The impact of nonsynchronous trading on differences in portfolio cross-autocorrelations*

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Abstract

It has been widely debated how much nonsynchronous trading drives asymmetric portfolio cross-autocorrelations: lagged returns on a portfolio of larger-capitalization stocks are far more heavily correlated with current returns on a portfolio of smaller-capitalization stocks than the converse. This paper proposes a new method to generate precise estimates of the extent to which nonsynchronous trading underlies these differences. By contrasting cross-autocorrelations using 24-hour portfolio returns based on trade prices before an arbitrary point in the trading day with those using returns based on prices after, our difference-in-differences approach isolates the impact of nonsynchronous trading on differences in portfolio cross-autocorrelations.

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A common problem faced by institutional investors is the desire to trade large portfolios of stocks in a manner that minimizes transaction costs and market impact. Portfolio trade orders are often handled by specialized brokers, who use algorithms to divide the orders into many small trades to be optimally executed over time. Optimal trade execution depends critically on the extent to which transaction prices reflect available information—their "freshness." Staleness in trade prices can manifest itself in cross-autocorrelation patterns in portfolio returns. These same patterns, however, could also be caused by differences in trade frequency across stocks, which result in nonsynchronous trading at prices that are (potentially) fresh, but observed at different times. A long-standing area of research has obtained conflicting estimates of the extent to which these, and other explanations, cause the patterns in the **levels** of cross-autocorrelations of portfolio returns based on closing prices.

Our focus is different: we provide a new method to generate precise estimates of the impact of nonsynchronous trading on **differences** in cross-autocorrelation patterns based on 24-hour returns, using intraday prices. It is well-established that short-horizon portfolio returns are highly cross-serially correlated (see, e.g., Boudoukh et al. (1994)), and that the lagged returns on a portfolio of larger stocks are **far** more highly correlated with the current returns on a portfolio of smaller stocks than the converse. To illustrate, Table I reports cross-autocorrelation matrices based on daily returns using closing prices for size-sorted and volume-sorted portfolios formed annually from the largest 1250 NYSE stocks during 1993–2003.[1] Panel A considers annual sorts by market capitalization into size quintiles (Q1 = smallest, Q5 = largest) of 250 stocks each. Observe that the correlation between the lagged daily portfolio return of the largest quintile and the current daily portfolio return of the smallest quintile of stocks of 0.107, is over three times the 0.031 correlation obtained when we reverse the lead-lag structure. The table highlights this property by reporting the off-diagonal differences: the difference between the correlation between lag Qj and Qk and the reverse, where $j > k$. For example, the difference between Q1 and Q5 based on market

[1]We consider both portfolios sorted by market capitalization (as is standard) and trade volume. This allows us to see how much stronger the impact of nonsynchronous trading is when we focus on portfolios sorted by trading volume, which is the more directly relevant variable for nonsynchronous trading.

Table I: **Cross-autocorrelation matrices for size-sorted and volume-sorted portfolios of NYSE stocks for 1993–2003, based on daily returns using closing prices.** Each year the largest 1250 NYSE firms by market capitalization on January 1st are selected, and then sorted into five portfolios of 250 firms annually according to size and trade volume quintiles: Q1 = smallest, Q5 = largest. Trade volume is measured by the number of trades in the first month of the year. The table also reports the off-diagonal differences in cross-autocorrelations, calculated as: corr(lag Qj, Qk)−corr(lag Qk, Qj), where $j > k$.

Panel A: Sorts based on market capitalization

	Cross-autocorrelations						Off-diagonal differences			
	Q1	Q2	Q3	Q4	Q5		Q2	Q3	Q4	Q5
lag Q1	0.151	0.095	0.090	0.092	0.031	Q1	0.042	0.055	0.048	0.076
lag Q2	0.137	0.094	0.094	0.101	0.042	Q2		0.015	0.011	0.049
lag Q3	0.145	0.109	0.107	0.109	0.050	Q3			0.001	0.045
lag Q4	0.140	0.112	0.110	0.113	0.053	Q4				0.050
lag Q5	0.107	0.091	0.095	0.103	0.044					

Panel B: Sorts based on trade volume

	Cross-autocorrelations						Off-diagonal differences			
	Q1	Q2	Q3	Q4	Q5		Q2	Q3	Q4	Q5
lag Q1	0.125	0.085	0.081	0.084	0.057	Q1	0.037	0.046	0.046	0.056
lag Q2	0.122	0.093	0.090	0.096	0.067	Q2		0.018	0.018	0.032
lag Q3	0.127	0.108	0.104	0.106	0.078	Q3			0.003	0.024
lag Q4	0.130	0.114	0.109	0.105	0.076	Q4				0.022
lag Q5	0.113	0.099	0.102	0.098	0.077					

capitalization sorts is 0.076 (i.e., 0.107−0.031). Panel B reports similar results when the same firms are divided into quintiles according to their trade volume in the first month of the year. The question is: what accounts for these large differences in portfolio cross-autocorrelations?

The contribution of this paper is to develop a way to quantify precisely how much of the differences in cross-autocorrelations are due to nonsynchronous trading. The potential qualitative impact of nonsynchronous trading on portfolio autocorrelations can be gleaned by considering the standard practice of calculating returns using closing prices. Consider two stocks, X and Y. Suppose that stock X consistently trades later in the day than stock Y.

If significant economic news arrives after stock Y has finished trading, but before stock X's last trade, then the closing price of stock X will reflect this information, but the closing price of stock Y will not. When the stocks resume trading the next day, stock Y's price will be updated to reflect this information. The consequence is that stock X's returns will lead (or predict) returns of stock Y, but not conversely. This cross-serial correlation across stocks contributes to the difference in observed portfolio return autocorrelations.

Our key insight is to recognize that the impact of nonsynchronous trading on correlation relationships is **reversed** if we compute daily returns using the first trade **after** the arbitrary time, rather than the last trade **before** that moment. We then implement a difference-in-differences approach to control for sources of intraday variation in portfolio cross-autocorrelations (e.g., due to time-varying information arrival rates), and large fixed portfolio effects (e.g., because information is incorporated into prices of larger stocks faster than smaller stocks), to isolate the impact of nonsynchronous trading on differences in portfolio cross-autocorrelations.

To understand our approach, contrast what happens when we compute daily (24 hour) returns using the price of the last trade **before** noon of each trading day, with that using the first trade **after noon**.[2] Trades of frequently-traded stocks will tend to occur closer to noon than will trades of infrequently-traded stocks. As a result, lagged prices of frequently-traded stocks will tend to contain economic news that arrived after the last trade (prior to noon) of infrequently-traded stocks—the impact of nonsynchronous trading using the last trade **before** noon to compute returns should be similar to that using closing prices. But, using the first trade **after** noon to compute returns, the impact of nonsynchronous trading is **reversed** precisely because the first trade after noon of infrequently-traded stocks tends to occur after the first trade of frequently-traded stocks—if stock prices reflect all market information, then prices of infrequently-traded stocks will contain economic news that arrived after the frequently-traded stocks traded.

[2]McInish and Wood (1991) calculate intraday-to-intraday 24-hour returns at different intervals throughout the trading day using a 1984 data tape of 1,400 NYSE stocks.

We use a difference-in-differences approach to control for any systematic intraday trends in correlations and thereby isolate the differential impact of nonsynchronous trading. So, continuing with our example, we first use the last trade before noon to compute the correlation between the lagged portfolio returns for the frequently-traded stocks and the current portfolio returns for the infrequently-traded stocks. From this correlation, we subtract the analogous correlation using the first trade after noon to compute returns. Ignoring factors (e.g., time-varying information arrival rates) that give rise to intraday variations in portfolio autocorrelations, the differential impact of nonsynchronous trading on the two portfolio autocorrelations will lead this difference to be positive. We then reverse the portfolios, computing the correlation of lagged infrequently-traded portfolio returns with current frequently-traded portfolio returns using the last trade before noon and subtract the analogous correlation when we use the first trade after noon. Again ignoring sources of intraday variations, nonsynchronous trading will lead this difference to be negative. Finally, to control for sources of intraday variations and portfolio fixed effects, we compute the difference in these two differences, which isolates the impact of nonsynchronous trading on the difference in portfolio cross-autocorrelations.

For the period 1993–2003, we sort our sample of stocks into quintile portfolios based on market capitalization or trading volume. We then calculate intraday-to-intraday 24-hour portfolio returns computed at 10:15am, 10:45am, . . ., 3:15pm. Using our approach, we find remarkably uniform evidence that nonsynchronous trade matters:

- Our difference-in-differences measure is positive at (i) **every** point in the trading day considered, for (ii) **every** pair of large and small stock portfolios and **every** pair of frequently-traded and infrequently-traded stock portfolios.

- Comparing pairs of portfolios that differ more in terms of size or trade frequency, the difference in differences is greater for portfolio pairs that differ more in terms of size or trade frequency. That is, for a fixed smaller (or less frequently traded) portfolio, as we pair it with a larger and larger (or more and more frequently traded) portfolio, the impact of nonsynchronous trade on portfolio cross-autocorrelation differences increases.

- Despite large intraday variations in portfolio cross-autocorrelations, the estimated difference in differences for given portfolio quintile pairs, and hence our estimated impact of nonsynchronous trading, varies little over the trading day. This highlights the importance of using our difference-in-differences approach to pin down the impact of nonsynchronous trading.

- The impact of nonsynchronous trading on portfolio cross-autocorrelation differences is larger for portfolios sorted on trading frequency, typically explaining 7-16% of the differences for portfolios sorted on trading frequency, versus 5-12% for portfolios sorted on market capitalization.

The fact that nonsynchronous trading explains only a moderate fraction of **differences** in portfolio cross-autocorrelations does **not** imply that nonsynchronous trading explains only a moderate portion of the **levels** of portfolio cross-autocorrelations. To see why this is so, consider portfolios sorted according to whether their CUSIP number is odd or even; while nonsynchronous trading may matter for the level of their cross-autocorrelations, the difference in cross-autocorrelations should be zero![3] Our difference-in-differences methodology is required to control for the multiple and large sources of intraday variation (in information and trade arrival, freshness of prices). The benefit is that we obtain precise estimates of the differences in portfolio cross-autocorrelations that are caused by nonsynchronous trading; the cost is that we cannot readily extend the methodology to estimate the impact of nonsynchronous trading on levels of portfolio cross-autocorrelations.

The remainder of the paper is organized as follows. Section I reviews related research. Section II provides a simple theoretical model of the impact of nonsynchronous trading and delayed incorporation of information for portfolio cross-autocorrelations. Section III outlines the data. Section IV provides the results. Section V concludes.

[3]We thank Bob Anderson for suggesting this example.

I Literature Review

The existing literature has focused on explaining the level of portfolio cross-autocorrelation patterns for returns based on closing prices. Many explanations have been proposed for the observed patterns. Conrad and Kaul (1988) proposed that the cross-autocorrelations are due to time-varying expected returns. A variant of this explanation suggests that cross-autocorrelations are simply a restatement of portfolio autocorrelations and contemporaneous correlations (Hameed (1997)). According to this explanation, once account is taken of portfolio autocorrelations, portfolio cross-autocorrelations should disappear. A second group of explanations (Boudoukh et al. (1994)) suggest that portfolio autocorrelations and cross-autocorrelations are due to market microstructure biases such as thin trading or discreteness in prices. A third explanation is that the cross-autocorrelations are caused by the tendency of some stocks to adjust more slowly to economy-wide information than others (Lo and MacKinlay (1990a) and Brennan et al. (1993)).

Our paper focuses on the impact of nonsynchronous trading. Atchison et al. (1987) and Lo and MacKinlay (1990b) derive explicit relations concerning the magnitude of autocorrelations caused by nonsynchronous trading. Both studies conclude that nonsynchronous trading explains only a small portion of the autocorrelation in the data. Boudoukh et al. (1994), however, argue that these studies greatly understate the potential effects of nonsynchronous trading. For instance, they show that portfolios with weekly autocorrelations of 0.07 under standard assumptions can have autocorrelations as high as 0.20 when the framework allows for heterogeneity in both non-trading probabilities and security betas.

Kadlec and Patterson (1999) 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. Their simulated weekly portfolio returns exhibit autocorrelations that are about 25% of observed autocorrelations.

Our methodological approach is related to that in Anderson et al. (2008), which uses closing prices to compute returns from days $t-1$ to t, and opening prices to compute returns from t to $t+1$. Chordia and Swaminathan (2000) find that daily returns on high turnover volume portfolios lead returns on low turnover volume portfolios, controlling for firm size. Other important papers on portfolio autocorrelations include McQueen et al. (1996), Mech (1993), Bessembinder and Hertzel (1993), Jegadeesh and Titman (1995), Lewellen (2002), Sias and Starks (1997), and Badrinath et al. (1995).

II Theory

To see the potential impact of nonsynchronous trading on the cross-autocorrelations of portfolio returns, consider two stocks, X and Y, that have identical end-of-date t value

$$V_t = V_{t-1} + \delta_t^0 + \delta_t^1 + \ldots + \delta_t^\ell + \delta_t^{\ell+1} + \ldots + \delta_t^c,$$

where, for simplicity, we assume that the innovations δ_t^j are independently distributed. Interpret δ_t^0 as an overnight innovation that arrives after the date $t-1$ market closes, δ_t^1 as the first innovation after the market opens and δ_t^c as the last innovation before market close.

The two stocks are distinguished solely by the fact that X trades more frequently than Y. Specifically, suppose that X trades before and after each innovation; while Y last trades just before δ_t^c has been realized, and first trades just after δ_t^1 has been realized. Then, if the innovations are immediately incorporated into prices, the closing price of X will be $p_t^{Xc} = V_t$, but the closing price of Y will not incorporate the last innovation so that $p_t^{Yc} = V_t - \delta_t^c$. In sharp contrast, the opening price of X will be $p_t^{Xo} = V_{t-1} + \delta_t^0$, but Y's opening price will incorporate the first innovation of the trading day, $p_t^{Yo} = V_{t-1} + \delta_t^0 + \delta_t^1$.

Consider the implications of these trading frequencies for the covariance in daily lead-lag price changes.[4] Using closing prices, the lagged price change of stock X contains the

[4]We consider daily price changes rather than returns because the qualitative insights are identical, and they are most easily presented via price changes; our presentation captures returns if innovations are multiplicative and prices are in logs.

innovation δ_t^c that enters the current price change of stock Y. As a result,

$$\begin{aligned}\text{cov}\left(p_{t+1}^{Yc} - p_t^{Yc}, p_t^{Xc} - p_{t-1}^{Xc}\right) &= \text{cov}\left(\delta_{t-1}^c + \delta_t^0 + \delta_t^1 + \ldots + \delta_t^{c-1}, \delta_{t-1}^0 + \delta_{t-1}^1 + \ldots + \delta_{t-1}^c\right) \\ &= \text{var}(\delta_{t-1}^c) > 0.\end{aligned}$$

This is the well-understood impact of nonsynchronous trading: changes in the closing prices of frequently-traded stocks contain information that has yet to be incorporated in the closing prices of infrequently-traded stocks, leading to a positive cross-autocorrelation.[5] Conversely, lagged price changes in the infrequently-traded stock, Y are uncorrelated with current price changes in X, because there is no information overlap,

$$\text{cov}\left(p_{t+1}^{Xc} - p_t^{Xc}, p_t^{Yc} - p_{t-1}^{Yc}\right) = \text{cov}\left(\delta_t^0 + \delta_t^1 + \ldots + \delta_t^c, \delta_{t-2}^c + \delta_{t-1}^0 + \delta_{t-1}^1 + \ldots + \delta_{t-1}^{c-1}\right) = 0.$$

Hence, the difference in the two covariances due to nonsynchronous trading is $\text{var}(\delta_{t-1}^c) - 0 = \text{var}(\delta_{t-1}^c)$.

The key observation that we make is that the impact of nonsynchronous trading on cross-autocorrelation patterns is reversed if we use opening prices—**precisely** because infrequently-traded stock Y's first trade occurs after X's. As a result, lagged prices changes in Y contain information about δ_t^1 that will enter the current price change in X. Hence, lagged price changes in Y are positively correlated with current price changes in X, but not conversely,

$$\text{cov}\left(p_{t+1}^{Xo} - p_t^{Xo}, p_t^{Yo} - p_{t-1}^{Yo}\right) = \text{var}\left(\delta_t^1\right); \text{ and } \text{cov}\left(p_{t+1}^{Yo} - p_t^{Yo}, p_t^{Xo} - p_{t-1}^{Xo}\right) = 0.$$

Next recognize that there is nothing special about using prices at the end of day or the beginning of the day to compute returns: the qualitative impact of nonsynchronous trading is the same if we instead compute returns using the last transaction before and the first transaction after a specified time ℓ near midday. Using the last transaction before time ℓ is akin to using closing prices—the last transaction of the frequently-traded stock before time ℓ will tend to be after the infrequently-traded stock, so lagged returns of the

[5] It is easier to present the discussion with covariances than correlations, but for statistical comparisons one must normalize for volatility by scaling the covariance with the product of the standard deviations of the two portfolios.

frequently-traded stock will contain information about current returns of the infrequently-traded stock. Conversely, using the first transaction after a moment in time, lagged returns in the infrequently-traded stock should predict current returns in the frequently-traded stock. See figure 1. As a result,

$$\mathrm{cov}\left(p_{t+1}^{Yb\ell} - p_t^{Yb\ell}, p_t^{Xb\ell} - p_{t-1}^{Xb\ell}\right) = \mathrm{var}\left(\delta_t^\ell\right), \quad \text{and} \quad \mathrm{cov}\left(p_{t+1}^{Xb\ell} - p_t^{Xb\ell}, p_t^{Yb\ell} - p_{t-1}^{Yb\ell}\right) = 0,$$

where the index $b\ell$ denotes the last transaction <u>**b**</u>efore time ℓ. Conversely if we used the first transaction price <u>**a**</u>fter ℓ, the lead-lag pattern is reversed:

$$\mathrm{cov}\left(p_{t+1}^{Ya\ell} - p_t^{Ya\ell}, p_t^{Xa\ell} - p_{t-1}^{Xa\ell}\right) = 0; \quad \text{and} \quad \mathrm{cov}\left(p_{t+1}^{Xa\ell} - p_t^{Xa\ell}, p_t^{Ya\ell} - p_{t-1}^{Ya\ell}\right) = \mathrm{var}\left(\delta_t^{\ell+1}\right).$$

This example supposes that stock Y trades only slightly less often than stock X. Were Y to trade even less frequently, more innovations would arrive between trades, raising the difference in covariances, but otherwise preserving the qualitative pattern.

Portfolios. In practice, the last trade of an infrequently-traded stock sometimes occurs after that of frequently-traded stocks. To determine how this affects cross-autocorrelations, consider portfolios of infrequently- and frequently-traded stocks that are otherwise identical. Suppose that fraction ρ_f of <u>**f**</u>requently-traded stocks trade after innovation δ_t^ℓ is realized, but before time ℓ; and for the remaining fraction $1 - \rho_f$, the last trade occurs before δ_t^ℓ is realized. In contrast, suppose that fraction $\rho_i < \rho_f$ of <u>**i**</u>nfrequently-traded stocks trade after innovation δ_t^ℓ is realized, but before time ℓ; and for the remaining fraction $1 - \rho_i$, the last trade occurs after $\delta_t^{\ell-1}$, but before δ_t^ℓ is realized.

Then $\rho_f - \rho_i$ measures the degree to which frequently-traded stocks are more likely than infrequently-traded stocks to trade after an innovation. Because large capitalization stocks tend to trade more frequently than small capitalization stocks, one interpretation is that portfolios of frequently- and infrequently-traded stocks are analogous to portfolios of large and small capitalization stocks. Then, computing returns using the last transaction <u>**b**</u>efore ℓ, the portfolio of lagged price changes for <u>**f**</u>requently-traded stocks will co-vary more strongly with current price changes for <u>**i**</u>nfrequently-traded stocks, than its opposite counterpart.

That is, because $\rho_f > \rho_i$,

$$\text{cov}\left(\Delta p_t^{ib\ell}, \Delta p_{t-1}^{fb\ell}\right) - \text{cov}\left(\Delta p_t^{fb\ell}, \Delta p_{t-1}^{ib\ell}\right) = [\rho_f(1-\rho_i) - \rho_i(1-\rho_f)]N\text{var}(\delta_t^\ell) > 0. \quad (1)$$

But, the opposite pattern arises if we instead use the first trade **a**fter time ℓ,

$$\text{cov}\left(\Delta p_t^{ia\ell}, \Delta p_{t-1}^{fa\ell}\right) - \text{cov}\left(\Delta p_t^{fa\ell}, \Delta p_{t-1}^{ia\ell}\right) = [(1-\rho_f)\rho_i - \rho_f(1-\rho_i)]N\text{var}(\delta_t^{\ell+1}) < 0. \quad (2)$$

While this analysis gives the qualitative nature of the relative impact of nonsynchronous trading on differences in lead-lag portfolio cross-autocorrelations, the patterns in (1) and (2) do not account for the huge, fixed portfolio effects in cross-autocorrelations that can also cause differences in cross-autocorrelations across portfolio pairs. For example, **independently** of whether we use the "before" or "after" transaction to compute returns, lagged returns of larger stocks are far more highly autocorrelated with current returns of smaller stocks than the converse. In part, this reflects that information tends to be incorporated more quickly into the prices of larger stocks, so their lagged returns better predict returns of smaller stocks even if we compute returns using the first transaction after the reference time point. We must separate out the impact of nonsynchronous trading from the fixed portfolio effects.

But, one also cannot simply control for portfolio fixed effects by selecting a given pair of portfolios and contrasting before/after cross-autocorrelations—the sign of such contrasts is not pinned down because information arrival rates vary over the trading day. For example, even though large stocks trade more frequently so that $\rho_f(1-\rho_i) > \rho_i(1-\rho_f)$, if information arrival rates increase later in the day so that $\text{var}(\delta_t^{\ell+1}) > \text{var}(\delta_t^\ell)$, we could have

$$\text{cov}\left(\Delta p_t^{ib\ell}, \Delta p_{t-1}^{fb\ell}\right) = \rho_f(1-\rho_i)N\text{var}(\delta_t^\ell) < (1-\rho_f)\rho_i N\text{var}(\delta_t^{\ell+1}) = \text{cov}\left(\Delta p_t^{ia\ell}, \Delta p_{t-1}^{fa\ell}\right). \quad (3)$$

Indeed, empirically we will find that if we consider times early or late in the day, such asymmetries appear to generate precisely this result.

Hence, to identify the impact of nonsynchronous trading, we must control for both portfolio fixed effects and intraday variation in information arrival rates. We do this by taking differences in differences. That is,

$$\tilde{\xi}(ft, it) = \underbrace{\left[\operatorname{cov}\left(\Delta p_t^{ib\ell}, \Delta p_{t-1}^{fb\ell}\right) - \operatorname{cov}\left(\Delta p_t^{fb\ell}, \Delta p_{t-1}^{ib\ell}\right)\right]}_{(+)} - \underbrace{\left[\operatorname{cov}\left(\Delta p_t^{ia\ell}, \Delta p_{t-1}^{fa\ell}\right) - \operatorname{cov}\left(\Delta p_t^{fa\ell}, \Delta p_{t-1}^{ia\ell}\right)\right]}_{(-)} > 0, \tag{4}$$

which can be re-arranged as

$$\tilde{\xi}(ft, it) = \left[\operatorname{cov}\left(\Delta p_t^{ib\ell}, \Delta p_{t-1}^{fb\ell}\right) - \operatorname{cov}\left(\Delta p_t^{ia\ell}, \Delta p_{t-1}^{fa\ell}\right)\right] - \left[\operatorname{cov}\left(\Delta p_t^{fb\ell}, \Delta p_{t-1}^{ib\ell}\right) - \operatorname{cov}\left(\Delta p_t^{fa\ell}, \Delta p_{t-1}^{ia\ell}\right)\right] > 0, \tag{5}$$

should give us twice the impact of nonsynchronous trading on the difference in portfolio cross-autocorrelations. The individual differences, $\operatorname{cov}\left(\Delta p_t^{ib\ell}, \Delta p_{t-1}^{fb\ell}\right) - \operatorname{cov}\left(\Delta p_t^{fb\ell}, \Delta p_{t-1}^{ib\ell}\right)$ and $\operatorname{cov}\left(\Delta p_t^{ia\ell}, \Delta p_{t-1}^{fa\ell}\right) - \operatorname{cov}\left(\Delta p_t^{fa\ell}, \Delta p_{t-1}^{ia\ell}\right)$, eliminate the portfolio fixed effects, leaving the information arrival rate effects for each portfolio pair; and differencing once more eliminates the information arrival rate effects, leaving only twice the impact of nonsynchronous trading.

III Data

We obtained trade and quote data from the TAQ database for the period 1993 to 2003. From CRSP, we obtain the market capitalization on January 1st of each year for all NYSE-listed stocks.[6] We eliminate stocks for which CRSP does not have market capitalization data, stocks based outside the United States, securities that are not ordinary common shares, and stocks that change their ticker symbol during the year.

From the remaining sample, on a yearly basis we select the largest 1250 firms by market capitalization and sort these into five portfolios of 250 firms according to size quintiles: Q1 = smallest, Q5 = largest. The same 1250 firms are also divided into five quintiles according to their trade frequency in the first month of the year.

[6] Results for Nasdaq-listed stocks are qualitatively similar and are available upon request.

We consider 24-hour portfolio returns calculated at half-hour intervals, $\ell \in \{10{:}15, 10{:}45, \ldots 2{:}45, 3{:}15\}$.[7] For each stock, a series of daily prices are created using (i) the first trade price after time ℓ, and (ii) the last trade price before time ℓ. Based on these price series, daily portfolio returns are calculated as: $r_t = \frac{1}{I}\sum_{i=1}^{I} \frac{P_{ti}+DIV_{ti}-P_{t-1,i}}{P_{t-1,i}}$. Note that the last trade prior to an arbitrary time can occur on the previous trading day and the first trade after an arbitrary time can occur on the next trading day (but within 24 hours). We eliminate potentially erroneous prices for which the absolute daily price change exceeds 50% or for which the bid price exceeds the ask. We use the method proposed by Anderson, et al. (2008) to calculate portfolio returns: on any given date, the portfolio return is calculated as the equally-weighted average of the returns of the individual stocks within the portfolio satisfying the screening criteria (e.g., at least one appropriate trade within the 24-hour period). As a result, the portfolio return is based on a portfolio of stocks that changes (very slightly) in composition from day-to-day. This approach eliminates the impact of non-trading on consecutive days, which would reduce cross-autocorrelations in daily returns because there is then no overlap in information arrival. Such non-trading days are rare (occurring in less than 2% of firm days for any given quintile), and our estimates are not qualitatively affected by this selection criterion.

IV Results

Our empirical results are based on the difference-in-difference statistic,

$$\begin{aligned}\xi(Qj,Qk) = &\left[\text{corr}_{before}(r_t^{Qj}, r_{t-1}^{Qk}) - \text{corr}_{after}(r_t^{Qj}, r_{t-1}^{Qk})\right] \\ &- \left[\text{corr}_{before}(r_t^{Qk}, r_{t-1}^{Qj}) - \text{corr}_{after}(r_t^{Qk}, r_{t-1}^{Qj})\right], \end{aligned} \tag{6}$$

for $j < k$. $\xi(Qj,Qk)$ is analogous to (5), except that it is expressed in terms of correlation (instead of covariance) and returns (instead of price changes) for portfolio quintiles.

Size-based Portfolios. We first consider portfolios sorted according to market capitalization. Table II reports the value of our difference-in-difference statistic $\xi(Qj,Qk)$ measured

[7] We chose our initial window of 10:15am, and final window of 3:15pm to minimize the impact of the unique features of the market at open and close, such as the opening and closing call auctions, specialist intervention, and reporting delays.

for all quintile combinations and times. Consistent with the predicted theoretical impact of nonsynchronous trading, **every** difference in differences is positive, independently of the time of day at which returns are calculated, and independently of which portfolio quintile size pairs is considered. This is overwhelming evidence in support of our theory: all 110 difference in differences are positive, without a single negative result. Indeed, for a fixed smaller portfolio, as we pair it with a larger and larger portfolio, the difference in differences **always** increases, consistent with the increasing impact of nonsynchronous trading.[8]

Individual Statistical Significance. To test for the significance of a particular $\xi(Qj, Qk)$ statistic, we use a block of blocks bootstrap approach that is designed to preserve the time dependence structure in the data.[9] If our original portfolio return data series is $(r_1, r_2, \ldots, r_n)$ and we seek to calculate its autocorrelation, we set

$$(r'_1, \ldots, r'_{n-1}) = \begin{pmatrix} r'_{11} & r'_{12} & \cdots & r'_{1,n-1} \\ r'_{21} & r'_{22} & \cdots & r'_{2,n-1} \end{pmatrix} = \begin{pmatrix} r_1 & r_2 & \cdots & r_{n-1} \\ r_2 & r_3 & \cdots & r_n \end{pmatrix}.$$

We then resample blocks of the new data, $r'_1, \ldots, r'_{n-m+1}$, where each of the observations is a block of the original data. The key point is that our statistic of interest should not compare observations adjacent in each row. We select a block length of $l = 5$. For example, with $n = 15$ observations and a block length of $l = 5$ a bootstrap replicate might be

$$\{r'^*_j\} = \begin{pmatrix} r_5 & r_6 & r_7 & r_8 & r_9 & & r_1 & r_2 & r_3 & r_4 & r_5 & & r_7 & r_8 & r_9 & r_{10} & r_{11} \\ r_6 & r_7 & r_8 & r_9 & r_{10} & & r_2 & r_3 & r_4 & r_5 & r_6 & & r_8 & r_9 & r_{10} & r_{11} & r_{12} \end{pmatrix}.$$

Robustness checks show that our results are not sensitive to using other reasonable block lengths.

For each difference-in-difference statistic, $\xi(Qj, Qk)$, we do 9,999 bootstrap replications, and for each replication b, we calculate the corresponding statistic, $\xi_b(Qj, Qk)$. We generate a basic (percentile) bootstrap confidence interval with nominal coverage of $(1-\alpha)$ by sorting the statistics $\xi_b(\cdot)$ from largest to smallest, $\xi^*_1, \xi^*_2, \ldots, \xi^*_B$ and then constructing the confidence interval with confidence limits $\hat{\theta}_\alpha = 2\xi - \xi^*_{(B+1)(1-\alpha)}$ and $\hat{\theta}_{1-\alpha} = 2\xi - \xi^*_{(B+1)\alpha}$. This approach

[8] Qualitatively similar estimates (available on request) obtain if we use quote midpoints to calculate returns rather than trade prices. This suggests that quotes are also updated in a nonsynchronous fashion.

[9] See Davison and Hinkley (1997, p. 398) for details.

to constructing confidence intervals is designed to account for the non-symmetric distribution of correlation estimates. We indicate in Table II when these confidence intervals exclude zero for α =10%, 5% and 1%. The vast majority of these individual $\xi(Qj, Qk)$ statistics are significant, and more than half are significant at the 1% significance level. Further, the statistical significance of these differences in differences grows for portfolios that are more distinct—for example, the correlation between quintiles 1 and 5—precisely as our theory predicts.

Percentage of difference explained. Table III calculates the percentage of the observed difference in cross-autocorrelations explained by nonsynchronous trading over the eleven different times at which we compute returns. It is calculated as

$$\frac{\xi(Qj,Qk)}{\left[\text{corr}_{before}(r_t^{Qj}, r_{t-1}^{Qk}) + \text{corr}_{after}(r_t^{Qj}, r_{t-1}^{Qk})\right] - \left[\text{corr}_{before}(r_t^{Qk}, r_{t-1}^{Qj}) + \text{corr}_{after}(r_t^{Qk}, r_{t-1}^{Qj})\right]},$$

for $j < k$, where we have averaged the level of the cross-autocorrelations before and after. With the exception of the Q3 – Q4 difference (which is tiny and difficult to measure), our results suggest that nonsynchronous trading typically explains 5% to 12% of the observed differences. It is worth noting that the estimated percentages are quite similar at different times of the day, which is remarkable given the evidence provided in Bernhardt and Davies (2007) that portfolio autocorrelations and cross-autocorrelations increase dramatically over the day.

Importance of Difference-in-Differences methodology. Typically, more information arrives near the market open and market close than during the middle of the day. So, too, day limit orders, which are fresh at open, tend to grow stale over the trading day, raising correlation measures later in the day. In addition, in U.S. markets, trade volume typically exhibits a U-shaped pattern over the trading day. These time-varying factors can affect correlation measures. For example, when market-wide information arrives more frequently, portfolio correlations typically increase as this information causes the prices of component stocks to tend to move in the same direction. Even more important, information arrival increases the variance of returns, and thereby potentially changes the ordering of our correlation measures (see, e.g., condition (3)). Figure 2 illustrates the impact of a U-shaped pattern in information arrival over the trading day. At earlier times in the day, there is greater information arrival prior to the time than after, causing an upward bias in correlations measured using trades before the time compared to those using trades after. At later times in the day, there is greater information and trade arrival after the time than before, causing an upward bias in correlations measured after compared to correlations measured before.

These time-varying factors would make inference problematic if we did not use the differences-in-differences approach. Table IV presents results when we do not do the last differencing, presenting the before-after portfolio autocorrelation differences at 12:15pm, 12:45pm and 1:15pm. We highlight in bold when the before/after difference bounds strictly positive or strictly negative numbers. The table reveals that at midday, 12:45pm, the before correlation uniformly exceeds the after correlation when we look at the correlation of lagged returns of larger-capitalization stocks with current returns of smaller-capitalization stocks, especially when the difference in portfolio size is greater. That is, at midday, the difference-in-difference methodology is not needed to glean the impact of nonsynchronous trading. This, however, is not true at other times in the day: just 30 minutes earlier, at 12:15pm, the before correlation tends to exceed the after correlation; and just 30 minutes later, at 1:15pm, the after correlation exceeds the before correlation, except when we use the lagged returns of the largest-capitalization stocks.

These results emphasize the importance of controlling for sources of intraday variation via the difference-in-differences methodology. In addition to the impact of the U-shaped arrival rate of information, all autocorrelations tend to rise later later in the trading day, which tends to raise correlations measured after a given time for all portfolios. These two effects are more pronounced for portfolios constructed even earlier or later in the day.

Frequency-based portfolios. Tables V–VII present analogous results for portfolios sorted according to trade frequency rather than market capitalization. Using the same set of stocks as in the market capitalization analysis, we re-sort according to the number of trades in the first month of the year. The sample is then divided into quintiles of 250 stocks according to the numbers of trades. The correlation between market capitalization and the number of trades is about 0.7. Despite only a loose correspondence between market capitalization and trade frequency, the empirical findings are qualitatively similar. As one would expect, the nonsynchronous trading effect is larger for portfolios sorted according to trading frequencies, as this increases the variation in trade times between the frequently and infrequently portfolios. Ignoring the tiny difference between Q3 and Q4, we find that nonsynchronous trading typically explains 7% to 16% of the observed differences in cross-autocorrelations. Once more, nonsynchronous trading matters most for differences involving the least frequently-traded stocks (Q1), and for a fixed smaller portfolio, the impact of nonsynchronous trading on the difference in differences invariably grows as we pair it with larger and larger portfolios.

The impact of nonsynchronous trading across time subsamples. Tables VIII and X reveal how the impact of nonsynchronous trading has evolved over time. We break the sample in half, contrasting the Jan. 1993 to Dec. 1997 with Jan. 1998 to Dec. 2003. Tables IX and XI reveal that the impact of the much higher trading volumes and automation of trading in the later years significantly reduced the impact of nonsynchronous trading, particularly for the smallest or least-actively traded stocks. Even so, the same qualitative impact of nonsynchronous trading remains in the later sample period, and roughly two-thirds of the estimates remains statistically significant at the 1% level for portfolios sorted by trading frequency: despite huge increases in trading frequency, nonsynchronous trading still matters for portfolio cross-autocorrelation differences.

V Conclusion

This paper examines the extent to which differences in trading frequencies can underlie intraday differences in cross-autocorrelations in 24-hour stock portfolio returns. Our central insight is that by using trade prices before and after an arbitrary point in the trading day to calculate returns, we can isolate the impact of nonsynchronous trading on portfolio correlation patterns using a difference-in-differences methodology. These difference in differences are uniformly positive—underlining that nonsynchronous trading contributes to differences in portfolio cross-autocorrelations. Furthermore, we find that the percentage impact of nonsynchronous trading on portfolio cross-autocorrelations is remarkably stable across the different times that we measure 24-hour intraday returns, despite large changes in the levels of portfolio correlations during the day.

Our findings suggest that over the full sample period, nonsynchronous trading typically explains 5–12% of the differences in portfolio cross-autocorrelations for portfolios sorted on market capitalization, and 7–16% of the differences for portfolios sorted on trading frequency. Increases in trading volume and advances in trade technology reduced, but did not eliminate, the effect in the latter half of the sample period.

These findings have implications for our understanding of market efficiency, and for intraday portfolio trading strategies. In particular, one does not want to attribute autocorrelation patterns to market inefficiencies when they simply reflect differences in trade timing. Furthermore, patterns caused by differences in trade timing cannot be directly exploited by portfolio trading strategies.[10]

Although our results indicate that nonsynchronous trading contributes significantly to observed cross-autocorrelation differences, it is clear that other factors, such as stale prices, contribute even more. Understanding why apparently inefficient market prices persist, despite the prevalence of proprietary trading strategies designed to exploit these patterns, is an important area for future research.

[10] It is conceivable that these patterns could be exploited by trading bundles that have “constructed” prices based on stale information, similar to what occurred with the late trading scandals for investors in mutual funds.

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Figure 1: **The typical effect of nonsynchronous trading on the information overlap between 24-hour returns of infrequently- and frequently-traded stocks.** The first timeline shows the overlap when 24-hour returns are calculated using the price of the last trade before 12:45pm and the second timeline shows the overlap when 24-hour returns are calculated using the price of the first trade after 12:45pm.

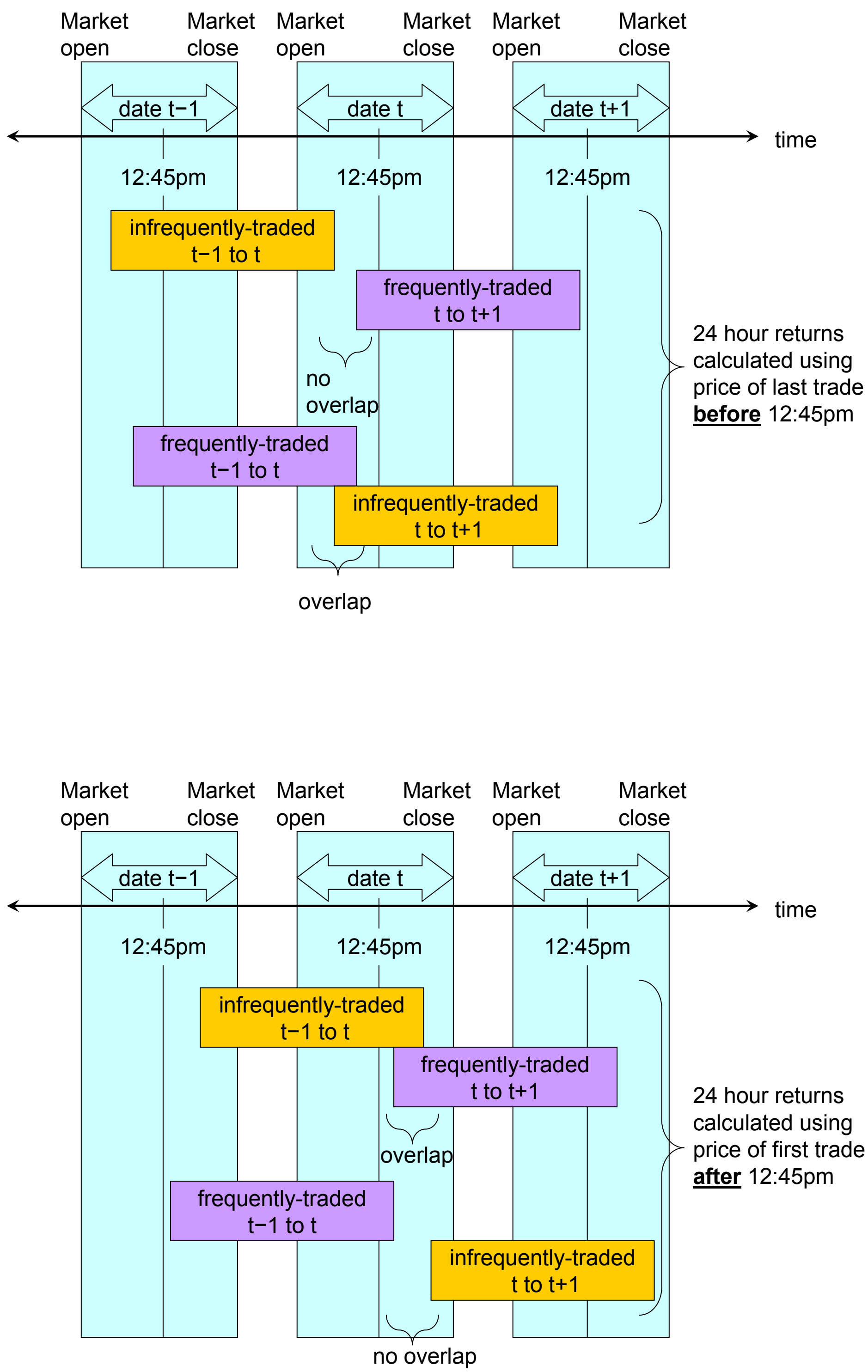

Figure 2: **The impact on portfolio cross-autocorrelations caused by a symmetric U-shaped intraday pattern in information arrival.**

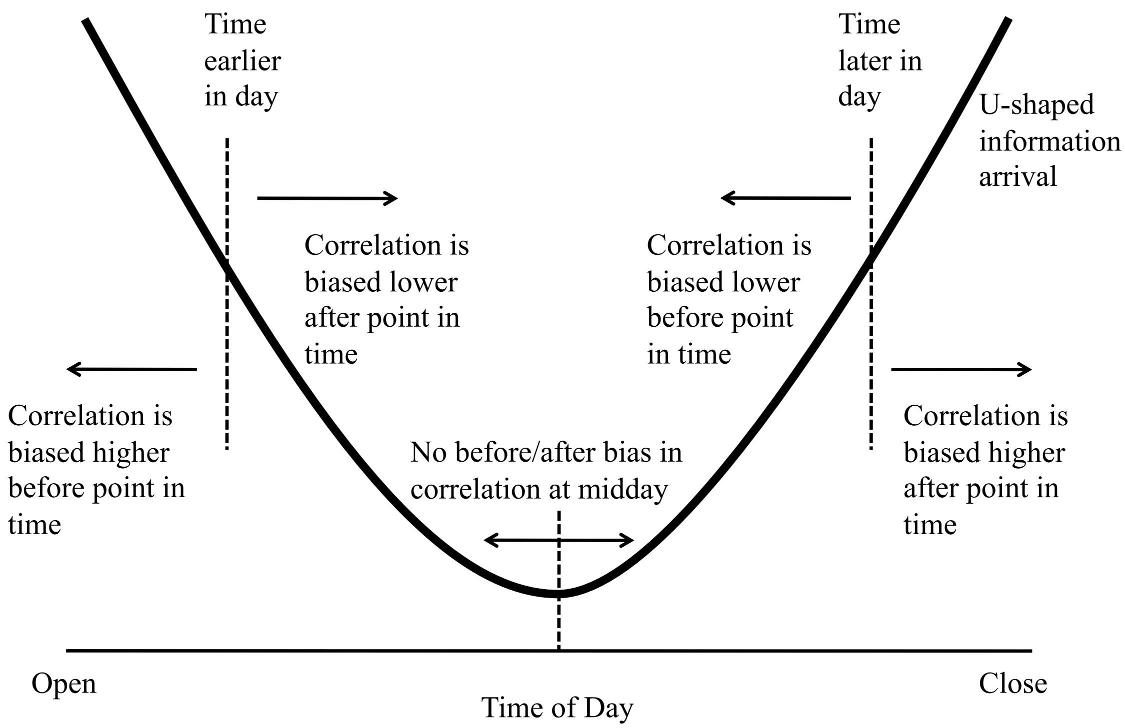

Table II: **Difference-in-difference statistics for size-sorted portfolios.** Each year (1993–2003) the largest 1250 NYSE firms are sorted into quintiles (Q1–Q5, Q5 = largest) of 250 firms according to market capitalization at the beginning of the year. 24-hour portfolio returns are calculated based on last trade before and first trade after the respective time. The table reports $\xi(Qj,Qk) = [\text{corr}_{before}(r_t^{Qj}, r_{t-1}^{Qk}) - \text{corr}_{after}(r_t^{Qj}, r_{t-1}^{Qk})] - [\text{corr}_{before}(r_t^{Qk}, r_{t-1}^{Qj}) - \text{corr}_{after}(r_t^{Qk}, r_{t-1}^{Qj})]$ for $j < k$. A *, **, and *** indicate significance at 10%, 5%, and 1%, respectively, based on a block of blocks bootstrap with a block length of 5.

Time: 10:15

	Q2	Q3	Q4	Q5
Q1	0.014***	0.026***	0.028***	0.029***
Q2		0.012***	0.014***	0.018***
Q3			0.002	0.006*
Q4				0.007**

Time: 10:45

	Q2	Q3	Q4	Q5
Q1	0.008**	0.021***	0.021***	0.025***
Q2		0.010***	0.011***	0.019***
Q3			0.002	0.008**
Q4				0.008**

Time: 11:15

	Q2	Q3	Q4	Q5
Q1	0.007**	0.013***	0.016***	0.018***
Q2		0.006**	0.008***	0.011***
Q3			0.003	0.005
Q4				0.003

Time: 11:45

	Q2	Q3	Q4	Q5
Q1	0.009***	0.014***	0.018***	0.017***
Q2		0.005*	0.007**	0.010***
Q3			0.004	0.004
Q4				0.002

Time: 12:15

	Q2	Q3	Q4	Q5
Q1	0.015***	0.016***	0.019***	0.022***
Q2		0.003	0.006**	0.011***
Q3			0.005*	0.008**
Q4				0.004

Time: 12:45

	Q2	Q3	Q4	Q5
Q1	0.009**	0.013***	0.017***	0.019***
Q2		0.004	0.008**	0.012***
Q3			0.004	0.007**
Q4				0.003

Time: 1:15

	Q2	Q3	Q4	Q5
Q1	0.011***	0.014***	0.014***	0.017***
Q2		0.003	0.004	0.009**
Q3			0.002	0.004
Q4				0.003

Time: 1:45

	Q2	Q3	Q4	Q5
Q1	0.008**	0.009**	0.011***	0.014***
Q2		0.000	0.002	0.006
Q3			0.002	0.004
Q4				0.002

Time: 2:15

	Q2	Q3	Q4	Q5
Q1	0.017***	0.021***	0.022***	0.023***
Q2		0.004	0.006*	0.010***
Q3			0.004	0.005
Q4				0.002

Time: 2:45

	Q2	Q3	Q4	Q5
Q1	0.018***	0.025***	0.026***	0.028***
Q2		0.008**	0.010***	0.014***
Q3			0.002	0.004
Q4				0.003

Time: 3:15

	Q2	Q3	Q4	Q5
Q1	0.013***	0.025***	0.025***	0.029***
Q2		0.011***	0.011***	0.016***
Q3			0.001	0.008**
Q4				0.006*

Table III: **The percentage of the difference in cross-autocorrelations explained by nonsynchronous trading for size-sorted portfolios.** Each year (1993–2003) the largest 1250 NYSE firms are sorted into quintiles (Q1–Q5, Q5 = largest) of 250 firms according to market capitalization at the beginning of the year. The reported percentage is calculated as the difference-in-difference statistic, $\xi(Qj, Qk)$, from Table II divided by $\left[\text{corr}_{before}(r_t^{Qj}, r_{t-1}^{Qk}) + \text{corr}_{after}(r_t^{Qj}, r_{t-1}^{Qk})\right] - \left[\text{corr}_{before}(r_t^{Qk}, r_{t-1}^{Qj}) + \text{corr}_{after}(r_t^{Qk}, r_{t-1}^{Qj})\right]$, for $j < k$.

Time: 10:15

	Q2	Q3	Q4	Q5
Q1	11.1	11.9	11.9	11.4
Q2		10.2	9.5	8.9
Q3			4.1	5.8
Q4				9.3

Time: 10:45

	Q2	Q3	Q4	Q5
Q1	6.6	10.4	10.7	11.7
Q2		9.5	9.5	11.7
Q3			10.2	10.2
Q4				13.0

Time: 11:15

	Q2	Q3	Q4	Q5
Q1	5.4	6.5	8.5	9.4
Q2		6.3	8.1	8.5
Q3			16.5	8.3
Q4				6.9

Time: 11:45

	Q2	Q3	Q4	Q5
Q1	8.3	7.6	10.4	9.8
Q2		4.6	6.9	8.6
Q3			28.2	10.6
Q4				6.7

Time: 12:15

	Q2	Q3	Q4	Q5
Q1	11.5	8.1	10.6	12.3
Q2		2.8	6.3	9.9
Q3			34.3	17.1
Q4				11.1

Time: 12:45

	Q2	Q3	Q4	Q5
Q1	7.2	6.7	9.5	10.5
Q2		4.8	9.6	11.2
Q3			55.5	14.1
Q4				6.7

Time: 1:15

	Q2	Q3	Q4	Q5
Q1	8.4	6.6	7.2	8.6
Q2		3.3	4.8	8.2
Q3			12.3	8.7
Q4				6.7

Time: 1:45

	Q2	Q3	Q4	Q5
Q1	6.5	4.7	5.6	7.1
Q2		0.5	2.1	5.4
Q3			8.5	6.2
Q4				4.0

Time: 2:15

	Q2	Q3	Q4	Q5
Q1	14.2	10.7	11.5	11.5
Q2		3.9	6.2	8.2
Q3			12.7	7.4
Q4				3.4

Time: 2:45

	Q2	Q3	Q4	Q5
Q1	14.9	12.6	12.5	11.3
Q2		8.5	9.0	8.3
Q3			6.0	3.9
Q4				3.3

Time: 3:15

	Q2	Q3	Q4	Q5
Q1	11.9	12.2	10.3	9.6
Q2		9.6	7.4	6.9
Q3			2.1	4.6
Q4				5.3

Table IV: **Cross-autocorrelation matrices at 12:15pm, 12:45pm, and 1:15pm, based on size-sorted portfolios.** Each year (1993–2003) the largest 1250 NYSE firms are sorted into quintiles (Q1–Q5, Q5 = largest) of 250 firms according to market capitalization at the beginning of the year. Reported cross-autocorrelations are based on 24-hour portfolio returns calculated using the price of last trade *before* or the price of the first trade *after* the respective time. Boxed numbers indicate the after correlation is larger than the before correlation. **Bold numbers** indicate that the difference between the before correlation and the after correlation is significant at 5% based on a block of blocks bootstrap with a block length of 5.

Time: 12:15

	Q1		Q2		Q3		Q4		Q5	
	Before	After	Before	After	Before	After	Before	After	Before	After
lag Q1	**0.147**	**0.155**	**0.073**	**0.085**	**0.042**	**0.053**	**0.033**	**0.044**	**0.001**	**0.011**
lag Q2	0.143	0.141	0.076	0.076	0.043	0.046	0.038	0.040	0.004	0.009
lag Q3	0.151	0.146	0.095	0.094	0.061	0.059	0.050	0.051	0.017	0.020
lag Q4	**0.135**	**0.126**	0.087	0.084	0.059	0.055	**0.048**	**0.044**	0.016	0.015
lag Q5	**0.103**	**0.092**	**0.066**	**0.059**	0.044	0.039	**0.037**	**0.032**	0.009	0.007

Time: 12:45

	Q1		Q2		Q3		Q4		Q5	
	Before	After	Before	After	Before	After	Before	After	Before	After
lag Q1	0.158	0.163	**0.088**	**0.095**	**0.054**	**0.061**	**0.045**	**0.052**	**0.009**	**0.017**
lag Q2	0.154	0.152	0.090	0.089	0.056	0.057	0.052	0.054	0.016	0.020
lag Q3	**0.158**	**0.152**	0.104	0.101	0.069	0.065	0.060	0.058	**0.025**	**0.026**
lag Q4	**0.142**	**0.133**	**0.095**	**0.089**	**0.066**	**0.060**	**0.057**	**0.051**	0.023	0.021
lag Q5	**0.111**	**0.100**	**0.074**	**0.067**	**0.052**	**0.046**	**0.049**	**0.044**	0.018	0.015

Time: 1:15

	Q1		Q2		Q3		Q4		Q5	
	Before	After	Before	After	Before	After	Before	After	Before	After
lag Q1	**0.151**	**0.164**	**0.078**	**0.094**	**0.043**	**0.059**	**0.031**	**0.045**	**−0.003**	**0.011**
lag Q2	0.147	0.152	0.083	0.087	**0.050**	**0.056**	0.043	0.048	**0.010**	**0.017**
lag Q3	0.154	0.155	0.099	0.102	0.065	0.067	0.052	0.056	0.021	0.025
lag Q4	0.138	0.138	0.090	0.091	0.061	0.063	0.049	0.049	0.018	0.020
lag Q5	0.103	0.100	0.066	0.064	0.044	0.044	0.038	0.037	0.009	0.007

Table V: **Difference-in-difference statistics for volume-sorted portfolios.** Each year (1993–2003) the largest 1250 NYSE firms are sorted into quintiles (Q1–Q5, Q5 = largest) of 250 firms according to the number of trades in the first month of the year. 24-hour portfolio returns are calculated based on last trade before and first trade after the respective time. The table reports $\xi(Qj, Qk) = [\text{corr}_{before}(r_t^{Qj}, r_{t-1}^{Qk}) - \text{corr}_{after}(r_t^{Qj}, r_{t-1}^{Qk})] - [\text{corr}_{before}(r_t^{Qk}, r_{t-1}^{Qj}) - \text{corr}_{after}(r_t^{Qk}, r_{t-1}^{Qj})]$ for $j < k$. A *, **, and *** indicate significance at 10%, 5%, and 1%, respectively, based on a block of blocks bootstrap with a block length of 5.

Time: 10:15

	Q2	Q3	Q4	Q5
Q1	0.025***	0.037***	0.036***	0.039***
Q2		0.017***	0.018***	0.022***
Q3			0.004	0.010***
Q4				0.007**

Time: 10:45

	Q2	Q3	Q4	Q5
Q1	0.020***	0.029***	0.028***	0.035***
Q2		0.012***	0.012***	0.019***
Q3			0.001	0.009***
Q4				0.008***

Time: 11:15

	Q2	Q3	Q4	Q5
Q1	0.017***	0.021***	0.021***	0.025***
Q2		0.007***	0.008***	0.011***
Q3			0.002	0.005*
Q4				0.003

Time: 11:45

	Q2	Q3	Q4	Q5
Q1	0.020***	0.022***	0.023***	0.023***
Q2		0.003	0.006**	0.008***
Q3			0.004	0.006*
Q4				0.003

Time: 12:15

	Q2	Q3	Q4	Q5
Q1	0.019***	0.022***	0.025***	0.029***
Q2		0.005**	0.009***	0.013***
Q3			0.004	0.009***
Q4				0.005*

Time: 12:45

	Q2	Q3	Q4	Q5
Q1	0.020***	0.022***	0.026***	0.030***
Q2		0.003	0.007**	0.010***
Q3			0.004*	0.008***
Q4				0.005*

Time: 1:15

	Q2	Q3	Q4	Q5
Q1	0.022***	0.022***	0.024***	0.028***
Q2		0.004	0.005*	0.009***
Q3			0.003	0.005*
Q4				0.004

Time: 1:45

	Q2	Q3	Q4	Q5
Q1	0.020***	0.022***	0.023***	0.028***
Q2		0.006**	0.005	0.007**
Q3			0.001	0.004
Q4				0.002

Time: 2:15

	Q2	Q3	Q4	Q5
Q1	0.028***	0.032***	0.034***	0.039***
Q2		0.008***	0.008***	0.014***
Q3			0.001	0.006*
Q4				0.006*

Time: 2:45

	Q2	Q3	Q4	Q5
Q1	0.032***	0.035***	0.037***	0.042***
Q2		0.008***	0.009***	0.015***
Q3			0.003	0.009***
Q4				0.006*

Time: 3:15

	Q2	Q3	Q4	Q5
Q1	0.033***	0.037***	0.038***	0.045***
Q2		0.009***	0.010***	0.019***
Q3			0.003	0.010***
Q4				0.007**

Table VI: **The percentage of the difference in cross-autocorrelations explained by nonsynchronous trading for volume-sorted portfolios.** Each year (1993–2003) the largest 1250 NYSE firms are sorted into quintiles (Q1–Q5, Q5 = largest) of 250 firms according to the number of trades in the first month of the year. The reported percentage is calculated as the difference-in-difference statistic, $\xi(Qj, Qk)$, from Table V divided by $\left[\text{corr}_{before}(r_t^{Qj}, r_{t-1}^{Qk}) + \text{corr}_{after}(r_t^{Qj}, r_{t-1}^{Qk})\right] - \left[\text{corr}_{before}(r_t^{Qk}, r_{t-1}^{Qj}) + \text{corr}_{after}(r_t^{Qk}, r_{t-1}^{Qj})\right]$, for $j < k$. A ** indicates that the difference in cross-autocorrelations was negative.

Time: 10:15

	Q2	Q3	Q4	Q5
Q1	12.3	11.8	11.6	9.9
Q2		12.3	11.7	9.1
Q3			16.9	7.2
Q4				5.9

Time: 10:45

	Q2	Q3	Q4	Q5
Q1	10.3	10.6	11.2	11.0
Q2		11.8	13.7	10.8
Q3			**	8.7
Q4				7.4

Time: 11:15

	Q2	Q3	Q4	Q5
Q1	9.0	8.2	8.8	8.8
Q2		8.7	10.0	7.9
Q3			**	6.6
Q4				3.7

Time: 11:45

	Q2	Q3	Q4	Q5
Q1	11.3	9.4	11.0	9.3
Q2		4.8	9.9	6.6
Q3			**	7.6
Q4				4.1

Time: 12:15

	Q2	Q3	Q4	Q5
Q1	10.5	8.9	11.5	11.0
Q2		6.6	13.5	10.6
Q3			**	12.5
Q4				7.1

Time: 12:45

	Q2	Q3	Q4	Q5
Q1	11.8	9.3	12.3	12.1
Q2		3.3	10.0	8.8
Q3			**	13.2
Q4				7.9

Time: 1:15

	Q2	Q3	Q4	Q5
Q1	12.9	9.3	10.5	11.3
Q2		4.4	6.1	6.9
Q3			**	9.8
Q4				7.4

Time: 1:45

	Q2	Q3	Q4	Q5
Q1	12.3	9.6	10.8	11.5
Q2		6.8	6.2	5.8
Q3			**	6.5
Q4				4.3

Time: 2:15

	Q2	Q3	Q4	Q5
Q1	17.6	14.8	16.1	15.8
Q2		9.3	10.0	10.8
Q3			**	8.5
Q4				9.1

Time: 2:45

	Q2	Q3	Q4	Q5
Q1	21.2	16.1	17.1	15.8
Q2		9.0	8.8	9.6
Q3			56.9	11.7
Q4				9.0

Time: 3:15

	Q2	Q3	Q4	Q5
Q1	21.6	16.3	15.2	14.7
Q2		9.4	7.6	9.6
Q3			7.1	8.6
Q4				10.8

Table VII: **Cross-autocorrelation matrices at 12:15pm, 12:45pm, and 1:15pm, based on volume-sorted portfolios.** Each year (1993–2003) the largest 1250 NYSE firms are sorted into quintiles (Q1–Q5, Q5 = largest) of 250 firms according to the number of trades during the first month of the year. Reported cross-autocorrelations are based on 24-hour portfolio returns calculated using the price of last trade *before* or the price of the first trade *after* the respective time. Boxed numbers indicate the after correlation is larger than the before correlation. **Bold numbers** indicate that the difference between the before correlation and the after correlation is significant at 5% based on a block of blocks bootstrap with a block length of 5.

Time: 12:15

	Q1		Q2		Q3		Q4		Q5	
	Before	After	Before	After	Before	After	Before	After	Before	After
lag Q1	**0.136**	**0.148**	**0.061**	**0.078**	**0.026**	**0.041**	**0.026**	**0.042**	**−0.007**	**0.010**
lag Q2	0.161	0.159	0.090	0.091	0.053	0.055	0.052	0.056	**0.014**	**0.019**
lag Q3	0.158	0.152	0.097	0.093	0.061	0.058	0.057	0.057	0.017	0.020
lag Q4	**0.149**	**0.140**	**0.090**	**0.085**	0.056	0.052	**0.049**	**0.045**	0.010	0.011
lag Q5	**0.137**	**0.125**	**0.084**	**0.076**	**0.056**	**0.050**	0.049	0.045	0.012	0.011

Time: 12:45

	Q1		Q2		Q3		Q4		Q5	
	Before	After	Before	After	Before	After	Before	After	Before	After
lag Q1	**0.150**	**0.161**	**0.077**	**0.092**	**0.039**	**0.052**	**0.036**	**0.052**	**0.006**	**0.022**
lag Q2	0.174	0.168	0.105	0.103	0.066	0.064	0.063	0.064	0.027	0.030
lag Q3	**0.168**	**0.159**	0.108	0.104	**0.071**	**0.066**	0.065	0.063	0.028	0.029
lag Q4	**0.156**	**0.146**	**0.099**	**0.094**	**0.063**	**0.057**	**0.056**	**0.051**	0.021	0.021
lag Q5	**0.144**	**0.130**	**0.090**	**0.083**	**0.062**	**0.054**	**0.056**	**0.051**	0.022	0.020

Time: 1:15

	Q1		Q2		Q3		Q4		Q5	
	Before	After	Before	After	Before	After	Before	After	Before	After
lag Q1	**0.146**	**0.164**	**0.071**	**0.094**	**0.031**	**0.053**	**0.027**	**0.048**	**−0.004**	**0.019**
lag Q2	0.167	0.168	**0.097**	**0.103**	**0.056**	**0.063**	**0.053**	**0.059**	**0.018**	**0.025**
lag Q3	0.161	0.160	0.101	0.104	0.062	0.066	0.057	0.061	0.022	0.026
lag Q4	0.152	0.149	0.097	0.097	0.056	0.057	0.050	0.049	0.016	0.019
lag Q5	0.136	0.130	0.084	0.083	0.052	0.051	0.045	0.044	0.012	0.012

Table VIII: **Difference-in-difference statistics for size-sorted portfolios for the sub-sample periods (Jan 1993 – Dec 1997; Jan 1998 – Dec 2003).** This table presents the results analogous to those in Table II for the sub-sample periods. Each year the largest 1250 NYSE firms are sorted into quintiles (Q1–Q5, Q5 = largest) of 250 firms according to market capitalization at the beginning of the year. 24-hour portfolio returns are calculated based on last trade before and first trade after the respective time. The table reports $\xi(Qj, Qk) = [\text{corr}_{before}(r_t^{Qj}, r_{t-1}^{Qk}) - \text{corr}_{after}(r_t^{Qj}, r_{t-1}^{Qk})] - [\text{corr}_{before}(r_t^{Qk}, r_{t-1}^{Qj}) - \text{corr}_{after}(r_t^{Qk}, r_{t-1}^{Qj})]$ for $j < k$. A *, **, and *** indicate significance at 10%, 5%, and 1%, respectively, based on a block of blocks bootstrap with a block length of 5.

	1993–1997					**1998–2003**			
Time: 10:15					**Time: 10:15**				
	Q2	Q3	Q4	Q5		Q2	Q3	Q4	Q5
Q1	0.006	0.030***	0.034***	0.047***	Q1	0.016***	0.024***	0.026***	0.024***
Q2		0.024**	0.031**	0.042***	Q2		0.009**	0.010**	0.011**
Q3			0.008	0.016*	Q3			0.000	0.004
Q4				0.014*	Q4				0.005
Time: 11:15					**Time: 11:15**				
	Q2	Q3	Q4	Q5		Q2	Q3	Q4	Q5
Q1	0.007	0.017*	0.028**	0.033***	Q1	0.007*	0.012***	0.013***	0.014***
Q2		0.011	0.022*	0.028***	Q2		0.006*	0.005	0.007*
Q3			0.011	0.012	Q3			0.001	0.003
Q4				0.005	Q4				0.002
Time: 12:15					**Time: 12:15**				
	Q2	Q3	Q4	Q5		Q2	Q3	Q4	Q5
Q1	0.012	0.020**	0.031***	0.034***	Q1	0.015***	0.015***	0.017***	0.019***
Q2		0.008	0.021**	0.029***	Q2		0.002	0.002	0.007**
Q3			0.009	0.009	Q3			0.004	0.008**
Q4				0.003	Q4				0.005
Time: 1:15					**Time: 1:15**				
	Q2	Q3	Q4	Q5		Q2	Q3	Q4	Q5
Q1	0.020**	0.032***	0.041***	0.039***	Q1	0.008**	0.009**	0.008*	0.011**
Q2		0.019**	0.026**	0.031***	Q2		0.000	0.000	0.003
Q3			0.007	0.005	Q3			0.001	0.003
Q4				0.003	Q4				0.003
Time: 2:15					**Time: 2:15**				
	Q2	Q3	Q4	Q5		Q2	Q3	Q4	Q5
Q1	0.028***	0.034***	0.048***	0.044***	Q1	0.014***	0.018***	0.017***	0.018***
Q2		0.005	0.023**	0.026***	Q2		0.003	0.002	0.006
Q3			0.014	0.009	Q3			0.001	0.004
Q4				0.001	Q4				0.002
Time: 3:15					**Time: 3:15**				
	Q2	Q3	Q4	Q5		Q2	Q3	Q4	Q5
Q1	0.027**	0.052***	0.064***	0.069***	Q1	0.010**	0.019***	0.015***	0.019***
Q2		0.021**	0.041***	0.049***	Q2		0.008**	0.005	0.008**
Q3			0.019**	0.028***	Q3			−0.003	0.002
Q4				0.012	Q4				0.004

Table IX: **The percentage of the difference in cross-autocorrelations explained by nonsynchronous trading for size-sorted portfolios during the sub-sample periods (Jan 1993 – Dec 1997; Jan 1998 – Dec 2003).** Each year the largest 1250 NYSE firms are sorted into quintiles (Q1–Q5, Q5 = largest) of 250 firms according to market capitalization at the beginning of the year. The reported percentage is calculated as the difference-in-difference statistic, $\xi(Qj, Qk)$, from Table VIII divided by $\left[\text{corr}_{before}(r_t^{Qj}, r_{t-1}^{Qk}) + \text{corr}_{after}(r_t^{Qj}, r_{t-1}^{Qk})\right] - \left[\text{corr}_{before}(r_t^{Qk}, r_{t-1}^{Qj}) + \text{corr}_{after}(r_t^{Qk}, r_{t-1}^{Qj})\right]$, for $j < k$. A ** indicates that the difference in cross-autocorrelations was negative.

1993–1997

Time: 10:15

	Q2	Q3	Q4	Q5
Q1	44.1	28.6	18.4	17.5
Q2		25.1	17.1	14.9
Q3			6.8	6.7
Q4				9.8

Time: 11:15

	Q2	Q3	Q4	Q5
Q1	47.4	17.7	17.8	16.2
Q2		10.4	12.0	11.1
Q3			10.0	6.2
Q4				4.3

Time: 12:15

	Q2	Q3	Q4	Q5
Q1	60.3	23.4	25.3	24.6
Q2		7.8	15.3	17.8
Q3			11.4	6.2
Q4				3.4

Time: 1:15

	Q2	Q3	Q4	Q5
Q1	47.9	26.0	24.6	21.5
Q2		18.1	17.4	17.8
Q3			8.7	4.0
Q4				3.7

Time: 2:15

	Q2	Q3	Q4	Q5
Q1	68.7	32.5	30.7	25.3
Q2		5.1	16.3	14.4
Q3			15.6	6.0
Q4				1.0

Time: 3:15

	Q2	Q3	Q4	Q5
Q1	97.7	43.5	29.8	20.9
Q2		17.2	18.1	13.9
Q3			14.3	10.1
Q4				6.4

1998–2003

Time: 10:15

	Q2	Q3	Q4	Q5
Q1	10.3	9.9	10.6	9.6
Q2		7.4	7.1	6.4
Q3			1.8	5.3
Q4				9.1

Time: 11:15

	Q2	Q3	Q4	Q5
Q1	4.5	5.4	6.6	7.5
Q2		5.4	6.1	6.9
Q3			**	14.6
Q4				11.1

Time: 12:15

	Q2	Q3	Q4	Q5
Q1	10.0	6.6	8.3	9.9
Q2		1.8	3.0	6.8
Q3			**	37.2
Q4				17.4

Time: 1:15

	Q2	Q3	Q4	Q5
Q1	5.7	4.0	3.8	5.4
Q2		**	**	3.6
Q3			**	19.4
Q4				9.3

Time: 2:15

	Q2	Q3	Q4	Q5
Q1	10.4	8.1	7.9	8.4
Q2		3.7	2.4	5.5
Q3			8.1	8.6
Q4				4.7

Time: 3:15

	Q2	Q3	Q4	Q5
Q1	7.9	8.3	6.1	6.4
Q2		7.7	3.4	4.0
Q3			**	1.7
Q4				4.8

Table X: **Difference-in-difference statistics for volume-sorted portfolios for the sub-sample periods (Jan 1993 – Dec 1997; Jan 1998 – Dec 2003).** This table presents the results analogous to those in Table V for the sub-sample periods. Each year the largest 1250 NYSE firms are sorted into quintiles (Q1–Q5, Q5 = largest) of 250 firms according to the number of trades in the first month of the year. 24-hour portfolio returns are calculated based on last trade before and first trade after the respective time. The table reports $\xi(Qj, Qk) = [\text{corr}_{before}(r_t^{Qj}, r_{t-1}^{Qk}) - \text{corr}_{after}(r_t^{Qj}, r_{t-1}^{Qk})] - [\text{corr}_{before}(r_t^{Qk}, r_{t-1}^{Qj}) - \text{corr}_{after}(r_t^{Qk}, r_{t-1}^{Qj})]$ for $j < k$. A *, **, and *** indicate significance at 10%, 5%, and 1%, respectively, based on a block of blocks bootstrap with a block length of 5.

1993–1997

Time: 10:15

	Q2	Q3	Q4	Q5
Q1	0.057***	0.072***	0.071***	0.077***
Q2		0.023***	0.021**	0.030***
Q3			0.010	0.019**
Q4				0.010

Time: 11:15

	Q2	Q3	Q4	Q5
Q1	0.041***	0.033***	0.035***	0.044***
Q2		0.006	0.004	0.013
Q3			0.005	0.013
Q4				0.007

Time: 12:15

	Q2	Q3	Q4	Q5
Q1	0.052***	0.038***	0.054***	0.062***
Q2		−0.001	0.005	0.020**
Q3			0.011	0.026**
Q4				0.014

Time: 1:15

	Q2	Q3	Q4	Q5
Q1	0.051***	0.049***	0.053***	0.068***
Q2		0.011	0.007	0.026***
Q3			0.004	0.018**
Q4				0.018**

Time: 2:15

	Q2	Q3	Q4	Q5
Q1	0.056***	0.058***	0.058***	0.074***
Q2		0.010	0.004	0.032***
Q3			−0.002	0.023**
Q4				0.026***

Time: 3:15

	Q2	Q3	Q4	Q5
Q1	0.070***	0.078***	0.092***	0.104***
Q2		0.015	0.021**	0.051***
Q3			0.018**	0.039***
Q4				0.021**

1998–2003

Time: 10:15

	Q2	Q3	Q4	Q5
Q1	0.018***	0.029***	0.027***	0.029***
Q2		0.015***	0.017***	0.020***
Q3			0.003	0.007***
Q4				0.006**

Time: 11:15

	Q2	Q3	Q4	Q5
Q1	0.012***	0.018***	0.017***	0.020***
Q2		0.008***	0.009***	0.011***
Q3			0.001	0.003
Q4				0.002

Time: 12:15

	Q2	Q3	Q4	Q5
Q1	0.012***	0.018***	0.019***	0.021***
Q2		0.007***	0.010***	0.012***
Q3			0.002	0.005*
Q4				0.003

Time: 1:15

	Q2	Q3	Q4	Q5
Q1	0.016***	0.016***	0.017***	0.019***
Q2		0.002	0.005	0.005
Q3			0.002	0.002
Q4				0.000

Time: 2:15

	Q2	Q3	Q4	Q5
Q1	0.021***	0.027***	0.027***	0.030***
Q2		0.007***	0.009***	0.009***
Q3			0.002	0.001
Q4				0.000

Time: 3:15

	Q2	Q3	Q4	Q5
Q1	0.024***	0.028***	0.026***	0.031***
Q2		0.008***	0.008**	0.011***
Q3			−0.001	0.003
Q4				0.004

Table XI: **The percentage of the difference in cross-autocorrelations explained by nonsynchronous trading for volume-sorted portfolios during the sub-sample periods (Jan 1993 – Dec 1997; Jan 1998 – Dec 2003).** Each year the largest 1250 NYSE firms are sorted into quintiles (Q1–Q5, Q5 = largest) of 250 firms according to the number of trades in the first month of the year. The reported percentage is calculated as the difference-in-difference statistic, $\xi(Qj, Qk)$, from Table X divided by $\left[\text{corr}_{before}(r_t^{Qj}, r_{t-1}^{Qk}) + \text{corr}_{after}(r_t^{Qj}, r_{t-1}^{Qk})\right] - \left[\text{corr}_{before}(r_t^{Qk}, r_{t-1}^{Qj}) + \text{corr}_{after}(r_t^{Qk}, r_{t-1}^{Qj})\right]$, for $j < k$. A * indicates that the percentage exceeded 100%. A ** indicates that the difference in cross-autocorrelations was negative.

1993–1997

Time: 10:15

	Q2	Q3	Q4	Q5
Q1	37.7	23.6	18.9	14.1
Q2		14.4	8.1	6.7
Q3			9.0	6.0
Q4				4.5

Time: 11:15

	Q2	Q3	Q4	Q5
Q1	24.5	11.3	10.1	8.7
Q2		4.4	2.1	3.5
Q3			5.7	4.9
Q4				3.6

Time: 12:15

	Q2	Q3	Q4	Q5
Q1	29.8	13.1	17.4	14.1
Q2		**	3.1	6.4
Q3			21.5	12.1
Q4				8.3

Time: 1:15

	Q2	Q3	Q4	Q5
Q1	27.9	15.2	15.8	14.9
Q2		8.2	4.1	8.3
Q3			10.9	9.2
Q4				10.6

Time: 2:15

	Q2	Q3	Q4	Q5
Q1	31.4	18.4	17.8	16.2
Q2		8.1	2.6	10.3
Q3			**	10.8
Q4				14.9

Time: 3:15

	Q2	Q3	Q4	Q5
Q1	41.8	23.2	23.7	18.8
Q2		8.9	8.4	12.0
Q3			19.6	13.8
Q4				11.3

1998–2003

Time: 10:15

	Q2	Q3	Q4	Q5
Q1	8.2	9.1	9.2	8.2
Q2		11.7	13.9	10.7
Q3			*	9.2
Q4				7.2

Time: 11:15

	Q2	Q3	Q4	Q5
Q1	6.1	7.3	8.2	8.8
Q2		10.3	18.3	13.0
Q3			**	11.4
Q4				3.8

Time: 12:15

	Q2	Q3	Q4	Q5
Q1	6.6	7.8	9.3	9.7
Q2		9.4	21.9	14.3
Q3			**	14.0
Q4				6.1

Time: 1:15

	Q2	Q3	Q4	Q5
Q1	9.4	7.4	8.5	9.5
Q2		3.1	7.8	6.2
Q3			**	14.1
Q4				2.1

Time: 2:15

	Q2	Q3	Q4	Q5
Q1	14.0	13.5	15.2	15.6
Q2		9.8	14.8	11.3
Q3			**	4.3
Q4				0.9

Time: 3:15

	Q2	Q3	Q4	Q5
Q1	16.6	13.7	11.7	12.5
Q2		9.6	7.0	7.7
Q3			**	3.6
Q4				10.5