varepsilon_4, \tag{1d}$$

$$\text{ADSEEN} = \beta_{58}\text{PAGEVIEW} + \varepsilon_5, \tag{1e}$$

$$\text{CLICKS} = \beta_{65}\text{TIMEPP} + \beta_{69}\text{ADSEEN} + \varepsilon_6, \tag{1f}$$

$$\begin{aligned}\text{SALES} = {} & \beta_{71}\text{SGA} + \beta_{73}\text{RND} + \beta_{75}\text{TIMEPP} + \beta_{76}\text{VISITSPP} \\ & + \beta_{77}\text{UNQAUD} + \beta_{78}\text{PAGEVIEW} + \beta_{79}\text{ADSEEN} \\ & + \beta_{710}\text{CLICKS} + \varepsilon_7. \end{aligned} \tag{1g}$$

Variables ending in "PP" are deflated by unique audience. All other measures are deflated by the total assets of the firm. Per-person measures are used for time spent online and visits as these are the variables reported on NNR and are more descriptive of the characteristics of a website's audience than total hours spent or visits would be. A summary of the predictions for the signs of these coefficients is given in Table 3.

[11]The subscripts are written here in a manner consistent with other statistical tests. The standard convention for path analyses is for the first number to indicate the causal variable and the latter the dependent variable.

**Table 3.** Predictions for direct effects. The following table summarizes the predictions made in Section 4 for the direct effects of each accounting or Internet-activity measure shown in Figure 2.

| | SGA | SGAPP | RND | RNDPP | TIMEPP | VISITSPP | UNQAUD | PAGEVIEW | ADSEEN | CLICKS |
|---|---|---|---|---|---|---|---|---|---|---|
| TIMEPP | | + | | ? | | | | | | |
| VISITSPP | | + | | ? | | | | | | |
| UNQAUD | + | | + | | | | | | | |
| VIEWS | | | | | + | + | + | | | |
| ADSEEN | | | | | | | | + | | |
| CLICKS | | | | | − | | | | + | |
| SALES | + | | 0 | | | | + | + | + | + |

Explanatory variables are given in the columns with the rows belonging to the relevant dependent variables. Variables ending in "PP" are deflated by unique audience. All other variables are deflated by total assets. See Appendix for further explanations of each term. A + (−) indicates an expected positive (negative) coefficient. A "0" indicates a variable that is being tested for which no prediction was made, while a "?" indicates a variable for which multiple, conflicting predictions are made.

As is the case with other statistical techniques, path analysis suffers from a number of limitations related to model specification. As mentioned previously, the most important among these is the fact that it cannot explicitly test for directionality in the relationships. The directions of the arrows in a path diagram represent the researcher's hypotheses regarding causality; however, the actual direction could be the reverse or the correlation could be spurious. In particular, if a variable specified as prior to another given variable is really consequent to it, it should be estimated to have no path effect. However, when it is included as a prior variable in the model, it could erroneously lead to changes in the coefficients for other variables in the model. Another important limitation is that techniques such as these often require substantially more data than single equation regressions in order to assess significance. The conventional wisdom in the literature is that the total number of observations should exceed the number of parameters tested by at least 10–20 times.

In addition, the coefficients in path analyses are sensitive to specification error when a significant causal variable is left out of the model. When this happens, the path coefficients will reflect their shared covariance with such unmeasured variables and will not be accurately interpretable in terms of their direct and indirect effects. Finally, the researcher's choice of variables and pathways represented will limit the model's ability to recreate the sample covariance and variance patterns that are observed in the data. Because of this, there may be several models that fit the data equally well. Nonetheless, the path analysis approach remains useful in structuring relational data which is a good first step in understanding the intricate nature of the data involved.

## 5. Results

The description of the path analysis above focuses on the actions of web-activity-dependent firms. While the sample studied here includes a small number of observations for business models in which activity is not *ex ante* expected to be a substantial source of long-term revenues (Kozberg, 2001), these firms are likely to prove exceptions to the rule. If firms are attempting to maximize revenue streams from multiple sources, primary or not, then website activity should translate into increased revenues for these companies as well.

Due to the use of partial regression coefficients in the path analysis, it would first be helpful to examine the overall correlations among the variables tested.[12] The correlations in Table 4 are sorted from left-to-right (top-to-bottom) based upon the particular variables' position in Figure 2. From Table 4, it can be seen that a number of pairs of variables are highly correlated, such as pageviews and advertisements shown (0.74). This result would seem to support the need for a mechanism to control for possible endogeneity problems suggested by high multicollinearity in the data. From the organization of the data, it can be seen that these high correlations among the variables tends to fall as the number of hypothesized steps between them increases. These correlations are, therefore, consistent with the predicted effects in the last section (e.g., pageviews influences advertisements shown which in turn has some, albeit smaller, effect on click-throughs as a result of this intermediate step).

With respect to the accounting data, SG&A and R&D are mildly positively correlated (0.24 and 0.41 when deflated by total assets and unique audience respectively). Interestingly, the two measures for SG&A are slightly *negatively* correlated ($-0.07$), suggesting that each measure may provide different insights during testing. The two R&D measures have a small positive correlation (0.26). SG&A deflated by total assets is significantly related to all the other variables (negatively for the per person measures). Deflating by unique audience, however, the correlations are largely negative and significant except with the other per-person measures. The R&D measures show a similar relationship, although generally not as strong as for SG&A.

Table 5, Panel A, displays the results of the full path analysis described in Figure 2.[13] Regressing time spent online per person on SG&A and R&D, the former variable is not significantly different from zero and the effect of R&D is *negative* and significant ($t$-statistic of $-2.33$). The latter result is consistent with the interpretation that firm expenditures on R&D have been more focused on improving page delivery times (reducing time spent) than on the expansion of content and/or services (which would increase time spent). With respect to visits per person, neither SG&A nor R&D is significantly different from zero.

The results for SG&A are particularly surprising when one considers that it is common practice for firms to use advertising to increase the use of its products and services by existing customers (which would increase time spent and/or visits per person). However, increases in spending on SG&A should

[12] In a perfectly specified model the sum of the effects from the direct and indirect pathways between any two variables would equal the correlation for those two variables.

[13] Results are calculated using the PROC CALIS procedure in SAS using the RAM statement.

**Table 4.** Web sample correlations. Pearson correlations for accounting and Internet usage variables deflated by total assets, with the exception of reach and per person variables.

| Variable | SGA | SGAPP | RND | RNDPP | UNQAUD | TIMEPP | VISITSPP | PAGEVIEW | ADSEEN | CLICKS | SALES |
|---|---|---|---|---|---|---|---|---|---|---|---|
| SGA | 1 | −0.07 | **0.24** | **−0.08** | **0.43** | **−0.14** | **−0.19** | **0.28** | **0.20** | **0.23** | **0.50** |
| SGAPP | | 1 | −0.03 | **0.41** | **−0.29** | −0.03 | −0.02 | **−0.26** | **−0.21** | **−0.21** | **−0.24** |
| RND | | | 1 | **0.26** | **0.13** | **−0.13** | **−0.12** | 0.05 | **0.21** | **0.14** | <0.01 |
| RNDPP | | | | 1 | **−0.21** | **−0.13** | **−0.15** | **−0.18** | **−0.13** | **−0.13** | **0.41** |
| UNQAUD | | | | | 1 | −0.03 | 0.05 | **0.76** | **0.65** | **0.50** | **0.20** |
| TIMEPP | | | | | | 1 | **0.63** | **0.28** | **0.25** | 0.03 | −0.02 |
| VISITSPP | | | | | | | 1 | **0.19** | **0.31** | **0.25** | −0.07 |
| PAGEVIEW | | | | | | | | 1 | **0.74** | **0.45** | **0.19** |
| ADSEEN | | | | | | | | | 1 | **0.54** | **0.09** |
| CLICKS | | | | | | | | | | 1 | **0.12** |
| SALES | | | | | | | | | | | 1 |

Variable definitions are given in the Appendix. Correlations shown in bold (italics) are significant at least at the 5% (10%) level.

**Table 5.** Path analysis of spending, site activity and revenues.

| Dependent | SGA | SGAPP | RND | RNDPP | TIMEPP | VISITSPP | UNQAUD | PAGEVIEW | ADSEEN | CLICKS |
|---|---|---|---|---|---|---|---|---|---|---|
| Panel A: Full diagram path analysis results (n = 377) | | | | | | | | | | |
| TIMEPP | | −0.010 | | **−0.146** | | | | | | |
| | | (−0.16) | | **(−2.33)** | | | | | | |
| VISITSPP | | −0.095 | | −0.082 | | | | | | |
| | | (−1.51) | | (−1.31) | | | | | | |
| UNQAUD | **0.421** | | **0.167** | | | | | | | |
| | **(8.08)** | | **(3.20)** | | | | | | | |
| PAGEVIEW | | | | | **0.449** | **−0.118** | **0.771** | | | |
| | | | | | **(8.81)** | **(−2.31)** | **(16.54)** | | | |
| ADSEEN | | | | | | | | **0.743** | | |
| | | | | | | | | **(20.12)** | | |
| CLICKS | | | | | **−0.111** | | | | **0.566** | |
| | | | | | **(−2.12)** | | | | **(15.36)** | |
| SALES | **0.590** | | −0.091 | | | | −0.104 | **0.159** | −0.073 | 0.019 |
| | **(10.46)** | | (*−1.73*) | | | | (*−1.65*) | **(2.62)** | (−1.23) | (0.36) |
| Panel B: Reduced diagram results (n = 583) | | | | | | | | | | |
| TIMEPP | | 0.027 | | **−0.142** | | | | | | |
| | | (0.59) | | **(−3.13)** | | | | | | |
| VISITSPP | | 0.044 | | **−0.167** | | | | | | |
| | | (0.96) | | **(−3.66)** | | | | | | |
| UNQAUD | **0.420** | | **0.031** | | | | | | | |
| | **(9.83)** | | **(0.72)** | | | | | | | |
| PAGEVIEW | | | | | **0.344** | −0.066 | **0.773** | | | |
| | | | | | **(8.38)** | (−1.61) | **(20.28)** | | | |
| SALES | **0.544** | | **−0.126** | | | | **−0.110** | **0.127** | | |
| | **(11.81)** | | **(−2.96)** | | | | **(−2.15)** | **(3.26)** | | |

also increase the number of new browsers. If new users are, on average, less active than existing users, then failure to account for this indirect path would negatively bias the coefficient. To test for this possibility, the path analysis is re-estimated including unique audience as an explanatory variable for both time spent and visits per person.[14] The resulting coefficients are negative but not significant and do not change the sign or significance for the other coefficients.

As suggested previously, regardless of the means by which SG&A and R&D improve website quality, unique audience is expected to increase in both of these measures. Results from Panel A are consistent with this expectation, as both measures are positively and significantly associated with unique audience. In addition, pageviews are found to be positively and significantly related to both time spent per person and the unique audience variable as predicted. Surprisingly, the coefficient for pageviews on visits per person is negative and significant. This result suggests that, once controlling for time spent per person, sites attracting more repeat activity over the course of a month may do so at the expense of depth of activity once browsers are at the site (i.e., through the use of bookmarks and/or greater experience with a site, users are better able to find desired content in a reduced number of pageviews).

Consistent with predictions, the direct effect of pageviews on advertisements shown is positive and significant. In turn, these advertisements are significantly positively related to click-throughs. Additionally, the direct effect on click-throughs of time spent per person is negative and significant, indicating that there are likely to be diminishing returns to increased time spent online as browsers become less sensitive to repeated advertisements. Finally, revenues are positively and significantly associated with SG&A and pageviews and negative and (marginally) significant with unique audience. Contrary to expectations, advertisements shown and click-throughs are not significantly different from zero.

As suggested previously, all three of these measures could proxy for additional revenue opportunities. After modeling the (indirect) effect of SG&A on time spent, visits, and unique audience, it is likely that the remaining (direct) effect contains information regarding non-audience related revenues. Pageviews, on the other hand, should proxy for the ability of the firms to leverage their existing site activity through such actions as new ventures, alliances

[14]The impact of the indirect effects on time and visits spent per person depends on the comparative magnitudes of the direct and indirect effects and on the ratio of new to existing browsers.

and more efficient targeting of content and promotions to audience members. The negative direct effect of unique audience probably controls for some un-modeled effects of the data or possibly serves as an indication of increased costs or decreasing benefits from attracting new browsers.[15]

The lack of significance on either advertisements or click-throughs may be the result of the smaller sample size and competing effects for these measures. The latter possibility is similar to problems experienced for visits and time spent per person. Advertising revenues include two major elements, the number of advertisements shown (or click-throughs) and the amount received per advertisement. If these two elements are negatively correlated, then the omission of the latter variable in the path diagram would result in a model mis-specification in which the coefficient on advertisements shown (click-throughs) would be negatively biased. Furthermore, if advertisements shown or click-throughs are negatively correlated with the rates charged, it is likely the result of individual users being shown more advertisements on each page (or altogether), thereby reducing the average value for each. This condition would also negatively bias the coefficients on unique audience and pageviews, which may explain the negative coefficient found on the former.

One possible method for detecting this hypothesized relationship would be to include interactive variables into the path analysis. The framework of the path analysis and the means by which it is calculated, however, makes the inclusion of such terms difficult. An alternative approach is to estimate the set of equations using per person deflation for all measures. If click-through rates are negatively correlated with the amount of advertising shown to a browser then the per person measures may be able to control for this.[16] In results not shown, the coefficient for advertisements shown per person is negative but not significantly related to revenues per person, similar to the asset deflated results above. On the other hand, click-throughs per person are positively and significantly associated with revenues per person ($t$-statistic of 3.73). Overall, these results are consistent with the interpretation that higher click-throughs lead to increased firm revenues, although the evidence of a negative effect from excessive advertising is inconclusive. With respect to the other variables,

[15]Newer browsers are likely to be among the slower adopters of the Internet and technology in general and may not be as valuable an audience.

[16]Since unique audience deflated by itself would result in a constant across all firms, this variable is replaced by the total audience deflated, "reach", measure to which it is nearly identical.

SG&A and pageviews retain their significance (the latter only marginally so) and R&D and reach are no longer significantly different from zero.

A second possible test is to regress the potential competing effects against revenues in a simple OLS framework. Assuming all revenues are generated from advertising, the ratio of revenues to total assets can be decomposed as follows:

$$\begin{aligned}\text{Sales/Assets} = {} & (\text{Pageviews/Assets}) * (\text{Ads shown/Pageviews}) \\ & * (\text{Click-throughs/Ads shown}) * (\text{Sales/Click-throughs}).\end{aligned} \tag{2}$$

Taking the natural logarithm of each side and replacing the variables with suggestive notation produces the following result:

$$\begin{aligned}\log(\text{SALES}) = {} & \log(\text{PAGEVIEW}) + \log(\text{EXPOSURE}) + \log(\text{CLKRATE}) \\ & + \log(\text{CPM}),\end{aligned} \tag{3}$$

where SALES and PAGEVIEW are the asset-deflated values used in the previous tests. EXPOSURE reflects the ratio of advertisements shown to the number of pages viewed. CLKRATE corresponds to the conventional “click-through rate” definition used for Internet firms (the percentage of advertisements that are clicked upon by the viewer). The final term, CPM, refers to the acronym usually quoted in the advertising industry for the cost per thousand viewers seeing an advertisement.[17] This final measure reflects overall conditions for the advertising market and is generally beyond the control of individual firms, after controlling for possible effects from the first three variables on CPM. Since any such relevant information would be contained in those variables and since CPM measures are only infrequently reported by firms, the final term is removed from the model leaving the following testable equation:[18]

$$\begin{aligned}\log(\text{SALES}) = {} & \beta_1 * \log(\text{PAGEVIEW}) + \beta_2 * \log(\text{EXPOSURE}) \\ & + \beta_3 * \log(\text{CLKRATE}) + \varepsilon.\end{aligned} \tag{4}$$

[17] In actual fact, the variable herein refers to a combination of the traditional CPM measure and the value placed on click-throughs on these advertisements.

[18] An initial examination of earnings announcements and quarterly statements indicates some firms report membership numbers and/or their cpms. The data, however, would be subject to a self-selection bias and the number of available observations appeared insufficient for testing purposes.

Similar to the per person path analysis, results (not shown) from this OLS equation indicate that pageviews and the click-through rate are positively and significantly related with sales ($t$-statistics of 12.40 and 24.08 respectively). The exposure measure is negative but not significantly different from zero ($t$-statistic of $-0.43$).

As mentioned above, in order to achieve interpretable results for the regression coefficients in a path analysis, it is customary to have at least 10–20 times as many observations as parameters. The ratio of about 20 for Panel A comes close to violating this condition. Therefore, it is uncertain whether the lack of significance for some of the coefficients above results from the reduction in observations imposed by requiring reported advertising data to be available. As a result of the insignificant findings on advertisements and click-throughs and as a check of robustness, Panel B shows a less restricted set of regressions conducted after removing Equations (1e) and (1f) and reducing (1g) to the following (resulting in an increase in the number of observations to 583 and a reduction of the number of parameters from 18 to 13):

$$\begin{aligned} \text{SALES} = {} & \beta_{71}\text{SGA} + \beta_{73}\text{RND} + \beta_{75}\text{TIMEPP} + \beta_{76}\text{VISITSPP} \\ & + \beta_{77}\text{UNQAUD} + \beta_{78}\text{PAGEVIEW} + \varepsilon_7. \end{aligned} \tag{1g$'$}$$

The results on this larger sample (with a ratio closer to 40) are consistent with those reported in Panel A for the equations with time spent and unique audience. R&D now appears to be negatively and significantly associated with visits as well, providing further evidence that increased spending in R&D has been focused on streamlining the amount of activity necessary from audience members. For pageviews as the dependent variable, visits per person remains negative but loses significance and the other variables remain positive and significant. The direct effect of R&D for revenues becomes marginally significant, whereas, there is a loss of significance for the effect of R&D for revenues. The direct effect of SG&A on revenues remains positive and significant, while the effect of unique audience continues to be negative and significant. In light of these results, one possible explanation for the possible (direct) controlling effect for unique audience would be that firms with a smaller, more focused audience (most likely to be included in this larger sample but not in the one with advertising levels restricted to being non-zero) are better able to leverage their audience through more targeted promotions, e-commerce initiatives, and the provision of premium "member" content and services.

To this point, the statistical tests have all been conducted with current SG&A and R&D explaining realized activity levels and firm revenues for the quarter. Evidence from the Internet valuation papers (e.g., Kozberg, 2001) have suggested that SG&A and R&D may be treated as investments by the investment community. If this interpretation is accurate, one should be able to predict future financial or non-financial data based upon these two variables. To examine this question, SG&A and R&D are replaced with their one-quarter lag values in Equations (1a)–(1c) and (1g). In results not shown, the lag versions of R&D and SG&A are shown to be of the same sign and significance as the contemporaneous variables, consistent with the viewpoint that these variables do represent investments in future firm activity levels and revenues. Results are not materially different for any of the other variables in the other equations with the exception of an increase in significance for advertisements seen and loss in significance for unique audience in Equation (1g).

In summary, results from this path analysis suggest that both SG&A and R&D have explanatory power over the website activity variables, consistent with the earlier contention in this dissertation that these expenditures represent investments in website quality. Evidence from the path analysis also indicates that both accounting and non-financial measures, in particular SG&A and pageviews, are significantly associated with firm revenues.

## 6. Expanded Testing

One limitation of any static, "levels", study is that the coefficient on any variable reflects the average effect of the data in question. As the Internet develops and the technologies change, the relationships among these variables are likely to change with the scope of the firm (e.g., through network effects, increased efficiency or changes in browser demographics or habits) and over time, respectively. In addition, as described in Section 5, it is possible that some of the variables tested have competing effects which may confuse the results and cannot be easily modeled out, even within a path analysis framework. To examine the marginal effect of these variables, the complete set of regressions (1a)–(1g) are estimated using a changes specification, where the changes are defined as the difference between the reported quarterly accounting data and its one-quarter lag value.[19]

[19] Changes in the non-financial measures are similarly calculated as the difference between the reported activity in the last month of the firm quarter less the 3-month lag reported value.

**Table 6.** Path analysis for changes in accounting and non-financial measures.

| Dependent | SGACH | SGAPPCH | RNDCH | RNDPPCH | TIMEPPCH | VISITSPPCH | UNQAUDCH | PAGEVIEWCH | ADSEENCH | CLICKSCH |
|---|---|---|---|---|---|---|---|---|---|---|
| Panel A: Full diagram path analysis results (n = 302) | | | | | | | | | | |
| TIMEPPCH | | −0.005 | | 0.055 | | | | | | |
| | | (−0.09) | | (0.95) | | | | | | |
| VISITSPPCH | | −0.016 | | 0.045 | | | | | | |
| | | (−0.27) | | (0.78) | | | | | | |
| UNQAUDCH | **0.175** | | 0.081 | | | | | | | |
| | **(2.96)** | | (1.37) | | | | | | | |
| PAGEVIEWCH | | | | | **0.483** | −0.042 | **0.510** | | | |
| | | | | | **(8.39)** | (−0.73) | **(9.03)** | | | |
| ADSEENCH | | | | | | | | **0.559** | | |
| | | | | | | | | **(11.90)** | | |
| CLICKSCH | | | | | −0.050 | | | | **0.289** | |
| | | | | | (−0.84) | | | | **(5.93)** | |
| SALESCH | 0.478 | | 0.031 | | | | < 0.001 | **0.127** | −0.019 | −0.059 |
| | (7.97) | | (0.53) | | | | (0.02) | **(2.09)** | (−0.31) | (−1.02) |
| Panel B: Reduced diagram results (n = 486) | | | | | | | | | | |
| TIMEPPCH | | −0.035 | | 0.043 | | | | | | |
| | | (−0.78) | | (0.95) | | | | | | |
| VISITSPPCH | | 0.004 | | 0.037 | | | | | | |
| | | (0.09) | | (0.80) | | | | | | |
| UNQAUDCH | **0.125** | | 0.060 | | | | | | | |
| | **(2.67)** | | (1.27) | | | | | | | |
| PAGEVIEWCH | | | | | **0.385** | <001 | **0.546** | | | |
| | | | | | **(8.50)** | (0.02) | **(12.16)** | | | |
| SALESCH | **0.448** | | 0.046 | | | | 0.051 | **0.111** | | |
| | **(9.49)** | | (0.98) | | | | (0.85) | **(2.62)** | | |

From Table 6, Panel A, it can be seen that, under this specification, neither SG&A nor R&D is significantly associated with either time spent online or visits per person. In addition, R&D is positive but no longer significantly related to unique audience, although the coefficient for SG&A and unique audience remains positive and significant. The lack of a coefficient for changes in R&D spending suggests that additional firm spending on R&D is most likely not associated with efforts to improve website activity. Overall the results for the changes specification are not as strong as those in the prior section. The results are, nonetheless, consistent with the interpretation that more primitive activity measures are relevant not only in the prediction of the other activity data but for the prediction of revenues as well (by way of pageviews). Additionally, while the evidence from R&D is mixed, SG&A shows strong evidence of being positively and significantly associated with firm revenues both directly and through its influence on unique audience (which in turn increases pageviews).

To examine whether the relationships among the variables tested has changed over time, the set of equations for the reduced diagram (1a)–(1d) and (1g′) are estimated for both the pre and post-crash period. In results not shown, R&D per person remains positive and significant in both time periods for both time spent and visits per person. SG&A, not significantly different from zero in Table 5, is now positively and significantly associated with visits per person in the pre-crash period and negative but not significant in the latter period. This result suggests that earlier firm expenditures on SG&A had been focused, at least in part, on increasing the user activity levels on their websites. With respect to unique audience, SG&A is positive and significant in both periods and R&D is not significantly different from zero in either period (most likely a victim of reduced sample sizes). Unique audience and time spent continue to be positively and significantly associated with pageviews for each time period and visits per person is negative and (marginally) significant in the later period. Similarly, the coefficients for both pageviews and SG&A with revenues remain robust to the time period selected. Unique audience remains negatively associated with revenues, although the significance is lost in the post-crash sample. On the other hand, the negative coefficient observed for R&D and sales appears to be isolated to the post-crash sample.

In addition to highlighting differences in the pricing of accounting and non-financial information over time, Kozberg (2001) stresses the importance of identifying and isolating different business models in order to reduce sample heterogeneity. In order to examine whether the type of business model employed by a firm influences the results, two sub-samples of firms are separately tested: (1) portal and content-community (P&C); and (2) (less advertising but still activity dependent) financial services and online retailing business models. Results for P&C firms are reported in Table 7. In the full sample of firms, SG&A per person is not significantly related to time spent per person. For P&C firms, however, this measure is positive and significant, consistent with these firms having a greater reliance on advertising and other promotional revenues which are generated directly from website activity levels of its users. In addition, unique audience (negative and marginally significant in the full sample) is positive but not significant in Equation (1g). Other results are generally consistent with the full sample, with exception of a loss of significance on visits per person in Equation (1d) and R&D in (1g).

Table 8 shows the reduced diagram results for financial services and online retailing firms.[20] For Equations (1a) and (1b), SG&A is positive and significant and R&D is negative and significant for time spent and visits per person, respectively. The results suggest that these firms engage in promotional activities designed to increase site activity while trying to use technology to decrease the amount of time it takes users to conduct the transactions necessary for the firm's success (e.g., e-commerce sales or security trades). Consistent with this interpretation, SG&A is significantly associated with unique audience, whereas R&D is not significantly related to efforts to increase audience. Similar to the full sample, both time spent and unique audience are positively and significantly related to pageviews.

Unlike for P&C firms, financial services and online retailing firms have a negative and significant coefficient on visits per person for pageviews and would appear to be driving the similar results for the full sample. This suggests that the efficiency gains mentioned as a possible explanation are more prominent for these types of firms, perhaps from the benefits of having financial and/or credit information previously stored by these firms (e.g., one-click checkouts). Finally, results for the regression of revenues on these other measures also seem to indicate that financial services and online retailing firms may be responsible

[20]Results for the full path diagram are not given as only 110 observations are available with advertising data which would result in an observation-parameter ratio of about six.

**Table 7.** Path analysis for portal and content-community business models.

| Dependent | SGA | SGAPP | RND | RNDPP | TIMEPP | VISITSPP | UNQAUD | PAGEVIEW | ADSEEN | CLICKS |
|---|---|---|---|---|---|---|---|---|---|---|
| Panel A: Full diagram path analysis results (n = 216) | | | | | | | | | | |
| TIMEPP | | **0.182** | | **−0.167** | | | | | | |
| | | **(2.53)** | | **(−2.33)** | | | | | | |
| VISITSPP | | 0.071 | | **−0.151** | | | | | | |
| | | (0.99) | | **(−2.09)** | | | | | | |
| UNQAUD | **0.413** | | **0.198** | | | | | | | |
| | **(6.01)** | | **(2.88)** | | | | | | | |
| PAGEVIEW | | | | | **0.515** | −0.020 | **0.740** | | | |
| | | | | | **(7.70)** | (−0.30) | **(12.03)** | | | |
| ADSEEN | | | | | | | | **0.737** | | |
| | | | | | | | | **(15.08)** | | |
| CLICKS | | | | | **−0.205** | | | | **0.486** | |
| | | | | | **(−2.95)** | | | | **(9.84)** | |
| SALES | **0.529** | | −0.006 | | | | 0.120 | **0.178** | −0.109 | 0.086 |
| | **(7.12)** | | (−0.09) | | | | (1.48) | **(2.25)** | (−1.44) | (1.29) |
| Panel B: Reduced diagram results (n = 262) | | | | | | | | | | |
| TIMEPP | | **0.173** | | **−0.204** | | | | | | |
| | | **(2.31)** | | **(−2.72)** | | | | | | |
| VISITSPP | | 0.059 | | **−0.203** | | | | | | |
| | | (0.79) | | **(−2.73)** | | | | | | |
| UNQAUD | **0.389** | | 0.046 | | | | | | | |
| | **(6.23)** | | (0.74) | | | | | | | |
| PAGEVIEW | | | | | **0.475** | −0.020 | **0.729** | | | |
| | | | | | **(7.80)** | (−0.32) | **(12.67)** | | | |
| SALES | **0.480** | | 0.030 | | | | 0.111 | **0.182** | | |
| | **(7.17)** | | (0.48) | | | | (1.50) | **(3.26)** | | |

**Table 8.** Other activity-dependent business models. Reduced diagram results (n = 189) for financial services and online retailing firms. Results are not shown for the full set of equations due the low number of observations (n = 101) relative to the number of parameters (18) leading to a ratio of about 6.

| Dependent | SGA | SGAPP | RND | RNDPP | TIMEPP | VISITSPP | UNQAUD | PAGE-VIEW |
|---|---|---|---|---|---|---|---|---|
| TIMEPP | | **0.626** | | **−0.397** | | | | |
| | | **(7.79)** | | **(−4.95)** | | | | |
| VISITSPP | | **0.573** | | **−0.347** | | | | |
| | | **(7.14)** | | **(−4.32)** | | | | |
| UNQAUD | **0.628** | | −0.110 | | | | | |
| | **(8.38)** | | (−1.47) | | | | | |
| PAGEVIEW | | | | | **0.249** | **−0.149** | **0.884** | |
| | | | | | **(3.85)** | **(−2.25)** | **(14.20)** | |
| SALES | **0.582** | | **−0.216** | | | | **−0.430** | **0.430** |
| | **(6.62)** | | **(−2.86)** | | | | **(−4.52)** | **(6.16)** |

for the negative coefficients for R&D and unique audience and that SG&A and pageviews are positively and significantly related for this sub-sample as well.

## 7. Conclusions and Suggestions for Further Research

In the absence of definitive results regarding the pricing of net income in the earlier Internet valuation literature, a number of papers have focused on revenues and other components used to calculate net income in order to explain firm valuations. To date, however, little empirical research has been conducted on how revenues are created by these firms. This paper examines firm revenue creation, while addressing the potentially endogenous and multicollinear nature of the internet activity measures. This is accomplished through the development and testing of a path diagram (Figure 2), which specifies the route firms take from expenditures on SG&A and R&D through activity generation to revenue creation. This methodology allows for simultaneously addressing issues of factor identification and endogeneity. The focus on intermediate pathways permits separate testing of direct and indirect (through intermediate variables) effects. Its application is particularly appealing for Internet firms, where understanding these relationships should provide a clearer understanding of what is driving the valuations of these firms.

The path analysis methodology presented in this paper could be easily adapted to other areas of accounting research. In particular, it could be used to improve measurement of other variables by decomposing components or effects of accounting and non-financial data. For instance, evidence from this and other papers suggests that expenditures on SG&A and R&D might be regarded as investments and should therefore be capitalized. Path analysis could help address issues like these for all types of firms. It would allow for better amortization schedules by eliminating more transitory elements of these variables from those which should be capitalized. Similarly, path analysis could be used to develop better (possibly more recursive) accruals models by isolating the effects accounting variables have on each other. This could lead to better measures of non-discretionary versus discretionary accruals. In addition, this framework could be used to isolate and test the effects of more or less permanent components of earnings, while simultaneously giving researchers the ability to control for decisions made by managers on when to recognize such items as write-offs. In fact, consistent with its in other literatures, path analysis may improve the specification and interpretability of results whenever competing incentives might influence decision making (e.g., for managerial decision making, actions by auditor and/or analyst forecasting).

Empirical testing of the path diagram for internet firms provides evidence that firm expenditures on SG&A and R&D have explanatory power over both the generation of website activity and firm revenues. R&D per person reduces the amount of time a browser needs to spend online at a firm's website. SG&A, on the other hand, is positively and significantly related to time spent and number of visits per person for financial services and online retailing firms. It is also positively and significantly related to time spent per person for portal and content-community firms. Both SG&A and R&D, deflated by total firm assets, are positively and significantly related to unique audience. Finally, SG&A is positively and R&D is negatively and significantly associated with firm revenues, with the latter relationship appearing to be driven by financial services and online retailing firms.

The Internet activity generated is systematically related to firm revenues as well. As unique audience and time spent per person increase so do pageviews. Pageviews have the direct effects of increasing firm revenues as well as increasing the amount of advertising seen. This direct effect on revenues is most likely the result of the ability of pageviews to proxy for other, non-advertising, firm revenue opportunities associated with greater site activity (e.g., mailing lists and user profiling for portal and content-community firms and transactions for financial services or online retailing firms). Finally, while initial results for advertising data do not show explanatory power over revenues, alternative tests provide evidence that click-throughs are positively and significantly associated.

## Acknowledgments

I would like to thank my dissertation committee: Stephen Ryan (Chairman), Jim Ohlson, Joshua Livnat, and Dan Gode as well as Christoper Mann, Bharat Sarath, and Christine Tan for their helpful comments. My appreciation also to AC Nielsen//NetRatings for allowing me to access to their data.

## Appendix

### *Variable definitions*

Historical accounting data is from the quarterly, June 2001 Compustat tapes.

SALES (data2)
SGA (data1) — Sales, general and administrative. When a firm reports no cost of goods sold this variable is COGS instead and this variable is reported as "C".
RND (data4) — Research and development expense.

From Nielsen//NetRatings (NNR):

UNQAUD — Unique audience as reported in the monthly audience measurement database.
VIEWS — Total pageviews as reported in the monthly audience measurement database.
REACH — Percentage of total estimated internet audience as reported in the monthly audience measurement database.
VIEWSPP — Average pageviews per person as reported in the monthly audience measurement database.
TIMEPP — Average time (in hours) spent per person as reported in the monthly audience measurement database.
PAGESPP — Redefined as VIEWS/UNQAUD since NNR rounds their reported variable.

ADSEEN — The number of ad impressions served by all the domains in a property, aggregated from domain level data reported by NNR.

ADSPP — TOTADS/UNQAUD.

CLKRATE — The percentage of ad impressions clicked upon.

CLICKS — The total number of ads clicked upon, defined as TOTADS $*$ CLKRATE for each domain and then aggregated to the property level.

CLICKSPP — CLICKS/UNQAUD.

Advertising by sample firms on the Internet is available as well but is not included in this study. Audience, views, and ad impressions are in millions. Rates are reported in percentages (10.3) rather than decimal form (0.103).

Changes in the variables above have the suffix CH attached.

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Chapter 4

# A Teaching Note on the Effective Interest Rate, Periodic Interest Rate and Compounding Frequency

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Students often experience problems in solving time-value-of-money problems — primarily because they do not know which interest rate to use from among the nominal, effective, and periodic rates. In this paper we show the relationships among different interest rates and clarify the use of these rates in the time-value-of money problems. In particular, we show how to calculate the periodic rate, given the nominal rate, because students must use the periodic rate when they use either the "formula" or "financial calculator" method to compute the interest rate.

**Keywords:** Annual interest rate; compounding frequency; effective interest rate; nominal interest rate; algebraic method; formula method; financial calculator method.

## 1. Introduction

Students often have problems with different interest rate concepts when confronted with time-value-of-money problems. In particular, they seem to struggle when cash flows do not match compounding periods. For example, suppose one invests \$1,000 every six months for the next two years in a bank account that pays 12% interest, compounding quarterly. What will be the future value of this investment in two years? Note that cash flows occur less frequently than compounding periods. In solving the above problem using a formula or financial calculator, students are not sure what interest rate to use — that is, 12% annual rate, 6% semi-annual rate, 3% quarterly rate, or something else? This paper addresses this important instructional issue.

In this paper, we first report the results of our investigation of different textbooks' treatments of different interest rates, when cash flows do not match compounding periods. We then illustrate and clarify the use of different interest rates in the two contexts: (1) when cash flows match compounding periods;

and (2) when cash flows do not match compounding periods. We also show how to calculate implied periodic rates from the effective interest rate formula. Finally, we show relationships among nominal, effective, and periodic interest rates for different compounding methods.

## 2. Different Textbook Approaches

We reviewed the treatments of this interest rate question in eight introductory finance textbooks. In particular, we focused on the use of a periodic interest rate in solving the time-value-of-money problems. Virtually all textbooks discuss the relationship between the nominal annual interest rate ($i_{\text{nom}}$) and the effective annual interest rate ($i_{\text{eff}}$), and this group of textbooks is no different (Brealey and Myers, 2000; Brigham and Houston, 2004; Keown *et al.*, 2003; Lasher, 2000; Lee *et al.*, 1996; Ross *et al.*, 1999; Smart *et al.*, 2004; Van Horne, 2002). The basic difference is that the nominal rate is calculated using the "simple interest rate method", whereas the effective rate is calculated using the "compounding interest rate method". It is shown that the effective interest rate is higher than the nominal interest rate when the number of compounding periods is greater than one. This is due to the effect of compounding.

Although the different textbooks use different terms (see Rich and Rose, 1997), they all provide a formula for calculating an effective annual interest rate, given a nominal interest rate. For example, Ross, Westerfield and Jaffe (1999) show that the effective annual interest rate can be calculated as

$$i_{\text{eff}} = (1 + i_{\text{nom}}/m)^m - 1 \tag{1}$$

Note that $i_{\text{nom}}$ is the nominal annual interest rate, $m$ is the number of compounding periods per year, and $i_{\text{nom}}/m$ is the periodic interest rate. Also, note that as the number of compounding periods increases, so does the effective annual interest rate.

However, we found that few textbooks show the use of a periodic rate in time value of money problems. Brigham and Houston (2004) illustrate the use of periodic interest rates in calculating the future value of a single cash flow. In addition, Lee, Finnerty and Norton (1996) provide a formula for the periodic rate and emphasize the use of the periodic rate for multiple cash flows. They stress that "when more than one annual cash flow occurs, the first step in solving a time value of money problem is to determine the periodic interest rate and the number of periods involved" (Lee *et al.*, 1996, p. 167). None of the textbooks reviewed, however, addresses a case where cash flows do not match compounding periods — for example, semiannual cash flows but quarterly compounding. In the following section, we illustrate how to calculate the periodic rate for different compounding methods using a simple example.

## 3. When Cash Flows Match Compounding Periods

### 3.1. *Example 1*

Assume one invests \$1,000 every six months for the next two years in a bank account that pays 12% interest, compounded semiannually. Further, assume that the cash flows occur at the end of the period. What is the future value of these savings?

| Year: | 0 | 1/2 | 1 | $1\frac{1}{2}$ | 2 |
|---|---|---|---|---|---|
| Savings: | | \$1,000 | \$1,000 | \$1,000 | \$1,000 |

This is a simple annuity calculation. Note that cash flows match compounding periods in this example. There are three alternative methods to calculating the future value of the annuity. First, the algebraic method calculates the future value of each cash flow and sums them. Students seem to understand this method most easily, even though it requires the largest investment of time. Second, the formula method calculates the future value using a formula. Finally, the calculator method requires the use of a financial calculator. We illustrate their applications using Example 1 information.

### 3.2. *Algebraic method*

Since each \$1,000 earns 6% interest for every six-month period, the future value (FV) of the annuity is calculated as

$$\begin{aligned}\mathrm{FV} &= \$1{,}000(1+0.06)^3 + \$1{,}000(1+0.06)^2 + \$1{,}000(1+0.06) + \$1{,}000\\ &= \$4{,}734.62\end{aligned}$$

The FV of the annuity is the sum of the future values of the individual cash flows.

### 3.3. *Formula method*

Ross, Westerfield and Jaffe (1999) provide a formula for calculating the future value of an annuity, as follows:

$$\mathrm{FV} = \mathrm{C}[(1+r)^{\mathrm{T}}/r - 1/r] \tag{2}$$

Using the above formula, we have

$$\mathrm{FV} = \$1{,}000[(1+0.06)^4 - 1/0.06] = \$4{,}374.62$$

Note that we use the 6-month periodic interest rate (6%) in the above calculation. Students are often confused with which interest rate to use in the formula. As we discuss later, the problem is exacerbated when a periodic rate is not given directly.

### 3.4. *Financial calculator method*

Using a common type of financial calculator (e.g., TI BA-35), the future value is calculated in the following manner:

(1) enter the annuity amount 1,000 and press ***PMT***;
(2) enter the periodic interest rate 6% and press ***I/Y***;
(3) enter the number of periods 4 and press ***N***; and
(4) then, press ***FV*** to calculate the future value of the annuity.

In summary, all three methods yield the same future value of \$4,374.62. Furthermore, since this is semi-annual compounding (i.e., $m = 2$), the effective interest rate is calculated as

$$i_{\text{eff}} = (1 + 0.12/2)^2 - 1 = 12.36\%$$

## 4. When Cash Flows Occur More Frequently than Compounding Periods

### 4.1. *Example 2*

Now assume one invests \$1,000 every six months for the next two years in a bank account that pays 12% interest, compounding annually. Again, cash flows occur at the end of the period. What is the future value of the savings?

In this instance, cash flows do not match compounding periods. That is, cash flows occur semi-annually and the compounding occurs annually. We now calculate the future value of this annuity using the three methods we utilized above.

### 4.2. *Algebraic method*

Since each \$1,000 earns 12% for a one-year period, the future value is calculated as

$$\begin{aligned} \text{FV} &= \$1{,}000(1 + 0.12)^{1.5} + \$1{,}000(1 + 0.12)^{1} + \$1{,}000(1 + 0.12)^{0.5} \\ &\quad + \$1{,}000 \\ &= \$4{,}363.60 \end{aligned}$$

In comparison with Example 1, the future value is smaller because the number of compounding periods is smaller (i.e., $m = 1$ for annual compounding).

### 4.3. *Formula method*

As we noted above, we need a 6-month periodic interest rate to calculate the future value using Formula (2). The problem is that the periodic rate is not available directly. We, therefore, must calculate it using the effective interest rate formula. The point here is that we calculate the implied 6-month periodic rate using the effective rate formula. From Formula (1), the periodic rate is calculated as

$$i_{\text{nom}}/m = (1 + i_{\text{eff}})^{1/m} - 1 \tag{3}$$

Using Formula (3), we have

$$\text{6-month periodic rate} = (1 + 0.12)^{1/2} - 1 = 5.83\%$$

Note that the effective annual interest rate ($i_{\text{eff}}$) is 12% for annual compounding (i.e., $m = 1$). Therefore, we must use 5.83% as the periodic rate to solve Example 2. Remember that we used 6% as the 6-month periodic rate in Example 1. Using Formula (2), the FV is then calculated as

$$\text{FV} = \$1{,}000[(1 + 0.0583)^4 - 1/0.0583] = \$4{,}363.60$$

### 4.4. *Financial calculator method*

We repeat the same four steps used in Example 1, except we use 5.83% as the interest rate. Then we calculate the FV as $4,363.60.

To summarize, all three methods yield the same future value of $4,363.60. In addition, Example 2 involves an annual compounding (i.e., $m = 1$) and, thus, the effective interest rate is the same as the nominal interest rate, as follows:

$$i_{\text{eff}} = (1 + 0.12/1)^1 - 1 = 12\%$$

## 5. When Cash Flows Occur Less Frequently than Compounding Periods

### 5.1. *Example 3*

Finally, assume that one invests $1,000 every six months for the next two years in a bank account that pays 12% interest, compounded quarterly. The cash flows occur at the end of the period as in the previous two examples. What is the future value of these savings?

As in Example 2, cash flows do not match compounding periods in this example. However, cash flows in this example occur semi-annually, while the compounding occurs quarterly instead of annually. Again, we illustrate the FV calculation, using the three approaches.

### 5.2. *Algebraic method*

Now, since each \$1,000 earns 3% for a three-month period, the future value is calculated as

$$\begin{aligned}\text{FV} &= \$1{,}000(1+0.03)^6 + \$1{,}000(1+0.03)^4 + \$1{,}000(1+0.03)^2 \\ &\quad + \$1{,}000 \\ &= \$4{,}380.46\end{aligned}$$

The future value is the largest in this case because the number of compounding periods is the largest (i.e., $m = 4$ for quarterly compounding).

### 5.3. *Formula method*

As in Example 2, the 6-month periodic interest rate is not readily available since cash flows do not match compounding periods. But, we can calculate the implied 6-month periodic rate using the effective interest rate formula. Therefore, Formula (3) yields

$$\text{6-month periodic rate} = (1+0.1255)^{1/2} - 1 = 6.09\%$$

For quarterly compounding, note that the effective annual interest rate ($i_{\text{eff}}$) is 12.55% (we show the calculation later). Using 6.09% as the 6-month periodic rate, Formula (2) yields

$$\text{FV} = \$1{,}000[(1+0.0609)^4 - 1/0.0609] = \$4{,}380.46$$

### 5.4. *Financial calculator method*

As we did in the previous two examples, we use the same four steps. However, we use 6.09% as the periodic interest rate in the calculation. The calculation results in the FV of \$4,380.46.

Again, all three methods yield the same future value of \$4,363.60. For quarterly compounding (i.e., $m = 4$), the effective interest rate is calculated as

$$i_{\text{eff}} = (1+0.12/4)^4 - 1 = 12.55\%$$

**Table 1.** Relationships among different interest rates.

| Compounding | Annual Compounding (%) | Semi-Annual Compounding (%) | Quarterly Compounding (%) |
|---|---|---|---|
| Nominal rate | 12 | 12 | 12 |
| Effective rate | 12 | 12.36 | 12.55 |
| 6-month periodic rate | 5.83 | 6 | 6.09 |

## 6. Relationships Among Different Interest Rates

As we saw in the above examples, different compounding methods yield different periodic and effective interest rates. The relationships among nominal, periodic, and effective interest rates are summarized in Table 1.

## 7. Conclusion

In this note, we examined the relationships among periodic, nominal, and effective interest rates. Students often experience difficulties with these interest rates when they attempt to solve time-value-of-money problems. Specifically, students often become confused with which interest rate to use when cash flows do not match the number of compounding periods. Using simple examples, we illustrated the use of these different interest rates in calculating the future value of an annuity. We employed three alternative methods in our calculations. Students seem to understand the algebraic method best — even though the other two methods are simpler in calculation. Finally, we illustrated how to calculate the periodic interest rate from the effective interest rate formula when cash flows do not match compounding periods. Students must use the periodic rate when they use either the formula or the financial calculator method.

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Chapter 5

# Voluntary Disclosure of Strategic Operating Information and the Accuracy of Analysts' Earnings Forecasts

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This paper examines whether earnings predictability would affects managerial decisions in the voluntary disclosure of non-financial information about business strategies and future plans. Specifically, the study investigates whether the accuracy of analysts' earnings forecasts is associated with the extent of managers' voluntary disclosure of strategic operating information (SOI). The empirical results show that managers of firms with greater analysts' forecast errors are more likely to voluntarily disclose strategic operating information. It is also found that enhanced SOIs are associated with improvement in forecast accuracy. The findings support the conjecture that firms whose earnings are difficult to accurately predict are more inclined to use SOI for investor communication.

**Keywords:** Voluntary disclosure; earnings predictability; accuracy of analyst forecasts.

## 1. Introduction

Voluntary corporate disclosure serves as an important catalyst for effective functioning of the markets and information sharing among companies, securities analysts and investors. Managers typically have better information than outsiders about the value of firm and business investment opportunities. In the process of narrowing the information asymmetry between managers and outside investors, managers face with disclosure decisions to communicate their information to investors. The disclosure literature suggests that effective disclosure strategy is important to the firm's competitive advantage (Rindova and Fombrun, 1999). Good investments and business plans may not improve stock price if their values are not apparent to investors and other constituents. Lev (1992) argues that an effective disclosure strategy to communicate corporate information can benefit companies by increasing management credibility, analysts' understanding of the firm, reduced cost of capital and improved valuation. This makes an examination of managers' disclosure decisions and factors that affect managers' disclosure choices an important research issue.

Much of the prior research on voluntary disclosures focuses on management earnings forecasts, perhaps because of significant advantages in the use of management forecasts as a voluntary disclosure proxy. For instances, their accuracy can be easily verified *ex post* when actual earnings are reported. Also, the timing of the disclosure is typically known. This enables researchers to conduct more powerful tests of motivations for and consequences of voluntary disclosure. However, examinations of management earnings forecasts are insufficient to fully understand corporate disclosure strategies because management earnings forecasts are only one component of managers' voluntary disclosure bundle. Managers can engage in other voluntary communications such as strategic operating information (e.g., long-term strategy and strategy changes, explaining the roles and impact of specific events such as a corporate restructuring and new major contracts). The examination of managerial disclosure about non-earnings information, such as the strategic operating information that this paper addresses, provides additional insights into understanding managers' disclosure decisions and disclosure strategies.

Strategic business information has been considered valuable in financial reporting and voluntary disclosure. For instance, Ernst and Young (1994) report that investors and financial analysts highly value non-financial strategic (soft) information about the firm's future plans and business strategies in the process of evaluating firm performance. Jenkins Report of AICPA Special Committee on Financial Reporting (AICPA, 1994) recommends the disclosure of operation reviews and management strategies for financial reporting. Despite the extensive literature on voluntary disclosure, surprisingly little is known about why and when managers disclose operating information to communicate their firms' performance to investors, although it seems clear from casual observations that disclosure of strategic operating information for investor communication is not unusual.

Financial analysts are information intermediaries in the capital market. They obtain firm-specific information from financial statements and other public and private sources to produce forecasts of earnings, growth rate as well as stock recommendations for the investors (Lees, 1981). I argue that firms whose future earnings are difficult to be predicted by financial analysts, as indicated by larger errors of analyst forecasts (AFE), face a higher information asymmetry between managers and investors. Realizing that financial statement information is usually less useful to investors in valuing the firms, managers of high-forecasts-errors firms are more likely to engage in the disclosure and discussions of strategic operation information (SOI), i.e., explanations of business strategies which provide non-financial and qualitative information on business operations in order to narrow the information gap and thus lower the cost of capital. Such disclosure can improve investors' understanding of business operations, corporate achievements, long-term plans and strategies, thus enabling investors to better understand the firms' performance and prospects. I investigate the association between AFE and SOI disclosure, and provide evidence in support of the conjecture that low predictability firms are more inclined to release strategic operating information for investor communication.

This paper makes two contributions. First, it extends the existing disclosure literature that mainly focuses on management earnings forecasts to cover managers' disclosure decisions of strategic non-financial information. Although SOI disclosures by managers are not unusual in the press and newswire, there is little research on why managers voluntarily disclose SOIs. The positive relationship between analyst forecast errors and managers' propensity to disclose more SOIs documented in this study provides evidence that managers do manage the disclosure of operating information in communicating their firms' performance to investors. Second, Healy and Palepu (2001, p. 411), in their review of empirical disclosure literature, call for a better understanding of management disclosure decisions and examination of factors that affect managers' disclosure choices. The empirical evidence in this paper suggests that when earnings are difficult to predict and financial statements are less useful to investors, managers are inclined to disclose more operating information in response to the increased demand by investors for more firm-specific information. The findings shed additional light on the understanding of managers' voluntary disclosure decisions.

The next section of this paper discusses prior related literature. Section Three describes the sample selection and research design. Section Four presents results and the final section summarizes the paper and provides concluding remarks.

## 2. Related Literature

Analytical research on voluntary disclosure considers disclosure in a general sense and suggests that managers are concerned that voluntary disclosure can damage their competitive position [see Verrecchia (2001) for a review of the analytical literature]. The analytical framework suggests that the threshold (or level) of disclosure is determined by a trade-off of propriety costs and benefits of disclosures.

Empirical literature suggests that there are potentially three benefits for firms that make voluntary disclosures: improved stock liquidity (Healy *et al.*, 1999; Leuz and Verrecchia, 2000), reductions in cost of capital (Botosan, 1997; Piotroski, 1999), and increased the number of financial analysts following the firms (Lang and Lundholm, 1996; Francis *et al.*, 1997). Healy and Palepu (2001) reviewed recent empirical studies on voluntary disclosure and summarize five motives for such disclosure: capital market transactions, corporate control contests, stock compensation, litigation risk, and management talent signalling. Despite the importance of understanding managers' disclosure decisions, there are relatively few studies that investigate disclosure choices. On the front of management earnings forecasts, Bamber and Cheon (1998) investigate how the venue of announcing management earnings forecasts and forecast specificity affect the information content of forecasts; Hutton, Miller and Skinner (2000) examine the nature of disclosures that are accompanied with managers' earnings forecasts. They find that managers are more likely to provide verifiable forward looking information (e.g., forecasts of sales) with good news earnings forecasts; and conversely, managers are more likely to provide softer explanations when they release bad news forecasts.

There are studies that examine the utilization of non-earnings information to update investors' expectations of firm value. Managers use costly changes in dividends payout to inform investors about management expectations of firm value (Healy and Palepu, 1988, 1993). Some studies examine the disclosure of non-financial information by technology firms. Kasznik (1996) finds that, among firms in the software industry (whose earnings are typically difficult to predict), reducing the amount of financial reporting discretion increases managers' propensity to disclose non-financial information such as new products and major contracts. In the case of CUC International its management believed that information about subscriber renewals was useful to investors (Healy and Palepu, 1995). There is also evidence that voluntarily disclosed qualitative information is value relevant (Narayanan *et al.*, 2000; Amir and Lev, 1996).

Financial analysts assimilate and process firm-specific information including financial statement information, evaluate the current performance of the firms they follow and make earnings forecasts and buy/sell recommendations. A greater analyst forecast error indicates that the firm's earnings are hard to be accurately predicted by financial analysts and that the information gap between managers and the markets is wide. Large analyst forecast errors also reveal that financial statement information is less useful in predicting future performance for low predictability firms and that firm value is less apparent to investors. In these circumstances, there is likely to be a greater demand for additional operating information about low predictability firms for a better evaluation of the firms' prospects (Kasznik, 1996; Healy and Palepu, 1995) or the investors protect themselves by selling the firms' stock (Das *et al.*, 1998). Managers of high-forecast-error firms, therefore, have incentives to disclose SOIs (e.g., business strategies, new products/markets and capital expenditure) which convey their business and investment plans to investors in order to lower the cost of capital (Botosan, 1997), raise stock prices and potentially increase managers' stock compensation.

Increased SOI disclosures by low predictability firms are also consistent with the litigation risk argument. There are two components of litigation risk, namely "inadequate" disclosure and "disclosure of untrue statement of a material fact" (Securities Exchange Act, 1934). Firms whose earnings are less accurately predicted are subject to a higher litigation risk of inadequate disclosure. SOI disclosures can reduce the risk of "inadequate" disclosure because SOI disclosures (i.e., discussions and explanations of business strategies) are timely and can improve investors' understanding of corporate achievements and long-term plans. Further, factual discussions of SOIs are unlikely to significantly expose the firm to the litigation risk of misstatement. Taken together, it is expected that firms with larger analyst forecast errors are more likely to release SOIs.

## 3. Research Design

### 3.1. *Sample*

This study examines the SOIs disclosed in the 1994 fiscal year by managers of the firms that have financial analysts' forecasts for 1993 annual earnings in the I/B/E/S database. Tests of association between forecast errors and SOI disclosures in the subsequent year are then performed. For example, if a firm's fiscal year end is December 31, 1993, the mean value of analyst forecasts made in January 1993 for 1993 annual earnings for the firm is used to calculate analyst forecast errors. I then examine whether managers' disclosure of SOI in 1994 is associated with the analyst forecast errors.

The first step of the sampling procedure is to search the I/B/E/S database for firms that have analysts forecast data for 1993. Compustat database is then

**Table 1.** Industry composition of the sample and I/B/E/S population.

| | Sample (500 firms) | I/B/E/S Population |
|---|---|---|
| Agriculture, forestry and fishing (SIC1-999) | 0.4% | 0.3% |
| Mining, extraction and construction (SIC1000-1999) | 6.8% | 4.9% |
| Food, textile, paper and chemical products (SIC2000-2999) | 24.2% | 18.7% |
| Manufacturing (SIC3000-3999) | 28.2% | 25.7% |
| Utilities (SIC4000-4999) | 12.6% | 12.5% |
| Durable and non-durable goods (SIC5000-5999) | 13.0% | 10.7% |
| Financial services (SIC6000-6999) | 6.4% | 16.7% |
| Leisure, personal and business services (SIC7000-7999) | 7.8% | 7.7% |
| Health, public and professional services | 1.0% | 2.3% |
| Government and administrative services | 0.4% | 0.5% |
| | 100% | 100% |

searched for data for control variables. This procedure results in an initial sample of 1,253 firms with necessary analysts forecast data and Compustat data for control variables. SOI disclosures are identified and collected by reading the full text of all article available in Dow Jones News Retrieval Service (DJNRS) for 1994 for each sample firm.[1] This process is time-consuming and expensive. As a trade-off, 500 firms are randomly drawn from the initial sample of 1,253 firms. Table 1 presents the industry distribution of the 500 sample firms as well as the I/B/E/S total population. It shows a similar industry composition between the sample and the population except for a lower percentage of financial services firms in the sample.

## 3.2. *Measurement of variables*

### 3.2.1. *Disclosure of strategic operating information (SOI)*

SOI Disclosures refer to the voluntary corporate announcements of non-financial information, which are characterized as being important to investors to understand a firm's business strategies, future plans and prospects. The following types of information are captured as strategic operating information in the study: (1) new contracts and new products/markets; (2) joint-ventures and strategic alliance; (3) strategic planning/business restructuring; (4) sales of assets and business downsizing; and (5) capital expenditure,

[1] Prior earnings forecast studies use keyword search, e.g., "see", "expect", "forecast", "estimate", "project" etc. for searching earnings forecasts. In this paper, full text search, a time-consuming procedure, is used to browse through each news article in the identification of SOI disclosures to avoid omission of disclosure.

business expansions and acquisitions. SOIs released by corporate officers of the sample firms in 1994 are collected from DJNRS. An example of SOIs is as follow:

> AMC Entertainment Inc. (April 27, 1994) today announced that they will install Sony digital sound systems for all 1,600 of its movie screens.... According to Stan Durwood, Chairman and Chief Executive Officer of AMC: *"This is a tremendous enhancement. We're out in front in most senses, and this puts us even further out front. We're trying to build the theatres for the year 2010. Our decision is further evidence of AMC's commitment to providing the very best moviegoing experience for our patrons.... The Sony system is the most expensive, but it offers greater flexibility and will prove cheaper over the long run."*

At the end of the search on DJNRS, a total of 765 SOI disclosures were identified during the test period. Table 2 shows that the disclosure of new contracts, markets and products is the most popular SOIs (30.7%), followed by the disclosure of capital expenditure, business expansions and acquisitions (30.1%). The average number of SOI disclosure for the sample is 1.53. Overall, 392 (78.4%) firms disclosed one or more SOIs and 108 (21.6%) firms made no SOI disclosure in the year of study.

### 3.2.2. *Analyst forecast errors (AFEs)*

The extent of how hard to predict earnings (earnings predictability) is measured by the absolute forecast errors of mean analysts annual earnings forecasts,

**Table 2.** Distribution of strategic operating information disclosed by the nature of disclosures.

| Type of Disclosure* | N | Percentage |
|---|---|---|
| 1 | 235 | 30.7% |
| 2 | 92 | 12.0% |
| 3 | 83 | 10.9% |
| 4 | 125 | 16.3% |
| 5 | 230 | 30.1% |
| Total | 765 | 100% |

*1. new contract or new products/markets.
2. joint-venture or strategic alliance.
3. sales of assets or business downsizing.
4. strategic planning/business restructuring.
5. capital expenditure, business expansions or acquisitions.

defined as the difference between forecasted and actual earnings per share divided by the actual earnings per share. Short-term (e.g., three-month-ahead) forecasts are not an appropriate benchmark because financial analysts will incorporate the firm's latest quarterly performance and financial position in updating their annual forecasts. In this study, twelve-month-ahead annual earnings forecasts (e.g., mean forecasts made in January 1993 for the December 1993 fiscal year's earnings) are used to compute AFEs.[2] Firms whose earnings are difficult to predict are associated with larger AFEs.

#### 3.2.3. *Control variables*

The analysis of the association between SOI disclosure and forecast errors controls for the variables which might affect the levels of disclosure such as size, firm risk, leverage, growth and technology status. Large firms are more likely to make voluntary disclosures because of the greater demand for information by financial analysts, lower marginal costs of disseminating information and greater demand for outside capital (Lang and Lundholm, 1993; Waymire, 1985). Investors demand more information about high-risk firm. Therefore they are more likely to make voluntary disclosure (Lev and Penman, 1990; Lang and Lundholm, 1993). High-debt firms might disclose more information to keep lenders and investors informed of the firm's prospects (Kross *et al.*, 1994). Firm growth is also likely to influence corporate disclosure (Waymire, 1985; Kross *et al.*, 1994). Technology firms might disclose more operating information because the traditional mandatory disclosures, i.e., financial statements of technology firms are likely to be less value-relevant (Cohen, 1992; Kasznik, 1996; Amir and Lev, 1996). Finally, dummies are included for 2-digit SIC industry code in the regression to control for possible industry effects on disclosure. Data for the control variables are based on the 1993 financial year.

## 4. Results

### 4.1. *Descriptive statistics and univariate analysis*

Panel A of Table 3 contains descriptive statistics of all independent variables. The mean value of earnings prediction errors is 0.406. Of the 77 firms in the

[2]A sensitivity test using six-month-ahead earnings forecasts instead of twelve-month-ahead forecasts in computing AFEs yields qualitatively the same results.

**Table 3.** Descriptive statistics and correlation matrix of independent variables.

Panel A: Descriptive statistics

| Continuous Variables | Mean | Median | Min. | Max. | Standard Deviation |
|---|---|---|---|---|---|
| AFE | 0.406 | 0.212 | 0.00 | 5.83 | 0.798 |
| SIZE | 6.876 | 6.768 | 2.62 | 12.29 | 1.795 |
| BETA | 1.113 | 1.071 | −0.66 | 2.78 | 0.554 |
| DEBT | 0.216 | 0.201 | 0.000 | 1.71 | 0.182 |
| GROWTH | 2.975 | 2.740 | −19.32 | 18.92 | 2.502 |
| Dichotomous Variable | | Yes | No | | |
| TECH | | 77(15.4%) | 423(84.6%) | | |

Panel B: Correlation matrix

| | AFE | SIZE | BETA | DEBT | GROWTH |
|---|---|---|---|---|---|
| SIZE | −0.028 | | | | |
| BETA | 0.008 | −0.079 | | | |
| DEBT | 0.159** | 0.338** | −0.104* | | |
| GROWTH | −0.121* | −0.109* | 0.061 | −0.212** | |
| TECH | 0.014 | −0.146** | 0.245** | −0.183** | 0.083 |

*Correlation is significant at the 0.05 level (2-tailed).
**Correlation is significant at the 0.01 level (2-tailed).
AFE: Absolute value of analyst forecast errors defined as the difference between 12-month- ahead mean forecast and actual 1993 earnings per share divided by the actual earnings per share.
SIZE: Natural log of the firm's total assets as at 1993 fiscal year end.
BETA: Firm risk as measured by the beta obtained from the Compustat database for 1993.
DEBT: Debt ratio of the firm, computed as the ratio of total liabilities to total assets for 1993.
GROWTH: Market-to-book-equity ratio for 1993.
TECH: Dummy variable, "1" for a technology firm if the firm belongs to the following SIC codes: Drugs (2833-2836), R&D Services (8731-8734), Programming (7371-7379), Computers (3570-3577), Electronics (3600-3674); and "0" otherwise.

sample, 15.4% are in high-technology industries. Panel B of Table 3 reports bivariate correlations between the independent variables. The correlation coefficients are low, suggesting that multicollinearity is unlikely to be a major cause of concern in the regression analysis.

Table 4 reports $t$-test and chi-square test results for differences in SOI disclosures between high-AFE and low-AFE firms. The mean number of SOI disclosure by the high-AFE firms is 1.732, which is 0.404 higher than the mean SOI number for the low-AFE firms. The difference in SOI disclosures is significant at the 0.01 level. The chi-square test also shows that the majority of SOI non-disclosers are low-AFE firms whereas the majority of SOI disclosers

**Table 4.** Univariate tests for differences in the disclosure of strategic operating information.

| Panel A: ($t$-test) | Number of SOI Disclosure | | |
|---|---|---|---|
| | N | Mean | $t$-test $p$-value |
| High AFE (above median split) | 250 | 1.732 | 0.009 |
| Low AFE (below median split) | 250 | 1.328 | |

| Panel B: (chi-square test) | | | |
|---|---|---|---|
| | SOI Discloser | SOI Non-discloser | chi-square $p$-value |
| High AFE (above median split) | 210 | 40 | 0.002 |
| Low AFE (below median split) | 182 | 68 | |

High AFE: A firm is classified as "high AFE" if its absolute analysts' forecast errors are above the median of the sample.
Low AFE: A firm is classified as "low AFE" if its absolute analysts' forecast errors are below the median of the sample.
SOI discloser: A firm is classified as a SOI discloser if it disclosed one or more pieces of strategic operating information.
SOI non-discloser: A firm is classified as a SOI non-discloser if it made no disclosure of strategic operating information.

are high-AFE firms, with the difference being significant at the 0.002 level. The univariate-test results indicate that firms with large analysts' forecast errors (low predictability firms) are more inclined to release SOIs.

### 4.2. *Regression results*

In the regression analysis, both the natural log of number of SOIs and a dummy variable (the dummy variable equals "1" if the firm has one or more SOI disclosure and "0" otherwise) are used as the dependent variable because there is no clue on the specific relationship between SOI disclosure and AFEs. As such, OLS and logistic regressions are applied to the experimental and control variables. The results are reported in Table 5.

The results, consistent with the findings in the univariate analysis, show that the AFE coefficient is positive and significant (two-tailed $p$-value $< 0.05$) in all panels. The findings provide evidence that managers' propensity to voluntarily disclose firm-specific information about their future plans and business strategies increases as financial analysts' ability to predict their firms' earnings performance declines. The results for the control variables indicate that firms of larger size, higher firm risk and higher growth opportunities are more inclined to disclose SOIs. Further, the coefficient for TECH is significantly positive,

**Table 5.** OLS and logistic regression result of SOI disclosures on analysts' forecast errors.

$$\text{SOI} = a + b_1\text{AFE} + b_2\text{SIZE} + b_3\text{BETA} + b_4\text{DEBT} + b_5\text{GROWTH} + b_6\text{TECH} + \text{Industry dummies} + e$$

| Independent Variables | Predicted Sign | OLS Regression* Coefficient Estimates (two-Tailed $p$-Value) | Logistic Regression** Coefficient Estimates (two-Tailed $p$-Value) |
|---|---|---|---|
| Intercept | | −3.279 | −5.739 |
| | | (0.023) | (0.026) |
| AFE | + | 1.367 | 1.151 |
| | | (0.039) | (0.019) |
| SIZE | + | 0.561 | 0.503 |
| | | (0.001) | (0.001) |
| BETA | + | 0.916 | 0.848 |
| | | (0.003) | (0.008) |
| DEBT | + | 0.105 | 0.138 |
| | | (0.384) | (0.201) |
| GROWTH | + | 0.222 | 0.205 |
| | | (0.023) | (0.051) |
| TECH | + | 0.803 | 0.737 |
| | | (0.036) | (0.024) |
| Industry dummies | | Yes | Yes |
| $R^2$ | | 0.163 | 0.184 |

*The dependent variable is the natural log of one plus the number of SOI disclosures.
**The dependent variable is a dummy indicator, equal "1" if the firm disclosed one or more SOI disclosures and "0" if the firm made no SOI disclosure.

AFE: Absolute value of analyst forecast errors defined as the difference between 12-month-ahead mean forecast and actual 1993 earnings per share divided by the actual earnings per share.
SIZE: Natural log of the firm's total assets as at 1993 fiscal year end.
BETA: Firm risk as measured by the beta obtained from the Compustat database for 1993.
DEBT: Debt ratio of the firm, computed as the ratio of total liabilities to total assets for 1993.
GROWTH: Market-to-book-equity ratio for 1993.
TECH: Dummy variable, "1" for a technology firm if the firm belongs to the following SIC codes: Drugs (2833-2836), R&D Services (8731-8734), Programming (7371-7379), Computers (3570-3577), Electronics (3600-3674); and "0" otherwise.

suggesting that high-technology firms are more likely to disclose strategic operating information to update investors of the firms' strategies and prospects.

### 4.3. *Sensitivity analyses*

Several tests are conducted to provide confidence in the robustness of the results. First, as discussed earlier, prior studies suggest that technology firms are more inclined to disclose operating information. To control for the possibility that technology firms in the sample may be driving the main results, the analysis is rerun after removing technology firms from the sample. However, the results do not change, thus suggesting that the results are not driven by the technology sub-sample.

Second, alternative specifications for AFEs are used for a sensitivity test. AFEs are ranked and then SOI are regressed on the ranked AFEs in the regressions. The coefficient for ranked AFEs remains significantly positive. Six-month-ahead analyst forecast earnings are adopted in computing AFEs and the regression analyses are repeated. The results are qualitatively the same.

Finally, the results reported in Table 5 are considered as to whether they are robust to the exclusion of business expansions, acquisitions and joint ventures from SOI disclosures. The regression results show that after deleting these items the earnings predictability variable remains significantly positively associated with SOI disclosures.

### 4.4. *Additional tests*

In this section, evidence, based on a random sub-sample of 200 firms, shows that firms with high AFEs have more SOI disclosures in 1994 than in 1993 whereas such increase was not observed for firms with low AFEs. It is also documented that firms with enhanced SOI disclosures are associated with improvement in forecast accuracy.

Two hundred sample firms are randomly drawn from the sample and they are then divided into a high and low-AFE group by the median split, based on their SOI disclosures in 1993. For each firm in each group, its SOI disclosure in 1994 is tracked using a full text search in DJNRS and the number of SOIs between 1994 and 1993 is compared. Paired-difference $t$-tests are then preformed to see if the difference is significant. The results reported in Panel A of Table 6 show that SOI disclosures in 1994 for the high-AFE group is higher than that in 1993. The difference is significant at the 0.062 level. However, there is no such effect for the low-AFE group. This result provides further support that firms with greater analysts' forecast errors tend to increase SOI disclosures and compliments the main results as reported earlier.

Next, the issue of whether enhanced SOI disclosure improves forecast accuracy is examined. The 200 firms are classified into "increase in SOI" if its 1994 SOIs are larger than its 1993 SOIs and "decrease in SOI" otherwise. To see whether enhanced SOI disclosures in 1994 subsequently improve forecast accuracy, the absolute forecast errors of 12-month-ahead I/B/E/S consensus forecasts for 1995 earnings (i.e., mean forecasts made in January 1995 for the

**Table 6.** Results of additional tests of enhanced SOI disclosures (n = 200).

| Panel A | | | |
|---|---|---|---|
| | Mean SOIs in 1993 | Mean SOIs in 1994 | $p$-value of the Paired-Difference $t$-Test (2-Tailed) |
| High AFE[a] | 1.524 | 1.713 | 0.062 |
| Low AFE[b] | 1.316 | 1.355 | 0.428 |

| Panel B | | | |
|---|---|---|---|
| | Increase in AFE[e] | Decrease in AFE[f] | |
| Increase in SOI[c] | 48 | 65 | |
| Decrease in SOI[d] | 48 | 39 | chi-square value = 3.18* |

| Panel C | | | |
|---|---|---|---|
| | Increase in Forecast Dispersion[g] | Decrease in Forecast Dispersion[h] | |
| Increase in SOI | 53 | 60 | |
| Decrease in SOI | 42 | 45 | chi-square value = 0.04 |

*Significant at 5% level, one-tailed.

[a] & [b]: A firm is classified as "High AFE" ("Low AFE") if its AFE is higher (lower) than the sample's median value.

[c] & [d]: A firm is classified as "Increase in SOI" if it disclosed more SOIs in 1994 than in 1993; otherwise, the firm is classified as "Decrease in SOI".

[e] & [f]: A firm is classified as "Increase in AFE" if the absolute value of 12-month-ahead mean analyst forecast error in 1995 (the subsequent year after SOI disclosure in 1994) is higher than AFE in 1994; otherwise, the firm is classified as "Decrease in AFE".

[g] & [h]: A firm is classified as "Increase in Forecast Dispersion" if its standard deviation of the 12-month-ahead inter-analyst earnings forecasts in 1995 is higher than AFE in 1994; otherwise, the firm is classified as "Decrease in Forecast Dispersion".

December 1995 fiscal year's earnings) are compared with 1994 forecast errors. If the firm's 1995 AFE is lower (higher) than its 1994 AFE, it is classified as "decrease in AFE" ('increase in AFE'). Panel B of Table 6 reports the result of the chi-square test, which shows that increase in SOIs is significantly associated with a reduction in AFEs, suggesting that SOI disclosure is useful to analysts in improving their forecasts of earnings.

An additional test is performed to examine whether enhanced SOI disclosure reduces forecast dispersion (or improve forecast precision). Similar to the analysis for forecast accuracy, the standard deviation of the inter-analyst earnings forecast distribution between 1995 and 1994 based on 12-month-ahead forecasts is compared. The result appears in Panel C of Table 6, which indicates no difference in forecast dispersion between IOS-increased and IOS-decreased firms. A possible explanation for the lack of results is that increased SOI disclosure could be useful to analysts but such information is interpreted differently by different analysts given the qualitative nature of SOIs, resulting in a lack of convergence in forecasts.

## 5. Conclusion

Voluntary disclosure is an important mechanism for managers to convey information about a firm's prospects and value to investors and other users. In a recent review of the disclosure literature, Healy and Palepu (2001) raise that managers' disclosure decisions and disclosure choices are important research questions in the disclosure framework. Although strategic business information appears to be a good choice in managers' disclosure decision, disclosure literature mainly focuses on management earnings forecasts and ignores SOIs in investigating managers' disclosure decisions. There is surprisingly little evidence of the circumstances under which firms are more likely to reveal nonfinancial information such as business plans and strategies. This paper complements prior studies by examining SOIs as voluntary disclosure choices and presents evidence that earnings predictability is an important determinant of managers' decisions in selecting SOI disclosures for investor communication.

Results show that managers of firms whose earnings are difficult to accurately predict are more likely to use SOIs for investor communication. Additional tests show that firms with enhanced SOI disclosure has improvement in forecast accuracy. These findings support the notion that as financial information becomes less predictable and the information asymmetry between managers and investors becomes wider, managers have incentives to convey more information on corporate strategies and business plans to lower the cost of capital and raise stock price.

## Acknowledgments

I am grateful for comments from Greg Clinch, Ferdinand Gul, Bin Srinidhi, an anonymous referee, and participants in the 2002 AAANZ and 2003 PBFEA annual meetings in earlier version of the manuscript.

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Chapter 6

# Intraday Trading of Island (As Reported to the Cincinnati Stock Exchange) and NASDAQ

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On March 18, 2002, Island began reporting its trades to the Cincinnati Stock Exchange. This change in reporting allows us to examine Island's trading behavior. We find distinct intraday patterns for the number of trades and volume. Both NASDAQ and Island exhibit intraday U-shaped patterns for the number of trades and volume, however, the difference in the two also shows a U-shaped pattern. In addition, we analyze the probability of informed trading around the reporting change. We find no difference in the probability of informed trading on NASDAQ and Island following the change, as well as no significant difference in the probability of informed trading for NASDAQ before and after the change.

**Keywords:** Intraday patterns of volume; probability of informed trading; electronic communication networks; Island; NASDAQ market system.

## 1. Introduction

On March 18 of 2002, Island, NASDAQ's largest Electronic Communication Network (ECN) began reporting trades to the Cincinnati Stock Exchange (CSE). Previously, trades on Island were reported to NASDAQ.[1] Island initiated this reporting change as a cost savings move.[2] The arrangement between the CSE and Island involves a revenue-sharing and rebate plan, where the CSE sends back part of the revenue it makes by packaging and selling Island's trading data to other financial institutions. Island gives some of that money back to its customers in the form of a rebate which, in turn, helps them increase market share in NASDAQ stocks. This reporting change allows us to study Island's

[1] Island announced that the reporting of quotes to the CSE would begin at a later point in time.
[2] For more information about this move, see Nguyen, Van Ness and Van Ness (2003).

trading behavior since we can now delineate their transactions from those of NASDAQ dealers.

Island is registered with the Securities and Exchange Commission as a broker-dealer. It operates within the NASDAQ market as an Electronic Communications Network for NASDAQ securities complying with paragraph (a)(8) of Rule 11Ac1-1 (the Quote Rule) of the Securities Exchange Act of 1934 (Exchange Act), and as an alternative trading system (ATS) pursuant to Regulation ATS of the Exchange Act. As of March 2002, Island represents approximately one out of five trades in NASDAQ securities[3] — making Island one of the technology leaders in electronic market places.

Island operates as a transparent automated limit order book with automatic matching capabilities. Trades occur on Island when a buy order and a sell order match on Island's limit order book, or when a buy/sell order on Island matches with another buy/sell order from another market maker. With the exception of All-or-None Orders, each order may receive either a full or partial execution. To enhance market transparency, Island makes its limit order book available for viewing through their web site.[4]

## 2. Literature and Background

Many researchers examine intraday patterns of trading activity and the bid-ask spread. Wood, McInish and Ord (1985) find that NYSE stocks exhibit a U-shaped pattern in returns. Harris (1986) finds that Monday has a slightly different intraday pattern than the rest of the week — but this difference is only during the first 45 minutes of trading.

Spreads exhibit intraday patterns somewhat similar to trading. McInish and Wood (1992), Brock and Kleidon (1992), Lee, Mucklow and Ready (1993), and Chan, Chung and Johnson (1995) document U-shaped patterns in spreads of NYSE stocks. These researchers explain the observed pattern in spreads by the specialist exploiting market power and/or dealing with inventory and information issues. Chung, Van Ness and Van Ness (1999) find that limit orders explain much of the intraday variation in the NYSE spreads. A different pattern is found for NASDAQ stocks. Chan, Christie and Schultz (1995) find that

[3] Nguyen, Van Ness and Van Ness (2003).

[4] Not all orders are publicly viewable. Subscribers may enter orders on Island's limit order book for display to all other subscribers, or may enter orders on the limit order book on a non-display basis. Orders designated for display are visible to all subscribers.

NASDAQ spreads decline throughout the entire day, with the largest decline occurring in the last 30 minutes of trading.

Interest in ECNs is increasing. Simaan, Weaver and Whitcomb (2003) examine data (September 15–26, 1997) after the SEC order handling rules and the change of NASDAQ to trading/quoting in 16ths of a dollar. They find that ECNs are alone at the best bid and offer about 19% of the time, and more often at the ask than at the bid. Additionally, the authors find that Instinet quotes at the BBO the most of any ECN.[5] Also, the authors find a distinct pattern for quotes — ECNs tend not to be at the inside (alone) of the quote in the first half-hour of trading, but they are more likely to be alone at the inside quote during the last hour of trading.

Barclay, Hendershott and McCormick (2003) examine competition between ECNs and market makers. They find that more private information is revealed to the market through transactions on ECNs than through trades occurring with market makers. Additionally, they find ECNs have lower effective spreads for medium and large trades than market makers, but not for small trades (unless the trade occurs on a non-integer price).

Bias, Bisiere and Spatt (2002) directly examine the ECN, Island. They find that NASDAQ spreads are constrained prior to decimalization, and that limit order traders use Island as a platform to compete for liquidity. After decimalization, the spreads on Island narrow and the rents earned by Island traders virtually disappear.

Hasbrouck and Sarr (2002) also study Island from October 1 to December 31, 1999. They find that Island's market share is positively related to the overall level of NASDAQ trading in the firm. Additionally, they find that over one quarter of the limit orders submitted to Island were cancelled, and that there is a substantial use of non-displayed limit orders on Island (Island allows investors the option of not displaying their order — but if the order transacts, the trade is shown to the market).

Huang (2002) and Tse and Hackard (2003) examine price discovery of ECNs. Huang investigates the ten most active NASDAQ stocks and finds that ECNs add to price discovery, and additionally, promote market quality rather than degrade market quality due to fragmentation. Tse and Hackard examine price discovery of Island for the exchange traded fund, QQQ. They find that Island dominates the price discovery process for QQQ.

[5] Island and Instinet merged in 2002.

The purpose of this study is to add to the understanding of ECNs. Specifically, we will analyze the intraday behavior of Island. Little research regarding the intraday trading behavior of ECNs is documented. Simaan, Weaver and Whitcomb (2003) study the intraday pattern of quotes for ECNs. Tse and Hackard (2003) look at the intraday pattern of volume, number of trades and spreads of Island for only one security, the exchange traded fund, QQQ. We add to this literature stream by examining multiple NASDAQ-listed common stocks, and the effect of Island changing its trade reporting venue to the Cincinnati Stock Exchange.

## 3. Data and Trading Characteristics

The transaction data for this study comes from the NYSE TAQ (Trade and Quote) database, and firm size data is obtained from CRSP (the day used is March 28, 2002). The first day that Island reported trades to the Cincinnati Stock Exchange (CSE) is March 18, 2002, therefore, our sample period begins on March 18, 2002 and extends for 30 trading days (ends April 26, 2002). In addition, we use the 30 trading days before March 18 to measure changes in the probability of informed trading — before/after Island began reporting trades to the CSE.

We begin with all available NASDAQ-listed stocks. We exclude any stocks that have a price less than $3.00, or that firm size is not available from CRSP. Additionally, we add the criteria that the stock must trade every day in the sample, with an average of at least 50 trades a day.[6] So that we can compare NASDAQ and Island, the stocks must trade on both NASDAQ and the CSE. The final sample consists of 872 stocks.[7]

Summary statistics for the 872 firms in the sample are presented in Table 1. The average number of trades per sample firm in is 2,050, or an average of slightly more than 68 trades a day. The mean volume for each stock in the sample is over one million shares (1,274,914).

Table 2 shows trading statistics of the sample segmented between NASDAQ and Island (reporting to the Cincinnati Stock Exchange). NASDAQ has an average of 1,622 trades per stock, while Island has only 428. Similar comparative

[6]This ensures that we have sufficient observations for each firm for each of the intraday periods. We divide the trading day into 13 intervals, and want to have an observation for each firm in each trading interval.

[7]We find that the average number of firms that trade each day on both the CSE and NASDAQ, but do not meet the other criteria for the sample is 1,905.

**Table 1.** Firm summary statistics. This table presents the summary statistics for our sample. Firm size is market value. Number of trades is the average number of trades for each firm in the sample during our sample time period. Trade size ($) is the average price multiplied by the volume. Trade size is the average size of a transaction. Volume is sum of the trade size for all trades. Volatility is the standard deviation of the closing quote midpoint. N is the number of firms.

| Variable | Mean | Std. Dev | Min | 50% | Max |
|---|---|---|---|---|---|
| Firm size ($000s) | 2,567,099 | 14,480,652 | 54,157 | 698,474 | 326,606,581 |
| Number of trades | 2,050.01 | 4,905.93 | 114.57 | 634.77 | 47,731.33 |
| Trade size ($) | 9,872.92 | 4,973.31 | 2,165.33 | 9,012.81 | 33,671.60 |
| Trade size | 524.18 | 199.01 | 195.25 | 477.36 | 1,796.52 |
| Volatility | 1.48 | 1.28 | 0.11 | 1.14 | 13.97 |
| Volume | 1,274,914 | 4,252,171 | 43,903 | 324,418 | 71,141,573 |
| N = 872 | | | | | |

**Table 2.** Trading characteristics. This table presents characteristics of trading activities on the NASDAQ and Island (the Cincinnati Stock Exchange). We show the mean number of trades, mean trade size in shares and in dollars and mean volume for the two trading venues. Number of trades is the total number of transactions that occur during the time period. Trade size ($) is the price times the size of the trade. Trade size is the average number of shares per trade. Volume is the sum of the trade size for each trade. The mean differences and corresponding $t$-statistics are computed using paired $t$-tests.

| Variable | NASDAQ | Cincinnati | Difference | $t$-Stat |
|---|---|---|---|---|
| Number of trades | 1,622.02 | 427.99 | 1,194.00 | 14.19* |
| Trade size ($) | 10,726.69 | 4,887.84 | 5,838.90 | 48.79* |
| Trade size | 564.34 | 258.99 | 305.36 | 57.41* |
| Volume | 1,140,105.48 | 134,808.73 | 1,005,297.00 | 8.91* |

*Statistically significant at the 0.01 level.

statistics emerge for trade size (both number of shares and dollar trade size) and volume. We conclude that the majority of trades occur on NASDAQ and that these trades are significantly larger than the trades on Island.

## 4. Intraday Trading Behavior

Intraday patterns of bid-ask spreads and trading activity are widely documented (for example, see McInish and Wood, 1992; Chan, Christie and Schultz, 1995; Wood, McInish and Ord, 1985).[8] We contrast the intraday behavior of Island

[8] Stoll and Whaley (1990) and Brock and Kleidon (1992) provide explanations regarding specialist (market maker) behavior to explain for these intraday patterns. Madhavan (1992) and

with that of NASDAQ. It is quite possible that the intraday trading patterns are different for ECNs than for traditional market makers. Chung, Van Ness and Van Ness (1999) find that intraday spreads from the limit order book exhibit a slightly different pattern than that of specialists.[9]

Tse and Hackard (2003) are the first to examine the intraday behavior of Island. Using data obtained from Island, they study the trading behavior of one Exchange Traded Fund, QQQ. These authors find that QQQ exhibits a distinct U-shaped pattern for volume and the number of trades. We will add to their study by investigating the intraday behavior of multiple common stocks that trade on Island.

In this study we examine the intraday patterns in trading activity of NASDAQ securities that trade on both NASDAQ and Island. ECNs (Island in our study) may exhibit different intraday patterns or trading than market makers. Barclay, Hendershott and McCormick (2003) state that ECN trades are smaller than trades by market makers and are more likely to occur during times of high volume and volatility. Given this, ECNs very well may exhibit different intraday patterns than is exhibited by market makers on NASDAQ. A comparative analysis of the differences of intraday patterns in trading activity between the NASDAQ and Island furthers previous research concerning the differences of NASDAQ and ECNs. We look at four activity variables: (1) number of trades; (2) average trade size in shares; (3) average trade size in dollars; and (4) trading volume.

## 4.1. *Number of trades and volume*

Table 3 and Figure 1 show the intraday pattern in number of trades. We conduct F-tests to test for differences in the number of trades across the 13 time intervals. The results suggest a U-shaped pattern for NASDAQ trades as well as for Island trades. The results are consistent with previous studies concerning intraday patterns in trading activity.

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Foster and Viswanathan (1994) provide explanations for the intraday patterns by explanations of differential intraday information (informational asymmetry is resolved during the trading day).

[9]Chung, Van Ness and Van Ness (1999) find that the spread from the limit order book increases at the close [consistent with the findings of McInish and Wood (1992)], but find that the spread of specialists is not increasing at the close [inconsistent with the J-shaped pattern of spreads found by McInish and Wood (1992)].

**Table 3.** Intraday behavior of number of trades for NASDAQ and Island (CSE). This table examines the intraday pattern of the number of trades of NASDAQ and Island (the Cincinnati Stock Exchange). The trading day is divided into one 31-minute interval and 12 consecutive 30-minute intervals. The mean differences and $t$-statistics are provided in the table. In addition, $F$-tests are conducted to test whether the means differ across the 13 time intervals.

| Time of Day | NASDAQ | Cincinnati | Difference | $t$-Stat |
|---|---|---|---|---|
| 9:30–10:00 | 253.72 | 62.81 | 190.92 | 14.35* |
| 10:01–10:30 | 182.47 | 55.18 | 127.29 | 14.14* |
| 10:31–11:00 | 136.46 | 39.48 | 96.98 | 14.05* |
| 11:01–11:30 | 110.98 | 30.96 | 80.03 | 14.18* |
| 11:31–12:00 | 97.89 | 26.06 | 71.83 | 14.06* |
| 12:01–12:30 | 89.97 | 22.61 | 67.35 | 14.11* |
| 12:31–1:00 | 80.60 | 19.56 | 61.04 | 14.45* |
| 1:01–1:30 | 83.15 | 20.47 | 62.68 | 14.62* |
| 1:31–2:00 | 86.31 | 22.03 | 64.28 | 14.45* |
| 2:01–2:30 | 104.00 | 27.92 | 76.08 | 14.47* |
| 2:31–3:00 | 112.61 | 32.45 | 80.17 | 14.44* |
| 3:01–3:30 | 128.79 | 36.21 | 92.58 | 14.45* |
| 3:31–4:00 | 190.29 | 43.36 | 146.93 | 15.88* |
| $F$-Stat | 25.44* | 13.44* | 31.37* | |

*Statistically significant at the 0.01 level.

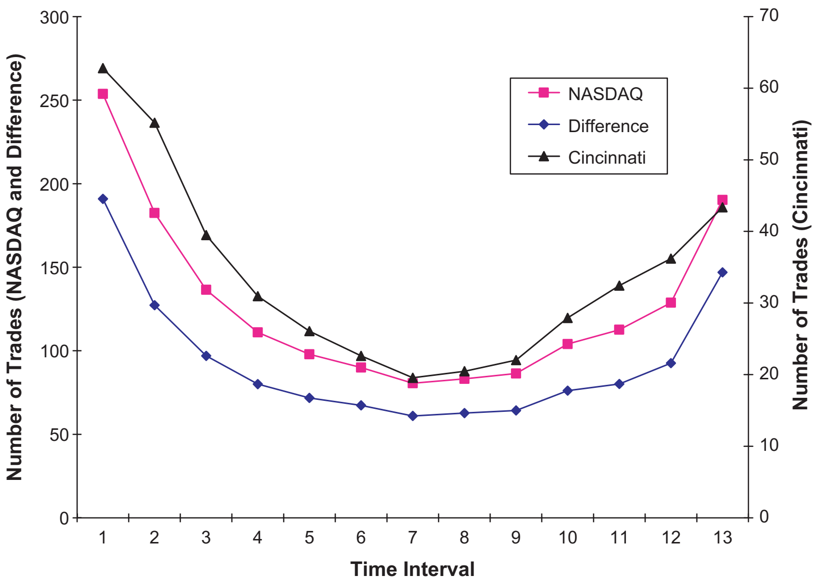


**Figure 1.** Intraday behavior of NASDAQ and Cincinnati trades.

The relatively high trading activity at the open and at the close can be explained by the theory that limit order traders trade early in the day to meet liquidity demands arising overnight or to take advantage of information asymmetry existing at the opening of the market. This theory is advanced by Admati and Pfleiderer (1988) who argue that the concentrated trading patterns arise endogenously as the result of the strategic behavior of informed traders and discretionary liquidity traders.

Brock and Kleiden (1992) analyze the effect of periodic stock market closure on transactions demand and volume of trade, and consequently, bid and ask prices. Their study demonstrates that transactions demand at the open and close is greater and less elastic than at other times of the trading day and that the market maker takes advantage of the inelastic demand by imposing a higher spread to transact at these periods of peak demand.

The most eye-catching result from our analysis is that the difference in number of trades on NASDAQ and Island also shows a U-shaped pattern. The difference is high in the beginning of the day, decreases during the day and increases at the end of the day. The U-shaped pattern in trading activity on NASDAQ and Island is expected due to extensive documentation by numerous researchers. However, we are perplexed as to how to explain the U-shaped pattern in the differences in trading activity. One possible explanation has to do with an institutional difference between NASDAQ and Island, where NASDAQ market makers maintain an inventory while Island is an automated limit order book void of a market maker holding an inventory. The relatively more intense trading activity for NASDAQ at the end of the day might be explained by NASDAQ market makers, faced with an inventory imbalance that has accumulated during the day, increasing their trading at the end of the day in order to minimize the imbalance.

Table 4 and Figure 2 show the intraday behavior of NASDAQ and Island volume. The findings are very similar to those of the number of trades (Table 4 and Figure 1). A distinctive U-shaped pattern is found for NASDAQ, Island and the difference between the two exchanges.

### 4.2. *Trade size (in shares and in dollars)*

Tables 5 and 6 and Figure 3 show the intraday patterns of trade size in shares and in dollars. We find a distinct pattern for NASDAQ and Island trade size in shares as well as in dollars. Island trade size decreases slightly immediately

**Table 4.** Intraday behavior of volume for NASDAQ and Island (CSE). This table examines the intraday pattern of the volume of trades of the NASDAQ and Island (the Cincinnati Stock Exchange). The trading day is divided into one 31-minute interval and 12 consecutive 30-minute intervals. The mean differences and $t$-statistics are provided in the table. In addition, $F$-tests are conducted to see whether the means differ across the 13 time intervals.

| Time of Day | NASDAQ | Cincinnati | Difference | $t$-Stat |
|---|---|---|---|---|
| 9:30–10:00 | 165,661.09 | 20,067.31 | 145,593.78 | 8.56* |
| 10:01–10:30 | 122,754.85 | 16,947.57 | 105,807.28 | 8.46* |
| 10:31–11:00 | 94,584.95 | 12,128.43 | 82,456.51 | 8.47* |
| 11:01–11:30 | 79,358.45 | 9,497.94 | 69,860.51 | 8.74* |
| 11:31–12:00 | 70,235.28 | 7,937.06 | 62,298.22 | 8.55* |
| 12:01–12:30 | 65,120.52 | 6,834.76 | 58,285.76 | 8.74* |
| 12:31–1:00 | 61,214.43 | 5,807.63 | 55,406.79 | 9.34* |
| 1:01–1:30 | 63,982.33 | 6,071.48 | 57,910.85 | 9.75* |
| 1:31–2:00 | 61,744.46 | 6,576.29 | 55,168.17 | 9.12* |
| 2:01–2:30 | 70,898.41 | 8,323.27 | 62,575.13 | 8.92* |
| 2:31–3:00 | 76,363.95 | 10,427.50 | 65,936.45 | 9.14* |
| 3:01–3:30 | 89,521.37 | 11,692.73 | 77,828.64 | 9.46* |
| 3:31–4:00 | 139,277.26 | 15,364.36 | 123,912.90 | 10.66* |
| $F$-Stat | 9.93* | 10.3* | 9.72* | |

*Statistically significant at the 0.01 level.

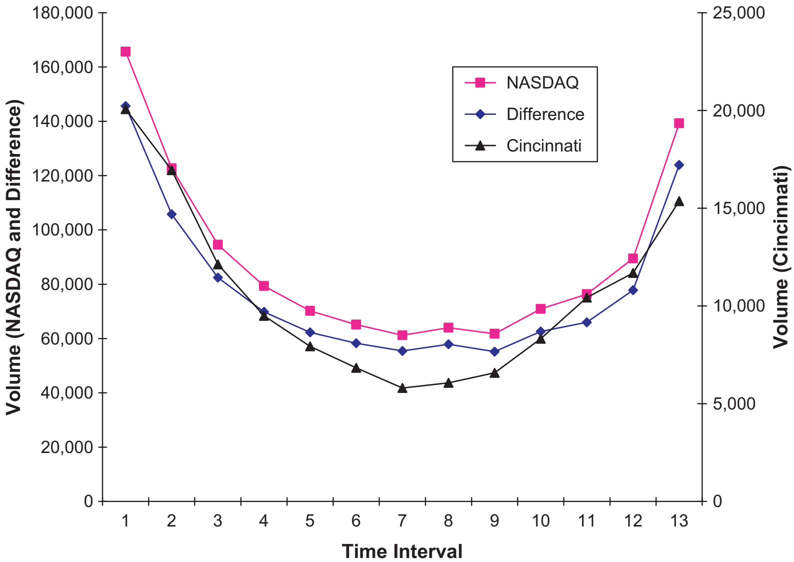


**Figure 2.** Intraday behavior of NASDAQ and Cincinnati volume.

**Table 5.** Intraday behavior of trade size for NASDAQ and Island (CSE). This table examines the intraday pattern of trade size of the NASDAQ and Island (the Cincinnati Stock Exchange). The trading day is divided into one 31-minute interval and 12 consecutive 30-minute intervals. The mean differences and $t$-statistics are provided in the table. In addition, the $F$-tests are conducted to test whether the means differ across the 13 time intervals.

| Time of Day | NASDAQ | Cincinnati | Difference | $t$-Stat |
|---|---|---|---|---|
| 9:30–10:00 | 464.14 | 257.53 | 206.61 | 39.06* |
| 10:01–10:30 | 515.20 | 242.67 | 272.54 | 45.62* |
| 10:31–11:00 | 528.08 | 237.43 | 290.66 | 45.96* |
| 11:01–11:30 | 576.27 | 242.76 | 333.50 | 21.43* |
| 11:31–12:00 | 557.45 | 243.87 | 313.58 | 37.40* |
| 12:01–12:30 | 584.92 | 238.05 | 346.87 | 42.35* |
| 12:31–1:00 | 587.06 | 236.78 | 350.29 | 39.67* |
| 1:01–1:30 | 621.24 | 235.28 | 385.96 | 31.51* |
| 1:31–2:00 | 575.91 | 230.92 | 345.00 | 32.14* |
| 2:01–2:30 | 580.91 | 230.32 | 350.58 | 38.78* |
| 2:31–3:00 | 557.83 | 252.45 | 305.38 | 41.27* |
| 3:01–3:30 | 587.96 | 257.45 | 330.52 | 45.45* |
| 3:31–4:00 | 603.68 | 301.56 | 302.12 | 32.92* |
| $F$-Stat | 16.35** | 24.47* | 23.96* | |

*Statistically significant at the 0.01 level.

**Table 6.** Intraday behavior of trade size ($) for NASDAQ and Island (CSE). This table examines the intraday pattern of the dollar trade size of the NASDAQ and Island (the Cincinnati Stock Exchange). The trading day is divided into one 31-minute interval and 12 consecutive 30-minute intervals. The mean differences and $t$-statistics are provided in the table. In addition, the $F$-tests are conducted to see whether the means differ across the 13 time intervals.

| Time of Day | NASDAQ | Cincinnati | Difference | $t$-Stat |
|---|---|---|---|---|
| 9:30–10:00 | 8,949.70 | 4,803.44 | 4,146.27 | 34.97* |
| 10:01–10:30 | 9,908.03 | 4,557.87 | 5,350.16 | 37.93* |
| 10:31–11:00 | 10,159.37 | 4,471.47 | 5,687.90 | 37.97* |
| 11:01–11:30 | 10,792.07 | 4,610.16 | 6,181.91 | 32.33* |
| 11:31–12:00 | 10,624.24 | 4,622.93 | 6,001.31 | 40.72* |
| 12:01–12:30 | 11,143.63 | 4,474.46 | 6,669.17 | 38.35* |
| 12:31–1:00 | 11,224.98 | 4,440.97 | 6,784.02 | 37.26* |
| 1:01–1:30 | 12,015.02 | 4,442.15 | 7,572.87 | 31.26* |
| 1:31–2:00 | 10,795.11 | 4,341.42 | 6,453.69 | 39.70* |
| 2:01–2:30 | 10,940.18 | 4,315.65 | 6,624.53 | 38.78* |
| 2:31–3:00 | 10,577.43 | 4,879.83 | 5,697.60 | 40.54* |
| 3:01–3:30 | 11,089.73 | 4,944.73 | 6,145.00 | 45.12* |
| 3:31–4:00 | 11,495.62 | 5,710.91 | 5,784.71 | 40.80* |
| $F$-Stat | 12.33* | 18.11* | 25.29* | |

*Statistically significant at the 0.01 level.

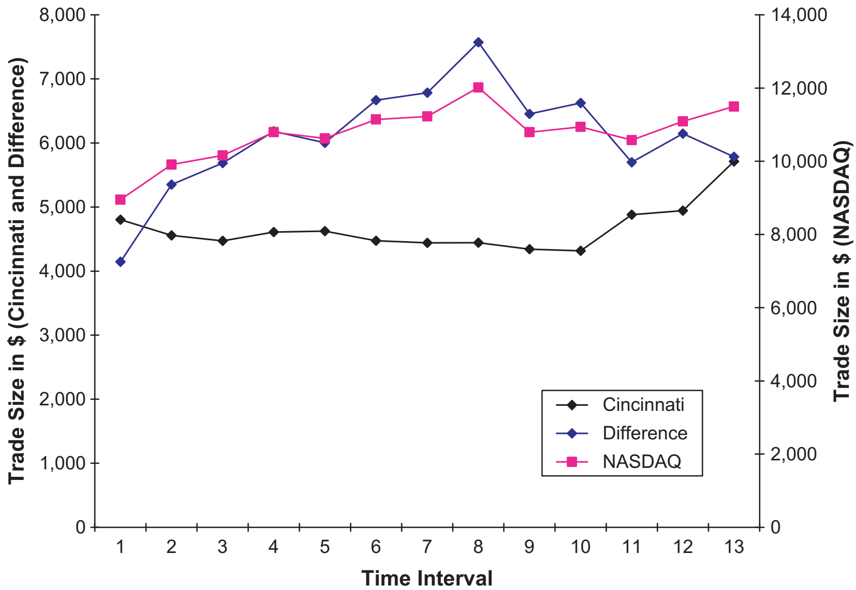


**Figure 3.** Intraday behavior of NASDAQ and Cincinnati trade size ($).

after the open, remains stable during day and increases at the end of the day. However, NASDAQ's trade size begins to rise after the open and continues to rise until after mid-day, where it drops sharply and rises again near the close.

A potential explanation for NASDAQ's pattern is that price discovery begins at the open. At and immediately following the open, equilibrium prices are revealed through a large number of relatively small trades. Faced with the risk of trading with informed traders, the dealers are unwilling to commit to large trades during this period of price discovery (Chan, Christie and Schultz, 1995). As the day progresses, new information is revealed and consequently, average trade size may increase.

## 5. Determinants of Trading and Volume

Barclay, Hendershott and McCormick (2003) examine the choice of trading with ECNs or with market makers by looking at 150 NASDAQ stocks in June 2000. They find that investors are more likely to use an ECN for small trades in high-volume stocks. We extend their analysis by studying

**Table 7.** Determinants of the number of trades. In this table we provide the results of the regression of the percentage number of trades on different stock and trading characteristics. Firm size is the market value of the firms. Volatility is the standard deviation of NASDAQ's closing mid-point quotes. Price is the average price of the stock. All explanatory variables are the same for the two regressions with the exception of trade size, which varies according to the trading venue. $T$-statistics are in the parentheses. We use the Box-Cox model to specify the functional form of the regression.

$$(\%\text{Number of Trades}_t^{\lambda} - 1)/\lambda = \beta_0 + \beta_1 \text{Firm Size}_t + \beta_2 \text{Volatility}_t + \beta_3 \text{TradeSize}_t + \beta_4 \text{Price}_t + \varepsilon_t$$

| Variable | NASDAQ | Cincinnati |
|---|---|---|
| Intercept | −0.07969 (−16.85*) | −1.5942 (−56.53*) |
| Firm size | −0.00000000023305 (−3.16*) | 0.00000000149006 (3.34*) |
| Volatility | −0.00797 (−8.63*) | 0.04799 (8.55*) |
| Trade size (T and C) | −0.00000674 (−1.15) | 0.00000813 (0.11) |
| Price | −0.00058145 (−5.94*) | 0.00317 (5.26*) |
| $\lambda$ | 4.15 | 0.35 |
| $R^2$ | 22.51% | 21.94% |
| $F$-value | 62.98* | 60.91* |
| No. of observations | 872 | 872 |

*Statistically significant at the 0.01 level.

stock characteristics associated with more trading on Island, and ENC, than on NASDAQ.

Table 7 shows the determinants of the number of trades for Island and NASDAQ. We use the Box-Cox transformation method to specify the functional form of the regression variables. We find distinct features of stocks trading on Island and NASDAQ. The percentage of trades on Island is positively correlated with market capitalization, trading volatility and price. However, all regressors are negatively correlated with the percentage of trades on NASDAQ. These findings imply that stocks with large market capitalizations, high trading volatility and higher prices are more likely to trade on Island. On the contrary, stocks with smaller market capitalizations, low trading volatility and lower prices are more likely to trade on the NASDAQ.

Table 8 analyzes the determinants of percentage volume on Island and NASDAQ. The results of our regressions indicate that Island volume positively related to volatility, trade size and price. For NASDAQ, percentage volume is negatively related to market capitalization, volatility and price, but positively related to trade size.

**Table 8.** Determinants of volume. In this table we provide the results of the regression of the percentage volume of trades on different stock and trading. Firm size is the market value of the firms. Volatility is the standard deviation of NASDAQ's closing mid-point quotes. Price is the average price of the stock. All explanatory variables are the same for the two regressions with the exception of trade size which varies according to trading venue. $T$-statistics are in the parentheses. We use the Box-Cox model to specify the functional form of the regressions.

$$(\%\text{Volume}_t^{\lambda} - 1)/\lambda = \beta_0 + \beta_1 \text{ Firm Size}_t + \beta_2 \text{Volatility}_t + \beta_3 \text{ TradeSize}_t + \beta_4 \text{ Price}_t + \varepsilon_t$$

| Variable | NASDAQ | Cincinnati |
|---|---|---|
| Intercept | −0.04799 (−22.23*) | −2.33979 (−67.67*) |
| Firm size | −0.00000000014107 (−4.19*) | 0.000000000776898 (1.42) |
| Volatility | −0.00368 (−8.74*) | 0.05638 (8.19*) |
| Trade size (T and C) | 0.0000142 (5.32*) | 0.00055371 (6.03*) |
| Price | −0.00008974 (−2.01**) | 0.0059 (8.00*) |
| $\lambda$ | 10.85 | 0.25 |
| $R^2$ | 22.39% | 23.09% |
| $F$-value | 62.55 | 65.07 |
| No. of observations | 872 | 872 |

*Statistically significant at the 0.01 level.

## 6. Probability of Informed Trading

We find that Island reports smaller volume than NASDAQ, and that Island's trades are smaller [consistent with the findings of Barclay, Hendershott and McCormick (2003)]. Another similar issue is whether Island has more or less informed trading than NASDAQ. Tse and Erenburg (2003) examine trading for QQQ, and find that ECNs contribute the most to QQQ's price discovery. So, if ECNs are providing a majority of the price discovery, we expect to see more informed traders for our sample on Island.

We use the model of Easley, Kiefer, O'Hara and Paperman (1996) to calculate the probability of informed trading. We analyze the probability of informed trading for NASDAQ and Island. We look at NASDAQ for 30 days before and 30 days after Island began reporting trades to the Cincinnati Stock Exchange. We also calculate the difference in the probability of informed trading for NASDAQ and Island 30 days after this reporting change.

Easley, Kiefer, O'Hara and Paperman (1996) develop a trade flow model using order imbalances of buys and sales to generate the probability that the market maker will face an informed trader. The inputs for the model are the total buys and sales per day for the estimation period. We compute buys ($B$) and sales ($S$) for the 30 trading days before and 30 days after Island began disseminating

**Table 9.** Probability of informed trading. This table examines the probability of informed trading. We calculate the probability of informed trading using the model of Easley, Kiefer, O'Hara and Paperman (1996).

| Probability of Informed Trading | 30 Days Before | 30 Days After | Differences | *T*-Stat |
|---|---|---|---|---|
| NASDAQ | 0.2428 | 0.2440 | −0.0015 | 0.1817 |
| Island | | 0.2559 | | |
| Difference in NASDAQ and Island (30 days after) | | | −0.0119 | 1.5366 |

*Statistically significant at the 0.01 level.

their trades through the Cincinnati Stock Exchange. The model parameters $\theta = (\alpha, \mu, \varepsilon, \delta)$ are estimated by maximizing the following likelihood function:

$$L(\theta|M) = \prod_{i=1}^{I} L(\theta \mid B_i, S_i), \tag{1}$$

where each day's likelihood is given by:

$$\begin{aligned} L\,(\theta|B, S) = (1-\alpha)e^{-\varepsilon}\frac{\varepsilon^B}{B!}e^{-\varepsilon}\frac{\varepsilon^S}{S!} + \alpha\delta e^{-\varepsilon}\frac{\varepsilon^B}{B!}e^{-(\mu+\varepsilon)}\frac{(\mu+\varepsilon)^S}{S!} \\ + \alpha(1-\delta)e^{-(\mu+\varepsilon)}\frac{(\mu+\varepsilon)^B}{B!}e^{-\varepsilon}\frac{\varepsilon^S}{S!}, \end{aligned} \tag{2}$$

and $\alpha$ is the probability of an information event, $\delta$ is the probability that a given signal is low, $\mu$ is the arrival rate of informed traders given a signal, and $\varepsilon$ is the arrival rate of uninformed traders. The probability of informed trading $(PI)$ is calculated as:

$$PI = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon}. \tag{3}$$

We find (Table 9) that the probability of informed trading on NASDAQ is not significantly different for the 30 days before (24.28%) and the 30 days after (24.40%) Island began reporting their NASDAQ trades to the Cincinnati Stock Exchange. Additionally, we find no significant difference in the probability of informed trading between Island (25.59%) and NASDAQ (24.40%) in the same 30 days after the trade reporting change.

## 7. Conclusion

We analyze differences between trading behavior on Island and NASDAQ after Island began reporting trades to the Cincinnati Stock Exchange. We find that

Island has a smaller number of trades, smaller trades and consequently, less volume.

We find distinct intraday patterns of trading. The number of trades and volume exhibit U-shaped patterns for both venues. However, the differences in the two activity variables between the venues also show a U-shaped pattern. Intraday trade size is different for the two venues. NASDAQ has smaller trade sizes at the open. The smaller trade size can be explained by the price discovery process where the market maker tries to avoid trading with informed traders. Island trade size shows a more stable intraday pattern.

Using the model of Easley, Kiefer, O'Hara and Paperman (1996), we find no significant difference in the probability of informed trading between Island and NASDAQ. We also find no significant difference in the probability of informed trading for NASDAQ before and after the change.

Finally, we examine the determinants of the percentage of trades and volume. The results suggest that market capitalization, volatility and price are important determinants of the percentage of trades for both venues. Stocks with high market capitalizations, high volatility and higher prices are more likely to trade with Island (on the Cincinnati Stock Exchange) whereas the opposite case holds for the NASDAQ.

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Chapter 7

# The Impact of the Introduction of Index Securities on the Underlying Stocks: The Case of the Diamonds and the Dow 30

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We test the hypothesis that uniformed traders prefer to invest in a basket of stocks rather than a portfolio of individual stocks by examining the impact of the introduction of the Diamond Index securities on the underlying Dow 30 stocks. We find that following the introduction, the bid-ask spreads of the Dow 30 increase relative to spreads of matching stocks. However, we do not find a consistent change in the adverse selection components of the Dow stocks relative to the matching sample. Our overall results are consistent with either a movement of uninformed traders to the Diamonds or the increase of another component of the spread, such as inventory holding costs.

**Keywords:** Index securities; exchange traded funds; spreads.

## 1. Introduction

The introduction of assets that trade baskets of securities has become increasingly common in recent years.[1] Subrahmanyam (1991) states that in a frictionless market these securities would be redundant, however the trading volume of index securities indicates that this is far from the case. In the presence of information asymmetries, these securities may provide liquidity traders with a low cost alternative to the direct investment in the underlying stocks. In this paper we examine the impact of the introduction of the Diamonds index securities on spreads and adverse selection.

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[1]For example, Diamonds (symbol — DIA) which track the Dow 30, SPDRs (symbol — SPY) which track the S&P 500 and NASDAQ 100 Trust (symbol — QQQ) which track the NASDAQ 100. DIA began trading on January 20, 1998 and QQQ began trading on March 10, 1999.

In a market populated with both informed and uninformed traders, the uninformed typically bears the cost of trading against those more informed. A common characterization of this cost is the adverse selection component of the spread, but indirectly the cost is also reflected in the overall magnitude of the bid-ask spread. Kyle (1985) argues that the presence of traders who possess superior knowledge of the value of a stock can impose adverse selection costs on liquidity traders and market makers. Market makers are compensated for bearing this cost by widening the bid-ask spread, and ultimately recouping the cost from liquidity traders. For liquidity traders who wish to merely own a diversified portfolio there is no way to avoid these costs, as they must purchase each stock individually. Furthermore, these liquidity costs cannot be diversified away. However, the introduction of index securities provides liquidity traders with a vehicle for investing in a diversified portfolio without having to purchase individual securities. The adverse selection costs associated with index securities are likely to be significantly less than those for the underlying securities because the pooling of the stocks greatly reduces the ability of informed traders to profit from their stock-specific knowledge.

Subrahmanyam (1991) hypothesizes that upon the introduction of index securities, there should be an increase in the spread and the adverse selection component of the spread for the underlying stocks. These increases are caused by uninformed investors migrating to the new index securities, leaving a greater proportion of informed investors trading the underlying stocks. Because the market maker now faces a greater percentage of informed traders, he must increase the spread (or adverse selection component) to cover his cost of trading with more informed traders. Jegadeesh and Subrahmanyam (1993) examine the impact of the introduction of S&P 500 futures contracts on the spreads of the underlying stocks. They find that the spreads for a sample of S&P 500 stocks increase significantly following the introduction of the futures contract. They also find weak evidence that adverse selection components increased in the post futures period. Several drawbacks exist with the Jegadeesh and Subrahmanyam data and method. First, S&P 500 futures were originally issued in 1982, a time when only daily spread data is available; and second, their sample represents only a portion of the total 500 firms due to data constraints.

In this paper, we use broadly the same method of Jegadeesh and Subrahmanyam (1993) to examine the microstructure effects of the introduction of the Diamond Index securities which track the Dow Jones 30 Industrial Average. By computing spread and spread component data for all 30 firms and by creating a more representative control sample, we are better able to test the impact of the index stock on the underlying stocks. Additionally, we examine the overall trading costs of the Diamonds contract compared to the underlying basket of stocks. By doing so we hope to shed light on the relative costs of trading the basket versus trading the individual stocks.

Our results are mixed. The time period surrounding the introduction of the Diamonds is also one of market-wide decline in spreads. Such a decline makes it more difficult to discern the impact, if any, of the introduction of the Diamonds. However, after extensively controlling for factors that influence spreads, we find that, relative to matching stocks, the Dow 30 experiences a smaller decline in spreads around the introduction of the Diamonds. This result is consistent with uninformed traders moving from the Dow 30 to the Diamonds, and causing the market maker to increase spreads on the Dow 30 relative to other stocks.

A comparison of the adverse selection components of the Dow 30 stocks with the control sample reveals no significant impact of the Diamonds introduction. However, the power of such tests is weakened by the reliability of the adverse selection estimates, and our limited sample size.

The paper proceeds as follows. Section 2 discusses the introduction of the Diamonds, Section 3 discusses data issues, Section 4 presents our results and analyses and Section 5 concludes.

## 2. Diamond Index Securities

On January 20, 1998 the American Stock Exchange (AMEX) began trading Diamonds. Diamonds are a security that allows investors to buy or sell shares in an entire portfolio of the Dow Jones Industrial Average (DJIA) stocks, so investors can mimic the DJIA returns at a minimal cost (minimal when compared to purchasing each stock within the DJIA) by purchasing units (shares) in a trust consisting of DJIA stocks. Investors receive proportionate monthly cash distributions corresponding to the dividends that accrue to the DJIA stocks in the Diamonds portfolio, less trust expenses. The AMEX introduced this product to provide investors the advantages of indexing with the benefits of intraday trading, as unlike stock index mutual funds, Diamonds may be purchased throughout the trading day. The net asset value of Diamonds is computed each business day at the close of trading.

## 3. Data and Matching Portfolio

The data for this paper comes from the New York Stock Exchange TAQ (Trade and Quote) database and CRSP. To control for other factors that might be affecting spreads around the introduction of the Diamonds, we assemble a matching portfolio of stocks that represents our control group. To be eligible for matching, a stock must trade on the NYSE, not be in the Dow 30, and have data available on CRSP and TAQ for the study time period.

We match each stock in the Dow 30 with a NYSE counterpart on the basis of four stock attributes.[2] These attributes are share price, trade size, return volatility and market capitalization. Previous work has found the first three of these factors to be important determinants of the spread.[3] We also include market value as Dow stocks tend to be much larger than the average stock on the NYSE. The matching procedure uses data from the 30 trading days prior to the introduction of the Diamonds. We calculate the following composite match score (CMS) for each Dow stock in our sample with each of our selected match stocks:

$$\mathrm{CMS} = \sum_{k=1}^{4} \left[ \frac{2\left(Y_k^{\mathrm{DOW}} - Y_k^{\mathrm{Match}}\right)}{\left(Y_k^{\mathrm{DOW}} + Y_k^{\mathrm{Match}}\right)} \right]^2,$$

where $Y_k$ represents one of the four stock attributes, and the superscripts, Dow and Match, refer to Dow 30 stocks and potential match stocks, respectively. For each Dow stock, we pick the NYSE stock with the smallest score — as long as the score is less than 2. This matching procedure results in 30 pairs of NYSE stocks (the matching stocks are listed in the Appendix). Summary statistics of the Dow 30 and the matching portfolio are displayed in Table 1. Overall the quality of the match appears good. The notable outlier in the matching process was the market value of General Electric, however, this stock matched well on the other criteria.

## 4. Results and Analysis

### 4.1. *Spread, effective spread and price improvement*

We use three measures of trading costs in this study (percentage spread, traded spread and effective spread) and a measure of trading inside the spread (price improvement). Each of these measures is computed using transaction data and

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[2]This procedure is similar to Huang and Stoll (1996) and Chung, Van Ness and Van Ness (2001).
[3]See Demsetz (1968), Benston and Hagerman (1974), Stoll (1978), McInish and Wood (1992), and Huang and Stoll (1996).

**Table 1.** Summary statistics for Dow 30 and matching stocks.

Time period is the 30 trading days before and the 30 trading days after the introduction of the Diamonds (January 20, 1998). All variables are measured daily. Score is the composite match score. A lower score indicates a better match. The score is computed using the following:

$$\mathrm{CMS} = \sum_{k=1}^{4}\left[\frac{2\left(Y_k^{\mathrm{DOW}} - Y_k^{\mathrm{Match}}\right)}{\left(Y_k^{\mathrm{DOW}} + Y_k^{\mathrm{Match}}\right)}\right]^2,$$

where $Y_k$ represents one of the four stock attributes, and the superscripts, DOW and Match, refer to Dow 30 stocks and potential NYSE match stocks, respectively. Price is closing stock price. Volume is the average daily number of shares traded. MVE is the market value of equity, measured in thousands. Risk is standard deviation of daily returns. The full list of the Dow 30 stocks and their matches are presented in the Appendix.

| | | Mean | Median | Std Dev | Min | Max |
|---|---|---|---|---|---|---|
| Price | DOW 30 | 65.69 | 62.08 | 20.56 | 37.30 | 113.65 |
| | Match | 66.91 | 64.40 | 23.52 | 35.70 | 125.62 |
| Volume | DOW 30 | 2,276,859 | 1,872,534 | 1,329,360 | 376,393 | 5,659,615 |
| | Match | 2,057,919 | 1,619,233 | 1,612,405 | 416,470 | 9,551,476 |
| MVE | DOW 30 | 64,545,004 | 49,000,000 | 54,923,178 | 6,002,367 | 241,000,000 |
| | Match | 42,669,196 | 45,700,000 | 23,057,133 | 6,607,693 | 97,700,000 |
| Risk | DOW 30 | 0.0185 | 0.0180 | 0.0030 | 0.0132 | 0.0251 |
| | Match | 0.0199 | 0.0187 | 0.0049 | 0.0104 | 0.0308 |
| Score | | 0.3611 | 0.1406 | 0.4551 | 0.0169 | 1.6017 |

averaged for each security for each day of the study period. The percentage spread is calculated as:

$$\text{Percentage Spread}_i = \frac{(\text{Ask Price}_i - \text{Bid Price}_i)}{(\text{Ask Price}_i + \text{Bid Price}_i)/2)},$$

where Ask Price$_i$, is the posted ask price for stock $i$, and Bid Price$_i$, is the posted bid price for stock $i$, for each quote within the sample. As quotes occur both when trades occur and when they do not, we also calculate the spread that occurs when a trade occurs:

$$\text{Traded Spread}_i = (\text{Ask Price}_i - \text{Bid Price}_i).$$

To measure trading costs when trades occur at prices inside the posted bid and ask quotes, we calculate the effective spread using the following formula:

$$\text{Effective Spread}_i = 2|\text{Trade Price}_i - \text{Midpoint}_i|,$$

where Trade $\text{Price}_i$ is the transaction price for security $i$ and $\text{Midpoint}_i$ is the midpoint of the most recently posted bid and ask quotes for security $i$. The effective spread measures the actual execution cost paid by the trader. Lastly, we measure the discount that is given during trading, namely, price improvement.

$$\text{Price Improvement} = (\text{Traded Spread} - \text{Effective Spread}).$$

Table 2 presents the means of the percentage spread and effective spread of the Dow 30 and the matching stocks for the 30 days before and 30 days after the introduction of the Diamonds. Surprisingly, for both the Dow and the matching stocks the effective spread and percentage spread declines in the

**Table 2.** Means tests of spread variables.

This table presents $t$-tests of the changes in the spread statistics for 30 trading days before and 30 trading days after the introduction of the Diamonds. The sample is the Dow 30 stocks and a sample of 30 matching stocks. The three spread measures are computed as:

$$\text{Percentage Spread}_i = \frac{(\text{Ask Price}_i - \text{Bid Price}_i)}{(\text{Ask Price}_i + \text{Bid Price}_i/2)},$$

$$\text{Effective Spread}_i = 2|\text{Trade Price}_i - \text{Midpoint}_i|,$$

$$\text{Traded Spread}_i = \text{Ask}_i - \text{Bid Price}_i.$$

| | DOW 30 | Matching Stocks | DOW-Match |
|---|---|---|---|
| Panel A: Effective Spread | | | |
| Before introduction | 0.0925 | 0.0985 | −0.006 |
| After introduction | 0.0903 | 0.0944 | −0.004 |
| Difference | 0.0022 | 0.0041 | −0.002 |
| $t$-stat | 2.787** | 4.2379** | −1.836* |
| Panel B: Percentage Spread | | | |
| Before introduction | 0.0019 | 0.0020 | −0.0001 |
| After introduction | 0.0018 | 0.0018 | −0.0000 |
| Difference | 0.0001 | 0.0002 | −0.0000 |
| $t$-stat | 5.0838** | 6.3238** | −1.4837 |
| Panel C: Traded Spread | | | |
| Before introduction | 0.1175 | 0.1274 | −0.0099 |
| After introduction | 0.1138 | 0.1210 | −0.0072 |
| Difference | 0.0037 | 0.0064 | −0.0085 |
| $t$-stat | 2.9131** | 4.2395** | −1.7016* |

**Significant at the 5% level.
*Significant at the 10% level.

post-introduction period. The decline in spreads appears to be market wide and we consider it highly unlikely that it was caused by the introduction of the Diamonds, given the volume of the Diamonds relative to the market overall. This decline can be seen in Figure 1 which presents the average daily equally-weighted percentage spread for NYSE stocks for the time period under consideration. After the introduction on January 20, 1998, spreads are lower overall than in the prior period. The higher spreads around the end of December and early January may be due to the presence of several market holidays during this time. Chordia, Roll and Subrahmanyam (2001) find that market wide spreads tend to increase around holidays.

Referring to Table 2, the decline in spreads is smaller for the Dow 30 than the decline for the matching stocks. This result is consistent with spreads declining overall (due to some other unmeasured factor) but the decline in the spreads on the Dow 30 is lessened to some degree by the introduction of the Diamonds. An alternative explanation for this result is that the Dow stocks had spreads that were narrower than the matching firms prior to the Diamond's introduction and that some stocks were already trading close to their minimum tick size. During this time period the minimum tick size is 1/16th or 6.25 cents. The smallest average daily quoted spread was 7.42 cents (for General Electric), while the median quoted spread was 11.56 cents. Therefore, it is possible that for some of the most liquid stocks in the sample, the minimum tick provides a lower bound below which the quote cannot fall. However, most of the stocks in the sample have quotes that are substantially above the minimum tick both before and after the introduction of the Diamonds.

To control for other factors that might impact spreads, we employ the method of Chordia, Roll and Subrahmanyam (2001) who examine the impact of market wide and macroeconomic factors on market liquidity and trading activity. Chordia *et al.* find that the overall market return, the day of the week, holidays, and the change in the level of key interest rates significantly affect traded and effective spreads. We incorporate these variables into our regression analysis in Table 3 to control for other factors that might impact spreads around the introduction of the Diamonds. We combine the Dow 30 and matching firms into one sample and estimate the following regression model which allows us to observe the different slope coefficients for the Dow stocks compared to the matching firms.

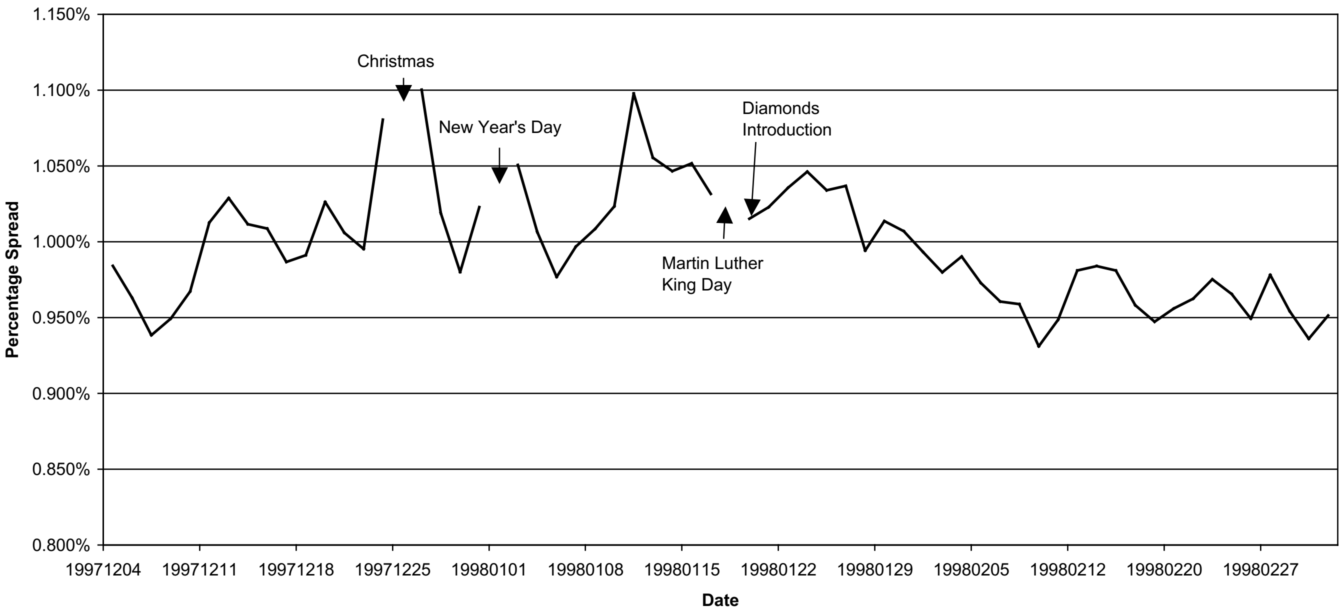


**Figure 1.** NYSE equally weighted daily quoted percentage spread.

**Table 3.** Feasible GLS estimates of the traded spread, effective spread and percentage spread.

FGLS is used to control for first order autocorrelation, heteroscedasticity, and cross sectional correlation. The data set is a panel of 30 Dow stocks and 30 match stocks. The time period is 30 days before and 30 days after the introduction of the Diamonds. The regression model is $[\text{Spread}_{it}] = a_0 + a_1\text{MD}_{it} + a_2\text{INTDUM}_{it} + b_2\text{MD}^*\text{INTDUM}_{it} + a_3\text{Price}_{it} + b_3\text{MD}^*\text{Price}_{it} + a_4\text{Trade Size}_{it} + b_4\text{MD}^*\text{Trade Size}_{it} + a_5\text{Trades}_{it} + b_5\text{MD}^*\text{Trades}_{it} + a_6\text{Sdmid}_{it} + b_6\text{MD}^*\text{Sdmid}_{it} + a_7\text{MKTUP}_t + b_7\text{MD}^*\text{MKTUP}_t + a_8\text{MKTDN}_t + b_8\text{MD}^*\text{MKTDN}_t + a_{9-12}\text{Day of the week Dummies}_t + b_{9-12}\text{MD}^*\text{DayoftheweekDummies}_t + a_{13}\text{Holiday}_t + b_{13}\text{MD}^*\text{Holiday}_t + a_{14}\text{Short Rate}_t + b_{14}\text{MD}^*\text{ShortRate}_t + a_{15}\text{Term Spread}_t + b_{15}\text{MD}^*\text{TermSpread}_t + a_{16}\text{Quality Spread}_t + b_{16}\text{MD}^*\text{QualitySpread}_t + \varepsilon_{it}$. In this regression, the matched sample is represented by the dummy variable MD which takes a value of 1 if the stock is a matching firm and zero otherwise. The interaction variables are presented in columns 1A, 2A, and 3A. The key variable of interest is INTDUM, a dummy variable, which takes the value of zero before the diamonds introduction and one after. The interaction term MD*INTDUM measures the differential change in spreads for the match firms relative to the Dow 30. Other control variables are: Price is the mean daily price for each stock, Trade Size is the mean daily trade size, Trades is the mean daily number of trades, SDMID is the standard deviation of the quote midpoint. MKTUP(DN) is the CRSP equally-weighted return if positive (negative) and zero otherwise. Monday, Tuesday, Wednesday and Friday are days of the week dummies. Holiday is a dummy if the trading day follows a holiday. Short rate is daily first difference in the Federal Funds rate, Term Spread is the daily change in the difference between the 10-year Treasury Bond and Short rate, Quality Spread is the daily change in the Moody's Baa or better corporate bond yield index and the yield on a ten year constant maturity Treasury Bond. $Z$ statistics are in parenthesis. Each regression has 3,600 observations.

| | Percentage Spread | | Effective Spread | | Traded Spread | |
|---|---|---|---|---|---|---|
| | | MD = 1 | | MD = 1 | | MD = 1 |
| | 1 | 1A | 2 | 2A | 3 | 3A |
| Intercept | 3.269 | | 76.602 | | 84.225 | |
| | (422.66)** | | (288.87)** | | (192.55)** | |
| MD | | −0.128 | | −9.232 | | −17.644 |
| | | (−23.12)** | | (−21.05)** | | (−28.05)** |

**Table 3.** (*Continued*).

| | Percentage Spread | | Effective Spread | | Traded Spread | |
|---|---|---|---|---|---|---|
| | | MD = 1 | | MD = 1 | | MD = 1 |
| | 1 | 1A | 2 | 2A | 3 | 3A |
| INTDUM | −0.043 | −0.021 | −1.922 | −2.012 | −2.661 | −3.460 |
| | (−36.10)** | (−13.94)** | (−19.08)** | (−10.78)** | (−9.72)** | (−11.60)** |
| Price | −0.018 | 0.001 | 0.281 | 0.120 | 0.418 | 0.233 |
| | (−230.93)** | (21.90)** | (55.55)** | (19.06)** | (101.91)** | (33.15)** |
| Trade size | −13.992 | 23.531 | −962.042 | 1310.520 | −1006.425 | 1798.619 |
| | (−43.52)** | (56.96)** | (−56.71)** | (52.31)** | (−35.28)** | (47.78)** |
| Trades | −305.533 | 66.817 | −9212.666 | 1942.798 | −14783.888 | 4679.595 |
| | (−206.05)** | (36.99)** | (−114.36)** | (16.36)** | (−123.74)** | (32.50)** |
| SDMID | 0.769 | −0.370 | 41.275 | −19.390 | 62.658 | −27.552 |
| | (479.53)** | (−208.54)** | (240.32)** | (−108.90)** | (278.63)** | (−125.45)** |
| MKTUP | −6.695 | −0.494 | −279.064 | 5.083 | −436.402 | −49.022 |
| | (−67.07)** | (−11.78)** | (−89.10)** | (0.60) | (−28.00)** | (−2.58)* |
| MKTDN | −1.263 | −2.844 | −25.714 | −146.154 | −41.538 | −189.689 |
| | (−11.05)** | (−63.02)** | (−7.92)** | (−15.78)** | (−2.41)* | (−9.07)** |

**Table 3.** (*Continued*).

| | Percentage Spread | | Effective Spread | | Traded Spread | |
|---|---|---|---|---|---|---|
| | | MD = 1 | | MD = 1 | | MD = 1 |
| | 1 | 1A | 2 | 2A | 3 | 3A |
| Monday | 0.011 | 0.026 | 0.595 | 0.411 | 1.210 | 1.001 |
| | (5.04)** | (26.05)** | (10.95)** | (2.72)** | (4.60)** | (3.12)** |
| Tuesday | −0.009 | 0.026 | −0.009 | 0.959 | −0.036 | 1.943 |
| | (−4.17)** | (28.13)** | (−0.17) | (6.70)** | (−0.15) | (6.56)** |
| Wednesday | −0.028 | 0.033 | −0.508 | 0.809 | −1.344 | 2.080 |
| | (−13.81)** | (46.27)** | (−12.86)** | (6.53)** | (−6.47)** | (8.18)** |
| Friday | 0.014 | 0.012 | 0.918 | −0.441 | 1.815 | −0.901 |
| | (7.23)** | (16.19)** | (23.59)** | (−3.58)** | (8.73)** | (−3.56)** |
| Holiday | 0.023 | −0.005 | 0.749 | 0.198 | 1.309 | 0.682 |
| | (20.02)** | (−7.15)** | (14.38)** | (1.62) | (5.46)** | (2.36)* |
| Short rate | −0.488 | −0.134 | −17.478 | −3.369 | −32.919 | −2.327 |
| | (−37.77)** | (−24.80)** | (−46.13)** | (−3.04)** | (−16.01)** | (−0.93) |
| Term spread | −0.426 | −0.174 | −15.446 | −6.057 | −29.112 | −6.394 |
| | (−32.69)** | (−31.96)** | (−40.12)** | (−5.38)** | (−13.90)** | (−2.50)* |
| Quality spread | −0.761 | −0.092 | −17.735 | −11.605 | −43.146 | −7.603 |
| | (−22.87)** | (−7.22)** | (−20.60)** | (−4.27)** | (−8.88)** | (−1.28) |
| Wald chi-sqr | 879,704 | | 282,967 | | 371,131 | |

**Significant at the 1% level.
*Significant at the 5% level.

$$
\begin{aligned}
[\text{Spread}_{it}] = a_0 &+ a_1\text{MD}_{it} + a_2\text{INTDUM}_{it} + b_2\text{MD}^*\text{INTDUM}_{it} + a_3\text{Price}_{it} \\
&+ b_3\text{MD}^*\text{Price}_{it} + a_4\text{Trade Size}_{it} + b_4\text{MD}^*\text{Trade Size}_{it} \\
&+ a_5\text{Trades}_{it} + b_5\text{MD}^*\text{Trades}_{it} + a_6\text{Sdmid}_{it} + b_6\text{MD}^*\text{Sdmid}_{it} \\
&+ a_7\text{MKTUP}_t + b_7\text{MD}^*\text{MKTUP}_t + a_8\text{MKTDN}_t \\
&+ b_8\text{MD}^*\text{MKTDN}_t + a_{9-12}\text{Day of the week Dummies}_t \\
&+ b_{9-12}\text{MD}^*\text{Day of the week Dummies}_t + a_{13}\text{Holiday}_t \\
&+ b_{13}\text{MD}^*\text{Holiday}_t + a_{14}\text{Short Rate}_t + b_{14}\text{MD}^*\text{Short Rate}_t \\
&+ a_{15}\text{Term Spread}_t + b_{15}\text{MD}^*\text{Term Spread}_t \\
&+ a_{16}\text{Quality Spread}_t + b_{16}\text{MD}^*\text{Quality Spread}_t + \varepsilon_{it},
\end{aligned}
$$

where $\text{Spread}_{it}$ is either the traded, effective or percentage spread. MD is an interaction dummy that takes the value of zero for the Dow stocks and one for the matching stocks. $\text{Price}_{it}$ is the average trade price, $\text{Trade Size}_{it}$ is the average trade size, $\text{Trades}_{it}$ is the average number of trades, and $\text{Sdmid}_{it}$ is the standard deviation of the quote midpoint. All of the variables are measured for $i = 1$ to 30 stocks on $t = 1$ to 60 trading days. INTDUM is an indicator variable that has the value of 0 on days before the Diamonds' introduction and 1 after the introduction. The remaining variables are those used by Chordia *et al.* (2001): $\text{MKTUP}_{t,}$, the CRSP equally-weighted daily return if positive and zero otherwise; $\text{MKTDN}_{t,}$ the CRSP equally-weighted return if negative and zero otherwise; days of the week dummies (Thursday is excluded); holiday dummies that take the value of 1 if the preceding day was a holiday; $\text{Short Rate}_t$, the change in the daily Federal Funds rate; $\text{Term Spread}_t$, the change in the difference between the 10-year Treasury rate and the Fed Funds rate; and $\text{Quality Spread}_t$, the change in the difference between the average yield on Moody's Baa rated corporate bonds and the 10-year Treasury rate.

Our data represents a balanced panel of 60 days with 60 observations per day. Such data will be subject to several econometric problems. Daily spreads are likely to be highly autocorrelated and heteroscedastic and there is the potential for cross-correlation in the panels. To control for these problems, we use Feasible Generalized Least Squares (FGLS) to estimate the regression models. By using FGLS, we control for autocorrelation, cross-correlation and heteroscedasticity.

The main results in Table 3 are contained in the coefficients of INTDUM (which measures the impact of the introduction on the Dow stocks) and the interaction between MD and INTDUM (which measures the marginal impact of the introduction on the matching stocks). In the table, we present each regression in pairs if columns, the first column of the pair (columns 1, 2, 3) being the Dow 30 stocks and the second column of the pair (columns 1A, 2A, 3A) being the matching firms' interactions, i.e., where MD = 1 in the main regression equation.

The dependent variable in the first regression (columns 1 and 1A) is the percentage spread. For both the Dow 30 and the matching sample, INTDUM is significantly negative, indicating that the introduction of the Diamonds reduces percentage spreads for both sets of stocks. In column 1A, the coefficient of INTDUM (the interaction of MD*INTDUM) is also negative and significant. This coefficient is important in our analysis as it presents the additional change in spreads for the matching firms. The total slope coefficient for the matching firms is the sum of the coefficients of INTDUM and MD*INTDUM. A negative MD*INTDUM indicates that while spreads decline for both the Dow 30 and the matching stocks, the decline is greater for the matching stocks. This result persists in columns 2A and 3A where the dependent variables are Effective Spread and Traded Spread, respectively.

Consistent with Chordia *et al.* (2001), we find that movements in the overall level of the market (captured by MKTUP and MKTDN) significantly impact the level of spreads. The change in the Fed Funds rate, the term spread and the quality spread are also significantly related to spreads for both the Dow 30 and matching stocks. Further, we find that holidays result in significantly higher spreads for both sets of stocks.

Overall, Table 3 shows that there is a significant reduction in spreads upon the introduction of the Diamonds and that this reduction is less for the Dow 30 than for the matching sample. This evidence is consistent with the hypothesis that uniformed traders in the Dow stocks migrate to the Diamonds, resulting in a relatively greater proportion of informed traders trading the Dow 30 stocks. The relative widening of spreads on the Dow 30 is also consistent with the market makers in those stocks anticipating an exodus of uninformed traders and widening spreads (relative to other stocks) to protect themselves accordingly. Our results could also be explained by an omitted variable problem, such as another unknown factor that could cause an impact on the Dow stocks around this time period. However, this factor would have to be correlated with Dow membership.

## 5. Adverse Selection Components

In this section we examine the impact of the Diamonds on the adverse selection components of the underlying Dow stocks and the matching sample. Following the introduction of the Diamonds, investors have the choice of two vehicles for investing directly in the Dow 30. If these investors are informed traders, they will trade the underlying stocks; however, if they are not informed, they should trade the Diamonds to avoid trading with the informed traders. The implication of this separation of traders is that the adverse selection costs for the underlying stocks should increase for the Dow 30 relative to the control group following the introduction of the Diamonds. We compute adverse selection components, using three different models,[4] for the 30 days before and for the 30 days after the introduction of the Diamonds. We use the models of Glosten and Harris (1988), George, Kaul and Nimalendran (1991) [both as modified by Neal and Wheatley (1998)], and Lin, Sanger and Booth (1995).

### 5.1. *Glosten and Harris (1988) (GH)*

GH present one of the first trade indicator regression models for spread decomposition. A unique characteristic of their model is that the adverse selection component, $Z_0$, and the combined order processing and inventory holding component, $C_0$, are expressed as linear functions of transaction volume. The basic model can be represented by:

$$\Delta P_t = c_0 \Delta Q_t + c_1 \Delta Q_t V_t + z_0 Q_t + z_1 Q_t V_t + \varepsilon_t,$$

where the adverse selection component is $Z_0 = 2(z_0 + z_1 V_t)$ and the order processing/inventory holding component is $C_0 = 2(c_0 + c_1 V_t)$. $P_t$ is the observed transaction price at time $t$, $V_t$ is the number of shares traded in the transaction at time $t$ and $\varepsilon_t$ captures public information arrival and rounding error. $Q_t$ is a trade indicator that is +1 if the transaction is buyer initiated and –1 if the transaction is seller initiated. Glosten and Harris did not have quote data, hence, they were unable to observe $Q_t$. Having both trade and quote data, we use the Lee and Ready (1991) procedure for trade classification. We use OLS to obtain estimates for $c_0$, $c_1$, $z_0$, and $z_1$ for each stock in our sample.

The bid-ask spread in the GH model is the sum of the adverse selection and order processing/inventory holding components. We use the average

[4] See Clarke and Shastri (2000), Hegde and McDermott (2000), and Van Ness, Van Ness and Warr (2001) for a comparison of these and other adverse selection models.

transaction volume for stock $i$ in the following to obtain an estimate of the percentage adverse selection component, for each stock:

$$Z_i = \frac{2(z_{0,i} + z_{1,i}\bar{V}_i)}{2(c_{0,i} + c_{1,i}\bar{V}_i) + 2(z_{0,i} + z_{1,i}\bar{V}_i)}.$$

## 5.2. *George, Kaul and Nimalendran (1991) (GKN)*

GKN allow expected returns to be serially dependent. The serial dependence has the same impact on both transaction returns and quote midpoint returns. Hence, the difference between the two returns filters out the serial dependence. The transaction return is:

$$TR_t = E_t + \pi(s_q/2)(Q_t - Q_{t-1}) + (1-\pi)(s_q/2)Q_t + U_t,$$

where $E_t$ is the expected return from time $t-1$ to $t$, $\pi$ and $(1-\pi)$ are the fractions of the spread due to order processing costs and adverse selection costs, respectively. $s_q$ is the percentage bid-ask spread, assumed to be constant through time. $Q_t$ is $a + 1/-1$ buy-sell indicator and $U_t$ represents public information innovations.

GKN assume the quote midpoint is measured immediately following the transaction at time $t$. As in Neal and Wheatley (1998), we will use an upper case $T$ subscript to preserve the timing distinction for the quote midpoint. The midpoint return is:

$$MR_T = E_T + (1-\pi)(s_q/2)Q_T + U_T.$$

Subtracting the midpoint return from the transaction return and multiplying by two yields:

$$2RD_t = \pi s_q(Q_t - Q_{t-1}) + V_t,$$
$$\text{where } V_t = 2(E_t - E_T) + 2(U_t - U_T).$$

Relaxing the assumption that $s_q$ is constant and including an intercept yields:

$$2RD_t = \pi_0 + \pi_1 s_q(Q_t - Q_{t-1}) + V_t.$$

As recommended by Neal and Wheatley, we use the Lee and Ready (1991) procedure to determine trade classification. We use OLS to estimate the adverse selection component, $(1-\pi_1)$, for each stock in our sample.

### 5.3. *Lin, Sanger and Booth (1995) (LSB)*

LSB develop a method of estimating empirical components of the effective spread following Huang and Stoll (1994), Lin (1993) and Stoll (1989). Huang and Stoll define the signed effective half-spread, $z_t$, as the transaction price at time $t$, $P_t$, minus the spread midpoint, $Q_t$. The signed effective half spread is negative for sell orders and positive for buy orders. To reflect possible adverse information revealed by the trade at time $t$, quote revisions of $\lambda z_t$ are added to both the bid and ask quotes. The proportion of the spread due to adverse information, $\lambda$, is bounded by 0 and 1. The dealer's gross profit as a fraction of the effective spread is defined as $\gamma = 1 - \lambda - \theta$, where $\theta$ reflects the extent of order persistence.

Since $\lambda$ reflects the quote revision (in response to a trade) as a fraction of the effective spread $z_t$, and since $\theta$ measures the pattern of order arrival, LSB model the following:

$$\begin{aligned} Q_{t+1} - Q_t &= \lambda z_t + \varepsilon_{t+1}, \\ Z_{t+1} &= \theta Z_t + \eta_{t+1}, \end{aligned}$$

where the disturbance terms $\varepsilon_{t+1}$ and $\eta_{t+1}$ are assumed to be uncorrelated.

Following LSB, we use OLS to estimate the following equation to obtain the adverse information component, $\lambda$, for each stock in our sample:

$$\Delta Q_{t+1} = \lambda z_t + e_{t+1}.$$

We use the logarithms of the transaction price and the quote midpoint to yield a continuously compounded rate of return for the dependent variable and a relative spread for the independent variable.

Table 4 shows the adverse selection measures for the 30 days before and after the initiation of the Diamonds on an equally-weighted basis. We measure adverse selection as a percentage of the spread and also, as a percentage of the price. The latter, "dollar" cost of adverse selection, is a better measure of the true cost of trading the stock as it controls for stock price and reflects the adverse selection cost based on the value of a trade rather than the number of shares traded.[5] All three models (both percentage and dollar) show a statistically significant decline in adverse selection for the Dow 30 (panel A) and for the matching stocks with the exception of dollar LSB (panel B) following the

[5] Dollar adverse selection is used in Brennan and Subrahmanyam (1995).

**Table 4.** Adverse selection component estimates for the Dow 30 and the matching stocks.

Adverse selection components are computed for 30 days before and 30 days after the introduction of the Diamonds. The component models used are Glosten and Harris — GH, George, Kaul and Nimalendran — GKN, and Lin, Sanger and Booth — LSB. Each panel presents adverse selection components computed as a percentage of the spread (%) and as a percentage of the stock price ($).

| | Before | After | Difference | Two-Tailed $T$-Test | Sign Rank Test $p$-Value | [Pos/Neg] |
|---|---|---|---|---|---|---|
| Panel A: Dow 30 Stocks | | | | | | |
| GH % | 0.2862 | 0.2729 | −0.0133 | −2.34** | 0.035** | [20/10] |
| GKN % | 0.3982 | 0.3721 | −0.0260 | −3.57** | 0.003** | [21/9] |
| LSB % | 0.4107 | 0.3872 | −0.0236 | −2.20** | 0.079* | [18/12] |
| GH $ | 0.000545 | 0.000487 | −0.000058 | −4.93** | <0.001** | [27/3] |
| GKN $ | 0.0007739 | 0.0006761 | −0.0000978 | −5.98** | <0.000** | [28/2] |
| LSB $ | 0.0007722 | 0.000684 | −0.0000881 | −4.39** | <0.001** | [23/7] |
| Panel B: Matching Stocks | | | | | | |
| GH % | 0.3012 | 0.2728 | −0.0283 | −3.26** | <0.001** | [26/4] |
| GKN % | 0.4340 | 0.4082 | −0.0256 | −2.19** | 0.013** | [17/13] |
| LSB % | 0.4043 | 0.3937 | −0.0106 | −0.59 | 0.766 | [16/14] |
| GH $ | 0.0006025 | 0.0004992 | −0.00010 | −5.48** | <0.001** | [26/4] |
| GKN $ | 0.0008804 | 0.0007465 | −0.00013 | −5.47** | <0.001** | [27/3] |
| LSB $ | 0.0008105 | 0.0007353 | −0.0000751 | −2.21** | 0.014** | [21/9] |
| Panel C: Dow-Match | | | | | | |
| GH % | −0.0150 | −0.0001 | 0.0150 | −1.48 | 0.131 | [10/20] |
| GKN % | −0.0358 | −0.0360 | −0.0002 | −0.02 | 0.586 | [17/13] |
| LSB % | 0.0064 | −0.0065 | −0.0130 | −0.64 | 0.271 | [21/9] |
| GH $ | −0.0000575 | −0.0000122 | −0.0000453 | −1.74* | 0.050* | [10/20] |
| GKN $ | −0.0001065 | −0.0000704 | −0.0000362 | −1.27 | 0.178 | [12/18] |
| LSB $ | −0.0000383 | −0.0000513 | 0.000013 | 0.35 | 0.271 | [21/9] |

**Significant at the 1% level.
*Significant at the 5% level.

introduction of the Diamonds. We prefer to concentrate on the decline in dollar adverse selection rather than the decline in percentage adverse selection as the dollar measure captures both the decline in the component as a percentage of the spread and the decline in the overall spread. Panel C examines whether the change in adverse selection is different for the Dow 30 compared to the matching sample. All differences (except for the dollar LSB component) are negative, however, only one difference (GH dollar) is statistically significant. Therefore, we cannot conclude that the introduction of the Diamonds had an effect on the adverse selection costs of the underlying stocks. While this result does not support the overall spread effect, it is not surprising given the noisiness of the adverse selection models. An alternative explanation for our results is that some other factor, such as inventory costs, increases for Dow stocks relative to the matching stocks around the introduction of the Diamonds, thus increasing the spread relative to the matched stocks and offsetting the spread effect on adverse selection costs. A speculative explanation is that higher inventory costs could be the result of greater volatility in the Dow 30 stocks induced by increased index arbitrage following the introduction of the Diamonds.

## 6. Microstructure Characteristics of the Diamonds versus the Dow 30

In this section we examine the microstructure characteristics of the Diamonds compared to the Dow 30. Table 5 presents descriptive statistics of various quote and adverse selection measures. In panel A the Diamonds have lower adverse selection costs than the average of the Dow 30 stocks[6] for two out of the three models. Note that we cannot assign significance levels to these estimates as we only have one observation for the Diamonds and one average observation for the portfolio of the Dow 30 stocks. Panel A indicates that the various adverse selection models generate quite different estimates. Clarke and Shastri (2000) and Van Ness, Van Ness and Warr (2001) report that adverse selection models can produce widely different results for the same stocks.

Since the Diamonds represent a basket of stocks, we expect that its adverse selection would be small and close to zero since no informed trader would be able to profit on private information by trading the basket. A similar argument is made by Neal and Wheatley (1998), who find that adverse selection components for closed-end mutual funds are significantly greater than zero although they theorize that there should be little or no adverse selection for these securities. A possible explanation for the Diamonds having non-zero adverse selection is that informed traders can profit by trading with stale orders in markets where limit order traders do not update their orders continuously. Thus, even in a market where there should be no benefit to being informed about the underlying

[6]We use a price-weighted average, consistent with the construction of the Dow 30 index. Our results hold if we use an equally-weighted index.

**Table 5.** Microstructure statistics of the Dow 30 and the Diamonds.

The time period is 156 days after the introduction through August 1998. The composition of the Dow 30 changed in September 1998. The Dow variables are a price-weighted average of the component stocks of the Dow 30. Panel A presents the average adverse selection components as a percentage of the spread for the Dow stocks and the Diamonds. Note that there is only one estimate for group, therefore, statistical tests of differences cannot be undertaken. Panels B and C present quote and trade statistics for the Dow 30 portfolio and the Diamonds.

| | DIA | Dow | Difference | Two-Tailed $T$-Test |
|---|---|---|---|---|
| Panel A: Adverse Selection | | | | |
| GH | 0.2025 | 0.2873 | −0.0848 | |
| GKN | 0.5769 | 0.3822 | 0.1947 | |
| LSB | 0.1577 | 0.4023 | −0.2446 | |
| Panel B: Quote Statistics | | | | |
| Spread | 0.0959 | 0.1217 | −0.0258 | −12.93** |
| Traded spread | 0.1020 | 0.1136 | −0.0116 | −4.28** |
| Effective spread | 0.0691 | 0.0954 | −0.0263 | −17.33** |
| Price improvement | 0.0329 | 0.0181 | 0.0148 | 10.82** |
| Panel C: Trade Statistics | | | | |
| Volume | 585,148.7 | 1,923,138 | −1,337,989 | −41.14** |
| Trade size | 1,940.12 | 2,090.13 | −150.01 | −2.77** |
| Number of trades | 296.01 | 867.83 | −571.83 | −62.48** |

**Significant at the 1% level.
*Significant at the 5% level.

security (such as the Diamonds), the adverse selection component of the spread may not be zero.[7]

The Dow 30 statistics shown in panels B and C are first calculated daily for each of the 30 stocks then averaged across the portfolio. Panel B shows the trading costs measures, and price improvement, for the Dow stocks and Diamonds. Diamonds have significantly lower spreads (0.0959) than the Dow 30 (0.1217). This implies that investors will have a cheaper round-trip transaction cost (approximately 2.5 cents) trading the Diamonds rather than the DJIA.[8] We find similar cost differences for traded spread (0.1020 for the Diamonds and 0.1136 for the Dow 30) and effective spreads. Additionally, we find that the amount of price improvement is larger for the Diamonds than for the Dow 30 (by approximately 1.5 cents). All of these findings are statistically significant indicating

[7] We would like to thank the referee for suggesting this explanation.
[8] These general results are robust when different trade sizes are examined.

that it is cheaper to trade the basket rather than the individual securities. Panel C presents the trade statistics for the sample, which show that the average volume of activity on a single stock in the Dow is greater than the total volume of the Diamonds. That the Diamonds are cheaper to trade yet have significantly lower volume than the Dow 30 stocks suggests that the order processing costs faced by the Diamond's market maker should not be lower than those faced by the individual stock market makers. Therefore the lower spreads of the Diamonds must be due to lower adverse selection or inventory costs. To the extent that making a market in the Diamonds exposes the market maker to less non-systematic risk than making a market in any single Dow stock, we would expect the Diamonds to have lower inventory costs as well.

In Table 6 we examine the factors that drive trading in the Diamonds securities. We proxy activity in two ways — trading volume (the number of shares

**Table 6.** Regression examining the causes of changes in the volume and number of trades of the Diamonds.

The time period is 156 days after the introduction of the Diamonds through August 1998. The dependent variables are the daily volume or the daily number of trades for the Diamond securities. DIA effective spread is the effective spread of the Diamonds. Dow 30 effective spread is a price-weighted average daily effective spread for the 30 Dow stocks. Volatility is the price-weighted average daily standard deviation of the quote midpoint return for the Dow 30. Volume is the price-weighted average daily volume of the Dow 30. Number of trades is the price-weighted average daily number of trades for the Dow 30. Newey West $T$-stats corrected for first order autocorrelation and heteroskedasticity are in parenthesis.

| | DIA Volume | DIA Number of Trades |
|---|---|---|
| Intercept | −6.583 | −2.609 |
| | (−2.779)** | (−4.826)** |
| DIA effective spread | −6.298 | −2.253 |
| | (−3.280)** | (−4.827)** |
| Dow 30 effective spread | −30.112 | −13.241 |
| | (−3.062)** | (−4.640)** |
| Dow 30 volatility | 166.854 | 73.9222 |
| | (4.466)** | (10.622)** |
| Dow 30 volume | 0.533 | — |
| | (3.102)** | |
| Dow 30 number of trades | — | 0.459 |
| | | (5.189)** |
| N | 156 | 156 |
| F(4, 151) | 9.57 | 56.66 |

**Significant at the 1% level.

*Significant at the 5% level.

traded), and the number of trades. Our variables are computed for each day during our time period. We find that the trading volume of the Diamonds is positively related to the daily trading volume of the Dow 30 and also, the volatility of the Dow 30 (as measured as the standard deviation of the quote midpoint return). We also find that the number of trades per day of the Diamonds is positively related to the daily volatility of the Dow 30, and the number of trades in the Dow 30 stocks. These results indicate that the activity in the Diamonds moves in line with the overall activity in the underlying stocks.

## 7. Conclusion

We examine the impact of the introduction of the Diamonds stock index securities on the microstructure characteristics of the underlying Dow 30 stocks, and find that, when compared to a matched control group, the Dow 30 stocks exhibit a smaller decline in spreads. That spreads decline at all around the introduction of the Diamonds is puzzling; however, we attribute this decline to some other un-measured variable. However our tests prevent us from ruling out the explanation that as the market-wide liquidity improves, stocks with low liquidity improve more than those with high liquidity, and that the difference in liquidity improvement has nothing to do with the introduction of the Diamonds.

Adverse selection for both the Dow 30 and the control sample declines significantly upon the introduction of the Diamonds. However, the difference in the adverse selection components between the two groups is not statistically significant. While we believe that uniformed traders will migrate to the index security, and that this migration will result in higher trading costs on the underlying stocks [Subrahmanyam's (1991) hypothesis], we are not able to rule out the possibility that some other component, perhaps inventory costs, increases in relative terms for the Dow 30 upon the introduction of the Diamonds.

We find that while the Diamonds have, in general, lower adverse selection costs than the Dow 30, and that the adverse selection costs for the Diamonds are not trivial. This finding is surprising as we expect market makers in the Diamonds to face little risk from informed traders. A possible reason for the mixed adverse selection results is the poor empirical performance of adverse selection models in general.

We find that trading costs (spreads) are significantly lower for the Diamonds despite much lower volume. Additionally, Diamonds traders seem to get significantly more price improvement on their trades than do the traders in the Dow 30 stocks. Volume and trading activity in the Diamonds contracts is directly correlated with activity in the Dow 30 stocks as well as volatility of the Dow 30. Our results suggest that, for liquidity traders, the Diamonds contracts are a cheaper vehicle for achieving a diversified representation of the Dow 30 compared to buying the stocks directly.

## Appendix: Dow Stocks and Matching Stocks

We match each stock in the Dow 30 with a NYSE counterpart on the basis of four stock attributes. These attributes are share price, trade size, return volatility, and market capitalization. Previous work has found the first three of these factors to be important determinants of the spread. We also include market value as Dow stocks tend to be much larger than the average stock on the NYSE. The data for matching comes from the 30 trading days prior to the introduction of the Diamonds (the matches are listed in the Appendix). We calculate the following composite match score (CMS) for each Dow stock in our sample with each of our selected match stocks:

$$\mathrm{CMS} = \sum_{k=1}^{4} \left[ \frac{2\left(Y_k^{\mathrm{DOW}} - Y_k^{\mathrm{Match}}\right)}{\left(Y_k^{\mathrm{DOW}} + Y_k^{\mathrm{Match}}\right)} \right]^2,$$

where $Y_k$ represents one of the four stock attributes, and the superscripts, Dow and Match, refer to Dow 30 stocks and potential match stocks, respectively. For each Dow stock, we pick the NYSE stock with the smallest score — as long as the score is less than 2. This matching procedure results in 30 pairs of NYSE stocks.

| Dow Ticker | Matching Ticker | Composite Match Score |
|---|---|---|
| AA | BAX | 0.1399 |
| ALD | MTC | 0.0446 |
| AXP | ABT | 0.1412 |
| BA | PEP | 0.1338 |
| CAT | MDT | 0.0819 |
| CHV | MOB | 0.0169 |
| DD | LLY | 0.0947 |
| DIS | G | 0.0469 |

| Dow Ticker | Matching Ticker | Composite Match Score |
|---|---|---|
| EK | RD | 0.0953 |
| GE | PFE | 0.9895 |
| GM | SGP | 0.1178 |
| GT | HON | 0.0395 |
| HWP | F | 0.1367 |
| IBM | BMY | 0.4423 |
| IP | TMX | 0.1013 |
| JNJ | FNM | 0.1801 |
| JPM | FCN | 0.2353 |
| KO | BAC | 1.3518 |
| MCD | FTU | 0.0898 |
| MMM | WLA | 0.1435 |
| MO | MOT | 1.4094 |
| MRK | CCI | 0.6670 |
| PG | SBC | 0.2654 |
| S | PNU | 0.0660 |
| T | CPQ | 0.9900 |
| TRV | LU | 0.3191 |
| UK | TEN | 0.0285 |
| UTX | CL | 0.0695 |
| WMT | GTE | 0.6936 |
| XON | CMB | 1.6017 |

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Chapter 8

# Hedging with Foreign-Listed Single Stock Futures

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The objective of this paper is to estimate the hedge ratios of foreign-listed single stock futures (SSFs) and to compare the performance of risk reduction of different methods. The OLS method and a bivariate GJR-GARCH model are employed to estimate constant optimal hedge ratios and the dynamic hedging ratios, respectively. Data of the SSFs listed on the London International Financial Future and Options Exchange (LIFFE) are used in this research. We find that the data series have high estimated constant optimal hedge ratios and high constant correlation in the bivariate GJR-GARCH model, except for three SSFs with their underlying stocks traded in Italy. Our findings provide evidence that distance is a critical factor when explaining investor's trading behavior. Results also show that in general, of the three methods examined (i.e., naïve hedge, conventional OLS method and dynamic hedging) the dynamic hedging performs the best and that naïve hedge is the worst.

**Keywords:** Hedging; GJR-GARCH; hedge ratios; SSFs; single stock futures; LIFFE; USFs.

## 1. Introduction

Since the trading of futures has become more frequent in recent years, there has been much attention given to the issue of hedging with futures.

Many studies have dealt with the issue of hedging with various futures, such as commodity futures, currency futures, index futures, and so on (e.g., Baillie and Myers, 1991; Kroner and Sultan, 1993; Park and Switzer, 1995, respectively). However, studies on hedging with the newly invented futures contracts, single stock futures (SSFs), are rare. SSFs provide several advantages for investors. For instance, investors hedging with SSFs could efficiently reduce tracking error, because investors can hedge with a particular instrument rather

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than a rough index. In addition, SSFs are cost effective for investors. The strategy of longing a call and shorting a put option is now achieved by longing a single stock future. Since SSFs were designed for investors to manage firm-specific risk in their stocks, the underlying stock markets could be very sensitive to SSF contracts. As a result, the interesting issue of hedging with SSFs is no longer being neglected.

Although SSFs or individual stock futures (ISFs) have had leading roles in some studies (e.g., McKenzie, Brailsford and Faff, 2000), most studies have focused on examining the impact of the domestic listed SSFs on their underlying stock markets. As the internationalization of worldwide financial markets becomes ever more rapid, firms have increasingly chosen to list their securities in foreign countries. Following this trend, numerous studies have been devoted to the effect of foreign listing. A growing amount of behavioral finance literature is available on the issue of "twin-securities". For example, Froot and Dabora (1998) provided evidence to challenge the efficient markets hypothesis, finding that fundamentally identical securities traded at disparate prices. Worldwide evidence has shown that the cumulated abnormal returns of the domestic firms are significantly influenced by their stocks that were listed in foreign exchanges after overseas listing (e.g., Foerster and Karolyi, 1993; Damodaran *et al.*, 1993; Foerster and Karolyi, 1996). Besides, much research has been done on the influence of such regional factors as language, culture, and distance on the phenomenon of "home bias". For example, Grinblatt and Keloharju (2001) concluded that the Finnish are prone to trade stocks of domestic firms that communicate in the same language with them, that are located near them, and whose CEOs are of identical culture background. While much work has been done on the relationship between foreign and domestic stock markets, there has been little attention given to the connection between foreign listed derivatives and their domestic underlying markets. Moreover, there has been little literature on the issue of hedging with foreign listed futures.

Many theoretical methods have been used in previous studies to estimate the optimal hedge ratios. Chen, Lee and Shrestha (2003) gave a clear summary of various methods. We summarize several important methods in Section 3. The conventional Ordinary Least Squares (OLS) approach is easy to apply but is criticized for its assumption of constant second moments. Thus, considering the features of heteroscedastic and leptokurtosis in time series data, many studies have gradually employed bivariate GARCH models to estimate time-varying hedge ratios.

The purpose of this paper is to estimate the hedge ratios of foreign-listed single stock futures (SSFs) and to compare the hedging performances of different methods.

The organization of this paper is as follows. A short report on the present situation of global SSFs markets is provided in Section 2. A brief literature review of hedge ratios is summarized in Section 3. The methodology employed is described in Section 4. The data and empirical results are described in Section 5, and the conclusions of the paper are presented in the final section.

## 2. Global SSFs Markets

We focused on the SSFs listed on the London International Financial Future and Options Exchange (LIFFE) in the United Kingdom; however, several exchanges other than LIFFE have SSFs listed. We give a short report on the present situation of worldwide SSFs markets in this section. Table 1 demonstrates a summary of the contract specifications of different exchanges.

### 2.1. *The United Kingdom*

As of June 23, 2003, LIFFE had SSFs traded on 116 individual stocks. The annual trading volumes of total SSFs listed on the LIFFE for 2001 and 2002 are 2,325,744 and 3,935,121 contracts, respectively. Each SSF represents 100 shares of the underlying stock in Europe (except for Italy and England), or 1,000 shares of the underlying stock in Italy, the United States, and England. The contracts have delivery dates of two consecutive months or two near quarter months. The contracts are settled in cash. In addition, there are no specific daily price movement limits or position limits. Refer to www.liffe.com for more details.

### 2.2. *The United States*

The Commodity Futures Modernization Act of 2000 (CFMA) allows the US securities and futures exchanges to trade SSFs. SSFs are restricted to regulation by both the Commodity Futures Trading Commission (CFTC) and the Securities and Exchange Commission (SEC). As of June 19, 2003, there have been 99 and 92 SSFs listed on NQLX and OneChicago, respectively. NQLX is a joint venture between NASDAQ/American Stock Exchange and LIFFE. OneChicago is a joint venture between the Chicago Board of Trade, Chicago Mercantile Exchange and Chicago Board of Options Exchange. The top five

**Table 1.** Contract specifications.

| Country | Exchanges | Number of SSFs Listed | Contract Unit | Delivery Months | Settlement | Daily Price Limits |
|---|---|---|---|---|---|---|
| The United Kingdom | London International Financial Future and Options Exchange (LIFFE) www.liffe.com | 116 | 100 shares of the underlying stock in Europe (except for Italy and England), or 1,000 shares of the underlying stock in Italy, the United States, and England | two consecutive months and two near quarter months | cash | none |
| The United States | NQLX www.nqlx.com | 99 | 100 shares of the underlying stock | two near term serial months and two quarterly months | physical delivery | none |
| | OneChicago www.onechicago.com | 92 | | | | |
| Australia | Sydney Futures Exchange (SFE) www.sfe.com.au | 40 | 200 shares of Ansell stock, or 1,000 shares of other underlying stock | up to 12 months ahead for Telstra Corporation ISFs, or four quarterly months for others | cash for Telstra Corporation ISFs, or physical delivery for others | minimum price movement of contract size multiplied by one cent of A$ |

**Table 1.** (*Continued*)

| Country | Exchanges | Number of SSFs Listed | Contract Unit | Delivery Months | Settlement | Daily Price Limits |
|---|---|---|---|---|---|---|
| Spain | MEFF www.meff.com | 9 | 100 shares of the underlying stock | four quarterly months, or other months if needed | holder-chosen between cash and psychical delivery | minimum price fluctuation of contract unit multiplied by one cent of EURO |
| Portugal | Euronext Lisbon www.euronext.pt | 7 | 100 shares of the underlying stock | the current month, the following calendar month and the two closest quarterly months | physical delivery | not available |

SSFs listed on the NQLX by volume in March, 2003 are iShares Russell 2000 (IWM), NASDAQ-100 Index Tracking Stock (QQQ), KLA-Tencor Corporation (KLAC), Microsoft Corporation (MSFT) and Exxon Mobile Corporation (XOM) in order. The first 21 SSFs began trading on the OneChicago in November 8, 2002, and obtained trading volumes of 184,081 contracts for 2002. Each SSF represents 100 shares of the underlying stock. The contracts have delivery dates of two near term serial months and two quarterly months. They are settled in physical delivery of underlying security on the third business day following the expiration day. There are no specific daily price movement limits. Refer to www.nqlx.com and www.onechicago.com for more details.

## 2.3. *Australia*

As of May 5, 2003, there have been 39 individual share futures (ISFs) listed on the Sydney Futures Exchange (SFE). Their underlying stocks are those listed on the Australian Stock Exchange. The annual trading volumes for 1999, 2000, and 2001 were 8,726, 8,817 and 12,545 contracts, respectively. Except that the ISFs on Telstra Corporation deliver monthly up to 12 months ahead, other contracts have delivery dates of four quarterly months. Each ISF represents 1,000 shares of the underlying stock except for Ansell ISF contracts, each which represent 200 shares of the underlying stock. Except that the ISFs on Telstra Corporation are settled in cash, other ISFs listed on SFE are settled in physical delivery of underlying security at the expiration day. The minimum price movement is set to be the contract unit multiplied by one cent of A$. Refer to www.sfe.com.au for more details.

## 2.4. *Spain*

MEFF, the Spanish official exchange for futures and options, has listed nine SSFs up to now. The first batch of SSFs was introduced in January 2001 and reached trading volumes of 8,766,165 contracts in the entire year. Each SSF represents 100 shares of the underlying stock. In general, the contracts have delivery dates of four quarterly months; however, other expiration months not included in the quarterly months may also be introduced if needed. Contract holders can choose between physical delivery of underlying security and cash for the difference with respect to the reference price, which refers to the closing price of the stock on the expiration day. The minimum price fluctuation is the contract unit multiplied by one cent of EURO, while the maximum price movement is of no regulation. Refer to www.meff.com for more details.

### 2.5. *Portugal*

Portugal is still in the developing stage of the new derivatives products, SSFs. Since the launch of the first of the SSFs, Portugal Telecom futures, there have been seven SSFs listed on the Euronext Lisbon. The underlying stocks are Portugal Telecom, EDP, BCP, Cimpor, PT Multimédia, Sonae and Telecel. Each SSF represents 100 shares of the underlying stock. The contracts have delivery dates of the current month, the following calendar month and the two closest months of March, June, September and December. The settlement at expiration date is made through physical delivery. Refer to www.euronext.pt for more details.

## 3. Brief Literature Review of Hedge Ratios

In this section, we briefly discuss the theoretical methods mentioned in previous works to estimate optimal futures hedge ratios. Interested readers can refer to the article written by Chen, Lee and Shrestha (2003) for more detailed expositions.

Based on the objective function to be optimized, the theoretical methods can be divided into five categories: minimum variance hedge ratio, optimum mean-variance hedge ratio, Sharpe hedge ratio, mean-Gini coefficient based hedge ratio and generalized semivariance based hedge ratio. And some of the above hedge ratios can be estimated by more than one method.

The minimum variance (MV) hedge ratio is one of the most prevailing hedging strategies (for example, Myers and Thompson, 1989). It is derived by minimizing the variance of the hedged portfolio. Suppose a portfolio containing one unit of a long spot position and $h$ units of a short futures position. Let $\Delta S_t = S_{t+1} - S_t$ and $\Delta F_t = F_{t+1} - F_t$ be the changes in spot prices and the changes in futures prices, respectively. Since the fluctuations in spot positions can be reduced by holding positions in the futures contracts, the whole portfolio is called the hedged portfolio. The change in the value of the hedged portfolio is given by $\Delta H_t = \Delta S_t - h\Delta F_t$. The objective function concerned here is given below:

$$\min_h \mathrm{Var}(\Delta H) = \mathrm{Var}(\Delta S) + h^2\mathrm{Var}(\Delta F) - 2h\mathrm{Cov}(\Delta S, \Delta F).$$

Then, the optimal hedge ratio $h = \frac{\text{Cov}(\Delta S, \Delta F)}{\text{Var}(\Delta F)}$ is derived by setting the first order condition of the objective function equal to zero. That is why the conventional approach to estimating the MV hedge ratio is to regress the changes in spot prices on the changes in futures price using the OLS technique. In order to take into consideration the feature of heteroscedastic in the error term of the above regression, the conditional second moments (i.e., variance and covariance) estimated from bivariate GARCH models are used to obtain time-varying hedge ratios. Investors can use this approach to update hedge ratios over time; hence, dynamic hedging strategies rather than a single hedge ratio for the entire hedging period is attainable. The random coefficient model suggested by Grammatikos and Saunders (1983) is another way that allows the hedge ratio to change over time, which in theory, can improve the effectiveness of the hedging strategy as well. Cointegration and error correction method is applied in the situation that spot price and futures price series could be non-stationary. The cointegration analysis is done by the following two steps. First, test if each series has a unit root (for example, Dickey and Fuller, 1981; Phillips and Perron, 1988). Then, if a single unit root is detected in both series, then implement cointegration test (for example, Engle and Granger, 1987). If the spot price and futures price series are verified to be cointegrated, then the hedge ratio needs to be estimated in two steps (for example, Ghosh, 1993; Chou, Fan and Lee, 1996). The first step is to estimate cointegrating regression of the spot prices on the futures prices. The second step is to estimate the error correction model containing the residual series obtained from step one.

The method of optimum mean-variance hedge ratio blends the effects of both risk and return (for example, Cecchetti, Cumby and Figlewski, 1988; Hsin, Kuo and Lee, 1994). Assuming that the investor trades off return and risk in a linear fashion, the objective function is a linear combination of mean and variance of the hedged portfolio. Thus, the objective function is represented by the following form: max $V(E(R_h), \sigma; A) = E(R_h) - 0.5A\sigma^2$, where $R_h$ and $\sigma^2$ are the mean and variance of the hedged portfolio, respectively; $A$ represents the risk aversion parameter. One potential problem inherent in this method is that the risk aversion parameter may vary with investors; hence, the optimal hedge ratio may depend on different individuals.

The method of Sharpe hedge ratio involves the maximization of the Sharpe ratio of the hedged portfolio (for instance, Howard and D'Antonio, 1984).

According to Chen, Lee and Shrestha (2003), when the expected value of risk-free interest rate is zero, the Sharpe hedge ratio degenerates to the MV hedge ratio estimated by the conventional approach.

Theoretically, the methods of mean-Gini (MEG) coefficient based hedge ratio and generalized semivariance (GSV) based hedge ratio hedge ratios are consistent with the second-order stochastic dominance principle. The mean extended-Gini coefficient based hedge ratio, however has no analytical solution and has to be estimated by numerically minimizing the mean extended-Gini coefficient, $\Gamma_\nu(R_h)$ defined as follows: $\Gamma_\nu(R_h) = -\nu \mathrm{Cov}(R_h, (1 - G(R_h))^{\nu-1})$, where $G$ is the cumulative probability distribution and $\nu$ is the risk aversion parameter. In practice, the theoretical covariance is replaced by the sample covariance, and the cumulative probability distribution function is estimated using the rank function:

$$\Gamma_\nu^{\text{sample}}(R_h) = -\frac{\nu}{N}\sum_{i=1}^{N}(R_{h,i} - \bar{R}_h)((1 - G(R_{h,i}))^{\nu-1} - \Theta),$$

where $\bar{R}_h = \frac{1}{N}\sum_{i=1}^{N} R_{h,i}$, $G(R_{h,i}) = \frac{\mathrm{Rank}(R_{h,i})}{N}$, and $\Theta = \frac{1}{N}\sum_{i=1}^{N}(1 - G(R_{h,i}))^{\nu-1}$. Shalit (1995) has proved that as long as the futures and spot returns are jointly normally distributed, the minimum-MEG hedge ratio and the MV hedge ratio are the same.

Generalized semivariance based hedge ratio has no analytical solution either. The optimal hedge ratio is obtained by minimizing the GSV given as follows: $V_{\delta,\alpha}(R_h) = \int_{-\infty}^{\delta}(\delta - R_h)^\alpha dG(R_h)$, where $G(R_h)$ is the probability distribution function of the return on the hedged portfolio $R_h$; $\delta$ represents the target return, and $\alpha > 0$ describes the attitude of risk aversion. Note that this method has a premise that the investors only regard the returns under the target return ($\delta$) as risky. The optimal GSV based hedge ratio can be estimated by using its sample counterpart: $V_{\delta,\alpha}^{\text{sample}}(R_h) = \frac{1}{N}\sum_{i=1}^{N}(\delta - R_{h,i})^\alpha U(\delta - R_{h,i})$, where $U(\delta - R_{h,i}) = 1$ if $\delta \geq R_{h,i}$; otherwise, $U(\delta - R_{h,i}) = 0$. Similar to the method of optimum mean-variance hedge ratio, no unique optimal hedge ratio is their common problem.

Even though the literature on estimating optimal hedge ratios has established a great many useful approaches, we concentrate on the MV-based approaches in this research. The following is our considerations. First, the MV hedge ratio is the most well-known and most widely-used hedge ratio. Second, all these methods mentioned above will converge to the same hedge ratio as the conventional MV hedge ratio if the futures price follows a pure martingale process and if the futures and spot prices are jointly normal. In order to investigate whether the dynamic hedging is more competent than the static hedging for risk reduction, we focus our attention on the comparison of the performance of the bivariate GARCH model with those of the conventional OLS method and the naïve hedge.

## 4. Methodology

Initially, we compute the constant optimal hedge ratios as references. Comparisons of hedging performances between the conventional OLS method and the dynamic hedging strategy have been found in many previous studies (for example, Kroner and Sultan, 1993; Lien, Tse and Tsui, 2000). The constant optimal hedge ratio $h = \frac{\mathrm{Cov}(\Delta S, \Delta F)}{\mathrm{Var}(\Delta F)}$ is derived by minimizing the variance of the hedged portfolio, containing spots and futures. Regressing $\Delta S_t$ on $\Delta F_t$ can capture this idea. To obtain the constant optimal hedge ratio, we estimate the coefficient ($\beta$) of the following regression:

$$\Delta S_t = \alpha + \beta \Delta F_t + e_t. \tag{1}$$

Then we move to estimate the dynamic hedge ratios. Bivariate GARCH models have proven useful in estimating time-varying hedge ratios in the literature (for example, Park and Switzer, 1995; Lien, Tse and Tsui, 2000; among many others). Baillie and Myers (1991) implemented bivariate GARCH models to estimate dynamic hedge ratios for six commodity futures. For each commodity, the optimal hedge ratio was computed as the estimated conditional covariance between cash and futures divided by the estimated conditional variance of futures. They claimed that the bivariate GARCH model fit their data well and that the dynamic hedging is more appropriate than the conventional OLS method. Kroner and Sultan (1993) proposed a bivariate GARCH error correction model to estimate the optimal hedge ratios for five currencies. Incorporating an error correction term into a bivariate GARCH model enabled them to consider the long-term cointegrating relationship between spot and futures. Their findings showed that the dynamic hedging strategy with error correction is more effective than the other two hedging strategies: the naïve hedge and the conventional hedge. They also noted that it may be important to incorporate an error correction term in currency markets while may not be necessary in other markets, such as commodity markets. Chen, Duan and Hung (1999) proposed an extended bivariate GARCH model with maturity variables to depict the dynamics of the Nikkei-225 index and the futures-spot basis. By means of this setting, they investigated the Samuelson effect, which refers to a raise in volatility of futures prices around the expiration date, and compared the optimal hedge ratios with and without the maturity effect. They showed that the conditional variance of the futures price reduces as the contract approaches its maturity, which rejects the hypothesis of Samuelson effect. They also noted that the maturity of the futures is a crucial factor in determining the effectiveness of hedging.

In order to estimate the dynamic hedge ratios, and to investigate the leverage effect, we set up the bivariate GJR-GARCH model described as follows:

$$\Delta S_t = c_{11} + \sqrt{h_t}\varepsilon_t, \tag{2}$$

$$h_t = \alpha_0 + \alpha_1 h_{t-1} + \alpha_2 \varepsilon_t^2 + \alpha_3 I_{t-1}\varepsilon_{t-1}^2, \quad \varepsilon_t \,|\mathcal{F}_{t-1} \sim N(0, 1), \tag{3}$$

$$\Delta F_t = c_{22} + \sqrt{q_t}\,\omega_t, \tag{4}$$

$$q_t = \beta_0 + \beta_1 q_{t-1} + \beta_2 \omega_t^2 + \beta_3 D_{t-1}\omega_{t-1}^2, \quad \omega_t \,|\mathcal{F}_{t-1} \sim N(0, 1), \tag{5}$$

where Equation (2) and Equation (4) are the mean equations of the change in spot prices and the changes in futures prices, respectively; $h_t$ and $h_{t-1}$ are the current and lagged values of conditional variance of the change in spot prices; $q_t$ and $q_{t-1}$ are the current and lagged values of conditional variance of the change in futures prices. The dummy variable $I_{t-1}$ in Equation (3) takes the value of one when $\varepsilon_{t-1}$ is negative, otherwise it takes the value of zero, reflecting the asymmetry effects of bad and good news on the conditional volatility in the GJR-GARCH model. Similarly, the dummy variable $D_{t-1}$ in Equation (5) takes the value of one when $\omega_{t-1}$ is negative, otherwise it takes the value of zero, reflecting the asymmetry effects of bad and good news on the conditional volatility. Following previous studies, the conditional correlation of two innovations is assumed constant in this model; thus we set $\mathrm{Cov}_{t-1}(\varepsilon_t, \omega_t) = \rho$, independent of time. The dynamic hedge ratio is obtained by minimizing the conditional variance of the change in value of the hedged portfolio as follows:

$$\min_{\eta_t} \mathrm{Var}_{t-1}(\Delta H_t) = \mathrm{Var}_{t-1}(\Delta S_t) + \eta_t^2 \mathrm{Var}_{t-1}(\Delta F_t) - 2\eta_t \mathrm{Cov}_{t-1}(\Delta F_t, \Delta S_t).$$

The first order condition of the objective function is $\frac{\partial \mathrm{Var}_{t-1}(\Delta H_t)}{\partial \eta_t} = 2\eta_t \mathrm{Var}_{t-1}(\Delta F_t) - 2\mathrm{Cov}_{t-1}(\Delta F_t, \Delta S_t)$. Setting this equal to zero, the dynamic hedge ratio is computed by $\eta_t = \frac{\mathrm{Cov}_{t-1}(\Delta F_t, \Delta S_t)}{\mathrm{Var}_{t-1}(\Delta F_t)}$, which can be rewritten as

$\frac{\rho\sqrt{h_t q_t}}{q_t}$ in our notation. After estimating the bivariate GJR-GARCH model, we collect the estimated values of conditional correlation of two innovations, conditional variance of the change in spot prices, and conditional variance of the change in futures prices to compute the dynamic hedge ratios. An observation is worth mentioning here, namely, that the formula of dynamic hedge ratios is similar to that of constant hedge ratios, except that the former uses conditional variances and covariances, while the latter uses unconditional counterparts.

Following Kroner and Sultan (1993), we evaluate $\mathrm{Var}(\Delta S_t - h_t \Delta F_t)$, the variance of the change in the value of the hedged portfolio, to compare hedging performance of different methods. $h_t$, the optimal hedge ratio, is set equal to unity, the constant optimal hedge ratios, and the time-varying dynamic hedge ratios for the naïve hedge method, the conventional OLS method, and the bivariate GJR-GARCH model, respectively.

## 5. Data and Empirical Results

The data used in this study are obtained from the LIFFE database. LIFFE is chosen because it has SSFs traded on over one hundred individual stocks in England, the United States, and Europe. More than 80% of the SSFs listed on the LIFFE are traded on securities outside England, and these SSFs are so-called "foreign-listed" for their domestic stock markets. The SSFs listed on the LIFFE are also called universal stock futures (USFs). For credibility reasons, the data initially included the top ten active SSFs listed on the LIFFE. However, among these SSFs, the underlying stock of the second one (i.e., Vodafone Group plc) is listed on the London Stock Exchange. Hence, based on our criterion of foreign listing, the data of that SSF is omitted from the analyses. The data was collected until April 19, 2002 but each SSF may have different data periods depending on their introduction dates. The average number of observations is about 280. Table 2 lists the dates of introduction of the remaining nine SSF contracts.

Table 3 displays the estimated constant optimal hedge ratios for the nine groups of data. Constant optimal hedge ratios are above 90%, except for the three SSFs (Eni SpA, Enel SpA and UniCredito Italiano SpA) whose underlying stocks are traded in Italy.

**Table 2.** The dates of introduction for the nine SSF contracts.

| Name (Symbol) | Country | Listing Exchange | Introduction Date | Data Period | Observations |
|---|---|---|---|---|---|
| Eni SpA (ENI) | Italy | Borsa Italiana[a] | 2001/01/29 | 2001/01/29–2002/4/19 | 303 |
| Telecom Italia SpA (TI) | Italy | Borsa Italiana | 2001/01/29 | 2001/01/29–2002/4/19 | 303 |
| Banco Bilbao Vizcaya Argentaria SA (BVA) | Spain | Bolsa De Madrid[b] | 2001/05/14 | 2001/05/14–2002/4/19 | 229 |
| Telecom Italia Mobile SpA (TIM) | Italy | Borsa Italiana | 2001/03/19 | 2001/03/19–2002/4/19 | 268 |
| Nokia OYJ (NOK) | Finland | Helsinki Exchange[c] | 2001/01/29 | 2001/01/29–2002/4/19 | 297 |
| Enel SpA (ENL) | Italy | Borsa Italiana[d] | 2001/03/19 | 2001/03/19–2002/4/19 | 268 |
| UniCredito Italiano SpA (UC) | Italy | Borsa Italiana | 2001/03/19 | 2001/03/19–2002/4/19 | 268 |
| Telefonica SA (TEF) | Spain | Bolsa De Madrid[e] | 2001/01/29 | 2001/01/29–2002/4/19 | 299 |
| Royal Dutch Petroleum Co (RD) | Netherlands | Euronext Amsterdam[f] | 2001/01/29 | 2001/01/29–2002/4/19 | 304 |

[a]ENI is also listed on the New York Stock Exchange (NYSE).
[b]BVA is also listed on the NYSE.
[c]NOK is also listed on the NYSE and the Stockholm Stock Exchange.
[d]ENL is also listed on the NYSE.
[e]TEF is also listed on the NYSE, the Buenos Aires Stock Exchange, the Lima Stock Exchange, the Sao Paulo Stock Exchange, the London Stock Exchange, the Paris Stock Exchange, the Frankfurt Stock Exchange and the Tokyo Stock Exchange.
[f]RD is also listed on the NYSE.

As shown in Table 4, the coefficient ($\alpha_3$) on the dummy variable $I_{t-1}$ in Equation (3) and the coefficient ($\beta_3$) on the dummy variable $D_{t-1}$ in Equation (5) are both significantly positive in Telecom Italia SpA and Royal Dutch Petroleum Co, reflecting that bad shocks, indeed, impact conditional volatility more than good news in the two groups of data. The leverage effect

**Table 3.** Constant optimal hedge ratios.

| Name (Symbol) | Eni SpA (ENI) | Telecom Italia SpA (TI) | Banco Bilbao Vizcaya Argentaria SA (BVA) | Telecom Italia Mobile SpA (TIM) | Nokia OYJ (NOK) | Enel SpA (ENL) | UniCredito Italiano SpA (UC) | Telefonica SA (TEF) | Royal Dutch Petroleum Co (RD) |
|---|---|---|---|---|---|---|---|---|---|
| Hedge ratio | 0.151168 | 0.915792 | 0.96013 | 0.902621 | 0.971574 | 0.191883 | 0.424539 | 0.942677 | 0.989487 |

**Table 4.** Estimates from the following bivariate GARCH model:

$$\Delta S_t = c_{11} + \sqrt{h_t}\varepsilon_t, h_t = \alpha_0 + \alpha_1 h_{t-1} + \alpha_2\varepsilon_t^2 + \alpha_3 I_{t-1}\varepsilon_{t-1}^2, \varepsilon_t \left| \mathcal{F}_{t-1} \right. \sim N(0, 1)$$
$$\Delta F_t = c_{22} + \sqrt{q_t}\omega_t, q_t = \beta_0 + \beta_1 q_{t-1} + \beta_2\omega_t^2 + \beta_3 D_{t-1}\omega_{t-1}^2, \omega_t \left| \mathcal{F}_{t-1} \right. \sim N(0, 1),$$
$$\mathrm{Cov}_{t-1}(\varepsilon_t, \omega_t) = \rho.$$

| Name (Symbol) | Eni SpA (ENI) | Telecom Italia SpA (TI) | Banco Bilbao Vizcaya Argentaria SA (BVA) | Telecom Italia Mobile SpA (TIM) | Nokia OYJ (NOK) | Enel SpA (ENL) | UniCredito Italiano SpA (UC) | Telefonica SA (TEF) | Royal Dutch Petroleum Co (RD) |
|---|---|---|---|---|---|---|---|---|---|
| (Estimated values) | | | | | | | | | |
| Stock dynamic | | | | | | | | | |
| $c_{11}$ | 0.006503 | −0.024387* | −0.015124 | −0.007717 | −0.050458 | 0.000475 | 0.004131 | −0.024098 | −0.037102 |
| | (0.69433) | (0.02306) | (0.48055) | (0.38662) | (0.39553) | (0.93545) | (0.29699) | (0.24341) | (0.5367) |
| $\alpha_0$ | 0.157214* | 0.020572* | 0.010834 | 0.017907 | 0.001394 | 0.000457 | 0.000344 | 0.039372 | 0.072089* |
| | (0.00000) | (0.00003) | (0.14047) | (0.16168) | (0.76311) | (0.24999) | (0.13199) | (0.18983) | (0.02208) |
| $\alpha_1$ | −0.990224* | 0.376154* | 0.81116* | 0.014178 | 0.981176* | 0.925811* | 0.825975* | 0.621068* | 0.872009* |
| | (0.00000) | (0.00129) | (0.00000) | (0.98412) | (0.00000) | (0.00000) | (0.00000) | (0.0181) | (0.00000) |
| $\alpha_2$ | 0.06268* | −0.056872 | 0.079961 | −0.035977 | 0.01428 | 0.057858 | 0.089084 | 0.083769 | −0.007455 |
| | (0.01235) | (0.16368) | (0.21652) | (0.53800) | (0.12962) | (0.1356) | (0.07339) | (0.16144) | (0.79886) |
| $\alpha_3$ | −0.021635 | 0.423939* | −0.011796 | 0.082984 | −0.001392 | −0.041358 | −0.017772 | −0.025814 | 0.128089* |
| | (0.23054) | (0.00011) | (0.85583) | (0.25992) | (0.89612) | (0.33818) | (0.776) | (0.64826) | (0.00782) |

**Table 4.** (*Continued*)

| Name (Symbol) | Eni SpA (ENI) | Telecom Italia SpA (TI) | Banco Bilbao Vizcaya Argentaria SA (BVA) | Telecom Italia Mobile SpA (TIM) | Nokia OYJ (NOK) | Enel SpA (ENL) | UniCredito Italiano SpA (UC) | Telefonica SA (TEF) | Royal Dutch Petroleum Co (RD) |
|---|---|---|---|---|---|---|---|---|---|
| SSF dynamic | | | | | | | | | |
| $c_{22}$ | −0.00576 | −0.025359* | −0.01503 | −0.006709 | −0.054293 | 0.002439 | 0.000425 | −0.029413 | −0.03595 |
| | (0.712379) | (0.01922) | (0.48046) | (0.46967) | (0.36808) | (0.7181) | (0.93718) | (0.16152) | (0.55913) |
| $\beta_0$ | −0.00013 | 0.016355* | 0.011598 | 0.027513* | −0.000095 | −0.000082* | 0.000444* | 0.04029 | 0.059263 |
| | (0.695165) | (0.00000) | (0.13102) | (0.00000) | (0.98024) | (0.00733) | (0.01195) | (0.06455) | (0.05418) |
| $\beta_1$ | 1.014871* | 0.4795* | 0.777268* | −0.439048* | 0.984757* | 1.010187* | 0.89373* | 0.616446* | 0.904706* |
| | (0.00000) | (0.00000) | (0.00000) | (0.03421) | (0.00000) | (0.00000) | (0.00000) | (0.00056) | (0.00000) |
| $\beta_2$ | −0.015337* | −0.057138 | 0.125033 | −0.020696 | 0.006028 | −0.007617* | −0.02635 | 0.138481* | −0.009304 |
| | (0.00000) | (0.07635) | (0.13928) | (0.6061) | (0.51144) | (0.00000) | (0.233812) | (0.01448) | (0.67291) |
| $\beta_3$ | 0.01146 | 0.483575* | −0.054571 | 0.099128* | 0.010291 | 0.000426 | 0.165203* | −0.107358 | 0.090732* |
| | (0.09965) | (0.00000) | (0.4463) | (0.03373) | (0.39604) | (0.89806) | (0.001438) | (0.11076) | (0.00822) |
| Constant | 0.711278* | 0.956246* | 0.947445* | 0.938606* | 0.974073* | 0.775616* | 0.626297* | 0.965296* | 0.971971* |
| correlation | (0.00000) | (0.00000) | (0.00000) | (0.00000) | (0.00000) | (0.00000) | (0.00000) | (0.00000) | (0.00000) |
| $\rho$ observations | 300 | 302 | 228 | 267 | 296 | 267 | 267 | 298 | 303 |

Figures in parentheses are $p$-values; an asterisk marks statistical significance at the 5% level.

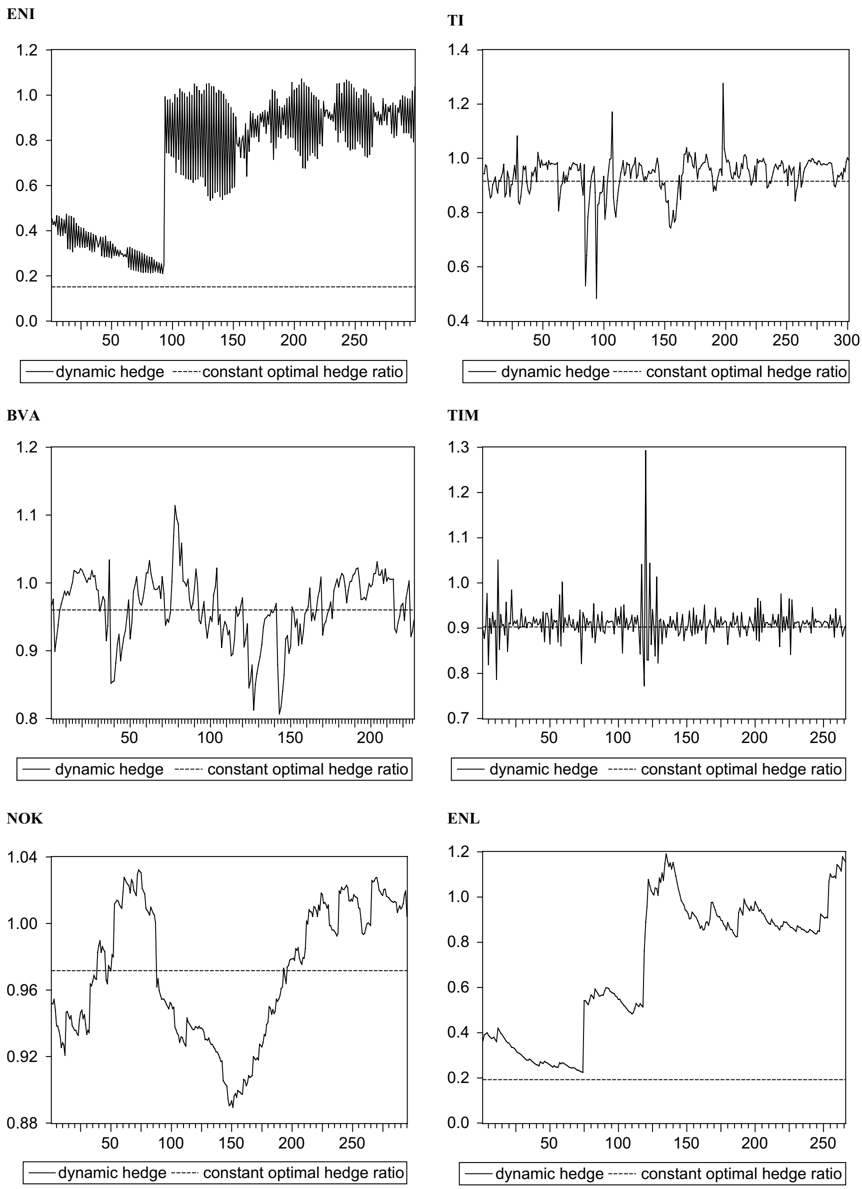


**Figure 1.** The optimal hedge ratio over the sample periods under two assumptions: time-varying volatility and constant volatility.

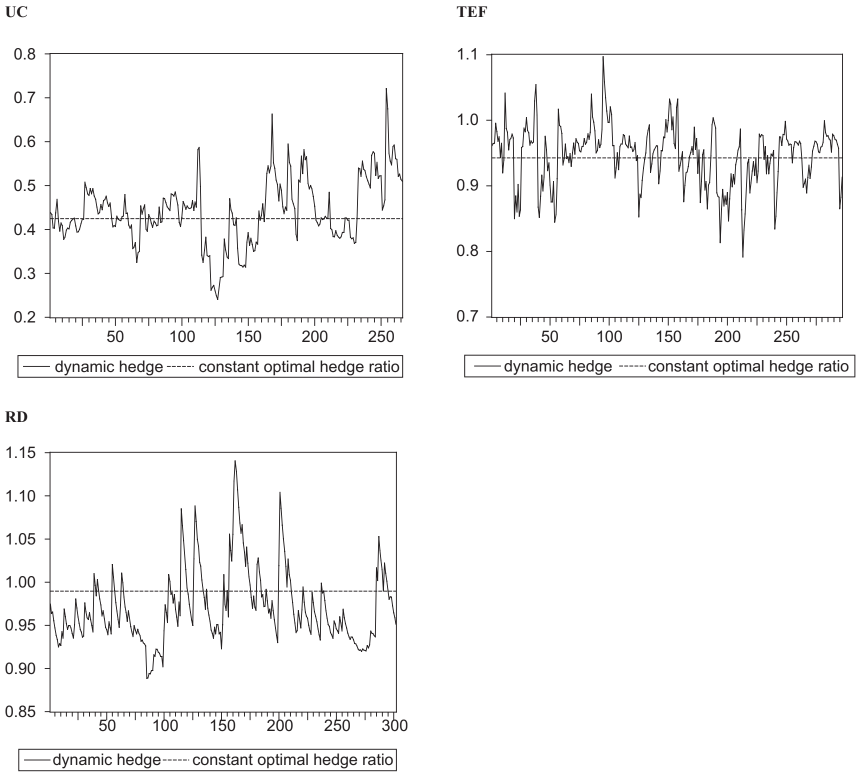


**Figure 1.** (*Continued*)

can also be found in the data series of Telecom Italia Mobile SpA's futures and that of UniCredito Italiano SpA's futures.

The constant correlation ($\rho$) is significantly positive for all nine groups of data. Except for Eni SpA, Enel SpA, and UniCredito Italiano SpA, $\rho$ is over 90%. Comparing Table 3 and Table 4, we find that there seems to be a positive relationship between constant optimal hedge ratios in Equation (1) and the constant correlation in the bivariate GJR-GARCH model. The significance of the other coefficients for the explanatory variables depends on the security.

Figure 1 plots the dynamic hedge ratios and conventional constant hedge ratios. After applying the augmented Dicky-Filler test (ADF) to check if the series of dynamic hedge ratios have a unit root, we find that except for those of Enel SpA and Nokia OYJ, the series of dynamic hedge ratios have no unit root at the 5% level. In addition, we find by visual examination that the conventional OLS method tends to under-hedge for the series of Eni SpA and Enel SpA.

The comparisons of hedging performance of various approaches are illustrated in Table 5. Based on minimum hedged portfolio variances, the performance of dynamic hedging is the best of the three methods and that of naïve hedge is the worst, excluding the data series of Banco Bilbao Vizcaya Argentaria SA and UniCredito Italiano SpA.

## 6. Conclusions

In this paper, we used data obtained from the London International Financial Future and Options Exchange (LIFFE) database to estimate the dynamic hedge ratios of foreign-listed SSFs and to compare the hedging performance of this method and those of the naïve hedge as well as the conventional OLS method. The estimated results of the GJR-GARCH model suggest that bad shocks may impact conditional volatility more than good news in our researched data, reflecting leverage effect reported in many studies.

The results show that the three SSFs — Eni SpA, Enel SpA, and UniCredito Italiano SpA — with their underlying stocks traded in Italy have both lower constant optimal hedge ratios and lower constant correlation in the bivariate GJR-GARCH model. This indicates that the relationship between the SSFs market and their domestic underlying market in Italy is less close. Since Italy is relatively farther from England, it seems that the tightness of relation between foreign listed derivatives and their domestic underlying markets varies with distance. Besides, we find that the series of dynamic hedge ratios display stationary, except for those of Enel SpA and Nokia OYJ with underlying stocks traded in Finland. The result implies that while the impact of shocks to hedge ratios of foreign listed SSFs with underlying stocks traded closer to England eventually decays, which is similar to the findings of currency markets mentioned by Kroner and Sultan (1993), the dynamic hedge ratios of foreign listed SSFs with underlying stocks traded farther from England behave as random walks, which is similar to the findings of commodity markets reported by Baillie and Myers (1991). It appears that the two findings listed above offer sufficient evidence supporting the hypothesis that locations or distance do matter in analyzing trading activities.

Since the constant optimal hedge ratios are over 90% for most series, the differences between the effectiveness of risk reduction of the naïve hedge and

**Table 5.** Comparisons of hedging performance by variances: $\mathrm{Var}(\Delta S_t - h_t \Delta F_t)$.

| Name (Symbol) | Eni SpA (ENI) | Telecom Italia SpA (TI) | Banco Bilbao Vizcaya Argentaria SA(BVA) | Telecom Italia Mobile SpA (TIM) | Nokia OYJ (NOK) | Enel SpA (ENL) | UniCredito Italiano SpA (UC) | Telefonica SA (TEF) | Royal Dutch Petroleum Co (RD) |
|---|---|---|---|---|---|---|---|---|---|
| (Portfolio variance) | | | | | | | | | |
| Naïve hedge ($h_t = 1$) | 0.21838 | 0.00430 | 0.00980 | 0.00239 | 0.06834 | 0.05334 | 0.00534 | 0.00940 | 0.05847 |
| Conventional hedge ($h_t = \beta$) | 0.06907 | 0.00400 | 0.00965 | 0.00220 | 0.06736 | 0.01155 | 0.00221 | 0.00896 | 0.05836 |
| Dynamic hedge ($h_t = \eta_t$) | 0.04770 | 0.00378 | 0.00984 | 0.00219 | 0.06603 | 0.00643 | 0.00223 | 0.00880 | 0.05677 |

that of the conventional OLS method are trivial. Nevertheless, our findings suggest that in general, the hedging performance of dynamic hedging is the best of the three methods, the performance of the conventional OLS method is the second best, and the naïve hedge is the worst. One possible explanation is that the dynamic hedging method gives more flexibility for the users to fine tune the hedge ratios when the market situation fluctuates, while the naïve hedging ratio and the conventional constant hedging ratio remain rigid regardless of market fluctuations.

We acknowledge that our research still has some limitations that should be kept in mind and need to be improved in future studies. As shown in Table 5, even though the dynamic hedging performs better than the other methods in our study, the outperformances are not significant. While several studies note that even taking transaction cost into consideration, dynamic hedging offers better a hedging strategy (e.g., Kroner and Sultan, 1993; Park and Switzer, 1995), other studies mention computational costs which may diminish the effectiveness of dynamic hedging (e.g., Lien, Tse and Tsui, 2000). Thus future research should be done in the presence of transaction costs and other costs such as computational costs and reexamination costs to investigate whether dynamic hedging could maintain its leading position among hedging strategies.

We have compared the hedging performances of three methods in our research. In addition to naïve hedge, conventional OLS method, and dynamic hedging, other methods such as generalized semivariance (GSV) or mean extended-Gini (MEG) may prove to be noteworthy as well. We plan to remedy this omission in future work by applying numerical methods to estimate the hedge ratios of GSV or MEG.

Horizon effect is another interesting topic worth exploring. However, this kind of research requires much longer sample periods. Unfortunately, since the SSFs are a newly developed type of derivative, we do not have enough samples to implement this kind of research. Hence, we suggest that questions such as whether the optimal hedge ratio approaches the naïve hedge ratio when the hedging horizon becomes longer can be investigated in a future study.

Finally, we merely focused our interest on the SSFs listed on the LIFFE in the United Kingdom. Since SSFs have already traded on several exchanges, including those in the United States, Spain, Portugal, Australia and so on, future work could potentially incorporate data from other exchanges to expand the scope of this research.

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Chapter 9

# Asset Pricing with Higher Moments: Empirical Evidence from the Taiwan Stock Market

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This study examines the effects of higher moments, skewness and kurtosis of stock returns on asset pricing for the Taiwan stock market. The traditional two-moment CAPM and Fama-French model with size and book-to-market factors included were used as base cases. Then the three-moment and four-moment CAPMs and Fama-French models with systematic skewness and kurtosis included were tested. In addition to the market models used to estimate the parameters of systematic skewness and kurtosis, some proxy measures obtained from a procedure similar to Harvey and Sidique (2000b) were also adopted. Following the Fama-Macbath procedure, the two-step cross-sectional regressions were adopted to test the pricing models. Weekly returns for 132 stocks on the Taiwan stock market over the period from January 1991 to August 2002 were used for empirical testing. The results show that the three-moment CAPM is significant, whereas the fourth moment is not consistent with the empirical data. In the case of the Fama-French model, the size and book-to-market effects seem to dominate the moment effects. Although the parameters are insignificant, their consistent signs confirm the existence of the third moment effect on asset pricing.

**Keywords:** Two-moment CAPM; three-moment CAPM; four-moment CAPM; beta; coskewness; cokurtosis.

## 1. Introduction

The traditional Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965) maintains that the first two moments of returns distribution, mean and variance are sufficient for determining the asset pricing. However, numerous empirical studies have shown that there is a significant bias for the CAPM, and to resolve this problem, researchers have sought different alternatives to explain the pricing bias. For example, Fama and French (1995) incorporate the size effect, particularly the SMB (defined as the return on a portfolio of small-size stocks minus the return on a portfolio of large-size stocks), and the book-to-market effect, particularly the HML (defined as the return on a

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portfolio of stocks with high book-to-market ratio minus the return on a portfolio of stocks with low book-to-market ratio) into the pricing model. Kraus and Litzenberger (1976), Friend and Westerfield (1980), Harvey and Siddique (2000a) and Harvey and Siddique (2000b) all claim that skewness plays an important role in security pricing. Fang and Lai (1997), Christie-David and Chaudhry (2001) and Dittmar (2002) state that expected excess rate of return is related not only to the systematic variance but also the systematic skewness and kurtosis. Others try to explain the empirical bias by ascribing it to market inefficiency (Roll, 1977 and Ross, 1977), to the errors-in-variable problem (Kim, 1995), to survivorship bias (Kothari, Shanken and Sloan, 1995), and to time-varying risk premium (Kan and Zhang, 1997).

Investment returns are usually assumed to be normally distributed, although certain assets or investment strategies have non-normal return distributions. For example, there are the presence of agency problems and limited liability (Brennan, 1993), the correlation between price and volatilities (Christie, 1982), and the compound return in a multi-periodic framework (Fama, 1996), all of which may induce asymmetry in portfolio returns. Thus, to describe asset return distributions, one must go beyond the first two moments to the third and the fourth moments, the skewness and the kurtosis, or even higher moments. Rubinstein (1973) and Kraus and Litzenberger (1976) extended the Sharpe-Lintner CAPM model by incorporating skewness into the valuation model. Their findings showed that when the CAPM was extended by including the systematic skewness, the prediction of a significant price of systematic skewness was confirmed and the prediction of a zero intercept for the market line in excess return space was not rejected. Friend and Westerfield (1980) provided some but not conclusive evidence in support of skewness, and suggested that investors may be willing to pay a premium for positive skewness in their portfolios. In order to avoid the problem caused by errors-in-variable and obtain consistent estimators of the parameters, Lim (1989) used Hansen's (1982) Generalized Method of Moments (GMM) to test the Kraus and Litzenberger (1976) three moments' model, concluding that the systematic skewness was priced in the security returns. Lee, Moy and Lee (1996) tested the importance of coskewness in asset pricing using the multivariate test procedure proposed by Gibbons, Ross and Shanken (1989). Their results also indicate statistical significance for coskewness in asset pricing, although their results show that Kraus and Litzenberger's model does not adequately describe expected returns. Chunhachinda, Dandapani, Hamid and Prakash (1997) considered skewness for portfolio selection, and their empirical findings suggest that the incorporation of skewness into an investor's portfolio decision causes a major change in the construction of an optimal portfolio. Furthermore, Fang and Lai (1997) incorporated the effect of unconditional kurtosis in the asset pricing, which supports the important role for unconditional kurtosis in asset pricing. Dittmar (2002) investigates nonlinear pricing kernels in a conditional setting that considers a link between nonparametric and parametric approaches to describing cross-sectional variation in equity returns. His results show that asset returns are affected by covariance, coskewness and cokurtosis.

Recently, Harvey and Siddique (1999) presented a new methodology for estimating time-varying conditional skewness in asset pricing. Subsequently they examined the relationship between time-varying conditional skewness and the market risk premium (Harvey and Siddique, 2000a). Moreover, Harvey and Siddque (2000b) used monthly US equity returns on NYSE, AMEX and NASDAQ to test different measurements of the systematic skewness. Their results show that conditional skewness plays an important role in explaining risk premiums, whether based on the traditional CAPM or Fama and French's (1995) three-factor model.

The aim of this study is to investigate the effect of higher moments, apart from the first two moments, namely the skewness and kurtosis of stock returns on asset pricing in the case of an emerging capital market, the Taiwan stock market. We first use the traditional two-moment CAPM and the two-moment Fama-French model with SMB and HML included as the base cases. We then investigate the three-moment and four-moment CAPM and Fama-French models with systematic skewness and kurtosis included in the models. Besides using market models to estimate parameters of systematic skewness and kurtosis, we also adopt some proxy measures obtained from a procedure similar to Harvey and Sidique (2000b) to substitute the market skewness and kurtosis risk factors. Following the Fama-Macbath procedure, the two-step cross-sectional regressions were adopted to test the pricing models. For robustness, stock portfolios were constructed by size and book-to-market ratio as well as by beta, coskewness, and cokurtosis. The empirical data used in this study includes weekly returns for 132 stocks traded on the Taiwan stock market over the period from January 1991 to August 2002.

The empirical results show that the three-moment CAPM is significant, whereas the fourth moment is not consistent with the empirical data. In the case of the Fama-French model, the size and book-to-market value effects seem to dominate the moment effects, causing most of the parameter in the pricing model to be insignificant. Although insignificant, however, the consistent signs confirm the existence of the third moment effect on asset pricing for the Taiwan stock market.

The rest of this paper is organized as follows. Section 2 reviews the model of asset pricing with systematic skewness and kurtosis included. Section 3 describes the research sample and presents the empirical evidence. Summaries and conclusions are presented in Section 4.

## 2. Methodology

Kraus and Litzenberger (1976) used coskewness as a supplement for covariance, in order to explain the discrepancies between return and risk for individual stocks. Realizing that the higher moments might be important, Fang and Lai (1997), Dittmar (2002), and Christie-David and Chaudhry (2001) further used kurtosis as the additional supplement factor for asset pricing. To explain their four-moment asset pricing model, we denote the first four moments of investor's wealth, as defined by Christie-David and Chaudhry (2001), as follows:

$$\bar{W} = \sum_i \theta_i \bar{R}_i + \theta_f R_f, \tag{1}$$

$$\sigma_W = \sum_i \theta_i \beta_{ip} \sigma_p, \tag{2}$$

$$S_W = \sum_i \theta_i \gamma_{ip} S_p, \tag{3}$$

$$K_W = \sum_i \theta_i \delta_{ip} K_p, \tag{4}$$

where

$\bar{R}_i$: expected return on the risky asset $i$ plus one;

$R_f$: risk-free rate plus one;

$\theta_i$: investor's holding proportion in the risky asset $i$;

$\theta_f$: investor's holding proportion in the risk-free asset;

$\beta_{ip} = E\left[\left(\tilde{R}_i - \bar{R}_i\right)\left(\tilde{R}_p - \bar{R}_p\right)\right] / \sigma_p^2;$

$\gamma_{ip} = E\left[\left(\tilde{R}_i - \bar{R}_i\right)\left(\tilde{R}_p - \bar{R}_p\right)^2\right] \Big/ S_p^3;$

$\delta_{ip} = E\left[\left(\tilde{R}_i - \bar{R}_i\right)\left(\tilde{R}_p - \bar{R}_p\right)^3\right] \Big/ K_p^4;$

$\sigma_p = \left[E\left(\tilde{R}_p - \bar{R}_p\right)^2\right]^{1/2};$

$S_p = \left[E\left(\tilde{R}_p - \bar{R}_p\right)^3\right]^{1/3};$

$K_p = \left[E\left(\tilde{R}_p - \bar{R}_p\right)^4\right]^{1/4}.$

The first-order conditions from the following Lagrangian are determined when the investor's end-of-period wealth is considered as,

$$L = \phi\left(\bar{W}, \sigma_W, S_W, K_W\right) - \lambda\left[\sum_i \theta_i + \theta_f - W_0\right]. \tag{5}$$

Taking partial derivatives with respect to $\theta_i$ and $\theta_f$ in Equation (5) and setting the partial derivative equations equal to zero, results in

$$\bar{R}_i - R_f = -\left(\phi_{\sigma_W}/\phi_{\bar{W}}\right)\beta_{ip}\sigma_p - \left(\phi_{S_W}/\phi_{\bar{W}}\right)\gamma_{ip}S_p - \left(\phi_{K_W}/\phi_W\right)\delta_{ip}K_p. \tag{6}$$

Equation (6) states that the risk premium for every asset is equal to the sum of three parts: (1) the marginal rate of substitution between expected return and standard deviation multiplied by the asset marginal contribution to the portfolio's standard deviation; (2) the marginal rate of substitution between expected return and skewness multiplied by the asset's marginal contribution to the portfolio's skewness; and (3) the marginal rate of substitution between expected return and kurtosis multiplied by the asset is marginal contribution to the portfolio's kurtosis. In market equilibrium, simplifying Equation (6), the four-moment capital asset pricing model can be obtained as:

$$\bar{R}_i - R_f = b_0 + b_1\beta_i + b_2\gamma_i + b_3\delta_i, \tag{7}$$

where

$$\beta_i = E\left[\left(\tilde{R}_i - \bar{R}_i\right)\left(\tilde{R}_M - \bar{R}_M\right)\right]/\sigma_M^2;$$
$$\gamma_i = E\left[\left(\tilde{R}_i - \bar{R}_i\right)\left(\tilde{R}_M - \bar{R}_M\right)^2\right]\Big/S_M^3;$$
$$\delta_i = E\left[\left(\tilde{R}_i - \bar{R}_i\right)\left(\tilde{R}_M - \bar{R}_M\right)^3\right]\Big/K_M^4;$$
$$b_1 = \left({}^{d\bar{W}}\!/_{d\sigma_W}\right)\sigma_M;$$
$$b_2 = \left({}^{d\bar{W}}\!/_{dS_W}\right)S_M;$$
$$b_3 = \left({}^{d\bar{W}}\!/_{dK_W}\right)K_M.$$

In Equation (7), $b_1$, $b_2$ and $b_3$ are the prices of systematic variance, skewness and kurtosis risks. According to the utility assumptions, when the returns on a well-diversified portfolio are positively (or negatively) skewed, the risk premium for the skewness risk should be negative (or positive). That is, investors forego the expected return for the benefit of increasing the systematic skewness. On the other hand, a greater covariance of asset return with the cube of market portfolio return implies a greater systematic kurtosis risk contributed by the asset. The greater the extreme return which cannot be diversified is, the higher would be the expected excess required rate of return. As a result, the expected rate of return is positively related to the systematic kurtosis risk. In summary, the above equation shows that the expected excess rate of return is related not only to the systematic variance, but also to the systematic skewness and systematic kurtosis. With higher systematic kurtosis as the systematic variance, there is higher expected return on the asset. On the other hand, the systematic skewness is reversely related to the expected return.

The cubic market model analogy of the single-index market model, consistent with the four-moment CAPM of Equation (7) is:

$$R_{it} - R_f = \alpha_i + \beta_i \left(R_{mt} - R_f\right) + \gamma_i \left(R_{mt} - R_f\right)^2 + \delta_i \left(R_{mt} - R_f\right)^3 + \varepsilon_{it}. \tag{8}$$

The regression coefficients, beta ($\beta_i$), coskewness ($\gamma_i$), and cokurtosis ($\delta_i$) in Equation (8) are identical to those in Equation (7), hence they can be used as the estimates of the pricing factors. Following the Fama-MacBeth (1973) procedure, after estimating the risk parameters, the cross-sectional regression of Equation (7) can be tested.

The coskewness coefficient represents the contribution of a security to the skewness of a portfolio. A security with negative measure of coskewness would add negative skewness to a broader portfolio, and hence should offer a higher expected return to investors. This is because a portfolio with negative skewness will offer higher probability for investors to obtain low returns and hence should be sold at lower price in order to attract investors. The cokurtosis coefficient represents the contribution of a security to the kurtosis of a portfolio. A security with negative measure of cokurtosis would add negative kurtosis to a broader portfolio, and hence should offer a lower expected return to investors. This is because a portfolio with negative kurtosis will offer lower risk for investors.

Following Harvey and Siddique (2000b), and in the same vein as Fama and French (1995), we construct two value-weighted hedge portfolios that capture the effect of market-wide systematic skewness. We first calculate the standardized coskewness coefficient for each stock based on its past returns. We then rank the stocks based on their realized coskewness and form two value-weighted portfolios. Here $S^-$ represents the return on the portfolio containing 30% of the sample stocks with the most negative (or lowest) coskewness, and $S^+$ represents the return on the portfolio containing 30% of the sample stocks with the most positive (or highest) coskewness. The returns on the hedge portfolios, that is $S^- - S^+$, are then used as a proxy for systematic skewness risks. For the hedge portfolios, the higher the factor loading is, the higher is the risk premium.

Similarly, following the procedure adopted by Harvey and Siddique (2000b) in calculating the proxy for systematic skewness, we also construct two value-weighted hedge portfolios in order to capture the effect of market-wide systematic kurtosis. The standardized cokurtosis coefficients for each stock are calculated first. Then we rank the stocks based on their realized cokurtosis and form two value-weighted portfolios. Here $K^-$ represents the return on the portfolio consisting of 30% of the sample stocks with the most negative (or lowest) cokurtosis, and $K^+$ represents the return on the portfolio consisting of 30% of the sample stocks with the most positive (or highest) cokurtosis. The returns on the hedge portfolios, that is $K^+ - K^-$, are then used as a proxy for systematic kurtosis risks. For the hedge portfolios, the higher the factor loading is, the higher is the risk premium.

With the proxies for systematic skewness and kurtosis, we can run the following regression to estimate the risk parameters:

$$R_{it} - R_f = \alpha_i + \beta_i \left(R_{mt} - R_f\right) + \gamma_i \left(S^- - S^+\right) + \delta_i \left(K^+ - K^-\right) + \varepsilon_{it}. \quad (9)$$

So the cross-sectional regression of Equation (7) can be tested.

For empirical investigation, recognizing that there is a significant bias from using the traditional CAPM, we should incorporate the firm-size effect and the book-to-market value effect into the pricing model as suggested by Fama and French (1995). The three-factor model that not only include market risk premium but also the SMB and HML is as follows:

$$\begin{aligned} R_{it} - R_f = \alpha_i + \beta_i \left(R_{mt} - R_f\right) + s_i \mathrm{SMB}_t + h_i \mathrm{HML}_t + \gamma_i \left(S^- - S^+\right) \\ + \delta_i \left(K^+ - K^-\right) + \varepsilon_{it}, \quad (10) \end{aligned}$$

where $\mathrm{SMB}_t$ is defined as the return on the smaller-sized stocks minus the return on the larger-sized stocks which capture the market-wide systematic size effect on risk premium. $\mathrm{HML}_t$ is defined as the return on the high book-to-market stocks minus the return on the low book-to-market stocks which can capture the market wide systematic book-to-market effect on risk premiums. As in Fama and French (1995), the risk premium for SMB and HML factor loadings should be positive. Although this is a worldwide phenomenon, it is based on empirical evidence rather than a theoretical explanation.

The cubic market model with SMB and HML included in the model is:

$$R_{it} - R_f = \alpha_i + \beta_i \left(R_{mt} - R_f\right) + s_i \mathrm{SMB}_t + h_i \mathrm{HML}_t + \gamma_i \left(R_{mt} - R_f\right)^2 + \delta_i \left(R_{mt} - R_f\right)^3 + \varepsilon_{it}. \quad (11)$$

Having estimated the risk parameters, the following cross-sectional regression model can be used:

$$\bar{R}_i - R_f = b_0 + b_1 \beta_i + b_{\mathrm{SMB}} s_i + b_{\mathrm{HML}} h_i + b_2 \gamma_i + b_3 \delta_i. \quad (12)$$

## 3. Empirical Results

### 3.1. *Sample description*

The main purpose of this study is to empirically test whether the coskewness and cokurtosis risks are priced in the Taiwan stock market, an important emerging market. The research sample contains weekly rate of returns on 132 common stocks listed on the Taiwan Stock Exchange, covering the period from January 1989 to August 2002. Sampling criteria simply require that individual stocks maintain complete trading records during the overall sample period. During the whole sample period, the empirical testing period is from January 1991 to August 2002. And we use the data back to January 1989 for estimating parameters and constructing portfolios. In total there are 556 weekly observations for each stock for empirical testing. For more robust testing, we divide the testing period into two sub-periods, the first sub-period from January 1991 to December 1995 with 261 observations, and the second sub-period from January 1996 to August 2002 with 295 observations. Other data used in this study includes the proxy for risk-free interest rate, which is the price of thirty-day commercial paper traded in the secondary market; and the market portfolio returns, which are calculated using the value-weighted stock index, the TAIEX.

In constructing portfolios we adopt two alternative grouping procedures. The first grouping procedure is based on estimated beta, coskewness, and cokurtosis, as in Fang and Lai (1997). Weekly returns two years prior to the week concerned were used to estimate the risk parameters. Stocks then were first assigned to three groups based on their beta estimates. Within each group, stocks were also classified into three subgroups according to their coskewness estimates. Finally stocks within each subgroup were further assigned to one of three classes by their cokurtosis estimates. As a result, 27 portfolios were constructed and the returns on these portfolios for the week concerned were then calculated from individual sample stocks. The portfolios were rebalanced every week and the same procedure was repeated until 556 weekly returns on the 27 portfolios for the whole testing period were obtained.

For the sake of robustness, we also adopted an alternative grouping procedure, similar to the Fama-French procedure. Stocks were first assigned to five groups according to their size. Within each group stocks were then classified into five subgroups according to their book-to-market ratio. The portfolios were rebalanced every week as well. In this procedure, 25 portfolios were obtained in total. The same procedures as described above were also followed to calculate returns for these stock portfolios for testing pricing models.

## 3.2. *Data analysis*

Table 1 provides some statistics on skewness and kurtosis for the returns of market portfolio and portfolios that were grouped by size and book-to-market,

**Table 1.** Skewness and kurtosis for Taiwan stock returns.

| | Whole Period 1991/1–2002/8 | First Sub-Period 1991/1–1995/12 | Second Sub-Period 1996/1–2002/8 |
|---|---|---|---|
| Market skewness | 0.1732* | 0.3091* | 0.1140 |
| Market excess kurtosis | 1.9633* | 1.3609* | 2.1601* |
| Average premium for market proxy of skewness $S^{-} - S^{+}$ | 0.0191 | 0.0693 | −0.0253 |
| Average premium for market proxy of kurtosis $K^{+} - K^{-}$ | −0.0218 | 0.0446 | −0.0805 |
| Portfolios formed by size and book-to-market | | | |
| Average portfolio skewness | 0.1316 | 0.2861 | 0.0799 |
| Portfolios with significant skewness (%) | 28% | 8% | 48% |
| Average portfolio excess kurtosis | 1.6714 | 1.5008 | 1.3448 |
| Portfolios with significant kurtosis (%) | 100% | 92% | 100% |
| Portfolios formed by beta, coskewness and cokurtosis | | | |
| Average portfolio skewness | 0.1025 | 0.2339 | 0.0670 |
| Portfolios with significant skewness (%) | 30% | 7% | 15% |
| Average portfolio excess kurtosis | 1.5236 | 1.4036 | 1.2321 |
| Portfolios with significant kurtosis (%) | 100% | 96% | 85% |

*Denotes significance at the 5% level.

as well as by beta, coskewness, and cokurtosis. Market returns exhibit significantly positive skewness for the first sub-period and for the overall sample period. Excess kurtosis of market returns for both of the two sub-periods are highly significant, as for the overall period. Moreover, the average premium of systematic skewness risk proxied as $S^- - S^+$ for the whole sample period is 1.91% measured in annualized return, and 6.93% for the first sub-period. In contrast for the second sub-period it is –2.53%, which is inconsistent with our expectations. Similarly, the average premium of systematic kurtosis risk proxied by $K^+ - K^-$ for the first sub-period is 4.46%, and –8.05% for the second sub-period, resulting in –2.18% for the whole period, which may not on average be consistent with the expectation for positive risk premiums.

Table 1 also shows the proportions of portfolios that exhibit significant skewness and kurtosis with these portfolios grouped by size and book-to-market ratio as well as by beta, coskewness, and cokurtosis. The proportion of significant skewness is much lower than that for the case of kurtosis. This may be because skewness can be diversified through a portfolio as, claimed by Lin and Yeh (2000), causing portfolio return skewness to be insignificant. However, it is the non-diversifiable part of skewness that has the effect on asset pricing. On the other hand, almost all portfolios constructed by either grouping procedure exhibit significant excess kurtosis.

### 3.3. *Testing for pricing models*

Table 2 shows the empirical results based on the tradition capital asset pricing model using portfolios grouped by size and book-to-market ratio. Panel A is the result of the base case, the case of traditional two-moment CAPM. The two-moment CAPM is generally significant, however, the explanation power is essentially low, with the adjusted R-square equal to 0.2507 for the whole period. Panel B incorporates the skewness factor into the pricing model, resulting in the three-moment CAPM. In the case of the market model approach, adding skewness factor increases the explanation power of the pricing model significantly. The parameters for skewness risk premium, $b_2$ are all significant, with the sign as expected for the whole period as well as for the two sub-periods. The adjusted R-square improves significantly from 0.2507 to 0.4916 for the whole sample period. In the case of the two sub-periods, the improvement is also significant. Panel C shows the result of CAPM with skewness and kurtosis factors in the model, the four-moment CAPM. In general, the skewness factor is

**Table 2.** Estimates of risk premiums for the CAPM models (portfolios formed by size and book-to-market ratio).

| Coefficient | Market Model Approach | | | Proxy Model Approach | | |
|---|---|---|---|---|---|---|
| | Whole Period (1991/1–2002/8) | First Sub-Period (1991/1–1995/12) | Second Sub-Period (1996/1–2002/8) | Whole Period (1991/1–2002/8) | First Sub-Period (1991/1–1995/12) | Second Sub-Period (1996/1–2002/8) |
| Panel A: Two-moment CAPM $R_i = b_0 + b_1\beta_i$ | | | | | | |
| $b_0$ | −0.0255* | −0.0233* | −0.0141 | −0.0255* | −0.0233* | −0.0141 |
| | (−2.8400) | (−2.3274) | (−1.8455) | (−2.8400) | (−2.3274) | (−1.8455) |
| $b_1$ | 0.0286* | 0.0262* | 0.0146 | 0.0286* | 0.0262* | 0.0146 |
| | (2.7742) | (2.4138) | (1.5977) | (2.7742) | (2.4138) | (1.5977) |
| Adjusted $R^2$ | 0.2507 | 0.2021 | 0.0999 | 0.2507 | 0.2021 | 0.0999 |
| Panel B: Three-moment CAPM $R_i = b_0 + b_1\beta_i + b_2\gamma_i$ | | | | | | |
| $b_0$ | −0.0071 | −0.0229* | −0.0038 | −0.0311* | −0.0240* | −0.0144 |
| | (−0.7522) | (−2.5257) | (−0.5467) | (−3.3090) | (−2.3284) | (−1.8632) |
| $b_1$ | 0.0105 | 0.0271* | 0.0059 | 0.0355* | 0.0268* | 0.0156 |
| | (1.0181) | (2.7663) | 0.7478 | (3.2522) | (2.4073) | (1.6687) |
| $b_2$ | 0.0028* | 0.0012* | 0.0039* | 0.0091 | 0.0023 | 0.0039 |
| | (3.4506) | (3.3017) | (3.5599) | (1.3603) | (0.4102) | (0.5249) |
| Adjusted $R^2$ | 0.4916 | 0.3791 | 0.4255 | 0.3266 | 0.2096 | 0.1184 |
| Panel C: Four-moment CAPM $R_i = b_0 + b_1\beta_i + b_2\gamma_i + b_3\delta_i$ | | | | | | |
| $b_0$ | −0.0056 | −0.0253* | −0.0017 | −0.0318* | −0.0348* | −0.0157 |
| | (−0.6937) | (−2.4907) | (−0.2813) | (−3.2813) | (−3.5353) | (−1.5959) |
| $b_1$ | 0.0086 | 0.0303* | 0.0042 | 0.0365* | 0.0397* | 0.0172 |
| | (0.9852) | (2.6533) | (0.6008) | (3.2208) | (3.6700) | (1.4345) |
| $b_2$ | 0.0029* | 0.0012* | 0.0036* | 0.0086 | 0.0069 | 0.0031 |
| | (4.1783) | (3.2997) | (3.6681) | (1.2472) | (1.3338) | (0.3684) |
| $b_3$ | −0.0001 | 0.0002* | −0.0002 | −0.0035 | 0.0025 | −0.0028 |
| | (−1.1772) | (2.0216) | (−0.9559) | (−0.7922) | (1.0537) | (−0.5696) |
| Adjusted $R^2$ | 0.6536 | 0.3885 | 0.5677 | 0.3333 | 0.4199 | 0.1205 |

*Denotes significance at 5% level; numbers in parentheses are $t$-test statistics for the coefficients. $R_i$ denotes the average of weekly deflated excess return on the portfolio $i$. $\beta_i$, $\gamma_i$, and $\delta_i$ denote the estimated beta, coskewness and cokurtosis for portfolio $i$ respectively. $b_1$, $b_2$, and $b_3$ denote the estimated market risk premiums for the systematic variance, skewness, and kurtosis risks respectively.

significant in the model for all sub-periods, whereas kurtosis is significant only in the first sub-period. And the explanation power increases only marginally moving from the three-moment CAPM to the four-moment CAPM, indicating that kurtosis risk may not be crucial in pricing Taiwan stock returns. In the case of proxy model approach, adding the proxy for skewness factor improves the explanatory power only marginally, leaving the parameter $b_2$ insignificant. Nevertheless, the signs for skewness factor are all positive, consistent with our expectation for all periods. On the other hand, the kurtosis factor is still not significant and the sign is inconsistent with our expectations. Thus the proxy might not be a perfect substitute for the skewness factor. In conclusion, for the CAPM case using portfolios constructed by size and book-to-market ratio, the skewness factor is significant in the model, whereas kurtosis is not significant in the model.

When portfolios are constructed using the alternative procedure by beta, coskewness, and cokurtosis, the CAPM results are shown in Table 3. Surprisingly, the traditional CAPM is sensitive to the portfolio grouping procedure. In panel A, the parameters for beta risk premium are insignificantly negative for the whole period and for the first sub-period. Apart from the two-moment CAPM, the results of Table 3 are similar to that of Table 2, and only the explanation power is weaker. Panel B shows that including the skewness factor in the three-moment CAPM increases the adjusted R-square from 0.0137 to 0.1905 for the whole period and from 0.1252 to 0.4935 for the first sub-period. At the same time, risk premium parameters for skewness factor are also significant. Panel C shows that adding kurtosis factors into the three-moment CAPM increases the explanatory power only marginally, leaving the parameters of kurtosis risk premium in the four-moment CAPM to be insignificant for all periods. Summarizing of the results in Table 3, the skewness parameters are significant for the whole period and for the first sub-period but not for the second sub-period. In addition, the kurtosis parameters are not significant, and even the sign is not consistent, as in the results of Table 2. As for the proxy model approach it is inconclusive, using the alternative portfolio grouping procedure as in the case of Table 2.

Furthermore we investigate the skewness and kurtosis effects on asset pricing using the Fama-French model with the SMB and HML factors included in the pricing model. Table 4 shows the results of the empirical test using portfolios constructed by size and book-to-market ratio. Panel A indicates that the SMB and HML explain the portfolio returns variation significantly with

**Table 3.** Estimates of risk premiums for the CAPM models (portfolios formed by beta, coskewness and cokurtosis).

| Coefficient | Market Model Approach | | | Proxy Model Approach | | |
|---|---|---|---|---|---|---|
| | Whole Period (1991/1–2002/8) | First Sub-Period (1991/1–1995/12) | Second Sub-Period (1996/1–2002/8) | Whole Period (1991/1–2002/8) | First Sub-Period (1991/1–1995/12) | Second Sub-Period (1996/1–2002/8) |
| Panel A: Two-moment CAPM $R_i = b_0 + b_1\beta_i$ | | | | | | |
| $b_0$ | 0.0003 | 0.0063* | −0.0030* | 0.0003 | 0.0063* | −0.0030* |
| | (0.2047) | (2.2278) | (−2.0690) | (0.2047) | (2.2278) | (−2.0690) |
| $b_1$ | −0.0009 | −0.0058 | 0.0014 | −0.0009 | −0.0058 | 0.0014 |
| | (−0.5888) | (−1.8912) | (0.8212) | (−0.5888) | (−1.8912) | (0.8212) |
| Adjusted $R^2$ | 0.0137 | 0.1252 | 0.0263 | 0.0137 | 0.1252 | 0.0263 |
| Panel B: Three-moment CAPM $R_i = b_0 + b_1\beta_i + b_2\gamma_i$ | | | | | | |
| $b_0$ | 0.0012 | 0.0028 | −0.0019 | −0.0014 | 0.0075* | −0.0042 |
| | (0.9183) | (1.2016) | (−1.0628) | (−0.4781) | (2.3457) | (−1.8605) |
| $b_1$ | −0.0007 | −0.0005 | 0.0007 | 0.0011 | −0.0070 | 0.0032 |
| | (−0.4862) | (−0.1923) | (0.3704) | (0.3126) | (−2.0477) | (1.0505) |
| $b_2$ | 0.0012* | 0.0009* | 0.0006 | 0.0022 | −0.0013 | 0.0019 |
| | (2.2775) | (3.7935) | (0.9611) | (0.6632) | (−0.7814) | (0.6757) |
| Adjusted $R^2$ | 0.1905 | 0.4935 | 0.0620 | 0.0307 | 0.1488 | 0.0465 |
| Panel C: Four-moment CAPM $R_i = b_0 + b_1\beta_i + b_2\gamma_i + b_3\delta_i$ | | | | | | |
| $b_0$ | 0.0012 | 0.0011 | −0.0017 | −0.0053 | 0.0052 | −0.0051 |
| | (0.9297) | (0.4356) | (−0.8823) | (−1.1849) | (1.8931) | (−1.3488) |
| $b_1$ | −0.0007 | 0.0015 | 0.0005 | 0.0059 | −0.0044 | 0.0042 |
| | (−0.4824) | (0.4843) | (0.2700) | (1.0882) | (−1.4664) | (0.8785) |
| $b_2$ | 0.0012* | 0.0008* | 0.0006 | 0.0012 | −0.0023 | 0.0015 |
| | (2.3366) | (3.3670) | (1.0030) | (0.3443) | (−0.8028) | (0.4556) |
| $b_3$ | 0.0001 | 0.0001 | −0.0001 | 0.0011 | 0.0080 | 0.0001 |
| | (0.2387) | (1.7894) | (−0.1032) | (1.3151) | (1.5964) | (0.0415) |
| Adjusted $R^2$ | 0.2097 | 0.5320 | 0.0790 | 0.0827 | 0.2733 | 0.0498 |

*Denotes significance at 5% level; numbers in parentheses are $t$-test statistics for the coefficients. $R_i$ denotes the average of weekly deflated excess return on the portfolio $i$. $\beta_i$, $\gamma_i$, and $\delta_i$ denote the estimated beta, coskewness and cokurtosis for portfolio $i$ respectively. $b_1$, $b_2$, and $b_3$ denote the estimated market risk premiums for the systematic variance, skewness, and kurtosis risks respectively.

**Table 4.** Estimates of risk premiums for the Fama-French models (portfolios formed by size and book-to-market value).

| Coefficient | Market Model Approach | | | Proxy Model Approach | | |
|---|---|---|---|---|---|---|
| | Whole Period (1991/1–2002/8) | First Sub-Period (1991/1–1995/12) | Second Sub-Period (1996/1–2002/8) | Whole Period (1991/1–2002/8) | First Sub-Period (1991/1–1995/12) | Second Sub-Period (1996/1–2002/8) |
| Panel A: Two-moment Fama-French model $R_i = b_0 + b_1\beta_i + b_{SMB}\beta_{SMB} + b_{HML}\beta_{HML}$ | | | | | | |
| $b_0$ | −0.0022 | 0.0022 | 0.0044 | −0.0022 | 0.0022 | 0.0044 |
| | (−0.4601) | (0.2895) | (0.9905) | (−0.4601) | (0.2895) | (0.9905) |
| $b_1$ | 0.0060 | −0.0002 | −0.0013 | 0.0060 | −0.0002 | −0.0013 |
| | (1.1220) | (−0.0216) | (−0.2586) | (1.1220) | (−0.0216) | (−0.2586) |
| $b_{SMB}$ | −0.0047* | −0.0035* | −0.0060* | −0.0047* | −0.0035* | −0.0060* |
| | (−7.7831) | (−5.2201) | (−6.1929) | (−7.7831) | (−5.2201) | (−6.1929) |
| $b_{HML}$ | −0.0083* | −0.0041* | −0.0094* | −0.0083* | −0.0041* | −0.0094* |
| | (−9.8038) | (−5.4410) | (−8.7549) | (−9.8038) | (−5.4410) | (−8.7549) |
| Adjusted $R^2$ | 0.8832 | 0.7692 | 0.8255 | 0.8832 | 0.7692 | 0.8255 |
| Panel B: Three-moment Fama-French model $R_i = b_0 + b_1\beta_i + b_{SMB}\beta_{SMB} + b_{HML}\beta_{HML} + b_2\gamma_i$ | | | | | | |
| $b_0$ | −0.0016 | 0.0019 | 0.0047 | −0.0010 | −0.0011 | 0.0053 |
| | (−0.3222) | (0.2333) | (1.0491) | (−0.1936) | (−0.1416) | (1.2397) |
| $b_1$ | 0.0054 | 0.0001 | −0.0015 | 0.0046 | 0.0033 | −0.0028 |
| | (1.0045) | (0.0145) | (−0.2980) | (0.7747) | (0.3807) | (−0.5839) |
| $b_{SMB}$ | −0.0047* | −0.0035* | −0.0059* | −0.0047* | −0.0034* | −0.0057* |
| | (−7.6957) | (−5.1021) | (−6.1306) | (−7.6345) | (−5.1162) | (−6.1639) |
| $b_{HML}$ | −0.0081* | −0.0041* | −0.0094* | −0.0082* | −0.0043* | −0.0091* |
| | (−9.3483) | (−5.3107) | (−8.6310) | (−9.3564) | (−5.6995) | (−8.8225) |
| $b_2$ | 0.0006 | −0.0001 | 0.0007 | −0.0015 | 0.0048 | −0.0052 |
| | (0.9873) | (−0.0539) | (0.9538) | (−0.4737) | (1.4420) | (−1.5262) |
| Adjusted $R^2$ | 0.8872 | 0.7696 | 0.8312 | 0.8849 | 0.7882 | 0.8490 |
| Panel C: Four-moment Fama-French model $R_i = b_0 + b_1\beta_i + b_{SMB}\beta_{SMB} + b_{HML}\beta_{HML} + b_2\gamma_i + b_3\delta_i$ | | | | | | |
| $b_0$ | −0.0016 | 0.0013 | 0.0049 | 0.0072 | 0.0002 | 0.0078 |
| | (−0.3095) | (0.1509) | (1.0812) | (0.9503) | (0.0193) | (1.1256) |
| $b_1$ | 0.0053 | 0.0009 | −0.0018 | −0.0048 | 0.0017 | −0.0057 |
| | (0.9658) | (0.0985) | (−0.3454) | (−0.5694) | (0.1698) | (−0.7196) |
| $b_{SMB}$ | −0.0048* | −0.0035* | −0.0061* | −0.0049* | −0.0035* | −0.0058* |
| | (−7.5847) | (−4.9853) | (−5.9950) | (−8.0228) | (−4.9302) | (−6.0360) |
| $b_{HML}$ | −0.0081* | −0.0040* | −0.0093* | −0.0081* | −0.0043* | −0.0090* |
| | (−9.0547) | (−4.9843) | (−8.4455) | (−9.5107) | (−5.5568) | (−8.3600) |
| $b_2$ | 0.0007 | 0.0001 | 0.0008 | 0.0012 | 0.0050 | 0.0040 |
| | (1.0982) | (0.0358) | (1.0401) | (0.3270) | (1.4611) | (0.8919) |
| $b_3$ | 0.0001 | 0.0001 | −0.0001 | −0.0040* | −0.0009 | −0.0018 |
| | (0.1443) | (0.1107) | (−0.4279) | (−2.1523) | (−0.2543) | (−0.8313) |
| Adjusted $R^2$ | 0.8893 | 0.7704 | 0.8342 | 0.8973 | 0.7899 | 0.8507 |

See the notes in Tables 2 and 3; $\beta_{SMB}$ and $\beta_{HML}$ are the estimated beta for SMB and HML; $b_{SMB}$ and $b_{HML}$ are the market risk premiums for the respective risks.

negative effects on the expected returns, a phenomenon contradictory to the normal size effect on asset pricing. The adjusted R-square is as high as 0.8832 for the whole period, meaning that the explanatory power is quite high when including the SMB and HML in the traditional capital asset pricing model. In panel C, when considering the effect of skewness and kurtosis factors, for both the case of market model approach and proxy model approach, the SMB coefficient, $b_{\mathrm{SMB}}$, and the HML coefficient, $b_{\mathrm{HML}}$, both remain significantly negative, leaving other risk parameters insignificant. Meanwhile the adjusted R-square increases only marginally when adding the third and fourth moments. Nevertheless, it is noteworthy that all coefficients concerning the coskewness $b_2$ for all periods and for the two different approaches are positive although insignificant. This is a promising result concerning the risk premium of coskewness in an asset pricing model.

Similarly Table 5 shows the empirical results based on the Fama-French three-factor model with skewness and kurtosis factors included in the pricing model, using portfolios constructed by beta, coskewness, and cokurtosis. Basically the results are quite similar to those shown in Table 4, apart from the lower explanatory power of the regression model. Moreover, the size effect remains negative, although it is insignificant in some cases. Panel C shows that the risk parameters for coskewness are significantly positive for the whole period and for the first sub-period. In any case, the parameters for the coskewness factor are all positive for all periods using either the market model approach or the proxy model approach. In addition, the kurtosis factor remains inconsistent and insignificant toward the pricing models.

In summary, the above empirical evidence shows that the skewness factor plays an important role in asset pricing for the Taiwan stock market. However, the role of the kurtosis factor is not as significant as the skewness factor in an asset pricing model. Size and book-to-market ratio is significant and they have negative effects on portfolio returns when portfolios are constructed by size and book-to-market. When considering the size and book-to-market effect, the skewness factor becomes insignificant in the pricing model. This is consistent with the result of Chung, Johnson and Schill (2001), which claims that the Fama-French factors, the SMB and HML, are merely proxies for omitted higher-order market-risk factors. Finally, the market proxies for coskewness and cokurtosis factors seem to be not quite valid for pricing models. Moreover, when portfolios are constructed by beta, coskewness, and cokurtosis, the explanatory power of pricing factors, especially the market

**Table 5.** Estimates of risk premiums for the Fama-French models (portfolios formed by beta, coskewness and cokurtosis).

| Coefficient | Market Model Approach | | | Proxy Model Approach | | |
|---|---|---|---|---|---|---|
| | Whole Period (1991/1–2002/8) | First Sub-Period (1991/1–1995/12) | Second Sub-Period (1996/1–2002/8) | Whole Period (1991/1–2002/8) | First Sub-Period (1991/1–1995/12) | Second Sub-Period (1996/1–2002/8) |
| Panel A: Two-moment Fama-French model $R_i = b_0 + b_1\beta_i + b_{SMB}\beta_{SMB} + b_{HML}\beta_{HML}$ | | | | | | |
| $b_0$ | 0.0006 | −0.0002 | −0.0028 | 0.0006 | −0.0002 | −0.0028 |
| | (0.3143) | (−0.0429) | (−1.2266) | (0.3143) | (−0.0429) | (−1.2266) |
| $b_1$ | −0.0005 | 0.0019 | 0.0018 | −0.0005 | 0.0019 | 0.0018 |
| | (−0.2639) | (0.4514) | (0.9714) | (−0.2639) | (0.4514) | (0.9714) |
| $b_{SMB}$ | −0.0015 | −0.0020* | −0.0001 | −0.0015 | −0.0020* | −0.0001 |
| | (−0.7114) | (−2.1665) | (−0.0170) | (−0.7114) | (−2.1665) | (−0.0170) |
| $b_{HML}$ | −0.0004 | 0.0025* | −0.0019 | −0.0004 | 0.0025* | −0.0019 |
| | (−0.1742) | (2.4323) | (−0.6236) | (−0.1742) | (2.4323) | (−0.6236) |
| Adjusted $R^2$ | 0.0383 | 0.3754 | 0.0478 | 0.0383 | 0.3754 | 0.0478 |
| Panel B: Three-moment Fama-French model $R_i = b_0 + b_1\beta_i + b_{SMB}\beta_{SMB} + b_{HML}\beta_{HML} + b_2\gamma_i$ | | | | | | |
| $b_0$ | 0.0008 | −0.0029 | −0.0022 | −0.0018 | −0.0007 | −0.0038 |
| | (0.4344) | (−0.8445) | (−0.8966) | (−0.5503) | (−0.1622) | (−1.2510) |
| $b_1$ | −0.0005 | 0.0056 | 0.0010 | 0.0028 | 0.0026 | 0.0031 |
| | (−0.3037) | (1.4940) | (0.5027) | (0.7070) | (0.5481) | (0.9802) |
| $b_{SMB}$ | −0.0012 | −0.0021* | 0.0002 | −0.0022 | −0.0022 | −0.0003 |
| | (−0.6372) | (−2.8020) | (0.0654) | (−1.0069) | (−2.0129) | (−0.0755) |
| $b_{HML}$ | 0.0003 | 0.0029* | −0.0017 | −0.0014 | 0.0024 | −0.0019 |
| | (0.1434) | (3.3179) | (−0.5584) | (−0.5450) | (2.0696) | (−0.5983) |
| $b_2$ | 0.0012* | 0.0010* | 0.0006 | 0.0033 | 0.0004 | 0.0016 |
| | (2.0956) | (3.6389) | (0.8858) | (0.9324) | (0.1986) | (0.5430) |
| Adjusted $R^2$ | 0.1945 | 0.5868 | 0.0785 | 0.0754 | 0.3796 | 0.0589 |
| Panel C: Four-moment Fama-French model $R_i = b_0 + b_1\beta_i + b_{SMB}\beta_{SMB} + b_{HML}\beta_{HML} + b_2\gamma_i + b_3\delta_i$ | | | | | | |
| $b_0$ | 0.0005 | −0.0030 | −0.0020 | −0.0046 | −0.0012 | −0.0051 |
| | (0.2676) | (−0.8585) | (−0.8010) | (−0.8676) | (−0.2161) | (−1.1886) |
| $b_1$ | −0.0004 | 0.0058 | 0.0008 | 0.0059 | 0.0032 | 0.0047 |
| | (−0.2255) | (1.5108) | (0.3698) | (0.9682) | (0.5054) | (0.9399) |
| $b_{SMB}$ | −0.0011 | −0.0020* | 0.0001 | −0.0017 | −0.0021 | −0.0005 |
| | (−0.5798) | (−2.5346) | (0.0420) | (−0.7191) | (−1.7312) | (−0.1284) |
| $b_{HML}$ | 0.0006 | 0.0027* | −0.0016 | −0.0015 | 0.0022 | −0.0022 |
| | (0.2693) | (2.7616) | (−0.5068) | (−0.5795) | (1.4628) | (−0.6671) |
| $b_2$ | 0.0013* | 0.0009* | 0.0006 | 0.0019 | 0.0004 | 0.0009 |
| | (2.2135) | (3.3448) | (0.9247) | (0.4507) | (0.2159) | (0.2445) |
| $b_3$ | 0.0001 | 0.0001* | −0.0001 | 0.0011 | 0.0012 | −0.0001 |
| | (0.2248) | (2.2032) | (−0.0008) | (1.2641) | (1.3568) | (−0.0254) |
| Adjusted $R^2$ | 0.2218 | 0.5928 | 0.0892 | 0.0952 | 0.3803 | 0.0670 |

See the notes in Tables 2 and 3; $\beta_{SMB}$ and $\beta_{HML}$ are the estimated beta for SMB and HML; $b_{SMB}$ and $b_{HML}$ are the market risk premiums for the respective risks.

risk factors, is quite low, indicating that some factors might be missing in the pricing model.

## 4. Conclusion

In this study we investigate the effect of higher moments, skewness and kurtosis of stock returns on asset pricing. We adopt the traditional two-moment CAPM and the Fama-French model with size and book-to-market ratio factors included, as the base cases. Then we test the three-moment and four-moment CAPM and Fama-French models with systematic skewness and kurtosis included in the models. For robustness, apart from using market models to estimate parameters for systematic skewness and kurtosis, we also adopt proxy measures obtained from a procedure similar to Harvey and Sidique (2000b). Following the Fama-Macbath procedure, the two-step cross-sectional regressions were adopted to test pricing models. For robust testing, stock portfolios were constructed by size and book-to-market ratio as well as by beta, coskewness, and cokurtosis. Weekly returns for 132 sample stocks from the Taiwan stock market over the period from January 1991 to August 2002 were used for empirical research. The empirical results show that the three-moment CAPM is significant, whereas the fourth moment is not consistent with the empirical data. In the case of Fama-French model, the size and book-to-market value effects seem to dominate the moment effects, leaving most of the parameters in the pricing model insignificant. However, although there are insignificant, their consistent sign indicates the existence of third moment effect on the asset pricing.

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Chapter 10

# Listing Switches from NASDAQ to the NYSE or AMEX: Is New Stock Issuance a Motive?

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We investigate whether firms that switch their listing from NASDAQ to either the NYSE or AMEX earn excess returns and increase shares outstanding. We find statistically positive cumulative excess returns around the switch day, but the cumulative excess returns turn negative two weeks after the switch and remain negative through the end of the study period at day +40. The number of sample firms that increase their shares outstanding at the time of the switch is not significantly larger than for a control group. We also find no evidence of significantly higher excess returns gained by firms that issue securities than for firms that do not issue securities. Hence, we conclude that our results do not support the view that firms increase their shares outstanding to take advantage of increased share value at the time of the switch.

**Keywords:** Listing; exchanges; NASDAQ; NYSE; AMEX.

## 1. Introduction

There has been considerable interest in studying excess returns associated with switches in a firm's primary listing from one exchange to another. These studies' results indicate positive excess returns around the listing date and negative excess returns over a longer time period after the listing. Studies such as Barclay, Kandel and Marx (1998), Kadlec and McConnell (1994), Dubois and Ertur (1997) report excess positive returns surrounding the announcement of listing (during the week of announcement) and the actual listing on an organized exchange (a day before, on the listing day and the day after). These studies conclude that stock price increases surrounding the announcement of listing can be explained by the decrease in the cost of equity, an increase in the liquidity, or the lower systematic risk of the company after the listing.

Other studies address the long-run negative price drift during the post listing period (e.g., Dharan & Ikenberry, 1995; Loughran & Ritter, 1995; Spiess & Affleck-Graves, 1995; McConnell and Sanger, 1987). After the listing on an exchange, these studies document that stock price performance is poor over long periods of time. They study the question of whether poor long-term post listing performance is a result of the new stock issuance of listed firms. They conclude that firms issuing equity around the time of listing show poor post-listing performance in the long-run, but firms that do not issue new equity also have poor performance. Therefore, post-listing long-term performance cannot fully be explained by the equity issuance.

In this study, we extend previous work by investigating the relationship between the incidence of new equity offerings and the positive excess returns earned around the listing day. Loughran and Ritter (1995) and Spiess and Affleck-Graves (1995) suggest that managers issue new equity when prices are higher. We, therefore, conjecture that firms benefit from short-term positive excess returns around the listing by issuing stocks. Even though previous studies address the relationship between the long-term performance of stocks after the listing and stock issuance, they do not study the relationship between the short-term performance and stock issuance. We expect that if firms list their stocks on the exchange and earn excess returns around the listing, they issue stocks just after the listing at the high stock prices before those prices begin to decrease. We first test whether, as previous studies find, there are positive excess returns associated with exchange listings from NASDAQ to the NYSE or AMEX, and negative excess returns in the long-run after the listing. Second, we investigate whether firms that issue stock have higher cumulative excess returns around the listing day than firms that do not issue stock.

Our results confirm previous findings that there are significantly positive excess returns on the day of the switch, and the cumulative returns become negative by the twelfth day following the switch. Hence, we suggest that the excess returns earned on the day of listing change are short-lived and consumed in two weeks. To investigate further, we examine the mean excess returns and the mean cumulative excess returns for the 17 sample firms that increased shares outstanding and for the remaining 70 firms that did not increase shares outstanding. We find that the mean of the cumulative returns for the 17 firms is not significantly greater than for the 70 firms on any of the days tested.

In addition, we extend previous work by investigating whether there is an increase in the incidence of new equity offerings at the time of the switch with a matched sample. We investigate a sample of 87 firms that switched listings in 1998 and a control sample matched on SIC code and stock price. We find that

17 of the switching firms increased shares outstanding by 5% or more in the days −5 through +40 relative to the switch. However, 11 of the control firms increased shares outstanding by 5% or more in the period −63 through +63 relative to the switch. We find that there is no significant difference between the proportion of firms with increases in shares outstanding for our sample group and the one for the control group. We show that there is also no significant difference between the cumulative excess returns of firms that issue stock and firms that do not issue stock. This shows that firms with the highest gain are not necessarily the ones issuing stock. We also find that firms that issue a security lose significantly more value than firms that do not issue a security in the long run.

The rest of the paper is organized as follows. Section 2 discusses the literature. Section 3 introduces our sample and the dataset. Section 4 develops our hypotheses, describes the methodology and presents our findings. Section 5 includes the summary and conclusions.

## 2. Literature Review

Sanger and McConnell (1986) study the returns of 329 OTC stocks listed on the NYSE over the period 1966–1977. They report that stocks earn on average of 1% excess return during the week of listing. More recently, Barclay, Kandel and Marx (1998) study stocks that move from NASDAQ to the NYSE or AMEX and from AMEX to NASDAQ. They find significantly positive excess returns from one day before until one day after the announcement of listing changes for both groups. Clyde, Schultz and Zaman (1997) find that one-third of the firms issue equity around the time stocks move to NASDAQ from AMEX. These authors also find positive excess returns around exchange switches. They argue that the issuance of new equity may be an effort to take advantage of the positive excess returns at the time of the switch.

There are two main hypotheses that explain the positive returns around the listing on the NYSE and AMEX: Merton's (1987) investor recognition hypothesis and, secondly, Amihud and Mendelson's (1986) liquidity hypothesis. Merton modifies the Shape-Lintner-Mossin Capital Assets Pricing Model (CAPM) by relaxing the assumption that all investors have the same information in the market. With this modification, Merton shows that the required return on a security increases with the systematic risk, the firm-specific risk, and the size of the firm and decreases with the relative size of the firm's investor base, defined by the degree of investor recognition. Therefore, the firm managers would want to take actions that increase the firm's investor base. Listing their stocks on an exchange is one of the ways to increase the degree of investor recognition. This leads to positive excess returns when a firm lists its stock on an organized exchange.

Secondly, Amihud and Mendelson (1986) suggest that exchange listing, as well as other corporate financial decisions, can be explained by the liquidity-increasing motives to decrease the cost of equity for the firm. They show that the required rate of return on a security decreases when the bid-ask spread decreases. A listing choice that leads to a lower bid-ask spread reduces the cost of equity for the firm. Thus, listing can increase the wealth of existing shareholders as well as allow the firm to benefit from the reduced cost of capital by borrowing from the market. Cowan, Carter, Dark and Singh (1992) postulate that firms choose to list on the NYSE "when the perceived benefits, including increased liquidity, are greater". Baker and Johnson (1990) report that managers view better liquidity as the main reason for choosing a NYSE listing.[1] Therefore, when firms move their listing from a less liquid market to a more liquid market, market participants view this as a positive event that reduces their cost of equity, resulting in positive excess returns around the listing change.

Kadlec and McConnell (1994) test both investor recognition and liquidity hypotheses for NYSE listings during the 1980s. They first study the stock prices to test whether NYSE listings result in a significant stock price increase during the announcement of listing and during the actual listing on the NYSE. Then, they study whether the change in share value that is associated with listing is related to changes in the investor base and to changes in liquidity.[2] They find that there is an average of 2.67% cumulative excess return (1.7% excess return) during the week of the announcement of listing on the NYSE and 2.82% cumulative excess return (1.1% excess return) around the week of actual listing

[1]Barclay, Kandel and Marx (1998) find that spreads decrease significantly when stocks move from NASDAQ to the NYSE or AMEX but increase significantly when stocks move from AMEX to NASDAQ. Christie and Huang (1994) report increased liquidity for stocks that move from NASDAQ to the NYSE. They document average reductions in trading costs of about five cents per share after the switch. Barclay (1997) examines 472 securities that were listed on NASDAQ and moved to the NYSE or AMEX. He also finds that spreads decline sharply with exchange listing.

[2]The change in investor base is measured by a change in the number of institutional holders and registered shareholders. The change in liquidity is measured by the change in the bid-ask spread.

on the NYSE. They find that exchange listing is associated with a 10% increase in the number of registered shareholders, a 27% increase in the number of institutional shareholders, and a 5% decrease in bid-ask spreads. Further, their cross-sectional regressions provide support for both investor recognition and liquidity hypotheses.

Dubois and Ertur (1997) also find excess price increases in the French market at both the announcement and the listing date of the securities on Marche a Reglement Mensuel. They test four hypotheses that explain the positive returns around the listing day. Their first hypothesis is that the increase in the informative content of the firms' operation leads to positive excess returns around the listing day. The other three hypotheses rely on a decrease in the cost of equity driven by less risky cash flows, an increase in liquidity, and an increase in the relative size of the firms' investor base. Their results support the conclusion that the change in the liquidity and the change in the systematic risk of the company after the listing can explain part of the excess returns around the listing change. They also show that excess returns are related to the changes in the parameters of the market model and the increase in liquidity after the listing.

Finally, there are studies that support the investor base hypothesis in international stock listings. For example, Baker, Nofsinger and Weaver (2002) study international firms listing on the NYSE and the London Stock Exchange (LSE). They show that firms experience a significant increase in visibility, as proxied by analyst coverage and print media attention after the listing. The increase in visibility is associated with a decrease in the cost of equity after the listing event. Their results are stronger for NYSE listing firms than for LSE listing firms. They suggest that this may partially compensate firms for the higher costs associated with NYSE listing.

## 3. Data

Using Center for Research in Security Prices (CRSP) data, we identify 65 firms that moved their primary listing from NASDAQ to the NYSE and 27 that moved from NASDAQ to AMEX in 1998. For each of these firms, we collect daily return and daily number of shares outstanding data from CRSP. The period under consideration is centered around the date of a switch in listing from NASDAQ to the NYSE or AMEX. We evaluate data 150 days prior to the date of the switch ($-150$) up to 150 days after the date of the switch ($+150$). We eliminate five firms that missed more than 30 days of trading, reducing our sample to 87. We also collect daily returns for the S&P 500 index and the CRSP NASDAQ index from CRSP.

## 4. Hypotheses, Methodology and Results

In this section, we discuss our hypotheses, the methodology used to test them and the results. We have two hypotheses that are related to the positive excess returns earned and the increase in the number of shares outstanding around the time of a switch.

### 4.1. *Excess returns*

As we have noted, Kadlec and McConnell (1994), Clyde, Schultz and Zaman (1997), and Barclay, Kandel and Marx (1998) report positive excess returns at the time of a switch in exchange listings. Hence, we test the following hypothesis:

> **Hypothesis 1.** There are positive excess returns associated with a switch in exchange listing from NASDAQ to the NYSE or AMEX.

To begin, we calculate excess returns for each firm in our sample. As the first step, we estimate the market model

$$\mathrm{R}_{f,t} = \alpha_f + \beta_f \mathrm{R}_{m,t} + \varepsilon_{f,t}, \quad t = -150, \ldots, -25, \tag{1}$$

where $\mathrm{R}_{f,t}$ is the return on the stock of firm $f$ on day $t$; $\mathrm{R}_{m,t}$ is the return on the S&P 500 stock index on day $t$; $\varepsilon_{f,t}$ is a random error term representing the unsystematic component of the return on firm $f$'s stock; and $\alpha_f$ and $\beta_f$ are parameters to be estimated.[3] Day 0 is the day the firm switched its listing. Then, the estimated excess return is given by

$$\mathrm{ER}_{f,t} = \mathrm{R}_{f,t} - (\hat{\alpha}_f + \hat{\beta}_f \mathrm{R}_{m,t}), \quad t = -24, \ldots, +150, \tag{2}$$

where $\hat{\alpha}$ and $\hat{\beta}$ are the estimates of $\alpha$ and $\beta$, respectively. We also adjust estimated beta for nonsynchronous trading by using Dimson (1979). To apply the Dimson technique, we first estimate the market model with two lagged and two lead market values. Next, the estimated Dimson beta is computed as a summation of all the estimated coefficients of two lead and two lagged market

[3]We also repeat our analysis with the CRSP NASDAQ index as proxy for the market index. We confirm that our results are not sensitive to the index chosen or to the time interval chosen for the estimation period.

values. The discussion of nonsynchronous trading and the Dimson technique can be found in the Appendix.

The cumulative excess return for day $t$ for firm $f$ is $\text{CER}_{f,t} = \text{ER}_{f,t} + \text{CER}_{f,t-1}$, where $\text{CER}_{-24} = \text{ER}_{-24}$.

We use a $t$-test and a non-parametric Wilcoxon rank sum test to test the null hypothesis that the mean of the ERs and CERs for day $t$ for the firms in our sample is different from zero. The reason for using the nonparametric test is that we reject the normal distribution of excess returns and cumulative excess returns for days around the listing with the Wilk-Shapiro test. The results for excess returns and cumulative excess returns are reported in Table 1 and

**Table 1.** Excess returns around the switch from NASDAQ to the NYSE or AMEX. We estimate excess returns (ERs) with Equation (2). For the day indicated, column two shows the average of the ERs across the firms in our sample. If there are no unusual price movements prior to the switch day, ERs fluctuate around zero. We use a $t$-test and a Wilcoxon rank sum test to test the null hypothesis that the mean of the ERs for day $t$ for the firms in our sample is different than zero. The results of a $t$-test and a Wilcoxon rank sum test are reported in column three and column four, respectively. The number of firms with positive (negative) excess returns is reported at column five. All days are relative to the day of switch from NASDAQ to the NYSE or AMEX.

| Day Relative | Mean Excess Return | $t$-Statistics | Signed Rank Test | Number of Positive (Negative) Excess Returns |
|---|---|---|---|---|
| −5 | 0.0007 | 0.1295 | 167 | 46(41) |
| −4 | −0.0019 | −0.6150 | −187 | 39(48) |
| −3 | −0.0019 | −0.5313 | −250 | 38(49) |
| −2 | −0.0010 | −0.2093 | −64 | 43(44) |
| −1 | 0.0027 | 0.4673 | 34.5 | 39(47) |
| 0 | 0.0127 | 2.9690* | 798* | 56(31) |
| 1 | −0.0011 | −0.2912 | −255 | 38(49) |
| 2 | −0.0043 | −1.2832 | −402 | 36(51) |
| 3 | −0.0046 | −1.4563 | −198 | 45(42) |
| 4 | −0.0001 | −0.0251 | −193 | 36(51) |
| 5 | −0.0004 | −0.1176 | −63 | 44(44) |
| 6 | −0.0044 | −1.3645 | −466 | 34(53) |
| 7 | 0.0041 | 1.2312 | 142 | 43(45) |
| 8 | −0.0062 | −2.3601* | −530* | 35(53) |
| 9 | −0.0037 | −1.1987 | −429* | 34(54) |
| 10 | −0.0009 | −0.2178 | −409* | 34(54) |
| 11 | −0.0054 | −1.2679 | −505* | 37(51) |
| 12 | −0.0111 | −2.9819* | −698* | 32(56) |

*Significant at 10% level.

Table 2, respectively. We confirm the findings of previous studies that there are significantly positive excess returns and cumulative excess returns on the date of the switch in exchange listing. On the listing day, 56 firms out of 87 have positive excess returns. That is the largest number of firms with positive excess returns over the sample period. The average excess return is 1.27% ($t = 2.96$ and Wilcoxon rank sum test = 798) and the average cumulative excess return

**Table 2.** Cumulative excess returns around the switch from NASDAQ to the NYSE or AMEX. We estimate excess returns (ERs) with Equation (2). Daily cumulative excess return for day $t$ for firm $f$ is: $\text{CER}_{f,t} = \text{ER}_{f,t} + \text{CER}_{f,t-1}$, where $\text{CER}_{-24} = \text{ER}_{-24}$. For the day indicated, column two shows the average of the CERs across the firms in our sample. If there are no unusual price movements prior to the switch day, CERs fluctuate around zero. We use a $t$-test and a Wilcoxon rank sum test to test the null hypothesis that the mean of the CERs for day $t$ for the firms in our sample is different than zero. The results of these tests are reported in column three and column four, respectively. The number of firms with positive (negative) cumulative excess returns is reported at column five. All days are relative to the day of switch from NASDAQ to the NYSE or AMEX.

| Day Relative | Mean Cumulative Excess Return | $t$-Statistics | Signed Rank Test | Number of Positive (Negative) Cumulative Excess Returns |
|---|---|---|---|---|
| −5 | 0.0238 | 1.4897 | 427* | 54(33) |
| −4 | 0.0218 | 1.3687 | 419* | 51(36) |
| −3 | 0.0199 | 1.1979 | 411* | 51(36) |
| −2 | 0.0189 | 1.0616 | 304 | 46(41) |
| −1 | 0.0209 | 1.0657 | 297 | 47(39) |
| 0 | 0.0343 | 1.7306* | 507* | 52(35) |
| 1 | 0.0332 | 1.6369 | 486* | 52(35) |
| 2 | 0.0288 | 1.3952 | 419* | 53(34) |
| 3 | 0.0242 | 1.1374 | 391* | 51(36) |
| 4 | 0.0241 | 1.1246 | 360 | 51(36) |
| 5 | 0.0236 | 1.0795 | 327 | 49(38) |
| 6 | 0.0193 | 0.8411 | 271 | 48(39) |
| 7 | 0.0233 | 1.0160 | 284 | 49(38) |
| 8 | 0.0172 | 0.7392 | 242 | 46(41) |
| 9 | 0.0134 | 0.5813 | 209 | 45(42) |
| 10 | 0.0125 | 0.5524 | 180 | 46(41) |
| 11 | 0.0071 | 0.3045 | 121 | 45(42) |
| 12 | −0.0040 | −0.1649 | 21 | 41(46) |

*Significant at 10% level.

is 3.43% ($t = 1.73$ and Wilcoxon rank sum test = 507) on the listing day.[4] Furthermore, the cumulative excess returns stay significantly positive for three days after the listing according to the Wilcoxon rank sum test. Our results confirm the previous findings of positive excess returns associated with listings. Hence, we accept Hypothesis 1.

However, the mean cumulative excess returns turn negative at day +12 and remain negative for the remainder of the period examined. This also confirms previous studies' finding of poor long term performance of listed firms. Our results indicate that firms should issue equity shortly after the listing before their excess positive returns become negative.

### 4.2. *Shares outstanding*

Nelson (1994), Loughran and Ritter (1995), and Spiess and Affleck-Graves (1995) report that managers issue new equity when prices are higher. Therefore, based on their conclusions, we suggest that firms benefit from short-term positive excess returns by issuing stocks and we test the following hypothesis:

> **Hypothesis 2.** There is an increase in shares outstanding at the time of a switch in exchange listing from NASDAQ to the NYSE or AMEX.

Our first step is to identify sample firms that increased their shares outstanding during the period −5 through +40. Of the 87 firms in our sample, 17 increased their shares outstanding by 5% or more during this period. Table 3 shows the day-by-day chronology for these increases.

To help ascertain whether an increase in shares outstanding by 17 out of 87 firms is unusual, we develop a control sample as follows. For the first firm in our sample, we identify firms with the same SIC code. We select the firm from this set that has the closest average price to that of the sample firm in 1998. We repeat this process for the remaining firms so that we have a control sample of 87 firms matched on SIC code and price. Next, we obtain the daily number of outstanding shares of each matching firm for the interval ±63 days relative to the switch date of a firm in our sample.

We test whether the proportion of firms with increases in shares outstanding is the same for the sample and control groups. We use a test statistic and

[4] With the Dimson beta, average excess return is 1.33% ($t = 3.06$ and Wilcoxon rank sum test = 756), and the average cumulative excess return is 2.89% ($t = 1.47$ and Wilcoxon rank sum test = 548).

**Table 3.** Number of firms with no change or an increase in number of outstanding shares from previous day. Our sample is comprised of 87 firms that moved their primary exchange listing from NASDAQ either to the NYSE or AMEX in 1998. For this sample of firms, we determine whether there was an increase in shares outstanding of 5% or more during the period from five days before the switch (day −5) to forty days after the switch (day +40). None of the firms in our sample had a substantial (5% or more) decrease in shares outstanding. We report each day for which there is at least one firm with an increase.

| Day Relative | No Change | Increase |
|---|---|---|
| 0 | 84 | 3 |
| 1 | 86 | 1 |
| 3 | 86 | 1 |
| 5 | 86 | 1 |
| 10 | 85 | 2 |
| 14 | 86 | 1 |
| 17 | 86 | 1 |
| 19 | 86 | 1 |
| 21 | 85 | 2 |
| 27 | 86 | 1 |
| 33 | 86 | 1 |
| 36 | 86 | 1 |
| 39 | 86 | 1 |
| | Total: | 17 |

procedure that we believe is conservative and favors acceptance of the proposition of equality of proportions. We believe that matching on SIC code and stock price will increase the likelihood that the sample and control group will be similar. Also, use of ±63 days for the control rather than the −5 through +40 range used for the sample will increase the chance of finding an increase in shares outstanding for the control. We know that the sample firms have an event that might have triggered an increase in shares outstanding. Hence, we can use a small window around the event for these firms. However, the exact timing of possible triggering events for the control firms is less certain, so we believe the use of a larger window is justified.

For our test, we use the 5% confidence limits for the test of equality of proportions, namely

$$(X_1 - X_2) \pm \frac{\alpha}{2}\left[\frac{X_1(1 - X_1)}{N_1} + \frac{X_2(1 - X_2)}{N_2}\right]^{\frac{1}{2}}, \tag{3}$$

where $\alpha/2 = 1.96$, $X_1 = (87 - 17)/87 = 0.8046$, $X_2 = (87 - 11)/87 = 0.8736$, $N_1 = N_2 = 87$. If the confidence limits span 0, we cannot reject the hypothesis of equality of proportions.

The results of the test of proportions are presented in Table 4. Column two indicates that only 17 firms out of 87 firms from our sample have an increase in their shares outstanding by 5% or more during the period $-5$ through $+40$. Column three shows that out of 87 control firms, 11 of them increase their shares outstanding and 76 of them have no change in their shares outstanding. Our test indicates that we cannot reject the hypothesis of equality of the proportion of firms increasing shares outstanding for the sample and control group. Hence, we reject Hypothesis 2.

To investigate further, for each day from $-5$ through $+40$, we examine the mean excess returns and the mean cumulative excess returns for the 17 firms that increased shares outstanding and for the remaining 70 firms. We test whether the mean of the excess returns for a given day for the 17 firms is significantly greater than for the 70 firms. First, for a given day, we jointly rank the 87 excess returns.[5] Then we perform a $t$-test on the ranks. This is equivalent

**Table 4.** Test of whether a listing switch leads to an increased incidence of new equity offerings. We identify 17 out of 87 firms in our sample that increased shares outstanding by 5% or more during the period $-5$ through $+40$ relative to a switch in listing from NASDAQ to the NYSE or AMEX. To help in ascertaining whether the number of firms increasing shares outstanding in our sample is unusual, we develop a control group. For our control group, 11 of 87 firms increased their shares outstanding during the period $\pm 63$. To test whether the proportions for the sample and control are the same we calculate the confidence limits as $X_1 - X_2 \pm \alpha/2[((X_1(1 - X_1))/N_1) + ((X_2(1 - X_2))/N_2)]^{1/2}$ where $\alpha/2 = 1.96$, $X_1 = 0.8046$, $X_2 = 0.8736$, $N_1 = N_2 = 87$. The 95% confidence limits are 0.0143 and – 0.1523, which span 0. Hence, we cannot reject the hypothesis of equality of proportions.

| Δ in Shares Outstanding | Sample | Control |
|---|---|---|
| No change | 70 | 76 |
| Increase | 17 | 11 |
| Total | 87 | 87 |

[5] We also use the Dimson beta to calculate excess returns for each group to test whether the mean of the excess returns for a given day for the 17 firms is significantly greater than for the 70 firms. Our results do not change when we use Dimson beta. For brevity, we do not report the Dimson adjusted returns.

to a Wilcoxon rank sum test. The results are reported in Table 5. We report the results for relative days −5 to +12 for brevity. The mean of the returns for the 17 firms is not significantly greater than for the 70 firms for any of the days tested. We perform a similar Wilcoxon rank sum test for the cumulative excess returns. The mean of the cumulative returns for the 17 firms is not significantly greater than for the 70 firms on any of the days tested.

Examining the results reported in Table 5, we find that the cumulative excess returns for the 17 firms that increased shares outstanding are positive on day

**Table 5.** Excess returns around the announcement of a switch from NASDAQ to the NYSE or AMEX, segregated by firms with and without an increase in shares outstanding. We estimate excess returns (ERs) with Equation (2). Daily cumulative excess return for day $t$ for firm $f$ is $\mathrm{CER}_{f,t} = \mathrm{ER}_{f,t} + \mathrm{CER}_{f,t-1}$, where $\mathrm{CER}_{-150} = \mathrm{ER}_{-150}$. For the day indicated, column two (three) shows the mean of the ERs across the 17(70) firms that (did not increase) increased shares outstanding during the period −5 through +40 days. For the day indicated, column five (six) shows the mean cumulative excess returns for the 17(70) firms that increased (did not increase) shares outstanding. For a given day, to test whether the equality of the means of columns two and three (the means of columns five and six), we jointly rank the 87 observations and perform a $t$-test on the ranks of the two groups. This is equivalent to Wilcoxon rank sum test.

| | Mean Excess Returns | | | Mean Cumulative Excess Returns | | |
|---|---|---|---|---|---|---|
| | 17 Firms | 70 Firms | Col. 2–3 | 17 Firms | 70 Firms | Col. 5–6 |
| −5 | 0.0070 | −0.0009 | 0.0079 | −0.0038 | 0.0304 | −0.0342 |
| −4 | 0.0006 | −0.0025 | 0.0031 | −0.0032 | 0.0279 | −0.0311 |
| −3 | −0.0076 | −0.0005 | −0.0071 | −0.0108 | 0.0274 | −0.0382 |
| −2 | −0.0092 | 0.0010 | −0.0103 | −0.0201 | 0.0284 | −0.0485 |
| −1 | 0.0007 | 0.0032 | −0.0025 | −0.0194 | 0.0308 | −0.0501 |
| 0 | 0.0227 | 0.0102 | 0.0124 | 0.0033 | 0.0418 | −0.0385 |
| 1 | 0.0071 | −0.0032 | 0.0103 | 0.0105 | 0.0387 | −0.0282 |
| 2 | 0.0009 | −0.0056 | 0.0065 | 0.0113 | 0.0331 | −0.0217 |
| 3 | −0.0087 | −0.0037 | −0.0051 | 0.0026 | 0.0294 | −0.0268 |
| 4 | −0.0087 | 0.0020 | −0.0107 | −0.0061 | 0.0314 | −0.0375 |
| 5 | −0.0011 | −0.0003 | −0.0009 | −0.0072 | 0.0311 | −0.0384 |
| 6 | −0.0105 | −0.0029 | −0.0076 | −0.0177 | 0.0283 | −0.0460 |
| 7 | 0.0032 | 0.0043 | −0.0011 | −0.0145 | 0.0325 | −0.0470 |
| 8 | −0.0042 | −0.0066 | 0.0024 | −0.0188 | 0.0259 | −0.0447 |
| 9 | −0.0043 | −0.0036 | −0.0007 | −0.0231 | 0.0223 | −0.0454 |
| 10 | −0.0200 | 0.0037 | −0.0237* | −0.0431 | 0.0260 | −0.0691 |
| 11 | 0.0024 | −0.0073 | 0.0097 | −0.0407 | 0.0187 | −0.0594 |
| 12 | −0.0186 | −0.0093 | −0.0092 | −0.0592 | 0.0094 | −0.0686 |
| MEAN** | −0.0025 | −0.0011 | −0.0014 | −0.0592 | 0.0111 | −0.0703* |

*Significant at 10% level.
**Over −5 to +40 relative days.

zero. However, these cumulative returns turn negative on day 4 and remain negative through day +40. Moreover, the cumulative excess returns for the 70 firms are also positive and larger than for the 17 firms over 40 days though the difference in means for the two groups is not statistically significant. For the entire period, the mean cumulative excess returns for the 70 firms, 1.11%, is significantly greater than for the mean of 17 firms, −5.92%. This suggests that firms that issue a security lose value in the long run. This evidence is consistent with other studies that find poor post listing performance observed following initial and seasoned equity offerings (Spiess & Affleck-Graves, 1995; Lougran & Ritter, 1995; Nelson, 1994). Further, since excess returns are not greater for firms issuing new shares than for other firms, we conclude that exchange switches are not motivated by a desire to issue a new security to benefit from the increase in share price around the listing date.

## 5. Summary and Conclusions

For a sample of 87 firms that switched their listing from NASDAQ to either the NYSE or AMEX in 1998, we investigate whether there are excess returns due to the switch. Confirming the results of previous researchers, we find significantly positive cumulative excess returns on the day of the switch and the following three days. However, we also find that the cumulative returns turn negative several days after the switch and remain negative through the end of our study period at day +40.

We also investigate whether firms that switch exchange listings increase their shares outstanding, possibly in an effort to take advantage of increased security price. We find that 17 out of 87 firms increase their shares outstanding by 5% or more around the time of the switch. This rate of increase is not statistically higher than that found for a control group matched on SIC code and share price. We also find that excess returns for the 17 firms that issue a security is positive on the switch day but are not significantly higher than the 70 firms that do not issue a security. Therefore, we conclude that a decision to switch an exchange listing cannot be explained by the stock issuance motive.

## Appendix: Nonsynchronous Trading

A potentially significant econometric problem is introduced in the estimation of excess returns when the market model is estimated for firms that trade less frequently than the market index used in the estimation (see Lo & Mackinlay, 1990). The market index used in estimation is based on a wide range of securities, often with more frequent trades than the underlying security. Accordingly, the market index value is observed for every trading day, while the security under study may not be. In our sample, most of the firms miss at least one day of trading but not more than 30 days of trading. In the estimation, the zero returns when a security has no trades in a day cause an estimated parameter, $\beta_f$, to be biased downward.

Several techniques were introduced in the literature to reduce the bias in the estimation of $\beta_f$, including Scholes and Williams (1977), Dimson (1979), and Fowler and Rorke (1983). They included lagged market index and lead market index values as additional variables in the market model. A comparison of these techniques was performed by McInish and Wood (1986), using a sample of NYSE firms from late 1971 to early 1972. In their study, security trading thinness was measured using the average time from last trade to market close, in minutes. The study showed that Dimson (1979) and Fowler and Rorke (1983) techniques outperformed the Scholes and Williams (1977) estimates, with the Dimson (1979) estimate yielding the best performance.

All the techniques mentioned are based on Ordinary Least Square regression (market model) of the firm's security return on lagged, current, and the lead values for the market. However, the computation of the firms' beta risk coefficient differs among the three. The Dimson technique takes the summation of the estimated $\beta_f$ on each market index value used. To apply the Dimson technique, we first estimate the market model with two lagged and two lead market values

$$\begin{aligned} \mathrm{R}_{f,t} = \alpha_f + \beta_{f,t-2}\mathrm{R}_{m,t-2} + \beta_{f,t-1}\mathrm{R}_{m,t-1} + \beta_{f,t}\mathrm{R}_{m,t} + \beta_{f,t+1}\mathrm{R}_{m,t+1} \\ + \beta_{f,t+2}\mathrm{R}_{m,t+2} + \varepsilon_{f,t}, \end{aligned} \tag{A1}$$

where $t = -150, \ldots, -25$.

Next, the estimated Dimson beta is computed as a summation of all the beta coefficients from above. The formula for the Dimson estimate is

$$\hat{\beta}_f = \sum_{k=-2}^{2} \hat{\beta}_{f,t+k}. \tag{A2}$$

We calculate Dimson adjusted excess returns by using the Dimson beta in Equation (A2) to test the robustness of our results. We use more lagged and lead market values in the model to test the sensitivity of the estimated Dimson beta to the number of lead and lagged market values chosen. We confirm that the estimated Dimson beta does not change when more than two lead and lagged market values are included in the estimation.

## Acknowledgments

We thank the editor, Cheng-few Lee, and the anonymous referee for valuable comments and suggestions.

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Chapter 11

# Is Covered Call Investing Wise? Evaluating the Strategy using Risk-Adjusted Performance Measures

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To evaluate portfolio performance, one needs to consider the risk associated with generating returns. Traditional performance metrics evaluate returns relative to the standard deviation of returns. These moments do not adequately take into account measures of interest to investors. Using improved risk-adjusted performance measures, we find the covered call portfolio is not an adequate investment strategy. Rather, investors are better off by holding the market index.

**Keywords:** Covered call investing; upside potential ratio; performance measures.

## 1. Introduction

The popular press touts the covered call investing strategy as a means or reducing risk while increasing an investor's return. In the academic literature, however, there is a lack of agreement on when to use the covered call strategy, and even if the strategy has value at all (Baldwin, 2002; Einhorn, 2001; Rattiner, 2001; Thackuk, 2000). Part of the difficulty stems from the fact that the metric we use to evaluate the performance for any investment strategy is questionable. While investors understand the concept of evaluating performance on a risk-adjusted basis, the traditional measure of risk may be inadequate. Additionally, recent studies question the means for determining return and the metric against which we gauge performance.

In this paper we will compare the risk-adjusted performance of two portfolios: an index portfolio and a covered call portfolio. To compare the strategies' success, we evaluate performance with three metrics: the Sharpe ratio, Sortino ratio, and the Upside Potential ratio (UPR). The Sharpe ratio looks at a traditional measure of reward per unit of risk; the Sortino ratio adjusts risk to more accurately reflect the variation that is of concern for investors; and the UPR adjusts both the risk metric and the measure for excess returns.

We find using either the Sharpe ratio or the Sortino ratio to measure performance, the covered call portfolio is the superior strategy. However, when evaluating performance with the Upside Potential ratio, the index portfolio becomes the preferred investing strategy. This contradiction in preferred investing strategy stems from the Upside Potential ratio's ability to properly measure risk-adjusted performance, whereas the Sharpe ratio and the Sortino ratio do not. The use of the appropriate performance evaluator has import beyond this study and calls into question the comparisons of other investing strategies that do not use UPR as the evaluator.

The paper will proceed as follows. Section 2 will review the existing literature and provide the theoretical framework for our model; Section 3 describes the data and methodology; Section 4 contains the results and analysis; and Section 5 details the conclusions.

## 2. Review of Literature

Financial managers frequently recommend to their customers a covered call portfolio investment strategy ostensibly as a means of increasing portfolio returns while reducing the overall investment risk. A covered call strategy requires the investor to write a call option on stocks that are purchased; a fully covered call strategy results when investors write one call for each share of stock purchased. The advantage to the covered call strategy lies in the up-front fee earned on writing the call; profits are made from the premium received and its time decay (Radoll, 2001). If the call expires without being exercised, the portfolio return is based on the call premium and the value of the stock that the call writer still owns. Alternatively, however, if the call is in the money and is exercised, the call writer receives the call premium and surrenders the stock at the strike price. The strategy is most profitable when shares are called (Tergesen, 2001). Otherwise, if the stock price falls, the losses occurring from owning the asset can eliminate the option premium received (Radoll, 2001). The covered call investor in essence trades off the upside potential of the stock investment with an up-front fee and limited exposure to downside risk.

Many investment advisory services claim that creating a portfolio using the covered call strategy will result in increased returns with reduced risk as compared to holding a portfolio of the stock alone (Rendleman, 2000). Early empirical work in this area using simulated option prices finds that the covered call strategy does not enhance the performance of the portfolio (Merton, Scholes, and Galdstein, 1978; Clarke, 1987; Brooks, Levy, and Yoder, 1987; Lhabitant, 1999). These results are consistent with the Black-Scholes option pricing model which derives a risk free rate of return for a continuously rebalanced portfolio of stocks and options (Black and Scholes, 1972). The CAPM-based option derivation shows that an option's instantaneous expected return should be the same as that implied by the CAPM (Black and Scholes, 1973). For risk averse investors wishing to maximize utility, the optimal portfolio will maximize expected return for a given level of risk. The covered call strategy purportedly increases returns while simultaneously reducing risk. Rendleman shows that there is theoretically no such thing as a free lunch: investors cannot reduce risk and increase returns in an efficient market (1981, 1999). Therefore, writing calls should only be done if the calls are consistently overpriced (Benninga and Blume, 1985).

But what if calls are mispriced? Green and Figlewski (1999) note that call writing is only profitable if the call is significantly overpriced and therefore is only a viable strategy for investors who can recognize and take advantage of mispriced options. This may be feasible for institutions that continually monitor option prices and can rebalance a portfolio at lower transaction costs; for individual investors, call writing is unlikely to be a profitable strategy.

The authors note call writers are exposed to risk from many sources including misspecified volatility estimates. Evidence exists that over the counter call option writers obtain the best forecast for volatility, then increase the volatility figure used in pricing the option or, alternatively, increase the option price by a predetermined amount (Green and Figlewski, 1999). This action serves to decrease the option writer's risk exposure. Either case (increasing the volatility estimate or increasing the option price) leads to overpricing of options in the over the counter market.

Others find similar evidence of option overpricing in the exchange traded market (Coval and Shumway, 2000; Isakov and Morard, 2000; Yan, 2000). Evidence indicates additional factors such as systematic stochastic volatility may be priced in option returns (Heston, 1993). Yan (2000) finds that after correcting for discretization biases associated with option returns, option returns are still 6% lower than returns suggested by CAPM forecasts. Yan finds evidence of systematic volatility, but not enough to explain a 6% mispricing. He notes the overpricing of options reflects both the volatility risk premium and the cost of writing options. Is this overpricing sufficient to make a covered call portfolio investing strategy beneficial?

Isakov and Morard (2000) analyze stocks traded simultaneously on the Zurich Stock Exchange and the Swiss Options and Financial Futures Exchange. The chosen options are the most out of the money but ones with transaction activity. The authors find the covered call portfolio outperforms the stock only portfolio and results in increased returns while decreasing the risk of the portfolio. However, this study uses deep out of the money options. These traded options have the least likelihood of being exercised and therefore the call writer benefits from receipt of the call premium up front with a low likelihood of exercise. Deep out of the money options, however, offer little in the way of returns to compensate investors for price decreases in the stock since the call option premiums for deep out of the money options are very small compared to the premiums received for writing nearby options; therefore, investors have little up front compensation to offset price decreases in the owned stock. Few studies to date have examined the covered call investment strategy using nearby options.

A question remains as to whether mean variance dominance is the appropriate measure of performance for portfolios that include options (Leland, 1999; Lhabitant, 1999). Introducing options to a portfolio changes the distribution of the portfolio. The variability of the portfolio decreases, and the portfolio is negatively skewed thus making the distribution of returns asymmetric (Bookstaber and Clark, 1981, 1984 and 1985). Traditional return measures look at the percentage change in portfolio value as a measure of return. Others look at excess returns, returns above some benchmark such as the risk free rate. An alternative measure of excess returns is found by using an index portfolio's return as the benchmark.

To measure risk, the typical metric is the standard deviation of the portfolio return. A common practice is to combine the measures of return and risk into one metric to use for evaluating performance. Despite some well-known limitations, the Sharpe ratio (i.e., the excess return per unit of standard deviation) has been widely adopted as a performance measure to evaluate and select investment alternatives. Variance is a two-sided measure, implying the individual dislikes any deviation from the mean regardless of the direction of the deviation. This is hardly the notion of risk perceived by an individual. In a recent survey, Adams and Montesi (1995) found that corporate managers are mostly concerned with the occurrence of bad outcomes compared to a reference point referred to as the "downside risk". Similar evidence was provided in Sortino and Price (1994).

Indeed, the prospect theory of Kahneman and Tversky (1979) suggests that an individual weighs losses much more than gains. Empirical evidence of the so-called "loss aversion" has been established in recent literature (Benartzi and Thaler, 1995; Thaler *et al.*, 1997; Ordean, 1998). More specifically, Shefrin and Staman (1993) and Shefrin (2000) explain covered call investment strategy with loss aversion. Empirical support for their arguments is provided in Leggio and Lien (2002).

The downside risk measure (i.e., the lower partial moment) we consider has long-standing support in the literature. Researchers note investors associate risk with the failure to attain a target return. This definition questions the ability of the variance, or any measure of dispersion relative to a parameter such as the mean, to be an acceptable measure of risk given that the reference parameter (the mean) changes with each distribution (Domar and Musgrave, 1944; Markowitz, 1959; Mao, 1970). Fishburn (1977) notes modeling risk as the dispersion below a target is appealing since it leads to an investor performing well in the long run while avoiding setbacks or failures in the short run. Holthausen (1981) extends Fishburn's work and models risk as below-target outcomes and allows for non-linear utility functions. Finally, Sortino and Satchell (2001) note the difference between uncertainty and risk, and detail the advantages of using alternatives to the standard deviation as measures of downside risk.

Dissatisfaction with the variance as a risk measure, coupled with other behavioral evidence, has led some researchers to propose alternative risk-adjusted performance measures. Two of these measures are the Sortino Ratio and the Upside Potential Ratio.

The Sortino Ratio constructs a risk-adjusted performance measure by replacing the standard deviation with the downside risk measure. Downside risk measures the lower partial moment, or the chance that an investment deviates below the benchmark. Balzer (1994) and Harlow (1991) find that investors prefer a risk metric that measures the deviations below a minimum acceptable return. Sortino (1996) notes that the standard deviation measures the risk of not achieving the mean, whereas downside risk captures the risk of not achieving the minimal acceptable return. The Sortino ratio measures the return relative to downside risk.

Sortino, van der Meer and Plantinga (1999) further suggest that the return should be replaced with the upside potential. Sortino (1994) argues that the reference point of interest for an investor should be related to the investor's objective. Typically, an investor is looking to earn more than the risk free rate;

therefore, excess return as measured with CAPM is inadequate. Mutual fund owners typically purchase mutual funds with the belief that the fund managers can at least outperform a passive market index. A more appropriate measure of excess returns, therefore, is to measure returns in excess of the market index. This is termed the upside potential. For a risk-return tradeoff to take place, we should consider only the upside potential for the return measure. The ratio of the upside potential to the downside risk is termed the "Upside Potential Ratio".

Plantinga, van der Meer and Sortino (2001) apply the Sharpe ratio, Sortino ratio, and the Upside Potential ratio to evaluate mutual fund performance. They demonstrate that the UPR is a better measure than the Sharpe ratio. Moreover, they attribute the difference to the skewness of the return distribution. Lien (2002) finds portfolio distributions with positive skewness and sufficiently large Sharpe ratios will have the opposite ranking using both the Sortino ratio and the Upside Potential ratio when compared to the Sharpe ratio. Sortino and Kuan (2002) find UPR to be a superior performance evaluator for mutual funds when compared to either the Sharpe or Sortino ratios. We will now test to see if these results hold for covered call investing.

## 3. Data and Methodology

### 3.1. *Data*

This study uses the Berkeley Options Database of Chicago Board Options Exchange bid-ask quotes.[1] The S&P 500 options data covers the nine year period of February 1987 to December 1995.[2] These options are European style, thus eliminating the possibility of early exercise. The covered call strategy presumes the investor purchases the S&P 500 index and sells a call option at the bid price of the first transaction on the Tuesday one month before the

[1] We are grateful to Tyler Shumway for sharing his data. The one month and six month covered call investment strategies presume the investor sells one option at the bid price reported on the first transaction on the option contract on the Tuesday either one month or six months prior to contract expiration; the position is evaluated with the first transaction on the Tuesday prior to the contract's expiration.

[2] The data excludes several months due to insufficient trading activity on the nearby contract. Our sample size is 105 monthly holding periods for just in the money contracts and 101 monthly holding periods for just out of the money contracts. For six month contracts, the sample size is 34 and 32, respectively.

Friday that the option contract expires.[3] We consider different types of options including deep out of the money calls, six month just in the money or just out of the money calls, and one month just in the money or just out of the money calls.[4] For one month calls, the investor essentially sells a contract with 32 to 35 days until expiration and holds the position until maturity. We calculate holding period returns for two portfolios: the portfolio consisting of only the index and the covered call portfolio.

Portfolio manager's anecdotal evidence indicates an investor's recommended strategy is to sell one month out of the money calls or six month deep out of the money calls. Investors benefit from the up-front fee received from writing the call. Radoll (2001) notes that a successful covered call strategy is to write calls near the strike price with a short time until expiration. One month calls allow investors to take advantage of the more rapid time decay; additionally, a short time until expiration is less risky in terms of predicting the future price direction.

For six month calls, at the money options have a high likelihood of finishing in the money given the additional time to maturity. An investor wishing to sell six month calls will be advised to sell deep out of the money options. These options have a lesser likelihood of expiring in the money than near term contracts; additionally, they also offer a lower up-front premium and less risk protection for the investor (Rattiner, 2001).

## 3.2. *Methodology*

For the covered call portfolio, this study assumes an investor sells a call and holds the index until the call expires. He then calculates his return for this holding period. The investor then creates the same portfolio structure for the next holding period. For example, an investor sells a one month call and purchases the index on June 14. He holds the position until the call expires on July 12. He then calculates his holding period return for this month. The investor next sells a one month call that expires on August 16 and continues to hold

[3] There are two types of at the money contracts: just in the money or just out of the money. We examine each type of at the money contract in turn. We then evaluate deep out of the money contracts with six months to expiration.

[4] A deep out of the money call is the contract with the largest spot — exercise price yet still with trading. Just in the money contracts are those with a call price — exercise price is less than or equal to $5.00; just out of the money contracts have an exercise price — call price of less than or equal to $5.00.

the index. The investor continues to sell a one month call each month after the previous position is closed. The investor will consistently sell either one month just in the money or one month just out of the money calls (we calculate holding period returns for both investing strategies). We also study investing strategies of selling six month deep out of the money calls while holding the index portfolio and holding this portfolio position until expiration.

The alternative investment strategy is for an investor to strictly hold the index portfolio during the same time period as the covered call portfolio is held, and at the conclusion of said time period, to then calculate the holding period return. The holding period percentage returns for the stock portfolio and the covered call portfolio are computed as follows:

$$R_s = (d + I_N - I_B)/I_B,$$
$$R_C = (d + I_N + C_P - I_B - C_V)/(I_B - C_P),$$

where

$R_S =$ percentage return on the stock portfolio;
$d =$ dividend yield on the stocks that comprise the S&P 500;
$I_N =$ spot price of the S&P 500 index at expiration;
$I_B =$ spot price of the index at the initiation of the option contract;
$R_C =$ percentage return on the covered call portfolio;
$C_P =$ call premium received at initiation of the option contract;
$C_V =$ terminal value of the call contract.

We compute holding period returns for each investment strategy during the sample period and compute different ratios from the sample.

### 3.3. *Ratio calculations*

Let $X$ denote the asset return with a probability density function $f(.)$. We denote the mean of $X$ by $\mu$ and denote the standard deviation of $X$ by $\sigma$. The Sharpe ratio is defined as the excess return over the standard deviation of $X$. That is,

$$SH = (\mu - r)/\sigma, \tag{1}$$

where $r$ is the risk-free rate of return. The Sortino ratio replaces the standard deviation with the downside risk measure $\delta$, where

$$\delta^2 = \int_{-\infty}^{r} (r - x)^2 f(x)\, dx. \tag{2}$$

Consequently, the Sortino ratio is

$$SO = (\mu - r)/\delta. \tag{3}$$

The Upside Potential ratio, advocated by Sortino, van der Meer and Plantinga (1999), refines the Sortino ratio by replacing the excess return with the upside potential, $\theta$, defined as follows:

$$\theta = \int_r^\infty (x - r) f(x)\, dx. \tag{4}$$

Consequently, the Upside Potential ratio (UPR) can be written as:

$$\text{UPR} = \theta/\delta. \tag{5}$$

We calculate the Sharpe ratio, Sortino ratio, and the Upside Potential ratio for both one month and six month option contracts, and for at the money and deep out of the money calls.

## 4. Results and Analysis

### 4.1. *Full sample summary statistics*

We compute the holding period returns for the portfolio of the S&P 500 index and for the covered call portfolio. The mean one month return for the index portfolio is 0.9521% (12.1% annualized); the mean monthly return for the covered call portfolio is 1.0868% (13.93% annualized) for just in the money one month options. For one month just out of the money options, the index portfolio return is 0.9055% (11.48% annualized); the covered call portfolio return is 1.1966% (15.44% annualized).[5] Although the covered call portfolio yields a higher return, the difference is not statistically significant. And, when considering transaction costs, the difference will also not be economically significant.

The annualized return for the covered call portfolio for the deep out of the money option strategy is superior for the covered call strategy but again, the difference in mean returns is not significant. For the investing strategy of selling near the money contracts (just in the money or just out of the money) for contracts with six months until expiration, we find the index portfolio returns

[5] The variation in index portfolio returns is a function of the number of monthly holding periods in the samples; 105 months for just in the money contracts and 101 months for just out of the money contracts.

exceed the returns for the covered call portfolio. The results from a mean variance perspective appear to favor the covered call strategy when investors sell calls with a short life span (namely, with calls with one month until expiration) or when the call is longer term but deep out of the money. Yet the portfolio of stocks only is preferred for a six month investing horizon for near the money contracts.

The covered call portfolio is believed to be a risk reduction strategy; indeed, we observe this with the lower standard deviation for the covered call portfolio in all investing scenarios as compared to the index portfolio investment. For instance, the standard deviation is 4.64% with the covered call strategy compared to 9.24% with the index portfolio and just in the money six month option contracts (Table 1). As expected, the covered call portfolio is more negatively skewed. This skewness calls into question the relevance of the return data based on a normal distribution. The preferred means of comparing the portfolio performance is by using risk-adjusted performance measures such as the Sharpe, Sortino and UP ratios.

### 4.2. *Ratio analysis*

Whereas the preferred portfolio strategy based on mean returns varies, the preferred portfolio using risk-adjusted performance metrics is consistent. For all five scenarios studied, the covered call portfolio is preferred using either the Sharpe or Sortino ratios (Table 2). Since the numerator is identical for these ratios (namely, the numerator is excess returns above the risk free rate), the difference in volatility is not significant enough to cause alternative rankings. The denominator for the Sharpe ratio is the portfolio's standard deviation, whereas the Sortino ratio uses downside risk. This consistency of preferred investing strategy does not hold when UPR is the preferred metric.

Regardless of the scenario considered, UPR indicates the index portfolio outperforms the covered call portfolio, and the results are statistically significant for all portfolios except the one month just out of the money portfolio. UPR requires the return exceeds the market index. Covered call portfolios reduce the overall portfolio risk; the strategy does limit the upside potential. If the index is in the money, the call will be exercised and the call writer is left with the up-front call premium and cash equivalent to the index call price. All additional upside goes to the owner of the call. These results call into question performance ranking measures that do not adjust both the return and risk metric to

**Table 1.** Summary statistics for return distributions for the S&P 500 index and for a covered call portfolio. The $p$-values reported are a result of the mean comparisons for the index portfolio and the covered call portfolio.

| | Index Portfolio | Covered Call Portfolio | $p$-Value |
|---|---|---|---|
| Panel A: Just In the Money One Month Options | | | |
| Mean return (%) | 0.9521 | 1.0868 | 0.5821 |
| Median return (%) | 1.4207 | 1.4321 | |
| Standard deviation (%) | 3.9300 | 2.4469 | |
| Skewness | −1.1984 | −5.9504 | |
| Kurtosis | 13.2640 | 47.8787 | |
| Panel B: Just In the Money Six Month Options | | | |
| Mean return (%) | 5.2493 | 4.2639 | 0.3583 |
| Median return (%) | 4.8768 | 5.0968 | |
| Standard deviation (%) | 9.2371 | 4.6397 | |
| Skewness | −0.5956 | −2.7169 | |
| Kurtosis | 0.7375 | 8.1570 | |
| Panel C: Just Out of the Money One Month Options | | | |
| Mean return (%) | 0.9055 | 1.1966 | 0.1741 |
| Median return (%) | 1.3454 | 1.7697 | |
| Standard deviation (%) | 4.0162 | 2.8231 | |
| Skewness | −1.1340 | −4.6286 | |
| Kurtosis | 12.5040 | 32.0495 | |
| Panel D: Just Out of the Money Six Month Options | | | |
| Mean return (%) | 5.2772 | 4.3049 | 0.3443 |
| Median return (%) | 4.8170 | 5.3715 | |
| Standard deviation (%) | 9.1176 | 5.1281 | |
| Skewness | −0.6572 | −2.3215 | |
| Kurtosis | 0.9022 | 6.2952 | |
| Panel E: Deep Out of the Money Six Month Options | | | |
| Mean return (%) | 5.9584 | 5.9919 | 0.9722 |
| Median return (%) | 4.5619 | 6.2066 | |
| Standard deviation (%) | 10.8126 | 8.7973 | |
| Skewness | 0.0935 | −0.6513 | |
| Kurtosis | 1.5487 | 0.8439 | |

accurately reflect the investor's interest; namely, returns in excess of the market and the risk of falling below the benchmark.

### 4.3. *Ex ante test*

To affirm the results using an alternative sampling period, we conduct the following *ex ante* study. Using the existing data set for one month options, we

**Table 2.** Summary risk-adjusted performance results for return distributions for the S&P 500 index and for a covered call portfolio. The $p$-values reported are a result of the performance comparisons for the index portfolio and the covered call portfolio using the Wilcoxon Sign Rank Test.

| | Index Portfolio | Covered Call Portfolio | $p$-Value |
|---|---|---|---|
| Panel A: Just In the Money One Month Options | | | |
| Sharpe | 0.24 | 0.44 | 0.0002*** |
| Sortino | 53.32 | 98.84 | 0.0313** |
| UPR | 0.71 | 0.33 | 0.0002*** |
| Panel B: Just In the Money Six Month Options | | | |
| Sharpe | 0.57 | 0.92 | 0.2295 |
| Sortino | 141.00 | 255.80 | 1.00 |
| UPR | 1.17 | 0.46 | 0.0129** |
| Panel C: Just Out of the Money One Month Options | | | |
| Sharpe | 0.23 | 0.42 | 0.0001*** |
| Sortino | 49.51 | 87.16 | 0.0001*** |
| UPR | 0.69 | 0.39 | 0.1048 |
| Panel D: Just Out of the Money Six Month Options | | | |
| Sharpe | 0.58 | 0.84 | 0.1214 |
| Sortino | 149.89 | 228.53 | 0.3915 |
| UPR | 1.20 | 0.52 | 0.0574* |
| Panel E: Deep Out of the Money Six Month Options | | | |
| Sharpe | 0.55 | 0.68 | 0.0029*** |
| Sortino | 143.85 | 163.92 | 0.0001*** |
| UPR | 1.08 | 1.04 | 0.0352** |

*, **, and *** indicate significance at the 0.10, 0.05 and 0.01 levels, respectively.

select the first 80 data points and calculate the mean and standard deviation of the index returns.[6] We use this information to compute a theoretical call option price for both one month nearby options using the Black-Scholes pricing model. We compute the portfolio moments using the theoretical call price applied to the remaining observations in the original sample, and we then compare the covered call portfolio based on a theoretically priced call to an index portfolio

[6]Two notes of importance: we chose to sample using 80 data points in order to guarantee enough remaining observations (25 for just in the money one month calls and 21 for just out of the money one month calls) to presume the normality of returns assumption holds. We test using alternative splits of the data and found the results to be consistent. We only study one month sample period observations since the sample size for six month options is too small for the data to be segmented.

investment strategy for the remaining observations. Table 3 reports the results for the first four moments for each sample.

The covered call portfolio continues to earn a higher mean return for the first sub-sample. The results are significant for the just out of the money one month call portfolio with the mean return of 0.758% for the index portfolio and 1.25% for the covered call portfolio ($p$-value = 0.0529). As with the

**Table 3.** Summary statistics for the return distributions using a split sample for the S&P 500 index and for a covered call portfolio. Returns are calculated using the first 80 observations and then calculated using the remaining observations. The covered call for the remaining observations is the theoretically priced covered call based on parameters obtained from the first 80 observations and applied to the Black-Scholes model to arrive at a call price. The $p$-values reported are a result of the mean comparisons for the index portfolio and the covered call portfolio.

| | Index | Covered Call Portfolio | $p$-Value |
|---|---|---|---|
| Panel A: Just In the Money One Month Options | | | |
| First 80 Observations | | | |
| Mean return (%) | 0.836 | 1.132 | 0.3238 |
| Median return (%) | 1.380 | 1.580 | |
| Standard deviation (%) | 4.280 | 2.740 | |
| Skewness | −1.140 | −5.590 | |
| Kurtosis | 12.190 | 40.340 | |
| Panel B: Just In the Money One Month Options | | | |
| Remaining Observations | | | |
| Mean return (%) | 1.32 | 1.29 | 0.9271 |
| Median return (%) | 1.56 | 1.67 | |
| Standard deviation (%) | 2.51 | 1.04 | |
| Skewness | −4.86 | −2.49 | |
| Kurtosis | −0.35 | 4.96 | |
| Panel C: Just Out of the Money One Month Options | | | |
| First 80 Observations | | | |
| Mean return (%) | 0.758 | 1.25 | 0.0529* |
| Median return (%) | 1.170 | 1.73 | |
| Standard deviation (%) | 4.290 | 3.07 | |
| Skewness | −1.070 | −4.53 | |
| Kurtosis | 12.050 | 29.23 | |
| Panel D: Just Out of the Money One Month Options | | | |
| Remaining Observations | | | |
| Mean return (%) | 1.47 | 1.39 | 0.8302 |
| Median return (%) | 1.90 | 2.06 | |
| Standard deviation (%) | 2.76 | 1.59 | |
| Skewness | −0.76 | −2.17 | |
| Kurtosis | −0.03 | 3.63 | |

*indicates significance at the 0.10 level.

full sample, the covered call portfolio also has a lower standard deviation than the index portfolio and is more highly negatively skewed for both the one month just in the money and one month just out of the money investing strategies.

For the remaining data points, the risk (as measured by the standard deviation) is lower for the covered call portfolio. However, the mean return is greater for the index portfolio for both the just in the money and the just out of the money investing strategy (the results, however, are not statistically significant). This result may reflect evidence found by Yan (2000) who notes that there are premiums priced in options that are not a reflection of the theoretical price obtained by using Black-Scholes to arrive at an option price.

To evaluate the performance of the two investment strategies, we again compute the risk adjusted performance measures (Table 4). Again, both the Sharpe and Sortino ratio indicate the covered call portfolio is preferable whereas UPR indicates the index portfolio will be preferred by investors.

## 5. Conclusion

Financial advisers are charged with creating portfolios to meet their client's needs. An investment strategy that increases the upside potential at lower levels of risk would certainly be a valuable addition to the advisor's offerings. Mean variance efficiency does not properly identify the return or risk metric of interest to investors. This belief is supported by research that considers portfolios consisting of calls priced theoretically according to the Black-Scholes option pricing models. Because call writers overprice options to cover the uncertainty associated with estimating volatility for assets, there does appear to be evidence that a covered call portfolio's returns are superior to the returns earned by strictly holding the stock index.

Investors measure returns relative to a reference point. Most investors understand they can buy the index and hold it as a passive investment strategy. The reason to hire an investment adviser is to devise a portfolio that outperforms a passive strategy. Returns in excess of the risk free rate are not relevant returns of interest; investors pay to exceed a passive market index strategy. Likewise, a performance measure that considers all variation from the mean is not relevant to investors; investors are only concerned with variation below the

**Table 4.** Summary risk-adjusted performance results for the return distributions using a split sample for the S&P 500 index and for a covered call portfolio. Returns are calculated using the first 80 observations and then calculated using the remaining observations. The covered call for the remaining observations is the theoretically priced covered call based on parameters obtained from the first 80 observations and applied to the Black-Scholes model to arrive at a call price. The $p$-values reported are a result of the performance comparisons for the index portfolio and the covered call portfolio using the Wilcoxon Sign Rank Test.

| | Index | Covered Call Portfolio | $p$-Value |
|---|---|---|---|
| Panel A: Just In the Money One Month Options First 80 Observations | | | |
| Sharpe | 0.19 | 0.41 | 0.0001*** |
| Sortino | 43.84 | 93.72 | 0.0023*** |
| UPR | 0.58 | 0.34 | 0.0101** |
| Panel B: Just In the Money One Month Options Remaining Observations | | | |
| Sharpe | 0.52 | 1.24 | 1.00 |
| Sortino | 109.09 | 186.96 | 1.00 |
| UPR | 1.20 | 0.17 | 0.0020*** |
| Panel C: Just Out of the Money One Month Options First 80 Observations | | | |
| Sharpe | 0.18 | 0.41 | 0.0001*** |
| Sortino | 41.19 | 89.28 | 0.0001*** |
| UPR | 0.49 | 0.39 | 0.2327 |
| Panel D: Just Out of the Money One Month Options Remaining Observations | | | |
| Sharpe | 0.53 | 0.87 | 1.00 |
| Sortino | 134.86 | 193.05 | 1.00 |
| UPR | 1.28 | 0.43 | 0.001*** |

** and *** indicate significance at the 0.05 and 0.01 levels, respectively.

mean. UPR adjusts both return and risk to more accurately reflect the variation of interest. Using UPR, the covered call strategy is always inferior to the index portfolio. These results hold regardless of the time frame for holding the call, and even hold for the split sample data. A long-term covered call strategy may not be in the best interest of investors.

## Acknowledgments

The authors wish to acknowledge an anonymous referee and the editor, Cheng-few Lee, for helpful comments and suggestions.

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Chapter 12

# CFA Designation, Geographical Location and Analyst Performance

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In this paper we examine the relation between analyst expertise and performance utilizing the stocks recommended by investment professionals featured in the *WSJ* "Dartboard" column. As documented in prior studies, we find that experts are better informed about a stock's intrinsic value. Moreover, we confirm a direct relationship between investment performance and expertise. Stocks recommended by CFA charterholders and non-CFA charterholders from New York City and California yield statistically significant higher abnormal daily returns.

**Keywords:** CFA charterholder; geographical location; analyst performance; *WSJ* "Dartboard" column.

## 1. Introduction

In this study, we examine the relation between analyst expertise and performance utilizing the stock recommendations published in the *Wall Street Journal (WSJ)* "Dartboard" column. We find that stocks recommended by the financial experts featured in the Dartboard column produced a statistically significant 4.0% abnormal return over the six-month contest period. The likelihood that stocks recommended by experts does better than the market only by chance can be rejected at reasonable levels of confidence. Moreover, we confirm a direct relationship between investment performance and expertise. Stocks recommended by Chartered Financial Analyst® (CFA) charterholders and non-CFA charterholders from New York City and California yield statistically significant abnormal returns.

Security analysts play a pivotal role in financial markets. Their information collection, assimilation, and dissemination activities affect investor awareness and knowledge about specific companies. Consequently, to the extent investors trade in securities they are familiar with and educated about, the breadth of

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information that is available will have a positive influence on security prices. Indeed studies show that expected returns are higher on stocks of neglected firms, and that firm value is positively related to the number of analysts that monitor the firm (Chung and Jo, 2000; Doukas, Kim and Pantazalis, 2000). Further, the price/demand for analyst services is higher/greater for lower priced stocks (Brennan and Hughes, 1991) and for larger and/or riskier firms.

The relation between analysts' reputations and their performance is, however, largely unexplored with several notable exceptions. Stickel (1992) finds that members of the *Institutional Investor* "All-American Research Team" revise their earnings forecasts more frequently and provide more accurate earnings forecasts. Consistent with their position as leaders, earnings forecasts by the All-American analysts are less likely to "follow the crowd" and less predictable (Stickel, 1990). Inexperienced analysts, on the other hand, seldom revise their forecasts and their forecasts deviate less from consensus because they are more likely to be terminated for inaccurate forecasts and for bold deviations from consensus (Hong, Kubik and Solomon, 2000). In addition, Stickel (1992) points out that compared to Non All-American analysts, large upward forecast revisions by All-American analysts resulted in significantly larger increases in stock prices immediately following these revisions.

Using the CFA designation as a proxy for analysts' reputations, Shukla and Singh (1994) find that equity funds with at least one CFA chartered manager were better diversified and outperformed other funds as a group.[1] Similarly, Miller and Tobe (1999) report that public-sector retirement systems which employ CFA charterholders in investment management functions maintained lower investment management expenses but achieved the same portfolio performance as public-sector retirement systems that did not employ CFA charterholders.[2]

The public disclosures of stock recommendations by investment professionals have been shown to convey valuable information to the market. Barber and Loeffler (1993) find that stocks appearing in the *WSJ* "Dartboard" column

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[1]The difference in performance was, however, statistically significant only for funds with equity-income as a stated investment objective and not statistically significant for funds where growth-income, growth, and aggressive growth were the stated investment objectives.

[2]The greater number of external investment managers employed and lower allocation of assets to each investment manager by CFA-managed public-sector funds reduced the dependency of the fund's performance on the skills and investment styles of external investment managers but at the cost of higher investment management fees paid.

gained an average 4.06% subsequent to and over the day of its announcement. Similarly, Liu, Smith and Syed (1990) report that stock recommendations featured in the *WSJ* "Heard-on-the-Street" column sustained a 1.69% abnormal return on the day of publication. The abnormal return was accompanied by a significant increase in volume and the cumulative returns over the 20 days following publication were negative but statistically insignificant. Moreover, the abnormal gains on buy and sell recommendations were similar in magnitude. Lastly, Peterson (1995) documents that stocks selected as highlights in *Value Line Investment Survey* "Selection and Opinion" section achieved a 2.42% abnormal gain over the three-day period around its publication. The subsequent cumulative return through day 20 following publication was negative but statistically insignificant. Moreover, the abnormal gains were unrelated to the length of time that elapsed between the stock's prior earnings announcement and its appearance as a stock highlight, and uncorrelated with the abnormal gains that took place at and after earnings announcements.

We employ two proxies for analyst expertise in our study. The first proxy uses the CFA charter as a surrogate for investment knowledge and skill. The CFA credential has in recent years become a globally recognized industry symbol for investment competence and commitment to the highest level of ethical and professional conduct. Candidates must go through an extensive program of study and pass a series of three comprehensive exams to earn the designation. More than 27,000 investment professionals have received the CFA charter since its first award by the Institute of Chartered Financial Analysts (ICFA) in 1963.[3]

The second proxy distinguishes New York City and California based analysts from those located in other geographic areas of the United States as a surrogate for relative compensation. As Stickel (1992) notes, there is a direct relation between compensation and analyst reputation. The 2001 Investment Management Compensation Survey sponsored jointly by AIMR and Russell Reynolds Associates provides support for this premise. Table 1 shows that compensation is strongly correlated with years of experience.

More importantly, as shown in Table 2, the same survey finds that there continue to be notable differences in compensation levels by regions of the United

[3]The Association for Investment Management and Research (AIMR), which was established in 1991 by the merger of the Financial Analysts Federation (FAF) and the Institute of Chartered Financial Analysts (ICFA), currently administers the CFA Program.

**Table 1.** Compensation by years of experience (United States).

| | Total | < 5 Years | 5- < 10 Years | 10- < 20 Years | 20+ Years | 5+ Years | 10+ Years |
|---|---|---|---|---|---|---|---|
| 2001 median salary | $115,000 | $85,000 | $107,000 | $134,000 | $150,000 | $125,000 | $140,000 |
| 2001 median bonus | $50,000 | $30,000 | $50,000 | $75,000 | $70,000 | $60,000 | $75,000 |
| 2000 median non-cash compensation | $10,000 | $2,500 | $10,000 | $20,000 | $15,000 | $15,000 | $20,000 |
| Median total compensation | $190,000 | $125,000 | $182,000 | $235,000 | $253,000 | $220,000 | $245,000 |
| 90th percentile | $650,000 | $350,000 | $525,000 | $825,000 | $1,025,000 | $745,000 | $900,000 |

**Table 2.** Regional differences in compensation (United States).

| | Total United States | Northeast | Midwest | South | West |
|---|---|---|---|---|---|
| 2001 median salary | $115,000 | $125,000 | $108,000 | $100,000 | $120,000 |
| 2001 median bonus | $50,000 | $75,000 | $40,000 | $35,000 | $50,000 |
| 2000 median non-cash compensation | $10,000 | $10,000 | $8,000 | $10,000 | $10,000 |
| Median total compensation | $190,000 | $225,000 | $170,000 | $155,000 | $190,000 |
| 90th percentile | $650,000 | $825,000 | $490,000 | $477,500 | $683,000 |

States. Confirming findings from similar surveys in prior years, investment management professionals located in the Northeast United States are among the highest paid followed by investment management professionals located in the Western United States. Across all levels of experience, investment professionals in the Northeast and West out earn their peers in the South by 45% and 23% respectively. The regional variations in compensation are not surprising and reflect in part differences in the type and size of the financial institutions. Investment professionals employed by mutual fund organizations earn the most, followed by investment counselors and securities broker/dealers. Compensation at insurance companies falls in the middle and is lowest at banks, plan sponsors, endowments and foundations and pension consulting firms. Moreover, the largest firms (with assets under management or revenues of US$5 billion or more) pay better.

We find that stocks recommended by the financial experts produced a statistically significant 0.04% daily abnormal return or 4.0% over the six-month contest period. The magnitude is consistent with those documented in Barber and Loeffler (1993), Liu, Smith and Syed (1990) and Peterson (1995). There is economically valuable information contained in the disclosures of stock recommendations. That stocks recommended by experts do better than the market only by chance can be rejected at reasonable levels of confidence. Moreover, we confirm a direct relationship between investment performance and expertise. Stocks recommended by CFA charterholders and non-CFA charterholders from New York City and California yield statistically significant abnormal daily returns of 0.8% and 0.13% respectively.

The remainder of this study is organized as follows. Section 2 describes the nature of the contests in the *WSJ* "Dartboard" column and the characteristics of our sample of recommended stocks, which the *WSJ* refers to as the "Pros Picks". Section 3 presents the empirical results. Concluding remarks and suggestions for improvements are made in Section 4.

## 2. Sample Design

For each contest in the *WSJ* "Dartboard" column, four investment experts are randomly selected and given the opportunity to recommend one stock that is traded on any of the three national exchanges.[4] The contest period was one month in length at the inception of the column in October 1988, and extended to its current six-month length in June 1990. At the end of each contest period, the experts whose stocks achieved the two highest returns over the contest period are invited back as participants in the subsequent contest along with two newly chosen individuals.

We use the AIMR annual membership directories for the years 1995 through 2000 to identify CFA charterholders that participated in the "Dartboard" column contests over the period January 1995 to June 2000.[5] As shown in panel A of Table 3, there are a total of 66 contests in our sample period, which average 120.4 trading days in length. A total of 144 individual contestants are involved, and the distribution of contest participation rates indicates that on average every

[4]According to the *WSJ* "Dartboard" column editor, the contestants chosen represent a diverse group of financial professionals that are diversified not only by geographic location but also by type of financial institution, position held, experience, gender, age, and investment style. Unfortunately, we could not accurately assess characteristics other than geographic location.

[5]We were unable to obtain membership directories from the AIMR for earlier years that are necessary to establish which of the experts appearing in the *WSJ* "Dartboard" column are CFA charterholders.

**Table 3.** Sample description.

Panel A

| Contest period | Number of Contests | Ave. No. of Trading Days | | |
|---|---|---|---|---|
| 1/1995–6/2000 | 66 | 120.4 | | |
| **Contest participation** | **Number** | **Actual %** | **Theoretical %** | **Chi-Square Statistic** |
| 1 | 76 | 52.78 | 50.00 | 1.00 |
| 2 | 39 | 27.08 | 25.00 | |
| 3 | 15 | 10.42 | 12.50 | |
| 4 | 8 | 5.56 | 6.25 | |
| $\geq 5$ | 6 | 4.17 | 6.25 | |
| Total | 144 | 100.00 | 100.00 | |
| | **CFA Group** | **Non-CFA Group** | **Overall** | |
| Stock recommendations | 98 | 166 | 264 | |
| Winners[a] | 55 | 77 | 132 | |
| % Winners[b] | 56.1 | 46.4 | 50.0 | |

Panel B

| Number of contestants | CFA Group | Non-CFA Group | Overall | Chi-Square Statistic |
|---|---|---|---|---|
| NYC-CA area[c] | 8 | 29 | 37 | 0.58 |
| Non NYC-CA area[d] | 44 | 63 | 107 | |
| Total | 52 | 92 | 144 | |
| **Stock recommendations** | **CFA Group** | **Non-CFA Group** | **Overall** | **Chi-Square Statistic** |
| NYC-CA area[c] | 21 | 62 | 83 | 0.89 |
| Non NYC-CA area[d] | 77 | 104 | 181 | |
| Total | 98 | 166 | 264 | |
| **Winners** | **CFA Group** | **Non-CFA Group** | **Overall** | **Chi-Square Statistic** |
| NYC-CA area[c] | 15 | 35 | 50 | 0.85 |
| Non NYC-CA area[d] | 40 | 42 | 82 | |
| Total | 55 | 77 | 132 | |

[a]Recommended stocks that yielded the two highest realized holding-period returns in their respective contests.
[b]Expressed as a percentage of the number of stocks recommended.
[c]Indicates that the contestant's main office is located in either New York City or California.
[d]Indicates that the contestant's main office is located in areas other than New York City or California.

contestant had an equal probability of being among the two best performers in any given contest.[6]

[6]One individual, Mr. Francis X. Curzio, participated in a total of seven consecutive contests within this period. There were 144 contestants in total, but only 142 different individuals. Two

The individual contestants collectively made 264 stock recommendations. Note from the distribution of stock recommendations that there are twice as many stock recommendations from the non-CFA group than from the CFA group, 62.9% (166/264) versus 37.1% (98/264) respectively. But not surprising, 50.0% (132/264) of all the stocks recommended are "winners", that is, are among the two best performing stocks over their respective contest periods. This proportion is not significantly different from what we expect assuming pure chance. The difference in the percentage of stocks recommended that are winners, 56.1% for the CFA group versus 46.4% for the non-CFA group, is not statistically significant.[7]

Although it appears that the stocks recommended by the CFA and non-CFA groups perform equally well, this result is deceptive. Investment professionals located in New York City (NYC) and California (CA) cities tend to be employed by larger and more prestigious investment firms and are relatively better compensated than those in other areas of the country. Since pay is correlated with performance (Stickel, 1992), geographic location can be an important surrogate for reputation particularly among contestants in the non-CFA group.

In panel B of Table 3, observe that only 31.5% (29/92) of the contestants in the non-CFA group are from the NYC-CA area but these contestants account for 37.3% (62/166) of the stock recommendations made by the non-CFA group. In the non-CFA group, contestants from the NYC-CA area have a significantly higher proportion of stock recommendations that are winners compared to those from the non-NYC-CA area, 56.5% (35/62) versus 40.4% (42/104) respectively.[8] The performance of the non-CFA group is clearly enhanced by those from the NYC-CA area.

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individuals, Francis X. Curzio and J. Carlo Cannell, were re-invited to join the October 1998 celebrating contest because of their outstanding performance records. Other than this exception, under the current "Dartboard" rules, a contestant can re-enter as a new contestant after five years has elapsed since his/her last participation.

[7]The overall average percentage of recommended stocks that are winners, $p_0 = 50.0\%(132/264)$, and the standard error of 0.0637 is computed as $\sqrt{p_0(1-p_0)\left(\frac{1}{n_1}+\frac{1}{n_1}\right)}$ where is $n_1 = 98$ and $n_2 = 166$. The $t$-statistic for the difference in percentage winners between the CFA and non-CFA groups is 1.53.

[8]The overall average percentage of recommended stocks that are winners in the non-CFA group, $p_0 = 46.4\%(77/166)$, and the standard error of 0.0800 is computed as $\sqrt{p_0(1-p_0)\left(\frac{1}{n_1}+\frac{1}{n_1}\right)}$ where $n_1 = 62$ and $n_2 = 104$. The $t$-statistic for the difference in the percentage of contestants that are in the NYC-CA areas between the CFA and non-CFA groups is 2.13.

Statistics describing the risk and investment style characteristics of the recommended stocks were computed. For each of the 264 stock recommendations, the stock's daily returns from day 300 to day 5 prior to the stock's publication in the *WSJ* "Dartboard" column were regressed against the daily returns on the S&P 500 index during the same period. The daily stock and S&P 500 returns, which include dividends, are obtained from CRSP.[9] $\beta_i$ and $\sigma_i$ are the estimated betas and standard deviations of the residual error from the market model regressions for each stock using the Scholes and Williams (1977) procedure.

Fama and French (1992) find that the earnings-price ratio, book-to-market ratio, and market capitalization explain the cross-sectional variation in return better than a Capital Asset Pricing Model based beta and/or residual risk measures. These variables describe the portfolio manager's investment style. Growth-oriented managers favor small market capitalization stocks with low earnings-price and book-to-market ratios. Value-oriented managers favor large market capitalization stocks with high earnings-price and book-to-market ratios. The earnings-price ratio, book-to-market ratio, and market capitalization are computed based on Compustat data at the end of the year prior to the stock recommendation's appearance in the *WSJ* "Dartboard" column.

The summary statistics describing the risk and investment style characteristics are presented in Table 4. Overall, the risk and investment style characteristics of CFA and non-CFA charterholders are indistinguishable from each other with two exceptions. First, stocks recommended by CFA charterholders are on average associated with larger firms than those recommended by non-CFA charterholders. Second, stocks recommended by non-CFA charterholders from the NYC-CA area have higher systematic risk than those recommended by non-CFA charterholders who are not from the NYC-CA area.

## 3. Empirical Results

Cross-sectional regressions are used to examine the relation between expertise and performance. Two different measures of performance are utilized in these regressions. The first, excess returns, are computed as the stock's daily returns less the daily riskfree rate of interest compounded over the six-month

[9] In contrast, the *WSJ* uses only capital appreciation to measure performance in the "Dartboard" contest.

**Table 4.** Risk characteristics of recommended stocks.

| | CFA Group A | Non-CFA NYC-CA Group B | Non-CFA Non NYC-CA Group C | Non-CFA Group D | Overall | A vs. B Difference ($t$-Statistic) | A vs. C Difference ($t$-Statistic) | A vs. D Difference ($t$-Statistic) | B vs. C Difference ($t$-Statistic) |
|---|---|---|---|---|---|---|---|---|---|
| E/P[a] | 0.020 | 0.003 | 0.007 | 0.006 | 0.011 | 0.017 | 0.013 | 0.014 | −0.004 |
| | (0.008) | (0.017) | (0.017) | (0.012) | (0.008) | (1.030) | (0.673) | (0.990) | (−0.160) |
| BE/ME[a] | 0.349 | 0.329 | 0.317 | 0.322 | 0.332 | 0.020 | 0.031 | 0.027 | 0.011 |
| | (0.024) | (0.042) | (0.025) | (0.022) | (0.016) | (0.421) | (0.912) | (0.800) | (0.233) |
| Ln(ME)[a] | 20.739 | 19.221 | 19.536 | 19.416 | 19.907 | 1.518 | 1.203 | 1.322 | −0.315 |
| | (0.463) | (1.051) | (0.810) | (0.640) | (0.439) | (1.486) | (1.289) | (1.674)* | (−0.238) |
| $\beta$[b] | 1.047 | 1.200 | 0.943 | 1.041 | 1.043 | −0.153 | 0.104 | 0.007 | 0.257 |
| | (0.066) | (0.142) | (0.082) | (0.075) | (0.053) | (−1.089) | (0.982) | (0.066) | (1.683)* |
| $\sigma$[b] | 0.030 | 0.034 | 0.032 | 0.033 | 0.032 | −0.004 | −0.001 | −0.002 | 0.002 |
| | (0.001) | (0.002) | (0.002) | (0.001) | (0.001) | (−1.379) | (−0.673) | (−1.223) | (0.832) |

[a]Earnings yield (E/P), book-to-market (BE/ME), and size (Ln(ME)) are computed using financial data at the end of the previous calendar year. Standard errors are reported in parentheses.
[b]Scholes and Williams (1977) beta ($\beta$) and residual risk ($\sigma$) are estimated from market model regressions of stock returns against the S&P 500 over the interval from 300 to five days prior to the announcement of security's selection. Standard errors are reported in parentheses.

contest period. Daily riskfree rates of interest are based on the six-month US Treasury bill auction yields reported in the FRED® database maintained by the Federal Reserve Bank of St. Louis. The second, Jensen's alpha, are computed from regressions of the stock's daily excess returns against the S&P 500 daily excess returns over the contest period. In contrast to excess returns, Jensen's alpha reflects the stock's (risk-adjusted) abnormal return; that is, the difference between the stock's excess return and the excess return on a portfolio of the riskfree asset and the S&P 500 that has the same systematic risk as the stock.

The excess returns and abnormal returns are reported in Table 5. Observe that the stocks recommended by the financial experts generated a 0.03% daily abnormal return, which is statistically significant at the 10% confidence level. Accounting for the average number of trading days in the six-month contest of 120.4 days, the abnormal returns over the six-month contest periods is 4.0%. The magnitude is consistent with those documented in the Barber and Loeffler (1993), Liu, Smith and Syed (1990) and Peterson (1995) studies. There is economically valuable information contained in the disclosures of stock recommendations.

Alternatively, if investment professionals do not have an informational advantage over other market participants, then the stocks they recommend should not beat the market consistently. That is, in a market that is strong form efficient, the likelihood that a recommended stock outperforms the S&P 500 on a (systematic) risk-adjusted basis in any given contest should be 0.50. We should expect only half of the 264 recommended stocks to post an abnormal return greater than zero. The probability that 147 of the 264 recommended stocks beat the S&P 500 strictly by chance is 3.7%.[10]

Further, note that the stocks recommended by non-CFA charterholders who are also not from the NYC-CA area turned in the worst performance with a negative mean abnormal daily return of −0.02%. In contrast, stocks recommended by CFA charterholders and non-CFA charterholders from the NYC-CA area yield positive mean abnormal daily returns of 0.04% and 0.11% respectively. The likelihood that stocks recommended by CFA charterholders and non-CFA

[10]The probability that at least $k^*$ out of $n$ recommended stocks beat the market on a risk-adjusted return basis is: $p(k^*, n) = \sum_{k=k^*}^{n} C(n, k) p_0^k (1 - p_0)^{n-k}$, where $p_0$ is the likelihood that a recommended stock beats the market and $C(n, k) = \frac{n!}{(n-k)!\,k!}$. Under the null hypothesis, $p_0$ is 0.5.

**Table 5.** Comparative return performance.

| | T-Bill | S&P 500 | CFA Group A | Non-CFA NYC-CA Group B | Non-CFA Non NYC-CA Group C | Non-CFA Group D | Overall | A vs. B Difference ($t$-Stat) | A vs. C Difference ($t$-Stat) | A vs. D Difference ($t$-Stat) | B vs. C Difference ($t$-Stat) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Daily return, %[a] | | | | | | | | | | | |
| Mean | 0.02 | 0.07 | 0.11 | 0.18 | 0.04 | 0.09 | 0.10 | | | | |
| Standard error | (0.00) | (0.00) | (0.03) | (0.05) | (0.03) | (0.03) | (0.02) | | | | |
| Minimum | | −0.09 | −0.63 | −0.92 | −1.44 | −1.44 | −1.44 | | | | |
| Maximum | | 0.22 | 1.17 | 0.97 | 1.24 | 1.24 | 1.24 | | | | |
| Excess return, %[b] | | | | | | | | | | | |
| Mean | | | 0.09 | 0.16 | 0.02 | 0.07 | 0.08 | −0.07 | 0.07 | 0.01 | 0.14 |
| Standard error | | | (0.03) | (0.05) | (0.03) | (0.03) | (0.02) | (−1.26) | (1.44) | (0.34) | (2.45)** |
| Jensen alpha, %[c] | | | | | | | | | | | |
| Mean | | | 0.04 | 0.11** | −0.02 | 0.03 | 0.03* | −0.06 | 0.07 | 0.02 | 0.13 |
| Standard error | | | (0.03) | (0.04) | (0.03) | (0.03) | (0.02) | (−1.14) | (1.51) | (0.43) | (2.50)** |
| No. of stocks with alpha > 0 | | | 58 | 42 | 47 | 89 | 147 | | | | |
| No. of stocks recommended | | | 98 | 62 | 104 | 166 | 264 | | | | |
| $p$-value[d] | | | (0.043)** | (0.004)*** | (0.860) | (0.197) | (0.037)** | | | | |

[a] Based on continuously compounded daily returns.
[b] Excess returns are computed as the stock's daily returns less the daily riskfree rate of interest compounded over the six-month contest period.
[c] Jensen's alphas are computed from regressions of the stock's daily excess returns against the S&P 500 daily excess returns over the contest period.
[d] The probability that at least $k^*$ out of $n$ recommended stocks beat the market on a risk-adjusted return basis is: $p(k^*, n) = \sum_{k=k^*}^{n} C(n,k)\, p_0^k (1 - p_0)^{n-k}$, where $p_0$ is the likelihood that a recommended stock beats the market and $C(n,k) = n!/[(n-k)!k!]$. Under the null hypothesis, $p_0$ is 0.5.
*, **, and *** indicate two-tail test significance at the 10%, 5% and 1% level respectively.

**Table 6.** Cross-sectional regressions.

| | Constant | CFA Dummy[a] | Non-CFA NYC-CA Dummy[b] | E/P[d] | BE/ME[c] | Ln(ME)[c] | $\beta$[d] | $\sigma$[d] | JAN[e] | OCT[e] | $F$-Statistic $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Dependent Variable: Excess Return (%) | | | | | | | | | | | |
| Coefficient | 0.09 | 0.07 | 0.12 | −0.37 | 0.09 | 0.00 | | | | | 2.85** |
| $t$-statistic[f] | (1.22) | (1.56) | (2.24)** | (−2.29)** | (1.39) | (−1.40) | | | | | 5.0% |
| Coefficient | 0.02 | 0.04 | 0.12 | | | | −0.02 | 1.11 | | | 1.76 |
| $t$-statistic[f] | (0.46) | (0.87) | (2.44)** | | | | (−0.86) | (0.80) | | | 3.0% |
| Coefficient | 0.07 | 0.08 | 0.12 | −0.36 | 0.07 | 0.00 | | | 0.04 | 0.01 | 2.16** |
| $t$-statistic[f] | (0.90) | (1.77)* | (2.33)** | (−2.17)** | (0.99) | (−1.42) | | | (1.00) | (0.27) | 6.0% |
| Coefficient | 0.01 | 0.04 | 0.12 | | | | −0.03 | 1.00 | 0.06 | 0.01 | 1.55 |
| $t$-statistic[f] | (0.14) | (0.99) | (2.32)** | | | | (−1.06) | (0.72) | (1.43) | (0.25) | 3.0% |
| Dependent Variable: Jensen's Alpha (%) | | | | | | | | | | | |
| Coefficient | 0.09 | 0.08 | 0.13 | −0.36 | 0.04 | −0.01 | | | | | 3.47*** |
| $t$-statistic[f] | (1.28) | (1.86)* | (2.52)*** | (−2.35)** | (0.55) | (−1.97)** | | | | | 6.3% |
| Coefficient | −0.03 | 0.05 | 0.13 | | | | −0.05 | 1.97 | | | 2.99** |
| $t$-statistic[f] | (−0.69) | (1.28) | (2.74)*** | | | | (−1.95)** | (1.49) | | | 4.4% |
| Coefficient | 0.10 | 0.07 | 0.12 | −0.35 | 0.05 | −0.01 | | | 0.00 | 0.00 | 2.37** |
| $t$-statistic[f] | (1.28) | (1.69)* | (2.36)** | (−2.25)** | (0.83) | (−2.09)** | | | (0.10) | (0.03) | 6.1% |
| Coefficient | −0.04 | 0.06 | 0.13 | | | | −0.05 | 2.05 | 0.03 | −0.02 | 2.22** |
| $t$-statistic[f] | (−0.83) | (1.55) | (2.82)*** | | | | (−1.97)** | (1.54) | (0.79) | (−0.44) | 4.9% |

[a] The CFA dummy variable is 1 if the contestant is a CFA charterholder and 0 otherwise.
[b] The non-CFA NYC-CA dummy variable is 1 if the contestant is a non-CFA charterholder located in the NYC-CA area and 0 otherwise.
[c] Earnings yield (E/P), book-to-market (BE/ME), and size (Ln(ME)) are computed using financial data at the end of the previous calendar year.
[d] Scholes and Williams (1977) beta ($\beta$) and residual risk ($\sigma$) are estimated from market model regressions of stock returns against the S&P 500 over the interval from 300 to 5 days prior to the announcement of security's selection.
[e] The January and October dummy variables take on a value of 1 for contest periods that include the month of January and October respectively; and 0, otherwise.
[f] All $t$-statistics are adjusted for heteroskedasticity using White's (1980) procedure.
*, **, and *** indicate two-tail test significance at the 10%, 5% and 1% level respectively.

charterholders from the NYC-CA area generate a positive abnormal return strictly by chance is 4.3% and 0.4% respectively.

Cross-sectional regressions between raw and risk-adjusted excess returns and expertise controlling for risk and investment style differences as well as seasonal factors are presented in Table 6. All reported $t$-statistics are corrected for heteroskedasticity using White's (1980) procedure. Significance is assessed using two-tail tests.

The results confirm the basic findings thus far. Growth-oriented small market capitalization stocks with low earnings-price ratios as well as low systematic risk exhibit higher returns. The well-documented January and October monthly seasonal effects in equity excess returns do not appear to be important.[11] In addition, investment performance is directly related to expertise. Stocks recommended by CFA charterholders and non-CFA charterholders from the NYC-CA area yield statistically significant mean abnormal daily returns of approximately 0.8% and 0.13% respectively.

## 4. Concluding Remarks

As noted in prior studies, there is economically valuable information contained in the disclosures of stock recommendations. We find that stocks recommended by the financial experts featured in the *WSJ* "Dartboard" column produced a statistically significant 4.0% abnormal return over the six-month contest period. The likelihood that stocks recommended by experts does better than the market only by chance can be rejected at reasonable levels of confidence. Moreover, we confirm a direct relationship between investment performance and expertise. Stocks recommended by CFA charterholders and non-CFA charterholders from New York City and California yield statistically significant abnormal returns.

## Acknowledgments

The authors are grateful for valuable comments from the editor and two anonymous referees. The authors remain fully responsible for the contents of the paper.

[11]The January and October dummy variables take on a value of 1 if the contest period includes the month of January and October; and 0, otherwise.

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