Online Investors: Do the Slow Die First?

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We analyze 1,607 investors who switched from phone-based to online trading during the 1990s. Those who switch to online trading perform well prior to going online, beating the market by more than 2% annually. After going online, they trade more actively, more speculatively, and less profitably than before—lagging the market by more than 3% annually. Reductions in market frictions (lower trading costs, improved execution speed, and greater ease of access) do not explain these findings. Overconfidence—augmented by self-attribution bias and the illusions of knowledge and control—can explain the increase in trading and reduction in performance of online investors.

[The giant] tortoise lives longer than any other animal.

Collier's Encyclopedia

"Online trading is like the old west," warns Fidelity Investments. "The slow die first." "Trading at home? Slow can kill you," echoes a provider of Internet connections. "If your broker's so great, how come he still has to work?" asks E*TRADE. Another E*TRADE ad notes online investing is "A cinch. A snap. A piece of cake." "I'm managing my portfolio better than my broker ever did," claims a middle-aged woman (Datek Online). In Ameritrade's "Momma's Gotta Trade," two suburban moms return from jogging. Straight to her computer, a few clicks and a sale later, one declares "I think I just made about $1,700!" Her kids cheer, while her friend laments, "I have mutual funds." And then there is Discover Brokerage's online trading tow-truck driver. He picks up a snobbish executive who spots a postcard on the dashboard and asks "Vacation?" "That's my home," says the driver. "Looks more like an island," says the executive. "Technically, it's a country," replies the driver.

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These advertisements entice and amuse. They assure the uninitiated that they have what it takes to trade online; tell them what to expect—sudden wealth; and what will be expected of them—frequent trades. They also reinforce cognitive biases, which, for the most part, do not improve investors' welfare.

In general, when the price of a product declines, the quantity demanded of the product increases, as does consumer welfare. This has been the case, for example, with personal computers over the last decade. While consumers are always better off paying less for the same goods, there are situations where the increased demand associated with lower prices is a questionable boon to individuals and a clear loss to society. An extreme example is increased consumption of cigarettes due to price cuts or greater ease of access.

In recent years there has been an explosion of online trading that is likely to continue. Forrester Research, Inc. [Punishill (1999)] projects "that by 2003, 9.7 million U.S. households will manage more than $3 trillion online—nearly 19 percent of total retail investment assets—in 20.4 million on-line accounts." The growth in online trading has been accompanied by a decrease in trading commissions.[1] Lower commissions, greater ease of access, and speedier trade executions constitute reductions in market frictions. Such reductions of friction generally improve markets. However, while these changes can obviously benefit investors, to the extent that they encourage excessive, speculative trading, this benefit is attenuated.

In this article we provide a description of those who switch from phone-based to online trading. Multivariate analyses document that young men who are active traders with high incomes and a preference for investing in small growth stocks with high market risk are more likely to switch to online trading. We find that those who switch to online trading experience unusually strong performance prior to going online, beating the market by more than 2% annually.

We also examine the change in trading behavior that takes place when investors go online. In doing so, we test the theory that overconfidence leads to excessive trading. Consistent with that theory, we find that, after going online, investors trade more actively, more speculatively, and less profitably than before. It is difficult to reconcile these results with rational behavior.

Human beings are overconfident about their abilities, their knowledge, and their future prospects. Odean (1998b) shows that overconfident investors trade more than rational investors and that doing so lowers their average utilities, since overconfident investors trade too aggressively when they receive information about the value of a security. Greater overconfidence leads to

[1] Credit Suisse First Boston Technology Group [Burnham and Earle (1999)] reports a 70% drop in the average commission charged by the top 10 online trading firms from 1996:Q1 to 1997:Q4, though commissions have remained largely unchanged from 1997:Q4 through 1999:Q1.

greater trading and to lower average utility.[2] Due to several cognitive biases, in addition to selection bias, the investors we observe switching from phone-based trading to online trading are likely to have been overconfident about their ability to profit from trading online. The reduced costs and increased ease of online trading are most appealing to active traders. Thus, particularly in these early years, online trading may have attracted more overconfident, more active investors. However, this selection bias alone will not cause online investors to perform worse after they commence online trading. (However, it is possible that investors whose confidence has recently increased are particularly likely to anticipate more active future trading and to therefore avail themselves of the benefits of trading online.)

We posit that online investors become more overconfident once online for three reasons: the self-attribution bias, an illusion of knowledge, and an illusion of control. People tend to attribute their successes to their own abilities, even when such attribution is unwarranted (self-attribution bias). Thus recent investment success is likely to foster overconfidence in one's stock picking abilities. We find that those who switched from phone-based to online trading did so after a period of unusually strong performance, which may have engendered greater overconfidence. People also become more overconfident when given more information on which to base a forecast (the illusion of knowledge) and they behave as if their personal involvement can influence the outcome of chance events (the illusion of control). Online investors have access to vast quantities of information, generally manage their own portfolios, and trade at the click of a mouse. These aspects of online trading foster greater overconfidence. And greater overconfidence leads to elevated trading and poor performance—precisely the portrait of the online investors that we study.

The article proceeds as follows. We motivate our test of overconfidence in Section 1. In Section 2 we describe the data and methods. We present our main results in Section 3. We discuss our results in Section 4 and conclude in Section 5.

1. A Test of Overconfidence

1.1 Overconfidence and trading on financial markets

Studies of the calibration of subjective probabilities find that people tend to overestimate the precision of their knowledge [Fischhoff, Slovic, and Lichtenstein (1977), Alpert and Raiffa (1982), see Lichtenstein, Fischhoff,

[2] Kyle and Wang (1997) and Benos (1998) show that under particular circumstances when both a rational insider and overconfident insider trade strategically and simultaneously with a market maker, the overconfident insider may earn greater profits than the rational insider. The overconfident insider earns greater profits by "precommitting" to trading aggressively. For this result to hold, traders must have sufficient resources and risk tolerance to trade up to the Cournot equilibrium, trade on correlated information, and know each other's overconfidence. It is unlikely that these models describe individual investors, who have limited resources, trade asynchronously, and do not know the overconfidence levels of those with whom they trade.

and Phillips (1982) for a review of the calibration literature]. Such overconfidence has been observed in many professional fields. Clinical psychologists [Oskamp (1965)], physicians and nurses, [Christensen-Szalanski and Bushyhead (1981), Baumann, Deber, and Thompson (1991)], investment bankers [Staël von Holstein (1972)], engineers [Kidd (1970)], entrepreneurs [Cooper, Woo, and Dunkelberg (1988)], lawyers [Wagenaar and Keren (1986)], negotiators [Neale and Bazerman (1990)], and managers [Russo and Schoemaker (1992)] have all been observed to exhibit overconfidence in their judgments. [For further discussion, see Lichtenstein, Fischhoff, and Phillips (1982) and Yates (1990).]

Overconfidence is greatest for difficult tasks, for forecasts with low predictability, and for undertakings lacking fast, clear feedback [Fischhoff, Slovic, and Lichtenstein (1977), Lichtenstein, Fischhoff, and Phillips (1982), Yates (1990), Griffin and Tversky (1992)]. Selecting common stocks that will outperform the market is a difficult task. Predictability is low; feedback is noisy. Thus stock selection is the type of task for which people are most overconfident.

Survey and experimental evidence supports our contention that investors are overconfident. Since October 1996, Paine Webber has sponsored 13 separate Gallup surveys of individual investors. In each of these 13 surveys, on average, investors expected their own portfolios to beat the market.[3] For example, in October 1999, investors expected their portfolios to return, on average, 15.7% over the next 12 months, while they expected the market to return 13.3%. Moore et al. (1999) generate similar results in an investment experiment using 80 MBA students.

DeBondt and Thaler (1995) note that the high trading volume on organized exchanges is perhaps the single most embarrassing fact to the standard finance paradigm, and that the key behavioral factor needed to understand the trading puzzle is overconfidence. DeLong et al. (1991), Kyle and Wang (1997), Benos (1998), Caballé and Sákovics (1998), Daniel, Hirshleifer, and Subramanyam (1998, 2001), Odean (1998b), and Gervais and Odean (2000) develop theoretical models based on the assumption that investors are overconfident. Most of these models predict that overconfident investors will trade more than rational investors.

In theoretical models overconfident investors overestimate the precision of their knowledge about the value of a financial security.[4] They may also overestimate the probability that their personal assessments of the security's

[3] In each of these surveys, investors were asked two questions: "What overall rate of return do you expect to get on your portfolio in the next 12 months," and "Thinking about the stock market more generally, what overall rate of return do you think the stock market will provide investors during the coming 12 months?" Across the 13 surveys, the average investor expects a return of 15% on their own portfolio, while they expect the market to return 13%.

[4] Odean (1998b) points out that overconfidence may result from investors overestimating the precision of their private signals or, alternatively, overestimating their abilities to correctly interpret public signals.

value are more accurate than the assessments of others. Thus overconfident investors believe more strongly in their own valuations and concern themselves less with the beliefs of others. This intensifies differences of opinion. And differences of opinion cause speculative trading [Varian (1989); Harris and Raviv (1993)]. Rational investors only trade and purchase information when doing so increases their expected utility [e.g., Grossman and Stiglitz (1980)]. Overconfident investors, on the other hand, lower their expected utility by trading too much and too speculatively; they hold unrealistic beliefs about how high their returns will be and how precisely these can be estimated; and they expend too many resources (e.g., time and money) on investment information [Odean (1998b).][5]

Odean (1999) and Barber and Odean (2000) test whether investors decrease their expected utility by trading too much. Using the same dataset from which the sample analyzed here is drawn, Barber and Odean (2000) show that after accounting for trading costs, individual investors underperform relevant benchmarks. Those who trade the most realize, by far, the worst performance. This is what the models of overconfident investors predict. Barber and Odean (2001) show that men, who tend to be more overconfident than women, trade nearly one and a half times more actively than women and thereby reduce their net returns more so than do women. With a different dataset, Odean (1999) finds that the securities individual investors buy subsequently underperform those they sell. When he controls for liquidity demands, tax-loss selling, rebalancing, and changes in risk aversion, investors' timing of trades is even worse. This result suggests that not only are investors too willing to act on too little information, but they are too willing to act when they are wrong.

The overconfidence models predict that more overconfident investors will trade more actively and will thereby reduce their net returns. In this article we argue that investors in our sample who switch to online trading are likely to be more overconfident than the average investor and to be more overconfident after going online than before. We test for differences in the turnover and returns of online and phone-based investors and for differences before and after investors go online.

1.2 Online investing and overconfidence

1.2.1 Self-attribution bias. Online investors in our sample outperform the market before going online. People tend to ascribe their successes to their personal abilities and their failures to bad luck or the actions of others [Langer and Roth (1975), Miller and Ross (1975)], and self-enhancing attributions following success are more common than self-protective attributions following failures [Fiske and Taylor (1991), see also Miller and Ross (1975)].

[5] In some models that assume investors are overconfident, the overconfident investors may improve their welfare by trading aggressively. However, the assumptions required to generate this result are unlikely to apply to individual investors, which is the focus of our empirical investigation (see footnote 2).

Gervais and Odean (2000) demonstrate that this self-attribution bias will cause successful investors to grow increasingly overconfident about their general trading prowess. [Daniel, Hirshleifer, and Subrahmanyam (1998) further argue that self-attribution bias can intensify overreactions and lead to short-term momentum and long-run reversals in stock prices.] Investors whose recent successes have increased their overconfidence will trade more actively and more speculatively. Because they anticipate that the effort of switching to online trading will be amortized over more trades, these investors are more likely to go online. If self-attribution-induced overconfidence triggers investors to go online, online investors will tend to be more overconfident than phone-based investors and more overconfident subsequent to going online than in the period before.

1.2.2 The illusion of knowledge. When people are given more information on which to base a forecast or assessment, the accuracy of their forecasts tends to improve much more slowly than their confidence in the forecasts. While the improved accuracy of forecasts yields better decisions, additional information can lead to an illusion of knowledge and foster overconfidence, which leads to biased judgments. In a widely cited study, Oskamp (1965) documents that pyschologists' confidence in their clinical decisions increased with more information, but accuracy did not. Several subsequent studies confirm the illusion of knowledge [e.g., Hoge (1970), Slovic (1973), Peterson and Pitz (1988)].

Online investors have access to vast quantities of investment data. We posit that online investors are more likely to access and use these data than investors with traditional brokerage accounts, thus fostering greater overconfidence for online investors. Online brokerages often tout their data offerings to customers. Waterhouse Securities, for example, claims to offer more "free investment research and research information on-line and in print than any other discount broker" including "real-time quotes, historical charts, real-time news, portfolio tracking, S&P stock reports, [and] Zack's earnings estimates." Data provider eSignal promises investors that "You'll make more, because you know more." Indeed, online investors have access to nearly all the same data as professional money managers, though in most cases they lack the same training and experience. Investors may be tempted to believe that so much data confers knowledge. Yet past data may not predict the future. And even when data does offer insights, investors may catch only glimmers of these. Individual investors, whose purchases habitually underperform their sales by approximately three percentage points in a year [Odean (1999)], need more than a glimmer of additional insight to profit from trading.

The tendency of more information to increase trading by increasing overconfidence may be augmented by "cognitive dissonance" [Festinger (1957)]. Investors who spend a considerable amount of time (or money) gathering data will generally believe themselves to be reasonable people. Since a reasonable person would not spend so much time gathering useless data, investors are motivated to believe that the data are useful. Furthermore, it would be unreasonable to spend so much time gathering data on how to trade if one didn't trade. And so, to resolve cognitive dissonance, information-gathering investors are disposed to trade.

1.2.3 The illusion of control. Langer (1975) and Langer and Roth (1975) find that people behave as if their personal involvement can influence the outcome of chance events—an effect they label the "illusion of control." These studies document that overconfidence occurs when factors ordinarily associated with improved performance in skilled situations are present in situations at least partly governed by chance. Langer finds that choice, task familiarity, competition, and active involvement all lead to inflated confidence beliefs. Presson and Benassi (1996) review 53 experiments on the illusion of control and conclude that "illusion of control effects have been found across different tasks, in many situations, and by numerous independent researchers" (p. 506).

Of the key attributes that foster an illusion of control (choice, task familiarity, competition, and active involvement), active involvement is most relevant for online investors. Online investors place their orders without the intermediation of a telephone broker. They may feel that such active involvement improves their chances of favorable outcomes and therefore choose to trade more. Balasubramanian, Konana, and Menon (1999) study survey results from 832 visitors to an online brokerage house's website. Survey respondents list "feeling of empowerment" as one of seven basic reasons given for switching to online trading.[6]

Advertisements for online brokerages often emphasize the importance of taking control of one's investments. Young Suretrade investors boast, "We're not relying on the government. We're betting on ourselves." Discover Brokerage states bluntly that online investing is "about control." A young woman in an Ameritrade ad proclaims, "I don't want to just beat the market. I want to wrestle its scrawny little body to the ground and make it beg for mercy." Such advertisements reinforce investors' illusion of control.

In summary, overconfident investors trade more actively and more speculatively. Excessive trading lowers their returns. Due to selection bias, those who go online (especially during the early years of online trading) are likely to be more overconfident than other investors. Because of self-attribution bias, the switch to online trading is likely to coincide with an increase in overconfidence. Furthermore, the illusion of knowledge and the illusion of

[6] The other six reasons are cost, speed and availability, convenience, easy access to reliable information, lack of trust in and unsatisfactory experiences with traditional brokers, and investor discomfort when communicating directly with traditional brokers.

control will lead online investors to become more overconfident once they are online. Thus online investors will tend to be more overconfident than other investors and more overconfident after going online than before.

1.2.4 Selection bias. Online trading is a recent innovation during our sample period (1991–1996). The effort and perceived risks of switching to trading online were probably greater then than they are today. Overconfidence reduces the perception of risk [Odean (1998b)]. Furthermore, more overconfident investors tend to trade more actively and thus potentially benefit more from online trading. If overconfident investors exist in financial markets, it is likely that they were disproportionately represented among early online investors. Thus there is a selection bias in our sample of investors who switched to online trading.

In summary, we have the following testable hypotheses:

Hypothesis 1. *Online investors trade more actively once online.*

Hypothesis 2. *Online investors trade more actively than phone-based investors.*

Hypothesis 3. *Online investors trade more speculatively once online.*

Hypothesis 4. *Online investors trade more speculatively than phone-based investors.*

Hypothesis 5. *By trading more, online investors hurt their performance more after going online than before.*

Hypothesis 6. *By trading more, online investors hurt their performance more than do phone-based investors.*

2. Data and Methods

2.1 The online and size-matched samples

The primary focus of our analysis is 1,607 investors who switched from phone-based trading to online trading; we refer to these investors as our online sample. These investors were identified from 78,000 households with brokerage accounts at a large discount brokerage firm.[7] (For expositional ease we often refer to households as investors.) For these households, we have all trades and monthly position statements from January 1991 through December 1996.[8] The trade data document how each trade was initiated (e.g., by phone

[7] Previous studies of the behavior of individual investors include Lewellen, Lease, and Schlarbaum (1977), Schlarbaum, Lewellen, and Lease (1978a, b), Odean (1998a, 1999), Barber and Odean (2000, 2001); Grinblatt and Keloharju (2001), and Shapira and Venezia (2001). These studies do not analyze online trading.

[8] The month-end position statements for this period allow us to calculate returns for February 1991 through January 1997. Data on trades are from January 1991 through November 1996. See Barber and Odean (2000) for a detailed description of these data.

or by personal computer). The online sample represents all households that had a common stock position in each month of our six-year sample period and initiated their first online (i.e., computer-initiated) trade between January 1992 and December 1995. We require six years of position statements so that we can analyze changes in household investment behavior subsequent to the advent of online trading.

To understand how the trading and performance of the online sample differs from other investors, we employ a matched-pair research design. Each online investor is size matched to the investor whose market value of common stock positions is closest to that of the online investor; this size matching is done in the month preceding the online investor's first online trade. As is the case for the online sample, the matched investor must have a common stock position in each month of our six-year sample period and at least one common stock trade during the six years. However, the size-matched households differ from the online households in that they made no online trades during the six years.[9]

Our size matching works well. The mean value of month-end common stock positions held by online investors is \$135,000, while that for the control sample is \$132,000; median values are \$45,400 and \$42,700, respectively. Of the 78,000 households from which these samples are drawn, 27,023 have common stock positions in all months. For these households, the mean (median) value of positions is \$62,700 (\$21,900). Thus the online investors have larger mean common stock positions than the sample at large.

We present descriptive statistics for the online and size-matched samples in Table 1. Data on marital status, children, age, and income are from Infobase Inc. as of June 1997. Self-reported data are information supplied to the discount brokerage firm by account holders when they opened their accounts. Income is reported within eight ranges, where the top range is greater than \$125,000. We calculate means using the midpoint of each range and \$125,000 for the top range. Equity:net worth (%) is the proportion of the market value of common stock investment at this discount brokerage firm as of January 1991 to total self-reported net worth when the household opened its first account at this brokerage. Those households with an equity:net worth greater than 100% are deleted when calculating means and medians.

Relative to the size-matched investors, online investors are more likely to be younger men with higher income and net worth. Their common stock investments also represent a smaller proportion of their total net worth. Online investors also report having more investment experience than the size-

[9] In auxiliary analyses, we matched the online sample to households with the most similar gross return in the 12 months prior to the switch to online traded. Our main results are very similar to those reported later in the article. Based on this analysis, the self-attribution bias alone cannot explain the increased trading and resulting poor performance of online investors. It may be that the successful investors most prone to self-attribution bias are the ones who, in anticipation of increased trading, go online. But we believe that other factors specific to the online environment, such as the illusion of knowledge and the illusion of control, also contribute to trading increases and poor performance.

Table 1
Demographics of online investors and size-matched investors

Variable	Online	Size-matched	All accounts
Panel A: Infobase data			
Percentage men	85.7	79.7	77.2
Percentage married	76.9	74.9	76.4
Percentage with children	26.5	25.1	26.6
Mean age	49.6	53.1	51.6
Median age	48.0	52.0	50.0
Mean income ($000)	79.6	74.9	73.9
Percentage with income > $125,000	12.9	11.1	9.8
Panel B: Self-reported data			
Net worth ($000)			
90th percentile	800.0	700.0	525.0
75th percentile	350.0	300.0	250.0
Median	175.0	125.0	100.0
25th percentile	87.5	75.0	75.0
10th percentile	37.5	37.5	37.0
Equity:net worth (%)			
Mean	16.7	19.6	16.4
Median	8.3	11.7	9.0
Investment experience (%)			
None	1.8	3.6	3.8
Limited	19.0	28.7	33.7
Good	57.2	49.3	47.9
Extensive	22.0	18.4	14.6

Online investors are 1,607 investors with 72 consecutive months of common stock positions, no online trades prior to January 1992, and at least one online trade between January 1992 and December 1995. Each size-matched investor is the investor with the closest account size (market value of common stocks held) to the sample firm in the month preceding its first online trade. The matched household must also have 72 consecutive months of common stock positions, no online trades during the 72 months, and at least one trade between January 1992 and December 1995. All accounts are 27,023 accounts with 72 months of common stock positions and no online trades during the 72 months. Data on marital status, children, age, and income are from Infobase Inc. as of June 1997. Self-reported data are information supplied to the discount brokerage firm by account holders on opening their account. Income is reported within eight ranges, where the top range is greater than $125,000. We calculate means using the midpoint of each range and $125,000 for the top range. Equity:net worth (%) is the proportion of the market value of common stock investment at this discount brokerage firm as of January 1991 to total self-reported net worth when the household opened its first account at this brokerage. Those households with a proportion of equity:net worth greater than 100% are deleted when calculating means and medians. Infobase data (panel A) are available for approximately 900 online investors, 900 size-matched investors, and 15,000 of all accounts. Self-reported data (panel B) are available for 510 online investors, 360 size-matched investors, and 9,500 of all accounts.

matched investors. For example, 79% of online investors report having good or extensive investment experience, while 68% of the size-matched investors report the same level of experience and 63% of all accounts report similar levels of experience. In Section 3 we provide a comprehensive multivariate analysis of the characteristics of those who switch from phone-based to online trading.

2.2 Calculation of trading costs

For each trade we estimate the bid-ask spread component of transaction costs for purchases (spr_b) and sales (spr_s) as

$$spr_s = \left(\frac{P^{cl}_{d_s}}{P^{s}_{d_s}} - 1\right), \text{ and}$$
$$spr_b = -\left(\frac{P^{cl}_{d_b}}{P^{b}_{d_b}} - 1\right). \tag{1}$$

Table 2
Mean transaction costs for trades of more than $1,000 for online and size-matched households before and after online trading

	Online households			Size-matched households		
	Buys	Sells	Round-trip	Buys	Sells	Round-trip
Panel A: Before online trading						
No. of trades	27,371	19,834		20,739	14,784	
Trade size ($)	9,074	11,414		11,059	14,076	
Trade price ($)	30.85	32.84		32.61	35.25	
Spread (%)	0.297	0.836	1.133	0.324	0.761	1.085
Commission (%)	1.697	1.568	3.265	1.637	1.473	3.110
Panel B: After online trading						
No. of trades	42,296	34,878		17,886	15,001	
Trade size ($)	13,719	16,795		13,780	16,735	
Trade price ($)	31.60	32.53		33.62	34.44	
Spread (%)	0.223	0.636	0.859	0.363	0.622	0.985
Commission (%)	1.315	1.192	2.507	1.348	1.246	2.594

Online investors are 1,607 investors with 72 consecutive months of common stock positions, no online trades prior to January 1992, and at least one online trade between January 1992 and December 1995. Each size-matched investors is the investor with the closest account size (market value of common stocks held) to the sample firm in the month preceding its first online trade. The matched household must also have 72 consecutive months of common stock positions, no online trades during the 72 months, and at least one trade between January 1992 and December 1995. Spread is calculated as the transaction price divided by the closing price on the day of the transaction minus one (and then multiplied by minus one for purchases). Commission is calculated as the commission paid divided by the value of the trade.

$P_{d_s}^{cl}$ and $P_{d_b}^{cl}$ are the reported closing prices from the Center for Research in Security Prices (CRSP) daily stock return files on the day of a sale and purchase, respectively; $P_{d_s}^{s}$ and $P_{d_b}^{b}$ are the actual sale and purchase price from our account database.[10] Our estimate of the bid-ask spread component of transaction costs includes any market impact that might result from a trade. It also includes an intraday return on the day of the trade. The commission component of transaction costs is calculated as the dollar value of the commission paid scaled by the total principal value of the transaction, both of which are reported in our account data.

We present descriptive statistics on the cost of trading for the online and size-matched samples for trades of more than $1,000 in Table 2. For both online investors and their-size matched counterparts, commissions and spreads are lower in the online periods, reflecting a market-wide decline in trading costs. For online investors, average round-trip commissions drop from 3.3% to 2.5% after they go online, while average round-trip spreads drop from 1.1% to 0.9%.[11,12] Transaction costs are similar for the size-matched households.

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[10] Kraus and Stoll (1972), Holthausen, Leftwich, and Mayers (1987), Laplante and Muscarella (1997), and Beebower and Priest (1980) use closing prices either before or following a transaction to estimate effective spreads and market impact. See Keim and Madhavan (1998) for a review of different approaches to calculating transaction costs.

[11] If trades valued at less than $1,000 are included in these calculations, average round-trip commissions drop from 5.1 percent to 3.4 percent when investors go online. Average round-trip spreads drop from 1.2 percent to 0.9 percent.

[12] Since 1996, online commissions have continued to drop while investor trading has increased. To determine whether investors have benefited from these offsetting trends will require additional research.

2.3 Measuring return performance

We analyze both the gross performance and net performance (after a reasonable accounting for commissions, the bid-ask spread, and the market impact of trades). We estimate the gross monthly return on each common stock investment using the beginning-of-month position statements from our household data and the CRSP monthly returns file. In so doing, we make two simplifying assumptions. First, we assume that all securities are bought or sold on the last day of the month. Thus we ignore the returns earned on stocks purchased from the purchase date to the end of the month and include the returns earned on stocks sold from the sale date to the end of the month. Second, we ignore intramonth trading (e.g., a purchase on March 6 and a sale of the same security on March 20), though we do include in our analysis short-term trades that yield a position at the end of a calendar month. In the current study, an accounting for intramonth trades and the exact timing of trades would increase the performance of online investors before the switch to online trading by 10 basis points per year and decrease the performance of online investors after the switch by 25 basis points per year (see Appendixes A and B).

Consider the common stock portfolio for a particular household. The gross monthly return on the household's portfolio (R_{ht}^{gr}) is calculated as

$$R_{ht}^{\text{gr}} = \sum_{i=1}^{s_{ht}} p_{it} R_{it}^{\text{gr}}, \tag{2}$$

where p_{it} is the beginning-of-month market value for the holding of stock i by household h in month t divided by the beginning-of-month market value of all stocks held by household h, R_{it}^{gr} is the gross monthly return for stock i, and s_{ht} are the number of stocks held by household h in month t.

For security i in month t, we calculate a monthly return net of transaction costs (R_{it}^{net}) as

$$\left(1+R_{it}^{\text{net}}\right) = \left(1+R_{it}^{\text{gr}}\right)\frac{(1-spr_{ib})}{(1+spr_{is})}\frac{(1-com_{is})}{(1+com_{ib})}, \tag{3}$$

where spr_{is} and com_{is} are the estimated spread and commission associated with a sale and spr_{ib} and com_{ib} are the estimated spread and commission associated with a purchase.[13] Because the timing and cost of purchases and sales vary across households, the net return for security i in month t will vary across households. The net monthly portfolio return for each household is

$$R_{ht}^{\text{net}} = \sum_{i=1}^{s_{ht}} p_{it} R_{it}^{\text{net}}. \tag{4}$$

[13] Had we estimated spreads by dividing transaction prices by closing prices, net returns would be calculated as $(1+R_{it}^{\text{net}}) = (1+R_{it}^{\text{gr}})\frac{(1-spr_{is})}{(1+spr_{ib})}\frac{(1-com_{is})}{(1+com_{ib})}$.

If only a portion of the beginning-of-month position in stock *i* was purchased or sold, the transaction cost is only applied to the portion that was purchased or sold.

In our analysis of returns, we focus on four monthly return series. The first is the average experience of online investors before online trading. In each month we average the returns of online investors who have not yet begun online trading. Thus we end up with a 58-month return series for online investors before switching to online trading (February 1991–November 1995; December 1995 being the month when the last online investors begin online trading). The second return series is the average experience of online investors after switching to online trading. In each month, we average the returns of online investors who have begun trading online. Thus we end up with a 60-month return series for online investors after online trading begins (February 1992–January 1997; January 1992 being the month when the first online investors begin online trading). We calculate two analogous return series for the size-matched investors.[14]

2.4 Risk-adjusted return performance

We calculate four measures of risk-adjusted performance. In the discussion that follows we describe the performance measures for the online sample; there are analogous calculations for their size-matched counterparts. First, we calculate the mean monthly market-adjusted abnormal return for online investors by subtracting the return on a value-weighted index of NYSE/AMEX/Nasdaq stocks from the return earned by online investors.

Second, we calculate an own-benchmark abnormal return for online investors, which is similar in spirit to that proposed by Grinblatt and Titman (1993) and Lakonishok, Shleifer, and Vishny (1992). In this abnormal return calculation, the benchmark for household h is the month t return of the beginning-of-year portfolio held by household h.[15] It represents the return that the household would have earned had it merely held its beginning-of-year portfolio for the entire year. The own-benchmark abnormal return is the return earned by household h less the own-benchmark return; if the household did not trade during the year, the own-benchmark abnormal return would be zero for all 12 months during the year. In each month, the abnormal returns for all online investors are averaged, yielding a monthly time series of mean monthly own-benchmark abnormal returns. Statistical significance is calculated using t-statistics based on this time series. The advantage of the own-benchmark abnormal return measure is that it does not adjust returns

[14] The general tenor of our results are the same if we weight the returns of the online and size-matched samples by account size rather than equally.

[15] When calculating this benchmark, we begin the year on February 1. We do so because our first monthly position statements are from the month end of January 1991. If the stocks held by a household at the beginning of the year are missing CRSP returns data during the year, we assume that stock is invested in the remainder of the household's portfolio.

according to a particular risk model. No model of risk is universally accepted; furthermore, it may be inappropriate to adjust investors' returns for stock characteristics that they do not associate with risk. The own-benchmark measure allows each household to self-select the investment style and risk profile of its benchmark (i.e., the portfolio it held at the beginning of the year), thus emphasizing the effect trading has on performance. Own-benchmark returns are our primary measure of the detrimental effect of overconfidence (and excessive trading) on returns.

Third, we employ the theoretical framework of the capital asset pricing model (CAPM) and estimate Jensen's alpha by regressing the monthly excess return earned by online investors on the market excess return. For example, to evaluate the gross monthly return earned by the average online investor (RO_t^{gr}), we estimate the following monthly time-series regression:

$$(RO_t^{\mathrm{gr}} - R_{ft}) = \alpha_i + \beta_i(R_{mt} - R_{ft}) + \varepsilon_{it}, \tag{5}$$

where R_{ft} is the monthly return on Treasury bills,[16] R_{mt} is the monthly return on a value-weighted market index, α_i is the CAPM intercept (Jensen's alpha), β_i is the market beta, and ε_{it} is the regression error term. The subscript i denotes parameter estimates and error terms from regression i, where we estimate four regressions for online investors and four for the size-matched control sample: one each for the gross and net performance before online trading and one each for the gross and net performance after online trading.

Fourth, we employ an intercept test using the three-factor model developed by Fama and French (1993). For example, to evaluate the performance of the average online investor, we estimate the following monthly time-series regression:

$$(RO_t^{\mathrm{gr}} - R_{ft}) = \alpha_j + \beta_j(R_{mt} - R_{ft}) + s_j SMB_t + h_j HML_t + \varepsilon_{jt}, \tag{6}$$

where SMB_t is the return on a value-weighted portfolio of small stocks minus the return on a value-weighted portfolio of big stocks and HML_t is the return on a value-weighted portfolio of high book-to-market stocks minus the return on a value-weighted portfolio of low book-to-market stocks.[17] The regression yields parameter estimates of α_j, β_j, s_j, and h_j. The error term in the regression is denoted by ε_{jt}. The subscript j denotes parameter estimates and error terms from regression j, where we again estimate four regressions for the online sample and four for the control sample.[18]

[16] The return on Treasury bills is from *Stocks, Bonds, Bills, and Inflation, 1997 Yearbook*, Ibbotson Associates, Chicago, IL.

[17] The construction of these portfolios is discussed in detail in Fama and French (1993). We thank Kenneth French for providing us with these data.

[18] Lyon, Barber, and Tsai (1999) document that intercept tests using the three-factor model are well specified in random samples and samples of large or small firms. Thus the Fama and French intercept tests employed here account well for the small stock tilt of individual investors.

Fama and French (1993) argue that the risk of common stock investments can be parsimoniously summarized as risk related to the market, firm size, and a firm's book-to-market ratio. We measure these three risk exposures using the coefficient estimates on the market excess return $(R_{mt} - R_{ft})$, the size zero-investment portfolio (SMB_t), and the book-to-market zero-investment portfolio (HML_t) from the three-factor regressions. Portfolios with above-average market risk have betas greater than one, $\beta_j > 1$. Portfolios with a tilt toward small (value) stocks relative to a value-weighted market index have size (book-to-market) coefficients greater than zero, $s_j > 0 (h_j > 0)$.

We suspect there is little quibble with interpreting the coefficient on the market excess return (β_j) as a risk factor. Interpreting the coefficient estimates on the size and the book-to-market zero-investment portfolios is more controversial. For the purposes of this investigation, we are interested in measuring risk as perceived by individual investors. As such, it is our casual observation that investors view common stock investment in small firms as riskier than that in large firms. Furthermore, theory supports the link between firm size and returns [Berk (1995)]. Thus we would willingly accept a stronger tilt toward small stocks as evidence that a particular group of investors is pursuing a strategy that they perceive as riskier. It is less clear to us whether investors believe a tilt toward high book-to-market stocks (which tend to be ugly, financially distressed firms) or toward low book-to-market stocks (which tend to be high-growth firms) is *perceived* as riskier by investors. Daniel and Titman (1997) provide evidence that book-to-market effects are attributable to firm characteristics rather than covariance with factor risks, while Davis, Fama, and French (2000) provide contrary evidence. Daniel, Hirshleifer, and Subrahmanyam (2001) argue that overconfidence itself can lead to a positive relation between book-to-market and returns. As such, we interpret the coefficient estimates on the book-to-market zero-investment portfolio with a bit more trepidation. Nonetheless, our primary results are unaffected if we exclude HML_t from the time-series regressions.

3. Who Goes Online?

The multivariate analyses presented in this section provide a profile of those who go online. Young men who are active traders with high incomes and no children are more likely to switch to online trading. Those who switch also have higher levels of self-reported investment experience and a preference for investing in small growth stocks with high market risk. We also document that those who switch to online trading experience unusually strong performance prior to going online.

These conclusions are based on a pooled time-series cross-sectional logistic regression from January 1992 through December 1995. All households with available data and six years of common stock positions (from January

1991 through December 1996) are included in the regression. The dependent variable for the regression is a dummy variable that takes on a value of one in the month that a household begins online trading and a zero otherwise. Households that go online are excluded from the sample after going online.[19]

The independent variables in the regressions fall into three broad categories: demographic characteristics, investor characteristics, and self-reported data. Demographic characteristics include gender, marital status, presence of children in the household, age, and income. The effect of gender, marital status, and the presence of children on the probability of going online are measured with dummy variables that take on a value of one for women, single investors, and households with children, respectively. Age is measured in years. Income is reported within eight ranges, where the top range is greater than $125,000. When estimating the logistic regression, we use the midpoint of each income range and include a dummy variable that takes on a value of one for households with income greater than $125,000.

Investor characteristics include account size, market-adjusted return, turnover, and preferences for market risk, small firms, and value stocks. Account size is measured as the log of the dollar value of common stock investments in January 1991, the start of our sample period. The market-adjusted return for month t is the mean gross monthly return on the household's common stock portfolio less a value-weighted market index from month $t-12$ to $t-1$. Monthly turnover for month t is one-half the sum of purchases and sales divided by the sum of month-end positions from month $t-12$ to $t-1$; when estimating the regression we use the log of one plus monthly turnover. Market-adjusted returns and monthly turnover are the only variables that vary from one month to the next for a particular household. Preferences for market risk, small firms, and value stocks are inferred from the Fama and French three-factor model, where a separate regression is estimated for each household.[20]

Self-reported data include net worth, the ratio of equity to net worth, and investment experience. Net worth is the log of self-reported net worth. Equity:net worth is the proportion of the market value of common stock investment at this discount brokerage firm as of January 1991 to total self-reported net worth when the household opened its first account at this brokerage. Three dummy variables, which take on a value of one for those reporting limited, good, or extensive investment experience (respectively), are used to measure the effect of experience. We suspect that while self-reported experience is largely based on objective criteria such as the number of years or the

[19] We estimate the logistic regression by pooling over time so that we can more precisely measure turnover and return performance in the period preceding a switch to online trading. When we estimate the regression using households rather than household months as the unit of observation, the results for the remaining independent variables are qualitatively similar.

[20] Using the full six-year sample period to estimate household investment preferences assumes that preferences of online households do not change significantly after going online. In Section 4.6 we document that there is not a significant change in investment style once households begin trading online.

amount of money that one has invested, people vary in how they interpret these criteria. We also suspect that, ceteris paribus, the more overconfident investors are likely to overstate their experience.

The results of this analysis are presented in Table 3. Self-reported data are available for only about one-third of the total sample. Consequently we estimate two regressions—one that includes only independent variables for demographics and investor characteristics and one that includes independent variables for demographics, investor characteristics, and self-reported data. The results of the first logistic regression are presented in columns 2 and 3 of Table 3. Of the variables considered, only marital status has no significant effect on the probability of going online. The remaining coefficient estimates are all reliably nonzero ($p < .10$). The results of the regressions requiring

Table 3
Logistic regression of the probability of switching to online trading

Number of households going on line	727		377	
Observations (household-months)	682,121		208,598	
Variable	Coefficient	p	Coefficient	p
Intercept	−9.197	< 0.001***	−10.209	< 0.001***
Demographics				
Women	−0.419	< 0.001***	−0.262	0.082*
Single	−0.087	0.368	−0.018	0.899
Children	−0.158	0.068*	−0.191	0.105*
Age (years)	−0.014	< 0.001***	−0.014	0.005***
Income ($000)	0.003	0.081*	0.002	0.258
Income > $125,000	0.050	0.694	0.020	0.906
Investor characteristics				
Account size (log)	0.165	< 0.001***	0.082	0.135
Market-adjusted return	4.629	0.002***	3.106	0.180
Monthly turnover (log)	0.352	< 0.001***	0.182	< 0.001***
Market risk preference	0.225	0.012**	0.120	0.357
Small firm preference	0.169	0.002***	0.133	0.101
Value firm preference	−0.256	< 0.001***	−0.192	0.027**
Self-reported data				
Net worth (log)	—	—	0.085	0.161
Stock/net worth	—	—	−0.146	0.721
Limited experience	—	—	0.974	0.174
Good experience	—	—	1.503	0.035**
Extensive experience	—	—	1.684	0.019**

***, **, *Significant at the 1%, 5%, and 10% levels, respectively.

A pooled time-series, cross-sectional, logistic regression is estimated from January 1992 through December 1995. The dependent variable for the regression is a dummy variable that takes on a value of one in the month that a household begins online trading and a zero otherwise. All households with six years of common stock positions are included in the estimation of the regression. Woman, single, and children are dummy variables that take on a value of one for households headed by a woman, a single person, and households with children. Age is measured in years. Income is reported in eight ranges, where the top range is over greater than $125,000. We also include a dummy variable that takes on a value of one if income is greater than $125,000. Account size is the log of the dollar value of common stock positions held in January 1991. Market-adjusted return in month t is the mean monthly return on the household's portfolio less a value-weighted market index from month $t-12$ to $t-1$. Monthly turnover in month t is one-half the sum of purchases and sales divided by the sum of monthly positions from month $t-12$ to $t-1$. The regression is estimated using the log of one plus monthly turnover. Market risk, small firm, and value preferences are based on coefficient estimates from the Fama and French three-factor model, which are estimated separately for each household. Net worth is the log of self-reported net worth. Proportion of equity to net worth is the value of common stock investments in January 1991 to self-reported net worth. Limited, good, extensive investment experience are dummy variables that take on a value of one for households reporting that level of experience.

self-reported data are present in the last two columns of Table 3. Of the self-reported data, experience has a significant effect of the probability of going online; those with greater self-reported investment experience (perhaps because they are more overconfident) are more likely to make the switch. The remaining independent variables have coefficient estimates that are generally consistent with those in the regression that exclude self-reported data, though the statistical significance of some coefficients is weakened—likely the result of the smaller sample size.

4. Results

In this section we test and confirm our hypotheses about the trading activity and return performance of online investors. Our four principal results are that those who switch from phone-based trading to online trading experience unusually strong performance prior to going online, accelerate their trading after going online, trade more speculatively after going online, and experience subpar performance (as a result of the accelerated trading) after going online. We consider each of these results in turn.

4.1 Performance before the switch

Before the switch to online trading, the average online investor outperforms both the market and the average size-matched investor. The returns both groups earned before the switch are presented in columns 2–4 of Table 4. Before switching, the gross returns of the average online investor beat the market by 35 basis points a month (4.2% annually, $p = 0.09$), and outpaced the average size-matched investor by 18 basis points a month (2.2% annually, $p = 0.02$). Even after netting out trading costs the average online investor still beat the market by 20 basis points a month (2.4% annually, not statistically significant) and outpaced the net returns of the average size-matched investor by 14 basis points a month (1.7% annually, $p = 0.08$).[21]

We argue that the strong performance of online investors before the switch fostered greater overconfidence. Thus our primary interest in this analysis is to identify how investors perceived their own performance before the switch to online trading. We believe market-adjusted returns are the most relevant measure of performance during this period. To the extent individual investors evaluate their own performance against a benchmark, it is likely that they use the market return. The average online investor comfortably beat the market before the switch to online trading. Many investors likely gauge the success of their investments on nominal rather than market-adjusted returns. Those that do so may attribute their high returns to their own abilities rather

[21] Before going online, the gross performance of online traders is positive for all of our return measures except the own-benchmark measure, which is essentially zero (-0.014, $t = -0.55$). Thus the superior returns earned before going online were due primarily to the portfolios these investors held at the beginning of our evaluation period, not to the trades they made during this period.

Table 4
Percentage monthly returns for online and size-matched investors

	Before online trading			After online trading		
	Online	Size-matched	Difference (online less match)	Online	Size-matched	Difference (online less match)
Panel A: Gross percentage monthly return						
Raw	1.649	1.467	0.182	1.198	1.174	0.024
			(2.32)**			(0.24)
Market adjusted	0.354	0.172	0.182	−0.094	−0.118	0.024
	(1.71)*	(1.10)	(2.32)**	(−0.49)	(−0.94)	(0.24)
Own benchmark	−0.003	−0.083	0.080	−0.100	−0.028	−0.073
	(−0.10)	(−1.75)*	(1.65)	(−2.23)**	(−0.92)	(−1.93)*
CAPM alpha	0.275	0.152	0.123	−0.324	−0.220	−0.104
	(1.27)	(0.92)	(1.54)	(−1.73)*	(−1.69)*	(−1.07)
Fama and French alpha	0.120	−0.015	0.135	−0.182	−0.193	0.011
	(0.88)	(−0.15)	(2.01)**	(−1.38)	(−1.85)*	(0.15)
Panel B: Net percentage monthly return						
Raw	1.492	1.355	0.137	1.002	1.082	−0.080
			(1.78)*			(−0.78)
Market adjusted	0.197	0.060	0.137	−0.291	−0.211	−0.080
	(0.97)	(0.39)	(1.77)*	(−1.52)	(−1.69)*	(−0.78)
Own benchmark	−0.160	−0.196	0.036	−0.297	−0.120	−0.177
	(−5.83)***	(−4.21)***	(0.76)	(−6.50)***	(−3.91)***	(−4.50)***
CAPM alpha	0.126	0.044	0.082	−0.519	−0.311	−0.208
	(0.59)	(0.27)	(1.03)	(−2.77)***	(−2.40)**	(−2.10)**
Fama and French alpha	−0.023	−0.117	0.094	−0.363	−0.280	−0.083
	(−0.17)	(−1.18)	(1.42)	(−2.76)***	(−2.67)***	(−1.11)

***, **, *Significant at the 1%, 5%, and 10% levels, respectively (two-tailed).

Returns are based on month-end position statements for 1,607 online investors and their size-matched counterparts from January 1991 to December 1996. Panel A (panel B) presents results for the gross (net) return on a portfolio that mimics the average investor. The columns labeled "Before online trading" are the returns of the average online and size-matched investor before online trading (February 1991–November 1995); those labeled "After online trading" are the returns of the average online and size-matched investor after online trading (February 1992–January 1997). Market-adjusted return is the return on the household portfolio less the return on a value-weighted NYSE/AMEX/Nasdaq index. Own-benchmark abnormal return is the return on the household portfolio minus the return on the portfolio the household held at the end of the previous January. CAPM alpha is the estimated intercept from a time-series regression of the household excess return on the market excess return ($R_{mt} - R_{ft}$). Fama and French alpha is the estimated intercept from a time-series regression of household excess return on the market excess return, a zero-investment book-to-market portfolio (HML_t), and a zero-investment size portfolio (SMB_t). t-statistics are in parentheses.

than market returns (about 18% annually during the six-year sample period). Regardless of the performance measure employed, the average online investor earned higher returns than the average size-matched investor prior to the switch.

4.2 Turnover

We begin our analysis of turnover by calculating aggregate turnover for online and size-matched investors in event time, where we define month 0 as the month of the first online trade. For example, for online investors we calculate aggregate turnover in event time as one-half the total value of purchases and sales by all online investors in an event month (the numerator) divided by the sum of month-end position statements for that event month (the denominator).

We present annualized turnover (monthly turnover times 12) in event time in Figure 1. In the two years prior to the switch to online trading, annualized turnover for the online investors averaged about 70%, while that for the size-matched investors averaged about 50%. In the month after the switch to online trading (month 1), annualized turnover of the online investors surges to 120%. While a temporary surge in trading activity is not surprising, a full two years after the switch to online trading annualized turnover is still 90% for the online investors—well above their turnover rate in the period prior to the switch. There is no such change in the observed turnover of the size-matched investors.

To more formally test whether the increase in turnover for online investors is reliably greater than that for their size-matched counterparts, we calculate turnover separately for each investor. Monthly turnover for each household is one-half the total value of purchases and sales, now summed over time (the numerator), divided by the sum of month-end position statements over time (the denominator). For each online and size-matched household we calculate two turnover measures: one before and one after online trading. (The month of the first online trade is excluded from both calculations.) The annual turnover (monthly turnover times 12) of online investors and their size-matched counterparts are presented in panel A of Table 5. Both before and after the switch, online investors trade more actively than their size-matched counterparts.

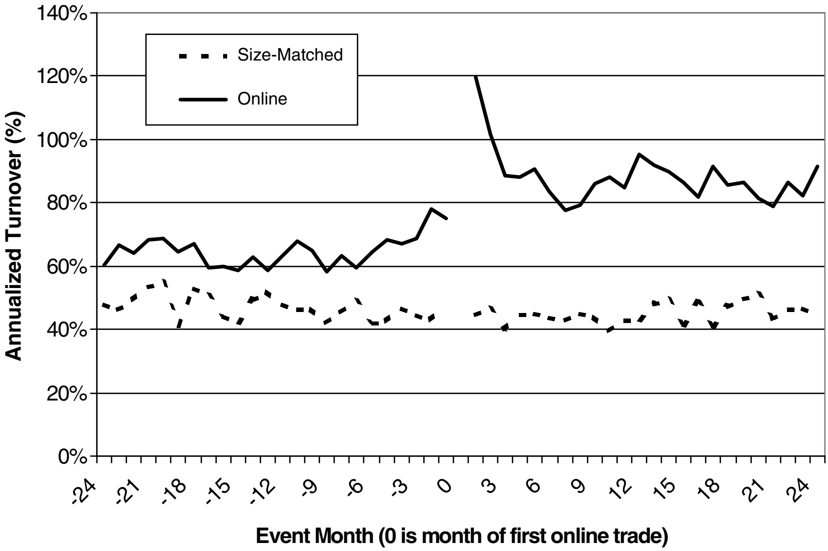

Figure 1
Aggregate turnover for online and size-matched investors in event time (month 0 = month of first online trade)

Table 5
Mean annual turnover of online households and size-matched households

	Before online trading	After online trading	Change (after online less before online)
Panel A: Total turnover			
Online households	73.7	95.5	21.8***
Size-matched households	53.2	48.2	−5.0**
Online less size-matched	20.5***	47.3***	26.8***
Panel B: Speculative turnover			
Online households	16.4	30.2	13.8***
Size-matched households	11.5	13.9	2.4
Online less size-matched	4.9***	16.3***	11.4***

***, **, *Significant at the 1%, 5%, and 10% levels, respectively (two-tailed).

Online households are 1,607 households with 72 consecutive months of common stock positions, no online trades prior to January 1992, and at least one online trade between January 1992 and December 1995. Each size-matched household is the household with the closest account size to the sample firm in the month preceding its first online trade. The matched household must also have 72 consecutive months of common stock positions, no online trades during the 72 months, and at least one trade between January 1992 and December 1995. Monthly turnover for each household is one-half the sum of all trades for that household divided by the sum of all month-end positions. Monthly turnover times 12 yields annual turnover. Speculative turnover is calculated using only trades classified as speculative. We define speculative trades as all profitable sales of complete positions that are followed by a purchase within three weeks and all purchases made within three weeks of a speculative sale. Test statistics for the difference in means are based on a two-sample t-statistic assuming unequal variance for the two samples.

After switching online, investors trade much more actively than before. Their average annual turnover increases from 73.7% to 95.5% ($p < 0.01$), thus confirming Hypothesis 1. While online investors trade more actively than their size-matched counterparts both before and after the switch, the difference in average turnover is much greater after the switch. This confirms Hypothesis 2. In the postswitch period, the average turnover of online investors is nearly double that of their size-matched counterparts (95.5% versus 48.2%, $p < 0.01$).[22]

Though the switch to online trading is associated with greater trading activity, it is possible that those who switched to online trading would have traded more actively regardless of whether they were online or not. Though we are unable to dismiss this possibility within the context of our study, Choi, Laibson, and Metrick (2001) provide corroborating evidence that it is the online environment that spawns greater trading. They document that at companies which adopted web-based interfaces for plan participants during the 1990s, turnover in 401(k) accounts increased by 50%; there was no such increase in trading activity for firms without web-based access.

[22] There is also an increase in the turnover of the median online household after the switch to online trading, though it is much smaller than the increase in average turnover (1.4%, $p < 0.10$). Twenty-five percent of the online households increase their turnover by 35% or more; 10% of the online households increase their turnover by 109% or more. Thus most households increase their trading activity, but some increase their trading dramatically.

4.3 Speculative trading

An investor may trade common stocks for many reasons. An investor with a bonus to invest or a large bill to pay may buy or sell for liquidity reasons. If one security in his portfolio appreciates considerably, he may rebalance to restore diversification to his portfolio (by selling part of his holding in that security and buying others). He may sell to capture a tax loss. Or he may trade to speculate by selling one stock from his portfolio and buying another in an effort to improve his performance.

To examine how speculative trading changes when investors go online, we screen out most trades that may have been motivated by liquidity needs, a desire to rebalance, or tax losses. We screen liquidity sales by considering only sales for which a new purchase follows within three weeks (15 trading days) of the sale; most investors who need to raise cash for less than three weeks have lower cost alternatives available than trading stocks (e.g., credit cards). We screen rebalancing sales by considering only sales of the complete holding of a position. We eliminate tax-loss sales by considering only sales for a profit. In short, we consider all profitable sales of complete positions that are followed by a purchase within three weeks as speculative and all purchases made within three weeks of a speculative sale as speculative. It is unlikely that we identify all (or even most) speculative trades, but those trades that meet our screens are very likely to be speculative.

As reported in panel B of Table 5, speculative turnover nearly doubles when investors go online (from 16.4% to 30.2%), confirming Hypothesis 3. Even with our conservative classification, speculative trading accounts for 60% of the increase in turnover for the average online investor. Both before and after the switch, online investors trade more speculatively than their size-matched counterparts. This confirms Hypothesis 4.

Do investors trade more speculatively because they are better able to identify and execute profitable speculative trades after going online? To answer this question, we compare the returns earned by stocks subsequent to speculative purchases and to speculative sales. In each month we construct a portfolio comprised of those stocks purchased speculatively in the preceding three months. The daily returns on this portfolio are calculated as

$$R_{\tau}^{pb} = \frac{\sum_{i=1}^{n} T_{i\tau}^{pb} R_{i\tau}^{pb}}{\sum_{i=1}^{n} T_{i\tau}^{pb}}, \qquad (7)$$

where $T_{i\tau}^{pb}$ is the aggregate value of all speculative purchases in security i from day $\tau - 63$ through $\tau - 1$ and $R_{i\tau}^{pb}$ is the gross daily return of stock i on day τ. We compound the daily returns within a month, which yields a time series of monthly returns for four portfolios: one for speculative purchases before going online (R_t^{pb}), one for speculative purchases after going online (R_t^{pa}), one for speculative sales before going online (R_t^{sb}), and one for speculative sales after going online (R_t^{sa}).

Before going online, the stocks online investors buy speculatively outperform those that they sell speculatively by 59 basis points per month ($p = 0.08$).[23] After going online, the stocks online investors buy speculatively underperform those that they sell speculatively by 27 basis points per month, though the underperformance is not reliably different from zero ($p = 0.29$). The difference in the relative performance of purchases and sales before and after going online is significant ($p = 0.10$).[24] Though the speculative trades of online investors performed well prior to switching online, these profits would not be sufficient to cover average round-trip transaction costs of 4% (see Table 2). Furthermore, online investors were unable to sustain their solid gross performance.

4.4 Performance after the switch

The returns earned by online investors after the switch to online trading and those of their size-matched counterparts are presented in columns 5–7 of Table 4. After the switch to online trading, online investors perform poorly. The gross returns of online investors underperform the market by 9 basis points a month (not statistically significant), while their net returns underperform by an economically large 29 basis points a month (3.5% annually, $p = 0.13$). Net own-benchmark returns indicate that after the switch, online investors lose 30 basis points a month (3.6% annually) through their trading activities, while the size match group loses only 12 basis points (1.4% annually); both shortfalls and their difference are significant at the 1% level, confirming Hypothesis 6.

4.5 Changes in performance

In this section we formally test whether the changes in performance—from before to after online trading—are significant. To do so we compare the returns earned by online investors who have not yet gone online to those earned during the same months by online investors who have already begun trading online. For our online sample, the first online trading begins in January 1992 and the last households commence online trading in December 1995. Thus we can calculate the before-after return series for 46 months: February 1992 to November 1995. The results of this analysis are presented in Table 6. (Returns in Tables 4 and 6 differ because their observation periods differ.)

Using any of our return measures, the gross and net returns of online investors who have already switched to online trading are less than those who have not yet made the switch. For example, the average net raw return

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[23] This t-statistic is calculated as $t = \frac{(R_t^{pb} - R_t^{sb})}{\sigma(R_t^{pb} - R_t^{sb})\sqrt{56}}$.

[24] If we look at all trades, not just speculative trades, the stocks online investors buy before going online outperform those they sell by an insignificant 29 basis points a month ($p = 0.15$). After going online their buys underperform their sells by a significant 31 basis points a month ($p = 0.05$).

Table 6
The performance of investors already online and investors who have not yet traded online (but do so before 1996): February 1992–November 1995

	Investors not yet online	Investors already online	Difference (already online − not yet online)
Panel A: Gross percentage monthly return			
Raw	1.284	0.993	−0.291
			(−3.15)***
Market adjusted	0.189	−0.104	−0.291
	(1.08)	(−0.52)	(−3.15)***
Own benchmark	0.001	−0.079	−0.080
	(0.03)	(−1.60)	(−1.75)*
CAPM alpha	0.083	−0.240	−0.323
	(0.46)	(−1.19)	(−3.32)***
Fama and French alpha	0.145	−0.106	−0.251
	(0.99)	(−0.75)	(−2.71)***
Panel B: Net percentage monthly return			
Raw	1.139	0.777	−0.362
			(−3.72)***
Market adjusted	0.043	−0.319	−0.362
	(0.25)	(−1.60)	(−3.72)***
Own benchmark	−0.144	−0.296	−0.152
	(−4.60)***	(−5.81)***	(−3.32)***
CAPM alpha	−0.057	−0.453	−0.396
	(−0.32)	(−2.23)**	(−3.85)***
Fama and French alpha	0.010	−0.301	−0.311
	(0.07)	(−2.11)**	(−3.23)***

***, **, *Significant at the 1%, 5%, and 10% levels, respectively (two-tailed).

Online households are 1,607 households with 72 consecutive months of common stock positions, no online trades prior to January 1992, and at least one online trade between January 1992 and December 1995. From February 1992 to November 1995 these 1,607 online households are broken into two groups, those that have already begun online trading (already online) and those that have not yet done so (not yet online). Market-adjusted return is the return on the household portfolio less the return on a value-weighted NYSE/AMEX/Nasdaq index. Own-benchmark abnormal return is the return on the household portfolio minus the return on the portfolio the household held at the end of the previous January. CAPM alpha is the estimated intercept from a time-series regression of the household excess return on the market excess return ($R_{mt} - R_{ft}$). Fama and French alpha is the estimated intercept from a time-series regression of household excess return on the market excess return, a zero-investment book-to-market portfolio (HML_t), and a zero-investment size portfolio (SMB_t). t-statistics are in parentheses.

of online investors who have commenced trading online is 36 basis points a month lower than that of online investors who have not yet made the switch (4.3% annually, $p < 0.01$). After going online net own-benchmark returns are 15 basis points a month lower ($p < 0.01$), confirming Hypothesis 5. Without equivocation, we can conclude that there is a dramatic erosion in the performance of online investors after they switch to online trading. This erosion is due to the combination of better than average (gross) performance before the switch and inferior performance (both gross and net) afterwards.[25]

[25] An analogous analysis for the size-matched households yields differences in net performance (after online less before online) ranging from 8 basis points (own-benchmark abnormal return) to −14 basis points (market-adjusted returns). The change in net performance of the online sample (after online less before online) less the change in performance for the size-matched households range from −21 basis points (Fama and French alpha) to −26 basis points (own-benchmark abnormal return); all of the differences between the online and size-matched samples are statistically significant at less than the 5% level (two-tailed).

4.6 The investment style of online investors

It is natural to wonder whether the investment style of online investors differs from other investors. The answer is yes and no. Yes, since relative to the size-matched sample, online investors tilt their investments toward small growth stocks with higher market risk.[26] No, since the tilt toward small growth stocks with high market risk is apparent *both* before and after online trading. There is some evidence that online investors increase their exposure to small growth stocks after going online (the test statistic is 1.36 for the coefficient estimate on the SMB_t and -2.11 for HML_t). However, there is a similar style change for the size-matched control group; there are no significant differences in these changes between the online investors and the control group. At face value it does not appear that the switch from phone-based to online investing is accompanied by a significant change in the style of stocks investors own.

5. Discussion

We find that those who switch from phone-based trading to online trading experience unusually strong performance prior to the switch, accelerate their trading after going online, trade more speculatively after going online, and experience subpar performance (as a result of the accelerated trading) after going online. The strong performance prior to going online is consistent with self-attribution bias. Investors with unusually good returns are likely to have taken too much credit for their success and grown more overconfident about their stock-picking abilities. Overconfident investors were more likely to go online and once online the illusion of control and the illusion of knowledge further increased their overconfidence. Overconfidence led them to trade actively and active trading caused subpar performance.

For overconfident investors, the greater effort of initiating trades by phone or, more recently, the higher commissions associated with phone trades may serve as unintended barriers to excessive trading. When these market frictions are reduced, the disutility of increased speculative losses may offset utility gains from lower trading effort and cost. While our results are consistent with the overconfidence model of trading and confirmed all of our hypotheses based on that model, other explanations warrant consideration.

Investors may be trading more after they go online simply because lower trading costs make more trades potentially profitable. If so, online trading should lead to improved performance, which it does not.

[26] These conclusions are based on the coefficient loadings and associated test statistics from the time-series regressions that employ the Fama and French three-factor model. The online investors also have a preference for stocks with poor recent return performance relative to their size-matched counterparts. This inference is drawn by adding a zero-investment portfolio that is long stocks that have performed well recently and short stocks that have performed poorly [see Carhart (1997)]. None of our conclusions regarding performance are altered by the inclusion of this price momentum variable. We thank Mark Carhart for providing us with these return data.

Some investors may anticipate unusual liquidity needs and switch online in hopes of facilitating liquidity-driven purchases or sales more easily. This could explain temporary increases in trading after going online. It does not account for higher permanent levels of online trading, unless traders experience permanent shifts in their liquidity-based trading needs. Furthermore, changes in liquidity based trading do not explain observed increases in speculative trading after investors go online.

It is conceivable that, through greater speed of execution, online trading allows investors to make profitable trades that would not have otherwise been available. If so, online trading should lead to improved performance, which it does not.

Investors may trade more when they go online simply because of greater ease of access. For rational investors this implies that there were potentially profitable trades that the investors declined to make before going online because the expected profits did not warrant the effort of calling a broker. Due to the greater ease of trading online, these investors now make such trades. Such investors must have placed a high cost on the effort required to phone their discount broker. While this explanation is consistent with increased trading after going online, it does not explain subpar performance.

Lower trading costs, liquidity needs, speed of execution, and ease of access do not explain why rational investors would trade more actively, more speculatively, and less profitably after going online. A final possibility is that rational investors trade more actively online simply because online investing is entertaining. We cannot rule out the possibility that we are observing the actions of fully rational investors who knowingly trade to their financial detriment simply for fun. We believe it more plausible that the investors who find trading most fun are those who are overconfident about their chances of success. The Gallup survey and experimental evidence cited earlier (Moore et al. 1999) show that investors expect to beat the market. If investors rationally trade for entertainment, they will recognize that the price of this entertainment is below-average performance; overconfident investors will expect to beat the market. For a more detailed discussion of this issue, see Barber and Odean (2000, 2001).

Another reason why investors trade more actively online may be that they simply misunderstand trading costs. While the commissions they pay are explicitly reported to investors, bid-ask spreads are not. Our online traders pay aggregate round-trip commissions of about 3.3% and bid-ask spreads of about 1.1% before going online. After going online, they pay about 2.5% round-trip commissions and 0.9% in spread. Commissions fell faster during this period, and subsequently, than spreads. If investors ignore spreads when assessing their trading costs, they may conclude that total costs have fallen much faster than is actually the case. This misapprehension will encourage trade.[27]

When overconfident investors go online, they are likely to trade more for the same reasons rational investors would trade more: lower costs, faster executions, easier access (and entertainment). Unlike rational investors, however, overconfident investors tend to incorrectly identify profitable speculative trades [Odean (1999)]. Therefore increased trading hurts their performance. Thus overconfidence, coupled with the lure of cheaper, faster, easier trading, explains increased trading and speculation as well as impaired performance after investors go online.

6. Conclusion

We analyze the characteristics, trading, and performance of 1,607 investors who switched from phone-based to online trading between 1992 and 1995. During this period, young men who were active traders with high incomes and no children were more likely to switch to online trading. Those who switched also had higher levels of self-reported investment experience and a preference for investing in small growth stocks with high market risk.

Investors who went online during the period 1992–1995 generally earned superior returns before switching to online trading. After the switch they increased their trading activity, traded more speculatively, and performed subpar. Rational investors would not do this. Overconfident investors, on the other hand, are inclined to trade excessively.

Several cognitive biases reinforce the overconfidence of online investors. Investors who earn strong returns before going online are likely to attribute this success disproportionately to their own investment ability (rather than luck) and become overconfident. Once online, investors have access to vast quantities of investment data; these data can foster an illusion of knowledge, which increases overconfidence. Finally, online investors generally manage their own stock portfolios and execute trades at the click of a mouse; this fosters an illusion of control, which reinforces overconfidence.

Investors who do not increase their trading clearly benefit from the convenience and low costs of trading online. But others, who trade more actively online, risk offsetting per trade savings with greater cumulative costs and speculative losses. This is the experience of the online investors we study here.

[27] An additional bias that may encourage some investors to trade online is loss aversion. Kahneman and Tversky (1979) argue that, when faced with losses, people will accept additional risks in hopes of recovering to the former status quo. While we do not believe that most investors are motivated to go online by loss aversion, some may be. An E*TRADE advertisement reads: "The Tooth Fairy, Santa Claus, Social Security." The implied failure of social security would be a loss of anticipated welfare for many people. The prospect of such a loss could prompt people to take risks they might not otherwise take. Some might even go so far as to open an E*TRADE account.

Online brokers encourage investors to trade speculatively and often. Some of their advertisements reinforce cognitive biases, such as overconfidence. Others create unrealistic expectations. While rational investors will consider only the relevant informational content of advertising, SEC Chairman Arthur Levitt worries that many of us may be unduly influenced by advertisements that "step over the line and border on irresponsibility."[28]

Advertisements compare online trading to the old West, where the first to draw prevailed. Investors are led to believe that profitable investment opportunities are ephemeral events, seized only by the quick and vigilant. Most investors, however, benefit from a slow trading, buy-and-hold strategy. Trigger-happy traders are prone to shoot themselves in the foot.

Appendix A: The Analysis of Trade Timing

In this appendix we analyze the timing of purchases and sales within a month. The timing of trades within a month are ignored in our main analysis, since we assume all purchases and sales are made at month end. The analysis that follows indicates that this assumption does not materially affect the conclusions presented in the main text. If anything, this assumption leads us to underestimate the performance of the online sample prior to the switch, while overestimating performance after the switch.

For each account with a beginning-of-month position statement in month t, we identify all purchases in month $t-1$ and sales in month t. For both purchases and sales, we calculate the compound return on the stock from the day following the trade to the last day of the month. For purchases, this return is excluded in our main results, while for sales this return is included. Note that in our main results we account for the intraday return on the trade day in our estimate of the bid-ask spread.

The results of our analysis are presented in Table A1. The second (and fourth) column of this table presents aggregate purchase (and sale) turnover calculated as the aggregate dollar value of purchases (or sales) divided by the aggregate dollar value of positions held. (This turnover measure is slightly different than that used in the Table 5, where turnover is calculated for each household and then averaged across households.) Abnormal returns are calculated for purchases and sales by subtracting the compound return on the CRSP NYSE/AMEX/Nasdaq value-weighted index. The trade-weighted mean abnormal returns are presented in columns 3 (for purchases) and 5 (for sales) of Table A1.

First, consider the results for the online sample (panel A). Prior to the switch to online trading, from the day following the trade to the end of the month, the stocks that these investors bought outperformed the value-weighted market index by 14 basis points per month, while those that they sold outperformed the index by nine basis points. After the switch to online trading, the stocks that these investors bought underperformed the value-weighted market index by 33 basis points per month, while those that they sold outperformed the index by 21 basis points. Based on these abnormal returns and our estimates of turnover, we estimate that the results we present in the main text underestimate the performance of online investors by 0.23 basis points per month prior to the switch and overestimate their performance by 3.38 basis points per month after the switch.

Second, consider the results for the size-matched sample (panel B). The same analysis as that outlined in the preceding paragraph indicates that we have overestimated the performance

[28] Speech at National Press Club, May 4, 1999, http://www.sec.gov/news/speeches/spch274.htm.

Table A1
The gross abnormal returns for stocks bought and sold from the trade date to the end of the month

Sample	Monthly purchase turnover(%)	Purchase abnormal return (%)	Monthly sale turnover (%)	Sale abnormal return (%)	Estimated effect on monthly abnormal return (%)
Panel A: Online households					
Prior to switch	4.157	0.137	3.774	0.091	0.0023
After switch	6.260	−0.327	6.311	0.211	−0.0338
Panel B: Size-matched households					
Prior to switch	3.395	−0.148	3.069	−0.023	−0.0043
After switch	3.081	−0.807	3.147	−0.029	−0.0240

Online households are 1,607 households with 72 consecutive months of common stock positions, no online trades prior to January 1992, and at least one online trade between January 1992 and December 1995. Each size-matched household is the household with the closest account size to the sample firm in the month preceding its first online trade. The matched household must also have 72 consecutive months of common stock positions, no online trades during the 72 months, and at least one trade between January 1992 and December 1995. Purchase turnover is the aggregate value of stocks purchased divided by the aggregate value of stocks held in each month. The purchase abnormal return is calculated by compounding the daily returns on the purchased security from the day following the purchase to the end of the month less the compound return on the value-weighted NYSE/AMEX/Nasdaq market index. Sales turnover and sales abnormal return are analogously calculated. The estimated effect on the monthly abnormal return is purchase turnover times purchase abnormal return minus sale turnover times sale abnormal return.

of the size-matched sample by 0.43 basis points per month prior to the switch and 2.40 basis points per month after the switch.

Consider how the accounting for the exact timing of trades relates to the return calculations contained in the main text. In Figure A1, we present an example of a security that is purchased in month 1 and sold in month 3. A time line for these transactions is depicted in Figure A1.

In the main text we calculate the return for this security from t_1 to t_3. In this appendix we calculate the return from timing as the return from t_b^{cl} to t_1 minus the return from t_s^{cl} to t_s. Our estimate of the bid-ask spread is the return from t_s to t_s^{cl} minus the return from t_b to t_b^{cl}. When the return from timing is added to the main calculation and the spread is subtracted, one gets the (approximate) return from t_b to t_s, the period in which the investor held the stock.

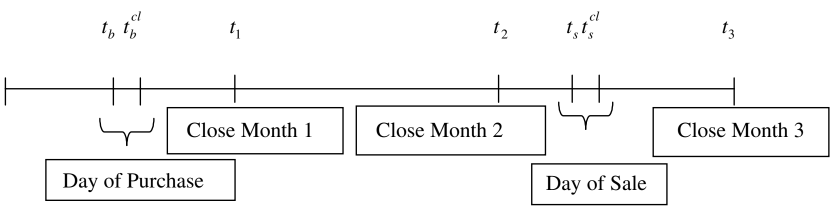

Figure A1
Time line of returns calculations
The time of purchase (sale) is t_b (t_s). The close on the purchase (sale) day is t_b^{cl} (t_s^{cl}). The close on the last day of the purchase (sale) month is t_1 (t_3).

Appendix B: The Analysis of Intramonth Trades

In this appendix we analyze the performance of stocks that are bought and then sold within a calendar month (e.g., purchased on January 3 and sold on January 10). These intramonth trades are excluded from our main analyses, since those analyses are based on monthly position statements.

For each account, we identify all purchases followed by a sale within the same month. In accounting for multiple purchases and sales, we assume that the first securities purchased are the first sold. We calculate the gross returns on these round-trip transactions using the CRSP daily return files, assuming the security is purchased and sold at the close of trading on the purchase and sale date, respectively. We calculate the net returns on these round-trip transactions by subtracting estimates of the bid-ask spread and commissions as is done in the main text for the case of monthly returns.

In Table B1 we summarize our analysis of the gross and net returns earned on intramonth trades. In this table we calculate market-adjusted abnormal returns by subtracting the daily value-weighted NYSE/AMEX/Nasdaq CRSP market index from the return earned on each intramonth trade. Both the gross and net abnormal returns in this table are weighted by the size of each trade, so we can estimate the aggregate impact of these intramonth trades on the performance of the online sample and their size-matched counterparts.

Panel A presents the results for the online sample. Prior to the switch to online trading, their intramonth trades earn impressive gross abnormal returns of 3.540%; the net abnormal returns are 1.812%. Since these intramonth trades represent 0.315% of the monthly positions, we estimate that these intramonth trades would improve the performance of online investors by 0.57 basis points per month (1.812 times 0.00315). After the switch to online trading, intramonth trades would improve the performance of online investors by 1.26 basis points per month (1.167 times 0.01078).

Panel B presents the results for the size-matched sample. Prior to the switch, intramonth trades improve the performance of the size-matched sample by 0.41 basis points per month. After the switch, these trades improve their performance by 0.55 basis points per month. These small improvements in performance for the online sample and their size-matched counterparts do not materially affect any of the conclusions that we present in the main text.

Table B1
The gross and net abnormal returns earned on intramonth trades

Sample	Mean trade size	Gross abnormal return (%)	Net abnormal return (%)	Intramonth trades as a percentage of total position value	Estimated change in monthly abnormal return (%)
Panel A: Online sample					
Prior to switch	$13,941	3.540	1.812	0.315	0.0057
After switch	$23,251	2.036	1.167	1.078	0.0126
Panel B: Size-matched households					
Prior to switch	$20,310	2.971	1.447	0.286	0.0041
After switch	$26,562	2.562	1.163	0.470	0.0055

Online households are 1,607 households with 72 consecutive months of common stock positions, no online trades prior to January 1992, and at least one online trade between January 1992 and December 1995. Each size-matched household is the household with the closest account size to the sample firm in the month preceding its first online trade. The matched household must also have 72 consecutive months of common stock positions, no online trades during the 72 months, and at least one trade between January 1992 and December 1995. The gross abnormal return on intramonth trades is calculated as the compound return from the day following the purchase to the day of the sale less the compound return on a value-weighted NYSE/AMEX/Nasdaq index. The net abnormal return is the gross abnormal return adjusted for the return earned on the day of the purchase or sale, the bid-ask spread, and the commission cost. The intramonth trades as a percentage of total position value are the average monthly value of intramonth purchases divided by the average monthly value of all stocks held. The estimated effect on monthly abnormal return is the net abnormal return times the intramonth trades as a percentage of total position value.

In conclusion, we should emphasize that the positive net returns earned on intramonth trades do not necessarily imply that individual investors have superior short-term trading ability. If investors have a disposition to sell winning investments and ride losing investments [as proposed by Shefrin and Statman (1985)], we would expect to observe positive abnormal returns on short-term round-trip trades.

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