The Response of Aggregate 401(k) Trading to Asset Returns

401(k) investors are known for inertia, meaning that they rarely change their asset allocations. This study examines a unique data set of daily net aggregate 401(k) transfers between mutual funds over a five-year period and investigates whether market movements can induce participants to trade. We find evidence of contemporaneous, or same day, positive-feedback trading. To the extent that this behavior is pervasive and leads to persistent deviations from optimal long-run allocations, financial education programs should explicitly address it.

The Response of Aggregate 401(k) Trading to Asset Returns

Past research focused on 401(k) trading has shown that participant behavior is characterized by extreme inactivity, or inertia (see Ameriks and Zeldes, 2001; Madrian and Shea, 2001; Agnew, Balduzzi, and Sundén, 2003; and Mitchell et al., 2006). Current research provides little insight into what, if anything, motivates participants to trade. As companies increasingly offer defined contribution plans over defined benefit plans and the idea of automatic IRAs is advanced, we need a clearer understanding of how the reluctant trader reacts to (or perhaps contributes to) market movements specifically in retirement accounts.

This paper aims to deepen our understanding of this growing class of investors by taking a close look at daily market returns and aggregate net 401(k) transfer activity for a new and unique sample of nearly 1.5 million 401(k) participants, backing up the Hewitt 401(k) Index, over the August 4, 1997 to September 30, 2002 timeframe.[1] The aggregate gross transfers in and out are netted in this dataset to generate one data point per day for each asset class. The sample of retirement-only daily aggregate net transfers and the relatively long time series of daily data distinguish this paper from prior work related to mutual fund flows. Focusing on the retirement-only net aggregate flows is particularly important because this segment of investors continues to grow rapidly. In addition, research suggests that these individuals trade very differently than those in brokerage accounts (Odean, 1999; Agnew, Balduzzi, and Sundén, 2003). Finally, our results also contribute to the literature by helping to increase our general understanding of how defined contribution investors may be reacting now and in the future to market returns.

Our results show that there is a relationship between market movements and aggregate net 401(k) transfers. Over the August 1997-September 2002 period, we find that net transfers into "safe" assets (money market funds and GICs) correlate strongly and negatively with equity returns.[2] These results suggest that, in the aggregate, 401(k) investors tend to shift funds between equities and cash or bonds.

These results hold even after controlling for lead-lag relationships between returns and transfers, day-of-the-week effects, and macroeconomic announcements.

Importantly, we address the simultaneity issue (do transfers cause returns or returns cause transfers) by implementing tests based on intra-day data (see Edelen and Warner, 2001; and Goetzmann and Massa, 2003): we study the correlations between daily transfers on the one hand, and stock returns during the first and second half of the trading day, on the other. We find that daily net equity transfers correlate significantly with *both* morning and afternoon stock returns. Hence, our results are consistent with some 401(k) investors observing returns and then changing allocations. This result is in contrast with Edelen and Warner (2001) and Goetzmann and Massa (2003), who find that net equity mutual fund flows correlate *only* with afternoon returns, and conclude that it is unlikely that flows respond to returns. In summary, our findings suggest that prices not only increase (fall) when investors are buying (selling), but we also find that investors buy (sell) when prices increase (fall). This result is one of the most significant contributions of this paper to the literature.

Table 1 summarizes the main features and results of our study and compares them with those of Edelen and Warner (2001) and Goetzmann and Massa (2003). We attribute the difference in results to the different nature of our data set. One advantage of our data set is that we focus on transfers only. The data sets used by Edelen and Warner (2001) and Goetzmann and Massa (2003) do not isolate the transfer component of the flows. As argued by Fant (1999), the net transfer component of mutual fund flows is subject to smaller frictions than net sales. In the case of 401(k) investors, transfers, unlike other 401(k) flows such as contributions and distributions, are the result of an explicit investor decision. Thus, transfers are important to isolate out because they best capture investor sentiment. Remember that new purchases of 401(k) funds through contributions are based on the timing of payroll deductions and in most cases are automated. Likewise, withdrawals are often motivated by exogenous “liquidity” shocks, which carry little information about investors’ intentions. Another advantage of our data is that 401(k) transfers, unlike overall mutual fund flows, reflect only the investment decisions of individuals. In addition, 401(k) transfers are free of tax implications, whereas changes in mutual fund allocations and withdrawals may lead to capital gains taxation. In summary, the data that we use are likely to be better indicators of small-investor preferences, or "sentiment," than the data used by Edelen and Warner (2001) and Goetzmann and Massa (2003).

[Insert Table 1 about here]

It is also worth noting that, in addition to having specific information on the transfer component of flows, our data set covers longer and more recent time periods than Edelen and Warner (2001) and Goetzmann and Massa (2003): Edelen and Warner (2001) use data for the February 1998-June 1999 period, while Goetzmann and Massa (2003) use data for the May 1994-December 1997 period. Furthermore, our data set is more disaggregated than the one of Edelen and Warner (2001)—they only look at aggregate equity mutual fund flows—and it is more comprehensive than the one used in Goetzmann and Massa (2003)—they only focus on three Fidelity equity index funds. One disadvantage of our data set relative to the one used by Goetzmann and Massa (2003), though, is that we only have information on net transfers and not, separately, on transfers in and transfers out of a given asset class; this limits somewhat the conclusions that we can draw from our analysis (more discussion of this below).

Overall, the strong correlation between 401(k) transfers and returns that we document is surprising in light of the limited amount of rebalancing activity documented in 401(k) plans. It appears that while 401(k) investors rarely change allocations, when they do so their (net) decisions are strongly correlated with market returns. Whether this finding is worrisome or not depends on the underlying investor behavior leading to our empirical results. If what we observe is the result of only few investors changing allocations in response to market returns, and if positive-feedback trading is the optimal policy, then there is nothing to worry about. On the other hand, if positive-feedback trading is widespread, and if, as a result of positive-feedback trading, investors persistently deviate from their long-run optimal allocations, then we are facing an important phenomenon that should be addressed by financial education programs.

Unfortunately, given the net aggregate nature of our data set, we cannot tell how pervasive positive-feedback trading behavior is. In addition, without a welfare analysis that includes all of an investor's assets, human capital, trading costs, family situation, etc., it is impossible to determine how costly positive-feedback trading in 401(k) accounts really is. Hence, a comprehensive investigation of the extent of positive-feedback trading in 401(k) accounts and its impact on investor welfare is left to future research.[3]

The paper is organized as follows. The next section describes the data set and provides some general summary statistics. Section 3 explores the relationship between the transfer and return series through a simple correlation analysis and then a vector autoregression representation (hereafter, referred to as a VAR) that jointly models the transfers and returns series. Section 4 replicates Edelen and Warner's (2001) tests in order to determine whether there is evidence of feedback trading. Section 5 concludes.

DATA AND GENERAL SUMMARY STATISTICS

Description of the Data and Comparison with Other Studies

This study is made possible by a data set compiled by Hewitt Associates LLC, a global management-consulting firm. The Hewitt data set is representative of the trading activity of employees of large plan sponsors (over 5,000 employees), offering daily valuation of plan balances and daily trading capabilities to employees. The representativeness of the Hewitt data set is highlighted by the fact that large employers represent 52% of the total assets in 401(k) plans, and Hewitt handles the administration for over 40% of the large-employer market, for over 10 million participants. Our data set is created from a subset of this larger group of participants.[4] Changes in the composition of individuals' existing assets can be communicated to the plan administrator until 4:00PM (ET) resulting in a transfer of funds at that day's net asset value (NAV) for the funds involved. Changes submitted after 4:00PM result in transfers at the next day's NAV.

As mentioned earlier, this paper focuses specifically on transfers, or investor-initiated movements of existing monies from one fund to another.[5,6] There are several advantages to this, which we have already mentioned in the Introduction and will discuss in more detail at the end of this section. As mentioned earlier, we do not look at asset flows generated from new contributions or distributions. Hewitt tracks the daily transfer activity among 13 different asset classes of mutual funds. On average, at the time of the data collection for this study, plan sponsors tracked by Hewitt offered ten investment options to employees. Nationally, according to the Hewitt annual 401(k) survey, employers on average offer eight investment options to employees and 64% allow participants to transfer existing balances between funds on a same-day basis. The data set starts on August 4, 1997, and ends on September 30, 2002.

The 13 asset classes identified in the Hewitt data are as follows: Money Market, GIC/Stable Value, Bond, Balanced, Lifestyle/Pre-Mix, Large U.S. Equity, Medium U.S. Equity, Small U.S. Equity, International, Emerging Markets, Specialty/Sector, Window, and Company Stock. Specialty/Sector includes mutual funds that concentrate their investment in a single industry/sector. Window represents an investment option available in some 401(k) plans, where participants can invest in different types of individual securities including individual stocks through a brokerage window. This option was not available and considered an asset class during the early years of our data sample. No information is available regarding where the funds are invested in the brokerage window. For each of the 13 classes, Hewitt provides the daily balances of each class, the daily new contributions to each class, the daily outflows from each class, and the daily net transfers (funds being transferred to or from another asset class).

For various reasons, we eliminated from the analysis of correlation patterns five asset classes: Company Stock, the Specialty/Sector, International, Window, and Emerging Markets. We eliminated Company Stock and the Window asset class because a clear return benchmark is not available for either.[7] We need a benchmark in order to control for outliers in the balance series and to investigate the origin of the contemporaneous relationship between transfers and returns. Since we do not have a clear benchmark return for Company Stock and the Window investments, there is no way to test if transfers in and out of these asset classes affect (or are affected by) prices. The Window asset class was also not always available through the sample. The Specialty/Sector (healthcare and technology sectors) is excluded because aggregate balances are modest. Finally, we also exclude International and Emerging Markets mainly to contain the dimensionality of the analysis.

We consolidate the remaining eight asset classes into six asset classes: Money Market/GIC/Stable Value ("GIC"), Bond, Balanced/Lifestyle/Pre-Mix ("Balanced"), Large U.S. Equity ("Large Equity"), Medium U.S. Equity ("Medium Equity"), and Small U.S. Equity ("Small Equity"). We use the J.P. Morgan U.S. Cash Three Month Return Index for the GIC benchmark; the Lehman U.S. Aggregate Bond Index for the Bond benchmark; the S&P 500 Index for the Large Equity benchmark; the S&P 400 Index for the Medium Equity benchmark; and the Frank Russell 2000 for the Small Equity benchmark. Finally, the Balanced benchmark is constructed from the S&P 500 and the Lehman Aggregate Bond Index. The weights are 60% and 40%, respectively. These daily returns series are from Datastream. (Daily returns are continuously-compounded and include re-invested coupons and dividends.)

Since previous research has shown that macroeconomic announcements impact bond and equity returns (e.g., McQueen and Roley, 1993; and Balduzzi, Elton, and Green, 2001), we have also collected data on 28 major macroeconomic announcements, using the Bloomberg database, to use as controls.[8] The data include the announcement release date, the announced indicator and the forecast compiled by a Bloomberg News Survey.

The two most important features of the data used in this study are that they are limited to trading activity by 401(k) investors and are at the daily frequency. The majority of previous mutual fund flow literature has used data sets that include flows generated by institutional investors and private investors in both retirement and non-retirement accounts. The non-retirement account activity can be easily dominated by large institutional investors.[9] Furthermore, there are only a handful of studies that use

401(k) trading data and returns, and their focus is either very different from ours or their data set is limited. For example, Yamaguchi et al. (2006) look at trading and subsequent portfolio performance not whether returns are motivating trading. Elton, Gruber and Blake (2006) use data derived from 11-k filings with an annual periodicity; while Agnew, Balduzzi, and Sundén (2003) use administrative data from only one 401(k) plan representing less than 7,000 participants, compared to our sample of nearly 1.5 million participants from multiple plans.

Another distinctive feature of our data set is that it has specific information on the transfer component of 401(k) flows. As mentioned in the Introduction, 401(k) transfers should be better indicators of small-investor preferences than overall mutual fund flows. In addition, focusing solely on transfers enables us to easily search for data errors by constructing data filters. By definition, the sum of net transfers across asset classes should equal zero on any given day and we use this to identify days with potential errors. Obviously, this condition cannot be imposed on total mutual fund flows. This is an advantage to our data because of the issues with of pre-flow *vs* post-flow NAV reporting in the TrimTabs data, as discussed by Greene and Hodges (2002). Further details on the treatment of outliers and the construction of the transfer series can be found in the Appendix.

Summary Statistics

Table 2 provides a summary of the average daily balances, transfers, and absolute transfers within the six asset classes that will be considered in the correlation and regression analysis. In addition, for completeness, we have included in Table 2 the five asset classes that are not part of the more detailed analysis for the reasons explained earlier. Of the classes reported, the Company Stock class has the highest daily average balance of $18.8 billion. The next most popular investment choice of the reported asset classes is the Large Equity asset class, with an average daily balance of $17.2 billion. These choices may be popular because they are common offerings in 401(k) plans and because company stock and large U.S. equity funds were among the earlier choices offered to investors. In comparison, the balances of the other asset classes are small, ranging between \$0.07 and \$15.5 billion. Note that, assuming an average allocation of 60% to equities for the Balanced asset class, and excluding the brokerage window from the calculations, we obtain an overall average aggregate allocation to equities of \$47.7 billion, or 70% of the total. This is roughly in line with the average allocation to equities in mutual funds documented by the Investment Company Institute for the year 2002 (Brady, Holden, and Short).[10]

[Insert Table 2 about here]

The Signed Dollar Transfers columns and the Absolute Dollar Transfers columns provide information on the direction of the flows and their absolute size, respectively. Transfers are on average positive for all asset classes, but for Balanced, Large Equity, International, and Company Stock.[11] The largest average positive daily transfers are associated with the GIC, averaging \$4 million. The GIC fund is also associated with the largest average absolute transfers (\$28.3 million). Company Stock transfers are the most negative (-\$2.8 million) on average; while the average absolute transfer is the third largest (\$12.8 million). The Window asset class is associated with the lowest average absolute transfer.

The Signed Dollar Transfers/Previous Day's Balance columns provide statistics for the dollar transfers standardized by the previous day's balance.[12] The means of the transfers are all very small, at most 9 basis points for Emerging Markets. The standard deviation of percentage transfers ranges from about 9 basis points (Balanced and Large Equity) to 3.6% (Emerging Markets). In addition, to quantify the percentage of each asset class that trades daily, we construct a percentage absolute transfer measure by dividing each asset class' absolute dollar transfers by the previous day's balance. This transfer measure quantifies the daily absolute percentage change in a given asset class, due exclusively to transfer activity. The means of the absolute percentage transfers series are at most 184 basis points for Emerging Markets, while standard deviations range from about 7 basis points (Balanced, Large Equity, and Company Stock) to 313 basis points (Emerging Markets). While the daily trading activity may seem small, these numbers are substantial when they are annualized. For example, average absolute annual turnover in the GIC asset class is 45% (0.0018 absolute dollar transfers/previous day's balance*250 trading days in a year).

WHAT IS THE RELATIONSHIP BETWEEN TRANSFERS AND RETURNS?

In this section, we explore whether daily aggregate 401(k) trading is related to market returns. Our goal is to determine whether market movements at the daily level prompt some 401(k) participants to trade away from poor performing investments into safer investments, and whether investors are treating equities and fixed income assets as two broad investment classes that they trade between.

There is limited research in this area examining retirement investments exclusively. Agnew, Balduzzi and Sundén (2003) find evidence of feedback trading with a one-day lag, but weak evidence of contemporaneous (or same day) feedback trading. Also, Elton, Gruber, and Blake (2006), using annual data, find that 401(k) investors tend to change their allocations in a way that accentuates the drift in allocations already occurring because of returns.

We begin our investigation in the next section by looking at simple correlations between aggregate asset-class transfers and asset-class returns. We then explore whether the contemporaneous relationships we observe in the simple correlations persist once lead-lag effects, the impact of news, and day-of-the-week effects are controlled for in a VAR framework that models jointly the returns and transfers. This analysis leads us to conclude that there is a strong contemporaneous effect. However, we cannot disentangle the nature of the contemporaneous effect with the VAR methodology. Are returns reacting to transfers or vice versa? Therefore, in the next main section, we use a method introduced by Edelen and Warner (2001) to investigate the nature of the contemporaneous relationship and determine whether there is evidence supporting contemporaneous positive-feedback trading.

Simple Correlations

We begin our analysis by looking at the transfer series and return series separately and focusing on their autocorrelations. Table 3, Panel A examines the transfer series. Transfers in all asset classes display moderate persistence, which is mainly limited to the first few lags: serial correlation coefficients at one lag vary between -19% and 27%, and only one transfers series (Bond) exhibits serial correlation above 10% beyond 5 lags**.** Table 3, Panel B looks at the time-series properties of the returns on the four benchmarks. As one would expect, there is little serial correlation in returns. Only one of the correlation coefficients is significant at the 1% level: the lag-three coefficient for Bond returns, at -8.1%.

[Insert Table 3 about here]

Table 4 documents the contemporaneous cross-correlations between transfers and returns. The upper left corner of the table focuses on the cross-correlations of transfers *only*. The fixed income classes (GIC and Bond) are all negatively related to the Equity classes. Transfers in Balanced and Equity funds are positively related to each other. Although not reported in this table, we also find the overall lack of serial dependence found in Table 3, Panel A and B, extending to the cross-correlation patterns. Overall, these results suggest that, in the aggregate, 401(k) investors tend to shift funds between equities and cash or bonds, and that this is driving much of the activity.

[Insert Table 4 about here]

The cross-correlations between returns can be found in the lower right hand corner of the table.[13] As one would expect, there are strong and significant positive contemporaneous correlations between returns in the equity classes, but weaker and negative correlations between bond and equity returns. While not reported in the table, there is a similar absence of serial dependence, with only two of the non-contemporaneous coefficients significant at the 1% level.

The lower left hand corner of Table 4 allows us to examine how returns relate to transfers. The contemporaneous correlations are strong: out of 24 correlation coefficients, 19 coefficients are significant at the 1% level. Bond returns correlate significantly and positively with bond transfers (10%), but correlations with other transfers are smaller and insignificant. All three equity-benchmark returns correlate negatively with GIC and Bond transfers, while they correlate positively with Balanced, Large Equity, Medium Equity, and Small Equity transfers. These correlations are both statistically significant and economically meaningful. The correlations between equity returns and GIC transfers, for example, range between -48% and -43%, while correlations between equity returns and equity transfers range between 16% and 45%. This suggests that some individuals may actually be reacting to returns on the same day. Given the documented inertia in 401(k) plans, this is a somewhat surprising finding.

Finally, we calculate, but do not report, the lag and lead cross-correlations between transfers and returns and a few of our findings are worth mentioning. First, we find evidence of positive-feedback trading from one day's returns to the next day's transfers. For example, we find that Bond returns correlate positively with next-day Bond transfers, and all three equity returns correlate positively with next-day Large Equity transfers. We also observe evidence of price reversals because returns at times correlate negatively with lagged transfers. Bond returns, for example, correlate significantly and negatively with Bond transfers over the previous two days: -7.5% and -8.2%, respectively. All three equity returns correlate negatively with all three equity transfers at one, two, and three lags, and several of these correlations are significant.

We further illustrate the relationships between transfers and returns by plotting standardized (de-meaned and divided by the standard deviation) transfers against standardized returns for the four pairs: Bond net transfers/Bond returns, Large Equity net transfers/Large Equity returns, Medium Equity net transfers/Medium Equity returns, Small Equity net transfers/Small Equity returns. The graphs are presented in Figures 1-4. In the same graphs we also report the regression lines of returns on transfers. The slopes of the regression lines correspond to the correlation coefficients reported in Table 4.

[Insert Figures 1-4 about here]

VAR

The contemporaneous correlations that we observe in the previous section could be a result of (or partially explained by) several factors other than transfers (returns) reacting to returns (transfers) on the same day. For example, these results could be influenced by the relationships between leads and lags of transfers and returns, the impact of macroeconomic events, or day-of-the-week effects. Therefore, to test this we use a VAR framework to determine the influence of these variables. A VAR model is used extensively in macroeconomics and finance to capture the dynamics of multiple time series in a simple framework (an excellent non-technical explanation of the methodology can be found in Stock and Watson, 2001). We find evidence of the significance of these variables and, therefore, control for their effects so that we can better understand the contemporaneous relationship between returns and transfers. This is accomplished by using the innovations estimated from the VAR and these results are found at the end of this section.

Our VAR includes ten equations. The dependent variables include the six transfers and the four daily benchmark returns. The explanatory variables are lagged values of the dependent variables, contemporaneous and one-day lagged values of the 28 macroeconomic surprises, and four dummy variables identifying day-of-the-week effects (the four daily dummies capture effects on Tuesday, Wednesday, Thursday, and Friday). Minimization of either the Schwartz Criterion or the Akaike Information Criterion leads to the same choice of lag length: one lag.[14]

Table 5, Panel A reports results from the first six equations, the equations corresponding to the six transfers. Consistent with Edelen and Warner (2001), we find that that lagged equity flows predict flows. Exclusion tests show how lagged transfers jointly explain future transfers at the 1% significance level or better, for all six transfers. Lagged returns are also significant in predicting future transfers, with the only exception of Small Equity. In addition, macroeconomic surprises have a joint significant effect on all six transfers series. Only the GIC and Large Equity transfer series report jointly significant day-of-the-week effects at the 1% level. Finally, R-squareds range from 2.93% (Small Equity) to 14.25% (Large Equity), confirming the limited degree of persistence in transfers already documented in Table 3, Panel A.

[Insert Table 5 about here]

Table 5, Panel B reports results for the last four returns equations. Findings mentioned in the previous section are supported in this analysis. Lagged transfers have some predictive ability with respect to future returns, with the exception of Small Equity returns. This predictability from transfers to returns is consistent with evidence of price reversals in the cross-correlation patterns mentioned earlier, but at odds with the results of Edelen and Warner (2001), who find insignificant evidence of price reversals. Macro innovations also are significant, while day-of-the-week effects are not.

The previous results suggest that any analysis of contemporaneous transfers and returns should control for lagged returns and transfers, macroeconomic events, and day-of-the-week effects. Therefore, to examine the contemporaneous correlations without the influence of these factors, we use the innovations (i.e., the errors) generated from the ten VAR equations and estimate their correlation coefficients. Similarly to Table 4, Table 6 also shows significant contemporaneous correlations between transfers and returns. Out of 45 coefficients reported in the entire table 41 are significant at the 5% level or better (40 at the 1% level). We see that GIC and Bond transfers are negatively related to equity transfers, while equity transfers are positively related with each other. In addition, returns in the equity classes are negatively related to transfers into GIC and bond asset classes and positively related to transfers into equities. In particular, it is worth noting the very strong negative correlation between Large Equity returns and GIC transfers: -51%. This means that if we condition on the innovations in 401(k) transfers into safe assets, we explain slightly more than 25% of the daily variation in the innovations S&P 500 returns.[15] This is a much stronger relationship to returns than documented between overall daily equity mutual fund flows and equity returns. For example, Edelen and Warner (2001) condition on aggregate daily equity mutual fund flows and explain at most 3.9% of the daily returns on the NYSE index.

[Insert Table 6 about here]

Thus, these results are consistent with, in the aggregate, 401(k) investors trading between equities and fixed income asset classes, as well as reacting to and/or contributing to returns. Unfortunately, the VAR analysis cannot determine the direction of contemporaneous causality between transfers and returns. Therefore, it is important that we perform further analysis to determine whether feedback trading actually occurs and that it is not exclusively transfers that lead returns. We do this in the next section.

INVESTIGATING FURTHER THE CONTEMPORANEOUS CORRELATIONS

The Current Debate and Our Contribution

The existing literature does not solidly point to causality between returns and transfers going in one direction only. For example, Chalmers, Edelen, and Kadlec (2001) document the profits that investors could realize by trading equities at stale prices through mutual funds. These profits constitute a strong incentive for investors to practice positive-feedback trading on the same day. Indeed, investors do appear to take advantage of this opportunity in international mutual funds, as documented by Greene and Hodges (2002).[16]

However, some studies argue that causality goes in the opposite direction. Both Edelen and Warner (2001) and Goetzmann and Massa (2003) find that equity-fund flows correlate significantly only with equity returns between 11:00 or 12:00 and the close of the market. If flows are responding to returns, then there would be no reason for the absence of correlation with returns early in the day. But if there is no feedback trading, that means that flows influence returns and why would this be? One view is that flows capture demand effects that immediately impact returns. This could be because mutual fund flows (or 401(k) transfers, in the case of this study) correlate with and/or contribute to order imbalance, which, in turn, directly affects valuations (see Chordia, Roll, and Subrahmanyam, 2002).[17] In addition, transfers may contain information about investors' risk aversion (Lee, Shleifer, and Thaler, 1991) or about news relevant for valuation. In this case, transfers would be a proxy for information, rather than for liquidity (price-pressure) effects.

Given that existing studies do not clearly support causality going uniquely in one direction, we use our new dataset to implement the intraday tests of Edelen and Warner (2001) and our new results conflict with their findings. To replicate the tests, we obtain data on intraday returns on the S&P 500 cash index from Tick Data (Source: http://www.tickdata.com/). We partition the trading day into two intervals. The first interval is between market opening, 9:30 (ET), and 1:00 (ET), and the second is between 1:00 (ET) and closing, 4:00 (ET). Following Edelen and Warner (2001), we regress returns on transfers and we also regress transfers on returns. The results are presented in Table 7. When we regress returns on transfers, we model the regressions using morning and afternoon returns within an exactly-identified Generalized Method of Moments (GMM; Hansen, 1982), and we test the equality of coefficients across regressions. GMM is a general estimation framework that includes ordinary least squares (OLS) as a special case. In our setting, modeling the regressions for morning and afternoon returns within GMM leads to the same estimates as standard OLS, but allows us to perform joint tests on the coefficients of the two regressions.

[Insert Table 7 about here]

We standardize all the series by their standard deviations over the sample. Our null hypothesis is that of *no intraday lead-lag effects*: morning returns (transfers) affect morning transfers (returns), but not afternoon transfers (returns). In other words, the relationship between transfers and returns is instantaneous, and returns (transfers) immediately affect transfers (returns). Under our null hypothesis, the regression coefficients of the morning- and afternoon-return regressions (or the coefficients associated with morning and afternoon returns in the same transfers regression) are in the ratio $\sqrt{h_1}/\sqrt{h_2}$, where

h_1 and h_2 are the lengths of the morning and afternoon intervals.[18] We test this restriction by means of a Wald-style test. The resulting chi-squared statistic has one degree of freedom.

Looking at Table 7, Panel A, when we regress returns on transfers, we find that for all three equity classes the effect of morning returns is positive and significant. Therefore, we do not reject the null of no lead-lag relationship. When we regress transfers on returns, the effect of morning returns is again positive and significant in all cases, and we do not reject the null of no lead-lag relations. To test the robustness of these findings, we repeated the exercise using returns on the NYSE cash index (not reported in the table), with essentially the same results. In addition, following Edelen and Warner (2001), we also consider the time intervals 9:40-11:00 (ET) and 11:00-4:00 (ET) in Panel B. Similarly, in Panel C, following Goetzmann and Massa (2003), we consider the time intervals 10:00-12:00 (ET) and 12:00-4:00 (ET). For these two alternative definitions of intraday returns, we still find evidence of correlation between morning returns and transfers suggesting our initial results are robust.

Taken together, these results suggest that positive feedback trading is occurring in retirement accounts. However, based on prior research, we still know very little about 401(k) trading except that individuals tend not to be active traders and generally make only a few trades over a long period of time.[19] In addition, previous studies show that demographics such as gender and salary can have an influence on the probability of trading. Unfortunately, given the aggregate nature of our data set, we cannot say whether this activity is generated by a few investors changing allocations frequently or infrequent rebalancing that is more or less evenly distributed across investors. We, therefore, leave this for future research when a more complete data set is available.

In summary, our new findings suggest that an immediate response of transfers to returns may exist in retirement accounts and this is a significant finding.[20] Notably, these results differ from Edelen and Warner (2001) and Goetzmann and Massa (2003), who find no evidence of significant correlations between morning returns and mutual fund flows.

CONCLUSIONS

This paper takes a closer look at the aggregate net behavior of 401(k) investors relative to same-day market returns using a unique dataset of daily transfer activity from nearly 1.5 million accounts over a five-year period beginning in 1997. Studying this type of trading activity is especially relevant given the current market movements. While previous research has demonstrated a tendency not to trade in retirement accounts, we find that some participants are reacting to asset returns on the same day, and tend to make trades from equities to fixed income or vice versa.

As discussed in the Introduction, the type of trading patterns we document could be of concern if they are a result of widespread but infrequent trading that leads participants to persistent deviations from their long-run optimal allocations. These deviations could have negative effects on expected utility. If future research were to provide further evidence supporting this scenario, then developing financial education programs to address this issue should become a priority. However, developing effective strategies will not be easy given that many individuals have limited financial experience and interest in the stock market. As a result, educators will have to consider creative ways of delivering the message, especially as there is mixed evidence regarding the effectiveness of standard company training seminars (Choi, Laibson, Madrian, and Metrick, 2006). "Just-in-time" training, such as requiring participants to view the pros and cons of trading immediately before they are permitted to proceed with a trade on the web, and using methods to help individuals "experience" the drawbacks of trading, such as video games, may make the lessons more salient and easier to remember when the time is right.[21] However, these methods are not without their own issues.[22] Plan sponsors should also consider launching targeted communication campaigns designed specifically to reach participants that might be more likely to trade and to not think of the future consequences.[23]

Endnotes

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1 It is estimated that in 2003, 40 million individuals were actively enrolled in 401(k) type plans, managing over $1.7 trillion in funds (Buessing and Soto, 2006). Hewitt provides the source for the number of participants included in the index and reports this figure on their website http://www.hewittassociates.com/intl/na/en-us/ourservices/RetirePlanFaq.aspx#1.

2 A GIC is a guaranteed income contract that is issued by an insurance company. It is often offered in retirement plans and provides a stable return with low risk to investors.

3 We do provide a limited investigation of these issues in the context of a simulation exercise (results of the simulation available in a separate Appendix on the authors' website). We simulate the behavior of a cohort of investors with identical initial wealth, who change their allocations infrequently, and who, when they change allocations, implement large changes. This behavior is consistent with what documented, for example, by Agnew, Balduzzi, and Sundén (2003). In addition, investors in our simulated cohort are all positive-feedback traders who change allocations in the direction dictated by market returns. We show that this behavior leads to realistic yearly asset turnover at the individual level, to realistic volatility of net aggregate transfers, and realistic correlations between transfers and returns. In addition, we perform a utility cost calculation: we compare the expected utility realized by a positive-feedback trader to the expected utility of an investor who optimally allocates assets based on her risk aversion. Assuming that the individual's total wealth is portfolio wealth, and abstracting from all other frictions and complications, we obtain utility costs as high as 20% of initial portfolio wealth. This is comparable to the utility costs computed by Poterba (2003) in association with overinvestment in company stock. In summary, our simulation analysis is broadly supportive of the more worrisome of the two scenarios described above.

4 Hewitt's stated objective is to create an index that represents the behavior of individuals participating in large 401(k) plans (i.e., plans with over 5,000 employees) that offer daily valuation of plan balances and daily trading capabilities to employees. On average, the companies in the Hewitt 401(k) Index employ 28,000 individuals. Hewitt selects the subset of the plans used in the index so that it is as representative

as possible. They do this by choosing companies that represent a variety of industries, plan designs and offerings. Demographic data is not available for the time period studied, but as of 2008, Hewitt reports that the average participant in the index was 42 years old with ten years of job tenure and reported an average salary of $42,000. Finally, Hewitt acknowledges that its data may include account from non-qualified, i.e., non-after-tax, plans. However, they maintain that balances from these plans would amount to less than one percent of total assets.

5 One limitation of our data set is that we only have data on the net transfers in and out of an asset class. Separate data on the inflows and outflows of money could be useful. Goetzmann and Massa (2003), for example, show that equity index fund inflows and outflows react differently to the previous day's equity index returns: outflows are significantly and negatively affected by past returns, whereas the effect of returns on inflows is insignificant.

6 Plan sponsors sometimes replace or liquidate funds leading to spikes in reported transfers that are sponsor-initiated. The architects behind the Hewitt Index are aware of this and are careful to control for this trading activity. Hewitt takes efforts to identify abnormal activity and eliminate the related company transfers when they occur. Therefore, the data used in the study should exclude most or all of the sponsor-initiated transfer activity.

7 The exclusion of company stock from the analysis is due to the fact that we do not have plan level data. When we relate aggregate transfers in company stock to the returns on the three equity indices, we find significant *negative* correlations, ranging between -30.06% and -23.59%. This is in contrast with the positive correlations documented for transfers in the different equity classes. This result is surprising and calls for further analysis of trading patterns in company stock.

8 Missing data from the Bloomberg database have been filled using a variety of other sources, such as LexisNexis, Briefing.com, Econoday.com, the Bureau of the Census, and the Board of Governors of the Federal Reserve. The announcements include: Advance Retails Sales, Business Inventories, Capacity Utilization, Chicago Area Purchasing Manager Index, Consumer Confidence, Consumer Credit,

Consumer Price Index, Consumer Price Index (core), Employment Cost Index, Existing Home Sales, Factory Orders, Federal Reserve Bank of Philadelphia Survey, FOMC Announcements, GDP, Housing Starts, Index of Leading Indicators, Industrial Production, Initial Jobless Claims, NAPM Index, New Home Sales, Nonfarm Payrolls, Personal Income, Personal Spending, Producer Price Index, Producer Price Index (core), Trade Balance, Unemployment Rate, Wholesale Inventories.

9 Two papers highlight the differences in behavior between institutional and retail mutual fund investors: Del Guercio and Tkac (2002) and James and Karceski (2002).

10 The Investment Company Institute reports historical figures for mutual fund holdings in defined contribution plans. Defined contributions plans can hold other assets in addition to mutual funds. If we consider their Hybrid category to be 60 percent equities, then the share of equity holdings of total defined contribution mutual fund holdings in 2002 was 74 percent.

11 Note that the sum of average net dollar daily transfers is not exactly zero, but amounts to $75,490. This is because the Window transfer series only covers the second half of the sample.

12 Note that these percentage transfer series are not exactly the series used later on in the analysis as two additional filters are applied; see the last section of the Appendix for details. As a result, caution should be taken when interpreting these results.

13 Note that the transfers series are winsorized by eliminating the observations that are more than three standard deviations from the mean (details in the Appendix). Hence, our results should not be driven by a few influential observations.

14 While the ten-equations VAR is a large system, note that the choice of lag length, one, is as parsimonious as possible. In addition, the number of degrees of freedom for each equation is very high: we have between 1,118 and 1,124 daily observations for the six transfers equations (the differences are due to differences in missing values) and 1,151 observations for the returns equations, with 71 total parameters to estimate in each equation (intercept, four day-of-the week dummies, ten lagged dependent variables, and 56 contemporaneous and lagged surprises in economic announcements). We also assess

the stability of the system by performing two exercises. First, we estimate the VAR allowing the coefficients on lagged transfers and returns to vary across the two subsamples August 1997-December 1999 and January 2000-September 2002 (this amounts to splitting the sample roughly into half) and we perform a Wald-style test of the null of no regime break. The evidence of regime breaks is not strong: the chi-squared statistics (ten degrees of freedom) lead to rejections at the 1% level in only two of the transfers equations (Bond, Small Equity) and two of the returns equations (Medium Equity, Small Equity). Second, we estimate the VAR separately on the two subsamples August 1997-December 1999 and January 2000-September 2002, and we compute the correlation matrices of the innovations. We find that the correlation matrices are similar across the two subsamples and analogous to those computed for the entire sample and reported in Table 6. Finally, it is worth noting that the cross-correlations between the original series and the cross-correlations between VAR innovations reported in Table 4 and Table 6, respectively, are very similar. This is consistent with the low persistence in transfers and returns and shows how the introduction of the VAR changes only marginally the basic results.

15 Note that the VAR equation regressing S&P 500 returns on lagged returns, lagged transfers, day-of-the-week dummies, and economic announcements explains an additional 4.36% of the daily variation of S&P 500 returns.

16 Note, though, that most 401(k) providers post-2003 (and some providers even before 2003) either assess redemption/transaction fees or restrict trading activity to protect longer term shareholders and reduce or eliminate the profitability of short-term trades.

17 Note that it is not clear how much net mutual fund flows actually contribute to order imbalance on the same day, as portfolio managers only know at the end of the day the exact net inflow or outflow.

18 It is clear that the coefficients are in the ratio $\sqrt{h_1} / \sqrt{h_2}$ when you note that the regression coefficients equal the correlation coefficients, and we have

$$\rho_1 = \frac{\sigma_{xr} h_1}{\sigma_x \sigma_r \sqrt{h_1}} = \frac{\sigma_{xr}\sqrt{h_1}}{\sigma_x \sigma_r}$$

$$\rho_2 = \frac{\sigma_{xr} h_2}{\sigma_x \sigma_r \sqrt{h_2}} = \frac{\sigma_{xr}\sqrt{h_2}}{\sigma_x \sigma_r},$$

where σ_{xr} is the instantaneous covariance between transfers and returns, and σ_x and σ_r are the instantaneous standard deviations of transfers and returns.

19 For example, in Agnew, Balduzzi and Sundén's (2003) sample 87.55% of the participant-year trade observations are zero, 11.80% of the observations are between one and five, and only 0.66% of the observations exceed five trades per year. Furthermore, Mitchell et al. (2006) find that 79.50% of their sample of 1.2 million workers make no trades over a two-year period and an additional 18.30% make only one to five trades. This leaves less than 3.00% that make more than 5 trades over the two-year period.

20 In an earlier version of this paper, we further investigated the nature of the contemporaneous relationship between transfers and returns, using the newly-developed identification-through-heteroskedasticity approach of Rigobon (2002, 2003), and Rigobon and Sack (2003, 2004). The results of this analysis, available in an Appendix on the authors' website, confirm the instantaneous response of transfers to returns and of returns to transfers.

21 There is evidence that high school students playing stock market games have higher literacy scores than those who did not play (Mandell, 2008). In addition, a new video game targeted at lower income women is showing some initial success increasing financial literacy scores after play (Doorways to Dreams Fund, 2009).

22 It is possible that being exposed to stock market simulations may also have the counterproductive effect of encouraging day trading or other short-run behaviors, given the typical short time frames of the experiments. We thank an anonymous referee for this comment.

23 Weiner and Doescher (2008) discuss how persuasive communications can be used to encourage savings and some of the approaches outlined may be effective in curbing unwanted trading. In addition, the communications could be targeted specifically to reach participants that might be more likely to trade and to not think of the future consequences. Howlett, Kees and Kemp (2008) show how future orientation, as well as self-regulation and financial knowledge, can influence long-term financial decisions. Thus, a potentially effective communication strategy would be to tailor the communications to participants based on their future orientation.

APPENDIX

Removing Outliers and Constructing the Transfer Series

We calculate daily transfers by dividing the signed transfer by the corresponding previous day's balance. Unfortunately, there are possible entry errors in the transfers and balances series. Moreover, due to changes in the plans covered by the Hewitt data set, there are also sudden changes in the balances series. This appendix describes how the possible errors in the transfers and balances series have been handled and how the percentage transfer series have been constructed.

Transfers

The sum of all asset-class transfers, the overall net daily transfer, should equal zero because funds transferring into one asset class must be transferred out of another asset class. Thus, the overall net daily transfer differing from zero identifies a data error. In some cases, the non-zero overall net transfer values are very small relative to the amount of funds transferred on that day. We do not want to consider these transfers data errors, so we establish a rule to determine whether the overall net transfers are large enough to be considered errors. To do this, we calculate the overall transfer among the various asset classes by summing the absolute values of all net transfers, and dividing this sum by two. We then compare the overall net transfer to the overall transfer. If the overall net transfer is greater than 5% of the overall transfer (in absolute value), the transfers for all asset classes are considered data errors and changed to missing values.

Balances

The treatment of the balances series is more involved. Here, we need to distinguish between data errors and sudden jumps in the series due to changes in plan coverage. We expect data errors to show up as abnormal one-day jumps, which are "re-absorbed" on the following day. We denote these observations as "mean-reverting" outliers. On the other hand, we expect changes in the plans covered by the Hewitt data to show up as one-day jumps in the balances series that persist during the following days. We denote these observations as "persistent" outliers.

Note that Hewitt calculates an index of transfer activity among the asset classes covered by their data set. This index relates current transfer activity to a moving average of past transfer activity. The index contains a "multiplier" that adjusts for the inclusion or exclusion of plans from the data set. In several instances, the persistent outliers that we identify correspond to changes in the multiplier.

To separate and handle these two types of outliers, we used Hewitt's data on daily contributions, outflows, transfers and balances. From these series, we can back out the *implied* daily return for each of the asset classes. Outliers are observations for which the following two criteria are met: i) the implied return is more than one standard deviation from its mean; ii) the difference between the implied return and the corresponding benchmark return is more than one standard deviation from the mean of the differences.

Once the outliers are identified, the next step is to classify them as mean reverting, persistent, or "unclassified." In order to do this, we look at the implied returns on the day before and on the day after the day in question. If these implied returns are within one standard deviation of the average of the implied return, the balance is considered a persistent jump. However, if the implied return on the next day has the opposite sign as the implied return on the outlier day, and the implied return calculated from the day before to the day after is within one standard deviation of the average implied return, then it is considered a mean-reverting outlier. Outliers that do not meet the previous two criteria are considered to be unclassified.

The classified outliers from this algorithm are then visually inspected. In some cases, the outlier classification is changed. This is typically done when there is a series of consecutive days considered unclassified outliers. The last day of the consecutive series typically can be re-classified as a persistent jump.

Once the final classifications have been made, the series are altered as follows. A mean-reverting outlier is changed to the previous day's balance times one plus that day's benchmark return. Persistent outliers are kept as valid observations. Since these observations should correspond to changes in plan coverage, we identify different "coverage regimes" for each balances series. Finally, unclassified outliers are changed to missing observations.

Percentage Transfers

The filtered series for dollar transfers and balances are then used to calculate the percentage transfers. For the series used in the correlation and regression analysis, we then apply two more filters. First, we eliminate transfers observations that are more than three standard deviations from the average transfer value for that asset class. Second, we regress each fund's transfers against a constant and against a set of dummies. These dummies identify the different regimes in terms of plan coverage. This last step removes the mean of the series and possible residual mean effects due to changes in plan coverage. The transfers used in the correlation and regression analysis are the residual from this regression.

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TABLE 1

Comparison with other Studies

Study:	Data	Sample	Main results
Edelen and Warner (2001)	Daily aggregate U.S. net equity mutual fund flows (424 funds) from TrimTabs	2/20/1998-6/30/1999	▪ Returns correlate positively with contemporaneous net flows. ▪ Correlation significant for afternoon returns, but not for morning returns.
Goetzmann and Massa (2003)	Daily aggregate inflows and outflows for three Fidelity index funds: Spartan U.S. Equity, Index, Spartan Market Index, and VIP Market Index	5/23/1993-12/31/1997	▪ Returns correlate positively (negatively) with contemporaneous inflows (outflows). ▪ Correlation with net flows significant for afternoon returns, but not for morning returns.
Present study	Daily aggregate net transfers across six asset classes for 1.5 million 401(k) investors	8/4/1997-9/30/2002	▪ Returns correlate positively with contemporaneous net flows. ▪ Correlation significant for both afternoon returns and morning returns.

TABLE 2
General Summary Statistics
(8/4/1997-9/30/2002)

	Dollar Balances	Signed Dollar Aggregate Net Transfers		Absolute Dollar Aggregate Net Transfers		Signed Dollar Aggregate Net Transfers/Previous Day's Balance		Absolute Dollar Aggregate Net Transfers/Previous Day's Balance	
Asset Class	**Mean**	**Mean**	**Std.**	**Mean**	**Std.**	**Mean**	**Std.**	**Mean**	**Std.**
GIC	$ 15,464,711,533	$ 4,022,648	$ 39,498,613	$ 28,257,351	$ 27,878,951	0.0002	0.0025	0.0018	0.0018
Bond	$ 1,737,737,716	$ 1,503,371	$ 7,465,323	$ 4,713,515	$ 5,979,836	0.0007	0.0034	0.0025	0.0025
Balanced	$ 7,345,886,222	$ (1,235,706)	$ 7,461,950	$ 3,531,922	$ 6,687,651	-0.0001	0.0009	0.0005	0.0007
Large Equity	$ 17,244,168,671	$ (2,209,538)	$ 15,849,741	$ 10,432,232	$ 12,131,943	-0.0001	0.0009	0.0006	0.0007
Medium Equity	$ 2,966,174,488	$ 348,340	$ 5,593,017	$ 3,382,202	$ 4,467,112	0.0000	0.0018	0.0011	0.0014
Small Equity	$ 1,362,977,809	$ 611,950	$ 5,527,093	$ 3,467,515	$ 4,346,322	0.0004	0.0038	0.0026	0.0028
International	$ 2,439,139,533	$ (325,213)	$ 28,786,620	$ 19,474,213	$ 21,195,175	-0.0001	0.0112	0.0079	0.0080
Emerging Markets	$ 69,932,948	$ 10,628	$ 3,328,174	$ 1,432,172	$ 3,004,021	0.0009	0.0363	0.0184	0.0313
Specialty Sector	$ 409,203,193	$ 27,663	$ 4,266,846	$ 1,293,138	$ 4,066,108	0.0001	0.0085	0.0031	0.0079
Window	$ 201,895,655	$ 167,526	$ 1,967,679	$ 620,857	$ 1,874,518	0.0007	0.0116	0.0034	0.0111
Company Stock	$ 18,791,284,423	$ (2,846,179)	$ 18,853,860	$ 12,780,431	$ 14,145,976	-0.0001	0.0010	0.0007	0.0007

Notes: The table reports means of the aggregate net daily balances; means and standard deviations of the aggregate net daily signed and absolute dollar transfers; and means and standard deviations of the absolute dollar aggregate net transfers scaled by the previous day's balance.

TABLE 3

Serial Correlations of Aggregate Net Transfers and Returns

(8/4/1997-9/30/2002)

Panel A: Serial Correlations of Aggregate Net Transfers

Aggregate Net Transfers	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8	Lag 9	Lag 10
GIC	-0.188**	-0.040	-0.013	0.035	-0.016	-0.010	0.036	0.009	-0.069	0.049
Bond	0.213**	0.150**	0.157**	0.144**	0.058	0.061	0.101**	0.037	0.046	0.019
Balanced	0.251**	0.176**	0.148**	0.082*	0.084*	0.067	0.018	0.008	0.076*	0.049
Large Equity	0.272**	0.128**	0.066	0.076*	0.049	0.047	0.007	-0.012	0.018	-0.004
Medium Equity	0.092**	-0.014	0.016	0.077**	0.051	0.013	0.053	0.059	0.033	0.055
Small Equity	0.039	0.020	0.070	0.097**	0.071	0.056	0.063*	-0.023	0.100**	0.076*

TABLE 3 (Continued)
Serial Correlations of Aggregate Net Transfers and Returns
(8/4/1997-9/30/2002)

Panel B: Serial Correlations of Returns

Returns	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8	Lag 9	Lag 10
Bond	0.069*	-0.031	-0.081**	-0.037	-0.039	-0.001	0.031	0.001	0.031	0.020
Large Equity	-0.000	-0.048	-0.033	0.003	-0.049	-0.019	-0.025	0.006	0.014	0.028
Medium Equity	0.054*	-0.085*	0.028	0.015	-0.024	-0.046	-0.015	-0.006	-0.001	-0.035
Small Equity	0.075*	-0.063	0.061	0.033	-0.038	-0.036	-0.002	0.016	0.003	-0.040

Notes: ** p<.01 and *p< .05. Panel A reports serial correlation coefficients of the aggregate net transfers series and Panel B reports the serial correlation of the returns series. Significance is based on standard errors adjusted for heteroskedasticity.

TABLE 4

Contemporaneous Cross-correlations of Returns and Aggregate Net Transfers

(8/4/1997-9/30/2002)

Panel A. Contemporaneous Cross-correlation

		Aggregate Net Transfers						Returns			
	Asset Class	**GIC**	**Bond**	**Balanced**	**Large Equity**	**Medium Equity**	**Small Equity**	**Bond**	**Large Equity**	**Medium Equity**	**Small Equity**
Aggregate Net Transfers	GIC	1.00									
	Bond	0.33**	1.00								
	Balanced	-0.25**	-0.21**	1.00							
	Large Equity	-0.35**	-0.39**	0.51**	1.00						
	Medium Equity	-0.53**	-0.39**	0.38**	0.54**	1.00					
	Small Equity	-0.46**	-0.28**	0.25**	0.30**	0.49**	1.00				
Returns	Bond	0.00	0.10**	-0.04	-0.05	-0.03	0.02	1.00			
	Large Equity	-0.48**	-0.21**	0.24**	0.16**	0.42**	0.35**	-0.14**	1.00		
	Medium Equity	-0.44**	-0.24**	0.26**	0.20**	0.44**	0.35**	-0.16**	0.87**	1.00	
	Small Equity	-0.43**	-0.28**	0.25**	0.21**	0.45**	0.37**	-0.17**	0.80**	0.92**	1.00

Notes: ** p<.01 and *p< .05. The table reports contemporaneous cross-correlations between returns and aggregate net transfers. Significance is based on standard errors adjusted for heteroskedasticity and serial correlation (five lags).

TABLE 5

Results from VAR

(8/4/1997-9/30/2002)

Panel A: VAR Results, Aggregate Net Transfers Equations

	Aggregate Net Transfers					
Dependent Variable:	**GIC**	**Bond**	**Balanced**	**Large Equity**	**Medium Equity**	**Small Equity**
R-Squared	0.1217	0.0790	0.1284	0.1425	0.0321	0.0293
Durbin-Watson Statistic	2.05	2.04	1.98	2.04	2.02	1.99
Exclusion Tests:						
Lagged Transfers	23.88**	54.58**	47.51**	62.48**	19.66**	19.12**
Lagged Returns	68.79**	25.42**	51.15**	41.57**	10.31*	5.83
Macro Innovations	133.14**	124.91**	109.12**	188.08**	177.15**	99.82**
Week Days	16.61**	4.07	6.22	18.04**	6.66	10.92*

Panel B. VAR Results from Four Returns

	Returns			
Dependent Variable:	**Bond**	**Large Equity**	**Medium Equity**	**Small Equity**
R-Squared	0.0982	0.0436	0.0483	0.0401
Durbin-Watson Statistic	1.99	1.98	2.03	2.04
Exclusion Tests:				
Lagged Transfers	12.89*	14.90*	17.26**	11.28
Lagged Returns	5.22	7.94	8.93	12.42*
Macro Innovations	224.49**	112.98**	125.84**	116.72**
Week Days	4.39	3.74	6.35	3.77

Notes: ** p<.01 and *p< .05. The table reports statistics for a VAR of the six aggregate net transfers series and four returns series. The VAR also includes two sets of exogenous variables: dummy variables for the day of the week and surprises in macroeconomic announcements. Panel A reports results for the six aggregate net transfers equations. Panel B reports results for the four returns equations. We report R-squareds and Durbin-Watson statistics for each equation. In addition, we test whether blocks of regression coefficients are jointly equal to zero. Chi-squared statistics, adjusted for heteroskedasticity, are reported for these exclusion tests.

TABLE 6

Correlations of VAR Innovations

(8/4/1997-9/30/2002)

	Innovations	Aggregate Net Transfers: GIC	Aggregate Net Transfers: Bond	Aggregate Net Transfers: Balanced	Aggregate Net Transfers: Large Equity	Aggregate Net Transfers: Medium Equity	Aggregate Net Transfers: Small Equity	Returns: Bond	Returns: Large Equity	Returns: Medium Equity	Returns: Small Equity
Aggregate Net Transfers	GIC	1.00									
	Bond	0.38**	1.00								
	Balanced	-0.35**	-0.16**	1.00							
	Large Equity	-0.46**	-0.36**	0.42**	1.00						
	Medium Equity	-0.56**	-0.37**	0.38**	0.58**	1.00					
	Small Equity	-0.48**	-0.25**	0.20**	0.30**	0.47**	1.00				
Returns	Bond	0.02	0.10**	-0.07*	-0.05	-0.03	0.03	1.00			
	Large Equity	-0.51**	-0.25**	0.30**	0.22**	0.42**	0.35**	-0.14**	1.00		
	Medium Equity	-0.49**	-0.27**	0.31**	0.25**	0.44**	0.37**	-0.16**	0.87**	1.00	
	Small Equity	-0.48**	-0.32**	0.29**	0.26**	0.44**	0.38**	-0.18**	0.80**	0.92**	1.00

Notes: ** p<.01 and *p< .05. The table reports the correlation matrix of the VAR innovations. Significance is based on standard errors adjusted for heteroskedasticity

TABLE 7
Intraday Tests Table
(8/4/1997-9/30/2002)

Panel A: Morning Returns from 9:30 a.m. to 1:00 p.m, Afternoon Returns from 1:00 p.m. to 4:00 p.m.

S&P 500 Returns on Aggregate Net Transfers	Morning Returns	Afternoon Returns	Test of Equality
Large Equity Transfers	0.10 **	0.15 **	1.61
Medium Equity Transfers	0.29 **	0.32 **	1.25
Small Equity Transfers	0.27 **	0.23 **	0.43

Aggregate Net Transfers on S&P 500 Returns	Large Equity Transfers	Medium Equity Transfers	Small Equity Transfers
Morning Returns	0.09 *	0.27 **	0.27 **
Afternoon Returns	0.15 **	0.31 **	0.23 **
Test of Equality	1.64	1.67	0.09

Panel B: Morning Returns from 9:40 am to 11:00 a.m., Afternoon Returns from 11:00 a.m. to 4:00 p.m.

S&P 500 Returns on Aggregate Net Transfers	Morning Returns	Afternoon Returns	Test of Equality
Large Equity Transfers	0.03	0.13 **	1.28
Medium Equity Transfers	0.13 **	0.37 **	3.15
Small Equity Transfers	0.13 **	0.26 **	0.13

Aggregate Net Transfers on S&P 500 Returns	Large Equity Transfers	Medium Equity Transfers	Small Equity Transfers
Morning Returns	0.02	0.10 **	0.11 **
Afternoon Returns	0.14 **	0.37 **	0.28 **
Test of Equality	1.70	6.10 **	0.88

Panel C: Morning Returns from 10:00 am to Noon , Afternoon Returns from Noon to 4:00 p.m.

S&P 500 Returns on Aggregate Net Transfers	Morning Returns	Afternoon Returns	Test of Equality
Large Equity Transfers	-0.01	0.14 **	7.11 **
Medium Equity Transfers	0.17 **	0.35 **	3.37
Small Equity Transfers	0.16 **	0.24 **	0.05

Aggregate Net Transfers on S&P 500 Returns	Large Equity Transfers	Medium Equity Transfers	Small Equity Transfers
Morning Returns	-0.02	0.15 **	0.15 **
Afternoon Returns	0.15 **	0.35 **	0.25 **
Test of Equality	7.51 **	5.02 *	0.44

Notes: ** $p<.01$ and * $p< .05$. This table reports the results of tests using intraday S&P 500 returns and daily transfers. All series are standardized by the corresponding standard deviations. We report results from regressing returns on aggregate net transfers and regressing aggregate net transfers on returns. We also report the results of tests of the null assumption of no intraday lead-lag effects. Panels A, B and C differ based on the definition of morning returns and afternoon returns.

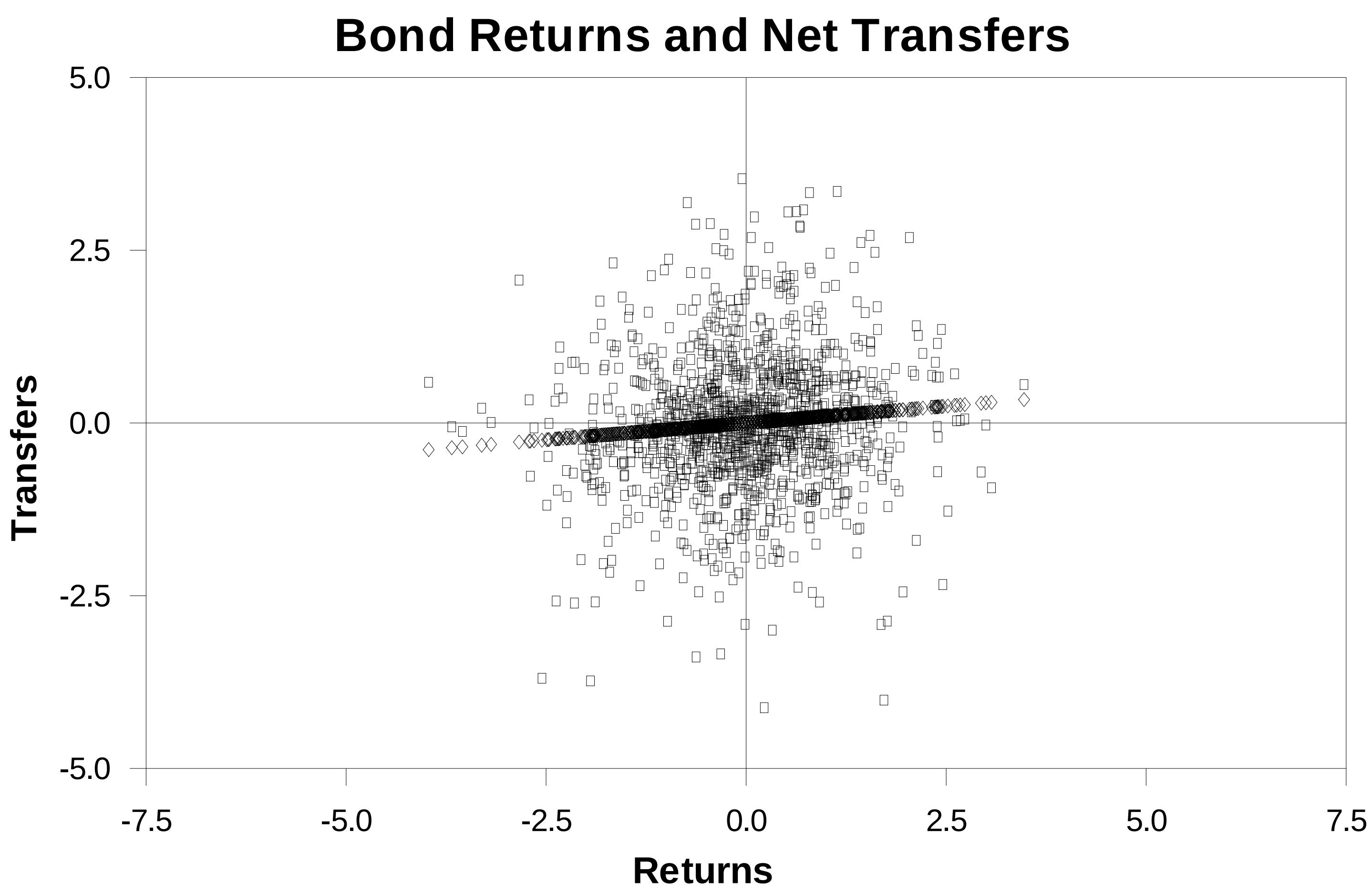

Figure 1: The figure plots standardized Bond aggregate net transfers against standardized Bond returns. The squares denote the data points, while the diamonds denote a regression line of aggregate net transfers on returns. The slope of the regression line corresponds to the correlation coefficient between the two series.

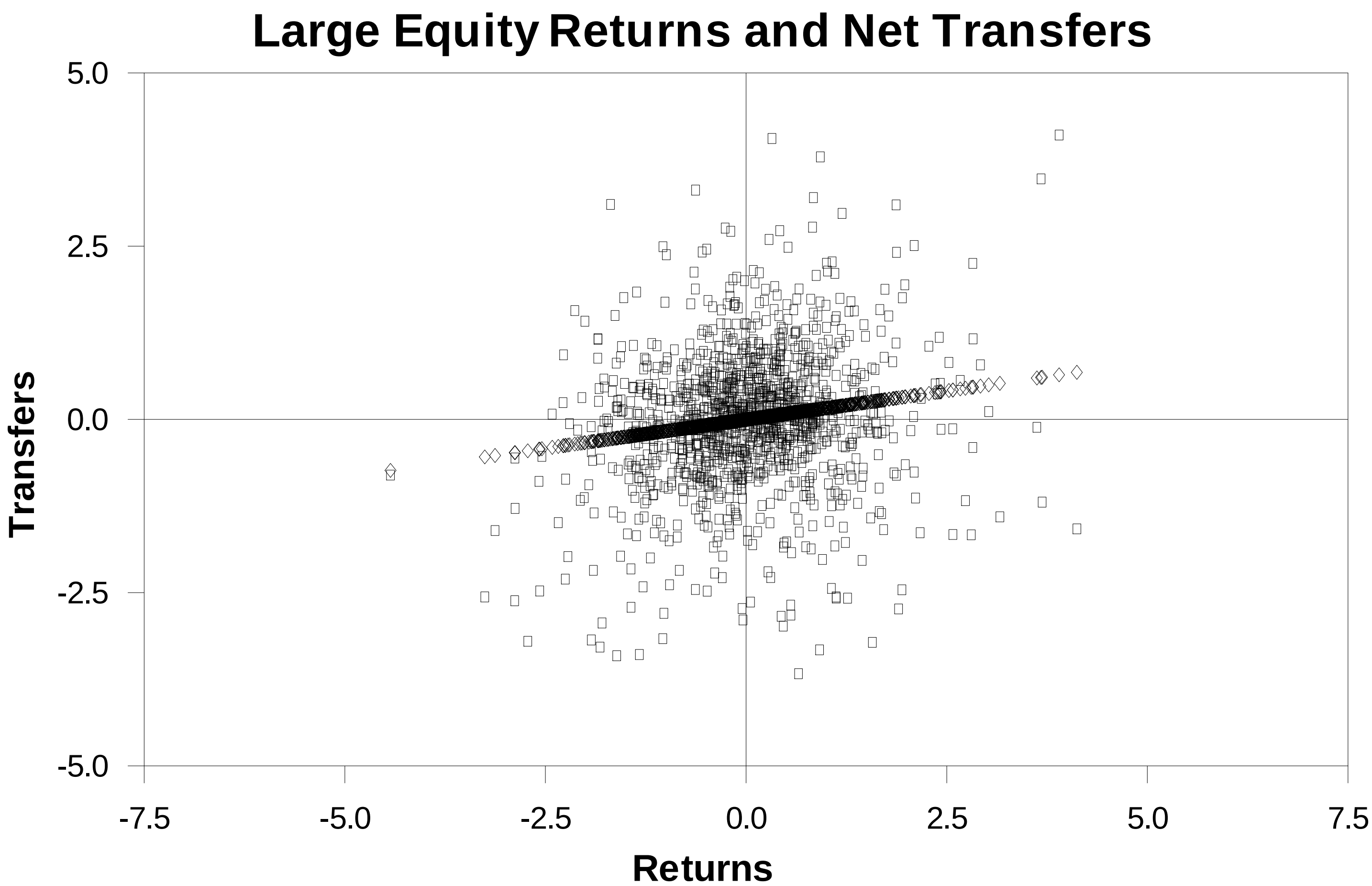

Figure 2: The figure plots standardized Large Equity aggregate net transfers against standardized Large Equity returns. The squares denote the data points, while the diamonds denote a regression line of transfers on returns. The slope of the regression line corresponds to the correlation coefficient between the two series.

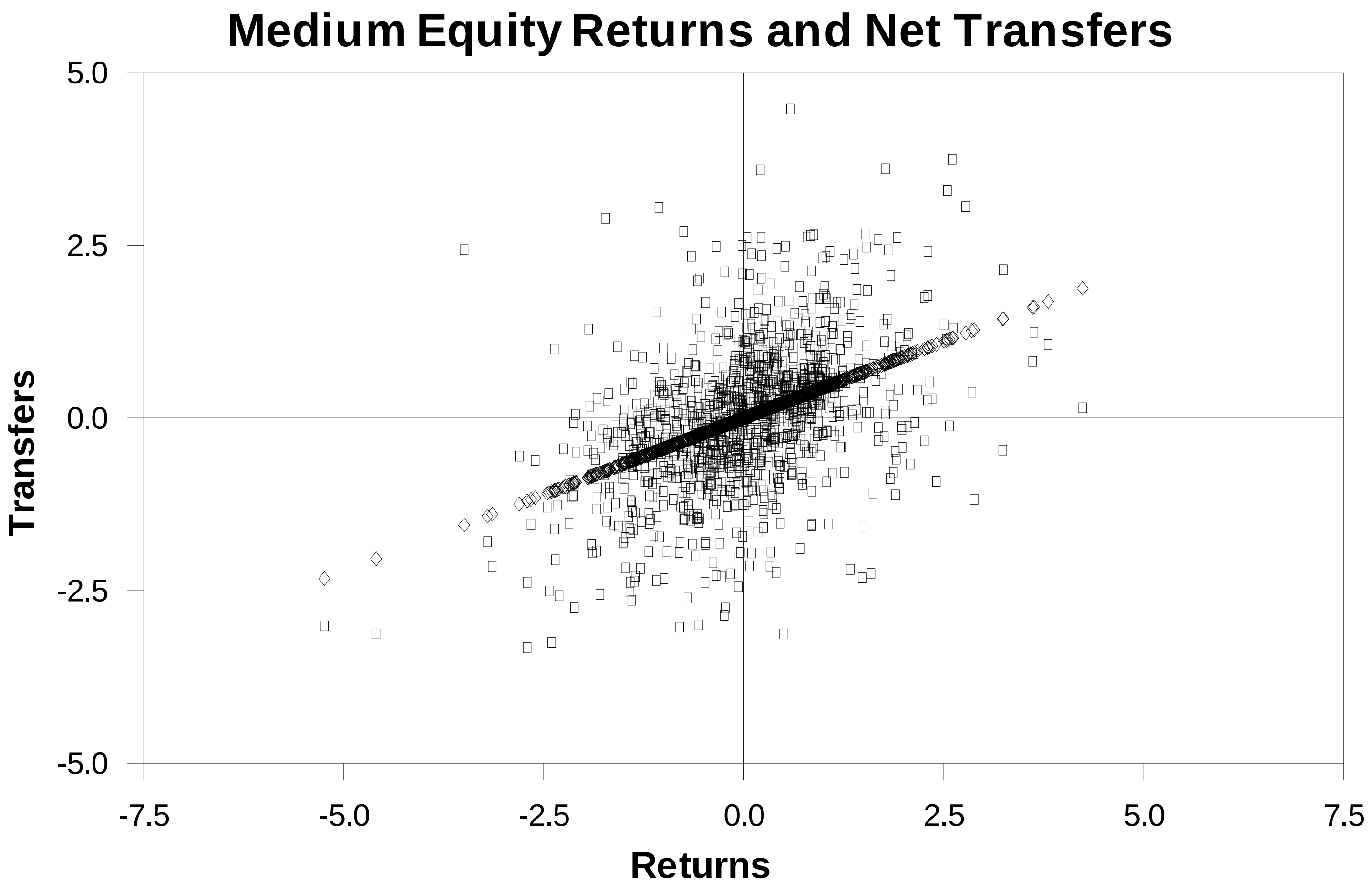

Figure 3: The figure plots standardized Medium Equity aggregate net transfers against standardized Medium Equity returns. The squares denote the data points, while the diamonds denote a regression line of aggregate net transfers on returns. The slope of the regression line corresponds to the correlation coefficient between the two series.

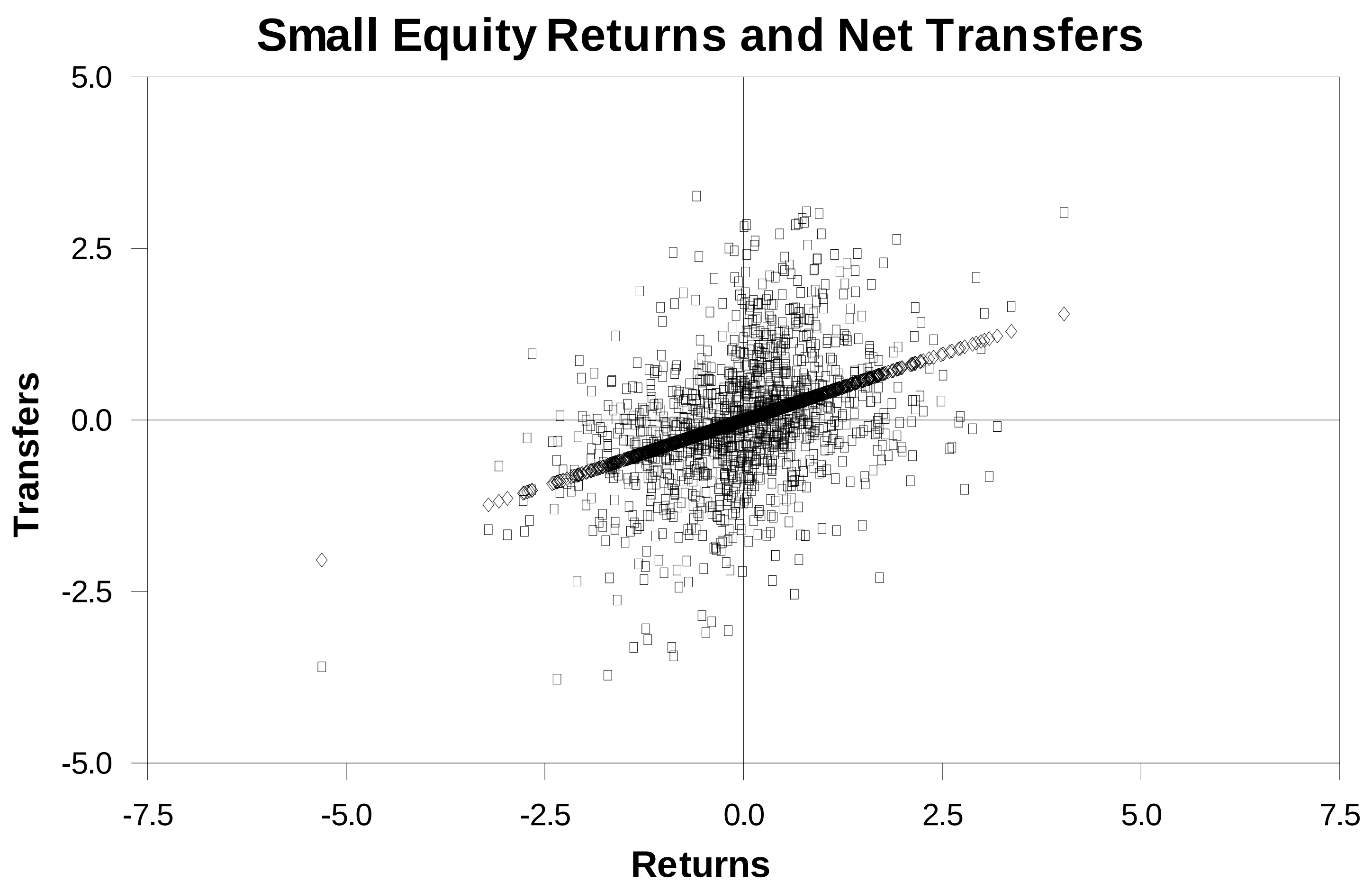

Figure 4: The figure plots standardized Small Equity aggregate net transfers against standardized Small Equity returns. The squares denote the data points, while the diamonds denote a regression line of aggregate net transfers on returns. The slope of the regression line corresponds to the correlation coefficient between the two series.