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LETTER FROM THE EDITORS

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ON DISCOUNTING DEFERRED INCOME TAXES

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ABSTRACT

This paper revisits the debate over whether the tax effects of temporary timing differences between pretax accounting income and taxable income should be discounted. The paper provides an overview of the history of that debate, identifies the conditions under which discounting is appropriate in current practice, and examines the extent to which the tax effects of four important types of timing difference satisfy those conditions. The paper concludes that discounting is conceptually inappropriate when revenues and expenses appear in the tax return before they appear in the financial statements. It further concludes that, while discounting is conceptually appropriate when revenues and expenses appear in the financial statements before they appear in the tax return, in most cases it will be unnecessary because the difference between discounted and undiscounted measures of the tax effects will usually be immaterial.

INTRODUCTION

With SFAS No. 109, *Accounting for Income Taxes* (1992), the Financial Accounting Standards Board (FASB) adopted the asset/liability method of comprehensive interperiod income tax allocation. One issue that the Board left unresolved with this standard was whether it is appropriate to report deferred income taxes at their discounted present value. In deciding not to address this question, the Board observed, "Conceptual issues, such as whether discounting income taxes is appropriate, and implementation issues associated with discounting income taxes are numerous and complex (para.199)." The Board also reported that "[m]ost respondents to the Discussion Memorandum opposed discounting (para.198)." Perhaps the FASB felt it would be more appropriate to deal with this issue as part of its broader study of the use of present value based measurements in accounting. In any case, deferred income taxes are currently reported at undiscounted amounts. Now that the Board has issued its Concepts Statement on the use of present value in accounting measurements (FASB, 2000), it is appropriate to revisit the debate over discounting deferred income taxes, which has been relatively dormant for the past several years. The purpose of this paper is to provide an overview of the history of that debate, identify the conditions under which discounting is appropriate in current practice, and suggest the extent to which the tax effects of the various types of temporary differences satisfy those conditions. The paper will demonstrate that discounting is either conceptually inappropriate or unnecessary in most situations involving temporary timing differences.

REVIEW OF THE PAST DEBATE: ARGUMENTS FOR DISCOUNTING

Most of the debate over discounting deferred income taxes has focused on the appropriate treatment of the tax effects of temporary timing differences that arise when a company uses accelerated depreciation in its tax return and straight-line depreciation in its financial statements. One reason is likely the thorny conceptual questions such tax effects raise. Another is the relative significance of such tax effects in the financial statements. At least two studies have examined the question of significance. Regarding the income statement effect, Chaney and Jeter (1989, 9) report that, for a sample of 882 firms over the time period 1981 to 1983, "deferred tax due to depreciation differences alone accounted for approximately 69 percent of total deferred tax charges." Regarding the balance sheet effect, Lukawitz, et al. (1990, 82) report that, for a preliminary sample of 38 firms, "[f]or the year 1984 an analysis of the breakdown of entries in the deferred tax account... shows that depreciation and other accelerated expenses accounted for over 95% of the total net deferred tax credit." These latter authors note, however (94, n1) that the 95 percent figure "must be discounted somewhat because in some cases, expense recognition and revenue realization credits were offset by early statement expensing of pension, facility writedowns and other reserves." In any case, authors taking the position that such tax effects should be discounted usually rely on one or a combination of the following arguments.

The "Asset/Liability (Balance Sheet)" Argument

According to this argument, by far the one most frequently cited in support of discounting deferred taxes, the tax effects of temporary differences are assets and liabilities. To the extent that they represent long-term future cash flows, failure to consider the time value of money: (1) is inconsistent with the current accounting model's treatment of long-term assets and liabilities such as long-term notes, capital leases and pensions (Hill, 1957, 360; Davidson and Weil, 1986, 44; Wolk and Tearney, 1980, 127; Rayburn, 1987; and Weil, 1990, 53), (2) implies an unrealistic zero discount rate (Hill, 1957, 360; Davidson and Weil, 1986, 45; and Chaney and Jeter, 1989, 11), or (3) results in overstatement of the asset/liability (Davidson, 1958, 179; Black, 1966, 83). Jeter and Chaney (1988, 47) also apply a variation of this argument in their discussion of long-term deferred tax liabilities that result from nonrecurring timing differences. They contend that reporting such tax affects at their discounted amounts is relevant "[i]f the objective is to provide information useful in predicting cash flows."

During the FASB's public hearing on SFAS No. 96, senior partners from Arthur Andersen, Touche Ross, and Arthur Young all presented this argument (Liebtag, 1987, 81-82). Proponents of discounting can also make a case that the FASB's change from the deferred method to the liability method in SFAS Nos. 96 (1987) and 109 (1992) gives added weight to this line of reasoning.

The "Income Statement" Argument

According to this argument, ceteris paribus, a firm that defers tax payments by using accelerated depreciation in the tax return is better off economically than one that does not. Discounting the tax effect of the resulting timing difference allows the firm to reflect this advantage through higher net income when the timing difference arises (Nurnberg, 1972, 658; Jeter and Chaney, 1988, 47). Furthermore, subsequent reporting of imputed interest on the deferred tax allows a firm to "disclose the interest savings inherent in deferring taxes (Nurnberg, 1972, 658)."

The "Compromise" Argument

Bublitz and Zuckerman (1988, 67) suggest that "discounting might represent a compromise between those who want total allocation and those who believe that the large deferred tax liabilities will never be paid." In other words, discounting mitigates the effects of comprehensive allocation and provides amounts closer to those associated with partial allocation.

Empirical Arguments

While a number of authors have examined empirically whether the stock market regards deferred income taxes as liabilities, most have not addressed the discounting issue directly. Nevertheless, studies by Chaney and Jeter (1989) and Givoly and Hayn (1992) deserve mention.

Chaney and Jeter divided firms by industry into four groups according to decreasing "ratio of predictably recurring items... to total deferred tax expense (1989, 10)." For each group, they then regressed firms' annualized rates of return against: (1) unexpected firm earnings excluding the deferred tax component, deflated by the market value of equity at the beginning of the period, (2) the change in the noncurrent deferred tax component of earnings, similarly deflated, and (3) the firms' market rates of return. Based on their data, these authors conclude (9, 11) that, while the market uses "some of the information conveyed by the deferred tax computation, ...deferred taxes which arise from predictably recurring items provide little or no information to the market." They use this result to argue that partial income tax allocation is more appropriate than comprehensive allocation. Then, contending that the tax effects of *nonrecurring* timing differences are true assets and liabilities because they represent actual future cash flows, Chaney and Jeter conclude that discounting is appropriate because failure to discount implies an unrealistic zero interest rate (11).

Givoly and Hayn (1992) examined stock market behavior during the period Congress deliberated the Tax Reform Act of 1986. This Act reduced tax rates substantially. The authors hypothesized that, if the market viewed deferred income taxes as a liability, the reduction in the corporate income tax rate should increase the equity value of firms. This increase would be in direct proportion to the firms' deferred tax liability balances, discounted by a factor that is a function of the likelihood and expected timing of settlement of the liability. Because their results were consistent with these expectations, Givoly and Hayn conclude (1992, 394) that "investors view deferred taxes as a real liability [and] ... appear to discount it according to the timing and likelihood of the liability's settlement." As the authors make quite clear, however, this "discount" factor incorporates an adjustment for uncertainty as well as the time value of money.

REVIEW OF THE PAST DEBATE: ARGUMENTS AGAINST DISCOUNTING

Available evidence indicates that most practicing accountants are opposed to discounting deferred income taxes. The FASB (1992) notes that "[m]ost respondents to the Discussion Memorandum [on accounting for income taxes] opposed discounting (para.198)." Kantor and Grosh (1987, 87) report that respondents to their survey of Canadian Chartered Accountants on issues related to accounting for income taxes "recommended against the use of present value calculations." In a similar survey of CPAs, financial analysts, bankers and financial executives, Ketz and Kunitake (1988) found that opinion ran against discounting better than 3-to-1 overall and at least 2-to-1 in every group.

Despite this fact, relatively few authors have argued explicitly against discounting deferred income taxes. Perhaps, given that the practice has never been generally accepted, its opponents feel less need to argue the status quo than its advocates feel to argue for change. Also, most authors arguing for discounting illustrate their arguments with examples based on depreciation timing differences. For authors who contend that the tax effects of such temporary differences are not liabilities at all but rather are either realization of the asset being depreciated (Moore, 1970; Kissinger, 1986; Bierman, 1990; and Defliese, 1991) or an equity contribution from the government (Graul and Lemke, 1976; Watson, 1979), the discounting issue is moot. In any case, authors who have explicitly opposed discounting generally rely on one or more of the following arguments.

The "Not Conventional Liabilities" Argument

Stepp (1985, 100) opposes discounting deferred income taxes because he perceives that deferred tax liabilities differ from "APB Opinion No. 21" liabilities in several important ways. First, he notes that, deferred tax liabilities are not fixed sums payable at fixed dates. Along similar lines, he points out that "reversals of certain timing differences may depend on future events and, for certain timing differences, the occurrence of reversals can be determined only by arbitrary ordering." (See Brown and Lippitt, 1987, 126-28, for a detailed discussion of the reversal pattern problem.) Another difference Stepp observes is that "transactions covered by Opinion No. 21 are negotiated between buyer and seller or borrower and lender and the interest rate used to impute interest is that presumably implicit in the negotiation." In contrast, deferred income taxes result from "availability of provisions of the tax law" and no negotiation occurs. In his view, "the most important timing differences represent economic incentives -- the temporary deferral of tax payments -- that the government provides for specific transactions. The 'discount' on the deferred taxes arguably measures the amount of the economic incentives."

The "No Incurred Cost" Argument

Interestingly, it is Nurnberg (1972, 658), an *advocate* of discounting who suggests this argument. He concedes that "whereas interest is implicit in postponing tax payments, it does not necessarily follow that implicit interest should be recognized in the accounts.... Discounting deferred tax liabilities constitutes a departure from the incurred cost standard underlying the accounting for other liabilities." In other words, because interest expense on deferred tax liabilities is an opportunity cost, not an incurred cost, recognizing it in the financial statements would represent a departure from generally accepted accounting principles. Nurnberg thus rejects the common argument that consistency with GAAP requires the discounting of deferred taxes. Instead, he urges a departure from GAAP on the grounds that discounting deferred taxes with separate recognition of the resulting implicit interest is more informative for financial statement users. Graul and Lemke (1981, 314) also make this point.

The "Zero Interest Rate" Argument

According to this argument, even if deferred income taxes are a liability and even if discounting might be appropriate, the discount rate should be zero either because deferred taxes are an interest-free loan from the government (Keller, 1961, 118; Stepp, 1985, 100) or because there is no cash equivalent price for government services obtained in exchange for income taxes and the amount paid for these services is the same regardless of when payment occurs (Wheeler and Galliart, 1974, 90).

The "Complexity (Cost/Benefit)" Argument

Stepp (1985, 106, 108) maintains that discounting would significantly increase the complexity of accounting for income taxes. He states, "Determining the discount period would require considerable mechanics. The cumulative timing differences at the balance sheet date would have to be scheduled by the expected year of reversal. This requirement would go well beyond the information about the period of reversal of timing differences required by the liability method." Stepp also points to difficulties in predicting when certain types of timing differences would reverse, particularly where "[r]eversal depends on future events." According to him, other potentially costly implementation complexities would include the need to account for changes in tax rates, changes in discount rates and changes in estimated periods of reversals. It would also be necessary to apply "separate discounting calculations... for each taxing jurisdiction, and [possibly] a different discount rate (or a series of rates) ... for each foreign jurisdiction." Noting concerns about "standards overload," he concludes that the costs of discounting deferred taxes would likely outweigh the benefits.

The "No Future Cash Flow" Argument (for Items that Appear First in the Tax Return)

Stepp (1985, 99) makes the argument that cash flows associated directly with temporary differences occur when taxable revenues or deductible expenses appear *in the tax return*. Thus, for items reported in the tax return before they are recognized in the financial statements, any cash flow effects occur when the temporary differences arise not when they reverse. As a result, the tax effects of such timing differences need no discounting to be measured at their present value. This argument applies to the depreciation timing difference but would not apply to temporary differences associated with warranties or installment sale income.

The "Explicit Interest Cost" Argument

While they do not argue explicitly against discounting deferred income taxes, Lemke and Graul (1981) advocate an approach to discounting that must always give the same result as not discounting. These authors contend that there is an explicit interest cost to deferred income taxes. They define this cost as the "tax payments on any incremental taxable income that the firm may derive from investment of the funds made available to it by way of tax deferrals (309)." They maintain that, analogous to interest payments on interest-bearing debt, such payments should be included in the stream of cash flows to be discounted. They also contend that the interest rate inherent in these payments is the appropriate discount rate. These requirements insure that, analogous to interest-bearing debt discounted at its coupon rate, the discounted present value of deferred taxes will always be equal to their absolute amount.

The "Uninterpretable Flow" Argument

Brown and Lippett (1987) present a mathematical derivation that concludes:

$$TB = \sum PV_t(tr \bullet TD) - \sum PV_t(tr \bullet BD)$$

where : TB is the total tax benefit at asset acquisition
PV_t is the present value factor for time period, t
tr is the tax rate
TD is tax depreciation, and
BD is book depreciation

The authors interpret the first summation as: "the present value of all future tax reductions resulting from depreciating the asset for tax purposes (128)." With regard to the second summation, they write: "The second term, relating to book depreciation is not so easily interpreted. The present value of tax adjusted book depreciation flows has no meaning. Since book depreciation flows are not cash flows or even economic flows, the appropriateness of discounting these amounts is seriously in question. While the calculations can easily be performed, there is no meaning to the result." The authors conclude that, because their equation involves "the discounting of cost allocations that are neither cash nor economic flows,... discounting is not appropriate. (129-30)"

While this is a clever argument, it has a serious flaw. *TB* in Brown and Lippitt's equation is not, as they contend, the (present value of) the total (expected) tax benefit at asset acquisition. Rather, the present value of the total expected tax benefit at acquisition is simply:

$$\sum PV_t(tr \bullet TD),$$

the first term in their expression. Assuming *TD* represents some given depreciation method (e.g., accelerated depreciation) and *BD* represents some other depreciation method (e.g., straight-line depreciation), the authors' *TB* actually gives the present value *of the benefit of using* TD *rather than* BD *in the tax return.* In this case, both expressions have an economic interpretation. They each represent the present value of the hypothetical expected benefit from adopting a given depreciation method. Their difference is thus the advantage of using one method over the other. Presumably, this calculation would be relevant in choosing which method to use in the tax return.

CONDITIONS UNDER WHICH DISCOUNTING IS APPROPRIATE

In 2000, the FASB issued Statement of Financial Accounting Concepts No. 7, *Using Cash Flow Information and Present Value in Accounting Measurements.* The Board chose to limit the scope of SFAC No. 7 to measurement issues and not to address recognition questions (FASB, 2000, para.12). As a result, the Statement does not provide an explicit set of conditions under which discounting is appropriate as a measurement tool. This limits the Statement's usefulness as a basis for deciding whether deferred income taxes should be discounted. However, the Board notes (para. 22), "To provide relevant information for financial reporting, present value must represent some observable measurement attribute of assets or liabilities." According to the Board, that attribute is "fair value" (para. 25), "the amount at which [an] asset (or liability) could be bought (or incurred) or sold (or settled) in a current transaction between willing parties (para. 24)." In making this choice, the Board rejected several other measurement attributes, including "value-in-use," "entity-specific measurement," "effective settlement," and "cost accumulation.'

In general, there is no separable market for deferred income taxes resulting from temporary timing differences. Therefore such differences have no fair market value. There is, however, an alternative observable measurement attribute appropriate to their case -- settlement value, "the current amount of assets that if invested today at a stipulated interest rate will provide future cash inflows that match the cash outflows for a particular liability (FASB 2000, para. 24)." In current practice, there are at least two important instances where [discounted] settlement value is prescribed as the measurement attribute. The first is employers' accounting for pensions where "[a]ssumed discount rates shall reflect the rates at which the pension benefits could be effectively settled (FASB 1985b, para. 44)." The second is employers' accounting for postretirement benefits other than pensions (FASB 1990, para. 31). In both cases, the objective is not to measure fair value but rather to show the amount that would be currently necessary to settle or defease a long-term obligation. While the Board's rejection of settlement value may give it grounds to reject discounting deferred taxes, that rejection cannot be justified simply on the grounds that it is not a measurable attribute (extensive economic property).

SFAC No. 7 includes an appendix (FASB 2000, para. 119) in which the Board summarizes “Applications of Present Value in FASB Statements and APB Opinions.” The situations reflected in this table all appear to have three characteristics in common: (1) expected future cash flows resulting from an existing obligation, property or right, (2) whose amounts and timing are known or can be estimated with a reasonable degree of reliability, and (3) which involve a relatively long waiting period. To the extent that the tax effect of a timing difference also satisfies these conditions, discounting should be appropriate. However, to the extent that the first condition is violated, there is, in effect, nothing to discount. To the extent that the second condition is violated, recognition of a tax effect (with or without discounting) is inconsistent with the current accounting model, interperiod tax allocation is inappropriate in any form, and again there is nothing to discount. Finally, to the extent that the last condition is violated, the effect of discounting can be ignored as immaterial.

The remainder of this paper will attempt to demonstrate that discounting is either inappropriate or unnecessary for measuring the tax effects of most types of timing difference. In doing so, the analysis will concede the second of the above conditions. The amount of future cash flow associated with a particular temporary difference depends on two factors: (1) the amount and timing of taxable revenue or deductible expenditure to be reported, and (2) the tax rate which will be in effect when the item is reported. At the present time, the FASB appears satisfied that these factors are predictable with reasonable accuracy. Whether or not the Board is correct, however, is an empirical -- not analytical -- issue and is beyond the scope of this paper. In any case, because most tax effects violate some aspect of the first condition, the second is not particularly critical to the discussion which follows.

TEMPORARY DIFFERENCES

A component of income does not affect tax payments until it appears in the tax return. Therefore, when a revenue or expense appears in the income statement earlier than the tax return, the reported tax effect of the temporary difference represents a future cash flow. When, on the other hand, a revenue or expense appears first in the tax return, the reported tax effect of the temporary difference represents a current cash flow (in the period when the difference arises) or a past cash flow (in subsequent periods until the difference reverses). Thus temporary differences should be distinguished according to whether an item of income appears first in the tax return or the income statement.

Temporary differences should also be distinguished according to whether the item of income is a revenue or an expense. While taxable revenues always create a government claim against entity assets, deductible expenses have no tax effect unless there is first some revenue (past, present or future) against which they may be offset. (There is no "negative" income tax.) Thus, while revenue tax effects may exist alone, expense tax effects can only exist as offsets to revenue tax effects.

Because of these distinctions, the analysis which follows will consider individually whether discounting is appropriate for measuring the tax effects resulting from:

1. Revenue (or gain) reported in the tax return before the income statement,
2. Expense (or loss) reported in the tax return before the income statement,
3. Revenue (or gain) reported in the income statement before the tax return, and
4. Expense (or loss) reported in the income statement before the tax return.

Revenue (or Gain) Reported in the Tax Return before the Income Statement

Temporary differences of this type result, e.g., if customer or client advances are taxed when collected but are not reported in the income statement until earned. Paying income tax on unearned fees relieves an entity of the obligation to pay such tax later when it completes the earning process. Also, if the entity must return advances because it is unable to provide the contracted merchandise or service, it is entitled to a tax refund. Thus, tax payments on unearned fees create a right to a probable future economic benefit that should be reported in the balance sheet as an asset.

For revenue or gain reported in the tax return before the income statement, the tax payment occurs in the period when the temporary difference arises. Therefore, the amount paid already reflects present value and further discounting is inappropriate. Those who would apply discounting in this situation make the mistake of equating the absence of a negative future cash flow with the existence of a positive one. In the case of taxable revenue, there is only one direction for tax cash flow – out to the government.

Expense (or Loss) Reported in the Tax Return before the Income Statement

Temporary differences of this type generally involve some past expenditure which is deducted in the tax return earlier or at a faster rate than it is expensed in the financial statements. The most common example (and the principal cause of deferred taxes for most enterprises) is the use of accelerated depreciation in the tax return but straight-line depreciation in the financial statements. If an expenditure is tax deductible, an enterprise has the opportunity to recover part of it through tax savings. These tax savings are a form of government subsidy -- a positive cash flow that occurs when the enterprise deducts the expenditure in its tax return. Because the expenditure is deducted in the tax return before the income statement, the cash flow occurs when the temporary difference arises. Thus, the amount of the tax effect is its present value, and discounting is unnecessary.

Some accountants contend that discounting is appropriate in this situation because the tax effects of such timing differences are liabilities that will have to be paid in the future. The fallacy in this assertion is that it confuses expiration (or, perhaps better, realization) of an asset with creation of a liability.

The FASB defines assets as "probable future economic benefits obtained or controlled by a particular entity as a result of past transactions or events" (FASB 1985a, para.19). The right to a probable future tax deduction created by the expenditure to purchase a depreciable asset satisfies all the conditions inherent in this definition. It is essentially a special type of receivable that is realized as the asset's depreciation is deducted in the tax return. Because this right is obtained jointly with other economic benefits inherent in the asset, accountants do not attempt to recognize it separately. Nevertheless, an asset account that reflects expected benefits from an economic resource's use or sale also reflects any tax benefits associated with the expenditure to obtain that resource. Tax savings that result when an asset's cost is deducted in the tax return are a realization of part of the asset. Claiming these savings does not create any liability.

Because the government is concerned only with the tax return, the methods of recognizing revenues and expenses there determine the amount and timing of cash flows between the enterprise and the government. Methods used in the financial statements have no effect on these cash flows whatsoever -- regardless of whether or not they agree with the methods used in the tax return. Even though the enterprise may have recorded more depreciation in its tax return than it did in its financial statements, it has not claimed any "excess" depreciation in the eyes of the government. Thus it has no obligation as a result of misstating deductions. Claiming a deduction currently may foreclose the opportunity of using that deduction in a future period. However, it does not, by itself, create any future tax obligation. Tax obligations only result from taxable revenue or gain.

When an expense or loss is reported in the tax return earlier than the financial statements, the cash flow occurs when the temporary difference arises. Furthermore, claiming the deduction results in realization of an existing asset -- not creation of a liability to be satisfied in the future. Thus for this important type of temporary difference, discounting is inappropriate for measuring the tax effect.

Revenue (or Gain) Reported in the Income Statement before the Tax Return

Examples of this type of temporary difference include "profits on installment sales ... recorded in the accounts on the date of sale but reported in tax returns when later collected and revenues on long-term contracts ... recorded in the accounts on a percentage-of- completion basis but reported in tax returns on a completed-contract bases (Black 1966, 108-109)."

According to SFAS No. 5, "an existing condition, situation, or set of circumstances involving uncertainty as to possible ... loss [or expense] ... that will ultimately be resolved when one or more future events occur or fail to occur" is recognized in the accounts as a liability whenever the following two conditions are met: (1) "[i]nformation available prior to issuance of the financial statements indicates that it is probable that ... a liability had been incurred at the date of the financial statements …[and] it [is] probable that one or more future events will occur confirming the fact , and (2) [t]he amount ... can be reasonably estimated (FASB 1975, para.1, 8)."

An entity may not recognize revenue on the accrual basis until collection of the sales price is reasonably assured (Committee on Accounting Procedure 1953, Ch. 1A, para.1). If, however, collection of the sales price is reasonably assured, then it is probable that a liability for taxes exists. The argument that no such liability arises until an enterprise reports revenue in the tax return confuses absence of a specific settlement date with absence of an obligation. Present tax laws obligate an enterprise to pay taxes on all taxable earnings. Consistency therefore requires that when revenue is recognized, its associated tax effect should be accrued as a liability if the amount is capable of reasonable estimation.

This liability signifies an expected future cash flow resulting from an existing obligation. At least in the case of installment sales and long-term construction contracts, the timing of this cash flow is likely to be known. Therefore, assuming the amounts are capable of reasonable estimation, discounting is conceptually appropriate.

While conceptually appropriate, however, discounting will likely be unnecessary for most timing differences in this category. In the case of installment sales where the time period involved is less than a year, the difference between discounted and undiscounted measures of the tax effect will usually be immaterial. Furthermore, with the exception of home construction contracts and certain other contracts of less than two years duration, the government requires the percentage-of-completion method for long-term contracts (26 USC Sec. 460). Given the term of most home construction contracts, the effects of discounting are not likely to be material.

Expense (or Loss) Reported in the Income Statement before the Tax Return

This category includes temporary differences that arise: (1) when expenses or losses are reported on the accrual basis in the financial statements but the cash basis in the tax return, or (2) when expenditures are charged to expense or loss in the financial statements earlier than they are deducted in the tax return. Examples of the first type include timing differences related to bad debts, product warranties and deferred compensation. Examples of the second type include timing differences that would arise if an enterprise used accelerated depreciation in the financial statements but straight-line depreciation in the tax return, or if it expensed organization costs immediately in the financial statements but amortized such costs in the tax return.

When expenses or losses are reported on the accrual basis in the financial statements but the cash basis in the tax return, the accompanying balance sheet liability or contra asset reflects a probable future sacrifice of economic benefits or probable asset impairment. This is not all it reflects, however. It also reflects a deferred tax deduction that will, to the extent that current (through carryback) or future taxable revenue exists against which it may be offset, result in a positive future cash flow. If the difference between discounted and undiscounted measures of this tax effect is material, discounting is conceptually appropriate. However, because most temporary differences of this type usually reverse within one accounting period, discounting should usually not be necessary. Certainly if discounting is not used to measure the liability or contra asset, it should not be necessary for measuring the associated tax effect.

Whenever a past expenditure is deducted in the tax return, the resulting tax savings are a recovery of part of the asset's cost, similar to residual value. If an expenditure is deducted in the tax return earlier or at a faster rate than it is expensed, the tax effect of the timing difference represents a present cash flow and discounting is not appropriate. If, however, the expenditure is expensed earlier or at a faster rate than it is deducted, the tax effect of the temporary difference represents an expected future cash flow and discounting is conceptually appropriate. Even in this case, one can make a case for not discounting because, in current practice, expected salvage value is not discounted. In fact, however, the issue of whether the tax effects of such timing differences should be discounted is probably moot. In practice, timing differences of this type are rare. Ordinarily, when a past expenditure is involved, the charge against reported income will occur after the tax deduction rather than before it. Thus, this type of temporary difference is unlikely to have a significant impact on many enterprises' financial statements.

SUMMARY AND CONCLUSIONS

The controversy over whether the tax effects of temporary differences between pretax accounting income and taxable income should be discounted is a longstanding one. The FASB's decision to regard all such tax effects as similar in nature virtually guarantees that a solution will not be found. One must recognize the conceptual distinction between different types of temporary difference in order to arrive at a solution. Whether or not discounting is appropriate depends upon whether the cash flow associated with the tax effect of a temporary difference occurs when the difference arises or when the difference reverses. Only in the latter case is discounting appropriate because only in the latter case is there any future cash flow to discount. In the former case, the tax effect of the temporary difference already represents the present value of the cash flow. Thus, for revenues and expenses that appear in the tax return before the income statement, it is not appropriate to use discounting when measuring the tax effect. On the other hand, for revenues and expenses that appear in the financial statements before the tax return, discounting is appropriate. However, because, in practice, such temporary differences are normally short-term in nature, in most cases, discounting will usually be unnecessary because the difference between the discounted and undiscounted amounts is immaterial.

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THE DOW JONES INDUSTRIAL AVERAGE IN THE TWENTIETH CENTURY - IMPLICATIONS FOR OPTION PRICING

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ABSTRACT

In this paper, the historical changes in the Dow Jones Industrial Average index are examined. The distributions of index changes over short to moderate length trading intervals are found to have tails that are heavier than can be accounted for by a normal process. This distribution is better represented by a mixture of normal distributions where the mixing is with respect to the index volatility. It is shown that differences in distributional assumptions are sufficient to explain poor performance of the Black-Scholes model and the existence of the volatility smile. The option pricing model presented here is simpler than autoregressive models and is better suited to practical applications.

INTRODUCTION

The Dow Jones Industrial Average (DJIA) has, for the past 100 years, been the single most important indicator of the health and direction of the U.S. capital markets. Composed of thirty of the leading publicly traded U.S. equity issues, the DJIA is reported in nearly every newspaper and newscast throughout the U.S. and the industrialized world. While the DJIA is not an equity issue itself, it has recently assumed this role through the advent of index mutual funds, depository receipts, and the DJX index option. Investors may "purchase" the DJIA through funds such as the TD Waterhouse Dow 30 fund (WDOWX) or through publicly traded issues such as the American Stock Exchange's "Diamonds," (DIA) a trust that maintains a portfolio of stocks mimicking the DJIA.

It is appropriate at the beginning of this new millennium to look back at the historic record of the DJIA to ascertain what information there might be in the record to assist analysts and investors.

This article advances the literature in three ways. The first contribution is to model the distribution of the DJIA over the past 100 years. The focus is on the relative frequency of index changes of various magnitudes - it is a tale about long tails. An analysis from theoretical, empirical, and practical perspectives leads to the conclusion that the distribution of changes over short to moderate length trading intervals (approximately one day to one month) can be represented by a mixture of normal distributions where the mixing occurs because the volatility of the index is not stationary (constant). Normally a mixture distribution is represented as the sum of several distributions weighted so the resulting sum is also a distribution. In our analysis the mixture is accomplished through a continuous mixing distribution on the index volatility and therefore the mixing is over an infinite array of normal distributions. If the mixing distribution for volatilities is a particular type of gamma distribution, the resulting distribution will be a member of the Student-t family of distributions as shown by Blattberg and Gonedes (1974). This result has important practical implications when one compares its ease of use to the stable Paretian family of distributions discussed by Fama (1965) and Mandelbroit (1963). The second contribution of this article is to develop and test a model of option prices based on the Student distribution. The model is simpler and thereby more suitable to practical applications than autoregressive models. Empirical tests demonstrate that this model is superior to the Black-Scholes model for pricing put options on the DJIA. The third contribution of this article is the development of a new method for estimating the parameters for the Student distribution. This new technique is based on the Q-Q plot and involves estimating the slope parameter as the value that maximizes the correlation between the observed log price relatives and the theoretical quantiles. While evaluating the statistical properties of this new method is beyond the scope of this paper, the new method is simpler and easier to use than maximum likelihood estimates. It also provides estimates in certain situations when maximum likely estimates can not be found.

The remainder of the article is organized as follows. In the following section, the data and methodology are discussed. Next, the mixture distribution model for index changes is presented. The analysis continues by examining the empirical distribution of the DJIA as compared to the normal and Student theoretical distribution functions. When the predictions from the mixture probability model for index changes are compared to the historic record of changes the quality of the fit is much better than one could obtain with a normal distribution without the mixing. This is in contrast to the findings of Blattburg and Gonedes (1974) who find that monthly returns are nearly normal. Next, an application of these findings is provided. The Black-Scholes model is examined in light of the theoretical arguments and empirical findings. An alternative model is introduced that is based on the Student family of distributions is. The model is tested using data on DJIA put options.

DATA AND METHODOLOGY

To examine the historical record of changes, data on the daily level of the DJIA were obtained. Data were obtained from the Carnegie Mellon University SatLib Library, and from Sharelynx Gold. Carnegie Mellon University provides historical data on the DJIA from 1900 through 1993, including Saturday data when trading occurred on those days. This data is supplemented with recent data from Sharelynx Gold. The final data set extends from January 1, 1900 through December 31, 1999.

The historical record of changes is examined through the use of Q-Q plots. Q-Q plots are used to analyze distributions by comparing theoretical distribution functions to empirical distribution functions. The Q-Q plot, described by Wilk and Gnanadesikan (1968), provides a visualization of the fit between an assumed distribution and data. By convention, the theoretical quantiles of the assumed distribution are plotted on the horizontal axis against the ordered values of the data plotted on the vertical axis. When the data are a random sample originating from the theoretical distribution, except for a possible linear transformation of the data, the plot will be approximately linear. Departures from linearity indicate that the data have a parent distribution other than that of the theoretical quantiles. When empirical values are related to the theoretical distribution such that the data are realizations of the random variable $X = \mu + \sigma Z$ and Z has the theoretical distribution, the plotted line will have a slope of approximately σ and will cross the vertical axis at approximately μ. To estimate the parameters for the Student distribution, we use maximum likelihood estimates. In addition, the parameters are estimated using a technique new to the literature. This new technique is based on the Q-Q plot and involves estimating the slope parameter by the value that maximizes the correlation between the observed log price relatives and the theoretical quantiles. One weakness of Q-Q plots is that they can hide extreme values near the origin which are the case in our analysis. To examine these observations in additional detail, P-P plots are prepared. The P-P plot treats both ends of the spectrum equally showing the theoretical cumulative probabilities of the observations (vertical axis) plotted against the cumulative relative frequencies of the observations.

To test the pricing precision of the option pricing model developed in this paper, data on put options on the DJIA were collected for a five year period commencing in November 1997 and ending in October 2002. Put option price data were collected from the Wall Street Journal. Prices were collected for each month, for options expiring in twenty-three trading days. Only put options with trading activity on the 23rd day prior to expiration have been included in this analysis. This procedure yielded 832 usable put option prices covering a time period of 60 months. Both the normal and Student models were optimized for the options prices of that month. The normal model was optimized with respect to the volatility while the student model was optimized with respect to both the volatility and the degrees of freedom parameter, ν. The optimization criterion was to minimize the relative error of the model's evaluations where the relative error is given by (model value - market value)/market value.

The raw relative errors, by themselves, do not provide a test of the inconsistency of the normal model relative to the Student model. To construct such a test, the inverse of the degrees of freedom parameter, say $\upsilon = 1/\nu$, is used to write the null hypothesis H_0: $\upsilon = 0$. When this hypothesis is true, the normal model is correct. The alternative considered here is that $\upsilon > 0$ indicating that the normal model is inconsistent with the data relative to the Student model. Gallant (1975) shows that an approximate test of the hypothesis that a parameter's value is equal to zero can be obtained by examining the sum of square residuals of the constrained and unconstrained models. Moreover, this test is quite analogous to the reduced model test commonly used in regression analysis. Let SS_0 and SS be the sum of squared residuals for the constrained model ($\upsilon = 0$) and the unconstrained model. Then $F = (n-p)SS_0/SS$, where n is the number of observations and p is the number of parameters determined by the data in the unconstrained model, will be approximately distributed as an F random variable with 1 and n-p degrees of freedom. For our purpose, p will always be 2 but n will vary from month to month depending on the number of different put options being traded.

THE MIXTURE DISTRIBUTION MODEL FOR INDEX CHANGES

A distribution function is the best guess of how future events will actually occur. It is a mapping of the possible outcomes from an event. The many different possible maps of the future that can be hypothesized have given rise to many different distribution functions in the literature, each with its own properties. A distribution function can be described based on its mean, variance, skewness and other higher order moments. The most basic of these distributions is the normal distribution, which appears as the well known bell curve. The normal distribution is specified by the mean and variance. Here, the focus is on the variance of the distribution function.

During the past two decades, a number of articles have appeared in the finance literature related to behavior of the variance (or its square root, the standard deviation or volatility) over time. Some investigators have attempted to model the behavior of the variance as a time series in order to predict its expected value at a future point in time. Most notable is the generalized autoregressive conditionalized heteroscedacity model (GARCH) presented by Bollerslev (1986). Integrating the GARCH framework into the valuation of options has been accomplished by Heston and Nandi (1997) up to the point of an integral equation requiring numerical evaluation. The valuation equation is derived by inverting the characteristic function of the distribution of the future value of the underlying asset.

Hull and White (1987) propose that variance be modeled as a stochastic process and they conclude that the value of an option is given by the expectation of the conditional value of the option given the volatility where the expectation is taken with respect to the probability distribution of the average volatility over the duration of the option. An essential difference in their approach *vis-à-vis* that given here is that we account for the changing variability in the distribution of the future value of the underlying asset by marginalizing the conditional distribution of log price relatives with respect to the distribution of the variance. The marginal distribution is then used to recast the option evaluation model.

A frequently used model in Bayesian statistics and decision analysis that accounts for uncertainty in the variance of the process is the normal-gamma natural conjugate relation. Briefly, this relation allows that a joint posterior distribution for the mean and variance of a normal process be in the same family as the joint prior distribution when the information is updated by a sample of values from a normal process (Raiffa and Schlaifer 1961). The marginal density of the uncertain variance *V*, up to a constant, is given by:

$$f(V|\alpha,\beta) \propto e^{-\beta/V} V^{-\alpha-1}. \tag{1}$$

This density is termed an inverted gamma density as h = 1/V will have the usual gamma density, which up to a constant, is given by:

$$f(h|\alpha,\beta) \propto e^{-\beta h} h^{\alpha-1}. \tag{2}$$

The parameter *h* is called the precision of the process.

Next consider a sequence of independent random variables each drawn from a normal distribution with mean μ, but each having a variance independently drawn from the inverted gamma distribution. This sequence of random variables will be indistinguishable from a similar sequence of student random variables having a centrality parameter of μ, a precision parameter of $h = \beta/\alpha$, and a shape parameter (degrees of freedom) of $\nu = 2\alpha$. The density of each of these random variables is:

$$f_s(x|\mu,h,\nu) = \frac{\nu^{\nu/2}}{B(\frac{1}{2},\frac{\nu}{2})} h^{1/2}[\nu + h(x-\mu)^2]^{-(\frac{\nu+1}{2})}. \tag{3}$$

What is important here is that modeling the uncertainty about the variance applicable to any price relative through the inverted gamma distribution leads to a distribution of price relatives different from that usually assumed. Moreover, the distribution of price relatives will have thicker tails as the Student density has greater kurtosis than the normal density.

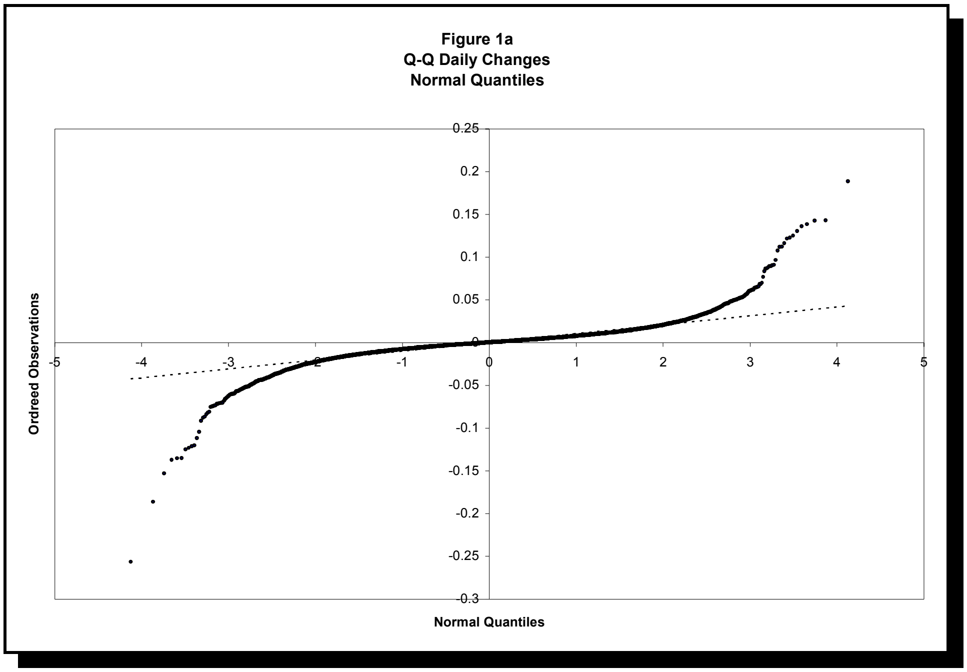
The conditions necessary for the distribution of log relative prices to be a member of the Student family will be given for both *ex post* and *ex ante* perspectives. Ex post, consider a sequence of log relative prices Y_1, Y_2... such that the sequence consists of subsequences of independent normal values with a constant variance in each subsequence and a mean common to all subsequences. Denote the length of the i^{th} such subsequence by n_i. Assume that the variance of the normal distribution generating values in the i^{th} subsequence is drawn randomly and independently (with respect to the variances of other subsequences) from the distribution given in equation (1). Let the total number log prices in the sequence be $m = n_1 + n_2 +$..... Then, if for each *i*, n_i/m approaches zero as *m* grows without bound, the sequence Y_1, Y_2,... will have an empirical distribution function that converges to a member of the student family whose parameters depend on the values of α and β in equation (1).

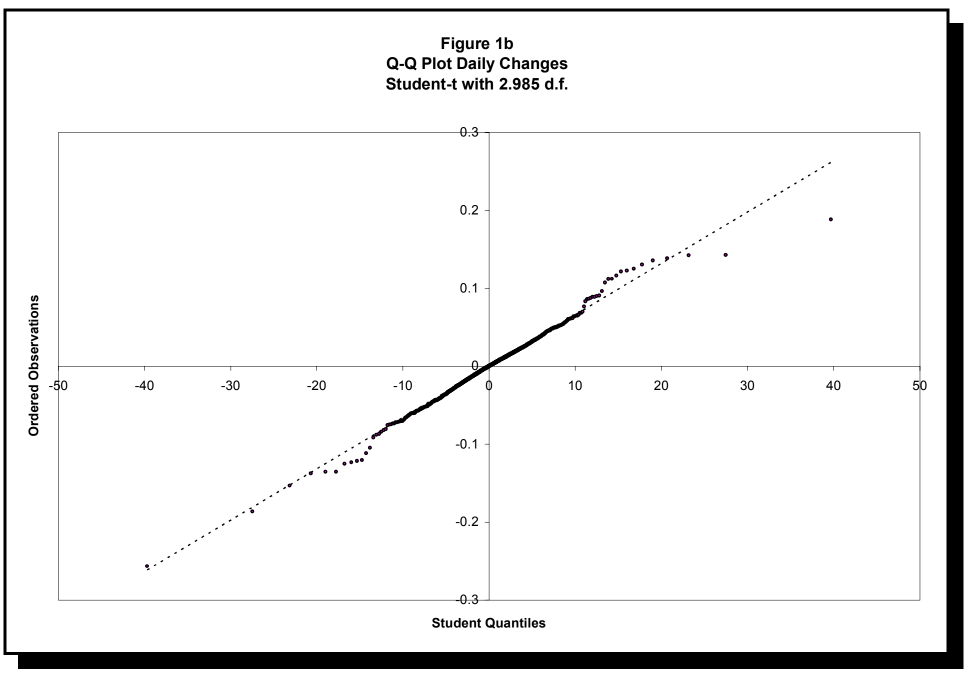
The essence of the condition stated above is that the volatility changes over time but remains fixed within time periods that are asymptotically negligible with respect to the length of the sequence. The lengths of the subsequences are arbitrary and restricted only by the negligibility assumption. This assumption is much weaker than those imposed by Garch models and the resulting model is simple enough to have practical application. From the *ex ante* perspective, the following assumptions lead to the Student model for the future value of an asset: a.) The distribution of the log of the future price relative to the current price has a normal distribution with a known mean but uncertain variance and b.) The uncertainty about the variance is expressed by the density in equation (1). In the following sections, both the *ex post* and *ex ante* perspectives will be examined empirically. First, the historical record of the DJIA is examined and compared to the student model to provide an evaluation from the *ex post* perspective. This is followed by an examination of the pricing of puts from an e*x ante* perspective where the valuations provided by the market are compared to valuations made using the Student model.

THE HISTORIC RECORD

In this section, the historical record of changes in the level of the DJIA is examined. The section begins with an examination of the daily price relatives given by $Y_i = \ln(X_i/X_{i-1})$ where X_i is the closing value of the DJIA on the i^{th} day. Note that the price relatives calculated here ignore any returns from dividends. Over the past century there have been 27,425 of these price relatives. One of these price relatives has been dropped from this analysis. This was done because the New York Stock Exchange was closed for a period of several months during World War I. The price relative from this close to the subsequent reopening has been eliminated because of the excessive period between prices. For other closings, such as weekends or holidays, the price relatives have been computed on the closing values of the consecutive trading days without adjustment for any intervening non-trading days. Lawrence Fisher suggested that the interposition of nontrading days could explain the thickness of the tails for stock price relatives (as noted in Fama, 1965). Such a model would employ a mixture of distributions differentiated by the presence and number of nontrading days between trading days. Fama (1965) however, found no empirical support for this argument. Examining a random sample of eleven stocks from the Dow Jones Industrial average, Fama (1965) found that the weekend and holiday variance is not three times the daily variance as is suggested by the mixture of distributions model. Rather, the weekend variance is found to be about 22 percent greater than the daily variance.

Figures 1a and 1b are the normal Q-Q plot and the Student Q-Q plot, respectively, for the 27,474 daily price relatives. The shape or degrees of freedom parameter for the Student plot was found using the method of maximum likelihood and is 2.985.





Nonlinearity is apparent in both Figures 1a and 1b but the amount of nonlinearity is much greater in Figure 1a than 1b indicating a poorer fit of the data to the theoretical distribution. The lack of fit is particularly pronounced in the tails in Figure 1a. A straight line appears in both figures. This line is the linear regression of the order observations (log price relatives) on the theoretical quantiles. The intercept provides an estimate of the location of the distribution while the slope provides a measure of the scale (standard deviation when it exists) of the data. The generalized log likelihood ratio test of the hypothesis of normality as compared to the alternative of a Student density produces a chi-squared statistic with one degree of freedom of $\chi_1^2 = 121{,}447$ clearly favoring the alternative.

Obtaining maximum likelihood estimates for the Student density is somewhat tricky. The Solver optimizer in Excel 2000 often failed to converge to the correct estimates. This failure was detected by examining the derivatives of the likelihood function at the estimates. If these derivatives were not zero, the maximum likelihood estimates had not been found. A change to Premium Solver (Frontline Systems, 2001) consistently produced usable results.

Another, simpler, method for estimating the shape parameter, ν, of the Student distribution was developed. This method is based upon the Q-Q plot. The shape parameter is estimated by the value that maximizes the correlation between the observed log price relatives and the theoretical quantiles. This method is new to the literature and at this time, the statistical properties (sampling distribution and confidence intervals) associated with this method have not been developed. The method is very easy to apply relative to maximum likelihood estimation. It can be implemented on a spreadsheet using native Excel functions and the solver distributed with Excel.

Table 1 contains both the maximum likelihood estimates and correlation-based estimates for ν for three holding periods; 1 day, 23 days (approximately one month), and 274 days (approximately 1 year.) When estimating ν for 274 day holding periods, it became apparent that one observation was particularly influential in determining the estimate of ν. The corresponding period was mid 1931 to mid 1932. Eliminating this value and repeating the estimation process lead to a substantial increase in the estimate of ν as seen in Table 1. Table 1 contains both the maximum likelihood estimates and correlation-based estimates for ν, the shape parameter, for three holding periods; 1 day, 23 days (approximately one month), and 274 days (approximately 1 year).

Table 1: Estimates of the Shape Parameter ν

Holding Period	Maximum Likelihood Estimate	Correlation Estimate from Q-Q Plot
One day	2.82	2.98
23 Day (monthly)	3.89	3.95
274 Day (annual)	4.15	3.58
274 Day with One Observation Removed	10.24	8.62

Moment estimators, when available, often provide a simpler route to obtaining estimates. Although a moment estimator for ν can be constructed from the fourth and second central moments (roughly the kurtosis and variance) such estimators fail for values of $\nu \leq 4$ as the kurtosis fails to exists for $\nu \leq 4$ just as the variance fails to exist for $\nu \leq 2$. But it is this range of values that is of interest in describing the price changes for DJIA and thus we have not employed moment estimators.

Another path to obtaining an estimate of ν is to examine the empirical volatility and to estimate the parameters of the gamma density from the empirical distribution of volatilities. While the historical record of daily closing values does not permit one to estimate one-day volatilities, as only one observation is available for each period, it does permit estimation for longer holding periods. Consider a 23 trading-day holding period, approximately one month. (Note: There are 1191 complete 23 day periods in the one-hundred year record versus 1200 months. During the early part of the 20th Century, the NYSE was open on Saturdays and thus there were more trading days per month during that period. Twenty-three days was chosen as the most representative integer number of days for a month for the entire period and consistently adhered to throughout the study.) We assume that in each 23 day holding period there is a constant volatility but the underlying volatilities differ from period to period according to the inverted-gamma process described earlier. Precisely, during each 23 day holding period there is a precision, say h, so that the daily price relatives during the period are normal with mean μ and standard deviation $h^{-1/2}$. Moreover, if the relative price changes in each holding period are independently and identically distributed normal random variables, the empirical volatilities, S_{23}, are related to the chi-square random variable χ_k^2 by $\chi_k^2 = k\, h\, S_{23}^2$ where k = n - 1 and n is the number of trading days in the holding period, in this case 23. The value k is the number of degrees of freedom for χ_k^2.

Now, $\chi_k^2 / [(n-1)\, h] = S_{23}^2$ so that S_{23}^2 depends on both Y and h. The joint distribution of χ_k^2 and h is given by:

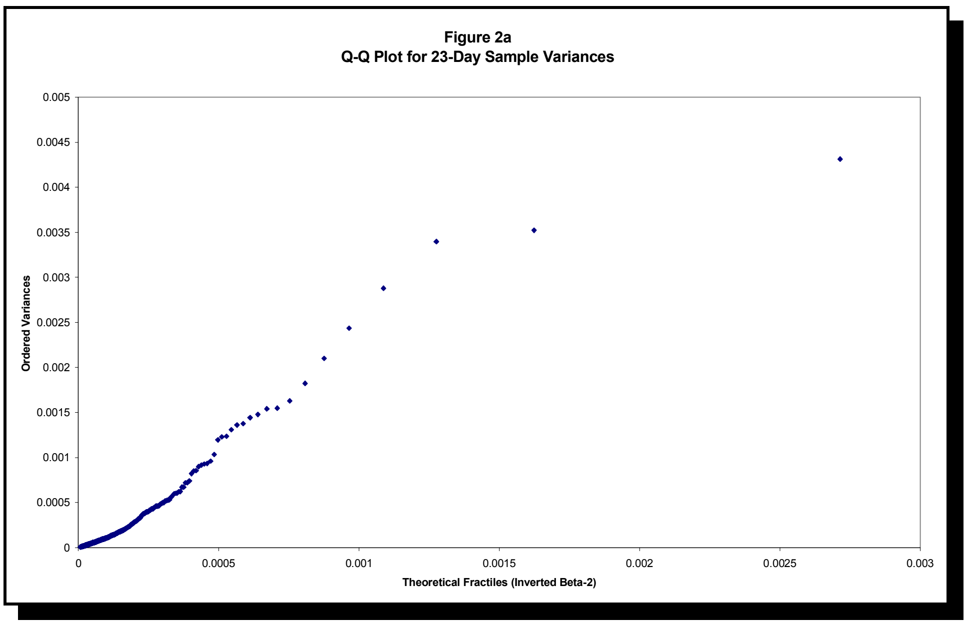
$$g(x,h) \propto x^{\frac{k}{2}-1} h^{\frac{k}{2}+\alpha-1} e^{-h(\beta+xk/2)}. \tag{4}$$

From this joint density, the unconditional density of S232 is easily found and is given by:

$$f(s) \propto \frac{s^{\frac{k}{2}-1}}{(\frac{2\beta}{k}+s)^{\frac{k}{2}+\alpha}}. \tag{5}$$

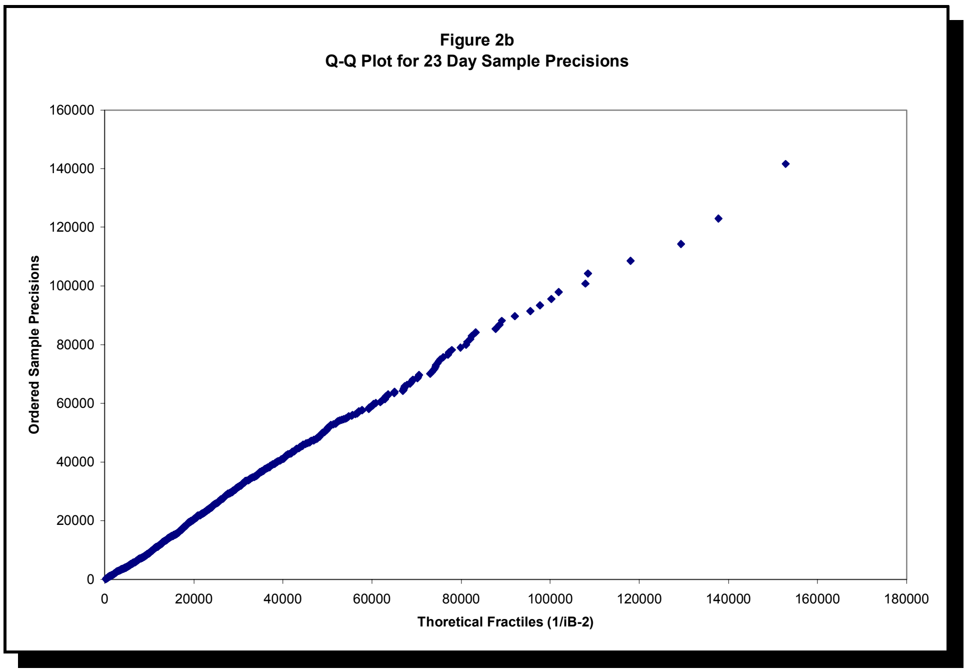
The unconditional density of the holding period variances, S_{23}^2, is known as an inverted beta-2 density with parameters k/2, α, and 2β/k. (Raiffa and Schlaifer, 1961). The quantiles of this density maybe found by direct transformation from the standard beta density with parameters k/2 and α. The required transformation is $s = 2\beta x/[k(1-x)]$ where x is a quantile of the beta distribution and s is the resulting quantile of the distribution of S_{23}^2.

Figure 2a displays a Q-Q plot of the 1191 values of S_{23}^2 against the theoretical quantiles of the inverted beta-2 distribution with k = 22 and α = 2.18. The plot shows good linearity with exception of the two most extreme values which are both somewhat smaller than one might expect. The value of α was found by maximizing the correlation between the ordered data values and the theoretical quantiles.



The companion figure, 2b, shows the inverses of the empirical variances, the empirical precisions, plotted against their theoretical quantiles which are just the inverses of the quantiles of the inverted beta-2 distribution for the 1191 values with 23-day holding periods. Here, the linearity is even stronger. This Q-Q plot "hides" the two extreme values identified in Figure 2a near the origin, however. It is clear that each of the two plots compresses a different end of the spectrum of values, accentuating one end at the cost of sensitivity in the other end of the spectrum. A plot that treats both ends of the spectrum equally is the P-P plot which shows the theoretical cumulative probabilities of the observations (vertical axis) plotted against the cumulative relative frequencies of the observations.

Figure 2c is the corresponding P-P plot for the empirical variances. The plot for the precisions would be identical except the order would be reversed. For the P-P plot, it is necessary to estimate the parameter β, for the plot to be meaningful. This was not the case for the Q-Q plot in which β determined the slope, but not the linearity, of the regression. The parameter β was estimated by maximizing the correlation between the theoretical cumulative probabilities and the cumulative relative frequencies. The resulting value is $\beta = .00011$. Alternative estimates of both α and β can be obtained using the methods of moments. Designating the i^{th} central moment as m_i we have $m_1 = \beta/(\alpha-1)$ and $m_2 = m_1^2[(n-1)/2 + \alpha - 1](2/k)/(\alpha-2)$. Solving for α and β in terms of the moments gives $\alpha = [k(2r-1)-2]/(rk-2)$ and $\beta = (\alpha-1)m_1$. Examining the expression for m_2 we see that the moment will not exist if $\alpha \leq 2$. This limits the usefulness of the moment estimators as, recalling that the degrees of freedom for the student distribution is twice α, it is this range of values that are of interest for the 23 day holding period.



Figures 3a and 3b are the normal and Student Q-Q plots for the 23 day holding periods. Figures 3a and 3b are the normal and student Q-Q plots for the 23 day holding periods of the Dow Jones Industrial Average Index from 1900-2000 respectively. Again the behavior of the price relatives is better modeled by the Student density than the normal density. This is particularly true of extreme changes, both positive and negative. The generalized log likelihood statistic is again highly significant (chi-squared with one degree of freedom with a value of 2884) leading to the conclusion that the distribution of price changes is better represented by the Student density than the normal density.

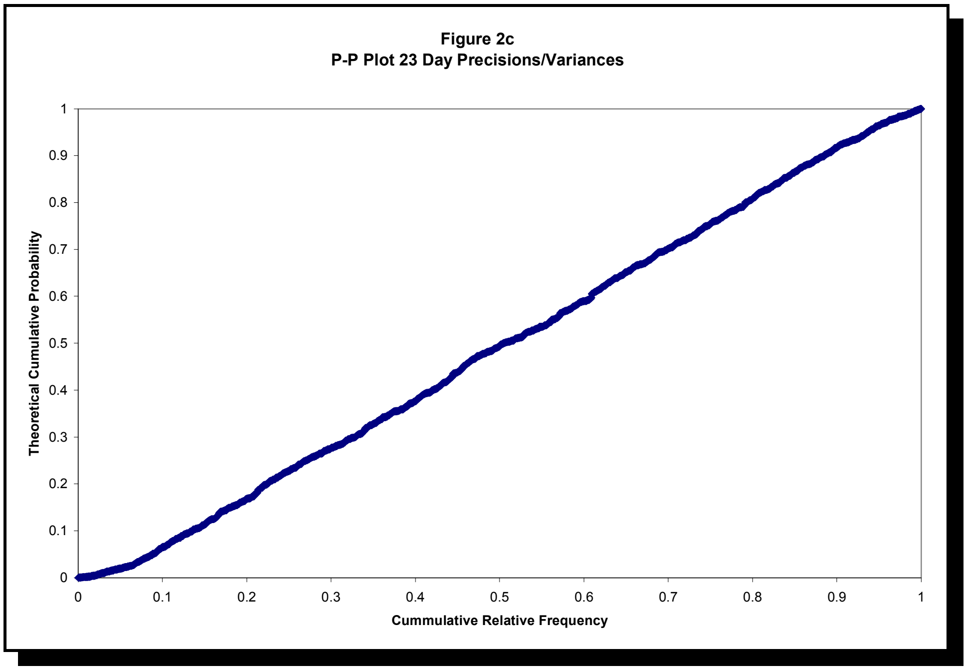


Figure 2c
P-P Plot 23 Day Precisions/Variances
Theoretical Cumulative Probability
Cummulative Relative Frequency
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1

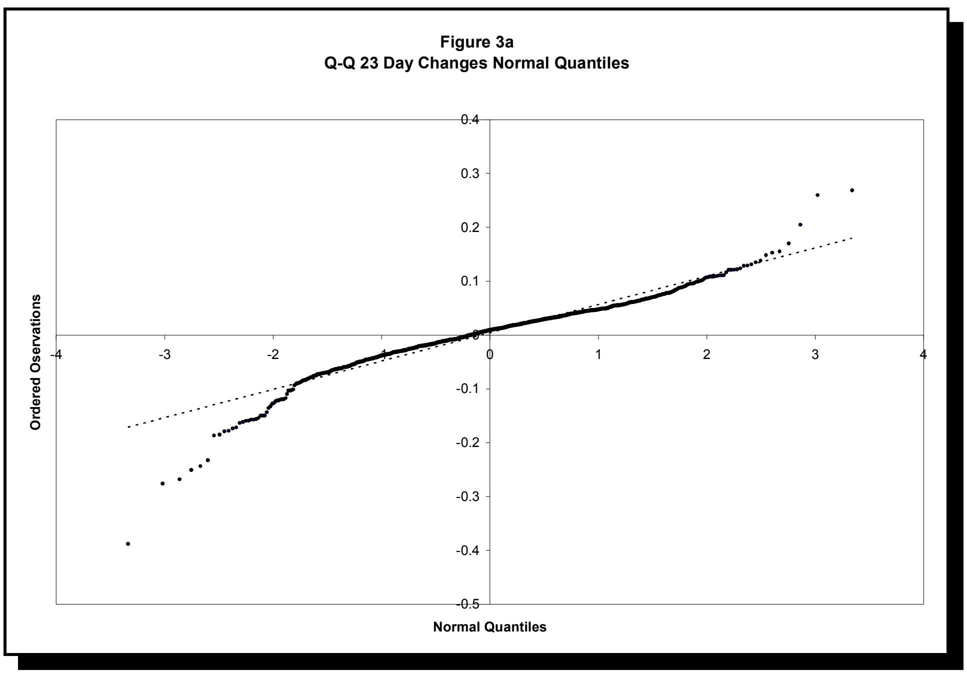
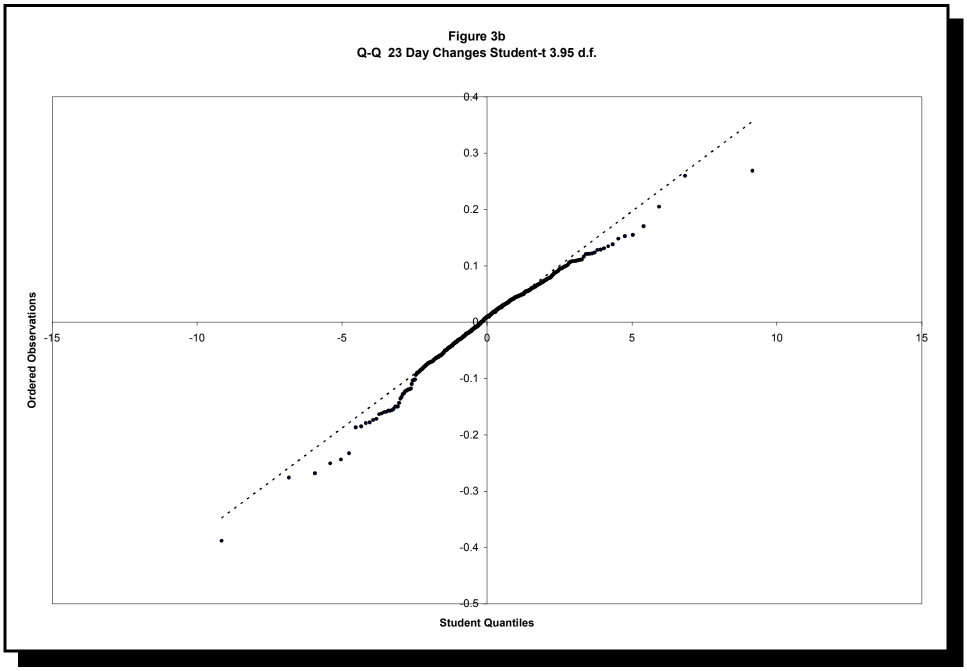
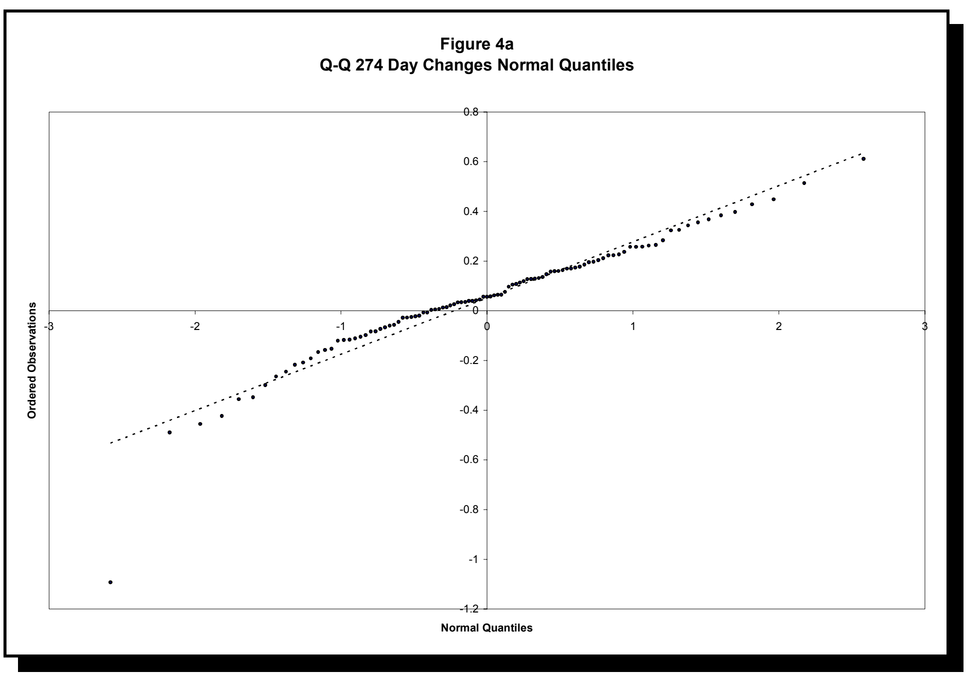
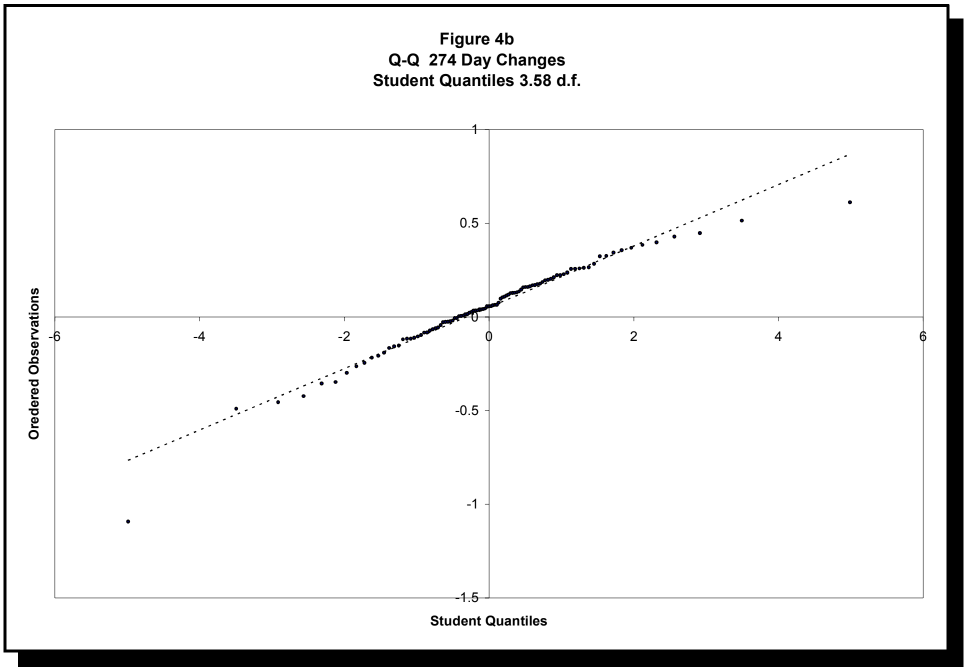


Figure 3a
Q-Q 23 Day Changes Normal Quantiles
Ordered Oservations
Normal Quantiles
-4
-3
-2
-1
0
1
2
3
4
0.4
0.3
0.2
0.1
-0.1
-0.2
-0.3
-0.4
-0.5



Finally, the historical record for 274 day holding periods is examined. Figures 4a and b display the Q-Q plots for the normal and Student densities, respectively.





The Student density has 3.58 degrees of freedom which maximizes the correlation between the theoretical and empirical quantiles. The case for the mixture densities is not as strong here as it was for the 23-day holding periods. Examination of the companion normal Q-Q plot shows reasonably good fit in the upper end of the distribution but poorer fit in the lower tail with one price relative being much larger than is consistent with the normal distribution. The Student Q-Q plot partially corrects for the most extreme observation and has better fit in the entire lower tail compared to the normal. Still, this extreme observation, which represents the period from mid 1931 to 1932, appears to be extraordinary. It is interesting to note that this extreme value is nearly five sample standard deviations below the sample mean. Using the maximum likelihood estimates of the parameters of the normal and Student distributions, gives cumulative probabilities for this observation of .0000005582 for the normal model and .0012 for the Student model. Once again the likelihood ratio test soundly rejects the hypothesis of normality with a chi-squared statistic of 79.

THE BLACK-SCHOLES MODEL

The Black Scholes Option Pricing Model (Black and Scholes, 1973) can be used to compute the value of an option. Consider an option with a strike price x and time to maturity of t, on a stock with a current asset price of p, t days before expiration, and the volatility of the log price relative over the entire t day period is s. With a risk free rate of interest of r, the Black Scholes model prices call and put options respectively as follows where n(d) is the value of the cumulative normal distribution evaluated at d1 or d2:

$$Vc = n(d1)p - x(e^{-rT})n(d2)$$

$$Vp = x(e^{-rT})n(-d2) - pn(-d1)$$

where: $$d1 = \frac{\ln\left(\frac{p}{x}\right) + [r + \frac{s^2}{2}]t}{s\sqrt{t}}$$ and $$d2 = d1 - s\sqrt{t}$$

In its raw form, the Black Scholes model is only applicable to non dividend paying European options. However, many revisions of the model have been developed to handle other situations and special applications. Merton (1973) modified the Black Scholes model to accommodate continuous dividends. Black (1975), Roll (1977), Geske (1979, Whaley (1981) and Broadie and Glasserman (1997) all developed models for valuing American options. Models for valuing options on futures have been developed by Black (1976) and Ramaswamy and Sundaresan (1985). Other models have been developed for pricing options on stock indexes (Chance, 1986), options on currencies, (Amin and Jarrow, 1991, Bodurtha and Courtadon 1987, and others), and options on warrants (Lauterbach and Schultz, 1990)

Development of the Black and Scholes model was based on a number of assumptions. One of the assumption inherent in the usual formulation of the Black-Scholes model (Black and Scholes, 1973), is that the log of the ratio of successive prices of an underlying asset follow a Weiner process (Feller, 1971). This, in turn, requires that successive changes over equal time intervals are independently and identically distributed normal random variables. In this paper, the primary concern is the assumption of identical distributions. Such a condition, often called stability, requires the mean and variance of returns to be constant over the period of concern. Suppose, in contrast, that the variance of the log of successive price-relatives varies so that the distribution of changes is not constant. One potential result is that the distribution will have thicker tails (greater kurtosis) than one would otherwise expect.

THE EVALUATION OF DEEP OUT OF THE MONEY OPTIONS

Deep out of the money options are those having a small value due to the strike price being much larger or smaller than the underlying asset's current value relative to the volatility of the asset's price over the remaining term of the option. For a call option, the strike price that is much greater than the current price relative to the volatility means that the option is deep out of the money.

Conversely, a put option is deep out of the money if the strike price is much lower than the current price relative to the volatility. The pricing of such options is sensitive to the tail behavior of the underlying asset's price -- the upper tail for deep out of the money call options and the lower tail for deep out of the money put options. While the well known Black-Scholes option pricing model has been shown to provide good estimations of option prices overall (See Black and Scholes, 1972, Galai 1977 and 1978), Macbeth and Merville (1979) and Rubenstein (1985) show that the Black and Scholes model miss prices deep out of the money options. That said, Rubenstien compares the Black and Scholes model to the jump model from Cox and Ross (1975), the mixed diffusion jump model from Merton (1976), the constant elasticity of variance model from Cox and Ross (1976), the compound option diffusion model of Geske (1979b) and the displaced diffusion model from Rubenstein (1983). He finds that none of the alternative pricing models consistently performed better than the Black and Scholes model. The evidence regarding the distributional properties of the DJIA presented above implies that pricing errors might be reduced by utilizing models that incorporate different distributional assumptions. The paper continues by developing such a model. Consider a theoretical European put option that has a strike price of x, a current asset price of p at t days before expiration, and drift of m for the t-day period. Further, assume that the volatility of the log price relative over the entire t day period is s. To be clear, s is the standard deviation of the log of the ratio of the price of the underlying asset t-days hence to the current price of the underlying asset. If we assume that the log price relative follows a normal distribution with mean m and standard deviation s, the present value of the expected return of the put option is given by the integral expression:

$$e^{-rt}\int_{-\infty}^{\ln(x/p)}(x-pe^{y})\frac{1}{\sqrt{2\pi}s}e^{\frac{1}{2}(\frac{y-m}{s})^2}dy=\left[\left[-p\Phi\left(-\frac{\ln(p/x)+m+s^2}{s}\right)+xe^{-rt}\Phi\left(-\frac{\ln(p/x)+m}{s}\right)\right]\right] \tag{6}$$

where r is the risk free interest rate, t is the time until expiration of the option, and Φ is the standard normal distribution function. This expression is equivalent to Black-Scholes option pricing model if one makes the substitutions $m = rt - s^2/2$ and $s = \sigma t^{1/2}$. Similarly, if the log price relative follows a Student distribution with parameters m, h, and ν, the value of the option is:

$$e^{-rt}\int_{-\infty}^{\ln(x/p)}(x-pe^{y})\frac{\nu^{\nu/2}h^{1/2}}{\beta(1/2,\nu/2)}[\nu+(y-m)^2/h]^{-\frac{1}{2}(\nu+1)}dy \tag{7}$$

The price of the option is affected by changes in the underlying parameters in the same direction as the Black-Scholes model. Like the Black-Scholes expression, this expression involves integration and cannot be stated in simple terms. However, numerical evaluation of the integral is fairly straightforward. Here, Simpson's extended rule is used for evaluation (Press et al., 1992). The intention is to show that 1) the use of the student distribution *vis-a-vis* the normal distribution makes a significant difference in evaluating out of the money put options and 2) the well known volatility smile can be accounted for by the tail behavior of the student distribution.

For the example, consider a put on an underlying asset with an annual volatility of $\sigma = .2$, a risk free interest rate of 0.1, and a current value of $100. To highlight the differences attributable to the differences in distributions, we will select parameters for the Student distribution that yield the same expected log price relative and the same variance of the log price relative as the normal distribution. Thus, we choose $m = (rt - \sigma^2/2)(T)$, $h = \nu/[(\nu - 2)\,\sigma^2]$. For the demonstration we will use $n = 4$ and $T = 1/12$, corresponding approximately to a one month put on the DJIA. Exercising the normal and Student models for the value of the put option at various strike prices from $85 to $110 produces the values shown in Figure 5. Options that are out of the money appear on the left hand side of the graph. Options that are at the money occur at a strike price of $100, and options that are in the money appear on the right hand side of the graph. It is clear that the Student model provides higher values for deep out of the money put options and lower values for options with strike prices near the current price. The longer tails of the Student density then provide an explanation for the phenomena of the under pricing of deep out the money put options by the Black-Scholes model. This further suggests that the problem can be corrected by altering the distributional assumptions utilized in the Black and Scholes model.

Figure 5
Put Valuations

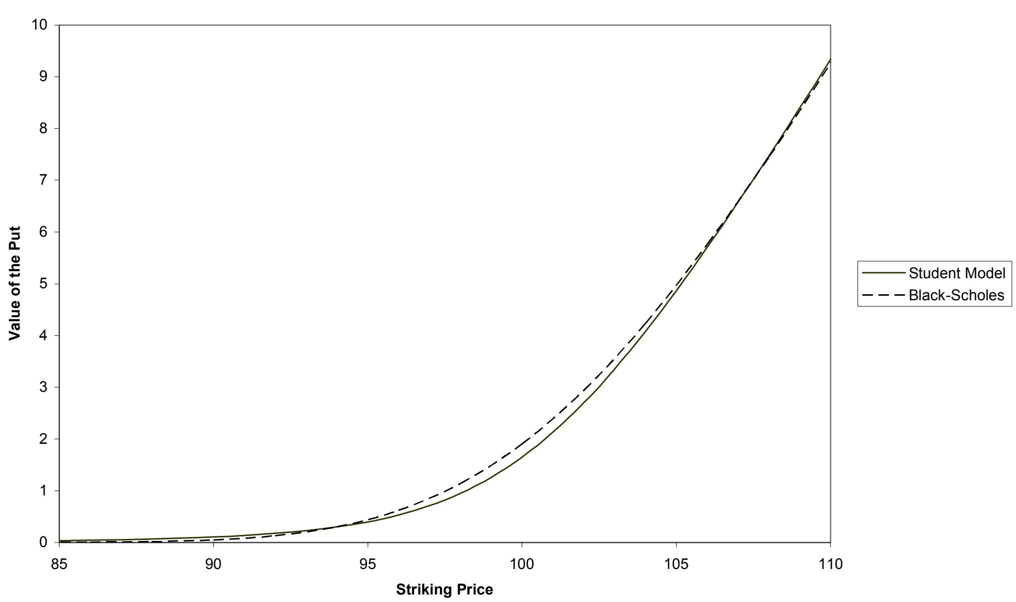
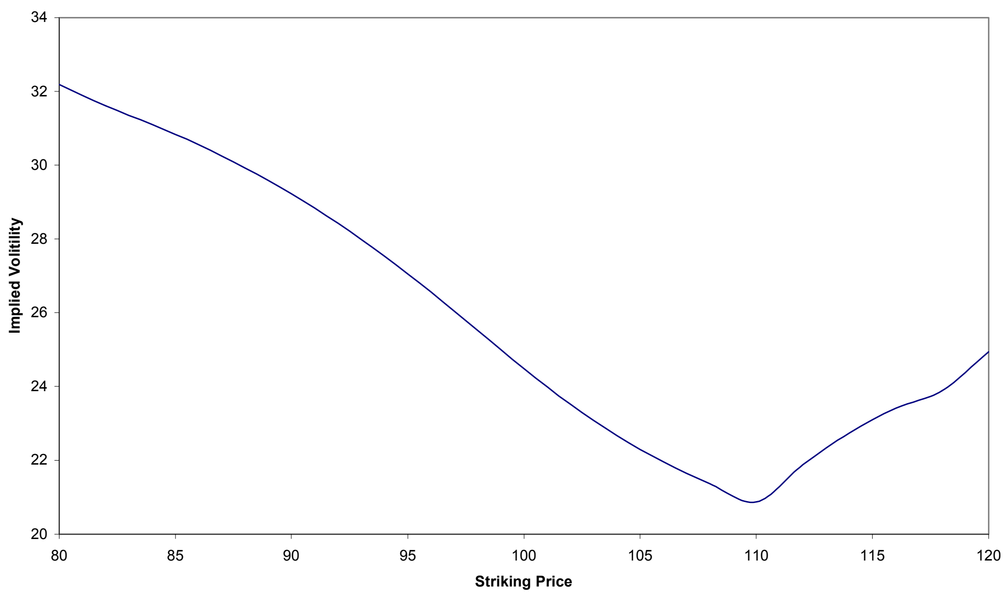


Figure 6 shows the implied volatilities needed to bring the Black-Scholes model (normal distribution) into equality with evaluations provided by the Student model. We note that the curve is similar to what analysts call a volatility smile curve (Hull, 1989), reinforcing the idea that the market prices options in a manner more similar to the Student model than the normal model.

Figure 6
Volitility Smile



Surprisingly, the Student model cannot be used in a risk neutral setting to price call options. The required integrals do not converge implying an infinite value to any call option. More precisely, $E(e^X)$ does not exist if X is a Student random variable. This holds for any finite degrees of freedom. Conversely, $E(e^X)$ does exist if X is a normal random variable. There are several possible explanations to reconcile the Student model and the obvious fact that these options have finite values in the market. First, an examination of the Q-Q graphs for 1-day, 23-day, and 274-day holding periods show some lack of symmetry in the tails of the distributions with the upper tail being somewhat less fat than the lower tail. If the upper tail were to have a distribution that approaches zero sufficiently fast, faster than a Student tail, the value of the option would be finite. Alternatively, the market may not evaluate options in a risk neutral manner. If the market were sufficiently risk averse, an argument could be constructed that would allow finite evaluations. Whether either of these explanations or some other explanation will bear fruit is an open question.

While the Student model can not be used in a risk neutral setting to price call options directly, all is not lost. Because put options can be valued in the risk neutral setting, put-call parity conditions can be utilized to price call options. Put-call option parity was first introduced by Stol (1969). Others have confirmed and refined the approach (Gould and Galai, 1974, Merton, 1973b). In order to price call options using put call parity, information on the current market value of a put option on the same asset with the same strike price and time to maturity, the strike price, the risk free rate of interest and the current market value of the underlying asset are needed. The put-call relationship is specified as $C = P + S - PV(X)$. Where X is the exercise price, P is the current price of the put option as estimated using Equation 7 and S is the current market value of the underlying security. The put-call parity relationship can be utilized to compute the implicit price of any call option given the implicit price of the put option.

As a final demonstration, the normal (Black-Scholes) and Student models were applied to put options on the DJIA during a five year period commencing in November 1997 and ending in October 2002 . Put option price data were collected from the Wall Street Journal. Prices were collected for each month, for options expiring in twenty-three trading days. Only put options with trading activity on the 23rd day prior to expiration have been included in this analysis. This procedure yielded 832 usable put option prices covering a time period of 60 months. The Treasury Bill rate for each month was used as the risk free rate and as the drift rate. Both the normal and Student models were optimized for the options prices of that month. The normal model was optimized with respect to the volatility while the student model was optimized with respect to both the volatility and the degrees of freedom parameter, ν. The optimization criterion was to minimize the relative error of the model's evaluations where the relative error is given by (model value - market value)/market value.

The results are presented in Table 2. The table contains pricing errors for the Black Scholes and Student models. MO is the option expiration month, N is the number of put options expiring in that month with trading on the 23rd trading prior to expiration, NV is the volatility that optimizes the normal model, NE is the average pricing error as computed by the Normal Model, SV is the volatility that optimizes the Student Model, NU is the degrees of freedom, SE is the average pricing error as computed by the Student Model, and RE is the error of the Student Model in relation to the Normal model. The spread parameter in the normal model is σ, the volatility rate. For the student model, we have reported $\{\nu/[(\nu - 2)h]\}^{1/2}$ which is the annualized standard deviation of the log price relatives when that standard deviation exists (i.e. $\nu > 2.$). This value is equivalent to σ for infinite ν

The average of the absolute values of these errors for the normal model is .2649 (26.49% error) while the Student model had an average error of 0.1458 (14.58% error). On average, the student mode error is 56.00% of the normal model error. Much of the error associated with both models is accounted for by options that are deep out of the money. Prices for options are quoted in discrete units ($1/16 increments prior to September of 2000 and $.01 increments after that date) and options that are worth very little will tend to exhibit a large relative error because of the relative lumpiness of prices at these low price levels.

Table 2
Analysis of Pricing Errors for Black-Scholes and Student Models

MO	N	NV	NE	SV	NU	SE	RE	MO	N	NV	NE	SV	NU	SE	RE	MO	N	NV	NE	SV
Nov-97	12	.2755	.1034	.3372	2.862	.0745	.7206	Jul-99	14	.2949	.4454	.4365	2.403	.3045	.6838	Mar-02	10	.2284	.2431	.3295
Dec-97	15	.3289	.2292	.4371	2.905	.147	.6414	Aug-99	15	.1954	.5625	.352	2.31	.4359	.775	Apr-02	21	.2813	.5261	.3219
Jan-98	9	.2738	.162	.3503	2.928	.1389	.8573	Sep-99	8	.2603	.2317	.3819	2.289	.1126	.4857	May-02	15	.2731	.3277	.4178
Feb-98	13	.2379	.2984	.441	2.266	.178	.5967	Oct-99	12	.2401	.2144	.3289	2.553	.1608	.7499	Jun-02	16	.2481	.3759	.362
Mar-98	14	.2312	.353	.3741	2.251	.1348	.3817	Nov-99	20	.2707	.2548	.4111	2.388	.1647	.6464	Jul-02	15	.2093	.3184	.4137
Apr-98	10	.2006	.2879	.4104	2.179	.1102	.3828	Dec-99	15	.2665	.4849	.3706	2.31	.3367	.6944	Aug-02	8	.247	.1542	.4381
May-98	14	.243	.346	.3458	2.429	.1619	.4679	Jan-00	14	.2833	.4556	.5045	2.192	.1797	.3945	Sep-02	10	.235	.3358	.3579
Jun-98	14	.2127	.2372	.3327	2.376	.1636	.6897	Feb-00	8	.2315	.1777	.3337	2.489	.0881	.4959	Oct-02	15	.3659	.1353	.4649
Jul-98	14	.2219	.1402	.2967	2.836	.1218	.8683	Mar-00	10	.2636	.1959	.3952	2.358	.1234	.6299	Nov-02	14	.3536	.2195	.4806
Aug-98	10	.2023	.2171	.3367	2.348	.1042	.4799	Apr-00	18	.2452	.3479	.4553	2.206	.1184	.3404	Dec-02	20	.3346	.2399	.4956
Sep-98	12	.2831	.18	.3725	2.839	.1532	.8512	May-00	15	.3011	.1911	.452	2.398	.0875	.4578	Jan-02	10	.2501	.3074	.4766
Oct-98	21	.3888	.2471	.5209	2.726	.1991	.8056	Jun-00	13	.2711	.1806	.4494	2.268	.0593	.3282	Feb-02	12	.2727	.2154	.41
Nov-98	24	.3811	.3226	.5735	2.411	.1979	.6135	Jul-00	7	.2591	.2551	.4572	2.225	.0907	.3554	Mar-02	12	.2369	.496	.4459
Dec-98	19	.3026	.3285	.5101	2.239	.1697	.5166	Aug-00	7	.1826	.2047	.3183	2.289	.0712	.3477	Apr-02	15	.1958	.2798	.3523
Jan-99	19	.2963	.2472	.4459	2.48	.1858	.7518	Sep-00	8	.1837	.1962	.3285	2.211	.0574	.2927	May-02	14	.1892	.2503	.3476
Feb-99	15	.317	.1337	.4478	2.586	.0944	.7063	Oct-00	14	.2098	.1257	.2528	2.845	.0809	.6442	Jun-02	13	.2345	.3833	.41
Mar-99	18	.281	.1937	.4194	2.474	.1567	.809	Nov-00	11	.3079	.1066	.3965	2.671	.081	.7594	Jul-02	7	.4283	.2003	.5929
Apr-99	17	.2791	.2307	.4	2.419	.1716	.7441	Dec-00	17	.2953	.337	.335	2.694	.1393	.4133	Aug-02	17	.3608	.0843	.4319
May-99	14	.3078	.2303	.4766	2.354	.0836	.363	Jan-02	15	.2565	.1876	.4048	2.383	.1088	.5803	Sep-02	22	.3485	.305	.5383
Jun-99	14	.2947	.4459	.4365	2.402	.3051	.6843	Feb-02	8	.2599	.2221	.318	2.579	.0814	.3664	Oct-02	19	.3916	.1869	.5101
																Mean	13.9	.272	.2649	.4091

Of course, the Student model must perform as least as well as the normal model because the normal model is a special case of the Student model with one less parameter -- that is, the normal model is nested within the Student model. Thus, the raw relative errors, by themselves, do not provide a test of the inconsistency of the normal model relative to the Student model. To construct such a test, the inverse of the degrees of freedom parameter, say $\upsilon = 1/\nu$, is used to write the null hypothesis H_0: $\upsilon = 0$. When this hypothesis is true, the normal model is correct. The alternative considered here is that $\upsilon > 0$ indicating that the normal model is inconsistent with the data relative to the Student model. Gallant (1975) shows that an approximate test of the hypothesis that a parameter's value is equal to zero can be obtained by examining the sum of square residuals of the constrained and unconstrained models. Moreover, this test is quite analogous to the reduced model test commonly used in regression analysis. Let SS_0 and SS be the sum of squared residuals for the constrained model ($\upsilon = 0$) and the unconstrained model. Then $F = (n\text{-}p)SS_0/SS$, where n is the number of observations and p is the number of parameters determined by the data in the unconstrained model, will be approximately distributed as an F random variable with 1 and n-p degrees of freedom. For our purpose, p will always be 2 but n will vary from month to month depending on the number of different put options being traded.

The test described above has been run for each of the sixty months. The sample sizes (number of unique put contracts available) range from seven to twenty-four with a median of fourteen. In Table 3, we provide an analysis of the frequency distribution of 60 p-values for the test of H_0: $\upsilon = 0$, where $\upsilon = 1/\nu$. The figure in each cell is the number of months having a p-value within the indicated range. Our conclusion is that the evidence is quite strong against the normal model relative to the Student model. In only three of the sixty months, using a significance level of .05, would one not be able to detect the inappropriateness of the normal model.

Table 3
Frequency Distribution of p-values for the Test of H_0: u = 0

$p \leq .001$	$.001 < p \leq .01$	$.01 < p \leq .05$	$.05 < p \leq .1$	$p > .1$
33	17	7	1	2

CONCLUSIONS

In this paper, the historical changes in the DJIA for the last 100 years are examined. There appears to be strong evidence that the log price relatives of the DJIA average do not follow a normal distribution - at least for one day to one month holding periods. A logical explanation of this non-normality is provided by the mixing model which accounts for changing volatility. The empirical record supports the use of a gamma type density for modeling the changing volatility. This has been show three ways: a.) Through Q-Q plots and likelihood tests of daily and monthly prices, b.) By examining the distribution of the variance of prices within 23 day periods and c.) Analyzing puts with varying strike prices by comparing normal (Black-Scholes) valuations and valuations using Student densities.

A practical conclusion that one can draw from the analysis is that the poor performance of the Black-Scholes model is due to the tail behavior of price changes. This behavior can be included in options pricing models to better reflect the behavior that markets price into options. The option pricing model developed here is much simpler than autoregressive formulations and is therefore better suited to practical applications. There is strong evidence to the support the Student model in favor of the normal model, from both *ex post* and *ex ante* perspectives. There are still open questions. While the Student model fits better for short and moderate periods, it has not been shown that this is the best model. Further, while the model indirectly provides finite prices for call options, it does not directly provide finite prices for call options. This issue suggests the opportunity for further research. To complete the analysis it was necessary to develop a new method for estimating the parameters for the Student distribution. This new technique is based on the Q-Q plot and involves estimating the slope parameter by the value that maximizes the correlation between the observed log price relatives and the theoretical quantiles. The new method is simpler and easier to use than maximum likelihood estimates. It also provides estimates in certain situations when maximum likely estimates can not be found. Fully investigating the statistical properties of this new method is another opportunity for future research.

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AN ANALYSIS OF THE INITIAL ADOPTION OF FAS 141 AND 142 IN THE PHARMACEUTICAL INDUSTRY

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ABSTRACT

In 2001 the Financial Accounting Standards Board issued FAS 141 Business Combinations, and FAS 142 Goodwill and Intangible Assets. These new accounting standards significantly changed the accounting for mergers and acquisitions, dramatically altering how business combinations are reflected in the surviving company's financial statements. These new rules are particularly relevant for companies in industries that rely heavily on intellectual capital to generate future cash flows, or those that are characterized by considerable mergers and acquisitions activity.

Documenting how these new standards are initially applied provides valuable insight into their impact on the structure and content of the resulting financial statements. This study addresses this issue by examining and documenting initial FAS 141 and 142 disclosures for firms in the pharmaceutical industry. We focus on the pharmaceutical industry because it is dominated by a few well defined business models, and is characterized by firms that rely heavily on intangible assets and have considerable mergers and acquisitions activity.

The results of our analysis identify several emerging trends within the pharmaceutical industry. First, strategic analysis indicates that a variety of business models currently exist in the pharmaceutical industry, and most pharmaceutical companies pursue more than one business model. Second, financial disclosure analysis reveals that although different business models led to some variation in disclosures, disclosure practice across firms in the pharmaceutical industry is fairly consistent. Finally, analysis of recent acquisitions provides evidence of consistent reporting and disclosure of purchase type business combinations under FAS 141 and 142. These results provide a benchmark for industry practice that can be used to identify trends in financial reporting and disclosure related to these two accounting standards.

INTRODUCTION

In 2001 the Financial Accounting Standards Board issued FAS 141 Business Combinations, and FAS 142 Goodwill and Intangible Assets. These new accounting standards represented a significant shift in the accounting for mergers and acquisitions, and dramatically changed how business combinations are reflected in the surviving company's financial statements. The most notable aspects of these new accounting rules were the elimination of the pooling-of-interest method of accounting for business combinations, the elimination of the periodic amortization of goodwill in favor of an impairment testing model, and the requirement that identifiable intangible assets be recognized separately in a business combination. These changes were particularly relevant for companies in industries that rely heavily on intellectual capital to generate future cash flows, or those that are characterized by considerable mergers and acquisitions activity.

Documenting how these standards are initially applied provides valuable insight into how these changes affect the structure and content of the resulting financial statements. This study addresses this issue by examining and documenting initial FAS 141 and 142 disclosures for firms in the pharmaceutical industry. We focus on the pharmaceutical industry because it is represented by a few well defined business models, and is characterized by firms that rely heavily on intangible assets and have considerable mergers and acquisitions activity. The analysis reviews financial disclosures of a sample of publicly listed pharmaceutical companies, documenting how these companies implement the new accounting standards, and examining the consistency in which these standards are applied. The results provide a benchmark for industry practice in the application of FAS 141 and 142. This data can then be used to identify trends in financial reporting and disclosure related to FAS 141 and FAS 142.

The study examines three categories of pharmaceutical companies that are directly related to business combinations and intangible assets: (1) company strategy and lines of business, (2) goodwill and intangible asset disclosures, and (3) strategic acquisitions. For each of these categories, company disclosures were reviewed, and data collected on specific elements that make up each category. The data was then analyzed for commonalities.

The results identified several emerging trends within the pharmaceutical industry. First, strategic analysis indicates that a variety of business models currently exist in the pharmaceutical industry, and most pharmaceutical companies pursue more than one business model. Second, financial disclosure analysis reveals that although different business models led to some variation in disclosures, disclosure practice across firms in the pharmaceutical industry is fairly consistent. Finally, analysis of recent acquisitions provides evidence of consistent reporting and disclosure of purchase type business combinations under FAS 141 and 142.

PHARMACEUTICAL INDUSTRY COMPETITIVE LANDSCAPE

The pharmaceutical industry can be divided into two primary sectors: major pharmaceuticals, and mid-cap / specialty pharmaceuticals. While considerable variation exists in pharmaceutical company business models, these two sector characterizations establish a starting point for first order delineation within the industry.

The major pharmaceutical sector is characterized by large, vertically integrated companies that are involved in the discovery, development, manufacture, and sale of pharmaceutical and heath care products. The research and development function of these companies is focused on finding new drug compounds that will ultimately lead to marketable drugs and products. As part of the research and development process, these entities typically pursue all stages of basic research, conduct all phases of clinical trials, and pursue FDA approval once the clinical trials have successfully been completed. Concurrent with attaining FDA approval, these companies pursue patents and trademarks on their drug compounds. Once FDA approval is received, major pharmaceutical companies manufacture the drug compound and leverage their vast sales force to market these new drugs to both physicians and patients.

The key to success for major pharmaceutical companies is having a continual pipeline of promising new drug therapies. To supplement their own research pipelines, most major pharmaceutical companies enter into research and development joint ventures in which they partner with other entities on basic research activities of mutual benefit. In addition to research and development joint ventures, major pharmaceutical companies also pursue acquisition strategies to acquire or in-license promising new technologies that enhance or complement their existing pipeline and drug portfolio.

The mid-cap/specialty pharmaceutical sector is less homogeneous than the major pharmaceutical sector, and can be delineated into 5 general sub-groups: new drug discovery, in-license and develop, drug delivery technology, buy and promote, and generic. While few mid-cap / specialty companies are accurately characterized by a single sub-group, these definitions provide a framework for understanding the different strategies that are pursued within this segment of the industry.

New drug discovery companies focus on performing basic research that is used to derive new therapeutic treatments, or find new uses for established chemical compounds. Basic research is the growth driver for the pharmaceutical industry, and new discovery companies serve as the breeding ground for new drug therapies. Historically, therapeutic chemical compounds have been discovered on a trial-and-error basis, where researchers have attempted to identify ex ante organic, animal, or inorganic compounds that may be effective in the treatment of diseases and medical conditions. As the application of genetic methodologies becomes more prevalent, rational drug design, which uses computers to screen vast numbers of molecules for suitable treatments, should enhance the speed with which new chemical compounds are identified and brought to market.

The opportunities presented by the discovery of new chemical compounds do not come without a significant amount of risk. Standard and Poors estimates that the success rate for a new drug compound is approximately 1 in 5,000, with only one third of those compounds that are approved by the FDA and marketed to the public actually generating enough revenue to cover the costs of research and development. Thus, new drug discovery companies face the daunting challenge of pursuing a product that has an extremely low probability of yielding an economically viable new drug. This challenge is exacerbated by the fact that these are relatively small companies with limited capital, which makes it difficult to see potential new products through the costly and extensive clinical trial and FDA approval process. As a result, discovery companies typically out-license their product to other specialty or major pharmaceutical companies prior to clinical trials.

In-license and develop companies acquire promising new chemical compounds prior to or early in the FDA approval process, pursue and complete the clinical trials, file the patent application, and market the new proprietary pharmaceutical product. In return for taking on the risk and costs of clinical trials and the FDA approval process, these companies are able to obtain promising therapies at a substantial discount to what the product would cost to acquire if the clinical trials process and the FDA approval process had been completed. Once FDA approval is received, these companies use their established sales force to promote and market the product. Thus, in-license and develop companies can be characterized as larger companies that have access to greater amounts of capital, and an established sales force.

Drug delivery companies focus on developing new methods for delivering drug therapies to a patient. These companies do not develop new chemical compounds for the therapeutic treatment of a medical condition, but rather focus on developing more effective methods for delivering existing FDA approved pharmaceuticals into a patient's system. New delivery technologies are used in conjunction with existing proprietary pharmaceuticals to add an additional level of product differentiation. This type of product enhancement may also allow the original patent holder to pursue and obtain a patent extension for the new drug delivery technology, especially when the new technology reduces side effects, increases patient compliance, or provides greater product efficacy. While new delivery technologies must receive FDA approval, the regulatory risk is much lower than that of new chemical compounds.

Specialty pharmaceutical companies with an "acquire and promote" strategy focus on acquiring branded FDA approved pharmaceutical products from other pharmaceutical companies, and then seek to expand the market penetration of these products through enhanced marketing efforts or by expanding the products treatment indications. These under marketed products are typically a low priority for major pharmaceutical companies, which often have a number of other products that generate more sales revenue and higher profit margins. By divesting themselves of these under marketed products, major pharmaceutical companies are able to generate immediate cash flow, recover some of the cost of the product and free up their sales force to focus on higher priority products. Conversely, the acquiring firm is able to obtain a promising branded pharmaceutical product at a discount to its market potential.

Generic drug companies focus on developing the chemical equivalents of branded pharmaceuticals, and marketing those off-brand equivalents after the proprietary branded drug's patent expires. Generic drug companies must still receive FDA approval for the off-brand equivalent through the filing of and approval of an abbreviated new drug application (ANDA). Because of the cost savings, generic equivalents are extremely popular, especially with HMO's and for patients on Medicaid and other forms of government assisted heath care benefits. Standard and Poors estimates that generic equivalents in the U.S. markets are priced 25% to 50% lower (on average) than the original branded drug. To encourage quick entry of generic equivalents into the market place, legislation passed in 1998 provided a 180 day period of exclusivity to the first generic equivalent to successfully achieve FDA approval for a chemical compound coming off patent.

SAMPLE DESCRIPTION

This study focuses on a broad sample of companies that span a variety of business models within the pharmaceutical industry. This broad focus was taken because the larger sample size provides a clearer indication of evolving pharmaceutical industry practice than an extremely small sample of companies with directly comparable business models. A summary of the key distinguishing characteristics and elements of each sample company's business is provided in Table 1. The analysis indicates that while many pharmaceutical companies (major, and mid cap/specialty) pursue acquisition activities in conjunction with their core drug development and distribution activities, few pursue a business model that relies predominantly on acquisitions.

The subsequent analysis of financial reporting practices utilizes a broad sample of firms in the pharmaceutical industry. By focusing on this more expansive sample, the analysis is able to better identify trends in financial reporting and disclosure relating to the transition and adoption of FAS 141 and FAS 142. Because the acquisition of products and companies occurs across almost all of the current pharmaceutical industry business models, this larger sample aids in determining how recent acquisitions are being handled under the newly adopted accounting rules.

ANALYSIS OF INITIAL FAS 141 AND FAS 142 DISCLOSURES

To assess the financial reporting impact of FAS 141 and FAS 142 on the pharmaceutical industry, disclosures from the 2001 annual reports and the 2002 second quarter 10-Q's were reviewed for a sample of major cap, mid cap, and specialty pharmaceutical companies identified by the research sponsor. These reviews provide initial insight into how the pharmaceutical industry has implemented these accounting standards going forward.

The sample companies were broken down into three broad divisions of pharmaceutical companies: (1) major, (2) mid cap, and (3) specialty. Major pharmaceutical companies are those companies with vast product lines, activities that range from research and development to manufacturing to sales and marketing, and have market capitalization in excess of $25 billion dollars. Mid cap pharmaceutical companies typically have numerous products, operations that span more than one aspect of the business (R&D, marketing), and have a market capitalization less than $25 million. Finally, specialty pharmaceutical companies tend to have product lines that focus on a few areas of treatment, have operations that focus on specific aspects of the business (e.g. R&D, in-licensing, or marketing), and have relatively small market capitalization. While these segregations are not based on strict quantitative criteria, we believe that these three divisions provide a reasonable dichotomization of the pharmaceutical industry.[1]

Table 1
Summary of Strategy and Business Lines

	Major Pharmaceuticals													
	ABT	BMY	JNJ	LLY	MRK	PFE	PHA	SGP	WYE					
Business Segments														
Prescription	x	x	x	x	x	x	x	x	x					
Over the counter			x		x	x	x	x	x					
Medical Devices			x											
Diagnostic Testing Equipment	x		x											
Drug Delivery Systems	x		x											
Medical Products	x	x	x											
Consumer Products			x			x	x	x						
Nutritional Products	x	x	x						x					
Pharmacy Benefits Management					x									
Animal Health Products				x	x	x	x	x	x					
Womens Health Care			x						x					
Acquisition of Products														
Develops Pharmaceutical Products	x	x	x	x	x	x	x	x	x					
Manufactures Pharmaceuticals	x	x	x	x	x	x	x	x	x					
Sells Pharmaceuticals	x	x	x	x	x	x	x	x	x					
Proprietary vs. Generic														
Proprietary Products	x	x	x	x	x	x	x	x	x					
Generic Products														
Market Capitalization	68.7B	46.3B	176.6B	70.7B	114.8B	207.3B	58.4B	27.8B	46.5B					
	Mid Cap Pharmaceuticals													
	AGN	ALO	ADRX	ELN	FRX	KG	MRX	MYL	NVAX	WPI				
Business Segments														
Pharmaceuticals														
Prescription	x	x	x	x	x	x	x	x	x	x				
Over the counter	x		x		x	x	x			x				
Medical Devices														
Diagnostic Testing Equipment														
Drug Delivery Systems				x					x	x				
Medical Products	x													
Consumer Products														
Nutritional Products														
Pharmacy Benefits Management														
Animal Health Products		x												
Women's Health Care						x			x					
Pharmaceutical Compound		x												
Areas of Operations														
Acquisition of Products		x	x	x			x		x	x				
Develops Pharmaceutical Products	x	x	x	x	x		x	x	x	x				
Manufactures Pharmaceuticals	x	x	x	x	x	x		x	x	x				
Sells Pharmaceuticals	x	x	x	x	x	x	x	x	x	x				
Proprietary vs. Generic														
Proprietary Products	x			x	x	x	x	x	x	x				
Generic Products		x	x		x			x		x				
Market Capitalization	8.1B	397.3M	947.7M	486.3M	17.9B	4.36B	1.21B	3.8B	93.9M	2.59B				

Table 1
Summary of Strategy and Business Lines

	Specialty Pharmaceuticals													
	AAII	BVF	CIMA	FHRX	GALN	ICN	IVX	KOSP	LBPFF	LJPC	MTEC	Schwartz	WFHC	SLXP
Business Segments														
Pharmaceuticals														
Prescription	x	x	x	x	x	x	x	x	x			x	x	x
Over the counter			x			x	x							
Medical Devices														
Diagnostic Testing Equipment											x			
Drug Delivery Systems	x	x	x	x	x			x	x		x			x
Medical Products						x								
Consumer Products														
Nutritional Products						x								
Pharmacy Benefits Management														
Animal Health Products							x							
Women's Health Care					x								x	
Pharmaceutical Compound														
Areas of Operations														
Acquisition of Products	x			x			x						x	
Develops Pharmaceutical Products	x	x			x	x	x	x	x	x	x	x		x
Manufactures Pharmaceuticals	x	x			x	x	x	x	x		x	x		x
Sells Pharmaceuticals				x	x	x	x	x				x	x	x
Proprietary vs. Generic														
Proprietary Products	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Generic Products			x				x							
Market Capitalization	251.4M	4.40B	315M	121M	1.14B	671.7M	2.22B	240M		175.5M	172.2M		113.3M	134.7M

Using the three-tier dichotomy, 9 companies were identified as major pharmaceuticals, 10 companies including King were identified as mid cap pharmaceuticals, and 13 were identified as specialty pharmaceuticals. Of this sample, one of the mid cap companies, and 4 of the specialty companies were not domiciled within the United States. Five of the sample companies did not have calendar year-ends (three mid cap and two specialty).

2001 10-K ANNUAL REPORT REVIEW

Review of 2001 Form 10-K's and company annual reports for the sample revealed little about their strategies for implementing FAS 141 and 142 going forward. The annual reports indicated that FAS 141 and FAS 142 would be effective for fiscal years beginning after December 31, 2001, and the provisions of these standards would be adopted beginning in 2002. Footnote disclosures provided little additional discussion of the impact that the adoption of FAS 141 and FAS 142 would have on financial results, other than to indicate that goodwill amortization would not be recognized going forward. Most companies reported that goodwill and intangible assets were being reviewed for impairment in accordance with the new procedures established by FAS 142.

SECOND QUARTER 2002 10-Q REVIEW (JUNE 30, 2002)

Second quarter 2002 10-Q's were reviewed for insight into the pharmaceutical industries application of FAS 142. The analysis focuses on second quarter filings to mitigate any disclosure volatility that might occur in quarter one as a result of the initial adoption of FAS 141 and 142. Table 2 summarizes these disclosures for the sample firms along the lines of disclosure patterns. This analysis indicates broad consistency in disclosure behavior, with systematic differences in disclosure associated within the underlying economics of the sample companies.

Of the identified sample, two major and three specialty companies indicated that the adoption of FAS 142 would not have a material impact on their financial statements. Of the two major companies, Eli Lilly had not reported goodwill, intangible assets, or amortization in prior years. Pfizer, however, had recorded goodwill amortization in prior years in excess of 5% of net income. As part of the adoption of FAS 142, Pfizer recorded impairment charges on two of its business segments, presumably reducing the impact of non-amortization on earnings post impairment. The specialty companies indicating no material impact were drug discovery companies that did not have an acquisition strategy, and therefore did not appear to be substantially impacted by the implementation of FAS 142. In addition to these 5 companies, two mid cap and three specialty companies provided no substantive discussion related to FAS 142. Of these 5 companies, three were foreign entities, one was a generic drug manufacturer, and one a drug delivery device manufacturer. The majority of sample companies indicated the existence of goodwill and / or intangible assets, and disclosed the relevant gross balance, accumulated amortization, and net balance for the two asset categories where applicable. The majority of companies with goodwill balances also presented pro forma earnings per share and / or net income amounts as if FAS 142 had been retroactively applied. In addition, some companies disclosed the specific reduction in amortization expense that would occur as a result of non-amortization of goodwill, and some provided a detailed breakdown of changes in the balance of goodwill from December 31, 2001 to June 30, 2002.

Five companies (two major, two mid cap, and one specialty) took goodwill impairment charges on at least one segment of their business in association with the adoption of FAS 142. In addition, three specialty companies, one major, and one mid cap company reclassified intangible asset amounts to goodwill upon adoption of FAS 142. These reclassifications related to assembled workforce intangible assets and negative goodwill. Two of the companies reclassifying were domiciled outside the United States. Only one company reported the reclassification of goodwill to intangible assets related to the valuation of certain product rights.

Three of the sample companies specifically indicated the decision to treat certain intangible assets as indefinite lived (two mid cap, one specialty). Of these companies, only one articulated the specific factors underlying the decision to treat existing assets as indefinite lived. An additional four companies (two major, one mid cap, and one specialty) separately disclosed amortized and unamortized intangible assets without specifically stating that they would be invoking indefinite life treatment, and without providing specific discussion on the factors relied upon to distinguish amortizable from unamortizable intangible assets.

Table 2
Summary of Goodwill and Intangible Asset Disclosures

	Big Cap Pharmaceuticals													
	ABT	BMY	JNJ	LLY	MRK	PFE	PHA	SGP	WYE					
Adoption of FAS 142 did not have a material impact														
Goodwill impairment charges taken				x		x								
Treated existing products as indefinite lived intangible assets						x	x							
Separate disclosure of amortized and unamortized intangible assets														
Disclosed rationale for treating products as indefinite lived						x	x							
Identified broad ranges for intangible asset useful lives														
Disclosure of weighted average amortization for each intangible asset classification					x			x	x					
Identified specific expected useful lives for intangible asset categories		x												
Explained the factors underlying the determination of expected useful lives of intangible assets														
Disclosure of goodwill amounts														
Disclosure of intangible assets amounts	x	x	x				x	x	x					
Pro Forma EPS and Net Income as if FAS 142 had been retroactively applied	x	x	x		x	x	x	x						
Reclassification of intangible assets to goodwill	x						x	x	x					
Reclassification of goodwill to intangible assets			x											
Detailed breakdown of changes in goodwill balance from 12/31/01 to June 30, 2002														
Disclosed reduction in amortization expense as a result of adopting FAS 142		x					x		x					
No substantive discussion		x	x		x				x					
Market Capitalization	68.7B	46.3B	176.6B	70.7B	114.8B	207.3B	58.4B	27.8B	46.5 B					

Table 2
Summary of Goodwill and Intangible Asset Disclosures

	Mid Cap Pharmaceuticals													
	AGN	ALO	ADRX	ELN	FRX	KG	MRX	MYL	NVAX	WPI				
Adoption of FAS 142 did not have a material impact														
Goodwill impairment charges taken	x				x									
Treated existing products as indefinite lived intangible assets						x		x						
Separate disclosure of amortized and unamortized intangible assets	x													
Disclosed rationale for treating products as indefinite lived						x								
Identified broad ranges for intangible asset useful lives									x					
Disclosure of weighted average amortization for each intangible asset classification					x					x				
Identified specific expected useful lives for intangible asset categories														
Explained the factors underlying the determination of expected useful lives of intangible assets														
Disclosure of goodwill amounts	x	x			x	x	x	x	x	x				
Disclosure of intangible assets amounts	x				x	x	x	x	x	x				
Pro Forma EPS and Net Income as if FAS 142 had been retroactively applied	x	x						x	x	x				
Reclassification of intangible assets to goodwill								x						
Reclassification of goodwill to intangible assets		x												
Detailed breakdown of changes in goodwill balance from 12/31/01 to June 30, 2002		x								x				
Disclosed reduction in amortization expense as a result of adopting FAS 142	x					x			x	x				
No substantive discussion			x	F										
Form 20-F, domicile country				Ireland										
Fiscal Year					31-Mar		30-Jun	31-Mar						
Market Capitalization	8.1B	397.3M	947.7M	486.3M	17.9B	4.36B	1.21B	3.8B	93.9M	2.59B				

Table 2
Summary of Goodwill and Intangible Asset Disclosures

	Specialty Pharmaceuticals													
	AAII	BVF	CIMA	FHRX	GALN	ICN	IVX	KOSP	LBPFF	LJPC	MTEC	Schwartz	WFHC	SLXP
Adoption of FAS 142 did not have a material impact			x				x		x				x	
Goodwill impairment charges taken						x								
Treated existing products as indefinite lived intangible assets	x													
Separate disclosure of amortized and unamortized intangible assets				x										
Disclosed rationale for treating products as indefinite lived														
Identified broad ranges for intangible asset useful lives											x			
Disclosure of weighted average amortization for each intangible asset classification	x													
Identified specific expected useful lives for intangible asset categories	x	x		x	x									
Explained the factors underlying the determination of expected useful lives of intangible assets	x											x		
Disclosure of goodwill amounts	x	x			x	x	x				x			
Disclosure of intangible assets amounts		x		x	x	x	x				x		x	
Pro Forma EPS and Net Income as if FAS 142 had been retroactively applied	x			x	x	x				x				
Reclassification of intangible assets to goodwill	x			x		x								
Reclassification of goodwill to intangible assets														
Detailed breakdown of changes in goodwill balance from 12/31/01 to June 30, 2002	x	x												
Disclosed reduction in amortization expense as a result of adopting FAS 142	x									x		x		
No substantive discussion			x						F			F		
Form 20-F, domicile country		Canada			Ireland				Canada			Germany		
Fiscal Year									28-Feb		30-Jun			
Market Capitalization	251.4M	4.40B	315M	121M	1.14B	671.7M	2.22B	240M		175.5M	172.2M		113.3M	134.7M

Disclosure of estimated useful lives for intangible assets was sporadic across the sample. Only three specialty companies identified specific expected useful lives for intangible asset categories, and of those, only one company explained the factors underlying the determination of expected useful lives. Of the remaining firms that discussed the expected useful life of intangible assets at all, the information disclosed focused on ranges or weighted average useful lives for broad asset categories. Only Biovail and Women First Healthcare explained the factors underlying the determination of the expected useful lives of its assets. In general, little detail was provided on the useful lives of specific intangible assets, and the economic rationale for arriving at these estimates.

SECOND QUARTER DISCLOSURES REGARDING RECENT ACQUISITIONS

To further understand evolving industry practice in the application of FAS 141 and 142, we also reviewed second quarter disclosures regarding business and product acquisitions made by our sample companies. In total, nine acquisitions were reported during the second quarter of 2002. Of these transactions, 7 were purchase business combinations, one was a rights acquisition, and one was an asset purchase agreement and license agreement. The rights agreement involved Watson Pharmaceuticals acquisition of the U.S. rights to a trademarked product, and negotiating rights to uses of the product for alternative indications. The purchase agreement involved the acquisition by Women's First Healthcare of product rights, trademarks, patents, and legal filings for Vaniqa cream, as well as all related products, and over-the-counter rights.

Each of the business combination transactions originating during the second quarter of 2002 disclosed the purchase price and the terms of the purchase. One of the purchase transactions involved the finalization of the purchase price of an acquisition made during 2001, and therefore was not representative of the application of FAS 141 and 142. Of the remaining transactions, only three clearly indicated the allocation of the purchase price to intangible assets, and the estimated useful lives of those intangible assets. The purchase price allocations for these acquisitions were based on initial valuations, but none provided detail on the factors driving the useful life assessment. In addition, four of the reported acquisitions allocated portions of the purchase price to in-process research and development that was immediately charged to earnings.

Because of the limited number of acquisitions that occurred and were reported during the second quarter of 2002, it is difficult to draw inferences about evolving pharmaceutical industry practice in the application of FAS 141 and 142. This analysis is particularly limiting because none of the acquisitions disclosed the application of indefinite life criteria to products acquired in the reported transactions. While estimated useful lives were disclosed for elements of the purchase price allocated to intangible assets, no disclosures were provided by any of the reporting companies on how these useful lives were determined, or the economic factors underlying these estimates. Given these results, it is difficult to draw inferences as to industry practice in applying FAS 141 and 142, or on the specific economic factors that define reporting practice and the application of these standards.

SUMMARY AND CONCLUSIONS

The review of business models, corporate strategy and recent financial disclosures for our sample provided initial insight into evolving industry practice. Strategy analysis indicates that a variety of business models currently exist in the pharmaceutical industry, and most pharmaceutical companies pursue more than one of these business models.

Annual report disclosures provided some general information on how FAS 141 and 142 would be applied, but little specific detail on their application. Second quarter 2002 disclosures were reviewed to obtain insight into how these standards have been initially applied. While different business models within the pharmaceutical industry led to some variation in disclosure due to differences in underlying economics, on a broad level disclosure practice within the industry is fairly consistent. Sample companies tended to distinguish between intangible assets and goodwill, provide pro forma information, and document expected useful lives of intangible assets for broad asset classes. Sample firms were also uniform in their limited discussion of the specific factors underlying their useful life assumptions. Few firms indicated that they had classified intangible assets as indefinite lived, and those firms that did pursue such classifications provided little explanation of the factors underlying this decision.

Finally, our review of recent acquisitions also provided some consistent evidence of trends in reporting and disclosure of purchase type business combinations under FAS 141 and 142, but the small number of transactions limits the ability to make generalizations about industry practice. Of those acquisitions that occurred during the second quarter, disclosure and reporting was consistent, but tended to stay on a very broad level.

ENDNOTES

1 Since these classifications are not used as the basis for any causal observations, we do not feel the lack of strict quantitative categorization criteria have an impact on our analysis.

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Exhibit A	
Sample Companies	
Sample Company	Ticker Symbol
Major Pharmaceutical Companies	
Abbott Labs	ABT
Bristol-Myers-Squibb	BMY
Johnson and Johnson	JNJ
Eli Lilly and Company	LLY
Merck	MRK
Phizer	PFE
Pharmacia	PHA
Schering-Plough	SGP
Wyeth	WYE
Mid-Cap Pharmaceuticals	
Allergan	AGN
Alpharma	ALO
Andrx Corp	ADRX
Elan	ELN
Forest Labs	FRX
King Pharmaceuticals	KG
Medicis	MRX
Mylan Labs	MYL
Novavax	NVAX
Watson Pharmaceuticals	WPI
Specialty Pharmaceuticals	
AaiPharma	AAII
Biovail	BVF
Cima Labs	CIMA
First Horizon	FHRX
Galen pharmaceuticals	GALN
ICN Biomedicals	ICN
Ivax	IVX
Kos Pharmaceuticals	KOSP
Labopharm	LBPFF
La Jolla Pharmaceuticals	LJPC
Meridian Medical Technologies	MTEC
SchwartzPharma	Schwartz
Womens First Health Care	WFHC
Salix Pharmaceuticals	SLXP

Table 3 Summary of Strategic Acquisitions

Company	Entity / Product Lines Acquired	Acquired From	Acquisition Structure	Acquisition Price Allocation	Pro Forma Presentation	Purchase Price	Inventory	Identifiable Intangible Assets	Goodwill	IPR&D
AAIPharma	Darvon & Darvocet-N: inventory, product lines and related intangibles. Product lines did not have separable assets and liabilities associated with them, other than inventory.	Eli Lilly	Purchase Business Combination	Purchase price allocated to acquired identifiable intangible assets. Excess of purchase price over identifiable intangible assets recorded as goodwill and tested for impairment.	Pro Forma prior period consolidated financial information including acquisition on an "as if" basis.	$211.4 million	$1.8 million	$ 51.2 million amortized over 20 years	$158.4million	
Abbot Labs	The cardiovascular stent business of Biocompatibles International plc and certain cardiovascular stent technology rights from Medtronic, Inc.	Biocompatibles Int'l & Medtronic	Purchase Business Combination	Acquired intangible assets, primarily product technology, will be amortized over 4 to 13 years (average of approximately 8 years).	Consolidated financial information in prior periods would not have been materially affected by the acquisition.	$586 million		$145 million	$257 million	$108 million charge
Alpharma	Finalized the purchase price of OPB acquisition		Purchase Business Combination	Finalization of the purchase price resulted in a reclassification of approximately $25,500 from goodwill to intangible assets related to the valuation of certain product rights, and a reduction of goodwill and deferred tax liabilities of approximately $26,000 as amortization of certain identified intangibles were determined to be deductible for tax purposes						
First Horizon Pharma	Certain U.S. rights relating to the antihypertensive prescription medication Sular. The Company also entered into a long-term manufacturing, supply, and distribution agreement with Sular's current manufacturer, Bayer AG. The agreements include the purchase of the Sular license rights, certain trade names and managed care contracts and a distribution agreement.	AstraZenca UK Limited	Purchase Business Combination	The purchase price paid was $185.6 million in cash, including $623,000 in acquisition costs, plus assumption of liabilities of $1,895,000 related to the return of product shipped prior to the acquisition. In addition, the Company must pay up to $30 million in additional purchase price after closing, based on the achievement of certain performance milestones during a specified period of time. The purchase price also included $6,246,000 of product inventory. The purchase price was allocated among the fair values of the intangible and tangible assets acquired and the liabilities assumed		$185.6 million cash plus the assumption of $1.85 million in liabilities related to product returns. The Company must pay up to $30 million in additional purchase price after closing, based on the achievement of certain performance milestones during a specified period of time.	$6.25 million	$181.3 million: $161.5 million in license rights (20 year amortization), $10.4 million in distribution agreement (10 year amortization), $6.9 million in managed care contracts (amortized over 5 years), and $2.6 million in trade names (20 year amortization).		

Table 3 Summary of Strategic Acquisitions

Company	Entity / Product Lines Acquired	Acquired From	Acquisition Structure	Acquisition Price Allocation	Pro Forma Presentation	Purchase Price	Inventory	Identifiable Intangible Assets	Goodwill	IPR&D
ICN Pharma	Circe Biomedical, Inc. ("Circe") a development stage company	Circe Biomedical Inc. ("Circe")	Purchase Business Combination	Purchase Business Combination - $5.9 million in cash, additionally the company will make milestone payments and royalties if the product is successfully developed. The Company recently decided not to continue with further development of Circe's main product.		$25.9 million				$6.2 million, charge taken in Q2
Johnson & Johnson	Tibotec-Virco NV, a privately held biopharmaceutical company focused on developing anti-viral treatments, with several promising compounds in development for the treatment of infectious diseases including HIV.	Tibotec-Virco NV	Purchase Business Combination			$320 million				$150 million charge, or $.05 per share in Q2
Johnson & Johnson	Obtech Medical AG, a privately held Swiss company that markets an adjustable gastric band.	Obtech Medical AG	Purchase Business Combination			$110 million				$39 million charge, or $.01 per share in Q2
Watson Pharma	US rights to Actigall, which contains ursodiol, a naturally occurring bile acid, introduced in the U.S. in 1988. It is indicated for the dissolution of certain types of gallbladder stones and prevention of gallstones in obese patients experiencing rapid weight loss. Watson also has negotiation rights relating to the commercialization of the product for the prevention of colorectal growths, an indication Novartis currently has under development	Novartis				$70 million				

Table 3 Summary of Strategic Acquisitions

Company	Entity / Product Lines Acquired	Acquired From	Acquisition Structure	Acquisition Price Allocation	Pro Forma Presentation	Purchase Price	Inventory	Identifiable Intangible Assets	Goodwill	IPR&D
Women's First Healthcare	Exclusive worldwide rights and title to Vaniqa ® (eflornithine hydrochloride) Cream,13.9%., including all related product rights, inventory, regulatory filings and patent rights. The Company also secured the right to pursue an over-the-counter strategy and to develop enhanced formulations of Vaniqa ®	A joint venture formed by Bristol-Myers Squibb Company ("BMS") and The Gillette Company ("Gillette").	An Asset Purchase Agreement and License Agreement to provide for the sale or license of all of the joint venture parties' Vaniqa ® assets.	The Company did not acquire any facilities, equipment or personnel in the transaction. BMS and the Company also entered into a related Supply Agreement, whereby BMS will continue to manufacture Vaniqa ® for three years following the acquisition. The Company financed the acquisition through the issuance of $28,000,000 of senior secured notes (the "Notes") and $13,000,000 of convertible preferred stock (the "Preferred Stock").		$38.5 million				

THE APPLICATION OF VARIABLE MOVING AVERAGES IN THE ASIAN STOCK MARKETS

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ABSTRACT

This paper examines the predictive ability and its returns from the application of variable moving averages rules (VMA) in seven selected Asian equity markets, namely Malaysia, Singapore, Hong Kong, Taiwan, Japan, Korea and China. The seven popular daily Asian market indices from January 1988 to December 2002 were studied with ten variations in length. The results indicated support for variable moving averages in particular for the shorter lengths with twenty-day as the most profitable among all. Interestingly, the mean returns of buy and sell signals from the VMA applications in the all seven markets enjoyed greater return against the unconditional buy-and-hold mean returns. The returns of the seven Asian market indices found to be statistically significant with the Japan stock market reported the least forecasting ability. Shanghai Composite Index with 0.1545% daily mean returns appeared to be the most attractive.

INTRODUCTION

There has always been much excitement about the use of the technical strategies as an investment approach. Both Wong, Manzur, and Chews (2003) and Tian, Wan, and Guo (2002) in their respective studies have provided strong support on the profitability of technical strategies. The significant growth and increased attractiveness of Asian market capitalisation has stimulated considerable interests among global investors. Can investors consistently apply the technical strategies such as moving averages to generate substantial profits? It is also interesting to investigate the use of technical strategies in various Asian stock markets in out-of-the-sample period with different length of technical indicators as compared to earlier studies. This paper, therefore, focuses on the investigation of the variable moving averages in seven popular Asian stock markets from January 1988 to December 2002. The findings of the study contribute to an expanded understanding of the predictive ability of technical strategies for the investment management. Section 3 describes the data and methodology while the analysis and discussion are presented in section 4. The section 5 presents the conclusion of the study.

LITERATURE REVIEW

The study of Brock, Lakonishok and LeBaron (1992) which examined the variable moving average rules (VMA) and fixed moving averages using the daily Dow Jones Industrial Average (DJIA) over the period of 90 years from 1897 to 1986, was a substantial finding which led to the re-emergence of technical analysis. The results provided strong support for the predictive ability of technical trading rules, and the suggestion that technical analysis had no value might have been premature. Based on the VMA rule, the annualised average return on buy signal days was 10.7% while the return on sell signal days was -6.1%. The difference of 16.8% was a significant finding, as an efficient market would expect the difference in the returns to be approximately equal to zero. The study however, did not take into consideration the trading cost, which were later examined by Bessembinder and Chan (1998). Nevertheless, the effort by Brock et al. (1992) was a significant contribution to the framework of technical trading rules for subsequent studies.

Hudson, Dempsey and Keasey (1996) replicated the technical trading rules of Brock et al. (1992) on the daily Financial Times Industrial Ordinary Index (FT30) from July 1934 to January 1994. Their results showed that the technical trading rules did have predictive ability in terms of UK market. However, the excess returns of 0.8% from the application of these rules were not attractive after taking into account of 1% per round trip transaction costs.

Bessembinder and Chan (1995) examined the same trading rules of Brock et al. (1992) on six Asian countries (i.e. Hong Kong, Japan, Korea, Malaysia, Thailand and Taiwan) using their daily stock market indices over the period of 1975 to 1991. The results indicated strong forecast ability for the emerging markets of Malaysia, Thailand and Taiwan even in the presence of the trading costs. It is worth noting that the trading rules were found to have less explanatory power in such developed stock markets as Hong Kong and Japan.

Ratner and Leal (1999) examined the potential profit from ten variable moving average (VMA) rules in ten emerging equity markets in Latin America and Asia from January 1982 to April 1995. Strong evidence of profitability was found in Taiwan, Thailand and Mexico. However, the forecast ability on stock prices disappeared after taking the transaction costs into consideration. This is therefore consistent with Bessembinder and Chan (1998) for Dow Jones Industrial Average and Hudson et al. (1996) for Financial Times Industrial Ordinary Index.

Ito (1999) applied the same trading rules of Brock et al. (1992) on six Pacific-Basin stock markets, namely Japan, U.S., Canada, Indonesia, Mexico and Taiwan. The test results indicated that the technical trading rules had significant forecasting ability for all the markets, except for the U.S. Stronger forecasting power of the technical trading rules was shown in emerging markets as compared to developed markets.

Ahmed, Beck and Goldreyer (2000) investigated the efficacy of variable moving average (VMA) rules in three volatile and declining Asian markets (i.e. Taiwan, Thailand and the

Philippines) from 1994 to 1999. The results revealed substantial returns from technical trading rules even in the presence of large return volatility and general market decline.

DATA AND METHOD

This paper examines ten variations of the variable moving average rules (VMA) of Brock et al (1992) on seven popular market indexes[1] of the Asian stock markets from January 1988 to December 2002. All the seven market indices are market-value-weighted series, namely, Kuala Lumpur Stock Exchange Composite Index, Straits Times Index, Hang Seng Index, Taiwan Weighted Index, Nikkei 225 Index, Seoul Composite Index, and Shanghai Composite Index. Due to the unavailability of data of the Shanghai Composite Index, the sample period starts from January 1991. The returns on day t, Ri,t can be defined as the differences of the logarithm of closing price index (i) on day (t) and the closing price index (i) on day (t-1), as per following formula:

$$R_{i,t} = LN\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \tag{1}$$

The daily closing price index is used as the short-term moving average. This is then compared against the long-term moving averages. They are 20-day (1 month), 60-day (3 months), 120-day (6 months), 180-day (9 months) and 240-day (12 months). This study also employs a one percent band around the long-term moving average, which is to eliminate 'whiplash' signals as highlighted by Brock et al. (1992), especially when the short-term and long-term moving averages are very close to each other. Hence, ten variations examined are as follows: (1,20,0), (1,60,0), (1,120,0), (1,180,0), (1,240,0), (1,20,0.01), (1,60,0.01), (1,120,0.01), (1,180,0.01) and (1,240,0.01).

When a short-term moving average exceeds (falls below) the long-term moving average, a buy (sell) signal is considered to be generated. Under VMA rule, each day (t) is considered as either a buy or sell signal (see formula 2).

$$\begin{aligned} &\textit{Buy signal}_{i,t} = \textit{short-term moving average}_{i,t-1} > \textit{long-term moving average}_{i,t-1} \\ &\textit{Sell signal}_{i,t} = \textit{short-term moving average}_{i,t-1} < \textit{long-term moving average}_{i,t-1} \end{aligned} \tag{2}$$

However, when VMA rule is introduced with a one percent band, a buy (sell) signal is initiated only when the short-term moving average exceeds (falls below) the long-term moving average by at least one percent. If the short-term moving average falls in between the upper (101%) and lower band (99%) of the long-term moving average, no signal or a neutral signal will be generated, which means no buy or sell investment decision is made (see formula 3).

$$\textit{Buy signal}_{i,t} = \textit{short-term moving average}_{i,t-1} > 101\% \textit{ of long-term moving average}_{i,t-1}$$

Sell signal $_{i,t}$ *= short-term moving average < 99% of long-term moving average* $_{i,t-1}$
No signal $_{i,t}$ *= 99% of long term moving average* $_{i,t-1}$ *< short-term moving average* $_{i,t-1}$ *< 101% of long-term moving average* $_{i,t-1}$ *(3)*

The conditional mean[2] (average) returns from each buy signal, b of each technical trading rule is as follows:

$$\mu_b = \frac{1}{N_b}\sum_{t=1}^{N} R_t I_{t-1}^{b} \tag{4}$$

Where:
N_b *= Number of days for buy signals*
R_t *= Daily index returns*
I^b_{t-1} *= Indicator function taking a value equals to one for a buy signal observed on day t-1 and zero otherwise*

Thus, the conditional mean returns for a buy signal is derived as the mean of daily returns over the period which includes all days when buy signals are generated. The conditional mean returns for the sell signals, s is calculated using the same method. The two hypotheses tested in this paper are as follows:

Hypothesis 1:
H0: The mean returns (buy and sell signals) generated by the VMA rules equal to zero.
H1: The mean returns (buy and sell signals) generated by the VMA rules are not equal to zero.
Hypothesis 2:
H0: The mean returns (buy and sell signals) generated by the VMA rules equal to the returns derived by the buy-and-hold strategy.
H1: The mean returns (buy and sell signals) generated by the VMA rules are not equal to the returns derived by the buy-and-hold strategy.

The T-statistic used to test hypothesis 1 is as follows:

$$T = \frac{\overline{R} - \mu}{(\sigma_R / \sqrt{n})} \tag{5}$$

Where:
$\overline{R}$ *= Mean daily rules returns*
μ *= Unconditional mean returns (buy-and-hold strategy) in which the population mean is equal to zero*
σ_R *= Standard deviation of daily rule returns*
n *= Number of daily observations*

This study also employs the similar T-statistic which was used by Brock et al. (1992) to test hypothesis 2 on the mean difference between each rule with the buy-and-hold strategy. The underlying assumption for this T-statistic is the two distributions have equal variances. The T-statistic is as follows:

$$T = \frac{\mu_r - \mu}{\sqrt{(\frac{\sigma^2}{N} + \frac{\sigma^2}{N_r})}} \quad (6)$$

Where:
μ_r = *Mean returns of buy and sell signals*
N_r = *Number of buy and sell signals*
μ = *Unconditional mean returns*
N = *Number of observations*
σ^2 = *Estimated variance for the entire sample*

For the difference between the buy and sell signals, the T-statistic is as follows:

$$T = \frac{\mu_b - \mu_s}{\sqrt{(\frac{\sigma^2}{N_b} + \frac{\sigma^2}{N_s})}} \quad (7)$$

Where:
μ_b = *Mean returns of buy signals*
N_b = *Number of buy signals*
μ_s = *Mean returns of sell signals*
N_s = *Number of sell signals*

We adapted the measurement of trading profits of Brock et al. (1992) and Bessembinder and Chan (1998). In our study, when a buy signal is generated, an investor will borrow at the risk free rate and invest his or her equity investment in the market. In response to sell signals, the investor will sell his or her shares and reap the returns from risk free interest rate as short selling practice is prohibited in most of the Asian Stock market.

In this case the profit in response to buy signals[3], π_b, will be in the equation $\pi_b = R_t - i_t$. In the case of sell signals, investor will dispose the shares at the return of R_t and then invest in risk free asset and earn i_t. The profit or cost savings earned for not being in the market, π_s is computed as $\pi_s = i_t - R_t$. Therefore, the profits or extra returns earned from applying technical trading rules and before deducting transaction costs are estimated as $\pi = \pi_b + \pi_s$.

We extended our study by taking the round-trip transaction costs into consideration. Investors need to pay for the transaction costs, which is made up of brokerage fee (applicable to all markets of study), clearing fee and stamp duty (for the Malaysian context). With reference to the breakeven transaction costs used by Bessembinder and Chan (1995), the percentage round trip transaction cost is denoted as . When a signal is generated (regardless whether it is buy or sell), C/2 transaction cost will be deducted from the return. When the position is closed out, another C/2 will be charged. Therefore, the breakeven transaction costs are as follows:

$$C = \frac{\pi}{(N_b + N_s)} \qquad (8)$$

Where:
C = Percentage round trip transaction costs
π = Profit before transaction costs generated from technical trading rules as compared to buy-and-hold strategy
N_b = Number of days in which a buy signal is generated in a year
N_s = Number of days in which a sell signal is generated in a year

Rearranging the above equation, the net profit derived from the application of technical trading rules is stated as $= \pi$(before transaction cost) - C*(N_b + N_s).

ANALYSIS AND DISCUSSION

The test results of the ten variations of VMA rules are analysed in each of the seven Asian stock markets from January 1988 to December 2002. The overall results are then summarised in Table 8.

Test Results on the Malaysian Stock Market

Table 1 reports the test results of the 10 variable moving average (VMA) rules of different lengths and with one percent band for the full sample from year 1988 to year 2002. All the daily average return for buy signals are significantly positive and therefore, provide evidence to reject the hypothesis 1 that the technical trading rules generate zero returns.

Table 1
Test Results of the VMA Rules for the Full Sample (January 1988 - December 2002) of Kuala Lumpur Stock Exchange Composite Index (KLSE CI)

Test Variation	N (Buy)	N (Sell)	Buy	Sell	Buy>0	Sell>0	Buy-Sell	Profit before transaction cost	Profit after transaction cost
1,20,0	2115	1778	0.1305	-0.1086	0.5163	0.4426	0.2391	13.1362B	16.9084
			(5.5615)1**	(-3.9082)1**			(4.6433)3**	-7.6133S	
			(2.4847)2*	(-2.8790)2**				20.7495T	
1,20,0.01	1660	1314	0.1648	-0.1703	0.5289	0.4247	0.3351	12.9735	19.6942
			(6.4899)**	(-5.5652)**			(5.6698)**	-9.6551	
			(3.0209)**	(-3.7910)**				22.6280	
1,60,0	2167	1686	0.0945	-0.0744	0.5178	0.4371	0.1689	8.3874	7.6869
			(4.6958)**	(-2.3595)*			(3.2495)**	-3.1011	
			(1.6642)	(-2.0926)*				11.4885	
1,60,0.01	1931	1464	0.1022	-0.0844	0.5199	0.4344	0.1867	7.8997	7.5281
			(4.9189)**	(-2.6314)**			(3.3657)**	-2.9782	
			(1.7767)	(-2.1942)*				10.8779	
1,120,0	2166	1627	0.0773	-0.0646	0.5102	0.4413	0.1420	5.9069	3.9115
			(4.0093)**	(-1.9567)			(2.7038)**	-1.7470	
			(1.2642)	(-1.8593)				7.6539	
1,120,0.01	1993	1476	0.0743	-0.0704	0.5108	0.4424	0.1447	4.6071	2.8495
			(3.7678)**	(-2.0596)*			(2.6324)**	-1.6652	
			(1.1606)	(-1.9138)				6.2723	
1,180,0	2253	1480	0.0608	-0.0503	0.5011	0.4480	0.1111	3.8700	-0.1121
			(3.1733)**	(-1.4528)			(2.0747)*	0.2989	
			(0.8893)	(-1.5042)				3.5711	
1,180,0.01	2179	1375	0.0674	-0.0542	0.5057	0.4422	0.1216	4.5281	0.7275
			(3.5236)**	(-1.5258)			(2.2059)*	0.2940	
			(1.0340)	(-1.5418)				4.2341	
1,240,0	2337	1336	0.0590	-0.0567	0.5066	0.4334	0.1157	3.9287	0.0943
			(3.0388)**	(-1.5662)			(2.1079)*	0.2104	
			(0.8564)	(-1.5751)				3.7183	
1,240,0.01	2249	1265	0.0616	-0.0613	0.5087	0.4277	0.1229	3.9803	0.4209
			(3.1679)**	(-1.6657)			(2.1858)*	0.0922	
			(0.9087)	(-1.6317)				3.8880	
	Average		**0.0892**	**-0.0795**					

Table 1
Test Results of the VMA Rules for the Full Sample (January 1988 - December 2002) of Kuala Lumpur Stock Exchange Composite Index (KLSE CI)

Notes:	
1	The student t-statistic ratio which tests the hypothesis that the mean returns generated by technical trading rules is zero. The second row of the each test represents the t-statistic values in parenthesis.
2	The t-statistic ratio that tests the mean returns generated by technical trading rules equal to the returns derived by the buy-and-hold strategy. The third row of the each test represents the t-statistic values in parenthesis.
3	The t-statistic ratio of the difference between the returns of the buy and sell signals.
N(Buy)	refers to the number of buy signals generated during the sample period.
N(Sell)	refers to the number of sell signals generated during the sample period.
	* denotes $p < 0.05$, ** denotes $p < 0.01$.
Buy>0	is the fraction of returns of the buy signal which are more than zero.
Sell>0	is the fraction of returns of the sell signal which are more than zero.
B	denotes profit for buy signals.
S	denotes profit for sell signals.
T	denotes total profit for buy and sell signals.

All buy returns are positive with an average daily return of 0.0892% while the sell returns are all negative with an average daily return of -0.0795%. These returns are compared with a mean daily return of 0.0232% from the buy-and-hold strategy. For the twenty tests of significance across the buy and sell decisions in Table 1, only six are significant and reject hypothesis 2 in which the returns from the technical trading rules and the buy-and-hold strategy are not significantly different. Column 8 indicates that the returns of the buy-sell differences are positive and highly significant. The last two columns, columns 9 and 10 show positive profits before and after transaction cost for all rules except for the (1,180,0) rule. The length of 20 days appears to produce the highest profits after transaction costs of 19.6942% among all in the Malaysian stock market. Overall, the results indicated the predictive ability of VMA and they are consistent with Bessimbinder and Chan (1995).

Test Results on the Singapore Exchange

The test results of the 10 VMA rules of the Straits Times Index of Singapore Exchange from year 1988 to year 2002 are shown in Table 2. Ninety percent of the daily average returns for buy signals (9 out of 10) are significantly positive and thus, provide evidence to reject hypothesis 1 in which the technical trading rules generate zero returns. The results reinforce the findings of the study of Wong, Manzur, and Chews (2003).

Table 2
Test Results of the VMA Rules for the Full Sample (January 1988 - December 2002) of Straits Times Index (STI)

Test Variation	N (Buy)	N (Sell)	Buy	Sell	Buy>0	Sell>0	Buy-Sell	Profit before transaction cost	Profit after transaction cost
1,20,0	2050	1843	0.0945	-0.0732	0.5068	0.4617	0.1676	10.7876B	15.0593
			(5.1800)1**	(-3.0995)1**			(3.9550)3**	-6.8672S	
			(2.1497)2*	(-2.4191)2*				17.6546T	
1,20,0.01	1524	1289	0.1095	-0.1181	0.5144	0.4523	0.2276	9.0016	15.1523
			(5.6623)**	(-4.6414)**			(4.5549)**	-8.026	
			(2.3180)*	(-3.1878)**				17.0276	
1,60,0	2060	1793	0.0744	-0.0565	0.5073	0.4590	0.1309	8.0903	10.1523
			(4.0927)**	(-2.3500)*			(3.0685)**	-4.6307	
			-1.5939	1.9538				12.7210	
1,60,0.01	1794	1535	0.0871	-0.0743	0.5128	0.4560	0.1613	8.2930	11.5510
			(4.7824)**	(-2.9592)**			(3.5146)**	-5.4773	
			-1.8596	(-2.2969)*				13.7703	
1,120,0	1959	1834	0.0685	-0.0484	0.5079	0.4586	0.1169	6.8231	8.0953
			(3.6936)**	(-2.0194)*			(2.7258)**	-3.8009	
			-1.4071	1.7535				10.6240	
1,120,0.01	1827	1694	0.0802	-0.0548	0.5129	0.4557	0.1350	7.6490	9.3703
			(4.3901)**	(-2.2312)*			(3.0323)**	-4.0687	
			-1.6879	1.8722				11.7177	
1,180,0	2005	1728	0.0457	-0.0268	0.5012	0.4612	0.0726	3.9884	2.4697
			(2.4895)*	1.0829			-1.6741	-0.9700	
			-0.7898	1.1515				4.9584	
1,180,0.01	1866	1588	0.0565	-0.0154	0.5059	0.4647	0.0719	4.9092	2.1137
			(3.0907)**	0.6075			-1.5952	0.4928	
			-1.062	0.8264				4.4164	
1,240,0	2068	1605	0.0429	-0.0239	0.5015	0.4598	0.0668	3.7936	1.7797
			(2.2936)*	0.9427			-1.521	-0.4348	
			-0.7197	1.0469				4.2284	
1,240,0.01	1945	1455	0.0345	-0.0334	0.4992	0.4543	0.0679	2.3467	1.2023
			-1.8252	1.2817			-1.4839	-1.1223	
			-0.4747	1.2462				3.4690	
	Average		**0.0694**	**-0.0525**					

Table 2
Test Results of the VMA Rules for the Full Sample (January 1988 - December 2002) of Straits Times Index (STI)

Notes:	
1	The student t-statistic ratio which tests the hypothesis that the mean returns generated by technical trading rules is zero. The second row of the each test represents the t-statistic values in parenthesis.
2	The t-statistic ratio that tests the mean returns generated by technical trading rules equal to the returns derived by the buy-and-hold strategy. The third row of the each test represents the t-statistic values in parenthesis.
3	The t-statistic ratio of the difference between the returns of the buy and sell signals.
N(Buy)	refers to the number of buy signals generated during the sample period.
N(Sell)	refers to the number of sell signals generated during the sample period.
	* denotes $p < 0.05$, ** denotes $p < 0.01$.
Buy>0	is the fraction of returns of the buy signal which are more than zero.
Sell>0	is the fraction of returns of the sell signal which are more than zero.
B	denotes profit for buy signals.
S	denotes profit for sell signals.
T	denotes total profit for buy and sell signals.

Similarly in the Malaysian stock market, the buy returns are all positive with average daily return of 0.0694% (annualised rate of approximately 18%) while all the sell returns are negative with average daily return of -0.0525% (approximately -14% at an annual rate). It is noted that the returns of the buy-sell differences are positive and highly significant.

Test Results on the Hong Kong Stock Market

As seen in Table 3, all the daily average returns for buy signals of VMA rules of the Hang Seng Index are significantly positive, and therefore rejects the null hypothesis 1. The number of buy signals exceeds the number of sell signals. The tests of significance across the buy and sell decisions do not provide sufficient evidence to reject null hypothesis 2 since only 3 out of 20 test results are significant. The forecast ability seems to have less explanatory power. The returns of the buy-sell differences are significant for only the length of 20 days and 60 days. As for the profits before and after transaction cost, only the shorter length of 20 days and 60 days gives positive profits.

Test Results on the Taiwan Stock Market

The test results of the 10 VMA rules of Taiwan Weighted Index from year 1988 to year 2002 are reported in Table 4. The returns of the buy-sell differences are only significant for the length of 20 days, 60 days and 120 days, but not for longer lengths of 180 days and 240 days. All the VMA rules are found to yield positive profits before and after transaction cost, with the length of 20 days producing the highest profits. It can be interpreted that VMA rules can be used as an investment tool by investors in Taiwan stock market. The VMA rules are technically attractive.

Table 3
Test Results of the VMA Rules for the Full Sample (January 1988 - December 2002) of Hang Seng Index (HSI)

Test Variation	N (Buy)	N (Sell)	Buy	Sell	Buy>0	Sell>0	Buy-Sell	Profit before transaction cost	Profit after transaction cost
1,20,0	2137	1756	0.1201	-0.0692	0.5077	0.4658	0.1894	12.3499B	14.3918
			(5.3041)1**	(-2.1950)1*			(3.4816)3**	-3.3396S	
			(1.8580)2	(-2.1642)2*				15.6895T	
1,20,0.01	1760	1308	0.1370	-0.1058	0.5148	0.4778	0.2428	11.3128	14.7507
			(6.1162)**	(-3.0436)**			(3.9390)**	-4.4605	
			(2.0899)*	(-2.6243)**				15.7734	
1,60,0	2379	1474	0.0831	-0.0462	0.5057	0.4697	0.1293	8.4198	6.9046
			(3.8209)**	1.3456			(2.3096)*	0.2310	
			-1.0796	1.5867				8.1889	
1,60,0.01	2154	1282	0.0709	-0.0524	0.5005	0.4657	0.1233	5.4175	3.9867
			(3.2135)**	1.4583			(2.0705)*	0.2855	
			-0.7763	1.6223				5.1321	
1,120,0	2415	1378	0.0549	-0.0062	0.4998	0.4681	0.0611	4.0782	-1.3843
			(2.4553)*	0.177			-1.0719	4.1982	
			-0.4392	0.7925				-0.1200	
1,120,0.01	2271	1226	0.0544	-0.0030	0.4971	0.4698	0.0574	3.4740	-2.2138
			(2.4457)*	0.0819			-0.9592	4.5221	
			-0.4194	0.7006				-1.0482	
1,180,0	2355	1378	0.0545	0.0021	0.4998	0.4710	0.0524	3.7901	-2.4148
			(2.4101)*	-0.06			-0.9145	4.9606	
			-0.4259	0.6356				-1.1705	
1,180,0.01	2262	1266	0.0593	0.0036	0.5022	0.4724	0.0558	4.1818	-2.0607
			(2.6185)**	-0.0985			-0.941	5.0665	
			-0.529	0.5894				-0.8847	
1,240,0	2393	1280	0.0645	-0.0229	0.4998	0.4680	0.0874	5.5274	1.4907
			(2.7237)**	0.6441			-1.4948	2.8123	
			-0.6567	1.0783				2.7151	
1,240,0.01	2304	1189	0.0577	-0.0187	0.5022	0.4693	0.0764	4.0940	-0.3525
			(2.4688)*	-0.5124			-1.267	3.2822	
			-0.4948	-0.9738				0.8118	
	Average		**0.0756**	**-0.0180**					

Table 3
Test Results of the VMA Rules for the Full Sample (January 1988 - December 2002) of Hang Seng Index (HSI)

Notes:

1 The student t-statistic ratio which tests the hypothesis that the mean returns generated by technical trading rules is zero. The second row of the each test represents the t-statistic values in parenthesis.

2 The t-statistic ratio that tests the mean returns generated by technical trading rules equal to the returns derived by the buy-and-hold strategy. The third row of the each test represents the t-statistic values in parenthesis.

3 The t-statistic ratio of the difference between the returns of the buy and sell signals.

N(Buy) refers to the number of buy signals generated during the sample period.

N(Sell) refers to the number of sell signals generated during the sample period.

* denotes $p < 0.05$, ** denotes $p < 0.01$.

Buy>0 is the fraction of returns of the buy signal which are more than zero.

Sell>0 is the fraction of returns of the sell signal which are more than zero.

B denotes profit for buy signals.

S denotes profit for sell signals.

T denotes total profit for buy and sell signals.

Table 4
Test Results of the VMA Rules for the Full Sample (January 1988 - December 2002) of Taiwan Weighted Index

Test Variation	N (Buy)	N (Sell)	Buy	Sell	Buy>0	Sell>0	Buy-Sell	Profit before transaction cost	Profit after transaction cost
1,20,0	2027	1866	0.1732	-0.1649	0.4919	0.4411	0.3381	18.4815B	33.3403
			(6.0018)1**	(-4.5021)1**			(5.1347)3**	-15.5985S	
			(2.7903)2**	(-3.1412)2**				34.0800T	
1,20,0.01	1717	1551	0.2140	-0.1985	0.4980	0.4410	0.4124	19.5738	34.5579
			(7.2496)**	(-5.1606)**			(5.7368)**	-15.6049	
			(3.3246)**	(-3.4902)**				35.1788	
1,60,0	1955	1898	0.1331	-0.1238	0.4946	0.4378	0.2569	12.4351	22.4505
			(4.5779)**	(-3.3747)**			(3.8853)**	-10.7475	
			(2.0530)**	(-2.4431)*				23.1826	
1,60,0.01	1791	1749	0.1533	-0.1171	0.4992	0.4368	0.2704	13.3909	21.4544
			(5.2525)**	(-3.1185)**			(3.9198)**	-8.7361	
			(2.3380)*	(-2.2623)*				22.1270	
1,120,0	1880	1913	0.0753	-0.0816	0.4963	0.4313	0.1570	4.5258	9.2966
			(2.4731)*	(-2.2725)*			(2.3551)*	-5.4915	
			-1.0228	1.7128				10.0172	
1,120,0.01	1810	1822	0.0895	-0.0912	0.4978	0.4292	0.1808	5.8869	11.3618
			(2.9361)**	(-2.5169)*			(2.6543)**	-6.1650	
			-1.2529	1.8501				12.0519	
1,180,0	1851	1882	0.0406	-0.0696	0.4846	0.4373	0.1101	0.0860	3.1867
			-1.3951	1.851			-1.639	-3.8099	
			-0.4163	1.494				3.8959	

Table 4 Test Results of the VMA Rules for the Full Sample (January 1988 - December 2002) of Taiwan Weighted Index									
Test Variation	N (Buy)	N (Sell)	Buy	Sell	Buy>0	Sell>0	Buy-Sell	Profit before transaction cost	Profit after transaction cost
1,180,0.01	1781	1804	0.0573	-0.0763	0.4896	0.4368	0.1336	1.8846	5.4585
			(1.9634)*	(-2.0146)*			-1.9483	-4.2551	
			-0.6963	1.5875				6.1397	
1,240,0	1865	1808	0.0393	-0.0643	0.4847	0.4364	0.1037	-0.0255	2.1121
			-1.3616	1.6844			-1.5306	-2.8356	
			-0.3966	1.384				2.8100	
1,240,0.01	1813	1722	0.0431	-0.0565	0.4859	0.4367	0.0995	0.2856	1.1812
			-1.4902	1.4658			-1.4414	-1.5673	
			-0.4563	1.2289				1.8529	
	Average		**0.1019**	**-0.1044**					

Notes:

1 The student t-statistic ratio which tests the hypothesis that the mean returns generated by technical trading rules is zero. The second row of the each test represents the t-statistic values in parenthesis.

2 The t-statistic ratio that tests the mean returns generated by technical trading rules equal to the returns derived by the buy-and-hold strategy. The third row of the each test represents the t-statistic values in parenthesis.

3 The t-statistic ratio of the difference between the returns of the buy and sell signals.

N(Buy) refers to the number of buy signals generated during the sample period.

N(Sell) refers to the number of sell signals generated during the sample period.

* denotes $p < 0.05$, ** denotes $p < 0.01$.

Buy>0 is the fraction of returns of the buy signal which are more than zero.

Sell>0 is the fraction of returns of the sell signal which are more than zero.

B denotes profit for buy signals.

S denotes profit for sell signals.

T denotes total profit for buy and sell signals.

Test Results on the Japan Stock Market

Table 5 reports the results of the 10 VMA rules of Nikkei 225 Index of the Japan stock market from year 1988 to year 2002. None of the daily average returns for buy signals are statistically significant and hence, do not provide evidence to reject the null hypothesis 1. The number of sell signals exceeds the number of buy signals and this is consistent with the downward trend of Japan stock market from 1988 to 2002. The average daily return for buy signals is 0.0088%, nonetheless, it is still higher than the returns from the buy-and-hold during the studied period. The overall test results fail to reject null hypothesis 2. The returns of the buy-sell differences are also found to be insignificant. The technical trading rules demonstrated less predictive ability in the Japan stock market and this is supported by Bessembinder and Chan (1995) and Tian, Wan, and Guo (2002). This is also in line with the higher degree of market efficiency of developed stock market such as Japan (Reily & Brown, 2003). The results shown in Nikkei 225 imply that passive management strategies such as buy-and-hold strategy and investing in index fund are more suitable. The passive strategies would help investors to earn market returns and reducing trading costs.

Table 5
Test Results of the VMA Rules for the Full Sample (January 1988 - December 2002) of Nikkei 225

Test Variation	N (Buy)	N (Sell)	Buy	Sell	Buy>0	Sell>0	Buy-Sell	Profit before transaction cost	Profit after transaction cost
1,20,0	1897	1996	-0.0003	-0.0503	0.4760	0.4584	0.0500	-0.9033B	4.0537
			(-0.0175)1	(-1.9749)1*			(1.0952)3	-5.8394S	
			(0.5829)2	(-0.6839)2				4.9361T	
1,20,0.01	1391	1490	0.0329	-0.0457	0.4788	0.4631	0.0786	2.1864	5.2173
			-1.6676	1.6738			-1.4805	-3.6839	
			-1.2691	0.5118				5.8703	
1,60,0	1832	2021	0.0013	-0.0557	0.4733	0.4567	0.0570	-0.6973	5.0677
			-0.0735	(-2.0841)*			-1.2406	-6.6383	
			-0.6176	0.8228				5.9410	
1,60,0.01	1544	1755	0.0123	-0.0704	0.4780	0.4553	0.0827	0.4106	7.0347
			-0.6696	(-2.5432)*			-1.6646	-7.3720	
			-0.839	1.144				7.7825	
1,120,0	1749	2044	0.0043	-0.0618	0.4791	0.4501	0.0661	-0.3612	6.3388
			-0.2463	(-2.2502)*			-1.4244	-7.5598	
			-0.6797	0.9837				7.1986	
1,120,0.01	1611	1912	0.0172	-0.0675	0.4817	0.4467	0.0847	0.9858	7.9282
			-1	(-2.4135)*			-1.7581	-7.7409	
			-0.9667	1.1053				8.7268	
1,180,0	1589	2144	0.0045	-0.0581	0.4840	0.4473	0.0626	-0.3838	6.2100
			-0.2704	(-2.0912)*			-1.3273	-7.4400	
			-0.6624	0.9019				7.0561	
1,180,0.01	1502	2062	0.0157	-0.0489	0.4854	0.4515	0.0646	0.7154	5.7650
			-0.9578	1.7513			-1.3374	-5.8575	
			-0.9091	0.6531				6.5728	
1,240,0	1462	2211	-0.0039	-0.0533	0.4726	0.4536	0.0494	-1.2426	4.9254
			0.2402	1.9063			-1.0293	-7.0006	
			-0.4499	0.7857				5.7580	
1,240,0.01	1349	2118	0.0042	-0.0448	0.4774	0.4528	0.0490	-0.4844	4.1932
			-0.2571	1.5898			-0.9871	-5.4634	
			-0.617	0.5525				4.9790	
	Average		**0.0088**	**-0.0557**					

Table 5
Test Results of the VMA Rules for the Full Sample (January 1988 - December 2002) of Nikkei 225

Notes:	
1	The student t-statistic ratio which tests the hypothesis that the mean returns generated by technical trading rules is zero. The second row of the each test represents the t-statistic values in parenthesis.
2	The t-statistic ratio that tests the mean returns generated by technical trading rules equal to the returns derived by the buy-and-hold strategy. The third row of the each test represents the t-statistic values in parenthesis.
3	The t-statistic ratio of the difference between the returns of the buy and sell signals.
N(Buy)	refers to the number of buy signals generated during the sample period.
N(Sell)	refers to the number of sell signals generated during the sample period.
	* denotes $p < 0.05$, ** denotes $p < 0.01$.
Buy>0	is the fraction of returns of the buy signal which are more than zero.
Sell>0	is the fraction of returns of the sell signal which are more than zero.
B	denotes profit for buy signals.
S	denotes profit for sell signals.
T	denotes total profit for buy and sell signals.

Test Results on the Korean Stock Market

The test results of the 10 VMA rules of Seoul Composite Index from year 1988 to year 2002 are reported in Table 6. All the VMA rules are found to produce positive profits before and after transaction cost except for the (1,120,0.01) rule. The VMA length of 20 days is found produced the highest profits among all rules.

Test Results on the China Stock Market

Table 7 reports on the results of the 10 VMA rules of the Shanghai Composite Index from year 1991 to year 2002. The daily average returns for buy signals are significantly positive for the length of 20 days, 60 days and 120 days but not for longer lengths of 180 days and 240 days. Therefore, the evidence from the test results is only sufficient to reject null hypothesis 1 for shorter lengths of 120 days and below. The number of buy signals exceeds the number of sell signals. All the buy returns are positive with average daily return of 0.1545% (annualised rate of approximately 40%) while the average daily return from sell signals is -0.0158% (approximately -4% at an annual rate). Positive profits before and after transaction cost are only obtainable for shorter lengths of 20 days, 60 days and 120 days. Consistent with the results from other stock markets, the length of 20 days yielding about 55% profits after transaction cost.

Table 6
Test Results of the VMA Rules for the Full Sample (January 1988 - December 2002) of Seoul Composite Index

Test Variation	N (Buy)	N (Sell)	Buy	Sell	Buy>0	Sell>0	Buy-Sell	Profit before transaction cost	Profit after transaction cost
1,20,0	1865	2028	0.1095	-0.1011	0.4890	0.4344	0.2106	7.3606B	13.1996
			(3.8226)1**	(-3.1386)1**			(3.4422)3**	-7.4222S	
			(1.9487)2	(-2.0321)2*				14.7828T	
1,20,0.01	1509	1657	0.1252	-0.1036	0.5003	0.4375	0.2288	6.3423	10.2447
			(4.1999)**	(-3.1021)**			(3.3709)**	-5.1899	
			(2.0813)*	1.9406				11.5322	
1,60,0	1818	2035	0.0883	-0.0787	0.4868	0.4359	0.1670	4.4502	7.3109
			(3.1090)**	(-2.4025)*			(2.7136)**	-4.4276	
			-1.5406	1.6043				8.8778	
1,60,0.01	1621	1812	0.0987	-0.0715	0.4935	0.4432	0.1702	4.4183	5.4071
			(3.3907)**	(-2.1118)*			(2.6108)**	-2.3849	
			-1.6656	1.4097				6.8032	
1,120,0	1846	1947	0.0586	-0.0614	0.4805	0.4397	0.1200	0.9610	1.1339
			(2.1317)*	1.7882			-1.9366	-1.7154	
			-0.9972	1.2531				2.6764	
1,120,0.01	1691	1830	0.0452	-0.0620	0.4755	0.4388	0.1072	-1.1577	-1.2794
			-1.618	1.7811			-1.6658	-1.3102	
			-0.7257	1.2384				0.1524	
1,180,0	1697	2036	0.0766	-0.0667	0.4838	0.4430	0.1433	2.4109	3.6939
			(2.8075)**	1.9198			(2.2853)*	-2.8010	
			-1.2928	1.3738				5.2120	
1,180,0.01	1619	1934	0.0754	-0.0695	0.4855	0.4426	0.1449	1.8905	3.1493
			(2.7352)**	(-1.9749)*			(2.2553)*	-2.7037	
			-1.2515	1.4027				4.5942	
1,240,0	1656	2017	0.0610	-0.0636	0.4771	0.4447	0.1246	0.4816	1.2933
			(2.1873)*	1.819			(1.9705)*	-2.3054	
			-1.0031	1.3111				2.7870	
1,240,0.01	1582	1953	0.0611	-0.0553	0.4772	0.4455	0.1165	0.1944	-0.2888
			(2.1763)*	1.5733			-1.8053	-0.9544	
			-0.9893	1.1402				1.1488	
	Average		**0.0800**	**-0.0733**					

Table 6
Test Results of the VMA Rules for the Full Sample (January 1988 - December 2002) of Seoul Composite Index

Notes:

1	The student t-statistic ratio which tests the hypothesis that the mean returns generated by technical trading rules is zero. The second row of the each test represents the t-statistic values in parenthesis.
2	The t-statistic ratio that tests the mean returns generated by technical trading rules equal to the returns derived by the buy-and-hold strategy. The third row of the each test represents the t-statistic values in parenthesis.
3	The t-statistic ratio of the difference between the returns of the buy and sell signals.
N(Buy)	refers to the number of buy signals generated during the sample period.
N(Sell)	refers to the number of sell signals generated during the sample period.
	* denotes p < 0.05, ** denotes p < 0.01.
Buy>0	is the fraction of returns of the buy signal which are more than zero.
Sell>0	is the fraction of returns of the sell signal which are more than zero.
B	denotes profit for buy signals.
S	denotes profit for sell signals.
T	denotes total profit for buy and sell signals.

Table 7
Test Results of the VMA Rules for the Full Sample (January 1991 - December 2002) of Shanghai Composite Index

Test Variation	N (Buy)	N (Sell)	Buy	Sell	Buy>0	Sell>0	Buy-Sell	Profit before transaction cost	Profit after transaction cost
1,20,0	1596	1514	0.3015	-0.1633	0.5620	0.4201	0.4648	37.9248B	54.5462
			(5.4539)1**	(-3.4299)1**			(4.5011)3**	-18.4356S	
			(2.5551)2*	(-2.6479)2**				56.3604T	
1,20,0.01	1332	1299	0.3526	-0.2010	0.5743	0.4203	0.5536	36.9660	55.0243
			(6.0637)**	(-4.1320)**			(4.9326)**	-19.5931	
			(2.9451)**	(-2.9086)**				56.5591	
1,60,0	1596	1474	0.1952	-0.0477	0.5551	0.4315	0.2429	23.7964	25.6968
			(3.5171)**	0.9769			(2.3366)*	-3.6913	
			-1.3551	1.3525				27.4876	
1,60,0.01	1508	1354	0.2122	-0.0501	0.5584	0.4350	0.2623	24.4942	26.3137
			(3.7880)**	1.0018			(2.4344)*	-3.4890	
			-1.5175	1.3395				27.9832	
1,120,0	1716	1294	0.1421	-0.0054	0.5268	0.4575	0.1475	18.1557	14.8131
			(2.5460)*	0.1078			-1.3922	1.5867	
			-0.7735	0.848				16.5690	
1,120,0.01	1626	1213	0.1354	-0.0042	0.5252	0.4575	0.1396	16.1798	12.7821
			(2.3818)*	0.0828			-1.2788	1.7416	
			-0.6837	0.8166				14.4381	
1,180,0	1740	1210	0.0735	0.0576	0.5098	0.4636	0.0159	8.4834	-1.2150
			-1.3122	-1.102			-0.1472	7.9776	
			0.0209	0.1812				0.5059	

Table 7
Test Results of the VMA Rules for the Full Sample (January 1991 - December 2002) of Shanghai Composite Index

Test Variation	N (Buy)	N (Sell)	Buy	Sell	Buy>0	Sell>0	Buy-Sell	Profit before transaction cost	Profit after transaction cost
1,180,0.01	1669	1158	0.0467	0.0678	0.5093	0.4629	-0.0211	4.3290	-6.0314
			-0.8284	-1.2845			0.1915	8.7113	
			0.3272	0.0754				-4.3823	
1,240,0	1726	1164	0.0434	0.0761	0.5017	0.4605	-0.0326	4.0743	-7.1580
			-0.7645	-1.4145			0.2991	9.5465	
			0.3692	-0.008				-5.4721	
1,240,0.01	1662	1096	0.0427	0.1122	0.5042	0.4681	-0.0695	3.7453	-10.2838
			-0.7432	(2.0608)*			0.6209	12.4203	
			0.3727	-0.3661				-8.6749	
	Average		**0.1545**	**-0.0158**					

Notes:
1 The student t-statistic ratio which tests the hypothesis that the mean returns generated by technical trading rules is zero. The second row of the each test represents the t-statistic values in parenthesis.
2 The t-statistic ratio that tests the mean returns generated by technical trading rules equal to the returns derived by the buy-and-hold strategy. The third row of the each test represents the t-statistic values in parenthesis.
3 The t-statistic ratio of the difference between the returns of the buy and sell signals.
N(Buy) refers to the number of buy signals generated during the sample period.
N(Sell) refers to the number of sell signals generated during the sample period.
* denotes $p < 0.05$, ** denotes $p < 0.01$.
Buy>0 is the fraction of returns of the buy signal which are more than zero.
Sell>0 is the fraction of returns of the sell signal which are more than zero.
B denotes profit for buy signals.
S denotes profit for sell signals.
T denotes total profit for buy and sell signals.

Table 8 summarises the average daily returns of the buy and sell signals from the application of the VMA rules, and the simple buy-and-hold strategy, round trip percentage transaction costs, beginning and ending closing indices for the seven Asian equity markets during the studied period. Figure 1 and 2 present the closing price of the seven Asian market indices from January 1988 to December 2002. The average daily return from the buy signals showed higher returns from the buy-and-hold strategy for all the seven markets. The Shanghai Composite Index of the China stock market demonstrated the highest returns from buy signals with an average daily return of 0.1545%. The superior returns produced by Shanghai Composite Index offer to global investors many profit opportunities as well as providing a good choice for portfolio diversification. The Shanghai stock market appears relatively less efficient in which past returns can be used to predict future returns.

On the other hand, the buy signal for Japan market produces the lowest average daily return of 0.0088%, nonetheless, it is still higher than -0.0236% derived from buy-and-hold strategy.

Table 8
Average Daily Returns of Buy, Sell Signals and Buy-and-hold Strategy, Transaction Costs and Closing Market Indices for the Seven Asian Stock Markets

Market	Average Daily Return			Round-trip (%) Transaction Cost	Closing Index on 1/1/1988	Closing Index on 31/12/2002
	Buy Signal	Sell Signal	Buy-and-hold Strategy			
Malaysia	0.0892%	-0.0795%	0.0232%	1.48%	261.19	646.32
Singapore	0.0694%	-0.0525%	0.0171%	1.00%	687.63	1341.03
Hong Kong	0.0756%	-0.0180%	0.0357%	0.50%	2302.75	9321.29
Taiwan	0.1019%	-0.1044%	0.0164%	0.285%	2339.86	4452.45
Japan	0.0088%	-0.0557%	-0.0236%	0.34%	21564.00	8578.95
Korea	0.0800%	-0.0733%	0.0049%	0.61%	517.99	627.55
China1	0.1545%	-0.0158%	0.0753%	0.70%	128.84	1357.654

Note 1: It starts on 2/1/1991

Figure 1: Closing Price Indices from January 1988 to December 2002

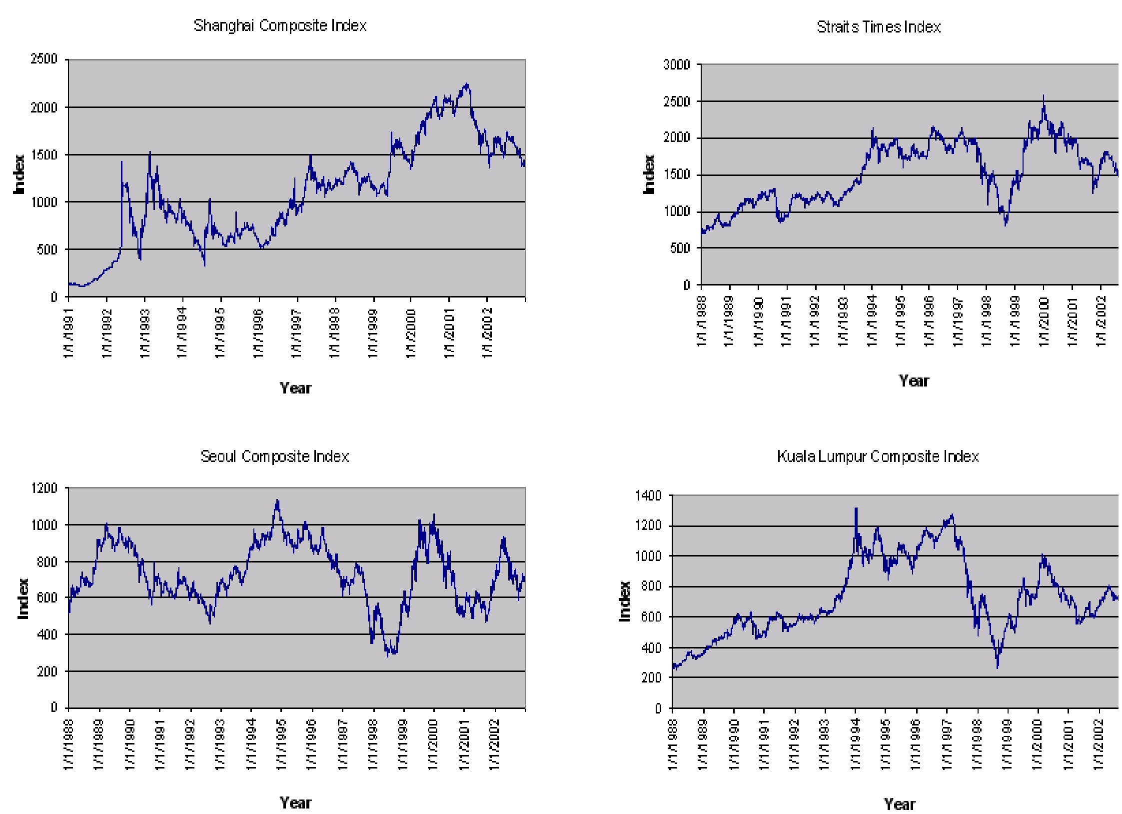
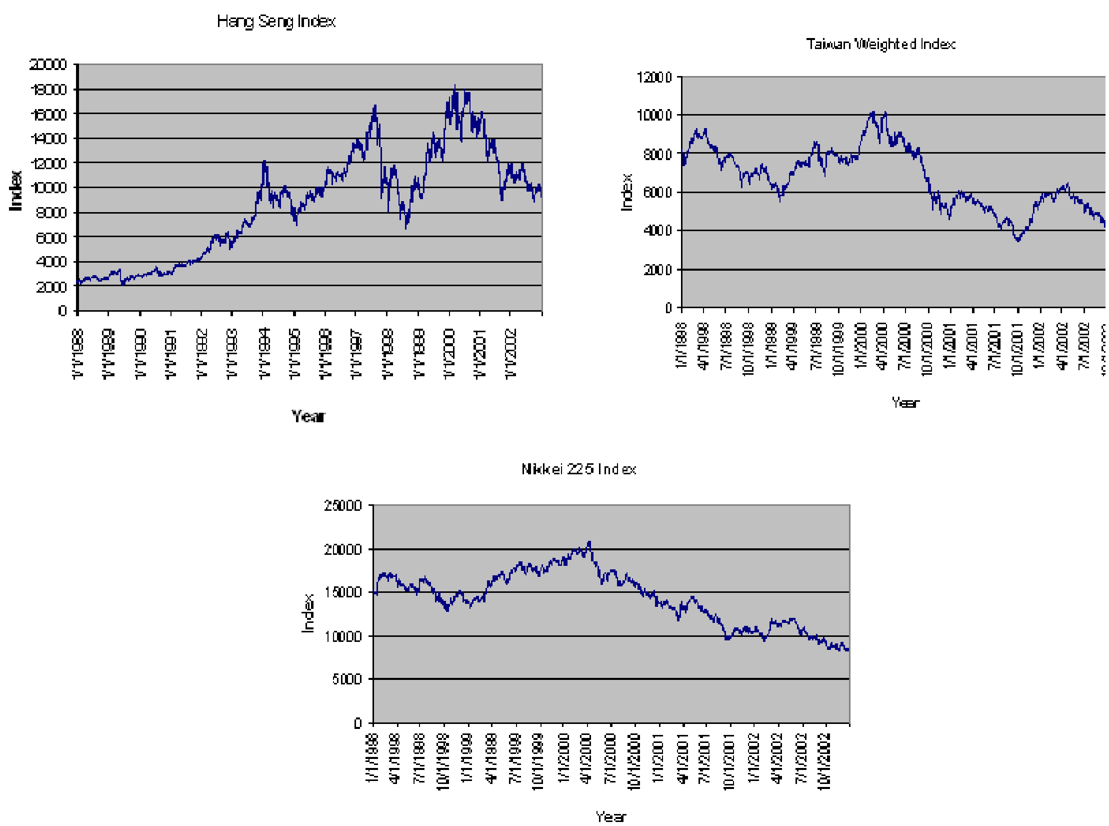


Figure 2 Closing Price Indices from January 1988 to December 2002



CONCLUSION

The test results of the VMA rules in the seven Asian markets are found to be statistically and economically significant particularly, for shorter lengths. However, the forecasting power reduces as the moving average length increases. The study suggests predictive ability of technical strategies in emerging markets, especially the China stock market in which its offers attractive profit opportunities. The study has important implications for the investment management. It explains the survival and application of technical strategies in marketplace by analysts, traders, and investors. Twenty-day VMA rules emerged as the most recommended and profitable rule in making financial decision. It would be of interest if future research may extend on potential applications of other technical strategies and individual stocks. It may also extend to take advantage of various stages of stock market development.

ENDNOTES

1 The stock market indexes are used to measure the total returns for an aggregate market. It is also used as a proxy of market portfolio of risky assets and served as benchmarks to evaluate the performance of professional money managers (Reilly and Brown, 2003).

2 For VMA rule, each day is either a buy or sell signal, thus there is no equity shall be hold in between buy or sell signal. The returns derived are just for buy or sell signal generated days, not for entire holding periods. Hence, the returns are calculated on daily basis for buy and sell signals that employ VMA rule. In other words, they are conditional buy or sell mean returns. We then compare the conditional daily mean returns to just merely daily returns from the buy and hold strategy (unconditional mean returns) of the sample studied period which does not employ VMA rule.

3 Using the example of (1,20,0) for the Kuala Lumpur Stock Exchange Composite Index, the profits of the buy signals b = (Mean Return x Signals per year) - Risk free interest rate = [0.1305% x (2115/15)] - 5.262% = 18.4005% - 5.262% = 13.1385%

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A MULTI-MARKET, HISTORICAL COMPARISON OF THE INVESTMENT RETURNS OF VALUE AVERAGING, DOLLAR COST AVERAGING AND RANDOM INVESTMENT TECHNIQUES

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ABSTRACT

As the title suggests, this paper compares two "formula" or mechanical investment techniques, value averaging (VA) and dollar cost averaging, to a form of random investing to determine if any technique yields superior investment return performance. The tests use historical market prices of chosen stock and commodity indices. Results seem to indicate that value averaging does provide a small but still superior expected investment returns under most conditions. Due to the relatively few real world "experiences" available, these results can only be anecdotally and not statistically confirmed at a high confidence level. Actual investment results reported here are consistent with prior statistically significant research supporting a small investment performance advantage for value averaging versus both other techniques using simulation to approximate market activity. Evidence builds that VA works!

INTRODUCTION

An earlier paper (Marshall and Baldwin, 1994) did a statistical comparison of simulation based investment results for Dollar-Cost Averaging (DCA) and random investment techniques. They calculated the internal rate of return (IRR) to an investor from each of many simulated investment scenarios under both techniques. Their research question was, "Does DCA yield superior investment performance compared to a purely random investment technique?" They found, with 99% confidence, that there is no statistical difference in the IRRs achieved by each technique. They also found, with 95% confidence that each technique had the same risk as measured by the standard deviation of the IRR distributions. They concluded that the null hypothesis was valid and that DCA was not superior to random investments. These results are contrary to most practitioner given investment advice, even including Vanguard's (Vanguard, 1988), and contrary to that presented in many texts on personal finance. See for example (Gitman and Joehnk, 2002.)

To most academics those results are not surprising. The weak and semi-strong forms of the efficient market hypothesis (EMH) suggest that there should be no investment technique that persists in giving meaningfully superior performance over time, transaction costs considered. Admittedly, some techniques have temporarily given superior performance such as those investing in low P/E stocks, investing to take advantage of the "size effect" and even investing based on the January and other calendar related effects. See for example the works of (Fama and French, 1992 and Rosenberg, et. al., 1985.) However, if the market is efficient, as the EMH obviously assumes, the benefits of such techniques should disappear as more and more investors participate in the anomalies to their hoped for advantage. What is interesting about tests of DCA and other purely mechanical techniques, that are influenced only by the absolute level of the stock market and its subsequent price fluctuations over time, is that the corrective mechanism suggested by the EMH can not work, since each investor may start using the technique at a different point in time and hence, at different stock price levels and thus receive investment signals at different price points and at different times.

Edleson has proposed another such mechanical technique (Edleson 1988, 1991), somewhat similar to DCA, which he calls "Value Averaging" (VA). He has tested VA using simulations to compare VA to DCA and to the purchase of a constant number of shares in each investment period. Without considering possible differences in risk, he (Edleson, 1991, pp. 191 and 192) concluded:

- "(There is an) inherent return advantage of value averaging (over dollar-cost averaging and purchase of a constant number of shares)."
- "It's about as close to 'buy low, sell high' as we're going to get without a crystal ball."

If Edleson was correct, and there were no compensating risk differences, then this was an important development. If so, he seemingly discovered a mechanical anomaly that produces superior investment returns that is not dependent on temporary inefficiencies in the EMH. Further research was clearly called for. And, if VA "works," then additional research on other mechanical investment techniques that may be even better than VA should be encouraged.

A 2000 follow-up paper (Marshall, 2000) proposed a simulation based three-way analysis (VA vs. DCA vs. random investing) and structured the research similarly, where possible, to both the prior work (Edleson, 1988 and Marshall and Baldwin, 1994). Like the latter, the analysis also provided a framework for considering the element of statistical risk. Similar to the earliest work, the research question was, "Does DCA or VA yield superior investment performance compared to a purely random investment technique or compared to each other?" As before the investment return of the three techniques were determined by the IRR of each simulation's cash flow. Many hundreds of simulations of investment results were used to calculate mean return and standard deviation of the IRR. The F-Test was used to test the variation among the three sample populations' mean IRR. Confirming earlier work (Edleson, 1988), Marshall's results strongly suggested that VA almost always actually did provide a small but consistent performance advantage over DCA and random investment techniques, without incurring additional risk, and did so with 99% confidence as measured by the F-Test, for simulations of volatile markets and for long investment time horizons. Finally, results also suggested that there is no statistical difference between DCA and random investment techniques either in expected return or in risk avoidance, thus confirming the earlier work of Marshall and Baldwin and others' less quantitative conclusions. See for example (Geer, 1995; Gibbs, 2000 and Hulbert, 1999.)

Even with those rather astounding results, recent discussion of VA has been sparse, save for a short favorable mention in the Wall Street Journal (Clements, 2001). Amazingly, no other published academic research other than Edleson and Marshall's has tested Value Averaging. Even the popular press is almost silent on VA, particularly when compared to continuing discussion of the now fully academically discredited DCA.

Why such silence? Who knows? Hopefully this research may help to correct that deficiency by continuing the debate by testing the investment performance of VA against both DCA and random investment techniques in the real world of actual market prices. Instead of a theoretical or simulation based approach, this paper proposes an empirical test of the investment performance of DCA, VA and random investing on actual market data over extended (and variable) investment time horizons. Furthermore tests will include foreign as well as domestic markets and other than equity markets, as suggested by some (Bacon, 1997). The research question employed in this paper is,

> "Is there evidence that VA yields superior investment return performance compared to DCA or to a purely random investment technique when tested on actual market data across multiple markets and variable investment time horizons?"

A DESCRIPTION OF TECHNIQUES: DOLLAR COST AVERAGING, VALUE AVERAGING AND RANDOM INVESTING

Instead of asking the reader to review other work as a primer on both DCA and VA, perhaps that chore can best be accomplished here? Also, the exact definition used for Random investing needs description. DCA is generally well understood. Perhaps Yahoo's glossary (Yahoo, 2004) definition for "constant dollar plan" (as they call DCA) is as good as any:

> "(DCA is…) a method of purchasing securities by investing a fixed amount of money at set intervals. The investor buys more shares when the price is low and fewer shares when the price is high, thus reducing the overall costs."

It is the essence of a buy and hold strategy. There is no talk of selling. Similarly, there is no suggestion as to how long DCA should be applied. Their choice of language is also interesting and biased. Can there be any doubt among average investors that, "…reducing overall costs," and by extension, DCA, is a good thing?

The inventor (Edleson, 1991) of Value Averaging, believes the idea behind it is simple. The investor sets a predetermined value or worth for his portfolio in each future time period, as a function of the size of the initial investment, the size of periodic investments and the investment return expected. The investor then buys or sells sufficient "shares" or units of the investment such that the predetermined portfolio worth is achieved at each revaluation point. On yield expectation, the author (Edleson, 1991, p. 119) suggests a long run equity return of 16% (which now seems absurdly high in this post-NASDAQ bubble world), based on an equity return 7.4% higher than the then existing rate on long term bonds. On revaluation timing, the author (Edleson, 1991, p. 162] suggests that, "…(using) value averaging two, three or four times a year would be reasonable..." In his own words, the author (Edleson 1988, p. 13) defines the value-averaging concept:

> "The rule under value averaging is simple: ... make the value not (the market price) of your stock go up by a fixed amount each month."

Considering movements in the investment's market price, the investor then either acquires or disposes of sufficient units of the investment such that the investment's required value is achieved at each subsequent revaluation point. During periods of market price decline, the investor is required to purchase relatively many units to maintain portfolio value. Conversely, during rising markets the technique requires the purchase of relatively few shares to achieve required value. During extended bull markets or during unusually large upward spikes in market price, the technique requires that units be sold to maintain portfolio value at the desired level.

The VA technique is even more intuitively appealing than DCA. As with DCA, more investment units are purchased when prices are low. However, VA magnifies the need to purchase relative to DCA since unit price declines reduce the value of the portfolio thus increasing the need for extra investment and initiating ever more aggressive "buy" signals. Furthermore, and contrary to DCA, VA gives a rule for selling. As the market price increases, beyond what it was recently, VA may require unit sales since the growing price rise may substantially increases the value of the portfolio. And, if the market price continues to increase dramatically, VA gives ever more aggressive "sell" signals to control the value of the portfolio to the level desired.

In the earlier work (Marshall and Baldwin, 1994, p. 61) it is stated that DCA was appealing because,

> "Intuitively, DCA is contrary in the sense that fewer shares are purchased when price are 'high' and more shares are purchased when price are 'low', facilitating the 'buy low' aspect of the ancient investment adage, 'buy low, sell high'."

VA conceptually does an even better job. Even more units are purchased at "low" prices and probably some, at least, are sold at "high" prices.

At this stage, a numerical description of VA and a comparison to DCA may be useful. The price pattern in Table 1 shows that whether the market price of an investment is rising, falling, or fluctuating over time, VA yields a lower average cost of shares purchased than does DCA and both are lower than the average price of shares. No proof, nor even contention, is offered here that this happens under all price patterns, but the specific price patterns used are not selected solely to achieve this goal. The price patterns are the same ones used by Vanguard to tout the supposed benefits of DCA, and the same ones used by Marshall and Baldwin and Marshall in their research.

Table 1: Average Prices, Average Costs and IRRs for VA and DCA in Rising, Declining, and Fluctuating Markets.

Rising Market

		Value Averaging				Dollar Cost Averaging		
Period	Market Price	Value Required	Shares Owned	Shares Bought	Period Invest	Period Invest	Shares Bought	Shares Owned
1	$5	$400	80	80	$400	$400	80	80
2	8	800	100	20	160	400	50	130
3	10	1200	120	20	200	400	40	170
4	10	1600	160	40	400	400	40	210
5	$16	$2000	125	(35)	$(560)	$400	25	235
AVG	$9.80				$600	$2000		
		Average Cost[1]:		$4.80		Average Cost:	$8.51	
		IRR:		33.83%		IRR:	32.01%	

Declining Market

		Value Averaging				Dollar Cost Averaging		
Period	Market Price	Value Required	Shares Owned	Shares Bought	Period Invest	Period Invest	Shares Bought	Shares Owned
1	$16	$400	25	25	$400	$400	25	25
2	10	800	80	55	550	400	40	65
3	8	1200	150	70	560	400	50	115
4	8	1600	200	50	400	400	50	165
5	$ 5	$2000	400	200	$1000	$400	80	245
AVG	$9.40				$2910	$2000		
		Average Cost:		$7.28		Average Cost:	$8.16	
		IRR:		24.08%		IRR:	24.80%	

Table 1: Average Prices, Average Costs and IRRs for VA and DCA in Rising, Declining, and Fluctuating Markets.

Fluctuating Market

		Value Averaging				Dollar Cost Averaging		
Period	Market Price	Value Required	Shares Owned	Shares Bought	Period Invest	Period Invest	Shares Bought	Shares Owned
1	$10	$400	40	40	$400	$400	40	40
2	8	800	100	60	480	400	50	90
3	5	1200	240	140	700	400	80	170
4	8	1600	200	(40)	(320)	400	50	220
5	$10	$2000	200	0	$0	$400	40	260
AVG	$8.20				$1260	$2000		
		Average Cost:		$6.30		Average Cost:		$7.69
		IRR:		15.22%		IRR:		13.15%

[1] Average cost can be calculated from the total of the "Period Invest" column divided by the number of shares owned at period 5. For example, using the Rising Market scenario, $600 total investment for VA bought 125 shares for an average cost of $4.80 a share, and $2000 total investment for DCA bought 235 shares for an average cost of $8.51.

The mathematical "certainty" (as reported by others, see (Edleson, 1991, p. 30) that DCA average cost is always lower than the average price has allowed some to promote DCA as an attractive way to assure superior investment performance. If that were sufficient to assure superior investment performance then by definition VA must be a superior to DCA since VA's average cost is lower than DCA's. But, as demonstrated by Marshall and Baldwin, if there is no statistical difference in investment returns as measured by IRR between DCA and random investing, then logically, random investing must on average acquire shares at the same cost as DCA, time and value considered. Therefore, by extension, the fact that VA acquires shares at lower average cost than DCA for these examples, or even in all cases, is not enough to assure that VA has a performance advantage over DCA. Statistical tests are necessary, and possible due to the essentially unlimited "testing" potential of simulation.

The IRRs for both VA and DCA are shown in Table 1. Interestingly, but not necessarily statistically significant, VA has a higher IRR than DCA for each market price pattern shown. To calculate each technique's cash flow pattern, the length of the investment time horizon, the dollar amount invested and the market price of the investment in each period are required. The IRR can then be calculated since the amount and timing of each periodic investment (or disinvestment) and the ending market value of the portfolio are known. For example, in a rising market as shown in

Table 1, the "Period Invest" column for DCA requires a cash outflow of $400 each period, 1 through 4. After a final investment of $400 in the fifth period, the DCA investor has acquired 235 shares with a market price of $16 a share for a total portfolio value of $3,760. The IRR of the cash flow is 32.01%, assuming annual time periods and no transaction costs or taxes.

Some may argue that Table 1 is flawed. The "Value Required" column of VA is simply equal to the cumulative investment shown under the "Total Invest" Column of DCA, implying that the VA investor expects no return on investment. To counter that argument, to better match Edleson's methodology, and to further demonstrate the VA investment technique, Table 2 is presented. Table 2 allows the "Value Required" column of VA to increase period to period by l0% of the prior period's "Value Required" plus the same $400 "Period Invest" shown for DCA, thus implying a 10% investment growth per period for VA. Again, the results are similar to Table 1. Each test shows VA with a lower average cost of shares than DCA and higher IRRs. However, the important question is not which technique yields the lower average cost of an investment. What really matters is which technique yields the statistically significant best investment performance.

Table 2: Average Prices, Average Costs and IRRs for VA and DCA in Rising, Declining, and Fluctuating Markets Assuming a 10% Return for Value Averaging.

Rising Market

		Value Averaging				Dollar Cost Averaging		
Period	Market Price	Value Required	Shares Owned	Shares Bought	Period Invest	Period Invest	Shares Bought	Shares Owned
1	$5	$400.0	80.0	80.0	$400.0	$400	80	80
2	8	840.0	105.0	25.0	200.0	400	50	130
3	10	1324.0	132.4	27.4	274.0	400	40	170
4	10	1856.4	185.6	53.2	532.4	400	40	210
5	$16	$2442.0	152.6	(33.0)	$(527.0)	$400	25	235
AVG	$9.80				$878.8	$2000		
		Average Cost:		$5.76		Average Cost:	$8.51	
		IRR:		33.89%		IRR:	32.01%	

Table 2: Average Prices, Average Costs and IRRs for VA and DCA in Rising, Declining, and Fluctuating Markets Assuming a 10% Return for Value Averaging.

Declining Market

		Value Averaging				Dollar Cost Averaging		
Period	Market Price	Value Required	Shares Owned	Shares Bought	Period Invest	Period Invest	Shares Bought	Shares Owned
1	$16	$400.0	25.0	25.0	$400.0	$400	25	25
2	10	840.0	84.0	59.0	590.0	400	40	65
3	8	1324.0	165.5	81.5	652.0	400	50	115
4	8	1856.4	232.1	66.6	532.8	400	50	165
5	$ 5	$2442.0	488.4	256.3	$1281.5	$400	80	245
AVG	$9.40				$3456.3	$2000		
		Average Cost:		$7.08		Average Cost:	$8.16	
		IRR:			-24.42%	IRR:		-24.80%

Fluctuating Market

		Value Averaging				Dollar Cost Averaging		
Period	Market Price	Value Required	Shares Owned	Shares Bought	Period Invest	Period Invest	Shares Bought	Shares Owned
1	$10	$400.0	40.0	40.0	$400.0	$400	40	40
2	8	840.0	105.0	65.0	520.0	400	50	90
3	5	1324.0	264.8	159.8	799.0	400	80	170
4	8	1856.4	232.1	(32.7)	(261.6)	400	50	220
5	$10	$2442.0	244.2	12.1	$121.0	$400	40	260
AVG	$8.20				$1587.4	$2000		
		Average Cost:		$6.30		Average Cost:	$7.69	
		IRR:			15.22%	IRR:		13.15%

This paper uses the same definition of "random" as in prior work. Random investing includes a 50% probability of investing in a particular period and a 50% probability of sitting idle. When an investment is made there is an equal chance of investing either 150% or 250% of the amount invested each period with DCA. This procedure carries three advantages. First, it probably better approximates normal investment pattern such as "on / off" or "more / less" common among many investors, particularly outside of 401K type retirement plans. Second, the probabilities assumed in the technique guarantee that the expected value of the investment is the same as in DCA. This prevents a potential bias in the comparisons by investing considerably more in one technique than the other. Third, it duplicates the method followed in prior work, thus making comparison to that work easier.

EXPERIMENTAL METHODOLOGY

This paper closely follows earlier methodology, (Marshall, 2000 and Marshall and Baldwin, 1994) and uses the same three-way analysis proposal (VA vs. DCA and random investing.) The method used in this paper to calculate the return associated with each investment technique is simply to calculate the IRR of the cash flow that results from employing the technique being evaluated over the investment time horizon chosen, then cashing-in the investment value at the end of the time horizon, just as shown in Tables 1 and 2. For both DCA and random techniques no money is returned to the investor except at the end of the time period. For VA money may be returned at any time the technique gives a partial "sell" signal. Each technique's return is determined by the procedure described and the actual performance of the underlying market in the particular time period under analysis.

IRRs are calculated for consecutive five and 10-year investment time horizons for each market studied as well as for the entire length of data utilized in each market. A five-year investment time horizon is suggested to be appropriate by many investment writers, (Gitman and Joehnk, 2002.) A ten-year (and for S&P 500 only a 20-year) time horizon is used when the effect of investment time horizon is tested to help prove or disprove VA's superior performance. The logic seems to be that any system that could improve investment returns would be favored over longer time horizons where VA had time to work its "magic" and its benefits would compound. Sometimes data is broken out for "up" markets and "down" and results are sometimes offered weighted by the number of years of data available in each index.

The multiple markets studied are represented by the following indices: the S&P 500 from 1871 to 2002 (Schiller, 2003) and from (Yahoo, 2003) the Dow Jones Industrial Average (1932-2002), the FTSE 100 (1984-2002), the Philadelphia Exchange Gold and Silver Index, the XAU (1983-2002) and the Dow Jones Commodity Index (1980 –2002.) Those market indices were chosen for the following reasons:

- ♦ The S&P 500 is generally recognized as representative of broad U.S. equity values. Schiller's data, is available free on-line and is perhaps the longest stock index consistently calculated save for one series (Siegel, 2002), with data going back to 1802.---The Dow just had to be included as the most popular stock market average, poorly constructed, as it may be to finance professionals. If VA "works" it must do so for badly constructed indices as well.

- ♦ The FTSE was included to reflect the performance of foreign stocks. If VA "works" it should not care which side of the Atlantic it is on.
- ♦ The Dow Jones Commodity Index and the Philadelphia Exchange Gold and Silver Index were included in the study for two reasons. First neither relates to equity markets. Clearly, if VA "works" it should work in all markets. How would it know whether the price changes input to it were stock prices, gold prices, or bananas prices at the local market? Secondly, neither gold nor commodities more generally have performed well over the period provided by YAHOO. Both have experienced slightly negative (about negative 1%) annual returns. If VA "works" it should do so long term in both increasing and decreasing markets.

Edleson's methodology requires that the VA technique employ an expected return assumption that along with the assumed periodic investment determines the required investment value at the end of each revaluation period. As mentioned earlier, Edleson [4] in 1991 thought 16% appropriate. Conversely, Schiller's work (Schiller, 2003) creating a very long term S&P 500 Index with dividends reinvested found 6.9% to be the average return. That return is used here. No initial investment was assumed for any analysis and equal, or the expectation of equal, periodic investments are used. A quarterly revaluation period for VA and a quarterly investment period for both DCA and random investing are used, consistent with prior work.

RESULTS OF COMPARABLE INVESTMENT ANALYSIS

Table 3, although totally unsophisticated statistically, is interesting. It shows how many times each technique placed first, second or third as measured by IRR, when applied to rolling 5-, 10-, 20-year periods of S&P 500 index data. This is the only application of the 20-year investment horizon. In other markets too few periods were available to be meaningful.

The entire S&P index running for more than 130 years was also tested. The highest IRR among the three investment techniques determines first place; the lowest, third place, with no regard as to size of the margin of victory or loss. Four results attract the eye!

- ♦ VA combined results appear to dominate DCA. VA scored 73% of all first place results, 11% of second place and 16% of third place, vs. 23%, 50% and 27% respectively for DCA.
- ♦ DCA combined results similarly appear to dominate random investing, which placed 5%, 39% and 57% respectively. Some numbers do not add due to rounding.
- ♦ VA relative performance increases as the investment time horizon moves from 5 years (54% first place finishes) to 10 years (92%) to 20 years (100%.)
- ♦ Less dramatically, DCA's total dominance of random investing at the 5-year time horizon becomes much less dominant at 10 and 20-year time horizons.

Table 3: A Comparison of the Rankings of Each Investment Technique for the S&P 500 Index as a Function of Investment Time Horizon.*			
	Value Averaging	Dollar Cost Averaging	Random Investing
Entire period			
1st Place	1 (100.0%)	0	0
2nd Place	0	1	0
3rd Place	0	0	1
20-Year Periods			
1st Place	6 (100.0%)	0	0
2nd Place	0	4	2
3rd Place	0	2	4
10-Year Periods			
1st Place	12 (92.3%)	0	1
2nd Place	1	8	4
3rd Place	0	5	8
5-Year Periods			
1st Place	13 (54.2%)	10	1
2nd Place	4	9	11
3rd Place	7	5	12
Combined Results			
Percentage 1st Place Finishes	72.7%	22.7%	4.6%
Percentage 2nd Place Finishes	11.4%	50.0%	38.6%
Percentage 3rd Place Finishes	15.9%	27.3%	56.8%

*A technique has a first place finish if it earns the highest IRR, irrespective of the margin of "victory." Definitions for second and third place finishes are obvious

Marshall (2000, 93) prepared a similar chart to Table 3 showing the number of times each investment technique was superior, i.e., a first place finish, for his 6,500 simulations. Interestingly, he found that VA finished first 74% (really 73.5%) of the time vs. 73% (really 72.7%) in this paper, using actual S&P 500 investment results. An amazing coincidence? Similarly, performance improved in both papers as the time horizon increased. Strangely, the same earlier chart showed random investing dominating DCA performance; opposite to results shown in Table 3. Recall though, earlier work showed no difference in risk or return for DCA vs. random investing when sophisticated statistical analysis was applied. Also suggesting the same may reoccur, DCA fails to improve (or even maintain) performance vs. random as the time horizon lengthens.

Table 4: Mean IRRs (%) for VA, DCA, and Random Investment Techniques for Each Market as a Function of Investment Time Horizon.

	Value Averaging	Dollar Cost Averaging	Random Investing
S&P 500			
Entire Period *	9.44	9.28	9.27
10-Year	8.86	8.61	8.33
5-Years	8.89	***9.16*****	7.61
Avg. All Periods	9.07	9.02	8.40
Dow Jones			
Entire Period	8.11	6.87	6.87***
10-Year	6.89	5.87	5.76
5-Years	7.01	5.92	6.20
Avg. All Periods	7.34	6.22	6.28
FTSE			
Entire Period	4.49	3.87	3.96
10-Year	4.34	4.18	4.29
5-Years	6.24	4.75	5.49
Avg. All Periods	5.02	4.27	4.58
XAU: Gold			
Entire Period	0.53	-1.11	-1.50
10-Year	-1.89	-3.20	-3.84
5-Years	-2.49	-2.09	***0.20***
Avg. All Periods	-1.28	-2.13	-1.71
Dow Jones Commodities			
Entire Period	-0.10	-1.17	-1.05
10-Year	0.08	-1.13	-0.99
5-Years	0.87	0.42	0.72
Avg. All Periods	0.25	-0.91	-0.44
Combined Results Avg. All Periods	**4.08**	**3.29**	**3.42**

* "Entire Period", by definition, has only one IRR.

** *Italicized* and Underlined entries are tests where VA did not have the highest IRR. There were only two such occurrences.

*** Winner at the next decimal point.

Table 4 presents mean IRRs (%) for all tests for VA, DCA, and random investment techniques for each market as a function of the investment time horizon. Again, four results attract the eye!

- ♦ VA produces the highest average mean IRRs for all markets—US stocks, foreign stocks gold and commodities.
- ♦ VA produces the highest mean IRR for all time periods except for the 5-year investment time horizons for the XAU, where Random was best, and for the 5-year investment time horizon for the S&P 500 where DCA was best. In the shorter run and particularly with random events, "anything" can happen.
- ♦ But, the absolute value of differences in investment returns among the techniques is generally small, usually on the order of 1% per year. Of course, over time an extra 1% return can be important. For example, increasing Schiller's long-run return of 6.9% to 7.9% for constant dollar annuity savings over a 35-year time horizon yields about a 25% larger nest egg.
- ♦ Even though DCA scored a higher IRR many more times than did Random investing (see comments on Table 3) Random's average IRR actual slightly exceeded DCA's, calling any contention of DCA superiority into question.

Table 5 presents the average of mean IRRs (%) for VA, DCA, and random investment techniques, weighted and un-weighted, in up markets and down as a function of the investment time horizon. And, in the final column VA's advantage (%) vs. the average of DCA and random investing. The Table shows the "average of the means" both un-weighted and weighted by the number of years of price data used for each index, and calculated for "up" indices (S&P 500, Dow and FTSE indices) and "down" indices (DJ Commodities and XAU indices) separately. Four results attract the eye!

- ♦ VA produces the highest combined mean IRR (i.e., the average of mean IRRs, and for both "Up" and "Down" markets, on both an un-weighted and weighted basis—everything!)
- ♦ VA produces the highest mean IRR for all time periods except for the 5-year investment time horizons for un-weighted "Down" markets, where Random was best. Of course, as mentioned earlier, in the short run and particularly with random events, "anything" can happen.
- ♦ It appears from looking at the combined mean IRR, for both weighted and un-weighted means, (from the last column to the right) that VA's dominance increases as the investment time horizon increases. For example, on a weighted basis VA's mean IRR advantage grows from 0.50% at 5-years to 0.71% at 10-years to 1.13% when entire periods are tested. This result is expected if VA were truly better.
- ♦ But, the same results discussed above, when broken out to show "Up" and "Down" markets, indicate an even stronger VA advantage as time increases in "Down" markets and no recognizable similar pattern for "Up" markets. Is that result meaningful? Future research may decide.

Different from the earlier work (Marshall and Baldwin, 1994 and Marshall, 2000) this paper does not report risk statistics. The reason is not that risk should not be considered; the reason is that creating enough tests to confirm risk differences statistically requires the creation of many, many actual investment scenarios to test—and each probably should be of sufficient length in time to be meaningful to real world investors. How many? Thousands were necessary to reach some statistically significant conclusions in earlier simulation based work. While that challenge is theoretically possible it clearly goes beyond the scope of this paper.

Table 5: Average of Mean IRRs (%) for VA, DCA and Random Investment Techniques, Weighted and Un-weighted, in Up Markets and Down as a function of Investment Time Horizon.

	Value Averaging	Dollar Cost Averaging	Random Investing	VA Less Avg of DCA + Random
Average of Means (Un-weighted)				
Entire Period	4.49	3.54	3.51	0.97
10-Year	3.66	2.87	2.71	0.87
5-Years	4.10	3.63	4.04	0.26
“Up” Market* Only				
Entire Period	7.35	6.67	6.70	0.67
10-Year	6.70	6.22	6.13	0.52
5-Years	7.38	6.61	6.43	0.86
“Down” Market Only				
Entire Period	0.22	-1.14	-1.28	1.43
10-Year	-0.91	-2.16	-2.42	1.38
5-Years	-0.81	-0.84	***0.64***	-0.43
Average of Means Weighted**				
Entire Period	7.73	6.65	6.55	1.13
10-Year	6.44	5.83	5.63	0.71
5-Years	6.65	6.38	5.93	0.50
“Up” Market Only				
Entire Period	8.59	8.03	8.05	0.55
10-Year	7.84	7.36	7.17	0.79
5-Years	8.06	7.75	6.98	0.74
“Down” Market Only				
Entire Period	0.10	-1.14	-1.26	1.30
10-Year	-0.84	-2.09	-2.32	1.36
5-Years	-0.69	-0.75	0.48	-0.42

* “Up” markets include the S&P 500, the Dow and the FTSE; “Down” markets include the XAU and the Dow Jones Commodities indices.

** Weighted by the number of years of market price data used for each. index.

The purpose of this paper was simply to see if there is evidence that VA has superior investment returns in the real world, not just in a simulated one. The suggestion here is to compare the results here of tests of actual investment results using real market data to simulation based results from prior work. If results are similar, then perhaps conclusions drawn can also be similar and useful?

CONCLUSIONS

What were those results and how do they compare to earlier work? First, VA provides consistently higher returns just as it did in earlier work! But, VA's advantage over other techniques, which ranged here from about ½ % or less for 5-year time horizons to about ¾ % or more for 10-year time horizons is substantially less than the approximate 1-¾ % advantage calculated earlier (Marshall, 2000). Perhaps given more data, VA's advantage might grow toward the theoretical simulation based return difference levels, particularly in times of high price volatility? Perhaps more work along other lines proposed (Fisher, 2003) might prove useful? Second, just as in prior work, there is no indication that DCA provides any benefit to Random investing.

This paper, using actual prices achieved in multiple markets indicates that the amount of extra return associated with VA appears to be small but still interesting and potentially important to both investors and the financial services industry. Particularly in this era of low risk free interest rates, investors could clearly use an extra ½ % or more. The financial services industry would also benefit from a technique offering a research based "sell" as well as their plentiful "buy" signals. Prior work based on simulation indicated that VA achieved a statistically meaningful advantage in highly volatile markets and over extended investment time horizons. It is not possible in this research to statistically confirm those results using actual investment price data. Let future research, if it be deemed worthwhile, be designed specifically to further address this statistical confirmation issue. Is VA really better than DCA or Random investing? Results based on actual investment opportunities are less convincing than simulation results, but the answer appears to be, "Yes!"

SUGGESTIONS FOR FURTHER RESEARCH

The issue of whether or not VA really provides superior investment performance in actual markets is still an open question, not totally resolved by this research though progress has been made and results seem useful if not conclusive. Earlier simulation-based research theoretically found evidence supporting the contention of VA's superiority in volatile markets and over extended time horizons. While results reported in this work do not contradict prior research, perhaps future work could be designed to focus on these issues?

Also, Edleson's description of VA requires an assumption of the yield expected on the investment portfolio. Recall, he proposed 16% and this paper used 6.9%. Does that assumption influence results? And, results reported in this paper seem to indicate that VA performs better in "Up" markets than in "Down" ones. Are those results meaningful? Future research may wish to investigate.

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UNEXPECTED CHANGES IN QUARTERLY FINANCIAL-STATEMENT LINE ITEMS AND THEIR RELATIONSHIP TO STOCK PRICES

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ABSTRACT

This study examines the value-relevance of six quarterly financial-statement line items (accounts receivable, inventory, current liabilities, gross margin, SGA expense, and depreciation expense) and finds the size of deviations from one-step-ahead predicted values of the six items is associated with abnormal stock returns. With the exception of inventory, results are consistent with the theory that transitory changes in line items introduce greater noise into the earnings number. Consistent with Jiambalvo, Noreen and Shevlin (1997), inventory changes are viewed as positive leading indicators of firm value. Both unsophisticated models (random walk and random walk with drift) and more complex models (Box-Jenkins ARIMA and vector autoregressive models) are developed for the line items. Overall findings are generally insensitive to the degree of sophistication of the expectation model employed.

INTRODUCTION

Fundamental information analysis, as defined by Lev and Thiagarajan (1993), aims at identifying financial variables that are useful in security valuation. In this paper, evidence is provided that unexpected changes in quarterly financial-statement line items affect the value of the underlying firm's stock. While there is considerable empirical evidence with respect to the relationship between both quarterly earnings numbers and annual financial-statement line items and security returns,[1] the current study extends this research, investigating the nature and extent of this relationship through examining quarterly values of selected financial-statement line items.

The line items chosen have been shown by past research to be closely related to earnings. Both income-statement and balance-sheet line items are examined, since each provide information useful in describing and predicting firm earnings or security returns (Lipe 1986, Bernard and Noel 1991, Ohlson and Penman 1992, Stober 1993, Cheng 1998). The line items are accounts receivable, inventory, current liabilities, gross margin, SGA expense, and depreciation expense. Four time-series models are employed as expectation models: account-specific Box-Jenkins ARIMA models, a random walk, a seasonal random walk, and a vector autoregressive model.

Once time-series models for the selected line items are developed, the value-relevance of unexpected changes in these items is examined. I examine the link between line items and stock prices, rather than the link between unexpected values of line items and unexpected earnings, due to the nature of the relationships among these various pieces of information. Unexpected values of line items may not have a transparent effect upon earnings, since the potential change in earnings may be offset through other accruals in an attempt to manage earnings. Indeed, some of the line items examined in this study have been manipulated by firms in order to misstate revenue.[2] However, in an efficient and rational security market, the price of a firm's stock should reflect not just current earnings, but earnings expectations based on all available information. It logically follows that current stock prices reflect information about future earnings – such as information contained in unexpected values of financial-statement line items – before that information is reflected in current earnings.

This study adds to the body of work that examines the relationship between outputs of the financial-reporting process and the market value of the firm. One reason line items are expected to be value-relevant is because they can provide information that is useful in ascertaining whether changes in earnings are transitory or permanent, a distinction that has been shown to be important in determining firm value.[3]

Evidence is provided that there is information in the transitory elements of financial statement line items that is consistent with the information set determining security prices. A long-window event study is performed to determine whether the market recognizes a distinction between permanent and transitory changes in quarterly earnings and in line items, as determined by different values of the Earnings Response Coefficient (ERC). When this hypothesis is tested empirically by least-squares regression, the coefficient for the variable of interest is statistically significant for all six of the line items. This is consistent with the transitory element in the line items having the predicted effect upon the ERC. However, once an additional term is added to the model in order to control for unexpected changes in earnings, the coefficient for the unexpected change in the line items is statistically significant only for three of the line items (accounts receivable, SGA expense, and inventory). This is consistent with the notion that some of the information contained in the transitory elements of the line items is also contained in unexpected earnings.

With respect to all the chosen line items except inventory, the results are consistent with the theory that the larger deviations from the expectation model are more likely to reflect transitory changes, thereby introducing greater amounts of noise into the earnings number. The larger deviations from the inventory models are related to an increase in the ERC, a result consistent with Jiambalvo, Noreen and Shevlin (1997), who find that the change in the percent of production added to inventory is positively related to security returns, indicating the market views this information as a positive leading indicator of firm performance.

The following section discusses the motivation for this work. Section III is discussion of the methodology and sample selection, followed by results of the study in Section IV and concluding remarks in Section V.

MOTIVATION

Disaggregation of the financial statements into line items and investigation of the time-series properties of these line items allows an examination of a richer information set than earnings alone can provide. Pope and Wang (1999) demonstrate that if financial reporting allows the identification of earnings components that follow fundamentally different dynamic processes, it should generally be expected that firm value will depend in part on those components. Thomas (1993) says that "perhaps (the) most important emerging issue in the earnings time-series literature is the contention that reported earnings cannot be described by a univariate time-series process alone. Earnings contain different components, these components follow different processes, and the shocks to these processes are not perfectly correlated with each other." Bao, Lewis, Lin and Manegold (1983) note that "underlying this approach is the belief that a firm's earnings react to changes in economic conditions that are reflected more directly in non-earnings accounting series." A better statistical fit should be attained through analysis of the line items than through analysis of the earnings series. According to Cogger (1981), line items have been shown to be more homogeneous than earnings, so the disaggregation of data generally will result in more efficient model estimation.

Several studies go beyond bottom-line earnings to seek value-relevance in other aspects of annual financial statements. Ou and Penman (1989) find a market reaction to selected ratios and changes in elements of the financial statements, indicating such information has content value-relevant to stock prices. Their research has been criticized (Greig 1992, Holthausen and Larcker 1992) for failing to control properly for size and risk, but Setiono and Strong (1998) analyze United Kingdom firms and find results similar to Ou and Penman. Fairfield, Sweeney and Yohn (1996) find that disaggregation of earnings into operating earnings, non-operating earnings and taxes, and special items improves one-year-ahead forecasts of return on equity. Swaminathan and Weintrop (1991), using *Value Line* forecasts of earnings and revenues as a proxy for market expectations of revenues and expenses, find incremental information content in both revenues and expenses. Lev and Thiagarajan (1993) and Abarbanell and Bushee (1998) extend this line of research by providing theoretical justification for the use of fundamental analysis in the decision-making process of market participants. Ramesh and Thiagarajan (1993) employ an unobservable components model to examine permanent and transitory components of earnings. A peripheral finding of their work is that certain line items (gross margin, operating expenses, and nonoperating income) were primarily related to the permanent component.

Lev and Thiagarajan (1993, henceforth LT) also link fundamental analysis to earnings persistence and ERCs through creation of a composite fundamentals score used to determine whether earnings are of high or low quality. They show that nine of the 12 items of annual accounting data they examine are significantly associated with contemporaneous stock returns and future earnings changes. Moreover, they find that analysts' earnings forecast revisions underreact to the information contained in these signals. Building on this finding and its potential implication of incomplete stock-price adjustment to the information, Abarbanell and Bushee (1998, henceforth AB) develop an investment strategy based upon the information contained in the fundamental signals; their strategy realizes an average annual abnormal return of 13.2 percent.

The current study employs four of the same line items as LT and AB: inventory, accounts receivable, gross margin, and SGA expenses. LT and AB use changes in the line items (in effect, using an annual random walk model) in their studies and relate the changes in the line items to changes in sales. However, it has been shown in the case of earnings that quarterly ARIMA models provide significantly more accurate one-year-ahead predictions than annual ARIMA models.[4] In fact, aggregating quarterly ARIMA predictions of earnings provides a better one-year-ahead prediction of annual earnings than those made by use of an annual prediction model (Lorek 1979). Therefore, this study develops ARIMA time-series models for quarterly values of these line items and employs those models to determine unexpected values of the items. Since quarterly information regarding earnings is relevant to predictions of annual earnings, and quarterly values of financial-statement line items affect current and future earnings, values of these line items and deviations from expected future values ought also to be relevant in the determination of firm value.

Employing quarterly instead of annual data increases the number of observations, reduces sampling error, and allows the unmasking of seasonal effects. Quarterly data also partially controls for the impact of structural changes. ARIMA modeling requires the use of a lengthy data series to estimate the model parameters, and structural change is much more likely to occur over the long period necessary to accumulate sufficient annual data.

Once the unexpected values of the line items are determined, they are ranked from lowest to highest. As shown by Freeman and Tse (1992) and Ali (1994) with respect to earnings and cash flows, larger deviations are more likely to contain value-irrelevant noise or be transitory. Freeman and Tse find that the marginal response of stock price to unexpected earnings declines as the absolute value of unexpected earnings increases. Ali allows for nonlinear relations between returns and three performance variables: earnings, working capital from operations (WCFO), and cash flows. He extends the Freeman and Tse analysis to show that the persistence of both WCFO and cash flows declines as the absolute value of changes in them increases.

The ranking scheme is adopted in order to mitigate the potential specification problems that exist in regressions of unexpected earnings response (Cheng, Hopwood and McKeown 1992, Kane and Meade 1997). Such a scheme is appropriate in this case since the functional form of the model that maps unexpected earnings into abnormal returns is unknown and the test is of the significance of the coefficient.

The distinction between transitory and permanent changes in the line items is important because it has been demonstrated that the market places different values upon permanent and transitory components of earnings (Ramakrishnan and Thomas 1998), that the magnitude of the return reaction to earnings innovations is positively related across firms to the persistence of earnings (Kormendi and Lipe 1987), and that the ERC is positively related to both earnings predictability and earnings persistence (Lipe 1990). Collins and Kothari (1989) also demonstrate that ERCs are positively related to earnings persistence. Transitory changes in line items or earnings are less likely to signal a permanent alteration in the underlying earnings stream. Therefore, they should not be as value-relevant as permanent changes to investors. This study incorporates changes in these line items into analysis of the permanence of earnings in order to extend our understanding of the relationship between such line items and the ERC.

METHODOLOGY

Four time-series models are employed as expectation models: account-specific Box-Jenkins ARIMA models, a random walk, a seasonal random walk, and a vector autoregressive model. ARIMA models have been shown to be more accurate than the two types of random walks in predicting future values of quarterly earnings (Brown and Rozeff 1979) and therefore are used for the quarterly line items in the current study. Little use has been made of the vector autoregressive (VAR) model in accounting research, but it has the ability to reflect the interdependencies among line items in a way the three univariate models do not. The ARIMA model and the two types of random walks rely on past values of a specific line item to predict future values, while the VAR model uses past values of all six line items and quarterly earnings to predict future values of each item. The line item-specific ARIMA models were estimated using data for the first 32 quarters, then firm-specific coefficients were then estimated for each of eight holdout quarters, using all previous quarters in the estimation process. The ARIMA models describe the time-series behavior of all six line items more accurately than the three competing models.[5]

This study distinguishes between permanent and transitory changes in quarterly earnings and financial-statement line items by the size of deviations from predicted future values in those line items, as measured by absolute percentage errors. The error metric employed is the absolute percentage error, calculated as follows, where Q_t is the actual value of a given line item for firm t and $E(Q_t)$ is the predicted value:

$$\text{APE} = \left| \frac{Q_t - E(Q_t)}{Q_t} \right| \qquad (1)$$

The largest deviations, whether positive or negative, are more likely to be transitory, and the more transitory the changes in the line items, the more likely it is that related changes in the earnings stream will be transitory.

The relationship between transitory changes in financial statement line items and the ERC is examined through use of the following regression model for each line item:

$$CAR_{t} = \alpha_0 + \beta_1\left(\frac{UE_{it}}{MVE_{it-1}}\right) + \beta_2\left(EFSC_{it} \times \frac{UE_{it}}{MVE_{it-1}}\right) + \beta_3\left(R_t \times \frac{UE_{it}}{MVE_{it-1}}\right) + \beta_4\left(Beta_{it} \times \frac{UE_{it}}{MVE_{it-1}}\right) + \varepsilon_{it} \qquad \textbf{(2)}$$

The terms in this model are defined as follows:

CAR_{it}: the cumulative abnormal return for firm i over period t. Values for this variable are determined as outlined below.

UE_{it}: unexpected earnings for firm i over period t, calculated through comparison of actual quarterly earnings to those predicted by the Brown-Rozeff model;[6]

MVE_{it-1}: the beginning-of-period market value of equity;

$EFSC_{it}$: the ranking of firm i based on the absolute value of the forecast error in the line item (from lowest to highest error). Rankings are computed for each of the expectation models.

R_t : the risk-free interest rate for period t, as proxied by the long-term yields of U.S. Government bonds.

$Beta_{it}$: the systematic risk of firm i over period t, estimated by regressing monthly returns over 60 months on the CRSP equally weighted market index.

ε_{it} : a random disturbance term assumed to be IID normal $(0, \sigma^2_u)$.

A statistically significant negative coefficient β_2 indicates that the transitory element in the financial statement line items, as determined by the ranked deviations from the various time-series expectation models, has a dampening effect upon the ERC.

The risk-free interest rate for period t, as proxied by the long-term yields of U.S. Government bonds, is included because Collins and Kothari (1989) found a significant negative association between the ERC and interest rates for each year of their study. The systematic risk beta of firm i over period t, estimated by regressing monthly returns over 60 months on the CRSP equally weighted market index, is included because many studies have found a significant negative correlation between beta and ERC (Collins and Kothari 1989, Easton and Zmijewski 1989). The economic logic behind inclusion of systematic risk and risk-free interest rates is that if unexpected earnings are a proxy for cash flows, they theoretically are discounted by the market model, and the market model expected return is based upon systematic risk and the risk-free interest rate. The average beta for the firms included in the sample was 1.07. The interest rates employed as independent variables ranged from 6.09 percent to 8.03. They were calculated by averaging the long-term yields of U.S. Government bonds for the three months in each quarter.

A second model is used to examine whether the transitory element in the line item has an effect upon the ERC beyond the effect of the transitory element in earnings. This model is a pooled, cross-sectional time-series regression as follows:

$$CAR_{it} = \alpha_0 + \beta_1\left(\frac{UE_{it}}{P_{it-1}}\right) + \beta_2\left(EE_{it}\times\frac{UE_{it}}{P_{it-1}}\right) + \beta_3\left(EFSC_{it}\times\frac{UE_{it}}{P_{it-1}}\right) + \beta_4 R_t + \beta_5 Beta_{it} + \varepsilon_{it} \quad (3)$$

where the variables are defined as previously, with the addition of the term EE_{IT} . This term is defined as the ranking of firm i based on the absolute value of the forecast error in earnings (from lowest to highest error), as determined by deviation from the Brown-Rozeff expectation model for quarterly earnings. Since EE_{IT} reflects the impact of the forecast error in earnings, a statistically significant negative coefficient b_3 indicates that the transitory element in the financial statement line items has the hypothesized dampening effect upon the earnings response coefficient, even after controlling for the transitory element in earnings.

Cumulative abnormal returns are calculated through use of data from the Center for Research in Security Prices (CRSP) tapes and are estimated using the following linear model:

$$CAR_{it} = \alpha_i + \beta_i\left(\frac{UE_{it}}{MVE_{it-1}}\right) + u \quad (4)$$

where CAR_{IT} is the cumulative abnormal return for firm i over period t, UE_{IT} is the unexpected earnings for firm i over period t, MVE_{IT-1} is the beginning-of-period market value of equity, b_J is the earnings response coefficient for firm i, and u is a random disturbance term assumed to be IID normal (0, s^2_u).

The abnormal returns are calculated for a given firm i during period t based upon the deviation of actual returns from the expected returns of an OLS market model using the equally weighted CRSP index. A 250-day estimation period ending the day prior to the t-1 quarterly earnings release date is used as the estimation period for the parameters of the model. Daily abnormal returns are compounded from two days after the issuance of the period t-1 financial statement[7] through the day after the issuance of the period t financial statement.[8] A long window is employed in this study because the underlying issue being examined is whether there is an association between the existence of transitory line items in the financial statements and the size of the related ERCs.

Determining the Sample

The data were extracted from the Compustat quarterly industrial tape.[9] In order to facilitate comparisons between line items, firms were required to have a complete series of 44 observations (from the first quarter of 1985 through the fourth quarter of 1995) for all six line items in order to be included in the sample. A total of 149 firms met this requirement. Of these firms, 123 are involved in manufacturing. All firms are December 31 firms in order to align calendar time across all tests.

Extracting the 149 firms from the Compustat tapes resulted in a sample of 1,192 firm-quarters. In order to perform the event study, the date of the financial-statement announcement for these 1,192 firm-quarters had to be determined. This was done through examination of the NEXIS database; the date used was the earliest date listed on the database for each firm-quarter, which usually was the date that the 10-Q was received by the Securities and Exchange Commission. The 168 firm-quarters for which no financial-statement date was found on the NEXIS database were eliminated. The resultant event window had a mean of 62.2 days.

In order to reduce the effects of outliers, the firms in the top and bottom 1 percent of the sample with respect to the variables CAR and (UE_{IT} /P_{IT-1}) were eliminated from further consideration for net income and for each line item.[10] This resulted in a sample of 952 firm-quarters, divided as follows:

First quarter 1993	107 firms
Second quarter 1993	122 firms
Third quarter 1993	121 firms
Fourth quarter 1993	121 firms
First quarter 1994	118 firms
Second quarter 1994	127 firms
Third quarter 1994	125 firms
Fourth quarter 1994	111 firms

RESULTS OF THE STUDY

Table 1 shows results of the analysis with respect for equation 2. P-values for the coefficients are reported; the rank transformation of the data means the actual values of the coefficients have no economic meaning. The coefficient b_2, which reflects the incremental effect of the unexpected line-item value upon the ERC, is statistically significant in 18 of the 24 potential cases, including every line item tested for at least one expectation model. The relationship is examined for each of the expectation models in order to test the sensitivity of the results across varying levels of expectation model sophistication.

Table 1: P-values of all coefficients for variables in Equation 2

$$CAR_{it} = \alpha_0 + \beta_1\left(\frac{UE_{it}}{MVE_{it-1}}\right) + \beta_2\left(EFSC_{it} \times \frac{UE_{it}}{MVE_{it-1}}\right) + \beta_3\left(R_t \times \frac{UE_{it}}{MVE_{it-1}}\right) + \beta_4\left(Beta_{it} \times \frac{UE_{it}}{MVE_{it-1}}\right) + \varepsilon_{it}$$

Model	Intercept	β_1	β_2	β_3	β_4	F-value	Adjusted R^2
ACCOUNTS RECEIVABLE							
ARIMA model	**.0001**	**.001**	**.001**	**.0001**	.148	**7.49**	2.8%
Random Walk	**.0001**	.279	.315	**.0001**	.179	**5.31**	1.8%
Seasonal Random Walk	**.0001**	.229	.161	**.0001**	.178	**5.50**	1.9%
VAR model	**.0001**	.069	.087	**.0001**	.169	**5.72**	2.0%
INVENTORY							
ARIMA model	**.0001**	**.002**	**.004**	**.0001**	.156	**7.03**	2.5%
Random Walk	**.0001**	**.0001**	**.0001**	**.0001**	.141	**8.66**	3.1%
Seasonal Random Walk	**.0001**	**.002**	**.004**	**.0001**	.172	**7.12**	2.5%
VAR model	**.0001**	**.0003**	**.001**	**.0001**	.149	**7.98**	2.9%
GROSS MARGIN							
ARIMA model	**.0001**	.157	**.01**	**.0001**	.146	**6.65**	2.3%
Random Walk	**.0001**	**.01**	**.004**	**.0001**	.139	**7.11**	2.5%
Seasonal Random Walk	**.0001**	**.013**	**.004**	**.0001**	.142	**7.01**	2.5%
VAR model	**.0001**	**.01**	**.003**	**.0001**	.137	**7.15**	2.5%
DEPRECIATION EXPENSE							
ARIMA model	**.0001**	.207	.177	**.0001**	.199	**5.61**	1.9%
Random Walk	**.0001**	.055	**.044**	**.0001**	.175	**5.99**	2.1%
Seasonal Random Walk	**.0001**	**.008**	**.003**	**.0001**	.142	**7.18**	2.5%
VAR model	**.0001**	.103	.084	**.0001**	.181	**5.74**	2.0%
CURRENT LIABILITIES							
ARIMA model	**.0001**	**.005**	**.003**	**.0001**	.154	**7.15**	2.5%
Random Walk	**.0001**	.258	.240	**.0001**	.179	**5.38**	1.8%
Seasonal Random Walk	**.0001**	**.029**	**.023**	**.0001**	.176	**6.23**	2.2%
VAR model	**.0001**	**.02**	**.016**	**.0001**	.157	**6.44**	2.2%
SGA EXPENSE							
ARIMA model	**.0001**	**.031**	**.012**	**.0001**	.152	**6.56**	2.3%
Random Walk	**.0001**	**.011**	**.003**	**.0001**	.14	**7.25**	2.6%
Seasonal Random Walk	**.0001**	**.02**	**.014**	**.0001**	.152	**6.48**	2.3%
VAR model	**.0001**	**.006**	**.002**	**.0001**	.14	**7.44**	2.6%

Significant values at .05 level are in bold.

CAR_{it} : the cumulative abnormal return for firm i over period t.

UE_{it} : unexpected earnings for firm i over period t, calculated through comparison of actual quarterly earnings to those predicted by the Brown-Rozeff model;

MVE_{it-1} : the beginning-of-period market value of equity;

$EFSC_{it}$: the ranking of firm i based on the absolute value of the forecast error in the line item (from lowest to highest error). Rankings are computed for each of the expectation models.

R_t : the risk-free interest rate for period t, as proxied by the long-term yields of U.S. Government bonds.

$Beta_{it}$: the systematic risk of firm i over period t, estimated by regressing monthly returns over 60 months on the CRSP equally weighted market index.

e_{it} : a random disturbance term assumed to be IID normal $(0, \sigma^2_u)$.

The coefficient b_2 on gross margin and SGA expense is significant for all four expectation models, on current liabilities is significant for the ARIMA and seasonal random walk models, on depreciation expense is significant except when using the ARIMA model, and on accounts receivable is significant for the ARIMA model.

The intercept and the coefficient on interest rates (β_3) are significant in all 24 cases, while the coefficient on firm-specific beta (β_4) is never significant. The unadjusted ERC (β_1) is significant in 12 of the 24 cases. The R^2 for the models range from 1.8% to 3.1%. Examination of the Durbin-Watson statistics and the condition indices for the regression model showed no significant problems with autocorrelation or multicollinearity.

With the exception of inventory, the sign on the coefficient β_2 is negative, consistent with the hypothesis that larger deviations from the expectation model introduce value-irrelevant noise and therefore will result in a lower ERC. The results with respect to inventory illustrate the necessity of examining line items carefully in an economic context, as discussed in LT and Bernard and Noel (1991). The coefficient on inventory is significant for all four expectation models, though its sign is positive. This is consistent with Jiambalvo, Noreen and Shevlin (1997), who examine the incremental information content of the change in the percentage of production added to inventory (CPAI) and find that there is a significant positive relationship between CPAI and security returns, consistent with the market viewing CPAI as a leading indicator of firm performance. As a form of sensitivity analysis in the current study, equation 2 was calculated using only 123 manufacturing firms, since Jiambalvo, Noreen and Shevlin examine manufacturing firms. The results were consistent with those for the entire sample. Consistent with Jiambalvo, Noreen and Shevlin, the market appears to view large changes in inventory as providing information about increased future sales, not as opportunistic behavior intended to manipulate income.

The significance of the results with respect to accounts receivable is consistent with the findings of Stober (1993) and the theories of O'glove (1987). Stober determines that unexpected accounts receivable is a strong negative leading indicator of earnings for all prediction horizons. O'glove writes that considerable increases in accounts receivable can forecast downward earnings and surprises.

An interesting aspect of the results in Table 1 is that the significance of the coefficient b_2 generally is insensitive to the relative sophistication of the expectation model. There are several possible explanations for this result. First, while there is considerable research showing that more sophisticated ARIMA expectation models are more accurate than random-walk models when predicting quarterly earnings, Lorek, Branson and Icerman (1992), and Lorek, Wheeler, Icerman and Fordham (1995) show ARIMA models are not significantly more accurate when predicting certain financial-statement line items. Second, less sophisticated expectation models often are better at predicting future earnings. The random walk model remains viable for annual earnings, despite existence of more sophisticated ARIMA models,[11] and the seasonal random walk is the best-performing model in Foster's (1977) capital-market association tests. The results in the current study also are consistent with such studies as Sloan (1996) and Ou and Penman (1989), which find that stock prices appear to reflect naïve expectations about signals that are relevant to fundamental valuation – even in cases where more sophisticated expectation models provide a better prediction of future line item values, deviations from the less sophisticated models appear informative to the market.

The dual disaggregation of annual data into quarterly data and of earnings into its various components may inadvertently introduce measurement error into the analysis, thereby lowering the R^2 of the models. For example, seasonality may introduce noise into many of the time series examined, and seasonally differencing the data, as done in this study, may not eliminate all such noise. Moreover, disaggregating audited annual data into unaudited interim results may also introduce additional measurement error, despite findings that such data is useful in such areas as providing timely bankruptcy predictions (Baldwin and Glezen 1992).

The second model tested, as described previously in equation 3, adds another term that reflects the ranked values of unexpected earnings. Once the size of the deviation from expected earnings is introduced into the model, the market appears to be much less influenced by deviations in the expected values of line items. The p-values for the coefficient β_3 for specific expectation models and line items are reported in Table 2.

For this model, the coefficient on 3 (the line item variable) is significant in eight of 24 cases - accounts receivable for the ARIMA and seasonal random walk expectation models, SGA expenses for the random walk and VAR model, and inventory for all four expectation models. As in equation 2, with respect to inventory, the coefficient (β_3 in equation 12) has a p-value less than .05 regardless of the expectation model employed, but the sign is positive, again consistent with the results of Jiambalvo, Noreen and Shevlin (1997).

The intercept and the coefficients on R_T and on $BETA_{IT}$ are statistically significant for all expectation models, and the coefficients β_1 and β_2 are never significant. The p-values for all coefficients are reported in Table 2. The R^2 for these models range from 2.7% to 4.2%.

CONCLUSION

This study examines the value-relevance of unexpected changes in six financial-statement line items. Except in the case of inventory, the results are consistent with the theory that transitory changes in line items introduce greater noise into the earnings number. The results with respect to inventory are consistent with the findings of Jiambalvo, Noreen and Shevlin (1997) that the information is viewed as a positive leading indicator of firm performance.

Table 2: P-values of coefficients in the model

$$CAR_{it} = \alpha_0 + \beta_1\left(\frac{UE_{it}}{P_{it-1}}\right) + \beta_2\left(EE_{it} \times \frac{UE_{it}}{P_{it-1}}\right) + \beta_3\left(EFSC_{it} \times \frac{UE_{it}}{P_{it-1}}\right) + \beta_4 R_t + \beta_5 Beta_{it} + \varepsilon_{it} \qquad (3)$$

Model	Intercept	β_1	β_2	β_3 (line item)	Interest Rates	Beta	F-value	Adj. R^2
ACCOUNTS RECEIVABLE								
ARIMA model	**.0001**	.3840	.1100	**.0363**	**.0001**	**.0006**	**6.78**	3.6%
Random Walk	**.0001**	.4576	.2396	.2749	**.0001**	**.0007**	**6.18**	2.8%
Seasonal Random Walk	**.0001**	.4121	.0646	**.0122**	**.0001**	**.0006**	**7.16**	3.3%
VAR model	**.0001**	.4772	.269	.395	**.0001**	**.0007**	**6.12**	2.7%
INVENTORY								
ARIMA model	**.0001**	.4630	.1701	**.0002**	**.0001**	**.0007**	**8.67**	4.0%
Random Walk	**.0001**	.3823	.4005	**.0033**	**.0001**	**.0005**	**7.64**	3.5%
Seasonal Random Walk	**.0001**	.2145	.3908	**.0001**	**.0001**	**.0004**	**8.90**	4.2%
VAR model	**.0001**	.3931	.4986	**.0224**	**.0001**	**.0006**	**6.87**	3.1%
GROSS MARGIN								
ARIMA model	**.0001**	.4747	.2821	.4565	**.0001**	**.0007**	**6.11**	2.7%
Random Walk	**.0001**	.4115	.2367	.2133	**.0001**	**.0007**	**6.24**	2.8%
Seasonal Random Walk	**.0001**	.4519	.1035	.0687	**.0001**	**.0009**	**6.57**	3.0%
VAR model	**.0001**	.3941	.2324	.1745	**.0001**	**.0007**	**6.29**	2.8%
DEPRECIATION EXPENSE								
ARIMA model	**.0001**	.4804	.2936	.4378	**.0001**	**.0010**	**6.18**	2.8%
Random Walk	**.0001**	.3908	.3474	.1888	**.0001**	**.0008**	**6.27**	2.8%
Seasonal Random Walk	**.0001**	.4924	.3096	.4509	**.0001**	**.0007**	**6.11**	2.7%
VAR model	**.0001**	.4273	.3266	.2925	**.0001**	**.0008**	**6.17**	2.8%
CURRENT LIABILITIES								
ARIMA model	**.0001**	.4861	.2772	.4332	**.0001**	**.0007**	**6.11**	2.7%
Random Walk	**.0001**	.4354	.3894	.1164	**.0001**	**.0010**	**6.40**	2.9%
Seasonal Random Walk	**.0001**	.4863	.3559	.3472	**.0001**	**.0008**	**6.14**	2.7%
VAR model	**.0001**	.4312	.4372	.0701	**.0001**	**.0011**	**6.56**	3.0%
SGA EXPENSE								
ARIMA model	**.0001**	.4002	.2168	.2136	**.0001**	**.0006**	**6.24**	2.8%
Random Walk	**.0001**	.1472	.3132	**.0164**	**.0001**	**.0004**	**7.05**	3.2%
Seasonal Random Walk	**.0001**	.4020	.4180	.1297	**.0001**	**.0007**	**6.37**	2.9%
VAR model	**.0001**	.05	.4031	**.0008**	**.0001**	**.0003**	**8.17**	3.8%

Significant values at .05 level are in bold.

CAR_{it} : the cumulative abnormal return for firm i over period t.

UE_{it} : unexpected earnings for firm i over period t, calculated through comparison of actual quarterly earnings to those predicted by the Brown-Rozeff model;

MVE_{it-1} : the beginning-of-period market value of equity;

EE_{it} : the ranking of firm i based on the absolute value of the forecast error in earnings (from lowest to highest error), based on the Brown-Rozeff model.

$EFSC_{it}$: the ranking of firm i based on the absolute value of the forecast error in the line item (from lowest to highest error). Rankings are computed for each of the expectation models.

R_t : the risk-free interest rate for period t, as proxied by the long-term yields of U.S. Government bonds.

$Beta_{it}$: the systematic risk of firm i over period t, estimated by regressing monthly returns over 60 months on the CRSP equally weighted market index.

ε_{it} : a random disturbance term assumed to be IID normal $(0, \sigma^2_u)$.

The results of the study validate empirically the analytical findings of Pope and Wang (1999), who show that if financial reporting allows the identification of earnings components that follow fundamentally different dynamic processes, it should generally be expected that firm value will depend in part on those components and that equity valuation will be enhanced by separate disclosure of earnings components.

The sophistication of the expectation model for the line item seldom affected the results. The change in the ERC was typically significant for a given line item no matter which expectation model is used. The robustness of this result to the choice of expectation model may reflect the findings of studies such as Bernard and Thomas (1990) and Sloan (1996) regarding the failure of stock prices to impound fully the information contained in current earnings, accruals or cash flows. It may also reflect the judgment of market participants that the additional benefit in some cases of employing a more sophisticated expectation model is outweighed by the cost thereof, as discussed in Brown (1993).

Once the ranked value of the deviation from the predicted net income is added into the model, the deviation for the line item is less significant in most cases. This may indicate that the information content of earnings and of certain line items is similar, which would tend to minimize the incremental contribution of the line item.

The results raise issues with respect to future research with regard to earnings management. O'glove (1987) indicates that inventory and accounts receivable may be manipulated by management in order to increase current-period earnings at the expense of future earnings. Dechow, Sloan and Sweeney (1995) find evidence consistent with earnings management contributing to the transitory nature of the accrual component of earnings. Time-series models of financial-statement line items might be employed to detect earnings management through line-item manipulation, as implied by the results of Scholes, Wolfson and Wilson (1992).

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ENDNOTES

1 See Foster (1977) and Bathke and Lorek (1984) for evidence of the link between quarterly earnings and security returns, and Ou and Penman (1989), Lev and Thiagarajan (1993) and Abarbanell and Bushee (1997,1998) regarding the link between annual financial-statement line items and security returns.

2 Such manipulation need not be fraudulent, but Beasley, Carcello and Hermanson (1998) find that in 204 cases of alleged financial-statement fraud investigated by the U.S. Securities and Exchange Commission between 1987 and 1997, 24 involved overstating inventory and 21 involved overstating accounts receivable.

3 Discussion of the importance of transitory vs. permanent earnings, and the role the distinction plays in firm value, can be found in O'glove (1987), Kormendi and Lipe (1987), Lipe (1990), Ramesh and Thiagarajan (1993) and Ramakrishnan and Thomas (1998), among many others.

4 See Brown (1993) for a complete discussion of this literature.

5 For brevity's sake, details of the choice of the ARIMA models are not provided.

6 The Brown-Rozeff model, (100)x(011) in the usual pdq x PDQ notation employed in time-series research, is chosen as the expectation model for quarterly earnings due to its superior predictive performance in many studies such as Brown and Rozeff (1979).

7 This date is after the date of the quarterly earnings release; Bernard and Stober (1989) found the mean and median difference in the quarterly earnings and financial statement release dates were 17 and 15 days, respectively.

8 This window has been chosen because Collins, Kothari and Rayburn (1987) and Freeman (1987), among others, have shown that most of the information in earnings is reflected in stock prices before earnings are announced.

9 The specific Compustat quarterly data items used are: gross margin, which is equal to sales (item 2) less cost of goods sold (30); selling and general administrative expense (1); accounts receivable (37); inventory (38); current liabilities (49); depreciation expense (5), and income before extraordinary items (8).

10 Running the tests with these firms included does not change the tenor of the reported results.

11 See Brown (1993) for a detailed discussion.

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MARKET NOISE, INVESTOR SENTIMENT, AND INSTITUTIONAL INVESTORS IN THE ADR MARKET

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ABSTRACT

This study examines the effects of market noise in the ADR market. We find ADR return affected by noise trader risk and increases (decreases) when investors are irrationally optimistic (pessimistic). Our results also suggest institutional investors have engaged in stealth trading to exploit their information advantage in the noisy ADR market. Through a Granger causality regression, we find the returns on ADR portfolios with high institutional ownership lead the returns of those with low institutional ownership in the low-noise period, confirming that institutional trades reflect market information that is ultimately incorporated into other securities. Finally, we find institutional investors help reduce volatilities of European ADRs. However, for ADRs of Asian and South American firms, magnitude of the stabilizing arbitrage positions taken by rational investors is insignificant.

INTRODUCTION

Fischer Black (1986) suggests that noise is as influential as information in financial markets. Investors who trade on noise are willing to trade even though it is better for them not to trade. They do so because they think the noise on which they base their trading is information.

From existing literature, we can identify three possible effects of noise on securities trading. First, market noise leads to the existence of noise trader risk. De Long et al. (1990) develop a noise trader risk model which argues that when investment decisions are made based on market noise, the decisions are irrational and unpredictable because they are led by investor sentiment in general. Hence, noise traders become a source of risk in the finanical markets. Second, the existence of noise in capital markets provides an opportunity for informed institutional investors to exploit their information advantage. Barclay and Warner (1993) show that informed institutional investors are more likely to engage in "stealth trading" strategies in which the institutions spread their trades gradually over time. Third, the irrational behavior of noise traders in a noisy market may cause asset prices to move away from their fundamental values and destabilize the market. On the other hand, rational institutional investors would take positions opposite to those of the noise traders and help stabilize the market despite De Long et al. (1990) predict that institutional investors would fail to totally encounter the irrational activities of noise traders.

We examine the three possible effects of noise in the ADR market. Our results show that ADR return is affected by investor sentiment in the ADR market. ADR return increases (decreases) when investors are irrationally optimistic (pessimistic). We also find that in the low-noise period, ADRs with high institutional ownership exhibit autocorrelation similar to ADRs with low institutional ownership. However, in the high-noise period, ADRs with high institutional ownership exhibit significant higher autocorrelation than ADRs with low institutional ownership. The result implies institutional investors may have engaged in stealth trading to expolit a noisy market. Through a Granger causality regression, we find returns on ADR portfolios with high institutional ownership lead the returns of those with low institutional ownership in the low-noise period, confirming that institutional trades reflect market information that is ultimately incorporated into other securities. Finally, we find that institutional investors help reduce volatility of European ADR returns. However, for ADRs of Asian and South American firms, the magnitude of the stabilizing arbitrage positions taken by institutional investors is insignificant.

LITERATURE AND MOTIVATION

Financial economists have hypothesized the existence of noise trading in stock markets (for example, Black (1986), Trueman (1988), De Long et al. (1989), (1990), Palomino (1996)). While Black (1986) does not give a reason why investors would rationally want to engage in noise trading, he asserts that it must account for an important fraction of total trading in securities markets. Trueman (1988) suggests that an investment manager has incentive to engage in noise trading because of the positive signal about his ability to collect private information. De Long et al. (1990) develop a noise trader risk model in which irrational noise trader sentiment drives security prices from their fundamental values. The tendency of noise traders to trade according to their sentiment renders their investment behavior totally unpredictable. According to the model, assets subject to unpredictable changes in investor sentiment must be underpriced in the market relative to their fundamental values. An application of this argument is the discounts of closed-end funds. A high level of noise trader risk is associated with large closed-end fund discounts, and a low level of noise trader risk is assoicated with small closed-end fund discounts. Moreover, movements in closed-end fund discounts result primarily from individual investors' irrational, but correlated trading patterns. Though De Long et al. (1990) suggest that rational institutional investors will take positions to offset the irrational tradings of individual investors, they also predict institutional investors would fail to fully offset the irrational behavior of individual investors.

Empirical studies providing direct evidence of noise trading have been very few. Golec (1997) examine bond activities of retailers after the release of weekly retail statistics by Johnson Reebok Service and find direct evidence that bond traders indeed trade on noise. Lee, Shleifer, and Thaler (1991) provide indirect evidence of noise trading by showing a significant link between investor sentiment and discounts of closed-end funds. They show that fluctuations in discounts of closed-end funds reflect changes in investor sentiment. That is, widening(narrowing) discounts reflect the irrational pessimism(optimism) of individual investors. Barclay and Warner (1993) confirm the presence of stealth trading among institutional investors and thus provide indirect evidence of the existence of market noise.

Regarding market destablization, the traditional theoretical view is that asset prices do not deviate significantly from their fundamental values as a result of noise trading. It is argued that incentives exist for skillful, rational speculators to compete against noise traders, and that these speculators are the marginal, price-setting investors (Friedman (1953), and Fama (1965)). However, De Long et al. (1990) suggest that asset prices can be much more volatile than traditioanl models would allow because rational arbitrageurs with short horizons will not offset noisy variations in asset price today given the self-fulling belief that asset prices will vary unpredictably with market noise in future. As a result, the noise trader risk caused by investor sentiment is unpredictable and renders rational arbitrages ineffective. Palomino (1996) echos this suggestion by saying that nosie traders are agents with unpredicatble beliefs and that the willingness of arbitrageurs to exploit noise traders' misconceptions is low in a capital market that is less than perfect. Empirical evidence on whether irrational (noise traders) investors destabilize financial markets or rational (institutional investors) traders stabilize markets in a noisy envirnoment is, however, lacking.

While theoretical papers on noise trading are many, empirical literature is rare and indirect. As such, this study examines the effects of noise in the American Depository Receipts (ADRs) market. The ADR market presents an interesting scenerio for studying this topic because of several reasons. First of all, Kim, Szakmary, and Mathur (2000) and Patro (2000) have shown that home-country information has a significant impact on ADR return. Given the difficulty in getting accurate information from foreign countries, investors in the ADR market are likely to subject to a considerable amount of market noise. Second, institutions are major players in the ADR market and they usually have better access to information about foreign companies. Evidence of stealth trading by institutional investors could therefore confirm the presence of a noisy ADR market in which insitutional investors exploit their information advantage. Third, the simultanoues presence of noise and informed investors in the ADRs market allows us to investigate if the interactions between noise traders and rational investors stabilize or destabilize asset prices. In short, the ADR market presents an unique environment in which we can examine the above-mentioned effects of market noise directly and simultaneously, rather than indirectly and separately, in a noisy environment.

DATA AND VARIABLES DEFINITIONS

Data

The sample analyzed in this study contains ADRs from 1995 to 2000.The sample period starts from 1995 because complete information about monthly discounts of closed-end country funds is available from the *Standard and Poor's Security Owners' Stock Guide* only after 1995. Daily returns of ADRs are obtained from the Center for Research in Security Prices (CRSP) database and converted into monthly returns. The numbers of shares held by institutional investors and shares outstanding are obtained from the *Standard and Poor's Security Owners' Stock Guide.* The market equity capitalization is determined by multiplying price with number of outstanding shares of the ADR.

The ADRs are grouped into three portfolios based on their continent of origin: Asia, Europe, and South America. Each continent's ADR portfolio is further divided into two groups, those with high (above the median) institutional ownership and those with low (below the median) institutional ownership.

The following table shows the sample distribution by year:

ADR distribution by year			
Year	Number of Asian ADRs	Number of European ADRs	Number of South American ADRs
1995	33	75	56
1996	44	95	60
1997	46	123	72
1998	50	127	71
1999	54	129	73
2000	56	132	74

Variables definitons

Following Lee, Shleifer, and Thaler (1991), we use the change in closed-end fund discount (Δ discount) to measure the amount of noise trader risk. For our purpose, we use closed-end country funds. The discount of each closed-end country fund is the difference between the fund's net asset value and its price divided by the net asset value. By grouping all the closed-end country funds in the US into Asian, European, and South American funds, the average change in discount (Δ discount) of the funds in each group serves as a proxy for investor sentiment regarding the investment outlook of the continent. According to Lee, Shleifer, and Thaler (1991), a widening of the discounts implies investors are more pessimistic whereas a narrowing of the discounts implies investors are more optimistic. De Long et al. (1990) and Lee, Shleifer, and Thaler (1991) have used the terms 'noise trader risk' and 'investor sentiment' interchangeably. Both noise trader risk and investor sentiment refer to the irrational behavior of investors. Noise trader risk, however, is not exactly the same as the market noise described by Black (1986). In the words of Fisher Black, "I use the word "noise" in several senses. Noise is contrasted with information. Noise is what makes our observations imperfect. Noise is the arbitrary element in expectations." That is, noise is something that is anti-information and thus not investor sentiment per se.

The literature has not yet developed a proxy to measure noise in the investment markets. In this study, we propose to use the level of closed-end country fund discount as a proxy for market noise. Our reason is that in a noisy market, noise trader risk is high because investor sentiment will change more abruptly in such an environment where there is an abundant supply of stimulus. In a less noisy market, noise trader risk is low because there are less stimulus to cause investor sentiment to shift suddenly. Given that the change in closed-end country fund discount (Δ discount) would be higher (lower) when the level of closed-end fund discount is high (low), it is therefore reasonable to suggest that the level of closed-end country fund discount could serve as a proxy for market noise of the given continent. A large discount implies the continent's market is noisy, and a small discount implies the continent's market is less noisy.[1] Consequently, a year is classified as either a high-noise year or low-noise year when the discount in that year is larger or smaller than the median. The average discounts in the high-noise and low-noise periods for Asia, Europe and South America are shown in the following table, and the F-statistic is calculated to test the null hypothesis that the average discounts in the high-noise and low-noise periods are equal.

Closed-end country funds average discounts (%) in high-noise and low-noise periods			
Continent	Low-noise period	High-noise period	F-statistic
Asia	3.8154	11.4722	20.44[a]
Europe	14.9132	16.1234	2.52
South America	9.7370	22.4369	46.38[a]

EFFECTS OF INVESTOR SENTIMENT AND INSTITUTIONAL INVESTORS ON ADR RETURNS

Investing in ADR provides a convenient way for diversifying portfolio risk internationally. As a result, the ADR market has experienced an explosive growth in the last 30 years. In 1970, there were only 18 ADRs traded in the U.S. In the year 2000, the number of listed ADRs had increased to 475. Although the ADR market is dominated by institutional investors, the difficulty of obtaining accurate and complete information from foreign countries suggests that influence of noise can be considerable in this market.

First of all, we study the effects of investor sentiment and institutional ownership in the ADRs market. The following regression is performed:

$$R_t = a_0 + a_1 R_{t-1} + a_2 \Delta \text{ Discount}_t + a_3 \Delta \text{ Institutional Ownership}_t + \epsilon_t$$

where R_t is the compounded monthly ADR portfolio return at time t for each continent and R_{t-1} is the ADR portfolio return at time t-1. Δ Discount is the change in the average discount of close-end country fund from period t to t-1 for each continent. According to Lee, shleifer, and Thaler (1991), when the change in average discount (Δ Discount) is positive (i.e., the average discount widens), individual investors are more pessimistic and asset returns would be affected negatively. Conversely, when Δ Discount is negative, the individual investors are more optimistic and asset returns would be affected positively. Thus, if investor sentiment is priced in the ADR market, the coefficient of Δ Discount should be negative and significant. Lee, Shleifer, and Thaler (1991) report a significant negative relation between the returns of NYSE stocks and the average ΔDiscount of a basket of domestic closed-end funds.

ΔInstitutional Ownership is the change in the ratio of institutional ownership from month t to month t-1 for each continent's ADR portfolio. A priori, we expect ADR return to be positively correlated with ΔInstitutional ownership. That is, ADR return would be higher or lower when institutions increase or decrease their holdings. The R_{t-1} is for controlling the effect for serial correlation in ADR return.

The regression results for each continent are shown in Table I.

In Table I, it is shown that the coefficients of R_{t-1} are 0.2470, 0.3190, and 0.3870, for Asia, Europe, and South America respectively. The t-statistics are 2.29, 2.74, and 3.68 and all are significant at the 5% level, implying that there is positive autocorrelation in ADR portfolios returns. The coefficients of ΔDiscount have the expected negative signs and are -0.0056 for Asia, -0.0060 for Europe, and -0.0113 for South America respectively. All their t-statistics are significant at the 1% level. That is, ADR return is affected by investor sentiment in the ADR market. When investor sentiment becomes irrationally optimistic or pessimistic, as reflected by a narrowing or widening of the discount of closed-end country funds, ADR return of the same continent moves higher or lower correspondingly. The result is consistent with that of Lee, Shleifer, and Thaler (1991). For Asian and South American ADRs, the coefficients of ΔInstitutional Ownership are positive and significant, that is, there is a positive relation between changes in institutional ownership and ADR portfolio returns. The coefficient of ΔInstitutional Ownership is also positive for Europe, though insignificant. It is possible that the information about European countries is more accessible than that of Asian and South American countries, the role of institutional ownership of European ADRs is therefore less influential. This conjecture is consistent with our earlier observation that the noise levels of the high-noise and low-noise periods are similar for Europe.

TABLE I: Effects of Investor Sentiment and Institutional Investor on ADR return					
Each year, all ADRs are grouped into three portfolios based on their country of origin: Asia, Europe, and South America. Rt is the ADRs portfolio return at time t for each continent and Rt-1 is the ADR portfolio return at time t-1 for each continent. We also group all the closed-end country funds in US into Asian, European, and South American funds. The discount is the difference between the fund's net asset value and its price divided by the net asset value. The discount of each continent is the average discount of the funds in each group, and Δ Discount is the difference of discount between month t and month t-1 for each continent. Δ Institutional Ratio is the change of the average institutional ownership between month t and month t-1 for each continent.					
Model: $R_t = a_0 + a_1R_{t-1} + a_2\Delta$ Discount$_t$ $+a_3$ Δ Institutional Ownership$_t$ $+ \varepsilon_t$					
	Intercept	R_{t-1}	Δ Discount	Δ Institutional Ownership	Adjusted R-square
All ADRs	0.0043	0.3110	-0.0075	1.2690	0.3020
	(0.92)	(5.02[a])	(-9.19[a])	(2.01[b])	
Asia	-0.0166	0.2470	-0.0056	3.5100	0.2910
	(-1.23)	(2.29[b])	(-4.93[a])	(2.10[b])	
Europe	0.0094	0.3190	-0.0060	0.7130	0.2410
	(1.79)	(2.74[a])	(-4.48[a])	(1.28)	
S.America	0.0058	0.3870	-0.0113	4.4090	0.3820
	(0.67)	(3.68[a])	(-6.46[a])	(1.67[c])	

[a] Significant at the1% level.
[b] Significant at the 5% level.
[c] Significant at the 10% level.

In the noise trader risk model of DeLong et al. (1990), they suggest that rational institutional investors may exploit irrational behavior of noise traders by taking positions opposite to those of the noise traders. However, the model also predicts that institutional investors would not be completely successful because the unpredictable noise trading will render the arbitrage activities of institutional investors futile. The significantly negative coefficients of ΔDiscount in Table I support the postulations of the noise trader risk model of DeLong et al. (1990). That is, investor sentiment has a significant effect even in the presence of rational institutional investors. In other words, institutional investors are unable to neutralize the effect of trading led by irrational investor sentiment.

Table I shows that noise trader risk is important even in the presence of institutional investors. It would be of interest to know then if the impacts of investor sentiment and institutional ownership on the ADR return are different in the high-noise and low-noise periods. To study this, we perform the previous regression on high-noise years and low-noise years separately. Regression results are shown in Table II.

TABLE II: Effects of Investor Sentiment and Institutional Investor on ADR return

Model: $R_t = a_0 + a_1R_{t-1} + a_2\Delta\ Discount_t + a_3\ \Delta\ Institutional\ Ownership_t + \varepsilon_t$

	Intercept	R_{t-1}	Δ Discount$_t$	Δ Institutional Ownership	Adjusted R-square
A: Low-noise period:					
All ADRs	-0.0003	0.2990	-0.0056	1.5230	0.25
	(-0.01)	(3.41[a])	(-5.33[a])	(1.60)	
Asia	-0.0022	0.4710	-0.0029	2.1500	0.22
	(-0.15)	(3.20[a])	(-2.38[a])	(1.16)	
Europe	0.0159	0.4050	-0.0037	0.7800	0.28
	(0.39)	(2.69[a])	(-2.14[a])	(1.09)	
S.America	0.0132	0.4320	-0.0110	7.6920	0.39
	(0.98)	(2.88[a])	(-4.25[a])	(1.36)	
B: High-noise period:					
	Intercept	R_{t-1}	Δ Discount$_t$	Δ Institutional Ownership	Adjusted R-square
All ADRs	-0.0092	0.1880	-0.0080	1.8460	0.25
	(-1.24)	(2.15[b]	(-5.79[a])	(1.98[b])	
Asia	-0.0343	0.0456	-0.0072	5.5660	0.30
	(-1.59)	(0.72)	(-3.61[a])	(2.01[b])	
Europe	0.0039	0.2500	-0.0060	0.4590	0.19
	(0.50)	(1.52)	(-3.22[a])	(0.61)	
S.America	-0.0242	0.0686	-0.0094	8.0250	0.24
	(-1.54)	(0.36)	(-3.05[a])	(2.02[b])	

[a] Significant at the1% level.
[b] Significant at the 5% level.

Table II shows that investor sentiment is important in determining ADR return in both the high-noise and low-noise periods. However, change in institutional ownership has a significant impact on the returns of Asian and South American ADRs only during the high-noise period. Institutional ownership is not significant at all in the low-noise period. Conceivably, when the market is noisy (such as Asia and South American), the information possessed by institutional investors becomes more important. During low-noise period, the information advantage of institutional investors may be less significant. This is probably why institutional ownership does not play a significant role in the pricing of European ADRs in both the high-noise and low-noise periods because information about European markets is more accurate and readily available to investors.

MARKET NOISE AND ADR RETURN AUTOCORRELATION

Table I and II confirm that noise trader risk is present in the ADR market. If the ADR market is noisy, then the private information of institutional investors would be valuable and it is logical that institutional investors will exploit their informational advantage. One possible way to do so is the use of "stealth trading" strategies in which institutional investors spread their trades gradually over time. According to Barclay and Warner (1993), stealth trading would induce ADR return autocorrelation. While insitutional investors may stealth trade frequently in the ADR market, we expect the likelihood to be higher in the high-noise period than the low-noise period. Thus, we expect that in the high-noise period, ADRs with high institutional ownership would exhibit significant higher autocorrelation than ADRs with low institutional ownership. In the low-noise period, we expect ADRs with high institutional ownership to exhibit similar or higher autocorrelation than ADRs with low institutional ownership. The return autocorrelations of all the individual ADRs in the high-noise and low-noise periods are shown in Table III.

Consistent with our expectation, panel A of Table III shows that in the low-noise period, for both Asia and South America, ADRs with high institutional ownership exhibit autocorrelations similar to ADRs with low institutional ownership. For Asia, the mean daily autocorrelation for individual ADRs with low institutional ownership and high institutional ownership are 0.0040 and 0.0164 respectively. The t-statistic is 0.46 and not significant. For South America, the mean daily autocorrelation for individual ADRs with low institutional ownership and high institutional ownership are 0.0185 and 0.0391 respectively. The t-statistic is 1.06 and not significant. For Europe, ADRs with high institutional ownership exhibit higher autocorrelation than ADRs with low institutional ownership.

For the high-noise period, panel B of Table III shows that ADRs with high institutional ownership exhibit significant higher autocorrelation than ADRs with low institutional ownership for Asia, Europe, and South America. For Asia, the mean daily autocorrelation for individual ADRs with low institutional ownership and high institutional ownership are –0.0030 and 0.0504 respectively. The t-statistic is 10.6, significant at the 1% level. For Europe, the mean daily autocorrelation for individual ADRs with low institutional ownership and high institutional ownership are –0.0169 and 0.0311 respectively. The t-statistic is 16.26 and significant at the 1% level. For South America, similar result is obtained.

Table III: Return Autocorrelations of ADRs

The mean daily return autocorrelations for individual ADRs in both the high-noise period and the low-noise period are reported. The t-statistic is calculated to test the null hypothesis that the mean daily return autocorrelation of individual ADRs with high institutional ownership is equal with the mean daily return autocorrelation of individual ADRs with low institutional ownership.

A: Autocorrelation of individual ADRs in the low noise period

:	Low institutional ownership ratio	High institutional ownership ratio	t-statistic
Asia	0.0040	0.0164	0.46
Europe	-0.0215	0.0419	20.42[a]
South America	0.0185	0.0391	1.06

B. Autocorrelation of individual ADRs in the high noise period:

	Low institutional Ownership ratio	High institutional ownership ratio	t-statistic
Asia	-0.0030	0.0504	10.61[a]
Europe	-0.0169	0.0311	16.26[a]
South America	0.0383	0.0767	5.68[a]

[a] Significant at the1% level.

In sum, the results in table III support our earlier conjecture that institutional investors exploit their information advantage in the noisy ADR market.

CROSS-PREDICTABILITY OF ADR PORTFOLIO RETURNS IN HIGH-NOISE AND LOW-NOISE PERIODS

From the above, we find that noise is present in the ADR market and institutional investors react differently in high-noise and low-noise environments. In order to confirm that institutional trades contain information not found in non-institutional trades, a Granger causality regression model is used. For each continent's ADR portfolio the following regressions are performed for the high-noise and low-noise periods separately:

$$R_{high,t} = \sum_{i=1}^{5} a_i d_{i,t} + \sum_{k=1}^{5} \left(a_{high,k} R_{high,t-k} + a_{low,k} R_{low,t-k} \right) + u_{high,t}, \tag{1}$$

$$R_{low,t} = \sum_{i=1}^{5} b_i d_{i,t} + \sum_{k=1}^{5} \left(b_{high,k} R_{high,t-k} + b_{low,k} R_{low,t-k} \right) + u_{low,t}, \tag{2}$$

where $R_{high,\, t}$ and $R_{low,\, t}$ are the returns at time t for ADR portfolios with high and low institutional ownership, the $d_{i,\, t}$ are dummy variables for each day of the week i, k is the lag in days and u is the error term.

According to Brennan et al. (1993), portfolios that are first to reflect market-wide information have a better ability to predict the returns of portfolios that are late to reflect market-wide information than the ability of the latter to predict the former. That is, if institutional investors trade on information, returns on portfolios with high institutional ownership should lead the returns of those portfolios that have low institutional ownership. For both the low-noise and the high-noise periods, we therefore expect returns on ADR portfolios with high institutional ownership to lead the returns of those with low institutional ownership if institutions trade on information. That is, we expect $R_{high,\, t\text{-}k}$ to predict $R_{low,\, t}$ better than $R_{low,\, t\text{-}k}$ to predict $R_{high,\, t}$. In the Granger causality regressions, we therefore expect $b_{high,\, k}$ to be larger than $a_{low,\, k}$.

TABLE IV: Cross-Predictability of ADR Portfolio Return

Each year, all ADRs are grouped into three portfolios based on their country of origin: Asia, Europe, and South America. Each continent's ADR portfolio is further divided into those with high institutional ownership and those with low institutional ownership. We also group all the closed-end country funds in US into Asian, European, and South American funds. The discount is the difference between the fund's net asset value and its price divided by the net asset value. The discount of each continent is the average discount of the funds in each group. We further classify the years in which the discount is larger than the median as high-noise years and those years in which the discount is smaller than the median as low-noise years for each continent. The daily return of each continent portfolio with high (low) institutional ownerships is regressed on its own previous five returns and the previous five returns for the same continent portfolio with low (high) institutional ownerships in both the high-noise period and the low-noise period. The sums of the coefficients are reported below. The F-statistic is calculated to test the null hypothesis that the ability of the lagged return on the high institutional portfolio to predict the return on the same continent portfolio with low institutional ownership is the same as the ability of the lagged return on the low institutional portfolio to predict the return on the high institutional portfolio of the same continent in both the high-noise period and the low-noise period. Wilcoxon Z value and Kruskal-Wallis Chi-square are also shown in Table IV.

TABLE IV: Cross-Predictability of ADR Portfolio Return

$$R_{high,t} = \sum_{i=1}^{5} a_i d_{i,t} + \sum_{k=1}^{5} \left(a_{high,k} R_{high,t-k} + a_{low,k} R_{low,t-k} \right) + u_{high,t}, \tag{1}$$

$$R_{low,t} = \sum_{i=1}^{5} b_i d_{i,t} + \sum_{k=1}^{5} \left(b_{high,k} R_{high,t-k} + b_{low,k} R_{low,t-k} \right) + u_{low,t}, \tag{2}$$

A: Low-noise period:

Dependent Variable		$R_{high,t-k}$ (Independent variable)	$R_{low,t-k}$ (Independent variable)	F-statistic	Wilcoxon Z-value	Kruskal-Wallis Chi-square
Asia	$R_{high,t}$	0.0500	0.0172	4.46[b]	1.87[b]	3.58[b]
Asia	$R_{low,t}$	0.0770	-0.0247			
Europe	$R_{high,t}$	0.0458	-0.0104	5.20[b]	2.10[b]	4.50[b]
Europe	$R_{low,t}$	0.0351	-0.0316			
S.Am	$R_{high,t}$	0.0518	-0.0290	5.47[b]	1.74[b]	3.11[c]
S.Am	$R_{low,t}$	0.0825	-0.0555			

B: High-noise period:

Dependent Variable		$R_{high,t-k}$ (Independent variable)	$R_{low,t}$- (Independent variable)	F-statistic	Wilcoxon Z-value	Kruskal-Wallis Chi-square
Asia	$R_{high,t}$	0.0474	0.0031	0.44	0.71	0.53
Asia	$R_{low,t}$	0.0213	0.0088			
Europe	$R_{high,t}$	0.0369	-0.0030	3.81[b]	1.52[c]	2.36[c]
Europe	$R_{low,t}$	0.0561	-0.0092			
S.Am	$R_{high,t}$	0.0713	0.0385	0.62	0.21	0.05
S.Am	$R_{low,t}$	0.0807	0.0183			

a Significant at the1% level.
b Significant at the 5% level.
c Significant at the 10% level.

Panel A of Table IV shows that in the low-noise period, returns on ADR portfolios with high institutional ownership lead the returns of those with low institutional ownership for all three continents. For Asia, a_{low} is 0.0172, and b_{high} is 0.0770. For Europe, a_{low} is -0.0104, and b_{high} is 0.0351. For South America, a_{low} is -0.0290, and b_{high} is 0.0825. That is, for all the three continents, a_{low} is less than b_{high}. The F-statistics, Wilcoxon Z - values, and Kruskal-Wallis Chi-squares are all significant at the 5% level. These results show that the ability of $R_{high, t-k}$ to predict $R_{low, t}$ is much greater than the ability of $R_{low, t-k}$ to predict $R_{high, t}$. That is, even though the market noise is low (relatively speaking) in the low-noise period, ADR portfolios with high institutional ownership still reflect market-wide information sooner than ADR portfolios with less institutional ownership.

In the high-noise period, we observe unexpected results. The returns of high institutional ownership ADR portfolios do not lead the returns of those with low institutional ownership for Asia and South America. For Asia, a_{low} is 0.0031, and b_{high} is 0.0213. For South America, a_{low} is 0.0385, and b_{high} is 0.0807. Despite in both cases, the size of b_{high} is larger than the size of a_{low}, the F-statistics, Wilcoxon Z values, and Kruskal-Wallis Chi-squares are all insignificant. These results mean that we cannot reject the null hypothesis that $b_{high} = a_{low}$, that is, the ability of $R_{high, t-k}$ to predict $R_{low, t}$ is not much greater than the ability of $R_{low, t-k}$ to predict $R_{high, t}$. We think there are two possible reasons for these results. One reason may be that in the high-noise period, institutions deliberately divulge their information very slowly over time through stealth trading, making their information advantage less useful for others to predict returns. This is consistent with our earlier results in Table III that insitutions stealth trade particularly in the high-noise period. The other possible reason is that in the high-noise period risk exposure is conceivably higher for investments in Asian and South American ADRs, institutional investors may be affected by their risk concern such that their ability to impound information in ADR prices is affected. Sias and Stark (1997) suggest that if institutional investors are motivated to trade for reasons not assoicated with information, then there is no reason to expect the returns on portfolios with high institutional ownership to lead the returns on portfolios with low institutional ownership. For European ADRs, the risk is conceivably lower than those of Asian and South American ADRs, returns on portfolios with high institutional ownership lead the returns on portfolios with low institutional ownership because institutional investors' ability to impound information in ADR prices is less affected by risk concern. This conjecture regarding the concern of risk by institutional investors is consistent with the results in the following section.

INSTITUTIONAL INVESTORS IN THE ADR MARKET: DESTABILIZING OR STABILIZING?

Noise traders move ADR prices away from their fundamental values as investment decisions are led by investor sentiment. One observable consequence is that the ADR return volatility would be higher in the high-noise period. The numbers in the following table confirms this; implying noise traders destabilize financial market.

ADR Return Volatility			
	Low-noise	High-noise	T-statistic
Asia	0.0230	0.0308	-13.96[a]
Europe	0.0232	0.0269	-14.66[a]
South America	0.0282	0.0347	-10.81[a]

On the other hand, De Long et al. (1990) suggest that rational investors such as institutions will offset, though incomplete, the irrational activities of the noise traders. Given such postulation, the next logical question is whether institutional investors help destabilize or stabilize volatility of the ADR market. The following regression is performed to answer this question.

$$\delta^2_{it} = a0 + a1\,\delta^2_{i,t-1} + a2\,(\Delta \text{ Discount})t + a3\,(\Delta \text{ Institutional Ownership})t + \varepsilon t$$

where δ^2_{it} is the volatility of the ADR return in time period t for each portfolio, and $\delta^2_{i,t-1}$ is the volatility of the ADR return in time period t–1.

Table V: Effect of Institutional Investors on ADR Return Volatilities

The volatility of the return for time t for each continent's ADR portfolio is then regressed on the volatility of the return for time t –1, the difference of discount between month t and month t-1 (Δ Discount), and the change of the institutional ownership between month t and month t-1(Δ Institutional Ratio).

$\delta^2_{it} = a0 + a1\,\delta^2_{i,t-1} + a2\,(\Delta \text{ Discount})t + a3\,(\Delta \text{ Institutional Ownership})t + \varepsilon t$

	Intercept	$\delta^2_{i,t-1}$	Δ Discount	Δ Institutional Ownership	Adjusted R-square
Asia	0.0518	0.4750	-0.0033	1.8900	0.3270
	(3.48)	(4.72[b])	(-3.76[a])	(1.43)	
Europe	0.0569	0.5090	-0.0011	-0.8370	0.3870
	(4.43)	(4.71[a])	(-1.40)	(-1.98[b])	
S.America	0.1210	0.3960	-0.0027	-1.1090	0.1790
	(1.82)	(3.60[a])	(-2.53[a]	(-0.58)	

[a] Significant at the1% level.
[b] Significant at the 5% level.
[c] Significant at the 10% level.

Table V shows that for Europe, the coefficient of the change in institutional ownership is –0.8370 and it is significant at the 5% level, that is, institutional ownership is negatively related to the volatility of the stock return. The result means that institutional investors help stabilize the market of European ADRs. That is, institutions have helped offset the irrational behavior of noise traders. The coefficients of the change in institutional ownership for Asia and South America, on the other hand, are negative but insignificant. That is, institutional investors have no significant effect on the volatilities of the ADRs from these two continents. This result deserves some explanations.

In finance literature, it is well known that rational investors arbitrage and bring prices closer to fundamental values. The effectiveness of arbitrageurs however relies crucially on the stabilizing powers of rational speculation. Some studies have questioned the effectiveness of such speculation in the presence of risk aversion. For example, DeLong et al. (1987) show that the unpredictability of noise traders' beliefs creates a risk that deters rational arbitrageurs from aggressively betting against them, and rational speculation is thus less effective. Figlewski (1979) also shows that it might take a very long time for noise traders to lose most of their money if rational investors must bear fundamental risk in betting against them, and such fundamental risk deters rational speculation. Both of these two papers suggest that the magnitude of the stabilizing arbitrage positions taken by rational investors might be limited. Investors may regard Asia and South America as more risky when compared with Europe, and rational investors are therefore less likely to counter the unpredictable noise trader risk in Asia and South America. Thus, the magnitude of the stabilizing arbitrage positions taken by rational investors might be small and insignificant for both Asia and South America.

The coefficients of ΔDiscount are all negative, though only significant for Asia and South America. That is, noise trader risk affects ADRs volatility. This is consistent with DeLong et al. (1990) that noise trading is a source of risk, particularly in Asian and South American financial markets.

We also perform the above regression for the high-noise period and the low-noise period separately, and the results are shown in Table VI.

Results similar to those of Table V are found. Table VI shows that for Europe, the coefficients of the change in institutional ownership are negative and significant in both the high-noise and low-noise periods. Again, this may be due to the lesser degree of risk aversion among arbitragers in this market. For Asia and South America, the coefficients of the change in institutional ownership are not significant in either the high-noise period or the low-noise period. For Asia and South America, the aversion to risk greatly limits rational investors' willingness to bet against noise traders in both the high-noise and low-noise periods.

SUMMARY

This study examines the effects of market noise in the American Depository Receipts (ADRs) market. From existing literature, we can identify three possible effects of noise on securities trading. First, market noise leads to the existence of noise trader risk. Second, the existence of noise in capital markets provides an opportunity for informed institutional investors to exploit their information advantage through stealth trading. Third, the irrational behavior of noise traders in a noisy market may cause the market to destabilize, though rational institutional investors would take positions opposite to those of the noise traders and help stabilize the market. We examine the three possible effects of noise in the ADR market. The ADRs market presents an unique environment in which we can examine the above-mentioned effects of noise directly and simultaneously in a noisy environment.

Table VI: Effect of Institutional Investors on ADR Return Volatility

The volatility of the return for time t for each continent's ADR portfolio is regressed on the volatility of the return for time t –1, the difference of discount between month t and month t-1 (Δ Discount), and the change of the institutional ownership between month t and month t-1.

$$\delta^2_{it} = a0 + a1\ \delta^2_{i,t-1} + a2\ (\Delta \text{ Discount})t + a3\ (\Delta \text{ Institutional Ownership})t + \varepsilon t$$

A: Low-noise period:

	Intercept	$\delta^2_{i,t-1}$	Δ Discount	Δ Institutional Ownership	Adjusted R-square
Asia	0.0270	0.5650	-0.0037	2.5890	0.42
	(1.24)	(4.07[b])	(-3.17[a])	(1.46)	
Europe	0.0593	0.5460	-0.0005	-1.4290	0.33
	(3.06)	(3.35[a])	(-0.68)	(-2.12[b])	
S.America	0.0342	0.7200	-0.0022	1.9590	0.49
	(1.97)	(5.50[a])	(-2.18[a])	(0.78)	

B: High-noise period:

	Intercept	$\delta^2_{i,t-1}$	Δ Discount	Δ Institutional Ownership	Adjusted R-square
Asia	0.0804	0.3290	-0.0035	1.9100	0.19
	(3.93)	(2.06[b])	(-2.31[b])	(0.87)	
Europe	0.0788	0.3100	-0.0014	-1.7020	0.46
	(4.01)	(1.83[c])	(-1.37)	(-2.58[a])	
S.America	0.1180	0.2240	-0.0032	1.6620	0.13
	(4.46)	(1.36)	(-1.83[c])	(0.63)	

[a] Significant at the1% level.
[b] Significant at the 5% level.
[c] Significant at the 10% level.

Our results show that the ADR return is affected by investor sentiment (noise trader risk) in the ADR market. ADR return increases (decreases) when investors are irrationally optimistic (pessimistic). We also find that in the low-noise period, ADRs with high institutional ownership exhibit autocorrelation similar to ADRs with low institutional ownership. However, in the high-noise period, ADRs with high institutional ownership exhibit significant higher autocorrelation than ADRs with low institutional ownership. The result implies institutional investors may have engaged in stealth trading. Through a Granger causality regression, we find returns on ADR portfolios with high institutional ownership lead the returns of those with low institutional ownership in the low-noise period, confirming that institutional trades reflect market information ultimately incorporated into other stocks. Finally, we find that rational investors help stabilize ADRs market in Europe. However, for Asia and South America, the magnitude of the stabilizing arbitrage positions taken by rational investors is insignificant.

ENDNOTES

Since noise and ΔDiscount may be correlated and cause selection bias, we perform tests for difference in means of ΔDiscount between the high-noise and low-noise periods for each portfolio. All the test statistics are insignificant, showing no selection bias.

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