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Individual Investor Trading and Stock Returns

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ABSTRACT

This paper investigates the dynamic relation between net individual investor trading and short-horizon returns for a large cross-section of NYSE stocks. The evidence indicates that individuals tend to buy stocks following declines in the previous month and sell following price increases. We document positive excess returns in the month following intense buying by individuals and negative excess returns after individuals sell, which we show is distinct from the previously shown past return or volume effects. The patterns we document are consistent with the notion that risk-averse individuals provide liquidity to meet institutional demand for immediacy.

FOR A VARIETY OF REASONS, financial economists tend to view individuals and institutions differently. In particular, while institutions are viewed as informed investors, individuals are believed to have psychological biases and are often thought of as the proverbial noise traders in the sense of Kyle (1985) or Black (1986). One of the questions of interest to researchers in finance is how the behavior of different investor clienteles or their interaction in the market affects returns. In this paper we focus on the interaction between individual investors and stock returns.

Specifically, we examine the short-horizon dynamic relation between the buying and selling by individuals and both previous and subsequent returns using a unique data set provided to us by the NYSE. The data set was constructed from the NYSE's Consolidated Equity Audit Trail Data (CAUD) files that contain detailed information on all orders that execute on the exchange. For each stock on each day we have the aggregated volume of executed buy and sell orders of individuals. This information enables us to create a measure of net individual investor trading.

We examine the extent to which intense net buying or selling by individuals in a stock is related to the stock's past returns and the extent to which such intense net trading by individuals predicts future returns. Consistent with earlier

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studies, we find that individuals tend to buy after prices decrease and sell after prices increase. The mean market-adjusted return in the 20 days prior to a week of intense individual selling is 3.15%, while that prior to a week of intense individual buying is −2.47%. More interestingly, we find that the trades of individuals can be used to forecast future returns. Specifically, we find that stocks experience statistically significant excess returns of 0.80% in the 20 days following a week of intense buying by individuals, and −0.33% following a week of intense individual selling.

Although this paper considers several potential explanations for this finding, the one that best explains our findings is that the contrarian tendency of individuals leads them to act as liquidity providers to institutions that require immediacy. Following Stoll (1978), Grossman and Miller (1988), and Campbell, Grossman, and Wang (1993), one can argue that institutional investors who require immediacy must offer price concessions to induce risk-averse individuals to take the other side of their trades, and that this results, in turn, in subsequent return reversals. This return dynamic is consistent with the return patterns we observe during and after weeks of intense buying or selling by individuals. We also find that the magnitude of the excess returns is greater in less liquid stocks, which is consistent with this explanation.

Since individuals tend to buy after prices decrease and sell after prices increase, their profits may also relate to the short-horizon return reversals first observed by Jegadeesh (1990) and Lehmann (1990). In principle, these reversals can be due to either illiquidity or investor overreaction.[1] If the return reversals are due to overreaction, then it may be the case that the short-horizon excess return observed after intense net individual trading simply reflects the fact that individuals buy after prices decrease and sell after they increase. If this is the case, then we might expect the predictability result we document to diminish after controlling for past returns. Alternatively, if return reversals arise because of illiquidity, and if the aggregate net trading of individuals provides a better measure of institutions' demand for immediacy than past price changes, then one might expect intense net individual trades to be a better predictor of short-horizon returns than past returns.

In addition to past returns, our analysis controls for trading volume in light of evidence that volume is related to short-horizon returns (e.g., Conrad, Hameed, and Niden (1994), Gervais, Kaniel, and Mingelgrin (2001), and Llorente et al. (2002)). Volume can arise from shocks to investor hedging needs, private information, or trader interest in a given stock. Since such shocks can give rise to demand by individuals, it is possible that volume and net individual investor trading contain the same information about future returns.

[1] Jegadeesh (1990) and Lehmann (1990) both discuss the possibility of overreaction. Lehmann (1990) also suggests that frictions in liquidity provision may explain the weekly reversals and Jegadeesh and Titman (1995), who examine the relation between return reversals and bid-ask spreads, provide evidence that is consistent with a liquidity explanation for daily reversals. More recently, Subrahmanyam (2005) finds no relation between past trade imbalances signed using the Lee and Ready (1991) algorithm and future returns, which is inconsistent with the liquidity explanation in a theoretical model he develops to distinguish between illiquidity and overreaction.

To evaluate these different possibilities, we examine the returns of portfolios constructed from independent sorts on net individual trading, volume, and returns. In a double-sort on net individual trading and returns we find a relation between net individual trading and future returns but no evidence of an independent past return effect. Sorting on net individual trading and volume shows that both variables predict returns but they seem to contain different information. We also run multivariate regressions of weekly returns on past returns, volume, and net individual trading. The results of these regressions indicate that trading by individuals is a powerful predictor of future returns that is not subsumed by either past returns or past volume. Correcting for bid-ask bounce and nonsynchronous trading causes past returns to lose predictive power in all but small stocks; net individual trading remains a significant predictor.

Finally, we look at the question of whether the actions of individuals are "systematic" in the sense that they affect all stocks at the same time. We conduct a principal components analysis of net individual trading but do not find strong evidence of correlated actions of individuals across stocks: The first principal component of this variable explains only 1.70% of the variance over and above a simulated benchmark created from independent data.

Our paper is part of a growing literature that examines the dynamic relation between individual investor trading and returns.[2] The evidence on this relationship (especially the direction of returns following individual trading) seems to differ depending on three dimensions that distinguish the different studies: (i) the horizon of the dynamic relation (a shorter horizon of days and weeks versus a longer horizon of several months to a couple of years), (ii) country (individual investors play different roles in the financial markets of different countries), and (iii) the nature of the data and whether individual investor trading is actually observed or has to be inferred. We believe that the evidence from different countries and different horizons can be reconciled. Accordingly, we devote Section VII to a thorough discussion of the literature and how our results relate to other findings.

The rest of the paper is organized as follows. The next section describes the sample and the unique data set we use. Section II presents analysis of the dynamic relation between net individual trading and returns. The investigation of short-horizon return predictability and its relation to net individual trading is carried out in Section III. Sections IV, V, and VI discuss interpretations of the results and provide additional evidence on competing explanations. Section VII offers a discussion of the literature on the dynamic relation between individual trading and returns. In particular, we relate our results to the literature and seek to understand (or reconcile) seemingly conflicting evidence. Section VIII

[2] See, e.g., Odean (1998, 1999), Choe, Kho, and Stulz (1999), Barber and Odean (2000, 2001, 2005), Grinblatt and Keloharju (2000, 2001), Coval, Hirshleifer, and Sumway (2002), Goetzmann and Massa (2002), Griffin, Harris, and Topaloglu (2003), Jackson (2003), Andrade, Chang, and Seasholes (2005), Barber et al. (2005), Barber, Odean, and Zhu (2005), Hvidkjaer (2005), Richards (2005), and San (2005).

looks at the question of whether the actions of individuals are "systematic" in the sense that they affect all stocks at the same time. Section IX concludes.

I. Data and Sample

We study the trading of individuals using a data set provided to us by the New York Stock Exchange (NYSE). The data set contains four years of daily buy and sell volume of executed individual investor orders for a large cross-section of NYSE stocks. The data set was constructed from the NYSE's Consolidated Equity Audit Trail Data (CAUD) files that contain detailed information on all orders that execute on the exchange, both electronic and manual (those handled by floor brokers). One of the fields associated with each order, Account Type, specifies whether the order comes from an individual investor.

The Account Type designation of individual investor orders has its origins in the aftermath of October 1987. The NYSE introduced the Individual Investor Express Delivery Service that provides priority delivery of orders that have been identified as individual investor orders.[3] The goal of the service is to ensure that individual investors are not disadvantaged relative to professional investors in periods of extreme market conditions. In order to implement the system, new Account Type categories that identify individual investors were created in October 1988. Orders coming from individual investors are now marked as such by their brokers (Account Type is a mandatory field that a broker has to fill for each order that is sent to the NYSE).

The Account Type field is not audited by the NYSE on an order-by-order basis. It is reasonable to assume, however, that individual investor orders are marked as such because designating an order as coming from an individual investor has some advantages. At the same time, NYSE officials monitor the use of this field by brokers. Any abnormal use of the individual investor designation in the Account Type field by a brokerage firm is likely to draw attention, which prevents abuse of the system. We therefore believe that the Account Type designation of individual investor orders is fairly accurate.

Our sample contains all common domestic stocks that were traded on the NYSE any time between January 1, 2000, and December 31, 2003. The scope of our data set is large: $1.55 trillion of individual trading in 2,034 NYSE stocks over 4 years.[4] We use the CRSP database to construct the sample, and match the stocks to the NYSE data set by means of ticker symbol and CUSIP. This procedure results in a sample of 2,034 stocks. An important advantage of this

[3] The service is activated when the Dow Jones Industrial Average moves more than a certain amount up or down from the previous day's close. When the Individual Investor Express Delivery Service was introduced in October 1988, the threshold was a 25-point move from the previous day's close.

[4] In comparison, Odean (1998, 1999) uses a sample with $1.1 billion of trading by individual clients of a certain discount broker during a seven-year period (1987 to 1993). Barber and Odean (2000, 2001), Coval et al. (2002), and Kumar and Lee (2005) use a different sample with $24.3 billion of individual trading from one discount broker over 6 years (1991 to 1996). Barber and Odean (2005) study another data set (clients of a full-service retail broker) with data from 1997 to 1999 and individual investor transactions totaling $128 billion.

Table I

Summary Statistics

The sample of stocks for the study consists of all common domestic stocks that were traded on the NYSE at any time between January 1, 2000, and December 31, 2003, with records in the CRSP database. We use ticker symbol and CUSIP to match the stocks to a special data set containing daily aggregated buying and selling volume of individuals provided by the NYSE. There are 2,034 stocks in our sample. In Panel A we provide summary statistics from the CRSP database. For each stock we compute the following time-series measures: AvgCap is the average monthly market capitalization over the sample period; AvgPrc is the average daily closing price; AvgTurn is the average weekly turnover (number of shares traded divided by the number of shares outstanding); AvgVol is the average weekly dollar volume; and StdRet is the standard deviation of weekly returns. We then sort the stocks by market capitalization into 10 deciles, and form three size groups: small stocks (deciles 1, 2, 3, and 4), mid-cap stocks (deciles 5, 6, and 7), and large stocks (deciles 8, 9, and 10). The cross-sectional mean and median of these measures are presented for the entire sample and separately for the three size groups. In Panel B we compute from the NYSE data set the following time-series measures for each stock: the average weekly Dollar Volume, defined as the sum of executed buy and sell orders, the average weekly Share Volume, and the Executed Order Size of individual investors in terms of both dollars and shares.

Panel A: Summary Statistics of Sample Stocks (from CRSP)

		AvgCap (in million $)	AvgPrc (in $)	AvgTurn (in %)	AvgVol (in million $)	StdRet (in %)
All stocks	Mean	5,303.2	59.80	2.52	113.18	0.0700
	Median	943.7	21.98	2.05	21.76	0.0589
Small stocks	Mean	317.1	13.57	2.37	8.77	0.0836
	Median	308.7	11.60	1.63	4.55	0.0697
Mid-cap stocks	Mean	1,311.8	25.94	3.22	42.47	0.0667
	Median	1,230.3	23.94	2.51	31.23	0.0591
Large stocks	Mean	14,054.0	136.87	3.10	302.56	0.0598
	Median	5,018.0	37.15	2.56	159.45	0.0532

Panel B: Summary Statistics of Individual Trading from the NYSE Data Set

		Individuals Dollar Volume (1000s $)	Individuals Share Volume (shares)	Individuals Executed Order Size (dollars)	Individuals Executed Order Size (shares)
All stocks	Mean	4,304.1	169,243	15,822.0	770.9
	Median	1,131.0	55,575	13,243.4	644.6
Small stocks	Mean	716.3	149,812	8,689.6	904.7
	Median	377.1	32,475	7,896.8	722.5
Mid-cap stocks	Mean	2,144.2	177,000	15,723.4	711.5
	Median	1,417.1	55,460	14,323.0	613.5
Large stocks	Mean	11,147.6	329,988	26,083.4	675.0
	Median	4,991.8	141,125	22,240.8	618.2

data set is that the information about daily buy and sell volume of individual investors was created by aggregating executed *orders*, rather than trades. In other words, the classification into buy and sell volume in our data set is exact, and thus we do not have to rely on classification algorithms such as the one proposed by Lee and Ready (1991). Panel A of Table I presents summary statistics from CRSP on the sample stocks (for the entire sample and for three size groups).

Panel B of Table I contains summary statistics for the data set. The weekly dollar trading volume of individuals in the average stock is 4.3 million dollars, but it ranges from 716,000 dollars in small stocks to over 11 million dollars in large stocks.[5] The average (median) trade size for an individual in our sample is \$15,822 (\$13,243), which is somewhat larger than in Barber and Odean (2000), who report an average trade size of \$13,707 for sells and \$11,205 for buys (but much smaller medians, of \$5,738 and \$4,988, respectively). On the other hand, the average trade size Barber and Odean (2005) report in the sample of individuals who use a full-service broker between 1997 and 1999 is \$15,209 for buys and \$21,169 for sells. The larger average trade size in their sample is consistent with ours, and may reflect a later period (closer to ours) or a different clientele (full service versus discount broker). Panel B of Table I also shows that the average order size of individuals is positively related to the market capitalization of the stock: The average order size in large stocks is more than twice that in small stocks.

We should note that some brokers either sell some of their order flow (in NYSE-listed stocks) to wholesalers for execution or internalize a certain portion of their clients' orders by trading as a principal against them. Since such prearranged trading practices cannot be carried out on the NYSE, these trades take place on one of the regional exchanges (or, alternatively, are reported to the NASD) and are therefore not in our sample of NYSE executions. For example, Schwab internalized 66% of its orders in the fourth quarter of 2003, while Fidelity sent about 38% of its volume in NYSE-listed stocks to the Boston Stock Exchange to be executed by its own specialist.[6] It is very likely that the fraction of volume these brokers send to the NYSE consists of orders that create an imbalance not easily matched internally. This means that imbalances in the orders of individuals find their way to the NYSE even if some of the more balanced individual volume is executed elsewhere. Therefore, our net individual trading measure (detailed below) that captures imbalances in individuals' executed orders on the NYSE probably reflects (even if not perfectly) the imbalances in the trading of individuals in the market as a whole.

We construct a daily measure of net individual investor trading by subtracting the value of the shares sold by individuals from the value of shares bought, and we standardize the measure by the average daily dollar volume. Specifically, we define Net Individual Trading (NIT) for stock i on day t as

$$\mathrm{NIT}_{i,t} = \frac{\text{Individual buy dollar volume}_{i,t} - \text{Individual sell dollar volume}_{i,t}}{\text{Average daily dollar volume in previous year}_{i,t}},$$

where the denominator is the stock's average daily dollar volume (from CRSP) for the year ending on day $t-1$.[7] For most of the work in this paper on short-horizon predictability of returns, we aggregate the measure to the weekly frequency to be compatible with prior literature.

[5] The reason we provide summary statistics at the weekly frequency is that most of our analysis is done at that frequency to be compatible with the literature on short-horizon return predictability.

[6] These figures are taken from an article by Kate Kelly in the *Wall Street Journal* ("SEC Overhaul Could Topple Best-Price Rule," March 5, 2004).

[7] E.g., to compute the denominator for February 3, 2000 (for a certain stock), we average the daily dollar volume over all trading days from February 3, 1999, to February 2, 2000.

Table II provides summary statistics on the weekly NIT measure. In Panel A we observe that for the average NYSE stock in our sample, the time-series mean of NIT during the years 2000 to 2003 is negative (i.e., individuals sold more than they bought).[8] Panel B demonstrates that the time-series standard deviation of a stock's Net Individual Trading measure is rather large, with an average magnitude of seven times the mean for small stocks or twice the mean for large stocks. What this means is that although NIT is typically quite small, there are observations of a rather large NIT.[9]

Panels A and B of Table II demonstrate that the extent of imbalances in individual trading varies over time, and can be rather large in magnitude for some stocks on some weeks. If we were to think in terms of a representative (aggregate) individual, then most weeks we would observe that the representative individual rebalances a bit of his or her holdings in each stock but does not have a strong, predominant direction. Since our goal is to look for dynamic patterns that relate the buying or selling desires of this aggregate individual to the returns of specific stocks, it is clear that such patterns would be more detectable by focusing on weeks when this individual is intensely buying or selling stocks. Therefore, in the next section we use a procedure that, for each week, forms portfolios of stocks that experience more intense buying or selling by individuals, and we investigate the return patterns around these occurrences.

II. Dynamic Relation between Net Individual Trading and Returns

Our goal is to look at whether intense imbalances are dynamically related to short-horizon returns. We believe that such return patterns should manifest themselves more clearly when one restricts the investigation to more intense imbalances. Therefore, we use two methods by which every week one can place stocks into portfolios with intense positive or negative imbalances. The first method is to cross-sectionally sort on the NIT measure every week and form decile portfolios (decile 1 is the intense selling portfolio, i.e., the 10% of the stocks with the most negative NIT that week, and decile 10 is the intense buying portfolio). By repeating this procedure every week in the sample period, we obtain a time series of the extreme portfolios that can then be examined.

The second method looks at each stock's past magnitude of NIT in order to determine whether net individual trading is "intense." Specifically, every week we put each stock into 1 of the 10 decile portfolios formed by comparing the NIT value of the stock that week to the NIT values of the same stock in the previous 9 weeks. If the NIT measure that week is more negative than the NIT measures of the same stock in the previous 9 weeks, the stock is put into decile 1 (most intense selling). If the NIT measure is more positive than

[8] Note that the time-series mean of weekly NIT is rather small in magnitude, with a median across stocks of between −0.0318 and −0.0659 for the different size quintiles. In dollar terms, the medians for the size quintiles (from small to large) are −\$5,835, −\$83,751, −\$209,456, −\$436,242, and −\$1,417,285.

[9] The first-order autocorrelation of the NIT measure is positive and seems to be somewhat lower for smaller stocks (0.2082) than for larger stocks (0.2825).

Table II

Summary Statistics of Individuals' Trading Imbalances

The sample of stocks for the study consists of all common domestic stocks that were traded on the NYSE at any time between January 1, 2000, and December 31, 2003, with records in the CRSP database. We use ticker symbol and CUSIP to match the stocks to a special data set containing daily aggregated buying and selling volume of individuals provided by the NYSE. There are 2,034 stocks in our sample. NIT_t for a stock on week t is defined as the dollar volume bought by individuals minus the dollar volume sold by individuals (both obtained from the NYSE), divided by a moving average of past 1-year average dollar volume (from CRSP). In Panel A we compute the time-series means of NIT for each stock over the 4-year sample period. We then sort stocks into five size quintiles according to average market capitalization (from CRSP), and present cross-sectional summary statistics of the stocks' NIT for the five size quintiles. In Panel B we compute the time-series standard deviation of NIT of each stock over the sample period and present cross-sectional summary statistics for the five size quintiles. Panel C presents summary statistics of NIT in weekly portfolios of stocks that experience intense buying or selling by individuals. For each week in the sample period, we use the previous 9 weeks to form NIT deciles. Each stock is put into 1 of 10 deciles according to the NIT value in the current week relative to its value in the previous 9 weeks. Decile 1 contains the stocks with the most intense selling (negative NIT) while decile 10 contains the stocks with the most intense buying (positive NIT). For each decile, we compute the average NIT for the stocks in the portfolio. We present time-series summary statistics of the average NIT in deciles 1 and 10 for the entire sample and separately for the three size groups.

Panel A: Cross-Sectional Distribution of Stocks' Average NIT

Size Quintiles	Mean	Std. Dev.	Min	25%	Median	75%	Max
Q1 (small stocks)	−0.0613	0.2208	−2.0811	−0.1245	−0.0318	0.0371	0.6708
Q2	−0.1208	0.2328	−2.6624	−0.1750	−0.0659	−0.0099	0.5938
Q3	−0.1037	0.1904	−2.8527	−0.1355	−0.0581	−0.0165	0.4683
Q4	−0.0715	0.1157	−0.8468	−0.0907	−0.0382	−0.0141	0.2743
Q5 (large stocks)	−0.0505	0.0943	−1.0200	−0.0550	−0.0320	−0.0158	0.0750

Panel B: Cross-Sectional Distribution of Stocks' Standard Deviation of NIT

Size Quintiles	Mean	Std. Dev.	Min	25%	Median	75%	Max
Q1 (small stocks)	0.4556	0.3489	0.0046	0.2134	0.4010	0.6061	3.2319
Q2	0.3475	0.3417	0.0100	0.1362	0.2636	0.4464	3.9161
Q3	0.2485	0.2723	0.0017	0.0991	0.1739	0.3014	3.7744
Q4	0.1731	0.1941	0.0060	0.0748	0.1197	0.1974	2.2564
Q5 (large stocks)	0.1041	0.1200	0.0119	0.0571	0.0758	0.1124	1.8754

Panel C: Summary Statistics of NIT in Portfolios of Intense Buying or Selling by Individuals

Portfolio		Mean	Std. Dev.	25%	Median	75%
Intense selling (decile 1)	All stocks	−0.4171	0.1334	−0.4978	−0.4047	−0.3262
	Small stocks	−0.6614	0.2316	−0.8119	−0.6241	−0.4910
	Mid-cap stocks	−0.3487	0.1557	−0.4507	−0.3207	−0.2326
	Large stocks	−0.1537	0.0582	−0.1939	−0.1455	−0.1079
Intense buying (decile 10)	All stocks	0.2048	0.0700	0.1580	0.1970	0.2417
	Small stocks	0.3812	0.1198	0.2911	0.3781	0.4473
	Mid-cap stocks	0.1118	0.0555	0.0784	0.1016	0.1352
	Large stocks	0.0507	0.0279	0.0329	0.0474	0.0657

the NIT measures of the same stock in the previous 9 weeks, the stock is put into decile 10 (most intense buying) for that week. Note that the decile portfolios may contain different stocks in different weeks, but the stocks in these portfolios share the characteristic that their net individual trading is much more negative (decile 1) or much more positive (decile 10) than the NIT these stocks experienced in the recent past. We would like to emphasize that the measure of Net Individual Trading used in the analysis is the *level* of the imbalance (not the *change* in imbalance). The procedure that places stocks into portfolios simply defines a benchmark that helps us decide whether a particular NIT in a given week for a given stock is more intense than the "normal" NIT of that stock.[10]

We carry out the first method described above as part of our robustness tests, choosing to present in the paper analyses based on the second methodology for placing stock/weeks into intense imbalance portfolios. The reason we adopt the methodology of forming deciles by comparing a stock's NIT each week to its own past NIT is because the impact of trading imbalances on future prices should be related to each stock's ability to absorb order flow.[11] This portfolio formation procedure, similar in spirit to the methodology in Gervais et al. (2001), has the advantage that it uses a moving window of past NIT values and therefore is robust to a potential trend in the measure. It turns out that both procedures yield similar findings, but we believe using own-stock past values for determining the deciles is more appropriate for our specific goal of looking at the relation between imbalances and returns, and hence we present only these results in the tables.[12]

Panel C of Table II presents time-series summary statistics for the average NIT of stocks in deciles 1 and 10 (intense selling and buying, respectively). The average magnitude of the imbalance for stocks in these deciles can be rather large: 41.71% of average daily volume when individuals sell and 20.48% when they buy. Since Panel A of Table II shows that individuals on average sold during the sample period, the deviation of intense buying or selling from the unconditional mean of NIT is approximately symmetric. Comparing the summary statistics of the intense NIT portfolios with the information for the entire sample (in Panels A and B of Table II), it appears that decile portfolios 1 and 10 tend to have average NIT values that are between one and two standard deviations above or below their time-series means. We check whether our portfolio formation procedure causes us to focus on a somewhat unrepresentative set of stocks, as we want to be sure that the procedure does not always put in the extreme

[10] To have an idea of the dollar magnitude of the intense imbalances of individuals, we compute the average dollar imbalance of the stocks in each decile portfolio. The time-series mean of the average dollar imbalance for the decile 1 (decile 10) portfolio is −$3,061,250 ($1,190,945), and the standard deviation is $1,153,572 ($744,578).

[11] Subrahmanyam (2005) makes a similar point, stating that inventory control effects predict downward pressure on the price of a stock in the absolute rather than the relative (cross-sectional) sense.

[12] The dynamic patterns we find are a bit stronger when we implement the cross-sectional sorting procedure.

portfolios the same few stocks that experience consistent buying or selling by individuals for the entire duration of the 4-year sample period. We therefore compute for each stock the fraction of weeks it is placed in the decile 1 or decile 10 portfolios. The mean value of this fraction across the sample stocks is 0.1239 (0.1109) for decile 1 (decile 10), which suggests that, indeed, we achieve our goal of looking at the majority of stocks exactly at those times when these stocks experience more extreme imbalances.[13]

Having created the time series of portfolios with intense individual trading imbalances, we turn to investigating the short-horizon dynamic relation between NIT and returns. Table III presents the cumulative market-adjusted returns around intense buying or selling by individuals.[14] We look at patterns associated with the intense selling and buying portfolios (decile 1 and decile 10, respectively), but for robustness we also present results for somewhat less intense trading by forming a selling portfolio from the stocks in deciles 1 and 2, and a buying portfolio from the stocks in deciles 9 and 10. We report the market-adjusted return during the week of intense individual imbalance, but our focus is on the short-horizon dynamics. Therefore, market-adjusted cumulative returns are calculated for 20, 15, 10, and 5 days before the first day or after the last day of the intense individual trading week. The cells in the table contain the time-series means and t-statistics for each of the cumulative return measures. We use the Newey-West correction in computing the t-statistics due to potential autocorrelation of the errors induced by overlapping periods (especially when the cumulative return measures are for periods longer than one week).

The first line of the table shows that intense individual selling (decile 1) follows an increase in stock prices. The mean excess return in the 20 days prior to the selling week is 3.15%, and the mean excess return in the 5 days prior to that week is 1.62%. These returns are highly statistically significant. The last line of the table describes the returns in the week prior to intense individual buying activity (decile 10). The excess return in the 20 days prior to intense buying is -2.47% and is highly statistically significant. We obtain similar results with the less extreme portfolios (deciles 1 and 2 for selling, and deciles 9 and 10 for buying), suggesting that our findings are not driven by outliers.

The table also reveals that there are positive excess returns following weeks with intense net buying or selling by individuals. The portfolio of stocks in decile 10 earns market-adjusted returns of 0.32% in the week after intense

[13] We also compute the faction of stocks in decile 1 (or decile 10) in week t that were also placed in the same decile in week $t + 1$. The time-series average of this fraction is 0.1939 (0.1652) for decile 1 (decile 10), which is a bit smaller than the first-order autocorrelation of NIT reported in footnote 9.

[14] We use the equal-weighted portfolio of all stocks in the sample as a proxy for the market portfolio. To create the cumulative returns of the market portfolio, say over a 20-day period, we first compute for each stock the cumulative (raw) return over the relevant 20-day period. The average of these returns across the stocks in the sample is what we define as the return on the equal-weighted market portfolio.

Table III

Returns around Intense Individual Trading

This table presents analysis of market-adjusted returns around intense buying and selling activity of individuals as given by the net individual trading measure (NIT). For each week in the sample period, we use the previous 9 weeks to form NIT deciles. Each stock is put into 1 of 10 deciles according to the NIT value in the current week relative to its value in the previous 9 weeks. Decile 1 contains the stocks with the most intense selling (negative NIT) while decile 10 contains the stocks with the most intense buying (positive NIT). We present the results for four portfolios: (i) decile 1, (ii) deciles 1 and 2, (iii) deciles 9 and 10, and (iv) decile 10. Let k be the number of days prior to or following the portfolio formation each week. In Panel A, we calculate eight cumulative return numbers for each of the stocks in a portfolio: CR($t-k$, $t-1$), where $k \in \{20, 15, 10, 5\}$ days and t is the first day of the formation week, and CR($t+1$, $t+k$), where $k \in \{5, 10, 15, 20\}$ days and t is the last day of the formation week. The return on each portfolio is then adjusted by subtracting the return on a market proxy (the equal-weighted portfolio of all stocks in the sample). We present the time-series mean and t-statistic for each market-adjusted cumulative return measure and for the market-adjusted return during the intense trading week ($k = 0$). In Panel B, we present the time-series mean and t-statistics for weekly market-adjusted returns in the 4 weeks around the formation week (i.e., CR($t-k$, $t-k+4$), where $k \in \{20, 15, 10, 5\}$ days and t is the first day of the formation week, and CR($t+k-4$, $t+k$), where $k \in \{5, 10, 15, 20\}$ days and t is the last day of the formation week). ** indicates significance at the 1% level and * indicates significance at the 5% level (both against a two-sided alternative). The t-statistic is computed using the Newey-West correction.

Portfolio		$k=-20$	$k=-15$	$k=-10$	$k=-5$	$k=0$	$k=+5$	$k=+10$	$k=+15$	$k=+20$
Panel A: Cumulative Market-Adjusted Returns around Intense Individual Trading										
Intense Selling	Mean	0.0315**	0.0299**	0.0247**	0.0162**	0.0180**	−0.0013**	−0.0020**	−0.0028**	−0.0033**
(decile 1)	t-statistic	(22.62)	(22.22)	(23.50)	(20.93)	(20.72)	(−2.77)	(−3.01)	(−3.49)	(−3.48)
Selling	Mean	0.0302**	0.0281**	0.0231**	0.0146**	0.0129**	−0.0013**	−0.0019**	−0.0028**	−0.0035**
(deciles 1&2)	t-statistic	(24.86)	(23.73)	(24.02)	(23.29)	(21.94)	(−3.95)	(−3.68)	(−4.65)	(−4.91)
Buying	Mean	−0.0251**	−0.0234**	−0.0192**	−0.0124**	−0.0087**	0.0025**	0.0042**	0.0055**	0.0066**
(deciles 9&10)	t-statistic	(−24.12)	(−24.43)	(−24.07)	(−23.85)	(−16.74)	(7.14)	(8.23)	(9.14)	(10.61)
Intense Buying	Mean	−0.0247**	−0.0236**	−0.0200**	−0.0131**	−0.0111**	0.0032**	0.0048**	0.0066**	0.0080**
(decile 10)	t-statistic	(−22.21)	(−22.61)	(−22.58)	(−22.04)	(−13.90)	(6.97)	(7.22)	(8.09)	(8.71)
Panel B: Weekly Market-Adjusted Returns around Intense Individual Trading										
Intense Selling	Mean	0.0018**	0.0051**	0.0084**	0.0162**	0.0180**	−0.0013**	−0.0008	−0.0009*	−0.0005
(decile 1)	t-statistic	(3.67)	(9.40)	(16.20)	(20.93)	(20.72)	(−2.77)	(−1.64)	(−2.29)	(−1.21)
Selling	Mean	0.0022**	0.0049**	0.0083**	0.0146**	0.0129**	−0.0013**	−0.0007	−0.0009**	−0.0007*
(deciles 1&2)	t-statistic	(5.88)	(13.01)	(18.91)	(23.29)	(21.94)	(−3.95)	(−1.86)	(−3.32)	(−2.30)
Buying	Mean	−0.0019**	−0.0043**	−0.0070**	−0.0124**	−0.0087**	0.0025**	0.0018**	0.0012**	0.0012**
(deciles 9&10)	t-statistic	(−6.41)	(−14.04)	(−18.41)	(−23.85)	(−16.74)	(7.14)	(5.80)	(4.07)	(4.76)
Intense Buying	Mean	−0.0013**	−0.0038**	−0.0072**	−0.0131**	−0.0111**	0.0032**	0.0018**	0.0016**	0.0016**
(decile 10)	t-statistic	(−3.35)	(−10.84)	(−15.67)	(−22.04)	(−13.90)	(6.97)	(4.10)	(3.69)	(3.62)

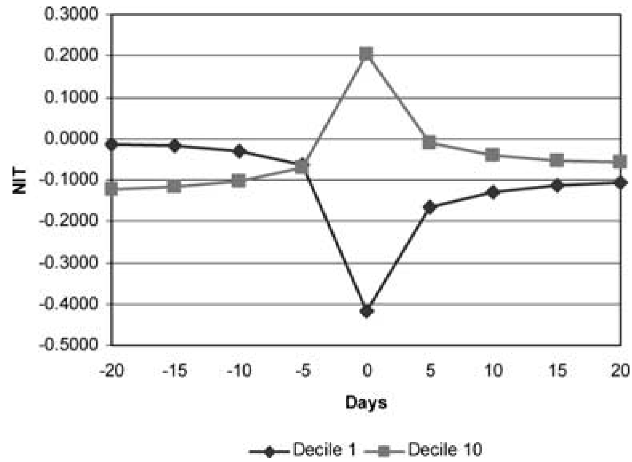

Figure 1. NIT around intense individual trading. This figure presents the Net Individual Trading (NIT) measure of stocks before, during, and after they experience weeks with intense buying and selling activity of individuals. For each week in the sample period, we use the previous 9 weeks to form NIT deciles. Each stock is put into 1 of 10 deciles according to the NIT value in the current week relative to its value in the previous 9 weeks. Decile 1 contains the stocks with the most intense selling (negative NIT) while decile 10 contains the stocks with the most intense buying (positive NIT). Let k be the number of days prior to or following portfolio formation each week. The figures show the average NIT measure of the stocks in decile 1 and 10 during the intense trading week as well as their average NIT in the 4 weeks around the formation week (i.e., $\mathrm{CR}(t-k, t-k+4)$, where $k \in \{20, 15, 10, 5\}$ days and t is the first day of the formation week, and $\mathrm{CR}(t+k-4, t+k)$, where $k \in \{5, 10, 15, 20\}$ days and t is the last day of the formation week).

buying and 0.80% in the 20 days following portfolio formation (both statistically significant). The excess return after intense individual selling is smaller in magnitude (−0.33% after 20 days) but nonetheless statistically significant. It is also interesting to note that excess returns during the intense trading week have opposite signs (positive when individuals sell and negative when individuals buy). We will return to this finding in Section V when we discuss potential explanations for the patterns we document.

Panel B of Table III looks at the weekly excess returns (as opposed to the cumulative excess returns) in the 4 weeks around intense trading by individuals. This enables us to statistically test the hypothesis that the excess return continues to increase (or decrease) every week. We observe that during the 4 weeks after intense trading by individuals, excess returns continue to accumulate and the weekly changes are for the most part statistically significant. This is not due to a continued abnormally large imbalance of individual trading over that period. Figure 1 shows the NIT of decile 1 and decile 10 stocks around the formation week. It is clear from the figure that NIT before and after the formation week does not have the same magnitude but is rather much closer to the "normal" level (which on average is negative, as Table II indicates).[15]

[15] The excess return does not continue to significantly increase beyond 4 weeks. In Section VI, when we discuss potential explanations of this pattern, we provide additional evidence on what happens after 4 weeks.

A. Robustness Tests

We carry out extensive robustness tests that consider how different elements of the analysis may affect the results. First, to examine the robustness of our findings to the portfolio formation procedure, we form NIT deciles based on a weekly cross-sectional sorting and replicate the analysis in Table III. The results are similar, and both the return patterns prior to individual trading and the return predictability are statistically significant.

Second, we examine the robustness of our results to different definitions of the net individual trading measure. We use a nonstandardized measure (without dividing by the average volume), a measure standardized by average volume over the entire sample period, a measure standardized by predicted volume from a regression model, and an imbalance measure constructed by dividing the dollar buying each week by the sum of dollar buying and selling by individuals. We also use several definitions of the deviations from net individual trading by subtracting the mean over the sample period, a moving average over the previous year, or the predicted value from a regression model. The results using all measures are very similar, showing significant returns prior to individual trading and return predictability following intense individual trading imbalances.

Third, we examine the robustness of our results to different definitions of returns. Specifically, we repeat the analysis with excess returns from a market model regression, with industry-adjusted returns, with raw returns, and with returns generated from end-of-day quote midpoints (constructed using the TAQ database).[16] All return definitions generate similar, statistically significant results.

Lastly, we repeat the analysis with two altered samples. Since our sample period includes a severe decline in the prices of technology stocks, we repeat our tests excluding the technology sector. We also use a sample that excludes all stock/weeks with dividend or earnings announcements. We find that the patterns in these subsamples are similar to those we identify in the complete sample.[17]

III. Short-Horizon (Weekly) Predictability of Returns

This section examines how our evidence relates to other evidence of short-horizon return predictability that is described in the existing literature. We first consider the Jegadeesh (1990) and Lehmann (1990) findings on

[16] For industry-adjusted returns we use a classification into 10 industry portfolios (based on four-digit SIC codes) made available by Kenneth French. The specification of the 10 industry portfolios can be obtained from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_10_ind_port.html.

[17] The questions of how individuals trade around earnings announcements and whether their trading can explain known return patterns around corporate events (such as the drift) are of independent interest (see, e.g., Lee (1992), Nofsinger (2001), Hirshleifer et al. (2002), Frieder (2004), Shanthikumar (2004), and Vieru, Perttunen, Schadewitz (2005)). We are currently pursuing an investigation of these questions in a separate paper due to the breadth of the issues associated with such an analysis.

short-horizon return reversals. Given that intense individual buying follows a month of negative returns and intense individual selling follows a month with positive returns, it is possible that the short-horizon excess returns we document following intense trading imbalances of individuals simply reflect the Jegadeesh and Lehmann return reversals. We then consider the Gervais et al. (2001) finding that volume increases predict returns. Since individual trading imbalances may be related to trading volume, it is possible our findings linking individual trading imbalances and future returns is related to evidence that increased trading volume predicts returns.

A. Short-Term Return Reversals

To examine this issue we form 25 portfolios by independently placing stocks into five quintiles based on their weekly return and five quintiles based on their NIT decile ranking for the week.[18] For each portfolio we compute the market-adjusted return in the following week.[19] Panel A of Table IV, which reports the time-series averages of the weekly market-adjusted returns for the 25 portfolios, reveals no apparent evidence of return reversals in our sample period when conditioning on NIT. The last two columns of the table look at the payoffs to a trading strategy that buys quintile 5 and sells quintile 1. If the return reversal strategy that buys the portfolio with last week's most negative return and sells the one with last week's most positive return can be used to generate profits, the payoffs in the column Q5–Q1 should be negative and significant. The table shows that the payoffs to this strategy are not statistically different from zero in any of the NIT quintiles.[20]

On the other hand, there is a pronounced pattern within each quintile of past returns going from past individual selling (NIT quintile 1) to past individual buying (NIT quintile 5). The market-adjusted return in each column of the table becomes more positive as we go from the stocks that individuals sold the previous week to those individuals bought. The bottom two rows of the panel provide information about the payoffs to buying a portfolio that is composed of stocks that experienced more intense individual buying in the previous week (NIT quintile 5) and selling those stocks that experienced intense individual selling (NIT quintile 1) in each return quintile. All these portfolios realize statistically significant positive payoffs, ranging from 0.24% to 0.60% per week.[21]

[18] As in Section II, every week a stock is assigned a separate decile ranking by comparing its NIT in that week to its NIT in the previous nine weeks.

[19] We examine the robustness of our findings to different definitions of returns by repeating the analysis using returns adjusted with a market model, industry-adjusted returns, raw returns, and returns computed from end-of-day quote midpoints (as in Section II). Our conclusions from all these return definitions are the same.

[20] We use the Newey–West correction in the computation of the t-statistics.

[21] The payoffs are in terms of percentage of dollars invested in the long position of this zero-investment strategy.

Table IV

Return Predictability: Portfolio Sorting Approach

This table presents analysis of weekly return predictability conditional on the previous week's return (Panel A) or turnover (Panel B) and the net individual trading measure (NIT). For each week in the sample period, we use the previous 9 weeks to form NIT quintiles. Each stock is put into one of the five quintiles according to the NIT value in the current week relative to its value in the previous 9 weeks (where quintile 1 has stocks with more negative NIT, or more selling, and quintile 5 has stocks with more positive NIT, or more buying). In Panel A, each week in the sample period stocks is also sorted on returns and put into five quintiles (quintile 1 has stocks with the most negative return and quintile 5 has stocks with the most positive return). We then form 25 portfolios as the intersection of the five return quintiles and five NIT quintiles, and compute for each portfolio the market-adjusted return in the week following the formation week. We present the time-series mean return for each of the 25 portfolios sorted by returns and net individual trading. The last two rows of the panel give the payoff to the strategy of buying NIT quintile 5 and selling NIT quintile 1, and the last two columns of the panel give the payoff to the strategy of buying return quintile 5 and selling return quintile 1. Panel B presents similar analysis except that we place stocks in portfolios based on past turnover (rather than past returns) and past NIT. The construction of the 25 portfolios is analogous to the one in Panel A, and the last two columns of the panel give the payoff to the strategy of buying turnover quintile 5 and selling turnover quintile 1. ** indicates significance at the 1% level (against a two-sided alternative). The t-statistic is computed using the Newey-West correction.

Panel A: Weekly Return Predictability Using Past Return and NIT

	Return(t)						
NIT(t)	Q1 (<0)	Q2	Q3	Q4	Q5 (>0)	Q5−Q1	t-statistic
Q1 (<0)	−0.0022	−0.0019	−0.0007	−0.0007	−0.0016	0.0006	(0.35)
Q2	−0.0010	−0.0012	−0.0011	−0.0013	−0.0026	−0.0016	(−0.90)
Q3	−0.0001	−0.0017	−0.0007	−0.0010	−0.0012	−0.0011	(−0.63)
Q4	0.0024	−0.0002	−0.0001	0.0005	0.0002	−0.0023	(−1.54)
Q5 (>0)	0.0038	0.0008	0.0017	0.0018	0.0022	−0.0016	(−1.00)
Q5−Q1	0.0060**	0.0027**	0.0024**	0.0025**	0.0038**		
t-statistic	(4.87)	(2.92)	(3.38)	(3.26)	(3.43)		

Panel B: Weekly Return Predictability Using Past Turnover and NIT

	Turnover(t)						
NIT(t)	Q1 (<0)	Q2	Q3	Q4	Q5 (high)	Q5−Q1	t-statistic
Q1 (<0)	−0.0033	−0.0031	−0.0021	−0.0005	0.0004	0.0037**	(2.78)
Q2	−0.0040	−0.0035	−0.0015	−0.0004	0.0015	0.0055**	(3.94)
Q3	−0.0041	−0.0021	−0.0012	0.0000	0.0013	0.0054**	(3.89)
Q4	−0.0026	−0.0012	0.0012	0.0028	0.0044	0.0070**	(5.41)
Q5 (>0)	0.0006	0.0003	0.0008	0.0030	0.0046	0.0040**	(2.98)
Q5−Q1	0.0039**	0.0034**	0.0029**	0.0035**	0.0042**		
t-statistic	(2.95)	(3.58)	(3.44)	(3.20)	(3.64)		

B. Trading Volume and Future Returns

We also consider the possibility that net individual trading predicts returns because of its correlation with volume, which was shown by Gervais et al. (2001)

to predict future returns. To examine whether the NIT-return relationship is independent of volume we repeat the analysis placing the stocks each week into five quintiles of NIT and five quintiles of turnover. The assignment of a stock into a turnover quintile in a given week follows the methodology in Gervais et al. and is similar in nature to the way we assign stocks into NIT quintiles each week (the turnover of a stock in a certain week is compared to the turnover of the same stock in the previous nine weeks). Twenty-five portfolios are formed as the intersection of the five turnover quintiles and the five NIT quintiles, and their excess returns in the following week are calculated.[22]

Panel B of Table IV reveals that the information in the NIT measure is distinct from that in turnover, and both provide independent information about future returns. In particular, the strategy of buying the stocks in NIT quintile 5 and selling the stocks in NIT quintile 1 produces statistically significant payoffs in each turnover column, and the strategy of buying the stocks in turnover quintile 5 and selling those in turnover quintile 1 generates statistically significant payoffs in each NIT row.

The finding that both net trading of individual investors and turnover predict the subsequent week's return is especially interesting. Gervais et al. (2001) suggest that the high-volume return premium, or the tendency of prices to increase after periods with high turnover, is due to shocks in trader interest. If high volume attracts investor attention to the stock, the investor recognition hypothesis (e.g., Merton (1987)) argues that the stock's value would increase due to better risk sharing. It is reasonable to assume that individual investors do not follow all the stocks all the time but may be attracted to a certain stock after a volume shock brings media attention to it. This reasoning suggests that conditioning on a variable that specifically measures individual investor trading could potentially explain the high-volume return premium, leaving no role for turnover.

Our findings, however, suggest that turnover and NIT contain different information and neither of them subsumes the other. One possible explanation for this result is that the short-horizon relation between net individual trading and returns is nonlinear. Since volume is an absolute value measure while NIT is a directional measure, the nonlinearity means that volume will show up significantly as well.

To examine turnover, NIT, and past returns simultaneously we estimate a series of Fama and MacBeth (1973) regressions, where returns in week t are regressed on week $t-1$ returns, NIT, and turnover.[23] To be consistent with the methodology we implement in Section II, we transform NIT into decile ranks

[22] We compute the correlation between the NIT ranks and the turnover ranks for each stock. The mean correlation across the stocks in the sample is -0.055 and the standard deviation is 0.1782. This relatively low correlation means that the independent sorting procedure results in a reasonable number of stocks in each of the 25 portfolios.

[23] Specifically, a cross-sectional regression is performed for each week in the sample period. We then construct test statistics based on the time series of the estimated coefficients (using the Newey–West correction for the standard errors).

(the NITDecile variable).[24] Similarly, we transform turnover into decile ranks because Gervais et al. (2001) find such a transformation of volume useful in predicting returns.

In Panel A of Table V we use CRSP returns to facilitate comparison with most of the papers in the return predictability literature. In both the univariate and multivariate regressions, the coefficients on NITDecile and TurnoverDecile are positive and highly statistically significant, which is consistent with the findings in the last table, but the coefficient on past return is negative and significant, which is consistent with past literature but seems inconsistent with the results from the portfolio-sorting approach.[25] In the separate regressions on small, mid-cap, and large stocks we observe that the significant relation between past returns and future returns is driven entirely by the smaller stocks.

The significant showing of past returns in the sample of small stocks prompted us to examine the robustness of these results to two issues: bid-ask bounce and nonsynchronous trading.[26] To eliminate the effect of bid-ask bounce we use the TAQ database to create a return series from end-of-day quote midpoints.[27] The closing TAQ midpoint may also mitigate the problem of nonsynchronous trading. Since the specialist keeps a binding quote in each stock and can change the quote even when there is no trading, the quote prevailing at the close of the market presumably contains updated pricing information even if the last trade occurred long before the close.

Panel B of Table V presents the results of the regressions with the midquote returns. While both NIT and turnover are strongly related to future returns in the entire sample and all subsamples, the past return effect is weaker with midquote returns. Here, the past return is not significant in the regression on the entire sample and it comes out significant only in the small-cap subsample, with a significance level that is weaker than that observed in the regressions using CRSP returns.

[24] For robustness, we also run the regressions using NIT, rather then the NIT decile ranks, as the independent variable. This specification is similar in spirit to the cross-sectional robustness tests that we conduct in Section II. The results are similar in that the mean coefficient on NIT is positive and statistically significant in all the models (univariate and multivariate).

[25] While the mean coefficient on past returns is much larger in magnitude than the mean coefficients on NITDecile and TurnoverDecile, the past return effect is in fact much smaller than the NIT or volume effects. To see this note that the magnitude of a typical weekly return is on the order of 10^{-2}, which means that its effect on future returns (after multiplying by the regression coefficient) is on the order of 10^{-4}. In contrast, the mean of the decile rank variable used for NITDecile (or TurnoverDecile) is about 5.5, which means that the effects of NIT and volume on future returns are on the order of 10^{-3}.

[26] Conrad, Gultekin, and Kaul (1997) claim that a large portion of the documented weekly return reversal can be explained by bid-ask bounce. Lo and MacKinlay (1990) present a framework in which nontrading induces negative serial correlation in the returns of individual stocks. While their simulations show that the impact of nontrading on short-horizon returns of individual stocks is negligible, it can still contribute to the significant coefficient that we find on past returns.

[27] Since the quality of intraday data in TAQ may not be as high as the quality of the CRSP data, if the absolute value of the difference between the TAQ return and the CRSP return is greater than 15%, we set the TAQ return to a missing value for the purpose of the regressions.

Table V

Return Predictability: Fama–MacBeth Approach

This table presents a regression analysis of short-horizon (weekly) return predictability. The dependent variable is weekly return, Return($t + 1$), and the independent variables are an intercept, Return(t), NITDecile(t), and TurnoverDecile(t). The TurnoverDecile variable is similar to that in Gervais et al. (2001). It classifies the weekly turnover (number of shares traded over the number of shares outstanding) into 10 deciles by comparing it to the same stock's turnover in the previous 9 weeks. The net individual trading (NIT) measure is described in Section I, and the NITDecile variable is constructed in a similar fashion to TurnoverDecile. We implement a Fama–MacBeth methodology for the regressions: (i) a cross-sectional regression is performed for each week in the sample period and (ii) test statistics are based on the time series of the coefficient estimates. We present the mean coefficient from the weekly regressions, and use the Newey-West correction for the standard errors to compute the t-statistics. In Panel A we use CRSP returns, while in Panel B we compute returns using end-of-day quote midpoints from the TAQ database. ** indicates significance at the 1% level and * indicates significance at the 5% level (both against a two-sided alternative).

Panel A: CRSP Returns

Size Groups	Intercept (t-statistic)	Return(t) (t-statistic)	NITDecile(t) (t-statistic)	Turnover Decile(t) (t-statistic)
All stocks	0.0035	−0.0225**		
	(1.93)	(−3.10)		
	0.0008		0.0005**	
	(0.45)		(7.28)	
	−0.0006			0.0007**
	(−0.31)			(6.87)
	−0.0030	−0.0215**	0.0004**	0.0007**
	(−1.53)	(−2.97)	(6.65)	(7.71)
Small stocks	0.0028	−0.0312**		
	(1.32)	(−3.93)		
	−0.0008		0.0006**	
	(−0.39)		(6.50)	
	−0.0028			0.0010**
	(−1.28)			(7.97)
	−0.0057*	−0.0316**	0.0005**	0.0010**
	(−2.56)	(−3.96)	(5.64)	(8.39)
Mid-cap stocks	0.0042*	−0.0053		
	(2.34)	(−0.54)		
	0.0024		0.0004**	
	(1.30)		(5.36)	
	0.0028			0.0003**
	(1.40)			(3.18)
	0.0004	−0.0033	0.0004**	0.0003**
	(0.19)	(−0.34)	(5.24)	(3.34)
Large stocks	0.0035*	−0.0203		
	(1.99)	(−1.68)		
	0.0015		0.0004**	
	(0.82)		(4.33)	
	0.0016			0.0003**
	(0.77)			(2.77)
	−0.0004	−0.0158	0.0003**	0.0003**
	(−0.17)	(−1.30)	(4.24)	(3.35)

(*continued*)

Table V—*Continued*

Panel B: Midquote Returns from the TAQ Database

Size Groups	Intercept (t-statistic)	Return(t) (t-statistic)	NITDecile(t) (t-statistic)	Turnover Decile(t) (t-statistic)
All stocks	0.0031	−0.0132		
	(1.73)	(−1.91)		
	0.0006		0.0005**	
	(0.33)		(7.03)	
	−0.0007			0.0007**
	(−0.37)			(6.76)
	−0.0031	−0.0122	0.0004**	0.0007**
	(−1.60)	(−1.76)	(6.84)	(7.44)
Small stocks	0.0024	−0.0177*		
	(1.15)	(−2.51)		
	−0.0011		0.0006**	
	(−0.52)		(6.19)	
	−0.0029			0.0009**
	(−1.30)			(8.35)
	−0.0057*	−0.0180*	0.0005**	0.0009**
	(−2.57)	(−2.54)	(5.71)	(8.67)
Mid-cap stocks	0.0039*	−0.0016		
	(2.18)	(−0.16)		
	0.0022		0.0004**	
	(1.21)		(5.06)	
	0.0026			0.0003**
	(1.29)			(2.97)
	0.0003	0.0005	0.0004**	0.0003**
	(0.15)	(0.05)	(5.06)	(3.02)
Large stocks	0.0032	−0.0167		
	(1.79)	(−1.38)		
	0.0012		0.0004**	
	(0.66)		(4.28)	
	0.0013			0.0003**
	(0.62)			(2.70)
	−0.0007	−0.0121	0.0003**	0.0003**
	(−0.36)	(−1.00)	(4.32)	(3.24)

The finding of no return reversals, even in a univariate specification, for mid-cap and large stocks seems surprising given the evidence in previous studies of short-horizon return dynamics. Since the 4-year sample period we consider does not overlap with the sample periods examined in the previous studies of weekly return reversals, we use the same methodology to examine return reversals over 4-year periods starting in 1964. This exercise is intended to shed light on whether this phenomenon has changed over time, and whether the period we study is unusual relative to the periods considered in earlier studies.

The results in Table VI indicate that the return reversal phenomenon has been changing. The second column of Table VI shows a very clear trend in the

Table VI

Return Predictability: Historical Trends

This table presents an investigation of historical trends in short-horizon (weekly) return predictability with past returns as the predictive variable. The dependent variable is weekly return (from CRSP), Return($t+1$), and the independent variables are an intercept and Return(t). We implement a Fama–MacBeth methodology for the regressions: (i) a cross-sectional regression is performed for each week in the sample period and (ii) test statistics are based on the time series of the coefficient estimates. We present the mean coefficient from the weekly regressions, and use the Newey-West correction for the standard errors to compute the t-statistics. Since our main analysis (e.g., Table V) uses 4 years of data (2000 to 2003), we examine historical trends by running the regressions on nonoverlapping 4-year periods going back from 2003 to the beginning of data availability in CRSP. The table presents regression results for all stocks and by size groups. We sort stocks according to market capitalization into 10 deciles, and define deciles 1, 2, 3, and 4 as small stocks, deciles 5, 6, and 7 as mid-cap stocks, and deciles 8, 9, and 10 as large stocks. ** indicates significance at the 1% level and * indicates significance at the 5% level (both against a two-sided alternative).

	All Stocks		Small Stocks		Mid-Cap Stocks		Large Stocks	
	Intercept	Return(t)	Intercept	Return(t)	Intercept	Return(t)	Intercept	Return(t)
1964–1967	0.0039**	−0.0765**	0.0054**	−0.0925**	0.0036**	−0.0695**	0.0024*	−0.0561**
	(3.21)	(−11.33)	(3.77)	(−12.32)	(2.95)	(−8.31)	(2.23)	(−7.27)
1968–1971	0.0013	−0.0920**	0.0013	−0.1084**	0.0013	−0.0848**	0.0012	−0.0786**
	(0.63)	(−12.63)	(0.58)	(−12.83)	(0.64)	(−9.67)	(0.72)	(−10.05)
1972–1975	0.0004	−0.0973**	0.0006	−0.1263**	0.0004	−0.0814**	0.0003	−0.0635**
	(0.16)	(−14.59)	(0.22)	(−17.86)	(0.16)	(−10.24)	(0.13)	(−7.64)
1976–1979	0.0046**	−0.0797**	0.0062**	−0.0930**	0.0046**	−0.0804**	0.0023	−0.0658**
	(3.04)	(−12.58)	(3.33)	(−13.98)	(3.06)	(−10.88)	(1.78)	(−9.06)
1980–1983	0.0051**	−0.0698**	0.0061**	−0.0765**	0.0050**	−0.0715**	0.0042*	−0.0657**
	(3.04)	(−13.34)	(3.38)	(−13.49)	(2.99)	(−10.67)	(2.52)	(−7.85)
1984–1987	0.0023	−0.0688**	0.0013	−0.0758**	0.0026	−0.0720**	0.0035	−0.0710**
	(1.10)	(−10.84)	(0.58)	(−10.50)	(1.26)	(−9.16)	(1.83)	(−7.80)
1988–1991	0.0036*	−0.0909**	0.0033	−0.1114**	0.0033*	−0.0358**	0.0036*	−0.0471**
	(2.16)	(−7.83)	(1.64)	(−7.06)	(2.19)	(−4.37)	(2.51)	(−5.31)
1992–1995	0.0031**	−0.0730**	0.0035**	−0.0936**	0.0026**	−0.0331**	0.0029**	−0.0446**
	(3.37)	(−12.63)	(3.14)	(−11.59)	(2.92)	(−4.50)	(3.57)	(−6.42)
1996–1999	0.0028	−0.0376**	0.0022	−0.0448**	0.0029	−0.0182	0.0033*	−0.0302**
	(1.74)	(−5.69)	(1.27)	(−6.75)	(1.72)	(−1.48)	(2.22)	(−3.52)
2000–2003	0.0031	−0.0229**	0.0038*	−0.0383**	0.0033	0.0099	0.0023	−0.0126
	(1.78)	(−3.27)	(1.98)	(−4.94)	(1.86)	(1.09)	(1.30)	(−0.99)

estimated mean coefficients over the past decade or so since the publication of the work by Lehmann (1990) and Jegadeesh (1990) on the predictability of short-horizon returns. While the magnitude of the mean coefficient on past returns fluctuates over the decades, it monotonically decreases from the 1988 to 1991 period (−0.0909) to the 2000 to 2003 period (−0.0229).[28] The analysis of size groups shows that the decline in the magnitude and significance of the mean coefficient over the past decade can be found in stocks of all sizes. Since small stocks demonstrate a higher degree of weekly return reversal than mid-cap or large stocks, the declining trend still leaves a statistically significant mean coefficient during our sample period, 2000 to 2003. The smaller magnitude of reversals in larger stocks coupled with the declining trend over the past decade result in nonsignificant mean coefficients for the mid-cap and large groups in the most recent 4-year period.

IV. Are the NIT Returns Associated with Increased Risk?

Before considering alternative explanations for the observed relation between NIT and returns, it is important to examine whether individual trading is associated with changes in the riskiness of stocks. One possibility is that institutions sell shares to individuals when they consider the shares too risky. Alternatively, following the logic of De Long et al. (1990a), one might conjecture that increased individual trading can make stocks more volatile or riskier. In either case, the higher returns in the weeks following an increase in NIT may simply be compensation for the increased risk.

To examine in more detail volatility patterns around intense trading by individuals, we follow the same basic procedures that generated the numbers in Table III but calculate volatility rather than mean returns. We compute for each stock in each of the four portfolios the standard deviation of daily returns in 9-day windows centered on $k = -20, -15, -10, -5, 0, +5, +10, +15$, and $+20$ days (where day 0 is the middle of the formation week). Since we are interested in abnormal volatility around intense individual trading activity, we subtract from these numbers the "normal" 9-day return standard deviation (which we compute as the average of daily return standard deviations on all nonoverlapping 9-day windows in the sample period). Table VII, which presents the mean of these abnormal volatility measures in each NIT portfolio, tells us how volatility of returns evolves around the intense trading of individuals.

A clear pattern emerges from the table: Volatility increases prior to intense individual activity and subsequently decreases. Take, for example, return volatility around intense individual selling (first line of the table, going across the columns). It is −0.0001 below average volatility at $k = -20$, then increases to 0.0012 above average volatility at $k = -5$, reaches 0.0018 at $k = 0$, and then decreases to −0.0008 by $k = +20$. The next two columns test the increase of

[28] One possible explanation for the decrease in magnitude of the reversals since the beginning of the 1990s is the decrease in bid-ask spreads over that period, which would result in less bid-ask bounce.

Table VII

Return Volatility around Individual Trading

This table presents analysis of daily standard deviation of returns around intense buying and selling activity of individuals as given by the net individual trading measure (NIT). For each week in the sample period, we use the previous 9 weeks to form NIT deciles. Each stock is put into 1 of 10 deciles according to the NIT value in the current week relative to its value in the previous 9 weeks. Decile 1 contains the stocks with the most intense selling (negative NIT) while decile 10 contains the stocks with the most intense buying (positive NIT). We present the results for four portfolios: (i) decile 1, (ii) deciles 1 and 2, (iii) deciles 9 and 10, and (iv) decile 10. For each stock and each week, we calculate the standard deviation of daily returns in a 9-day window centered on day $k \in \{-20, -15, -10, -5, 0, 5, 10, 15, 20\}$, where $k = 0$ is the middle of the formation week. We subtract from these numbers the "normal" 9-day return standard deviation (which we compute as the average of daily return standard deviations on all nonoverlapping 9-day windows in the sample period). Every week we calculate the average of these standard deviations across all the stocks in each of the four portfolios. Each cell in the table contains the time-series mean for each portfolio and a t-statistic testing the hypothesis of a zero mean. The last three columns provide the differences in standard deviations from $k = -20$ to $k = 0$, $k = 0$ to $k = +20$, and $k = -20$ to $k = +20$, with t-statistics testing the hypothesis of zero differences. ** indicates significance at the 1% level and * indicates significance at the 5% level (both against a two-sided alternative).

Portfolio	$k = -20$	$k = -15$	$k = -10$	$k = -5$	$k = 0$	$k = +5$	$k = +10$	$k = +15$	$k = +20$	$k = -20$ to $k = 0$	$k = 0$ to $k = +20$	$k = -20$ to $k = +20$
Intense selling	−0.0001	−0.0002	−0.0001	0.0012**	0.0018**	0.0002	−0.0006	−0.0007	−0.0008	0.0020**	−0.0027**	−0.0007
(decile 1)	(−0.29)	(−0.38)	(−0.29)	(2.60)	(4.22)	(0.45)	(−1.30)	(−1.73)	(−1.91)	(4.41)	(−5.53)	(−1.34)
Selling (deciles 1	0.0001	0.0001	0.0002	0.0008	0.0009*	−0.0002	−0.0006	−0.0007	−0.0008	0.0008	−0.0016**	−0.0009
and 2)	(0.22)	(0.22)	(0.42)	(1.88)	(2.07)	(−0.44)	(−1.35)	(−1.78)	(−1.79)	(1.75)	(−3.49)	(−1.68)
Buying (deciles 9	−0.0008	−0.0008*	−0.0004	0.0005	0.0013**	0.0007	0.0001	0.0000	−0.0001	0.0020**	−0.0014*	0.0006
and 10)	(−1.89)	(−2.05)	(−1.09)	(1.22)	(2.66)	(1.57)	(0.18)	(0.04)	(−0.28)	(4.05)	(−2.91)	(1.23)
Intense buying	−0.0010**	−0.0011**	−0.0008*	0.0008	0.0022**	0.0013**	0.0003	0.0001	−0.0001	0.0033**	−0.0023**	0.0010
(decile 10)	(−2.62)	(−2.83)	(−2.00)	(1.83)	(4.50)	(2.68)	(0.62)	(0.17)	(−0.15)	(6.44)	(−4.71)	(1.88)

volatility from $k = -20$ to $k = 0$, which is 0.0020 and statistically significant, and the decrease of -0.0027 from $k = 0$ to $k = +20$, again statistically significant. The last column of the table tests the more "permanent" change in volatility, from $k = -20$ to $k = +20$, and finds no significant change. An even greater increase in volatility (0.0033) is observed from $k = -20$ to $k = 0$ before intense buying activity (decile 10), and most of it is subsequently reversed (-0.0023) from $k = 0$ to $k = +20$.[29]

There is some evidence of a gradual decline in volatility, and at $k = +5$ the return standard deviation following intense buying by individuals is still 0.0013 higher than average, which is statistically significant. However, the magnitude of the elevated volatility is quite small (about 10% of the average standard deviation), and volatility goes down back to the normal level in the following week. Therefore, it seems that the increase in volatility we observe is too small and too temporary in nature to explain the excess returns we observe.[30]

V. Individual Investors as Liquidity Providers

Up to this point we have established that there is a positive association between NIT and future returns, that these return patterns are not subsumed by existing return patterns observed in the literature, and that NIT does not seem to be associated with increases or decreases in volatility.

In this section we discuss what we believe is a plausible explanation for the finding of positive (negative) short-horizon excess returns following intense individual buying (selling). At the outset, we emphasize that although we find that individual investor trades contain information that can be used to forecast returns over short horizons, this does not necessarily imply that individual investors, who have much longer holding periods, realize abnormal returns. The question of interest to us is not whether individuals realize these excess returns, but rather why we observe them.

The explanation that we find most consistent with the data is that individuals earn a small excess return following periods of high NIT as compensation for providing liquidity to institutions that require immediacy. Price pressure exerted by institutional trading is consistent with both the contemporaneous pattern we observe—positive excess returns when individuals intensely sell and negative excess returns when individuals intensely buy—and with the patterns of excess returns following intense individual trading. What may be happening is that individuals sell shares when buying pressure from institutions pushes prices up and buy shares when selling pressure from institutions pushes prices down. We do not claim that individuals provide liquidity by trading actively like

[29] We also test the hypothesis that the increase in volatility before a week of intense trading is equal to the decrease in volatility afterwards, and cannot reject it at conventional significance levels.

[30] In addition to examining changes in volatility, we examine changes in the betas and conduct a similar analysis to that in Table VII using the beta of stocks (with respect to the value-weighted index) instead of the standard deviation of returns. As in Table VII, there is no statistically significant change between the betas computed at $k = -20$ and at $k = +20$.

dealers making two-sided markets. Rather, it could be that when institutions trade large positions in a certain direction and start moving prices, individuals end up taking the other side of these positions.[31]

The pattern we observe whereby individuals buy when prices decline and sell when prices increase makes them natural liquidity providers irrespective of whether they use market or limit orders. In fact, practitioners often define liquidity-supplying orders as buy orders placed when the stock price is falling and sell orders placed when the stock price is rising.[32] We know from models of risk-averse liquidity provision such as Grossman and Miller (1988) and Campbell et al. (1993) that investors who require immediacy (e.g., institutions) must offer price concessions to induce other risk-averse investors, in this case individuals, to take the other side of their trades. These price concessions result in subsequent return reversals because the future cash flows of the stock do not change, and these could be the short-horizon excess returns we find following intense individual trading.

Note that the negative excess return after individuals sell is smaller in magnitude than the positive excess return during the week of intense selling (the "$k = 0$" column in Table III). Similarly, the positive excess return after individuals buy is smaller in magnitude than the negative excess return during the week in which they buy. This seems to suggest that there is a "permanent" price impact to the institutional trading activity in addition to the "temporary" price impact that is due to risk-averse liquidity provision. Our results are therefore consistent with studies that show that the price pressure associated with institutional trading is only partially reversed subsequently (see, e.g., Chan and Lakonishok (1993, 1995), Keim and Madhavan (1997), and Campbell, Ramadorai and Vuolteenaho (2005)). Our results are also consistent with Campbell et al. (2005), who use institutional 13-F filings and trade information from TAQ to identify institutional trading. Their results suggest that institutions demand rather than provide liquidity, and seem particularly likely to demand liquidity when they sell stocks. They note that our results complement theirs, and indeed the two studies document return patterns that mirror each other using very different data sources.

If the excess returns we document following intense net individual trading represent "compensation" for providing liquidity to institutions, we should expect to find larger compensation for accommodating institutional order flow in less liquid stocks. To test this hypothesis we use the percentage effective spread (the distance of the transaction price from the quote midpoint divided by the

[31] Institutional investors often seek to acquire or dispose of large positions in a stock and therefore the impact of their trading on market prices can be significant. Furthermore, when different portfolio managers chase after the same alpha (i.e., correlated trading strategies), the price impact of their trading can be further amplified. The investment style of portfolio managers and their motivation for the change in position often determine the demand for immediacy of execution and, in turn, the price impact of trading (see, e.g., Wagner and Edwards (1993), Chan and Lakonishok (1995), and Keim and Madhavan (1997)).

[32] See, e.g., Wagner and Edwards (1993).

quote midpoint) as a proxy for the liquidity of a stock.[33] The larger the effective spread, the greater the price movement on trades and therefore the less liquid the stock. We sort stocks each week according to the average percentage effective spread and put them into three groups: small, medium, and large. We then form the intense buying and intense selling portfolios of individuals separately for each spread group. We find that the excess returns are indeed larger in less liquid stocks, especially when individuals buy: The 20-day excess return on portfolio 10 is 0.42% in the small spread group, 0.59% in the medium spread group, and 1.40% in the large spread group.[34]

There is a vast literature in market microstructure on the cost of trade execution, but much less work exists on the liquidity implications of aggregate imbalances of a specific clientele.[35] Two studies that use trade imbalances report return reversals of similar magnitude to ours. Chordia and Subrahmanyam (2004) look at the profitability of trading strategies that use previous-day trading imbalances signed with the Lee and Ready (1991) algorithm. They find that return reversals in the following day (which they attribute to an "inventory" effect or the provision of liquidity by risk-averse agents) can be used to form a strategy that yields a statistically significant daily average return of 0.09%. Barber et al. (2005) look at imbalances of small trades signed by the Lee and Ready (1991) algorithm and report a return of 0.73% (−0.64%) in the month after a week with intense positive (negative) small-trade imbalances.[36]

VI. Other Potential Explanations

Probably the most straightforward explanation for our finding of positive (negative) short-horizon excess returns following intense individual buying (selling) is that individuals whose trades are executed on the NYSE have private information about the fundamentals of stocks. Coval et al. (2002) suggest that individual investors are better able to exploit their private information (because they are small relative to institutions) and look for evidence in the 1991 to 1996 discount broker data set. They document persistence in the performance

[33] The percentage effective spread measure is constructed using the TAQ database.

[34] In light of the literature on the relation between liquidity and expected returns, one could argue that sorting on spread is basically sorting on a stock characteristic that could be priced. As such, the result of higher excess returns following purchases by individuals in the high effective spread group could mean that individuals buy riskier stocks. We therefore compute excess returns by subtracting the return on a portfolio of stocks with similar spreads as opposed to subtracting the return on the proxy for the market. E.g., the excess return on the intense buying portfolio in the small spread group is its raw return minus the return on the entire small spread group.

[35] The market microstructure literature often looks at more basic units of liquidity demand (e.g., trades) and quantifies the compensation for liquidity provision using a measure such as the realized spread (the reversal from the trade price to a post-trade benchmark price). Owing to the aggregate nature of the daily data we obtain from the NYSE, however, we cannot relate our results directly to those studies.

[36] Campbell et al. (1993) use another approach to demonstrate return reversals due to liquidity provision. They regress the current return on past daily volume (signed by the past return) and find a significant negative coefficient. This approach is also used in Pástor and Stambaugh (2003).

of some individual investors, and while on average individuals in their sample underperform, they document that some traders earn 12 to 15 basis points per day during the week after they trade.

However, adopting such an interpretation to explain our results would suggest that individuals in the aggregate, or at least those individuals who heavily influence our sample on weeks when there is an intense imbalance of trading, are somehow better informed than the institutions with whom they trade. While plausible, we find this explanation less appealing since it is unclear how individuals, who have far fewer resources than institutions, could gain the upper hand in discovering private information and trading on it profitably in such a widespread fashion.[37]

Figure 2 shows the cumulative excess returns up to 50 days following a week with intense individual imbalances. It seems that the magnitude of the excess returns stabilizes starting 20 days after intense individual buying or selling. Coval, Hirshleifer, and Shumway note that the average holding period for individuals in the 1991 to 1996 discount broker sample is 378 days (301 days for traders with at least 25 trades). If this is also the typical holding period of individuals who trade on the NYSE, then they do not trade frequently enough to take advantage of whatever short-lived private information they have. Another piece of evidence that seems inconsistent with the hypothesis that the return patterns are due to individual investors trading on short-lived private information can be seen in Table III. Prices during the intense trading week seem to go in the opposite direction to what this hypothesis would imply: negative returns when individuals intensely buy and positive returns when they sell.[38]

Another potential explanation for our results is that increased individual buying is associated with increases in the visibility of the stocks, and this could lead to the subsequent increase in share prices. As we mentioned earlier, Merton (1987) suggests that increased recognition by individual investors can lead to broader risk sharing, which in turn can reduce required rates of return and as a result increase stock prices. However, Merton's story requires an immediate increase in share prices as the visibility of the stock increases, which is inconsistent with what we observe. Indeed, we find a contemporaneous decline in stock prices in weeks in which individuals accumulate shares.

One might also consider the possibility that the serial correlation of order imbalances by individual investors generates our returns. This is essentially the argument made in a recent paper by Barber et al. (2005), who find that an increase in small-trade buying in week 1 is associated with high contemporaneous

[37] It is possible that the orders executed on the NYSE come from relatively sophisticated individual investors. In other words, it could be that the distribution across individuals in our data set is different from the one in the data set of the discount broker's clients, and that more individuals in our data set are like the skillful individuals that Coval, Hirshleifer, and Shumway document. One piece of evidence inconsistent with this explanation, however, comes from Jones and Lipson (2004), who also use proprietary NYSE order-level data. They find that orders coming from individuals have smaller permanent price impacts relative to institutional orders, suggesting that individuals have less private information than institutions about stocks' fundamentals.

[38] We thank the referee for pointing out this test of the short-lived private information hypothesis.

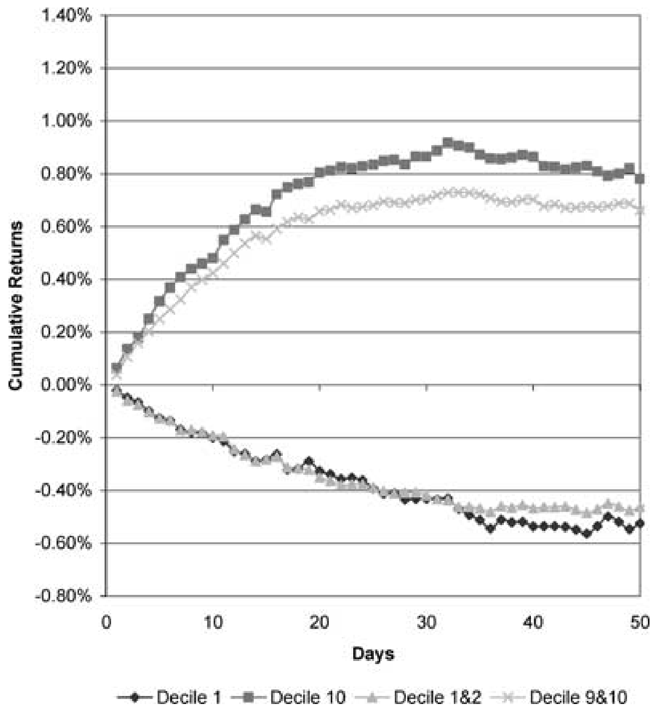

Figure 2. Returns following intense individual trading. This figure presents cumulative market-adjusted returns following weeks with intense buying and selling activity of individuals as given by the net individual trading measure (NIT). For each week in the sample period, we use the previous 9 weeks to form NIT deciles. Each stock is put into 1 of 10 deciles according to the NIT value in the current week relative to its value in the previous 9 weeks. Decile 1 contains the stocks with the most intense selling (negative NIT) while decile 10 contains the stocks with the most intense buying (positive NIT). We present the results for four portfolios: (i) decile 1, (ii) deciles 1 and 2, (iii) deciles 9 and 10, and (iv) decile 10. We calculate cumulative return numbers for each of the stocks in a portfolio: $\mathrm{CR}(t+1, t+k)$, where t is the last day of the portfolio formation week and k is the number of days in the cumulative return calculation. The return on each portfolio is then adjusted by subtracting the return on a market proxy (the equal-weighted portfolio of all stocks in the sample).

returns and both a high magnitude of small-trade buying in week 2 as well as higher returns in week 2. It should be noted that in our case, however, a positive order imbalance is associated with negative rather than positive returns in the contemporaneous week, and the serial correlation of the order imbalance is actually quite small.

VII. Our Results in the Context of the Literature

The literature on the trading behavior of individual investors has been evolving rapidly and it is useful to describe how the results in this paper relate to both earlier and contemporaneous research that examines individual trading behavior.

The first thing to note is that there is widespread agreement in the literature that individuals tend to be contrarian, at least in the short term, which is consistent with our argument that individuals tend to supply liquidity to institutions. Choe, Kho, and Stulz (1999) report short-horizon contrarian patterns of Korean individual investors (i.e., buying after prices go down and selling after prices go up), Grinblatt and Keloharju (2000, 2001) report contrarian tendencies (both long- and short-term) using Finnish data, Jackson (2003) demonstrates such short-horizon patterns using Australian data, and Richards (2005) reports similar findings in six Asian markets. In the United States, Goetzmann and Massa (2002) examine individuals who invest in an index fund and find that contrarians outnumber momentum traders two to one, and Griffin et al. (2003) document a short-horizon contrarian tendency of traders who submit orders in Nasdaq stocks through a set of retail brokers.[39]

There is less agreement, however, about the relation between individual trades and future stock returns. Starting with the longer horizon (several months to 2 years), Odean (1999) finds that the stocks individuals buy underperform those they sell. Barber and Odean (2000) look at the overall performance of individual portfolios and find that they underperform the index by about 1%. Similarly, Grinblatt and Keloharju (2000) report poor performance of individual investors at the 6-month horizon in Finland. San (2005), who infers individual trading from signed total volume by subtracting institutional changes in 13-F filings, finds the opposite result, namely, that excess return is positive in the 2 years following individual buying. Two recent papers, Barber et al. (2005) and Hvidkjaer (2005), use small-trade volume signed with the Lee and Ready (1991) algorithm as a proxy for individual investor trading. Both papers find that stocks with heavy small-trade buy volume underperform stocks with heavy small-trade sell volume. The performance difference is detected up to 3 years in the future.[40] Barber et al. (2005) also provide some evidence on short-horizon return patterns that we discuss below.

[39] San (2005) does not have data that identifies individuals. She creates a proxy for net individual trading by signing total volume and subtracting from it changes in institutional holdings. She finds that prices decline in the 2 years prior to individual buying. Bailey, Kumar, and Ng (2004), who examine a sample from a discount broker (1991 to 1996), find that U.S. individuals who invest abroad also exhibit contrarian behavior (relative to the foreign country's stock index).

[40] The advantage of using signed small-trade volume to proxy for individual investor trading is that a long time series can be constructed (both papers use a sample period that starts in 1983). The disadvantage is that small-trade volume may not come just from individuals. Lee and Radhakrishna (2000) use 3 months of NYSE data (similar to ours) and show that this proxy worked reasonably well in 1990. However, Hvidkjaer (2005) notes that in the final years of his sample (that ends in 2004), small-trade volume increases markedly and it no longer seems to be negatively related to changes in institutional holdings. The bulk of the increase in small trading probably comes from institutions that split orders into small trades. Campbell et al. (2005) reach the same conclusion when looking at the relation between changes in institutional holdings and small-trade volume. In fact, their methodology finds that trades below $2,000 are more likely to come from institutions than from individuals. While signed small-trade volume is probably a reasonable proxy for individual investor trading over a large portion of the sample used in Barber et al. (2005) and Hvidkjaer (2005), Hvidkjaer notes that this proxy may be a poor one in the future.

It should be noted that because of our limited time series we are unable to contribute to the literature on the long-term effect of individuals' purchases and sales. Our focus, therefore, is on short-horizon return patterns. Looking at evidence from outside the United States, our results are consistent with evidence presented by Jackson (2003), who finds that the net flows of small investors positively predict future short-horizon returns in Australia. In contrast, Barber et al. (2005) find that in Taiwan, individual investors realize small losses in the short horizon (0.17% in the first 25 days). Similarly, Andrade et al. (2005) report that margin traders in Taiwan (most of whom are individuals) tend to earn negative returns over short horizons.

It may not be particularly surprising that the findings in Australia are consistent with our results but the Taiwanese results have a different flavor. The Australian market, like the U.S. market, is dominated by institutions, so our conjecture that individuals provide liquidity to institutions is equally plausible in the United States and Australia. However, Barber et al. (2005) report that 89.5% of dollar volume on the Taiwan Stock Exchange comes from individuals, and that day trading (most of which is carried out by individuals) is 23% of dollar volume, which suggests that our liquidity provision story is unlikely to be applicable in Taiwan. They also show, however, that individuals do make money from liquidity-providing trades (1.06% in the first 10 days). It should also be noted that our experimental design is somewhat different from that in Barber et al. (2005), and therefore their results could potentially be consistent with ours. They look at return patterns following all imbalances, while we focus on those intense imbalances where individuals in the aggregate have a strong, predominant direction.

To the best of our knowledge, the only paper prior to our study that looks at the short-horizon dynamic relation between the trading of individual investors in the United States and returns is Griffin et al. (2003). They find no evidence that individual imbalances predict future daily returns. One potential explanation for the differences in our findings is that there is a fundamental difference between the NASDAQ stocks examined in their study and the NYSE stocks we examine. Another potential explanation is that their proxy for individual investor trading (trading through brokers who mostly serve retail clients) may contain some noise that masks a weaker relationship.[41]

Recent evidence that is consistent with ours can be found in Barber et al. (2005). They suggest a possible reconciliation of our finding of positive (negative) excess returns after intense buying (selling) by individuals and the result

[41] The data set used by Griffin et al. does not provide information on whether certain trades or orders come from individuals. However, they observe an identifier that tells them something about the broker or the venue of execution (i.e., they can separate institutional brokers, wirehouses, ECNs, regional firms, wholesalers, small firms, and regional exchanges). Griffin et al. classify the order flow of all ECNs (except Instinet), regional firms, wholesalers, and the Chicago Stock Exchange as order flow coming from individuals. Each small firm is classified depending on the executed order size of the majority of its orders (if most orders are small, all the order flow of that firm is classified as coming from individuals).

in Odean (1999) of poor longer-horizon performance of individual investor trading. Using signed small-trade volume as a proxy for individual trading, they find similar results to ours on the return patterns in the several weeks after heavy buying or selling by individuals. They conclude that the pattern reverses itself subsequently, and therefore it is consistent with the longer-horizon underperformance that they document.

VIII. On the Issue of Systematic Noise

A natural question to ask of our data set is whether the actions of individual investors on the NYSE are "systematic" in the sense that they affect all stocks at the same time. The importance of this issue rests in part on the suggestion of the behavioral finance literature that, if individual investors are indeed "noise" traders, systematic variation in their behavior would affect expected returns. This argument is succinctly made by Lee, Shleifer, and Thaler (1991): "If different noise traders traded randomly across assets, the risk their sentiment would create would be diversifiable, just as the idiosyncratic fundamental risk is diversifiable in conventional pricing models. However, if fluctuations in the same noise trader sentiment affect many assets and are correlated across noise traders, then the risk that these fluctuations create cannot be diversified. Like fundamental risk, noise trader risk will be priced in equilibrium."

Since we find a dynamic relation between net individual trading and returns on a stock-by-stock basis, we also look at whether the dynamic relation exists between the value-weighted market return and a value-weighted measure of net individual trading. We find no statistically significant patterns, suggesting that the behavior of individuals may not be highly correlated across stocks. The lack of dynamic patterns at the market portfolio level prompts us to carry out additional analysis.

In Table VIII we aggregate the dollar buying and selling of all individuals every day in all NYSE common domestic stocks and provide summary statistics on the time-series distribution of this aggregated imbalance measure. The table demonstrates that aggregate imbalances of individuals can be rather large in magnitude. One could think of two different scenarios for how such large aggregate imbalances are created. First, they could potentially reflect just a few stocks that individuals intensely buy (or sell) on a particular day, with the rest of the stocks having more-or-less balanced individual trading. Second, it could be that these large aggregate imbalances arise when most stocks exhibit on the same day the same predominant direction of individual trading (either buying or selling). Only the second scenario would suggest systematic behavior of individual investors across stocks.

To examine this issue, we conduct a principal components analysis of the daily net individual trading measure and look at the percentage of variance of NIT that is explained by the first 10 principal components. We construct 1,000 random subsamples of 180 stocks each from among the stocks that have a complete set of daily returns, and look at the mean and standard deviation of the

Table VIII

Summary Statistics of the Aggregate Net Individual Trading Measure

The sample of stocks for the study consists of all common domestic stocks that were traded on the NYSE at any time between January 1, 2000, and December 31, 2003, with records in the CRSP database. We use ticker symbol and CUSIP to match the stocks to a special data set containing daily aggregated buying and selling volume of individuals provided by the NYSE. There are 2,034 stocks in our sample. Stocks are sorted by market capitalization and put into three groups: small (deciles 1, 2, 3, and 4), mid-cap (deciles 5, 6, and 7), and large (deciles 8, 9, and 10). For each size group and for the entire market we compute the dollar imbalance of individuals aggregated across all stocks in the group, and provide time-series summary statistics for this dollar imbalance measure.

	Mean (million \$)	Std. Dev. (million \$)	Min (million \$)	25% (million \$)	Median (million \$)	75% (million \$)	Max (million \$)
Entire sample	−240.58	170.98	−1,063.72	−316.19	−217.38	−132.51	1,690.68
Small stocks	−87.78	7.96	−40.29	−13.85	−7.62	−3.05	20.44
Mid-cap stocks	−28.54	19.36	−115.77	−39.86	−27.48	−14.17	31.70
Large stocks	−203.27	157.28	−956.59	−269.45	−184.80	−107.48	1,740.01

percentage of variance across the 1,000 random subsamples.[42] We use simulations to generate principal components for independent random matrices, and use these as a benchmark for evaluating the percentage of variance explained by the principal components in the real data (details of the methodology are provided in the Appendix).[43]

Panel A of Table IX shows the results of the principal components analysis of the net individual trading measure and also of daily returns. We present the daily return analysis just to provide a sense of the magnitude of co-movement observed in the cross-section of stocks. For example, 21.25% of the daily variation in returns of stocks in our sample is explained by the first five principal components. However, the third line of the panel shows that the percentage of variance explained by the first five principal components of the simulated independent data is 5.33%, and therefore the difference between these two numbers, roughly 15.92%, is a better measure of the structure in the real data. As for NIT, we cannot find strong evidence of a common component in the imbalances of individual investors across stocks. Indeed, the first (and largest) principal component of NIT explains only 1.70% of the variance (adjusted using the simulated data) compared with 12.07% for returns.

Since some papers (e.g., Lee et al. (1991) and Kumar and Lee (2005)) claim that "noise" trading of individuals is potentially stronger in small stocks, we

[42] We choose 180 stocks as the size of a subsample because it is approximately a tenth of the number of stocks, and is therefore roughly comparable to the number of stocks in a size decile. We present the principal components analysis of size deciles later in this section.

[43] We use simulations to create a benchmark because any arbitrary decision on the size of the subsamples affects the estimates. E.g., the percentage of the variance explained by the first principal component is at least 1% in a 100-stock subsample because each stock contributes one unit of variance to the analysis. The simulated benchmark helps us determine whether the structure observed in the data is really there, as opposed to being generated by our particular choices or simply by chance (see Freedman and Lane (1983)).

Table IX

Principal Components Analysis

This table presents a principal components analysis of returns and the net individual trading measure (NIT) at the daily frequency. Panel A reports the results of a principal components analysis of 1,000 subsamples of 180 stocks each (since we have more stocks in our sample than days in the sample period). We perform a principal components analysis on each subsample, and report the mean (Real Mean) and standard deviation (Real Std.) across subsamples of the percentage of the variance explained by the first 10 principal components. We then construct 1,000 additional 180-stock random subsamples. We compute for each stock the mean and standard deviation of the variable of interest (say, NIT) and generate an artificial time series for each stock drawn from a normal distribution with the same mean and standard deviation. We perform a principal components analysis on the simulated data of each subsample, and report the mean (Simulated Mean) across subsamples of the percentage of the variance explained by the first 10 principal components. We then report the difference in the percentage of the variance explained by the different principal components (PC1, PC2, sum of PC1–5, sum of PC1–10) between the real data and the simulated data. Panel B reports the results of a principal components analysis of NIT done separately on each size decile. We sort the stocks according to average market capitalization over the sample period into 10 deciles. We perform a principal components analysis on each decile and report the percentage of the variance explained by both the first 5 and the first 10 principal components (PC1–5 and PC1–10, respectively). We then use the mean and standard deviation of each stock to generate 500 artificial time series drawn from the normal distribution to form 500 independent subsamples for each decile. We perform a principal components analysis on each subsample and save the mean across the subsamples of the percentage of the variance explained by the first 5 and 10 principal components. We then report the difference in the percentage of the variance explained by the principal components between the real data and the simulated data.

Panel A: Percentage of Variance Explained by Principal Components (1,000 Random Samples of 180 Stocks)

		PC1	PC2	PC1–5	PC1–10
Returns	Real mean	0.1317	0.0267	0.2125	0.2709
	Real std.	0.0079	0.0027	0.0097	0.0100
	Simulated mean	0.0111	0.0108	0.0533	0.1033
	Difference	0.1207	0.0159	0.1592	0.1676
NIT	Real mean	0.0280	0.0239	0.1007	0.1641
	Real std.	0.0022	0.0017	0.0044	0.0052
	Simulated mean	0.0111	0.0108	0.0533	0.1033
	Difference	0.0170	0.0131	0.0474	0.0608

Panel B: Percentage of Variance of NIT Explained by Principal Components (Size Deciles)

		Decile 1 (small)	Decile 2	Decile 3	Decile 4	Decile 5	Decile 6	Decile 7	Decile 8	Decile 9	Decile 10 (large)
PC	Real	0.0805	0.0945	0.0872	0.0941	0.0946	0.0994	0.0995	0.1096	0.1202	0.1521
1–5	Diff.	0.0313	0.0454	0.0382	0.0450	0.0456	0.0503	0.0504	0.0606	0.0710	0.1031
PC	Real	0.1427	0.1536	0.1456	0.1552	0.1526	0.1558	0.1573	0.1678	0.1846	0.2191
1–10	Diff.	0.0474	0.0583	0.0506	0.0599	0.0576	0.0605	0.0619	0.0727	0.0893	0.1241

sort the sample into 10 deciles according to each stock's average market capitalization over the sample period.[44] Panel B of Table IX presents the results. Contrary to what one might have expected based on the above papers, the percentage of the NIT variance explained by the first five principal components (adjusted using the simulations) is higher for large stocks (10.31% for decile 10) than for small stocks (3.13% for decile 1).

Our findings do not seem as strong as those of Kumar and Lee (2005), who examine correlations among order flow imbalances of portfolios of stocks traded by clients of a U.S. discount broker (using the 1991 to 1996 data set). They find that their measure of order flow imbalance is moderately correlated across portfolios of stocks, concluding that there is evidence of a systematic component in retail investor trading. They also note that the difference between their results and ours could be due to a different research methodology, sampling frequency (daily for us versus monthly for them), aggregation mode (individual stock imbalances here versus portfolio imbalances there), data source, and sample period (ours is 2000 to 2003 while theirs is 1991 to 1996). It is also interesting to note that when Kumar and Lee look at portfolios of different sizes, the correlation becomes smaller as the size of the portfolio decreases, raising the possibility that the relation would not be as strong at the individual stock level. This question therefore awaits additional research.[45]

IX. Conclusions

Our analysis of the trading of individual investors on the NYSE provides two important results. First, we document that net individual trading is positively related to future short-horizon returns: Prices go up in the month after intense buying by individuals and go down after intense selling by individuals. This is the first time such a pattern is documented for individual investors trading in the United States and a large portion of the paper investigates this pattern.

Second, we find that the predictive ability of net individual trading with respect to returns is not subsumed by volume or the return reversal phenomenon. Our results seem to contrast with Subrahmanyam (2005), who finds that net trade imbalances do not predict returns. Perhaps the net order flow of individuals that we consider is a better measure of the demand for liquidity than the net trade imbalance of Subrahmanyam, who uses the Lee and Ready (1991) algorithm to indirectly infer whether trades are initiated by buyers or sellers. The Lee and Ready algorithm establishes which party to a trade used a market order (by comparing the transaction price to the quote midpoint), and classifies that party as a liquidity demander. In contrast, we classify individuals as

[44] Each decile contains less than 200 stocks, and therefore we do not need to draw random subsamples to analyze the data. Nonetheless, we still need to adjust the estimates using simulations of independent normally distributed data (details are provided in the Appendix).

[45] Barber, Odean, and Zhu (2003) do not focus on the correlation in individual trading across many stocks, but they show that clients of two different brokers tend to trade the same stocks at the same time. They also show temporal persistence in that if individuals are buying a stock one month, they are more likely to be buying it the following month as well.

liquidity providers regardless of how they execute their orders, which allows for very different interpretations of the data. For example, institutions that want to move large positions might use dynamic limit order strategies and their demand for immediacy might be accommodated by contrarian individuals who offer their shares with market orders. In this example, the Lee and Ready algorithm would classify the institutions as liquidity providers and the individuals as liquidity demanders, while we would make the opposite classification.

In general, the contrarian behavior we document of individual investors on the NYSE seems important for understanding short-horizon return predictability. The underlying reason individuals act in such a way is not well understood, and one can find arguments in the behavioral literature supporting both contrarian tendencies (e.g., loss aversion in Odean (1998)) as well as a tendency to buy winners (e.g., positive feedback trading in De Long et al. (1990b) or attribution bias in Daniel, Hirshleifer, and Subrahmanyam (1998)). Whatever the reason, the contrarian choices of individuals lead them to implicitly provide liquidity to other market participants who demand immediacy.

In theory, the extent to which price reversals are observed depends on the risk aversion of the liquidity providers and the amount of capital available for liquidity provision. Suppose that individual investors are the only ones providing liquidity in the market. If contrarian individual investors are in some sense too active relative to the demand for immediacy, there will be an excess supply of liquidity in the market. If this is the case, then the return pattern compensating the individuals for providing liquidity could be overwhelmed by the (presumed) information content of the institutional order flow, leaving no excess returns (or even excess returns going in the opposite direction). On the other hand, if there are too few contrarian investors relative to the demand for immediacy, then the excess returns we observe when individuals implicitly provide liquidity could be even more pronounced.

In reality, liquidity is provided by professional traders (e.g., NYSE specialists) as well as those individuals who buy when prices go down and sell when prices go up. One would expect that the amount of capital that these professionals devote to their market-making activity is determined by the aggregate demand for liquidity as well as the amount of liquidity implicitly supplied by individual investors. In equilibrium, these professional traders will supply liquidity up to the point where their trading profits just cover their costs. Over the past 20 years, institutional trading has increased and the importance of individual investors has declined, suggesting that there may have been a positive shift in the demand for immediacy and a negative shift in the supply of liquidity. If this is indeed the case, and if the amount of capital devoted to liquidity provision is slow to adjust, then this shift could create a potential short-term profit opportunity for those traders that provide liquidity.

The evidence in this paper is consistent with the view that a short-term liquidity provider could have generated profits by mimicking the trades of individual investors during our sample period. There is also anecdotal evidence suggesting that in response to this opportunity, there has been an increase in the number of professional investors who specialize in short-term contrarian trading strategies, and thus indirectly provide such services.[46] Indeed, the presence of these traders may be responsible for the reduction we document in the return reversals first observed by Jegadeesh (1990) and Lehmann (1990).

Why don't the strategies implemented by these short-term traders eliminate the excess returns associated with the trading of individuals? This is a difficult question that clearly warrants additional research. The most natural explanation is that these high-frequency strategies are quite costly to implement, and thus we expect to observe high pretransaction costs returns. It is also possible that the remaining return is needed to compensate those firms for the risk associated with undertaking the liquidity-supplying trading strategies. Moreover, it may be the case that mechanical strategies are unable to implement the strategies implicitly implemented by individual investors. While the trades of all market participants (including individuals) are public information, the Account Type information identifying the orders of individual investors could not be used to implement a trading strategy in real time because it was not publicly available during the time period considered (it was not available even to the specialists who oversee trading on the NYSE floor). Therefore, institutions could not simply use NIT to formulate their strategies; rather, they would have to base a strategy on an imperfect proxy for net individual trading.

The evidence we present suggests that understanding short-horizon return predictability requires understanding the implicit liquidity provision of individuals as well as the explicit liquidity provision of professional investors. In particular, liquidity provision may be viewed as the interplay between different types of investors who populate the market. At the very least, our work suggests that understanding the behavior of one investor type, individuals, holds some promise for explaining observed return patterns.

Appendix

Our sample consists of 2,034 stocks and 1,004 trading days. For the analysis in Panel A of Table IX, we first construct 1,000 random subsamples of 180 stocks each from among the stocks that have a complete set of daily returns. We perform a principal components analysis using the Principal Axis method for each subsample, and then compute the mean and standard deviation across the 1,000 subsamples of the percentage of the variance explained by the first 10 principal components. These summary statistics are reported in the panel as "Real Mean" and "Real Std."

[46] E.g., Automated Trading Desk (ATD) is one of the firms that pioneered the use of computerized expert systems applied to liquidity provision. While currently they also work on an agency basis for institutional investors, their core competency has been proprietary limit-order strategies that provide liquidity to the market and profit from short-term price movements. ATD's trading in 2003 accounted for about 5% of Nasdaq volume and more than 2% of the volume in listed stocks. It is also interesting to note that there has been a tremendous drive for consolidation among NYSE specialist firms in the past 15 years. The number of specialist firms trading NYSE common stocks declined from 52 in 1989 to 7 in 2004. One argument made to support these consolidations was that liquidity will be enhanced by having better-capitalized market-making firms.

The adjustment using simulations is conducted as follows. We construct another set of 1,000 random subsamples of 180 stocks each. We calculate the mean and standard deviation of the variable analyzed (say, the net trading of individual investors) for each stock in a subsample. We then generate an artificial time series for each stock drawn from a normal distribution with the same mean and standard deviation. We conduct a principal components analysis on the 180 independent time series and note the percentage of the variance explained by the first 10 principal components. We repeat this process for each subsample 10 times and average the percentage of the variance explained by each principal component in order to get estimates that are less noisy. We end up with 1,000 estimates for subsamples of simulated, independent data (reported in the table as "Simulated Mean"), and look at the differences ("Difference") between the real and simulated means.

The results demonstrate the importance of considering a simulated benchmark. For example, the first principal component in Panel A explains on average 1.11% of the variance of the simulated, independent data. The fact that the first eigenvalue explains considerably more than 1/180 of the variance of a 180-stock sample of randomly generated returns is not entirely surprising. It is well known that the distribution of the spacing x between adjacent eigenvalues of a random matrix whose elements are i.i.d Gaussian is closely approximated by the "Wigner surmise" $P(x) \approx Axe^{-Bx^2}$ (see, e.g., Porter (1965)). Furthermore, numerical experiments show that the surmise holds for a wide range of distributions (e.g., Lehman (2001)). Therefore, the use of a simulated benchmark aids in evaluating the strength of the structure found in the real data.

For the analysis in Panel B of Table IX we sort the sample into 10 deciles according to each stock's average market capitalization over the sample period. We perform a principal components analysis on each decile separately. To create the simulated benchmark for these estimates we start by using the mean and standard deviation of each stock to generate 500 artificial time series drawn from the normal distribution. We then use these simulated data to run 500 separate principal components analyses for each decile, and we report in the table the difference between the estimate of the percentage of variance in the real data and the mean of the 500 estimates of the simulated data.

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