Investor Overconfidence and Trading Volume

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The proposition that investors are overconfident about their valuation and trading skills can explain high observed trading volume. With biased self-attribution, the level of investor overconfidence and thus trading volume varies with past returns. We test the trading volume predictions of formal overconfidence models and find that share turnover is positively related to lagged returns for many months. The relationship holds for both market-wide and individual security turnover, which we interpret as evidence of investor overconfidence and the disposition effect, respectively. Security volume is more responsive to market return shocks than to security return shocks, and both relationships are more pronounced in small-cap stocks and in earlier periods where individual investors hold a greater proportion of shares. (*JEL* G11, G12)

Financial economists have long puzzled over investors' enthusiasm for active trading in highly competitive securities markets where, as Odean (1999) found, those who trade the most lose the most. Empirical evidence in competitive settings outside of security markets suggests that overconfidence in one's own talent is a pervasive behavioral norm. Investors' overconfidence in their security valuation skills has recently become a formalized hypothesis among financial economists. Specifically, Daniel, Hirshleifer, and Subrahmanyam (1998), hereafter DHS, and Odean (1998a) develop equilibrium results that incorporate the assumption that some investors overestimate the precision of their private information. These theories provide testable implications under two general assumptions; first, that investors are overly confident about the precision of their private information, and second, that biased self-attribution causes the degree of overconfidence to vary with realized market

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outcomes. Gervais and Odean (2001) further develop the theory that overconfidence is enhanced in investors that experience high returns, even when those returns are simultaneously enjoyed by the entire market.

Odean (1998a) and Gervais and Odean (2001) suggest that intertemporal changes in trading volume are the primary testable implication of overconfidence theory. Alternatively, DHS focus on security return implications and explain a number of previously documented pricing anomalies. To date, little empirical research has been directly motivated by the theoretical treatments of investor overconfidence. The paucity of overconfidence-related empirical work is due in part to the lack of well-defined and testable implications. In this study, we focus on the distinct implications associated with changes in trading volume over time for both the market and individual securities. While our motivation is an examination of investor overconfidence, we acknowledge that there may be alternative explanations to our empirical results. However, the magnitude and persistence of the lead–lag relationship between returns and trading volume is so strong that the empirical results are interesting independent of one's interpretation.

We differentiate investor overconfidence from the disposition effect of Shefrin and Statman (1985). The disposition effect describes a desire for investors to realize gains by selling stocks that have appreciated, but to delay the realization of losses. Empirical research by Shefrin and Statman (1985), Odean (1998b), and others documents trading patterns among individual investors that are consistent with the disposition effect. We interpret the more recently developed overconfidence hypothesis as a separate theory of trading activity that relates to investors beliefs about trading in general, rather than an attitude about individual stocks they currently hold. Empirical research on behavioral assertions, including overconfidence and the disposition effect, is sometimes based on proprietary trading records and portfolio holdings of specific individual investors. While such studies help us understand the motives of some investors, they do not address the larger issue of whether these motivations are pervasive enough to impact the structure of the market in terms of realized trading volume and price discovery.

Our empirical research is time-series oriented and based on monthly observations of turnover for the NYSE/AMEX market and individual securities. We use vector autoregressions (VAR) and impulse response functions to test specific implications of how trading activity relates to lagged returns. Our results can be summarized into three key findings. First, we find a statistically and economically significant positive relationship between market-wide turnover and lagged market-wide returns, consistent with the prediction of the overconfidence hypothesis. Second, we find that individual security turnover is positively related to both lagged security returns and lagged market returns. The positive security turnover response to own lagged return is consistent with the disposition effect, while we interpret the positive turnover response to lagged market returns as evidence of changes in investor overconfidence. The relatively pronounced dependence of security turnover on lagged market returns in a regression that also includes lagged security turnover and security returns is striking. Our third key finding is that the lead–lag relationship between returns and turnover is stronger in small-capitalization stocks and in earlier time periods, perhaps due to the relatively larger role of individual versus institutional investors in these subsamples. In addition to these key findings, we develop and conduct further tests using signed volume (i.e., positive or negative contemporaneous return) in an attempt to differentiate between various versions of overconfidence theory that have been proposed, as well as the disposition effect.

Beyond overconfidence and disposition-based explanations, there are few behavioral or rational expectations models that are as convincingly consistent with the positive lead–lag relationship between returns and volume we document. Specifically, portfolio rebalancing in the wake of large price movements might induce trading activity, but the implication would be for higher volume after large price increases and decreases (i.e., following large positive and large negative returns). Similarly, heterogeneous interpretation of informational events might lead to a correlation between return volatility and concurrent volume but not a dependency between volume and the sign of the lagged return. In any event, we use concurrent and lagged observations of return volatility and return dispersion to help control for heterogeneous beliefs, rebalancing, and other possible alternative explanations.

The study proceeds as follows. In Section 1, we review overconfidence theory, the disposition effect, and past empirical work on trading volume. In Section 2, we introduce our data and empirical methodologies. Specifically, Section 2 reviews the vector autoregression and impulse-response function methodology we employ and describes a number of related econometric issues. Section 3 reports our empirical results on the single market-wide time series in some detail to introduce the econometric framework. In Section 4, we estimate vector autoregression models on many (hundreds) of individual security time series and report average results on impulse-response function coefficients. Section 4 also discusses sub-period and firm-size-based findings, and further signed volume tests of alternative overconfidence models and the disposition effect. We state our conclusions in Section 5.

1. Overconfidence Theory and Volume Research

Black (1986) was the first to argue that noise traders offer an exit from the no-trading equilibrium of perfectly rational models of securities markets.

Recently, Odean (1998a) and then Gervais and Odean (2001) developed a multiperiod model where the overconfidence of noise traders increases as they attribute high returns in bull markets to their trading skills. These models do not specify an exact time frame for the lead–lag relationship between returns and trading activity, only that high (low) market returns lead to high (low) subsequent volume. Models of investor overconfidence and biased self-attribution are also developed by DHS. DHS make a distinction between public and private informational events and develop predictions about stock price over and under reaction. Under certain circumstances, security returns in the DHS model are positively autocorrelated in the short run but negatively autocorrelated over longer horizons.

The overconfidence model of Gervais and Odean (2001) and Odean (1998a) predicts that high total market returns make some investors overconfident about the precision of their information. Although the returns are market wide, investors mistakenly attribute gains in wealth to their ability to pick stocks. Overconfident investors trade more frequently in subsequent periods because of inappropriately tight error bounds around return forecasts. Alternatively, market losses reduce investor overconfidence and trading, although perhaps not in a symmetric fashion. Glaser and Weber (2004) distinguish between the "miscalibration" version of overconfidence and the idea that most investors simply believe their investment skills are better than average. We find little difference in the trading patterns implications between these two versions of investor overconfidence, and the tests we conduct do not distinguish between them.

The disposition effect was first proposed by Shefrin and Statman (1985) who combined prospect theory from Kahneman and Tversky (1979) with the emotions of pride and regret. Investors in the Shefrin–Statman model think about stocks within mental accounts, one for each stock. Pride accompanies the realization of paper gains, and regret accompanies the realization of paper losses. The disposition effect describes behavior that is not rational since investors subject to the effect forego the tax benefits of the realization of losses and suffer the tax costs of the realization of gains. Past empirical evidence for the disposition effect is found by many researchers including Lakonishok and Smidt (1986), Ferris, Haugen and Makhija (1988), Odean (1998b), and Heath, Huddart, and Lang (1999).

The empirical implications of the more recently developed theory of investor overconfidence differ from the disposition effect in two important ways. First, the disposition effect only explains the direct motivation for one side of a trade. The desire to sell a specific stock with a paper gain is expressed by trading with other investors who may not have a bias, and thus may affect the pricing equilibrium for that stock. If disposition-related selling (for gains) or a resistance to sell (for loses) comprises a material part of total volume, prices will be slow to react to new information. Specifically, Grinblatt and Han (2005) argue that disposition-motivated trading is the root cause of the Jegadeesh and Titman (1993) momentum anomaly; positive autocorrelations in returns lasting several months. Goetzmann and Massa (2003) refine the notion that the one-sided nature of disposition-motivated trades can affect prices. In contrast to the disposition effect, overconfidence in stock picking expertise among investors can explain both sides of a given transaction. Differences of opinion together with inappropriately tight error bounds by two investors will result in a trade that need not include other liquidity traders or rational information traders.

Second, the disposition effect is generally understood to refer to an investor's attitude toward specific stocks in his or her portfolio. Consequently, recent empirical research on the disposition effect (Odean 1998b; Ranguelova 2001; and Dhar and Zhu 2005) employs data on individual investor transactions in specific stocks at various prices. In contrast, the theory of intertemporal changes in investor overconfidence suggests an attitude about the market. If investors overestimate their ability to increase wealth by active trading, they are likely to maintain this belief about stocks in general rather than the specific securities they currently hold. Observations of a specific investor's portfolio return and trading activity are valuable in explaining some phenomenon. However, to be useful in tests of overconfidence the individual investor portfolio return data would have to span much longer periods than investor-specific databases currently allow. We believe the best chance of finding evidence for the overconfidence hypothesis is in the long-term trading volume data available from the Center for Research in Security Price (CRSP). In addition, the more important variable to explain for market observers may be variations in realized aggregate trading volume as opposed to the trades of a specific set of investors.

Considerable empirical research relates *contemporaneous* volume and returns including Karpoff (1987); Stoll and Whaley (1987); Bessembinder and Seguin (1993); Bessembinder, Chan, and Seguin (1996); Chordia, Roll, and Subrahmanyam (2000); and Lo and Wang (2000). However, little prior empirical research relates *current* volume to *lagged* returns. Gallant, Rossi, and Tauchen (1992) document several regularities, but the nonparametric methodology of their research does not yield interpretations relevant to the overconfidence hypothesis. Chordia and Swaminathan (2000) examine volume and return cross-autocorrelations at very short (i.e., daily) horizons to explore the speed at which information is priced. Recent research by Cooper (1999); Lee and Swaminathan (2000); Llorente et al. (2002); and Gervais, Kaniel, and Mingelgrin (2001) examine the ability of volume to predict returns, not the ability of returns to predict volume. Another large branch of theoretical and empirical research relates volume to concurrent return volatility, as well and lead–lag relationships between volatility and volume, for example Harris and Raviv (1993) and Shalen (1993). We therefore include contemporaneous and lagged observations of return volatility and cross-sectional security return dispersion in our vector autoregression models.

2. Data and Methodology

2.1 Data description

Our database consists of monthly observations on all NYSE/AMEX common stocks, excluding closed-end funds, REITs, and ADRs, from August 1962 to December 2002, the span of the daily CRSP files.[1] We exclude NASDAQ stocks because the dealer market has volume measurement conventions that differ from exchange-traded securities [Atkins and Dyl (1997), among others]. In separate unreported regressions, we verify that NASDAQ stocks exhibit results similar to the smallest three size-based quintiles of the NYSE/AMEX database.

An examination of long-term US trading activity must account for the fact that the number of outstanding shares for the typical stock has increased markedly over the last four decades. The median number of outstanding shares per security has increased almost 20-fold from 1.8 million to 34 million, making raw share volume a poor measure of trading activity.[2] Following Lo and Wang (2000), we measure trading activity with turnover (shares traded divided by outstanding shares) and aggregate security turnover into market turnover on a value-weighted rather than equal-weighted basis. Value-weighted market turnover is algebraically equivalent to total dollar turnover; the dollar value of all shares traded divided by the total dollar value of the market.[3]

Figure 1 presents NYSE/AMEX turnover from August 1962 to December 2002. Turnover generally stayed below 2% per month until the mid-1970s, equivalent to a complete (i.e., 100%) turnover time of more than four years. Turnover gradually increased to a level of about 6% per month by the late 1980s, reducing the complete turnover time to

[1] We use monthly observations for turnover and returns, but our estimate of volatility is constrained by the availability of daily returns which start in July 1962. Our start date is delayed to August 1962 to obtain uniform availability of the prior month-end shares outstanding data.

[2] Only a portion of the dramatic increase in the average number of shares per stock is attributable to increases in real company size. Rather, institutional considerations such as price discreteness and listing requirements, expressed though stock splits, have kept the median share price between 15 and $20 over the last four decades, despite a six-fold increase in the Consumer Price Index.

[3] Let V_i be trading volume and S_i be outstanding shares for security i, so that turnover is $T_i = V_i/S_i$. Market-wide turnover is defined as the value-weighted average of individual security turnover, $T_M = \Sigma w_i T_I$, where the weights, w_i, are based on the capitalization of the security divided by the sum of capitalization for all securities in the market. Capitalization is the beginning of period price per share, P_i, times shares outstanding, S_i, for each security. Some algebra indicates that T_M is equal to the sum of the dollar volume for each security, $P_i{*}S_i$, divided by the sum of the capitalizations.

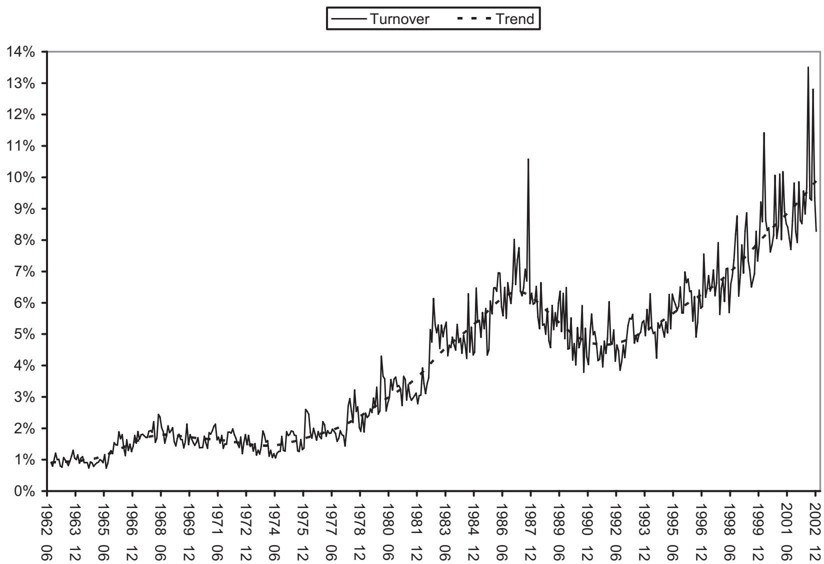


Figure 1
Monthly turnover for NYSE/AMEX market with trend line.

18 months. Trading dropped off for a few years after the spike associated with the October 1987 market crash but then picked up through the 1990s and the turn of the century, ending in 2002 at almost 10% per month or a complete turnover time of 10 months. One possible explanation for the long-term trends in trading activity are changes in investor overconfidence induced by realized portfolio returns, the focus of this study. Alternative explanations include the deregulation of brokerage fees (May Day 1975) and other changes in transaction costs, trading associated with financial derivatives arbitrage, and the growing influence of institutional rather than individual traders (Smidt 1990).

The secular trends in Figure 1 indicate that the turnover time-series is nonstationary, leading to bias in the coefficient standard errors of VAR we employ. Turnover is definitionally non-negative and the natural log transformation helps, eliminating the visual correlation in Figure 1 between the level of the trend and volatility around the trend. However, logged turnover still exhibits nonlinear secular trends over time, and we fail to reject to null-hypothesis of a unit root using the Phillips and Perron (1988) test.[4] We employ the Hodrick and Prescott (1997) (henceforth HP) algorithm for detrending turnover, although the qualitative results we

[4] The Phillips and Perron (1988) test statistic is –1.8 for log market turnover and –16.0 for detrended log market turnover. The 5% critical value for the test statistic is –2.9.

present are invariant to alternative detrending methodologies.[5] While simpler (e.g., linear time-trend) detrending methodologies may be adequate for the market turnover in Figure 1, they are not flexible enough for the many turnover patterns in individual security turnover time-series we also examine. For reference purposes, Figure 1 includes the exponentiated HP trend (dotted line) computed from log turnover. The detrended time-series used in this study is the monthly difference between log turnover and its trend.

Removing the trend from the market turnover time-series may present a bias *against* finding long-term trading activity responses to market returns. Gervais (1998) and Gervais and Odean (2001) hypothesize that realized returns impact trading activity for some unspecified period of time, leading to possible long-term trends in turnover. For example, the long-term drop in activity after the 1987 crash could be indicative of a drop in investors' confidence in the value of active trading. Similarly, the long-term increases in trading starting in the late 1970s and early 1990s are coincident with long-term bull markets. While consistent with the overconfidence hypothesis, as well as the disposition effect, these long-term observations are anecdotal, too infrequent for statistical analysis and hypothesis testing. We therefore present detrended log turnover as our base-case in this study and comment on how the results differ for nondetrended log turnover.

Table 1 presents summary statistics on monthly market-wide turnover and returns, as well as two market-wide control variables; market volatility and cross-sectional dispersion. Table 1 has descriptive data on the full (August 1962–December 2002) sample as well as four nonoverlapping 120-month (decade long) sub-periods that are used later in robustness checks. The sub-period means and standard deviations for raw turnover again suggest a nonstationary series. For example, the average turnover in the last sub-period, 7.07%, is several standard deviations above the average value of 1.48% in the first sub-period. On the contrary, the sub-period descriptive statistics for detrended monthly log turnover, *mturn*, indicate a stationary time-series.

Market return, *mret,* in Table 1 is the monthly return with dividends on a value-weighted portfolio of all NYSE/AMEX nonfund common stocks. For example, the mean monthly return over the full sample is 0.94%; a simple annualized average return of $12 \times 0.94 = 11.28\%$. Unreported

[5] The Hodrick–Prescott (1997) algorithm creates trend series, s, by minimizing the variance of the raw series, y, around the trend, subject to a penalty on the second difference of the trend. Specifically, for a time series of length T, the HP filter chooses S_t to minimize $\sum_{t=1}^{T} (y_t - s_t)^2 + \eta \sum_{t=2}^{T-1} [(s_{t+1} - s_t) - (s_t - s_{t-1})]^2$ where η is the penalty parameter (the trend becomes more smooth as η is increased). We follow the common practice of setting $\eta = 14,400$ for monthly observations. The HP filter is two-sided, meaning that data before and after time t is used in the smoothing process. Our motivation for detrending is to extract a stationary time-series not to predict the trend.

Table 1
Market descriptive statistics

	Full	A	B	C	D
Period	August 1962–December 2002	1963–1972	1973–1982	1983–1992	1993–2002
Observations	485	120	120	120	120
Market turnover					
Mean	4.04	1.48	2.38	5.37	7.07
SD	2.52	0.40	0.99	1.02	1.72
Minimum	0.73	0.73	1.06	3.79	4.23
Maximum	13.50	2.45	6.14	10.58	13.50
Detrended log market turnover (*mturn*)					
Mean	0.00	0.23	–0.70	–0.26	0.45
SD	14.25	15.13	17.70	12.65	10.68
Minimum	–45.52	–45.52	–38.51	–27.71	–22.63
Maximum	52.73	35.41	43.27	52.73	34.29
Market return (*mret*)					
Mean	0.94	0.87	0.72	1.31	0.83
SD	4.35	3.63	5.07	4.49	4.05
Minimum	–21.97	–10.52	–11.75	–21.97	–14.96
Maximum	16.61	9.42	16.61	13.03	9.69
Market volatility (*misg*)					
Mean	3.70	2.80	4.37	3.67	3.97
SD	2.06	1.59	1.79	2.40	2.09
Minimum	0.58	0.58	1.43	1.20	0.99
Maximum	24.52	12.41	11.31	24.52	14.12
Dispersion (*disp*)					
Mean	7.10	6.08	7.25	6.79	8.36
SD	1.88	1.13	1.82	1.01	2.40
Minimum	3.93	3.93	4.72	4.59	5.54
Maximum	15.76	8.98	14.88	9.93	15.76

This table gives descriptive statistics (reported in percentage points) on market-wide variables, where the market is defined as the value-weighted composite of all NYSE/AMEX nonfund common stocks. Market turnover is the monthly value-weighted turnover (shares traded divided by outstanding shares). Detrended log market turnover (*mturn*) is the Hodrick and Prescott (1997) detrended natural log of market turnover. Market return (*mret*) is the monthly value-weighted market return. Market volatility (*misg*) is the French, Schwert, and Stambaugh (1987) monthly volatility measure based on daily return standard deviation. Dispersion (*disp*) is the monthly cross-sectional standard deviation of security returns. The first column reports on the full-sample period, August 1962–December 2002, and the last four columns report on four 120-month (decade-long) subsamples.

statistics on the higher moments of the returns data in this study are consistent with established distributional characteristics of monthly market returns; significant leptokurtosis and slight negative skewness. The subsample means and standard deviations for *mret* are relatively stable, indicative of a stationary time-series.

Our first control variable, market volatility, *misg*, is the monthly observations of market return volatility for the value-weighted composite of all NYSE/AMEX nonfund common shares, measured in percentage points. The volatility control is based on Karpoff's (1987) survey of research on the contemporaneous volume–volatility relationship and is similar to the mean absolute deviation (MAD) measure in the trading volume study of Bessembinder, Chan, and Seguin (1996). The monthly realized volatility estimates are based on daily market returns within the month, correcting for realized autocorrelation, as specified in French, Schwert, and Stambaugh (1987).[6]

The second control variable, dispersion, *disp*, is the monthly cross-sectional standard deviation of returns for the previously defined list of NYSE/AMEX nonfund common stocks, measured in percentage points. Consistent with calculation of market return as the value-weighted mean security return, the cross-sectional standard deviation of returns is value-weighted (i.e., market-cap weights are used in the averaging of squared deviations from the mean). Return dispersion is related to the level of realized idiosyncratic risk in stocks and has been relatively stable around the 7.10% full-sample mean shown in Table 1, although somewhat higher in recent years as reported by Campbell et al. (2001). Return dispersion is included as a control variable to account for potential trading activity associated with portfolio rebalancing. For example, large spreads between the individual stock returns might lead to trading activity among investors seeking to maintain fixed (e.g., equal) portfolio weights.

In addition to the market data presented in Table 1, we perform time-series analysis on the returns and trading volume of individual stocks. The full-sample span of 485 months on 2000–2500 NYSE/AMEX securities per month results in over one million individual stock observations. These observations are organized as multivariate time-series for each stock with heterogeneous start and stop dates associated with the listing of that stock. The VAR models we estimate require a continuous time series with a sample size that allows for the estimation of relatively large number of parameters. We establish a requirement of at least 10 years (120 months) of contiguous volume, return, and standard deviation data in the CRSP monthly and daily files.[7] The data sufficiency requirement yields 1878 securities with start and stop months at least 10 years apart, but within the August 1962–December 2002 full-sample period. The time-series that meet the data sufficiency requirement contain about one-half a million monthly observations, as shown in Table 2.

Table 2 presents summary statistics for raw turnover and the three security variables used in the individual stock VAR estimations: detrended log turnover, return, and volatility. Turnover is the volume

[6] Specifically, we calculate month t's volatility as $msig_t^2 = \sum_{\tau=1}^{T} r_\tau^2 + 2\sum_{\tau=1}^{T} r_\tau r_{\tau-1}$, where r_τ is day τ's return and T is the number of trading days in month t.

[7] The frequency of missing volume observations in the CRSP database is high enough that excluding an entire time-series for one missing month may be an overly strict criterion that introduces unintended biases associated with the exclusion of certain types of stocks (i.e., small cap). We replace occasional (not more than 1% of a given time-series) isolated (single occurrence) missing turnover observations with the prior month turnover before a security time series is measured against the ten-year contiguous data criterion.

Table 2
Security descriptive statistics

	Full	A	B	C	D
Period	August 1962–December 2002	1963–1972	1973–1982	1983–1992	1993–2002
Observations	530,608	121,154	146,367	134,065	134,067
Turnover					
Mean	4.69	3.14	3.05	5.54	7.27
SD	6.14	5.11	3.44	5.98	8.31
Minimum	0.00	0.01	0.00	0.01	0.00
Maximum	709.23	322.05	137.88	449.23	709.23
Detrended log turnover (*turn*)					
Mean	0.00	1.22	–1.42	0.08	0.40
SD	48.41	49.12	49.22	49.72	45.40
Minimum	–416.79	–224.01	–364.75	–416.79	–341.69
Maximum	464.54	464.54	420.89	384.42	350.37
Return (*ret*)					
Mean	1.26	1.19	1.36	1.36	1.12
SD	11.78	10.27	11.89	12.04	12.75
Minimum	–98.13	–56.54	–78.95	–80.00	–98.13
Maximum	1100.00	250.00	300.00	1100.00	452.63
Volatility (*sig*)					
Mean	9.23	8.57	9.62	9.11	9.60
SD	6.77	5.50	6.16	7.40	7.76
Minimum	0.00	0.00	0.00	0.00	0.00
Maximum	624.27	111.85	133.18	624.27	399.06

This table gives descriptive statistics (measured in percentage points) on security variables for all NYSE/AMEX nonfund common stocks with sufficient (120 months of contiguous) time-series data. Turnover is the monthly turnover (shares traded divided by outstanding shares) for each stock. Detrended log turnover (*turn*) is the Hodrick and Prescott (1997) detrended natural log of turnover. Return (*ret*) is the monthly stock return with dividends. Volatility (*sig*) is the French, Schwert, and Stambaugh (1987) monthly volatility measure based on the daily security return standard deviation. The first column reports on the full-sample period, August 1962 to December 2002, and the last four columns report on four 120 month (decade-long) subsamples.

of shares traded in month t divided by the prior month-end shares, adjusting for stock splits that occur during the month. The security turnover averages in Table 2 are slightly higher than the value-weighted market composite in Table 1 because smaller capitalization stocks tend to have higher turnover rates. The standard deviation of turnover rates across securities and time in Table 2 is large, with rare minimum values of zero turnover for some securities in some months, as well as extraordinary maximum turnover rates of several hundred percent. An examination of unreported turnover time-series charts for individual securities, similar to Figure 1, reveals long-term trends and nonstationarities similar to, but often more complex than, the market composite. As with the market, we log and detrend individual security turnover using the HP filter, producing the detrended monthly log turnover variable, *turn*.

Individual security return, *ret*, is the monthly return with dividends measured in percentage points. As with turnover, the variation in returns across stocks and months shown in Table 2 is substantial, with extreme minimum and maximum values common to a large return database. Individual security volatility, *sig*, is the return volatility for a given firm and month, measured in percentage points. As with the market, we use daily security return data and the French, Schwert, and Stambaugh (1987) method to calculate realized volatility for each stock each month.

2.2 Empirical methodology

We use VAR and associated impulse response functions to study the interaction of turnover and return time-series for both the market and individual securities. The general form of the VAR model is

$$\mathbf{Y}_t = \alpha + \sum_{k=1}^{K} A_k \mathbf{Y}_{t-k} + \sum_{l=0}^{L} B_l \mathbf{X}_{t-l} + \mathbf{e}_t \tag{1}$$

where $\mathbf{Y}_t$ is a $n \times 1$ vector of period t observations of endogenous variables, for example, turnover and return, $\mathbf{X}_t$ is a vector of period t observations of the exogenous (i.e., control) variables, and $\mathbf{e}_t$ is a $n \times 1$ residual vector. The regression coefficients, A_k and B_l, estimate the time-series relationships between the endogenous and exogenous variables, where K is the number of lagged endogenous observations and L is the number of lagged exogenous observations. The VAR methodology allows for a covariance structure to exist in the residual vector, $\mathbf{e}_t$, that captures the contemporaneous correlation between endogenous variables.

Formal overconfidence theories do not specify a time frame for the relationship between returns and turnover, so we let the data determine the number of monthly lags to include. Specifically, we set $K = 10$ based on the Schwartz Information Criteria (SIC).[8] The SIC model selection criterion is based on the log likelihood function adjusted by a penalty for the number of parameters and performs well for model selection with large sample sizes (Lutkepohl 1991). The model selection criterion also leads to $L = 2$, so that contemporaneous and two lagged monthly observations of the exogenous variables are used to explain and predict the endogenous variables. The optimal lag lengths of $K = 10$ and $L = 2$ are established based on the market-wide time series and then applied uniformly to the individual VAR estimations for each security. While the SIC suggests some variation in the optimal lag lengths for individual security models, we fix the lag lengths at $K = 10$ and $L = 2$ to facilitate the cross-sectional comparison of the coefficient estimates.

[8] The SIC takes the form $SIC = -2\Omega/T - p(\log(T)/T)$, where p is the number of estimated parameters, T is the number of observations, and Ω is the value of the log likelihood function using the p estimated parameters.

Based on the VAR model, we employ impulse response functions to aggregate over coefficient estimates and illustrate how the endogenous variables relate to each other over time (Hamilton 1994). Impulse response functions trace the effect of a one standard deviation shock (measured within sample) in one residual to current and future values of the endogenous variables through the dynamic structure of the VAR. For example, the market version of the general model in Equation (1) contains two endogenous variables, market turnover and market return, and two exogenous variables, market volatility and dispersion:

$$\begin{bmatrix} mturn_t \\ mret_t \end{bmatrix} = \begin{bmatrix} \alpha_{mturn} \\ \alpha_{mret} \end{bmatrix} + \sum_{k=1}^{10} A_k \begin{bmatrix} mturn_{t-k} \\ mret_{t-k} \end{bmatrix} + \sum_{l=0}^{2} B_l \begin{bmatrix} msig_{t-l} \\ disp_{t-l} \end{bmatrix} + \begin{bmatrix} e_{mturn,t} \\ e_{mret,t} \end{bmatrix} \quad (2)$$

Changes in one residual, say $e_{mturn,t}$, will immediately change the current value of *mturn* but will also affect future values of *mturn* and *mret* since lagged values of *mturn* appear in both equations through the coefficient matrix A_k.[9] For example, to test the market prediction of the overconfidence hypothesis, we shock the market return residual, $e_{mret,t}$, by one sample standard deviation. Using the estimated parameters and the dynamic structure of the VAR, we track how market turnover responds over time to the $e_{mret,t}$ shock. Thus, while the VAR model is dense in parameters, the impulse response function provides a simple picture of how the endogenous variables are related over time.

The VAR model for individual securities is trivariate, with endogenous variables security turnover, security return, and market return, and has a single exogenous variable, security volatility:

$$\begin{bmatrix} turn_t \\ ret_t \\ mret_t \end{bmatrix} = \begin{bmatrix} \alpha_{turn} \\ \alpha_{ret} \\ \alpha_{mret} \end{bmatrix} + \sum_{k=1}^{10} A_k \begin{bmatrix} turn_{t-k} \\ ret_{t-k} \\ mret_{t-k} \end{bmatrix} + \sum_{l=0}^{2} B_l sig_{t-l} + \begin{bmatrix} e_{turn,t} \\ e_{ret,t} \\ e_{mret,t} \end{bmatrix} \quad (3)$$

As with the market-wide model, we are primarily concerned with how security turnover responds to shocks in return, both security return and market-wide return.[10] We also examine the response of security returns to shocks in

[9] The residuals often have a common component which cannot be associated with a specific variable. For the purpose of impulse-response functions, the residuals are sometimes orthogonalized (for example, by the Cholesky decomposition) resulting in a diagonal covariance matrix. Unreported orthogonalized impulse-response functions are qualitatively similar to those we report.

[10] We investigated other forms of Equation (3) to test the robustness of this specification, including versions with lagged market turnover as an explanatory variable, and found that the inclusion of additional variables has no meaningful impact on the results.

security wide turnover to test some of the overconfidence implications in DHS. Market returns are not predictable based on a single security in any plausible theory, so the third endogenous variable, *mret*, could have been introduced as an exogenous variable in Equation (3). However, the Shefrin and Statman (1985) disposition effect motivates a direct comparison of past individual and market return impacts on security turnover, so we introduce the market return, *mret*, in the same format as the individual security return, *ret*.

We estimate Equation (3) on the 1878 individual NYSE/AMEX securities that meet the minimum data sufficiency requirement. Each of these VAR models has a full set of coefficient estimates and standard errors, producing extensive output that cannot be reported on a security by security basis. For brevity, we report the average coefficient across all securities for each individual element of the endogenous coefficient matrix, A_k. While the VAR coefficient standard error estimates are valid for each security, there are material dependencies between the coefficient estimates across securities making the statistical significance of the mean coefficient we report difficult to ascertain. For example, simply estimating the standard error of a coefficient mean by the cross-sectional standard deviation divided by the square root of the sample size grossly underestimates the standard error, leading to spurious power in associated t-tests.

To address this problem, we introduce a bootstrap procedure that provides standard errors for the cross-sectional mean of each VAR coefficient, as well as the security impulse response function coefficients. The time-series nature of the VAR model and the size of the security database lead to an econometrically complicated and computationally intensive bootstrap procedure, which we outline briefly below. Our choices generally follow the VAR-bootstrap specifications in Runkle (1987) as reviewed by Hamilton (1994). The bootstrap program creates 5000 artificial databases with time-series structure and dependencies similar to the single historical database. The observed variation of the coefficient means among these artificial databases provides an accurate estimate of the standard error of the actual database means.

We first estimate Equation (3) for each security using the historical data and store the estimated coefficients and fitted residuals. Then, for each security we create a $T \times 3$ matrix of random variables, u, by sampling with replacement from the appropriate set of fitted residuals. A key aspect of the bootstrap is that each sampling of residuals has one random sequencing of months that is applied consistently across the 1878 securities to preserve the cross-sectional dependencies in the original data. Given our matrix of sample residuals, we construct simulated data using the structure of Equation (3) and estimated coefficients for each security. Essentially, we create a time series of simulated values of security turnover, security return, and market return for all 1878 securities. Using the simulated data, we then estimate Equation (3) and retain the estimated coefficients and associated impulse response functions.[11] By repeating this process 5000 times, we obtain sufficiently precise estimates of the standard error for each mean coefficient in the endogenous coefficient matrix, A_k (i.e., the standard error for each of the sixty coefficient means reported in Table 3), and the standard errors for the mean coefficients of the security impulse response functions. The bootstrap results indicate that a naive employment of the sample standard deviation of coefficient values in the single historical database understates the actual standard error by as much as a degree of magnitude, confirming the need for the bootstrapping program.

3. Market VAR Estimation and Test Results

3.1 Market vector autoregression

Table 4 summarizes the results of the full-sample bivariate VAR of detrended log market turnover, *mturn*, and market return, *mret*. The table is organized by rows for each dependent variable (*mturn* and *mret*) and by columns for lagged dependent variable and exogenous variable coefficients. For each coefficient, we report the estimated value, standard error, and the p-value for a two-sided t-test that the true coefficient value is zero. Significance levels (in parentheses) are rounded to two digits so that a reported p-value of 0.00 indicates significance at the 0.005 level or less. In our review of test results, we generally refer to coefficients with p-values of 0.05 or less as significant, and coefficients with p-values of 0.01 or less as highly significant.

Table 4 summarizes that market turnover is autocorrelated, with a highly significant first lagged coefficient of 0.284 (standard error of 0.047) and coefficients of generally declining magnitude on the second and higher lags. Notably, market turnover is also dependent on lagged market returns even in a regression that includes lagged observations of turnover and other control variables. The first lagged market return coefficient in the *mturn* dependent variable regression is 0.819 (standard error of 0.133) and highly significant, as is the second lagged market return. Indeed, the magnitude of the first lagged market return coefficient estimate is about three times greater than lagged turnover (compare 0.819 to 0.284), although with a correspondingly larger standard error. The positive and highly significant association between market turnover and lagged market returns represents the first key empirical finding of this

[11] Our bootstrap method results in 1878 unique time-series of the market return for each simulated database, while the historical database naturally has only one. As an alternative, we constructed one time-series of the market return for each database by using the average security coefficients and average residuals. Preliminary results of this alternative are not materially different from the adopted bootstrap method.

Table 3
Security vector autoregressions (VAR) estimations

		$turn_{t-1}$	$turn_{t-2}$	$turn_{t-3}$	$turn_{t-4}$	$turn_{t-5}$	$turn_{t-6}$	$turn_{t-7}$	$turn_{t-8}$	$turn_{t-9}$	$turn_{t-10}$
Lagged turnover											
$turn_t$	Mean coefficient	0.306	0.043	0.039	–0.032	–0.008	–0.003	–0.024	–0.033	0.000	–0.031
	p-value	0.00	0.27	0.26	0.29	0.45	0.47	0.32	0.26	0.50	0.25
ret_t	Mean coefficient	0.005	–0.012	0.000	–0.006	–0.008	–0.003	–0.004	–0.001	–0.004	–0.004
	p-value	0.29	0.11	0.49	0.27	0.19	0.37	0.32	0.45	0.33	0.33
Lagged return											
$turn_t$	Mean coefficient	0.171	0.043	0.030	0.069	0.036	0.071	0.064	0.041	0.049	0.087
	p-value	0.08	0.46	0.47	0.43	0.46	0.43	0.44	0.46	0.45	0.41
ret_t	Mean coefficient	–0.053	–0.021	–0.010	–0.007	0.011	0.014	0.013	0.003	0.024	0.020
	p-value	0.33	0.43	0.47	0.48	0.46	0.45	0.46	0.49	0.42	0.43
Lagged market return											
$turn_t$	Mean coefficient	0.990	0.709	0.324	0.128	0.397	–0.072	–0.034	–0.088	0.254	–0.061
	p-value	0.00	0.00	0.01	0.18	0.00	0.31	0.41	0.27	0.03	0.33
ret_t	Mean coefficient	0.228	–0.031	0.064	–0.036	0.050	–0.072	0.005	–0.080	–0.002	–0.008
	p-value	0.00	0.33	0.17	0.28	0.21	0.11	0.46	0.08	0.49	0.44

This table reports mean coefficients and t-statistic significance levels (p-value) from 1878 individual security VAR on detrended logged turnover (*turn*), return (*ret*), and market return (*mret*), with 10 lags, for the full-sample summarized in Table 4. The VAR estimations include contemporaneous and two lags of the exogenous variable volatility (*sig*), as described in Table 4. Exogenous variable and *mret* dependent variable coefficient means are not reported for the sake of brevity. The p-values in this table are based on bootstrap-based standard errors and test the null hypothesis that the mean coefficient estimate across all securities is zero.

Table 4
Market vector autoregressions (VAR) estimation

		Lagged market turnover									
		$mturn_{t-1}$	$mturn_{t-2}$	$mturn_{t-3}$	$mturn_{t-4}$	$mturn_{t-5}$	$mturn_{t-6}$	$mturn_{t-7}$	$mturn_{t-8}$	$mturn_{t-9}$	$mturn_{t-10}$
$mturn_t$	Coefficient	0.284	0.204	0.089	–0.107	0.109	–0.091	0.000	–0.118	0.114	–0.031
	SE	0.047	0.048	0.040	0.041	0.041	0.041	0.041	0.040	0.040	0.038
	p-value	0.00	0.00	0.03	0.01	0.01	0.03	0.99	0.00	0.00	0.42
$mret_t$	Coefficient	0.019	–0.027	0.013	–0.001	–0.017	–0.009	0.012	–0.029	–0.007	0.002
	SE	0.018	0.018	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.014
	p-value	0.28	0.13	0.38	0.96	0.25	0.56	0.41	0.06	0.66	0.90
		Lagged market return									
$mturn_t$	Coefficient	0.819	0.433	–0.065	0.042	0.220	–0.214	–0.172	–0.002	0.149	–0.118
	SE	0.133	0.136	0.128	0.123	0.121	0.122	0.122	0.122	0.121	0.120
	p-value	0.00	0.00	0.61	0.74	0.07	0.08	0.16	0.99	0.22	0.33
$mret_t$	Coefficient	–0.024	–0.002	0.045	–0.028	0.125	–0.070	0.024	–0.028	0.050	0.001
	SE	0.050	0.050	0.047	0.046	0.045	0.045	0.045	0.045	0.045	0.045
	p-value	0.63	0.97	0.34	0.55	0.01	0.13	0.60	0.54	0.27	0.99

		Exogenous variables						
		Constant	$msig_t$	$msig_{t-1}$	$msig_{t-2}$	$disp_t$	$disp_{t-1}$	$disp_{t-2}$
$mturn_t$	Coefficient	–0.080	1.712	–1.033	–0.762	5.024	–1.583	–2.440
	SE	0.024	0.296	0.338	0.339	0.416	0.497	0.470
	p-value	0.00	0.00	0.00	0.02	0.00	0.00	0.00
$mret_t$	Coefficient	0.005	–0.999	0.069	0.602	0.946	–0.463	–0.264
	SE	0.009	0.110	0.125	0.126	0.154	0.185	0.174
	p-value	0.60	0.00	0.58	0.00	0.00	0.01	0.13

This table reports coefficient (coefficient), coefficient standard errors (SE), and t-statistic significance levels (p-value) from a VAR of detrended logged market turnover (*mturn*) and market return (*mret*), with 10 lags, for the full sample summarized in Table 1. The VAR also includes contemporaneous and two lags of the exogenous variables, market volatility (*misg*) and dispersion (*disp*), as described in Table 1.

study. We will discuss this key result in more detail in the context of impulse response functions.

Consistent with previous trading volume studies (Karpoff 1987), the association of turnover with contemporaneous volatility is large and positive, with a coefficient estimate of 1.712. The first and second lagged *misg* coefficients indicate that the volatility–volume relationship reverses sign in subsequent months. However, individual coefficients on lagged *misg* must be interpreted with caution because of well-known autocorrelation in volatility. Market returns exhibit significant second moment (i.e., GARCH) temporal dependencies causing substantial multicollinearity among the lagged *misg* observations in the VAR model. We find that the lagged *misg* coefficient estimates vary greatly with the number of lags included in model, as well as the inclusion of the other exogenous control variable, *disp*.

Dispersion also has a highly positive contemporaneous association with market turnover as shown by the concurrent *disp* coefficient of 5.024. Like volatility, the sign of the first and second lagged *disp* coefficients is negative. However, univariate analysis indicates that dispersion exhibits even more autocorrelation than volatility, and dispersion and volatility are contemporaneously correlated. We include the exogenous variables, *misg* and *disp*, to control for alternative explanations of trading activity, although their inclusion and specified lag structure does not materially change our key findings.[12] Presumably, the strong positive contemporaneous association between trading activity and both inter-temporal market price changes (*misg*) and cross-sectional variation in security price changes (*disp*) is due to the impact of information events in the market.

We also included calendar month (i.e., January through December) dummies in the market and security VARs and found that trading activity is the highest in December and January, possibly due to tax-related trading, and drops off slightly in the summer months. The high turnover rates around the turn of the year for the typical stock are less evident in value-weighted market-wide turnover, suggesting that the seasonality in trading activity is more pronounced in small market capitalization stocks. The mean individual security return is higher in January than any other month, consistent with the small-firm effect first identified by Banz (1981) and Reinganum (1983). The inclusion of calendar month dummies confirms well-established empirical regularities in the US equity market but does not impact any of our key findings. We do not include dummies in our reported model to reduce the already high number of parameter estimates.

Generally consistent with weak-form market efficiency, the *mret* dependent variable regression in Table 4 summarizes few statistically significant

[12] We examined alternative specifications for the exogenous variables *disp* and *msig*, including exclusion of one or both, different lag structures [variations in the value of L in Equation (2)], and log transformations. None of these perturbations to the base-case specification exhibited materially different results in terms of the impulse-response functions of the endogenous variables.

coefficients. For example, the first lagged *mturn* coefficient is 0.019 (standard error of 0.018). Cooper (1999); Lee and Swaminathan (2000); and Gervais, Kaniel, and Mingelgrin (2001), among others, found that past volume can be used to predict returns; however, those studies are for individual securities. The only market return prediction anomaly in Table 4 is a positive and significant autocorrelation at the 5th lagged *mret* (coefficient estimate of 0.125), offset by an almost significant negative autocorrelation coefficient at the 6th lagged *mret*. While statistically significant, this result is likely due to a few coincidental large market return observations that are separated by five months. For example, the October 1987 market crash happened to be followed by another negative return in March 1988.

3.2 Market impulse response functions

As explained in the methodology section, individual VAR coefficient estimates do not capture the full impact of an exogenous variable observation. Impulse response functions use all the VAR coefficient estimates to trace the impact of a residual shock that is one standard deviation from zero. Figure 2 contains the four possible impulse-response function graphs using the bivariate VAR estimation shown in Table 4. Panels A and B plot the response of *mturn* to a one standard deviation shock in *mturn* and *mret*, respectively, along with two standard-error confidence bands. Because of the log transformation, the vertical axis in Panels A and B measures the percentage increase in turnover relative to the nonshock turnover level. For example, in Panel A, the first period impulse-response indicates that a one standard deviation shock to market turnover results in approximately a 3.0% increase in the next month's turnover relative to trend. Panel A verifies the serial dependence of turnover, in that the positive impact of a turnover shock persists for about five months. Note that the impulse response function is forced to zero over time because turnover is detrended. Impulse response functions on raw log turnover (unreported) show declining but generally positive values for all 24 months.

Figure 2 Panel B indicates a large and persistent positive response in turnover to a market return shock; the first key finding of this study. We interpret this result as an evidence that market returns impact investor confidence and subsequent trading activity. The figure shows that a one standard deviation market return shock results in an 8.6% increase in the next month's turnover and a 7.3% increase in the following month's turnover. The accumulated response over the first six months is a 30% increase in turnover compared to average levels, an economically as well as statistically significant event. As a measure of economic significance, consider the descriptive statistics in Table 1 which give the average monthly market return as about 1.0%, with a standard deviation of

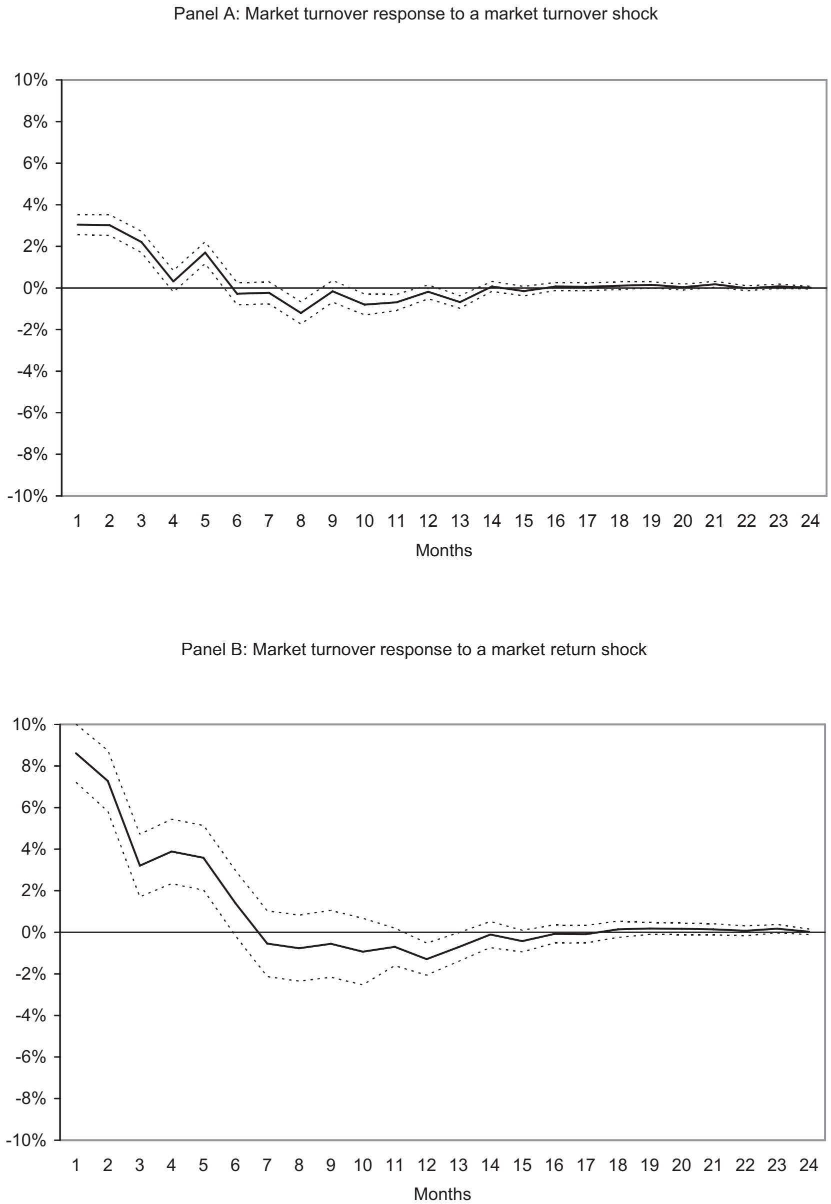
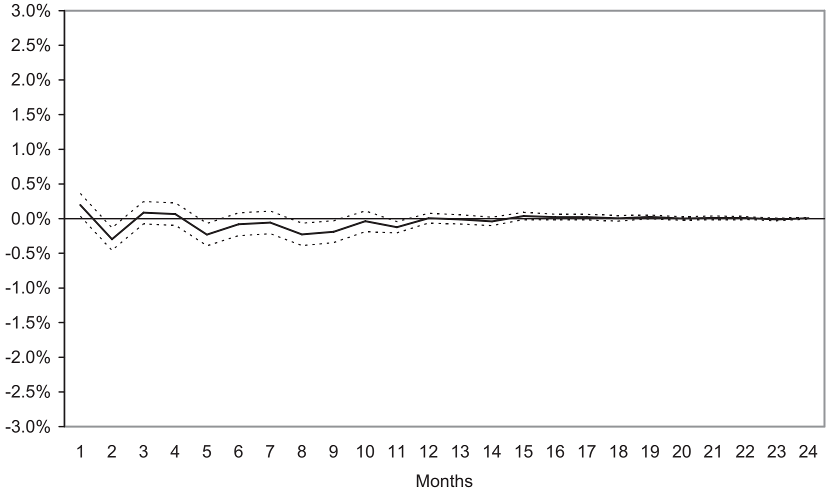


Figure 2
Market impulse response functions with two-standard error bands
(Panel A) Market turnover response to a market turnover shock. (Panel B) Market turnover response to a market return shock. (Panel C) Market return response to a market turnover shock. (Panel D) Market return response to a market return shock.

Panel C: Market return response to a market turnover shock



Panel D: Market return response to a market return shock

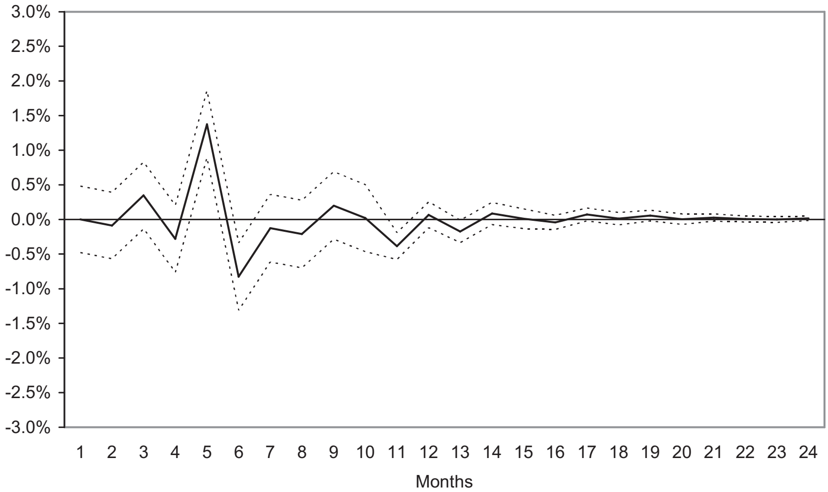


Figure 2
Continued

about 4.0%. Compare a relatively high market return in one month of say 7.0% (1.5 standard deviations above the mean) with a relatively low market return of negative 5.0% (1.5 SD below the mean). The impulse response function suggests that a high return of 7.0% compared to negative 5.0% adds the equivalent of an extra month of trading volume (30% times 3 standard deviations) over the next six months.

Interestingly, the shape of the true impulse response function may not be monotonically declining. In unreported sensitively analysis, we replicate the market portion of this study using weekly rather than monthly observations, following the trading volume research of Lo and Wang (2000). VAR estimations using weekly market turnover and return observations over the full sample period suggest that the impulse response to a market return shock increases for a couple of weeks before beginning a gradual decline that lasts for about twenty weeks. While the weekly finding for market-wide data is interesting, we focus on monthly observations under the perspective that changes in investor overconfidence should be evident over long time periods.

An unreported impulse response function similar to Panel B using raw (nondetrended) data declines but remains persistently positive over all 24 months. As suggested in the methodology section, an interpretation of this fact favorable to the overconfidence hypothesis is that market returns impact trading activity over a long enough time frame that the impact is identified as a trend and removed by the HP algorithm. Strictly predictive but less sophisticated detrending methodologies, for example a moving average of the prior 60 months of turnover, yield results that are similar to HP detrended data we report. The process used to detrend turnover does not resolve the question of whether the long-term trends are due to a concentration of positive monthly returns or a result of unrelated events that might impact volume.

For completeness, Figure 2 Panels C and D plot the response of *mret* to a one standard deviation shock to *mturn* and *mret*, respectively, along with a two standard error confidence bands. The vertical axis in Panels C and D measures the difference in market return compared to the average return. For example, in Panel C, the first period impulse-response indicates that a one standard deviation shock to market turnover results in a 20 basis point increase in the next month's return. The two standard error bands suggest that this result is weakly significant, but in general the impulse response function coefficients in Panel C are not significantly different from zero. The market return to market return impulse response function in Panel D is also unremarkable and consistent with weak-from market efficiency, with the exception of lagged months 5 and 6, based on the anomalous coefficients in the market VAR estimation in Table 4.

4. Security VAR Estimation and Test Results

4.1 Security VAR

As reported in the previous section, we find strong empirical evidence for the overconfidence hypothesis in which market-wide trading activity is positively related to past market returns. However, this finding is also consistent with the disposition effect. Investors may be trading more after high market returns because of an increased confidence in their trading skills or simply because they enjoy realizing paper gains on individual securities. Alternatively, investors may be trading less after negative market returns, because the loss reduces their confidence in the value of trading or simply because they do not want to sell individual securities and acknowledge the loss.

One distinguishing characteristic of the two alternative explanations is that the Gervais and Odean (2001) overconfidence hypothesis related to trading in general, whereas the Shefrin and Statman (1985) disposition effect had generally been understood to describe investor attitudes toward specific securities in their portfolio. In this section, we attempt to disentangle the two theories by examining the trading activity of individual stocks. If overconfidence plays a role in explaining volume in addition to the disposition effect, we should find positive coefficients in regressions of security turnover on lagged market returns even when lagged returns on that stock are also included. A definitive disentanglement of the overconfidence and disposition hypothesis may prove difficult. For example, one could argue that when investors sell other securities for the disposition effect, they raise cash that can then be used to purchase the security in question, thus increasing its volume. Despite this limitation in interpretation, an examination of individual security volume will at least ensure that the market-wide turnover patterns we have documented are not a simple summation of direct disposition effect evidence in individual security VAR.

As described in Table 2, we use monthly turnover and returns on 1878 NYSE/AMEX nonfund common stocks that have at least 120 months of contiguous time-series data. We estimate the trivariate VAR in Equation (3) for each security and report the mean coefficient estimates in Table 3. The security VAR model has three endogenous variables, *turn*, *ret*, and *mret*, and one exogenous variable, *sig*. Detrended log security turnover, *turn*, and security return, *ret*, parallel the endogenous market variables in the bivariate market VAR, and the endogenous variable and security volatility, *sig*, parallels market volatility. Although the SIC for optimal model selection varies across firms, we abide by the $K = 10$ and $L = 2$ lag specification used in the market VAR for all individual firm VAR to ensure consistency in the summary results reported in Table 3. We also find that the specification of $K = 10$ and $L = 2$ yields the minimum average SIC across all securities.

The voluminous output associated with 1878 separate security VAR estimations requires a compact way to communicate the results. We show cross-sectional mean coefficient values in Table 3, along with the *p*-value of a two sided *t*-test that each average coefficient value is equal to zero. As explained in the methodology section, the significance tests are based on bootstrapped standard errors for each mean coefficient. Although the security VAR is trivariate in endogenous variables, we do not report the market return-dependent variable regression or the exogenous variable coefficients. As one would expect, the unreported coefficients indicate that nothing on a security-specific basis predicts market returns. As with market turnover, the unreported exogenous variable coefficients indicate that security turnover is positively and significantly correlated with contemporaneous security volatility, consistent the volume–volatility relationship documented in prior volume research.

The critical results in Table 3 relate the dependence of security turnover, *turn*, on lagged security and market returns. None of the lagged security return, *ret*, mean coefficients are individually significant but are notable in that all 10 lags have a positive sign. For example, first-lagged *ret* mean coefficient is 0.171 and has a *p*-value of (0.33). On the contrary, the first-lagged *mret* mean coefficient is 0.990 and highly significant, as are the second- and third-lagged mean coefficients. Thus, not only does the impact of past market returns on a typical security's trading activity survive the inclusion of lagged security returns in the same regression but also appears that the lagged market return impact is actually larger (compare 0.990 to 0.171). Note that lagged observations of security turnover are also included in each security VAR, so the estimated impact of market returns cannot be dismissed based on the notion that they are a proxy for turnover autocorrelation. We focus further on our second key finding that security turnover depends on both lagged security and market returns in the context of impulse response functions that follow.

4.2 Security impulse response functions

Figure 3 Panel A shows the security turnover response to a one standard deviation shock in security return. Despite the use of detrended security turnover, the response is reliably positive over many months, consistent with the prediction of the disposition effect. The mean value of the first-lagged security return coefficient of 2.29% is statistically significant at the 0.02 level (shown later in the top row of Table 5). The relatively large standard error bands in Figure 3 Panel A suggest that although the mean coefficient is positive, there is considerable variation in the impulse response functions of the 1878 individual security VAR estimations.

Figure 3 Panel B shows the average security turnover response to a one standard deviation shock in market return. Although the duration of the market return shock appears shorter (in months) compared with the

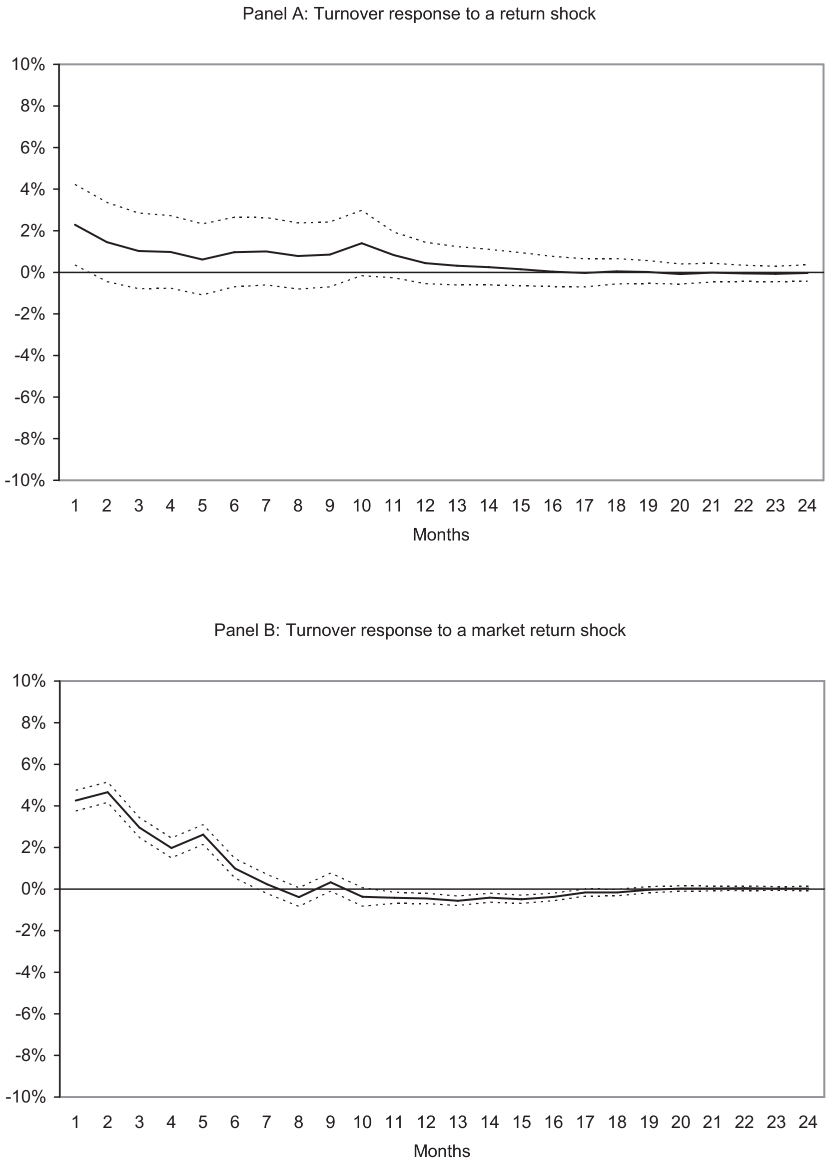


Figure 3
Security average impulse response functions with two-standard error bands
(Panel A) Turnover response to a return shock. (Panel B) Turnover response to a market return shock. (Panel C) Return response to a turnover shock. (Panel D) Return response to a return shock.

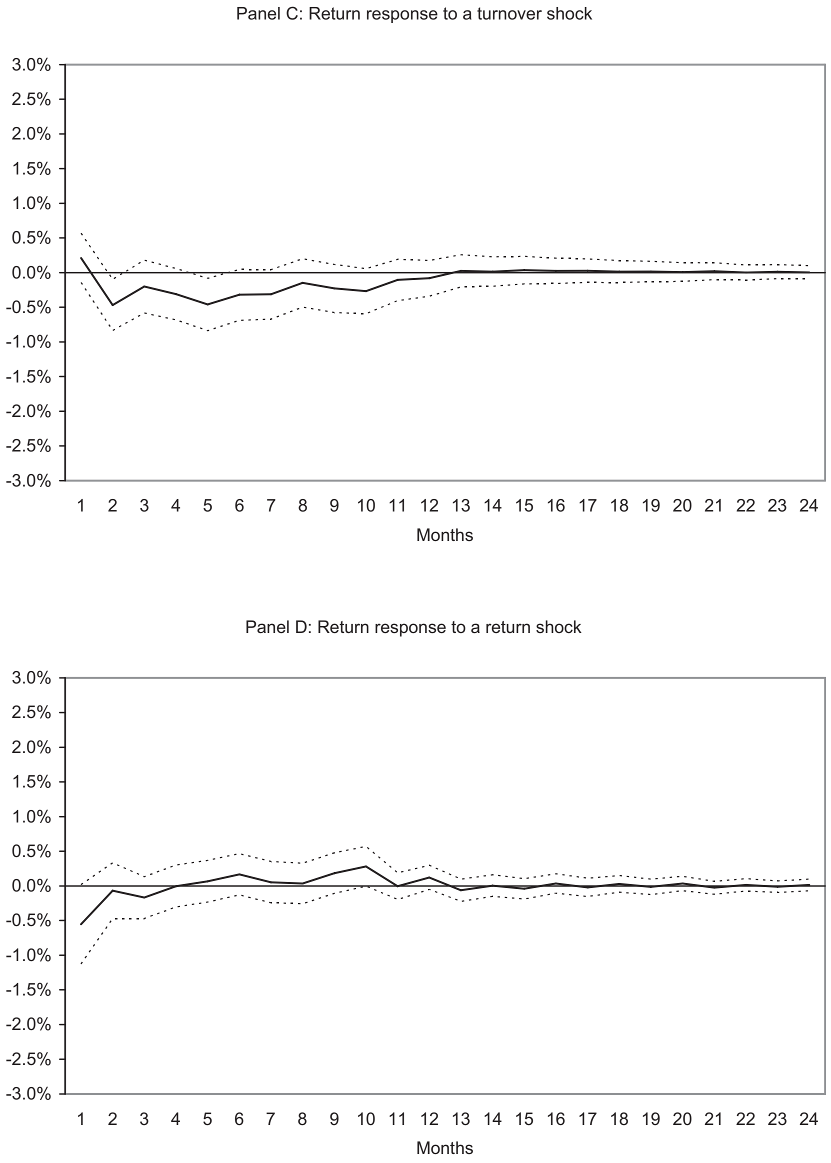


Figure 3
Continued

Table 5
Security turnover impulse response function: security return shock

	Lags	1	2	3	4	5	6
Full sample	Mean coefficient	2.29%	1.45%	1.03%	0.96%	0.62%	0.99%
	p-value	0.02	0.13	0.26	0.27	0.47	0.24
All stocks							
1963–1972	Mean coefficient	1.60%	0.50%	0.02%	0.22%	0.68%	0.48%
	p-value	0.02	0.44	0.98	0.71	0.25	0.41
1973–1982	Mean coefficient	4.16%	3.38%	2.35%	1.20%	0.69%	1.44%
	p-value	0.00	0.02	0.08	0.35	0.58	0.24
1983–1992	Mean coefficient	1.41%	0.41%	0.42%	1.01%	0.28%	0.36%
	p-value	0.18	0.69	0.67	0.29	0.76	0.70
1993–2002	Mean coefficient	–0.13%	–0.17%	–0.09%	0.48%	0.55%	0.75%
	p-value	0.88	0.85	0.91	0.54	0.48	0.32
Large-cap stocks							
1963–1972	Mean coefficient	–2.71%	–2.64%	–2.09%	–1.02%	–0.74%	–1.09%
	p-value	0.00	0.00	0.00	0.06	0.17	0.04
1973–1982	Mean coefficient	2.11%	1.93%	1.90%	0.32%	0.07%	0.74%
	p-value	0.14	0.17	0.16	0.81	0.96	0.55
1983–1992	Mean coefficient	0.39%	–0.28%	–0.59%	0.30%	–0.20%	0.01%
	p-value	0.70	0.78	0.54	0.75	0.82	1.00
1993–2002	Mean coefficient	–1.34%	–0.86%	–0.41%	–0.06%	0.10%	–0.09%
	p-value	0.13	0.33	0.62	0.94	0.89	0.91
Mid-cap stocks							
1963–1972	Mean coefficient	3.12%	1.56%	0.23%	0.42%	0.72%	0.83%
	p-value	0.00	0.01	0.69	0.45	0.19	0.11
1973–1982	Mean coefficient	4.48%	3.81%	2.32%	1.70%	1.02%	2.12%
	p-value	0.00	0.01	0.09	0.19	0.42	0.09
1983–1992	Mean coefficient	0.95%	0.10%	–0.08%	0.91%	0.03%	–0.38%
	p-value	0.37	0.92	0.93	0.34	0.97	0.68
1993–2002	Mean coefficient	–1.04%	–0.67%	–0.68%	0.00%	0.01%	0.63%
	p-value	0.23	0.43	0.40	1.00	0.99	0.40
Small-cap stocks							
1963–1972	Mean coefficient	4.17%	2.43%	1.78%	1.19%	1.98%	1.61%
	p-value	0.00	0.00	0.01	0.07	0.00	0.01
1973–1982	Mean coefficient	7.71%	5.27%	3.42%	1.65%	1.08%	0.92%
	p-value	0.00	0.00	0.01	0.20	0.39	0.46
1983–1992	Mean coefficient	2.70%	1.27%	1.73%	1.68%	0.92%	1.35%
	p-value	0.01	0.22	0.08	0.08	0.32	0.14
1993–2002	Mean coefficient	2.93%	1.55%	1.33%	1.97%	2.02%	1.97%
	p-value	0.00	0.07	0.10	0.01	0.01	0.01

This table reports mean impulse response functions coefficients (mean coefficient) for a security turnover response to a security return shock. The full-sample base case in the first row is shown in Figure 3a, based on the vector autoregressions (VAR) estimation in Table 3. The other rows provide sensitivity analysis by time period for all stocks and then by time period for large-cap (top size quintile), mid-cap (second size quintile), and small-cap (bottom three size quintiles) stocks. The significance levels (*p*-value) of the mean coefficient estimates are based on bootstrapped standard errors.

security return shock, the market return shock has a relatively larger impact on security turnover. The impact is also more uniform across securities as indicated by the relatively narrow standard error bands. The first-lagged market return mean coefficient of 4.25% is statistically significant at less than the 0.01 level (shown later in the top row of Table 6). The impact of the market return shock remains statistically significant for the first six months. In aggregate, the security VAR

Table 6
Security turnover impulse response function: market return shock

		1	2	3	4	5	6
Full sample	Mean coefficient	4.25%	4.65%	2.96%	1.97%	2.62%	0.99%
	p-value	0.00	0.00	0.00	0.00	0.00	0.00
All stocks							
1963–1972	Mean coefficient	7.44%	8.15%	3.68%	4.38%	3.51%	4.02%
	p-value	0.00	0.00	0.00	0.00	0.00	0.00
1973–1982	Mean coefficient	5.18%	5.87%	3.01%	3.22%	3.70%	1.00%
	p-value	0.00	0.00	0.00	0.00	0.00	0.08
1983–1992	Mean coefficient	3.81%	3.34%	2.53%	–0.25%	1.25%	0.27%
	p-value	0.00	0.00	0.00	0.12	0.00	0.10
1993–2002	Mean coefficient	2.39%	1.95%	2.34%	0.37%	1.63%	–0.27%
	p-value	0.00	0.00	0.00	0.08	0.00	0.20
Large-cap stocks							
1963–1972	Mean coefficient	5.94%	6.39%	2.41%	2.92%	2.61%	2.89%
	p-value	0.00	0.00	0.00	0.00	0.00	0.00
1973–1982	Mean coefficient	4.35%	4.00%	2.32%	3.31%	2.91%	0.18%
	p-value	0.00	0.00	0.00	0.00	0.00	0.61
1983–1992	Mean coefficient	2.31%	2.30%	1.72%	–1.10%	1.19%	0.34%
	p-value	0.00	0.00	0.00	0.00	0.00	0.17
1993–2002	Mean coefficient	1.03%	1.00%	1.56%	0.20%	1.20%	0.14%
	p-value	0.00	0.00	0.00	0.35	0.00	0.51
Mid-cap stocks							
1963–1972	Mean coefficient	7.16%	8.17%	3.72%	4.66%	3.57%	3.73%
	p-value	0.00	0.00	0.00	0.00	0.00	0.00
1973–1982	Mean coefficient	5.64%	6.48%	3.53%	2.90%	3.89%	0.82%
	p-value	0.00	0.00	0.00	0.00	0.00	0.02
1983–1992	Mean coefficient	3.55%	3.65%	2.16%	0.02%	1.47%	0.82%
	p-value	0.00	0.00	0.00	0.94	0.00	0.00
1993–2002	Mean coefficient	2.50%	2.21%	2.47%	0.46%	1.83%	–0.16%
	p-value	0.00	0.00	0.00	0.03	0.00	0.45
Small-cap stocks							
1963–1972	Mean coefficient	9.10%	9.77%	4.80%	5.46%	4.28%	5.34%
	p-value	0.00	0.00	0.00	0.00	0.00	0.00
1973–1982	Mean coefficient	5.62%	8.17%	2.99%	3.98%	4.90%	3.37%
	p-value	0.00	0.00	0.00	0.00	0.00	0.00
1983–1992	Mean coefficient	5.30%	3.88%	3.56%	0.17%	1.08%	–0.32%
	p-value	0.00	0.00	0.00	0.51	0.00	0.21
1993–2002	Mean coefficient	3.84%	2.66%	3.06%	0.41%	1.82%	–0.98%
	p-value	0.00	0.00	0.00	0.05	0.00	0.00

This table reports mean impulse response functions coefficients (mean coefficient) for a security turnover response to a market return shock. The full-sample base case in the first row is shown in Figure 3b, based on the vector autoregressions (VAR) estimation in Table 3. The other rows provide sensitivity analysis by time-period for all stocks and then by time-period for large-cap (top size quintile), mid-cap (second size quintile), and small-cap (bottom three size quintiles) stocks. The significance levels (*p*-value) of the mean coefficient estimates are based on bootstrapped standard errors.

estimations and associated impulse response functions indicate that both past security and past market wide returns are important predictors of trading activity for the average security. We interpret the volume impact of past security returns as confirmation of the disposition effect in securities. However, the second key empirical result of this article is the positive volume impact of past market returns on security volume. Our interpretation is that market return-induced investor overconfidence positively impacts realized trading volume even after accounting for the impact of security return.

For completeness, we include an impulse response function plots of security turnover and return shocks on security return in Figure 3 Panels C and D. In Figure 3 Panel D, the first-lagged coefficient is negative, although only weakly significant. Subsequent months turn positive although without statistical significance. The results are similar to the well-established cross-sectional finding that stocks exhibit positive momentum in returns up to a year, except for the first month which often exhibits negative auto-correlation perhaps because of bid-ask bounce in price quotations.

4.3 Sub-period and firm size sensitively analysis

We next perform a subperiod analysis by estimating the security VAR in Equation (3) using data samples from four 120-month (decade long) subperiods that span the full 1963–2002 sample period. The last five months of 1962 were not included to obtain equal subperiod sample sizes. Our sensitivity analysis focuses on the security turnover impulse responses to both security and market returns, as summarized in Tables 5 and 6, respectively.

Table 5 presents the subsample results for the first six lags of the security turnover impulse response function to a security return shock. The full-sample results in the top row of Table 5 correspond to Figure 3 Panel A, which we associate with the disposition effect. Most of the subperiod mean coefficient estimates are positive, with the strongest evidence in the second subperiod, 1973–1982, where the first two lags are statistically significant. The generally positive coefficient values are not evident in the latest subperiod, 1993–2002, where there is no evidence of disposition effect trading.

Table 5 breaks the subperiod analysis further into three size-based samples. Securities naturally migrate between size rankings over time based on realized returns, one of the endogenous variables. Consequently, to avoid unintended biases, we measure each securities market capitalization at the beginning of each subperiod and assign the entire time series to a size quintile. We label the sample of largest quintile securities as large-cap stocks, and the second quintile as mid-cap stocks. The requirement of 120 months of contiguous time-series data (i.e., all possible subperiod observations) excludes a relatively larger proportion of smaller capitalization stocks, so all three of the smaller size quintiles are grouped together in the sample labeled small-cap stocks. This procedure results in approximately equal sample sizes within each size category. For example, the early 1963 to 1972 subperiod sample includes 313 large-cap security VAR estimations, 319 mid-caps, and 337 small-caps. Approximately equal groupings allow for a direct comparison of mean coefficient standard errors, which depend in part on sample size. The impulse response functions in Table 5 are clearly stronger for small-cap securities, with positive value and statistical significance for most of the individual coefficient estimates, even in the most recent subperiod. The mid-cap results are more mixed, and there is little evidence of the disposition effect in the large-cap stocks. In the first subperiod, some of the large-cap coefficients are significantly negative, explaining the weak results in the first subperiod for all stocks.

Table 6 is similar to Table 5, but with security turnover impulse response function results for lagged market returns instead of lagged security returns. The first row of Table 6 corresponds to Figure 3 Panel B. The results in the rest of Table 6 are noteworthy in terms of consistency of the findings that market returns positively impact security turnover, which we interpret as evidence of investor overconfidence. Almost all of the mean coefficients in Table 6 are positive and highly significant including all subperiods and size groupings. The magnitude of the mean values suggest that overconfidence-based trading is more pronounced for smaller capitalization stocks. There also appears to be an almost monotonic decline in mean coefficient magnitudes over time, with the largest values in the first subperiod and the smallest values in last subperiod. Consequently, the weakest results are in the large-cap sample of the latest 1993–2002 subperiod, where the first-lagged coefficient value is only 1.03%, and some of the later lags are not statistically significant.

Tables 5 and 6 collectively produce our third key empirical finding; the impact of both disposition and overconfidence trading is more pronounced in small capitalization stocks and appears to be declining over time. Both the subperiod and the size regularities may be because of the impact of retail level investors, who own a higher proportion of smaller capitalization stocks and whose share of total trading volume has declined in recent years [see Gompers and Metrick (2001), among others].

4.4 Tests of alternative explanations

Although we interpret the strong positive relationship between turnover and prior market and security returns found in Tables 5 and 6 as overconfidence and disposition trading, respectively, the exact empirical distinctions between these two theories are somewhat unclear. In addition, given the generally unspecific nature of the empirical implications of overconfidence theory (e.g., no specified time frame), one could probably construct alternative explanations for the relationships we document. In this subsection, we extrapolate from the models presented in the overconfidence theory literature as well as the disposition effect in an effort to find sharper empirical implications.

The turnover tests in this article are motivated by stated implications of the investor overconfidence theory in Odean (1998a) and Gervais and Odean (2001). The Gervais and Odean investor overconfidence model does not explicitly predict any impact on share prices. Alternatively, a central theme in the DHS overconfidence model is that the distinction between private and public signals reconciles short-term overreaction (positive autocorrelation in returns) and longer-term correction (negative autocorrelation in returns) into one theory of security price formation. DHS do not explicitly model trading volume dynamics, although extending their model suggests that private signals generate higher contemporaneous volume than public signals. For example, the public announcement that a firm has accounting irregularities should cause a large price drop, although little volume if investors agree on the informational content of the announcement. On the contrary, private signals lead to heterogeneous beliefs about security value and thus high trading volume. Finally, some authors, for example, Grinblatt and Han (2005), suggest that disposition motivated trading will lead to a delay in price movements as investors are behaviorally motivated to sell securities with recent price gains and not sell securities with recent losses.

One natural extension of the return and turnover time-series analysis in this article is an examination of signed volume; volume in an up (concurrent positive return) market for a security in contrast to volume in down (concurrent negative return) market for a security. The signing of volume in the context of the VAR empirical methodologies leads to some possible additional tests. Specifically, we re-examine the results in Table 5 by estimating the signed volume response to a security return shock. In addition, we test the predictability of returns based on signed volume but find little to report.

For our additional test, we replace security turnover with signed security turnover and re-estimate the impulse response functions associated with a security return shock, in a manner similar to Table 5. For references purposes, the first row of Table 7 corresponds to the first row of Table 5, which gives the mean (across 1878 securities) *unsigned* turnover impulse response coefficients to a one standard deviation shock in security return. To review, a one standard deviation shock to the security return residual results in a positive mean turnover coefficient in the first month, followed by positive coefficients in subsequent months, although only the first month is statistically significant. The second (third) row of Table 7 reports the mean coefficient response of positive-(negative-) signed turnover to a security return shock. The results in Table 7 indicate that a positive security return shock leads to more volume associated with positive returns than volume associated with negative returns. In addition, statistical tests (unreported) reject the null hypothesis that the mean coefficients for the positive-signed volume and negative-signed volume are equal for the first two-lagged months. Depending on one's priors about the relevant time frame, these results can be interpreted as being consistent with either the disposition effect or DHS overconfidence.

Table 7
Signed turnover impulse response function: return shock

Lags	1	2	3	4	5	6
Turnover response to lagged return						
Mean coefficient	2.29%	1.45%	1.03%	0.96%	0.62%	0.99%
p-value	0.02	0.13	0.26	0.27	0.47	0.24
Positive-signed turnover response to lagged return						
Mean coefficient	2.68%	1.48%	0.90%	0.56%	0.36%	0.68%
p-value	0.00	0.01	0.09	0.25	0.45	0.13
Negative-signed turnover response to lagged return						
Mean coefficient	0.70%	0.80%	0.64%	0.64%	0.47%	0.46%
p-value	0.22	0.13	0.18	0.15	0.28	0.27

This table reports mean impulse response function coefficients (mean coefficient) for a security turnover response to a security return shock across the 1878 vector autoregressions (VAR) estimations. The first row is the security turnover response to security return, also shown in the first line of Table 5. The second (third) row is for the security turnover response that is associated with a contemporaneous positive (negative) security return. The significance levels (*p*-value) of the mean coefficient estimates are based on bootstrapped standard errors.

In an additional attempt to distinguish between the various versions of investor overconfidence and the disposition effect, we conducted several tests of security return prediction using lagged signed volume. To review, security return prediction using *unsigned* volume in Table 3 was generally consistent with weak-form market efficiency in that none of the lagged turnover coefficients is statistically significant. We also conducted tests (unreported) of security return response to signed volume and found only weak evidence of the returns reversal effects predicted in DHS. However, we note that the prediction of security returns based on prior return and volume data has been a focus of financial economics for decades in numerous tests of market efficiency and equilibrium pricing models. Typically, security return prediction is based on powerful cross-sectional tests that sort securities into factor mimicking portfolios. For example, the Fama and French (1993) size and value factors and the Jegadeesh and Titman (1993) momentum factors are statistically significant predictors of the cross-sectional variation in security returns. In contrast, the time-series nature of our methodology is not as powerful, which may explain to our inability to confirm DHS overconfidence and by contrast makes our findings on turnover even more striking.

5. Conclusion

An old *Wall Street* adage warns investors not to "confuse brains with a bull market." More recently, formalized theories of investor overconfidence have called for an empirical analysis of time-series patterns in both market-wide and security-specific trading activity. The proposition that some investors become overconfident about the value of active trading after positive portfolio returns, and less overconfident after negative portfolio returns, can be examined by multivariate (turnover and return) time-series analysis using VAR and associated impulse response functions.

In our first key finding, we document a material and statistically significant tendency for market-wide turnover to increase in the months following high market returns, after accounting for contemporaneous and lagged volatility associations. However, the market-wide results we document can also be interpreted as a manifestation of previously documented disposition effect trading. We extend the VAR and impulse response function specifications to time series on individual stocks in an attempt to distinguish between the two theories. In support of the overconfidence hypothesis, our second key finding is that security turnover levels are responsive to past market returns even when past security returns are included in the model. Our third key finding is that the phenomena we interpret as overconfidence and disposition effect trading are both more pronounced in small-cap stocks and in earlier periods where individual investors hold a greater proportion of shares.

Our finding of a lead-lag relationship between market returns and turnover confirms the conventional wisdom of market making professionals as well as formal theories of investor overconfidence. Market makers (i.e., specialists and brokers) typically celebrate market-wide gains, because they portend increases in trading activity and thus market-making revenues. The economic significance of high market returns on subsequent volume can be substantial. For example, the estimated VAR indicates that a high market return of say 7% compared with negative 5% in a given month leads to an "extra month" of trading volume spread out over the next six months. These results are for detrended turnover; the long-run economic impact on raw share turnover may be much greater.

Although our analysis was motivated by theories of investor overconfidence, the finding that trading activity is dependent on past returns is an important empirical fact that should be acknowledged by theorists and empirical researchers, independent of one's interpretation. The contemporaneous association between volume and return volatility has been understood in financial economics literature for many years. More recently, the predictability of security returns based on lagged volume has been documented as a possible violation of strict market efficiency. Our research adds the new finding that trading volume is dependent on past returns over many months. We interpret aspects of this finding as confirmation of the overconfidence hypothesis that motivated the study, although precise distinctions between the overconfidence trading and the disposition effect are somewhat subjective. Our findings suggest that further theoretical development and empirical research on investor types (i.e., individual versus institutional) may yield finer distinctions and testable implications.

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