AN ANALYSIS OF HOW INDIVIDUALS REACT TO MARKET RETURNS IN ONE 401(K) PLAN

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An Analysis of How Individuals React to Market Returns in One 401(k) Plan

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Abstract:
This paper studies a unique dataset of trades in one 401(k) plan. The most novel feature of this dataset is that each trade can be classified based on its source and destination. Thus, the results from this study provide an even closer examination of how individuals trade relative to daily asset returns. Understanding how individuals trade based on past market returns is important, because theoretical literature suggests that certain trading strategies can influence the returns and volatility of the market. Several interesting results emerge from this analysis. First, the results confirm earlier findings from Goetzmann and Massa (2003) that lagged returns are in most cases only significantly related to fund outflows, rather than fund inflows. This paper is a useful complement to their study because a different measure of flows is used. Second, the strong correlation between flows and lagged returns is only significant when fund returns are extremely low. This suggests that extremely negative returns are required to induce 401(k) participants to trade based on past returns. This is consistent with responses made by participants in a recent defined contribution survey. Third, the results support the assertion that most trades are from equities to risk-free assets, or vice versa. In this case, 48 percent of the total trades fit this category. The ability to classify the trades into these categories is one of the most important contributions of this paper. Finally, it is only the flows from equities to GICs that show a strong correlation with one-day lagged returns. This suggests that most of the trades are "flights to safety" not return chasing.

An Analysis of How Individuals React to Market Returns in One 401(k) Plan

Recent financial research has focused on how individual trading behavior relates to daily asset returns (for example, Agnew and Balduzzi 2003, Goetzmann and Massa 1999, Goetzmann and Massa 2003, Goetzmann, Massa and Rouwenhurst 1999, Edelen and Warner 1999). A strong motivating factor behind this research is the potential influence individual traders may have on the financial markets. Indeed, several theoretical findings suggest that certain trading strategies can influence the returns and volatility of these markets (for example, Balduzzi, Bertola and Foresi 1995; DeLong, Shleifer, Summers and Waldman 1990). As a result, research on individuals' trading strategies has broad market implications. Furthermore, this research is becoming increasingly more important as the number of individuals trading in their own accounts increases and the debate over the introduction of private Social Security accounts intensifies in Washington. This paper contributes to the literature by analyzing a new and unique dataset of individual trades in one 401(k) plan. The most novel feature of this dataset is that each trade can be classified based on its source and destination. Thus, the results from this study provide an even closer examination of how individuals trade relative to daily asset returns.

This paper uses administrative data from one 401(k) plan. This study focuses on approximately four years of trading data from April 1994 to August 1998. The dataset follows 4,783 participants who were enrolled in the plan the entire time period. The individuals are permitted to trade daily between eight different funds: one Guaranteed Income Contract fund (GIC), three equity funds (a large capitalization stock fund "Large

Cap Stock", a small and medium capitalization stock fund "Small/Medium Cap Stock", and an international stock fund "International Fund") and four lifestyle funds composed of the original four. The dates of each individual's trade and the changes to the allocations to each fund are included. One important feature of these data is that each trade can be broken down into its inflow components and its outflow components. In addition, each trade can be broadly classified into seven categories: 1) trades from GIC to equities, 2) trades from equities to GIC, 3) trades from equity funds to equity funds, 4) trades from lifestyle funds to GIC or equity funds, 5) trades from GIC or equity funds to lifestyle funds, 6) trades from lifestyle funds to lifestyle funds and 7) other trades. The ability to classify each trade in this manner is the distinguishing feature of this dataset.

Several interesting results emerge from the analysis of these data. First, there is weak evidence of a contemporaneous relationship between returns and flows but strong evidence of lagged feedback trading.

Second, results suggest that equity fund outflows, not inflows, are significantly negatively related to their own past fund returns. In other words, today's outflow from an equity fund increases as that fund's performance over the previous day deteriorates. These results are consistent with Goetzmann and Massa (2003), who find a significantly negative relationship between yesterday's returns and today's outflows. These results also highlight the importance of studying inflows and outflows separately.

Third, the relationship of flows to lagged returns is only significant when fund returns are extremely low. This supports findings by Agnew and Balduzzi (2003). They find that the correlation between same-day net dollar flows and returns is greatest when returns are abnormally high or low.

Fourth, the analyses of the broad classifications of trades support the theory that most trades are between risk free/fixed income securities and equities. Of the 5,689 trades, 48 percent fit this category. Also, only flows from the equity funds to the GIC funds were significantly negatively related to past equity index returns and this relationship is most significant when the index performance is the lowest.

This paper is organized as follows. Section II describes the dataset. Section III presents the empirical results related to the analysis of inflows and outflows. Section IV presents the results related to the broad characterization of the trades. Section V concludes.

II. Data

The dataset in this study is from one 401(k) plan. These data were supplied by A large benefits provider. The dataset includes asset allocations and trading information for 4,783 participants enrolled in their plan over the time period April 1994-August 1998. The dataset originally included more participants but those individuals who were not in the plan over the entire time period were eliminated. In addition, participants were eliminated if they did not have unique participant numbers, plan entry dates or their allocations did not sum to 100 percent.

Participants in this plan may invest in four investment choices: a GIC fund; a large cap stock fund; a small/medium stock fund; and an international stock fund. For ease of exposition, the three latter funds are referred to as the equity funds. In addition, the individuals can choose among four "lifestyle" funds that consist of different mixes of the original four asset choices. If an individual chooses a lifestyle fund, his entire contribution must be allocated to that fund. Each individual's percentage allocation must sum to 100 percent and no short selling is allowed.

Investors can change the allocations of their 401(k) assets on a daily basis. When their allocations are changed, the participant's funds are redistributed according to the new allocation. In addition, the allocations of their future contributions are changed. This event is considered a trade.[1] For each individual, the dataset includes a record of the dates of each allocation change and the new and old allocations into each fund. From these data, it is possible to count the number of daily inflows and outflows made by each individual for each fund. Because the focus of this study is on individual trading behavior, count data is preferred to dollar flow data because it cannot be biased by a few traders who trade large dollar amounts. One important note is that one trade can result in inflows into several funds, as well as outflows from several funds.

Finally, each individual's trade is broadly classified into one of seven categories based on where the funds for the trade originated from (the source) and where those funds were invested (the destination). The seven categories of trades are: 1) trades from GIC to equities, 2) trades from equities to GIC, 3) trades from equity funds to equity funds, 4) trades from lifestyle funds to GIC or equity funds, 5) trades from GIC or equity funds to lifestyle funds, 6) trades from lifestyle funds to lifestyle funds and 7) other trades. The ability to classify each trade in this manner is an important and unique feature of this dataset. From these data, a times series of the daily sum of each trade by classification is calculated.

[1] These employees were all participants as of April 1994. Prior to that date, these participants were given only one investment option, the GIC fund. Thus after this date, if the participants wanted to invest in equities they had to make one trade. This first trade is very different in nature to subsequent trades and is therefore excluded from the analysis.

A large benefits provider also supplies the daily return data for each fund. From these returns, an equally-weighted index from the three equity funds is constructed. This index is the return series used to study the behavior of GIC flows and classified trade flows to returns. Table 1 provides summary statistics of returns for each fund, as well as returns for the index.

The data used in this study is refined from data used in an earlier study (Agnew, Balduzzi and Sunden 2003). In the earlier study, the trades were not disaggregated to the fund level but divided into two main categories: equities and bond investments. In addition, in the earlier study the analysis of the daily changes in equity allocations focused on the overall *average net changes in percent allocations* in the *total equity holdings* among all the individuals in the plan. In contrast, this study analyzes the *number* of daily inflows and outflows to each fund.

III. An Analysis of the Daily Inflows and Outflows into Each Fund

The following section investigates how daily inflows and outflows react to market returns and whether individuals successfully time the market. The analysis explores several questions including: 1) do outflows react differently than inflows to past returns, 2) are individuals practicing feedback trading strategies and 3) is the relationship between trades and flows related to the magnitude of the returns? In addition, the analysis will determine whether individuals are taking advantage of the wildcard option in mutual fund shares (Chalmers, Edelen and Kadlec 2001).

A. Autocorrelation Analysis

This section begins with an examination of the autocorrelations of the daily fund returns and the inflows and outflows from each fund. Table 2 presents these results.

Panel A reports the autocorrelations of returns for each fund. For all the funds and the index returns, the only statistically significant autocorrelation exists at the one day lag. In all cases, this lag is positive. The source of this persistence is most likely due to nonsynchronous trading. Nonsynchronous trading arises when fund shares are marked to market at the end of the day based on their last trade price. This last trade may occur far before the market closes resulting in a “stale” price. The stale price will most likely not equal the true price that the security could be traded for at the exact close of the market. The presence of stale pricing leads to the positive autocorrelation in the fund returns. Kadlec and Patterson (1999) demonstrate that 50 percent of positive autocorrelations in portfolio shares can be attributed to this effect.

Panel B and Panel C report the autocorrelations of the number of fund inflows and outflows, respectively. Interestingly, the three equity funds and the GIC fund exhibit strong autocorrelations for both the inflows and the outflows. However, with the exception of Lifestyle Four Fund, the lifestyle funds do not demonstrate the same persistence. Furthermore, the magnitude of the lag one autocorrelation is substantially lower for lifestyle funds one through three compared to the four non-lifestyle funds.

The observed difference in autocorrelations could be a result of how and if individuals are trading based on prior news. The strong autocorrelations in the three equity funds and the GIC fund are consistent with the idea that some participants react to news more quickly than others. Such delays in the reaction to news could produce significant autocorrelations for many lags. Likewise, the lack of consistency in the autocorrelations in the lifestyle funds may exist because individuals investing in lifestyle funds tend not to react to news. Lifestyle fund investors most likely choose to invest in these types of funds because they have long-term investment objectives. Therefore, these individuals are probably less likely to trade in and out of these funds based on news.

B. Cross-Correlation Analysis

Table 3 reports the correlations between inflows and outflows for each fund and, with the exception of the GIC fund, each fund's own lead and lagged returns. Note that the return series used in relation to the GIC fund is the equally-weighted index constructed from the three equity funds.

Notice that there is no evidence of market timing. In all but one case, today's fund flows (inflows and outflows) are not significantly related to future returns in the funds. In fact, the only significant correlation is a positive (.11) relationship between the today's GIC inflows and tomorrow's equally-weighted stock index returns. In other words, individuals are trading into GICs the day before the market increases. This suggests that participants may actually be mistiming the market and leaving some returns on the table.

Interestingly, with the exception of international stock outflows, a strong contemporaneous correlation between returns and flows does not exist. Such a relationship has been found in previous studies (Goetzmann and Massa 2003, Agnew and Balduzzi 2003). However, the results presented here are consistent with aggregate net findings found in an earlier study that used data from this same plan.

A strong contemporaneous relationship would suggest that individuals might be taking advantage of the persistence in mutual fund returns discussed earlier. Chalmers, Edelen and Kadlec (2001) devise a profitable trading strategy that requires investors to trade between cash and fund shares based on whether the predicted next day fund return is "high" or "low." This strategy forces individuals to exercise what the authors term the "the mutual fund wild card option." A byproduct of individuals following this strategy is a strong contemporaneous relationship between returns and flows. Lack of a strong contemporaneous correlation suggests that individuals in this plan do not exercise this option.

Why the strong contemporaneous relationship does not exist in this plan is unclear. Perhaps the documented inertia (Madrian and Shea 2000) in individuals' behavior in retirement accounts causes the participants to respond more slowly to news. However, this argument is weakened by the significant contemporaneous relationship found in Agnew and Balduzzi's (2003) study of aggregate net 401(k) flows generated by 1.5 million participants. Another possible explanation is the early time period of the data, which ends in 1998. The Agnew and Balduzzi (2003) data spans the 1997-2001 time frame. It is plausible that less readily available financial information during the time period of this dataset causes individuals to react with a one day delay.

One of the most striking results is that lagged returns are significantly related to equity outflows but *not* equity inflows. In addition, the correlation coefficients are much smaller for the inflows than for the outflows. Not surprisingly, it is the inflow component, not the outflow component, of the GIC fund that is significantly related to the equity index returns, meaning that inflows fall as the lagged equity index returns increase.

These results support Goetzmann and Massa's (2003) findings. In their study, they examine the relationship between daily returns and aggregate dollar inflows and outflows. The dollar inflows and outflows are generated from investments in three different S&P 500 Index funds. They find asymmetric evidence of positive feedback trading. In particular, they find that outflows react to past returns, while inflows do not. It is important to note that their inflows and outflows are measured in dollars rather than by the number of inflow trades and outflow trades as in this study. Since dollar flows can be biased by a small number of large dollar trades, the results of this study prove a useful complement to their findings.

Finally, with the exception of the lifestyle four fund, there is less evidence linking past returns and lifestyle flows. Once again, this is most likely because those individuals investing in these funds have a more long-term investing approach and so are less likely to trade on news.

C. Regression Analysis

This section jointly tests the effects of lagged returns and flows. The analysis excludes the lifestyle funds because earlier evidence suggests that limited trading is based on returns in these assets.

To study the joint effects of returns and flows, two regressions are estimated for each equity fund and the GIC fund. The dependent variable in these regressions is either the *number* of inflows or the *number* outflows to that fund. Since the dependent variables are count variables, estimating a classical linear regression model is not appropriate because the assumption of normally distributed residual errors is violated. This violation results in inefficient, inconsistent, and biased estimates.

More appropriate models for count data are the Poisson model or the negative binomial model. The latter is used in this study. In the negative binomial model it is assumed that the count variable is generated by a Poisson-like process. The process differs from the Poisson in that it does not require equidispersion (meaning the conditional mean of the count variable must equal to the conditional variance of the count variable). Instead the negative binomial model allows the conditional variance to be greater than the conditional mean which is consistent with the data in this study. If a Poisson model is used when overdispersion exists, the standard errors will generally be underestimated resulting in erroneously high levels of significance. One failing of this model in this dataset is that it does not control for autocorrelated errors, which are likely to exist in time-series data. The regressions used in future versions of this paper will attempt to correct for this obvious shortcoming. Hausman, Hall and Griliches (1984) and Long and Freese (2001) provide a more technical and detailed discussion of the negative binomial model.

Table 4 reports the results from the negative binomial regressions. The first column for each regression reports the predicted percentage change in flows given a one unit change in the explanatory variables.[2] The results largely support the preceding analysis. Inflows for the both the Large Cap Stock and the Medium/Small Cap Stock funds are not significantly related to contemporaneous and lagged returns but outflows exhibit a strong negative relationship with one-day lagged returns. For example, Large Cap Stock outflows are expected to *increase* by 16.3 percent with a one percent *decrease* in Large Cap Stock fund returns. Similarly, Medium/Small Cap Stock Funds outflows are

[2] The reported percent coefficients are calculated using a program written by Long and Freese and discussed in their econometrics textbook (Long and Freese (2001)).

expected to *increase* by 18.2 percent with a one percent *decrease* in Medium/Small Cap Stock Funds.

The results also show a relationship between International Fund outflows and returns. However, this relationship is not limited to the one-day lagged return. A strong contemporaneous relationship and two-day lagged relationship is also found.

Given the earlier results it is not surprising that all the funds show a positive relationship between flows and past flows.

Finally, only inflows to the GIC funds are related to equity index returns. This is consistent with the notion that funds are flowing out of equity funds to the relatively safer asset when equity returns are falling. Both Goetzmann and Massa (2003) and Agnew and Balduzzi (2003) find suggestive evidence of a polarity in trades, meaning trades are moving between risk-free /fixed income assets and equities. This finding will be tested more directly in Section III.

D. A Closer Look at the Relationship of Flows and the Relative Magnitude of Returns

This section is motivated by the findings of Agnew and Balduzzi (2003), where they find a stronger association between same-day returns and net 401(k) transfer flows when equity returns are *abnormally* high or *abnormally* low (.642 vs. .423). [3] This difference is statistically significant. The question is whether the general magnitude of the previous day's returns affects the relative size of the correlation of inflows and outflows to returns. The focus on the relationship between today's flows and yesterday's returns is motivated by the regression results of the preceding section.

[3] They define abnormal as more than one standard deviation from the mean.

To test how the correlation between flows and returns might vary depending on the size of the returns, each fund's one-day lag return is sorted into deciles. The lowest decile corresponds to the lowest lagged returns and the top decile corresponds to the highest lagged returns. Within each decile, the correlation between flows and returns is calculated. The index returns are sorted into deciles for the analysis of the GIC flows. Table 5 reports the results.

It is clear immediately that the most significant relationship between flows and returns is in the worst performing decile. The equity fund outflows are all significantly negatively related to returns. This means that when returns are extremely low, a *decrease* in returns results in a large *increase* in outflows. The evidence suggests that some individuals are practicing positive feedback trading strategies. This might also indicate that it requires extremely negative returns to induce individuals to trade. Since 401(k) investors are known to trade infrequently and exhibit inertia in their allocation and participation decisions, it is logical that an extreme event would have to occur to overcome their tendency to do nothing. Furthermore, Nofsinger (2002) explains that a sudden drop in stock price can cause more emotional pain in the memory of investors than a slow decline in a stock price over time. Thus, individuals reacting to the emotional pain caused by the sudden drop in price could explain why the extremely negative returns induce the most trades, and there is little evidence showing inflows chasing gains. Turning to the GIC flows, the negative correlation of the GIC inflows to the stock index returns in the lowest decile is also consistent with a flight to safety when equity returns are low and losses are extreme.

The analysis also produces some evidence of contrarian trading strategies. For example, the inflow to the Large Cap Stock fund is significantly negatively related to returns in the lowest decile. This suggests that some individuals are increasing their allocations to this fund when the fund's returns fall substantially. In addition, outflows are positively related to their own fund returns in the top decile for Medium/Small Cap and Int'l funds and GIC outflows are negatively related to returns in the lowest index decile. These results might also be evidence of contrarian strategies.

The evidence in this section supports findings in John Hancock Services most recent Defined Contribution Plan Survey. Seventy nine percent of respondents in the survey who are stock investors state that there is a level of stock market decline that would prompt them to change their investments. The results report that "the most common actions would be to transfer money out of stocks and to allocate less to stocks in the future".[4] They report that this trading behavior dominates contrarian behavior by a margin of three to two. Thus, their findings are consistent with the behavior in this plan. Furthermore, they find that while individuals say they will change their investment strategy, few actually do. This can also explain why limited trading is observed in this plan.

Finally, Table 5 also reports the number of inflow and outflow trades in each decile. Interestingly, the most extreme deciles tend to have the highest number of trades.

IV. Classified Trades and Their Relationship to Returns

A. *Trade Classification*

The strong observed negative correlation between GIC inflows and lagged equity returns, combined with the negative correlation between equity fund outflows and their own lagged returns suggests that individuals may be trading between risk-free/fixed income assets and equity assets based on lagged stock market performance. In support of this theory, Goetzmann, Massa and Rouwenhorst (1999) find a negative (but contemporaneous) correlation between equity flows and flows to cash in their analysis of net dollar flows into nearly 1,000 mutual funds over the January 1998 through July 1999 period. Further support for this "polarity" in flows is found in Agnew and Balduzzi's (2003) results. They also find flows to equity funds negatively related to flows to GIC and Bond funds. However, neither paper can directly test this finding because the flows studied were aggregate net flows. It is impossible to trace the source of the inflows or the destination of the outflows in these datasets. Importantly, the dataset used in this paper allows this to be done for the first time.

In order to test this theory, each individual trade in this study is classified into one of seven broad categories: 1) trades from GIC to equities, 2) trades from equities to GIC, 3) trades from equity funds to equity funds, 4) trades from lifestyle funds to GIC or equity funds, 5) trades from GIC or equity funds to lifestyle funds, 6) trades from lifestyle funds to lifestyle funds and 7) other trades.

Table 6 reports the breakdown of the 5,689 trades into the seven classifications. Indeed, the evidence suggests that a majority of trading is motivated by individuals shifting funds between equities and cash. In fact, 48 percent of these trades are trades from GIC to equities or vice versa. These two types of trades are further broken down into their sources and destinations in Figure 1 and 2. The next two largest categories are trades between equities (20 percent) and trades into lifestyle funds from the four non-lifestyle funds (11 percent). Since the trades between equities and the GIC funds

[4] Eighth Defined Contribution Survey, John Hancock Financial Services, p. 15.

dominate the trading activity, the remainder of this section will focus on this largest category of trades.

B. *Correlation Analysis of Classified Trades*

This section repeats the correlation analysis in Section II for the two largest categories of trades. The results are reported in Table 7. Notice the strong correlations between index returns and flows to the GIC fund from the equity funds. These flows are negatively correlated (-.25) with a one-day lag in index returns, meaning that these flows increase with a decrease in equity returns. Once again this is evidence of individual's flight to safety. The flow to GIC is also positively related to next day index returns suggesting again that individuals might be mistiming the market.

On the other hand, investors do not appear to chase returns. The inflows to equities from the GIC fund are unrelated to lagged index returns. If individuals are chasing returns, a strong positive correlation between lagged returns and flows would be expected. However, there exists a significantly positive contemporaneous relationship (.07) between index returns and trades from GIC into equities. Without the earlier analysis, the conclusion from this result might be that individuals are taking advantage of the wildcard option in mutual funds shares. However, the earlier analysis shows that most inflows to each separate equity fund are not contemporaneously correlated with the fund's own return. In light of this, the evidence in this section *cannot* be used to support this theory.

C. *Regression Analysis of Classified Trades*

A negative binomial model is used once again to jointly test the influence of lagged returns and flows on flows. Table 8 reports the results. Consistent with the earlier results, it is only the trades into the GIC fund that are related to past returns. Furthermore, it is only the one day lagged return that is significant. The results suggest that a one percent decrease in equity index returns will increase flows from equity to GICS by 27 percent. Finally, trades from GIC to equities show a stronger relationship to past flows than trades in the opposite direction.

D. *A Closer Look at the Relative Magnitude of Returns and Classified Trades*

Table 9 reports the final results of the paper. Once again, the index returns are sorted into ten deciles to test the influence of the magnitude of the return. As in the earlier results, it is in the lowest decile that returns and flows are significantly correlated. In addition, the significant relationship only holds for the trades from equities into GICs. Table 9 reports a -.66 correlation between equity index returns and flows from equities into GICs.

In summary, the results from each section appear to be telling a consistent story. First, individuals must be prompted by extremely negative stock performance in order to trade. Second, this aversion to sudden drops in prices results in trades that can be characterized as flights to safety.

V. Conclusions

The ability to trace the source and destination of each individual's trade in this dataset provides a unique opportunity to study more closely the trading behavior of individuals in a 401(k) plan. Understanding how individuals trade based on past market returns is important because theoretical literature suggests that certain trading strategies can influence the returns and volatility of the market.

Several interesting results emerge from this analysis. First, the results confirm earlier findings from Goetzmann and Massa (2003) that lagged returns are in most cases only significantly related to fund outflows, rather than fund inflows. This paper is a useful complement to their study because a different measure of flows is used. Second, the strong correlation between flows and lagged returns is only significant when fund returns are extremely low. This suggests that extremely negative returns are required to induce 401(k) participants to trade based on past returns. Third, the results support the assertion that most trades are from equities to risk-free assets, or vice versa. In this case, 48 percent of the total trades fit this category. The ability to classify the trades into these categories is one of the most important contributions of this paper. Finally, it is only the flows from equities to GICs that show a strong correlation with one-day lagged returns. This suggests that most of the trades are "flights to safety" not return chasing.

The results in this study have important implications for further research. First, it reinforces the importance of focusing on inflow and outflows separately, as well as extreme return days, in this type of research. It seems possible that when net flows to equities are studied, that the outflows are driving all the results. The results also have important policy implications because of the potential influence that observed trading behavior might have on the markets. The results from this sample suggest that if returns are extremely low in equities, then this performance will induce infrequent traders to "fly to safety." This flight could depress the market even further. As the number of 401(k) participants grows, this is an important consideration.

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Table 1: General Summary Statistics of Daily Fund Returns

This table summarizes the daily returns of the three equity funds and the four lifestyle funds offered in this one 401(k) plan. In addition, summary statistics are presented for an equally-weighted stock index composed of the three equity funds.

Time Period: April 1994- August 1998

	Obs	Mean (%)	Std. Dev (%)	Min (%)	Max (%)
Large-Cap Stock Fund	1,151	0.0758	0.7699	-6.1756	3.7142
Medium/Small Cap Stock Fund	1,151	0.0437	0.9388	-7.4094	6.7817
International Stock Fund	1,151	0.0157	0.5589	-3.3524	3.1035
Equally-Weighted Stock Index	1,151	0.0451	0.6257	-5.2119	2.6870
Lifestyle One Fund	1,151	0.0330	0.1679	-1.2784	0.6024
Lifestyle Two Fund	1,151	0.0412	0.3336	-2.7371	1.2097
Lifestyle Three Fund	1,151	0.0446	0.4830	-4.0500	1.6677
Lifestyle Four Fund	1,151	0.0463	0.6404	-5.4115	2.6946

Table 2: Autocorrelations of Fund Returns, Fund Inflows and Fund Outflows

Panel A reports the autocorrelations of the three equity funds, the four lifestyle funds and the equally weighted index. Panels B and C report the autocorrelations of the inflows and outflows fromthe eight investment options, respectively. The inflow and outflows are the *number* of trades in and out of the funds. One (two) asterisk(s) denote significance at the 5-percent (1-percent) significance level based on t-ratios that are adjusted for heteroskedasticity.

Panel A: Autocorrelations of Fund Returns

	Autocorrelation of Fund Returns							
	Lag 1		Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7
Large-Cap Stock Fund	0.1155	*	-0.0399	-0.0425	-0.0211	-0.0431	-0.0052	-0.0497
Medium/Small Cap Stock Fund	0.1830	**	-0.0471	-0.0121	-0.0032	-0.0418	0.0339	-0.0354
International Stock Fund	0.1080	*	0.0316	-0.0128	0.0096	-0.0335	-0.0029	-0.0175
Equally-Weighted Stock Index	0.2524	**	-0.0355	-0.0232	-0.0063	-0.0274	0.0121	-0.0458
Lifestyle One Fund	0.1924	**	-0.0368	-0.0263	-0.0113	-0.0424	0.0022	-0.0624
Lifestyle Two Fund	0.2037	**	-0.0303	-0.0419	-0.0123	-0.0383	0.0023	-0.0419
Lifestyle Three Fund	0.2281	**	-0.0348	-0.0290	-0.0082	-0.0341	0.0056	-0.0471
Lifestyle Four Fund	0.2471	**	-0.0351	-0.0240	-0.0069	-0.0260	0.0069	-0.0444

Panel B: Autocorrelation of Fund Inflows

	Autocorrelation of Fund Inflows													
	Lag 1		Lag 2		Lag 3		Lag 4		Lag 5		Lag 6		Lag 7	
GIC	0.3481	**	0.1471	**	0.0750	**	0.0824	*	0.1293	**	0.1091	**	0.0612	
Large-Cap Stock Fund	0.4210	**	0.3388	**	0.2584	**	0.2578	**	0.2437	**	0.1716	**	0.1843	**
Medium/Small Cap Stock Fund	0.4551	**	0.3426	**	0.2786	**	0.2782	**	0.2770	**	0.1920	**	0.2021	**
International Stock Fund	0.2451	**	0.1822	**	0.1901	**	0.2034	**	0.1849	**	0.1750	**	0.1524	**
Lifestyle One Fund	0.0118		0.0605		0.1087	*	0.0710		0.1181	**	0.0238		0.0238	
Lifestyle Two Fund	0.0390		-0.0006		0.0840		0.0135		0.0558		0.0558		-0.0147	
Lifestyle Three Fund	0.0368		0.0956	*	-0.0074		0.0000		0.0147		-0.0074		0.0441	
Lifestyle Four Fund	0.2279	**	0.1266	*	0.1383	*	0.1266	**	0.1149	**	0.0364		0.0714	*

Panel C: Autocorrelation of Fund Outflows

	Autocorrelation of Fund Outflows													
	Lag 1		Lag 2		Lag 3		Lag 4		Lag 5		Lag 6		Lag 7	
GIC	0.3979	**	0.2453	**	0.2451	**	0.2493	**	0.1974	**	0.1744	**	0.1580	**
Large-Cap Stock Fund	0.2774	**	0.1142	**	0.0907	**	0.0860	*	0.0929	*	0.0695	**	0.0477	
Medium/Small Cap Stock Fund	0.3654	**	0.2409	**	0.1802	**	0.1322	**	0.1676	**	0.2053	**	0.1747	**
International Stock Fund	0.3310	**	0.2552	**	0.2230	**	0.1355	**	0.1308	**	0.0714		0.0380	
Lifestyle One Fund	0.0368		0.0230		-0.0205		-0.0205		0.0608		0.0230		0.0303	
Lifestyle Two Fund	0.0872	*	0.1089	**	0.1186	**	0.0553		0.1235	**	0.0359		0.0310	
Lifestyle Three Fund	0.0848	*	0.0002		0.0931	*	0.0322		0.0675		0.0354		0.0707	*
Lifestyle Four Fund	0.1779	**	0.0591	*	0.0348		0.0070		0.0631		0.1079	**	0.0980	

Table 3. Cross-Correlations of Inflows and Outflows Relative to Lead and Lag Returns

This table reports the cross-correlations of the inflows and outflows from the seven non-GIC investment options offered in the plan relative to each fund's lead and lag returns. The correlation of the GIC fund's flows are calculated with respect to the lead and lag returns of the equally-weighted stock index. The inflow and outflows are the *number* of trades in and out of the funds. One (two) asterisk(s) denote significance at the 5-percent (1-percent) significance level based on t-ratios that are adjusted for heteroskedasticity.

		Lead 3	Lead 2	Lead 1	Lead 0	Lag 1	Lag 2	Lag 3
One Day Lead and Lags of Equally-Weighted Stock Returns								
GIC	in_flows	0.0268	0.0234	0.1077 *	-0.0509	-0.2812 **	-0.1555 **	-0.1134 *
	out_flows	0.0248	-0.0026	0.0476	0.0732 *	0.0304	0.0056	-0.0002
One Day Lead and Lags of Large Cap Stock Returns								
Large Cap Stock	in_flows	0.0274	-0.0146	0.0082	0.0373	-0.0156	-0.0143	-0.0409
	out_flows	0.0332	-0.0277	0.0558	0.0340	-0.1906 *	-0.1070 **	-0.0923 *
One Day Lead and Lags of Small/ Med Cap Stock Returns								
Small / Med Cap Stock	in_flows	0.0327	-0.0308	0.0108	0.0571	0.0370	0.0470	0.0383
	out_flows	-0.0235	0.0077	0.0409	-0.0330	-0.2474 **	-0.1685 **	-0.1136 **
One Day Lead and Lags of International Stock Returns								
Int'l Equity	in_flows	-0.0361	-0.0045	0.0378	-0.0331	-0.0013	0.0614	0.0315
	out_flows	-0.0413	-0.0527	-0.0051	-0.1189 *	-0.1143 **	-0.1455 **	-0.1040 **
One Day Lead and Lags of Lifestyle 1 Returns								
Life-style One	in_flows	0.0648	-0.0430	0.0139	-0.0056	-0.0766	-0.0980 **	-0.0136
	out_flows	-0.0377	-0.0381	-0.0129	0.0245	0.0023	-0.0299	-0.0218
One Day Lead and Lags of Lifestyle 2 Returns								
Life-style Two	in_flows	0.0008	-0.0055	0.0403	-0.0032	-0.0832	-0.0526	-0.0527
	out_flows	0.0319	-0.0392	-0.0226	0.0113	-0.0470	-0.0755 *	0.0152
One Day Lead and Lags of Lifestyle 3 Returns								
Life-style Three	in_flows	0.0076	-0.0081	0.0048	0.0536	-0.0383	-0.0147	0.0143
	out_flows	0.0422	-0.0527	-0.0081	-0.0046	-0.0117	0.0242	-0.0413
One Day Lead and Lags of Lifestyle 4 Returns								
Life-style Four	in_flows	-0.0103	-0.0892	-0.0139	0.0030	0.0160	-0.0516	-0.0729 *
	out_flows	0.0400	-0.0115	0.0431	-0.0280	-0.2177 *	-0.0997 *	-0.0623

Table 4. Negative Binomial Regressions of Inflows and Outflows

This table presents results of a negative binomial regression of the number of inflows (outflows) to each fund against past daily returns and contemporaneous /past inflows (outflows). The % column reports the predicted percentage change in flows given a one unit change in the explanatory variables. A one unit change in returns is equivalent to a one percent change in the daily return and a one unit change in flows is equivalent to one trade. Z-ratios are adjusted for heteroskedacity. One (two) asterisk(s) denote significance at the 5-percent (1-percent) significance level.

	Dependent Variable: Fund Flows							
	Guaranteed Income Contract				Large Cap Stock Fund			
	Inflows		Outflows		Inflows		Outflows	
Independent Variables	%	z-Statistic	%	z-Statistic	%	z-Statistic	%	z-Statistic
$Return_t$	-11.5	-2.11 *	8.0	1.48	2.1	0.53	-3.8	-0.67
$Return_{t-1}$	-27.1	-5.20 **	-2.1	-0.30	-2.9	-0.66	-16.3	-4.09 **
$Return_{t-2}$	-4.5	-0.07	5.4	1.20	3.6	0.98	-5.9	-1.33
$Return_{t-3}$	-3.4	-0.60	-1.5	-1.50	-1.9	-0.48	-5.2	-1.16
Fund's $Flows_{t-1}$	10.5	5.76 **	15.2	15.20 **	11.2	10.07 **	10.4	5.15 **
Fund's $Flows_{t-2}$	3.6	1.99 *	3.1	3.10	6.5	4.28 **	3.2	1.50
Fund's $Flows_{t-3}$	2.6	1.67	6.5	6.50 **	3.0	2.39 *	4.2	2.04 *
Pseudo R-squared (%)	4.72		4.73		4.95		3.00	

	Dependent Variable: Fund Flows							
	Medium/ Small Cap Stock Fund				Int'l Fund			
	Inflows		Outflows		Inflows		Outflows	
Independent Variables	%	z-Statistic	%	z-Statistic	%	z-Statistic	%	z-Statistic
$Return_t$	5.3	1.53	-4.7	-1.48	-8.1	-1.25	-16.3	-3.49 **
$Return_{t-1}$	1.5	0.35	-18.2	-5.75 **	0.9	0.13	-11.5	-2.11 *
$Return_{t-2}$	6.2	1.78	-5.0	-1.44	16.3	2.14 *	-14.2	-2.41 *
$Return_{t-3}$	1.3	0.35	-2.3	-0.58	3.5	0.51	-3.9	-0.67
Fund's $Flows_{t-1}$	13.6	9.75 **	11.1	7.79 **	20.3	6.11 **	14.5	5.58 **
Fund's $Flows_{t-2}$	6.2	3.78 **	6.7	3.55 **	11.7	3.65 **	6.3	2.32 *
Fund's $Flows_{t-3}$	3.9	2.77 **	4.8	3.07 **	12.6	4.11 **	6.1	2.35 *
Pseudo R-squared (%)	5.78		5.48		3.53		4.44	

Table 5. Correlations of Inflows and Outflows to One Day Lagged Daily Returns by Return Decile

This table presents the correlation coefficients for the three equity funds between their inflows (outflows) and their own lagged one day return. The GIC flow correlations are relative to the equally-weighted index's returns. The returns are sorted into deciles. The lowest decile corresponds to the lowest lagged return. The inflow and outflows are the *number* of trades in and out of the funds. The number of each inflow and outflow are also reported for each fund based on return decile. One (two) asterisk(s) denote significance at the 5-percent (1-percent) significance level based on t-ratios that are adjusted for heteroskedasticity.

	Guaranteed Income Contract				Large Cap Stock Fund			
	Inflows		Outflows		Inflows		Outflows	
	Total Number	*r*	Total Number	*r*	Total Number	*r*	Total Number	*r*
Decile 1	388	-0.71**	238	-0.39*	351	-0.57**	304	-0.72**
Decile 2	177	-0.21	168	0.04	237	-0.01	167	-0.13
Decile 3	154	0.02	163	0.09	228	-0.19*	126	0.05
Decile 4	167	0.03	186	0.08	211	0.00	162	-0.01
Decile 5	131	0.01	176	-0.12	216	0.07	154	0.01
Decile 6	135	-0.15*	197	0.13	243	-0.03	141	-0.09
Decile 7	136	-0.04	198	-0.02	246	0.00	162	-0.09
Decile 8	137	0.04	236	-0.04	263	-0.01	127	-0.07
Decile 9	148	0.04	255	0.16	301	0.12	148	-0.04
Decile 10	178	0.09	275	0.01	360	0.27	205	0.06

	Medium/ Small Cap Stock Fund				Int'l Fund			
	Inflows		Outflows		Inflows		Outflows	
	Total Number	*r*	Total Number	*r*	Total Number	*r*	Total Number	*r*
Decile 1	251	-0.42	381	-0.57**	107	0.02	174	-0.43**
Decile 2	184	0.03	215	-0.20	105	0.06	111	0.01
Decile 3	238	0.17	143	0.02	106	-0.01	139	-0.08
Decile 4	156	-0.05	176	0.05	96	0.04	133	-0.08
Decile 5	195	-0.02	149	-0.08	92	-0.03	113	0.02
Decile 6	231	-0.06	113	0.13	94	-0.07	106	-0.08
Decile 7	199	-0.11	165	0.05	108	0.08	98	0.04
Decile 8	239	0.17	154	0.05	102	-0.01	121	0.10
Decile 9	271	0.16	163	0.24	113	-0.06	105	-0.05
Decile 10	321	0.10	192	0.11**	105	0.00	106	0.13*

Table 6. Breakdown of Trades based on Type

This table classifies the 5,689 trades into seven trade types based on the source and destination of the flows.

Destination	Source	No. of Trades	% of Trades
Equity	GIC	1,539	27%
GIC	Equity	1,182	21%
Equity	Equity	1,113	20%
GIC & Equity	Life	634	11%
Life	GIC & Equity	382	7%
Life	Life	306	5%
GIC & Equity	GIC & Equity	533	9%
	Total	5,689	100%

Table 7. Cross-Correlations of Trades by Type to Lead and Lag Equally-Weighted Index Returns

This table reports the cross-correlations of the two most common trade types to the lead and lag daily returns of the equally-weighted index. The flows represent the *number* of trades fitting the type classification. One (two) asterisk(s) denote significance at the 5-percent (1-percent) significance level based on t-ratios that are adjusted for heteroskedasticity.

		One Day Lead and Lags of Equity Index Returns						
Destination	Source	Lead 3	Lead 2	Lead 1	Lead 0	Lag 1	Lag 2	Lag 3
Equity	GIC	0.0369	0.0002	0.0569	0.0697*	0.0358	0.0172	0.0166
GIC	Equity	0.0334	0.0335	0.1060*	-0.0481	-0.2536**	-0.1454**	-0.0954

Table 8. Negative Binomial Regressions of the Two Most Common Trade Types

This table presents results of negative binomial regression of the number of trades going into GICs from equities or going into Equities from GICs against past daily returns and contemporaneous /past flows of the same type. The % column reports the predicted percentage change in flows given a one unit change in the explanatory variables. A one unit change in returns is equivalent to a one percent change in the daily return and a one unit change in flows is equivalent to one trade. Z-ratios are adjusted for heteroskedacity. One (two) asterisk(s) denote significance at the 5-percent (1-percent) significance level.

	Dependent Variable: Fund Flows			
	Destination Equity	Source GIC	Destination GIC	Source Equity
Independent Variables	Sign	z-Statistic	Sign	z-Statistic
Index Return$_t$	8.8	1.28	-11.2	-1.63
Index Return$_{t-1}$	-2.5	-0.25	-26.6	-4.39 **
Index Return$_{t-2}$	5.6	1.02	-4.1	-0.59
Index Return$_{t-3}$	0.6	0.10	-3.5	-0.52
Fund's Flows$_{t-1}$	17.9	10.09 **	14.3	5.96 **
Fund's Flows$_{t-2}$	5..6	2.58 *	4.3	1.56
Fund's Flows$_{t-3}$	7.4	3.56 **	0.5	0.18
Pseudo R-squared (%)	4.01		3.98	

Table 9. Correlations of the Two Most Common Trade Types to One Day Lagged Daily Equally-Weighted Index Returns by Return Decile

This table presents the correlation coefficients for the two most common trade type and the lagged one day equally-weighted index return. The GIC flow correlations are relative to the equally-weighted index's returns. The returns are sorted into deciles. The lowest decile corresponds to the lowest lagged return. The flows are the *number* of trades of each type . The number of trades are also reported for each trade type based on return decile. One (two) asterisk(s) denote significance at the 5-percent (1-percent) significance level based on t-ratios that are adjusted for heteroskedasticity.

Lagged	Market Trades			
Index	Dest: GIC Source: Equity		Dest: Equity Source: GIC	
Returns	Total Number	*r*	Total Number	*r*
Decile 1	259	-0.66**	171	-0.34
Decile 2	121	-0.15	128	0.05
Decile 3	101	0.03	121	0.14
Decile 4	110	0.08	122	0.09
Decile 5	85	-0.03	131	-0.06
Decile 6	84	-0.08	148	0.11
Decile 7	98	-0.04	156	-0.02
Decile 8	95	-0.01	166	0.00
Decile 9	104	0.03	192	0.10
Decile 10	122	0.05	204	-0.01
Total Trades	1,179		1,539	

Figure 1. Breakdown of Trades in Equities from GIC
This chart breaks down the destination of trades from GIC into Equities.

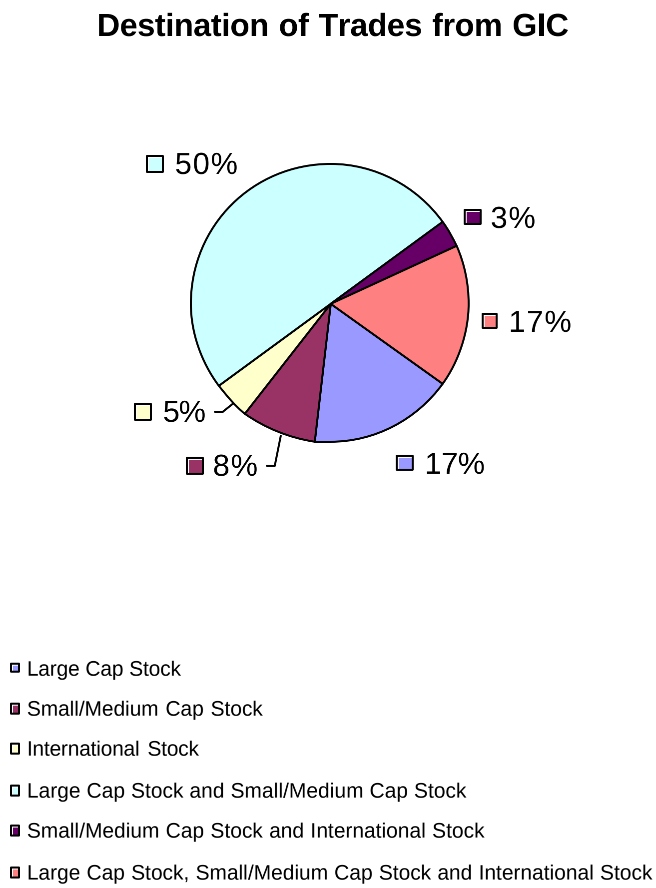
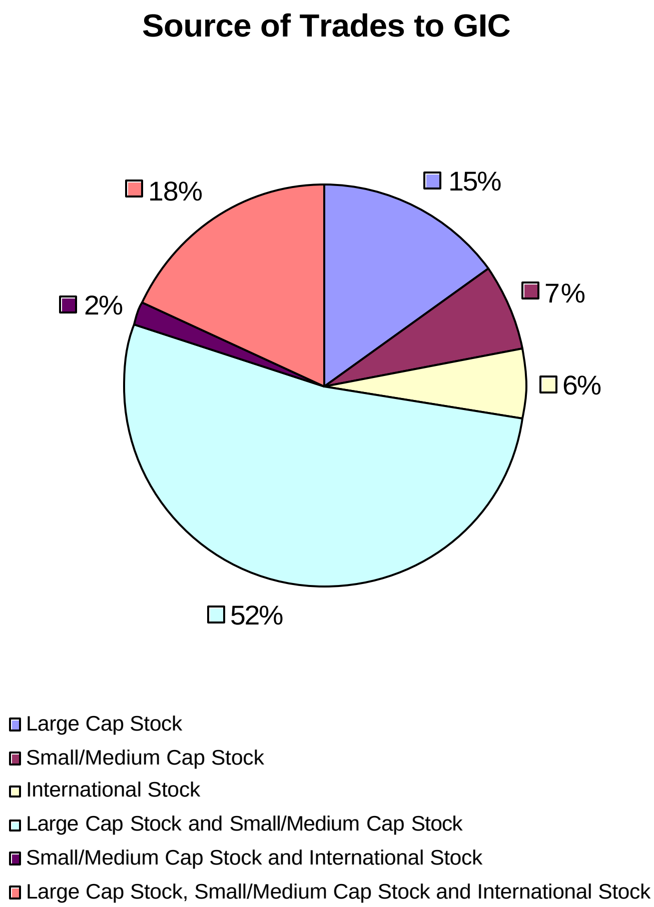


Figure 2. Breakdown of Source of Trades from Equities to GIC
This chart breaks down the sources of the trades from Equities to GIC.



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