# Testing the Monday Effect using High-frequency Intraday Returns: A Spatial Dominance Approach

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*This paper employs a new testing procedure for detecting the presence of Monday effects using high-frequency intraday data. Our approach to test the Monday effect is based on spatial dominance, which enables us to analyze the expected sum of instantaneous utilities during trading hours by considering the intraday patterns of returns. The testing of the methods used in previous studies compares the expected utilities only at a specific time, usually market closing time. Empirical results from our tests provide strong evidence of the Monday effect for the 1983 to 1987 period. We also find that the Monday effect is driven by large negative returns accrued during early Monday mornings, The conventional analyses for the Monday effect, such as regression analysis and stochastic dominance, cannot provide strong evidence of the Monday effect for the same period because these testing methods do not consider the return behavior during Monday mornings.*

## I. Introduction

The efficient market hypothesis asserts that stock prices fully reflect all relevant information available in the stock market. Therefore, the revealing of information to all participants should not affect the stock prices should be unaffected by revealing information to all participants, and no investor should be benefited in predicting

stock returns by using publicly available information. However, there is some body of evidence for anomalies in financial markets including seasonal anomalies and size effects.[1] These anomalous findings are seemingly inconsistent with the efficient market hypothesis, but, as Fama (1991) pointed out, it is difficult to decide whether these occur because of market inefficiency or a bad model of market equilibrium.

The Monday effect (Weekend effect) is one of the well-known stock anomalies in finance literature. It states that the average return on Mondays is significantly negative and is lower than the returns on all other weekdays. This puzzling phenomenon has gained extensive research attention since 1980[2]; see, for example, French (1980), Gibbons and Hess (1981), Lakonishok and Levi (1982), Keim and Stambaugh (1984), and Jaffe and Westerfield (1985). Major findings from these studies are that the persistent negative Monday effect can be observed for many representative stock indices not only in the U.S. stock market, but also in other stock markets in many developed countries. Some findings after mid-1990s, however, indicated that the Monday effect in the U.S. stock market has weakened or reversed for large cap indices,; see, for example, Kamara (1997), Mehdian and Perry (2001), and Brusa et al. (2003, 2005).

While the majority of studies mentioned above focused mainly on examining daily close-to-close returns, some previous studies attempted to analyze intraday data to shed additional light on the Monday effect. By distinguishing between trading and non-trading day returns, Rogalski (1984) finds that the significant Monday effect occurs before the market opens. Harris (1986) analyzes transaction-by-transaction data for stocks listed in the New York Stock Exchange (NYSE) and reports that significantly negative Monday returns occur during the first 45 minutes after the market opens. Smirlock and Starks (1986) also find the significant negative Monday returns, but the timings of the Monday effect are different across their sample periods. Cornett et al. (1995) find significant weekly patterns in hourly return on the foreign currency futures contract.

Our methodology is different from the previous approaches in the sense that we focus on the performance of intraday cumulative returns and compare the performances of weekday returns on the basis of investor's expected sum of utilities generated during trading hours. As reported in the previous studies using intraday data, the Monday effect can occur not just at market closing time, but at any time during trading hours. This possibility can be effectively analyzed by using intraday cumulative returns in our framework. Moreover, our approach for testing the Monday effect can explicitly consider the important intraday information such as intraday volatility and trading patterns during the trading day. Conversely, most previous studies have concentrated on the behavior of daily close-to-close returns

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[1] See Keim and Ziemba (2000) for an extensive review on anomalies in the stock market.

[2] Pettengill (2003) gives an excellent review of published Monday effect research.

based only on the daily closing price or on the performances of intraday returns at a certain fixed time, which can neglect crucial intraday information.

More specifically, our approach to test the Monday effect is based on the notion of spatial dominance that can be treated as a generalization of stochastic dominance. As is well known, stochastic dominance approach provides the natural economic criterion for analyzing investors who follow the expected utility paradigm. Various applications of stochastic dominance to income distribution inequality and poverty analysis have been proposed in the literature, see e.g., Davidson and Duclos (2000), Barrett and Donald (2003). However, the stochastic dominance can only be applied to a stationary time series and thus may not be as useful for non-stationary processes with varying distributions over time. In this case, the concept of spatial dominance can be applied to more general time series econometric models. The main idea of stochastic dominance is comparing the distribution of two random variables at fixed time and hence it has a static property, whereas spatial dominance has a dynamic feature in the sense that it compares the spatial distribution of two stochastic processes over a given time interval. Since this paper considers cumulative intraday returns that are believed to be nonstationary processes, the concept of spatial dominance is more appropriate in analyzing the behavior of cumulative intraday return over a given period of time.

Testing results for the Monday effect using the concept of the spatial dominance are quite interesting. We find strong evidence of the Monday effect for the 1983-1987 period. More specifically, the cumulative return distribution of Monday is dominated by those of all other weekdays in the sense of first-order spatial dominance that will be explained in the following section. Average one-minute cumulative returns suggest that the Monday effect is driven by large negative returns accrued on early Monday mornings. On the other hand, testing results from existing methods such as regression analysis and stochastic dominance indicate that there is no significant Monday effect in the same period. In fact, we find very weak evidence of the Monday effect in stochastic dominance tests, but the conclusion of stochastic dominance is not significant at a conventional level of 5%. These conflicting results may come from different information used for testing the Monday effect. As mentioned earlier, the spatial dominance considers expected utility during trading hours as well as expected utilities at the market closing time, whereas existing methods measure expected utilities at a certain fixed time. Therefore, the large negative returns accrued on Monday mornings can be ignored in existing methods. Our results are comparable to Harris (1986). He finds the evidence of the Monday effect for the period December 1981 to January 1983 and argues that the negative returns cumulated during the first 45 minutes after the market open cause the Monday effect. We also find that the Monday effect using the spatial dominance after 1988 is not strong and disappeared as reported in the previous literature. In particular, our testing results for post-2000 period indicate that there is no

dominance relationship between Monday and the other weekdays.

The rest of this paper is organized as follows. Section 2 provides the theoretical backgrounds for spatial dominance and as well as defines the hypotheses and test statistics. Section 3 presents the empirical results, and section 4 concludes.

# II. Spatial Dominance and Testing Procedures

Since the concept of spatial dominance is based on the spatial distribution of underlying stochastic processes, we need to give some basic notions of spatial analysis to define the spatial distribution in this section, and then introduce the first and second order spatial dominance. The detailed discussions about the spatial dominances are given in Park (2007) and Kim (2009).

## 2.1 Spatial Distributions

We first introduce discounted integrated local time that is defined by

$$L(T,x) = \int_0^T e^{-rt} 1\{X_t \le x\} dt. \tag{1}$$

As the name ,indicates, the integrated local time can be also defined as an integral of local time. Readers are referred to Park (2007) for the rigorous definition of local time and its role in the spatial analysis of time series. As is obvious from (1), integrated local time is a stochastic process defined on the underlying stochastic process $X$. and hence we take the expectation and define

$$\Lambda(T,x) = \mathbf{E}L(T,x) = \int_0^T e^{-rt} \mathbf{P}\{X_t \le x\} dt. \tag{2}$$

We call $\Lambda$ the spatial density and the spatial distribution function. We also need to introduce integrated local time for the second order spatial dominance that we will explain in the following section. Let $IL(T,x)$ be integrated integrated local time, then it can be defined as

$$IL(T,x) = \int_{-\infty}^x L(T,y) dy.$$

The integrated spatial distribution can also be obtained by taking the expectation on the integrated integrated local time of the underlying stochastic process $X$. Thus, the integrated spatial distribution is given by

$$I\Lambda(T,x) = \mathbf{E}IL(T,x) = \int_0^x \Lambda(T,y)dy.$$

The integrated local times for the third- and higher-order spatial dominances can be similarly defined as those in higher-order stochastic dominances. However, we focus on the first- and second-order spatial dominances in subsequent applications. Thus, only the integrated integrated local time and integrated spatial distribution function are used in our empirical applications.

## 2.2 Estimation of Spatial Distributions

The local time and its variants are to be estimated for further analysis in spatial dominance, and therefore we introduce estimators needed for testing the first and second order spatial dominance and present an essential part of theoretical results for our analysis that were obtained in Park (2007). Suppose that we have discrete observations $(X_{i\delta})$, $i = 1, \cdots, n$ from the underlying stochastic process $X$, where $\delta$ indicates an observation interval, then the number of observations is therefore given by $n = T / \delta$ for the given time interval $[0, T]$. All the asymptotic results developed in Park (2007) were obtained under the assumption that $n \to \infty$ as $\delta \to \infty$ for a fixed $T$. Obviously, the $n \to \infty$ as $\delta \to \infty$ conditions are more appropriate for the spatial analysis, which intends to investigate the given time series in a given time interval. Moreover, the nonstationarity of underlying process can be dealt with this asymptotics in a very general way. The requirement here is not restrictive especially when considering high frequency time series data that we will use in our empirical analysis.

We now introduce the estimator of integrated local time that is a building block for the estimation of spatial distributions for the subsequent analysis. Given the observations $(X_{i\delta})$, $i = 1, \cdots, n$ from $X = (X_t)$, the integrated local time in (1) can be consistently estimated by the following sample analogue estimator:

$$\hat{L}(T,x) = \delta \sum_{i=1}^n e^{-ri\delta} 1\{X_{i\delta} \leq x\}. \tag{3}$$

The estimator in (3) is more convenient to use in practice compared to the estimation method by integrating the estimated local time directly.[3] The suggested sample analogue estimator is shown to be uniformly consistent under the given conditions. We use this rather simple sample analogue estimator in our applications to estimate the spatial distribution. The consistent estimation of the integrated integrated local time $IL(T,x)$ can be estimated by the sample analogue methods

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[3] From this reason, we do not present the estimator of local time. Readers referred to Kim (2009) for detailed descriptions of the estimator.

as

$$\widehat{IL}(T,x) = \delta \sum_{i=1}^{n} e^{-ri\delta}(x - X_{i\delta})1\{X_{i\delta} \le x\}. \tag{4}$$

Let $\hat{L}_k(T,x)$ and $\widehat{IL}_k(T,x)$ for $k = 1, \cdots, N$ be the estimators for the integrated local time and integrated integrated local time respectively that are given in (3) and (4) using discrete samples $(X_{i\delta}^k)$ observed from $X^k$. Then we define the estimators of the spatial distribution function and integrated spatial distribution function by

$$\hat{\Lambda}_N(T,x) = \frac{1}{N} \sum_{k=1}^{N} \hat{L}_k(T,x), \widehat{I\Lambda}_N(T,x) = \frac{1}{N} \sum_{k=1}^{N} \widehat{IL}_k(T,x), \tag{5}$$

respectively. The estimators here are the averages of estimated the integrated local time and the integrated integrated local time estimators for each of $(X^k)$, $i = 1, \cdots, N$. Theorem 5.1 and 5.2 in Park (2007) give the consistency and asymptotic distributions of the spatial estimators $\hat{\Lambda}_N(T,x)$ and $\widehat{I\Lambda}_N(T,x)$ under some technical conditions. In fact, the limit distributions of all the spatial estimators are very complicated and dependent upon the probability law of the underlying stochastic process $X$. Therefore, subsampling methods will be most appealing to obtain the limit distribution of test statistics involving the spatial distribution estimators given above in practice.

### 2.3 Spatial Dominance

It is well-known that the theory of stochastic dominance gives a more general framework for analyzing economic behavior under uncertainty compared to the mean-variance analysis. (see e.g., Levy (2006)). Post (2003) mentioned main advantages of stochastic dominance approach for this area: much flexible on investor preferences and asset return distributions and nonparametric analysis based on high-quality data. Recently, Linton, Maasoumi, and Whang (2005) have provided a comprehensive theory of inference for the Kolmogorov-Smirnov class of test statistics for standard pairwise comparisons. Linton, Post, and Whang (2005) extend their work to the portfolio case, and Cho et al. (2007) apply the stochastic dominance tests to the Monday effect in stock returns.

The spatial dominance can be applied to time series econometric models in a similar way to stochastic dominance. Spatial dominance has a dynamic aspect in the sense that it compares the spatial distribution of two stochastic processes over a given periods of time whereas stochastic dominance has only static property since it compares the distributions of two random variables at two different fixed points in

time. Therefore, the concept of the spatial dominance is more appropriate in analyzing the dynamic behavior of economic agents over a given period of time.

We now introduce the definitions of the first order spatial dominance. Let $X_1$ and $X_2$ be two stochastic processes, and $\Lambda^{X_1}$ and $\Lambda^{X_2}$ denote the spatial distribution functions of $X_1$ and $X_2$, respectively. Now, let $\mathcal{U}$ denote the class of all Von Neumann-Morgenstern type utility functions $u$, such that $u' \leq 0$: set of every monotone nondecreasing utility functions. Then we define

**Definition 1.** $X_1$ *first order spatially dominates* $X_2$ *if and only if either*

(a) $\Lambda^{X_1}(T,x) \leq \Lambda^{X_2}(T,x)$ *for all* $x \in \mathbb{R}$, *with* $<$ *for some x or*,

(b) $\mathbf{E}\int_0^T e^{-rt} u(X_{1t})dt \geq \mathbf{E}\int_0^T e^{-rt} u(X_{2t})dt$ *for all* $x \in \mathcal{U}$, *with* $>$ *for some u*.

The above definitions involve not only the ordering for spatial distribution functions but the inequality of the expected sum of instantaneous utilities. Therefore, we can interpret that the stochastic process $X_1$ yields at least the same expected value of the sum of discounted utilities as that of $X_2$ over a period of time $[0,T]$ for the utility functions in $\mathcal{U}$. The second-order spatial dominance criterion can be analogically defined in terms of the integrated spatial distribution functions for concave utility functions.[4] Obviously, the concept of spatial dominance is equivalent to the stochastic dominance if the underlying processes $X_1$ and $X_2$ are time invariant stationary.

The first order spatial dominance gives an economic criterion to the economic agents who have nonsatiated expected utility functions over the given period time, and the second order spatial dominance provides the rule to those who have nonsatiated and risk averse expected utility functions over the given time period $[0,T]$. Therefore, the theory of spatial dominance offers a decision-making rule under uncertainty provided the decision-maker's utility function share certain properties. That is, if there is spatial dominance over a given time period, then the expected utility of the investor is always higher under the portfolio with dominant return than under the dominated portfolio over a given time period $[0,T]$. Consequently, the portfolio with dominated return would never be chosen. The spatial dominance rule is more satisfactory from an economic theory point of view than stochastic dominance rule or mean-variance approach since it is defined with reference to a much larger class of utility functions as well as with time varying return distribution.

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[4] See Definition 2 in Kim (2009).

## 2.4 Test Statistics for Spatial Dominance and Hypotheses of Interests

Most of previous tests about the Monday effect focused on the mean return of Monday compared to other week days. However, those approaches cannot really capture the main characteristics of the Monday effect since either the alternative is too general or the null is too strong. Cho et al. (2007) instead used the following hypotheses, and we use those eight hypotheses for testing the Monday effect.

$H_0^1$ : Monday is dominated by all other weekdays.
$H_0^2$ : Monday dominates at least one other weekday.
$H_0^3$ : Monday dominates all other weekdays.
$H_0^4$ : Monday is dominated by at least one of the weekdays.
$H_0^5$ : One day dominates all others.
$H_0^6$ : One day is dominated by all others.
$H_0^7$ : Either Monday or the rest of the weekdays dominate the other
$H_0^8$ : All weekdays have the same distribution.

Obviously, $H_0^1$ is the main hypothesis of interest, however we also test more hypotheses for a more detailed investigation of the Monday effect without mutual conflicts and contradictions. We can see that $H_0^1$, $H_0^4$, $H_0^6$ and $H_0^7$ are consistent with the Monday effect and $H_0^2$, $H_0^3$, $H_0^5$ and $H_0^7$ are consistent with the reverse Monday effect. In particular, $H_0^5$, $H_0^6$ and $H_0^7$ do not indicate one specific day effect. In fact, there has been some evidence about Tuesday or Wednesday effects in the European market. For example, Martikainen and Puttonen (1996) found some significant negative return in Finnish stock market return. $H_0^8$ implies the equal distribution of all days, which is consistent with the efficient market hypothesis. Therefore, $H_0^8$ is inconsistent with either the Monday or the reversed Monday effects.

Next, we need to express the eight hypotheses using functionals of the spatial distribution functions of the cumulative returns to provide the test statistics. Let $X_1$ denote the Monday cumulative returns and $X_2, \cdots, X_5$ denote the other weekday (i.e., Tuesday,..., Friday, respectively) cumulative returns, and let $s = 1,2$ represent the order of spatial dominance. For each $r, l = 1, \cdots 5,$ we let

$$\Delta_{r,l}^1(x) = \Lambda^{X_r}(T,x) - \Lambda^{X_l}(T,x), \quad \Delta_{r,l}^2(x) = I\Lambda^{X_r}(T,x) - I\Lambda^{X_l}(T,x),$$

then each $\Delta_{r,l}^{(s)}(s=1,2)$ indicates the difference between (integrated) spatial distribution functions.

Now, define

$$d_{1s}^* = \max_{r \neq 1} \sup_{x \in \mathbb{R}} \Delta_{r,1}^{(s)}(x); \quad d_{2s}^* = \max_{r \neq 1} \sup_{x \in \mathbb{R}} \Delta_{1,r}^{(s)}(x)$$

$$d_{3s}^* = \max_{r \neq 1} \sup_{x \in \mathbb{R}} \Delta_{1,r}^{(s)}(x); \quad d_{4s}^* = \max_{r \neq 1} \sup_{x \in \mathbb{R}} \Delta_{r,1}^{(s)}(x)$$

$$d_{5s}^* = \min_{r} \max_{r \neq l} \sup_{x \in \mathbb{R}} \Delta_{r,l}^{(s)}(x); \quad d_{6s}^* = \min_{r} \max_{r \neq l} \sup_{x \in \mathbb{R}} \Delta_{l,r}^{(s)}(x)$$

$$d_{7s}^* = \min_{r} \left\{ \max_{r \neq 1} \sup_{x \in \mathbb{R}} \Delta_{r,1}^{(s)}(x), \max_{r \neq 1} \sup_{x \in \mathbb{R}} \Delta_{1,r}^{(s)}(x) \right\}; \quad d_{8s}^* = \max_{r \neq 1} \sup_{x \in \mathbb{R}} \left| \Delta_{1,r}^{(s)}(x) \right|.$$

Then the null and alternative of the above hypotheses can be simply written as

$$\mathbf{H}_0^p : d_{ps}^* \leq 0 \quad v.s. \quad \mathbf{H}_0^p : d_{ps}^* > 0 \quad \text{for} \quad p = 1, \cdots, 8.$$

Eight quantities, $d_{1s}^*, \cdots, d_{8s}^*$ represent our null hypotheses. For instance, $d_{1s}^* \leq 0$ implies that the distribution of all weekdays except Monday lie below the distribution of Monday. This relationship among distributions indicates that Monday is spatially dominated by all other weekdays.

## 2.5 Test Statistics for Spatial Dominance

We now give the test statistics for the testing of first and second order spatial dominance. We will consider the Kolmogorov-Smirnov statistic that is based on the uniform distance of estimated expected integrated local times or integrated integrated local times of $X_r$ and $X_l$ for each $r, l = 1, \cdots, 5$. For example, the test statistic based on the Kolmogorov-Smirnov uniform distance for the first order spatial dominance for $\mathrm{H}_0^1$ is given by

$$D_{N,1}^1(T) = \sqrt{N} \max_{r \neq 1} \max_{x \in \mathbb{R}} \left( \hat{\Lambda}^{X_r}(T,x) - \hat{\Lambda}^{X_1}(T,x) \right) \tag{6}$$

The asymptotic distribution of $D_{N,1}^1(T)$ was obtained in Park (2007), and it is a function of mean zero Gaussian process with a complicated form of covariate kernel defined in Corollary 5.4 in Park (2007). In a similar way the test statistics for the second order spatial dominance can be defined using the estimators for integrated spatial distribution function in (5).

That is,

$$D_{N,1}^2(T) = \sqrt{N} \max_{r \neq 1} \sup_{x \in \mathbb{R}} \left( \widehat{I\Lambda}^{X_r}(T,x) - \widehat{I\Lambda}^{X_1}(T,x) \right). \tag{7}$$

The test statistics for the other seven $\mathrm{H}_0^2 - \mathrm{H}_0^8$ hypotheses can be obtained likewise for the first and second order spatial dominance tests. By an immediate

application of continuous mapping theorem, the asymptotic distributions of the second order test statistics can be easily obtained, but it is clear that the distributions are dependent upon the probability law of the underlying stochastic process $X_r$ and $X_l$ in a very complicated manner.

As briefly mentioned before, subsampling methods are appealing and are most readily available to obtain the limit distributions of test statistics given above. The details and the general theory of subsampling are given in Politis et al. (1999). We will follow the subsampling method given in Linton, Maasoumi and Whang (2005) and Cho et al. (2007) as follows.

Let $M$ be the subsample size, and then $N-M+1$ will be the number of subsamples. The subsample size $M$ should be chosen such that $M \rightarrow \infty$ and $M/N \rightarrow 0$ as $N \rightarrow \infty$. We will discuss the choice of the subsample size in the subsequent section. For each subsample $j=1,\cdots N-M+1$, we estimate the spatial distribution functions of the stochastic processes $X_r$ for $r=1,\cdots,5$ as

$$\hat{\Lambda}_{M_j}^{X_r}(T,x) = \frac{1}{M} \sum_{W=1}^{M} \hat{L}_{j,W}^{X_r}(T,x),$$

and compute the statistic for the first order spatial dominance in (6) by

$$D_{M_{j,1}}^{1}(T) = \sqrt{M} \max_{r \neq 1} \sup_{x \in \mathbb{R}} \left( \left[ \hat{\Lambda}_{M_j}^{X_r}(T,x) - \hat{\Lambda}^{X_r}(T,x) \right] - \left[ \hat{\Lambda}_{M_j}^{X_1}(T,x) - \hat{\Lambda}^{X_1}(T,x) \right] \right).$$

Here we demean the spatial distribution function estimators based on subsamples by subtracting the $\hat{\Lambda}^{X_r}(T,x)$ and $\hat{\Lambda}^{X_1}(T,x)$ which are the spatial distribution function estimators based on $N$ samples. We then compute the test statistic from each subsample $j=1,\cdots N-M+1$ then obtain critical values for the test statistic. Subsampling procedures are briefly explained as below.

Let $W_N$ denote any of the test statistics. Then,
1. Calculate the test statistic $W_N$ using the original full sample $W_N = \{Z_k = (X_1^k,\cdots,X_5^k)^h : k=1,\cdots,N\}$.
2. Generate subsamples $W_{N,M,j} = \{Z_j,\cdots,Z_{j+M-1}\}$ of size $M$ for $j=1,\cdots N-M+1$.
3. Compute the test statistic $W_{N,M,j}$ using the subsamples $W_{N,M,j}$ for $j=1,\cdots N-M+1$.
4. Approximate the asymptotic *p*-value by

$$p_{ab=} \frac{1}{N-M+1} \sum_{j=1}^{N-M+1} 1\{W_{N,M,j} > W_N\}.$$

The choice of subsample size is very important, and Politis et al. (1999) proposed

several different methods for selecting subsample size in the context of estimation and testing problems. Here, we follow the suggested method in Linton, Maasoumi and Whang (2005). They proposed 'majority rule approach' which determines subsample size in the range $[N^{0.3}, N^{0.7}]$, and reported the median of the corresponding $p$-values. Cho et al. (2007) also used this majority rule and considered 30 different subsample sizes in the range.

# III. Empirical Results

## 3.1 Data

We use one-minute cumulative returns constructed from the intraday data of the S&P 500 index[5] . The sample period is from February 1, 1983 to July 30, 2010. To examine the behavior of the Monday effect for different time periods, we consider three subperiods: February 1, 1983-October 1, 1987; January 1, 1988-December 31, 1999; January 1, 2000-July 30, 2010. The first subperiod is the pre-1987 crash period in our sample period. The second one matches with some studies finding the disappearance or reversal of the Monday effect (see Mehdian and Perry (2001) and Alt et al. (2011) for the disappearance; see Brusa et al. (2003, 2005) for the reversal). The third subperiod includes recent 10 and 1/2 years for the testing of the Monday effect. One-minute cumulative returns are calculated as $R_{i\delta} = \log\left(\frac{P_{i\delta}}{P_0}\right)100, i = 1, \cdots, n$ : where $R_{i\delta}$ is one-minute cumulative return at time $i\delta$, $P_{i\delta}$ is a stock prices at time $i\delta$ and $P_0$ is the closing price of the previous day. Since the NYSE was open six hours per a day (from 10 am to 4 pm) before September 30, 1985 and six and a half hours per a day (from 9:30 am to 4 pm) thereafter. Therefore, the number of observations for one-minute cumulative returns per day is 361 for the six-hour trading period and 391 for the later period. We excluded weeks including holidays in order to accommodate general dependence among the returns in each week, and annual discount rate is set to be 4%[6] for estimating the discounted local time and its variants.

We use daily returns in regression analysis and the stochastic dominance tests procedures proposed by Cho et al. (2007). Daily returns are calculated as close-to-close returns, that is, the percentage change from the close of the previous day to the close of the current day. Following Rogalski (1984), Smirlock and Starks (1986), and Harris (1986), we also consider the trading day and non-trading day returns. Accordingly, we decompose the close-to-close return into two parts: close-to-open

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[5] The dataset was purchased from the private company TickData Inc.

[6] Some experimental studies provide 4% annual discount rate; see Shelley (1994) and Hesketh (2000).

and open-to-close returns. We denote the close-to-close return, close-to-open return, and open-to-close by $R^{cc}$, $R^{co}$ and $R^{oc}$, respectively. Thus, $R^{co}$ is defined as the percentage change from the close of the previous day to the opening of the current day. Similarly, $R^{co}$ is defined as the percentage change from the opening of the current day to the close of the current day.

The availability of high frequency data provides researchers with an opportunity to learn about financial return and its volatility (see the review of Andersen et al. (2009)). Nonetheless, it is well-accepted that the observations of asset prices sampled at high frequencies contain a nonnegligible microstructure friction component and hence there are theoretical and empirical limitations on the exploitation of the informational content in high frequency data. Therefore, the true price process and, as a consequence, the return data are contaminated by market microstructure effects, such as discrete clustering and bid-ask spreads, among others. In other words, asset prices diverge from their efficient values due to a variety of market frictions. However, the use of infill asymptotic arguments (i.e., increasingly frequent observations over a fixed time span) seems appropriate in our spatial dominance approach using high frequency data, since it can capture intraday pattern in returns effectively and time varying properties of the underlying process well. Moreover, we want to evaluate the performances of two portfolios over a given period of time with cumulative returns continuously in spatial dominance rather than to compare the returns of the two portfolios at the end of investment time. Recently, Aït-Sahalia et al. (2005) suggested that sampling as often as possible would be a better solution for the optimal sampling frequency even though one misspecifies the noise distribution in the modeling. Following their suggestion, we use one-minute interval observations, but using different frequencies (5-minute) data does not change our main results[7].

## 3.2 Results

### 3.2.1 Regression Analysis

We start our analysis by considering the following regression equation that has been extensively used in previous studies:

$$R_t = \beta_1 D_{1t} + \beta_2 D_{2t} + \beta_3 D_{3t} + \beta_4 D_{4t} + \beta_5 D_{5t} + u_t \qquad (8)$$

where $R_t$ is the daily return on day $t$, $D_{1t}$ is a dummy variable for Monday which takes the value 1 if day $t$ is a Monday and 0 otherwise, $D_{2t}$ is a dummy variable for Tuesday which takes the value 1 if day $t$ is a Tuesday and 0 otherwise, and so on.

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[7] We will not report the results from five-minute data analysis to save space.

**[Table 1]** Daily average returns by day of the week

Daily close-to-close returns are decomposed into close-to-open (overnight) returns and open-to-close (daytime) returns. $R^{cc}$, $R^{co}$, and $R^{oc}$ denote the close-to-close, close-to-open, and open-to-close returns, respectively. $R^{cc}$ is defined by the percentage change from the close of the previous day to the close of the current day. $R^{co}$ is computed as the percentage change from the close of the previous day to the opening of the current day. Similarly, $R^{oc}$ is computed as the percentage change from the opening of the current day to the close of the current day. The $t$-values are corrected using Newey and West's (1987) heteroskedasticity and autocorrelation consistent covariance estimator with automatic lag selection procedure. $W$ is the Wald statistics for the null hypothesis of equal returns across all five weekdays. The corresponding 5% critical value is 9.4877. *(**) Significance at 5% (1%) level is denoted for a two-tailed $t$-test or a chi-square-test, and $N$ represents the number of samples.
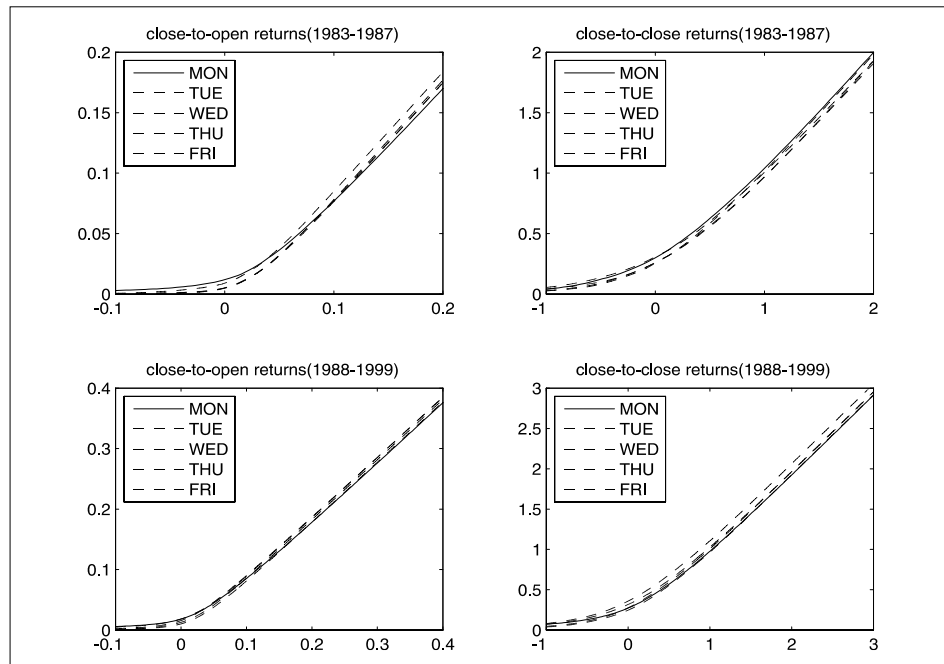
|  |  | Monday | Tuesday | Wednesday | Thursday | Friday | $W$ |
|---|---|---|---|---|---|---|---|
|  |  | Panel A: February 1, 1983 - July 30, 2010 (N=1152) | | | | | |
| $R^{cc}$ | Mean | 0.0007 | 0.0490 | 0.0413 | 0.0080 | -0.0028 | 1.9876 |
|  | t-value | 0.0167 | 1.5283 | 1.2142 | 0.2295 | -0.0933 |  |
| $R^{co}$ | Mean | 0.0227 | 0.0202 | 0.0090 | 0.0161 | 0.0101 | 9.8763* |
|  | t-value | 6.0110** | 5.7143** | 2.4102** | 4.0504** | 2.1977* |  |
| $R^{oc}$ | Mean | -0.0220 | 0.0287 | 0.0323 | -0.0081 | -0.0129 | 2.2813 |
|  | t-value | -0.5335 | 0.9204 | 0.9889 | -0.2415 | -0.4446 |  |
|  |  | Panel B: February 1, 1983 - October 1, 1987 (N=194) | | | | | |
| $R^{cc}$ | Mean | 0.0152 | 0.0884 | 0.0885 | 0.1094 | 0.0323 | 1.9866 |
|  | t-value | 0.2671 | 1.4599 | 1.6101 | 1.7903 | 0.6398 |  |
| $R^{co}$ | Mean | 0.0350 | 0.0262 | 0.0170 | 0.0239 | 0.0259 | 11.5528* |
|  | t-value | 5.5295** | 8.5950** | 5.3967** | 9.2491** | 9.7859** |  |
| $R^{oc}$ | Mean | -0.0197 | 0.0622 | 0.0715 | 0.0855 | 0.0064 | 2.4786 |
|  | t-value | -0.3421 | 1.0329 | 1.2886 | 1.3928 | 0.1262 |  |
|  |  | Panel C: January 1, 1988 - December 31, 1999 (N=509) | | | | | |
| $R^{cc}$ | Mean | 0.0941 | 0.0543 | 0.0886 | -0.0440 | 0.0523 | 8.0727 |
|  | t-value | 2.4120* | 1.4498 | 2.7007** | -1.0318 | 1.2275 |  |
| $R^{co}$ | Mean | 0.0254 | 0.0243 | 0.0209 | 0.0158 | 0.0164 | 7.3557 |
|  | t-value | 6.0227** | 8.4392** | 6.5244** | 4.0260** | 4.6296** |  |
| $R^{oc}$ | Mean | 0.0687 | 0.0300 | 0.0678 | -0.0597 | 0.0359 | 6.5421 |
|  | t-value | 1.7603 | 0.8003 | 2.0921* | -1.4336 | 0.8496 |  |
|  |  | Panel D: January 1, 2000 – July 30, 2010 (N=438) | | | | | |
| $R^{cc}$ | Mean | -0.0424 | 0.0167 | -0.0588 | 0.0373 | -0.0758 | 2.1881 |
|  | t-value | -0.5826 | 0.2553 | -0.8270 | 0.5656 | -1.3629 |  |
| $R^{co}$ | Mean | 0.0154 | 0.0136 | -0.0083 | 0.0120 | -0.0031 | 1.7909 |
|  | t-value | 1.7877 | 1.6498 | -0.9572 | 1.3401 | -0.2907 |  |
| $R^{oc}$ | Mean | -0.0578 | 0.0030 | -0.0506 | 0.0253 | -0.0727 | 5.6750 |
|  | t-value | -0.8374 | 0.0485 | -0.7473 | 0.4016 | -1.3932 |  |

Panels A, B, C, and D of Table 1 report the OLS estimates of Equation (8) for the full sample period and the three subperiods. The $t$-values are corrected using

Newey and West's (1987) heteroskedasticity and autocorrelation consistent covariance matrix. $W$ is the Wald test statistics for the null hypothesis $H_0 : \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5$. First, we consider the close-to-close returns. As can be seen, results from $R^{cc}$ show that there is no significant difference among weekdays for three subperiods as well as for the full sample period. $W$'s are not significant for all periods and the weekday returns are also insignificant except for the 1988-1999 period. These results confirm the earlier findings. Mehdian and Perry (2001) reported insignificantly positive Monday returns for the 1983-1993 period and Cho et al. (2007) also provides similar results for the 1988-2004 period. For the 1988-1999 period, unlike other periods, the Monday return is significantly positive. However, in contrast to Brusa et al. (2003, 2005), the reverse Monday effect is not supported since $W$ is not significant.

The weekly pattern of $R^{co}$ is quite different from that of $R^{cc}$. With exception of the 2000-2010 period, returns are significantly positive for all weekdays, and $W$'s are significant for the full sample and 1983-1987 periods. In addition, the estimated mean returns on Monday are generally higher than those on the other days. These results indicate that the Monday's return is not less than the other weekday's returns for this period. Results from $R^{oc}$ are generally similar to those from $R^{cc}$. While the Monday returns are negative for some sample periods, they are not significant, and the hypothesis of equal means across weekdays cannot be rejected.

[**Figure 1**] Integrated cumulative distribution functions

### 3.2.2 Stochastic Dominance Analysis

In the tests of stochastic dominance, we use the testing procedures proposed by Cho et al. (2007). Figure 1 shows the estimated integrated cumulative distribution functions (hereafter CDF) of daily returns. To save space, we display CDF's for some daily returns and for chosen sample periods. As discussed in the formulation of our null hypothesis, if the Monday effect exists, then the distribution of Monday should lie above those of other days. Conversely, the Monday's distribution should lie below the other days' distributions when there is a reversal of the Monday effect. For the 1983-1987 period, the Monday CDF of $R^{co}$ crosses the other day's distributions at low level of returns. Similarly, the Monday CDF's in the other three figures crosses other weekdays CDF's at low level of returns. While the empirical distributions provide economic meaning of difference in daily returns, it is difficult to draw definite dominance relationship from the figures presented. Therefore, we need to conduct hypothesis test to formally verify these findings.

The results of the stochastic dominance tests are tabulated in Table 2. As mentioned earlier, the null hypothesis $H_0^1$ is the main focus of our test and it states that returns on Mondays are dominated by those on all other weekdays. Since the null hypothesis $H_0^2$ is the negation of $H_0^1$, we expect to reject $H_0^2$ but not $H_0^1$ when there exists Monday effect. On the other hand, if the reverse Monday effect exists, we expect to reject $H_0^4$ but not to reject $H_0^3$. For the full sample period, the results from $R^{cc}$ and $R^{oc}$ show little evidence of the Monday effect since the null hypothesis $H_0^2$ and $H_0^4$ are not rejected at any order of the stochastic dominance. Though the test results from $R^{co}$ in regression analysis shows some evidence of reversal of the Monday effect, we cannot reject the null hypothesis $H_0^4$ for the second order stochastic dominance test. In addition, rejecting hypothesis $H_0^5$ in the second order stochastic dominance test implies that no single weekday returns dominate all other days' returns. We therefore conclude that the test results from stochastic dominance do not support the reverse Monday effect in this period.

The results for the 1983-1987 period provide weak evidence of the Monday effect since the conclusion is not significant at conventional level of 5% although the null hypotheses $H_0^2$ for $R^{cc}$ and $R^{oc}$ are rejected at the same level. For $R^{co}$, the null hypothesis $H_0^1$ is rejected at the first and second order stochastic dominance test, but we cannot accept the reversal of the Monday effect for this period since the rejection of the null hypothesis $H_0^5$ contradicts the non-rejection of the null hypothesis $H_0^3$. Moreover, the null hypothesis $H_0^6$ and $H_0^7$ are rejected in the second order test, which suggests that there should no single day that dominates the other days or that is dominated by the other weekdays.

As seen in the Table 1, the Monday returns during the 1988-1999 period are significantly positive and numerically higher than the other weekday's returns, which implies that the null hypothesis $H_0^4$ is rejected for $R^{cc}$ and $R^{oc}$. However,

the null hypothesis $H_0^4$ is not rejected for $R^{cc}$ and $R^{oc}$. Therefore, testing results from stochastic dominance analysis do not support the reversal of the Monday effect for this period. The test results from the 2000-2010 period, as those from regression analysis for the same period, do not provide any significant weekday effect for all different daily returns.

[Table 2] Median *p*-values of the stochastic dominance tests

The values in this table present median *p*-values of stochastic dominance tests. Three types of daily returns are used just like Table 1: close-to-close returns ($R^{cc}$), close-to-open returns ($R^{co}$) and open-to-close returns($R^{oc}$). In subsampling, 30 different subsample sizes are used and ranged from $N^{0.3}$ to $N^{0.7}$. $N$ represents the number of samples. 'SD' is used as an acronym for 'Stochastically Dominate', and null hypotheses are as follow. $H_0^1$: *All other weekdays SD Monday*, $H_0^2$: *Monday SDs at least one weekday*, $H_0^3$: *Monday SDs all other weekdays*, $H_0^4$: *At least one weekday SDs Monday*, $H_0^5$: *At least one weekday SDs all others*, $H_0^6$: *At least one weekday is SDed by all other weekdays*, $H_0^7$: *Either Monday or the rest of weekdays SDs the other*, $H_0^8$: *The distributions are all identical*.

| | Order | $H_0^1$ | $H_0^2$ | $H_0^3$ | $H_0^4$ | $H_0^5$ | $H_0^6$ | $H_0^7$ | $H_0^8$ |
|---|---|---|---|---|---|---|---|---|---|
| | | Panel A: February 1, 1983 - July 30, 2010 ($N$ =1152) | | | | | | | |
| $R^{cc}$ | 1st | 0.384 | 0.490 | 0.781 | 0.418 | 0.333 | 0.086 | 0.668 | 0.755 |
| | 2nd | 0.869 | 0.146 | 0.225 | 0.745 | 0.131 | 0.600 | 0.771 | 0.255 |
| $R^{co}$ | 1st | 0.029 | 0.605 | 0.565 | 0.041 | 0.061 | 0.742 | 0.421 | 0.041 |
| | 2nd | 0.054 | 0.595 | 0.246 | 0.190 | 0.039 | 0.242 | 0.148 | 0.123 |
| $R^{oc}$ | 1st | 0.426 | 0.491 | 0.751 | 0.520 | 0.210 | 0.115 | 0.527 | 0.583 |
| | 2nd | 0.912 | 0.160 | 0.176 | 0.741 | 0.158 | 0.752 | 0.912 | 0.274 |
| | | Panel B: February 1, 1983 - October 1, 1987 ($N$ =194) | | | | | | | |
| $R^{cc}$ | 1st | 0.552 | 0.076 | 0.308 | 0.385 | 0.278 | 0.116 | 0.420 | 0.094 |
| | 2nd | 0.769 | 0.075 | 0.407 | 0.257 | 0.060 | 0.130 | 0.667 | 0.123 |
| $R^{co}$ | 1st | 0.000 | 0.271 | 0.217 | 0.000 | 0.000 | 0.568 | 0.033 | 0.000 |
| | 2nd | 0.023 | 0.212 | 0.155 | 0.071 | 0.000 | 0.024 | 0.000 | 0.086 |
| $R^{oc}$ | 1st | 0.533 | 0.090 | 0.200 | 0.708 | 0.174 | 0.110 | 0.366 | 0.100 |
| | 2nd | 0.818 | 0.067 | 0.332 | 0.226 | 0.173 | 0.207 | 0.740 | 0.079 |
| | | Panel C: January 1, 1988 - December 31, 1999 ($N$ =509) | | | | | | | |
| $R^{cc}$ | 1st | 0.000 | 0.756 | 0.705 | 0.221 | 0.376 | 0.759 | 0.633 | 0.302 |
| | 2nd | 0.017 | 0.248 | 0.453 | 0.333 | 0.334 | 0.278 | 0.306 | 0.252 |
| $R^{co}$ | 1st | 0.081 | 0.526 | 0.350 | 0.034 | 0.000 | 0.321 | 0.048 | 0.034 |
| | 2nd | 0.186 | 0.413 | 0.146 | 0.270 | 0.114 | 0.125 | 0.000 | 0.187 |
| $R^{oc}$ | 1st | 0.006 | 0.522 | 0.752 | 0.208 | 0.470 | 0.498 | 0.696 | 0.268 |
| | 2nd | 0.027 | 0.263 | 0.469 | 0.388 | 0.631 | 0.222 | 0.294 | 0.244 |
| | | Panel D: January 1, 2000 – July 30, 2010 ($N$ =438) | | | | | | | |
| $R^{cc}$ | 1st | 0.723 | 0.525 | 0.314 | 0.529 | 0.757 | 0.483 | 0.564 | 0.710 |
| | 2nd | 0.618 | 0.220 | 0.299 | 0.408 | 0.058 | 0.060 | 0.370 | 0.533 |
| $R^{co}$ | 1st | 0.030 | 0.409 | 0.749 | 0.120 | 0.117 | 0.665 | 0.620 | 0.532 |
| | 2nd | 0.148 | 0.462 | 0.761 | 0.215 | 0.126 | 0.085 | 0.606 | 0.746 |
| $R^{oc}$ | 1st | 0.823 | 0.462 | 0.110 | 0.662 | 0.455 | 0.690 | 0.688 | 0.870 |
| | 2nd | 0.775 | 0.172 | 0.273 | 0.426 | 0.068 | 0.266 | 0.609 | 0.335 |

### 3.2.3 Spatial Dominance Analysis

Figure 2 presents the spatial distribution function and the integrated spatial distribution functions of one-minute cumulative returns. For the 1983-1987 period, we can find that the most part of Monday's spatial distribution function lies above the other days' spatial distribution functions. The integrated spatial distribution function of Monday is greater than those of the other days for all levels of returns without crossing other weekdays' distributions. On the other hand, the graphs for the 1988-1999 period show that the integrated spatial distribution of Monday is very slightly below those of other weekdays and even they cross one another at a low level of returns. Similarly, the integrated spatial distribution function for Monday in the 2000-2010 period cross those for other weekdays at all level of returns.
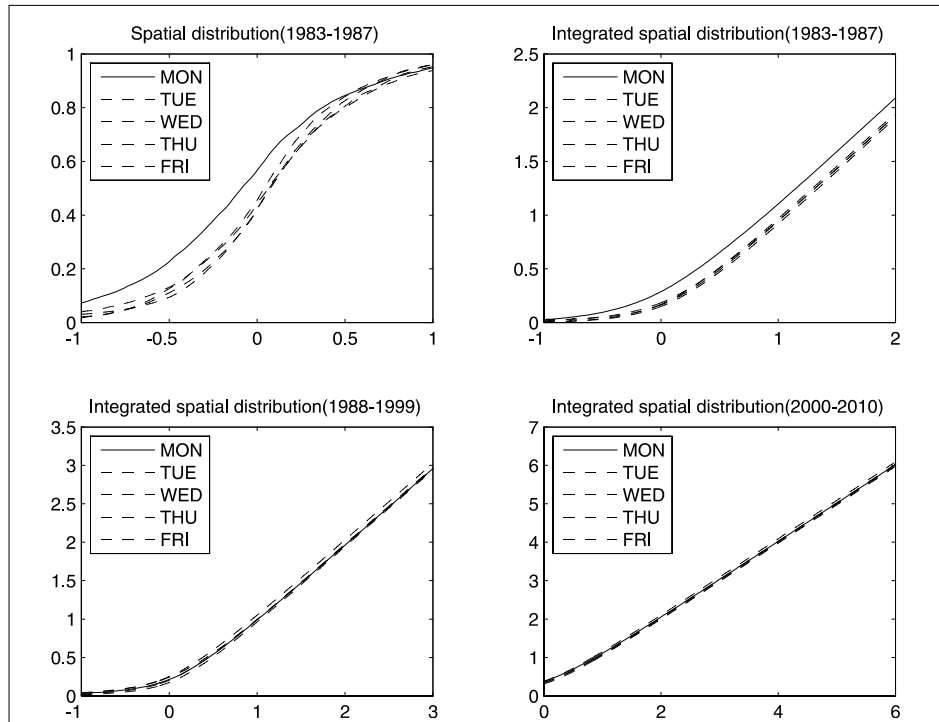
**[Figure 2]** Spatial Distributions



Table 3 provides test results of spatial dominance. As can been seen, the full sample period results do not show any evidence of the Monday effect. The null hypotheses $H_0^1$, $H_0^2$, $H_0^3$ and $H_0^4$ are not rejected at any order of spatial dominance for this period. As previously explained, since the null hypotheses $H_0^2$ and $H_0^4$ are the negations of the null hypotheses $H_0^1$ and $H_0^3$ respectively, non-rejections of these four hypotheses indicate that there is no evidence of the Monday effect. For the pre-1987 period, however, we find strong evidence of the Monday

effect. We can see that the null hypotheses $H_0^2$, $H_0^3$ and $H_0^8$ are rejected at the 1% significance level, which implies that the Monday's cumulative returns are dominated by the other days' cumulative returns.

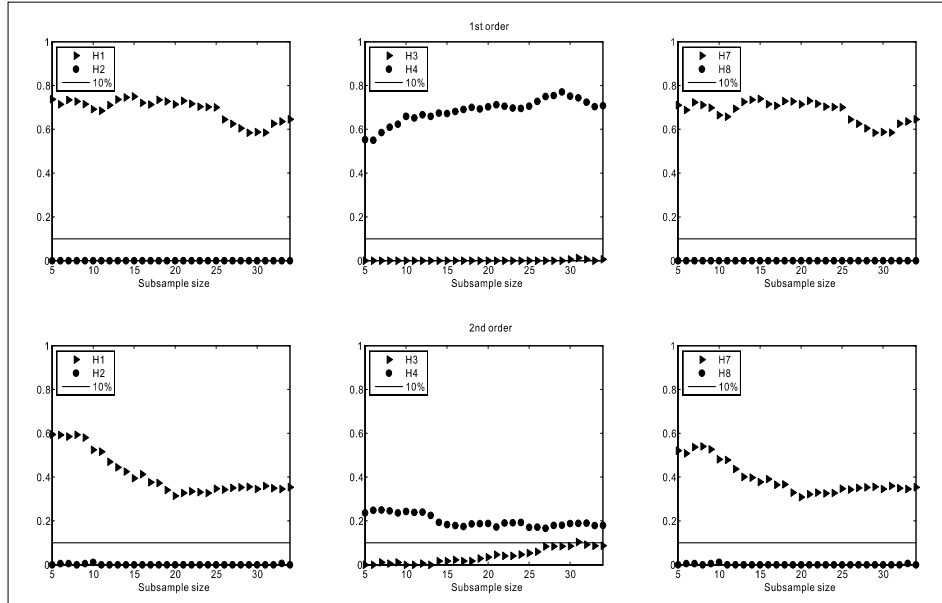**[Table 3]** Median *p*-values of the spatial dominance tests

The values in this table present median *p*-values of stochastic dominance tests. 'SD' is used as an acronym for 'Spatially Dominate', and null hypotheses are as follow. $H_0^1$ : *All other weekdays SD Monday*, $H_0^2$ : *Monday SDs at least one weekday*, $H_0^3$ : *Monday SDs all other weekdays*, $H_0^4$ : *At least one weekday SDs Monday*, $H_0^5$ : *At least one weekday SDs all others*, $H_0^6$ : *At least one weekday is SDed by all other weekdays*, $H_0^7$ : *Either Monday or the rest of weekdays SDs the other*, $H_0^8$ : *The distributions are all identical*.

| Order | $H_0^1$ | $H_0^2$ | $H_0^3$ | $H_0^4$ | $H_0^5$ | $H_0^6$ | $H_0^7$ | $H_0^8$ |
|---|---|---|---|---|---|---|---|---|
| | Panel A: February 1, 1983 - July 30, 2010 | | | | | | | |
| 1st | 0.669 | 0.394 | 0.203 | 0.311 | 0.186 | 0.219 | 0.437 | 0.801 |
| 2nd | 0.898 | 0.217 | 0.115 | 0.426 | 0.208 | 0.843 | 0.843 | 0.237 |
| | Panel B: February 1, 1983 - October 1, 1987 | | | | | | | |
| 1st | 0.712 | 0.000 | 0.000 | 0.697 | 0.401 | 0.615 | 0.701 | 0.000 |
| 2nd | 0.358 | 0.000 | 0.031 | 0.189 | 0.772 | 0.212 | 0.358 | 0.000 |
| | Panel C: January 1, 1988 - December 31, 1999 | | | | | | | |
| 1st | 0.266 | 0.773 | 0.359 | 0.274 | 0.002 | 0.897 | 0.041 | 0.164 |
| 2nd | 0.156 | 0.418 | 0.351 | 0.541 | 0.736 | 0.736 | 0.103 | 0.550 |
| | Panel D: January 1, 2000 – July 30, 2010 | | | | | | | |
| 1st | 0.392 | 0.457 | 0.603 | 0.648 | 0.058 | 0.697 | 0.295 | 0.967 |
| 2nd | 0.173 | 0.251 | 0.320 | 0.445 | 0.661 | 0.050 | 0.020 | 0.325 |

The test results for the post-1988 period show no significant weekly patterns of cumulative returns, as expected from the figures of spatial distributions. The null hypotheses $H_0^1$, $H_0^2$, $H_0^3$ and $H_0^4$ are not rejected not only for the post-1988 period, but for the full sample period. Moreover, rejecting the null hypotheses $H_0^6$ and $H_0^7$ for the 2000-2010 period implies that there is no dominance relationship between Monday and other weekdays.

As previously explained, we calculate the *p*-values of each hypothesis by using the subsampling method. The choice of the subsample size can affect the *p*-values that can be sensitive to different subsample sizes. Therefore, it is important to check whether the given *p*-values are insensitive to different subsample sizes within a 'reasonable' range, so one can conclude that inferences are likely to be robust, and will yield similar results. Figure 3 present *p*-values corresponding to different subsample sizes for the 1983-1987 period. The median *p*-values for the null hypotheses $H_0^2$, $H_0^3$ and $H_0^8$ are less than the 10%, which gives us robustness of our results over the different subsample sizes.
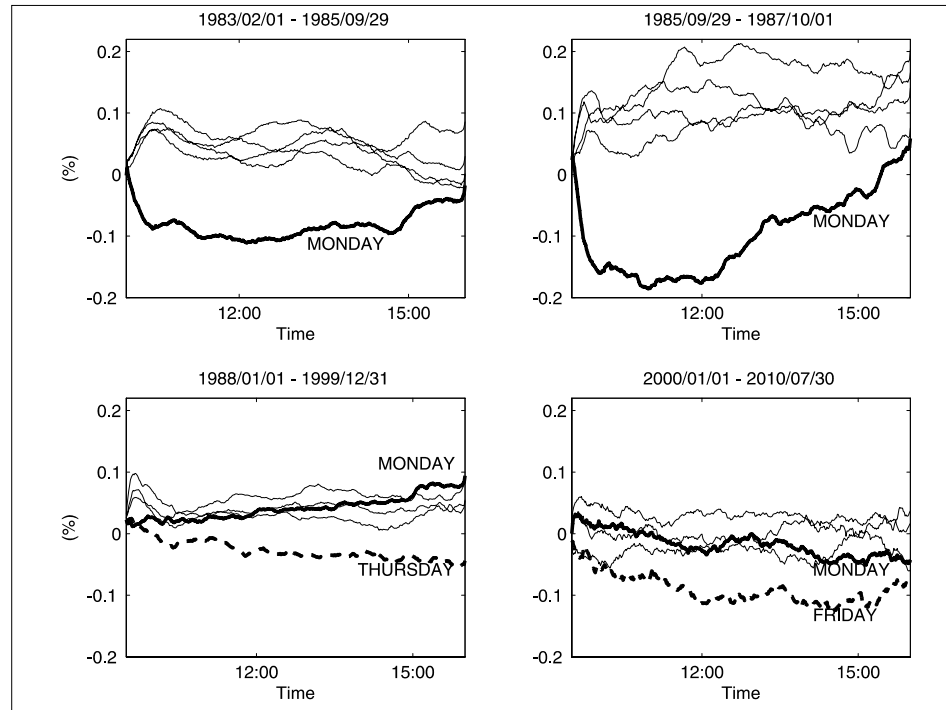
**[Figure 3]** p-values of the spatial dominance test over 1983-1987 period



To provide an intuitive explanation for the difference between our results and the those from existing methods like stochastic dominances and regression analysis, we present average one-minute cumulative returns by subsample periods in Figure 4. We plot the cumulative returns during the 1983-1987 period separately because of different trading hours. As seen in the upper panels, most prominent is the large negative returns on Monday mornings for the 1983-1987 period. The Monday cumulative return rapidly decreases after the market open, while those on other weekdays sharply increase for the same time. Accordingly, we can see a substantial difference between the cumulative returns on Monday and those on the other weekdays especially in the morning. The return differential increases until 12:00 noon, and then it begins to decline. For the 1988-1999 and 2000-2010 periods, on the other hand, the cumulative returns on Monday do not show very different features from those on other weekdays during trading hours. For these reasons, the Monday $R^{cc}$ are not significantly different from the other weekday returns.

Consequently, our findings from spatial dominance test imply that the Monday effect for the 1983-1987 period is driven by the large negative returns accrued on Monday mornings. This evidence of the Monday effect cannot be found in either the regression analysis or stochastic dominance tests since they evaluate returns or expected utilities at a given fixed time. In fact, Harris (1986) provides a similar pattern of returns for the period December 1981 to January 1983. Using 15-minute intraday returns for the period, he finds that Monday returns during first 45 minutes after the market open are significantly less than the other weekday returns.

**[Figure 4]** One-minute average cumulative returns



## IV. Conclusion

This paper explored the presence of the Monday effect in S&P 500 returns during the 1983 2010 time period by employing the concept of spatial dominance. In a spatial dominance framework, we can analyze the expected sum of utilities generated in a day as mentioned earlier. Therefore, important and useful information for testing the Monday effect such as intraday volatility of returns or trading patterns in a day can be taken into account in our approach. We can hardly find the Monday effect for the full sample, 1988-1999 and 2000-2010 periods similar to the previous empirical findings. For the 1983-1987 period, however, we find strong evidence of the Monday effect under spatial dominance criterion. Moreover, analyzing intraday returns enables us to find that the Monday effect is driven by large negative returns accrued during early Monday mornings. However, the conventional analyses for the Monday effect such as regression analysis and stochastic dominance cannot provide the strong evidence of the Monday effect for the same period since those testing methods cannot take into account the return behavior during Monday mornings.

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