A Transactions Data Analysis of Nonsynchronous Trading

Gregory B. Kadlec
Douglas M. Patterson
Virginia Polytechnic Institute

Weekly returns of stock portfolios exhibit substantial autocorrelation. Analytical studies suggest that nonsynchronous trading is capable of explaining from 5% to 65% of the autocorrelation. The varying importance of nonsynchronous trading in these studies arises primarily from differing assumptions regarding nontrading periods of stocks. We simulate the effects of nonsynchronous trading by sampling stock returns from a return generating process using transactions data to obtain the precise time of each stock's last trade. We find that simulated weekly portfolio returns exhibit autocorrelations that are roughly 25% that of their observed (CRSP) weekly returns.

It is well documented that *observed* short-horizon returns of portfolios exhibit positive autocorrelation. For example, Boudoukh, Richardson, and Whitelaw (1994) report first-order autocorrelations of .23 for weekly returns of an equally weighted index and .36 for weekly returns of a small-stock portfolio.[1] The source of the autocorrelation, however, remains the subject of much debate. Explanations include nonsynchronous trading, market-maker inventory control, transactions costs, time-varying expected returns, and market inefficiency.[2] Nonsynchronous trading — the tendency for prices recorded at the end of the day to represent the outcome of transactions that occur at different points in time for different stocks — is perhaps the most widely recognized source of autocorrelation in portfolio returns. To the extent that nonsynchronous trading is responsible, the autocorrelations are an artifact of the data sampling process and have no economic meaning. There

We are grateful for many helpful comments from Yakov Amihud, John Chalmers, Don Chance, Andrew Lo, Raman Kumar, Abon Mozumdar, and an anonymous referee. This work has been partially supported by a summer research grant from the Pamplin College of Business. Address correspondence to Gregory B. Kadlec, Pamplin College of Business, Blacksburg, VA 24060-0221.

1 These estimates are for ASE/NYSE stocks over the period 1962 to 1990 using returns computed from closing prices. For additional evidence of autocorrelation in portfolios returns see, for example, Cowles and Jones (1937), Fisher (1966), Perry (1985), Lo and MacKinlay (1990b), Lebaron (1992), and Mech (1993).

2 As examples of the literature on sources of autocorrelation in portfolio returns see Atchison, Butler, and Simonds (1987), Lo and MacKinlay (1990a), and Boudoukh, Richardson and Whitelaw (1994) for nonsynchronous trading; Cohen et al. (1986) and Mech (1993) for market friction-induced price adjustment delays; and Keim and Stambaugh (1986), Conrad and Kaul (1988) for time-varying expected returns.

The Review of Financial Studies Fall 1999 Vol. 12, No. 3, pp. 609–630
© 1999 The Society for Financial Studies 0893-9454/99/$1.50

is, however, considerable disagreement as to the amount of autocorrelation that can be explained by nonsynchronous trading.

Atchison, Butler, and Simonds (1987) and Lo and MacKinlay (1990a) derive explicit relations concerning the magnitude of autocorrelations caused by nonsynchronous trading. Both studies conclude that nonsynchronous trading is capable of explaining only a small portion of the autocorrelation that is observed. Boudoukh, Richardson, and Whitelaw (1994) (hereafter BRW) show that inferences from nonsynchronous trading models are highly sensitive to assumptions regarding nontrading intervals and security betas. They argue that prior studies seriously understate the potential effects of nonsynchronous trading. For example, they report that portfolios with weekly autocorrelations of .07 under the standard assumptions can have autocorrelations as high as .20 when the nonsynchronous trading framework allows for heterogeneous nontrading probabilities and heterogeneous betas.

From BRW it is clear that the precise distribution of nontrading intervals is crucial to inferences drawn from nonsynchronous trading models. What remains unclear is the level of autocorrelation that true patterns of nonsynchronous trading are capable of explaining. For even BRW's analysis requires assumptions regarding nontrading. In particular, BRW assume that nontrading intervals are uncorrelated across stocks. They note that their analysis will overstate the effects of nonsynchronous trading if nontrading is positively correlated across stocks. To assuage this concern they argue that trade (in a given stock) is likely to be largely idiosyncratic. However, they provide no empirical evidence regarding the validity of this assumption, nor do they explore the potential magnitude of its effect.

This study conducts an analysis of the effects of nonsynchronous trading that is free of assumptions concerning the distributions of nontrading intervals and security betas. Using transactions data to obtain the precise time of the last trade for each stock on each day, we simulate observed returns by sampling each stock's return according to the time of last trade from a return-generating process that is free of autocorrelation in the underlying factor.

We find that portfolios of simulated daily stock returns exhibit levels of autocorrelation that are more than 50% that of their observed (CRSP) daily returns. For example, the first-order autocorrelation of simulated daily returns for portfolios of randomly selected stocks, small stocks, and large stocks are 0.13, 0.28, and 0.04, respectively. By comparison, the first-order autocorrelation of observed (CRSP) daily returns for these portfolios are 0.25, 0.33, and 0.11, respectively. Chow tests cannot reject the hypothesis that the autocorrelations of simulated and observed daily returns are equal for the small stock and large stock portfolios.

We find that portfolios of simulated weekly stock returns exhibit levels of autocorrelation that are roughly 25% that of their observed (CRSP) weekly returns. For example, the first-order autocorrelation of simulated weekly returns for portfolios of randomly selected stocks, small stocks, and large stocks are 0.05, 0.12, and 0.02, respectively. By comparison, the first-order autocorrelation of observed (CRSP) weekly returns for these portfolios are 0.21, 0.44, and -0.04, respectively. Chow tests cannot reject the hypothesis that the autocorrelations of simulated and observed weekly returns are equal for the large-stock portfolio.

In addition to using actual trade times, our simulation model allows us to examine the effects of nonsynchronous trading under alternative specifications for the underlying return-generating process. The existing literature on nontrading assumes that true returns are generated by a continuous i.i.d. random normal process. We find that the effects of nonsynchronous trading are insensitive to noncontinuous returns (price discreteness) and nonnormal returns (t-distributed) and, for the most part, independent of the level of "genuine" autocorrelation in security returns.[3]

In summary, our results occupy middle ground in the debate concerning the effects of nonsynchronous trading on portfolio autocorrelation. Nonsynchronous trading appears to be more important than Atchison, Butler, and Simonds (1987) and Lo and MacKinlay (1990a) suggest but less important than BRW suggest. Researchers should consider nonsynchronous trading as an important source of autocorrelation in observed short-horizon portfolio returns. However, much of the autocorrelation remains to be explained.

The remainder of the article is organized as follows. Section 1 reviews analytical models of nonsynchronous trading and presents our simulation model. In Section 2 we compare the autocorrelations of simulated and observed (CRSP) portfolio returns. Section 3 considers refinements and extensions to the basic simulation model. Section 4 summarizes our findings.

1. Models of Nonsynchronous Trading

1.1 Review of analytical models

Fisher (1966) is perhaps the first to recognize that nonsynchronous trading can cause biases in statistical inferences concerning the temporal behavior of security returns. Scholes and Williams (1977) (hereafter SW) analyze the effects of nonsynchronous trading on estimates of systematic risk.[4] They assume that unobservable (true) returns are generated by a single-factor model

$$r_{nt} = \alpha_n + \beta_n r_{mt} + \epsilon_{nt}, \tag{1}$$

where r_{nt} is the return on security n during period t, α_n is the average return of security n that is not due to the common factor, β_n is the sensitivity

[3] We thank the referee for pointing out these refinements and extensions to our simulation model.

[4] Dimson (1979) and Cohen et al. (1983) examine the effects of nonsynchronous trading and price adjustment delays on estimates of systematic risk using similar models.

of the return of security n to the common factor, r_{mt} is a common factor with zero mean that is independently and identically distributed, and ϵ_{nt} is an idiosyncratic noise term that is independent of r_{mt} and temporally and cross-sectionally independent.

The observed returns, r^s_{nt}, of each security are given by

$$r^s_{nt} = \alpha^s_n + \beta^s_n r^s_{mt} + \epsilon^s_{nt}, \tag{2}$$

where r^s_{nt} is the observed return on security n during period t and r^s_{mt} is the observed return on the common factor during period t. The t's are a uniformly spaced sequence of time points, with intervals $[t-1, t]$. During a particular interval there may be no trade, or at some random time $t - s_{nt}$, $0 =< s_{nt} <= 1$, the last trade of the interval may occur. In the literature the intervals $[t-1, t]$ are usually thought of as corresponding to a trading day. If no trade occurs in $[t-1, t]$, then there is no observed price for that day, and no calculated return. If over two consecutive days closing prices are available, then a rate of return r^s_{nt} can be calculated for the interval $[t - 1 - s_{nt-1}, t - s_{nt}]$.

To derive closed form relations of the effects of nonsynchronous trading on estimates of systematic risk, SW make a number of assumptions regarding the distributions of nontrading intervals, s_{nt}, and security betas, β_n. In particular, SW assume that (1) all securities trade at least once during each return interval, (2) nontrading intervals are identically and independently distributed both temporally and cross-sectionally, and (3) securities have equal betas $\beta_1 = \beta_2 = \ldots \beta_n$). With these assumptions SW demonstrate that nonsynchronous trading causes a downward bias in estimates of systematic risk for infrequently traded securities and an upward bias in estimates of systematic risk for frequently traded securities.

A number of studies have used the SW framework to analyze the effects of nonsynchronous trading on portfolio return autocorrelation. The intuition for the autocorrelation caused by nonsynchronous trading is that information is impounded into observed prices of infrequently traded securities with a lag relative to that of frequently traded securities. This lag induces positive autocorrelation in the returns of a portfolio of frequently and infrequently traded securities. The magnitudes of the autocorrelations are greater the greater the cross-sectional variation in trade frequencies. These autocorrelations, however, are an artifact of how returns are measured and have no economic meaning.

Atchison, Butler, and Simonds (1987) demonstrate that, within the SW framework, nonsynchronous trading is capable of explaining less than 16% of the autocorrelation of observed daily returns for an equally weighted portfolio. Lo and MacKinlay (1990a) generalize SW's model to allow nontrading to persist beyond some fixed time interval (i.e., a day). Within their framework nonsynchronous trading is capable of explaining less than 7%

of the autocorrelation of observed weekly returns for an equally weighted index. In short, Atchison, Butler, and Simonds (1987) and Lo and MacKinlay (1990a) arrive at the same conclusion — nonsynchronous trading is capable of explaining only a small portion of the autocorrelation found in the observed short-horizon returns of portfolios.

BRW argue that the SW model's assumptions of homogeneous and temporally independent nontrading probabilities and homogeneous betas are unrealistic and play an important role in Atchison, Butler, and Simonds (1987) and Lo and MacKinlay's (1990a) conclusions. More specifically, BRW cite two empirical results from Keim (1989) and Foerster and Keim (1994): (1) the conditional probability of a nontrade in one period given a nontrade in the previous period is greater than the unconditional probability, and (2) there is considerable heterogeneity in nontrading among ASE/NYSE stocks even within size deciles. Using the empirical evidence on nontrading from Keim (1989) and Foerster and Keim (1993), BRW demonstrate that the effect of nonsynchronous trading on portfolio return autocorrelation is seriously understated in prior studies. For example, using Keim's (1989) evidence on time dependence of nontrading, BRW's model yields autocorrelations of 0.13 for weekly returns of a portfolio of small stocks as compared with 0.07 implied by Lo and MacKinlay's (1990a) model. Similarly, using Foerster and Keims' (1993) evidence on heterogeneity of nontrading, BRW's model yields autocorrelations of 0.18 as compared with 0.09 implied by Lo and MacKinlays' model.

While the analysis of BRW provides important insights into the effects of nonsynchronous trading, it does have some potentially important limitations. First, BRW rely on aggregated data for their estimates of nontrading distributions. Specifically, the nontrading evidence of Keim (1989) and Foerster and Keim (1993) are daily observations for portfolios. Thus BRW's analysis cannot fully capture the effects of nontrading for individual stocks within the trading day. Second, while BRW relax most of SW's assumptions regarding nontrading distributions, they still require nontrading to be uncorrelated across stocks. If nontrading is positively correlated across stocks BRW's analysis overstates the cross-sectional variation in nontrading, and thus overstates the effects of nonsynchronous trading. To assuage this concern BRW argue that nontrading is likely to be largely idiosyncratic — however, this question cannot be addressed with the aggregated data of Keim (1989) and Foerster and Keim (1993). Finally, due to the complexity of the analytic derivations, BRW are unable to relax the time independence and homogeneity assumptions simultaneously. As a result, one can only speculate as to their combined impact.

1.2 A simulation model of nonsynchronous trading

This study uses a simulation model with actual trade times obtained from transactions data to analyze the effects of nonsynchronous trading. This approach allows us to investigate the effects of nonsynchronous trading without restrictive assumptions concerning the distributions of nontrading intervals or security betas.

1.2.1 The basic model. Our simulation model is straightforward and follows the conceptualization first developed by SW and later generalized by Lo and MacKinlay (1990a). In particular, "true" but unobservable continuously compounded returns, r_{nt}, for security n are generated by a single-factor model:

$$r_{nt} = \alpha_n + \beta_n r_{mt} + \epsilon_{nt}, \quad n = 1, \ldots, N, \tag{3}$$

where r_{mt} is a zero mean random normal factor, α_n and β_n are the constant mean return and beta of security n, and ϵ_{nt} is a zero mean normally distributed noise term that is independent of r_{mt} and temporally and cross-sectionally independent. A trading day consists of 390 equally spaced time points — the time points correspond to the 390 minutes of a New York Stock Exchange (NYSE) trading day. The simulation model generates a return using Equation (3) for each minute in the trading day. The sequence $\{r_{nt}\}$ is converted to a price sequence through exponentiation of the returns:

$$p_{nt} = p_{nt-1} \exp(r_{nt}). \tag{4}$$

Observed prices, p^s_{nt}, are found by sampling the process at the time of the last trade as obtained from the transactions data. The last p^s_{nt} in $[t-1, t]$ is taken as the closing price; that is, the price at integer values of t. If the stock did not trade then p_{nt} is not available and the last observed p^s_{nt-1} is assigned to be the closing price. The prices, $\{p^s_{nt}\}$, are transformed into returns, $\{r^s_{nt}\}$, by the rule

$$r^s_{nt} = \ln(p^s_{nt}/p^s_{nt-1})/ \tag{5}$$

An equally weighted portfolio of pseudo-security returns, denoted r^s_{It}, is created by aggregating the r^s_{nt} for each integer t, that is $t = 1, 2, \ldots, T$. The resulting sequence of portfolio returns, $\{r^s_{It}\}$, is the time series used to study the effect of nonsynchronous trading on serial correlation. Because studies of short-horizon serial correlation often work with weekly return intervals we simulate weekly returns as well, the only difference being that the weekly return interval has 1,950 (5×390) trading minutes. In the event of a holiday a week may consist of fewer than five trading days, and thus fewer than 1,950 trading minutes.

1.2.2 Estimation of model parameters. This section presents details concerning the estimation of parameters necessary to conduct the simulations. The data we use comes from two sources: the Center for Research in Security Prices (CRSP) daily returns files, and the Institute for the Study of Security Markets (ISSM) transactions files. Our initial sample includes all U.S. domiciled common stocks whose shares were traded on either the American Stock Exchange (ASE) or the New York Stock Exchange (NYSE) at any time during the period from January 1988 through December 1992. From this universe we construct three portfolios of 400 stocks: a random sample, the 400 smallest stocks, and the 400 largest stocks. The portfolios are revised on an annual basis using those stocks for which sufficient data are available for obtaining market model estimates and end-of-day trade times. Specifically we require at least 30 monthly return observations surrounding the simulation year for market model estimates and 252 observations of end-of-day trade times during the simulation year. A typical year has 1,900 eligible stocks from which to construct the portfolios.

The return generating process [Equation (1)] requires estimates of the variance of the common factor, σ_m^2, the mean return of the common factor, α_m , security mean returns, α_n, security betas, β_n, and security residual variances, $\sigma_{\epsilon n}^2$. To estimate the variance of the common factor, we first compute 15-minute returns of a value weighted portfolio of all S&P 500 stocks listed on either the ASE or the NYSE for the sample period 1988–1992.[5] The variance of these 15-minute returns is 1.4×10^{-6}. Because estimates of portfolio return variance obtained from observed returns are likely to be understated due to nonsynchronous trading, we adjust our estimate using Equation (2.24) in Lo and MacKinlay (1990a) and the average nontrading probability for the 15-minute interval ($\pi = 0.13$). The adjusted 15-minute return variance is 1.8×10^{-6}. Finally, we convert the 15-minute return variance to a minute-to-minute return variance by dividing by 15. For purposes of comparison, our estimate of the standard deviation of the common factor, 0.00035, lies between Harris, Sofianos, and Shapiro's (1994) estimates of the standard deviation of minute-to-minute returns of the S&P 500 cash index, 0.00021, and futures contracts, 0.00045, over a similar period.

Because the effects of nonsynchronous trading on portfolio autocorrelation do not depend on the mean returns of either the common factor or the individual securities [Lo and MacKinlay (1990a)] we take $\alpha_m = 0$ and $\alpha_n = 0$ as our estimate of the constant mean return for the common factor and individual securities, respectively. Estimates of security betas are obtained from regressions of monthly stock returns on the contemporaneous and lagged monthly return of the CRSP equally weighted ASE/NYSE index over a five-year period centered on the simulation year. Estimates of security residual variances are obtained from daily market model residu-

[5] Ideally we would like to estimate the variance of the common factor using minute-to-minute returns of the ASE and NYSE indexes. Unfortunately the incidence of nonsynchronous trading for this portfolio would render such estimates unreliable. Our choice of S&P 500 stocks and a 15-minute return interval is an attempt to minimize the nonsynchronous trading problem while obtaining as direct an estimate as possible for the minute-to-minute variance of the common factor.

als during the simulation year. The daily estimates are then converted to minute-by-minute estimates using a linear transformation based on the 390 minutes within each trading day.

Turning to the return sampling process, the precise time of the last trade for each stock on each trading day is obtained from the trade time stamp on the ISSM transaction file. We use these trade times to sample the "closing" price for each stock from their sequence of virtual (simulated) prices. A standard trading day on the NYSE is from 9:00 A.M. to 3:30 P.M., thus there are 61/2 hours or 390 minutes in each trading day. However, some stocks trade "after hours," and thus the last time stamp for these stocks may exceed 390 (3:30 P.M.). Because these trades take place at prices established at the normal close they do not effect prices. So we truncate the end-of-day trade times at 390. On each day each stock is assigned an end-of-day trading time of 0 to 390. When simulating weekly returns each stock is assigned an end-of-week trading time of 0 to 1,950.[6]

1.2.3 Model validation. Before turning to the simulation results we perform two checks on the model. First, we examine the autocorrelation of the random normal index to assure that we are not introducing autocorrelation into returns from the underlying return-generating process. The first-order autocorrelation of daily returns for our random normal index is 0.02 and the first-order autocorrelation of weekly returns for our random normal index is 0.02. By comparison, the autocorrelation of daily returns of the equally weighted NYSE/ASE index over the sample period is 0.32 and the autocorrelation of weekly returns of the equally weighted NYSE/ASE index is 0.24. Although the random normal index does exhibit positive autocorrelation, it is well within the sampling error of the correlation estimator and quite small when compared to the levels of autocorrelation found in observed portfolio returns.

Second, it is the cross-sectional variation (nonsynchroneity) of trade times that causes observed portfolio returns to be autocorrelated — not the frequency of trade itself. For example, if all stocks traded for the last time at noon on each day, the infrequent trading would not induce any autocorrelation in the observed returns of portfolios. To ensure that our model produces this basic result we simulate returns with infrequent, yet perfectly synchronous trading. Specifically we set the end-of-day trade time of all stocks equal to the midpoint of the trading day. The autocorrelation of simulated daily returns for the random portfolio is 0.01. Likewise, when we set the end-of-week trade time equal to the midpoint of the trading week the autocorrelation of simulated weekly returns for the random portfolio

[6] In the event of a holiday a trading week may consist of fewer than five trading days, and thus a stock would be assigned an end-of-week trading time of 0 to $t < 1,950$.

is 0.00. Thus our model's results are consistent with this basic property of nonsynchronous trading.

2. Autocorrelations of Simulated and Observed Returns

In this section the simulation model of Section 1.2 is used to examine the effects of nonsynchronous trading on the serial correlation of portfolio returns. More specifically, we compare first-order autocorrelation coefficients of simulated and observed (CRSP) returns for portfolios of randomly selected stocks, small stocks, and large stocks. The autocorrelation coefficients of simulated and observed returns are estimated using data over the five-year period from January 1988 through December 1992. Thus daily autocorrelation coefficients are estimated using 1,264 daily returns and weekly coefficients are estimated using 260 weekly returns. All standard errors and test statistics for observed (CRSP) returns have been adjusted for heteroscedasticity and serial correlation using the method of Newey and West (1987).

2.1 Trade time distributions

Before discussing the simulation results it is of interest to examine the distributions of the two critical inputs to the simulation model — trade times and betas. Figure 1 depicts frequency plots of end-of-day trade times for stocks in each of the three portfolios over the five-year sample period.

From Figure 1 there are notable differences in the location and dispersion of the trade time distributions of the three portfolios. The mean end-of-day trade time for the random stock, small stock, and large stock portfolios are 329, 233, and 388, respectively. Thus the average random stock trades within 1 hour of the close, the average small stock trades within 3 hours of the close, and the average large stock trades within 3 minutes of the close on each day. As previously mentioned, it is the cross-sectional variation (nonsynchroneity) in trade times that causes portfolio returns to be autocorrelated. This, however, cannot be directly inferred from the cross-sectional and times-series frequencies depicted in Figure 1. The time-series mean of the cross-sectional standard deviations of the end-of-day trade times for the random-stock, small-stock, and large-stock portfolios are 113, 154, and 10 minutes, respectively. Given the cross-sectional standard deviations of end-of-day trade times we expect the returns of the small-stock portfolio to exhibit the greatest autocorrelation and the returns of the large-stock portfolio to exhibit little if any autocorrelation.

Figure 2 depicts frequency plots of end-of-week trade times for stocks in each of the three portfolios. The mean end-of-week trade time for the random-stock, small-stock, and large-stock portfolios are 1,856, 1,675, and 1,947 minutes, respectively. Thus the average random stock trades within 2 hours of the close, the average small stock trades within 4 hours of the close, and the average large stock trades within 4 minutes of the close of each

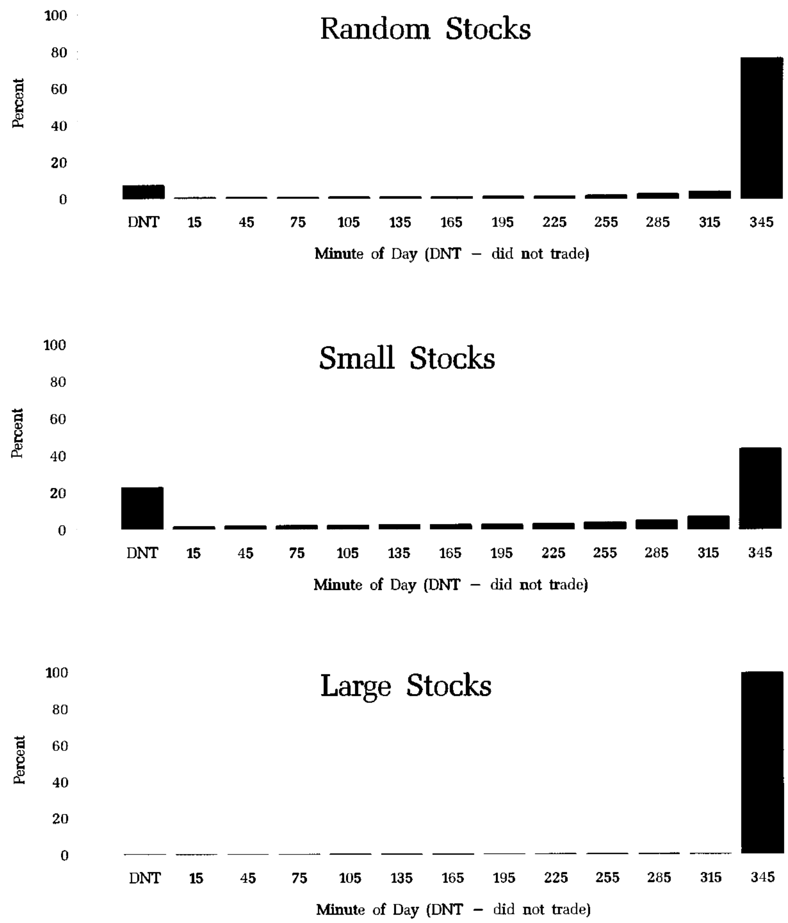

Figure 1
Frequency plots of end-of-day trade times

week. Note that nontrading periods as a percentage of the return interval are smaller for the weekly return interval than for the daily return interval. For example, the mean nontrading period for the small stock portfolio is roughly 40% of the daily return interval and less than 15% of the weekly return interval. This is to be expected since the nontrading period of a stock is fixed, and thus is a declining percentage of the time interval. As a result, we expect the weekly returns of the three portfolios to exhibit less autocorrelation than the daily returns.

Finally, the mean of the beta estimates for the random-stock, small-stock, and large-stock portfolio are 1.0, 1.2, and 0.9, respectively. The cross-

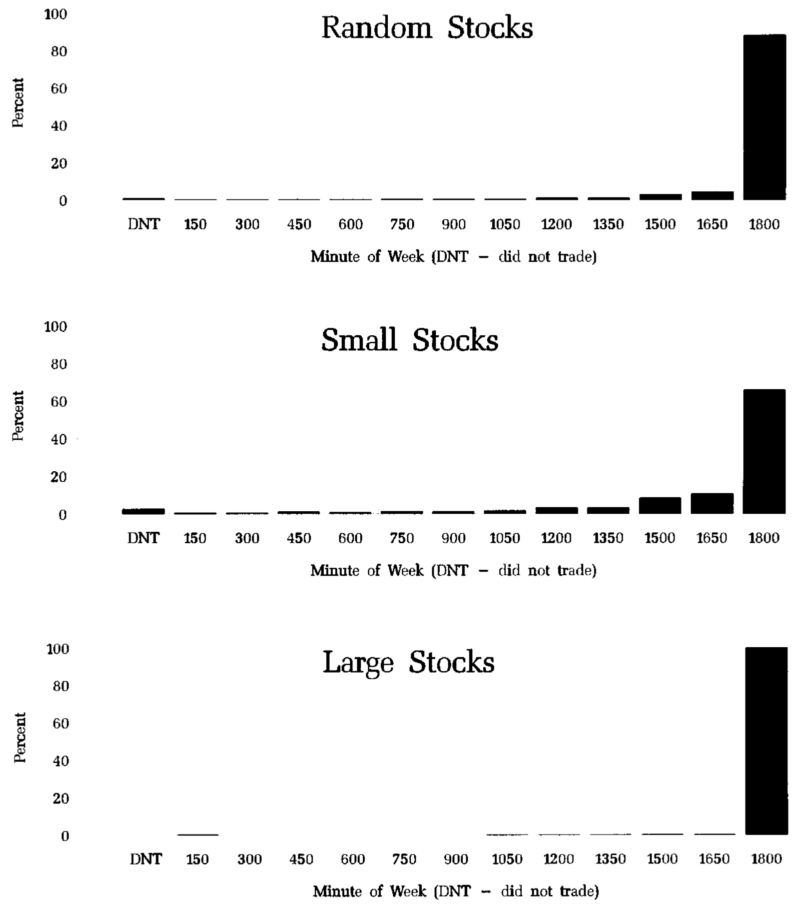

Figure 2
Frequency plots of end-of-week trade times

sectional standard deviation of the beta estimates for the random-stock, small-stock, and large-stock portfolios are 0.35, 0.52, and 0.26, respectively. We will now examine whether these distributions of end-of-period trade times and betas are capable of explaining the magnitude of autocorrelation of observed portfolio returns in the context of our nonsynchronous trading model.

2.2 Results

2.2.1 Autocorrelation of daily returns. We begin with the autocorrelations of daily portfolio returns. Table 1 reports first-order autocorrelation coefficients of daily returns for each of the three portfolios. Column 1 reports coefficient estimates for observed (CRSP) returns while columns 2 through 4 report coefficient estimates for simulated returns. The simulated returns of columns 2 through 4 differ according to how the simulation model is parameterized with respect to end-of-day trade times and security betas. In column 2, returns are simulated using actual end-of-day trade times for each stock on each trading day and market model estimates for each security's beta. This model (hereafter the KP model) makes no assumptions concerning the distributions of end-of-day trade times or security betas and is the primary focus of our analysis. For purposes of comparison, we also consider two alternative parameterizations. In column 3, returns are simulated using end-of-day trade times that are bootstrapped from each stock's empirical distribution of end-of-day trade times and market model estimates for each security's beta. This model assumes that end-of-day trade times are uncorrelated across stocks and is in the spirit of BRW's (1994) model. Finally, in column 4, returns are simulated using end-of-day trade times drawn from a Poisson distribution with trade intensity parameter, λ, equal to the average trade intensity of all stocks in the portfolio.[7] Furthermore, we assign a common beta ($\beta = 1$) to all stocks. This model assumes homogeneous, temporally, and cross-sectionally independent nontrading and homogeneous betas and is in the spirit of Lo and MacKinlay's (1990a) (hereafter LM) model. Thus our analysis allows us to compare the effects of nonsynchronous trading under various assumptions used in the literature.

Table 1 documents a number of interesting results. First, the autocorrelations of the KP model's daily returns are comparable to those of the observed (CRSP) daily returns. From column 1 the first-order autocorrelation coefficients for observed (CRSP) daily returns are 0.25, 0.33, and 0.11 for the random-stock, small-stock, and large-stock portfolios, respectively. From column 2, the first-order autocorrelation coefficients for the KP model's daily returns are 0.13, 0.28, and 0.04 for the random-stock, small-stock, and large-stock portfolios, respectively. The t-statistics for Chow tests against the null hypothesis that the autocorrelations of observed and KP model returns are equal are 2.96, 1.26, and 1.78 for the random-stock, small-stock, and large-stock portfolios, respectively. Thus we cannot reject the hypothesis that nonsynchronous trading is the primary source of autocorrelation of observed daily returns for the small-stock and large-stock portfolios.

Second, the autocorrelations of the BRW model's returns are somewhat higher than those of the KP model. From column 3, the first-order autocorrelation coefficients for the BRW model's returns are 0.16, 0.31, and 0.04 for

[7] Details concerning the estimation of the Poisson trade intensity parameter, λ, used for each portfolio are provided in the Appendix.

Table 1
Autocorrelations of daily returns

	Return series			
	(1) CRSP	(2) KP model	(3) BRW model	(4) LM model
Random-stock portfolio	0.25^{***} [0.031]	0.13^{***} [0.028]	0.16^{***} [0.028]	0.05^{*} [0.028]
Small-stock portfolio	0.33^{***} [0.038]	0.28^{***} [0.028]	0.31^{***} [0.028]	0.22^{***} [0.028]
Large-stock portfolio	0.11^{***} [0.032]	0.04 [0.028]	0.04 [0.028]	−0.01 [0.028]

Autocorrelations of daily returns for portfolios of random stocks, small stocks, and large stocks are estimated using CRSP returns (1) and returns generated from three models of nonsynchronous trading: the KP model (2), the BRW model (3), and the LM model (4). Models 2–4 generate minute–by-minute returns for each stock using a single-i.i.d.-factor model. The portfolio return series of models 2-4 differ by how the minute-by-minute returns of each stock are sampled. In (2) returns are sampled according to each stock's end-of-day trade time as obtained from the ISSM transaction files. In (3) returns are sampled using bootstrapped end-of-day trade times from each stock's empirical distribution of end-of-day trade times. In (4) returns are sampled using end- of-day trade times drawn from a Poisson distribution with common trade intensity parameter, , for a given portfolio (see Appendix). Standard errors are reported in brackets []. Standard errors for estimates using CRSP returns are adjusted for heteroscedasticity and serial correlation using the method of Newey and West (1987). * indicates significant at 0.10, ** indicates significant at 0.05, and *** indicates significant at 0.01 using a two-tailed test.

the random-stock, small-stock, and large-stock portfolios, respectively. The higher autocorrelations of the BRW model's returns are, however, consistent with BRW's observation that their assumption of cross-sectional independence in nontrading may cause their analysis to overstate the effects of nonsynchronous trading.

BRW argue that trade is likely to be largely idiosyncratic, and thus independent across stocks. However, it is quite plausible that investors' reactions to systematic information leads to systematic trade across stocks. Given the fact that the autocorrelation caused by nonsynchronous trading also depends on systematic information suggests that cross-sectional dependence in trade may have an important impact on the level of autocorrelation caused by nonsynchronous trading. To formally investigate the cross-sectional dependence in trade we estimate the pairwise correlation of end-of-day trade times for all NYSE and ASE stocks. The average of the pairwise correlations is .26 ($p < .01$). This result, combined with the fact that the KP and BRW models differ only in the sequencing of trade times, suggests that the lower autocorrelations of the KP model are due to this feature of the trade time distributions.

Finally, the autocorrelations of the LM model's returns are smaller than those of the KP and BRW models. From column 4, the first-order autocorrelation coefficients of the LM model's returns are 0.05, 0.22, and -0.01

for the random-stock, small-stock, and large-stock portfolios, respectively. These results are consistent with BRW's argument that the assumptions of homogeneous and temporally independent nontrading times and homogeneous betas cause the LM model to understate the effects of nonsynchronous trading. The t-statistics for Chow tests against the null hypothesis that the autocorrelations of observed and LM model returns are equal are 5.09, 2.89, and 3.09 for the random-stock, small-stock, and large-stock portfolios, respectively. Thus we reject the hypothesis that nonsynchronous trading is the primary source of autocorrelation in the observed daily returns for all three portfolios under the LM model of nonsynchronous trading.

2.2.2 Autocorrelations of weekly returns. The autocorrelations of the KP model's daily returns (Table 1) are consistent with the hypothesis that nonsynchronous trading is the primary source of autocorrelation in the observed (CRSP) daily returns of portfolios. However, studies examining potential sources of autocorrelation in portfolio returns typically focus on weekly returns. Weekly returns are not believed to be seriously affected by nonsynchronous trading because periods of nontrading are smaller relative to the return interval. Lo and MacKinlay (1990a) derive a number of results concerning this time aggregation principle and show that portfolio autocorrelations caused by nonsynchronous trading are monotonically decreasing in the interval over which returns are measured. Thus it is of interest to examine whether the KP model of nonsynchronous trading is capable of explaining the magnitude of autocorrelations found in weekly returns of portfolios.

Before we examine the autocorrelations of weekly returns we must first address a methodological issue that is related to the day of the week seasonal in daily autocorrelations. Bessembinder and Hertzel (1993) and Keim and Stambaugh (1984) document patterns in daily autocorrelations across days of the week. BRW note that these patterns in daily autocorrelations lead to different estimates of weekly autocorrelations for return intervals ending on different days of the week. For example, during the period 1984–1990 the estimated autocorrelation of weekly returns of a small-stock portfolio for weeks ending on Friday is .35, while that for weeks ending on Wednesday is .27. To avoid a potential day of the week bias in our estimates of autocorrelations of observed (CRSP) weekly returns we use overlapping weekly returns data. Autocorrelations computed from overlapping weekly returns are an average of the autocorrelations for weeks ending on different days of the week.[8]

[8] See Richardson and Smith (1991) and Hansen and Hodrick (1980) for a detailed discussion of how to estimate parameters from overlapping time-series data.

A natural question is whether these patterns in autocorrelations across days of the week are due to patterns in nonsynchronous trading. A comparison of the distributions of end-of-day trade times across days of the week suggests that this is not the case. The mean end-of-day trade time for the portfolio of small stocks is 232 on Mondays, 233 on Tuesdays, 233 on Wednesdays, 232 on Thursdays, and 233 on Fridays. The cross-sectional standard deviation of end-of-day trade times is 153 on Mondays, 153 on Tuesdays, 154 on Wednesdays, 154 on Thursdays, and 154 on Fridays. Thus the distributions of end-of-day trade times are nearly identical across days of the week.

To further investigate the potential effect of temporal patterns in nonsynchronous trading we simulate weekly returns for the small-stock portfolio for weeks ending on different days of the week. The first-order autocorrelations for the KP model's returns of the small-stock portfolio for weeks ending on Monday through Friday are .14, .13, .10, .14, and .12, respectively. Although the autocorrelations of simulated weekly returns vary somewhat for weeks ending on different days, the variation is within one standard error of the estimator and is small when compared to the variation in the autocorrelations of observed (CRSP) returns. In short, nonsynchronous trading does not appear to be responsible for seasonal patterns in autocorrelations. Thus for computational reasons we simulate weekly returns for weeks ending on Friday as opposed to simulating weekly returns for weeks ending on each day of the week.

Table 2 replicates the analysis of Table 1 using weekly returns. As before, column 1 reports coefficient estimates for observed (CRSP) returns while columns 2 through 4 report coefficient estimates for simulated returns. From Table 2 it is apparent that nonsynchronous trading plays a smaller role in explaining the magnitudes of the autocorrelations of weekly portfolio returns. From column 1 the first-order autocorrelation coefficients for observed (CRSP) weekly returns are 0.21, 0.44, and -0.04 for the random-stock, small-stock, and large-stock portfolios, respectively. From column 2 the first-order autocorrelation coefficients for the KP model's weekly returns are 0.05, 0.12, and 0.02 for the random-stock, small-stock, and large-stock portfolios, respectively. Thus the autocorrelations of the KP model's weekly returns are roughly 25% the magnitude of observed (CRSP) weekly returns. The t-statistics for Chow tests against the null hypothesis that the autocorrelations of observed and KP model returns are equal are 2.21, 4.08, and -1.57 for the random-stock, small-stock, and large-stock portfolios, respectively. Thus we are unable to reject the hypothesis that nonsynchronous trading is the primary source of autocorrelation of observed weekly portfolio returns only for the large-stock portfolio.

The autocorrelations of the BRW model's returns are, again, somewhat higher than those of the KP model. From column 3 the first-order autocorrelation coefficients for the BRW model's weekly returns are 0.07,

Table 2
Autocorrelations of weekly returns

	Return series			
	(1) CRSP	(2) KP model	(3) BRW model	(4) LM model
Random-stock portfolio	0.21** [0.054]	0.05 [0.062]	0.07 [0.062]	0.04 [0.062]
Small-stock portfolio	0.44*** [0.059]	0.12** [0.062]	0.17** [0.062]	0.08 [0.062]
Large-stock portfolio	−0.04 [0.045]	0.02 [0.062]	0.01 [0.062]	0.01 [0.062]

Autocorrelations of weekly returns for portfolios of random stocks, small stocks, and large stocks are estimated using CRSP returns (1) and returns generated from three models of nonsynchronous trading: the KP model (2), the BRW model (3), and the LM model (4). Models 2–4 generate minute-by-minute returns for each stock using a single-i.i.d.-factor model. The portfolio return series of models 2–4 differ by how the minute-by-minute returns of each stock are sampled. In (2) returns are sampled according to each stock's end-of-week trade time as obtained from the ISSM transaction files. In (3) returns are sampled using bootstrapped end-of-week trade times from each stock's distribution of end-of-week trade times. In (4) returns are sampled using end-of-week trade times drawn from a Poisson distribution with common trade intensity parameter, λ, for a given portfolio (see Appendix). Standard errors are reported in brackets []. Standard errors for estimates using CRSP returns are adjusted for heteroscedasticity and serial correlation using the method of Newey and West (1987). * indicates significant at 0.10, ** indicates significant at 0.05, and *** indicates significant at 0.01 using a two- tailed test.

0.17, and 0.01 for the random-stock, small-stock, and large-stock portfolios, respectively. It is interesting to note that the autocorrelation of weekly returns for the small-stock portfolio using the BRW model is nearly identical to that reported in BRW (1994). In particular BRW obtain an autocorrelation of 0.18 for the weekly returns of a small-stock portfolio using their model and the nontrading evidence of Foerster and Keim (1993).[9]

The autocorrelations of the LM model's returns are, again, smaller than those of the KP and BRW models. From column 4 the first-order autocorrelation coefficients of the LM model's weekly returns are 0.04, 0.08, and 0.01 for the random-stock, small-stock, and large-stock portfolios, respectively. Once again it is interesting to note that the autocorrelation of weekly returns for the small-stock portfolio using the LM model is nearly identical, .07, to that obtained by BRW (1994) using LM's model with the nontrading evidence of Foerster and Keim (1993).

[9] BRW's analysis focuses on small stocks, and thus no comparison can be made with the autocorrelations of the random-stock and large-stock portfolios of the current study.

3. Refinements and Extensions

The maintained hypothesis in our analysis, as well as other studies on non-trading, is that returns are drawings from a continuous, i.i.d., random normal process. However, the reasonableness of this assumption can be questioned on a number of grounds. Stocks can only trade at discrete prices. This implies that returns will cluster at discrete points. Further, empirical evidence suggests that actual stock returns are nonnormal and dependent. In this section we consider refinements and extensions to the KP model in an attempt to better capture the properties of actual return data.

Prices of ASE and NYSE stocks are discrete by virtue of the 1/8 minimum tick convention. Price discreteness increases the variance of individual security returns [see, e.g., Campbell, Lo, and Mackinlay (1997)] and thus may affect the sampling distribution of the autocorrelations. To examine the effects of price discreteness on portfolio autocorrelation we run the simulations rounding each sampled price to the nearest 1/8.[10]

Fama (1965) finds that daily stock returns are too leptokurtic to come from a normal distribution. Blattberg and Gonedes (1974) argue that a t-distribution provides a better description of daily stock returns than the normal distribution. To examine the effect of departures from normality on portfolio autocorrelation we run the simulations using t-distributed index returns and t-distributed residuals.

Finally, given the evidence in Hinich and Patterson (1985, 1989) of nonlinearities in daily as well as intraday returns and in Gibbons and Hess (1981) of a day of the week seasonal in returns, independence in return-generating process is not supported by the data. To examine the effects of nonsynchronous trading in the presence of dependence we run the simulations with various levels of autocorrelation in the underlying factor. Specifically we model dependence in the underlying factor for daily returns according to

$$r_{mt} = \rho r_{mt-390} + e_t, \tag{6}$$

where e_t is i.i.d. white noise, and $\rho = 0.10, 0.20, 0.30$. A similar scheme is used to model dependence in the underlying factor for weekly returns, but with a lag of 1,350 minutes.[11]

Table 3 reports autocorrelations of daily returns (panel A) and weekly returns (panel B). Columns 1 and 2 report the coefficient estimates for observed returns and the basic KP model returns from Tables 1 and 2 for comparison. Columns 3 through 7 report coefficient estimates for the vari-

[10] For stocks priced less than \$1 we follow the NYSE's rules which allow the minimum tick size to be less than 1/8 (i.e., 1/16, 1/32).

[11] Because the lag of the underlying factor in Equation (6) is 390 (1,350) minutes, sampling should be done no more frequently than every 780 (2,700) minutes in order to eliminate aliases [see Hinich and Patterson (1989)]. However, the single positive autoregressive term on the right side will mitigate any serious aliasing effects.

Table 3
Autocorrelations of small-stock portfolio returns

Panel A: Daily returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Basic (KP)	Discrete	t-Distributed	Factor autocorrelation		
	CRSP	model	prices	returns	0.10	0.20	0.30
Small-stock	0.33***	0.28**	0.28**	0.32	0.36	0.42	0.49
portfolio	[0.038]	[0.028]	[0.028]	[0.028]	[0.028]	[0.028]	[0.028]
Panel B: Weekly returns							
Small-stock	0.44***	0.12**	0.12**	0.14	0.20	0.26	0.37
portfolio	[0.059]	[0.062]	[0.062]	[0.062]	[0.062]	[0.062]	[0.062]

Autocorrelations of small-stock portfolio returns are estimated using CRSP returns (1) and returns generated from alternative specifications of the KP model of nonsynchronous trading: the basic model (2), discrete prices (3), t-distributed returns (4), and varying levels of autocorrelation for the underlying factor (5-7). The simulation model generates minute-by-minute returns for each stock using a single-factor model. The returns are then sampled according to each stock's end-of-period trade time as obtained from the ISSM transaction files. * indicates significant at 0.10, ** indicates significant at 0.05, and *** indicates significant at 0.01 using a two-tailed test.

ous refinements/extensions to the basic KP model. In particular, column 3 reports coefficient estimates for the discrete price simulations, column 4 reports coefficient estimates for the t-distributed returns simulations, and columns 5 through 7 report coefficient estimates for the autocorrelated factor simulations. Since autocorrelations are most prominent for small stocks, we restrict our analysis to the small-stock portfolio.

We begin with the issue of price discreteness. From column 3 the autocorrelations of the discrete price simulations are virtually identical to those of the basic KP model (column 2). Specifically the coefficients are 0.28 for the daily returns and 0.12 for the weekly returns. Thus the continuous returns assumption does not appear to be critical to our conclusions. This result does, however, make sense when one considers the fact that our rounding of prices is cross-sectionally independent and thus inconsequential in the context of a large portfolio.

Turning to the nonnormality issue, the autocorrelations of the t-distributed returns simulations are somewhat higher than those of the basic KP model. From column 4 the coefficients of the t-distributed returns simulations are 0.32 for the daily returns and 0.14 for the weekly returns. By comparison, the coefficients of the basic KP model are 0.28 for the daily returns and 0.12 for the weekly returns. These differences, however, are not significant. Thus the normality assumption does not appear to be critical to our conclusions.

Finally, with respect to the issue of dependence in the return-generating process, the effects of nonsynchronous trading appear to be roughly additive. That is, the autocorrelation of simulated returns in columns 5 through 7 are roughly equal to the level of autocorrelation in the underlying factor plus the autocorrelation induced by nonsynchronous trading in the absence of factor autocorrelation. For example, the autocorrelation of daily returns for the autocorrelated factor of column 5, 0.36, is approximately equal to the autocorrelation of daily returns for the basic KP model, 0.28, plus the autocorrelation of the underlying factor, 0.10. Similarly the autocorrelation of weekly returns for the autocorrelated factor of column 5, 0.20, is approximately equal to the autocorrelation of daily returns for the basic KP model, 0.12, plus the autocorrelation of the underlying factor, 0.10.

The results of Table 3 suggest that our inferences regarding the effects of nonsynchronous trading on portfolio autocorrelation are robust with respect to issues of price discreteness, nonnormality of returns, and dependence in the underlying factor. Admittedly the analysis of Section 3 is incomplete. Our model of price discreteness is, perhaps, oversimplified.[12] Our analysis of nonnormality considers only a single specification of the t-distribution. The analysis of dependence in the underlying return-generating process considers only linear dependence, that is, autocorrelation. Finally, as with all of the existing literature on nontrading we assume independence between the return-generating process and nonsynchronous trading itself. Thus it is still possible that the effects of nonsynchronous trading are misstated here. However, until further evidence is brought to bear on this issue, we must conclude that nonsynchronous trading is responsible for most of the autocorrelation found in observed daily returns but much of the autocorrelation in observed weekly returns is real.

4. Summary and Conclusion

Ever since Cowles and Jones (1937) first documented positive autocorrelation in daily and weekly portfolio returns, researchers have sought to explain it. Perhaps the most recognized explanation is that of Fisher (1966), who attributes at least a portion of the autocorrelation to nonsynchronous trading. There is, however, considerable disagreement as to the magnitude of autocorrelation nonsynchronous trading is capable of explaining. Atchison, Butler, and Simonds (1987) and Lo and MacKinlay (1990a) argue that nonsynchronous trading is capable of explaining only a very small portion of the autocorrelation that is observed. Boudoukh, Richardson, and Whitelaw (1994) argue that these studies seriously understate the effects of nonsynchronous trading.

This study uses a simulation model with actual trade times obtained from transactions data to analyze the effects of nonsynchronous trading on portfolio autocorrelation. This approach has a distinct advantage over prior analytical studies in that it allows us to investigate the effects of nonsynchronous trading without restrictive assumptions concerning the distributions of nontrading intervals and to consider alternative specifications of the

[12] For a discussion of alternative models of transaction data see Campbell, Lo, and Mackinlay (1997).

underlying return-generating process. Our results occupy middle ground in the debate. In other words, researchers should consider nonsynchronous trading an important source of autocorrelation in observed short-horizon returns of portfolios, however, there appear to be other sources.

Appendix A: Estimation of the Trade Intensity Parameter (λ)

In order to run the simulation under the assumption that trade times are generated by a homogeneous Poisson process, we need an estimate of λ, the Poisson intensity parameter, for each of the three portfolios. Our task is to infer λ from the empirical distribution of end-of-day and end- of-week trade times. The theory of the Poisson processes states that the inter-arrival time of the *n*th trade, t_n, is exponentially distributed with parameter λ regardless of the number of previous trades and when they occurred. If $w_1, w_2, \ldots, w_n$ are the trade times for a stock, then the conditional probability that no trade is made for a period of T minutes following the $(n-1)$th trade is

$$P[t_n > T | w_1, \ldots, w_{n-1}] = \exp(-\lambda T)$$

[see, i.e., Snyder (1975)]. Let $F_w^{(\tau)}(W)$ denote the cumulative occurrence distribution (COD) for a homogeneous Poisson process with constant intensity parameter λ. $F_w^{(\tau)}(W)$ is the probability that in the interval $[t_0, t)$, the last occurrence (trade) of the process occurred at $w_n \leq W \leq t$. $F_w^{(\tau)}(W)$ can be estimated from the histogram of end-of-day or end-of-week trade times. If $F_w^{(\tau)}(W)$ is the estimated COD, then the conditional probability that $t_n \geq T$ can be written as

$$P[t_n > T | w_1, \ldots, w_{n-1}] = \exp(-\lambda T) = 1 - F_w^{(T)}(W).$$

This result is applied in the following manner. With the randomly selected stocks the mean end-of-day trade time is 329 minutes out of a 390-minute trade day. From the histogram of end-of-day trade times, the probability that the last trade was $\leq$ 329 minutes is 0.767. Therefore

$$P[t_n > 329 | w_1, \ldots, w_{n-1}] = \exp(-\lambda * 329) = 1 - .767 = .233,$$

and it follows that $\lambda = 0.0239$. This procedure was followed to estimate λ for the other two portfolios and for weekly return intervals. The estimated λ for the daily return interval are 0.0239, 0.0058, and 1.1600 for the random-stock, small-stock, and large-stock portfolios, respectively. The estimated λ for the weekly return interval are 0.0175, 0.0044, and 0.8260 for the random-stock, small-stock, and large-stock portfolios, respectively.

References

Atchison, M., K. Butler, and R. Simonds, 1987, "Nonsynchronous Security Trading and Market Index Autocorrelation," *Journal of Finance*, 42, 111–118.

Blattberg , R., and N. Gonedes, 1974, "A Comparison of the Stable Student Distributions as Statistical Models for Stock Prices," *Journal of Business*, 47, 244–280.

Bessembinder, H., and M. Hertzel, 1993, "Return Autocorrelations Around Nontrading Days," *Review of Financial Studies*, 6, 155–189.

Boudoukh, J., M. Richardson, and R. Whitelaw, 1994, "A Tale of Three Schools: Insights on Autocorrelations of Short-Horizon Returns," *Review of Financial Studies*, 7, 539–573.

Campbell, J., A. Lo, and A. C. Mackinlay, 1997, *The Econometrics of Financial Markets*, Princeton, N.J., Princeton University Press.

Cohen, K., G. Hawawini, S. Maier, R. Schwartz, and D. Whitcomb, 1983, "Frictions in the Trading Process and the Estimation of Systematic Risk," *Journal of Financial Economics*, 12, 263–278.

Cohen, K., S. Maier, R. Schwartz, and D. Whitcomb, 1986, *The Microstructure of Securities Markets: Theory and Implications*, Englewood Cliffs, N.J., Prentice-Hall.

Conrad, J. and G. Kaul, 1988, "Time Varying Expected Returns," *Journal of Business*, 61, 409–425.

Cowles, A., and H. Jones, 1937, "Some a Posteriori Probabilities in Stock Market Action," *Econometrica*, 5, 280–294.

Dimson, E., 1979, "Risk Measurement When Shares Are Subject to Infrequent Trading," *Journal of Financial Economics*, 7, 197–226.

Fama, E., 1965, "The Behavior of Stock Market Prices," *Journal of Business*, 38, 34–105.

Fisher, L., 1966, "Some New Stock Market Indices," *Journal of Business*, 39, 191–225.

Foerster, S., and D. Keim, 1993, "Direct Evidence of Non-Trading of NYSE and AMEX Stocks," working paper, University of Pennsylvania.

Gibbons, M., and P. Hess, 1981, "Day of the Week Effects and Asset Returns," *Journal of Business*, 54, 579–596.

Hansen, L., and R. Hodrick, 1980, "Forward Exchange Rates as Optimal Predictors of Future Spot Rates: An Econometric Analysis," *Journal of Political Economy*, 88, 829–853.

Harris, L., G. Sofianos, and J. Shapiro, 1994, "Program Trading and Intraday Volatility," *Review of Financial Studies*, 4, 654–685.

Hinich, M., and D. Patterson, 1985, "Evidence of Nonlinearity in Daily Stock Returns," *Journal of Business and Economic Statistics*, 3, 47–73.

Hinich, M., and D. Patterson, 1989, "Evidence of Nonlinearity in the Trade-by-Trade Stock Market Returns Generating Process," *Economic Complexity: Chaos, Sunspots, Bubbles, and Nonlinearity*, Cambridge, Cambridge University Press, 383–409.

Keim, R., and F. Stambaugh, 1984, "A Further Investigation of the Weekend Effect of Stock Returns," *Journal of Finance*, 39, 819–835.

Keim, D., and R. Stambaugh, 1986, "Predicting Returns in the Stock and Bond Markets," *Journal of Financial Economics*, 17, 357–390.

Keim, D., 1989, "Trading Patterns, Bid-Ask Spreads, and Estimated Security Returns: The Case of Common Stocks at Calendar Turning Points," *Journal of Financial Economics*, 15, 75–98.

LeBaron, B., 1992, "Some Relations Between Volatility and Serial Correlations in Stock Market Returns," *Journal of Business*, 65, 199–219.

Lo, A., and A. C. MacKinlay, 1990a, "An Econometric Analysis of Nonsynchronous Trading, *Journal of Econometrics*, 45, 181–211.

Lo, A., and A. C. MacKinlay, 1990b, "When are Contrarian Profits Due to Stock Market Overreaction?," *Review of Financial Studies*, 3, 175–205.

Mech, T., 1993, "Portfolio Return Autocorrelation," *Journal of Financial Economics*, 34, 307–344.

Newey, W., and K. West, 1987, "A Simple Positive Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix," *Econometrica*, 55, 703–705.

Perry, P., 1985, "Portfolio Serial Correlation and Nonsynchronous Trading," *Journal of Financial and Quantitative Analysis*, 20, 517–523.

Richardson, M., and T. Smith, 1991, "Tests of Financial Models in the Presence of Overlapping Observations," *Review of Financial Studies*, 4, 277–254.

Scholes, M., and J. Williams, 1977, "Estimating Betas from Nonsynchronous Data," *Journal of Financial Economics*, 5, 309–327.

Snyder, D., 1975, *Random Point Processes*, New York, Wiley.