Return Autocorrelations around Nontrading Days

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We document a pattern in the serial dependence of security returns around non trading days. The correlation of returns the second day after a weekend or holiday with returns the first day after is unusually low, and in many return series is negative, implyng a reversal of price movements. We also document unusually large positive return autocorrelations the last day before and the first day after weekends and holidays. The pattern has existed in equity returns for over 100 years, and also exists in several futures markets, implying that the pattern is robust to alternative market microstructures.

The implications of periodic market closures for equilibrium in security markets are not well understood. There is, however, evidence of anomalous return behavior during trading intervals around regular closings. Perhaps the best known of these is the weekend effect, consisting of negative equity returns on Mondays and abnormally high returns on the last trading day of the week. [See Cross (1973), French (1980), Gibbons and Hess (1981), Lakonishok and Levi

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(1982), Keim and Stambaugh (1984), Jaffe and Westerfield (1985), and Lakonishok and Smidt (1988) .] There is also evidence of abnormal return behavior around market closings due to holidays. Several studies document abnormally high equity returns on the last trading day prior to holidays.[1]

In addition to the anomalous regularity in mean returns around market closings, there is also some evidence of unusual serial dependence in equity returns around nontrading periods. Cross (1973) examines the S&P 500 index and finds that a price increase on Monday is twice as likely if the price increased rather than decreased the preceding Friday. He also reports that price declines on Mondays occur with greater frequency following price declines on Fridays. Keim and Stambaugh (1984), investigating the possibility that positive measurement error in Friday closing prices contributes to the observed weekend effect, examine the correlation of Friday with Monday returns for the 30 stocks comprising the Dow Jones Industrial Average. In contrast to the negative autocorrelation implied by such measurement error, they find that the mean autocorrelation between Friday and Monday returns is the *highest* of any pair of successive days. Jaffe and Westerfield (1985) conduct a similar analysis and obtain similar results for stock returns in Australia, Canada, Japan, and the United Kingdom.

In this study, we undertake a further investigation of return behavior around regularly scheduled periods of nontrading. We find that the tendency for Monday returns to reinforce Friday returns, documented by Cross (1973), Keim and Stambaugh (1984), and Jaffe and Westerfield (1985), is part of a broader and more pervasive pattern that applies to holiday as well as weekend closings. Consistent with these studies, we find unusually high positive correlation between Friday and Monday equity returns. Moreover, we document a similar phenomenon around holiday closings: there is unusually high positive correlation between returns the first day after and returns the last day before holidays. Perhaps our most striking finding concerns the correlation of returns the second day after a nontrading period (either weekend or holiday) with returns the day after the nontrading period. This correlation is typically lower than correlations measured at one lag on other days, and is *negative* in most of the return series we examine, implying a *reversal* of price movements. For example, the correlation of Tuesday with Monday returns for the economically

[1] Lakonishok and Smidt (1988) report that preholiday trading accounts for 50 percent of the appreciation in the Dow Jones Industrial Average from 1897 to 1986. Other studies documenting abnormal mean returns around holidays include Roll (1983) and Ariel (1990).

important S&P 500 futures market is -0.24.[2] Finally, we document that the correlation of returns the last trading day of the week with returns the previous day tends to be unusually large.

Lakonishok and Smidt (1988) discuss reasons to be skeptical of reported return anomalies, particularly when generated from a dataset that has been frequently examined by other researchers. To guard against the danger of spurious results, we follow Lakonishok and Smidt in utilizing an equity return series from a considerably longer time interval than that covered by the CRSP daily returns files. We find that the anomalous pattern in autocorrelations around nontrading intervals is quite persistent, having existed in U.S. equity index returns for over 100 years. Additionally, we examine Japanese equity index returns and returns in 10 U.S. futures markets during more recent intervals for which daily data are available. Since sample periods for these return series overlap with the sample period for U.S. equity index returns, results of these tests are not independent of those based on U.S. equity index returns.[3] Still, the evidence from these markets suggests that the anomalous return pattern is quite pervasive. The finding that the autocorrelation pattern exists in futures markets is of particular interest, since it demonstrates that the pattern is robust to alternative market microstructures and exists in markets other than equities.

The autocorrelation pattern does not appear to be due to the averaging process implicit in index returns, as we find a similar pattern in individual equity returns. Nor does the pattern appear to be explained by bid-ask bounce; we find similar results for CRSP OTC returns computed using the mean of closing bid and ask prices. The autocorrelation pattern is not unique to firms of a specific size. Also, sensitivity tests indicate that the autocorrelation pattern is not driven by a few large outliers; rather, the majority of returns conform to the documented pattern. Finally, the regularity in daily autocorrelations around nontrading days implies an economically significant degree of return forecastability; mean returns conditioned on prior day returns are substantially larger than unconditional mean returns in most markets.

The observed autocorrelation pattern is difficult to reconcile with the most prominent explanation for return serial correlation, nonsynchronous trading, which is known to cause positive autocorrela-

[2] This correlation coefficient is based on all trading days from the introduction of S&P futures In April 1982 through December 1989. If the influential outliers of October 1987 are excluded, the coefficient is -0.14.

[3] We note, however, that with the exception of equity index futures, returns in the futures markets are not highly correlated with U.S. equity index returns. Pearson correlation coefficients between U.S. equity index returns and nonequity futures returns range from -0.017 (Yen futures) to 0.344 (Treasury bond futures), with the mean correlation coefficient equal to 0.080.

tion in measured portfolio returns [Scholes and Williams (1977)]. While changes in the frequency of trading could allow for measured autocorrelations to change across days, it is difficult to reconcile the evidence of negative autocorrelation with nonsynchronous trading explanations. For example, Lo and MacKinlay (1990) present a model of nonsynchronous trading that implies that the serial correlation of portfolio returns at one lag is an unbiased estimate of the probability that the representative component security does not trade during the return interval. Since probabilities cannot be negative, their model implies that nonsynchronous trading alone cannot explain the findings documented here.

An alternate route to an explanation lies in models of strategic behavior, as in Admati and Pfleiderer (1989). In their model, market-makers seek to mitigate losses to better informed traders by using “divide and conquer” pricing rules that encourage discretionary liquidity buyers and sellers to trade in separate periods. An equilibrium consequence of this behavior is that price moves in periods following concentrated trading tend to reverse price moves in the concentrated trading period (their proposition 4). If, as Foster and Viswanathan (1990) suggest, information asymmetries are most pronounced after periods of nontrading, market-maker incentives to invoke these price-reversal-inducing strategies may also be greatest following periods of nontrading. While this link is conjectural, it does suggest that potential explanations for the pattern documented here may lie in models of strategic interactions between rational agents, and need not rely on measurement error or market inefficiencies.

Our analysis proceeds as follows. In Section 1, we discuss the data series and estimation procedures we employ. In Section 2, we document the behavior of return autocorrelations around weekends and holidays for U.S. equity indices since 1885. In Section 3, we present evidence on the pervasiveness of the autocorrelation pattern by documenting its existence in 10 U.S. futures markets and in Tokyo equity returns. In Section 4, we provide evidence on the economic significance of the observed pattern. In Section 5, we address some potential explanations by examining patterns in size-ranked portfolio returns, individual equity returns, and returns that are free of bid-ask bounce. We conclude in Section 6.

1. Estimation Procedures and Data

To evaluate serial dependence in returns around nontrading periods, we regress returns on prior day returns while employing indicator variables to allow daily coefficient estimates to vary depending on proximity to the nontrading period of interest. When estimating parameters around weekends, the indicator variables simply identify the day of the week. For datasets without Saturday returns, we use five indicators to denote the trading days Monday through Friday. For datasets with some Saturday trading, we use eight indicators: six to denote the trading days Monday through Saturday, and two to distinguish Friday and Monday returns that surround weekends with Saturday trading from those without Saturday trading. When estimating parameters around holidays, we use four indicator variables: one each to denote the day before, and the first and second trading days after the holiday; the fourth identifies all other days.

To provide a basis of comparison, we initially estimate the first-order autocorrelation (ARl) coefficient using all days in the sample. To measure the overall ("all days") AR1 coefficient, we estimate *B* from the regression

$$R_t = \sum_{i=1}^{n} a_i d_{it} + BR_{t-1} + \epsilon_t, \tag{1}$$

where R_t is the return from the close of trading on day t-l to the close of trading on day t, and $d_{1t},...,d_{nt}$[4] are the indicator variables that identify specific trading days around the nontrading period. Intercepts are allowed to vary across days in order to control for differences in daily mean returns that can induce nonzero return autocorrelations.

To measure AR1 coefficients for individual days around nontrading periods ("daily" coefficients), we use the indicator variables to allow slope coefficients as well as intercepts to vary. The regression equation we estimate is

$$R_t = \sum_{i=1}^{n} a_i d_{it} + \sum_{i=1}^{n} B_i d_{it} R_{t-1} + \mu_t. \tag{2}$$

Estimates of B_i for $i = 1,...,n$ measure the autocorrelation of day i returns with prior-day returns, after controlling for differing daily mean returns. Equation (2) is identical to equation (5) in Keim and Stambaugh (1984).

We also report the results of tests designed to determine whether the AR1 parameter on a particular day differs significantly from the average parameter on other days. These tests are motivated by existing evidence of time-varying first-order return autocorrelation in markets we study. [See, e.g., Goldenberg (1988), Lo and MacKinlay (1990), and Schwert (1990).] In return series where significant overall autocorrelation exists, a comparison of daily AR1 coefficient estimates to

[4] For example, the well-documented negative mean Monday return will tend to induce negative first-order autocorrelation.

a benchmark of zero will not reveal the extent to which the coefficient is unusual. Tests for differences from other days are based on "difference" coefficients, B_j, obtained by estimating

$$R_t = \sum_{i=1}^{n} a_i d_{it} + BR_{t-1} + B_j d_{jt} R_{t-1} + \zeta_t \tag{3}$$

separately for $j = 1,...,n$. The coefficient B_j measures the difference between the AR1 coefficient for day j and the AR1 coefficient estimated using all days other than j.

In addition to estimating autocorrelation coefficients, we test whether the daily AR1 coefficients are jointly equal to zero and whether they jointly equal each other. Letting B denote the $n \times 1$ vector of parameter estimates and R the appropriate $q \times n$ restriction matrix, we test whether $RB = 0$, employing the test statistic $Q = (RB)'(RZR')^{-1}(RB)$, where Z is the parameter estimate covariance matrix. Since diagnostic tests indicate that, for most databases we examine, residuals from estimating Equation (2) are both heteroskedastic and autocorrelated, we employ the Newey-West (1987) heteroskedasticity and autocorrelation consistent covariance matrix.[5] The test statistic is asymptotically distributed x^2 with q degrees of freedom.

As discussed earlier, we measure return autocorrelations in several databases, including U.S. equity index returns, size-ranked equity portfolios, individual equities, Japanese equity index returns, and 10 futures markets. The return series, sample periods, and data sources for this study are summarized in Table 1. As indicated in Table 1, our sample sizes are relatively large. The sample of U.S. equity index returns consists of more than 29,000 daily observations. Sample sizes on other series are more moderate, ranging from about 1900 observations for S&P 500 futures returns to 6900 observations on CRSP equity returns.

A consideration with large samples is that almost any test statistic will differ significantly from zero at conventional levels (Lindley's paradox).[6] Thus, for large samples, classical statistical tests may not be as informative as simple parameter estimation. While we do report asymptotically consistent standard errors, they provide only one measure by which to gauge significance of the parameter estimates. In Section 4, we address the issue of whether the autocorrelations are large enough to be important in an economic sense.

[5] We employ 12 lags to compute the Newey-West matrix for the results reported. Sensitivity tests using 6-30 lags indicate that elements of the covariance matrix are quite insensitive to the truncation lag, and inference is unaltered over this range.

[6] Lindley's paradox is based on the observation that, *ceteris paribus*, standard errors decline with sample size. In the return series we study, a relatively high degree of heteroskedasticity partially counters the effect of large sample sixes. Heteroskedasticity consistent standard errors are generally several times larger than (inconsistent) OLS standard errors.

Table 1
Datasets and sample periods

Dataset	Sample period	No. of observations
Equities		
U.S. index returns[1]	1885–1989	29,384
U.S. size-ranked portfolios[2]	1/64–12/89	6,536
Dow 30 firms[2]	7/62–12/89	6,914
OTC firms[2]	12/72–12/89	4,284
Japanese index returns[3]	1/73–12/89	4,451
Futures[4]		
S&P 500	5/82–12/89	1,938
Japanese yen	5/72–12/89	4,443
Deutsche mark	5/72–12/89	4,443
Silver	1/67–12/89	5,749
Gold	1/75–12/89	3,773
Treasury bonds	10/77–12/89	3,120
Treasury bills	1/76–12/89	3,530
Wheat	5/66–12/89	5,948
Live cattle	2/66–12/89	6,016
Cotton	1/67–12/89	5,746

[1] From Schwert (1990).

[2] From the Center for Research in Security Prices.

[3] From Barclay, Litzenberger, and Warner (1990).

[4] From Columbia University Futures Center and Data Resources, Inc. Each sample period begins with the earliest data on the Columbia tape.

2. Autocorrelations in U.S. Equity Returns, 1885-1989

We estimate daily autocorrelations in U.S. equity index returns using the 105 years of daily data described in detail by Schwert (1990). Returns from 1885 to 1927 are based on the Dow Jones Composite Portfolio, and returns from 1928 to 1989 are based on the Standard & Poors Composite Portfolio (comprised of 90 firms until March 1957 and 500 firms since). Until June 1, 1952, the New York Stock Exchange was open for a half day of trading on most Saturdays.

2.1 Estimates of AR1 parameters around weekends

In Table 2, we report parameter estimates for Equations (l)-(3) for the full sample period (panel A), the full sample excluding outliers (panel B), and for 10 subperiods excluding outliers (panel C). Estimates of the "all days" and "daily" AR1 coefficients are reported in the rows labeled "coefficient." The difference coefficients obtained by estimating Equation (3) are reported in the rows labeled "difference." Test statistics for the hypotheses that the daily coefficients $(B_1,\ldots,B_8)$ are jointly equal to zero and that the coefficients are jointly equal to each other are reported in the last two columns. This analysis excludes observations involving a holiday.

Table 2
AR1 coefficients in U.S. equity returns, 1885–1989

	AR1 coefficients estimated using all days	Daily AR1 coefficients: Monday following trading Saturday	Daily AR1 coefficients: Monday following nontrading Saturday
			A: Full sample 1885–1989
Coefficient	.043 [.011]	.151 [.052]	.375 [.095]
Difference		.114 [.056]	.346 [.089]
Observations	27,333	2940	1897
			B: Full sample (excluding outliers)[3] 1885–1989
Coefficient	.070 [.007]	.166 [.032]	.331 [.032]
Difference		.101 [.033]	.274 [.034]
Observations	26,359	2831	1889
			C: Subperiods (excluding outliers)[3] 1885–1895
Coefficient	−.040 [.018]	.155 [.076]	.539 [.191]
Difference		.220 [.081]	.579 [.194]
Observations	3058	505	8
			1896–1906
Coefficient	.032 [.017]	.192 [.074]	.628 [.286]
Difference		.182 [.082]	.600 [.286]
Observations	3010	494	14
			1907–1917
Coefficient	.011 [.019]	.089 [.086]	.648 [.161]
Difference		.086 [.094]	.640[.156]
Observations	2941	486	15
			1918–1927
Coefficient	.050 [.019]	.173 [.077]	.580 [.306]
Difference		.135 [.082]	.526 [.306]
Observations	2738	445	13
			1928–1937
Coefficient	.017 [.019]	.147 [.065]	−.142 [.201]
Difference		.148 [.069]	−.161 [.202]
Observations	2457	408	21
			1938–1948
Coefficient	.117 [.021]	.295 [.082]	.178 [.167]
Difference		.189 [.087]	.050 [.168]
Observations	2626	386	67
			1949–1958
Coefficient	.157 [.019]	.364 [.192]	.421 [.082]
Difference		.191 [.192]	.299 [.087]
Observations	2415	107	348
			1959–1968
Coefficient	.245 [.029]	—	.553 [.076]
Difference		—	.356 [.091]
Observations	2251		451
			1969–1978
Coefficient	.272 [.018]	—	.415 [.062]
Difference		—	.174 [.075]
Observations	2323		441
			1979–1989
Coefficient	.058[.017]	—	.190 [.053]
Difference		—	.160 [.061]
Observations	2540		482

Table 2
Extended

Daily AR1 coefficients		
Tuesday	Wednesday	Thursday
−.064 [.037] −.137 [.043] 4824	.034 [.039] −.011 [.049] 4829	.012 [.033] −.038 [.038] 4960
−.038 [.017] −.137 [.019] 4631	.046 [.018] −.031 [.020] 4654	.038 [.017] −.041 [.018] 4792
−.180 [.047] −.175 [.052] 509	−.126 [.056] −.104 [.063] 503	−.089 [.045] −.059 [.053] 512
−.065 [.049] −.122 [.056] 494	−.002 [.052] −.041 [.058] 492	−.072 [.053] −.124 [.059] 509
−.028 [.052] −.048 [.054] 485	−.086 [.051] −.117 [.060] 488	.040 [.051] .036 [.058] 496
−.095 [.051] −.182 [.058] 454	.066 [.060] .020 [.069] 451	.028 [.053] −.026 [.060] 460
−.070 [.048] −.106 [.056] 407	−.057 [.053] −.088 [.058] 402	−.072 [.053] −.107 [.056] 414
−.004 [.052] −.137 [.056] 441	.116 [.049] −.002 [.055] 437	.140 [.045] .029 [.051] 452
−.013 [.054] −.187 [.059] 453	.155 [.050] −.003 [.060] 460	.106 [.050] −.063 [.056] 470
.062 [.062] −.248 [.070] 480	.234 [.061] −.014 [.065] 441	.270 [.050] .032 [.055] 455
.166 [.046] −.136 [.057] 450	.294 [.058] .027 [.065] 469	.176 [.044] −.124 [.051] 488
−.081 [.045] −.177 [.058] 488	.046 [.046] −.014 [.056] 511	.040 [.046] −.023 [.048] 538

Table 2
Extended

	Daily AR1 coefficients		
	Friday prior to trading Saturday	Friday prior to nontrading Saturday	Saturday
			A: Full sample 1885–1989
Coefficient	−.007 [.043]	.155 [.051]	.114 [.025]
Difference	−.057 [.045]	.118 [.053]	.083 [.029]
Observations	2884	2044	2954
			B: Full sample (excluding outliers)[3] 1885–1989
Coefficient	.031 [.023]	.205 [.028]	.131 [.020]
Difference	−.045 [.024]	.143 [.029]	.069 [.022]
Observations	2740	2011	2840
			C: Subperiods (excluding outliers)[3]
			1885–1895
Coefficient	−.109 [.056]	−.036 [.278]	.186 [.043]
Difference	−.082 [.065]	.003 [.281]	.273 [.051]
Observations	498	13	510
			1896–1906
Coefficient	.051 [.046]	−.167 [.140]	.144 [.038]
Difference	.023 [.049]	−.200 [.141]	.136 [.046]
Observations	483	28	496
			1907–1917
Coefficient	−.002 [.051]	.113 [.245]	.056 [.048]
Difference	−.016 [.056]	.103 [.242]	.055 [.055]
Observations	463	31	477
			1918–1927
Coefficient	.090 [.046]	.188 [.199]	.106 [.044]
Difference	.048 [.050]	.139 [.199]	.068 [.052]
Observations	439	23	453
			1928–1937
Coefficient	.076 [.059]	−.063 [.132]	.124 [.046]
Difference	.070 [.064]	−.081 [.133]	.133 [.053]
Observations	369	27	409
			1938–1948
Coefficient	.036 [.056]	.137 [.108]	.197 [.048]
Difference	−.095 [.062]	.021 [.110]	.094 [.051]
Observations	380	74	389
			1949–1958
Coefficient	.086 [.081]	.189 [.054]	.273 [.085]
Difference	−.075 [.083]	.037 [.060]	.121 [.088]
Observations	105	365	107
			1959–1968
Coefficient		.262 [.059]	
Difference	—	.021 [.065]	—
Observations	—	454	—
			1969–1978
Coefficient		.355 [.062]	
Difference	—	.101 [.070]	—
Observations	—	475	—
			1979–1989
Coefficient		.123 [.049]	
Difference	—	.082 [.052]	—
Observations	—	521	—

Table 2
Extended

	Tests			
	Specification		Hypothesis	
$\bar{R}^2$	Heter[1]	Auto[2]	All zero	All equal
.018	99.73 (.000)	91.17 (.000)	56.09 (.000)	38.99 (.000)
.022	138.18 (.000)	44.85 (.000)	261.18 (.000)	149.02 (.000)
.027	33.78 (.000)	6.69 (.878)	64.97 (.000)	63.83 (.000)
.016	25.63 (.000)	49.17 (.000)	43.76 (.000)	36.34 (.000)
.009	40.72 (.000)	12.56 (.402)	25.03 (.002)	24.81 (.002)
.023	50.35 (.000)	11.29 (.504)	24.08 (.002)	15.27 (.054)
.016	27.84 (.000)	16.86 (.155)	24.71 (.002)	23.61 (.003)
.034	68.02 (.000)	38.60 (.000)	67.14 (.000)	15.48 (.051)
.065	41.65 (.000)	42.83 (.000)	89.16 (.000)	22.50 (.004)
.098	15.30 (.004)	28.01 (.006)	140.71 (.000)	22.23 (.004)
.091	6.86 (.144)	28.42 (.005)	235.97 (.000)	12.87 (.025)
.019	2.53 (.640)	8.15 (.773)	22.81 (.004)	16.72 (.005)

Consistent with previous studies, we find positive first-order autocorrelation in equity index returns; the "all days" AR1 coefficient estimated over the period 1885-1989 is 0.043. When autocorrelations are allowed to vary by day, the hypothesis that AR1 coefficients are equal across days is rejected ($p < .001$). Examination of the daily point estimates indicates that substantial deviations of daily autocorrelations from the overall autocorrelation occur around weekends, while midweek autocorrelations are close to the "all days" coefficient.

Consistent with results reported by Keim and Stambaugh (1984) for a more recent sample of individual equity returns, Monday equity index returns tend to reinforce prior trading day returns. The AR1 coefficient estimates are 0.375 for Mondays following Friday trading and 0.151 for Mondays following Saturday trading. The difference coefficients show that the Monday AR1 coefficient significantly exceeds the average AR1 coefficient on other days, whether Monday follows Friday or Saturday trading.

Evidence that AR1 coefficient estimates for Mondays following two-day weekends exceed coefficient estimates for Mondays following single-day weekends is consistent with the reasoning that larger autocorrelations are associated with longer nontrading intervals. However, two-day weekends occur primarily in the last 35 years of the sample, and the overall autocorrelation is higher late in the sample. We examine the effect of a longer nontrading period by comparing AR1 coefficients around three-dayweekends with AR1 coefficients around two-day weekends. Our findings, which are not reported in the tables, indicate the patterns do not significantly differ from each other.

There is also evidence that returns on the last trading day of the week tend to reinforce prior-day returns to a greater extent than normal. Estimated AR1 coefficients for Saturdays and for Fridays that are the last trading day of the week are both substantially larger than on other days. In contrast, the AR1 coefficient estimate for Fridays that are *not* the last trading day of the week (i.e., Fridays that are

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Excludes periods involving a holiday. AR1 coefficients are estimated by regressing daily returns on prior-day returns. *Newey-West* standard errors on coefficient estimates are in brackets; *p values on* the hypothesis tests are in parentheses. Daily and "all days" AR1 parameter estimates are reported in rows labeled "coefficient." The "all days" coefficient is the estimate of B from the regression R_t $a_i d_{it} + BR_{t-1} + \epsilon_t$, where the d_{it} denote daily indicator variables. The daily AR1 coefficients are estimates of $B_1, \ldots B_8$, from the regression $= \Sigma_{i=1}^{n} a_i d_{it} + \Sigma_{i=1}^{n} B_i d_{it} R_{t-1} + \mu_t$. The "difference" coefficients are the estimates of B_j from estimating $= \Sigma_{i=1}^{n} a_i d_{it} + BR_{t-1} + B_j d_{it} R_{t-1} + \zeta_t$ separately for $j = 1, \ldots, 8$.

[1]White (1980) test for heteroskedasticity.

[2]Box-Pierce test for residual autocorrelation to 12 lags.

[3]Excludes 1% largest, 1% smallest, and matching next-day returns.

[4]All inference is based on the Newey-West heteroskedasticity and autocorrelation consistent covariance matrix.

followed by Saturday trading) is near zero and is not significantly different from the average AR1 parameter estimate on other days. This suggests that the autocorrelation pattern we observe reflects proximity to nontrading days rather than the day of the week, per se.

Perhaps the most striking finding is the negative AR1 coefficient estimate for Tuesdays. The point estimate of -0.064 implies that, on average, Tuesday returns tend to reverse Monday returns. The Tuesday difference coefficient is -0.137, implying that autocorrelations on Tuesdays are substantially lower than on other days.

2.1.1 The effect of influential outliers. The autocorrelation pattern documented above could be attributable to relatively few large price movements. In particular, the extreme price moves during October 1987 contribute to the observed pattern. To examine the importance of outliers, we reestimate the regression equations after deleting the 1 percent largest and 1 percent smallest returns (and matching next-day returns) from the sample. Since the excluded observations are not data errors, this analysis is not an attempt to verify the accuracy of the point estimates reported in panel A of Table 2. Rather, we exclude the unusually large positive and negative returns to determine whether the autocorrelation pattern is typical of the majority of observations.

Results, reported in panel B of Table 2, indicate that the pattern in autocorrelations is largely unaffected by the exclusion of outliers. The “all days” coefficient increases slightly to 0.070. The Tuesday point estimate is slightly higher at -0.038, while the Tuesday difference coefficient remains -0.137. AR1 coefficients on the first and last trading days of the week remain abnormally large. We conclude that the observed pattern in autocorrelations around weekends is not driven by a few large outliers.

2.1.2 Subperiod results. To assess the extent to which the autocorrelation pattern has existed throughout the past 105 years or is unique to certain time periods, we estimate Equations (1)-(3) for 10 subperiods of 10 or 11 years each. Since extreme price moves can have relatively large effects on point estimates obtained from shorter return series, we exclude outliers for this analysis. Results are reported in panel C of Table 2. In addition, estimated difference coefficients for each subperiod are displayed in Figure 1.[7]

The main implication of the subperiod analysis is that the observed daily autocorrelation pattern is not unique to one or a few subperiods;

[7] Because of small sample sizes in some subperiods, Friday and Monday difference coefficients displayed in Figure 1 are estimated without distinguishing on the basis of Saturday trading.

rather, the pattern is fairly consistent over time. Notably, the Tuesday difference coefficient is negative in all 10 subperiods, and the point estimate of the Tuesday AR1 coefficient is negative in eight of the 10 subperiods. The Saturday difference coefficient is positive in all seven subperiods with Saturday trading, and Monday and Friday difference coefficients are predominantly positive. Also noteworthy is the magnitude of Monday with Friday AR1 coefficient estimates, which have exceeded 0.40 in three of the four most recent subperiods.

To summarize, the evidence for U.S. equity index returns over the period 1885-1989 indicates that, after controlling for differing daily means, (i) the correlation of Tuesday returns with Monday returns is significantly lower than for other pairs of days, and in most subperiods Tuesday returns tend to reverse Monday returns; (ii) Monday returns tend to reinforce prior trading day returns; and (iii) returns on the last trading day of the week tend to reinforce prior-day returns.

2.2 Estimates of AR1 parameters around holidays

Estimates of AR1 coefficients around holidays, without regard to the day of the week, are reported in Table 3. We include the Wednesday closings in 1968 as holidays since market participants knew of the closings in advance. Panel A shows results based on all observations; panel B shows results after excluding outliers. Overall, the pattern in autocorrelations around holidays is similar to the pattern found around weekends. The AR1 coefficient for the second day after a holiday is, like the estimated Tuesday coefficient, unusually low. The point estimate for the full sample is -0.086, and the difference coefficient is -0.132. Excluding outliers, the point estimate for the second day after increases to -0.014, but remains significantly less than other days. The AR1 coefficient for the first trading day after a holiday is, like the estimated Monday coefficient, positive and significantly higher than other days. For the full sample, the point estimate is 0.146 and the difference estimate is 0.109. When outliers are excluded these estimates increase to 0.270 and 0.203, respectively. The AR1 coefficient for the last trading day before a holiday is, like the coefficient for the last trading day of the week, positive, although this coefficient is not significantly different from other days. Overall, these findings reinforce the notion that the observed changes in return serial dependence occur around regularly scheduled nontrading days, as opposed to reflecting a day of the week pattern, per se.

Additional evidence that the autocorrelation pattern reflects proximity to nontrading periods is provided by examining autocorrelations around holiday weekends. Though the relatively small sample size precludes statistical significance, point estimates are illustrative. In the case of Monday holidays, where Tuesday is the first trading day

Table 3
AR1 coefficients in U.S. equity returns around holidays, 1885-1989

	AR1 coefficient estimated using all days	Trading day relative to holiday			
		Day before	1st day after	2nd day after	Other days
		A: Full sample			
Coefficient	.040 [.015]	.049 [.074]	.146 [.051]	−.086 [.046]	.043 [.016]
Difference		.007 [.076]	.109 [.053]	−.132 [.049]	.004 [.020]
Observations	29,384	1026	1026	1026	26,306
		B: Full sample (excluding outliers)[1]			
Coefficient	.072 [.007]	.077 [.038]	.270 [.045]	−.014 [.034]	.070 [.008]
Difference		.005 [.039]	.203 [.046]	−.088 [.036]	−.002 [.009]
Observations	28,302	971	971	971	25,389

AR1 coefficients are estimated by regressing daily returns on prior-day returns. Newey-West standard errors are in brackets. Daily and "all days" AR1 parameter estimates are reported in rows labeled "coefficient." The "all days" coefficient is the estimate of B from the regression $R_t = \Sigma_{i=1}^{4} a_i d_{it} + BR_{t-1} + \epsilon_t$, where the d_{it} denote daily indicator variables. The daily AR1 coefficients are estimates of $B_1, \ldots, B_4$ from the regression $= \Sigma_{i=1}^{4} a_i d_{it} + \Sigma_{i=1}^{4} B_i d_{it} R_{t-1} + \mu_t$. The "difference" coefficients are the estimates of B_j from estimating $R_t = \Sigma_{i=1}^{4} a_i d_{it} + BR_{t-1} + B_{it} d_{jt} R_{t-1} + \zeta_t$ separately for $j = 1, \ldots, 4$.
[1]Excludes 1% largest, 1% smallest, and matching next-day returns.

of the week, the return autocorrelation on Tuesday is 0.187, rather than negative as for other Tuesdays. In the case of Friday holidays, where Thursday is the last trading day of the week, the correlation of Thursday returns with Wednesday returns is 0.193, as compared to a point estimate near zero for other Thursdays.

3. Evidence on the Pervasiveness of the Autocorrelation Pattern

To provide evidence on the robustness of the observed pattern in return autocorrelations, we examine returns in 10 U.S. futures markets and on Japanese equities. Daily return series for these applications are available for substantially shorter intervals than the 105-year sample used in Section 2. Because return outliers (particularly those of October 1987) have a large effect on point estimates obtained from these smaller samples, we exclude the 1 percent largest and 1 percent smallest returns (and matching next-day returns) for results reported in this and subsequent sections of this article. In general, inclusion of outliers reinforces the results. Also, because of the relatively small sample of holidays, tests are confined to patterns around weekends.

3.1 Evidence from futures markets

Evidence from futures markets is of particular interest for three reasons. First, nine of the markets examined are for future delivery of assets other than equities, allowing determination of whether the autocorrelation pattern is unique to equities. Second, futures markets

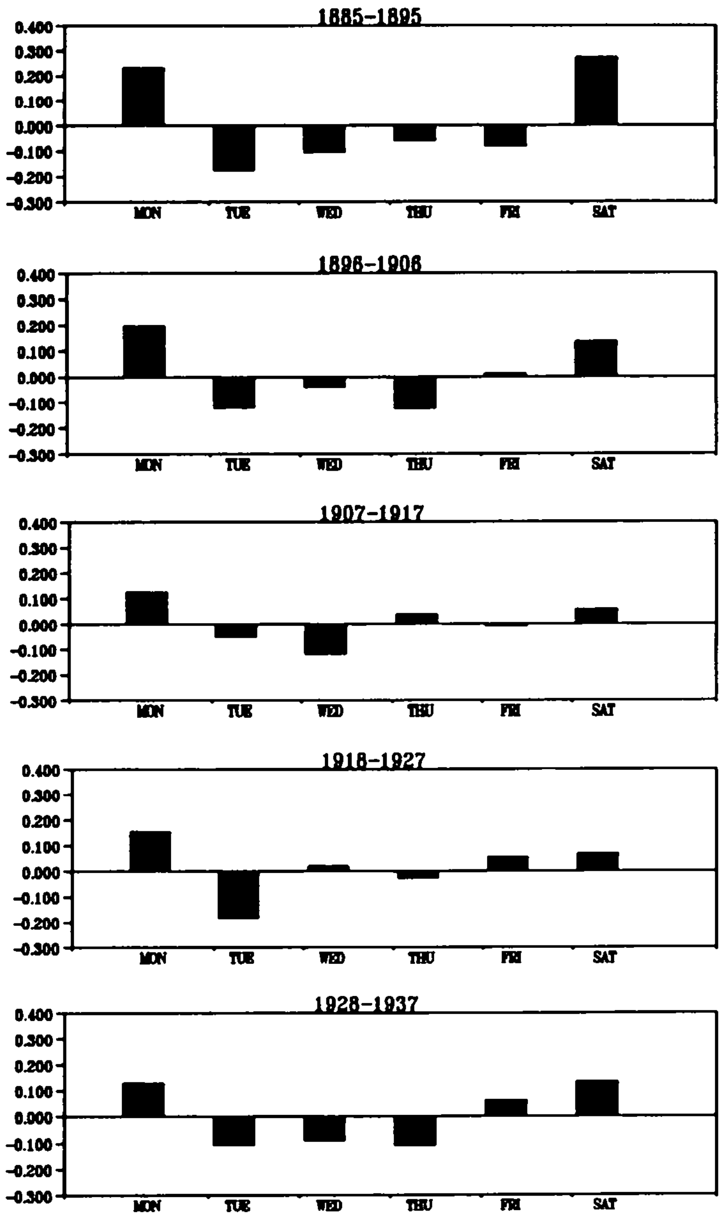
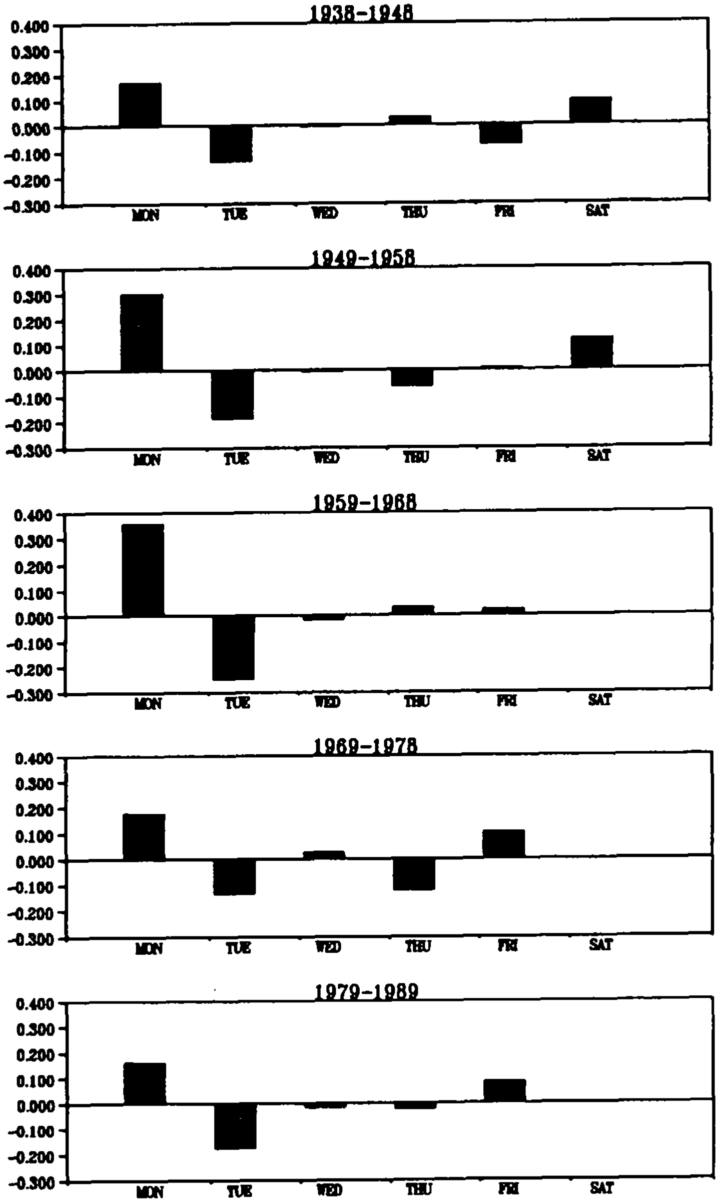


Figure 1

Difference coefficients in U.S. equity index returns-

"Difference" coefficients are estimates of B_j in the relation

$$R_t = \sum_{i=1}^{n} a_i d_{it} + BR_{t-1} + B_j d_{jt} R_{t-1} + \zeta_t,$$



where R_t is the return on day t and $d_{1t}, \ldots, d_{nt}$ are indicator variables that identify specific days of the week. The difference coefficient measures the difference between the AR1 coefficient estimate for day j and the AR1 coefficient estimated using all days other than j.

operate on the "open outcry" system without specialists, allowing us to determine whether the findings are robust in markets characterized by alternative trading structures. Third, futures markets are quite liquid, with small transactions costs, low bid-ask spreads, and prices that are not comprised of averages of underlying components. Therefore, we anticipate that futures returns are largely free of measurement error due to nonsynchronous trading or the bid-ask spread.

In Table 4, we report parameter estimates and, in Figure 2, we display estimated difference coefficients for returns in 10 futures markets.[8] Futures returns exhibit less overall autocorrelation than equity portfolio returns; this is consistent with the existence of less measurement error. Point estimates of the "all days" AR1 coefficient range from -0.078 for gold to 0.075 for cotton. However, as indicated by the test statistics in the second to last column of Table 4, when AR1 coefficients are allowed to vary by day, significant return autocorrelation is observed in all 10 markets.

The autocorrelation pattern observed in spot equity markets is, with few exceptions, also present in the futures markets. In all 10 futures markets, the Tuesday AR1 coefficient is smaller than the average coefficient on other days. Point estimates of Tuesday AR1 coefficients are negative in eight of the 10 markets, implying that Tuesday price movements tend to reverse Monday movements. The Tuesday point estimate for S&P equity index futures is -0.142. Reversals also occur in nonequity futures; sizable negative Tuesday coefficients are found for the Japanese yen (-0.075), Deutsche mark (-0.095), gold (-0.191), Treasury bonds (-0.164), and live cattle (-0.126).

Futures markets also exhibit positive serial dependence in price movements the last day before and first day after weekends. In nine of the 10 futures markets, the Monday AR1 coefficient is positive; and in eight of the 10 markets, the Monday coefficient is larger than the average coefficient on other days. The estimated Friday AR1 coefficient is positive and exceeds the average estimate for other days in nine of the 10 futures markets.

Finally, for comparison purposes, we also estimate Equations (l)-(3) for returns to the S&P 500 spot index (excluding outliers) over the same sample period used to estimate parameters for S&P futures. (Results are not reported in the tables.) The overall autocorrelation in the two return series differ: the "all days" coefficient estimates are 0.049 in the spot and -0.053 in the future. However, the difference

[8] We define the futures return as the percentage change in the settlement price of the closest to expiration futures contract, except within the delivery month when the second nearest to delivery contract is used. The settlement price determines the gains or losses on the futures contract. The long (short) futures position receives (pays) the change in the settlement price since the prior trading day.

coefficient estimates in the spot and the future are quite similar. For example, Monday difference estimates are 0.161 in the spot and 0.155 in the future, and Tuesday difference estimates are -0.144 in the spot and -0.110 in the future. These results suggest that market structure and measurement error due to nonsynchronous trading affect overall return autocorrelations, but do not substantially affect intraweek shifts in serial dependence.

3.2 Evidence from the Tokyo Stock Exchange

We next consider whether the observed autocorrelation pattern is unique to U.S. markets. Some evidence on this issue can be gleaned from Jaffe and Westerfield (1985). Following Keim and Stambaugh (1984), they test the “measurement error” explanation for negative mean Monday returns, using data on stock returns in Australia, Canada, Japan, the United Kingdom, and the United States. Like Keim and Stambaugh, they find higher-than-average correlation between Monday and Friday returns for all five countries, thus rejecting the explanation that measurement error in Friday closing prices causes the “weekend effect.” Point estimates in their table VII also indicate that, for all five countries, the correlation of Tuesday with Monday returns is lower than the average correlation on other days. They do not, however, discuss these findings or report significance tests for the daily serial correlation estimates.

We estimate Equations (1)-(3) for returns to the Tokyo Stock Exchange Composite Index from January 1973 to December 1989. These results are reported in Table 5. Our results are consistent with those reported by Jaffe and Westerfield, in that AR1 coefficients are highest on Mondays and lowest on Tuesdays. The Tuesday “difference” coefficient indicates that the shift is statistically significant. The overall AR1 coefficient for Japanese equities is relatively large (0.218), and the estimated Tuesday AR1 coefficient, while lower than other days, is positive. This evidence, in combination with the point estimates reported by Jaffe and Westerfield, indicates that the observed autocorrelation pattern is not unique to U.S. markets.

4. Economic Significance of the Autocorrelation Pattern

In the preceding sections, we present evidence of a statistically significant pattern in security return autocorrelations around nontrading periods. However, statistical significance need not imply that the pattern matters in an economic sense.

One way to gauge the importance of an anomalous return pattern is by its prevalence. The pattern in autocorrelations around nontrad-

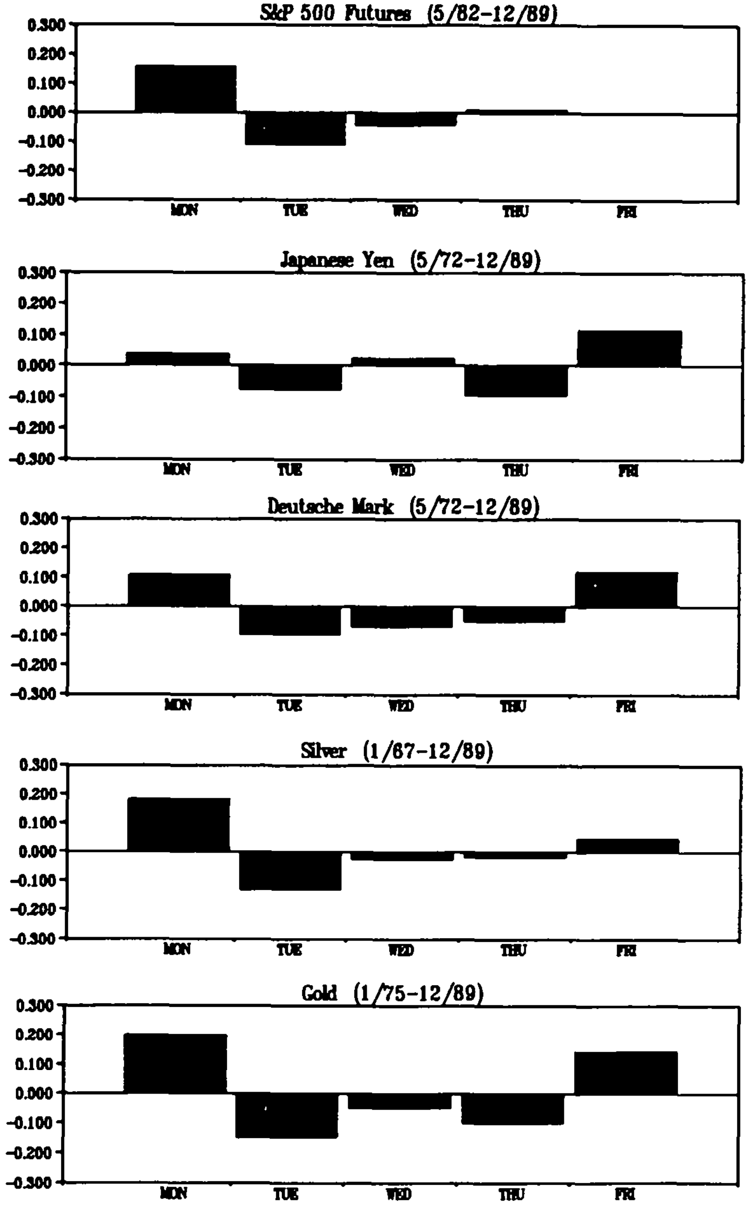
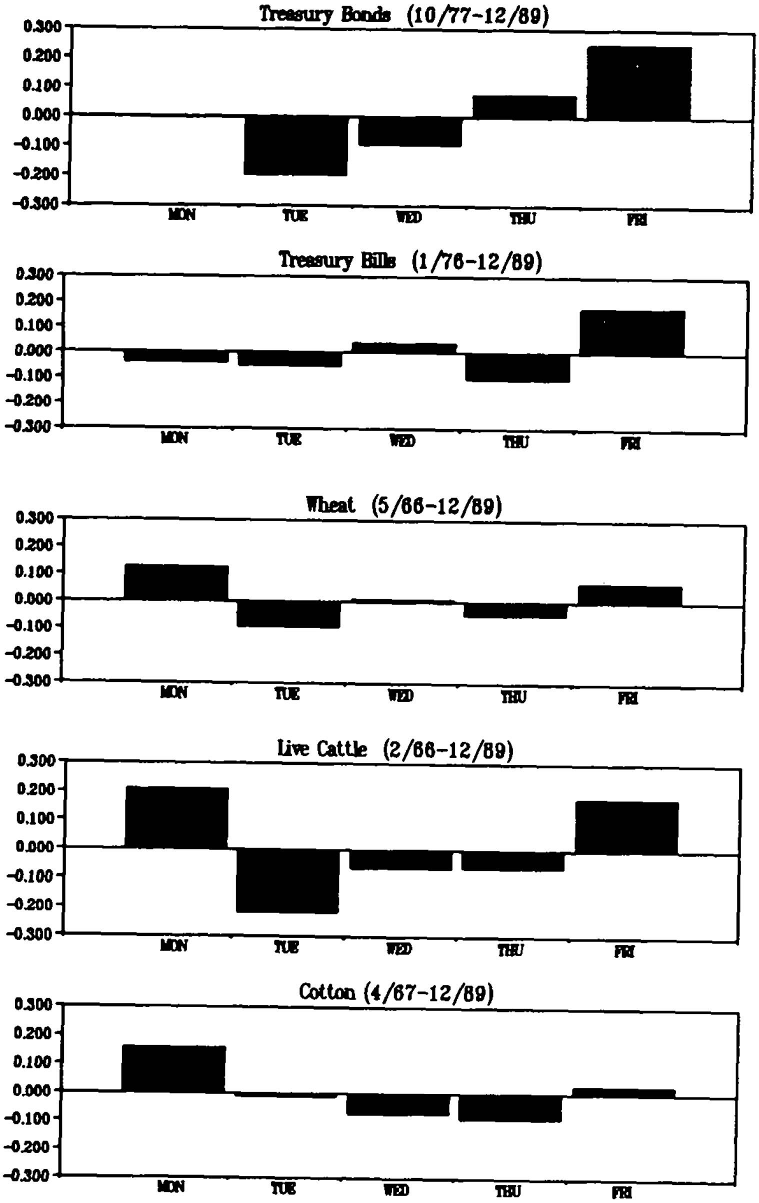


Figure 2

Difference coefficients in futures markets

"Difference" coefficients are estimates of B_j in the relation

$$R_t = \sum_{i=1}^{n} a_i d_{it} + BR_{t-1} + B_j d_{jt} R_{t-1} + \zeta_t,$$



where R_t is the percentage change in **the** futures settlement price on day t, and $d_1, \ldots, d_5$ *are* indicator variables that identify specific days of the week. The difference coefficient measures the difference between the AR1 coefficient estimate for day j and the AR1 coefficient estimated using all days other than j

Table 4
AR1 coefficients for returns in futures markets

	AR1 coefficients estimated using all days	Daily AR1 coefficients						Tests			
								Specification		Hypothesis	
		Monday	Tuesday	Wednesday	Thursday	Friday	$\bar{R}^2$	Heter[1]	Auto[2]	All zero	All equal
				S&P 500 futures (5/82–12/89)							
Coefficient	−.053 [.024]	.073 [.073]	−.142 [.059]	−.087 [.060]	−.046 [.047]	−.052 [.059]	.008	1.267	17.17	10.32	7.35
Difference		.155 [.086]	−.110 [.063]	−.043 [.068]	.008 [.056]	.000 [.067]		(.866)	(.143)	(.066)	(.196)
Observations	1756	334	340	350	371	361					
				Japanese yen (5/72–12/89)							
Coefficient	−.015 [.018]	.014 [.046]	−.075 [.041]	.003 [.037]	−.092 [.042]	.076 [.043]	.013	8.02	43.51	11.91	11.37
Difference		.037 [.052]	−.076 [.047]	.023 [.041]	−.094 [.047]	.113 [.049]		(.090)	(.000)	(.036)	(.047)
Observations	3993	751	767	804	845	826					
				Deutsche mark (5/72–12/89)							
Coefficient	.019 [.017]	.069 [.040]	−.095 [.040]	−.075 [.039]	−.060 [.039]	.074 [.038]	.016	4.92	51.32	18.33	17.48
Difference		.108 [.044]	−.096 [.046]	−.070 [.042]	−.051 [.043]	.118 [.043]		(.295)	(.000)	(.002)	(.003)
Observations	3994	750	763	806	847	828					
				Silver (1/67–12/89)							
Coefficient	.026 [.022]	.179 [.051]	−.073 [.037]	.006 [.035]	.012 [.041]	.062 [.036]	.010	53.63	15.23	18.66	18.31
Difference		.182 [.051]	−.131 [.043]	−.025 [.038]	−.017 [.041]	.045 [.038]		(.000)	(.229)	(.002)	(.002)
Observations	5106	964	971	1028	1081	1062					
				Gold (1/75–12/89)							
Coefficient	−.078 [.024]	.083 [.062]	−.191 [.042]	−.118 [.045]	−.159 [.049]	.040 [.043]	.017	22.08	13.35	34.78	23.57
Difference		.198 [.069]	−.148 [.055]	−.049 [.044]	−.100 [.047]	.144 [.048]		(.005)	(.344)	(.000)	(.000)
Observations	3401	640	652	690	718	701					
				Treasury bonds (10/77–12/89)							
Coefficient	−.010 [.019]	−.012 [.045]	−.164 [.039]	−.089 [.050]	.050 [.041]	.189 [.051]	.016	28.54	7.48	35.13	33.90
Difference		−.002 [.051]	−.197 [.049]	−.095 [.056]	.073 [.047]	.247 [.056]		(.000)	(.824)	(.000)	(.000)
Observations	2805	523	531	565	602	584					

Table 4
Continued

	AR1 coefficients estimated using all days	Daily AR1 coefficients: Monday	Tuesday	Wednesday	Thursday	Friday	$\bar{R}^2$	Tests: Specification: Heter[1]	Auto[2]	Hypothesis: All zero	All equal
				Treasury bills (1/76–12/89)							
Coefficient	.053 [.026]	.025 [.055]	.013 [.051]	.084 [.062]	−.034 [.055]	.199 [.076]	.007	0.00	26.39	9.48	6.65
Difference		−.038 [.067]	−.052 [.058]	.037 [.066]	−.104 [.063]	.175 [.084]		(1.00)	(.009)	(.091)	(.248)
Observations	3181	593	608	647	677	656					
				Wheat (5/66–12/89)							
Coefficient	.030 [.018]	.135 [.052]	−.042 [.035]	.024 [.044]	−.009 [.039]	.084 [.035]	.008	32.42	42.69	16.19	13.13
Difference		.125 [.054]	−.095 [.040]	.007 [.048]	−.050 [.041]	.068 [.044]		(.000)	(.000)	(.006)	(.022)
Observations	5334	1009	1019	1078	1125	1103					
				Live cattle (2/66–12/89)							
Coefficient	.042 [.017]	.213 [.039]	−.126 [.031]	−.008 [.036]	−.006 [.035]	.188 [.036]	.021	12.55	26.48	69.94	66.81
Difference		.208 [.042]	−.218 [.036]	−.063 [.040]	−.062 [.037]	.179 [.038]		(.014)	(.009)	(.000)	(.000)
Observations	5393	1038	1046	1080	1124	1105					
				Cotton (4/67–12/89)							
Coefficient	.075 [.017]	.205 [.043]	.066 [.034]	.016 [.040]	.004 [.040]	.096 [.037]	.014	44.88	31.55	34.49	16.55
Difference		.157 [.046]	−.012 [.041]	−.073 [.046]	−.088 [.045]	.026 [.042]		(.000)	(.002)	(.000)	(.005)
Observations	5130	972	974	1028	1086	1070					

AR1 coefficients are estimated by regressing daily returns on prior-day returns. Newey-West standard errors on coefficient estimates are in brackets; p values on hypothesis tests are in parentheses. Daily and "all days" AR1 parameter estimates are reported in rows labeled "coefficient." The "all days" coefficient Is the estimate of B from the regression $R_t = \sum_{i=1}^{5} a_i d_{it} + BR_{t-1} + \epsilon_t$, where the d_{it} denote day-of-the-week indicator variables. The daily AR1 coefficients are estimates of $B_1,..,B_5$ from the regression $R_t = \sum_{i=1}^{5} a_i d_{it} + \sum_{i=1}^{5} B_i d_{it} R_{t-1} + {}_t$ The "difference" coefficients are the estimates of B, from estimating $R_t = \sum_{i=1}^{5} a_i d_{it} + BR_{t-1} + B_j d_{jt} R_{t-1} + \zeta_t$ separately for j = 1,...,5. Excludes 1% largest, 1% smallest. and matching next-day returns.

[1]White (1980) test for heteroskedasticity.

[2]Box-Pierce test for residual autocorrelation to 12 lags.

ing periods is both persistent, having existed in US. equity returns for over 100 years, and pervasive, existing in foreign equity markets and in 10 U.S. futures markets. Lakonishok and Smidt (1988, p. 421), in a survey of calendar anomalies, state "their [the anomalies'] persistence demands explanation and focuses attention on the processes by which prices in securities markets are set." The findings documented here focus particular attention on the effects of regular market closings for equilibrium security pricing.

Another measure of the economic significance of an anomaly is the magnitude of the mean return it implies. To obtain a simple measure of the magnitude of return forecastability implied by the autocorrelation pattern documented here, we compare the means of two time series: the raw return series, R_t, and a "signed" return series, S_t. The signed return series is defined as $S_t = X_tR_t$, where X_t is an indicator variable that reflects the prior-day return and the documented autocorrelation pattern. To reflect the tendency for Friday, Saturday, and Monday returns to reinforce prior-day price moves, X_t is set equal to 1 on these days if the prior-day return is zero or positive; otherwise, X_t is set equal to - 1. On Tuesdays the definition is reversed to reflect the negative AR1 coefficient: X_t is set equal to -1 if the prior-day return is positive; otherwise, X_t equals 1. On Wednesdays and Thursdays, when AR1 coefficients are near zero, X_t is set equal to 1. Since X_t is known prior to trading on date t, the mean of the signed return series is an estimate of the expected return *conditional* on knowledge of the prior-day return and the documented autocorrelation pattern.

Analysis of raw and signed returns is similar to comparing returns to a "buy-and-hold" strategy with returns (before transactions costs) to a very naive trading strategy. The naive trading strategy is as follows: On Fridays, Saturdays, and Mondays, hold a long position if the prior-day return is positive; otherwise, go short. On Tuesdays, go short if the prior-day return is positive; otherwise, go long. On Wednesdays and Thursdays, hold a long position.[9]

We first examine U.S. equity index returns from 1885 to 1989. The mean of the raw return series is 0.033 percent per day (approximately 9.7 percent per year), while the mean of signed return series is 0.077 percent per day (approximately 24.1 percent per year). Thus, the mean equity index return conditional on the sign of the prior-day return is 2.5 times as large as the unconditional mean return.

Comparisons of mean raw and signed returns in the 10 futures markets are provided in Table 6. Results are reported for full samples and for samples excluding outliers. Mean signed returns exceed mean raw returns in all 10 markets, whether or not outliers are excluded.

[9] Note that the signed return series does not account for interest earned on short sale proceeds.

Table 5
AR1 coefficients for Tokyo Stock Exchange returns, January 1973-December 1989

	AR1 coefficients estimated using all days	Daily AR1 coefficients				
		Monday following trading Saturday	Monday following nontrading Saturday	Tuesday	Wednesday	Thursday
Coefficient	.218 [.019]	.307 [.064]	.283 [.084]	.105 [.048]	.195 [.044]	.160 [.042]
Difference		.096 [.070]	.066 [.086]	−.129 [.053]	−.028 [.047]	−.071 [.046]
Observations	4293	507	242	752	742	761

AR1 coefficients are estimated by regressing dally returns on prior-day returns. Newey-West standard errors on coefficient estimates are In brackets, *p* values on hypothesis tests are in parentheses. Daily and "all days" AR1 parameter estimates are reported in rows labeled "coefficient." The "all days" coefficient is the estimate of B from the regression $R_t = \Sigma_{i=1}^{8} a_i d_{it} + BR_{t-1} +$ where the d_{it} denote day-of-theweek indicator variables. The dally AR1 coefficients are estimates of $B_i, \ldots, B_8$. from the regression $R_t = \Sigma_{i=1}^{8} a_i d_{it} + \Sigma_{i=1}^{8} B_i d_{it} R_{t-1} + \mu_t$. The "difference" coefficients are the estimates of B_j from estimating $R_t = \Sigma_{i=1}^{8} a_i d_{it} + BR_{t-1} + B_j d_{jt} R_{t-1} + \xi$ separately for j - 1,...,8. Excludes 1% largest, 1% smallest, and matching next-day returns.

[1]White (1988) test for heteroskcdasticity.

[2]Box-Pierce test for autocorrelation to 12 lags.

Table 5
Continued

	Daily AR1 coefficients				Tests			
					Specification		Hypothesis	
	Friday prior to trading Saturday	Friday prior to nontrading Saturday	Saturday	$\bar{R}^2$	Heter[1]	Auto[2]	All zero	All equal
Coefficient	.262 [.054]	.211 [.068]	.311 [.046]	.069	35.62	17.51	163.20	13.62
Difference	.050 [.057]	−.008 [.070]	.108 [.050]		(.000)	(.215)	(.000)	(.092)
Observations	500	261	528					

The differences in annualized means are generally substantial. For example, based on the full sample, differences are 27.7 percent in silver, 16.6 percent in gold, 12.1 percent in Treasury bonds, 11.3 percent in wheat, 10.0 percent in cattle, 6.4 percent in the S&P 500, and 5.8 percent in the Deutsche mark.[10] The general magnitude of these differences is not altered by exclusion of outliers.

These differences between conditional and unconditional mean returns raise the question of whether a trader could have used knowledge of the daily autocorrelation pattern to earn abnormal returns after transactions costs. We note that while the existence of trading profits would comprise dramatic evidence of economic significance, trading profits are not a necessary condition for establishing the economic importance of an anomaly. For example, the weekend effect is widely viewed as economically important, even though authors documenting it [e.g., French (1980, p. 67)] recognize that transactions costs would eliminate profits from trading strategies based on it.

For equity index returns, two considerations suggest that unusual profits would not have been attainable. First, to the extent that the overall positive autocorrelation in index returns is due to nonsynchronous trading, the difference in mean returns is partially due to errors in measuring true returns, and thus cannot be captured. Second, the time series X_t changes sign an average of 110 times per year, indicative of the number of long/short reversals that would be required to realize the signed returns instead of the raw returns. Therefore, transactions costs as low as 0.13 percent per reversal would eliminate any advantage to capturing the signed return series instead of the raw return series.

Trading profits are perhaps more plausible in futures markets where transactions costs are relatively low and measurement error due to nonsynchronous trading is minimal. While a formal evaluation of trading strategies is beyond the scope of this article, we present some calculations which suggest that the possibility of trading profits in futures markets should not be dismissed out of hand.

In Table 6, we present "break-even" costs for each futures market, calculated as the excess of the mean signed return over the mean raw return divided by the number of annual sign changes in the X_t series. Assuming one transaction per sign change, this ratio measures the percentage transactions cost that would eliminate the difference between the two means. For comparison, we also present two simple estimates of the percentage transactions cost in each market: the first

[10]Note that these are unlevered rates of change in settlement prices. Posting of 10 percent margin levers an X percent annual price change into a 10X percent return on the posted margin.

estimates costs incurred by large traders, while the second estimates costs incurred by retail customers using discount brokers.[11]

Results based on the full sample indicate that, in four of the 10 markets (S&P 500, silver, gold, and Treasury bonds), both transaction cost estimates are less than break-even costs, suggesting the possibility of trading profits. In three markets (yen, Treasury bills, and wheat), both cost estimates exceed break-even costs. For the other three markets, break-even costs are higher than the lower cost estimate but less than the upper-bound cost estimate. Since estimated costs do not uniformly exceed break-even costs, we do not dismiss the possibility that trading profits could have been earned. This conclusion is not sensitive to the exclusion of outliers.

For several reasons, these calculations are only suggestive, and do not provide direct evidence on market efficiency or profits to trading strategies. The hypothetical trader would have to be aware ex ante of the pattern we document ex post. Also, the calculations implicitly assume that the trader's order flows do not alter settlement prices or the bid-ask spread, and that the settlement prices that comprise our database (which are not transactions prices) are appropriate for evaluating the trader's experience. Finally, we have not accounted for the relative riskiness of the naive trading strategy. Thus, while the trading strategy may have yielded a higher mean return than a "buy-and-hold" strategy, it cannot be concluded without further analysis that "excess" profits were available. Still, these calculations do underscore our contention that the observed autocorrelation pattern is large enough to be economically important.

5. Potential Explanations: Size, Portfolio Averaging, and the Bid-Ask Spread

In this section, we present some evidence on potential explanations for the observed pattern in autocorrelations around nontrading days. **We** investigate whether the daily autocorrelation pattern in equities is unique to firms of a particular size, whether the pattern exists for individual equities, and whether bid-ask spreads can provide an explanation.

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[11] Futures traders pay two transactions costs: a flat commission on each contract traded and the implicit bid-ask spread. Conversations with discount brokers indicate a commission of $30 per contract for retail customers. Conversations with large traders indicate commissions as low as $15 per contract. According to Chance (1989), bid-ask spreads in futures are typically one "tick" (the minimum price move) and sometimes two ticks. Smith and Whaley (1991) estimate the effective bid-ask spread for S&P 500 futures to be very near one tick on average. For our analysis, the lower cost estimate is computed based on a $15 commission and a bid-ask spread of one tick, while the higher cost estimate is computed based on a $30 commission and a spread of two ticks.

Table 6
Evidence on the economic significance of the autocorrelation pattern

Futures market (sample period)	Mean raw return	Mean signed return	Mean difference	Break-even costs (%)	Estimated cost range (%)
S&P 500 (5/82–12/89)					
Full sample	12.84 [7.97]	19.22 [7.95]	6.38 [11.04]	.063	.024–.048
Excluding outliers[1]	15.02 [5.59]	15.51 [5.60]	0.49 [6.73]	.005	
Japanese yen (5/72–12/89)					
Full sample	1.76 [2.39]	4.20 [2.38]	2.44 [3.14]	.024	.032–.064
Excluding outliers[1]	0.89 [2.10]	3.64 [2.10]	2.75 [2.75]	.027	
Deutsche mark (5/72–12/89)					
Full sample	0.48 [2.46]	6.33 [2.46]	5.84 [3.25]	.058	.038–.077
Excluding outliers[1]	−0.21 [2.20]	4.81 [2.20]	5.02 [2.83]	.050	
Silver (1/67–12/89)					
Full sample	2.83 [6.63]	30.54 [6.62]	27.71 [9.17]	.270	.071–.141
Excluding outliers[1]	6.39 [5.80]	26.76 [5.78]	20.37 [7.55]	.198	
Gold (1/75–12/89)					
Full sample	−0.40 [6.11]	16.19 [6.10]	16.59 [8.08]	.163	.060–.120
Excluding outliers[1]	−0.87 [5.27]	15.56 [5.26]	16.43 [6.75]	.161	
T-bonds (10/77–12/89)					
Full sample	1.99 [3.87]	14.09 [3.86]	12.11 [5.03]	.119	.046–.093
Excluding outliers[1]	3.63 [3.45]	9.67 [3.46]	6.04 [4.27]	.059	
T-bills (1/76–12/89)					
Full sample	0.12 [0.16]	0.38 [0.16]	0.26 [0.23]	.003	.004–.008
Excluding outliers[1]	0.11 [0.14]	0.33 [0.14]	0.22 [0.19]	.002	
Wheat (5/66–12/89)					
Full sample	0.89 [4.76]	12.17 [4.76]	11.28 [6.12]	.111	.126–.253
Excluding outliers[1]	−0.23 [4.30]	14.79 [4.30]	15.02 [5.50]	.148	
Cattle (2/66–12/89)					
Full sample	6.85 [3.60]	16.81 [3.60]	9.96 [4.53]	.097	.071–.143
Excluding outliers[1]	6.83 [3.38]	15.59 [3.37]	8.76 [4.30]	.085	
Cotton (4/67–12/89)					
Full sample	7.39 [4.50]	11.00 [4.50]	3.61 [5.89]	.036	.067–.133
Excluding outliers[1]	6.96 [4.06]	13.17 [4.06]	6.21 [5.26]	.061	

This table presents mean raw and signed returns for 10 futures markets. *News-West* standard errors are in brackets. Raw returns are percentage changes in settlement prices (annualized by multiplying by 250). The signed return series is defined as $S_t = X_t R_t$, where R_t is raw return on date t, and X_t is an indicator variable. On Fridays and Mondays, $X_t = 1$ if $R_{t-1} > 0$, and $X_t = -1$ if $R_{t-1} < 0$. On Tuesdays the definition of X_t is reversed. On Wednesdays and Thursdays, $X_t = 1$. The break-even cost is the ratio of the difference between mean signed returns and mean raw returns to the annual number of sign changes in the X_t time series. This represents the percentage transaction cost that, based on one transaction per sign change in the X_t series, eliminates the difference in means. The lower estimated cost is based on a $15 commission and a bid-ask spread of one tick. The larger estimated cost is based on a commission of $30 and a spread of two ticks.

[1]Excludes 1% largest, 1% smallest, and matching next-day returns.

5.1 Estimates of AR1 parameters for size-ranked equity portfolios

Measured return autocorrelations have been shown to vary as a function of firm size [see, e.g., Lo and MaKinlay (1990)]. To investigate whether firm size is important in determining the daily autocorrelation pattern identified in this study, we examine autocorrelations in returns to five size-ranked equity portfolios. Of the firms listed on the CRSP tapes, the 20 percent with the smallest equity capitalization at the beginning of a year comprise portfolio 1 for that year, the 20 percent with the largest equity capitalization comprise portfolio 5, etc. Portfolio returns are based on equal-weighing at the beginning of each year, and a buy-and-hold strategy within the year. All firms continuously listed on the CRSP tape for a given year are included in that year's sample.

Results for the period 1964 to 1989 are reported in Table 7. Consistent with results reported by Lo and MacKinlay (1990), the "all days" AR1 coefficients indicate that there is substantial positive autocorrelation in each portfolio's returns, with higher autocorrelation for the portfolios comprised of smaller firms. The test statistic in the last column of Table 7 indicates that the hypothesis that the autoregressive coefficient is constant across days of the week can be rejected for each of the five portfolios. For each of the size-ranked portfolios, the difference coefficient indicates that the Tuesday AR1 coefficient is significantly lower than the AR1 coefficient on other days. Similarly, difference coefficients indicate that Monday returns reinforce prior-day returns to a greater extent than other days for each of the five portfolios. In contrast to results for Mondays, the finding that the Friday coefficient exceeds other days by a significant margin is unique to large firms, holding only for portfolio 5. On net, we conclude that shifts in autocorrelations around nontrading periods are not unique to firms of any given size.

5.2 Estimates of AR1 parameters for individual equities

To determine whether the observed autocorrelation pattern is due to the averaging process implicit in portfolio and index returns, we estimate AR1 coefficients over the interval 1963 to 1989 for the 30 individual equities that comprise the Dow Jones Industrial Average as of March 1990. Estimates of autocorrelation in individual security returns are free of the upward bias due to nonsynchronous trading known to exist in portfolio returns [Scholes and Williams (1977)]. We use the heavily traded Dow 30 equities to obtain a sample with little remaining bias due to light trading. Our analysis of individual equities closely parallels that of Keim and Stambaugh (1984), who also examine the Dow 30. There are three distinctions. First, we correct standard errors for heteroskedasticity. Second, the composition of the Dow 30 is not constant across the two studies. Third, we include more recent data. Nevertheless, our findings closely reflect theirs.

In panel A of Table 8, we report the average of the 30 AR1 coefficient

Table 7
AR1 coefficients for CRSP size-ranked equity portfolios, January 1964–December 1989

	AR1 coefficients estimated using all days	Daily AR1 coefficients						Tests			
								Specification		Hypothesis	
		Monday	Tuesday	Wednesday	Thursday	Friday	$\bar{R}^2$	Heter[1]	Auto[2]	All zero	All equal
Observations	6295	1205	1228	1257	1319	1286					
Portfolio 1 (smallest 20% of firms)											
Coefficient	.402 [.015]	.602 [.035]	.337 [.027]	.319 [.035]	.393 [.031]	.422 [.032]	.206	10.53	221.36	798.9	47.53
Difference		.238 [.037]	−.088 [.032]	−.104 [.039]	.011 [.035]	.025 [.035]		(.032)	(.000)	(.000)	(.000)
Portfolio 2											
Coefficient	.359 [.013]	.569 [.034]	.260 [.025]	.314 [.035]	.342 [.029]	.393 [.030]	.177	27.25	116.11	903.4	55.90
Difference		.248 [.037]	−.133 [.031]	−.056 [.040]	−.020 [.032]	.041 [.034]		(.000)	(.000)	(.000)	(.000)
Portfolio 3											
Coefficient	.335 [.013]	.567 [.040]	.222 [.027]	.306 [.033]	.322 [.033]	.352 [.034]	.152	23.10	86.93	641.3	46.98
Difference		.272 [.044]	−.151 [.033]	−.036 [.038]	−.016 [.037]	.022 [.039]		(.000)	(.000)	(.000)	(.000)
Portfolio 4											
Coefficient	.321 [.013]	.535 [.038]	.190 [.027]	.304 [.030]	.312 [.031]	.351 [.031]	.139	24.63	80.22	662.9	51.45
Difference		.251 [.043]	−.174 [.032]	−.021 [.035]	−.012 [.036]	.036 [.035]		(.000)	(.000)	(.000)	(.000)
Portfolio 5 (largest 20% of firms)											
Coefficient	.226 [.015]	.383 [.037]	.117 [.030]	.213 [.029]	.189 [.029]	.283 [.034]	.073	9.36	29.23	268.8	39.75
Difference		.186 [.041]	−.142 [.032]	−.017 [.037]	−.047 [.031]	.070 [.036]		(.053)	(.004)	(.000)	(.000)

Firms on the CRSP tile are ranked according to market value of equity at the beginning of each year and sorted into live size-ranked portfolios. Portfolio returns are based on equal weighting at the beginning of the year without rebalancing during the year. AR1 coefficients are estimated by regressing daily returns on prior-day returns. Newey-West standard errors on coefficient estimates are in brackets; *P* values on hypothesis tests are in parentheses. Daily and "all days" AR1 parameter estimates are reported in rows labeled "coefficient." The "all days" coefficient is the estimate of *B* from the regression: $R_t = \sum_{i=1}^{5} a_i d_{it} + BR_{t-1} + \epsilon_t$, where the d_{it} denote day-of-the-week indicator variables. The daily AR1 coefficients are estimates of B_1 to B_5 from the regression: $R_t = \sum_{i=1}^{5} a_i d_{it} + \sum_{i=1}^{5} B_i d_{it} R_{t-1} + \mu_t$. The "difference" coefficients are the estimates of B_j from estimating $R_t = \sum_{i=1}^{5} a_i d_{it} + BR_{t-1} + B_j d_{jt} R_{t-1} + \zeta_t$ separately for $j = 1,...,5$. Excludes 1% largest, 1% smallest, and matching next-day returns.

[1]White (1980) test for heteroskedasticity.

[2]Box-Pierce test for autocorrelation to 12 lags.

estimates for the Dow 30 firms, and the percent of coefficient estimates that are positive. The results indicate that the autocorrelation pattern evident in portfolio and index returns also exists in individual equity returns. The average “all days” AR1 coefficient for the 30 Dow firms is 0.053, which is statistically significant, but substantially smaller than the coefficient for equity indices or for any of the size-ranked portfolios over a similar interval. The Monday AR1 coefficient is positive for 29 of the 30 firms and higher than the average coefficient on other days for 23 of the 30 firms. The mean difference coefficient for Mondays is positive and significant ($p = .002$). By contrast, the Tuesday AR1 coefficient is positive for only 15 of the 30 firms, and lower than the average coefficient on other days for 25 of the 30 firms. The mean difference coefficient for Tuesdays is negative and significant ($p < .001$). The Friday AR1 coefficient is positive for 28 of the 30 firms and is higher than the average coefficient on other days for 24 of the 30 firms. The mean difference coefficient on Friday is positive and significant ($p = .001$). We conclude from these results that the autocorrelation pattern documented above is not explained by the averaging process implicit in calculating index and portfolio returns.

5.3 Autocorrelation estimates from bid-ask midpoints

Keim (1989) reports that the frequency with which closing trades occur at the bid price or the ask price varies systematically across days of the week. Such nonrandomness could contribute to the autocorrelation pattern documented here. To investigate this possibility, we obtain a sample of 80 OTC firms for which a time series of at least 4000 closing bid and ask prices is available on the CRSP OTC tape.[12] We report return autocorrelations computed from the mean of closing bid and ask prices. Results from returns based on closing bid prices are similar.

Average AR1 coefficient estimates for the 80 OTC firms are reported in panel B of Table 8. The autocorrelation pattern in the OTC returns closely mirrors the pattern in the Dow 30 close-to-close returns. In particular, the mean difference coefficient on Monday is positive and significant, while the mean difference coefficient on Tuesday is negative and significant. These results suggest that the clustering of closing trades at bid or ask prices on specific days does not provide an explanation for the documented autocorrelation pattern.

[12]The variables BIDLO and ASKHI on the CRSP OTC tape report either end-of-day bid and ask prices, or intraday low and high transaction prices. We restrict our analysis to the subset of firms for which a large time series of bid and ask prices is reported.

Table 8
Average AR1 coefficients for individual firm returns

	AR1 coefficients estimated using all days	Daily AR1 coefficients				
		Monday	Tuesday	Wednesday	Thursday	Friday
		A: Dow 30 firms, July 1962–December 1989 (returns computed using closing prices)				
Mean coefficient	.053 [.008]	.077 [.012]	.005 [.012]	.055 [.008]	.043 [.011]	.093 [.011]
(% positive)	(90)	(97)	(50)	(93)	(87)	(93)
Mean difference		.029 [.010]	−.060 [.011]	.002 [.008]	−.013 [.010]	.049 [.011]
(% positive)		(77)	(17)	(47)	(33)	(80)
		B: Eighty OTC firms, December 1972–December 1989 (returns computed using mean of bid and ask prices)				
Mean coefficient	.047 [.010]	.080 [.014]	.023 [.012]	.063 [.010]	.051 [.014]	.057 [.009]
(% positive)	(81)	(78)	(56)	(79)	(76)	(73)
Mean difference		.039 [.014]	−.036 [.013]	.021 [.011]	.003 [.016]	.012 [.010]
(% positive)		(65)	(36)	(55)	(49)	(56)

AR1 coefficients for each firm are estimated by regressing daily returns on prior-day returns. The table reports the average of the coefficients. For each firm the "all days" coefficient is the estimate of B from the regression: $R_t = \sum_{i=1}^{5} a_i d_{it} + BR_{t-1} + \epsilon_t$, where the d_t denote day-of-the-week indicator variables. Daily AR1 coefficients are estimates of B_1 to B_5 from the regression: $R_t = \sum_{i=1}^{5} a_i d_{it} + \sum_{i=1}^{5} B_i d_{it} R_{t-1} + \mu_t$. For each firm the "difference" coefficients are the estimates of B_j from estimating. $R_t = \sum_{i=1}^{5} a_i d_{it} + BR_{t-1} + B_j d_{jt} R_{t-1} + \zeta_t$ separately for j - 1,...,5. Newey-West standard errors are in brackets. The table also reports the percent of individual firm coefficients that are greater than zero. Excludes 1% largest, 1% smallest, and matching next-day returns.

6. Conclusion

In this article we document a pattern in the autocorrelation of security returns around weekend and holiday nontrading periods. Specifically, we find that the correlation of returns the second day after a nontrading period with returns the day following the nontrading period is significantly lower than autocorrelations measured at one lag on other days, and is often significantly negative, implying reversals of prior-day price movements on average. We also find that returns the day before and the first day after nontrading periods are more highly correlated with prior-day returns than are returns on other days. The overall pattern has existed in US. equity returns for over 100 years, and is quite consistent across markets with differing microstructures, including several futures markets. The pattern implies a nontrivial degree of return forecastability. For example, from 1885 to 1989 mean U.S. equity returns conditional on the sign of the prior-day return are more than twice unconditional mean returns.

The observed autocorrelations could be due to a pattern in true (transactable) prices, or a pattern in the errors with which reported prices measure true prices, or both. For two reasons, we believe that a pattern in true prices is the more likely explanation. First, the most prominent measurement error theory, nonsynchronous trading, appears to be inconsistent with the documented tendency for Tuesday price moves to reverse Monday price moves. Second, the observed pattern in S&P 500 futures (in particular, the Tuesday reversal) mimics the spot equity index pattern. This is important because index arbitrage activities keep the *transactable* prices of the spot and the future close to each other, but need not keep reported prices similarly close. Given the high transactions volume in S&P futures and that the S&P futures price is not an average of component prices, we anticipate that measurement errors in futures prices will be small, and in any event need not mimic measurement errors in the spot index. We view the similar pattern in the spot and futures returns as indirect evidence that the pattern reflects true price movements.

It is possible that the observed autocorrelation pattern reflects pricing errors or trading noise. However, any pattern in returns can be viewed as consistent with some version of the trading noise hypothesis. We believe that more likely routes to an explanation lie in models of frictions in the trading process as suggested by Cohen et al. (1980), or in models incorporating strategic behavior by market participants, along the lines of Admati and Pfleiderer (1989), whose model allows for price reversals. While these may be fruitful areas to investigate in seeking an explanation for the daily autocorrelation pattern documented here, any potential explanation cannot rely on a particular market structure, as the observed results are quite uniform across specialist and open outcry markets.

Our empirical analysis is confined to documentation of patterns in daily returns around days without trading. Of course, the most common regular interval of nontrading is the overnight market closure. A natural extension of this line of research is to examine serial dependence in intraday returns around overnight closings, and to test for possible shifts in serial dependence patterns as global markets evolve toward 24-hour trading.

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