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Momentum and Reversals in Equity-Index Returns During Periods of Abnormal Turnover and Return Dispersion

ROBERT CONNOLLY and CHRIS STIVERS*

ABSTRACT

We document new patterns in the dynamics between stock returns and trading volume. Specifically, we find substantial momentum (reversals) in consecutive weekly returns when the latter week has unexpectedly high (low) turnover. This pattern is evident in equity indices, index futures, and individual stocks. Similarly, we also find that the autocorrelation in equity-index returns is increasing with the unexpected dispersion across the latter week's firm-level returns. Weeks with extreme turnover and dispersion shocks (both high and low) tend to have more macroeconomic news releases. Our findings bear on understanding price formation and the economic interpretation of turnover and dispersion shocks.

IN THIS PAPER, we document new patterns in the dynamics between stock returns and trading volume. Specifically, we find substantial momentum in consecutive weekly stock returns when the latter week has abnormally high turnover.[1] Conversely, we find substantial reversals in consecutive weekly returns when the latter week has abnormally low turnover. By abnormal turnover, we mean the shock in the turnover time series after controlling for its autoregressive properties and for normal movements with the market return.[2] We find this return pattern in equity indices, index futures, individual stocks, and in the U.S., Japan, and U.K. stock markets.

* Connolly is from the Kenan-Flagler Business School at the University of North Carolina at Chapel Hill, and Stivers is from the Terry College of Business at the University of Georgia. We thank Jennifer Conrad; Mike Cooper; Shane Corwin; Roger Edelen; Rick Green (the editor); John Heaton; Charles Jones; Marc Lipson; Stewart Mayhew; Joe Sinkey; Jiang Wang; Harold Zhang; an anonymous referee; and seminar participants at the 2000 American Finance Association meeting, the 1999 Financial Management Association meeting, and the University of Georgia for their comments. Stivers also thanks the Federal Reserve Bank of Atlanta for research support. The views expressed here are the authors' and not necessarily those of the Federal Reserve Bank of Atlanta or the Federal Reserve System. All errors are our own.

[1] In this paper, we are interested in momentum and reversals in consecutive weekly returns. To clarify our terminology, hereafter we refer to the first of the consecutive periods as the "former period" and the second of the consecutive periods as the "latter period." By momentum (reversals), we mean positive (negative) autocorrelation.

[2] Our empirical work uses turnover shocks that are unpredictable, approximately normally distributed with mean zero, and approximately homoskedastic over time.

The following example illustrates the magnitude and timing of this autoregressive behavior in weekly equity-index returns. For our U.S. large-firm portfolio over the July 1962 to December 2000 period, the implied autoregressive coefficient between returns in week t and week $t-1$ is 0.401 when the abnormal turnover in week t is at its 95th percentile. In contrast, the implied autoregressive coefficient is -0.309 when the abnormal turnover in week t is at its 5th percentile. In subperiod analysis using rolling 10-year periods, the autoregressive coefficient increases an average of 0.80 as the abnormal turnover moves from its 5th to its 95th percentile, and an increasing autocorrelation is reliably evident for every 10-year period.

We also document a second finding that complements our turnover results. We find momentum in consecutive weekly equity-index returns when the latter week has abnormally high firm-level return dispersion. Conversely, we find reversals in consecutive equity-index returns when the latter week has abnormally low dispersion.[3] Further, as suggested by the similarity of the turnover and dispersion results, our turnover and return-dispersion shocks are substantially positively correlated.

We are interested in turnover shocks and dispersion shocks because they are likely to reflect unexpected variation in portfolio reallocations across investors, and understanding the implications and information from portfolio reallocations is an important issue in financial economics. Our research is related to prior literature on the dynamic relation between return behavior and volume. Lo and Wang (2000) provide an excellent, concise review of this literature in their study of the time-series and cross-sectional behavior of trading volume. They conclude that "trading activity is fundamental to a deeper understanding of economic interactions" and that more research is needed to understand better "the time-series variation in volume and the relations between volume, prices, and other economic quantities" (p. 296). Our work takes a step in this direction by examining the behavior of turnover shocks and dispersion shocks and by examining whether these shocks are related to variations in intertemporal return behavior and macroeconomic news flows.

Our empirical exploration differs substantially from earlier studies. First, we introduce new measures of turnover shocks and return-dispersion shocks and show how these shocks are related to momentum and reversals in equity-index returns. Second, our study evaluates whether serial correlation in returns varies with lagged, contemporaneous, and lead versions of turnover and dispersion shocks. In contrast, prior work has only evaluated the role of volume in predicting serial correlation in returns and has used volume measures that exhibit substantial autocorrelation (rather than turnover shocks). Our comprehensive

[3] By firm-level return dispersion, we mean a period's cross-sectional standard deviation of firm returns. Analogous to our turnover shocks, abnormal return dispersion refers to the shock in the dispersion time series after controlling for its autoregressive properties and for normal movements with the market return. It is important to note that our primary momentum and reversal findings are descriptive in nature, rather than predictive, since the relevant turnover and dispersion shocks are from the latter period. Thus, our primary findings do not challenge market efficiency in the sense of Fama (1998).

approach facilitates comparison with existing work and further qualifies the joint price-volume dynamics. Third, we focus on weekly equity-index returns. As in Lo and Wang (2000), we examine the weekly return horizon as a good compromise between maximizing sample size while minimizing daily volume and return fluctuations that may have less direct economic relevance. Prior work on conditional autocorrelations has focused on daily equity-index returns or only examined individual firm returns. Finally, to supplement our main empirical investigation and better understand turnover and dispersion shocks, we also explore whether turnover and dispersion shocks are related to variation in macroeconomics news flows. We find that weeks with extreme turnover shocks and dispersion shocks (both extremely high and extremely low) tend to have more macroeconomic news releases.

Our findings make a number of contributions to the study of security returns, price formation, and return-volume dynamics. First, we believe this paper is the first to document conditions where weekly returns of large-cap portfolios and equity-index futures exhibit substantial momentum and reversals. Second, by documenting new connections between return dynamics, turnover shocks, dispersion shocks, and macroeconomic news flows, we contribute to the literature on understanding time-series variation in volume, prices, and other economic quantities. For example, our findings may help us better understand the economic implications of turnover shocks and dispersion shocks. Third, our findings address how news is incorporated into prices and suggest the need for new theory that might encompass our empirical evidence and generate new testable empirical implications. Finally, our results on dispersion suggest an intriguing role for micro (firm-level) data in understanding macro (market-level) return behavior. In turn, this implies that theory may need to incorporate multiple risky assets, even if the theory is directed only at understanding market-level return behavior.

This paper is organized as follows. In the next section, we discuss related theory and evidence to provide motivation and intuition for our subsequent empirical investigation. The next section also includes more background on turnover and cross-sectional return dispersion. Section II discusses the data and Section III explains our methods for measuring turnover and dispersion shocks. The main empirical results are presented in Section IV. Section V presents additional analysis, including firm-level turnover results, a comparison of our findings to earlier studies, and the relation of macroeconomic news releases and bond returns to our turnover and dispersion shocks. Section VI concludes.

I. Related Literature and Background Discussion

A. Related Literature

The literature on joint price-volume behavior is extensive. However, to our knowledge, no existing theory directly predicts the empirical patterns that we uncover or perfectly fits our empirical setting. Presumably, such theory would need to model the joint dynamics of returns and trading volume, would need to focus on conditional serial correlations, and would need to include multiple risky assets and risk aversion. For brevity in our paper, we limit our discussion here to several important papers that are closely related to our work and that are useful in providing both motivation and intuition for our study. We direct readers to Lo and Wang (2000) and Llorente et al. (2002) for more discussion on this vast literature.

Wang (1994) presents a dynamic model of competitive trading volume where volume conveys important information about how assets are priced in the economy. In his model, there are two types of heterogeneity across risk-averse investors: (1) diverse information about the publicly traded stock, and (2) diverse investment opportunities outside the public stock market.

Wang's model includes two groups of traders. "Informed investors" have access to private information about the single publicly traded stock and also have investment opportunities outside the public stock exchange. These informed investors may trade either because of better information about the publicly traded stock or to adjust their portfolios due to changes in their outside investment opportunities. "Uninformed investors" rationally extract information from realized dividends, prices, and public signals. By trading, they provide liquidity and hope to earn profits by taking advantage of stock price changes that are not related to information about the stock's fundamentals.

In Wang's framework, the dynamic relation between volume and returns varies depending upon the motive for trading by the "informed investors." A reversal in consecutive returns is likely if the primary motive for the informed's trading in the former period is changes in their outside investment opportunities. Prices move with turnover in the former period due to risk aversion and because the uninformed investors do not know whether trading is information based. Thus, the subsequent price movement in the latter period tends to exhibit some reversal from the former period's price movement.

Conversely, momentum in consecutive returns is likely if the primary motive for the informed's trading in the former period is better information about the stock's fundamentals. The partial incorporation of information in the former period tends to generate positive autocorrelation between the former and latter-period returns.

Wang's model includes several promising features that pertain to our empirical investigation. First, Wang's framework provides multiple economic rationales for turnover (rather than simply assuming noisy liquidity shocks). Second, it directly predicts alternating (but unpredictable) momentum and reversals in returns, related to the underlying economics behind turnover. Third, it incorporates two types of heterogeneity across investors. Fourth, as discussed below, it also includes implications about turnover patterns around public news releases.

However, Wang's framework does not directly apply to our empirical setting. First, his framework only has a single risky asset and, thus, does not address our return-dispersion findings. Second, Wang does not directly analyze the implications of turnover shocks in the latter period, but rather focuses on the economics behind turnover in the former period.

A formal extension of Wang's framework to our empirical setting is beyond the scope of our paper. However, in our view, Wang's framework may be consistent with our principal findings if different economics behind turnover in the former period are associated with different conditional distributions for the turnover shocks in the latter period. If so, then the latter-period turnover shock may tell us something both about the economics behind the former-period turnover and also about variation in return momentum and reversals.

Also relevant to our study is the prediction from Wang that "the greater the information asymmetry (and diversity in expectations), the larger the abnormal trading volume when news arrives" (p. 129). In Section V, we report how our turnover shocks and dispersion shocks are related to public macroeconomic news flows and discuss our findings from the context of Wang's framework.

Llorente et al. (2002) present a model closely related to the Wang framework, where turnover is motivated by either hedging purposes (related to changing investment opportunity sets outside the stock market) or by asymmetric information about a stock's fundamentals. They examine the predictive role of volume on the autocorrelation of individual firm daily returns and find evidence consistent with their model and Wang's model.

Cooper (1999) also examines the predictive role of volume for subsequent return dynamics. He analyzes the conditional autocorrelation of weekly large-cap individual stock returns and finds that increasing-volume stocks exhibit weaker return reversals or positive return autocorrelation. To measure turnover variation, Cooper uses a weekly percentage change in turnover. He argues that his evidence seems consistent with Wang's model.

Campbell, Grossman, and Wang (1993; hereafter CGW) present an alternate theory where price changes accompanied by higher volume will tend to be reversed because, in this case, risk-averse traders are likely to be absorbing liquidity shocks with the expectation that they will earn a higher subsequent return. They find supporting evidence in daily index returns. Consistent with CGW's model, Conrad, Hameed, and Niden (1994) find that the subsequent autocorrelation of weekly individual firm returns is decreasing in the number of firm transactions. We compare our results to Cooper (1999) and CGW in Section V.C, after first establishing our new findings in Section IV.

Other related studies include Brown and Jennings (1989) and Blume, Easley, and O'Hara (1994; hereafter BEO). Brown and Jennings study technical analysis and the behavior of return serial correlation with private information trading. BEO consider the informational role of volume from the perspective of investors. In contrast to Wang (1994) and Llorente et al. (2002), volume matters in BEO because it affects the behavior of the market, rather than merely describing the market.

B. Background on Turnover and Return Dispersion

Prior literature suggests several reasons for turnover. These include asymmetric information with disperse beliefs across investors, changes in investment opportunity sets outside the traded stock market, and changes in the investment opportunity set of traded stocks (or changing stock return distributions). See Harris and Raviv (1993), Shalen (1993), Wang (1994), and Chen, Hong, and Stein

(2001) for discussion that relates turnover to heterogeneous information and beliefs. See Wang (1994), Heaton and Lucas (1996), Lo and Wang (2000), and Llorente et al. (2002) for discussion that relates turnover to changes in investment opportunity sets. Also, see Wang and Lo and Wang for additional motives for trading volume.

Abnormal return dispersion might also reflect portfolio reallocations. Before proceeding, we note that linear, common-factor, return-generating models imply a substantial relation between return dispersion and the absolute market return, due to the dispersion in factor loadings (see Stivers (2003)). Here we are interested in dispersion shocks, beyond the variation in dispersion that is related to the magnitude of the period's market return.

Related literature includes the following. First, Loungani, Rush, and Tave (1990) find that high return dispersion leads unemployment. Second, Christie and Huang (1994) find that dispersion is higher during recessions and is positively related to the yield spread between risky and safe corporate bonds. Third, Stivers (2003) finds that higher dispersion is associated with higher future market volatility, even while controlling for standard GARCH relations in the market return. These three papers suggest that abnormally high dispersion may be associated with changing investment opportunities. To the extent that differential information and expectations may generate turnover, it also seems likely to generate abnormally high dispersion across firm returns as investors reallocate across firms.

Finally, as reported later, we note that our turnover shocks and our dispersion shocks are positively correlated. In contrast, the notion of herding in financial markets suggests that abnormally low dispersion might be observed during periods with unusually high volume. Consistent with our observed positive correlation between turnover and dispersion shocks, Christie and Huang (1995) and Chang, Cheng, and Khorana (2000) use return dispersion to evaluate herding and find no evidence of herding in the United States.[4]

II. Data Description

We gather our data from two primary sources. We use CRSP as our source for U.S. equity data and DataStream International as our source for U.S. futures market data and for international data.

We obtain daily firm returns for the July 1962 to December 2000 sample period from the CRSP return files, and then aggregate them in the usual way to form weekly returns using Wednesday as the week's end. We then form weekly decile-portfolio returns over the same period by sorting firms on their market capitali-

[4] Other recent papers use return dispersion (RD) as follows. Bekaert and Harvey (1997, 2000) find that, for developed markets, markets with higher RD tend to have a higher volatility level. In contrast, for emerging markets, they find that markets with a lower RD tend to have a higher volatility level. In the case of emerging markets, a low RD may reflect a market with little industry diversification and hence greater market volatility. Bessembinder, Chan, and Seguin (1996) use firm RD as a measure of firm information flows and find that RD is correlated with aggregate firm-level volume.

zation, with the size-based sorts reperformed every week. All NYSE and AMEX firms with return and market capitalization data for the week are included. The decile-portfolio returns are an equal-weighted average of the component firm returns. Throughout this paper, we refer to the largest size-based, decile-portfolio as our U.S. large-firm portfolio and the second smallest size-based, decile-portfolio as our U.S. small-firm portfolio.

We also use the individual firm returns that make up each portfolio to construct a return dispersion (RD) metric for each decile-portfolio every week. The return dispersion of our large-firm portfolio is defined as follows:

$$RD_{L,t} = \log \sqrt{\left[\frac{1}{n-1}\sum_{i=1}^{n}(R_{i,t} - R_{L,t})^2\right]} \quad (1)$$

where n is the number of firms in our large-firm portfolio, $R_{i,t}$ is the return of large firm i in period t, $R_{L,t}$ is the return of our U.S. large-firm portfolio in period t, and *log* indicates the natural log.

Throughout this paper, we use this notation for time-series variables. The first subscript on the variable identifies the asset (either our large-firm portfolio, L, our small-firm portfolio, S, or firm i) and the second subscript indicates the time period. In some of the discussion, we omit the asset subscript and just use a single time subscript. In these instances, we are referring to the variable, in general, and it is not necessary to specifically identify the particular asset.

For the U.S. futures data, we construct returns implied by the S&P 500 futures prices, using the continuous futures price series from DataStream. The sample period, June 1982 to December 2000, reflects data availability from DataStream. Finally, risk-free rates are from three-month T-bills.

We also collect daily trading volume and shares outstanding for U.S. firms from CRSP over the July 1962 through December 2000 period. Using this data, we construct a weekly turnover measure for each size-based, decile-portfolio. Turnover is defined as shares traded divided by shares outstanding. A portfolio's turnover is the equally weighted average of the individual firm turnovers for the firms that comprise the portfolio. Following from Lo and Wang (2000), our weekly turnover is the sum of five daily turnovers starting at a Wednesday end-of-week and working backward.[5] See Wang (1994) and Lo and Wang (2000) for a theoretical justification for using turnover in our setting, instead of other volume metrics.

Figure 1 graphically displays the time series of raw turnover and raw return dispersion for our U.S. large-firm portfolio. By raw, we mean the primitive turnover and primitive dispersion without the log transformation that we use in equations (1), (2), and (3).

We focus on the large-firm statistics for several reasons. First, our large-firm portfolio return, R_L, is a good proxy for the market return. The correlation

[5] The benefit of our procedure is that our weekly turnover is a standard sum of five consecutive daily turnovers when the market is open. The disadvantage is that a few daily turnovers are counted in two consecutive weeks.

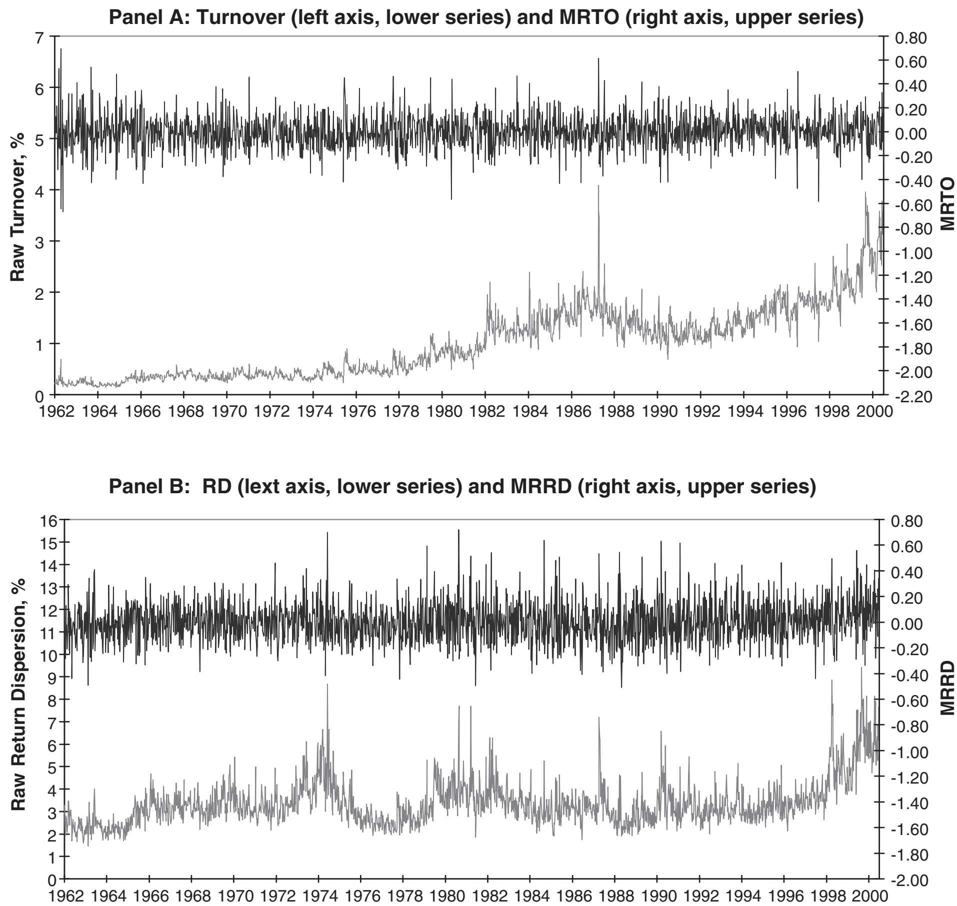

Figure 1. Aggregate turnover and return dispersion of large U.S. firm stocks. This figure displays the time series of weekly average firm turnover and return dispersion (RD) for our U.S. large-firm portfolio over July 1962 to December 2000. Panel A presents the raw turnover and the market-adjusted relative turnover (MRTO). Panel B presents the raw firm return dispersion and the market-adjusted relative return dispersion (MRRD).

between R_L and the CRSP value-weighted market return is 0.975 for our weekly return sample. Second, the turnover and return dispersion of the large firms may be more indicative of the economic environment because small firms may add noise through nonsynchronous trading or high idiosyncratic volatility. Third, this approach enables us to examine differences in large- and small-firm portfolios.

Panel A of Figure 1 shows that turnover increases from 1962 through 1987, with a drop-off following the 1987 crash, followed by an increase again in 1990 through 2000. This figure is very similar to the value-weighted turnover index of Lo and Wang (2000) in Panel A of their Figure 1. Panel B of our Figure 1 shows that the time series of large-firm return dispersion does not exhibit a similar time trend.

We do note that dispersion is fairly high in 1974 and 1981, which were difficult economic times.

We also study weekly returns and turnover from the Japanese and U.K. equity markets. Here, the return sample spans from January 1982 through December 2000. For these markets, the sample is the group of individual firms that comprise a major large-cap equity index (the Nikkei-225 index for Japan and the FTSE-100 index for the United Kingdom), based on data availability from DataStream. We construct the market return and return dispersion from the individual firm returns of each index. For the turnover series for Japan and the United Kingdom, we use the turnover by value (series VA) from DataStream. The turnover series spans November 1986 to December 2000 for the United Kingdom and January 1991 to December 2000 for Japan.

III. Measuring Abnormal Turnover and Return Dispersion

A. Turnover Shocks

Our primary empirical investigation explores whether the autoregressive behavior of equity-index returns varies with abnormal turnover and dispersion across firm returns. As such, it is critical to select measures of abnormal turnover and dispersion that have a clear interpretation as shocks and that have desirable time-series statistical properties. Here, we present and justify our choice for these measures. Later, in Section V.C, we compare our turnover-shock series to other turnover metrics used in previous related studies.

For our primary measure of turnover shocks, we construct a market-adjusted relative turnover (MRTO) series. The $MRTO_t$ of a portfolio is defined as the unexpected variation in turnover after controlling for the autoregressive properties of turnover and for the variation associated with the sign and magnitude of both the week t and $t-1$ portfolio return. The $MRTO_{L,t}$ of our large-firm portfolio is the residual, u_t, obtained from estimating the following time-series regression model:

$$\begin{aligned} TO_{L,t} = \gamma_0 + \sum_{k=1}^{6} \gamma_k TO_{L,t-k} + \gamma_7 |R_{L,t}| + \gamma_8 D_t^- |R_{L,t}| + \gamma_9 |R_{L,t-1}| \\ + \gamma_{10} D_{t-1}^- |R_{L,t-1}| + u_t \end{aligned} \tag{2}$$

where $TO_{L,t}$ is the natural log of the turnover for our U.S. large-firm portfolio, $|R_{L,t}|$ is the absolute excess return of our U.S. large-firm portfolio, $D_t^- = 1$ if $R_{L,t}$ is negative and is zero otherwise, and the γ's are estimated coefficients. The excess return is equal to the nominal return less the three-month T-bill rate.

The return terms are included as explanatory variables in (2) for two reasons. First, by including these terms, we can interpret MRTO as the shock in turnover, beyond the normal variation associated with the sign and/or the magnitude of the market return. Second, we believe it is desirable to have a turnover shock that is orthogonal to both the return and absolute return in periods t and $t-1$, so that any turnover-related variation in the autoregressive behavior cannot be attributed to the sign or the magnitude of the portfolio return. We choose an AR(6) for (2) because, up to six lags, the estimated coefficient on each lagged term is individually positive and statistically significant for both the log(turnover) and the RD series.

We choose to use the log transformation of the raw turnover in (2) for several reasons. First, the log transformation produces a MRTO series that exhibits little heteroskedasticity over time. Second, the resulting MRTO series exhibits nearly no skewness (value of 0.08) and only modest excess kurtosis (value of 1.65).[6] Finally, (2) captures the positive time trend in turnover.

Table I, Panel A, reports the estimated coefficients for our MRTO model (2) for the full sample and one-half sample subperiods. The estimated coefficients indicate that turnover exhibits substantial positive autocorrelation, is positively related to the absolute portfolio return, and tends to be smaller for negative returns as compared to positive returns of the same magnitude.

Alternate specifications of (2) produce series that are very similar to our primary MRTO. For example, if we include linear and squared time-trend explanatory terms in (2), then the correlation between our primary MRTO and the alternate MRTO (with time-trend explanatory terms) is 0.989. Or, if we replace the absolute return terms with squared return terms in (2), then the correlation between our primary MRTO and the alternate MRTO (with squared market return terms) is 0.979. Finally, if we use 10 turnover lags in (2), then the correlation between our primary MRTO and the alternate MRTO (with 10 lags) is 0.989.

Figures 1 and 2 illustrate the properties of our large-firm MRTO series. Figure 1, Panel A, plots the time series of our $MRTO_{L,t}$ over the July 1962 through December 2000 period. Figure 2, Panel A, plots the sample density of our $MRTO_{L,t}$.

B. Return-Dispersion Shocks

For our primary measure of dispersion shocks, we construct a market-adjusted relative return dispersion (MRRD) measure. The MRRD of a portfolio is defined as the unexpected variation in dispersion, after controlling for the autoregressive properties of dispersion and for the variation in dispersion associated with the sign and magnitude of both the week t and $t-1$ portfolio return. The $MRRD_{L,t}$ for our large-firm portfolio is the residual, u_t, obtained from estimating the following time-series regression:

$$RD_{L,t} = \gamma_0 + \sum_{k=1}^{6} \gamma_k RD_{L,t-k} + \gamma_7 |R_{L,t}| + \gamma_8 D_t^- |R_{L,t}| + \gamma_9 |R_{L,t-1}| + \gamma_{10} D_{t-1}^- |R_{L,t-1}| + u_t \tag{3}$$

where $RD_{L,t}$ is the dispersion from our large-firm portfolio per equation (1), and the other terms are as defined for (2). We choose six lags and include the return

[6] By contrast, if we use the raw turnover series in (2) to calculate the turnover shock, the variance of the turnover shock in the second half of the sample is over twice that of its variance in the first half. Further, the alternate shock series from the raw turnover exhibits substantial positive skewness (value of 1.37) and very substantial excess kurtosis (value of 14.7).

Table I
Measuring Turnover Shocks

This table reports on the construction of our relative turnover (RTO) and market-adjusted RTO (MRTO) measures. We estimate two variations of the following model:

$$TO_{L,t} = \gamma_0 + \sum_{k=1}^{6} \gamma_k TO_{L,t-k} + \gamma_7 |R_{L,t}| + \gamma_8 D_t^- |R_{L,t}| + \gamma_9 |R_{L,t-1}| + \gamma_{10} D_{t-1}^- |R_{L,t-1}| + u_t$$

where $TO_{L,t}$ is the log of the average weekly turnover of the individual firms that comprise our U.S. large-firm portfolio, $|R_{L,t}|$ is the absolute excess return of our U.S. large-firm portfolio for week t, $D_t^- = 1$ if $R_{L,t}$ is negative and is zero otherwise, and the γ's are estimated coefficients. The coefficients are estimated by OLS and t-statistics are in parentheses. The $MRTO_{L,t}$ is defined as the residual u_t from estimating the model variation in Panel A below. The $RTO_{L,t}$ is defined as the residual u_t from estimating the model variation in Panel B below. The sample period is listed for each column. The last row reports the residual standard deviation.

	Panel A			Panel B		
Coefficient	7/62–12/00	7/62–9/81	10/81–12/00	7/62–12/00	7/62–9/81	10/81–12/00
γ_1	0.587	0.605	0.521	0.570	0.602	0.508
	(26.4)	(19.1)	(16.5)	(25.6)	(19.0)	(16.1)
γ_2	0.103	0.074	0.135	0.122	0.086	0.154
	(4.26)	(2.16)	(4.08)	(4.76)	(2.31)	(4.37)
γ_3	0.063	0.087	0.020	0.068	0.085	0.036
	(2.64)	(2.60)	(0.60)	(2.62)	(2.29)	(1.02)
γ_4	0.109	0.119	0.076	0.089	0.108	0.050
	(4.56)	(3.57)	(2.29)	(3.44)	(2.92)	(1.42)
γ_5	0.046	−0.006	0.100	0.054	0.013	0.094
	(1.91)	(−0.19)	(3.05)	(2.10)	(0.34)	(2.64)
γ_6	0.079	0.074	0.075	0.088	0.068	0.101
	(3.82)	(2.58)	(2.56)	(3.96)	(2.16)	(3.21)
γ_7	5.166	6.319	4.313			
	(18.5)	(14.6)	(12.3)			
γ_8	−2.704	−4.741	−0.853			
	(−8.77)	(−10.03)	(−2.19)			
γ_9	−0.725	−0.802	−0.358			
	(−2.44)	(−1.71)	(−0.97)			
γ_{10}	−0.957	−0.834	−0.861			
	(−3.02)	(−1.67)	(−2.18)			
$R^2\%$	96.7	88.4	80.5	96.1	85.7	77.1
$\sigma(u_t)$	0.139	0.144	0.129	0.151	0.160	0.140

terms for the same reasons as for the MRTO (also see related discussion in Section I.B).

We choose to use the log transformation of the raw dispersion for several reasons. First, the log transformation produces a series that exhibits little heteroskedasticity over time. Second, the resulting MRRD series has only modest skewness (value of 0.42) and excess kurtosis (value of 1.02).[7]

[7] In contrast, using the raw return dispersion in (3) yields an alternate MRRD with substantial positive skewness (value of 1.28) and substantial excess kurtosis (value of 5.19).

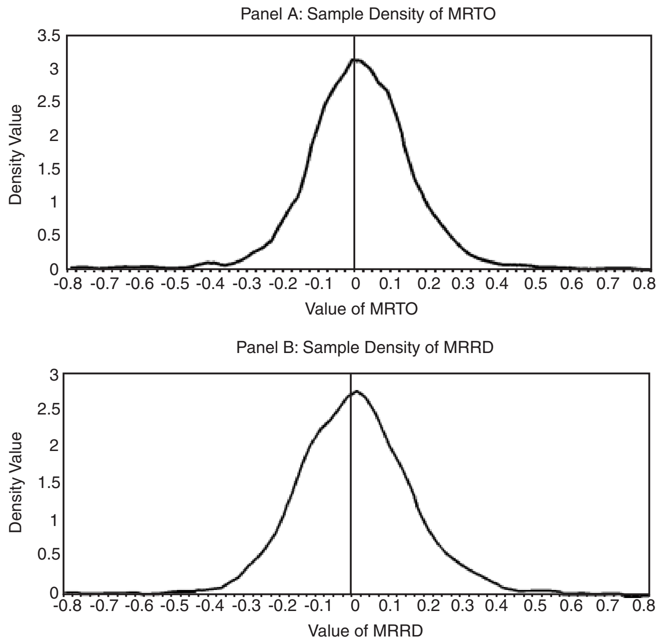

Figure 2. MRTO and MRRD densities. This figure displays the sample density of the market-adjusted relative turnover ($MRTO_t$) and market-adjusted relative return dispersion ($MRRD_t$) from our U.S. large-firm portfolio. We calculate the sample density using an Epanechnikov kernel with bandwidth set to 10 percent of the interquartile range. We use 400 grid points for the figure. The sample period is July 1962 to December 2000.

Table II, Panel A, reports the estimated coefficients for the MRRD model (3) for the full sample and one-half sample subperiods. The estimated coefficients indicate that dispersion exhibits substantial positive autocorrelation, is positively related to the absolute portfolio return, and tends to be smaller for negative returns.

Alternate specifications for estimating MRRD produce series that are very similar to our primary MRRD. For example, if we include linear and squared time-trend explanatory terms in (3), then the correlation between our primary MRRD and the alternate MRRD (with time-trend explanatory terms) is 0.995. Or, if we replace the absolute return terms in (3) with squared return terms, then the correlation between our primary MRRD and the alternate MRRD (with squared return terms) is 0.981. Finally, if we use 10 RD lags in (3), then the correlation between our standard MRRD and alternate MRRD (with 10 lags) is 0.990.

Figures 1 and 2 illustrate the properties of our large-firm MRRD series. Figure 1, Panel B, plots the time-series of $MRRD_{L,t}$ over the July 1962 to December 2000 period. Figure 2, Panel B, plots the sample density of $MRRD_{L,t}$.

C. Univariate Measures of Turnover and Dispersion Shocks

For comparison purposes and subsequent robustness tests, we construct alternate turnover and dispersion shocks that simply measure deviations from the expectation of a univariate time-series model. Our relative turnover (RTO) and relative return dispersion (RRD) are the residuals from estimating a univariate AR(6) model on the log of the respective raw turnover and raw dispersion series. The RTO and RRD are attractive measures because of the simplicity of the univariate AR(6) model. The estimated coefficients from the AR(6) model are reported in Table I, Panel B, for RTO, and Table II, Panel B, for RRD.

However, as compared to our MRTO and MRRD, our RTO and RRD have one unattractive feature. Specifically, both turnover and dispersion tend to be larger

Table II

Measuring Return-Dispersion Shocks

This table reports on the construction of our relative return dispersion (RRD) and market-adjusted RRD (MRRD) measures. We estimate two variations of the following model:

$$RD_{L,t} = \gamma_0 + \sum_{k=1}^{6} \gamma_k RD_{L,t-k} + \gamma_7 |R_{L,t}| + \gamma_8 D_t^- |R_{L,t}| + \gamma_9 |R_{L,t-1}| + \gamma_{10} D_{t-1}^- |R_{L,t-1}| + u_t$$

where $RD_{L,t}$ is the log of the weekly cross-sectional standard deviation of the individual firm returns that comprise our U.S. large-firm portfolio, $|R_{L,t}|$ is the absolute excess return of our U.S. large-firm portfolio for week t, $D_t^- = 1$ if $R_{L,t}$ is negative and is zero otherwise, and the γ's are estimated coefficients. The coefficients are estimated by OLS and t-statistics are in parentheses. The $MRRD_{L,t}$ is defined as the residual u_t from estimating the model variation in Panel A below. The $RRD_{L,t}$ is defined as the residual u_t from estimating the model variation in Panel B below. The sample period is listed for each column. The last row reports the residual standard deviation.

	Panel A			Panel B		
Coefficient	7/62–12/00	7/62–9/81	10/81–12/00	7/62–12/00	7/62–9/81	10/81–12/00
γ_1	0.369	0.406	0.331	0.379	0.423	0.342
	(16.5)	(12.8)	(10.5)	(16.9)	(13.4)	(10.9)
γ_2	0.152	0.088	0.211	0.160	0.084	0.224
	(6.88)	(2.87)	(6.67)	(6.72)	(2.45)	(6.73)
γ_3	0.106	0.099	0.126	0.136	0.120	0.153
	(4.77)	(3.25)	(3.89)	(5.64)	(3.50)	(4.50)
γ_4	0.065	0.081	0.039	0.066	0.106	0.025
	(2.91)	(2.65)	(1.20)	(2.73)	(3.10)	(0.72)
γ_5	0.080	0.094	0.056	0.065	0.085	0.038
	(3.61)	(3.05)	(1.78)	(2.73)	(2.46)	(1.15)
γ_6	0.072	0.057	0.089	0.091	0.072	0.108
	(3.48)	(2.02)	(2.97)	(4.06)	(2.28)	(3.41)
γ_7	5.665	6.785	4.608			
	(17.8)	(15.5)	(10.1)			
γ_8	−3.275	−4.976	−1.609			
	(−9.42)	(−10.6)	(−3.17)			
γ_9	−0.956	−0.880	−1.074			
	(−2.80)	(−1.81)	(−2.25)			
γ_{10}	1.037	1.049	1.272			
	(2.88)	(2.09)	(2.46)			
R^2%	66.0	68.2	62.7	60.2	59.7	58.1
$\sigma(u_t)$	0.157	0.143	0.168	0.170	0.161	0.177

for large absolute returns (magnitude effects) and tend to be larger for positive returns (sign effects). Thus, any variation in serial correlation related to the RTO/RRD measures may also be picking up variation associated with the magnitude and/or the sign of the return.

In contrast, our primary MRTO and MRRD series are constructed to have no relation to the magnitude or sign of the market return. In practice, the RTO (RRD) series is highly correlated with the MRTO (MRRD) series with a correlation of 0.924 (0.923).

D. Correlation of Turnover and Dispersion Shocks

Next, we calculate the correlation between the MRTO and MRRD series. The sample correlations are 0.457, 0.392, and 0.517, respectively, for the full sample and the two one-half subperiods. This suggests that both measures are capturing a similar aspect of the week's market environment.

We also find that the MRTO and MRRD cannot be explained by lagged economic variables including the risk-free rate, a recession-state indicator, the yield spread between Moody's Baa and Aaa rated bonds, and U.S. bond returns. The R^2 of a regression of MRTO and MRRD against these variables is less than 0.7 percent for both variables. This result supports our use of MRTO/MRRD as measures that reflect shocks in turnover and dispersion.

E. Lagged and Lead Measures of Turnover and Dispersion Shocks

Our primary turnover and dispersion shocks for period $t-1$ are also obtained from the estimation of (2) and (3). Our $MRTO_{L,t-1}$ and $MRRD_{L,t-1}$ are the week $t-1$ residuals from estimating (2) and (3), respectively.

However, the construction of our lead shock measures, $MRTO_{\mathrm{L,t+1}}$ and $MRRD_{L,t+1}$, is different. Specifically, we construct lead shocks with models that use no explanatory terms from period t. We make this choice for two reasons. First, this choice provides "clean" temporal separation in the sense that the construction of the $t+1$ shocks uses no information from period t. Second, if we include explanatory variables from period t, then the $MRTO_{t+1}/MRRD_{t+1}$ would be essentially orthogonal to $MRTO_{L,t}/MRRD_{L,t}$. Instead, we desire a model where the lead shocks are likely to be substantially correlated with the contemporaneous shocks, depending upon how much incremental information the $MRTO_{L,t}$ ($MRRD_{L,t}$) contains for the turnover (dispersion) level in period $t+1$. We further discuss our reasons for analyzing the lead shocks at the end of Section IV.B, after first presenting the empirical results.

The $MRTO_{L,t+1}$ for our large-firm portfolio is the residual from the following model, where the terms are as defined for (2):

$$TO_{L,t+1} = \gamma_0 + \sum_{k=1}^{6} \gamma_k TO_{L,t-k} + \gamma_7 |R_{L,t+1}| + \gamma_8 D_{t+1}^{-} |R_{L,t+1}| + \gamma_9 |R_{L,t-1}| + \gamma_{10} D_{t-1}^{-} |R_{L,t-1}| + u_{t+1} \tag{4}$$

To construct the $MRRD_{L,t+1}$, we use (4) but with RD terms replacing the turnover terms. For the lead RTO/RRD measures, we estimate a variation of (4) without the γ_7 through γ_{10} return terms.

We find that the intertemporal correlation between the $MRTO_{L,t+1}$ from (4) and the $MRTO_{L,t}$ from (2) is substantial at 0.486. Similarly, the intertemporal correlation between the $MRRD_{L,t+1}$ and the $MRRD_{L,t}$ is 0.335.

IV. Main Empirical Results

A. Return Momentum and Reversals with Abnormal Turnover

To explore whether the autoregressive behavior of equity-index returns varies with turnover shocks, we estimate variations of the following model where the coefficient of interest is β_2:

$$R_{L,t} = \beta_0 + (\beta_1 + \beta_2 MRTO_{L,j}) R_{L,t-1} + \varepsilon_t \tag{5}$$

where $R_{L,t}$ is the excess weekly return of our U.S. large-firm portfolio in week t; $MRTO_{L,j}$ is the market-adjusted relative turnover of our large-firm portfolio in week j; $j = t$, $t-1$, or $t+1$ so that we may investigate contemporaneous, lagged, and lead associations; and the β's are estimated coefficients.

In our tables, we report coefficients estimated by OLS with t-statistics based on heteroskedastic- and autocorrelation-consistent standard errors, using the Newey and West (1987) method with three lags. We report OLS estimation for several reasons. First, this method provides consistent parameter estimates. Second, our findings are very similar across subperiods, for different model specifications, for variations in constructing the turnover and dispersion shocks, and for different econometric estimation methods. Given this robustness, we favor reporting OLS estimates because of the familiarity and intuition of OLS. We elaborate on robustness analysis in Section IV.C, IV.E, and Appendix A.

Table III, Panels A, B, and C, report results from estimating (5) for the overall sample and the first- and second-half subsamples, respectively. The results in column two show that the relation between $R_{L,t}$ and $R_{L,t-1}$ is substantially increasing in the $MRTO_{L,t}$. The β_2 estimate is reliably positive for the overall sample and both subperiods (t-statistics of 5.23 or greater). For the three sample periods, the implied first-order autoregressive coefficient increases by 0.709, 0.872, and 0.592 as $MRTO_{L,t}$ moves from its 5th to its 95th percentile. For this comparison, we use the percentiles from the MRTO distribution of each respective period (rather than the overall sample percentiles).

Next, the results in column three indicate that the autocorrelation also varies positively with $MRTO_{L,t-1}$, but the magnitude is much smaller. For the three sample periods, the implied first-order autoregressive coefficient increases by 0.211, 0.186, and 0.296 as $MRTO_{L,t-1}$ moves from its 5th to its 95th percentile. While this lag relation seems economically small, this pattern does suggest that nonsynchronous trading does not have a material role in our findings (see Appendix B).

Finally, the results in column four show that the autocorrelation is increasing in the lead $MRTO_{L,t+1}$ measure. The β_2 estimate is reliably positive for the overall

Table III

Return Momentum and Reversals during Periods of Abnormal Turnover

This table reports the results from estimating four variations of the following model:

$$R_{L,t} = \beta_0 + (\beta_1 + \beta_2 MRTO_{L,j})R_{L,t-1} + \varepsilon_t$$

where $R_{L,t}$ is the excess weekly return of our U.S. large-firm portfolio in week t, $MRTO_{L,j}$ is the market-adjusted relative turnover of our U.S. large-firm portfolio in week j, j is either t (column 2), $t-1$ (column 3), or $t+1$ (column 4), ε_t is the residual, and the β's are estimated coefficients. The coefficients are estimated by OLS, with t-statistics in parentheses that are calculated with autocorrelation- and heteroskedastic-consistent standard errors by the Newey and West method using three lags. Rows 3 and 4 report the implied first-order autoregressive coefficient at the $MRTO_{L,j}$'s 5th and 95th percentiles. Row 5 reports the increase in the implied first-order autoregressive coefficient as the $MRTO_{L,j}$ moves from its 5th to its 95th percentile.

		1. Base	2. Contemp. ($j=t$)	3. Lag ($j=t-1$)	4. Lead ($j=t+1$)
		Panel A: July 1962 to December 2000 Period			
1.	β_1	0.030 (0.96)	0.035 (1.15)	0.024 (0.90)	0.036 (1.13)
2.	β_2		1.62 (7.55)	0.480 (2.66)	0.687 (4.55)
3.	AR(1)-5th MRTO		−0.309	−0.078	−0.137
4.	AR(1)-95th MRTO		0.401	0.133	0.220
5.	Increase		0.709	0.211	0.357
6.	R^2 (%)	0.09	6.06	0.88	1.56
		Panel B: July 1962 to September 1981 Period			
1.	β_1	0.081 (2.10)	0.089 (2.81)	0.084 (2.31)	0.085 (2.32)
2.	β_2		1.91 (8.51)	0.407 (2.04)	0.859 (4.84)
3.	AR(1)-5th MRTO		−0.338	−0.007	−0.138
4.	AR(1)-95th MRTO		0.534	0.179	0.330
5.	Increase		0.872	0.186	0.468
6.	R^2 (%)	0.66	9.82	1.12	3.31
		Panel C: October 1981 to December 2000 Period			
1.	β_1	−0.018 (−0.370)	−0.006 (−0.11)	−0.031 (−0.83)	−0.010 (−0.19)
2.	β_2		1.45 (5.23)	0.725 (2.40)	0.554 (2.41)
3.	AR(1)-5th MRTO		−0.290	−0.174	−0.131
4.	AR(1)-95th MRTO		0.302	0.123	0.122
5.	Increase		0.592	0.296	0.252
6.	R^2 (%)	0.03	4.00	1.60	0.78

sample and both subperiods. The implied first-order autoregressive coefficient increases by 0.357, 0.468, and 0.252, respectively, for the three periods, as $MRTO_{L,t+1}$ moves from its 5th to its 95th percentile. We discuss the implications in Section IV.B. below, after first presenting the return-dispersion results.

B. Return Momentum and Reversals with Abnormal Return Dispersion

To explore whether the autoregressive behavior of equity-index returns varies with dispersion shocks, we estimate variations of the following model where the

Table IV

Return Momentum and Reversals during Periods of Abnormal Dispersion

This table reports the results from estimating four variations of the following model:

$$R_{L,t} = \beta_0 + (\beta_1 + \beta_2 MRRD_{L,j})R_{L,t-1} + \varepsilon_t$$

where $R_{L,t}$ is the excess weekly return of our U.S. large-firm portfolio in week t, $MRRD_{L,j}$ is the market-adjusted relative return dispersion of the firms that comprise our U.S. large-firm portfolio in week j, j is either t (column 2), $t-1$ (column 3), or $t+1$ (column 4), ε_t is the residual, and the β's are estimated coefficients. The coefficients are estimated by OLS, with t-statistics in parentheses that are calculated with autocorrelation- and heteroskedastic-consistent standard errors by the Newey and West method using three lags. Rows 3 and 4 report the implied first-order autoregressive coefficient at the $MRRD_{L,j}$'s 5th and 95th percentiles. Row 5 reports the increase in the implied first-order autoregressive coefficient as the $MRRD_{L,j}$ moves from its 5th to its 95th percentile.

		1. Base	2. Contemp. ($j=t$)	3. Lag ($j=t-1$)	4. Lead ($j=t+1$)
	Panel A: July 1962 to December 2000 Period				
1.	β_1	0.030 (0.96)	0.026 (0.95)	0.028 (0.98)	0.035 (1.14)
2.	β_2		0.837 (3.06)	0.125 (0.56)	0.621 (3.41)
3.	AR(1)-5th MRRD		−0.175	−0.002	−0.116
4.	AR(1)-95th MRRD		0.251	0.062	0.204
5.	Increase		0.426	0.064	0.320
6.	R^2 (%)	0.09	1.95	0.14	1.26
	Panel B: July 1962 to September 1981 Period				
1.	β_1	0.081 (2.10)	0.084 (2.21)	0.083 (0.08)	0.084 (2.24)
2.	β_2		0.956 (3.62)	−0.156 (−0.52)	0.688 (3.22)
3.	AR(1)-5th MRRD		−0.128	0.117	−0.076
4.	AR(1)-95th MRRD		0.311	0.045	0.248
5.	Increase		0.439	−0.072	0.324
6.	R^2 (%)	0.66	2.75	0.73	1.94
	Panel C: October 1981 to December 2000 Period				
1.	β_1	−0.018 (−0.370)	−0.025 (−0.60)	−0.025 (−0.61)	−0.010 (−0.21)
2.	β_2		0.910 (2.25)	0.337 (1.21)	0.647 (2.10)
3.	AR(1)-5th MRRD		−0.256	−0.111	−0.177
4.	AR(1)-95th MRTO		0.235	0.071	0.177
5.	Increase		0.491	0.182	0.354
6.	R^2 (%)	0.03	2.34	0.45	1.38

coefficient of interest is β_2.

$$R_{L,t} = \beta_0 + (\beta_1 + \beta_2 MRRD_{L,j})R_{L,t-1} + \varepsilon_t \tag{6}$$

where $MRRD_{L,j}$ is the market-adjusted relative return dispersion of our U.S. large-firm portfolio in period j, and all other terms are as defined for (5).

Table IV, Panels A, B, and C, report results from estimating (6) for the overall sample and the first- and second-half subsamples, respectively. First, as reported in column two, the autoregressive relation is increasing in $MRRD_{L,t}$. The β_2 estimate is reliably positive for the overall sample and both subperiods (t-statistics of 2.25 or greater). For the three sample periods, the implied first-order autoregressive coefficient increases by 0.426, 0.439, and 0.491, as $MRRD_{L,t}$ moves from its 5th to its 95th percentile.

Next, as reported in column three, the autocorrelation varies little with $MRRD_{L,t-1}$. However, if a high $MRRD_{L,t-1}$ was primarily attributed to relatively high nonsynchronous trading in period $t-1$, then the positive autocorrelation effects from NST should be increasing in $MRRD_{L,t-1}$ (see Appendix B).

Finally, as reported in column four, the autocorrelation is increasing in the $MRRD_{L,t+1}$. For the three periods, the implied first-order autoregressive coefficient increases by 0.320, 0.324, and 0.354, as $MRRD_{L,t+1}$ moves from its 5th to its 95th percentile.

In our view, the lead findings in column four of Tables III and IV suggest an economic interpretation for our primary $MRTO_t/MRRD_t$ findings in column two (rather than a measurement-related or statistical-only reason with no underlying economics). This is because one concern about our primary findings is that the turnover and dispersion shocks are contemporaneous with the dependent variable, $R_{L,t}$, in (5) and (6). Although we cannot envision how, it may be possible that we have overlooked some statistical issue (not related to economics) that could have a material influence when estimating (5) and (6) with the contemporaneous shocks. With our construction method, the lead MRTO (MRRD) should be correlated with the $MRTO_t$ ($MRRD_t$) if the economics behind the $MRTO_t$ ($MRRD_t$) shocks also provides incremental information about the turnover (dispersion) in period $t+1$. Thus, one can think of our lead models as using $MRTO_{t+1}/MRRD_{t+1}$ to proxy for $MRTO_t/MRRD_t$ (where the proxies have temporal separation from the dependent variable in (5) and (6)). Also see related discussion and results in Section III.E.

C. Additional Subperiod Analysis

There are two prominent new results in Tables III and IV. First, consecutive equity-index returns tend to display substantial momentum when there is unexpectedly high turnover or dispersion in the latter period. Second, consecutive equity-index returns tend to display substantial reversals when there is unexpectedly low turnover or dispersion in the latter period. We conduct further subperiod analysis of these results.

We estimate our MRTO model and MRRD model, given by (5) and (6) with $j=t$, for 29 different rolling 10-year subperiods over our July 1962 through December 2000 sample. Specifically, our procedure is to estimate a 10-year subperiod (520 weekly observations), roll forward by one year (52 weeks), then estimate the next subsequent 10-year period, and so forth. We use the portfolio return, dispersion, and turnover of our U.S. large-firm portfolio.

We find that the autocorrelation is reliably increasing in $MRTO_t$ for all 29 of the 10-year periods (t-statistic of 2.86 or greater for the estimated β_2's of (5)). For the 29 subperiods, the average increase in the autoregressive relation as $MRTO_t$

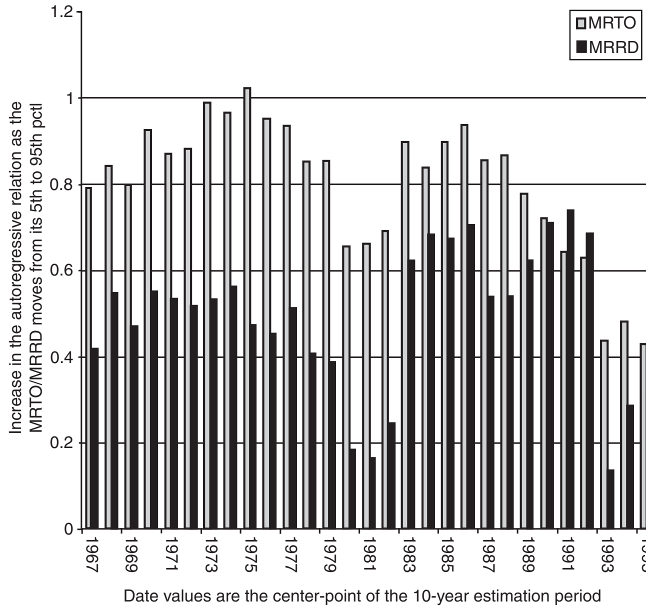

Figure 3. Ten-year subperiod results. This figure displays results from estimating our primary models (5) and (6) (with $j = t$) over 10-year subperiods for our weekly U.S. large-firm portfolio returns. The overall sample period is July 1962 to December 2000. We use a rolling 10-year estimation period with 52-week step intervals to yield 29 different overlapping periods. The *y*-axis displays the increase in the implied autoregressive coefficients as the $MRTO_t/MRRD_t$ moves from its 5th percentile to its 95th percentile. The date on the *x*-axis is the center point of the estimation period.

moves from its 5th to its 95th percentile is 0.795. This increase is greater than 0.4 for all 29 subperiods. Figure 3 presents these subperiod results graphically.

Similarly, for 25 of the 29 10-year periods, the autocorrelation is reliably increasing with the $MRRD_t$ (with a *t*-statistic of 1.67 or greater on the estimated β_2's of (6)). For the 29 subperiods, the average increase in the autoregressive relation as $MRRD_t$ moves from its 5th to its 95th percentile is 0.489. This increase is greater than 0.25 for 26 of the 29 subperiods.

Figure 3 suggests that this autoregressive phenomenon may be somewhat weaker in the latter part of our sample. To further explore this issue, we estimate the $MRTO_t$ model (5) and the $MRRD_t$ model (6) over the last five years of our sample for our U.S. large-firm portfolio. For the $MRTO_t$ ($MRRD_t$) model, the estimated β_2 is 1.38 (0.582) with a *t*-statistic of 3.11 (1.51). Taken together, these results indicate that the autoregressive phenomenon is still reliably evident in this most recent five-year period, but the magnitude is somewhat smaller as compared to earlier periods.

D. Simple Discrete Comparison

In Table V, we present an alternate illustration of this volume-return dynamic. This table uses a simple, discrete comparison to contrast the momentum and re-

Table V

Simple Discrete Illustration of Return Momentum and Reversals

This table illustrates how return momentum and reversals are related to the turnover and dispersion shocks with a simple discrete comparison. The $R_{L,t}$ is the weekly excess return of our U.S. large-firm portfolio and the sample period is July 1962 through December 2000. Column 1 identifies conditions based on the magnitude of $R_{L,t-1}$ and the value of the subsequent $MRTO_{L,t}/MRRD_{L,t}$. Column 2 lists the mean of the $R_{L,t-1}$ observations that meet these conditions, and Column 3 lists the mean of the subsequent $R_{L,t}$ observations that follow these $R_{L,t-1}$ observations. Column 4 lists the percentage of the weekly observations that meet the conditions in column 1.

	1. Conditions	2. Mean of $R_{L,t-1}$ (%)	3. Mean of $R_{L,t}$ (%)	4. % of observations
	Panel A: MRTO Results			
1.	$R_{L,t-1} < -1.0\%$ & $MRTO_{L,t} > 75$ percentile	−2.51	−0.75	5.79
2.	$R_{L,t-1} < -1.0\%$ & $MRTO_{L,t} < 25$ percentile	−2.36	+1.10	6.64
3.	$R_{L,t-1} > +1.0\%$ & $MRTO_{L,t} > 75$ percentile	+2.37	+0.79	9.39
4.	$R_{L,t-1} > +1.0\%$ & $MRTO_{L,t} < 25$ percentile	+2.40	−0.29	8.64
5.	Unconditional mean of $R_{L,t}$	+0.25	+0.25	100
	Panel B: MRRD Results			
1.	$R_{L,t-1} < -1.0\%$ & $MRRD_{L,t} > 75$ percentile	−2.50	−0.69	5.34
2.	$R_{L,t-1} < -1.0\%$ & $MRRD_{L,t} < 25$ percentile	−2.25	+0.40	6.54
3.	$R_{L,t-1} > +1.0\%$ & $MRRD_{L,t} > 75$ percentile	+2.26	+0.36	8.94
4.	$R_{L,t-1} > +1.0\%$ & $MRRD_{L,t} < 25$ percentile	+2.27	−0.12	9.39
5.	Unconditional mean of $R_{L,t}$	+0.25	+0.25	100

versals in the weekly returns of our U.S. large-firm portfolio. We identify conditions based on the magnitude of $R_{L,t-1}$ and the value of the subsequent $MRTO_{L,t}$ ($MRRD_{L,t}$). Then, we compare the mean of the identified $R_{L,t-1}$ observations to the mean of the subsequent $R_{L,t}$ observations that follow these $R_{L,t-1}$ periods. Table V, Panel A (B), reports the MRTO (MRRD) results.

First, we consider substantial negative returns in week $t-1$. In this discussion, μ indicates the unconditional mean of the weekly returns. For observations where $R_{L,t-1}$ is less than negative one percent and the subsequent $MRTO_{L,t}$ is greater than its 75th percentile, the mean return in week $t-1$ is 2.76 percent below μ and the mean return in the subsequent week t is 1.01 percent below μ (indicating return momentum). In contrast, when $R_{L,t-1}$ is less than negative one percent and the subsequent $MRTO_{L,t}$ is less than its 25th percentile, then the mean return in week $t-1$ is 2.61 percent below μ and the mean return in the subsequent week t is 0.85 percent above μ (indicating return reversals).

Next, we consider substantial positive returns in week $t-1$. For observations where $R_{L,t-1}$ is greater than one percent and the subsequent $MRTO_{L,t}$ is greater than its 75th percentile, the mean return in week $t-1$ is 2.12 percent above μ and the mean return in the subsequent week t is 0.54 percent above μ (indicating return momentum). In contrast, when $R_{L,t-1}$ is greater than one percent and the subsequent $MRTO_t$ is less than its 25th percentile, the mean return in week $t-1$ is $+2.15$ percent above μ and the mean return in the subsequent week t is 0.54 percent below μ (indicating return reversal). The results for the MRRD are qualitatively similar but somewhat weaker.

E. Robustness and Pervasiveness of our Primary Findings

In this subsection, we report additional evidence to evaluate the robustness and pervasiveness of our primary findings. Appendix A contains further robustness analysis that indicates our findings are robust to other concerns, including conditional heteroskedasticity, generated regressors, and extreme observations.

E.1. Alternate U.S. Equity Return Series

We find the same autoregressive behavior in the CRSP value-weighted index and the S&P 500 futures index. The futures results seem particularly important given the results of Ahn et al. (2002), who find that futures index returns typically have an autocorrelation near zero rather than the positive autocorrelation observed in the underlying spot index returns. Specifically, we estimate our primary models, equations (5) and (6), with $j=t$ and with the futures return replacing the large-firm portfolio return. Over the June 1982 to December 2000 future's sample period, we find that the estimated β_2 is 1.27 (0.86) for the MRTO (MRRD) model with a t-statistic of 4.13 (1.77). These results are quite close to the comparable results in Tables III and IV, Panel C, column 2, for our large-firm portfolio.

E.2. Univariate Measures of Turnover and Dispersion Shocks

We also investigate univariate measures of turnover and dispersion shocks. We estimate the following RTO model:

$$R_{L,t} = \beta_0 + (\beta_1 + \beta_2 RTO_{L,k})R_{L,t-1} + \varepsilon_t \tag{7}$$

where $RTO_{L,k}$ is the relative turnover of our large-firm portfolio in period k, as defined in Section III.C, and the other terms are as defined for (5).

The results in Table VI, Panel A, show that the autoregressive behavior is substantially increasing in the contemporaneous RTO, modestly increasing in the lead RTO, and marginally increasing in the lag RTO. The results are very similar to the MRTO results in Table III.

We also estimate the following RRD model:

$$R_{L,t} = \beta_0 + (\beta_1 + \beta_2 RRD_{L,k})R_{L,t-1} + \varepsilon_t \tag{8}$$

Table VI

Results with Univariate Measures of Abnormal Turnover and Dispersion

Panel A reports the results from estimating the following model on the weekly returns of our U.S. large-firm portfolio

$$R_{L,t} = \beta_0 + (\beta_1 + \beta_2 RTO_{L,j})R_{L,t-1} + \varepsilon_t$$

where $R_{L,t}$ is the excess weekly return of our U.S. large-firm portfolio in week t, $RTO_{L,j}$ is the relative turnover of our U.S. large-firm portfolio in week j, j is either t (column 2), $t-1$ (column 3), or $t+1$ (column 4), ε_t is the residual, and the β's are estimated coefficients. The coefficients are estimated by OLS, with t-statistics in parentheses that are calculated with autocorrelation- and heteroskedastic-consistent standard errors by the Newey and West method using three lags. Rows 3 and 4 report the implied first-order autoregressive coefficient at the $RTO_{L,j}$'s 5th and 95th percentiles. Row 5 reports the increase in the implied first-order autoregressive coefficient as the $RTO_{L,j}$ moves from its 5th to its 95th percentile. Panel B reports results for an identical model, except that $RRD_{L,j}$ replaces $RTO_{L,j}$, where $RRD_{L,j}$ is the relative return dispersion of our U.S. large-firm portfolio in week j.

		1. Base	2. Contemp. ($i=t$)	3. Lag ($i=t-1$)	4. Lead ($i=t+1$)
			Panel A: RTO Results		
1.	β_1	0.030 (0.96)	0.043 (1.37)	−0.010 (−0.03)	0.045 (1.39)
2.	β_2		1.37 (7.57)	0.441 (2.94)	0.632 (4.20)
3.	AR(1)-5th RTO		−0.257	−0.106	−0.118
4.	AR(1)-95th RTO		0.393	0.103	0.225
5.	Increase		0.649	0.209	0.343
6.	R^2 (%)	0.09	5.37	1.03	1.55
			Panel B: RRD Results		
1.	β_1	0.030 (0.96)	0.021 (0.80)	0.011 (0.39)	0.027 (0.92)
2.	β_2		0.667 (2.93)	0.186 (1.10)	0.546 (2.13)
3.	AR(1)-5th RRD		−0.152	−0.038	−0.122
4.	AR(1)-95th RRD		0.217	0.066	0.192
5.	Increase		0.369	0.103	0.315
6.	R^2 (%)	0.09	1.69	0.26	1.32

where $RRD_{L,k}$ is the relative return dispersion across the firms of our large-firm portfolio, as defined in Section III.C, and the other terms are as defined for (6).

The results in Table VI, Panel B, show that the autoregressive behavior is increasing with the contemporaneous and lead RRD, but is not reliably related to the lagged RRD. These findings are similar to the results for the MRRD model in Table IV. Overall, we conclude that our principal results are robust to using RTO and RRD as alternate univariate measures of turnover and dispersion shocks.

E.3. International Evidence

We also check whether our principal results extend to non-U.S. markets. Specifically, we estimate models (5) through (8) for Japan and the United Kingdom. For both countries, we find that the autocorrelation is reliably increasing in the own-country $MRTO_t$ and $MRRD_t$. For the Japanese market, the implied autoregressive coefficient increases by 0.454 (0.502) as the $MRTO_t$ ($MRRD_t$) moves from its 5th to its 95th percentile value. For the U.K. market, the implied autoregressive coefficient increases by 0.250 (0.165) as the $MRTO_t$ ($MRRD_t$) moves from its 5th to its 95th percentile value.

For both countries, the autocorrelation is essentially unrelated to any of the lagged measures. For Japan, the autocorrelation is reliably increasing in both the lead MRRD/RRD and the lead MRTO/RTO. For the United Kingdom, the autocorrelation is only reliably increasing in the lead MRRD and RRD. Overall, the variations in the autoregressive behavior for Japan and the United Kingdom are qualitatively similar to those in the United States.

E.4. The Asymmetric Lead-lag Phenomenon

An enduring puzzle in the serial-correlation literature is the large cross-serial correlation between small-firm portfolio returns and lagged large-firm portfolio returns (see Lo and MacKinlay (1990), Boudoukh, Richardson, and Whitelaw (1994), and Campbell, Lo, and MacKinlay (1997)). We also investigate this phenomenon with our MRTO and MRRD models. We are interested in whether the cross-serial relation also varies with turnover and dispersion shocks, and, if so, whether the large-firm portfolio's shocks or the small-firm portfolio's shocks are more important in explaining the variation in the cross-serial relation.

Table VII provides the model specification and reports the results. While controlling for the lagged small-firm returns, we find that the relation between the small-firm returns and lagged large-firm returns varies positively with the $MRTO_t$ and $MRRD_t$ from both the large-firm and small-firm portfolios. The magnitude seems substantial: The implied cross-serial relation increases by 0.933 (0.664) as the large-firm $MRTO_{L,t}$ ($MRRD_{L,t}$) moves from its 5th to its 95th percentile. The increase in the implied cross-serial relation is smaller for the small-firm turnover and dispersion shocks. This evidence seems at odds with a market-friction explanation for our findings (see Appendix B).

Table VII
Asymmetric Lead-lag with Turnover and Dispersion Shocks

This table reports on the cross-serial relation between the returns of our U.S. small-firm portfolio and our lagged U.S. large-firm portfolio as a function of the MRTO_t and MRRD_t of each respective portfolio. Panel A reports on the following model:

$$R_{S,t} = \beta_0 + (\beta_1 + \beta_2 MRTO_{k,t})R_{L,t-1} + \beta_3 R_{S,t-1} + \varepsilon_t$$

where $R_{S,t}$ is the excess weekly return of our U.S. small-firm portfolio in week t, $MRTO_{k,t}$ is the MRTO of portfolio k in week t, k is either our large-firm portfolio, L, or small-firm portfolio, S, and the other terms are as defined in Table III. Rows 4 and 5 report the implied cross-serial relation (CSR) on $R_{L,t-1}$ at the respective $MRTO_{k,t}$'s 5th and 95th percentiles. Row 6 reports the increase in the implied cross-serial relation as the respective $MRTO_{k,t}$ moves from its 5th to its 95th percentile. Panel B reports on the same model except that MRRD replaces MRTO. The coefficients are estimated by OLS, with t-statistics in parentheses that are calculated with autocorrelation- and heteroskedastic-consistent standard errors by the Newey and West method using three lags. The sample period is July 1962 to December 2000.

		1. Base	2. $k = L$	3. $k = S$
		Panel A: MRTO Results		
1.	β_1	0.034 (0.80)	0.037 (0.86)	0.031 (0.81)
2.	β_2		2.12 (6.46)	1.10 (2.42)
3.	β_3	0.326 (6.73)	0.330 (8.41)	0.319 (6.84)
4.	CSR-5th MRTO		−0.416	−0.279
5.	CSR-95th MRTO		0.517	0.331
6.	Increase		0.933	0.610
7.	R^2 (%)	11.89	18.65	15.39
		Panel B: MRRD Results		
1.	β_1	0.034 (0.80)	0.035 (0.87)	0.001 (0.02)
2.	β_2		1.31 (3.43)	1.02 (2.54)
3.	β_3	0.326 (6.73)	0.317 (6.53)	0.335 (7.32)
4.	CSR-5th MRRD		−0.279	−0.242
5.	CSR-95th MRRD		0.384	0.269
6.	Increase		0.664	0.511
7.	R^2 (%)	11.89	14.84	13.92

V. Further Analysis and Discussion of Results

A. Firm-level Turnover Results

Since much of the existing work on volume-return dynamics has examined firm-level data, the connection between our index results and this work is not immediately clear. To bridge the gap, we also examine individual large-firm returns and jointly examine: (1) the relation between a firm's turnover shock and the firm's return autocorrelation, and (2) the relation between our large-firm portfolio's turnover shock and the cross-serial relation between the firm's return and the lagged large-firm portfolio return. With this approach, we can better see the connections between the existing literature and the new results reported in this paper. Additionally, this exploration may prove useful in distinguishing between a marketwide economic interpretation of our findings versus explanations that rely more on the aggregation of firm-level phenomenon.

We estimate the following model on the returns of 25 large U.S. firms:

$$R_{i,t} = \beta_0 + (\beta_1 + \beta_2 FRTO_{i,j})R_{i,t-1} + (\beta_3 + \beta_4 MRTO_{L,j})R_{L,t-1} + \varepsilon_t \tag{9}$$

where $R_{i,t}$ is the excess weekly return of firm i in week t, $FRTO_{i,j}$ is the firm-adjusted relative turnover of firm i in period j, and the other terms are as defined for (5). Our firm sample is comprised of firms in the Dow Jones Industrial Average, as of September 30, 1999, that had the entire July 1962 to December 2000 time series of daily data in CRSP.

The $FRTO_{i,t}$ is formed analogously to our $MRTO_{L,t}$ but with firm values replacing portfolio values. The $FRTO_{i,t}$ is the residual from estimating the following model for each firm:

$$\begin{aligned} TO_{i,t} = \gamma_0 + \sum_{j=1}^{6} \gamma_j TO_{i,t-j} + \gamma_7 |R_{i,t}| + \gamma_8 D_t^- |R_{i,t}| + \gamma_9 |R_{i,t-1}| \\ + \gamma_{10} D_{t-1}^- |R_{i,t-1}| + u_t \end{aligned} \tag{10}$$

where subscript i indicates firm values and all other terms are defined for equation (2).

Table VIII reports estimates of (9) for the 25 large firms. First, in Panel A, we find that the relation between $R_{i,t}$ and $R_{i,t-1}$ is reliably increasing with $FRTO_{i,t}$ For 20 of the 25 firms, the estimated β_2 is positive and statistically significant. Across the 25 firms, the average increase in the autoregressive relation is 0.295 as the $FRTO_{i,t}$ increases from its 5th to its 95th percentile.

Second, the cross-serial relation between $R_{i,t}$ and $R_{L,t-1}$ is reliably increasing with $MRTO_{L,t}$. For all 25 firms, the estimated β_4 is positive and highly statistically significant. Across the 25 firms, the average increase in the relation between $R_{i,t}$ and $R_{L,t-1}$ is 0.606 as the $MRTO_{L,t}$ increases from its 5th to its 95th percentile. Since the reliability and magnitude of this cross-effect is larger than the own-firm effects, these results suggest that marketwide influences are more important. Note that the average pairwise correlation between a firm's $FRTO_{i,t}$ and the $MRTO_{L,t}$ is $+0.368$ (see column 6). Thus, the firm turnover shocks and the portfolio's turnover shocks are far from collinear, which suggests reasonable power for estimating (9).

Finally, Table VIII, Panel B, reports the results for the $MRTO_{L,t-1}$ and $FRTO_{i,t-1}$ conditioning. Consistent with our Table III results and Cooper's (1999) results, the autocorrelation tends to increase with the lagged turnover shocks, but the effect is much more modest than the results in Panel A for the contemporaneous shocks. Again, the market effect is larger and more reliable than the own-firm effect.

B. Macroeconomics News Flows and U.S. Treasury Bond Returns

The last part of our work explores the relation of macroeconomic news releases and bond returns to our turnover and dispersion shocks. Our findings here may suggest direction for future work related to our primary return-volume dynamic findings and may help us better understand the economic interpretation of turnover and dispersion shocks.

First, we investigate the relation between our turnover/dispersion shocks and macroeconomic news releases. We evaluate macroeconomic news flows for weeks

Table VIII

Firm-level Return and Turnover Analysis

This table reports the results from estimating the following model on the returns of 25 large U.S. firms:

$$R_{i,t} = \beta_0 + (\beta_1 + \beta_2 FRTO_{i,j})R_{i,t-1} + (\beta_3 + \beta_4 MRTO_{L,j})R_{L,t-1} + \varepsilon_t$$

where $R_{i,t}$ is the excess weekly return of firm i in week t, $FRTO_{i,j}$ is the firm-adjusted relative turnover of firm i in week j, j is t for the Panel A results and $t-1$ for the Panel B results, and the other terms are as defined in Table III. Columns 2 and 4 report the estimated β_1 and β_3 for each firm. Instead of the estimated coefficient, column 3 (5) reports the implied increase in the coefficient on $R_{i,t-1}$ ($R_{L,t-1}$) as the $FRTO_{i,j}$ ($MRTO_{L,j}$) moves from its 5th to its 95th percentile, based on the estimated β_2 (β_4). The coefficients are estimated by OLS, with t-statistics in parentheses that are calculated with autocorrelation- and heteroskedastic-consistent standard errors by the Newey and West method using three lags. Columns 6 and 7 reports the correlations between $FRTO_{i,t}/MRTO_{L,t}$ and $R_{i,t}/R_{L,t}$ for firm i, respectively. The sample period is July 1962 to December 2000.

Panel A: Conditional on $FRTO_t$ and $MRTO_t$

1. Firm	2. β_1	3. β_2	4. β_3	5. β_4	6. ρ_{RTOs}	7. $\rho_{Returns}$
ALD	−0.109 (−3.41)	0.394 (3.52)	0.178 (2.90)	0.764 (5.64)	0.340	0.566
AA	−0.072 (−2.45)	0.390 (4.49)	0.121 (1.84)	0.767 (3.46)	0.368	0.532
ATT	−0.066 (−1.88)	−0.096 (−0.98)	0.055 (1.28)	0.344 (3.40)	0.342	0.425
BA	−0.012 (−0.46)	0.343 (4.28)	0.101 (1.58)	0.471 (2.55)	0.326	0.499
CAT	−0.080 (−2.78)	0.224 (2.06)	0.191 (3.07)	0.742 (3.52)	0.378	0.561
CHV	−0.070 (−2.62)	0.274 (3.55)	0.062 (1.27)	0.446 (3.72)	0.374	0.523
KO	−0.053 (−1.57)	0.238 (2.30)	−0.001 (−0.01)	0.549 (3.95)	0.379	0.563
DD	−0.014 (−0.48)	0.490 (6.02)	0.076 (1.63)	0.733 (4.66)	0.433	0.615
EK	−0.091 (−3.37)	0.239 (2.69)	0.149 (3.02)	0.480 (3.78)	0.410	0.523
XON	−0.155 (−5.93)	0.389 (5.00)	0.095 (2.39)	0.386 (3.98)	0.472	0.504
GE	−0.045 (−1.33)	0.317 (3.58)	0.050 (0.79)	0.496 (4.06)	0.491	0.699
GM	−0.045 (−1.35)	0.404 (4.28)	0.009 (0.16)	0.414 (3.12)	0.381	0.576
GT	0.022 (0.76)	0.271 (2.70)	0.109 (1.69)	0.866 (5.20)	0.289	0.555
HWP	−0.052 (−2.08)	0.348 (4.31)	0.112 (1.62)	0.925 (4.79)	0.312	0.545
IBM	0.029 (1.06)	0.362 (4.14)	0.013 (0.25)	0.458 (3.56)	0.497	0.564
IP	−0.065 (−2.43)	0.414 (6.13)	0.170 (2.79)	0.895 (4.77)	0.362	0.597
JNJ	−0.107 (−3.30)	0.101 (0.64)	−0.001 (−0.01)	0.655 (4.59)	0.303	0.533
MRK	−0.065 (−2.49)	0.547 (6.09)	0.045 (0.97)	0.358 (2.58)	0.395	0.544
MMM	−0.065 (−2.24)	0.048 (0.57)	0.100 (2.13)	0.709 (5.06)	0.390	0.612
MO	−0.042 (−1.57)	0.286 (4.73)	−0.034 (−0.58)	0.572 (4.37)	0.348	0.501
PG	−0.036 (−1.31)	0.149 (2.33)	0.017 (0.39)	0.456 (3.55)	0.372	0.508
S	−0.122 (−4.02)	0.482 (5.85)	0.157 (2.36)	0.365 (2.81)	0.333	0.581
UK	−0.056 (−1.48)	0.192 (1.72)	0.168 (2.21)	0.803 (4.41)	0.279	0.563
UTX	−0.064 (−2.25)	0.139 (1.62)	0.111 (1.91)	0.678 (3.80)	0.307	0.558
DIS	0.011 (0.37)	0.434 (5.33)	0.104 (1.42)	0.817 (5.32)	0.322	0.547
Mean	−0.057	0.295	0.086	0.606	0.368	0.552

Table VIII— *Continued*

Panel B: Conditional on $FRTO_{t-1}$ and $MRTO_{t-1}$

1. Firm	2. β_1	3. β_2	4. β_3	5. β_4
ALD	– 0.097 (– 2.83)	0.073 (0.73)	0.151 (2.36)	0.202 (1.73)
AA	– 0.073 (– 2.41)	– 0.027 (– 0.34)	0.102 (1.55)	0.305 (3.12)
ATT	– 0.067 (– 1.89)	– 0.050 (– 0.50)	0.049 (1.17)	0.181 (2.03)
BA	– 0.011 (– 0.40)	0.026 (0.34)	0.078 (1.26)	0.417 (3.34)
CAT	– 0.076 (– 2.59)	0.014 (0.19)	0.163 (2.71)	0.313 (1.98)
CHV	– 0.068 (– 2.49)	– 0.055 (0.62)	0.044 (0.94)	0.360 (3.35)
KO	– 0.053 (– 1.60)	– 0.072 (– 0.60)	– 0.016 (– 0.30)	0.127 (1.07)
DD	– 0.011 (– 0.34)	– 0.064 (– 0.94)	0.055 (1.08)	0.115 (1.36)
EK	– 0.093 (– 3.57)	0.140 (1.80)	0.140 (3.03)	0.268 (3.08)
XON	– 0.150 (– 5.61)	– 0.062 (– 0.69)	0.075 (1.95)	0.281 (3.84)
GE	– 0.034 (– 1.00)	0.081 (1.00)	0.022 (0.40)	0.263 (1.98)
GM	– 0.052 (– 1.52)	– 0.026 (– 0.31)	0.001 (0.02)	0.271 (3.05)
GT	0.025 (0.90)	0.204 (2.51)	0.090 (1.52)	0.173 (1.18)
HWP	– 0.054 (– 2.14)	0.043 (0.57)	0.097 (1.34)	0.350 (2.84)
IBM	0.022 (0.76)	0.117 (1.47)	0.006 (0.12)	0.164 (2.05)
IP	– 0.065 (– 2.36)	0.129 (1.95)	0.141 (2.38)	0.358 (2.74)
JNJ	– 0.095 (– 3.22)	– 0.080 (– 1.40)	– 0.022 (– 0.47)	0.095 (1.15)
MRK	– 0.062 (– 2.21)	0.126 (1.68)	0.033 (0.68)	– 0.001 (– 0.01)
MMM	– 0.075 (– 2.51)	0.018 (0.26)	0.094 (2.04)	0.244 (2.42)
MO	– 0.030 (– 1.17)	0.106 (1.94)	– 0.048 (– 0.94)	0.218 (1.47)
PG	– 0.041 (– 1.47)	0.184 (2.34)	0.019 (0.42)	– 0.069 (– 0.83)
S	– 0.113 (– 3.80)	0.178 (2.86)	0.132 (2.28)	0.169 (1.16)
UK	– 0.066 (– 1.75)	– 0.046 (– 0.45)	0.152 (2.21)	0.512 (2.95)
UTX	– 0.075 (– 2.68)	0.135 (1.95)	0.114 (2.01)	0.368 (3.97)
DIS	0.007 (0.23)	0.111 (1.52)	0.080 (1.24)	0.401 (2.59)
Mean	– 0.056	0.048	0.070	0.243

when both the realized $MRTO_{L,t}$ and $MRRD_{L,t}$ are unusually high, unusually low, and near their expected values of zero. We search only for important economic news that is widely considered to be informative about stock market-wide fundamentals. Primarily, the news releases cover such items as GDP, inflation, industrial production, and the trade deficit. Details on the news search are in Appendix C.

To summarize, the mean number of news releases during the extreme MRTO/MRRD weeks (both unusually high and unusually low) is nearly three times the mean number of news releases during the weeks when the MRTO and MRRD are essentially zero. This difference in news flows is statistically significant (p-value < 0.005).

Recall the prediction from Wang (1994) that "the greater the information asymmetry (and diversity in expectations), the larger the abnormal trading volume when news arrives" (p. 129). Thus, in the case where high turnover is observed during news-release periods, the news may have altered relatively diverse beliefs, which promotes an associated substantial change in portfolio holdings across investors. If high turnover during news-release periods reflects a "high dispersion-in-beliefs" environment, then it seems likely that turnover in the former period largely reflected diverse beliefs about the stock market. If so, returns are likely to exhibit momentum in Wang's framework.

On the other hand, consider when low turnover is observed during news-release periods. In this case, the economic news might have done little to change beliefs or even acted to reinforce relatively homogeneous beliefs. If low turnover during news-release periods reflects a "low dispersion-in-beliefs" environment, then turnover in the former period seems more likely to have been due to noise or changing investment opportunities outside the stock market. If so, returns are more likely to exhibit reversals in the Wang framework. Our return-volume dynamic findings, along with our news-release results, seem consistent with these conjectures motivated by the news-volume implications from Wang.

We also undertake a test based on Scruggs' (1998) argument that U.S. bond returns may reflect intertemporal changes in the investment opportunity set. Specifically, we regress 10-year U.S. Treasury bond returns on the contemporaneous stock market return and MRTO (MRRD). In this regression, we find that both the MRTO and MRRD are positively related to bond returns (p-values <0.001). This finding suggests that bond prices tend to increase, relative to stocks, when there is abnormally high turnover and dispersion in the stock market. These results seem to support Scruggs' argument and suggest that abnormally high turnover and dispersion are related to stock market uncertainty and changes in stock–bond portfolio allocations.

Overall, the macroeconomic-news and bond-return results suggest that our turnover and dispersion shocks reflect economic and market information that extends beyond equity price dynamics. However, these results do not pinpoint the mechanism behind the momentum and reversals, and it may be that these associations are even unrelated to our autoregressive findings.

C. Comparison to Prior Literature on Turnover and Serial Correlation

In this subsection, we compare our findings to previous evidence on turnover and serial correlation. Specifically, we reexamine findings in Cooper (1999) and CGW (1993) from the context of our data and empirical setting.

As previously noted, Cooper (1999) uses a "weekly percentage change in turnover" and finds that the returns of high-turnover firms tend to exhibit less negative autocorrelation or even positive autocorrelation. Our results seem consistent with his findings.

For further comparison, we calculate Cooper's weekly percentage changes in turnover for our U.S. large-firm portfolio and each of our 25 individual stocks from Section V.A. We then use Cooper's turnover measure in place of our MRTO and FRTO in our conditional models. We find that the autoregressive behavior varies similarly with Cooper's measure but the magnitude and reliability are smaller, as compared to our MRTO and FRTO results.

We also note that Cooper's measure exhibits a substantial negative autocorrelation of -0.303 for the turnover series of our U.S. large-firm portfolio and an average autocorrelation of -0.247 for the turnover series of the 25 individual stocks. In contrast, our MRTO exhibits essentially zero time-series predictability.

The contemporaneous correlation between our MRTO and Cooper's metric for our large-firm portfolio is 0.832, and the average correlation between our FRTO and his metric for the 25 individual firms is 0.777. Thus, our turnover shocks and Cooper's turnover metric are substantially related, but we prefer our measure because of its superior performance in our setting and its clear interpretation as a shock.

CGW (1993) examine daily equity returns and find that returns accompanied by a high volume tend to exhibit stronger return reversals. At first blush, this result appears to be at odds with our findings and Cooper's. However, CGW's empirical analysis is substantially different. First, CGW study daily returns, not the weekly returns that we and Cooper investigate. This may be an important difference. For our U.S. large-firm portfolio, the unconditional daily (weekly) return autocorrelation for the July 1962 to December 2000 period is 0.166 (0.027). Second, CGW construct their detrended turnover measure by subtracting a one-year moving average of log(turnover) from the day's log(turnover). Their detrended measure exhibits a very substantial positive autocorrelation of 0.70, in contrast to the near zero autocorrelation in our measure and the negative autocorrelation in Cooper's.

We further explore the CGW measure in our setting. First, using the weekly turnover series of our large-firm portfolio and the 25 individual stocks, we form the CGW detrended turnover metric. In our weekly data, we find that the CGW measure exhibits an autocorrelation of 0.626 for our large-firm portfolio and an average autocorrelation of 0.460 for the 25 stocks. We also note that the contemporaneous correlation between the CGW turnover measure and our MRTO is modest at 0.575, which suggests economic differences between these measures.

We also rerun our basic tests (specifically, the models reported in Table III) using the CGW measure in place of our MRTO. The findings are consistent with our results in Table III, but the conditioning effect is weaker. These results suggest interesting differences between the daily and weekly horizon, which may prove to be an interesting avenue for future research.

VI. Conclusions

We find substantial momentum in consecutive weekly stock returns when the latter week has unexpectedly high turnover. Conversely, we find substantial reversals in consecutive weekly stock returns when the latter week has unexpectedly low turnover. We find this empirical regularity in the weekly returns of large- and small-firm portfolios, equity-index futures, individual firm returns, and in the U.S., Japanese, and U.K. stock markets. Similarly, the autocorrelation of index returns also increases with the latter-week's dispersion shock across individual firm returns.

Our results appear striking in several ways. First, increases in the first-order autoregressive coefficient of around 0.80 (0.50) as the turnover (dispersion) shock moves from its 5th to its 95th percentile seem economically sizable, especially for weekly returns of large-firm portfolios. Second, we identify periods of both substantial return momentum and reversals. The reversals seem especially noteworthy since portfolio returns exhibit unconditional positive autocorrelation. We also find that the serial correlation is similarly (but more modestly) related to our lead turnover and dispersion shocks, which casts doubt on measurement-based explanations for our results.

Since no existing theory directly addresses our empirical setting and findings, the theoretical interpretation of our evidence remains an open question. The economic interpretation of turnover and dispersion shocks is critical to future efforts. Motivated by this concern, we present secondary findings in Section V.B that indicate our turnover and dispersion shocks are related to variations in macroeconomic news flows and government bond returns.

Wang (1994) provides one promising theoretical framework from which to consider our findings. He models two types of heterogeneity across investors, diverse information and diverse investment opportunities. In his model, consecutive stock returns tend to exhibit momentum if trading in the former period is primarily motivated by diverse information and dispersion-in-beliefs about the stock's fundamentals. Conversely, consecutive stock returns tend to exhibit reversals if trading in the former period is primarily motivated by changes in investment opportunities outside the public stock market. Our findings seem consistent with Wang's framework if different economic rationales behind turnover in the former period are associated with different conditional distributions for the turnover shocks and dispersion shocks in the latter period. Also, see related empirical evidence in Llorente et al. (2002).

Intuition and insights from other areas of the literature may prove useful in understanding our findings. For example, recent literature on economic-state uncertainty (Veronesi (1999, 2000)) suggests that the price response to information increases with the uncertainty about the economic state. If turnover shocks and dispersion shocks are associated with economic-state uncertainty, then this insight might prove useful in understanding our results. Or, in Blume et al. (1994), investors directly extract useful information from volume. Thus, volume affects the behavior of the market, rather than merely describing it. This feature might also prove useful in understanding our findings.

Other readers may see a link to our results and other areas of the literature on asset pricing, market microstructure, and technical trading. We do note that, in our view, the economic associations from Section V.B cast doubt on explanations that rely strictly on asymmetric private information. Thus, our findings suggest that models that combine imperfect information with other types of heterogeneity across agents may prove useful in characterizing price formation. Future theory that encompasses our findings is likely to generate new empirical implications, and should provide additional insight into price formation and the information in turnover and dispersion shocks. We look forward to future theoretical and empirical research on these and related issues.

Appendix A: Robustness Issues and Additional Analysis

A. Alternate Specifications

We also estimate the following nonlinear GARCH model to see if our results generalize to other econometric settings and to see if our primary findings are robust to the following: (1) Allowing the autoregressive relation to also vary with the conditional variance (the β_3 term), (2) adding the MRTO/MRRD to the mean equation separately as additional explanatory terms (the β_4 term), (3) allowing for a GARCH-in-mean term (the β_5 term), and (4) allowing for time variation in volatility that includes the $MRTO_{L,t-1}$ ($MRRD_{L,t-1}$) as explanatory terms (the δ_4 term).

$$R_{L,t} = \beta_0 + (\beta_1 + \beta_2 MRTO_{L,t} + \beta_3 V_{L,t})R_{L,t-1} + \beta_4 MRTO_{L,t} + \beta_5 V_{L,t} + \varepsilon_t \quad \text{(A1)}$$

$$V_{L,t} = \delta_0 + \delta_1 \varepsilon_{t-1}^2 + \delta_2 D_{t-1}^- \varepsilon_{t-1}^2 + \delta_3 V_{L,t-1} + \delta_4 MRTO_{L,t-1} \quad \text{(A2)}$$

where $V_{L,t}$ is the conditional variance of our large-firm portfolio, D_{t-1}^- is a dummy variable that equals one if the lagged return residual (ε_{t-1}) is negative and is zero otherwise, the β's and δ's are estimated coefficients, and all other terms are as defined for (5). To incorporate the leverage asymmetry in volatility, we adopt the asymmetric GARCH(1,1) model of Glosten, Jagannathan, and Runkle (1993).[8]

We estimate (A1) and (A2) simultaneously by maximum likelihood, assuming a conditional normal density for ε_t. We use the Bollerslev and Wooldridge (1992) approach for calculating standard errors that are robust to departures from conditional normality. We also estimate a second version of the model where MRRD terms replace the MRTO terms.

We find the following. For the MRTO model, the estimated β_2 is 1.51 (t-statistic of 8.17); and the estimated β_3, β_4, and δ_4 are all insignificant. The estimated β_5 is positive and modestly significant, which indicates a positive relation between the expected return and expected volatility. For the MRRD model, the estimated β_2 coefficient is 0.477 (t-statistic of 2.85); and the estimated β_3, β_4, and β_5 are all insignificant. The estimated δ_4 coefficient is positive and significant (t-statistic of 3.72), which indicates a positive relation between last week's MRRD and this week's volatility.

Based on these results, we draw the following conclusions. First, the autoregressive phenomenon documented in Section IV is quite robust in more complex, nonlinear models. Second, the MRTO/MRRD by themselves do not have separate effects in the mean equation. Third, measures of return dispersion may provide incremental information in modeling conditional market volatility (see Stivers (2003) for related evidence at the monthly horizon).

[8] Engle and Ng (1993) find that the asymmetric GJR model is among the best parametric GARCH models.

B. Impact of "Generated Regressors"

In (5) and (6), the MRTO and MRRD terms are constructed from a first-stage regression. Thus, as pointed out by Murphy and Topel (1985), the standard errors for the estimated coefficients in the second stage should be adjusted to reflect the error in estimating the generated regressor. We calculate the adjustment suggested by Murphy and Topel and find that the adjusted standard errors for the β_2 coefficients are less than one percent greater than the nonadjusted standard errors.

As an additional check, we estimate the following one-stage model:

$$R_{L,t} = \beta_0 + (\beta_1 + \beta_2 TO_{L,t} + \beta_3 TO_{L,t-1} + \beta_4 TO_{L,t-2} + \beta_5 TO_{L,t-2})R_{L,t-1} + \varepsilon_t \quad \text{(A3)}$$

where $\mathrm{TO}_{L,t}$ is the log(turnover) of our large-firm portfolio and other terms are as defined for model (5). We also estimate a second version of (A3) where the RD series replaces the log(turnover) series.

For the turnover model, the estimated β_2 is 1.23 (t-statistic of 6.60) and the estimated β_3, β_4, and β_5 are all negative and individually statistically significant. For the RD model, the estimated β_2 is 0.619 (t-statistic of 2.82) and the estimated β_3, β_4, and β_5 are all negative and jointly statistically significant. These results largely match our results in Tables III, IV, and VI, so we conclude that the "generated regressor" issue is not a material concern for our study.

C. Autoregressive Behavior with Both MRTO and MRRD

We also estimate the following model to investigate turnover and dispersion effects jointly:

$$R_{L,t} = \beta_0 + (\beta_1 + \beta_2 MRTO_{L,t} + \beta_3 MRRD_{L,t})R_{L,t-1} + \varepsilon_t \quad \text{(A4)}$$

where the terms are as defined for (5) and (6). We find that the estimated β_2s (β_3s) are 1.51, 1.82, and 1.19 (0.21, 0.23, and 0.45), respectively, for the overall sample, the first-half subperiod, and the second-half subperiod. The β_2s are highly reliably positive (t-statistics of 3.3 or greater) but the β_3s are statistically insignificant with t-statistics near one. Thus, in the joint model, the turnover effect remains near its magnitude in Table III, but the RD effect is substantially smaller than its magnitude in Table IV. We conclude that turnover largely dominates the RD effect, but the marginal RD effect perhaps remains positive.

D. Winsorized Sample

We also check whether our results are sensitive to the exclusion of extreme observations. We replace the return, MRTO, and MRRD observations that are beyond their 99th and 1st percentiles with their 99th and 1st percentile values, respectively. Then, we reestimate our primary models, given by equations (5) and (6), on the winsorized sample. Our results are very similar and the estimated β_2s are even more reliably positive for the Winsorized sample, as compared to our results for the full sample.

Appendix B: Nonsynchronous Trading (NST) Concerns

First, we examine assets and horizons where NST should have a minimal effect. We focus on the largest decile of NYSE/AMEX stocks at the weekly horizon. These stocks are very widely traded. Further, NST should have no effect on the autocorrelation of the equity-index futures which we also examine; see Ahn et al. (2002). Finally, NST can induce a positive autocorrelation in portfolio returns but NST cannot explain negative autocorrelation.

Here, we use the definition and model of NST from Campbell, Lo, and MacKinlay (1997, pp. 84–98; hereafter CLM) to explain our references to NST in this paper. CLM present a simple model where NST can induce biases in the moments and comoments of returns. In their model, true security returns are generated by an unobserved continuous return process. During each discrete period, there is some probability π_i that security i does not trade. Then, with a linear common-factor return process, the discrete returns of firms that traded will incorporate common-factor information sooner than the discrete returns of firms that did not trade. This process will generate a positive autocorrelation in portfolio returns.

Our arguments about NST and serial correlations in portfolio returns are based on possible time-series variation in firm π_is. First, higher turnover seems likely to be associated with lower average π_is in the period, which suggests lower positive autocorrelation attributed to NST. However, we find that turnover shocks in period $t-1$ are positively associated with the autocorrelation between the returns in period t and $t-1$ (Section IV.A). Second, if NST promotes higher return dispersion (as some firms lag in incorporating information), then high dispersion might reflect higher average π_is in the period, which suggests higher positive autocorrelation attributed to NST. However, we find that the autocorrelation is largely unrelated to the former-period's dispersion shock (Section IV.B). Finally, under simple models of NST, Boudoukh et al. (1994) point out that own lagged portfolio returns should completely capture the predictable portfolio return due to NST (and, accordingly, cross-serial relations to other lagged portfolio returns should provide no additional explanatory power beyond the own lagged portfolio returns). However, while controlling for the lagged small-firm portfolio return, we find that the cross-serial correlation between small-firm returns and lagged large-firm returns also varies with the turnover and dispersion shocks (Section VI.E.4). Further, variation in this cross-serial correlation is more related to large-firm turnover and dispersion shocks, rather than comparable small-firm shocks. If our cross-serial findings are because the turnover and dispersion shocks in period t tell us something about small-firm π_is in period $t-1$, then it seems likely that the small-firm shocks would be more informative than the large-firm shocks.

Appendix C: Macroeconomic News, Turnover Shocks, and Dispersion Shocks

In this appendix, we describe our procedure for examining the relation between macroeconomic news flows and turnover and dispersion shocks. Since very few economic news releases are picked up in electronic searches for dates before 1980, we focus all of our news-related analysis on the second-half subsample. For this period of October 1981 to December 2000, we first sort the 1,004 weekly observations on $MRTO_{L,t}$. We then form a ranked "low MRTO" subset that includes the 150 weeks with the lowest MRTO values and a ranked "high MRTO" subset that includes the 150 weeks with the highest MRTO values. Second, we perform equivalent sorts on the $MRRD_{L,t}$ to form a "low MRRD" subset and a "high MRRD" subset. Then, we form a combined "low MRTO/MRRD" subset consisting of the 30 weeks with the combined lowest ranks (based on the rankings in the low MRTO and MRRD samples). Similarly, we form a combined "high MRTO/MRRD" subset consisting of the 30 weeks with the combined highest ranks. Using a similar method, we also identify 30 weeks where both the MRTO and MRRD are near their median values of approximately zero. This median grouping provides a set of near-zero MRTO/MRRD weeks for comparison.

Using Lexis-Nexis, we then search the *New York Times* and the *Financial Times* for economic news stories corresponding to the weeks identified in the respective subsets of weekly observations. We then compile a count of news releases for each of these weeks. Our goal is to find news releases that are generally acknowledged as being informative of marketwide valuation. After a set of initial experiments with different search terms, we settled on the keywords "stock market," "economy," and "Federal Reserve." Primarily, the identified news releases cover such items as GDP, inflation, industrial production, and the trade deficit.

We test a number of hypotheses using the counts of news releases. First, we cannot reject the null hypothesis that an equal number of news releases occur in the high MRTO/MRRD weeks and the low MRTO/MRRD weeks. On the other hand, we find compelling evidence against the null that the high and low MRTO/MRRD weeks have the same number of new releases as the near-zero MRTO/MRRD weeks. Specifically, the mean number of news releases for the high (low) MRTO/MRRD weeks is 2.63 (2.93) against a mean value of 1.00 for the near-zero MRTO/MRRD weeks. The p-value for the rejection of equal news releases per period is less than 0.005 (0.005) when comparing the high (low) MRTO/MRRD weeks to the near-zero MRTO/MRRD weeks.

REFERENCES

Ahn, Dong-Hyun, Jacob Boudoukh, Matthew Richardson, and Robert Whitelaw, 2002, Partial adjustment or stale prices? Implications from stock index and futures return autocorrelations, *The Review of Financial Studies* 15, 655–689.

Bekaert, Geert, and Harvey Campbell, 1997, Emerging equity market volatility, *Journal of Financial Economics* 43, 29–77.

Bekaert, Geert, and Harvey Campbell, 2000, Foreign speculators and emerging equity markets, *The Journal of Finance* 55, 565–613.

Bessembinder, Hendrik, Kalok Chan, and Paul Seguin, 1996, An empirical examination of information, differences of opinion, and trading activity, *Journal of Financial Economics* 40, 105–134.

Blume, Lawrence, David Easley, and Maureen O'Hara, 1994, Market statistics and technical analysis: The role of volume, *The Journal of Finance* 49, 153–181.

Bollerslev, Tim, and Jeffrey Wooldridge, 1992, Quasi-maximum likelihood estimation and inference in dynamic models with time-varying covariances, *Econometric Reviews* 11, 143–172.

Boudoukh, Jacob, Matthew Richardson, and Robert Whitelaw, 1994, A tale of three schools: Insights on autocorrelations of short-horizon stock returns, *The Review of Financial Studies* 7, 539–573.

Brown, David, and Robert Jennings, 1989, On technical analysis, *The Review of Financial Studies* 2, 527–551.

Campbell, John, Sanford Grossman, and Jiang Wang, 1993, Trading volume and serial correlation in stock returns, *The Quarterly Journal of Economics* 108, 905–938.

Campbell, John, Andrew Lo, and A.Craig MacKinlay, 1997, *The Econometrics of Financial Markets* (Princeton University Press, Princeton, NJ).

Chang, Eric, Joseph Cheng, and Ajay Khorana, 2000, An examination of herd behavior in equity markets: An international perspective, *Journal of Banking and Finance* 24, 1651–1679.

Chen, Joseph, Harrison Hong, and Jeremy Stein, 2001, Forecasting crashes: Trading volume, past returns, and conditional skewness in stock prices, *Journal of Financial Economics* 61, 345–381.

Christie, William, and Roger Huang, 1994, Equity return dispersions, Working paper, Vanderbilt University.

Christie, William, and Roger Huang, 1995, Following the pied piper: Do individual returns herd around the market?, *Financial Analyst Journal* 51, 31–37.

Conrad, Jennifer, Allaudeen Hameed, and Cathy Niden, 1994, Volume and autocovariances in short-horizon individual security returns, *The Journal of Finance* 49, 1305–1329.

Cooper, Michael, 1999, Filter rules based on price and volume in individual security overreaction, *The Review of Financial Studies* 12, 901–935.

Engle, Robert, and Victor Ng, 1993, Measuring and testing the impact of news on volatility, *The Journal of Finance* 48, 1749–1778.

Fama, Eugene, 1998, Market efficiency, long-term returns, and behavioral finance, *Journal of Financial Economics* 49, 283–306.

Glosten, Lawrence, Ravi Jagannathan, and David Runkle, 1993, On the relation between the expected value and the volatility of the nominal excess return on stocks, *The Journal of Finance* 48, 1779–1801.

Harris, Milton, and Artur Raviv, 1993, Differences of opinion make a horse race, *The Review of Financial Studies* 6, 473–506.

Heaton, John, and Deborah Lucas, 1996, Evaluating the effects of incomplete markets on risk sharing and asset pricing, *Journal of Political Economy* 104, 443–487.

Llorente, Guillermo, Roni Michaely, Gideon Saar, and Jiang Wang, 2002, Dynamic volume-return relation of individual stocks, *The Review of Financial Studies* 15, 1005–1047.

Lo, Andrew, and Jiang Wang, 2000, Trading volume: Definitions, data analysis, and implications of portfolio theory, *The Review of Financial Studies* 13, 257–300.

Lo, Andrew, and A.Craig MacKinlay, 1990, When are contrarian profits due to stock market overreaction?, *The Review of Financial Studies* 3, 175–205.

Loungani, Prakash, Mark Rush, and William Tave, 1990, Stock market dispersion and unemployment, *Journal of Monetary Economics* 25, 367–388.

Murphy, Kevin, and Robert Topel, 1985, Estimation and inference in two-step econometric models, *Journal of Business and Economic Statistics* 3, 370–379.

Newey, Whitney, and Kenneth West, 1987, A simple positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703–708.

Scruggs, John, 1998, Resolving the puzzling intertemporal relation between the market risk premium and conditional market variance: A two-factor approach, *The Journal of Finance* 53, 575–604.

Shalen, Catherine, 1993, Volume, volatility, and the dispersion of beliefs, *The Review of Financial Studies* 6, 405–434.

Stivers, Christopher, 2003, Firm-level return dispersion and the future volatility of aggregate stock market returns, *Journal of Financial Markets* 6, 389–411.

Veronesi, Pietro, 1999, Stock market overreaction to bad news in good times: A rational expectations equilibrium model, *The Review of Financial Studies* 12, 975–1007.

Veronesi, Pietro, 2000, How does information quality affect stock returns? Results from a dynamic model of learning, *The Journal of Finance* 55, 807–837.

Wang, Jiang, 1994, A model of competitive stock trading volume, *Journal of Political Economy* 102, 127–168.