The Rodney L. White Center for Financial Research

How Does the Internet Affect Trading?
Evidence from Investor Behavior in 401(k) Plans

James J. Choi
David Laibson
Andrew Metrick

014-01

The Wharton School
University of Pennsylvania

The Rodney L. White Center for Financial Research

The Wharton School
University of Pennsylvania
3254 Steinberg Hall-Dietrich Hall
3620 Locust Walk
Philadelphia, PA 19104-6367

(215) 898-7616
(215) 573-8084 Fax
http://finance.wharton.upenn.edu/~rlwctr

The Rodney L. White Center for Financial Research is one of the oldest financial research centers in the country. It was founded in 1969 through a grant from Oppenheimer & Company in honor of its late partner, Rodney L. White. The Center receives support from its endowment and from annual contributions from its Members.

The Center sponsors a wide range of financial research. It publishes a working paper series and a reprint series. It holds an annual seminar, which for the last several years has focused on household financial decision making.

The Members of the Center gain the opportunity to participate in innovative research to break new ground in the field of finance. Through their membership, they also gain access to the Wharton School's faculty and enjoy other special benefits.

Members of the Center

2001 – 2002

Directing Members

Ford Motor Company Fund
Geewax, Terker & Company
Morgan Stanley
The Nasdaq Stock Market, Inc.
The New York Stock Exchange, Inc.
Twin Capital Management, Inc.

Members

Aronson + Partners
Credit Suisse Asset Management
Exxon Mobil Corporation
Goldman, Sachs & Co.
Merck & Co., Inc.
The Nasdaq Stock Market Educational Foundation, Inc.
Spear, Leeds & Kellogg

Founding Members

Ford Motor Company Fund
Merrill Lynch, Pierce, Fenner & Smith, Inc.
Oppenheimer & Company
Philadelphia National Bank
Salomon Brothers
Weiss, Peck and Greer

How Does the Internet Affect Trading? Evidence from Investor Behavior in 401(k) Plans

James J. Choi
Department of Economics
Harvard University

David Laibson
Department of Economics
Harvard University

Andrew Metrick
Department of Finance
The Wharton School
University of Pennsylvania

March 2001

We thank Lori Lucas, Jim McGee, and Scott Peterson of Hewitt Associates, LLC for generously providing the data and extensive resources that made this project possible. We also acknowledge the technical help of Hewitt employees Lonnie Lee Buresh and Prema Palicharla. Outside of Hewitt, we benefited from the suggestions of Michael Kremer, Andrei Shleifer, Nick Souleles, Rob Stambaugh, Richard Zeckhauser, and seminar participants at Dartmouth, Harvard, L.S.E., and Wharton. Kunal Merchant, Parag Pathak, Kristy Piccinini, and Stephen Weinberg provided outstanding research assistance. Choi acknowledges support from a National Science Foundation Graduate Fellowship. Laibson acknowledges financial support from the Olin Foundation. Metrick acknowledges financial support from the Rodney White Center at the Wharton School of the University of Pennsylvania.

How Does the Internet Affect Trading?
Evidence from Investor Behavior in 401(k) Plans

ABSTRACT:

We analyze the impact of a Web-based trading channel on trader behavior and performance in two large corporate 401(k) plans. After 18 months of Web access, trading frequency at the sample firms doubles relative to a control group of firms without a Web channel. Web trades tend to be smaller than trades made through other channels and Web traders tend to have smaller portfolios than other traders, so the Web's impact on portfolio turnover is substantially smaller than its effect on trading frequency. There is no evidence that any of this new trading on the Web is successful; if anything, Web traders underperform in their market-timing trades. We find no evidence of a Web impact on "speculative behavior" such as positive feedback trading, herding, or short-term trading. While Web traders do differ from other traders in some of these speculative activities, these differences appear to be driven by selection effects rather than caused by the Web.

JEL classification: D0, G0, L0, O0.

Keywords: 401(k), asset allocation, Internet, World Wide Web, online trading, new economy, retirement saving.

Online trading of stocks through the Internet and the World Wide Web has been proposed as a cause of excessive trading, excessive herding, higher volatility in the stock market, excessive risk-taking, the Internet "bubble" of the late 1990s, and the bursting of this bubble in 2000.[1] Concern that online ("Web") traders might do damage to themselves or to markets has prompted several policy statements from the SEC.[2] Despite all of these concerns, hard evidence on the causal impact of Web trading is scarce. Before blame is laid and policies are made, it is important for researchers to answer some basic questions: Has the Web itself led to an increase in trading? If so, by how much? Does the Web affect traders' performance? Does the Web induce "herd-like" behavior by traders? Does the Web induce positive feedback trading?

This paper attempts to answer these questions using a unique data source with exogenous variation in access to Web-based transactions. We exploit such variation to examine the impact of the Web on the trading decisions in two large corporate 401(k) plans. Both of these plans opened a Web channel in August 1998, and we have about three years of detailed trading data for each plan. As a comparison, we also have a measure of trading activity for a set of large 401(k) plans that have not introduced a Web channel.

As an analogy to the opening of a Web trading channel, suppose that the residents of a town are accustomed to driving 20 miles to do their grocery shopping, and

[1] Claims about the impact of the Web are found in numerous press reports; some examples are Dugan (1999), Kunath (1999), Livingston (2000), and Financial Times (2000). For an academic discussion of some of these issues, see Barber and Odean (2001b) and Shiller (2000, pp. 39-40).

[2] Levitt (1999a) and (1999b).

then a new supermarket opens just one mile away. In this case, we would expect the typical resident to make more shopping trips and buy fewer groceries on each trip. If the first visit to this new supermarket were particularly costly for some reason, then we would expect average shopping patterns to adjust slowly over time before reaching a new equilibrium where all residents shopped at the new store. If the new supermarket organized its products differently than other stores, then we might also expect the composition of the average purchased bundle to change as well. The introduction of Web trading can be seen in much the same way. By changing the transactions costs faced by investors, the Web should induce changes in trading frequency and size.[3] By changing the information sources and capacity for interpersonal communication, the Web may also alter the types of trades. What makes asset trading more interesting than grocery shopping is its capacity to affect asset prices and, ultimately, the allocation of capital.

To our knowledge, the only careful previous analysis of the behavior of online investors is Barber and Odean (2000b), who focus on the trading behavior and investment performance of investors who switch from the phone to an online channel. While their data are more useful for many purposes than is our sample, the self-selected nature of discount-brokerage customers who choose to trade online makes it difficult to draw inferences about the impact of new trading technologies on the typical investor.[4]

[3] In our sample, traders are not charged a direct transaction cost for any of their trades. The "transaction costs" in this paper are time costs.

[4] There is also a substantial literature on 401(k) savings and average asset allocation choices, but only a few papers address trading behavior (Ameriks and Zeldes (2000) and Agnew, Balduzzi, and Sunden (2000)), and none focus on the determinants of trading frequency and performance or the impact of trading technologies.

In Section I, we describe the dataset and sketch an empirical portrait of Web trading and Web traders. Participants in our two sample firms have the option of using either the phone or, since August 1998, the Web for making trades in their 401(k) plan. We use regression analysis to determine the characteristics of participants who choose to use the Web: we find, perhaps not surprisingly, that young, wealthy, male investors are the early adopters. We also discuss the asset-allocation options in the two 401(k) plans and document the general patterns of trading by channel.

In Section II, we measure the impact of the Web on the volume of trade. As a preview of the results, Figure 1 plots a 21-trading-day moving average of the daily trading frequency for one of our companies, code-named Alpha. At first glance, the Web effect appears dramatic. Within 18 months after the Web channel was opened, Web transactions represent approximately 60 percent of all transactions, and the trading rate has quadrupled from its pre-Web level. But, of course, all Web trading is not necessarily "new" trading. Participant trading is driven by many factors that have been trending up over our sample period. For example, stock price volatility has risen recently, and trading volume might be expected to rise as a result. When we control for such changes — including use of a trading index for a set of firms that do not have a Web channel — we continue to find a huge Web effect: after 18 months, the Web channel nearly doubles the daily trading frequency. Over the same period, the impact on daily turnover — the fraction of balances traded — is about half the size and is not always statistically significant. We reconcile the results for trading frequency and turnover by showing that trade sizes — both in dollars and as a fraction of portfolio — are smaller by Web than by phone.

In Section III, we evaluate the performance of traders by channel. We analyze the absolute and relative (Web vs. phone) performance for both asset-allocation ("market-timing") trades and trades in own-company stock. In addition to providing insight into the role of the Web on trader performance, this analysis provides a rare glimpse at the asset-allocation trading decisions of individual investors. We find some evidence of underperformance in the market-timing trades of Web traders at one of the firms: that is, the magnitude of Web trading is a contrarian indicator for S&P 500 returns. We also find that company-stock trades have no predictive power for company-stock returns, and there are no significant differences between Web and phone performance in such trades.

In Section IV, we compare the behavior – beyond just changes in trading frequency and trade size – of Web and phone traders. We find that Web traders exhibit more "momentum" or "positive feedback" behavior in their market-timing trades than do phone traders, but that this tendency is likely to be a selection effect on the type of traders who use the Web rather than a Web-induced effect. We also find that Web traders are no more likely to "herd" in the same direction than are phone traders. Finally, in a somewhat surprising result, we find that *phone traders* are more likely than Web traders to engage in "short-term" trading – trades that are reversed within five days – and are also more likely to place trades in the last hour before markets close at 4 P.M. Thus, the Web has not led to an increase in the proportion of such short-term trading. All in all, we conclude that while the Web has increased trading frequency in this sample, it has had no effect on several specific types of speculative activity to which it has been connected in the popular press. Finally, Section V concludes the paper.

I. Data and Descriptive Statistics

401(k) plans are now the primary vehicle for retirement savings in the United States. In 1999, 401(k) plans held \$1.6 trillion in assets, 72% of which represents equity holdings.[5] Thus, equity holdings through 401(k) plans, directly or indirectly, constitute about ten percent of the equity holdings for the household sector.[6] In the typical 401(k) plan, an employer ("plan sponsor") offers a menu of investment options to their employees ("participants"). At the time of plan enrollment, participants choose a percentage of their pay to be regularly deposited to the 401(k) plan ("contribution rate"), and also choose how to allocate these regular flows among the available investment options. After enrollment, participants have three main policy instruments for managing their 401(k) assets: (1) changes in the contribution rate, (2) changes in the allocation of the regular contributions, and (3) direct transfers of plan balances across investment options.[7] These direct transfers are the "trades" analyzed in this paper.

Our data is provided by Hewitt Associates LLC, a large provider of administrative and consulting services to firms with 401(k) plans. With their help, we identified two large companies that had recently introduced Web access to their 401(k) plans. In choosing these firms, we were careful to minimize any selection biases. Less than one half of Hewitt's large-client firms offered Web trading as of January 2000. We asked Hewitt to identify the subset of these firms that had made the fewest changes to their plan rules for a wide window around the Web introduction. For ex-

[5]See the Employee Benefit Research Institute: http://www.ebri.org/ret_findings.htm.

[6]Calculated from figures in the Federal Reserve Board (2000).

[7]Participants can also make withdrawals (with penalties before age $59\frac{1}{2}$) and take loans from their accounts. Rules governing these actions vary significantly across plans.

ample, changes to the menu of investment offerings, rules for matching contributions, or participant eligibility dates could all introduce noise into our attempts to identify a Web-trading effect. We also asked that Hewitt not calculate or prescreen the level of Web trading for any of these firms, so there was no chance of selecting firms based on unusual usage patterns. Finally, we required that the selected firms have at least one year of data both before and after the Web introduction. Two 401(k) plans of two firms – code-named Alpha and Omega – survived these filters; summary statistics for these plans are given in Table I. The sample period for Alpha begins in May 1997 and includes all of the data stored by Hewitt. Our sample period for Omega begins in January 1997. We ignore earlier data for Omega because participants were allowed to trade only once a month before this time. The data include records for every trade by all participants as well as snapshots of demographic information, contribution rates, and asset allocation at year-end 1998 and year-end 1999 for all participants who had positive total balances on these days or who had some plan activity during 1998 or 1999.

As shown in the table, Omega has considerably more participants and investment options than Alpha. Omega has over 50,000 participants, who choose among 36 investment options covering every major asset class. Alpha offers its 10,000+ participants 11 investment options but still includes several U.S. equity funds and one bond fund. Participants in both of these plans are able to transfer assets between investment options (= "trade") through either a phone call or, as of August 1998, the Web. The phone order can be either through an automated touchtone menu system (the majority of calls) or a live representative (which may entail a wait). All trades placed before 4 P.M. Eastern Time will be executed that day at closing prices.[8] Trades in international funds are executed at their most recent (past) closing prices. Note that no direct transactions costs are charged for any kind of trade: any trading costs come from the opportunity cost of the time it takes to place the trade.

Of course, someone has to bear the real transactions costs associated with trading. Normally, the costs are shared by all plan participants, and the short-run incidence of any increases in these costs depends on the contracts among the plan sponsors, plan administrators, and the managers of the investment options. In the long run, at least some of the incidence must fall on the plan sponsors and add to the cost of providing the 401(k) benefit, which is at least partly borne by employees. Even in this case, however, unless plans begin charging directly for trades, the partial incidence of a specific trade will not fall on the trader, but rather on all participants.

One interesting feature of many large 401(k) plans is the option to invest in the stock of one's own company, which is available to participants in Omega. While many experts have pointed out the diversification costs of such own-company investment, company stock remains a popular choice among employees. Nationwide, participants in large ($>$ 5,000 participants) plans invest more than 35 percent of their balances in company stock, and a significant portion of this is discretionary (Holden, VanDerhei, and Quick (2000)). In contrast to many other large plans, participants in Omega are not required to hold the company's matching contributions in company stock. This partially explains the relatively low holding of company stock – 6.6 percent of

[8] A participant may place numerous trades in one day. Since such trades will be added together and executed at closing prices by the plan, we follow the same convention and treat the aggregate amount as one single trade. Some parts of our analysis require that we assign each trade a specific time and channel (Web vs. phone). When there are multiple trades aggregated into one, we assign the characteristics of the last trade to the aggregate.

balances as of year-end 1999 – by Omega's participants. Across all forms of domestic equity – in company stock, equity mutual funds, and the equity portion of balanced or lifestyle funds – average allocations vary widely between the two plans, with Alpha at 75.6 percent and Omega at 40.8 percent.

The Web channel was opened in August 1998 by both plans. The channel introduction was announced by either a memo or a later article in the plan's newsletter. In no case was there any extra inducement to use the Web channel. The lack of any special inducements is consistent with the overall focus of plan sponsors on long-term retirement planning and away from short-term trading. In discussions with representatives of these companies, we learned that the primary reasons for Web introduction were better communication with participants and a desire to give participants easier access to their account information.[9]

The last four rows of Table I suggest the same "Web effect" for Omega that is seen for Alpha in Figure 1. In both plans, the average monthly level of trading is higher after the Web channel is introduced than it is before, and this difference is approximately the same as the average number of Web trades made per month. In Section II, we show that these patterns are significant even after careful controls for other factors.

What are the demographic characteristics of Web traders? To investigate this question, we construct a sample of participants who executed at least one trade, either

[9]The preceding paragraph is based on private communications with an employee of Alpha and with Hewitt employees who administer these plans. Since both Alpha and Omega chose when to adopt this new technology, we cannot consider their Web introductions as purely random "natural" experiments. Nevertheless, our conversations with Hewitt and our specific findings of no immediate Web impact (discussed in Section II) suggest that the exact timing of the Web introduction was not motivated by participants' trading demands.

by phone or by Web, since the date that the Web channel was opened. Conditional on being in this sample, we then estimate the likelihood of executing at least one trade on the Web. As independent variables, we include age, tenure at the firm, salary, total balance in the 401(k) plan, length of time participating in the plan, contribution rates to the plan, monthly frequency of trading before the Web introduction, and dummy variables for sex, marital status, retirement status, and current employment status at the firm, all as of year-end 1999. All the continuous variables, except age and trading frequency, are in logs.

Table II summarizes the results of logit estimations for both firms. The coefficients on age are negative and significant for both firms. The coefficients on both salary and plan balances are positive and significant in both regressions. We only have gender data for Alpha: in that regression, the coefficient on the male dummy variable is positive and significant. The evidence on other demographic variables also demonstrates some interesting patterns. Retired participants are less likely to try the Web for trading at Omega. Participants coded as "terminated," a mutually exclusive set from those who are retired, are also less likely to try the Web, with negative and significant coefficients at both firms. It is plausible that such participants are in less active information networks about plan changes and thus are less likely to know about plan changes. While they might receive the same formal documents as other participants, they are no longer able to hear about plan changes through word-of-mouth at the workplace. Finally, the coefficient on "pre-Web trades per month" is negative and significant at the one percent level for Alpha, and is negative and insignificant for Omega. This evidence suggests that traders who are already experienced and familiar with phone trading are less likely to try the Web.

What exactly are all these participants trading? Table III summarizes the asset allocation and trading at both firms. The asset classes organized this table are organized into seven groups:

(1) GIC – guaranteed income funds that promise a lower bound on the nominal rate of return.

(2) Bond - Mutual funds that invest predominantly in domestic bonds.

(3) Lifestyle/balanced – Balanced funds are mutual funds that have target ratios of stocks and bonds. Lifestyle (or “pre-mix”) funds have preset ratios of stocks and bonds, and are targeted at investors either by their time horizon (e.g. “20- years until retirement”) or risk tolerance (e.g. “Conservative”).

(4) Large U.S. Equity – Mutual funds that invest predominantly in large-capitalization domestic stocks.

(5) Other U.S. Equity – Mutual funds that invest predominantly in equity outside of the largest stocks. This includes “mid-cap”, “small-cap” and “sector” funds.

(6) International – Mutual funds that invest predominantly in non-U.S. stocks, including both emerging-market and developed-country funds.

(7) Company Stock – The common stock of Omega. (Alpha does not offer company stock in its plan.)

As can be seen in Table III, the two plans differ significantly in the distribution of holdings and trading. At Alpha, there is only one bond fund out of the 11 choices, and 21.8 percent of all assets were invested in this fund as of year-end 1999. Nevertheless, 39.3 percent (purchases) and 38.2 percent (sales) of the dollars traded by phone and 32.0 percent (purchases) and 32.6 percent (sales) of the dollars traded by Web involved this single bond fund. At Omega, over 57 percent of the holdings are in the GIC fund, with this fund representing 36.0 percent (purchases) and 38.3 percent (sales) of the dollars traded by phone and 32.7 percent (purchases) and 36.4 percent (sales) of the dollars traded by Web. Many participants at Omega seem to view the GIC fund as a substitute for bonds, since only a tiny percentage of assets in Omega's plan are held in bond funds. Overall, participants at both plans trade a significant share of their assets between bond/GIC and equity funds. In Section III.A, we investigate the performance of these market-timing trades and test whether this performance differs across channels. The last column of Table III shows that the holdings of company stock in Omega's plan are only 6.6 percent, but this asset class constitutes a disproportionate share of the trading (15.2 percent of purchases and 16.2 percent of sales by phone and 12.2 percent of purchases and 11.0 percent of sales by Web). In Section III.B, we investigate the performance of these company stock trades.

II. Does the Web affect trading volume?

Do the patterns in Figure 1 and Table I demonstrate a "Web effect," or are they caused by other factors? To answer this question we estimate regressions of the form

$$y_{it} = \alpha_i + \alpha_{iw} Web_{it} + \beta_{iw} * Web_{it} * Time_{it} + \beta_i X_{it} + \varepsilon_{it}, \tag{1}$$

where y_{it} is a measure of trading volume in firm i on day t (described below), Web_{it} is a dummy variable that takes on the value of 1 when Web trading is available and 0 otherwise, $Time_{it}$ is the number of days since the Web channel was introduced at company i, X_{it} is a vector of factors that influence and covary with trading activity, ε_{it} is a (possibly autocorrelated) error term, α_{iw} is the estimated level effect for Web trading, and β_{iw} is the estimated slope effect. If α_{iw} and β_{iw} are both zero, then there is no Web effect. If opening the Web channel causes an immediate increase in trading activity, then α_{iw} should be positive. If the Web channel causes trading to rise over time, then β_{iw} should be positive. It is worth noting at the outset that the restriction to a linear impact for the Web over time is made only in order to ease the interpretation of the results. There is no theoretical reason against higher-order trends nor is there any reason to extrapolate any trends beyond the sample period. Rather, the specification in (1) is a reduced-form attempt to measure the impact of the Web on trading over the sample period.

We consider three measures of trading activity on the left-hand-side of (1). Our first measure, $Trades_{it}$, is the percent of participants that trade in plan i on day t. As a description, we refer to $Trades_{it}$ as the "trading frequency" and express it in units of percent. Thus, $Trades_{it} = 0.05$ means that 0.05 percent of all participants in plan i executed some trade on day t. Our second measure, $Turnover_{it}$, is the total dollars traded by participants in plan i on day t, divided by total balances for all participants in that plan on that day. Thus, if 0.05 percent of all participants in plan i each shift 20 percent of their portfolios on day t, then $Turnover_{it}$ would be 0.01 on that day. Our third measure, $Company\ Index_{it}$, is measured the same way as the $Turnover_{it}$ variable, except that it includes only net turnover across different asset classes. This third measure is useful because it corresponds exactly to a control variable that we have for seventeen other firms. We discuss the construction of this control variable below. (For notational ease, we omit the it subscripts in remainder of this discussion.)

The main difficulty in this analysis is in determining the elements of the X vector.

In the end, controlled experiments are the cleanest way to test for treatment effects. Ideally, we would have introduced Web trading for only a random sample of the participants at each firm, and then measured the differences between the Web and non-Web groups. Barring this possibility, we would like to identify some measure of trading activity that has been unaffected by the Web. Hewitt gathers data that allows us to construct such a measure. The "Hewitt 401(k) Index™" is designed to measure trading activity between asset classes on a daily basis. The index is constructed from the trading activity in 40 different large-company plans. For each plan, Hewitt calculates the aggregate net dollar amount traded between asset classes on each day.[10] Individual trades between mutual funds in the same asset class are not counted, and trades of all individuals are added up and netted out to produce an aggregate figure for each firm. For example, if participant i transfers \$10,000 from a large U.S. equity fund to a bond fund, and participant j does the opposite, then Hewitt would cancel these transactions and show no aggregate activity from these two participants. By dividing this aggregate figure by the total assets in the plan, they calculate an index for each firm. Note this index has the same denominator as but a different numerator than the $Turnover$ variable; the numerator of $Turnover$ is the sum of the dollar value of all transactions, irrespective of whether they are within or between asset classes, and without netting any offsetting trades. To construct our non-Web subsample of the Hewitt 401(k) Index™, we started with the same 40 plans as Hewitt, then eliminated the 13 firms who had a Web channel by the end of the

[10] For this calculation, the full set of asset classes is slightly larger than the group represented in Table III of Section I. This full set is (1) money market, (2) GIC/stable value, (3) bond, (4) balanced, (5) lifestyle/premix, (6) large US equity, (7) midsize US equity, (8) small US equity, (9) international, (10) emerging markets, (11) specialty sector, (12) company stock, and (13) self-directed window. Most plans, including Alpha and Omega, do not offer options in every class.

sample and the ten firms that joined the sample after August 4, 1997, which is the first day the index was calculated. We then averaged the indices for these 17 firms on each day to arrive at our $Non-Web\ Index$ variable, which is included in each X_i vector.

As discussed above, we construct a third measure of trading activity for Alpha and Omega, $Company\ Index$ and use it as a left-hand side variable in our estimation of (1). $Company\ Index$ is measured exactly the same way as $Non-Web\ Index$ for each firm. Figure 2 plots the three measures of trading activity – $Trades$, $Turnover$,and $Company\ Index$ – for Alpha (Panel A) and Omega (Panel B), and gives correlations between each pair of measures.

While the $Non-Web\ Index$ is our main control variable, there may be other factors that affect 401(k) trading differentially across firms and could be useful as additional elements of the X vector. One obvious set of factors is day-of-the-week and day-of-the-month effects. Since participants cannot trade over the weekend, it is reasonable to expect heavier trading on the first and last (trading) day of the week. Also, since many financial decisions and transactions are made at month-end, participants may also engage in heavier trading around those times. Thus, we include dummy variables for the first and last trading days of the week and month. Our data series is too short to identify any end-of-the-year or tax-day effects, but we do include an overall time trend as part of the X vector. Then, the coefficient β_{iw} in equation (1) can be interpreted as the additional time trend after the Web introduction.

Our control variables also include some past returns on the plans' investment options. Studies of individual trading behavior show that past returns on a portfolio's securities affect trading (Odean (1998 and 1999), Barber and Odean (2000a), Grinblatt and Keloharju (1999)). Similarly, many studies of mutual-fund flows indicate that funds with high past returns attract high net flows (Sirri and Tufano (1993), Chevalier and Ellison (1997), Edelen (1999), Goetzmann, Massa and Rouwenhorst (2000), Bergstrasser and Poterba (2000)), with this relationship significantly nonlinear for funds with the highest past returns. Although each plan only offers a limited set of investment options, there are many possible choices of lags and powers, so that it is necessary to restrict this set to produce some interpretable results. Across both plans, an average of 60 percent of assets are invested either in equity mutual funds or in company stock. Even though participants in Alpha cannot invest in company stock, its past returns may still be salient when participants are forming expectations for future market returns. Thus, it seems reasonable to include the returns to both company stock and to a broad equity index, the S&P 500, as elements of X. Past studies, cited above, suggest that higher orders of returns may also affect trading, perhaps because more extreme returns are more salient for investors. Thus, for both asset classes, company stock and the S&P 500, we include the absolute value of the contemporaneous daily price return, the absolute value of the price return on the previous day, each of these daily returns squared, and, lastly, the standard deviation of daily price returns over the previous 20 trading days.

In total, each X vector includes ten return-based variables, four timing dummies, a trend variable, and $Non-Web\ Index$. In the regressions for Omega, we also include a dummy variable, *Rule Change*, to reflect a change in trading rules made during 1999. This change prevented all transfers into one of the international funds; prior to this change, trades involving this fund constituted more than 15 percent of all trades. The dummy variable takes on the value of zero on all days before the rule change and a value of one after the rule change.

Tables V shows the results of estimating (1) for each firm with the variables described above and $y = Trades$, the trading frequency, as the dependent variable.[11] As a baseline case, we also report results for a specification of (1) where the X vector includes only $Non - Web\ Index$. The table reports coefficient estimates and standard errors for all regressors, with the key test variables given in bold at the top. We use a Newey-West (1987) correction with maximum lag length of five trading days to estimate robust standard errors. The results demonstrate economically and statistically significant evidence of the Web's effect on trading frequency. In the baseline specification (columns one and three), the coefficient on $Web * Time$ is positive and significant at the one-percent level for both firms. In the full specification (columns two and four), the coefficient on $Web*Time$ is significant at the one-percent level for Alpha and the five-percent level for Omega. The level effects are statistically insignificant in all specifications. Our calibrations, described below, indicate that all the point estimates for the level effects are economically small compared to the trend effects. From this evidence, we conclude that there is strong evidence that the Web's effect on trading frequency was growing over time, and no significant evidence of a jump at the time of introduction.

To calibrate the economic significance of the level and trend Web effects, we can compare their estimated effects over the horizon of our sample to the trading frequency before the Web channel was open. We use the results from the full specification for these calibrations. For Alpha, the estimated coefficient on $Web * Time$ is 0.00072. Over one and a half years – 548 days – approximately the time the Web channel is

[11] Since $NON - WEB\ INDEX$ can only be calculated after August 4, 1997, the sample period for the regressions is truncated somewhat from the period listed in Table I.

open in our sample, this point estimate implies an increase in trading frequency of $548 * 0.00072 = 0.395$. If we subtract out the (insignificant) point estimate of the level effect, -0.095, we arrive at a total Web effect over the sample period of 0.300. In Table I, we report that the average monthly trades per participant before the Web was 0.0564; this translates into a daily trading frequency of (0.0564/21) * 100 = 0.269 percent. Thus, the total Web effect for Alpha is calibrated to be about $0.300/0.269 = 112$ percent of pre-Web trading. An analogous calculation for Omega yields an increase in trading frequency of $(0.00064*548-0.024)/0.402 = 81$ percent of pre-Web trading. Averaging these two calibrations, we estimate that the Web nearly doubles trading at an 18-month horizon.

We conclude from this evidence that the pattern in Figure 1 is no illusion: the introduction of Web trading has a large effect on the trading frequency of plan participants. This result leads to a natural follow-up question: does the Web also affect the dollar volume of trade? It is possible, for example, that the large increase in trading frequency occurs because participants break up large trades into smaller pieces, with only a small or negligible increase in the total dollars traded. Also, if Web trading is predominantly an activity of young participants with small balances, then the Web's impact on dollar volume would be smaller than its impact on trading frequency. We analyze the Web's effect on dollar volume by using $Turnover$ as the dependent variable in (1).

Table V summarizes the results for both the baseline and full specifications. In the baseline case, the coefficient on $Web * Time$ is positive and significant at the 1 percent level for both firms. In the full specification, the coefficient on $Web * Time$ for Omega is positive and significant at the 1 percent level. The analogous coefficient for Alpha is positive and has a t-statistic of 1.88, implying a two-tailed p-value of 0.06. To evaluate the economic significance of these point estimates, we follow a procedure analogous to the one used to assess trading frequency. That is, we compute the total effect on $Turnover$ over 18 months that is implied by the point estimates, and then we compare this effect to the average turnover before the Web channel was opened. This computation yields an estimated increase of 45 percent for Alpha and 64 percent for Omega.[12] The average effect across the two firms is about 55 percent, or a little more than half the estimated effect on trading frequency. Thus, the evidence suggests that the Web increased turnover, but not by as much as it increased trading frequency.

As a final test, we use $Company\ Index$ as the dependent variable in (1). Recall that $Company\ Index$ is measured in the same way as $Non - Web\ Index$, so that it includes only the net turnover across asset classes. The results of these regressions are summarized in Table VI. In the baseline specification for Alpha, the coefficient on $Web * Time$ is positive and significant at the 1 percent level. In the baseline specification for Omega, the coefficient on $Web * Time$ is positive but insignificant, while the coefficient on Web is positive and significant at the 1 percent level. In the full specification, while the coefficient on $Web * Time$ is positive for both firms, it is insignificant in both cases. Note that while these estimates are not statistically significant, the average calibrated effect for the point estimates, 47 percent, is about the same as the average calibrated effect for the coefficients in Table V.[13]

[12] This computation uses the coefficients reported in the top two rows of Table III. The total Web effect for Alpha was $0.00038 * 548 - 0.059 = 0.149$ percent. The average daily pre-Web turnover in Alpha, not reported elsewhere in the paper, is 0.334 percent. Thus, the Web increased turnover by $0.149/0.334 = 45$ percent. The analogous calculation for Omega is $0.00026 * 548 - 0.021 = 0.122$ percent. The average daily pre-Web turnover at Omega was 0.192, implying an increase of $0.122/0.192 = 64$ percent.

[13] For Alpha, the baseline index before Web introduction is 0.147, so the coefficients in the table

Taken together, the results given in Tables IV, V, and VI demonstrate the strongest impact for the Web on trading frequency, with smaller or insignificant impacts on dollar turnover and net dollar trading across asset classes. One possible explanation of these results is that the main control variable, $Non - Web\ Index$, is not a very good control for the regressions in Table IV, and the stronger effect found there is due to omitted-variable bias. Under this interpretation, one must posit that concurrent with the increase in trading frequency at Alpha and Omega, there was also a similar increase in trading frequency at the index firms, and that this increase is not captured in $Non - Web\ Index$. A second possible explanation of the results is that the Web itself induced a shift in trader behavior towards smaller but more frequent trades, and this shift led to larger increases in trading frequency than in dollar volume. A similar effect on trade size would occur if Web traders had, on average, smaller portfolios than phone traders. If average trade size were indeed smaller by Web than by phone, then the $Turnover$ and $Company\ Index$ measures would be expected to grow more slowly than the $Trades$ measure. While one can never rule out the possibility of omitted variable bias, we believe that the evidence points to this trade-size change as the more likely explanation. This evidence is discussed below.

Panel A of Table VII gives the average dollar value, the average turnover (as a fraction of the portfolio), and the average portfolio size for all sales made after the Web was introduced. At both Alpha and Omega, the average dollar amount per sale is significantly higher by phone than by Web. Phone sales at Alpha average \$99,924, while Web sales at Alpha average \$59,344. At Omega, average sale size

imply a calibrated 18-month increase of only 0.13 percent. For Omega, however, the baseline index before Web introduction is 0.063, so the coefficients, albeit insignificant, imply a calibrated 18-month effect of 94.3 percent.

by phone is nearly double the average sale size by Web ($64,422 to $32,552). This relationship is driven by both the forces discussed in the preceding paragraph. First, the average turnover per sale is higher by phone than by Web: 70.90 percent to 55.25 percent at Alpha and 42.10 percent to 29.89 percent at Omega. Second, the average portfolio held by phone traders is larger than the average portfolio held by Web traders: $135,921 to $113,294 at Alpha and $178,261 to $129,654 at Omega. Thus, trades by Web make up a smaller slice of a smaller pie than do trades by phone.

Simple comparisons between trade sizes are only the beginning of the story. It is possible, for example, that Web traders are people who generally make small trades, and that the differences between Web and phone traders are a selection effect, rather than a treatment effect of the Web. In this case, the Web would not affect the overall size distribution of trades, but only the channel for different sizes of trades. To test for a selection effect, we take all participants who made at least one trade after the Web channel was opened. From this group, the "Web sample" is comprised of all traders who made at least one trade by Web. All remaining traders are placed in the "phone sample". Panel B of Table VII shows the average dollar value, the average turnover (as a fraction of the portfolio), and the average portfolio size for these two groups. The sample includes all trades made by these samples of traders *before* the Web channel was opened. Panel B shows that while average trade size is higher for the phone sample than for the Web sample ($73,062 vs. $60,911 at Alpha and $47,567 vs. $36,684 for Omega), this difference is driven entirely by different portfolio sizes, and not by different turnover percentages. The average turnover per trade is very similar for the two samples at both firms (62.88 percent vs. 64.60 percent at Alpha and 36.83 percent vs. 34.24 percent of Omega), while the average portfolio size (at the time of trade) was larger for the phone sample at both firms ($110,085 vs. $100,597 at Alpha and $153,333 vs. $125,179 at Omega).[14]

The analysis in this section is best viewed as an estimate of the Web's impact over the first 18 months after its introduction in these 401(k) plans. The evidence does not imply that this impact can be extrapolated indefinitely into the future. Indeed, one reasonable interpretation of these results is that they describe a transition state as investors move to a "cheaper" trading technology. Under this scenario, the trading frequency would grow during the transition period as traders switch to the Web, but this growth would slow down over time. The eventual long-run equilibrium would have higher trading frequency and lower turnover per trade than before the Web's introduction.[15]

III. Does the Web affect trading performance?

Does the increased trading on the Web lead to poor performance by traders? Researchers have only recently started to study these questions, with the work of Barber and Odean (2000b) on discount-brokerage investors as the first example. Our data differs from the sample of Barber and Odean (2000b) along three main dimensions.

[14] At first glance, there appears to be some tension between Table VII and our earlier finding in Table II that wealthier participants are more likely to try the Web. If wealthy participants are more likely to try the Web, why is it that the balances of phone traders are higher than the balances of Web traders? The resolution of this apparent tension is in the distinction between traders and trades. The most *frequent* traders tend to be relatively wealthy participants who are engaging in short-term trades by phone (see Section IV.C below). The results of Table VII average across all *trades*, so that these frequent traders are counted many times. By contrast, the demographic results of Table II count each trader once. Thus the high-balance frequent phone traders do not dominate that analysis.

[15] Indeed, this latter effect is already apparent: the average turnover for all trades at Alpha (with Newey-West standard errors in parentheses) was 67.17 percent (1.08) in the three months before the Web's introduction and had fallen to 60.81 (1.29) percent in the last three months of the sample. The corresponding percentages at Omega were 37.19 percent (0.55) in the three months before the Web's introduction and 34.20 percent (0.83) in the last three months of the sample.

First, while the investment choices within equities are limited relative to those in discount brokerages, there is significant range of choices available *across* asset classes, and we can exploit this range to study asset-allocation trading performance. Second, the participants in our sample face no transactions costs or taxes. This is both a strength – because the absence of friction make it easier to evaluate performance – and a weakness – because it is difficult to generalize the results to taxable environments. Third, unlike the customers in discount-brokerage plans, the participants in employer-based retirement plans are not self-selected based on their expected trading behavior.

Taken together, these features of our sample allow us to study trading performance and the role of the Web in a near-experimental setting. While many investment advisors and plan sponsors encourage investors to view their retirement accounts as long-term investments that should not be disturbed, there is substantial evidence from our sample that many investors ignore such advice and trade actively. This behavior has some justification: if someone is determined to implement an active trading strategy, then, given the absence of direct transactions costs and capital-gains taxes, retirement accounts are ideal places to do it. This temptation may induce traders to behave, and perform, very differently in their retirement accounts than they do outside of them, so the results here cannot necessarily be extended to other environments. With this caveat in mind, this section analyzes trader performance, with a focus on the differences between trades executed by Web and by phone. Section IV.A analyzes performance in asset-allocation trades and Section IV.B analyzes performance by Omega's participants when they trade company stock.

A. The performance of asset-allocation trades

In testing for performance differences between Web trades and phone trades, we first examine asset-allocation decisions between equity and other assets. While this "market-timing" decision has been well-studied for professional managers and advisors, most studies do not have transactions data and instead infer market-timing ability from the relationship between portfolio returns and market returns.[16] Among studies of the asset-allocation performance of individual investors, only Goetzmann and Massa (2000) make use of transactions data.[17] Thus, the transactions data used here offers a rare glimpse – especially for individual investors – at the details of asset-allocation behavior and performance.

To evaluate asset-allocation performance, we adopt the methodology of Graham and Harvey's (1996) study of the market-timing ability of investment newsletters. As in their study, we test whether explicit changes in equity portfolio weights can forecast equity returns. We then interpret this forecasting result as a proxy for asset-allocation performance. We begin by building indices of net changes in equity holdings for each firm on each day. In building these indices, our first measure is just the net flow, in dollars, on each day. This is computed separately by each channel, so that *Web Flow* is equal to the difference between the dollar value of equity purchases by Web and the dollar value of equity sales by Web in the firm. In computing this measure, any trade in the categories (see Table III) "Large U.S. Equity", "Other U.S. Equity", or "Company Stock" counts as equity. For balanced funds, we count

[16] Papers that do make use of transaction data or specific transaction recommendations are Chance and Hemler (1999), Graham (1999), Graham and Harvey (1996, 1997), and Wagner, Shellans, and Paul (1992).

[17] Bange (2000) and Durell (1999) both analyze the forecasting power of individual investors using survey evidence of holdings and expectations, but do not use transactions data.

a purchase of \$1 as 60 cents of equity and 40 cents of bonds.[18] For the "lifestyle/pre-mix" funds, we use the target percentages of each fund.[19] For example, one of the lifestyle funds at Omega uses a fixed ratio of 75 percent equity and 25 percent bonds. If a participant at Omega were to buy \$1 of this lifestyle fund and sell \$1 of a bond fund, then this would count as a net flow of 75 cents into equities. Finally, we exclude both sides of all trades that have an international equity component.[20] *Phone Flow* is calculated analogously using purchases and sales by phone. We then ask, can *Web Flow* or *Phone Flow* for each firm forecast returns?

To answer this question, we start with a simple test. We compute the probability of an up-move in the S&P 500 as a function of whether *Web Flow* or *Phone Flow* is negative or positive. Table VIII shows the frequency of up-moves and down-moves as a function of the sign of the flow measures. The table shows a slight tilt towards negative forecasting ability for Web trades in Alpha, but this tilt is not statistically significant. In a logit regression of "up-move?" (1 if yes, 0 if no) on "positive *Phone Flow*?" (1 if yes, 0 if no) and "positive *Web Flow*?" (1 if yes, 0 if no), the coefficient on *Phone Flow* is 0.05 with a standard error of 0.21 and the coefficient on *Web Flow* is -0.29 with a standard error of 0.22.

The results for Omega, summarized in Panel B, show some in-sample evidence of forecasting differences between *Phone Flow* and *Web Flow*. In a logit regression of "up-move?" (1 if yes, 0 if no) on "positive *Phone Flow*?" (1 if yes, 0 if no) and

[18]There is only one balanced fund at Omega, and none at Alpha. The 60/40 ratio is the target as given in this one fund's prospectus.

[19]These percentages were provided to us by Hewitt. There is a fixed ratio for each of the six lifestyle funds (three at Alpha, three at Omega). See the discussion of Table III in Section I.

[20]We exclude international equity trades because we are focusing on the ability of traders to forecast S&P 500 returns.

"positive *Web Flow*?" (1 if yes, 0 if no), the coefficient on *Phone Flow* is 0.48 with a standard error of 0.23, and the coefficient on *Web Flow* is -0.26 with a standard error of 0.24. Taking into account the covariances of these estimates, the coefficients on *Phone Flow* and *Web Flow* are significantly different at the 1 percent level.

While these results are suggestive of some performance differences between Web and phone traders, a more complete analysis must pay attention to the magnitudes of flows and returns, and must also take into account other state variables that may predict returns. Since overall trading activity by Web and phone is changing significantly over time, before testing for this relationship it is necessary to normalize the flow measures in order to avoid spurious correlations. To normalize, we divide the *Web Flow* and *Phone Flow* measures by their respective gross flows. That is, for *Web Flows,*

$$\begin{aligned} Web\ Flow_{it} = {} & \text{Dollars of equity purchased by Web by participant } i \text{ in the plan on day } t - \\ & \text{Dollars of equity sold by Web by participant } i \text{ in the plan on day } t, \end{aligned} \tag{2}$$

and

$$Web\ Flow_t = \sum_{\forall i} Web\ Flow_{it}, \tag{3}$$

where (3) is the measure of *Web Flow* used for the statistics in Table VIII. To normalize this measure we calculate

$$Gross\ \ Web\ \ Flow_t = \sum_{\forall i} |\,Web\ \ Flow_{it}|, \tag{4}$$

and compute

$$Normalized\ \ Web\ \ Flow_t\ = Web\ \ Flow_t\ /\ Gross\ \ Web\ \ Flow_t, \tag{5}$$

with an analogous calculation for *Normalized Phone Flow*. These normalized measures are bounded between -1 and 1: if every Web trade in equity is a purchase, then the *Normalized Web Flow* will be 1; if every Web trade is a sale, then *Normalized Web Flow* will be -1.

Next, to evaluate the asset-allocation performance in these plans, we estimate predictability regressions for S&P 500 returns using the *Normalized Web Flow* and *Normalized Phone Flow* variables. These regressions take the form

$$SP500_{t+1} = \alpha_i + \beta_i F_{i,t} + \delta_i Z_t + \varepsilon_{i,t+1} \tag{6}$$

where $SP500_{t+1}$ is the return on the S&P 500 on day $t+1$, $F_{i,t}$ are normalized flow variables (either Web or phone or both) on day t, and Z_t is a vector of state variables used to forecast expected returns. The variables chosen for Z include the union of the sets of variables used by Graham and Harvey (1996) and Ferson and Khang (1999): *Term* is the spread between the yields on the 10-year and 1-year Treasuries;

Default is the spread between the yields on Baa and Aaa bonds; *3-month yield* is the yield on the 3-month Treasury bill; *Dividend Yield* is the yield over the past year (= 252 trading days) on the S&P 500; $SP500_t$ is the return on the S&P 500 for day t; $SP500_{(t-21,t-1)}$ is the return on the S&P 500 over the 21 trading-day period ending on day $t-1$; *JANUARY* is a dummy variable equal to 1 in the month of January, and 0 otherwise. The interest rate variables were obtained from the Federal Reserve website and are updated weekly. The stock return and dividend yield variables were obtained from CRSP and are updated using the daily return files.

Table IX summarizes the results for Alpha, and Table X summarizes the results for Omega. In each table, the first two columns give the results with *Normalized Web Flow* as an independent variable; the middle two columns give the results with *Normalized Phone Flow* as an independent variable; the last two columns give the results with both flow measures simultaneously as independent variables. For each choice of flow variable(s) on the right-hand-side, we estimate (6) both with and without the vector Z of predictive variables. Standard errors are computed using the Newey-West procedure with five lags.

The results show some evidence that Web trades are a contrarian indicator for S&P 500 returns. In Table IX (Alpha), the coefficients on the *Normalized Web Flow* variable are always negative and significantly different from zero at the five-percent level. Also, the coefficients on *Normalized Web Flow* are significantly different at the one-percent level from the coefficients on *Normalized Phone Flow* in the full specification (column 6).[21] In all specifications for Omega, the coefficients on the flow variables are insignificant at the five-percent level.

[21] To perform this calculation, we use the coefficient standard errors (shown in the tables) and the covariances between the estimated coefficients from the last column (=−0.0000004 for Table IX).

In untabulated results, we also estimated (6) using monthly (= 21 trading-day) S&P returns as the independent variable. In these specifications, we set the Newey-West lag length to 25 to account for the overlapping data. The results are qualitatively similar to those reported in Tables IX and X: for Alpha, the coefficients on *Normalized Web Flow* are negative and significant, except that in this case they are not significantly different from the coefficients on *Normalized Phone Flow*; for Omega, none of the flow coefficients are significant.

If we interpret the coefficients on the flow variables as performance measures, then the regression results provide some evidence that Web traders at Omega underperform in their equity "market-timing" trades. Taken together, the results of Tables VIII, IX, and X provide some evidence that phone traders outperform Web traders, and no evidence of the reverse. We believe that these results should be interpreted cautiously. The prior literature on market-timing ability should lead researchers to have strong prior beliefs that are skeptical of any evidence – positive or negative – of market-timing ability. Furthermore, market microstructure effects can induce small correlations, such as those found here, between flows and subsequent returns.[22] Filtered through such beliefs, the evidence presented here should induce only small changes in beliefs. Nevertheless, the absence of any empirical evidence in support of either absolute or relative timing ability for Web traders provides another arrow in the quiver for those who argue against active trading. The absence of market-timing ability may not hurt the net performance of Web traders in 401(k) plans, but it could be very costly to the net performance of market-timers who face taxes and significant transactions costs.

[22] See Keim (1989).

B. The performance of company-stock trades

In contrast to the large literature on the performance of professional money managers, little was known about the common-stock performance of individual investors until very recently. Except for the work of Lewellen, Lease and Schlarbaum (1977), Schlarbaum, Lewellen, and Lease (1978a, 1978b), data constraints prevented detailed studies of individual investor's behavior and performance. The recent work of Barber and Odean (Odean 1998 and 1999, Barber and Odean 2000a, 2000b, and 2001b) has discovered many stylized facts about investor performance in discount brokerage accounts, including (1) the stocks that investors sell subsequently outperform the stocks that they buy, (2) the more that investors trade the worse they perform (after transactions costs), (3) men perform worse than women, and, most related to our topic, (4) investors that trade online perform worse than similar investors who stay "offline". A common theme running through these results is that individual investors show no evidence of investment skill, and thus all trading – which incurs transactions costs through commissions, trade impact, and the bid-ask spread – is likely to reduce net returns. Barber and Odean show that many of these results can be reconciled if investors are overconfident of their investment success, this overconfidence is a function of past investment success (or gender), and if overconfidence leads to trading.

The database used in our paper differs from the Barber and Odean data in that the only common stock available is the company stock of Omega. Thus, many of the questions investigated by Barber and Odean will not be relevant to our dataset. We can, however, analyze whether trading in company stock can forecast future returns. In this respect, our analysis links up with the long literature on insider trading, since participants are also employees of the firm. The main findings of this literature show that insider trading can forecast returns.[23] The strength of this effect is large enough to yield profits, after transactions costs, to "outsiders" who follow trading rules based on insider activity. Although most 401(k)-plan participants are not corporate officers with access to high-level information and thus are not subject to reporting requirements as "legal insiders", they do have access to at least as much information as typical investors.

Trading in company stock is more active than holdings might suggest, with purchases (sales) of company stock representing 15.2 (16.2) percent of the dollar value of all purchases (sales) made by phone, and 11.0 (12.2) percent of the dollar value of all purchases (sales) made by Web. To evaluate the performance of these trades, we build indices of the flow of trading in Omega's stock on each day, and we test whether these indices forecast the returns to Omega's stock. Our first measure is just the net flow by channel, in dollars, on each day. These measures are analogous to the *Web Flow* and *Phone Flow* measures for all equities that we computed in Section III.A., except that here we only consider the flows in the "Company Stock" category and we do not exclude trades that involve international funds. As in the previous section, the measures are computed separately by each channel, so that *Cstock Web Flow* is equal to the differences between the dollar value of purchases of Omega stock by Web and the dollar value of sales of Omega stock by Web. The literature on insider trading has discovered that small and medium sized trades are often more informative than

[23]The seminal papers in this area are Lorie and Niederhoffer (1968), Jaffe (1974) and Finnerty (1976). Seyhun (1998) is an exhaustive summary of the academic evidence.

large ones about future returns.[24] Thus, our dollar-weighted flow measures may not be the best measure of investor forecasts. To handle this issue, we also compute *Cstock Web Count* and *Cstock Phone Count* measures that equally-weight each trade. *Cstock Web Count* is equal to the number of traders that added to their holdings of Omega company stock by Web minus the number of traders that subtracted from their holdings of Omega company stock by Web. The *Cstock Phone Count* measure is computed analogously using phone traders. Both of the count measure are computed separately for each day.

As in Section III.A, we start our analysis with some simple tests. Panel A of Table XI shows the frequency of up-moves and down-moves as a function of the sign of the flow measures. The table shows little evidence that the direction of trade forecasts the sign of subsequent returns in Omega's stock. In a logit regression of "up-move?" (1 if yes, 0 if no) on "positive *Cstock Phone Flow*?" (1 if yes, 0 if no) and "positive *Cstock Web Flow*?" (1 if yes, 0 if no), neither of the coefficients are significantly different from zero or from each other: the coefficient *Cstock Phone Flow* is -0.27 with a standard error of 0.25 and the coefficient on *Cstock Web Flow* is 0.18 with a standard error of 0.26. The frequency table using the count measures is given in Panel B of Table XI. The results are similar to the flow measures, with no significant evidence that the sign of either count measure forecasts the sign of Omega's return in sample. In a logit regression of "up-move?" (1 if yes, 0 if no) on "positive *Cstock Phone Count*?" (1 if yes, 0 if no) and "positive *Cstock Web Count*?" (1 if yes, 0 if no), neither of the coefficients is significantly different from zero or from the other: the coefficient on *Cstock Phone Count* is -0.30 with a standard error of 0.30 and the

[24] See Seyhun (1998), chapter 3.

coefficient on *Cstock Web Count* is 0.12 with a standard error of 0.30.

From the results of Table XI and the logit regressions, it is clear that there is no simple relationship between the overall direction of trade in Omega's stock and the sign of Omega's return on the subsequent day. It is still, possible, however, that taking into account the magnitude of trade will allow forecasting of returns. Furthermore, there is evidence in the insider-trading literature that purchases are more informative than sales for subsequent returns, and our simple flow and count measures may be hiding such relationships.[25] To tests for these effects, we normalize the flow and count measures for Omega's company stock in the same way that we normalized the flow measures in Section III.A for all equities (see equations (2) - (5)). This yields the measures *Normalized Cstock Web Flow, Normalized Cstock Phone Flow, Normalized Cstock Web Count*, and *Normalized Cstock Phone Count*. We also compute separate measures for purchases and sales. *Cstock Web Purchases* on day t is defined as the total number of participants who purchased Omega company stock on that day. *Normalized Cstock Web Purchases* is defined as *Cstock Web Purchases* divided by the 21-trading-day moving-average level of Web purchases.[26] *Normalized Cstock Web Sales, Normalized Cstock Phone Purchases,* and *Normalized Cstock Phone Sales* are defined analogously.

Table XII shows the results of regressing Omega's day $t+1$ returns on the normalized flow, count, purchase, and sales measures. In no case are any of the regression coefficients significantly different from zero or from each other. In untabulated results, we also included the predictive variables from Table X and, separately, used

[25] See Seyhun (1998), chapter 3.

[26] We use the 21-day moving-average to normalize the purchase and sales measures so we can get a proxy for the relative magnitude of purchases and sales compared to recent history.

monthly returns for Omega as the dependent variable. In each of these estimations, we found no evidence that any of the trading measures could forecast subsequent returns in Omega's stock. We conclude that neither Web traders nor phone traders display any differential ability to time the movements in company stock.

IV. Does the Web affect "speculative" trading?

In Section II, we concluded that the Web affected both trading frequency and trade size. In this section, we further explore the impact of the Web the types of trading sometimes associated with speculative behavior. We analyze whether there are any differences in such behavior between the phone and the Web, and whether any such differences can be attributed to the Web itself or to selection effects on the traders who use the Web. Section IV.A studies the propensity of Web and phone traders to engage in "momentum" and "contrarian" trading in their asset-allocation trades. Section IV.B looks at the evidence on "herding" among Web and phone traders. Section IV.C analyzes whether Web traders or phone traders are more likely to engage in "short-term trading", which we define as trades that are reversed within five days or made during the last hour of a trading day.

A. Momentum vs. contrarian behavior in asset-allocation trades

Researchers in finance have long been interested in questions about prevalence and implications of positive and negative feedback trading, i.e. "momentum" and "contrarian" behavior.[27] If feedback trading of either kind is driven by frequent checking of returns and searching for patterns, then Web access could be expected

[27]See Goetzmann and Massa (2000) for a thorough review of this extensive theoretical and empirical literature.

to increase such activity. Since the prevalence of such behavior, especially when motivated by "noise", can play a role in stabilizing or destabilizing markets, it is useful to know whether such activity is indeed increased by this new technology.

In this subsection, we investigate whether Web traders and phone traders differ in their tendencies to follow momentum or contrarian strategies in their asset-allocation decisions. Our main variables of study are the *Normalized Web Flow* and *Normalized Phone Flow* measures discussed in Section III.A. (See equation (5)). Recall that *Normalized Web Flow* varies between -1 and 1, and measures the dollar-weighted direction of equity (vs. fixed income) trading on the Web each day. If *Normalized Web Flow* is equal to 1, then every equity trade made by Web on that day was a purchase; if *Normalized Web Flow* is equal to -1, then every equity trade made by Phone on that day was a sale. *Normalized Phone Flow* is defined analogously using phone trades. In Section III.A, we analyzed the power of these flow measures to forecast S&P 500 returns. In this subsection, we turn that analysis around and study the power of S&P 500 returns to forecast flows.

For this analysis, we estimate

$$Flow_t = \alpha + \beta_1 SP500_t + \beta_2 SP500_{t-1} + \beta_3 SP500_{(t-5,t-2)} + \beta_4 SP500_{(t-21,t-6)} + \epsilon_t \quad (7)$$

where $Flow_t$ is a normalized flow measure on day t, and the $SP500$ terms represent S&P 500 returns measured over the same day ($SP500_t$), the previous day ($SP500_{t-1}$), the remainder of the previous week ($SP500_{(t-5,t-2)}$), and the remainder of the previous month ($SP500_{(t-21,t-6)}$). If a β coefficient is positive, then this implies that participants, on average, are behaving as positive feedback, or "momentum", investors relative to the respective horizon. If a β coefficient is negative, then it implies contrarian behavior.

Table XIII summarizes the results of estimating (**??**) for both *Normalized Phone Flow* and *Normalized Web Flow* at both Alpha and Omega. The results show that average behavior in both plans is more contrarian relative to short-horizon returns, as the coefficients on the return variables increase with the horizon in all cases. Web trading also appears to be more momentum-driven than is phone trading, with the respective coefficients on the return variables higher for the Web than the phone at both firms for all horizons.

While this evidence suggests the Web has more positive feedback trading than the phone, it is not possible to do any formal tests without imposing some additional assumptions. For example, if we assume that the coefficients are independent across regressions, then we can test whether the coefficients in the Web regressions are significantly higher than in the phone regressions. Under this assumption of independence, the only pair of Web/phone coefficients that are significantly different from each other are the coefficients on the previous day's return (β_2) for Alpha.

The apparent differences between Web and phone traders in their feedback trading behavior may be due to chance, selection effects (i.e. if Web traders are predisposed to momentum trading), or real effects that are induced by the Web. To test for a selection effect, we take all participants who made at least one trade after the Web channel was opened. From this group, the "Web sample" is comprised of all traders who made at least one trade by Web. All remaining traders are placed in the "phone sample". These are the same subgroups that we used to investigate sample selection in trade size in Table VII of Section II. We then estimate (**??**) on these samples of traders using their trades from *before* the Web channel was opened.

We summarize the results of these estimations in Table XIV. As before, under the assumption of independence for pairs of Web/phone coefficients, there is only one pair of coefficients that significantly differ: the β_2 coefficients in the regressions for Alpha. Since these are the same coefficients that showed significant differences in Table XIII, it seems likely that the differences in momentum/contrarian behavior, if they are real, are driven by sample selection effects, and not by any characteristic of the Web channel. We conclude that there is no evidence that the Web has changed the momentum/contrarian behavior of investors in this sample.

B. Herding and the Web

Speculative booms and market manias have long been blamed on the herd-like behavior of investors.[28] Some authors have argued that the growth of the Internet has made the spread of such contagion more likely.[29] If the Web makes herding more likely, then we may find evidence of this in the trading decisions made on the Web.

To analyze herding one first needs to measure it. To do this, we adopt a modification of the Lakonishok, Shleifer, Vishny (1992) herding measure. Specifically, we use the absolute value of the difference between the number of net buyers and net sellers in a day as a proportion of all traders that day.[30] We compute this propor-

[28] Careful historical studies with this claim date back (at least) to Mackay (1841). Recent theoretical work on herding in financial markets includes Avery and Zemsky (1998), Banerjee (1992), Bikchandani, Hirshleifer, and Welch (1992), Froot, Scharfstein and Stein (1992), and Scharfstein and Stein (1990). Empirical studies of herding and its impact on prices are Grinblatt, Titman, and Wermers (1995), Graham (1999), Lakonishok, Shleifer, and Vishny (1992), and Wermers (1999).

[29] See, for example, Shiller (2000), p.151 - 153.

[30] The Lakonishok, Shleifer, Vishny (1992) measure is designed to detect whether the absolute level of herding is abnormally high. Thus, they start with the proportion of buyers and then subtract an "expected" amount of herding before performing inference. Here, we are only interested in

tion separately for each channel on each day for both "equity herding" (trading in equities as defined in Section III.A, computed separately for Alpha and Omega), and "company-stock herding" (trading in Omega company stock as defined in Section III.B). Note that these herding measures are identical to the absolute value of the *Normalized Cstock Web Count* and *Normalized Cstock Phone Count* variables as defined in Section III.B and can be interpreted as "indices of agreement". For example, if the *Normalized Cstock Web Count* for Omega's company stock on day t is equal to 1, then all Web trades in company stock on that day were purchases. Similarly, a *Normalized Cstock Web Count* of -1 would mean that all Web trades in company stock were sales. The company-stock herding measure by Web is the absolute value of this *Normalized Cstock Web Count* (= 1 in both cases). The herding measure reaches its minimum when the number of purchases equals the number of sales on that day: in that case, the normalized count and the herding measure are zero. Equity-herding measures are defined analogously using the definition of equities as given in Section III.A..

We do not attempt to analyze whether these herding measures, by themselves, are higher than would be expected under a null hypothesis of "no herding". Rather, we focus only on whether herding is higher by Web than by phone over the period since the Web channel was opened. The equity herding measures for Alpha are 0.341 by phone and 0.332 by Web, with standard errors of 0.012 and 0.014, respectively.[31] The equity herding measures for Omega are 0.616 by phone and 0.545 by Web, with standard errors of 0.043 and 0.034, respectively. For company-stock herding at

---

the relative levels of herding between the Web and phone, so we do not need to subtract out an "expected" term.

[31] All standard errors are computed by Newey-West estimation with five lags.

Omega, the measures are 0.379 by phone and 0.413 by Web, with standard errors of 0.016 and 0.019. None of these herding measures significantly differ between Web and phone; thus, there is no significant evidence of greater herding by Web than by phone.[32]

C. "Short-term" trading and the Web

The results of Section II established that the Web increased trading frequency in these plans, but what kind of trading increased? Does the fact that trading is only a "click" away lead participants to more short-term behavior? For example, since participants do not have to pay any capital gains taxes in 401(k) plans, they may be inclined to use them as vehicles to make short-term bets on the relative movements between asset classes.

In this section, we use two different measures to classify trades as "short-term", and then we study the pattern of speculative trading through each channel. Our first definition of a short-term trade is a trade that is at least partially reversed within five trading days. We will call these "reversed trades". Under this definition, we would classify both the original trade and its reversal as a reversed trade. While not exactly day-trading – it is more like "week-trading" – such trades are likely to have been made with the intention of capturing some perceived short-term profit opportunity. Of course, there may be many trades that have this intention and are not reversed so quickly, so this filter is imperfect.

A popular strategy among participants in some plans is to take advantage of stale prices by buying (selling) funds with thinly or asynchronously traded securities on

[32]We assume independence of the estimates in order to make this inference.

days with large market increases (decreases).[33] This strategy is particularly profitable in international funds, and some 401(k) plan sponsors (including Omega) have taken steps to prevent it. Since we are trying to focus on "speculative" short-term trading, rather than arbitrage-like activities, we attempt to filter out these arbitrage trades before doing the calculations described below. Our filters remove all reversed trading occasions for a participant where an international fund was sold on an S&P 500 down day or an international fund bought on an S&P 500 up day.

For reversed trades, three interesting patterns are apparent.[34] First, there are many reversed trades. By the end of the sample, these trades make up about one-half of the trading at Alpha and one-third at Omega. Second, there is an upward trend in reversed trades over the whole sample period for both firms. This trend begins before the Web channel is opened. In the first three months of the sample, reversed trades comprise 19.5 percent of all trades at Alpha and 18.5 percent of all trades at Omega. These percentages rise to 37.4 at Alpha and 23.1 at Omega in the three months before the Web channel was opened, and 50.7 at Alpha and 35.2 at Omega in the last three months of the sample. Third, reversed trades constitute a smaller fraction of Web trades than of phone trades. At both firms, subsequent to the Web channel opening, phone trades were more likely to be reversed than are Web trades: 57.4 percent to 42.1 percent at Alpha and 36.7 percent to 24.8 percent at Omega. Thus, by this measure, the Web has proportionally *decreased* short-term trading.

Our second filter for speculation uses the time-of-day for a trade. Recall that participants' trades may be placed at any time but are executed only once per day

[33] For descriptions of this strategy, see Atchison, Butler, and Simonds (1987), Chalmers, Edelen and Kadlec (2000), and Goetzmann, Ivkovich, and Rouwenhorst (2000).

[34] All three of these patterns are stronger if we include the international "arbitrage" trades described in the previous paragraph.

and use market closing prices. For both firms, this means that all trades placed before 4 P.M., Eastern Time, are executed at that day's closing price, while any trades executed after that time must wait until the close on the next day. Short-term traders – whatever definition one uses – are likely to be trying to take advantage of perceived predictability in short-run price movements. Since such traders will place a relatively high value on up-to-date information, we expect that short-term traders will be more likely to trade in the hour before the market closes, the only time in which 401(k) participants are able to trade at prices that aren't stale.

To examine the timing issue, we classify all trades by the time of day they were placed. Table XV summarizes the results. All times are Eastern Time. We define trades placed between 3 P.M. and 4 P.M. – the hour before the market closes – as "last-hour trades" and use them as our second proxy for short-term trades. As shown in the table, a large fraction of trades are made in the last hour, and this fraction is significantly higher by phone than by Web: 46.4 percent of the phone trades and 26.7 percent of the Web trades for Alpha, and 51.2 percent of the phone trades and 29.1 percent of the Web trades for Omega. This reinforces the findings about reversed trades and suggests that a large fraction of trades are driven by short-term motives. In fact, the categories overlap considerably: of all the last-hour trades, 81.3 percent for Alpha and 54.5 percent for Omega are also reversed trades. For trades made at all other times, only 39.3 percent for Alpha and 24.9 percent for Omega are reversed.

There is no way to know for sure if some participants are using the Web to gather information for their trades, but then using the phone to execute these trades. The fact that this trading goes on during the working day means that some participants may feel the need to hide this activity from their co-workers, and in the absence of a private office, it may be more discreet to use an automated menu on the phone than a computer screen.[35] Such concerns could explain why short-term traders seem to have a preference for phone transactions. On the other hand, the regression evidence in Table II shows that frequent traders – who do most of the reverse and last-hour trading – are less likely to try the Web for even one trade. It may be that these active traders have very low "costs" for phone trades and see no need to switch to a new technology. Overall, the evidence suggests that it is the infrequent and longer-term traders who are the first to move to the Web, and that opening a Web channel does not increase the proportion of short-term trades.

V. Conclusion

This paper exploits a unique "natural experiment" – the introduction of a Web-trading channel in two large 401(k) plans – to study the impact of this new technology on trading behavior. Our study focuses on the impact of the Web on trading volume, trader performance, and behavior that is sometimes associated with speculative activity: positive-feedback trading, herding, and short-term trading.

While this experiment has several nice features, we emphasize that these results do not generalize to other contexts since 401(k) accounts are unlike other types of investment accounts. It is possible that participants view 401(k) accounts as "long-term" retirement investments and thus trade less in these accounts than in their standard taxable accounts. Furthermore, the restricted set of investment options in a typical 401(k) means that there is a smaller set of possible trading opportunities, which could again result in less trading in 401(k) accounts than elsewhere.

[35]Not all participants have computer access from their desks, but instead must use public computer kiosks.

Conversely, it is also possible that the absence of taxes and direct transactions costs induces participants to trade more in these accounts then in taxable accounts. All in all, 401(k) accounts are not directly comparable to standard investment accounts and one should not broadly generalize from our results. However, 401(k) accounts are important in themselves, since they contain a substantial fraction of US financial assets. For example, 401(k) accounts contain, directly or indirectly, approximately ten percent of the value of all US equities held by the household sector. Moreover, 401(k) accounts are very similar to other tax-deferred retirement accounts, like IRA's, 403(b) accounts, and Keogh accounts.

To measure the Web's impact on trading volume in our two 401(k) plans, we control for numerous other sources of variability in trading activity. We find that at a horizon of 18 months, a Web channel nearly doubles trading frequency. The point estimates for the 18-month impact of the Web on turnover – measured as the fraction of total portfolio value traded – are smaller (about 50 percent) and are not statistically significant in all specifications. Trading frequency increases by more than turnover because Web trades tend to be smaller than phone trades both in dollars and as a portfolio fraction.

We find no evidence that any of this new trading on the Web is successful; if anything, Web traders underperform phone traders in their market-timing trades. For trades in the company stock of their own firm, participants show no ability to successfully time their trades either by phone or by Web. Overall, we do not find any robust evidence that traders can positively forecast returns either for the broad market or for company stock. Since there are no direct transactions costs or taxes in 401(k) plans, such trading may not harm performance of the individual investor, although it does generate trading costs that are eventually partially born by all plan participants.

As an innovative communication medium and information source, the Web has a great capacity to alter trading behavior along many dimensions. We looked for differences between Web traders and phone traders in their momentum ("positive-feedback") trading, tendency to "herd", and propensity to engage in "short-term" trading. In each of these areas, we found no evidence of a Web impact. We did find some differences between Web traders and phone traders, but these seemed to be driven more by selection effects than by the Web itself. These results demonstrate the need to beware of selection effects before attributing causal impact to these new technologies. In the end, although the Web appears to induce an increase in trading in these 401(k) plans, it has not measurably increased the proportion of "speculative" trading.

References

Agnew, Julie, Pierluiggi Balduzzi, and Annika Sunden, 2000, Portfolio choice, trading, and returns in a large 401(k) Plan, Working paper, Boston College.

Ameriks, John, and Steve Zeldes, 2000, How do household portfolio shares vary with age?, Working paper, Columbia University.

Atchison, Michael, Kirt Butler, and Richard Simonds, 1987, Nonsynchronous security trading and market index correlation, *Journal of Finance* 42, 111-118.

Avery, Christopher and Peter Zemsky, Multidimensional uncertainty and herd behavior in financial markets, *American Economic Review* 88, 724-747

Banerjee, Abhijit, 1992, A simple model of herd behavior, *Quarterly Journal of Economics* 107, 797-817.

Bange, Mary M., "Do the portfolios of individual investors reflect positive feedback trading?", *Journal of Financial and Quantitative Analysis* 35, 239-255.

Barber, Brad M., and Terrance Odean, 2000a, Trading is hazardous to your wealth: The common stock investment performance of individual investors, *Journal of Finance* 55, 773-806.

Barber, Brad M., and Terrance Odean, 2000b, Online investors: Do the slow die first?, Working paper, UC Davis.

Barber, Brad M., and Terrance Odean, 2001a, Boys will be boys: Gender, overconfidence, and common stock investment, *Quarterly Journal of Economics* 116, 261-292.

Barber, Brad M., and Terrance Odean, 2001b, The Internet and the investor, *Journal of Economic Perspectives* 15, 41-54.

Bergstrasser, Daniel, and James Poterba, 2000, Do after-tax returns affect mutual fund flows, National Bureau of Economic Research, Working paper No. 7595.

Bikchandani, Sushil, David Hirshleifer, and Ivo Welch, 1992, A theory of fads, fashion, custom, and cultural change as informational cascades, *Journal of Political Economy* 100, 992-1026.

Chance, Don M., Michael L. Hemler, 1999, The performance of professional market timers: Daily evidence from executed strategies, Working paper, Virginia Tech University.

Chalmers, John M.R., Roger M. Edelen, and Gregory Kadlec, 1999, The wildcard option in transacting in mutual fund shares, Rodney L. White Center for Financial Research, Working paper No. 00-03.

Chevalier, Judith, and Glenn Ellison, 1997, Risk taking by mutual funds as a response to incentives, *Journal of Political Economy* 105, 1167-1200.

Delong, Bradford, Andrei Shleifer, Lawrence Summers, and Robert Waldmann, 1990, Noise trader risk in financial markets, *Journal of Political Economy* 90, 903-738.

Dugan, Ianthe Jeanne, 1999, Senate hearings to probe day trading; Impact on market, traders at issue, *Washington Post* (September 14), Financial Section, E01.

Durell, Alan, 1999, *Essays in Applied Behavioral Microeconomics*, Ph.D. dissertation, Harvard University.

Edelen**,** Roger M., 1999, Investor flows and the assessed performance of open-end mutual funds, *Journal of Financial Economics* 53 (3). 439-466.

Federal Reserve Board, 2000, *Flow of Funds*, December 8th release.

Ferson, Wayne, and Kenneth Khang, 1999, Conditional performance measurement using portfolio weights: evidence for pension funds, Working paper, University of Washington.

Financial Times, 2000, “Market divides on Internet effect”, February 15, Companies & Finance: UK, News Digest.

Finnerty, J. E., 1976, Insiders and market efficiency, *Journal of Finance* 31, 1141-1148.

Froot, Kenneth, David Scharfstein, and Jeremy Stein, Herd on the street: informational inefficiencies in a market with short-term speculation, *Journal of Finance* 47, 1461-1484.

Goetzmann, William N., Zoran Ivkovich, and Geert Rouwenhorst, 2000, Day-trading international mutual funds: evidence and policy solutions, Working paper, Yale University.

Goetzmann, William N., Massimo Massa, Geert Rouwenhorst, 2000, Behavioral factors in mutual-fund flows, Working paper, Yale University.

Graham, John, 1999, Herding among investment newsletters, *Journal of Finance* 54, 237-268.

Graham, John, and Campbell Harvey, 1996, Market-timing ability and volatility implied in investment newsletters’ asset allocation recommendations, *Journal of Financial Economics* 42, 397-421.

Graham, John, and Campbell Harvey, 1997, Grading the performance of market timing investment newsletters, *Financial Analysts Journal* 53, 54-66.

Grinblatt, Mark and Matti Keloharju, 1999, What makes investors trade? Working paper, UCLA.

Grinblatt, Mark, Sheridan Titman, and Russ Wermers, 1995, Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior, *American Economic Review* 85, 1088-1105.

Holden, Sarah, Jack VanDerhei, and Carol Quick, 1999, 401(k) plan asset allocation, account balances, and loan activity in 1998, *Investment Company Institute Perspective* 6 (1).

Jaffe, Jeffrey F., 1974, Special information and insider trading, *Journal of Business* 47, 410-428.

Keim, Donald B., 1989, Trading patterns, bid-ask spreads, and estimated security returns: the case of common stocks at calendar turning points, *Journal of Financial Economics* 25, 75-97.

Kunath, Brian D., 1999, Day trading: The 'Dealerization' of the Market, *Global Investment Magazine* (December), 51.

Lakonishok, Shleifer, and Vishny (1992), The impact of institutional trading on stock prices, *Journal of Financial Economics* 32, 23-44.

Levitt, Arthur, 1999a, Chairman, Securities and Exchange Commission, "Concerning Online Trading", Statement issued on January 16, 1999, http://www.sec.gov/news/press/pressarchive/1999/99-9.txt.

Levitt, Arthur, 1999b, Chairman, Securities and Exchange Commission, Testimony before the Senate Permanent Subcommittee on Investigations Committee on Governmental Affairs, Concerning Day Trading, September 16, 1999, http://www.sec.gov/news/testimony/testarchive/1999/tsty2199.htm.

Lewellen, Wilbur G., Ronald C. Lease, and Gary G. Schlarbaum, 1977, Patterns of investment strategy and behavior among individual investors. *The Journal of Business*, 50, 296-333.

Livingston, Brian, 2000, "Although online trading is hot: you may get burned", cnet news.com, August 4, http://news.cnet.com/news/0-1278-210-3287313-1.html.

Lorie, James H., and Victor Niederhoffer, 1968, Predictive and statistical properties of insider trading, *Journal of Law and Economics* 11, 35-53.

MacKay, Charles, *Extraordinary Popular Delusions and the Madness of Crowds*, Volume I, Richard Bentley, London.

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

Odean, Terrance, 1998, Are investors reluctant to realize their losses, *Journal of Finance* 53, 1775-1798.

Odean, Terrance, 1999, Do investors trade too much? *American Economic Review* 89, 1279-1298.

Scharfstein, David, and Jeremy Stein, 1990, Herd behavior and investment, *American Economic Review* 80, 465-479.

Schlarbaum, Gary G., Wilbur G. Lewellen, and Ronald C. Lease, 1978a, The common-stock-portfolio performance record of individual investors, *Journal of Finance* 33, 429-441.

Schlarbaum, Gary G., Wilbur G. Lewellen, and Ronald C. Lease, 1978b, Realized returns on common stock investments: The experience of individual investors, *Journal of Business* 51, 299-325.

Seyhun, H. Nejat, 1998, *Investment Intelligence from Insider Trading*, MIT Press, Cambridge, MA.

Shiller, Robert J., 2000, *Irrational Exuberance*, Princeton University Press, Princeton, N.J.

Sirri, Eric and Peter Tufano, 1993, Buying and selling mutual funds: funds, performance, fees, and service, Working paper, Harvard Business School.

Stillwell, Dennis, 2000, High-speed danger alert, *Journal of Commerce*, April 5, Global Commerce Section, 13.

Wagner, J., S. Shellans, and R. Paul, 1992, Market-timing works where it matters most … in the real world, *Journal of Portfolio Management*, 86-90.

Wermers, Russ, 1999, Mutual fund herding and the impact on stock prices, *Journal of Finance* 54, 581-622

Table I
401(k) Plan Characteristics

This table presents summary statistics for the 401(k) plans of firms Alpha and Omega. Because of data availability, demographic information is limited to participants who had positive plan balances or plan activity in 1998 or 1999.

	Alpha	Omega
Number of participants[1]	More than 10,000	More than 50,000
Data range	5/19/97 - 3/3/00	1/27/97 - 1/26/00
Number of investment options	11	36
Company stock available in plan?	No	Yes
Percent of plan assets in equity[2, 3]	75.6%	40.8%
Percent of plan assets in company stock[2]	0.0%	6.6%
Average age[2, 4]	40.7	52.8
Average years since original hire[2, 4]	8.6	18.6
Average plan balance[2, 4]	\$68,202	\$112,456
Average contribution rate[2, 5]	6.49%	9.27%
Percent of participants who trade at least once in sample	41%	45%
Month of Web introduction	August 1998	August 1998
Average trades per month per participant before Web introduction[6]	0.0564	0.0844
Average trades per month per participant after Web introduction[6]	0.1285	0.1407
Average trades per month per participant on Web[6]	0.0666	0.0597
Percent of participants who trade at least once on Web	24%	15%

[1] All participants in sample, including those who drop out of the plan before the end of the sample.
[2] At year-end 1999.
[3] Includes all equity mutual fund and company stock balances.
[4] Participants who had positive plan balances at year-end 1999 or plan activity in 1998 or 1999.
[5] Current employees as of year-end 1999 only.
[6] All sales and purchases on a given day by a participant are counted as one "trade."

Table II
Demographics of Web Traders

This table presents the results of a binary logit regression of the likelihood of trading at least once on the Web in the sample, conditional upon trading at least once since Web trading was introduced. Participants must have been enrolled before Web introduction and had a positive plan balance or plan activity in 1998 or 1999 in order to have a full set of right-hand-side variables and be included in the regression. *Male* and *Married* are dummies set to one if the participant is male and married, respectively. *Age* is the participant's age at December 31, 1999, and *Tenure* is the log of the number of years since the participant's original hire date, as of December 31, 1999. *Salary* is the log of 1999 salary, and *Balances* is the log of total plan balance at year-end 1999. *Participation Length* is the log of the number of years since the participant originally enrolled in the plan. *Pre-Web Trades per Month* is the number of trades per month the participant executed before the introduction of the Web. *Contribution Rate is* the contribution rate effective at year-end 1999, in integers (e.g. "5" percent). *Terminated* and *Retired* are dummies set to one if the participant has been terminated or retired, respectively as of year-end 1999. Standard errors are given in parentheses below the point estimates.

	Alpha	Omega
Male	0.4093**	
	(0.0675)	
Married	0.0564	0.2783**
	(0.0639)	(0.0406)
Age	-0.0369**	-0.0479**
	(0.0039)	(0.0028)
Tenure	-0.0059	0.0674
	(0.1496)	(0.0578)
Salary	0.1879**	0.0619**
	(0.0231)	(0.0063)
Balances	0.3264**	0.2080**
	(0.0444)	(0.0205)
Participation Length	-0.3683**	0.0287
	(0.1360)	(0.0567)
Pre-Web Trades per Month	-0.3811**	-0.0535
	(0.0864)	(0.0275)
Contribution Rate	0.0129	-0.0076*
	(0.0103)	(0.0032)
Terminated	-0.4862**	-0.1978**
	(0.1615)	(0.0706)
Retired	-0.2244	-0.3655**
	(0.5898)	(0.0916)
Constant	-2.7538**	-0.7128**
	(0.3831)	(0.1927)

* Significant at the 5 percent level
** Significant at the 1 percent level

Table III
Asset Class Summary Statistics

This table presents the asset class composition of plan flows (entire sample period) and balances (year-end 1999), in dollar percentages. "Lifestyle/Balanced" includes funds from both the lifestyle/premix and balanced asset classes. "Other U.S. Equity" includes mid-cap U.S. equity, small-cap U.S. equity, and specialty sector funds, but *not* company stock. "International" includes international and emerging markets funds.

	GIC	Bond	Lifestyle/ Balanced	Large U.S. Equity	Other U.S. Equity	Inter- national	Company stock
Alpha							
Phone purchases		39.3	4.0	32.7	9.2	14.8	
Phone sales		38.2	4.6	35.8	7.1	14.3	
Web purchases		32.0	4.3	29.5	25.0	9.2	
Web sales		32.6	5.4	40.0	14.3	7.7	
Payroll contributions		17.7	11.9	64.1	2.5	3.8	
Year-end 1999 holdings		21.8	7.5	56.7	11.0	3.0	
Omega							
Phone purchases	36.0	1.2	3.6	16.2	16.4	11.4	15.2
Phone sales	38.3	0.9	3.1	13.2	17.0	11.2	16.2
Web purchases	32.7	1.2	3.7	16.0	25.4	8.8	12.2
Web sales	36.4	1.3	4.4	15.5	22.4	9.0	11.0
Payroll contributions	61.0	0.7	7.3	12.5	11.8	2.7	4.1
Year-end 1999 holdings	57.4	0.5	4.2	13.2	15.2	2.9	6.6

Table IV
Determinants of Trading Frequency

The dependent variable, *Trades*, is the percent of participants in each company who trade on each day. *Web* is a dummy set to one if Web trading has been introduced. *Web* * *Time* is the interaction of *Web* and *Time*, the number of calendar days that have passed since Web trading was introduced. *Non-Web Index* is the equally-weighted average of the daily percent of plan balances traded between asset classes for 17 companies without Web trading. |*S&P 500*| and |*Lag S&P 500*| are the absolute values of the S&P 500 return today and yesterday, respectively. *(S&P 500)*^{2} and *(S&P 500)*^{2} are the squares of |*S&P 500*| and |*LAG S&P 500*|, respectively. *Std(S&P 500)* is the twenty-day lagged standard deviation of the S&P 500 price return. |*Company Stock*| and |*Lag Company Stock*| are the absolute values of the company stock's return today and yesterday, respectively. *(Company Stock)*^{2} and *(Lag Company Stock)*^{2} are the squares of |*Company Stock*| and |*Lag Company Stock*|, respectively. *Std(Company Stock)* is the twenty-day lagged standard deviation of the company stock price return. *Start Week*, *End Week*, *Start Month*, and *End Month* are dummies set to one if the day is the first trading day of the week, the last trading day of the week, the first trading day of the month, and the last trading day of the month, respectively. *Rule Change* is a dummy set to one for Omega after March 19, 1999 to reflect a new rule instituted to restrict trading in an international fund. *Trend* is the number of calendar days that have elapsed since January 1, 1997. Newey-West robust standard errors (five lags) are reported in parentheses below the OLS point estimates.

SEE NEXT PAGE FOR TABLE

	Alpha		Omega	
Web	**0.0656 (0.0437)**	**-0.0952 (0.0582)**	**-0.0023 (0.0032)**	**-0.0241 (0.0518)**
Web * Time	**0.00061** (0.00013)**	**0.00072** (0.00020)**	**0.00094** (0.00019)**	**0.00064* (0.00028)**
Non-Web Index	143.7358** (24.6713)	140.0920** (22.3813)	214.8540** (27.3142)	81.6954** (18.6263)
|S&P 500|		0.2079 (1.8021)		3.4935* (1.7030)
(S&P 500)^2		60.3637 (41.8465)		-1.0643 (32.3171)
|Lag S&P 500|		-1.5036 (1.7831)		-1.1995 (1.8917)
(Lag S&P 500)^2		202.9359** (37.9670)		149.2298** (52.8017)
Std(S&P 500)		-2.7578 (3.9289)		-5.2980* (2.4152)
|Company Stock|		0.9426 (0.8968)		2.5601** (0.8864)
(Company Stock)^2		-0.9552 (13.0412)		41.8645** (9.5403)
|Lag Company Stock|		0.2651 (0.9386)		0.2604 (1.1452)
(Lag Company Stock)^2		-1.4287 (12.6027)		32.0787** (12.1468)
Std(Company Stock)		7.7854** (2.5549)		7.5359** (1.7749)
Start Week		0.1208** (0.0173)		0.1287** (0.0172)
End Week		-0.0070 (0.0122)		0.0352* (0.0152)
Start Month		-0.0488 (0.0410)		-0.0379 (0.0298)
End Month		-0.0149 (0.0308)		-0.0113 (0.0318)
Rule Change				-0.0547 (0.0863)
Trend		0.00030 (0.00016)		0.00034** (0.00009)
Constant	0.2288** (0.0303)	-0.1894* (0.0953)	0.0327 (0.0321)	-0.0696 (0.0656)

* Significant at the 5 percent level
** Significant at the 1 percent level

Table V
Determinants of Turnover

The dependent variable, *Turnover*, is the daily dollar value of all sales as a percent of total balances on that day. *Web* is a dummy set to one if Web trading has been introduced. *Web * Time* is the interaction of *Web* and *Time*, the number of calendar days that have passed since Web trading was introduced. *Non-Web Index* is the equally-weighted average of the daily percent of plan balances traded between asset classes for 17 companies without Web trading. |*S&P 500*| and |*Lag S&P 500*| are the absolute values of the S&P 500 return today and yesterday, respectively. *(S&P 500)*^{2} and *(S&P 500)*^{2} are the squares of |*S&P 500*| and |*Lag S&P 500*|, respectively. *Std(S&P 500)* is the twenty-day lagged standard deviation of the S&P 500 price return. |*Company Stock*| and |*Lag Company Stock*| are the absolute values of the company stock's return |*Lag Company Stock*|, respectively. *Std(Company Stock)* is the twenty-day lagged standard deviation of the company stock price return. *Start Week*, *End Week*, *Start Month*, and *End Month* are dummies set to one if the day is the first trading day of the week, the last trading day of the week, the first trading day of the month, and the last trading day of the month, respectively. *Rule Change* is a dummy set to one for Omega after March 19, 1999 to reflect a new rule instituted to restrict trading in an international fund. *Trend* is the number of calendar days that have elapsed since January 1, 1997. Newey-West robust standard errors (five lags) are reported in parentheses below the OLS point estimates.

SEE NEXT PAGE FOR TABLE

	Alpha		Omega	
Web	**0.0998**	**-0.0591**	**0.0147**	**-0.0205**
	(0.0526)	**(0.0577)**	**(0.0089)**	**(0.0119)**
Web * Time	**0.00092****	**0.00038**	**0.00016****	**0.00026****
	(0.00021)	**(0.00020)**	**(0.00004)**	**(0.00006)**
Non-Web Index	290.7297**	194.0439**	44.1762**	31.6382**
	(33.5053)	(25.9074)	(5.8371)	(4.3597)
|S&P 500|		0.1820		0.1188
		(2.6553)		(0.3925)
(S&P 500)^2		83.1802		11.0200
		(73.1748)		(9.9516)
|Lag S&P 500|		-3.3204		-0.4162
		(2.5653)		(0.3861)
(Lag S&P 500)^2		302.6174**		44.1060**
		(64.2860)		(8.7565)
Std(S&P 500)		-4.1020		-0.3025
		(4.1555)		(0.4919)
|Company Stock|		0.5350		-0.0198
		(1.2829)		(0.2006)
(Company Stock)^2		9.5484		1.8339
		(20.8628)		(1.8384)
|Lag Company Stock|		-0.4893		-0.0768
		(1.1520)		(0.1800)
(Lag Company Stock)^2		11.0976		-0.2390
		(13.7542)		(1.7718)
Std(Company Stock)		8.5034**		1.3509**
		(2.4703)		(0.3771)
Start Week		0.1200**		0.0208**
		(0.0217)		(0.0033)
End Week		0.0407*		0.0062*
		(0.0195)		(0.0032)
Start Month		-0.0442		-0.0093
		(0.0487)		(0.0076)
End Month		-0.0222		-0.0029
		(0.0408)		(0.0064)
Rule Change				-0.0586**
				(0.0147)
Trend		0.00064**		0.00011**
		(0.00016)		(0.00002)
Constant	0.0005	-0.3360**	-0.0034	-0.0643**
	(0.0403)	(0.0956)	(0.0070)	(0.0180)

* Significant at the 5 percent level
** Significant at the 1 percent level

Table VI
Determinants of Total Net Movements Between Asset Classes

The dependent variable, *Company Index*, is the daily percent of plan balances traded between asset classes in Alpha and Omega, respectively. This variable is the company-specific analogue of *Non-Web Index*, which is defined below. *Web* is a dummy set to one if Web trading has been introduced. *Web * Time* is the interaction of *Web* and *Time*, the number of calendar days that have passed since Web trading was introduced. *Non-Web Index* is the equally-weighted average of the daily percent of plan balances traded between asset classes for 17 companies without Web trading. |*S&P 500*| and |*Lag S&P 500*| are the absolute values of the S&P 500 return today and yesterday, respectively. $(S\&P\ 500)^2$ and $(S\&P\ 500)^2$ are the squares of |*S&P 500*| and |*Lag S&P 500*|, respectively. *Std(S&P 500)* is the twenty-day lagged standard deviation of the S&P 500 price return. |*Company Stock*| and |*Lag Company Stock*| are the absolute values of the company stock's return |*Lag Company Stock*|, respectively. *Std(Company Stock)* is the twenty-day lagged standard deviation of the company stock price return. *Start Week*, *End Week*, *Start Month*, and *End Month* are dummies set to one if the day is the first trading day of the week, the last trading day of the week, the first trading day of the month, and the last trading day of the month, respectively. *Rule Change* is a dummy set to one for Omega after March 19, 1999 to reflect a new rule instituted to restrict trading in an international fund. *Trend* is the number of calendar days that have elapsed since January 1, 1997. Newey-West robust standard errors (five lags) are reported in parentheses below the OLS point estimates.

SEE NEXT PAGE FOR TABLE

	Alpha		Omega	
Web	**0.0262** **(0.0249)**	**-0.0491** **(0.0263)**	**0.0385**** **(0.0101)**	**0.0170** **(0.0118)**
Web * Time	**0.00036**** **(0.00009)**	**0.00009** **(0.00008)**	**0.00004** **(0.00003)**	**0.00007** **(0.00006)**
Non-Web Index	144.5633** (18.3100)	105.8942** (14.3106)	45.2262** (4.4876)	40.5760** (4.6599)
|S&P 500|		-2.4388 (1.7026)		0.4478 (0.6097)
(S&P 500)^2		108.1347* (48.4681)		-3.6632 (13.5472)
|Lag S&P 500|		-1.9756 (1.3328)		1.1069* (0.5385)
(Lag S&P 500)^2		106.0516** (26.6180)		-9.5863 (9.5108)
Std(S&P 500)		-1.0153 (2.0671)		-1.2177 (0.7032)
|Company Stock|		0.0804 (0.8888)		0.0297 (0.3223)
(Company Stock)^2		9.9195 (13.7175)		16.7004** (5.3141)
|Lag Company Stock|		0.2776 (0.6298)		-0.7145* (0.3637)
(Lag Company Stock)^2		9.4590 (7.7504)		17.0443** (3.8735)
Std(Company Stock)		3.3825** (1.2227)		0.9947* (0.3980)
Start Week		0.0335* (0.0165)		0.0030 (0.0050)
End Week		0.0053 (0.0137)		0.0116* (0.0051)
Start Month		-0.0449 (0.0242)		-0.0169* (0.0080)
End Month		0.0102 (0.0273)		-0.0044 (0.0065)
Rule Change				-0.0326 (0.0175)
Trend		0.00031** (0.00007)		0.00008* (0.00004)
Constant	-0.0232 (0.0217)	0.1631** (0.0440)	0.0108 (0.0068)	-0.0384* (0.0195)

* Significant at the 5 percent level
** Significant at the 1 percent level

Table VII
Summary Statistics on Trades

This table presents mean statistics for sales for each company before and after Web introduction. Each "sale" is the aggregation of all sales of funds ordered by the participant on a given day through a given channel. Panel A shows figures from sales after Web introduction. The first row contains the average dollars transacted per sale through each channel. The second row contains turnover per sale, where turnover is defined as the dollar value of sales by a participant on a given day through a given channel divided by the participant's plan balance on that day. The third row presents the average plan balance of sellers through each channel. Panel B shows analogous statistics for phone trades before Web introduction within two samples of participants: the "Web sample," which consists of participants who traded at least once on the Web, and the "phone sample," which consists of participants who traded at least once after Web introduction but never traded on the Web. Only transfers between funds are considered; sales that occur in order to make a withdrawal from the plan are excluded. We compute averages for each day and then average equally across all days to arrive at our means. Note that a participant can be included in the sample multiple times if he or she orders sales in more than one day in the sample. Newey-West robust standard errors (five lags) are reported below the sample means.

Panel A: After Web introduction

	Alpha		Omega	
	Web trades	Phone trades	Web trades	Phone trades
Dollars per sale	$59,343.69	$99,923.50	$32,552.06	$64,421.90
	(1,172.63)	(1,930.48)	(559.78)	(1,316.15)
Turnover per sale	55.25%	70.90%	29.89%	42.10%
	(0.59)	(0.47)	(0.38)	(0.42)
Plan balance of seller	$113,294.40	$135,921.20	$129,654.30	$178,260.60
	(1,758.82)	(1,981.19)	(1,484.10)	(2,206.36)

Panel B: Before Web introduction

	Alpha		Omega	
	Web sample	Phone sample	Web sample	Phone sample
Dollars per sale	$60,910.64	$73,061.82	$36,684.49	$47,566.67
	(1,639.92)	(3,043.62)	(687.07)	(813.94)
Turnover per sale	64.60%	62.88%	34.24%	36.83%
	(0.80)	(1.09)	(0.46)	(0.37)
Plan balance of seller	$100,597.10	$110,084.90	$125,179.20	$153,333.00
	(1,974.87)	(3,057.73)	(1,722.40)	(2,249.43)

Table VIII

S&P 500 Performance Versus Net Plan Dollar Flows Into Equity

This table presents the distribution of positive and negative movements in the S&P 500 index on day $t + 1$, conditional on the sign of day t's net dollar flows into equity (i.e. the difference between the dollar value of purchases and the dollar value of sales) in each of Alpha and Omega's plans through the Web and phone channels. Only transfers between funds are considered; sales that occur in order to make a withdrawal from the plan and purchases that occur through payroll deductions are excluded. In addition, trades that involve an international fund are excluded. The date range is from the day of Web introduction to the end of the sample. The top number in each cell is the number of observations corresponding to that cell, and the bottom number is the sample probability that the S&P 500's $t + 1$ return is positive/negative, conditional on the sign of t's net plan equity flow through that channel.

Panel A: Alpha				
	Web		Phone	
	Web Flow positive on day *t*	*Web Flow* negative on day *t*	*Phone Flow* positive on day *t*	*Phone Flow* negative on day *t*
S&P 500 return positive on day $t + 1$	81 49.1%	125 56.1%	101 52.6%	105 53.6%
S&P 500 return negative on day $t + 1$	84 50.9%	98 44.0%	91 47.4%	91 46.4%

Panel B: Omega				
	Web		Phone	
	Web Flow positive on day *t*	*Web Flow* negative on day *t*	*Phone Flow* positive on day *t*	*Phone Flow* negative on day *t*
S&P 500 return positive on day $t + 1$	125 51.9%	69 53.1%	111 56.6%	83 47.4%
S&P 500 return negative on day $t + 1$	116 48.1%	61 46.9%	85 43.4%	92 52.6%

Table IX
Predictive Power of Alpha's Normalized Equity Flows
for Future One-Day S&P 500 Returns

The dependent variable is the S&P 500 return on day $t + 1$. All independent variables are as of day t. *Normalized Web Flow* is Alpha's daily net dollar flow to equities for trades ordered through the Web, divided by the sum of the absolute value of each Alpha investor's net dollar flow through the Web to equities on that day. (See equation (5).) *Normalized Phone Flow* is analogously defined for Alpha's equity transactions through its phone channel. Only transfers between funds are considered; sales that occur in order to make a withdrawal from the plan and purchases that occur through payroll deductions are excluded. In addition, trades that involve an international fund are excluded. $SP500_t$ is the S&P 500 return on day t, and $SP500_{(t-21,t-1)}$ is the cumulative return on the S&P 500 from day t - 21 to t - 1. *Dividend Yield* is the dividend yield on the NYSE value-weighted index. *Term* is the spread between the yields of the ten-year and one-year Treasuries. *Default* is the Moody's Baa-Aaa yield spread. *3-Month Yield* is the yield on the three-month Treasury bill. *January* is a dummy set to 1 when t is in the month of January. Newey-West robust standard errors (five lags) are reported in parentheses below the OLS point estimates.

Normalized Web Flow	-0.0033*	-0.0038**			-0.0029*	-0.0039**
	(0.0013)	(0.0013)			(0.0014)	(0.0014)
Normalized Phone Flow			-0.0023	-0.0013	-0.0011	0.0002
			(0.0013)	(0.0013)	(0.0013)	(0.0012)
$SP500_t$		-0.0390		-0.0410		-0.0384
		(0.0533)		(0.0541)		(0.0533)
$SP500_{(t-1,t-21)}$		-0.0033		-0.0139		-0.0033
		(0.0141)		(0.0144)		(0.0141)
Dividend Yield		0.3547		0.3380		0.3558
		(0.2942)		(0.2946)		(0.2935)
Term		0.0048		0.0046		0.0048
		(0.0042)		(0.0042)		(0.0042)
Default		0.0111		0.0110		0.0112
		(0.0100)		(0.0101)		(0.0101)
3-Month Yield		-0.0534		0.0225		-0.0489
		(0.4241)		(0.4256)		(0.4284)
January		0.0006		0.0007		0.0006
		(0.0032)		(0.0030)		(0.0033)
Constant	0.0005	0.0019	0.0006	-0.0017	0.0005	0.0016
	(0.0006)	(0.0231)	(0.0006)	(0.0231)	(0.0006)	(0.0235)

* Significant at 5 percent level
** Significant at 1 percent level

Table X
Predictive Power of Omega's Normalized Equity Flows for Future One-Day S&P 500 Returns

The dependent variable is the S&P 500 return on day $t + 1$. All independent variables are as of day t. *Normalized Web Flow* is Omega's daily net dollar flow to equities for trades ordered through the Web, divided by the sum of the absolute value of each Omega investor's net dollar flow through the Web to equities on that day. (See equation (5).) *Normalized Phone Flow* is analogously defined for Omega's equity transactions through its phone channel. Only transfers between funds are considered; sales that occur in order to make a withdrawal from the plan and purchases that occur through payroll deductions are excluded. In addition, trades that involve an international fund are excluded. $SP500_t$ is the S&P 500 return on day t, and $SP500_{(t-21,t-1)}$ is the cumulative return on the S&P 500 from day t - 21 to t - 1. *Dividend Yield* is the dividend yield on the NYSE value-weighted index. *Term* is the spread between the yields of the ten-year and one-year Treasuries. *Default* is the Moody's Baa-Aaa yield spread. *3-Month Yield* is the yield on the three-month Treasury bill. *January* is a dummy set to 1 when t is in the month of January. Newey-West robust standard errors (five lags) are reported in parentheses below the OLS point estimates.

Normalized Web Flow	-0.0010	-0.0009			-0.0015	-0.0011
	(0.0019)	(0.0019)			(0.0021)	(0.0021)
Normalized Phone Flow			-0.00004	-0.0002	0.0009	0.0004
			(0.00193)	(0.0021)	(0.0022)	(0.0023)
$SP500_t$		-0.0411		-0.0389		-0.0396
		(0.0552)		(0.0555)		(0.0557)
$SP500_{(t-1,t-21)}$		-0.0179		-0.0184		-0.0177
		(0.0133)		(0.0129)		(0.0133)
Dividend Yield		0.3169		0.3170		0.3159
		(0.2859)		(0.2864)		(0.2852)
Term		0.0041		0.0042		0.0040
		(0.0036)		(0.0037)		(0.0036)
Default		0.0106		0.0107		0.0103
		(0.0090)		(0.0093)		(0.0091)
3-Month Yield		0.0456		0.0490		0.0345
		(0.4138)		(0.4156)		(0.4121)
January		0.0009		0.0007		0.0008
		(0.0031)		(0.0031)		(0.0031)
Constant	0.0009	-0.0025	0.0008	-0.0029	0.0009	-0.0017
	(0.0006)	(0.0218)	(0.0006)	(0.0224)	(0.0006)	(0.0221)

* Significant at 5 percent level
** Significant at 1 percent level

Table XI
Company Stock Performance Versus Net Plan Dollar Flows

This table presents the distribution of positive and negative movements in Omega's company stock price on day $t + 1$, conditional on the net direction of trade in company stock in Omega's plan through the Web and phone channels on day t. In Panel A, trade direction is calculated as day t's difference between the dollar value of company stock purchases and the dollar value of company stock sales ("flow"), and Panel B subtracts the number of participants who traded out of company stock from the number of participants who traded into company stock on day t ("count"). Only transfers between funds are considered; sales that occur in order to make a withdrawal from the plan and purchases that occur through payroll deductions are excluded. The date range is from the day of Web introduction to the end of the sample. The top number in each cell is the number of observations corresponding to that cell, and the bottom number is the sample probability that the $t + 1$ company stock return is positive/negative, conditional on the sign of t's net company stock trade flow in Omega's plan through that channel.

Panel A: Dollar flow

	Web		Phone	
	Cstock Web Flow positive on day t	*Cstock Web Flow* negative on day t	*Cstock Phone Flow* positive on day t	*Cstock Phone Flow* negative on day t
Company stock return positive on day $t + 1$	95 46.1%	75 45.5%	87 44.4%	83 47.4%
Company stock return negative on day $t + 1$	111 53.9%	90 54.6%	109 55.6%	92 52.6%

Panel B: Participant count

	Web		Phone	
	Cstock Web Count positive on day t	*Cstock Web Count* negative on day t	*Cstock Phone Count* positive on day t	*Cstock Phone Count* negative on day t
Company stock return positive on day $t + 1$	80 44.7%	90 46.9%	85 43.4%	85 48.6%
Company stock return negative on day $t + 1$	99 55.3%	102 53.1%	111 56.6%	90 51.4%

Table XII
Predictive Power of Omega's Normalized Company Stock Flows for Future One-Day Company Stock Returns

The dependent variable is Omega's company stock return on day $t + 1$. *Normalized Cstock Web Count* is the number of people who increased their company stock holdings through the Web minus the number of people who decreased their company stock holdings through the Web, divided by the total number of people who traded in company stock through the Web on day t. *Normalized Cstock Web Flow* is the net dollars that flowed into company stock through the Web channel, divided by the sum of the absolute dollar value of every company stock trade through the Web on day t. *Normalized Cstock Web Purchases* is the percent of people in the plan who on net purchased company stock through the Web on day t, divided by a 21-day (day t to day t - 20) moving average of the percent of people in the plan who on net purchased company stock through the Web. *Normalized Cstock Web Sales* is the percent of people in the plan who on net sold company stock through the Web on day t, divided by a 21-day (day t to day t - 20) moving average of the percent of people in the plan who on net sold company stock through the Web. All *Phone* variables are defined analogously. Only transfers between funds are considered; sales that occur in order to make a withdrawal from the plan and purchases that occur through payroll contributions are excluded. Newey-West robust standard errors (five lags) are reported in parentheses below the OLS point estimates.

Normalized Cstock Web Count	0.0002 (0.0034)				-0.0014 (0.0058)
Normalized Cstock Phone Count	-0.0017 (0.0037)				0.0067 (0.0068)
Normalized Cstock Web Flow		-0.0006 (0.0019)			-0.0007 (0.0029)
Normalized Cstock Phone Flow		-0.0015 (0.0023)			-0.0029 (0.0029)
Normalized Cstock Web Purchases			-0.0020 (0.0026)		-0.0015 (0.0033)
Normalized Cstock Phone Purchases			0.0023 (0.0029)		0.0012 (0.0036)
Normalized Cstock Web Sales				0.0017 (0.0023)	0.0019 (0.0033)
Normalized Cstock Phone Sales				-0.0039 (0.0031)	-0.0046 (0.0045)
Constant	-0.0005 (0.0010)	-0.0005 (0.0009)	-0.0007 (0.0013)	-0.0027 (0.0021)	-0.0029 (0.0027)

Table XIII
Reaction of Normalized Equity Flows to Past S&P 500 Returns After Web Introduction

The dependent variables are defined as follows for each plan and each channel. The plan's day *t* net dollar flow to equities for trades ordered through the channel is divided by the sum of the absolute value of each investor's net dollar flow through that plan's channel to equities on day *t*. (See equation (5) for the normalization for Web flows. Phone flow normalization is calculated analogously.) Only transfers between funds are considered; sales that occur in order to make a withdrawal from the plan and purchases that occur through payroll deductions are excluded. In addition, trades that involve an international fund are excluded. The date range for both channels is from the day of Web introduction to the end of the sample. $SP500_t$ is the return on the S&P 500 on day t, $SP500_{t-1}$ is the return on the S&P 500 on day t - 1, $SP500_{(t-2,\ t-5)}$ is the cumulative returns on the S&P 500 for days t - 2 to t - 5, and $SP500_{(t-6,\ t-21)}$ is the cumulative returns on the S&P 500 for days t - 6 to t - 21. Newey-West robust standard errors (five lags) are reported in parentheses below the OLS point estimates.

	Alpha		Omega	
	Normalized Web Flow	*Normalized Phone Flow*	*Normalized Web Flow*	*Normalized Phone Flow*
$SP500_t$	1.1001	-2.2692	-3.4347	-5.3245**
	(2.1346)	(1.9736)	(1.8879)	(1.4357)
$SP500_{t-1}$	10.0068**	-1.0869	-1.5044	-2.8310
	(1.9649)	(1.9615)	(1.6428)	(1.5347)
$SP500_{(t-2,t-5)}$	4.9692**	3.6030**	0.2053	-0.3700
	(1.0658)	(1.0872)	(0.8966)	(0.9075)
$SP500_{(t-6,t-21)}$	2.5627**	0.8798	1.0296	0.4841
	(0.6292)	(0.6081)	(0.6883)	(0.6037)
Constant	-0.1181**	-0.0521	0.1140**	0.0371
	(0.0292)	(0.0289)	(0.0332)	(0.0287)

* Significant at 5 percent level

** Significant at 1 percent level

Table XIV
Reaction of Normalized Equity Flows to Past S&P 500 Returns by Future Web Traders and Phone Traders Before Web Introduction

The dependent variables are constructed as follows. Participants in each firm are segregated into two groups: those who traded at least once on the Web in sample ("Web sample") and those who traded at least once since Web introduction but did not make any trades on the Web ("phone sample"). We then calculate each group's day t net dollar flow to equities and divide by the sum of the absolute value of net dollar flow to equities of each investor in the group on day t. (See equation (5) for the normalization calculation for the Web sample. The phone sample calculation is made analogously.) Only transfers between funds are considered; sales that occur in order to make a withdrawal from the plan and purchases that occur through payroll deductions are excluded. In addition, trades that involve an international fund are excluded. The date range is from the beginning of the sample to the day before Web introduction. $SP500_t$ is the return on the S&P 500 on day t, $SP500_{t-1}$ is the return on the S&P 500 on day t - 1, $SP500_{(t-2,\ t-5)}$ is the cumulative returns on the S&P 500 for days t-2 to t-5, and $SP500_{(t-6,\ t-21)}$ is the cumulative returns on the S&P 500 for days t - 6 to t - 21. Newey-West robust standard errors (five lags) are reported in parentheses below the OLS point estimates.

	Alpha		Omega	
	Web sample	Phone sample	Web sample	Phone sample
$SP500_t$	6.5333*	5.4447	-0.0235	-3.1728
	(2.9876)	(2.8171)	(2.2192)	(2.3499)
$SP500_{t-1}$	13.3435**	3.7656	-1.9856	0.9178
	(3.2715)	(3.5185)	(2.0963)	(2.0610)
$SP500_{(t-2,t-5)}$	5.4473**	4.1803*	1.2226	0.1839
	(2.0577)	(1.6912)	(1.2503)	(1.1045)
$SP500_{(t-6,t-21)}$	1.1963	2.6941*	-0.3885	-0.2171
	(1.1101)	(1.0993)	(0.8963)	(0.7401)
Constant	0.0295	-0.0179	0.0628	0.0453
	(0.0435)	(0.0412)	(0.0342)	(0.0303)

* Significant at 5 percent level
** Significant at 1 percent level

Table XV
Distribution of Trade Entry Times By Channel

This table presents the trades that have been entered through each channel at each hour (U.S. Eastern Time) since Web trading was introduced, as a percent of all trades that have gone through each channel since the introduction of Web trading.

	Alpha		Omega	
Time	Phone	Web	Phone	Web
12:00 A.M. – 8:59 A.M.	5.8%	12.0%	4.2%	13.6%
9:00 A.M. – 9:59 A.M.	2.6%	4.0%	3.1%	4.1%
10:00 A.M. – 10:59 A.M.	3.5%	4.9%	3.6%	4.7%
11:00 A.M. – 11:59 A.M.	4.2%	4.8%	3.7%	5.1%
12:00 P.M. – 12:59 P.M.	4.4%	5.7%	5.1%	7.0%
1:00 P.M. – 1:59 P.M.	5.2%	6.9%	6.1%	7.9%
2:00 P.M. – 2:59 P.M.	8.6%	8.6%	9.7%	10.5%
3:00 P.M. – 3:59 P.M.	46.4%	26.7%	51.2%	29.1%
4:00 P.M. – 4:59 P.M.	5.3%	4.6%	6.3%	2.9%
5:00 P.M. – 11:59 P.M.	13.9%	21.9%	7.0%	15.0%
Total	100.0%	100.0%	100.0%	100.0%

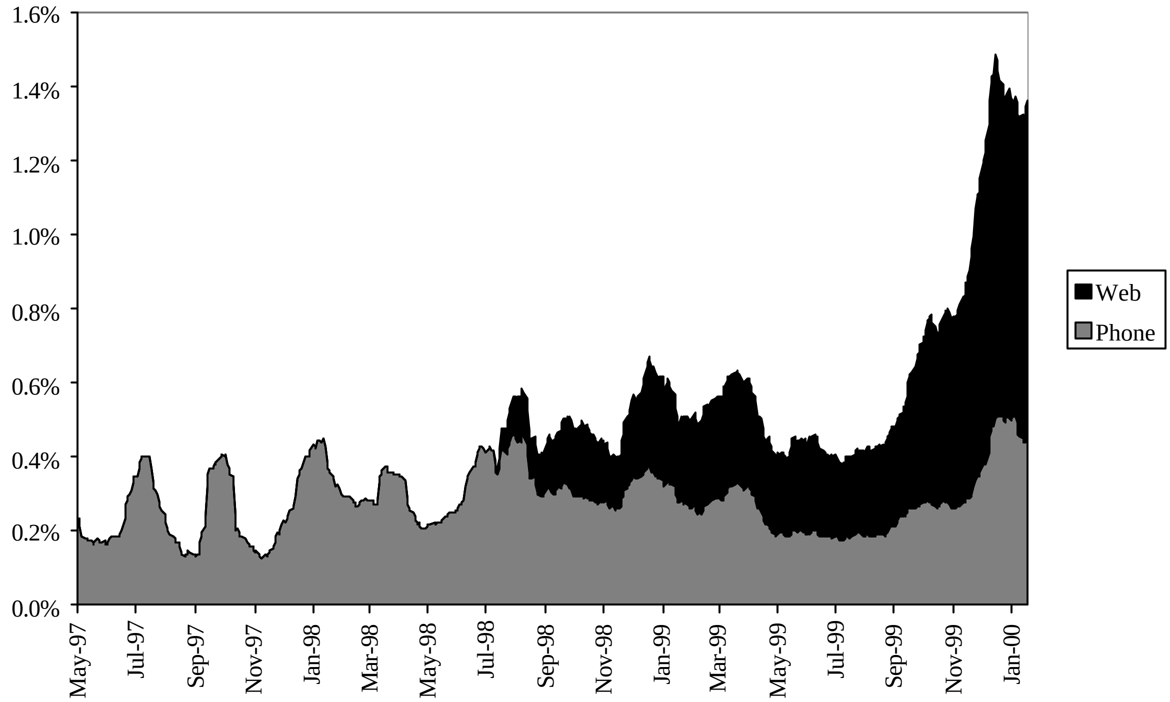
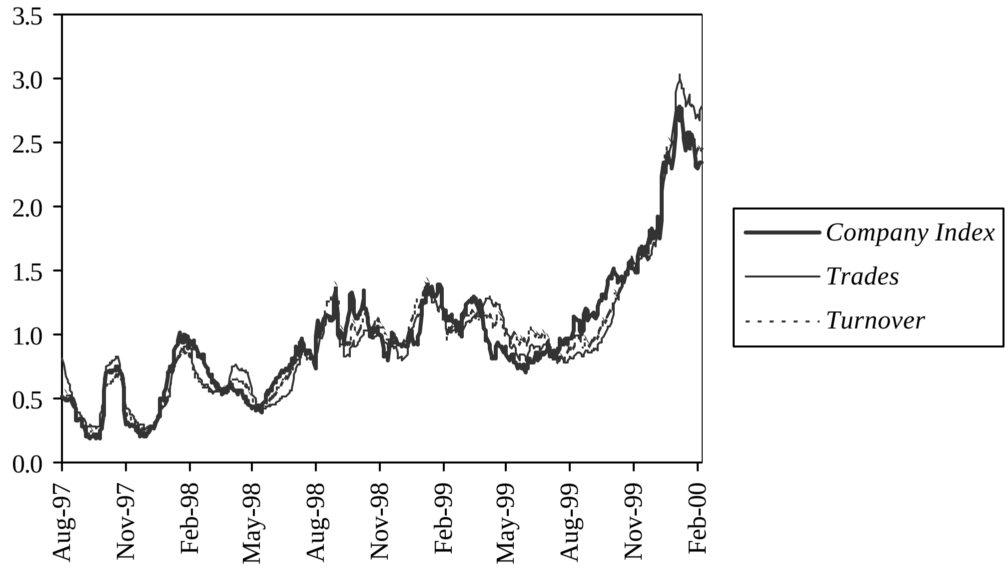


Figure 1. Alpha: Daily trading frequency. On each trading day, we calculate the percent of participants enrolled in company Alpha's 401(k) plan who traded on that day. We then plot the 21-day moving average of this daily trading frequency. After the introduction of the Web, the Web and phone frequencies are plotted separately.

Panel A: Alpha



Panel B: Omega

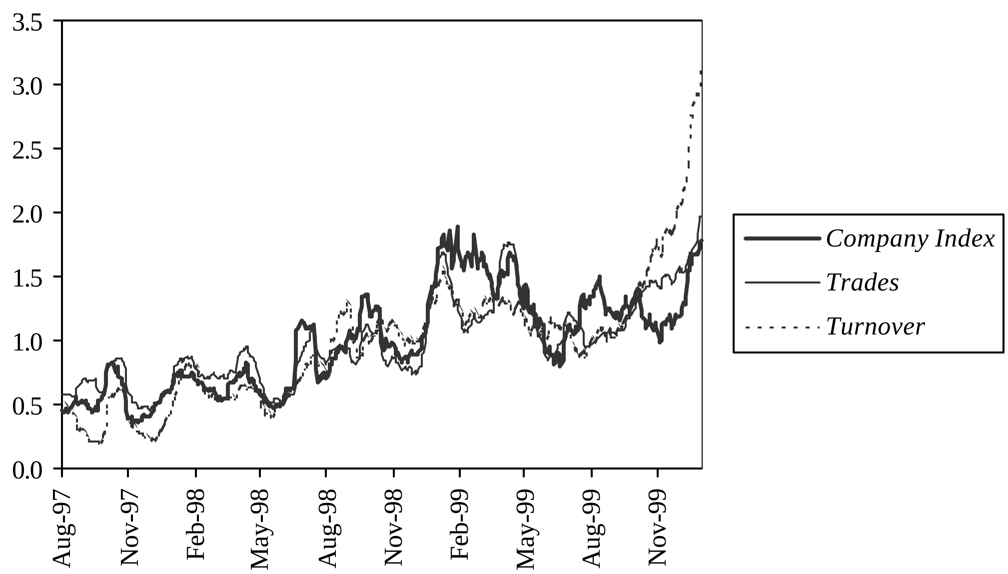


Figure 2. Relationship among the three trading measures. 21-day moving averages of the three dependent variables, *Trades*, *Turnover*, and *Company Index*, are plotted. Each series has been normalized so that its sample mean corresponds to 1. *Trades* is the percent of participants in each company who trade each day. *Turnover* is the daily dollar value of all sales in each plan as a percent of total plan balances on that day. *Company Index* is the daily percent of plan balances traded between asset classes. The correlation between *Trades* and *Turnover* is 0.81 for Alpha and 0.71 for Omega. The daily correlation between *Trades* and *Company Index* is 0.66 for Alpha and 0.64 for Omega. The daily correlation between *Turnover* and *Company Index* is 0.84 for Alpha and 0.53 for Omega.