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Significance tests of probability non-stationarity of security price returns

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The Ohio State University, 1992

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Significance Tests of Probability Non-stationarity of Security Price Returns

DISSERTATION

Presented in Partial Fulfillment of the Requirements for the Degree Doctor of Philosophy in the Graduate School of The Ohio State University

By

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CHAPTER I

Introduction

1.1 Issues investigated in this Paper

This paper seeks to develop evidence both empirical and theoretical to support several related hypotheses. The principal hypothesis offers the notion that security prices are not measurable functions on a stationary probability space nor adapted functions with respect to a filtration σ-algebra.

Nonintegrability is shown to be potentially an explanation for the existence of markets. According to this conception, markets provide "price discovery," establishing standards of value despite expectational difficulties rooted in weaknesses in availability and reliability of relevant information.

Nonintegrability offers a unified explanation of three well-documented "anomalies" in returns observed for some classes of stocks. For example, information flows are particularly unreliable for small firms and for stocks being sold for the first time, Initial Public offerings or IPO's. On average investment opportunities in both types of enterprises have shown extraordinary returns (Banz 1981, Reinganum 1981, 1983, Schwert 1983, Williams 1986, Ibbotson 1975) [5, 87, 88, 94, 103, 49]. Further, nonintegrability can justify the anomaly of a lack of predicted diversification in real world-

portfolios (Lease, Lewellen and Schlarbaum 74, 77, Blume and Friend 74, Williams 1979)[85, 8, 86, 104] can be explained in part as a reaction to nonintegrability. Parties may avoid stocks in which they do not have sufficient information to make reasonable probability assessments. As a result, rational investors might restrict themselves to a few securities that they know about and specialize in.

The paper focuses on explaining the existence of particular financial entities and phenomena, not on modeling or deriving equilibrium (i.e., market-clearing) prices. Interpreting many of the probabilities encountered in security analysis as subjective assessments provides a basis for tying variations in information flow to efforts to restructure institutional and individual portfolios. This idea traces back to Keynes (1921, 1936)[60, 59].

This investigation advances a class of distribution-free significance tests for the equality of empirical distribution functions. The tests are able to check the assumption of identically distributed error terms that researchers routinely make when estimating parameters in security price regressions. These tests constitute a new method for developing evidence on the issue of whether probabilities are non-stationary in security markets.

1.2 Risk and Uncertainty

In common usage, risk refers to danger. When applied to investments, risk refers to exposure to loss. Loss exposure comes from one's inability to predict future events precisely.

A **portfolio** is an allocation of wealth over a set of assets and liabilities. It may

be represented mathematically as a vector of weights summing to 1, each component of which represents the proportion of an investor's wealth that is held in assets and liabilities. Negative weights are used to designate liabilities or assets that are sold short. This definition makes the concept of portfolio independent of the magnitude of the investor's nonzero wealth.

Standard portfolio analysis and theories of capital market equilibrium employ the naive simplification that risk may be represented as variance in asset returns. Frank Knight (1921)[61] defines **risk** to be variance, and uses the general term **uncertainty** to tack onto risk various other contingencies that are not fully deterministic.

Knight (1921)[61] identifies the particularly interesting case created by assuming that the probability distributions and their parameters are not known. Markets can not reveal non-existent information. Unknowable information creates forms of uncertainty other than variance. We can characterize this type of uncertainty as probability-estimation uncertainty.

1.3 Scientific Investigations

Theoretical economics has sought to pattern itself on an exact science (Samuelson 1948)[91]. However, in economics increases in exactness are purchased at the price of a substantial lessening in realism. The economic abstractions that contribute to exactness and analysis of these abstractions must be weighed against the ultimate goal of the science which is to explain observable economic phenomena.

Hempel (1952)[45] discusses that good scientific constructs must possess both a *theoretical import* as well as a *empirical import.* We discuss four criteria that are

necessary for scientific admissibility of any empirical investigation. These are: (1) observability, (2) interpretability, (3) replicability, and (4) robustness. Let us briefly examine each criterion in turn.

Observability. Empirical science seeks to check conjectures against reality. For this purpose, one has to focus on observable information. If a subject-matter variable is not observable, one can introduce another observable variable to act as a proxy or instrument for it. Tests of any scientific hypothesis will only be as good as the proxy or instrument selected. Statistical procedures jointly test all "subsidiary" proxying assumptions that are used to operationalize the unproxied subject-matter hypothesis with that main hypothesis. More generally, scientists can not run a simple test of a main hypothesis without simultaneously testing subsidiary hypotheses together as a group with that main hypothesis. In practice, conforming or rejecting various operationalizing joint hypothesis can not conclusively reject the main hypothesis. Observed results may trace to one of several combinations of problems with the subsidiary hypotheses.

Interpretability. Empirical scientists seek to make verifiable or refutable predictions about reality. For empirical scientists, mathematical models must be assigned an interpretation to render them scientifically admissible. In abstract mathematics, propositions are true if they are deduced from the axioms. However, no proposition from a mathematical theory *directly* proves anything about observable reality, which by definition treats perceptible things of experience. To quote Cramér (1946)[21, page 146] "Mathematical arguments are fundamentally incapable of proving physical

facts." Cramér makes the further point that even models that are in full agreement with the data every time the models have been tested so far can only be viewed as *practically certain.* Cramér cites the model that the sum of the interior angles of an physical triangle is π as an example of such a model.

Replicability. A replicable experiment is one that can be rerun by an independent party. If a scientific phenomenon occurs in one environmental setting, it should reoccur in a similar setting. If not, why not? Was the phenomenon happenstance or genuine? Requiring replicability is an important dimension of keeping scientists accountable for their findings. One advantage of insisting on reproducibility is its implied demand that researchers state explicitly all the underlying assumptions on which an argument depends. It also helps to clarify when an inference may go beyond a particular set of empirical evidence that has been developed.

Robustness. The most comprehensive criterion is robustness. In empirical science, researchers often find it necessary to make counterfactual assumptions. After all, every model seeks to simplify reality. Preferring a less complicated explanation for some phenomenon to a more complicated one is justified by the principle of parsimony. This principle is widely known as Occam's Razor.

When a practitioner forms a model, he is assembling a set of unrealistic simplifying assumptions: every model is a set of such assumptions. A modeler's goal is to explain complex phenomena with just a few variables. A model's success or failure is ultimately judged by how well a particular model does at predicting a designated set of observable variables. A model may be good for some phenomena and poor with

respect to others.

The question of whether a particular model is absolutely correct is not a practical one. Empirical scientists merely want to know how good an approximation a model is. Empirical scientists make assumptions that they know are not fully correct. As long as these assumptions do not affect the final result in any substantial way, it is presumed to be reasonable to posit them. For example, physicists sometimes assume a surface is frictionless when the amount of friction from a surface is negligible. Conversely, if an assumption that is known to be false is shown to greatly affect a set of scientific findings, then it is less reasonable to base scientific theorems upon this simplification. The criterion of robustness emphasizes the value of models which show an insensitivity in results to small changes in underlying assumptions.

A trade-off exists between robustness and specificity. Assumptions that are not robust lessen a model's range of explanation. The more one assumes, the sharper one's predictions become. The danger is that simplifying assumptions may limit the applicability of the model to a narrow set of circumstances. To check robustness, care must be taken to devise and perform an appropriate battery of sensitivity tests.

1.4 Existence Evidence

A primary goal of financial economics is to give a rationale for financial agents, institutions and interactions that are observed. The universal statement that all sheep are white is contradicted by the existence of a single non-white sheep. When a modeler makes unrealistic assumptions that assume away the economic rationale for an object to exist, one can correctly assert that the existence of those objects *challenges*

the assumptions. If our goal is to help explain the existence of certain specific institutional or instrumental characteristics such as the price and return volatility or the liquidity observed in specific financial markets it is not enough for a model to be able to explain security prices. Models that can account for security prices may not be able to provide an economic rationale for many observable economic entities and phenomena that exist in security markets. On the other hand, models that explain characteristics such as price and return volatility may not adequately explain security prices themselves. This paper seeks to provide an extended rationale for price and return volatility that does not easily generalize into a computationally useful formula for determining market-clearing security prices.

1.5 Tests of Significance and Test of Hypothesis

Although significance tests and hypothesis tests have almost identical mathematics underlying them, they differ markedly in their relevance and their uses (Kempthorne 1976)[58]. A hypothesis test is a procedure to *decide* whether or not some formulated hypothesis is plausible when confronted with a set of observed data. One either *rejects* the formulated hypothesis or one *fails to reject* (accepts) the formulated hypothesis. A *decision* procedure for such a choice of action is referred to as a hypothesis test. One has a sample space, and a statistical hypothesis, H_0, which one wants to test. One must choose a criterion α, $0 < \alpha < 1$ and a critical region, R, in a designated sample space such that the probability that an observed test statistic, X, is in R given H_0, is less than or equal to α. The key idea behind the Neyman-Pearson lemma (1928) [79] is to choose R such that the probability that $X \in R$, given H_A is as large

as possible, where H_A is some alternative hypothesis.

The same concepts of a test statistic, t(y), and a corresponding random variable T=t(y), are used to define a significance test of the hypothesis H_0. In a significance test, the level of significance obtained is also referred to as a **p-value**, $P(\text{observed data}) = P(T \geq t_{\text{observed}}|H_0)$. This probability (level) has a uniform [0,1] distribution under H_0, and the statistic P(observed data) is a measure of the consonance of the data and the model H_0. If one treats the available data as *evidence* against H_0, then one would be forced to accept all data with larger values of t(y) as even *stronger evidence* (Kempthorne 1976)[58]. Consequently, P(observed data) is the probability that we would incorrectly assert that there is *evidence against* H_0, given that the data under analysis are just decisive against H_0.

Cox and Hinkley (1974)[19, page 90] give the following formal definition of a **test of significance**: it is a set of regions w_α, for each $\alpha, 0 < \alpha < 1$ such that

$$w_{\alpha_1} \subset w_{\alpha_2} \text{ if } \alpha_1 < \alpha_2,$$

$\text{Prob}(Y \in w_\alpha|H_0) = \alpha$, for each α with the level of significance defined as

$$P(\text{observed data}) = \inf(\alpha|y \in w_\alpha).$$

(Kempthorne 1976)[58] points out that imposing the set containment condition on the regions is necessary if one regards a test as *evidential*, but such nesting is clearly irrelevant if one adopts a *decision* stance.

We interpret a test's level of significance as measuring the discrepancy of the data from the hypothesized distribution of possible sets of data. Significance has been

placed on the [0,1] probability scale, where values near zero indicate large discrepancies and values near one indicate small discrepancies. This is the interpretation we use for significance tests employed for model selection.

Empirical scientists dare not put much weight on any single test, paper or study. It is unreasonable to decide to reject well-credentialed theories on the basis of a single hypothesis test. We are interested in far more than whether a given test statistic has a corresponding p-value that is less than some particular value α, say $\alpha = 0.05$. Most individual test results are simply noted and filed in one's memory banks, with no immediate decision made. To quote Kempthorne (1976)[58, page 776], "scientific investigation is a learning process with no terminal decision." Theories are not overturned on the basis of a few tests. Before one overturns old theories for new theories, an accumulation of evidence must be develop, which are reinforced by failed reconciliation attempts to salvage old theories (Kuhn 1970)[64].

CHAPTER II

Probability Preliminaries

This paper applies probability theory more carefully to issues of information processing in financial analysis than has been done traditionally. This chapter serves to summarize the theory to be applied. The summary offered does not itself advance the mathematical literature in any way.

2.1 σ-Algebras

Let Ω be a probability space. It is a set of points ω of all observable outcomes. A subset of Ω is an event, and an element $\omega \in \Omega$ is a sample point. For a non-empty space Ω, we define the class $\mathcal{F}$ of subsets of Ω to be an **algebra** [1] if three conditions are met:

(1) $\Omega \in \mathcal{F}$;

(2) $A \in \mathcal{F}$ implies $A^c \in \mathcal{F}$, where $A^c = \{\omega\colon\ \omega \in \Omega, \omega \notin A\}$;

(3) $A, B \in \mathcal{F}$ implies $A \bigcup B \in \mathcal{F}$.

By DeMorgan's law, we have $A \bigcap B = (A^c \bigcup B^c)^c$ and $A \bigcup B = (A^c \bigcap B^c)^c$. Thus (3) may be replaced by (3′) $A, B \in \mathcal{F}$ implies $A \bigcap B \in \mathcal{F}$. If $A, B \in \mathcal{F}$ implies that $A - B \equiv A \bigcap B^c \in \mathcal{F}$, and $A \triangle B \equiv (A - B) \bigcup (B - A) \in \mathcal{F}$.

[1] The term field is sometimes used instead of algebra.

A class $\mathcal{F}$ of subsets of Ω is a σ-algebra, if it is also closed under the formation of countable [2] unions.

(3′) $A_1, A_2, \ldots \in \mathcal{F}$ implies $A_1 \bigcup A_2 \bigcup \ldots \in \mathcal{F}$.

Again, by the infinite version of DeMorgan's law and closure of complements, $\mathcal{F}$ is closed under countable intersections if and only if $\mathcal{F}$ is closed under countable unions.

The smallest σ-algebra consists only of Ω and the empty set, ϕ. The largest consists of all subsets of Ω, which is called the power set. Consider the class $\mathcal{Q}$, define $\sigma(\mathcal{Q})$ to be the σ-algebra defined as the intersection of all σ-algebras that contain $\mathcal{Q}$. Clearly, $\mathcal{Q}$ is contained in the power set, so this intersection is non-empty. An arbitrary intersection of σ-algebras is itself a σ-algebra. Suppose that $\mathcal{F} = \bigcap_\Theta \mathcal{F}_\theta$, where θ ranges over an arbitrary index set and each $\mathcal{F}_\theta$ is a σ-algebra. Then $A \in \mathcal{F}$ implies for every $\theta, A \in \mathcal{F}_\theta$, implies $A^c \in \mathcal{F}_\theta$ for every θ. So $A^c \in \mathcal{F}$. If $A_n \in \mathcal{F}$ for each n, then $A_n \in \mathcal{F}_\theta$ for every θ, hence $\bigcup_n A_n \in \mathcal{F}_\theta$ for every θ , so $\bigcup_n A_n \in \mathcal{F}$.

Suppose that a countably infinite σ-algebra does exist. Define an atom to be $A \in \mathcal{F}$, such that for any $B \in \mathcal{F}, A \bigcap B = A$ or ϕ. As an example of an atom, consider an arbitrary $\omega \in \Omega$. Take all $A_i \in \mathcal{F}$ such that $\omega \in A_i$, then $V_\omega = \bigcap A_i \neq \phi$. $\bigcap A_i \in \mathcal{F}$, since our σ-algebra is countable, there are countably many A_i that contain ω, and σ-algebras are closed under countable intersections. All elements of our σ-algebra can be expressed as $\bigcup_{\omega \in A} V_\omega = A$. Clearly, $A \subset \bigcup_{\omega \in A} V_\omega$. Suppose there exists $\omega' \in V_\omega$ for some ω, but $\omega' \notin A$. Yet, $\omega \in A$ implies $\omega' \notin \bigcap_{\omega \in A_i} A_i = V_\omega$, which would contradict our definition of V_ω. Since all elements of our σ-algebra can be expressed as a union of atoms, all sets in our σ-algebra either contain a given atom

[2] A countable set is either finite or in one-to-one correspondence with the integers.

or they do not. Consequently there are $2^{\text{number of atoms}}$ many elements to our σ-algebra. If the number of atoms is finite, then our σ-algebra is finite, contradicting the presumption that it is countably infinite. If the number of atoms is countably infinite, then our σ-algebra has uncountably many elements, a contradiction. So a σ-algebra has either finitely many elements or it has uncountably many events. Countably infinite σ-algebras do not exist. If we are modeling information by a probability measure on a σ-algebra, we need to assign probabilities to an uncountable set if we assume that we have infinitely many sets in our σ-algebra. This requires a large amount of information, or at least a reliable assignment procedure for uncountably many sets. This realization makes it likely that if an underlying σ-algebra exists for security prices, the σ-algebra is finite.

2.2 Probability Measures

A set function is a real-valued function defined on some class of subsets of Ω. A set function P on algebra $\mathcal{F}$ is a **probability measure** if:

(1) $0 \leq P(A) \leq 1$ for $A \in \mathcal{F}$;

(2) $P(\phi) = 0$, $P(\Omega) = 1$;

(3) If $A_1, A_2, \ldots$ is a disjoint sequence of $\mathcal{F}$-sets and if $\bigcup_{j=1}^{\infty} A_j \in \mathcal{F}$, then $P(\bigcup_{j=1}^{\infty} A_j) = \sum_{j=1}^{\infty} P(A_j)$.

Condition (3) is known as countable additivity. It requires that countable unions of disjoint sets are closed in our algebra, in which case we have merely an algebra and not a σ-algebra. When $\mathcal{F}$ is a σ-algebra in Ω, and P is a probability measure on $\mathcal{F}$,

the triple $(\Omega, \mathcal{F}, P)$ is called a probability measure space.

Let P be a probability measure on a algebra $\mathcal{F}$, and if $A, B \in \mathcal{F}$ and $A \subset B$, then since $P(B) = P(A) + P(B - A)$, and $P(B - A) \geq 0$. P is monotone: $P(A) \leq P(B)$ if $A \subset B$. Also, $P(B - A) = P(B) - P(A)$ and specifically $P(A^c) = 1 - P(A)$.

Let $A_1 \subseteq A_2 \subseteq \ldots, \bigcup_{n=1}^{\infty} A_n = A$, we denote this as $A_n \uparrow A$. Similarly, $A_1 \supseteq A_2 \supseteq \ldots, \bigcap_{n=1}^{\infty} A_n = A$. We denote this as $A_n \downarrow A$.

Suppose P is a probability measure on a algebra $\mathcal{F}$.

(1) **Continuity from below:** If $A_n, A \in \mathcal{F}$ and $A_n \uparrow A$, then $P(A_n) \uparrow P(A)$.

Define $B_1 = A_1, B_2 = A_2 - A_1, B_n = A_n - A_{n-1}$, then $A = \bigcup_{n=1}^{\infty} B_n$ and the B_n are disjoint. Hence, by countable additivity

$$P(A) = \sum_{n=1}^{\infty} P(B_n) = \lim_{N \to \infty} \sum_{n=1}^{N} P(B_n) = \lim_{N \to \infty} P(A_N).$$

(2) **Continuity from above:** If $A_n, A \in \mathcal{F}$ and $A_n \downarrow A$, then $P(A_n) \downarrow P(A)$.

Note $A_n \downarrow A$ implies $A_n^c \uparrow A^c$ by continuity from below implies $1 - P(A_n) \uparrow 1 - P(A)$.

(3) **Countable Sub-additivity:** If $A_1, A_2, \ldots, \bigcup_{n=1}^{\infty} A_n \in \mathcal{F}$ then $P(\bigcup_{n=1}^{\infty} A_n) \leq \sum_{n=1}^{\infty} P(A_n)$.

Let the B_n be as before, then by countable additivity

$$P(\bigcup_{n=1}^{N} A_n) = \sum_{n=1}^{N} P(B_n) \leq \sum_{n=1}^{\infty} P(B_n) = P(A) \leq \sum_{n=1}^{\infty} P(A_n)$$

by $B_n \subseteq A_n$, monotonicity. Now, $\bigcup_{n=1}^{N} A_n \uparrow \bigcup_{n=1}^{\infty} A_n$ so by continuity from below $P(\bigcup_{n=1}^{\infty} A_n) \uparrow P(A)$ as $N \to \infty$, and the result is obtained.

2.3 Subjective versus Objective Interpretation of Probabilities

What is the probability of a particular coin being tossed and landing on heads? Ex post, the probability is either 0 or 1, depending on the result of the coin toss. However, uncertainty concerns the *ex ante* probability. If one makes the assumption that successive coin tossings are *ex ante* identical to the desired coin tossing, one can speak of a repeated experiment of coin tosses(von Mises 1928, 1931)[75, 76]. A frequentist would assert that the observed **relative frequency**, defined as $1/n$ times the number of heads in the n trials, tends in the limit ($n \to \infty$) to the true probability, p (von Mises 1928, 1931, Borel 1934)[75, 76, 9]. This is a "reasonable" definition provided that the underlying notion of an infinitely repeatable experiment is defensible.

As an example of a non-repeatable event consider a boxing match starting at a pre-specified time: Either a boxer will win the bout or he will lose the bout, we exclude ties for definiteness. Just what is the "event" that a hypothetical experimenter could repeat? The boxers' constitutions would not allow for independent repetitions of the bout. An experimenter could space out the bouts, but the injuries, mental attitudes, and age of the boxers would not stay the same. Each boxing match between the same opponents is a distinct event, because they happen at distinct moments in time. It would not be "reasonable" to assert that the ex ante probability is the limit of the relative frequency of the result of successive fights. In such instances, a frequentist would say that a probability assignment is meaningless (Borel 1934)[9]. However, a

subjectivist would be willing to assign a probability, *a degree of reasonable belief*, to each possible outcome of a given boxing match based on knowledge the subjectivist has learned about the two boxers (Keynes 1921)[60].

Abstractly, it is sufficient to satisfy the conditions of the definition of a probability measure. In applying a probability measure to observed data, how to interpret the probability measure is a critical issue that poses itself naturally. This investigation analyzes financial events. As in the boxing example, objective interpretations of the probability of repetitive events are forced.

A subjectivist looks for relevant information to help analyze the situation. A bettor on a boxing match would use past experience learned from other boxing matches, and other relevant information to reach an informed judgement about the likely outcome of the match. Different parties might use different information to form their judgments. They might value the same information differently. Different parties with the same or different information might form different judgments. For this reason, these probabilities are labeled subjective. It is logical to assert that when a person's set of relevant information changes with regard to an event, that the person's subjective probability could change as well.

To assess a price, many non-infinitely repeatable events exist that a security analyst needs to evaluate. New products are constantly being developed and marketed. The success of these new products can not be experimentally repeated infinitely. Of course, companies might undertake test marketing exercises to help judge the success of a proposed new product. These tests may have some objective components to them,

but ultimately the assessments of the company and security-market participants is subjective. *In this paper we explore the hypothesis that, through markets, society lets security analysts compete in information evaluation to shape an ever-evolving social consensus judgment of the future prospects of given securities.*

2.4 Filtration σ-Algebras

Consider a probability measure space $(\Omega, \mathcal{F}, P)$. Let us define a **filtration** on this sample space. Let $\{\mathcal{F}_t; t \geq 0\}$ be a nondecreasing family of sub-σ-algebras of $\mathcal{F}$: $\mathcal{F}_s \subseteq \mathcal{F}_t \subseteq \mathcal{F}$ for $0 \leq s < t < \infty$. $\mathcal{F}_\infty \equiv \sigma(\bigcup_{t \geq 0} \mathcal{F}_t)$. We note that the probabilities on events in this σ-algebra at time s can not change at any future time t. Only the number of elements in the σ-algebra increase. Hence, the implied probability assignment becomes finer and finer, in that more and more subsets of sets already in the σ-algebra receive probability assignments.

Unfortunately, the concept of filtration does not allow for a subjective interpretation of the underlying probabilities. In security market analysis, the information available is non-decreasing, but the σ-algebras indexed over time need not be nested as time increases. It is conceivable that probability assignments based on an evolving information flow may change or even become unassigned. Removing the imposed nesting structure on the σ-algebras would permit the information to "move" the prices, where in the alternative random walk conception of prices, only random noise could "move" the market.

2.5 Borel Measurable Functions

The **Borel sets** in $\Re$ are elements of the σ-algebra generated by a class of infinite intervals of the form $[-\infty, x), x \in \Re$. A real-valued function $X(\omega)$ on a space $(\Omega, \mathcal{F})$ is a **borel measurable function** if $\{X(\omega) > x\} \in \mathcal{F}, x \in \Re$. A function $X(t)$ is $\mathcal{F}_t$ **measurable** if $X_t(\omega)$ is a borel measurable function on $(\Omega, \mathcal{F}_t)$.

2.6 Stochastic Processes and Martingales

A **stochastic process** is a collection of random variables on $(\Omega, \mathcal{F})$, $\mathbf{X} = \{X_t; 0 \leq t < \infty\}$ which takes values on a measurable state space. The stochastic process $\mathbf{X}$ is **adapted** to the filtration $\{\mathcal{F}_t\}$ if, for every $t \geq 0, X_t$ is an $\mathcal{F}_t$-measurable random variable. To use powerful stochastic analysis techniques, we need price functions to be adapted to our filtration. This may not be reasonable for an arbitrary information set.

Let $\mathbf{X} = \{X_t; 0 \leq t < \infty\}$ be a real-valued stochastic process, defined on a probability space $(\Omega, \mathcal{F}, P)$ adapted to a given filtration $\{\mathcal{F}_t\}$ such that $\mathrm{E}[|X_t|] < \infty$, holds for every $t \geq 0$. We say the process $\mathbf{X}$ is a **martingale** if for every $0 \leq s < t < \infty$, we have except for sets of probability zero, $\mathrm{E}[X_t \mid \mathcal{F}_s] = X_s$.

Measurable security price functions are modeled as martingales (Harrison and Kreps 1979, Muller 1985, Leroy 1989)[41, 78, 66]. Otherwise, arbitrage opportunities would exist. However, if the existence of a commonly agreed upon probability measure is in doubt, then the condition defining a martingale can not be imposed. Burton Malkiel, author of *A Random Walk Down Wall Street*, was asked if he believed the

martingale assumption was a reasonable assumption. He replied, "I am a random walker with a crutch, the crutch being information." This statement recognizes that the all relevant information may not be uniformly available to all participants. Those who have better information than other market participants, can do better than those other market participants.

2.7 Brownian Motion

The first quantitative work on Brownian motion is due to Bachelier (1900)[4], who had our same interest, stock market price fluctuations. We give a formal definition from Karantzas and Shreve (1988)[57]: A standard one-dimensional **Brownian motion** is a continuous, adapted stochastic process $B = \{B_t, \mathcal{F}_t; 0 \leq t \leq \infty\}$, defined on some probability space $(\Omega, \mathcal{F}, P)$, with properties that $B_0 = 0$ except for sets of probability zero and for $0 \leq s < t$, the increment $B_t - B_0 = 0$ except for sets of probability zero and for $0 \leq s < t$, the increment $B_t - B_s$ is independent of $\mathcal{F}_s$ and is normally distributed with a mean zero and variance $t - s$.

2.8 Relevance of this chapter to the rest of the Investigation

The concept of information is an informal extra-mathematical term(page 52, Billingsley 1986)[6]. Existing asset pricing theories have failed to give a precise mathematical definition to information, nor have they given a plausible interpretation to their allegedly "objective" probabilities that underlie their investigations. This investigation seeks to test empirically whether the assumption of identically distributed random price variation that empirical financial investigators use to estimate state-space prob-

abilities is "reasonable."

CHAPTER III

Expectations and Related Topics

3.1 Homogeneous Expectations

This paper challenges the assumption that is traditionally made in the random price-change sub-literature that all market participants have the same probability estimates and information set. This assumption is known as **homogeneous expectations**. With sufficient "information", homogeneous expectations implies that the future value of all assets are measurable functions defined on a probability space.

Full information means that all the relevant elements of the σ-algebra and corresponding probabilities are completely known. **Weak information** is when all the relevant information required for security prices to be measurable functions defined on a probability space is deficient. Full and homogeneous expectations means that all relevant elements of the σ-algebra and corresponding probabilities are completely known and fully agreed upon by all agents.

Many activities exist that can be interpreted as indicating that the assumptions of full and homogeneous expectations are unrealistic. For example, these assumptions are inconsistent with intermediated betting on sporting events, in the cases where bettors know the possible outcomes. The simplest nontrivial wager is: win or lose,

with bets returned on all other possible outcomes. This wager turns on a single parameter, p, the probability of the first side's winning. We may interpret the odds set by professional bet-takers as the bettors' consensus. This consensus would be weighted by the amount of money actually bet and would adjust for any commissions make by the bet-takers.

Negotiating a wager means parties, presumably rational, bet on one side and other parties, also presumably rational, bet against them, even when there are bet-takers who remove commissions that leave the bets less than zero sum. Ignoring the entertainment value of betting, we may infer, under the assumption that both sides are rational and bet, that the bettors on the two sides disagree on p, the probability of the first side's winning.

If pivotal disagreements arise in such a simple case where the distribution is known and only one parameter has to be estimated, how can complete agreement exist in financial markets where the σ-algebra contains many more elements? This is consistent with the results of an important Cragg and Malkiel (1968)[20] survey of security analysis firms. Cragg and Malkiel found that different firms' estimates differed greatly, and that a financial analyst firm had little information of value to offer its clients.

Informational efficiency is said to exist when prices reflect all the relevant information that is available, such that one can not earn above-normal returns by trading on existing information. Security analysts firms can take heart in the realization that tests of informational efficiency simultaneously test a subsidiary assumption that a specified market-pricing model obtains. Chapter 1 clarifies that all hypothesis tests

are really joint tests. This leaves the reliability of a hypothesis test only as good as the reliability of the subsidiary hypothesis it incorporates.

Full and homogeneous expectations buttresses the theory of "preference-free" pricing. The concept of "preference-free" pricing is not robust to relaxations of the homogeneous-expectations assumption. Specifying an agreed-upon probability distribution and parameters comes close to specifying a representative-agent model with a single "relevant" utility function. This aggregated objective function may tolerate different attitudes toward risk and variation in other preference elements, but specifying a common set of subjective probabilities is in important respects the same as specifying the existence of a common utility function over the asset space for all the agents. The subsequent discussion seeks to clarify this point.

A state is called **insurable** if a security can be constructed from existing securities such that it pays 1 dollar if a particular state occurs and 0 otherwise. These securities are called **state securities**. Other names in the literature are **Arrow-Debreu securities**, and **state-contingent** claims (Ingersoll 1986)[50]. A market is said to be **complete** if every possible contingency is insurable. Market completeness means a natural basis given by the state securities spans the space of contingent states.

In the preference-free framework, two buttressing assumptions are made: Market completeness and zero transaction costs. Together, these two assumptions imply that all risk can be *costlessly* hedged by properly balancing one's portfolio. Proper balancing means appropriately buying and selling of securities until all risk is removed from the new portfolio. This fully hedged portfolio becomes risk-free and earns an

identical rate regardless of which contingencies actually occur.

A **cash flow** is any time-dated stream of money paid out or received. The flow envisioned need be continuous. A **discounted cash flow** is a cash flow that is adjusted by a discount factor to incorporate the time value of money. This concept recognizes that a dollar today is worth more than a dollar specified in the future.

An **arbitrage opportunity** is defined as a portfolio that can be assembled with no net outlay of wealth, yet offers a non-negative discounted cash flow, and has a strictly positive expected discounted cash flow. If the discounted cash flow is allowed to be negative on some set of positive probability, then there is the possibility of losing wealth and this would not represent an arbitrage opportunity. Muller (1985) [78] defines the variance of an arbitrage portfolio to be zero. In the context of market completeness and zero transaction costs, our arbitrage portfolios can be costlessly modified to have zero variance. Our definition of arbitrage allows for the incompleteness of markets. The existence of arbitrage opportunities implies the existence of opportunities for obtaining wealth without taking risk or putting up capital. In the absence of arbitrage opportunities, any risk-free portfolio must earn the same rate as any other risk-free portfolio. With costless contracting, any risk-free portfolio is ex ante indistinguishable from a straightforwardly risk-free investment, no matter how numerous and complicated its component parts may be. The assumption that ex ante returns differ across risk-free opportunities means that selling one investment strategy short and buying the other would generate opportunities for arbitrage profits.

Assuming full and homogeneous expectations, plus no transaction costs and mar-

ket completeness permits securities to be characterized by their probability measures. Because the probabilities are fully agreed upon by all agents, the agents collectively act as one. This means their decisions may be analyzed as if they were made by a single representative agent. These conditions specify that risks are irrelevant, because net exposure to loss can be reconfigured out of existence without cost. This condition is referred to as **risk-neutral** pricing because no premiums are paid for holding risk.

Suppose that markets were "nearly" complete in the sense that, relative to a fixed number of risks, precisely one type of risk is still missing from our state securities. In this case, the addition of a single appropriate state security would make markets complete with respect to the fixed number of risks. To be specific, let the missing risk concern the possible non-performance of forward contracts. A forward contract is a promise to deliver goods or services at some future date at a price that is agreed upon today. Anyone undertakes to substitute for the missing state security, can be described as providing "market-completion services." In these circumstances, we can talk about the existence and value of these services and analyze the premium paid for these services. To quote E. Kane (1980)[56]:

> "Recognizing that it is costly to guarantee future-market performance is sufficient to destroy any presumed identity between futures and forward interest rates. Introducing a positive price for risk-bearing services, applicable to whatever non-arbitrageable risk inheres in every risky opportunity, suffices both to make forward interest rates differ from expected rates and, especially when capital gains are taxed preferentially, to make the representation of futures rates very complicated indeed. When PET[1] assumptions are relaxed, expected, forward, and futures yields are free to travel different roads. Movements in comparable expected, forward, and futures yields *constrain* each other, but not to the point of equality."

[1]The PET assumptions are: risk neutrality, identical expectations, perfect divisibility, costless transacting, identical tax treatment of interest and capital gains income, and costless guarantees of futures-market performance.

3.2 Anomalies

An anomaly means etymologically (a-nomos: away from law) "something contrary to what 'should' be"(e.g., an exception to a rule). Value anomalies in finance are exceptions to accepted no-arbitrage pricing paradigms based on full and homogeneous expectations. Schwert (1983)[94] describes anomalies as "unexplained empirical regularities." Anomalies have no theoretical standing whatsoever; since anomalies by definition are not predicted by any respectable asset-pricing theory. Anomalies challenge existing theories. If this challenge can not be "explained away", anomalies lead to a "scientific revolution" (Kuhn 1970)[64], where new paradigms overthrow old paradigms on the battlefield of the scientific community's acceptance.

The introduction mentions three anomalous effects that finance theorists find troublesome, for which nonintegrability provides a unified explanation: the small-firm effect, IPO effect, and the lack of full diversification effect. We also cited studies that developed evidence of their existence.

Many of the existing asset pricing paradigms assert that under equilibrium conditions that investor's portfolios should blend some fraction of the market aggregate and risk-free investments (Ingersoll 1986)[50]. In practice, investors restrict themselves to a few securities and hold portfolios that are not similar in composition to everyone else's portfolio (Lease, Lewellen and Schlarbaum 1974, Blume and Friend 1975)[85, 8]. Risk-adjusted return on a stock is negatively related to the total market value of the common stock of a firm (Banz 1981, Reinganum 1981, 1983, Schwert 1983, Williams 1986) [5, 87, 88, 94, 103]. In the small-firm effect, "size" is defined in terms of market

capitalization not total assets. This means that size is down-scaled for the effects of leverage: the ratio of debt to equity. Market capitalization, the market value of the common shares, is a significant predictor of average return when it is added to a traditional market model. Total capitalization would include some other claims on equity (e.g., employee stock option plans). The size effect implies an apparent opportunity for persistent "extra-normal returns." However, our no-arbitrage paradigm finds this empirical finding inadmissible. Similarly extra-large returns have also been documented for new issues of stock (Ibbotson 1975)[49].

Of course, other well-documented and credentialed anomalies exist that nonintegrability does not explain. Still other anomalies have been documented, which fail additional professional standards of "seriousness" or "credentialing" for their observed correlation. For example, the "Super Bowl market predictor" states that if the Super Bowl is won by a team with an old National Football League affiliation the stock market will finish higher than it began (Stoval 1989)[96]. The Super Bowl predictor correctly predicted the sign of the annual return 20 out of the first 22 times it could be applied (Krueger and Kennedy 1990)[63]. The Super Bowl predictor has succeeded twice more since and is now correct for 22 out of 24 times.

3.3 Heterogeneous Expectations

Alternatively, we may suppose that individual parties have cash flow estimates that differ across the group. This state of affairs is referred to as **heterogeneous expectations**. Heterogeneous expectations requires that at least some individuals' estimates also differ from the market's weighted aggregate value that is observed as the trans-

action price. Heterogeneous expectations can be compatible with a homogeneous-expectations interpretation whenever some reasonable aggregation regularity conditions can be imposed that allow all agents to be modeled as one representative agent. This investigation considers the consequences of replacing the assumption of homogeneous expectations with a model of incompatible heterogeneous ones.

Full and heterogeneous expectations could be applied to the case where each agent has its own idiosyncratic expectation operator, with a corresponding conditional σ-algebra and a probability measure associated with this individual σ-algebra. However, the information available to an agent may be insufficient to allow him to assign a robust probability measure on enough sets in the σ-algebra to make some or all of the security prices measurable functions with respect to this probability measure. We define a **nonintegrability** problem to encompass both weak expectations and heterogeneous expectations. Nonintegrability means that there is difficulty or disagreement involved in defining an expectation operator to evaluate security prices among various agents.

The question is how does an agent go from its information set to the agent's σ-algebra to assign probabilities to the relevant sets to allow the agent to take expectations of security prices. This information-translation process is non-trivial and should not just be assumed away.

It is reasonable to *suspect* that market analysts use more information than just past prices and time-series analysis techniques, since their employment exists in a long-run equilibrium over less costly time-series regressions. Consequently, market

analysts' predictions should be better than time-series regressions. This hypothesis has been empirically investigated and supported (Brown and Rozeff 1978, 1980)[12, 13]. The issue is what estimation methods should an agent optimally use to assign its probabilities. Do all parties perform careful analysis of future cash flows, or do some parties fly by the seat of their pants and play hunches?

3.4 Rationale for Markets

In the context of weak and heterogeneous expectations, a primary reason for markets to exist is to help to mitigate the implied nonintegrability problem. To allocate resources optimally, society needs values for all assets. Markets produce values in settling on transactions emphasized by Schwartz (1988)[93]. Society makes no a priori assumptions as to what is the best way to form these estimates. Parties compete among themselves for the best estimation procedure. Further, if new information or improved analysis techniques arrive, parties have a strong incentive to use the best available information or techniques.

A portfolio is perfectly **liquid** when its manager can costlessly "flow" money from one investment to another quickly, just as water can be directed to flow from an uphill location to a downhill site. For illiquid investments, parties know that they may not be able to find a complementary trading partner instantaneously at a price mutually agreeable to both parties for illiquid investments.

Other things equal, investors desire to keep their portfolios liquid. They do this to maintain flexibility to adapt to evolving informational changes. The cost of reversing positions justifies the existence of flexibility premia into process (Keynes 1936,

Marschak 1949, Tobin 1958, Hirshleifer 1972)[59, 72, 100, 48].

Markets provide two other major services: offering a mechanism for buy and sell orders to meet and insuring the reliability of at least some of the bids and offers made by market participants. Financial markets channel investment capital to firms, in ways that maintain liquidity for individual investors. In allowing investors to sell their shares of long-term "fixed" investments to other parties, markets create opportunities to avoid being committed in a long-term way to physically fixed investments. Of course, the investment decisions of society as a whole remain "fixed". Liquidity encourages investment undertakings by giving investors the option of reversing past decisions when and as new information arrives. If investment decisions were less liquid, investors would be less willing to invest. They would demand higher anticipated returns for making inflexible commitments (Keynes 1936, Marschak 1949, Tobin 1958, Green 1967, Hirshleifer 1972)[59, 72, 100, 39, 48].

Markets provide an incentive-compatible way of allocating resources. If a common and easily accessible probability measure did exist, portfolio managers could simply apply expectation operators, variance operators, and covariance operators. There would be no need to bother with markets for price discovery at all.

The existence of financial intermediaries challenges another widely used and convenient assumption in finance: namely that parties are fully informed and markets are perfect. **Perfect markets** means that there are no transactions costs and all agents are price-takers in that individual agents' transactions are assumed not to move prices. A large literature clarifies that financial intermediaries would have no

reason to exist in such a framework (Modigliani and Miller 1958 is the seminal piece; Fama 1980 is a nice literature review.)[77, 28]. Similarly, the existence of active and volatile securities markets challenges the assumption of unanimous agreement as to what parties feel a security is worth. Under unanimous agreement, there is no explanation for why observed security prices fluctuate as much as they do, nor why parties trade as often as they do. Existing theories ignore issues of excess volatility and illiquidity which are observable phenomena that need explanations. Brownian motion models have the *testable implication* that the variance should be linear in time. Variance bounds test performed by Lo and McKinlay (Lo and Mackinlay 1988)[69] demonstrate with weekly data that stock prices are too volatile to be explained by Brownian Motion.

Of course, non-market mechanisms also allocate resources. One alternative is to allocate resources by command. In large conglomerate corporations, decisions often are made by committees. Committees lack the incentive compatibility that markets have. This is because committee members tend to have a diminished stake in the outcome of their decisions. They may risk their reputations or careers to some extent, but they need not bet their non-human wealth on their opinions. Any agent influences what society thinks a resource is worth simply by investing its money accordingly. Such an investor's investments influence opinion regardless of the investor's corporate or social status. Of course, an agent's economic status influences the amount of money it has available to invest. If an investor does well, its status increases. If it does poorly, its status decreases.

3.5 Rationale for Regulation in Information Processing

In ordinary usage, a regulation is a rule designed to control another party's behavior or conduct. However, regulation is also used by the economics profession to mean the *process* under which individual rules are set and enforced. Throughout this paper, regulation has this second meaning. We use rule or law to cover the narrower interpretation.

In the context of regulation, existence evidence is capsulized in the **regulatory dialectic**(E. Kane 1977)[55]. The regulatory dialectic asserts that all existing regulations come from acts of re-regulation. Every time a regulator writes a rule, the regulated party perceives and exploits loopholes inherent in the rule. This is because, unless ex post facto laws are allowed, the regulator can not strictly enforce the intent of the law, but merely the letter of the law. Parties must be expected to practice regulatory avoidance whenever it is beneficial and feasible for them to do so. They will search for loopholes in the letter of the law. Further, interested parties are constantly trying to manipulate and pervert the rule-making and enforcement processes for their individual benefit, in full knowledge that this does not benefit society as a whole.

Observation tell us that society allows huge profits to be earned by those who have access to information relevant for asset valuation and establish good analytic skills or recognized track records in information evaluation. A trade-off is made between a market's informational efficiency and its fairness. If society allows parties who have "inside information" the right to trade on this information, markets can be made more

efficient. However, permitting insider trading runs the risk of preventing outsiders from perceiving the process as being fair enough for them to participate directly. This perception could lead outside parties to use intermediaries or portfolio managers to overcome their lack of access to the superior information.

In practice, most societies take the view that gains from efficient resource allocation are large enough to tolerate some informational unfairness. This means sometimes large profits are realized by those well-positioned in the information flow. The careers of Ivan Boesky and Michael Milliken can be interpreted as "existence" evidence that large fortunes can be amassed from engaging in insider trading. The fact that some of their activity proved to be illegal testifies to the strength of temptations to "evade" as well as to avoid regulation. Ostensibly and ex officio, regulators maintain that their interventions and penalties are intended to level the playing field, but considerable unevenness is allowed to remain. In this respect, the consequences of regulators' actions (for example, in making Mr. Milliken eligible for parole after serving two years in prison) speak volumes that their words belie.

3.6 Risk and the CAPM

The **Capital Asset Pricing Model**, CAPM, assumes homogeneous expectations, no transactions costs and investors who only hold portfolios that are **mean-variance efficient.** An efficient portfolio is one that offers minimal variance for given levels of expected return, and also maximum return for each given level of risk.

The CAPM determines market prices for bearing two categories of risk: diversifiable and undiversifiable risk. In turn, **perfectly diversifiable** risk is defined as

variance in asset returns that can be *costlessly* reduced by rebalancing one's portfolio. A principal implication of this model is that the price of perfectly diversifiable risk must be zero.

Of course, with *nonzero* transaction costs, diversification may be costly. This implies the possibility of a third class of risk, which may be termed **imperfectly diversifiable.** Whenever a type of variance can be eliminated cheaply, the market should not pay much of a premium for holding this type of risk. In applying mean-variance portfolio theory, it may be reasonable to assume zero transaction costs as a way of recognizing that premiums paid for holding easily diversified types of risk are small. If these costs were truly negligible, the no-transaction-costs assumption would be robust.

Undiversifiable risk encompasses variance that can not be hedged *at any cost* in the market. In this case, the risk is uncorrelated with other securities. In this respect, the CAPM explicitly considers a case where markets are not complete. In the CAPM and a generalization of this theory known as the Arbitrage Pricing Theory, APT, investors earn higher expected returns only by accepting undiversifiable risk.

In modern economies, so much uncertainty exists that it is hard to envision enough securities to span the many contingencies we could catalogue. Market completeness is a mathematical convenience, not a scientifically observed phenomenon.

Assuming the existence of a probability measure, and prices as corresponding measurable functions, some people - - not I - - would say that risk-taking investors help to complete markets (Cox, Ingersoll and Ross 1985)[52]. Dispensing with these au-

thors' assumptions about the measurability of security prices, this investigation seeks to develop evidence that investors who accept undiversifiable risk and other uncertainties merely help to span an incremental portion of an inherently "incompletable" heterogeneous-expectations space. From either perspective, investors establish a price for bearing various classes of less than perfectly diversifiable risks and uncertainties.

The arguments used to derive zero-arbitrage pricing conditions explicitly assume that a derivative security can be expressed as a linear combination of other securities. This assumption leaves the *market* for the derivative security itself with no economic reason to exist. The economic reason for a derivative security to trade is to help hedge or counter-balance uncertainty which is otherwise *less perfectly hedgeable* in the market. Why spend resources making markets in a security if one can create the security costlessly using other securities that already exist? Even a cynical, non-hedging answer to this question would have to make use of the assumption of weak and heterogeneous expectations. Creators of new financial products that they know to be useless must think investors can be persuaded by manipulating information flows to buy the useless products. If marketing executives produce products no one needs, they must project that they can convince people to buy them.

As an example of unhedgeable risk, we may consider the failed coup in the U.S.S.R. in August of 1991. Stock market prices swung wildly as this event unfolded. There was no way for investors to hedge the resulting uncertainty completely. It is well known that in troubled political times "safe" securities like gold and United States Treasury bills perform well relative to less "safe" securities. But is one only betting

on unstable political times and against stable political times when one hedges by buying "safe" securities? Is it reasonable to assert that an agent could perfectly hedge all unanticipatable contingencies of alternative Soviet coups in advance of their occurrence? Further, if markets were truly complete, wide diversification would be the norm. We would observe much more diversification of individual portfolios than we actually observe in practice (Lease, Lewellen and Schlarbaum 1974, Blume and Friend 1975)[85, 8].

Recent years have witnessed tremendous expansion in the number of securities available in asset markets (Edwards 1988)[25]. If security markets had been complete, how did it become profitable for so many new assets to be introduced? The cynical explanation would be that it reflects confusion stemming from disinformation that is used to deceive parties for profit. This explanation argues for the assumption of heterogeneous expectations by making divergence in individual information sets into a permanent and endogenous activity.

Another possibility is that markets are quasi-complete, but that from time to time, specific new risks emerge that may be neutralized by innovations in hedging vehicles. The "quasi" is to recognize that even in this case the assumed evolution in uncertainty means that markets are never perfectly complete. However, by refusing to assume completeness, we can explain expansion in the security universe by the market's willingness to reward new mechanisms for more perfectly hedging new *and* old forms of previously less perfectly diversifiable uncertainties.

3.7 Security Analysis

Markets can price securities without revealing all the relevant information about a given security, just as an advertiser can sell a consumer a product without telling the consumer much about the actual product. In some cases, advertisers go to great lengths to convey seductively false impressions that serve to deceive and exploit the consumer. Even if one can not consistently fool all market participants all of the time, no one has to reveal everything that is relevant.

Investors seldom know precisely what most securities are worth. They undertake information gathering and analysis to form estimates of this value. Estimation formation processes may differ, in that the same information may imply different values for different people. We wish to test the hypothesis that there is not enough available information to assign with certainty a probability measure on security prices. Uncertainty exists about what are the right conditional distributions to estimate and what are each distribution's true parameters. Further uncertainty exists about the identity of the major factors that will influence the future price of a given security. Uncertainty reduces to variance only in the case where the distribution is restricted to a particular form whose corresponding parameters are known.

Estimation-uncertainty premiums should exist. A price may be conceived as society's consensus about what an asset is worth. When good reason exists to believe that this consensus is incorrect, strong incentives encourage knowledgeable parties to state their case and make their profits. Every asset holder runs a possibility of being wrong. Uncertainty-adverse investors are going to command a higher anticipated re-

turn as long as this uncertainty exists. Because there is estimation uncertainty, the party who is content to hold a given asset is going to be among those that value it the highest. In the context of auction bidding, this condition is referred to as the buyer's curse.

Casual experience suggests that parties seldom bother to make themselves maximally informed. Because information gathering and processing is costly, parties should undertake information gathering and processing only as long as the marginal anticipated benefit exceeds the marginal anticipated cost of uncertainty reduction (Arrow 1982)[3]. Parties may choose to acquire information or seek to infer analysis from parties who are perceived to perform better analysis or to be better positioned to receive information. If one is buying a car, one may rely on analysis provided by *Consumer Reports* and other consumer groups. It would be impractical and uneconomic to attempt a thorough analysis of all cars just to purchase one automobile. However, if one were buying a large fleet of cars, it would pay to engage in more thorough analysis and shopping. Still, even a fleet consumer would waste resources if it were to try to find out all there is to know about cars.

What information does a security analysis firm look for and sell? It is not sufficient for it to find securities that are misvalued. A security is only worth the most someone is willing and able to pay for it. This is a major difference between securities markets and commodities markets. No one can consume a non-dividend-paying security. The value of a security can not be converted to commodities until it is sold to someone else. Individuals buy securities as investments. To undertake planned consumption,

parties must sell the asset at future dates. Non-dividend-paying securities are bought speculatively to be resold at a later date.

To maximize future consumption opportunities, investors and security analysts look for securities today that they can subsequently be successfully marketed as misvalued. However, one can not accrue a return from this strategy until the market perceives that a security has been misvalued. Securities firms are in the information business. They both supply and receive information analysis. An optimal location in the information flow may exist. The need to build and maintain a reputation for reliability makes it dangerous to attack a security that is not misvalued in a long-term believable way. If one wants to have a credible reputation as an information analyst able to influence future evaluations, persuading others of the correctness of one's analysis is key. It is critical that the market can be influenced to believe one's allegations of misevaluation. The need to move the market partially explains why securities analysis firms voluntarily give away analysis which is costly to produce. They can not cash in on their analysis until and unless the market is made to accept its value.

Securities firms are both consumers and producers of information. A great deal of resources and marketing effort are expended in selecting a location in the information flow and in investigating what sort of informational analysis sells to which segments of the market and what does not sell to those segments. Additional effort must be devoted to determining what is the best way to release information to optimize its effect on the market, so as to maximize the value of the analyst enterprise. In

turn, investors must undertake research to ascertain which information brokers do a credible job and which do not.

Securities markets correspond to a rich game in which parties try to guess what everyone else thinks securities prices should be, and then work to influence what everybody else thinks. This recalls Keynes' beauty contest analogy (Keynes 1936)[59]:

> "...professional investment may be likened to those newspaper competitions in which the competitors have to pick out the six prettiest faces from a hundred photographs, the prize being awarded to the competitor whose choice most nearly corresponds to the average preferences of the competitors as a whole; so that each competitor has to pick, not the faces which he himself finds the prettiest, but those faces which he thinks likeliest to catch the fancy of the other competitors, all of whom are looking at the problem from the same point of view. It is not a case of choosing those which, to the best of one's judgment, are really the prettiest, nor even those which average opinion genuinely thinks is prettiest. We have reached the third degree where we devote our intelligences to anticipating what average opinion expects average opinion to be. And there are some, I believe, who practise the fourth, fifth and higher degrees."

If this process were done iteratively with the goal to pick tomorrow's security-market winners today, then it would be rational for analysts to vote for today's under-appreciated contestants and to promote their virtues, while criticizing today's over-appreciated contestants. Of course, there is a systematic component even to analysts' subjective judgments. Generally, genuinely ugly contestants do not win beauty contests. Market participants must be sensitive to the tastes of the other judges.

3.8 Testable Implication

This chapter's offers some economic intuition as to why probability estimation uncertainty should exist. The next chapter seeks to develop empirical evidence consis-

tent with the existence of probability estimation uncertainty. This evidence comes from statistical tests run to generate evidence of probability non-stationarity for the stochastic component of security price changes.

CHAPTER IV

The Significance Tests

4.1 Introduction

We *advocate* the tests presented in this chapter be run and conceived as sensitivity tests that serve to investigate the "reasonableness" of the identically distributed assumption used by financial researchers to support strong assumptions about probability estimates. This assumption is fundamental to the relative frequency interpretation of a probability measure. A stochastic process is stationary with respect to time, when the underlying probabilistic components are time invariant. We identify stationarity as a key assumption that is used to justify the application of powerful optimal stochastic control and other stochastic calculus techniques to stochastic partial differential equations.

We can develope only indirect evidence that there does not exists a stationary probability measure for certain security prices. Direct evidence is impossible, since we can only test one specification at a given time. We can merely state that our results are consistent with our assertion. Since we only indirectly tested our assertion, we can not rule out other assertions or models that are consistent with our result of non-stationarity for a particular model. However, the methods developed in this chapter

can and should be applied to other model specifications. Since our choice of where to place the time-blocks was ad hoc, it may be that the underlying probability measure could be quasi-stationary, temporally stationary but with random break points where the probability measure changes.

Previous empirical research investigating the plausibility of identically distributed error terms in financial returns have made distributional assumptions about the error terms in the models (Mandelbrot 1963, Fama 1965, Hsu, Miller and Wichern 1974, Epps and Epps 1976, Akgiray 1989) [71, 27, 22, 26, 2]. These papers are in the framework of testing the efficient market hypothesis. In our framework the notion of a martingale does not make sense. A martingale requires an expectation operator which requires a probability measure. Nevertheless, our tests generalize these works, in the sense that our tests are distribution-free (Bradley, 1968)[10], because they make no assumptions about the underlying probability distributions that the error terms are drawn from. Our robust tests have the added burden that they are computationally intensive. However, recent computer advances have reduced the cost of intensive computations and rendered our tests affordable.

4.2 What Are We Testing?

To test operationally whether a stationary probability measure exists for which a security's returns is a measurable function, we must first define an observable probability space, which includes an underlying σ-algebra and probability measure. Each such definition must assume the applicability of a particular class of return generating model and a companion sub-model of the so-called error term that represents the

stochastic return.

Tests are joint tests of specific models. We test the main hypothesis that the stochastic component of returns portrayed in each model is identically distributed over time. Reflecting a concern for robustness, the tests consider three models, chosen to represent alternative models of stochastic returns for a given security:

(4.1); $P_{t+1} = P_t + \epsilon_{t+1}$

(4.2); $(P_{t+1} - P_t)/P_t = \delta_{t+1}$

(4.3); $\log(P_{t+1}/P_t) = u_{t+1}$

In testing these models the longest time interval used is two days, short enough not to include a drift term.

(4.1) contains additive Brownian motion, in which security price differences, ϵ_{t+1}, can be specified to follow any distribution. The error terms distribution may, but need not, be the normal distribution.

(4.2) is a rate of return. The stochastic element in returns is proportional to the initial price. Again the distribution of the error term, δ_{t+1}, is not specified.

(4.3) is a log difference model. A similar model was recently employed by (Hinich and Patterson 1992)[46]. This specification is similar to the model chosen by Fama (1965)[27]. Again, we make no assumption about the form of the distribution of u_{t+1}.

These models were chosen to be representative of random-walk models. Other model specification could be chosen. Our estimates of p-values for these models were fairly insensitive to which model specification that was chosen. (4.1) and (4.2) differ only by the normalization of dividing the difference by P_t. (4.1) and (4.3) are also

similar in specification. This is because $x-1$ is an accurate approximation for $log(x)$ for values close to 1. In fact, considering $f(z) = log(z+1)$, expanding its Taylor series about z=0, substituting x=z+1, and taking the first two terms yields x-1. Since our observed values are relatively close to adjacent values, the insensitivity of the p-values might well have been anticipated.

4.3 The Data

An important component of financial research is to recognize possibilities for creating new and different data sets. Where do data sets come from? In many cases an individual researcher sees that a potential data set contains valuable information about subject-matter models or hypotheses that the data set can be made to surrender.

Matched trades are chosen because they are consummated trades, not proposed trades represented by price quotes or derived from last trades, which can become stale. Economic paradigms distinguish phenomena of the mind from phenomena of the market. What people say they will sell something for is less relevant than what they actually sell it for. Focusing on market-tested evaluations is analogous to judging a person's intentions from the consequences of their action, without regard to their stated intentions. Human actions may be said to reveal intentions which are not themselves expressed on directly observables. Considering trades need not introduce any bias, because we can observe trades at prevailing prices without those trades inducing any price movements.

Price quotes have the advantage that they are available for all time intervals that the markets are open, even when no transactions are taking place. The stocks used

in our sample were not randomly chosen. They were chosen for the activeness of their trading, so as to overcome the possibility of infrequent transactions. We study price changes of four stocks: International Business Machine Corporation (IBM), Merck and Company Incorporated (MRK), Boeing Company (BA), and Aluminum Company of America (AA).

Another motivating factor in choosing consummated trades is that all three model specifications difference the data. Differencing may destroy significant digits. The New York Stock Exchange records transaction and quotes in one-eights of a dollar. Parties that exchange several hundred shares of stock often trade incremental hundred blocks of shares at different prices to permit the transaction price to vary within an eighth of a dollar.

The data cover ten weeks from April 6 to June 12 of 1992. Markets were open for 48 trading days during this time interval, because of Good Friday and Memorial Day holidays. All the securities in the sample are listed on the New York Stock Exchange (NYSE) and are members of the Dow-Jones Thirty. The sample consists of matched trades taken from the Bridge system network. The Bridge system posts all matched trades that occur on national and regional exchanges, and all over-the-counter transactions that take place during the time these exchanges are open. The regional stock exchanges are: Boston, Cincinnati, Midwest (headquartered in Chicago), Pacific (headquartered in San Francisco), and Philadelphia. Recently, the NYSE has been experimenting with after hours trading (after 4 p.m.). We excluded after-hours transactions from our sample. Advertised trades[1] appeared in the tabular trades

[1]The author is grateful to Lynn McKinnon of Bridge system network for explaining what these

quote file. These are excluded because they are not consummated trades.

The volume and prices of transactions observed in any time span are random variables. A time-series of volume-weighted average price was constructed for time spans of 10 and 30 minutes, resulting in 12-span time blocks of 2 hours and 1 day respectively. Missing observations when the market was open and idle were handled by placing the observation recorded in the previous span into the missing time span. IBM showed no missing time spans. MRK had one missing time interval due to a trading halt. Due to a computer operator error, observations were missing for BA on the days of May 12, and May 14. There were no missing observations over 10 and 30 minute time spans when the data were properly retrieved. Finally, AA had four missing observations over the 30 minute time spans. AA traded too infrequently to analyze its prices using 10 minute time spans.

In the 10-minute spans, 2 hour time blocks, we tested a wide array of time blocks against each other, not just adjacent time blocks. There is usually an auction to start the trading day, and there are orders that are specified to be executed at close. Further, the observed volume varied during the day, being the highest at open and close similar to a retail store. so we allowed for the possibility that adjacent blocks are not the most similar. Regardless of the time blocks, the test results were similar for given securities.

In the 30-minute spans, one-day time block, we checked price changes over a given day against the next day. We used the opening period from 9:30 to 10:00 as our initializing time span, to have no carry over from the previous day.

entries were.

4.4 Some Definitions

A **cumulative** or **empirical distribution function** of a sample of n observations is a step function with jumps of 1/n at the observed values in the sample. We form our cumulative distribution functions for a given time-block by ordering the error terms of a given model in non-decreasing order and placing jumps of 1/n at the observed error term value, $F_n(x) = \{\text{number of data points} \leq x\}/n = \sum_{x_i \leq x} 1/n$.

A function d(x,y) is a **distance function** on a space Z if it satisfies the four conditions:

(1) for all $x, y \in Z, d(x, y) \geq 0$.

(2) $d(x, y) = 0$ if and only if $x = y$.

(3) (Symmetry): for all $x, y \in Z, d(x, y) = d(y, x)$

(4) (Triangle inequality): for all $x, y, z \in Z, d(x, y) \leq d(x, z) + d(y, z)$.

In our context, a **norm**[2] is a function that takes as its domain cumulative distribution functions and has the non-negative real numbers as its range. We chose to define our distributions such that they are right continuous, making our norms to be valid distance functions restricted on the set of right continuous distribution functions. Otherwise we could encounter two distributions that were not equal everywhere, but had the same norm. This would violate condition (2) of the definition of a distance function.

We will use the standard L_p-norms as our distance functions for our empirical

[2]More generally a norm is defined on a space X whenever for all $x \in X$, there is a non-negative number $\|x\|$ such that (1)$\|x\| = 0$ if and only if $x = 0$;(2)$\|\alpha x\| = |\alpha|\|x\|$ for all $\alpha \in \Re$;(3) $\|x + y\| \leq \|x\| + \|y\|$ for all $x, y \in X$.

distribution functions. for $0 < p < \infty$, we have $(\int_E |F_n(x) - G_m(x)|^p dx)^{1/p}$ as normed distance function. We use $p = 1, p = 2$, and $p = \infty$. To see why this is called $p = \infty$, consider the following: Let $G_m(x), F_n(x)$ be two empirical distributions functions for time blocks containing n and m spans respectively.

$$E = \{x \in \Re : \text{least from both samples} \leq x \leq \text{greatest from both samples}\}.$$

Let $M = \max_E |G_m(x) - F_n(x)|, A = \{x \in E : |G_m(x) - F_n(x)| = M\}$

$$(\int_A M^p dx)^{1/p} \leq (\int_E |F_n(x) - G_m(x)|^p dx)^{1/p} \leq (\int_E M^p dx)^{1/p}$$

or

$$M(\text{measure}(A))^{1/p} \leq (\int_E |F_n(x) - G_m(x)|^p dx)^{1/p} \leq M(\text{measure}(E))^{1/p},$$

Since, $\infty > \text{measure}(E) \geq \text{measure}(A) > 0$, we deduce that

$$\lim_{p \to \infty} (\int_E |F_n(x) - G_m(x)|^p dx)^{1/p} = M.$$

4.5 Test Statistics

The null hypothesis of the significance tests is that the two sample cumulative distributions of the error terms of a model from different time-blocks are taken from the same underlying probability distribution. We test this null hypotheses in three steps. First, we compute empirical distribution functions for the return errors over different time-blocks. Next, we form the difference of pairs of empirical distribution functions. Then we compute the L_1, L_2, L_∞ norms of the difference of pairs of empirical distribution functions. Our test focus on the issue of whether this normed distance is probabilistically small.

Each distribution is a step function with jumps at observed values in the given sample. The distributions agree before the first data point in the combined sample (both are 0), and also agree after the last data point in the sample (both are 1). So when computing the test statistic we have only to consider a finite interval between the smallest and largest value of the data set. The L_2-norm test statistic is known as Cramér-Von Mises test, and the L_∞-norm is known as the Kolmogorov-Smirnov test (Durbin 1973)[24].

Let $G_m(x), F_n(x)$ be cumulative distribution functions, our tests statistics can be written as[3]:

$$L_1 \text{ norm: } \int_{\Re} |G_n(x) - F_m(x)|dx$$

$$L_2 \text{ norm: } (\int_{\Re} |G_n(x) - F_m(x)|^2 dx)^{1/2}$$

$$L_\infty \text{ norm: } \max_{\Re} |G_n(x) - F_m(x)|.$$

Statistical tests *implicitly* treat numbers as intervals. In establishing the equality of two means, statistical tests do not assess that the two means are equal to the same fixed value. Rather, statistical tests assess whether the sample means are probabilistically close to each other. The difference in the sample estimates for the two means is computed and relying on the operationalizing subsidiary assumptions of the test, the probability that the difference is as large as observed is estimated. Analogously, our tests assess whether two empirical distribution functions for a model's observed

[3]We are able to write $\max_{\Re}$ instead of the essential supremum of a function f(x) over $\Re$, the smallest extended real number (allows M to take the values $-\infty, +\infty$) such that $f(x) \leq M$ except for a set of measure zero on $\Re$, which is L_∞-norm in the general case when considering equivalence class of function that agree except for set of measure zero (imposed to satisfy condition (2) of a distance function). Right continuity specifies a distinct representative from our equivalence class of functions making our presentation simpler.

error terms in different time-blocks are probabilistically close with respect to three specific norms, not that they are precisely equal. Therefore, our tests *implicitly* treat an empirical distribution function as being indistinguishable from another empirical distribution function that is close to it in the normed distance sense.

Robustness is the key motivating factor for every test that we run. We seek to make as few distributional assumptions as possible. A natural choice is to use empirical distribution functions instead of making additional distributional assumptions. As the sample size increases more data points are taken in each empirical distribution function. Let us assume that the underlying probability distribution function is the same function for two empirical distribution functions. In this case, the empirical distributions functions *are likely* to converge in probability for any norm chosen. The Glivenko-Cantelli theorem (Billingsley 1986) [6, pages 275-6] tells us this is true for L_∞.

We analyze the behavior of finite L_p. For well-behaved thin-tailed distribution functions, the convergence holds. For example, for an arbitrary $\epsilon > 0$, $(\int_{|x|\geq N} |G_n(x) - F_m(x)|^p dx)^{1/p} \leq \epsilon$ for some N, when the number of spans in the time blocks, n and m, are sufficiently large. The above convergence holds if price changes can be assumed to be bounded in absolute value over a given time span. We compare our empirical distribution functions in the L_1, L_2, and L_∞ norms integrated against standard Lebesgue measure on $\Re$.

Tests using the L_1 and L_2 norms are parametric because we use all observed data values in loading probability masses on the observed data points in producing the

empirical distribution function. We use the relative order of our data to compute p-values, so our test are similar in spirit to many nonparametric tests, which use the relative order of the data without employing all the actual values. Tests using the L_1 and L_2 norms are properly called distribution-free (Bradley 1968)[10].

The L_∞-norm test is nonparametric. This test concentrates on the point of worst agreement between the two empirical distribution functions. It does not assess the overall agreement of the two empirical distribution functions.

Consequently, two empirical distributions can be close with respect to one norm and far away with respect to another norm. In referring to different norms, the null hypotheses require that the empirical distributions be close in different senses.

If two sample empirical distributions are taken from the same underlying probability distribution, then it is a *logical consequence* that any particular combination of the pooled data points should be equally likely. This allow us to assign a p-value to our test statistic. The use of p-values lets us interpret our results as probabilities and to draw scientific inferences.

The detailed procedure for computing the test statistics is straightforward. For a given stock observed in two different time blocks, we first arrange the errors in non-decreasing order allowing for ties, keeping track of which time block the data points came from. Next, we compute the value of the three test statistics observed, then we compute the norms for all other possible combinations of the data, with the actual values of individual observations remaining the same.

Inference focuses on p-values that can be reasonably assigned to the test statistics.

The hypothesis that every given combination of the error values is as equally likely as any other lets us define this p-value. It becomes the relative frequency of those combinations with norms bigger than or equal to the norm found coresponding to the actual data. These are the combinations that can be interpreted as unfavorable to the null hypothesis. We interpret this p-value as a significance level for the null hypothesis that the two empirical distributions function are taken from the same underlying distribution.

4.6 Pseudo-Random Sampling

Naively, if the number of spans in the time blocks, n and m, are both small (12 or less), we can compute the p-value directly by the definition of a relative frequency probability. We run through all possible combinations of n subsets of an (n+m) set. However, as n and m increase, the number of combinations increases exponentially. This makes the method impractical in that it requires too much computer time to run the tests. We naturally try pseudo-random sampling, choosing k-many pseudo-random n sets from a (n+m) set to obtain an approximate p-value.

It is impossible that a computer, a deterministic machine, can be used to generate truly random numbers (Knuth 1981, Flannery, Press, Teuskolsky and Veterling 1989)[62, 101]. To produce their sequences, pseudo-random number generators require initializing values that are called "seeds." Once the seeded numbers are chosen, the generated sequence is deterministic. However, we only require a representative number generator, one that will give us good estimates for our significance levels. A subsidiary assumption is needed to choose k many n-subsets of our (n+m)-set to

produce a reliable approximation to the true p-value. With n and m both equal to 12, we experimentally found that k=1,000 produced p-values that agreed within 2 decimal places to the p-values estimated by considering all possible combinations. For n=m=12 we used k=10,000 in the 10 minute time span tests. In the 30 minute time span tests we used k=1,000,000.

All our time-blocks consisted of 12 observations. This was because number of 12-element subsets of a 24-element set (approximately 2.7×10^6) is small enough that the p-values for our tests can be computed explicitly by considering all possible subsets. Our random sampling technique can then be compared against the exhaustion method. With approximately 2.7×10^6 many subsets our tests have a lot of statistical power, i.e., the probability of obtaining a small pre-specified p-value for a pronouncedly false H_0 is near 1. If we increased the number of observations in our time-blocks, we increase the chance of collecting two different probability measure regimes in the same time block. The choice of k many n-subsets from our (n+m)-set for our sample can not be easily checked against exhaustively considering all subsets. Further, larger n and m require more computer time. If the goal is to increase the time duration of the blocks, then this can be accomplished by increasing the length of the time spans in the blocks. This may give observations that may be spaced further apart in distance, which is desirable, since our specifications difference the data.

4.7 Computational Difficulty

We choose to work in double-precision to help mitigate a potential problem. The problem is that many alternative combinations have values for the norm that are

close to the value of the norm of the observed data. As an example, we consider working in single precision, if .10 of the possible combinations were within 10^{-5} of the observed norm, then we could only compute the p-value of our norm to one decimal place of accuracy. In practice our situation was never this severe. Further, we allowed for round-off errors, potentially over-estimating our p-values, considering p-values larger but within 10^{-5} of the observed p-value in our relative frequency counts. This accommodation is consistent with the conservative nature of statistical tests.

It is not important that we compute our p-values to many decimal places of accuracy. We need a rough idea of the p-value to form an impression about the hypothesis in question, but a very accurate value does not add to much to the evidential nature of the test.

4.8 Computational Benefit

There is a benefit to our probability computation method. Standard statistical hypothesis tests, face the problem of the Lindley paradox (1965)[67]. In many applications, the test statistics, as the norms of differences of two empirical distributions, would be converging in probability to zero under the null hypothesis as the sample size increases. Consequently, the probability of the test statistic being closer to zero should *roughly* increase as the sample size increases. A careful decision maker would choose to lower the value of α, the critical value for the test statistic, when the decision maker was only interested in whether the difference of the two distributions was less than a fixed error tolerance as n and m are increased. Our significance tests already

adjust the probabilities avoiding the Lindley paradox, because the probabilities are automatically changed by the relative-frequency interpretation. This interpretation adjusts the probabilities for changing values of n and m, because the n element subsets of a (n+m) element set chosen for our representative sample change with n and m changing.

4.9 Which Norms to Choose?

Our results are ambiguous as to what was *the* right norm to choose. It seems that there was not much difference between the L_1 and L_2 normed tests. This is not surprising since the tests statistics are quite similar. The change being whether we square the absolute value of the difference of the two empirical distributions, and latter take the square root of the integral. The L_∞-norm test had p-values that varied noticeably from the L_1 and L_2 tests. This is because the L_1 and L_2 norms and the L_∞-norm take into account very different things. The L_1 and L_2 norms assess overall agreement of the two empirical distributions, whereas the L_∞-norm assess the point of worst agreement. However, the two tests statistics have corresponding p-values that are highly correlated. We interpret different time-blocks significance tests that have large p-values with respect to one norm and small p-values with respect to another norm as revealing the limitations of any one norm test statistic. There are many ways to assess the closeness of two empirical distribution functions and our p-values are sensitive to our choice of closeness. The evidence for non-stationarity is strongest when the both the L_1-norm test statistic and the L_∞-norm test statistic have small p-values. Similarly the evidence for stationarity is strongest when both

the p-values are large. In these cases the p-values are not an artifact of the norm chosen. It is the author's opinion that at least the L_1 and the L_∞ norm tests should be run in tandem to diagnose potential sensitivity to the particular norm chosen.

4.10 Interpretation of the Significance Tests

Our null hypothesis, H_0, is that the error terms from the models over different time-blocks are identically distributed. Our alternative hypothesis is the most general one possible, namely not H_0. Due to the unspecified nature of our alternative hypothesis, we desired to make the least stringent assumptions possible. Consequently, we chose our specific tests. This robustness allows for our model's error specification to be as encompassing as possible.

The standard summary statistics of mean and variance are given for the p-values of the significance tests. Small p-values (near 0) for certain time-blocks against other time-blocks is evidence of probability non-stationarity. Similarly, large p-values (near 1) are evidence of probability stationarity. A large and small p-values have an inferential bite despite dependence of the p-values on common or nearby time-blocks. We compute the percentage of significance tests that have p-values less than the fixed values: .05, .1, .2, .5, .8, .9, .95. These quantiles have the hypothesis test interpretation of the percentage of rejections at the given α-levels.

Could our test results be due to chance? Analysis of p-values of statistical tests is a sub-discipline of statistics know as meta statistics. Let test i denote a particular test of the equal of two empirical distribution functions from different time blocks. Under H_{0i}, all possible combinations of the data are equally likely. Each combination

has its normed test statistic computed. The p-value is defined and computed to be the relative frequency of combinations bigger than or equal to the value computed for the normed test statistic of the observed data. Because the number of normed test statistic tied with the value of the observed data was negligible, and since 24 choose 12 is a larger number, approximately 2.7×10^6, it is reasonable to use the approximating simplification that under H_{0i} the p-value of test i is distributed uniform (0,1).

By making the operationalizing assumptions that the p-values from similar hypothesis tests are independently distributed uniform (0,1), we can test whether our test results are due to chance, (Fisher 1932)[29]. Fisher's test procedure assess whether the product, $\Pi_{i=1}^{n} P_1 P_2 \ldots P_n$ is small, where P_i is the p-value of the i-th hypothesis test. Since some of our tests have identical time blocks in adjacent tests, successive p-values may not be fully independent of each other. Nevertheless, we can use the approximation that our p-values are independent. Let our main hypothesis, $H_0 = \bigcap_{i=1}^{n} H_{0i}$, and our alternative hypothesis is that least one of the distributions is not equal to the others. If a given p-value is distributed uniform (0,1) then, $-2log(P_i)$ is distributed χ_2^2. By the independence we have that $-2\sum_{i=1}^{n} log(P_i)$ is distributed χ_{2n}^2 under our combined null hypothesis, H_0. There are other procedures more powerful than Fisher's method, for example see (Scholz 1982)[92]. We present Fisher's test for its simplicity and because it is powerful enough for our needs.

We are trying to ascertain whether or not our p-values are uniformly distributed (0,1). The Appendix contains tables that present relevant information. The first

table lists the p-values, under their corresponding norm test statistic. The next page contains tables that summarizes each norm test statistic. The sample size is presented under the number header. If the p-values are distributed uniformly (0,1) then we would anticipate the average to be near .5 and the sample variance to be close to 1/12, approximately .8333. The quantile statistics are used to investigate if our p-values are approximately uniformly distributed (0,1). The percentage of p-values less than or equal to a given value should be approximately that given value. We compute the linear correlation coefficient, Pearson's r;

$$r = \sum_i (x_i - \bar{x})(y_i - \bar{y}) / (\sqrt{\sum_i (x_i - \bar{x})^2} \sqrt{\sum_i (y_i - \bar{y})^2})$$

between successive p-values. If adjacent p-values were independent then estimated linear correlation should be close to zero. The Fisher test statistic and corresponding p-value is then presented. Finally the Pearson's r is computed to gauge linear correlation between p-values of different normed test statistics.

4.11 Limitations of the Results

The evidence produced in this paper is limited. We used only 4 stocks over a 10 week period. There was no effort made to make them representative of any given population of securities. Because of our small changes in prices due to the shortness of our time spans we effectively had only one model specification.

We did not consider jointly distributed securities. If security prices are jointly distributed then the probabilities that we are estimating are really projections onto a given security. If one were confident that two securities were jointly distributed

the tests used in this paper could be adapted despite the fact that $\Re^n$ is not totally ordered for $n > 1$. We did not have a total ordering of our data even in our case of n=1, this is because when we measure something we place it in discrete intervals allowing for ties. We would have to order points in $\Re^n$, say by Euclidean distance from the origin, or other base point, and treat observations that were equal distant from the base point as tied as we did in the one dimensional case.

All empirical investigations by themselves are just a few drops of water in a giant bucket of scientific evidence. Our tests are only as good as the computer programing, and it is easy to make a myriad of computer errors. The computer programs and test results need to be replicated by independent researchers. Until these programs and test results have been properly replicated, the results should be viewed with scientific suspicion.

4.12 Summary of the Test Results

We theorize there does not exists a stationary probability measure for certain security prices. In chapter 2, we argued that the underlying probabilities must be subjective due to the non-repeatability of relevant events. In chapter 3, we presented some "existence" evidence in the form of financial institutions, regulations, and other structures that are inconsistent with there existing stationary probability measures for security prices. In this chapter, we developed some quantitative evidence of probability non-stationarity of specific models.

The test results for IBM and MRK over the 10-minute spans, 2 hour blocks, show strong evidence of probability non-stationarity. This was reflected in quantile

statistics being skewed to the left of a uniform distribution on (0,1), and large values for the Fisher test statistic, regardless of the time blocks tested.

The result for BA over the 10-minute spans show little evidence of probability non-stationarity. Fewer p-values than would be anticipated under the uniform distribution (0,1) were less than or equal to .05. Consequently, the Fisher test statistic was not statistically large, regardless of the time blocks tested.

The results for all 4 securities showed significant evidence of probability non-stationarity, even for BA which showed little evidence over the 2 hour time blocks.

4.13 Follow-up to Our Tests

A logical follow-up to these tests would be to consider general time-series regressions with an error term that is independent and identically distributed, because the estimated auto-correlation in the data is slightly negative, leading a scientist to doubt the assumption of independence of consecutive terms.

Econometricians frequently perform unit-root tests to investigate the possible non-stationarity of time-series used in regression. When they are unable to reject the existence of a unit root, they often transform the model they wish to estimate into a relation whose variables are specified as differences, or other co-integrated transformations (Campbell and Shiller, 1987)[16]. Such differencing represents an attempt to avoid estimating a spurious regression. Our significance tests can be used in tandem with unit root tests.

Ostensibly, the timing of parameter shifts could be inferred from outside information. Such information would be treated as generating subsidiary "partitioning"

hypotheses. However, whatever partitioning is specified should be tested independently at least by covariance analysis (Harvey 1989)[42] or by Goldfeld-Quandt (1972, 1973, 1976)[34, 35, 36] tests that seek to determine statistically whether and how to time any shifts. However, a researcher could use the significance tests developed in this chapter for the same purpose of placing the partioning blocks. The significance test would focus on the probability distribution non-stationarity of the error term, as opposed to the non-stationarity of the regression parameters estimated.

In the statistical literature this problem is referred to as the "change-point" or "disorder" problem. It has an extensive literature (Brodskii and Darhovskii 1990)[11]. The nonparametric focus has been on the asymptotic efficiency of various detection techniques. Our method can be equipped with a decision procedure to be used in small time intervals to detect change-points.

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Appendix

IBM
SUMMARY STATISTICS
10-MINUTE SPANS, 2-HOUR BLOCKS

TOTAL QUANTILES FOR THE 1-NORM TEST STATISTIC

NUMBER LESS THAN OR EQUAL TO:						
05	*10*	*20*	*50*	*80*	*90*	*95*
59.0	117.0	189.0	377.0	531.0	584.0	604.0
PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:						
0.097	0.191	0.309	0.617	0.869	0.956	0.989

TOTAL QUANTILES FOR THE 2-NORM TEST STATISTIC

NUMBER LESS THAN OR EQUAL TO:						
05	*10*	*20*	*50*	*80*	*90*	*95*
56.0	108.0	193.0	384.0	529.0	583.0	605.0
PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:						
0.092	0.177	0.316	0.628	0.866	0.954	0.990

TOTAL QUANTILES FOR THE MAX-NORM TEST STATISTIC

NUMBER LESS THAN OR EQUAL TO:						
05	*10*	*20*	*50*	*80*	*90*	*95*
61.0	93.0	207.0	395.0	541.0	608.0	608.0
PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:						
0.100	0.152	0.339	0.646	0.885	0.995	0.995

MRK
SUMMARY STATISTICS
10-MINUTE SPANS, 2-HOUR BLOCKS

TOTAL QUANTILES FOR THE 1-NORM TEST STATISTIC
NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
70.0	112.0	201.0	378.0	538.0	585.0	606.0
PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:						
0.115	0.183	0.329	0.619	0.881	0.957	0.992

TOTAL QUANTILES FOR THE 2-NORM TEST STATISTIC
NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
65.0	115.0	194.0	380.0	542.0	584.0	606.0
PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:						
0.106	0.188	0.318	0.622	0.887	0.956	0.992

TOTAL QUANTILES FOR THE MAX-NORM TEST STATISTIC
NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
73.0	93.0	209.0	389.0	526.0	607.0	607.0
PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:						
0.119	0.152	0.342	0.637	0.861	0.993	0.993

BA

SUMMARY STATISTICS

TOTAL QUANTILES FOR THE 1-NORM TEST STATISTIC

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
23.0	59.0	121.0	315.0	478.0	541.0	566.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.039	0.101	0.207	0.538	0.817	0.925	0.968

TOTAL QUANTILES FOR THE 2-NORM TEST STATISTIC

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
19.0	53.0	118.0	320.0	479.0	538.0	567.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.032	0.091	0.202	0.547	0.819	0.920	0.969

TOTAL QUANTILES FOR THE MAX-NORM TEST STATISTIC

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
39.0	59.0	146.0	338.0	488.0	578.0	578.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.067	0.101	0.250	0.578	0.834	0.988	0.988

STRAIGHT DIFFERENCES DAYS
IBM

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.1574	0.0359	0.0131
0.1512	0.0431	0.0256
0.3842	0.3815	0.5358
0.8033	0.8312	0.8693
0.4281	0.4203	0.1877
0.0495	0.0619	0.0445
0.8730	0.8805	0.6507
0.9643	0.9258	0.6499
0.8013	0.8154	0.8353
0.7456	0.7705	0.6930
0.6965	0.6746	0.5359
0.4176	0.4246	0.2556
0.6106	0.5649	0.4902
0.4210	0.4606	0.3444
0.7877	0.8034	0.6923
0.7768	0.6865	0.4025
0.0118	0.0188	0.0448
0.0759	0.0770	0.0872
0.1571	0.2165	0.4030
0.2795	0.2627	0.4027
0.0428	0.0452	0.0866
0.0794	0.1030	0.2553
0.0891	0.1227	0.1634
0.3402	0.3358	0.3046
0.2128	0.1695	0.1638
0.4161	0.4928	0.6510
0.0917	0.0585	0.0079
0.6640	0.7129	0.6930
0.1301	0.1648	0.1637
0.0183	0.0280	0.0132
0.0278	0.0292	0.0447
0.3523	0.2999	0.1269
0.4897	0.4695	0.3045
0.4504	0.5524	0.6929
0.2880	0.3723	0.5362
0.8955	0.9069	0.8693
0.4900	0.5911	0.6927
0.8855	0.8731	0.3036
0.9499	0.9517	0.8696
0.5088	0.5268	0.6931
0.3549	0.3288	0.4031
0.0026	0.0033	0.0133
0.0276	0.0283	0.0313
0.2711	0.3108	0.4025
0.1627	0.1329	0.1872
0.0798	0.0952	0.1879
0.7658	0.7884	0.4909

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.3974	0.0937

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
7.0	12.0	17.0	32.0	40.0	45.0	46.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.149	0.255	0.362	0.681	0.851	0.957	0.979

SERIAL COR.	FISHER TS.	P-V OF TS.
0.4338	137.35	0.0024

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.4010	0.0964

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
8.0	12.0	17.0	30.0	39.0	44.0	46.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.170	0.255	0.362	0.638	0.830	0.936	0.979

SERIAL COR.	FISHER TS.	P-V OF TS.
0.4535	137.64	0.0023

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.3727	0.0759

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
9.0	11.0	18.0	31.0	43.0	47.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.191	0.234	0.383	0.660	0.915	1.000	1.000

SERIAL COR.	FISHER TS.	P-V OF TS.
0.2897	141.95	0.0010

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9892
CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.8271
CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.8753

LOG DIFFERNCES DAYS
IBM

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.1662	0.0392	0.0133
0.1507	0.0428	0.0257
0.3770	0.3741	0.5355
0.8042	0.8312	0.5360
0.4123	0.4102	0.1878
0.0473	0.0597	0.0448
0.8701	0.8789	0.6499
0.9643	0.9253	0.6499
0.7947	0.8108	0.8352
0.7296	0.7531	0.6926
0.6943	0.6721	0.5366
0.4153	0.4244	0.2560
0.6102	0.5649	0.4909
0.4205	0.4593	0.3443
0.7843	0.7996	0.6932
0.7745	0.6844	0.4029
0.0120	0.0191	0.0450
0.0764	0.0774	0.0869
0.1501	0.2074	0.4039
0.2801	0.2657	0.4035
0.0424	0.0449	0.0861
0.0786	0.1025	0.2549
0.0891	0.1226	0.1636
0.3373	0.3340	0.3042
0.2138	0.1705	0.1636
0.4139	0.4903	0.6494
0.0907	0.0573	0.0081
0.6626	0.7112	0.6928
0.1289	0.1640	0.1640
0.0182	0.0278	0.0131
0.0280	0.0291	0.0448
0.3524	0.2961	0.1262
0.4778	0.4586	0.3039
0.4492	0.5474	0.6939
0.2892	0.3730	0.5367
0.9010	0.9116	0.8691
0.4869	0.5905	0.6929
0.8831	0.8695	0.3040
0.9492	0.9510	0.8694
0.5085	0.5217	0.6925
0.3664	0.3379	0.4037
0.0027	0.0034	0.0134
0.0264	0.0270	0.0317
0.2715	0.3094	0.4031
0.1632	0.1329	0.1868
0.0810	0.0957	0.1881
0.7646	0.7905	0.4910

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.3960	0.0931

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
7.0	12.0	17.0	32.0	41.0	44.0	46.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.149	0.255	0.362	0.681	0.872	0.936	0.979

SERIAL COR.	FISHER TS.	P-V OF TS.
0.4296	137.66	0.0023

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.3994	0.0959

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
8.0	12.0	17.0	30.0	40.0	44.0	46.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.170	0.255	0.362	0.638	0.851	0.936	0.979

SERIAL COR.	FISHER TS.	P-V OF TS.
0.4504	137.96	0.0021

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.3656	0.0711

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
9.0	11.0	18.0	31.0	44.0	47.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.191	0.234	0.383	0.660	0.936	1.000	1.000

SERIAL COR.	FISHER TS.	P-V OF TS.
0.3120	142.81	0.0009

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9890
CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.8187
CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.8668

RETURNS DAYS
IBM

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.1671	0.0387	0.0131
0.1528	0.0433	0.0258
0.3773	0.3740	0.5354
0.8047	0.8311	0.5356
0.4130	0.4106	0.1886
0.0473	0.0598	0.0442
0.8694	0.8785	0.6504
0.9644	0.9251	0.6505
0.7948	0.8104	0.8349
0.7294	0.7526	0.6924
0.6928	0.6711	0.5364
0.4158	0.4249	0.2559
0.6097	0.5628	0.4905
0.4213	0.4602	0.3453
0.7845	0.7996	0.6929
0.7752	0.6848	0.4029
0.0119	0.0189	0.0447
0.0758	0.0768	0.0863
0.1497	0.2070	0.4018
0.2799	0.2657	0.4029
0.0420	0.0449	0.0860
0.0786	0.1028	0.2560
0.0888	0.1227	0.1638
0.3381	0.3345	0.3047
0.2139	0.1707	0.1633
0.4153	0.4924	0.6510
0.0900	0.0571	0.0078
0.6616	0.7101	0.6925
0.1290	0.1645	0.1639
0.0182	0.0278	0.0131
0.0277	0.0288	0.0441
0.3528	0.2972	0.1275
0.4792	0.4598	0.3046
0.4496	0.5480	0.6925
0.2883	0.3717	0.5357
0.9003	0.9109	0.8690
0.4873	0.5909	0.6927
0.8826	0.8692	0.3050
0.9491	0.9509	0.8689
0.5091	0.5219	0.6927
0.3655	0.3378	0.4032
0.0025	0.0032	0.0131
0.0261	0.0268	0.0312
0.2712	0.3093	0.4020
0.1642	0.1333	0.1873
0.0809	0.0958	0.1878
0.7651	0.7905	0.4907

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.3960	0.0931

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
7.0	12.0	17.0	32.0	41.0	44.0	46.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.149	0.255	0.362	0.681	0.872	0.936	0.979

SERIAL COR.	FISHER TS.	P-V OF TS.
0.4296	137.86	0.0022

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.3994	0.0958

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
8.0	12.0	17.0	30.0	40.0	44.0	46.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.170	0.255	0.362	0.638	0.851	0.936	0.979

SERIAL COR.	FISHER TS.	P-V OF TS.
0.4503	138.11	0.0021

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.3655	0.0711

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
9.0	11.0	18.0	31.0	44.0	47.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.191	0.234	0.383	0.660	0.936	1.000	1.000

SERIAL COR.	FISHER TS.	P-V OF TS.
0.3122	143.03	0.0008

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9889
CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.8191
CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.8672

STRAIGHT DIFFERENCES DAYS
MRK

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.0585	0.0372	0.0256
0.2882	0.3219	0.4907
0.2341	0.1492	0.1271
0.1685	0.1382	0.1266
0.7458	0.6986	0.4904
0.7463	0.7549	0.5362
0.0302	0.0289	0.1880
0.6885	0.6662	0.8119
0.6712	0.7625	0.9613
0.4705	0.4832	0.3455
0.3366	0.4273	0.4024
0.2636	0.2003	0.0313
0.5955	0.6904	0.8693
0.4348	0.4823	0.6930
0.1056	0.0936	0.1875
0.3174	0.2851	0.1871
0.3955	0.4428	0.3439
0.6735	0.7494	0.8691
0.1810	0.2310	0.1641
0.0552	0.0363	0.0080
0.5128	0.5894	0.6927
0.3620	0.4910	0.4024
0.5631	0.5598	0.6930
0.5475	0.6265	0.6930
0.0063	0.0087	0.0079
0.5506	0.4119	0.1002
0.5381	0.5351	0.3045
0.3701	0.4188	0.5362
0.6665	0.5707	0.4026
0.0180	0.0330	0.0994
0.0004	0.0006	0.0015
0.0501	0.0482	0.0314
0.1911	0.2290	0.2562
0.0028	0.0038	0.0132
0.1167	0.1348	0.4026
0.0736	0.0911	0.1269
0.0031	0.0042	0.0080
0.0476	0.0105	0.0130
0.0670	0.0680	0.0314
0.7923	0.7765	0.6931
0.8810	0.8053	0.6929
0.2708	0.2249	0.0860
0.7712	0.7225	0.6493
0.2513	0.3423	0.6506
0.1204	0.1631	0.4025
0.0532	0.0584	0.0864
0.0748	0.1127	0.1878

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.3269	0.0717

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
7.0	14.0	20.0	32.0	46.0	47.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.149	0.298	0.426	0.681	0.979	1.000	1.000

SERIAL COR.	FISHER TS.	P-V OF TS.
0.2320	172.33	0.0000

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.3345	0.0731

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
10.0	14.0	19.0	33.0	46.0	47.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.213	0.298	0.404	0.702	0.979	1.000	1.000

SERIAL COR.	FISHER TS.	P-V OF TS.
0.2400	170.29	0.0000

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.3431	0.0827

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
10.0	13.0	22.0	33.0	43.0	46.0	46.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.213	0.277	0.468	0.702	0.915	0.979	0.979

SERIAL COR.	FISHER TS.	P-V OF TS.
0.1551	166.93	0.0000

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9792

CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.8006

CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.8773

LOG DIFFERNCES DAYS
MRK

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.0585	0.0370	0.0261
0.2916	0.3260	0.4909
0.2432	0.1567	0.1265
0.1592	0.1305	0.1270
0.7491	0.7003	0.4900
0.7330	0.7416	0.5359
0.0305	0.0287	0.1880
0.7029	0.6827	0.8124
0.6993	0.7828	0.9614
0.4715	0.4818	0.3446
0.3367	0.4277	0.4036
0.2424	0.1890	0.0314
0.5846	0.6784	0.6932
0.4305	0.4791	0.6928
0.1057	0.0935	0.1873
0.3136	0.2768	0.1877
0.3896	0.4372	0.3445
0.6712	0.7476	0.8692
0.1845	0.2358	0.1641
0.0542	0.0353	0.0079
0.5148	0.5911	0.6933
0.3603	0.4894	0.4020
0.5625	0.5581	0.6926
0.5435	0.6213	0.6924
0.0061	0.0086	0.0078
0.5515	0.4115	0.0997
0.5294	0.5237	0.2558
0.3715	0.4211	0.5363
0.6680	0.5715	0.4031
0.0190	0.0347	0.0990
0.0004	0.0006	0.0014
0.0492	0.0472	0.0313
0.2026	0.2446	0.2556
0.0099	0.0148	0.0449
0.1177	0.1363	0.4037
0.0736	0.0914	0.1271
0.0031	0.0041	0.0077
0.0493	0.0106	0.0133
0.0679	0.0685	0.0313
0.7882	0.7711	0.6925
0.8830	0.8098	0.6929
0.2653	0.2207	0.0864
0.7793	0.7264	0.6501
0.2545	0.3470	0.6506
0.1168	0.1597	0.4015
0.0530	0.0580	0.0868
0.0726	0.1098	0.1873

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.3269	0.0720

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
8.0	14.0	19.0	32.0	46.0	47.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.170	0.298	0.404	0.681	0.979	1.000	1.000

SERIAL COR.	FISHER TS.	P-V OF TS.
0.2262	169.83	0.0000

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.3345	0.0731

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
10.0	14.0	20.0	33.0	46.0	47.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.213	0.298	0.426	0.702	0.979	1.000	1.000

SERIAL COR.	FISHER TS.	P-V OF TS.
0.2351	167.73	0.0000

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.3390	0.0791

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
10.0	14.0	22.0	33.0	44.0	46.0	46.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.213	0.298	0.468	0.702	0.936	0.979	0.979

SERIAL COR.	FISHER TS.	P-V OF TS.
0.1609	165.34	0.0000

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9793

CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.8044

CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.8783

RETURNS DAYS
MRK

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.0578	0.0366	0.0257
0.2911	0.3259	0.4906
0.2419	0.1564	0.1265
0.1590	0.1303	0.1268
0.7491	0.7006	0.4911
0.7320	0.7405	0.5357
0.0302	0.0284	0.1881
0.7025	0.6825	0.8124
0.7003	0.7837	0.9610
0.4704	0.4807	0.3445
0.3361	0.4273	0.4029
0.2413	0.1879	0.0314
0.5850	0.6792	0.6927
0.4315	0.4797	0.6930
0.1059	0.0936	0.1880
0.3150	0.2778	0.1872
0.3888	0.4372	0.3445
0.6711	0.7473	0.8685
0.1842	0.2358	0.1642
0.0539	0.0349	0.0078
0.5140	0.5915	0.6929
0.3608	0.4901	0.4036
0.5619	0.5580	0.6927
0.5449	0.6226	0.6927
0.0061	0.0086	0.0079
0.5516	0.4124	0.0995
0.5309	0.5244	0.2551
0.3706	0.4208	0.5356
0.6671	0.5708	0.4030
0.0190	0.0348	0.0998
0.0004	0.0006	0.0014
0.0497	0.0477	0.0313
0.2033	0.2454	0.2562
0.0100	0.0151	0.0447
0.1171	0.1356	0.4028
0.0732	0.0910	0.1268
0.0032	0.0042	0.0079
0.0485	0.0106	0.0132
0.0677	0.0682	0.0315
0.7883	0.7711	0.6927
0.8825	0.8094	0.6931
0.2659	0.2209	0.0867
0.7785	0.7259	0.6501
0.2543	0.3469	0.6503
0.1178	0.1607	0.4033
0.0534	0.0585	0.0868
0.0725	0.1101	0.1878

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.3268	0.0720

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
8.0	14.0	19.0	32.0	46.0	47.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.170	0.298	0.404	0.681	0.979	1.000	1.000

SERIAL COR.	FISHER TS.	P-V OF TS.
0.2262	170.16	0.0000

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.3345	0.0731

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
10.0	14.0	20.0	33.0	46.0	47.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.213	0.298	0.426	0.702	0.979	1.000	1.000

SERIAL COR.	FISHER TS.	P-V OF TS.
0.2346	167.87	0.0000

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.3390	0.0790

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
10.0	14.0	22.0	33.0	44.0	46.0	46.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.213	0.298	0.468	0.702	0.936	0.979	0.979

SERIAL COR.	FISHER TS.	P-V OF TS.
0.1615	165.28	0.0000

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9793
CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.8046
CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.8784

STRAIGHT DIFFERENCES DAYS

BA

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.3505	0.3975	0.2548
0.4156	0.3679	0.2553
0.7230	0.6381	0.4905
0.2283	0.2964	0.3443
0.3051	0.3212	0.3046
0.5481	0.5718	0.4025
0.2525	0.2912	0.3445
0.3486	0.4050	0.4024
0.5866	0.5911	0.6510
0.9460	0.9397	0.5368
0.7706	0.7579	0.5359
0.1347	0.1554	0.1874
0.1280	0.1526	0.4032
0.5365	0.5645	0.5365
0.5022	0.4647	0.3039
0.3254	0.2096	0.1265
0.2118	0.1803	0.0315
0.5473	0.3380	0.1883
0.2764	0.3174	0.4030
0.9454	0.9525	0.6506
0.5149	0.4640	0.1266
0.7679	0.7169	0.5353
0.5488	0.4102	0.3042
0.5519	0.5670	0.6505
0.5249	0.5032	0.4028
0.7140	0.6344	0.4034
0.3098	0.4493	0.6924
0.0745	0.0820	0.0993
0.9134	0.9218	0.8686
0.3115	0.3192	0.4027
0.3788	0.3948	0.6935
0.4401	0.3924	0.4031
0.0481	0.0434	0.0132
0.5533	0.6514	0.5363
0.9558	0.9397	0.5362
0.8118	0.8268	0.6503
0.0857	0.0673	0.1878
0.0431	0.0664	0.1865
0.8808	0.8970	0.8696
0.5926	0.5946	0.3040
0.0614	0.0613	0.0996
0.0043	0.0009	0.0002
0.8096	0.8250	0.8349
0.0523	0.0598	0.0448
0.0644	0.0535	0.1263

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
45	0.4466	0.0819

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
3.0	8.0	10.0	23.0	38.0	41.0	44.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.067	0.178	0.222	0.511	0.844	0.911	0.978

SERIAL COR.	FISHER TS.	P-V OF TS.
0.0049	105.99	0.1197

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
45	0.4412	0.0793

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
2.0	8.0	11.0	27.0	38.0	41.0	44.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.044	0.178	0.244	0.600	0.844	0.911	0.978

SERIAL COR.	FISHER TS.	P-V OF TS.
0.0103	109.20	0.0823

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
45	0.3850	0.0546

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
4.0	6.0	13.0	30.0	42.0	45.0	45.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.089	0.133	0.289	0.667	0.933	1.000	1.000

SERIAL COR.	FISHER TS.	P-V OF TS.
-.1626	122.25	0.0134

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9791
CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.7520
CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.8243

LOG DIFFERNCES DAYS

BA

P-VALUES

L1-NORM	L2-NORM	MAX-NORM
0.3496	0.3936	0.2566
0.3791	0.3487	0.2558
0.7160	0.6323	0.4901
0.2368	0.3108	0.3444
0.2823	0.2984	0.3040
0.5410	0.5709	0.4028
0.2527	0.2898	0.3442
0.3470	0.4036	0.4024
0.5768	0.5834	0.6512
0.9455	0.9410	0.5360
0.7793	0.7685	0.5366
0.1310	0.1512	0.1873
0.1318	0.1557	0.4030
0.5392	0.5665	0.5355
0.5188	0.4818	0.3040
0.3097	0.2004	0.1269
0.2092	0.1776	0.0315
0.5479	0.3369	0.1881
0.2730	0.3148	0.4039
0.9463	0.9531	0.6510
0.5241	0.4731	0.1267
0.7544	0.7031	0.5353
0.5501	0.4103	0.3040
0.5526	0.5668	0.6499
0.5199	0.4988	0.4023
0.7150	0.6357	0.4022
0.3115	0.4500	0.6928
0.0750	0.0817	0.0995
0.9141	0.9232	0.8690
0.3068	0.3156	0.4029
0.3781	0.3944	0.6927
0.4376	0.3887	0.4020
0.0474	0.0434	0.0133
0.5573	0.6547	0.5375
0.9553	0.9362	0.5367
0.8149	0.8321	0.6504
0.0841	0.0658	0.1870
0.0436	0.0672	0.1878
0.8756	0.8929	0.8694
0.6149	0.6193	0.3044
0.0604	0.0604	0.1000
0.0042	0.0010	0.0002
0.7847	0.7987	0.8347
0.0522	0.0593	0.0446
0.0654	0.0530	0.1265

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
45	0.4447	0.0818

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
3.0	8.0	10.0	23.0	39.0	41.0	44.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.067	0.178	0.222	0.511	0.867	0.911	0.978

SERIAL COR.	FISHER TS.	P-V OF TS.
0.0119	106.47	0.1134

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
45	0.4401	0.0794

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
2.0	8.0	11.0	28.0	39.0	41.0	44.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.044	0.178	0.244	0.622	0.867	0.911	0.978

SERIAL COR.	FISHER TS.	P-V OF TS.
0.0184	109.52	0.0792

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
45	0.3851	0.0546

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
4.0	6.0	13.0	30.0	42.0	45.0	45.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.089	0.133	0.289	0.667	0.933	1.000	1.000

SERIAL COR.	FISHER TS.	P-V OF TS.
-.1631	122.34	0.0133

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9792

CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.7492

CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.8203

RETURNS DAYS

BA

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.3477	0.3925	0.2554
0.3778	0.3474	0.2557
0.7152	0.6315	0.4899
0.2369	0.3108	0.3437
0.2823	0.2992	0.3053
0.5397	0.5699	0.4030
0.2533	0.2905	0.3450
0.3466	0.4029	0.4026
0.5770	0.5832	0.6500
0.9454	0.9408	0.5358
0.7783	0.7684	0.5364
0.1315	0.1517	0.1876
0.1316	0.1557	0.4028
0.5386	0.5669	0.5369
0.5185	0.4819	0.3044
0.3090	0.2000	0.1268
0.2086	0.1774	0.0314
0.5478	0.3363	0.1874
0.2713	0.3134	0.4018
0.9461	0.9528	0.6504
0.5225	0.4721	0.1269
0.7548	0.7032	0.5363
0.5512	0.4111	0.3046
0.5538	0.5676	0.6506
0.5212	0.5001	0.4028
0.7176	0.6382	0.4040
0.3105	0.4491	0.6916
0.0742	0.0812	0.0998
0.9134	0.9228	0.8687
0.3069	0.3153	0.4018
0.3777	0.3938	0.6925
0.4391	0.3908	0.4023
0.0474	0.0431	0.0131
0.5564	0.6529	0.5364
0.9552	0.9357	0.5357
0.8146	0.8310	0.6506
0.0850	0.0664	0.1879
0.0435	0.0669	0.1878
0.8749	0.8920	0.8689
0.6143	0.6188	0.3037
0.0599	0.0602	0.0996
0.0041	0.0009	0.0002
0.7832	0.7975	0.8349
0.0521	0.0590	0.0446
0.0654	0.0533	0.1268

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
45	0.4445	0.0818

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
3.0	8.0	10.0	23.0	39.0	41.0	44.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.067	0.178	0.222	0.511	0.867	0.911	0.978

SERIAL COR.	FISHER TS.	P-V OF TS.
0.0121	106.58	0.1120

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
45	0.4399	0.0793

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
2.0	8.0	11.0	27.0	39.0	41.0	44.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.044	0.178	0.244	0.600	0.867	0.911	0.978

SERIAL COR.	FISHER TS.	P-V OF TS.
0.0184	109.78	0.0767

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
45	0.3850	0.0545

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
4.0	6.0	13.0	30.0	42.0	45.0	45.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.089	0.133	0.289	0.667	0.933	1.000	1.000

SERIAL COR.	FISHER TS.	P-V OF TS.
-.1630	122.31	0.0133

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9792
CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.7493
CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.8203

STRAIGHT DIFFERENCES DAYS
AA

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.0324	0.0167	0.0256
0.0819	0.0508	0.0131
0.6972	0.7346	0.3042
0.6295	0.5470	0.2552
0.0624	0.0890	0.1570
0.3106	0.2222	0.1825
0.2978	0.3421	0.3445
0.5399	0.5566	0.4024
0.9610	0.9623	0.9613
0.1920	0.1706	0.1273
0.7991	0.8040	0.5359
0.4575	0.5216	0.8124
0.3720	0.4094	0.5360
0.0583	0.0177	0.0057
0.0406	0.0245	0.0256
0.1821	0.0816	0.0443
0.4014	0.3256	0.3036
0.0265	0.0253	0.0451
0.0658	0.0326	0.0259
0.0512	0.0341	0.0450
0.0537	0.0535	0.0449
0.1050	0.0694	0.0133
0.2550	0.2364	0.3444
0.1367	0.0507	0.0132
0.0324	0.0473	0.0448
0.9391	0.9447	0.8692
0.9588	0.9427	0.6924
0.1359	0.1703	0.3452
0.0122	0.0203	0.1267
0.8017	0.8074	0.6927
0.2559	0.2022	0.1270
0.9877	0.9877	0.9829
0.9978	0.9978	0.9924
0.5776	0.6232	0.6929
0.7353	0.7475	0.6930
0.6082	0.5968	0.6926
0.7526	0.7184	0.4908
0.1131	0.0802	0.0311
0.1009	0.0629	0.0314
0.4919	0.4079	0.3040
0.3192	0.3395	0.3043
0.9488	0.9490	0.9826
0.7922	0.8107	0.6920
0.3733	0.2021	0.0994
0.5310	0.4439	0.2552
0.8214	0.8328	0.6937
0.7387	0.7518	0.6928

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.4220	0.1108

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
5.0	11.0	18.0	28.0	39.0	41.0	43.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.106	0.234	0.383	0.596	0.830	0.872	0.915

SERIAL COR.	FISHER TS.	P-V OF TS.
0.3005	129.26	0.0093

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.4057	0.1187

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
8.0	16.0	18.0	28.0	37.0	41.0	44.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.170	0.340	0.383	0.596	0.787	0.872	0.936

SERIAL COR.	FISHER TS.	P-V OF TS.
0.3267	143.37	0.0008

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.3638	0.1052

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
14.0	15.0	20.0	31.0	41.0	43.0	43.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.298	0.319	0.426	0.660	0.872	0.915	0.915

SERIAL COR.	FISHER TS.	P-V OF TS.
0.3797	161.10	0.0000

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9913
CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.9039
CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.9327

LOG DIFFERNCES DAYS
AA

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.0326	0.0171	0.0261
0.0749	0.0486	0.0131
0.6877	0.7247	0.3038
0.6181	0.5433	0.2556
0.0614	0.0879	0.1569
0.3091	0.2273	0.1826
0.3025	0.3451	0.3442
0.5558	0.5660	0.4898
0.9549	0.9579	0.9614
0.1964	0.1752	0.1272
0.8030	0.8064	0.5366
0.4607	0.5244	0.8125
0.3651	0.4049	0.5361
0.0586	0.0172	0.0058
0.0405	0.0246	0.0258
0.1808	0.0814	0.0444
0.4162	0.3461	0.3044
0.0270	0.0258	0.0451
0.0654	0.0320	0.0258
0.0515	0.0342	0.0449
0.0528	0.0530	0.0445
0.1051	0.0692	0.0133
0.2577	0.2388	0.3443
0.1419	0.0511	0.0133
0.0320	0.0467	0.0443
0.9388	0.9444	0.8687
0.9593	0.9450	0.6928
0.1359	0.1693	0.3453
0.0124	0.0203	0.1271
0.7954	0.8010	0.6932
0.2501	0.1984	0.1271
0.9885	0.9885	0.9828
0.9961	0.9961	0.9923
0.5779	0.6231	0.6939
0.7352	0.7477	0.6934
0.6099	0.6000	0.6923
0.7573	0.7227	0.4906
0.1136	0.0804	0.0316
0.0952	0.0589	0.0313
0.4931	0.4075	0.3044
0.3176	0.3400	0.3049
0.9515	0.9518	0.9826
0.7962	0.8142	0.6926
0.3714	0.2013	0.0996
0.5229	0.4386	0.2545
0.8367	0.8535	0.6932
0.7449	0.7592	0.6928

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.4224	0.1112

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
5.0	12.0	18.0	28.0	39.0	41.0	42.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.106	0.255	0.383	0.596	0.830	0.872	0.894

SERIAL COR.	FISHER TS.	P-V OF TS.
0.3018	129.40	0.0091

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.4066	0.1191

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
9.0	16.0	19.0	28.0	37.0	41.0	43.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.191	0.340	0.404	0.596	0.787	0.872	0.915

SERIAL COR.	FISHER TS.	P-V OF TS.
0.3275	143.39	0.0008

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.3657	0.1055

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
14.0	15.0	20.0	31.0	41.0	43.0	43.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.298	0.319	0.426	0.660	0.872	0.915	0.915

SERIAL COR.	FISHER TS.	P-V OF TS.
0.3893	160.64	0.0000

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9917
CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.9060
CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.9346

RETURNS DAYS
AA

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.0317	0.0168	0.0257
0.0743	0.0482	0.0132
0.6875	0.7238	0.3043
0.6185	0.5432	0.2551
0.0627	0.0893	0.1576
0.3102	0.2282	0.1817
0.3043	0.3462	0.3450
0.5566	0.5665	0.4906
0.9547	0.9576	0.9610
0.1954	0.1741	0.1270
0.8018	0.8059	0.5364
0.4596	0.5234	0.8133
0.3642	0.4037	0.5358
0.0592	0.0173	0.0057
0.0407	0.0246	0.0258
0.1800	0.0814	0.0446
0.4135	0.3442	0.3040
0.0268	0.0256	0.0446
0.0655	0.0322	0.0261
0.0510	0.0337	0.0448
0.0528	0.0529	0.0443
0.1060	0.0699	0.0132
0.2580	0.2388	0.3447
0.1430	0.0508	0.0131
0.0323	0.0469	0.0445
0.9391	0.9446	0.8694
0.9594	0.9450	0.6916
0.1354	0.1689	0.3447
0.0123	0.0203	0.1270
0.7960	0.8015	0.6923
0.2479	0.1966	0.1266
0.9886	0.9886	0.9827
0.9961	0.9961	0.9924
0.5763	0.6216	0.6925
0.7328	0.7452	0.6918
0.6092	0.5994	0.6927
0.7579	0.7233	0.4912
0.1128	0.0800	0.0315
0.0949	0.0586	0.0315
0.4918	0.4069	0.3037
0.3172	0.3396	0.3045
0.9516	0.9519	0.9826
0.7961	0.8138	0.6926
0.3707	0.2009	0.0993
0.5242	0.4397	0.2559
0.8370	0.8532	0.6932
0.7438	0.7584	0.6931

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.4222	0.1111

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
5.0	12.0	18.0	28.0	39.0	41.0	42.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.106	0.255	0.383	0.596	0.830	0.872	0.894

SERIAL COR.	FISHER TS.	P-V OF TS.
0.3010	129.46	0.0090

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.4064	0.1191

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
9.0	16.0	19.0	28.0	37.0	41.0	43.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.191	0.340	0.404	0.596	0.787	0.872	0.915

SERIAL COR.	FISHER TS.	P-V OF TS.
0.3268	143.50	0.0008

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.3656	0.1055

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
14.0	15.0	20.0	31.0	41.0	43.0	43.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.298	0.319	0.426	0.660	0.872	0.915	0.915

SERIAL COR.	FISHER TS.	P-V OF TS.
0.3890	160.74	0.0000

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9917
CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.9058
CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.9344

FIRST TWO HOURS OF YESTERDAY WITH TODAY
IBM

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.0233	0.0215	0.0451
0.8626	0.8834	0.8681
0.4885	0.4440	0.6910
0.0695	0.0787	0.1259
0.0199	0.0083	0.0018
0.1596	0.1941	0.3986
0.4326	0.4526	0.5315
0.7598	0.7667	0.5392
0.7114	0.6371	0.4810
0.6305	0.7215	0.8383
0.4466	0.4067	0.1731
0.1403	0.1381	0.1886
0.7713	0.7790	0.6859
0.0907	0.1101	0.1839
0.7711	0.8198	0.8696
0.5117	0.3368	0.1879
0.0584	0.0438	0.0334
0.2277	0.2644	0.4835
0.4405	0.4966	0.4886
0.6683	0.7405	0.5352
0.6162	0.7190	0.5388
0.6788	0.7031	0.6990
0.3722	0.2712	0.1865
0.0840	0.0651	0.0442
0.0538	0.0270	0.0449
0.9918	0.9918	0.8730
0.5562	0.4326	0.2500
0.8038	0.8465	0.9823
0.1465	0.1821	0.4044
0.1144	0.1652	0.1846
0.3637	0.4675	0.3465
0.9376	0.9290	0.6433
0.3468	0.3676	0.3496
0.0553	0.0603	0.0291
0.2134	0.1996	0.1873
0.3383	0.3770	0.6441
0.4953	0.5553	0.5339
0.2345	0.2243	0.3457
0.5011	0.4681	0.4043
0.6815	0.5923	0.1006
0.8740	0.9051	0.5427
0.0394	0.0442	0.0466
0.6681	0.6974	0.8107
0.1136	0.0918	0.1014
0.6180	0.5952	0.3012
0.8915	0.8947	0.5374
0.4897	0.4019	0.1809

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.4375	0.0864

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
3.0	9.0	14.0	27.0	41.0	45.0	46.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.064	0.191	0.298	0.574	0.872	0.957	0.979

SERIAL COR.	FISHER TS.	P-V OF TS.
-.0060	114.33	0.0756

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.4387	0.0903

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
5.0	9.0	15.0	29.0	40.0	44.0	46.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.106	0.191	0.319	0.617	0.851	0.936	0.979

SERIAL COR.	FISHER TS.	P-V OF TS.
-.0580	117.24	0.0526

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.3971	0.0759

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
7.0	7.0	18.0	29.0	41.0	46.0	46.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.149	0.149	0.383	0.617	0.872	0.979	0.979

SERIAL COR.	FISHER TS.	P-V OF TS.
-.2024	127.33	0.0126

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9827

CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.7710

CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.8330

TODAYS FIRST WITH YESTERDAY LAST TWO HOURS
IBM

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.6298	0.6063	0.4008
0.0488	0.0674	0.0790
0.3991	0.4760	0.6889
0.3214	0.3417	0.2955
0.9039	0.9054	0.5454
0.4921	0.4218	0.4021
0.7727	0.6984	0.6999
0.2836	0.2928	0.1900
0.1263	0.1321	0.0931
0.2736	0.1918	0.0328
0.7358	0.7094	0.3429
0.0544	0.0523	0.0845
0.3874	0.4133	0.4883
0.0273	0.0352	0.0333
0.1406	0.1208	0.1872
0.0200	0.0258	0.0073
0.3772	0.4697	0.5340
0.4106	0.4849	0.4101
0.6833	0.7292	0.8721
0.4894	0.5575	0.5441
0.5629	0.6086	0.6966
0.2373	0.2673	0.1261
0.6500	0.6659	0.4877
0.5608	0.6200	0.6505
0.6742	0.6119	0.6960
0.1915	0.1694	0.1042
0.7132	0.7211	0.5331
0.8132	0.8574	0.8667
0.3563	0.3528	0.4898
0.3115	0.3162	0.2509
0.0137	0.0195	0.0432
0.5588	0.5540	0.3557
0.8161	0.7847	0.6529
0.6676	0.6016	0.8153
0.8403	0.8565	0.8727
0.5639	0.5695	0.6944
0.7623	0.7192	0.6954
0.1514	0.1521	0.3336
0.9400	0.9195	0.6550
0.6806	0.5314	0.3397
0.5081	0.6338	0.6974
0.0110	0.0100	0.0084
0.5288	0.5411	0.3010
0.8746	0.8907	0.8708
0.8400	0.8665	0.6910
0.6537	0.5269	0.3047
0.7735	0.7884	0.8315

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.4858	0.0774

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
5.0	6.0	10.0	22.0	40.0	45.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.106	0.128	0.213	0.468	0.851	0.957	1.000

SERIAL COR.	FISHER TS.	P-V OF TS.
0.1511	102.58	0.2559

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.4870	0.0758

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
4.0	6.0	11.0	21.0	41.0	45.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.085	0.128	0.234	0.447	0.872	0.957	1.000

SERIAL COR.	FISHER TS.	P-V OF TS.
0.0818	100.59	0.3022

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.4467	0.0750

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
5.0	8.0	12.0	26.0	41.0	47.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.106	0.170	0.255	0.553	0.872	1.000	1.000

SERIAL COR.	FISHER TS.	P-V OF TS.
0.1516	112.91	0.0894

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9825

CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.8266

CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.8717

LAST TWO HOURS OF YESTERDAY WITH TODAY
IBM

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.0079	0.0123	0.0847
0.0275	0.0322	0.0848
0.4578	0.3253	0.1980
0.0376	0.0493	0.0854
0.2091	0.2319	0.1824
0.7457	0.7460	0.6892
0.2029	0.1983	0.2663
0.0998	0.0978	0.0356
0.0440	0.0262	0.0083
0.0529	0.0239	0.0118
0.8999	0.9160	0.8707
0.7960	0.7620	0.6495
0.6459	0.6873	0.6878
0.4496	0.5151	0.6833
0.0204	0.0175	0.0085
0.5473	0.5039	0.4018
0.6846	0.7081	0.7034
0.6374	0.5648	0.4042
0.5778	0.6055	0.4025
0.5710	0.6229	0.6923
0.1956	0.2798	0.4021
0.7618	0.7506	0.6906
0.9151	0.9301	0.9652
0.3113	0.2921	0.1317
0.1201	0.1344	0.1889
0.2823	0.3215	0.2560
0.7817	0.8303	0.5370
0.8503	0.8283	0.2535
0.7964	0.8339	0.8351
0.0085	0.0044	0.0047
0.0036	0.0040	0.0008
0.0946	0.1313	0.1926
0.1536	0.1967	0.3106
0.9784	0.9814	0.8720
0.5163	0.4587	0.2637
0.4837	0.5528	0.8353
0.0362	0.0501	0.1875
0.3714	0.3367	0.3959
0.8659	0.8890	0.8744
0.3956	0.4179	0.3994
0.4958	0.5779	0.6933
0.5387	0.4859	0.4878
0.5624	0.6440	0.8666
0.9761	0.9779	0.8663
0.3903	0.4560	0.4086
0.1125	0.0424	0.0137
0.0043	0.0055	0.0020

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.4195	0.1003

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
9.0	12.0	16.0	27.0	41.0	44.0	45.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.191	0.255	0.340	0.574	0.872	0.936	0.957

SERIAL COR.	FISHER TS.	P-V OF TS.
0.2844	142.82	0.0009

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.4268	0.1032

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
10.0	12.0	16.0	26.0	39.0	43.0	45.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.213	0.255	0.340	0.553	0.830	0.915	0.957

SERIAL COR.	FISHER TS.	P-V OF TS.
0.3038	143.14	0.0008

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.4061	0.0951

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
8.0	11.0	17.0	30.0	39.0	46.0	46.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.170	0.234	0.362	0.638	0.830	0.979	0.979

SERIAL COR.	FISHER TS.	P-V OF TS.
0.1817	152.90	0.0001

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9906
CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.8664
CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.9062

TODAYS FIRST TWO HOURS WITH NEXT TWO
IBM

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.5355	0.6373	0.6956
0.1437	0.1227	0.3059
0.2264	0.2281	0.3408
0.6767	0.6420	0.6869
0.0016	0.0014	0.0008
0.8680	0.8480	0.6576
0.1827	0.2005	0.1266
0.5499	0.6125	0.6962
0.2377	0.3214	0.4949
0.7176	0.7820	0.8702
0.2683	0.3068	0.4017
0.3411	0.3542	0.1660
0.0497	0.0537	0.1882
0.0640	0.0562	0.0882
0.0970	0.1070	0.1232
0.1442	0.1633	0.2611
0.8310	0.7859	0.6938
0.9508	0.9453	0.5312
0.1388	0.1586	0.1821
0.8134	0.8384	0.8364
0.7182	0.7479	0.5505
0.2448	0.3506	0.5335
0.7679	0.7663	0.6990
0.7476	0.4462	0.1975
0.3679	0.2779	0.1602
0.4145	0.3716	0.1859
0.9490	0.9534	0.8647
0.2603	0.3336	0.3443
0.5440	0.5485	0.5349
0.0690	0.0631	0.1836
0.3520	0.3496	0.3365
0.2038	0.2504	0.4088
0.6977	0.7172	0.6499
0.0650	0.0442	0.0291
0.1604	0.2373	0.4058
0.4430	0.5456	0.6906
0.0832	0.1348	0.3006
0.2256	0.1805	0.3512
0.5934	0.6048	0.6937
0.0769	0.0580	0.1847
0.2673	0.2917	0.3985
0.5176	0.6212	0.8664
0.1384	0.1018	0.0994
0.0633	0.0840	0.2948
0.8454	0.7627	0.3999
0.3742	0.3549	0.4041
0.4733	0.5139	0.5386
0.0900	0.1003	0.1284

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.3873	0.0813

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
2.0	10.0	16.0	31.0	42.0	46.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.042	0.208	0.333	0.646	0.875	0.958	0.979

SERIAL COR.	FISHER TS.	P-V OF TS.
-.1607	130.45	0.0111

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.3954	0.0785

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
2.0	7.0	15.0	30.0	44.0	46.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.042	0.146	0.312	0.625	0.917	0.958	0.979

SERIAL COR.	FISHER TS.	P-V OF TS.
-.1835	128.00	0.0162

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.4121	0.0602

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
2.0	4.0	15.0	30.0	44.0	48.0	48.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.042	0.083	0.312	0.625	0.917	1.000	1.000

SERIAL COR.	FISHER TS.	P-V OF TS.
-.1994	115.62	0.0843

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9742

CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.7579

CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.8541

TODAYS FIRST TWO HOURS WITH TODAYS 12-14
IBM

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.2028	0.2252	0.1840
0.0970	0.0645	0.1026
0.2050	0.2465	0.6885
0.5491	0.5500	0.7046
0.0087	0.0078	0.0013
0.9070	0.9047	0.6468
0.2292	0.2608	0.3507
0.3924	0.4383	0.6886
0.2121	0.2238	0.1911
0.3989	0.4959	0.5438
0.6567	0.7246	0.6877
0.2644	0.1523	0.0147
0.0327	0.0369	0.1797
0.0218	0.0227	0.0874
0.5595	0.5997	0.3474
0.0937	0.0964	0.1810
0.8435	0.8069	0.4874
0.3812	0.3790	0.3410
0.1020	0.1240	0.1835
0.1844	0.2003	0.1878
0.4587	0.5698	0.6872
0.2990	0.4352	0.5338
0.7763	0.6974	0.3390
0.7542	0.6404	0.3965
0.7100	0.6854	0.3980
0.9727	0.9757	0.9931
0.5400	0.5801	0.5265
0.4692	0.5339	0.5359
0.8515	0.8756	0.8713
0.0620	0.0637	0.1850
0.3780	0.3911	0.3489
0.0895	0.1070	0.1880
0.5414	0.5814	0.3050
0.0981	0.0962	0.0309
0.1212	0.1446	0.4076
0.8814	0.8909	0.8688
0.1866	0.2365	0.3988
0.2073	0.1805	0.3461
0.6456	0.6517	0.6946
0.0571	0.0360	0.0846
0.0647	0.0994	0.1892
0.5028	0.5878	0.8422
0.4097	0.3441	0.3190
0.0160	0.0106	0.0449
0.5777	0.6032	0.7011
0.7461	0.8036	0.8715
0.3293	0.3475	0.4114
0.0385	0.0556	0.1287

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.3776	0.0817

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
5.0	12.0	16.0	31.0	43.0	46.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.104	0.250	0.333	0.646	0.896	0.958	0.979

SERIAL COR.	FISHER TS.	P-V OF TS.
-.0544	137.73	0.0034

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.3914	0.0826

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
5.0	11.0	16.0	29.0	42.0	46.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.104	0.229	0.333	0.604	0.875	0.958	0.979

SERIAL COR.	FISHER TS.	P-V OF TS.
-.0677	134.74	0.0056

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.4051	0.0709

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
4.0	6.0	17.0	31.0	43.0	47.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.083	0.125	0.354	0.646	0.896	0.979	0.979

SERIAL COR.	FISHER TS.	P-V OF TS.
-.0408	123.84	0.0294

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9859
CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.7730
CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.8356

TODAYS FIRST TWO WITH TODAYS 13-15
IBM

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.1521	0.1993	0.1888
0.0382	0.0493	0.0950
0.1935	0.2326	0.6955
0.3567	0.3380	0.4034
0.0087	0.0059	0.0015
0.5078	0.4236	0.2980
0.4276	0.4641	0.6894
0.1238	0.1754	0.4013
0.2282	0.2512	0.4091
0.8988	0.9179	0.8683
0.8678	0.7682	0.5338
0.3315	0.2841	0.0437
0.0376	0.0433	0.0904
0.0180	0.0214	0.0848
0.1965	0.2069	0.0314
0.3690	0.3970	0.5355
0.8903	0.8912	0.6967
0.2772	0.2829	0.1280
0.3690	0.3633	0.4008
0.0877	0.0833	0.0469
0.4634	0.5774	0.5332
0.4363	0.4989	0.5380
0.4775	0.5076	0.3542
0.9660	0.9682	0.8670
0.1888	0.1655	0.0511
0.4467	0.5285	0.5443
0.7226	0.6616	0.2548
0.4684	0.5591	0.6928
0.8494	0.8685	0.8674
0.1251	0.1406	0.4008
0.1039	0.1266	0.1878
0.4117	0.4904	0.6931
0.7120	0.7636	0.8692
0.0907	0.0942	0.0969
0.1891	0.1952	0.1924
0.9252	0.8432	0.3991
0.4702	0.3839	0.4067
0.1016	0.0883	0.1268
0.3301	0.3081	0.3405
0.5239	0.5935	0.6956
0.0857	0.1314	0.1305
0.7603	0.7278	0.8341
0.6196	0.4594	0.3371
0.0976	0.0917	0.0984
0.6170	0.6553	0.6990
0.1865	0.1775	0.1234
0.4476	0.4129	0.3979
0.0423	0.0659	0.1258

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.3800	0.0789

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
5.0	9.0	19.0	35.0	42.0	46.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.104	0.188	0.396	0.729	0.875	0.958	0.979

SERIAL COR.	FISHER TS.	P-V OF TS.
0.0044	132.06	0.0086

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.3851	0.0749

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
4.0	9.0	17.0	33.0	43.0	46.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.083	0.188	0.354	0.688	0.896	0.958	0.979

SERIAL COR.	FISHER TS.	P-V OF TS.
0.0040	128.14	0.0158

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.3854	0.0732

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
4.0	10.0	18.0	31.0	43.0	48.0	48.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.083	0.208	0.375	0.646	0.896	1.000	1.000

SERIAL COR.	FISHER TS.	P-V OF TS.
-.1022	131.57	0.0093

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9827

CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.7566

CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.8274

TODAYS FIRST TWO HOURS WITH TODAYS 14-16
IBM

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.0063	0.0043	0.0115
0.0714	0.1075	0.3032
0.9455	0.9401	0.6901
0.3214	0.2921	0.1830
0.0029	0.0018	0.0004
0.2581	0.3232	0.4065
0.4334	0.3891	0.6936
0.0520	0.0842	0.2499
0.1279	0.1632	0.2555
0.5841	0.5390	0.3083
0.6543	0.5188	0.3472
0.7275	0.6333	0.3961
0.1355	0.1507	0.1880
0.5503	0.5731	0.5336
0.0264	0.0283	0.0322
0.3422	0.3722	0.6862
0.2539	0.2304	0.3435
0.5010	0.4924	0.3435
0.9404	0.9466	0.9919
0.8007	0.7416	0.4066
0.7677	0.8140	0.8706
0.8234	0.8017	0.3478
0.7264	0.7371	0.6938
0.8047	0.7690	0.3472
0.0394	0.0319	0.0132
0.2122	0.1937	0.0999
0.9409	0.9278	0.5352
0.9841	0.9847	0.8693
0.4418	0.3549	0.0990
0.1928	0.1555	0.1893
0.2798	0.1812	0.1811
0.7891	0.7764	0.6420
0.5546	0.5451	0.6924
0.1271	0.1038	0.0993
0.6747	0.6498	0.4027
0.5567	0.5848	0.5337
0.2324	0.2609	0.4037
0.1330	0.1804	0.4003
0.6080	0.6163	0.5295
0.8988	0.9125	0.9612
0.3697	0.4466	0.6901
0.7988	0.8181	0.5418
0.1422	0.1341	0.1893
0.1635	0.1415	0.0986
0.7202	0.7209	0.5356
0.7634	0.6983	0.5350
0.6317	0.5595	0.6905
0.0036	0.0066	0.0831

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.4607	0.0979

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
5.0	7.0	14.0	24.0	40.0	44.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.104	0.146	0.292	0.500	0.833	0.917	0.979

SERIAL COR.	FISHER TS.	P-V OF TS.
0.1695	124.16	0.0281

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.4508	0.0939

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
5.0	6.0	16.0	25.0	40.0	43.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.104	0.125	0.333	0.521	0.833	0.896	0.979

SERIAL COR.	FISHER TS.	P-V OF TS.
0.1608	125.35	0.0238

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.4093	0.0690

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
4.0	9.0	14.0	29.0	44.0	46.0	46.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.083	0.188	0.292	0.604	0.917	0.958	0.958

SERIAL COR.	FISHER TS.	P-V OF TS.
0.0099	127.63	0.0171

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9907

CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.7549

CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.8013

TODAYS 10-12 WITH TODAYS 12-14
IBM

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.4587	0.2373	0.1882
0.5038	0.5248	0.5348
0.2242	0.2252	0.4109
0.7474	0.6768	0.6980
0.0796	0.0943	0.0460
0.7620	0.8083	0.8670
0.6598	0.6244	0.3423
0.8931	0.8445	0.2553
0.5216	0.5544	0.6910
0.6794	0.7139	0.8381
0.8652	0.8722	0.6994
0.0867	0.0423	0.0012
0.0394	0.0372	0.1928
0.0568	0.0885	0.1247
0.9792	0.9798	0.8743
0.0591	0.0628	0.1848
0.3851	0.4224	0.5373
0.0722	0.1017	0.1268
0.0421	0.0580	0.1012
0.1002	0.1015	0.0470
0.1885	0.1654	0.1669
0.1784	0.2618	0.2996
0.5105	0.4950	0.3417
0.8437	0.8733	0.8757
0.9539	0.9491	0.6900
0.7619	0.7152	0.5293
0.0696	0.1079	0.3429
0.8603	0.8670	0.5339
0.8233	0.8523	0.8715
0.3048	0.3716	0.6890
0.7625	0.8000	0.8713
0.2309	0.2700	0.3992
0.4454	0.4208	0.3044
0.3024	0.3567	0.2523
0.2998	0.3357	0.6875
0.9970	0.9970	0.8742
0.4603	0.5438	0.6986
0.1206	0.1243	0.3450
0.6201	0.6607	0.6910
0.1228	0.0826	0.0925
0.0999	0.1395	0.1912
0.9333	0.8855	0.6567
0.2685	0.2331	0.3140
0.0239	0.0207	0.1291
0.6298	0.4534	0.4074
0.9724	0.9737	0.9930
0.5914	0.4747	0.4012
0.0417	0.0739	0.1307

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.4507	0.1084

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
4.0	11.0	16.0	26.0	38.0	43.0	44.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.083	0.229	0.333	0.542	0.792	0.896	0.917

SERIAL COR.	FISHER TS.	P-V OF TS.
0.0250	117.99	0.0634

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.4495	0.1049

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
3.0	9.0	15.0	28.0	37.0	44.0	45.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.062	0.188	0.312	0.583	0.771	0.917	0.938

SERIAL COR.	FISHER TS.	P-V OF TS.
0.0397	115.59	0.0846

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.4488	0.0808

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
3.0	4.0	14.0	27.0	40.0	47.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.062	0.083	0.292	0.562	0.833	0.979	0.979

SERIAL COR.	FISHER TS.	P-V OF TS.
0.1054	110.55	0.1471

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9847
CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.8016
CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.8533

TODAYS 10-12 WITH TODAYS 13-15
IBM

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.2795	0.2216	0.1897
0.2734	0.3555	0.5395
0.0932	0.1017	0.3408
0.4552	0.4594	0.5310
0.0663	0.0702	0.1244
0.3888	0.3254	0.4149
0.9145	0.9226	0.8745
0.5295	0.6615	0.8703
0.5254	0.5892	0.6924
0.5828	0.6705	0.5317
0.8042	0.8425	0.8674
0.0984	0.0783	0.0117
0.0466	0.0424	0.0910
0.0535	0.0786	0.1252
0.6442	0.6393	0.2584
0.5371	0.4517	0.4870
0.2633	0.2768	0.4004
0.0480	0.0646	0.0460
0.1482	0.1795	0.3044
0.0245	0.0308	0.0451
0.4724	0.4926	0.3500
0.2137	0.2851	0.3021
0.5181	0.3748	0.3373
0.4876	0.5835	0.8691
0.4306	0.3367	0.1267
0.2422	0.2283	0.1236
0.2801	0.2867	0.1267
0.8960	0.9081	0.8703
0.6881	0.6408	0.6892
0.2972	0.3475	0.3540
0.1390	0.0834	0.0909
0.8285	0.8554	0.8655
0.8219	0.8532	0.8712
0.3345	0.4140	0.5340
0.6321	0.5886	0.4012
0.9467	0.9281	0.6973
0.6524	0.6324	0.6946
0.0505	0.0524	0.1270
0.3122	0.2722	0.3128
0.6210	0.6693	0.8350
0.1173	0.1759	0.2598
0.8731	0.8850	0.9634
0.4487	0.3295	0.3064
0.1604	0.1834	0.2556
0.5715	0.4270	0.3989
0.2554	0.3079	0.3475
0.5309	0.3906	0.4022
0.0442	0.0831	0.1260

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.4092	0.0749

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
4.0	9.0	13.0	29.0	41.0	46.0	48.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.083	0.188	0.271	0.604	0.854	0.958	1.000

SERIAL COR.	FISHER TS.	P-V OF TS.
0.1157	118.77	0.0575

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.4099	0.0755

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
2.0	9.0	13.0	32.0	41.0	45.0	48.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.042	0.188	0.271	0.667	0.854	0.938	1.000

SERIAL COR.	FISHER TS.	P-V OF TS.
0.1726	116.22	0.0786

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.4247	0.0792

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
3.0	5.0	13.0	31.0	39.0	47.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.062	0.104	0.271	0.646	0.812	0.979	0.979

SERIAL COR.	FISHER TS.	P-V OF TS.
0.1206	112.27	0.1228

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9739
CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.8388
CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.9020

TODAYS 10-12 WITH TODAYS 14-16
IBM

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.0094	0.0030	0.0131
0.3053	0.2533	0.3958
0.2602	0.3479	0.4048
0.3878	0.3851	0.3941
0.0348	0.0392	0.0824
0.2594	0.2525	0.1867
0.6258	0.4624	0.3962
0.2284	0.3085	0.2521
0.2185	0.2553	0.2575
0.2880	0.2513	0.0324
0.9117	0.8079	0.6961
0.3287	0.2705	0.1876
0.2118	0.1636	0.1834
0.2347	0.2608	0.2512
0.0994	0.1213	0.1850
0.1783	0.1617	0.3403
0.1566	0.2000	0.3513
0.2633	0.3175	0.3438
0.7089	0.6848	0.6549
0.3700	0.3802	0.4025
0.5264	0.5380	0.3421
0.6736	0.6883	0.3411
0.5078	0.3784	0.1902
0.3790	0.4432	0.2501
0.1088	0.0701	0.0419
0.5444	0.4825	0.3051
0.5544	0.5260	0.2506
0.7791	0.8330	0.9834
0.3205	0.2539	0.0971
0.3343	0.4043	0.3465
0.0255	0.0332	0.0418
0.4531	0.3786	0.4027
0.9912	0.9912	0.9857
0.1774	0.2622	0.5460
0.9497	0.9472	0.6923
0.8811	0.8968	0.8692
0.2488	0.3088	0.5353
0.0836	0.1100	0.1799
0.5616	0.4631	0.3063
0.9557	0.9596	0.9616
0.2654	0.3183	0.4102
0.1133	0.1271	0.1302
0.0927	0.0890	0.0985
0.2754	0.3063	0.2528
0.6818	0.7150	0.6942
0.8610	0.8628	0.6909
0.0585	0.0763	0.1268
0.0028	0.0046	0.0492

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.3852	0.0806

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
4.0	8.0	13.0	32.0	42.0	44.0	46.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.083	0.167	0.271	0.667	0.875	0.917	0.958

SERIAL COR.	FISHER TS.	P-V OF TS.
0.1347	132.42	0.0082

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.3832	0.0758

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
4.0	7.0	13.0	36.0	41.0	45.0	46.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.083	0.146	0.271	0.750	0.854	0.938	0.958

SERIAL COR.	FISHER TS.	P-V OF TS.
0.1502	131.61	0.0093

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.3569	0.0663

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
5.0	8.0	16.0	37.0	44.0	45.0	45.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.104	0.167	0.333	0.771	0.917	0.938	0.938

SERIAL COR.	FISHER TS.	P-V OF TS.
0.1340	130.49	0.0111

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9812
CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.8309
CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.8826

TODAYS 11-13 WITH TODAYS 13-15
IBM

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.5513	0.6223	0.8082
0.0783	0.1073	0.0480
0.0780	0.1334	0.3449
0.8411	0.8000	0.6917
0.3332	0.2650	0.1624
0.2537	0.2389	0.4046
0.2468	0.2484	0.3018
0.8423	0.8586	0.5355
0.9258	0.8678	0.6545
0.3096	0.4039	0.5299
0.2164	0.2588	0.2515
0.3379	0.3389	0.3034
0.8677	0.8848	0.8651
0.7234	0.6417	0.6860
0.9191	0.8788	0.5367
0.6883	0.6620	0.7003
0.4039	0.4654	0.4988
0.4162	0.4860	0.5442
0.2685	0.3475	0.5381
0.0365	0.0621	0.1228
0.3705	0.3662	0.1888
0.6706	0.6557	0.4071
0.8903	0.9030	0.8669
0.2683	0.1870	0.1832
0.8955	0.8724	0.5461
0.2143	0.1591	0.0133
0.4018	0.4206	0.2602
0.2996	0.3585	0.5254
0.4655	0.4645	0.6922
0.0624	0.0767	0.0443
0.0244	0.0188	0.0258
0.8680	0.8851	0.8687
0.4584	0.4727	0.6982
0.8640	0.8842	0.8724
0.2429	0.2862	0.1300
0.8565	0.8756	0.5400
0.1043	0.1082	0.1939
0.2990	0.2590	0.1261
0.0738	0.0786	0.1315
0.1723	0.1959	0.2603
0.2015	0.2343	0.1896
0.4996	0.5869	0.8283
0.7397	0.7923	0.9623
0.8330	0.8445	0.5381
0.5717	0.4805	0.4970
0.0190	0.0316	0.0429
0.9226	0.9328	0.8719
0.9823	0.9823	0.9813

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.4710	0.0962

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
3.0	7.0	9.0	29.0	35.0	44.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.062	0.146	0.188	0.604	0.729	0.917	0.979

SERIAL COR.	FISHER TS.	P-V OF TS.
0.0956	105.64	0.2353

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.4789	0.0926

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
2.0	5.0	11.0	29.0	36.0	45.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.042	0.104	0.229	0.604	0.750	0.938	0.979

SERIAL COR.	FISHER TS.	P-V OF TS.
0.0568	100.66	0.3524

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.4586	0.0831

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
5.0	5.0	14.0	24.0	39.0	46.0	46.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.104	0.104	0.292	0.500	0.812	0.958	0.958

SERIAL COR.	FISHER TS.	P-V OF TS.
0.0842	107.47	0.1991

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9898
CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.8185
CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.8579

TODAYS 11-13 WITH TODAYS 14-16
IBM

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.0174	0.0099	0.0116
0.1039	0.0931	0.1812
0.1687	0.1916	0.3467
0.3637	0.4045	0.3985
0.2063	0.2422	0.3993
0.1896	0.1942	0.1888
0.4387	0.5171	0.6928
0.5289	0.3433	0.1006
0.2490	0.2157	0.1050
0.1586	0.1894	0.0316
0.4989	0.5933	0.6890
0.7915	0.8142	0.5292
0.9230	0.8600	0.4067
0.1163	0.1294	0.1829
0.4420	0.3566	0.4899
0.0215	0.0307	0.0502
0.0899	0.1041	0.2994
0.3564	0.3375	0.3471
0.8164	0.8350	0.6529
0.4133	0.4937	0.6936
0.3554	0.3889	0.4028
0.6509	0.7271	0.8408
0.9268	0.8624	0.4911
0.3587	0.3305	0.1235
0.5057	0.3821	0.1803
0.5034	0.4931	0.3108
0.6507	0.6434	0.5367
0.4752	0.6093	0.8355
0.2248	0.1965	0.0982
0.1196	0.0993	0.0431
0.0041	0.0057	0.0063
0.1677	0.1260	0.1877
0.2620	0.3058	0.2614
0.5677	0.6904	0.8641
0.7089	0.6610	0.2562
0.9835	0.9847	0.8654
0.0224	0.0343	0.1221
0.3870	0.2884	0.1876
0.1300	0.1450	0.1301
0.0767	0.1006	0.4058
0.1891	0.2080	0.1914
0.0842	0.0657	0.1835
0.4029	0.4324	0.4863
0.8890	0.9049	0.8692
0.6304	0.6273	0.6911
0.1367	0.1611	0.0439
0.3051	0.3029	0.2550
0.2148	0.3050	0.4073

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.3714	0.0739

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
4.0	7.0	17.0	34.0	43.0	45.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.083	0.146	0.354	0.708	0.896	0.938	0.979

SERIAL COR.	FISHER TS.	P-V OF TS.
0.3310	134.71	0.0056

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.3758	0.0741

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
4.0	7.0	17.0	34.0	42.0	46.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.083	0.146	0.354	0.708	0.875	0.958	0.979

SERIAL COR.	FISHER TS.	P-V OF TS.
0.3817	132.47	0.0081

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.3557	0.0675

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
5.0	7.0	20.0	36.0	43.0	48.0	48.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.104	0.146	0.417	0.750	0.896	1.000	1.000

SERIAL COR.	FISHER TS.	P-V OF TS.
0.1150	137.85	0.0033

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9766
CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.6992
CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.8040

TODAYS 12-14 WITH TODAYS 14-16
IBM

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.0191	0.0092	0.0137
0.0560	0.0670	0.1856
0.3835	0.4253	0.6892
0.0709	0.0948	0.1862
0.8163	0.8424	0.9633
0.1622	0.1851	0.4008
0.6932	0.7079	0.6924
0.2315	0.2035	0.1024
0.1500	0.1400	0.1015
0.0875	0.1038	0.0308
0.8377	0.8495	0.6962
0.7582	0.5761	0.4861
0.5509	0.4085	0.1790
0.1190	0.0959	0.1929
0.3649	0.2807	0.3093
0.0040	0.0063	0.0075
0.2258	0.1862	0.3019
0.2078	0.2108	0.3445
0.1001	0.1141	0.1576
0.7834	0.7292	0.5334
0.5722	0.5370	0.3465
0.4482	0.4673	0.5326
0.8935	0.9008	0.8345
0.7896	0.6976	0.1274
0.2155	0.1195	0.0437
0.3527	0.3125	0.3072
0.5778	0.6510	0.8131
0.6786	0.7492	0.8376
0.3598	0.4047	0.2629
0.3503	0.3022	0.3414
0.0151	0.0276	0.0869
0.0368	0.0203	0.0242
0.3849	0.3307	0.2510
0.6570	0.7159	0.5295
0.5196	0.5684	0.6935
0.9688	0.9706	0.8665
0.0376	0.0577	0.1296
0.2957	0.2985	0.4037
0.9569	0.9573	0.8661
0.0752	0.0463	0.0875
0.0354	0.0439	0.0863
0.1762	0.1756	0.3970
0.5464	0.3867	0.1904
0.2507	0.2499	0.3413
0.7232	0.7573	0.8323
0.5090	0.5237	0.4036
0.1347	0.0989	0.0468
0.2122	0.2996	0.4058

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.3832	0.0854

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
6.0	10.0	16.0	30.0	43.0	46.0	46.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.125	0.208	0.333	0.625	0.896	0.958	0.958

SERIAL COR.	FISHER TS.	P-V OF TS.
0.0678	139.09	0.0027

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.3731	0.0853

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
6.0	11.0	18.0	32.0	43.0	45.0	46.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.125	0.229	0.375	0.667	0.896	0.938	0.958

SERIAL COR.	FISHER TS.	P-V OF TS.
0.0842	141.89	0.0016

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.3680	0.0779

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
6.0	9.0	19.0	34.0	41.0	47.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.125	0.188	0.396	0.708	0.854	0.979	0.979

SERIAL COR.	FISHER TS.	P-V OF TS.
0.0675	138.14	0.0032

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9816

CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.8016

CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.8711

FIRST TWO HOURS OF YESTERDAY WITH TODAY
MRK

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.1663	0.1680	0.4072
0.4147	0.3848	0.2575
0.1245	0.1405	0.0306
0.0392	0.0328	0.0316
0.7738	0.6586	0.3049
0.7315	0.6192	0.1280
0.0629	0.0900	0.1823
0.8699	0.8050	0.8188
0.2002	0.2517	0.3373
0.5540	0.6401	0.6977
0.4057	0.3776	0.1964
0.0989	0.1081	0.1472
0.2287	0.2150	0.0742
0.6913	0.7525	0.8713
0.3220	0.3749	0.3040
0.2293	0.1800	0.1238
0.2406	0.2247	0.1287
0.9078	0.9217	0.9614
0.1121	0.1379	0.1899
0.0912	0.1353	0.2997
0.7069	0.7525	0.8697
0.2992	0.3170	0.0843
0.1482	0.1607	0.1865
0.0708	0.0897	0.1856
0.0359	0.0327	0.1846
0.5187	0.4811	0.1865
0.2232	0.2397	0.4000
0.0178	0.0208	0.1629
0.8970	0.8776	0.6523
0.6191	0.5089	0.3023
0.0765	0.0638	0.0427
0.7060	0.7436	0.6433
0.1760	0.1892	0.1694
0.0020	0.0037	0.0071
0.0240	0.0165	0.0263
0.4435	0.5357	0.5275
0.0392	0.0554	0.0431
0.0584	0.0336	0.0124
0.0934	0.0551	0.0295
0.4314	0.4592	0.5368
0.6413	0.7060	0.8787
0.7371	0.7491	0.6952
0.8374	0.8658	0.8668
0.4715	0.4907	0.5468
0.3447	0.3331	0.3012
0.6559	0.7353	0.8701
0.5278	0.6052	0.5257

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.3631	0.0823

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
6.0	13.0	18.0	31.0	43.0	46.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.128	0.277	0.383	0.660	0.915	0.979	1.000

SERIAL COR.	FISHER TS.	P-V OF TS.
-.0001	144.32	0.0007

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.3689	0.0828

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
6.0	11.0	19.0	31.0	43.0	46.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.128	0.234	0.404	0.660	0.915	0.979	1.000

SERIAL COR.	FISHER TS.	P-V OF TS.
0.0229	142.15	0.0010

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.3496	0.0859

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
8.0	10.0	23.0	32.0	40.0	46.0	46.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.170	0.213	0.489	0.681	0.851	0.979	0.979

SERIAL COR.	FISHER TS.	P-V OF TS.
0.0949	147.01	0.0004

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9866
CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.8094
CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.8742

TODAYS FIRST WITH YESTERDAY LAST TWO HOURS
MRK

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.3531	0.3995	0.5405
0.2036	0.2112	0.1210
0.8500	0.8795	0.8689
0.5837	0.6511	0.6429
0.9423	0.9427	0.8424
0.5025	0.5280	0.4021
0.1630	0.1918	0.4118
0.5112	0.5190	0.3442
0.1604	0.1946	0.3927
0.5482	0.5160	0.6900
0.0472	0.0680	0.1879
0.5237	0.4028	0.0230
0.1308	0.1780	0.3430
0.2781	0.3542	0.6922
0.7164	0.6480	0.5325
0.3870	0.4544	0.6936
0.5110	0.4438	0.1283
0.5269	0.5615	0.4994
0.5778	0.5965	0.4035
0.5532	0.5640	0.5441
0.7956	0.8335	0.8402
0.0774	0.0487	0.0865
0.1562	0.2360	0.4010
0.9498	0.9284	0.6893
0.2884	0.2049	0.1904
0.1561	0.1380	0.0897
0.3431	0.3576	0.3484
0.2558	0.3032	0.3947
0.4467	0.3219	0.3057
0.0815	0.0759	0.0441
0.1861	0.2535	0.1219
0.6101	0.6855	0.6552
0.3419	0.2494	0.1309
0.0370	0.0178	0.0239
0.8591	0.8737	0.7012
0.0387	0.0668	0.0423
0.0027	0.0034	0.0009
0.1733	0.1005	0.0119
0.1423	0.1016	0.1925
0.6156	0.6250	0.5320
0.4685	0.4666	0.4022
0.0222	0.0279	0.1919
0.0101	0.0161	0.0404
0.5392	0.5074	0.1237
0.3729	0.3576	0.3421
0.3340	0.4603	0.5370
0.2870	0.3376	0.2551

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.3758	0.0687

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
6.0	8.0	16.0	29.0	43.0	45.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.128	0.170	0.340	0.617	0.915	0.957	1.000

SERIAL COR.	FISHER TS.	P-V OF TS.
-.0595	132.90	0.0051

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.3809	0.0697

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
5.0	8.0	14.0	31.0	42.0	45.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.106	0.170	0.298	0.660	0.894	0.957	1.000

SERIAL COR.	FISHER TS.	P-V OF TS.
0.0271	130.81	0.0073

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.3617	0.0645

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
7.0	9.0	18.0	32.0	44.0	47.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.149	0.191	0.383	0.681	0.936	1.000	1.000

SERIAL COR.	FISHER TS.	P-V OF TS.
0.1045	141.04	0.0012

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9796
CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.7459
CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.8266

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.4023	0.1101

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
8.0	11.0	20.0	28.0	37.0	44.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.170	0.234	0.426	0.596	0.787	0.936	1.000

SERIAL COR.	FISHER TS.	P-V OF TS.
0.2283	146.22	0.0005

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.4165	0.1093

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
7.0	11.0	17.0	28.0	38.0	44.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.149	0.234	0.362	0.596	0.809	0.936	1.000

SERIAL COR.	FISHER TS.	P-V OF TS.
0.2156	137.97	0.0021

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
47	0.4074	0.0891

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
6.0	7.0	17.0	27.0	40.0	47.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.128	0.149	0.362	0.574	0.851	1.000	1.000

SERIAL COR.	FISHER TS.	P-V OF TS.
0.0936	128.24	0.0109

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9929
CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.8040
CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.8516

TODAYS FIRST TWO HOURS WITH NEXT TWO
MRK

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.5670	0.5626	0.2561
0.4919	0.5845	0.6519
0.6889	0.6179	0.6946
0.1618	0.1613	0.1255
0.6683	0.6438	0.4028
0.1049	0.1417	0.4949
0.3398	0.4184	0.6930
0.2035	0.2286	0.1858
0.6879	0.6053	0.4949
0.3481	0.3700	0.4939
0.2988	0.4333	0.6887
0.4962	0.4518	0.4063
0.5058	0.4758	0.2164
0.9212	0.9288	0.8661
0.1031	0.1477	0.3008
0.5356	0.6684	0.8663
0.1295	0.0946	0.1302
0.4549	0.5572	0.6919
0.8023	0.8250	0.8668
0.7231	0.7000	0.6460
0.6981	0.6816	0.3116
0.0605	0.0958	0.2578
0.4215	0.3617	0.4096
0.2420	0.3355	0.2612
0.5929	0.6313	0.6928
0.2993	0.1858	0.4000
0.2310	0.2642	0.1857
0.0364	0.0351	0.1613
0.2701	0.3546	0.3990
0.2943	0.3354	0.6507
0.3462	0.1650	0.1265
0.5897	0.5150	0.6529
0.5735	0.6086	0.5361
0.0080	0.0020	0.0013
0.0292	0.0232	0.0442
0.9410	0.9414	0.8314
0.0466	0.0390	0.0434
0.6168	0.6621	0.8139
0.2762	0.2763	0.3110
0.0209	0.0258	0.0847
0.1566	0.1828	0.1856
0.1823	0.1488	0.1824
0.0993	0.1134	0.1846
0.0120	0.0201	0.1173
0.2970	0.3559	0.5314
0.7361	0.8011	0.8721
0.0756	0.0995	0.2591
0.1409	0.1941	0.3437

LAST TWO HOURS OF YESTERDAY WITH TODAY
MRK

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.0956	0.1446	0.1859
0.0359	0.0485	0.0423
0.7603	0.7079	0.3581
0.8506	0.8769	0.8724
0.2835	0.2302	0.0832
0.1287	0.0736	0.0261
0.1998	0.2119	0.4086
0.9414	0.9310	0.5341
0.5965	0.6565	0.6898
0.1884	0.3004	0.5367
0.0434	0.0643	0.1332
0.0237	0.0320	0.1229
0.0528	0.0783	0.2560
0.3630	0.3844	0.6833
0.2210	0.2136	0.2503
0.5980	0.5893	0.6982
0.2659	0.2493	0.1678
0.1392	0.0778	0.0117
0.1259	0.1608	0.1892
0.8881	0.9058	0.8689
0.2370	0.2990	0.3437
0.0742	0.1256	0.1630
0.8578	0.8831	0.8739
0.8546	0.8625	0.6968
0.9084	0.8984	0.8355
0.5991	0.5792	0.6977
0.8661	0.8438	0.6891
0.8154	0.8576	0.8738
0.9162	0.9123	0.6886
0.4165	0.4065	0.2559
0.1194	0.1364	0.1292
0.7283	0.7748	0.8676
0.7674	0.7758	0.5388
0.0320	0.0388	0.1068
0.6170	0.7255	0.8736
0.0030	0.0044	0.0249
0.0009	0.0013	0.0086
0.1161	0.1158	0.1286
0.7651	0.7550	0.2518
0.5379	0.5948	0.6877
0.0351	0.0464	0.1004
0.3584	0.3956	0.5316
0.1199	0.1222	0.2543
0.8307	0.7905	0.3354
0.3100	0.4057	0.6923
0.1773	0.2508	0.3470
0.0433	0.0351	0.0329

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.3651	0.0691

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
6.0	9.0	16.0	32.0	45.0	46.0	48.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.125	0.188	0.333	0.667	0.938	0.958	1.000

SERIAL COR.	FISHER TS.	P-V OF TS.
-.0817	138.57	0.0029

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.3765	0.0697

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
6.0	9.0	18.0	31.0	44.0	46.0	48.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.125	0.188	0.375	0.646	0.917	0.958	1.000

SERIAL COR.	FISHER TS.	P-V OF TS.
-.1132	136.39	0.0043

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.4172	0.0682

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
3.0	4.0	14.0	31.0	42.0	48.0	48.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.062	0.083	0.292	0.646	0.875	1.000	1.000

SERIAL COR.	FISHER TS.	P-V OF TS.
-.1581	115.86	0.0819

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9740

CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.7662

CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.8383

TODAYS FIRST TWO HOURS WITH TODAYS 12-14
MRK

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.3180	0.3504	0.1218
0.7063	0.7679	0.8701
0.8618	0.8248	0.6885
0.3301	0.3715	0.3453
0.6017	0.5529	0.4032
0.2070	0.2481	0.4883
0.3679	0.4272	0.3507
0.5709	0.6611	0.8074
0.5097	0.3590	0.1911
0.2464	0.2809	0.3534
0.1191	0.1713	0.4034
0.5908	0.3942	0.1944
0.2899	0.2209	0.0766
0.5843	0.6152	0.6920
0.1969	0.1961	0.4068
0.5489	0.6636	0.8332
0.1175	0.0939	0.1277
0.3436	0.4631	0.5339
0.7286	0.7506	0.8093
0.8107	0.8497	0.9621
0.3815	0.3566	0.2982
0.2572	0.3361	0.5338
0.7591	0.7858	0.6910
0.4751	0.5715	0.6891
0.7367	0.7761	0.9623
0.8253	0.8088	0.5301
0.1381	0.1907	0.2486
0.0473	0.0422	0.1632
0.2142	0.2986	0.4140
0.2090	0.1933	0.1597
0.4790	0.3070	0.3082
0.7337	0.6506	0.8130
0.5055	0.4772	0.4052
0.0141	0.0099	0.0073
0.0332	0.0259	0.0463
0.9045	0.9116	0.6395
0.0374	0.0240	0.0066
0.3993	0.4276	0.2556
0.2030	0.2690	0.3060
0.0260	0.0260	0.0846
0.2336	0.2389	0.3383
0.0835	0.0922	0.1955
0.2815	0.2654	0.4135
0.0035	0.0046	0.0129
0.2207	0.2916	0.3042
0.8594	0.8740	0.8715
0.1297	0.1681	0.1019
0.1267	0.1696	0.4066

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.3827	0.0726

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
6.0	7.0	13.0	31.0	43.0	47.0	48.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.125	0.146	0.271	0.646	0.896	0.979	1.000

SERIAL COR.	FISHER TS.	P-V OF TS.
0.0616	132.82	0.0077

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.3928	0.0723

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
6.0	8.0	14.0	33.0	43.0	47.0	48.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.125	0.167	0.292	0.688	0.896	0.979	1.000

SERIAL COR.	FISHER TS.	P-V OF TS.
0.0828	130.24	0.0115

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.4139	0.0761

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
4.0	6.0	14.0	32.0	40.0	46.0	46.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.083	0.125	0.292	0.667	0.833	0.958	0.958

SERIAL COR.	FISHER TS.	P-V OF TS.
0.0560	122.33	0.0362

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9706
CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.7940
CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.8753

TODAYS FIRST TWO WITH TODAYS 13-15
MRK

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.6478	0.6449	0.6948
0.4951	0.5224	0.8149
0.4154	0.3942	0.4874
0.3042	0.3827	0.5349
0.0975	0.0927	0.1268
0.1228	0.1422	0.1872
0.3360	0.4300	0.5407
0.6804	0.5752	0.2536
0.3718	0.3538	0.3451
0.9473	0.9522	0.9815
0.2462	0.3099	0.6952
0.1979	0.2258	0.6842
0.1067	0.0728	0.0227
0.1563	0.1145	0.0848
0.9279	0.9274	0.6894
0.7534	0.7368	0.6460
0.1508	0.1450	0.1332
0.1585	0.2086	0.2586
0.6305	0.6293	0.3455
0.7538	0.7508	0.8352
0.5626	0.5302	0.8099
0.7266	0.7766	0.8732
0.7049	0.4590	0.1943
0.6649	0.7057	0.6873
0.5400	0.5749	0.3533
0.6286	0.5622	0.4088
0.3763	0.4715	0.6478
0.0164	0.0129	0.0842
0.2001	0.3035	0.5336
0.1591	0.0451	0.0326
0.5543	0.4791	0.6488
0.9215	0.9274	0.8697
0.6417	0.7279	0.6523
0.0402	0.0401	0.0414
0.0103	0.0087	0.0068
0.7649	0.6949	0.3004
0.1548	0.1884	0.1675
0.8015	0.7723	0.6540
0.5968	0.6283	0.5274
0.1518	0.2046	0.4958
0.1205	0.1258	0.3534
0.0856	0.0896	0.1860
0.3056	0.3092	0.3974
0.0266	0.0420	0.0437
0.4041	0.4521	0.5396
0.8466	0.8641	0.8712
0.7888	0.7676	0.3379
0.1860	0.2589	0.5339

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.4267	0.0837

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
4.0	6.0	17.0	27.0	43.0	45.0	48.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.083	0.125	0.354	0.562	0.896	0.938	1.000

SERIAL COR.	FISHER TS.	P-V OF TS.
0.2416	118.82	0.0572

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.4299	0.0797

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
5.0	8.0	13.0	28.0	44.0	45.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.104	0.167	0.271	0.583	0.917	0.938	0.979

SERIAL COR.	FISHER TS.	P-V OF TS.
0.2076	118.45	0.0599

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.4503	0.0757

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
5.0	7.0	13.0	25.0	41.0	47.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.104	0.146	0.271	0.521	0.854	0.979	0.979

SERIAL COR.	FISHER TS.	P-V OF TS.
0.1363	111.13	0.1385

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9776
CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.6798
CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.7680

TODAYS FIRST TWO HOURS WITH TODAYS 14-16
MRK

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.2832	0.2765	0.4097
0.6363	0.4925	0.4896
0.4121	0.4276	0.2525
0.3156	0.2382	0.1594
0.6572	0.6201	0.5328
0.1482	0.1075	0.1930
0.6168	0.5237	0.4060
0.6046	0.6294	0.3424
0.9945	0.9945	0.8694
0.7367	0.7860	0.9608
0.3838	0.4257	0.5381
0.0905	0.1062	0.1814
0.0122	0.0118	0.0242
0.3635	0.4422	0.6906
0.5937	0.6696	0.5371
0.1232	0.1042	0.1298
0.6928	0.7105	0.8336
0.3899	0.4426	0.4009
0.0198	0.0317	0.0438
0.4948	0.4894	0.4945
0.8612	0.8819	0.8706
0.6398	0.6638	0.5327
0.7009	0.7312	0.6938
0.1815	0.2039	0.1870
0.4660	0.5462	0.6935
0.3602	0.1801	0.1928
0.2657	0.3326	0.4897
0.3884	0.4604	0.5388
0.5297	0.5939	0.6537
0.4949	0.4593	0.3493
0.3346	0.3276	0.4000
0.9337	0.9367	0.8659
0.9008	0.9179	0.9638
0.8497	0.8419	0.8270
0.0226	0.0151	0.0066
0.5879	0.5897	0.3075
0.5861	0.5371	0.4037
0.3454	0.3918	0.6900
0.8464	0.7973	0.8090
0.4102	0.3173	0.3032
0.1617	0.1830	0.3476
0.0471	0.0516	0.1324
0.0365	0.0610	0.1893
0.0906	0.0879	0.0466
0.7435	0.7751	0.6926
0.7313	0.7583	0.6961
0.9756	0.9781	0.8669
0.6194	0.5052	0.3489

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.4725	0.0796

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
5.0	7.0	11.0	26.0	41.0	44.0	46.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.104	0.146	0.229	0.542	0.854	0.917	0.958

SERIAL COR.	FISHER TS.	P-V OF TS.
0.2506	105.74	0.2333

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.4720	0.0816

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
3.0	6.0	11.0	26.0	42.0	44.0	46.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.062	0.125	0.229	0.542	0.875	0.917	0.958

SERIAL COR.	FISHER TS.	P-V OF TS.
0.2285	105.67	0.2347

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.4706	0.0751

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
4.0	4.0	12.0	27.0	39.0	46.0	46.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.083	0.083	0.250	0.562	0.812	0.958	0.958

SERIAL COR.	FISHER TS.	P-V OF TS.
0.1417	101.59	0.3287

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9806
CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.8545
CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.9039

TODAYS 10-12 WITH TODAYS 12-14
MRK

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.3585	0.3643	0.1265
0.3752	0.4396	0.5348
0.4151	0.4364	0.4109
0.1965	0.1877	0.1716
0.8887	0.9052	0.8402
0.5815	0.6807	0.8670
0.1484	0.1931	0.0391
0.6609	0.6512	0.6525
0.5288	0.4341	0.3959
0.2144	0.2543	0.3493
0.4943	0.6073	0.9605
0.0875	0.0397	0.0259
0.3354	0.3677	0.0808
0.0477	0.0589	0.0883
0.2994	0.2550	0.4089
0.7787	0.7949	0.5332
0.2818	0.2315	0.3432
0.3090	0.2563	0.1014
0.3692	0.3984	0.3986
0.7950	0.8359	0.8715
0.3622	0.2605	0.1894
0.3718	0.4740	0.8699
0.5360	0.5753	0.3993
0.7199	0.6388	0.4876
0.8417	0.8609	0.9638
0.8696	0.8664	0.5293
0.2885	0.3550	0.2508
0.3696	0.4244	0.6929
0.2466	0.3168	0.4005
0.2184	0.2068	0.1672
0.3732	0.2266	0.3962
0.4923	0.5217	0.3992
0.2172	0.2567	0.1847
0.1635	0.1825	0.1227
0.0893	0.0886	0.1849
0.7888	0.6608	0.3427
0.0867	0.0582	0.0282
0.4667	0.5288	0.2562
0.3674	0.4294	0.5355
0.0898	0.0742	0.1958
0.1751	0.2134	0.3442
0.1161	0.1300	0.1656
0.2176	0.2242	0.4120
0.0323	0.0318	0.0127
0.4296	0.4794	0.5402
0.8236	0.8172	0.8359
0.3017	0.2952	0.0920
0.1401	0.1030	0.1036

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.3825	0.0588

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
2.0	6.0	12.0	36.0	44.0	48.0	48.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.042	0.125	0.250	0.750	0.917	1.000	1.000

SERIAL COR.	FISHER TS.	P-V OF TS.
0.0981	115.72	0.0833

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.3894	0.0611

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
2.0	6.0	11.0	34.0	43.0	47.0	48.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.042	0.125	0.229	0.708	0.896	0.979	1.000

SERIAL COR.	FISHER TS.	P-V OF TS.
0.0616	116.19	0.0788

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.3813	0.0741

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
4.0	7.0	18.0	34.0	41.0	46.0	46.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.083	0.146	0.375	0.708	0.854	0.958	0.958

SERIAL COR.	FISHER TS.	P-V OF TS.
-.0619	127.18	0.0182

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9739

CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.7372

CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.8041

TODAYS 10-12 WITH TODAYS 13-15
MRK

P-VALUES

L1-NORM	L2-NORM	MAX-NORM
0.4772	0.5139	0.6920
0.1282	0.1346	0.1882
0.1297	0.0914	0.0432
0.2029	0.2125	0.2502
0.4257	0.4270	0.3425
0.3139	0.4385	0.5475
0.0615	0.0825	0.0986
0.2631	0.1238	0.0300
0.7322	0.6434	0.4905
0.9226	0.9302	0.8711
0.6978	0.7503	0.8674
0.0667	0.0752	0.1297
0.1576	0.1727	0.0224
0.0042	0.0042	0.0069
0.9681	0.9692	0.9613
0.9130	0.9202	0.8313
0.3252	0.3206	0.3431
0.1192	0.0655	0.0317
0.2356	0.3191	0.1266
0.7613	0.7543	0.8377
0.6216	0.4985	0.4063
0.8250	0.8555	0.8726
0.0607	0.0567	0.0236
0.6413	0.6045	0.2532
0.6119	0.6383	0.3381
0.7771	0.7810	0.6892
0.5966	0.6151	0.6904
0.1729	0.1933	0.3057
0.2336	0.3402	0.2433
0.1751	0.0480	0.0303
0.4061	0.3348	0.4107
0.8151	0.7520	0.3383
0.8463	0.8667	0.9602
0.3883	0.4903	0.5340
0.0343	0.0325	0.0266
0.3832	0.3172	0.1267
0.4323	0.4124	0.3458
0.9011	0.8619	0.6456
0.8869	0.8651	0.5419
0.4624	0.4998	0.5359
0.0520	0.0620	0.1256
0.1134	0.1110	0.3444
0.1575	0.2293	0.3476
0.1450	0.1521	0.0455
0.7302	0.7725	0.6516
0.7526	0.7653	0.8394
0.6926	0.5569	0.1578
0.2641	0.1957	0.0979

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.4393	0.0917

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
2.0	6.0	15.0	29.0	40.0	44.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.042	0.125	0.312	0.604	0.833	0.917	0.979

SERIAL COR.	FISHER TS.	P-V OF TS.
0.3412	116.32	0.0776

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.4345	0.0918

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
3.0	9.0	16.0	29.0	41.0	45.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.062	0.188	0.333	0.604	0.854	0.938	0.979

SERIAL COR.	FISHER TS.	P-V OF TS.
0.2871	119.63	0.0515

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.3883	0.0903

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
9.0	11.0	17.0	31.0	40.0	46.0	46.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.188	0.229	0.354	0.646	0.833	0.958	0.958

SERIAL COR.	FISHER TS.	P-V OF TS.
0.1485	140.15	0.0022

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9811

CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.8265

CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.8835

TODAYS 10-12 WITH TODAYS 14-16
MRK

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.1621	0.1675	0.3524
0.0372	0.0374	0.0873
0.1627	0.1994	0.2526
0.2885	0.1717	0.1658
0.9526	0.9568	0.8704
0.2170	0.1830	0.1867
0.1032	0.0738	0.0426
0.3697	0.4087	0.5337
0.7320	0.7766	0.6892
0.6898	0.7613	0.8723
0.2383	0.3140	0.3466
0.0399	0.0627	0.1022
0.0206	0.0245	0.0224
0.1013	0.1410	0.1552
0.6689	0.7346	0.8332
0.0703	0.0510	0.0294
0.8453	0.7521	0.4122
0.3104	0.2527	0.1631
0.0144	0.0238	0.0454
0.4456	0.4699	0.4919
0.6651	0.6567	0.6957
0.5817	0.6029	0.4906
0.2335	0.2665	0.4038
0.9701	0.9709	0.8704
0.5894	0.6581	0.6899
0.7510	0.7177	0.6898
0.3844	0.4674	0.6946
0.9169	0.9275	0.8680
0.6185	0.7096	0.5434
0.5270	0.5159	0.3465
0.2160	0.1633	0.1886
0.8387	0.8688	0.8720
0.5330	0.6170	0.5387
0.6173	0.6387	0.5460
0.0734	0.0545	0.0281
0.1152	0.1747	0.1305
0.1813	0.2454	0.2617
0.3054	0.3662	0.6950
0.9181	0.8598	0.8128
0.6742	0.7013	0.3050
0.0535	0.0907	0.1305
0.0308	0.0394	0.1302
0.0118	0.0227	0.0125
0.1533	0.1619	0.1619
0.9788	0.9798	0.8686
0.9928	0.9928	0.9642
0.7260	0.7444	0.5297
0.0273	0.0405	0.0492

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.4199	0.1066

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
7.0	10.0	17.0	27.0	40.0	42.0	44.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.146	0.208	0.354	0.562	0.833	0.875	0.917

SERIAL COR.	FISHER TS.	P-V OF TS.
0.2116	134.04	0.0063

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.4337	0.1077

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
6.0	11.0	19.0	27.0	41.0	43.0	44.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.125	0.229	0.396	0.562	0.854	0.896	0.917

SERIAL COR.	FISHER TS.	P-V OF TS.
0.2250	126.69	0.0196

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.4203	0.0922

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
7.0	8.0	18.0	28.0	39.0	47.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.146	0.167	0.375	0.583	0.812	0.979	0.979

SERIAL COR.	FISHER TS.	P-V OF TS.
0.2793	125.71	0.0226

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9907

CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.8979

CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.9258

TODAYS 11-13 WITH TODAYS 13-15
MRK

P-VALUES

L1-NORM	L2-NORM	MAX-NORM
0.4420	0.5072	0.6901
0.2416	0.2332	0.1932
0.3916	0.3314	0.4920
0.9530	0.9540	0.8686
0.0639	0.0784	0.1257
0.2141	0.2417	0.2563
0.1536	0.1814	0.3998
0.0008	0.0006	0.0017
0.8677	0.8083	0.3453
0.0355	0.0344	0.0451
0.5973	0.6924	0.8680
0.2580	0.2663	0.1626
0.8609	0.8371	0.6618
0.0076	0.0088	0.0055
0.4316	0.3548	0.2582
0.7346	0.7480	0.8163
0.7792	0.7286	0.4988
0.3905	0.3260	0.1274
0.1715	0.1831	0.0334
0.9707	0.9720	0.9598
0.5822	0.6158	0.8397
0.8850	0.9024	0.8132
0.0416	0.0292	0.0066
0.3948	0.3816	0.2495
0.9437	0.9446	0.8382
0.7014	0.7377	0.5302
0.7710	0.6635	0.6966
0.4101	0.4218	0.2998
0.5696	0.6119	0.5416
0.2339	0.1971	0.2508
0.6504	0.6954	0.6958
0.8043	0.5528	0.1280
0.8967	0.8644	0.6558
0.0325	0.0506	0.1697
0.5602	0.5663	0.4059
0.7115	0.6215	0.2604
0.9546	0.9443	0.8364
0.4203	0.4434	0.3465
0.8982	0.9143	0.8731
0.3872	0.4913	0.6497
0.3365	0.3401	0.6927
0.5828	0.5549	0.6844
0.5661	0.6179	0.6927
0.8089	0.6758	0.4072
0.7307	0.7668	0.6525
0.6589	0.6410	0.6459
0.3100	0.1929	0.0414
0.9061	0.9192	0.8680

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.5274	0.0909

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
5.0	6.0	8.0	22.0	36.0	43.0	45.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.104	0.125	0.167	0.458	0.750	0.896	0.938

SERIAL COR.	FISHER TS.	P-V OF TS.
-.1568	101.73	0.3251

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.5176	0.0880

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
4.0	6.0	10.0	21.0	38.0	41.0	46.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.083	0.125	0.208	0.438	0.792	0.854	0.958

SERIAL COR.	FISHER TS.	P-V OF TS.
-.2166	103.34	0.2863

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.4705	0.0876

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
6.0	6.0	12.0	25.0	38.0	47.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.125	0.125	0.250	0.521	0.792	0.979	0.979

SERIAL COR.	FISHER TS.	P-V OF TS.
-.1795	118.23	0.0615

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9796

CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.7629

CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.8448

TODAYS 11-13 WITH TODAYS 14-16
MRK

P-VALUES

L1-NORM	L2-NORM	MAX-NORM
0.0780	0.0982	0.2579
0.0578	0.0668	0.1812
0.3566	0.4536	0.2564
0.9643	0.9577	0.6481
0.2754	0.3706	0.5380
0.0115	0.0143	0.0427
0.1675	0.1147	0.0442
0.0176	0.0178	0.0884
0.7638	0.7249	0.4071
0.3349	0.3582	0.3492
0.0472	0.0465	0.1212
0.1175	0.1544	0.3308
0.1782	0.2259	0.3306
0.0847	0.1109	0.1602
0.5335	0.4394	0.2482
0.0567	0.0792	0.1299
0.3127	0.2582	0.1252
0.5260	0.5729	0.6867
0.0103	0.0105	0.0087
0.8852	0.8810	0.8326
0.8492	0.8715	0.8641
0.3881	0.2966	0.1898
0.1781	0.2219	0.1637
0.7811	0.7267	0.6977
0.9636	0.9623	0.8396
0.5043	0.4162	0.2623
0.7175	0.5858	0.6940
0.7138	0.7701	0.8713
0.8320	0.8158	0.4951
0.7176	0.7732	0.8653
0.2453	0.2890	0.4009
0.6309	0.6073	0.5392
0.4803	0.5150	0.5374
0.0294	0.0198	0.0452
0.8380	0.7730	0.4102
0.3963	0.4356	0.4924
0.0087	0.0100	0.0089
0.1111	0.1413	0.2591
0.7694	0.6966	0.8186
0.6320	0.6749	0.6578
0.3770	0.4163	0.6970
0.0377	0.0400	0.0964
0.0302	0.0387	0.1236
0.2528	0.2954	0.3501
0.9798	0.9739	0.6494
0.9971	0.9971	0.8712
0.1253	0.1683	0.1313
0.0757	0.1014	0.1912

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.4050	0.1097

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
8.0	13.0	19.0	29.0	40.0	44.0	44.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.167	0.271	0.396	0.604	0.833	0.917	0.917

SERIAL COR.	FISHER TS.	P-V OF TS.
0.2094	144.99	0.0009

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.4081	0.1030

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
8.0	11.0	17.0	30.0	41.0	44.0	44.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.167	0.229	0.354	0.625	0.854	0.917	0.917

SERIAL COR.	FISHER TS.	P-V OF TS.
0.2290	139.93	0.0023

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.3960	0.0778

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
5.0	7.0	17.0	31.0	41.0	48.0	48.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.104	0.146	0.354	0.646	0.854	1.000	1.000

SERIAL COR.	FISHER TS.	P-V OF TS.
0.1622	127.15	0.0183

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9894
CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.8538
CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.8885

TODAYS 12-14 WITH TODAYS 14-16
MRK

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.0442	0.0625	0.1272
0.2025	0.2392	0.4047
0.1595	0.2011	0.1283
0.8231	0.8100	0.3426
0.8747	0.8793	0.8349
0.0668	0.0758	0.1284
0.1784	0.2276	0.4028
0.3531	0.3899	0.3445
0.6948	0.5811	0.0875
0.5880	0.5961	0.3451
0.0240	0.0393	0.1363
0.1126	0.1375	0.4015
0.1829	0.2379	0.3406
0.2360	0.2485	0.7005
0.2731	0.3002	0.4065
0.1046	0.1419	0.2978
0.1970	0.1158	0.0302
0.6566	0.7206	0.8687
0.0116	0.0139	0.0121
0.8597	0.8629	0.8379
0.3932	0.4543	0.6943
0.1243	0.0757	0.1831
0.7230	0.7831	0.8674
0.4955	0.3199	0.1912
0.9831	0.9839	0.9933
0.3340	0.3110	0.4006
0.7745	0.7708	0.5329
0.2779	0.3638	0.7010
0.7943	0.8323	0.9622
0.5829	0.5037	0.3414
0.5555	0.5255	0.5374
0.4243	0.3567	0.3998
0.4232	0.3933	0.1836
0.0628	0.0595	0.0983
0.7237	0.7046	0.4083
0.6160	0.5901	0.4920
0.0029	0.0027	0.0019
0.0996	0.1282	0.2518
0.1796	0.2268	0.2515
0.4659	0.4512	0.6517
0.5572	0.5004	0.3957
0.0475	0.0338	0.0441
0.2550	0.2590	0.2545
0.0539	0.0797	0.1281
0.6744	0.6826	0.5349
0.8915	0.8994	0.8123
0.0912	0.0979	0.0320
0.1147	0.0975	0.1893

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.3826	0.0856

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
5.0	10.0	19.0	31.0	43.0	47.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.104	0.208	0.396	0.646	0.896	0.979	0.979

SERIAL COR.	FISHER TS.	P-V OF TS.
0.0298	138.95	0.0027

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.3827	0.0828

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
4.0	11.0	15.0	31.0	42.0	47.0	47.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.083	0.229	0.312	0.646	0.875	0.979	0.979

SERIAL COR.	FISHER TS.	P-V OF TS.
-.0602	136.11	0.0045

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
48	0.3898	0.0762

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
5.0	7.0	16.0	34.0	41.0	46.0	46.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.104	0.146	0.333	0.708	0.854	0.958	0.958

SERIAL COR.	FISHER TS.	P-V OF TS.
-.1615	130.77	0.0106

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9864
CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.7296
CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.7963

FIRST TWO HOURS OF YESTERDAY WITH TODAY

BA

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.5438	0.5697	0.3471
0.1617	0.1452	0.1622
0.9612	0.9635	0.9929
0.0883	0.1345	0.4015
0.2601	0.2433	0.1889
0.3031	0.3475	0.6935
0.5764	0.4848	0.4853
0.8965	0.8983	0.8382
0.9858	0.9858	0.8684
0.5337	0.5749	0.6539
0.5822	0.6197	0.4905
0.2767	0.3819	0.6895
0.1300	0.1827	0.2492
0.3172	0.2544	0.1258
0.3615	0.4207	0.4081
0.2681	0.3205	0.3004
0.2152	0.2463	0.2989
0.1104	0.1791	0.3429
0.0511	0.0675	0.1286
0.7192	0.7420	0.5352
0.4644	0.4205	0.4961
0.4186	0.5334	0.5340
0.6053	0.4172	0.1261
0.4211	0.5336	0.6873
0.7698	0.8048	0.5374
0.7357	0.7286	0.5422
0.7881	0.8036	0.5295
0.8250	0.8091	0.5301
0.8020	0.8271	0.5360
0.7382	0.7155	0.3023
0.3879	0.4282	0.4590
0.3400	0.2358	0.1858
0.0782	0.0885	0.0421
0.1105	0.1174	0.0955
0.3133	0.4144	0.5383
0.3186	0.3863	0.5275
0.4088	0.3852	0.3497
0.2433	0.3282	0.5318
0.7478	0.7864	0.6975
0.1075	0.1497	0.3475
0.0820	0.0656	0.0326
0.8243	0.8504	0.8721
0.8468	0.8191	0.4108
0.9241	0.9178	0.2615
0.9976	0.9976	0.8713

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
45	0.4809	0.0865

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
0.0	4.0	9.0	25.0	36.0	41.0	42.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.000	0.089	0.200	0.556	0.800	0.911	0.933

SERIAL COR.	FISHER TS.	P-V OF TS.
0.4060	89.02	0.5093

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
45	0.4961	0.0819

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
0.0	3.0	9.0	25.0	34.0	41.0	42.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.000	0.067	0.200	0.556	0.756	0.911	0.933

SERIAL COR.	FISHER TS.	P-V OF TS.
0.3854	83.19	0.6813

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
45	0.4499	0.0573

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
2.0	3.0	9.0	25.0	40.0	44.0	44.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.044	0.067	0.200	0.556	0.889	0.978	0.978

SERIAL COR.	FISHER TS.	P-V OF TS.
0.0369	90.51	0.4649

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9810
CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.6389
CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.7248

TODAYS FIRST WITH YESTERDAY LAST TWO HOURS

BA

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.0462	0.0655	0.1593
0.4080	0.2138	0.0435
0.4019	0.4616	0.5302
0.4059	0.3024	0.3959
0.5737	0.5309	0.3106
0.2279	0.2321	0.4021
0.6921	0.6908	0.5474
0.4671	0.5718	0.6480
0.8091	0.7919	0.5236
0.2024	0.2791	0.3095
0.8051	0.7322	0.6901
0.4521	0.4747	0.4022
0.0631	0.0940	0.2543
0.7175	0.6239	0.3997
0.1094	0.1470	0.3406
0.7596	0.6491	0.4980
0.2722	0.1702	0.1283
0.4932	0.5035	0.4994
0.6379	0.7053	0.8181
0.2111	0.2933	0.4086
0.5610	0.4292	0.1646
0.8148	0.8464	0.8705
0.2666	0.2400	0.4010
0.5566	0.6288	0.6893
0.9036	0.9197	0.8723
0.7410	0.7360	0.8373
0.2865	0.2846	0.2596
0.7842	0.8178	0.8667
0.5545	0.5517	0.1269
0.2289	0.3239	0.2509
0.3885	0.3346	0.1581
0.3981	0.5016	0.4981
0.0220	0.0188	0.0444
0.9715	0.9728	0.8700
0.2175	0.2006	0.1914
0.3484	0.3528	0.3979
0.2003	0.1727	0.4003
0.2811	0.2529	0.0902
0.3044	0.3378	0.2594
0.7066	0.7442	0.6900
0.1046	0.1084	0.1883
0.8809	0.8182	0.5281
0.8301	0.8606	0.8643
0.7412	0.6303	0.3463
0.0854	0.0959	0.1230

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
45	0.4652	0.0729

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
2.0	4.0	6.0	26.0	38.0	43.0	44.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.044	0.089	0.133	0.578	0.844	0.956	0.978

SERIAL COR.	FISHER TS.	P-V OF TS.
-.3076	92.10	0.4188

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
45	0.4603	0.0704

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
1.0	4.0	8.0	24.0	39.0	43.0	44.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.022	0.089	0.178	0.533	0.867	0.956	0.978

SERIAL COR.	FISHER TS.	P-V OF TS.
-.2207	91.69	0.4307

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
45	0.4289	0.0632

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
2.0	3.0	11.0	30.0	38.0	45.0	45.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.044	0.067	0.244	0.667	0.844	1.000	1.000

SERIAL COR.	FISHER TS.	P-V OF TS.
-.1135	96.32	0.3051

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9698
CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.7415
CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.8380

LAST TWO HOURS OF YESTERDAY WITH TODAY

BA

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.0713	0.0791	0.0440
0.0245	0.0182	0.0083
0.8657	0.8680	0.7001
0.5833	0.4785	0.0447
0.7063	0.6662	0.6878
0.5751	0.5567	0.4034
0.4626	0.4848	0.6968
0.2418	0.3121	0.3411
0.3811	0.3681	0.2581
0.6465	0.6667	0.6942
0.6335	0.7051	0.6913
0.2624	0.3357	0.4033
0.8598	0.8814	0.8607
0.5963	0.5609	0.6833
0.6341	0.6728	0.6868
0.6331	0.6333	0.4884
0.7019	0.4326	0.1308
0.7805	0.7182	0.2558
0.4118	0.3057	0.3035
0.2671	0.2773	0.1706
0.7411	0.6579	0.3437
0.5949	0.6313	0.6906
0.9808	0.9816	0.9823
0.9261	0.9319	0.8698
0.6658	0.6744	0.4045
0.6063	0.6560	0.6977
0.1799	0.1695	0.0470
0.7003	0.4851	0.1677
0.1859	0.2543	0.2514
0.1602	0.2213	0.2559
0.8175	0.7918	0.8359
0.0951	0.1523	0.2574
0.1512	0.1773	0.4066
0.1597	0.1185	0.0473
0.0286	0.0251	0.0073
0.1493	0.2005	0.3992
0.2523	0.1684	0.1005
0.1251	0.0947	0.0323
0.8864	0.8945	0.7001
0.9342	0.9432	0.8746
0.5206	0.6158	0.8415
0.4373	0.4824	0.4014
0.8679	0.8832	0.8666
0.6553	0.5947	0.4815
0.0867	0.1042	0.1692

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
45	0.4944	0.0847

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
2.0	5.0	12.0	20.0	37.0	42.0	44.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.044	0.111	0.267	0.444	0.822	0.933	0.978

SERIAL COR.	FISHER TS.	P-V OF TS.
0.2647	89.97	0.4810

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
45	0.4874	0.0805

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
2.0	4.0	10.0	23.0	38.0	42.0	44.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.044	0.089	0.222	0.511	0.844	0.933	0.978

SERIAL COR.	FISHER TS.	P-V OF TS.
0.3106	90.40	0.4684

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
45	0.4374	0.0863

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
7.0	7.0	12.0	28.0	38.0	44.0	44.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.156	0.156	0.267	0.622	0.844	0.978	0.978

SERIAL COR.	FISHER TS.	P-V OF TS.
0.2474	113.61	0.0470

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9706
CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.7473
CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.8534

TODAYS FIRST TWO HOURS WITH NEXT TWO

BA

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.3480	0.4119	0.6956
0.0426	0.0670	0.1843
0.4421	0.3872	0.1573
0.8258	0.8625	0.8671
0.7050	0.7491	0.5344
0.2284	0.3183	0.5420
0.0589	0.0427	0.0857
0.7936	0.8165	0.6962
0.5451	0.6628	0.8405
0.8442	0.8457	0.8133
0.3020	0.3607	0.4928
0.8224	0.8116	0.8357
0.5333	0.4025	0.1267
0.8516	0.8339	0.6503
0.2296	0.2438	0.1832
0.5181	0.5468	0.6928
0.8916	0.8268	0.3469
0.9596	0.9616	0.9618
0.1445	0.1950	0.1234
0.1179	0.1042	0.1259
0.0444	0.0689	0.3546
0.7742	0.7804	0.8303
0.2017	0.2863	0.6990
0.2694	0.3421	0.5406
0.4886	0.5395	0.4886
0.9219	0.9196	0.8143
0.8017	0.8113	0.5288
0.5868	0.3824	0.1215
0.0883	0.0491	0.0298
0.5813	0.4987	0.3994
0.9591	0.9635	0.8715
0.4642	0.3682	0.4088
0.2591	0.2812	0.3995
0.3274	0.3327	0.2983
0.1270	0.1397	0.4058
0.3546	0.3842	0.3350
0.3550	0.2707	0.4021
0.3352	0.3097	0.2603
0.2581	0.3527	0.6937
0.5993	0.5970	0.6956
0.1987	0.1357	0.1263
0.5980	0.5748	0.2502
0.6053	0.5196	0.4041
0.8759	0.8839	0.6874
0.1311	0.1799	0.3415
0.6887	0.7343	0.6928

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
46	0.4804	0.0822

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
2.0	4.0	9.0	24.0	36.0	43.0	44.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.043	0.087	0.196	0.522	0.783	0.935	0.957

SERIAL COR.	FISHER TS.	P-V OF TS.
0.0518	91.54	0.4940

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
46	0.4817	0.0798

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
2.0	4.0	9.0	26.0	35.0	43.0	44.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.043	0.087	0.196	0.565	0.761	0.935	0.957

SERIAL COR.	FISHER TS.	P-V OF TS.
0.0374	90.13	0.5357

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
46	0.4790	0.0680

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
1.0	2.0	10.0	25.0	38.0	45.0	45.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.022	0.043	0.217	0.543	0.826	0.978	0.978

SERIAL COR.	FISHER TS.	P-V OF TS.
-.0528	87.61	0.6100

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9765
CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.6561
CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.7655

TODAYS FIRST TWO HOURS WITH TODAYS 12-14

BA

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.2888	0.3215	0.4888
0.0665	0.0810	0.1941
0.3944	0.5211	0.5290
0.9419	0.9492	0.8784
0.4572	0.5171	0.6906
0.1919	0.2523	0.5346
0.3273	0.3335	0.4130
0.9699	0.9715	0.8640
0.6800	0.7288	0.6910
0.8643	0.8619	0.8140
0.3958	0.2232	0.1916
0.9051	0.8560	0.6941
0.9245	0.9232	0.5327
0.9161	0.9282	0.8663
0.3604	0.1906	0.0463
0.8781	0.8941	0.8674
0.8911	0.8197	0.3436
0.7134	0.7882	0.8756
0.2564	0.3037	0.3400
0.0602	0.0436	0.0489
0.2312	0.3124	0.3953
0.4690	0.4371	0.3043
0.2464	0.3326	0.6910
0.3872	0.4522	0.6891
0.3444	0.3869	0.4897
0.6882	0.7476	0.8669
0.5188	0.4914	0.2486
0.6734	0.6851	0.6942
0.1773	0.1601	0.1324
0.2010	0.1912	0.3012
0.9696	0.9698	0.8666
0.6131	0.4761	0.4971
0.3669	0.4775	0.5399
0.4288	0.3960	0.3074
0.4484	0.4981	0.6939
0.3027	0.3991	0.5300
0.1050	0.1362	0.1256
0.1206	0.1303	0.0972
0.5119	0.6476	0.8730
0.1864	0.2043	0.4083
0.2614	0.3655	0.5294
0.5570	0.6254	0.5487
0.2774	0.2708	0.1709
0.7916	0.7391	0.4008
0.3709	0.4515	0.5371
0.4127	0.4593	0.4050

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
46	0.4814	0.0761

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
0.0	2.0	7.0	28.0	37.0	40.0	44.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.000	0.043	0.152	0.609	0.804	0.870	0.957

SERIAL COR.	FISHER TS.	P-V OF TS.
0.2751	85.65	0.6664

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
46	0.4989	0.0736

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
1.0	2.0	7.0	28.0	37.0	41.0	44.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.022	0.043	0.152	0.609	0.804	0.891	0.957

SERIAL COR.	FISHER TS.	P-V OF TS.
0.1043	81.58	0.7734

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
46	0.5054	0.0639

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
2.0	3.0	8.0	22.0	37.0	46.0	46.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.043	0.065	0.174	0.478	0.804	1.000	1.000

SERIAL COR.	FISHER TS.	P-V OF TS.
-.2183	80.48	0.7989

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9699

CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.6813

CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.7982

TODAYS FIRST TWO WITH TODAYS 13-15

BA

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.1000	0.0945	0.1888
0.1750	0.2033	0.4083
0.6032	0.7051	0.9632
0.8827	0.8820	0.8334
0.0543	0.0858	0.1897
0.1788	0.2316	0.2980
0.8592	0.8607	0.6894
0.9265	0.9354	0.8659
0.8449	0.8271	0.6951
0.2566	0.2834	0.1641
0.3420	0.1571	0.1816
0.3804	0.2754	0.1834
0.9338	0.9379	0.8679
0.9196	0.9351	0.8687
0.2152	0.2652	0.1697
0.5670	0.4657	0.4029
0.4706	0.5622	0.6967
0.6165	0.5888	0.3469
0.2991	0.3792	0.5312
0.0447	0.0479	0.1651
0.8343	0.8511	0.6854
0.2763	0.2833	0.0962
0.1061	0.1886	0.3542
0.2200	0.2444	0.1839
0.9626	0.9598	0.8422
0.7227	0.6337	0.4088
0.9149	0.9195	0.8301
0.5127	0.4586	0.3371
0.2487	0.2493	0.2539
0.0688	0.0784	0.0464
0.9895	0.9895	0.8643
0.2512	0.3023	0.2538
0.8488	0.7918	0.6937
0.2128	0.2213	0.0969
0.5588	0.5530	0.4950
0.1346	0.1876	0.4873
0.4654	0.3701	0.3485
0.3773	0.3978	0.6923
0.5913	0.5221	0.1660
0.5455	0.5482	0.4958
0.6632	0.7274	0.6889
0.7991	0.8143	0.8341
0.2274	0.2176	0.0993
0.4279	0.4407	0.2567
0.1683	0.1797	0.4024
0.4800	0.5211	0.3999

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
46	0.4843	0.0891

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
1.0	4.0	9.0	25.0	35.0	40.0	44.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.022	0.087	0.196	0.543	0.761	0.870	0.957

SERIAL COR.	FISHER TS.	P-V OF TS.
-.0152	90.74	0.5175

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
46	0.4864	0.0861

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
1.0	4.0	8.0	25.0	35.0	40.0	44.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.022	0.087	0.174	0.543	0.761	0.870	0.957

SERIAL COR.	FISHER TS.	P-V OF TS.
0.0076	87.81	0.6044

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
46	0.4570	0.0748

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
1.0	4.0	13.0	29.0	37.0	45.0	45.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.022	0.087	0.283	0.630	0.804	0.978	0.978

SERIAL COR.	FISHER TS.	P-V OF TS.
-.1120	92.81	0.4568

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9826

CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.8127

CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.8703

TODAYS FIRST TWO HOURS WITH TODAYS 14-16

BA

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.2085	0.2059	0.4097
0.7585	0.8060	0.8326
0.6571	0.6846	0.5310
0.6250	0.6397	0.3884
0.0677	0.0349	0.0422
0.3869	0.3275	0.0997
0.9254	0.9325	0.8711
0.9227	0.9275	0.8642
0.6411	0.6556	0.5360
0.8004	0.8016	0.6571
0.4832	0.5707	0.6880
0.6892	0.5941	0.3961
0.8662	0.8817	0.8686
0.2748	0.2510	0.4013
0.1972	0.2111	0.4006
0.3831	0.3630	0.3461
0.3120	0.3400	0.2557
0.4394	0.3794	0.1260
0.3927	0.4288	0.4884
0.0632	0.0717	0.0430
0.9692	0.9707	0.8706
0.9939	0.9939	0.8682
0.5324	0.5139	0.5434
0.1584	0.2020	0.1870
0.9790	0.9804	0.9607
0.3271	0.3547	0.3066
0.5959	0.5878	0.4897
0.6318	0.4589	0.3545
0.3367	0.4260	0.5401
0.0515	0.0766	0.1308
0.8992	0.9184	0.9844
0.3776	0.4554	0.5301
0.0839	0.1020	0.1954
0.0988	0.1106	0.0993
0.2274	0.1764	0.0488
0.0628	0.1022	0.1888
0.7630	0.7994	0.8711
0.6274	0.5317	0.3446
0.8857	0.7836	0.3347
0.4283	0.5095	0.4869
0.7076	0.7539	0.8346
0.3777	0.3247	0.2667
0.8480	0.8716	0.9619
0.5513	0.4888	0.2607
0.0801	0.0938	0.0935
0.9893	0.9893	0.8682

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
46	0.5147	0.0917

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
0.0	7.0	9.0	23.0	35.0	40.0	42.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.000	0.152	0.196	0,500	0.761	0.870	0.913

SERIAL COR.	FISHER TS.	P-V OF TS.
0.0197	86.25	0.6493

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
46	0.5149	0.0904

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
1.0	4.0	8.0	23.0	35.0	39.0	42.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.022	0.087	0.174	0.500	0.761	0.848	0.913

SERIAL COR.	FISHER TS.	P-V OF TS.
0.0140	84.89	0.6875

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
46	0.4754	0.0867

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
3.0	6.0	11.0	27.0	34.0	43.0	43.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.065	0.130	0.239	0.587	0.739	0.935	0.935

SERIAL COR.	FISHER TS.	P-V OF TS.
-.0599	93.93	0.4245

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9852
CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.8436
CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.9029

TODAYS 10-12 WITH TODAYS 12-14

BA

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.5055	0.5283	0.4014
0.1157	0.1517	0.1326
0.2339	0.1717	0.1929
0.9426	0.9489	0.8720
0.1581	0.2029	0.4005
0.2794	0.3813	0.5394
0.9450	0.9486	0.8699
0.6172	0.7081	0.8159
0.6208	0.6221	0.6910
0.4344	0.3760	0.1937
0.2769	0.2282	0.1815
0.9634	0.9616	0.5323
0.9772	0.9777	0.9609
0.5249	0.4558	0.2570
0.1187	0.0683	0.0314
0.7847	0.7055	0.4873
0.2089	0.2057	0.1634
0.6439	0.6154	0.6962
0.5656	0.6585	0.8699
0.1907	0.1400	0.1869
0.7046	0.7021	0.3979
0.0261	0.0191	0.0135
0.3548	0.3938	0.6947
0.4129	0.4392	0.4044
0.8547	0.8621	0.8356
0.1577	0.2247	0.5293
0.4445	0.4016	0.2508
0.7456	0.8084	0.9591
0.7934	0.7974	0.5362
0.2256	0.2115	0.3029
0.9626	0.9635	0.8713
0.8804	0.8058	0.8096
0.7041	0.6636	0.5252
0.5307	0.4560	0.3015
0.8603	0.8787	0.9841
0.3145	0.4546	0.5400
0.0554	0.0719	0.0404
0.0378	0.0521	0.0991
0.7314	0.6895	0.8114
0.1054	0.1389	0.4086
0.5314	0.6337	0.5352
0.4140	0.3998	0.4138
0.2591	0.2257	0.1666
0.6663	0.6529	0.3961
0.8282	0.7166	0.1294
0.5146	0.5560	0.4018

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
46	0.5049	0.0863

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
2.0	3.0	9.0	21.0	37.0	41.0	43.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.043	0.065	0.196	0.457	0.804	0.891	0.935

SERIAL COR.	FISHER TS.	P-V OF TS.
-.0736	87.95	0.6002

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
46	0.5060	0.0842

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
1.0	4.0	8.0	23.0	37.0	41.0	43.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.022	0.087	0.174	0.500	0.804	0.891	0.935

SERIAL COR.	FISHER TS.	P-V OF TS.
-.0989	87.35	0.6176

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
46	0.4747	0.0820

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
3.0	4.0	12.0	25.0	35.0	43.0	43.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.065	0.087	0.261	0.543	0.761	0.935	0.935

SERIAL COR.	FISHER TS.	P-V OF TS.
0.0144	95.39	0.3837

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9828
CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.7332
CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.8080

TODAYS 10-12 WITH TODAYS 13-15

BA

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.0941	0.1074	0.0434
0.2100	0.2284	0.0999
0.1135	0.1308	0.1833
0.9047	0.8974	0.8297
0.0192	0.0301	0.0841
0.2227	0.3367	0.5475
0.6419	0.6585	0.5460
0.8175	0.8477	0.8703
0.3905	0.4512	0.5337
0.4951	0.5106	0.3978
0.1987	0.1543	0.1937
0.7111	0.7142	0.5385
0.6690	0.7210	0.6953
0.6201	0.5307	0.3434
0.0408	0.0602	0.1674
0.3434	0.2315	0.0489
0.4158	0.4364	0.4004
0.5768	0.5501	0.3454
0.6718	0.7249	0.8676
0.1439	0.1567	0.3058
0.8790	0.8918	0.9595
0.0164	0.0183	0.0006
0.2010	0.2911	0.3971
0.3345	0.4075	0.6945
0.9797	0.9806	0.8676
0.3115	0.2803	0.3923
0.5828	0.6629	0.8336
0.8576	0.8765	0.8703
0.9990	0.9990	0.9990
0.1017	0.0777	0.0440
0.7439	0.7712	0.6969
0.6203	0.6757	0.5164
0.5022	0.5206	0.3950
0.2992	0.2634	0.1011
0.8284	0.8397	0.5351
0.3021	0.3665	0.5365
0.2137	0.1353	0.1012
0.1873	0.1984	0.4870
0.4588	0.3863	0.1664
0.5339	0.4831	0.4903
0.0612	0.0771	0.0842
0.5854	0.5989	0.6936
0.3326	0.2378	0.0984
0.4208	0.4274	0.2556
0.8322	0.8530	0.6926
0.6293	0.6606	0.6589

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
46	0.4590	0.0804

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
3.0	5.0	10.0	25.0	38.0	43.0	44.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.065	0.109	0.217	0.543	0.826	0.935	0.957

SERIAL COR.	FISHER TS.	P-V OF TS.
-.1391	101.08	0.2428

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
46	0.4665	0.0840

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
2.0	5.0	11.0	25.0	38.0	44.0	44.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.043	0.109	0.239	0.543	0.826	0.957	0.957

SERIAL COR.	FISHER TS.	P-V OF TS.
-.1117	98.44	0.3039

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
46	0.4480	0.0843

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
4.0	8.0	14.0	25.0	38.0	44.0	44.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.087	0.174	0.304	0.543	0.826	0.957	0.957

SERIAL COR.	FISHER TS.	P-V OF TS.
-.0668	112.17	0.0751

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9863

CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.8290

CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.8869

TODAYS 10-12 WITH TODAYS 14-16

BA

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.2367	0.2692	0.3524
0.5202	0.3353	0.0991
0.0713	0.0885	0.0976
0.8350	0.8026	0.6393
0.0252	0.0102	0.0411
0.3645	0.3842	0.2513
0.5629	0.6306	0.5281
0.6784	0.7279	0.6871
0.2438	0.2698	0.2575
0.5779	0.6578	0.6940
0.4177	0.4658	0.5335
0.9384	0.9426	0.8684
0.5390	0.5548	0.6878
0.1902	0.1833	0.3392
0.0445	0.0649	0.4070
0.2001	0.2293	0.1824
0.2110	0.2437	0.1872
0.4171	0.4145	0.1284
0.8669	0.8650	0.8354
0.2003	0.1483	0.0459
0.7990	0.8223	0.8691
0.3642	0.3587	0.4906
0.6839	0.6436	0.7051
0.4417	0.5507	0.6922
0.8113	0.7993	0.3969
0.5046	0.5080	0.6476
0.5526	0.5363	0.4886
0.8390	0.8421	0.6567
0.9503	0.9436	0.6987
0.0443	0.0674	0.1257
0.5595	0.6725	0.8682
0.6935	0.6849	0.5401
0.0479	0.0582	0.1883
0.1669	0.1498	0.1029
0.4576	0.2855	0.0457
0.1473	0.2273	0.4062
0.4702	0.4368	0.3130
0.4610	0.4681	0.6950
0.2596	0.2987	0.3063
0.5309	0.5377	0.4877
0.2117	0.2610	0.2573
0.7612	0.7803	0.8362
0.6632	0.7296	0.8710
0.4739	0.4542	0.2528
0.8054	0.7478	0.3124
0.5891	0.6033	0.6457

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
46	0.4659	0.0704

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
4.0	5.0	8.0	24.0	39.0	44.0	45.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.087	0.109	0.174	0.522	0.848	0.957	0.978

SERIAL COR.	FISHER TS.	P-V OF TS.
-.0979	95.24	0.3879

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
46	0.4730	0.0700

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
1.0	5.0	8.0	24.0	40.0	44.0	46.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.022	0.109	0.174	0.522	0.870	0.957	1.000

SERIAL COR.	FISHER TS.	P-V OF TS.
-.0156	93.26	0.4436

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
46	0.4514	0.0693

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
3.0	5.0	11.0	26.0	40.0	46.0	46.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.065	0.109	0.239	0.565	0.870	1.000	1.000

SERIAL COR.	FISHER TS.	P-V OF TS.
-.0110	97.03	0.3398

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9787

CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.7226

CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.8110

TODAYS 11-13 WITH TODAYS 13-15

BA

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.0944	0.1005	0.0449
0.3422	0.2152	0.0340
0.5759	0.6439	0.6505
0.9871	0.9876	0.8686
0.0835	0.0959	0.1880
0.7897	0.6640	0.3438
0.1146	0.1316	0.3413
0.8264	0.8060	0.5355
0.4028	0.4263	0.5395
0.1138	0.1199	0.1646
0.1572	0.2016	0.3965
0.4416	0.4311	0.4045
0.3826	0.3782	0.4892
0.8843	0.9070	0.8705
0.0607	0.0966	0.6541
0.1935	0.1740	0.0428
0.9716	0.9746	0.8643
0.6600	0.6496	0.3525
0.6342	0.6631	0.6949
0.1286	0.2041	0.3978
0.3633	0.4061	0.6944
0.0078	0.0122	0.0073
0.6300	0.6202	0.6918
0.4435	0.5247	0.6953
0.8730	0.8876	0.5461
0.4783	0.4484	0.3949
0.4213	0.4490	0.4107
0.9694	0.9704	0.9820
0.7055	0.6546	0.5416
0.2767	0.2697	0.1633
0.8785	0.8943	0.8690
0.8949	0.9076	0.8687
0.1455	0.1632	0.4100
0.7900	0.7664	0.5416
0.5201	0.5077	0.5355
0.5248	0.5188	0.4964
0.1232	0.0611	0.0278
0.8325	0.7774	0.4047
0.0283	0.0304	0.0463
0.9040	0.9008	0.8335
0.0219	0.0279	0.0936
0.6703	0.7006	0.6844
0.7147	0.7576	0.8669
0.7461	0.7048	0.5381
0.2223	0.3000	0.5410
0.8736	0.8901	0.9583

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
46	0.4979	0.1010

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
3.0	6.0	13.0	23.0	35.0	42.0	43.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.065	0.130	0.283	0.500	0.761	0.913	0.935

SERIAL COR.	FISHER TS.	P-V OF TS.
-.3322	99.96	0.2678

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
46	0.5005	0.0980

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
3.0	6.0	11.0	22.0	36.0	40.0	43.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.065	0.130	0.239	0.478	0.783	0.870	0.935

SERIAL COR.	FISHER TS.	P-V OF TS.
-.2848	96.76	0.3468

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
46	0.4939	0.0787

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
6.0	7.0	10.0	22.0	37.0	44.0	44.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.130	0.152	0.217	0.478	0.804	0.957	0.957

SERIAL COR.	FISHER TS.	P-V OF TS.
-.1470	97.11	0.3377

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9911
CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.7644
CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.8238

TODAYS 11-13 WITH TODAYS 14-16

BA

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.2319	0.2441	0.3519
0.3521	0.1710	0.0297
0.1475	0.1383	0.1036
0.7885	0.5757	0.1236
0.0264	0.0288	0.0784
0.7470	0.7332	0.3466
0.0831	0.1071	0.3428
0.6921	0.7456	0.5342
0.3872	0.3277	0.2600
0.4634	0.4306	0.4044
0.2988	0.3000	0.3380
0.8616	0.8387	0.6858
0.2216	0.2614	0.5354
0.2613	0.3358	0.3969
0.0538	0.0799	0.4022
0.1426	0.1969	0.1914
0.5919	0.5356	0.2534
0.5358	0.4716	0.1316
0.8326	0.8071	0.4924
0.2837	0.2804	0.3037
0.2158	0.2684	0.3423
0.3310	0.3320	0.4078
0.9585	0.9568	0.8316
0.6607	0.7192	0.6977
0.8969	0.8629	0.4008
0.4396	0.4444	0.3108
0.2555	0.3531	0.5367
0.9205	0.9280	0.8713
0.3237	0.3293	0.3020
0.0910	0.1545	0.3382
0.7450	0.7406	0.8301
0.8992	0.9134	0.8691
0.0175	0.0262	0.1937
0.6297	0.6274	0.5337
0.2625	0.1454	0.0490
0.2519	0.2874	0.1869
0.2593	0.2376	0.1827
0.2420	0.2255	0.0967
0.0335	0.0421	0.0465
0.6055	0.6440	0.5429
0.1136	0.1098	0.1914
0.9425	0.9268	0.8365
0.5138	0.5464	0.6481
0.4562	0.5119	0.5373
0.8887	0.9055	0.9598
0.7774	0.8289	0.9622

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
46	0.4507	0.0879

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
3.0	6.0	9.0	27.0	38.0	43.0	45.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.065	0.130	0.196	0.587	0.826	0.935	0.978

SERIAL COR.	FISHER TS.	P-V OF TS.
-.1539	104.34	0.1787

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
46	0.4495	0.0849

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
3.0	4.0	11.0	27.0	37.0	41.0	45.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.065	0.087	0.239	0.587	0.804	0.891	0.978

SERIAL COR.	FISHER TS.	P-V OF TS.
-.0751	101.55	0.2327

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
46	0.4133	0.0690

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
3.0	5.0	13.0	30.0	39.0	44.0	44.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.065	0.109	0.283	0.652	0.848	0.957	0.957

SERIAL COR.	FISHER TS.	P-V OF TS.
0.3928	105.92	0.1522

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9806

CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.7084

CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.8008

TODAYS 12-14 WITH TODAYS 14-16

BA

P-VALUES		
L1-NORM	L2-NORM	MAX-NORM
0.9351	0.9397	0.8682
0.1918	0.2386	0.1631
0.1478	0.1419	0.1019
0.6719	0.6651	0.6462
0.1583	0.1791	0.1884
0.9038	0.9147	0.8736
0.3394	0.4357	0.5379
0.9118	0.9204	0.8724
0.3666	0.2931	0.2537
0.6160	0.6406	0.6513
0.5288	0.6149	0.6962
0.9815	0.9833	0.8666
0.6624	0.6797	0.8343
0.3032	0.3196	0.4144
0.1064	0.1179	0.3469
0.5408	0.5903	0.3368
0.4631	0.3473	0.2522
0.7746	0.7535	0.5385
0.9973	0.9973	0.9919
0.6500	0.7079	0.5334
0.3933	0.4190	0.1665
0.5585	0.4297	0.2476
0.9832	0.9787	0.5350
0.5262	0.5790	0.5377
0.4754	0.3519	0.1861
0.2443	0.1753	0.1044
0.0792	0.0899	0.1207
0.6873	0.5776	0.3385
0.6450	0.6144	0.5394
0.1747	0.2419	0.5275
0.8117	0.7942	0.8420
0.8274	0.8164	0.8348
0.0190	0.0315	0.1248
0.9817	0.9819	0.8653
0.2659	0.1547	0.0446
0.0541	0.0731	0.1866
0.1335	0.1478	0.3058
0.0971	0.0815	0.0306
0.1806	0.2762	0.2515
0.2349	0.2928	0.3388
0.5158	0.5356	0.5247
0.3261	0.4224	0.5326
0.2301	0.2888	0.3050
0.4285	0.5179	0.5403
0.5007	0.3315	0.1252
0.4563	0.4540	0.4036

SUMMARY OF 1-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
46	0.4800	0.0863

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
1.0	4.0	11.0	24.0	37.0	39.0	42.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.022	0.087	0.239	0.522	0.804	0.848	0.913

SERIAL COR.	FISHER TS.	P-V OF TS.
0.0089	92.67	0.4609

2-NORM SUMMARY STATISTICS FOR THE P-VALUE

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
46	0.4813	0.0846

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
1.0	4.0	10.0	25.0	38.0	39.0	42.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.022	0.087	0.217	0.543	0.826	0.848	0.913

SERIAL COR.	FISHER TS.	P-V OF TS.
0.0154	90.34	0.5293

SUMMARY STATISTICS FOR THE MAX-NORM P-VALUES

NUMBER:	AVERAGE:	SAMPLE VARIANCE:
46	0.4462	0.0746

NUMBER LESS THAN OR EQUAL TO:

05	*10*	*20*	*50*	*80*	*90*	*95*
2.0	2.0	12.0	24.0	37.0	45.0	45.0

PERCENTAGE OF THE NUMBER LESS THAN OR EQUAL TO:

0.043	0.043	0.261	0.522	0.804	0.978	0.978

SERIAL COR.	FISHER TS.	P-V OF TS.
0.1143	97.56	0.3261

CORRELATION BETWEEN 1-NORM AND 2-NORM P-VALUES
0.9767
CORRELATION BETWEEN THE 1-NORM AND MAX-NORM P-VALUES
0.8133
CORRELATION BETWEEN THE 2-NORM AND MAX-NORM P-VALUES
0.8845