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How does the Internet affect trading? Evidence from investor behavior in 401(k) plans

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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 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 than any of this new trading on the Web is successful.

JEL classification: D0; G0; L0; O0

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1. Introduction

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 (Levitt, 1999a,b). 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?

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 did not introduce a Web channel during our sample period.

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 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

[1]Claims about the impact of the Web are found in numerous press reports; some examples are Washington Post (1999), Global Investment Magazine (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).

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.[2] 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. 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, performance, or the impact of trading technologies.

In Section 2, we describe the data set 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

[2] 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.

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 3, we measure the impact of the Web on the volume of trade. As a preview of the results, Fig. 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. 18 months after the Web channel opens, Web transactions represent approximately 60% of all transactions, and the trading rate quadruples 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 4, we evaluate the performance of traders by channel. We analyze the absolute and relative (Web vs. phone) performance for asset-allocation ("market-timing") trades. 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 and direction of Web trading is a contrarian indicator for S&P 500 returns. However, there is no significant difference between Web and phone performance. Finally, Section 5 concludes the paper.

2. 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.[3] Thus, equity holdings through 401(k) plans, directly or indirectly, constitute about 10% of the equity holdings for the household sector.[4] 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.[5] 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.

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

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

[5]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.

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 example, 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 1. 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 are executed that day at closing prices.[6] 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 transaction 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 passed on to 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% 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 par-

[6] 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.

tially explains the relatively low holding of company stock by Omega's participants, which is 6.6% of balances as of year-end 1999. 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% and Omega at 40.8%.

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.[7]

The last four rows of Table 1 suggest the same Web effect for Omega that is seen for Alpha in Fig. 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 3, 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

[7]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 3) 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 2 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 3 summarizes the asset allocation and trading at both firms. The asset classes in 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 3, 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% of all assets were invested in this fund as of year-end 1999. Nevertheless, 39.3% (purchases) and 38.2% (sales) of the dollars traded by phone and 32.0% (purchases) and 32.6% (sales) of the dollars traded by Web involved this single bond fund. At Omega, over 57% of the holdings are in the GIC fund, with this fund representing 36.0% (purchases) and 38.3% (sales) of the dollars traded by phone and 32.7% (purchases) and 36.4% (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 4, we investigate the performance of these market-timing trades and test whether this performance differs across channels. The last column of Table 3 shows that the holdings of company stock in Omega's plan are only 6.6%, but this asset class constitutes a disproportionate share of the trading (15.2% of purchases and 16.2% of sales by phone and 12.2% of purchases and 11.0% of sales by Web).

3. Does the Web affect trading volume?

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

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

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 one when Web trading is available and zero 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 Eq. (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 Eq. (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% 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% of all participants in plan i each shift 20% 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 section.)

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.[8] 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 start with the same 40 plans as Hewitt and eliminate the 13 firms who had a Web channel by the end of the sample and the ten firms that joined the sample after August 4, 1997, which is the first day the index was calculated. We then average 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

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

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. Fig. 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 *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 Eq. (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, 2000 and 2001). 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% of assets is 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. It therefore 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 calendar 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.

Table 4 shows the results of estimating Eq. (1) for each firm with the explanatory variables described above for each of the three trading measures. 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 1. 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 first two columns of the table give the results for $y = Trades$, the trading frequency, as the dependent variable. The results demonstrate economically and statistically significant evidence of the Web's effect on trading frequency: the coefficient on $Web * Time$ is significant at the 1% level for Alpha and the 5% level for Omega. The level effects are statistically insignificant for both firms. 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. 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 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 1, 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%. Thus, the total Web effect for Alpha is calibrated to be about 0.300/0.269 = 112% of pre-Web trading. An analogous calculation for Omega yields an increase in trading frequency of $(0.00064 * 548 - 0.024)/0.402 = 81\%$

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 Fig. 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 Eq. (1).

The results of this estimations are summarized in the middle two columns of Table 4. The coefficient on $Web * Time$ for Omega is positive and significant at the 1% 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% for Alpha and 64% for Omega.[9] The average effect across the two

[9] This computation uses the coefficients reported in the top two rows and middle two columns of Table 4. The total Web effect for Alpha was $0.00038 * 548 - 0.059 = 0.149\%$. The average daily pre-Web turnover in Alpha, not reported elsewhere in the paper, is 0.334%. Thus, the Web increased turnover by $0.149/0.334 = 45\%$. The analogous calculation for Omega is $0.00026 * 548 - 0.021 = 0.122\%$. The average daily pre-Web turnover at Omega was 0.192, implying an increase of

firms is about 55%, 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 Eq. (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 the last two columns of Table 4. Here, while the coefficients on $Web*Time$ are positive for both firms, they are also insignificant in both cases. Note that while these estimates are not statistically significant, the average calibrated effect for the point estimates, 47%, is about the same as the average calibrated effect for the coefficients in the *Turnover* regressions.[10]

Overall, we find 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 when *Trades* is the dependent variable, 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

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$0.122/0.192 = 64\%$.

[10]For Alpha, the baseline index before Web introduction is 0.147, so the coefficients in the table imply a calibrated 18-month increase of only 0.13%. For Omega, however, the baseline index before Web introduction is 0.063, so the coefficients, although insignificant, imply a calibrated 18-month effect of 94.3%.

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 5 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 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% to 55.25% at Alpha and 42.10% to 29.89% 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 5 shows the average dollar value, the average turnover (as a fraction of the portfolio), and the average portfolio size for these two groups. These trades include only those made by the Web sample and phone sample 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% vs. 64.60% at Alpha and 36.83% vs. 34.24% of Omega), while the average portfolio size (at the time of trade) is larger for the phone sample at both firms ($110,085 vs. $100,597 at Alpha and $153,333 vs. $125,179 at Omega).

At first glance, there appears to be some tension between Table 5 and our earlier finding in Table 2 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. The results of Table 5 average across all *trades*, so that these frequent traders are counted many times. By contrast, the demographic results of Table 2 count each trader once. Thus, the high-balance frequent phone traders do not dominate that analysis.

As a final check on whether the results are driven solely by an imperfect control, we compute a different control variable, *NYSE Turnover*, defined as the daily dollar volume of the NYSE divided by market value of the NYSE at the end of the day. We then reestimate all the regressions from Table 4 using *NYSE Turnover*, instead of the *Non-Web Index*, as the main control variable. Relative to the *Non-Web Index*, *NYSE Turnover* has the advantage of being a true turnover measure, and the disadvantage of contamination with Web trading, since there is no way to separate Web and phone trades in the aggregate measure. In untabulated results, we find that the coefficients on *NYSE Turnover* are, as expected, positive and significant in all specifications. Furthermore, the coefficients on $Web * Time$ are positive and significant at the 1% level for both firms when *Trades* is the dependent variable, positive and significant at the 5% level (for Alpha) and at the 1% level (for Omega) when *Turnover* is the dependent variable, and positive but insignificant when *Company Index* is the dependent variable.[11] Since *NYSE Turnover* has an unknown and likely time-varying dependence on Web activity, it is difficult to draw strong conclusions or calibrate a net Web effect from these results. Nevertheless, it is a useful robustness check that the general pattern of the coefficients on $Web * Time$ – strongest results for *Trades* and weakest results for *Company Index* – are consistent with the evidence in Table 4.

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

[11] Detailed results of these regressions are available from the authors.

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. Indeed, this latter effect is already apparent: the average turnover for all trades at Alpha (with Newey-West (1987) standard errors in parentheses) was 67.17% (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% (0.55) in the three months before the Web's introduction and 34.20% (0.83) in the last three months of the sample.

4. 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. First, while the investment choices within equities are limited relative to those in discount brokerages, there is a 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.

While the 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.[12] Among studies of the asset-allocation performance of individual investors, only Goetzmann and Massa (2000) make use of transactions data.[13] 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

[12] 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).

[13] 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.

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 3) Large U.S. Equity, Other U.S. Equity, or Company Stock counts as an equity trade. For balanced funds, we count a purchase of $1 as 60 cents of equity and 40 cents of bonds.[14] For the "lifestyle/pre-mix" funds, we use the target percentages of each fund.[15] 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.[16] *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?

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

[14]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.

[15]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 3 in Section 2.

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

Phone Flow measures by their respective gross flows. That is, for *Web Flows,*

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

and

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

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 monthly S&P 500 returns using the *Normalized Web Flow* and *Normalized Phone Flow* variables. These regressions take the form

$$SP500_{(t+1,t+21)} = \alpha_i + \beta_i F_{i,t} + \delta_i Z_t + \varepsilon_{i,t+1} \tag{6}$$

where $SP500_{(t+1,t+21)}$ is the 21-day (= one month) return on the S&P 500 beginning on day $t+1$, $F_{i,t}$ are the normalized flow variables 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 ten-year and one-year Treasuries; *Default* is the spread between the yields on Baa and Aaa bonds; *3-Month Yield* is the yield on the three-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 one in the month of January, and zero otherwise. The interest rate variables were obtained from the Federal Reserve website and are updated daily. The stock return and dividend yield variables were obtained from CRSP and are updated using the daily return files.

Table 6 summarizes the results for both firms. Columns 1 and 3 of the table give the results without the Z vector included; columns 2 and 4 give the results with the full Z vector included. To adjust for the overlapping time periods and for possible additional autocorrelation in returns, standard errors are computed using the Newey-

West (1987) procedure with 25 lags. The results show some weak evidence that Web trades are a contrarian indicator for S&P 500 returns. In column 2, the coefficients on the *Normalized Web Flow* variable are negative and significantly different from zero at the 5% level. Nevertheless, the coefficients on *Normalized Web Flow* are not significantly different from the coefficients on *Normalized Phone Flow* in any of the specifications.[17] We also estimated a version of Eq. (6) using daily (rather than monthly) returns as the dependent variable. The results were qualitatively similar. Thus, there is no significant evidence that Web traders underperform phone traders in their asset-allocation trades.

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.

5. 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. 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

[17] To perform this calculation, we use the coefficient standard errors (shown in the tables) and the (unreported) covariances between the estimated coefficients.

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. 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 U.S. 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%) 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, and no significant difference in the performance of Web traders and phone traders. 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 born by all plan participants.

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Table 1
Summary statistics for the 401(k) plans of firms Alpha and Omega

This table summarizes features of the two 401(k) plans we study, including the size and range of the sample, investment options and allocations in the plan, demographic information on the participants, and stylized facts about trading behavior during the sample period.

	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 2
Demographic characteristics of Web traders, from Web introduction to end of sample

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 between the participant's original enrollment and year-end 1999. *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. *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% level
** Significant at the 1% level

Table 3
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 4

Determinants of trading activity from 8/4/1997 to end of sample period

There are three dependent variables in the table. *Trades* is the percent of participants in each company who trade on each day. *Turnover* is the daily dollar value of all sales in a plan as a percent of total balances in the plan on that day. *Company Index* is the daily percent of plan balances traded between asset classes in Alpha and Omega, respectively. The independent variables are as follows. *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 20-day lagged standard deviation of the daily 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 20-day lagged standard deviation of the daily 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 (1987) robust standard errors (five lags) are reported in parentheses below the OLS point estimates.

	Trades		Turnover		Company Index	
	Alpha	*Omega*	*Alpha*	*Omega*	*Alpha*	*Omega*
Web	**-0.0952**	**-0.0241**	**-0.0591**	**-0.0205**	**-0.0491**	**0.0170**
	(0.0582)	**(0.0518)**	**(0.0577)**	**(0.0119)**	**(0.0263)**	**(0.0118)**
Web * Time	**0.00072****	**0.00064***	**0.00038**	**0.00026****	**0.00009**	**0.00007**
	(0.00020)	**(0.00028)**	**(0.00020)**	**(0.00006)**	**(0.00008)**	**(0.00006)**
Non-Web Index	140.0920**	81.6954**	194.0439**	31.6382**	105.8942**	40.5760**
	(22.3813)	(18.6263)	(25.9074)	(4.3597)	(14.3106)	(4.6599)
|S&P 500|	0.2079	3.4935*	0.1820	0.1188	-2.4388	0.4478
	(1.8021)	(1.7030)	(2.6553)	(0.3925)	(1.7026)	(0.6097)
(S&P 500)^2	60.3637	-1.0643	83.1802	11.0200	108.1347*	-3.6632
	(41.8465)	(32.3171)	(73.1748)	(9.9516)	(48.4681)	(13.5472)
|Lag S&P 500|	-1.5036	-1.1995	-3.3204	-0.4162	-1.9756	1.1069*
	(1.7831)	(1.8917)	(2.5653)	(0.3861)	(1.3328)	(0.5385)
(Lag S&P 500)^2	202.9359**	149.2298**	302.6174**	44.1060**	106.0516**	-9.5863
	(37.9670)	(52.8017)	(64.2860)	(8.7565)	(26.6180)	(9.5108)
Std(S&P 500)	-2.7578	-5.2980*	-4.1020	-0.3025	-1.0153	-1.2177
	(3.9289)	(2.4152)	(4.1555)	(0.4919)	(2.0671)	(0.7032)
|Company Stock|	0.9426	2.5601**	0.5350	-0.0198	0.0804	0.0297
	(0.8968)	(0.8864)	(1.2829)	(0.2006)	(0.8888)	(0.3223)
(Company Stock)^2	-0.9552	41.8645**	9.5484	1.8339	9.9195	16.7004**
	(13.0412)	(9.5403)	(20.8628)	(1.8384)	(13.7175)	(5.3141)
|Lag Company Stock|	0.2651	0.2604	-0.4893	-0.0768	0.2776	-0.7145*
	(0.9386)	(1.1452)	(1.1520)	(0.1800)	(0.6298)	(0.3637)
(Lag Company Stock)^2	-1.4287	32.0787**	11.0976	-0.2390	9.4590	17.0443**
	(12.6027)	(12.1468)	(13.7542)	(1.7718)	(7.7504)	(3.8735)
Std(Company Stock)	7.7854**	7.5359**	8.5034**	1.3509**	3.3825**	0.9947*
	(2.5549)	(1.7749)	(2.4703)	(0.3771)	(1.2227)	(0.3980)
Start Week	0.1208**	0.1287**	0.1200**	0.0208**	0.0335*	0.0030
	(0.0173)	(0.0172)	(0.0217)	(0.0033)	(0.0165)	(0.0050)
End Week	-0.0070	0.0352*	0.0407*	0.0062*	0.0053	0.0116*
	(0.0122)	(0.0152)	(0.0195)	(0.0032)	(0.0137)	(0.0051)
Start Month	-0.0488	-0.0379	-0.0442	-0.0093	-0.0449	-0.0169*
	(0.0410)	(0.0298)	(0.0487)	(0.0076)	(0.0242)	(0.0080)
End Month	-0.0149	-0.0113	-0.0222	-0.0029	0.0102	-0.0044
	(0.0308)	(0.0318)	(0.0408)	(0.0064)	(0.0273)	(0.0065)
Rule Change		-0.0547		-0.0586**		-0.0326
		(0.0863)		(0.0147)		(0.0175)
Trend	0.00030	0.00034**	0.00064**	0.00011**	0.00031**	0.00008*
	(0.00016)	(0.00009)	(0.00016)	(0.00002)	(0.00007)	(0.00004)
Constant	-0.1894*	-0.0696	-0.3360**	-0.0643**	0.1631**	-0.0384*
	(0.0953)	(0.0656)	(0.0956)	(0.0180)	(0.0440)	(0.0195)

* Significant at the 5% level. ** Significant at the 1% level

Table 5
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 (1987) 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 6
Predictive power of normalized equity flows for future one-month S&P 500 returns over entire sample period

The dependent variable is the S&P 500 return from trading day $t + 1$ to $t + 21$. All independent variables are as of day t. *Normalized Web Flow* is the company's daily net dollar flow to equities for trades ordered through the Web, divided by the sum of the absolute value of each investor's net dollar flow through the Web to equities on that day in that company. (See Eq. (5).) *Normalized Phone Flow* is analogously defined for the company'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 yield over the past year on the S&P 500. *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 one when t is in the month of January. Newey-West (1987) robust standard errors (25 lags) are reported in parentheses below the OLS point estimates.

	Alpha		Omega	
Normalized Web Flow	-0.0091 (0.0059)	-0.0084* (0.0041)	0.0024 (0.0086)	-0.0005 (0.0065)
Normalized Phone Flow	-0.0048 (0.0050)	-0.0064 (0.0039)	0.0015 (0.0102)	0.0083 (0.0056)
$SP500_t$		-0.2175* (0.0959)		-0.0179 (0.1178)
$SP500_{(t-21,t-1)}$		0.0513 (0.1181)		0.0770 (0.1269)
Dividend Yield		23.4372** (5.8135)		25.2018** (6.5593)
Term		0.0476 (0.0322)		0.0620 (0.0335)
Default		0.1221* (0.0518)		0.1478** (0.0562)
3-Month Yield		-1.4147 (1.0755)		-1.3637 (1.1468)
January		-0.0406** (0.0069)		-0.0484** (0.0070)
Constant	0.0192* (0.0082)	-0.3436** (0.0873)	0.0174* (0.0088)	-0.3971** (0.1012)

* Significant at 5% level
** Significant at 1% level

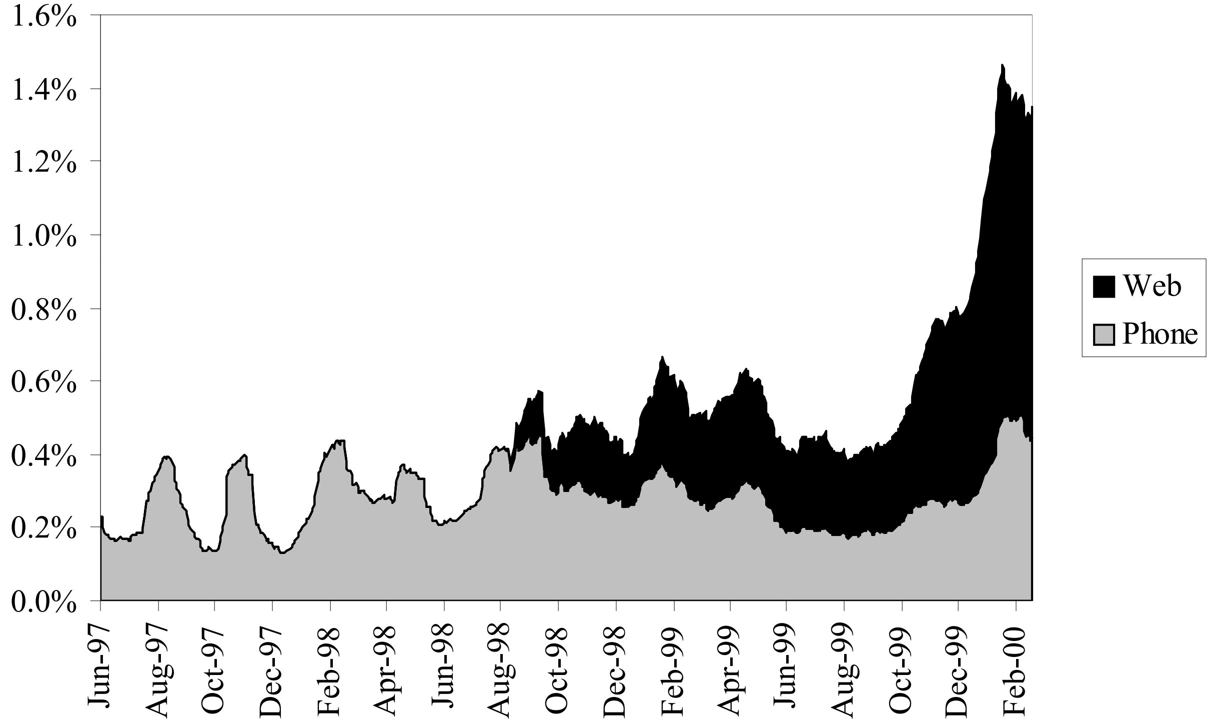
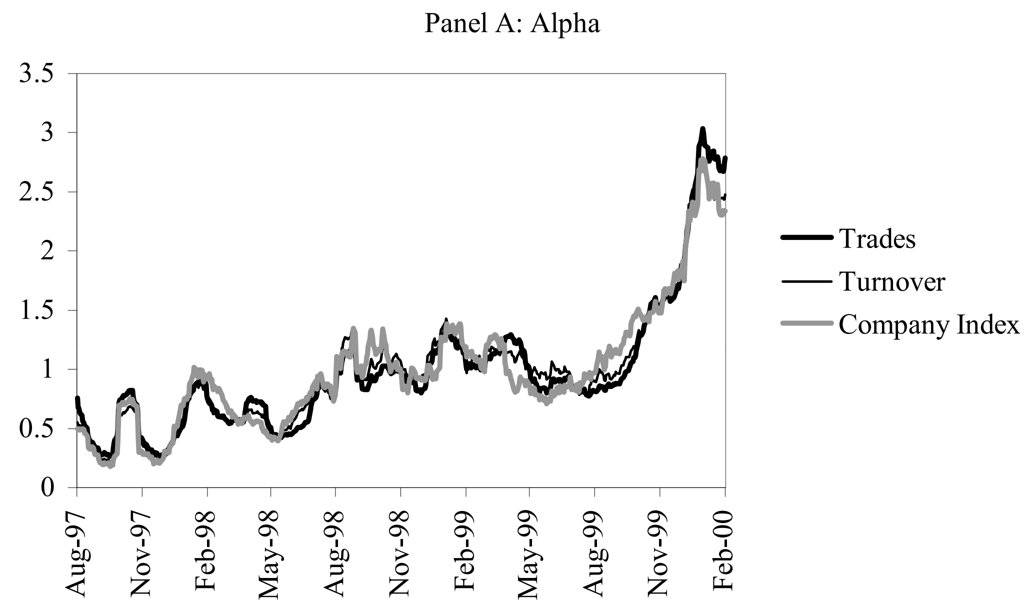


Fig. 1. Alpha: Daily trading frequency, 6/17/1997 - 3/3/2000. On each trading day, we calculate the percent of participants enrolled in company Alpha's 401(k) plan who traded on that day. We then plot the 21-day moving average of this daily trading frequency. After the introduction of the Web, the Web and phone frequencies are plotted separately.



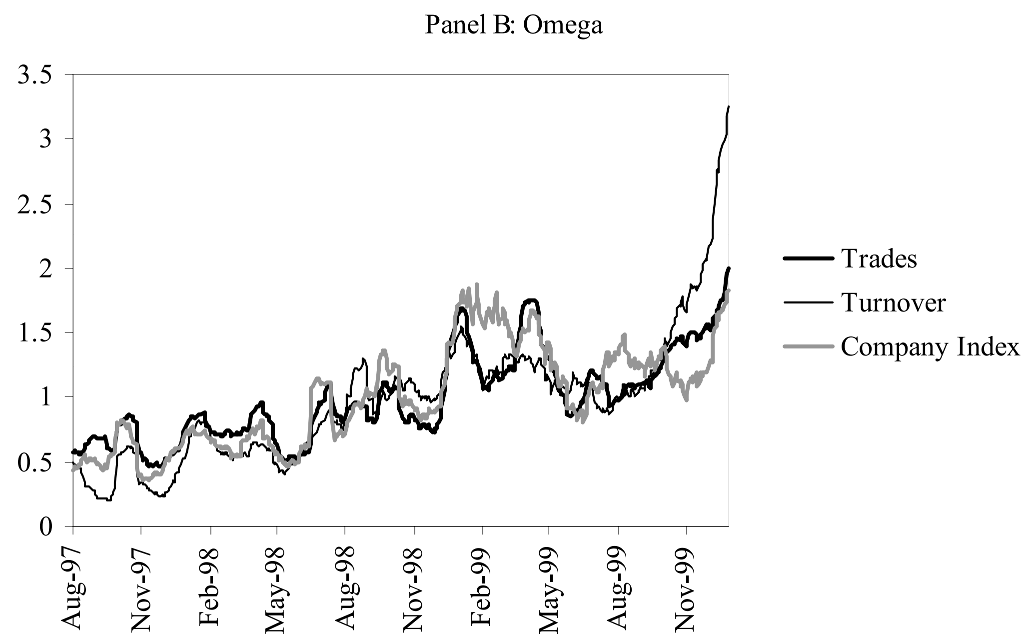


Fig. 2. Relation among the three trading measures over entire sample period. 21-day moving averages of the three dependent variables, *Trades*, *Turnover*, and *Company Index*, are plotted. Each series has been normalized so that its sample mean corresponds to 1. *Trades* is the percent of participants 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 correlation between *Trades* and *Company Index* is 0.66 for Alpha and 0.64 for Omega. The correlation between *Turnover* and *Company Index* is 0.84 for Alpha and 0.53 for Omega.