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The Reluctant Retirement Trader: Do Asset Returns Overcome Inertia?
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Abstract: We study a new and unique data set of daily aggregate transfers of funds between mutual funds held in 401(k) accounts. We find that 401(k) transfers correlate strongly and positively with contemporaneous daily returns in the corresponding asset class. GMM estimation based on the identification-through-heteroskedasticity methodology attributes part of this correlation to investors following positive-feedback strategies. A simulation shows that these strategies may lead to substantial utility costs. These findings have implications for 401(k) plan sponsors.

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1. Introduction

On January 22, 2008, the Dow Jones Index declined over 500 points during intraday trading. On the same day, Hewitt Associates reported that its 401(k) Index, an index that tracks transfer activity between mutual fund investments in individuals' 401(k) plans, recorded transfers at eleven times their normal level (Hewitt 401(k) Index, 2008). This is noteworthy, given that 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 Sunden, 2003, and Mitchell, Mottola, Utkus, and Yamaguchi, 2006). Thus, while 401(k) participants trade infrequently, recent events suggest that market movements may induce some participants to take action. As companies increasingly offer defined contribution plans over defined benefit plans, and the idea of private accounts in Social Security is advanced, we need a clearer understanding of how the reluctant trader, specifically in retirement accounts, reacts to (or perhaps contributes to) market movements.

This paper aims to deepen our understanding of this growing class of investors by taking a close look at daily market returns and 401(k) transfer activity for a new and unique sample of nearly 1.5 million 401(k) participants derived from the Hewitt 401(k) Index.¹ The sample of retirement-only daily transfers, the relatively long time series of daily data, as well as the new econometric techniques employed, distinguish this paper from prior work related to mutual fund flows. Our research also contributes to the literature by examining how the growing number of defined contribution investors may react to market returns in the future.

Our results show that the relationship to market movements and 401(k) transfers observed on January 22, 2008, was not an anomaly. We find that transfers into “safe” assets (money market funds and GICs) correlate strongly and negatively with equity returns. These results hold even after controlling for lead-lag relationships between returns and transfers, day-of-the-week effects, and macro-economic announcements. Furthermore, we find evidence of *contemporaneous* positive-feedback trading. That is, we find a positive effect of an asset class' performance on the transfers into that asset class on the same day. Overall, these results are 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 decisions are strongly correlated with market returns. This is potentially worrisome, as it suggests that some investors may deviate from their long-run investment objectives in response to one-

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).

day market returns. We provide evidence that these deviations can lead to substantial utility costs. The upper bounds on these costs are comparable to the costs of overinvestment in company stock documented by Poterba (2003).

We also show that 401(k) transfers have a stronger relationship to returns than that documented between overall daily equity mutual fund flows and equity returns. 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. In our sample, we find that innovations in transfers into safe assets and innovations in S&P 500 returns have a correlation of 51%. This means that if we condition on the innovations in 401(k) transfers into safe assets, we explain slightly over 25% of the daily variation in the innovations S&P 500 returns.² Hence, this paper also contributes to the mutual fund flow literature by showing that the 401(k) transfer component of mutual fund flows is more correlated to asset returns than the overall mutual fund flows studied in previous work.

So, what explains why 401(k) investor transfers correlate more strongly with market returns than overall mutual fund flows? We believe the answer is that our data on transfers has several advantages over the standard mutual fund flow data used in other research. First, equity mutual fund flows include both net sales and net transfers. Our sample focuses exclusively on net transfers, which Fant (1999) argues are subject to smaller frictions than net sales and, in the case of 401(k) investors, are the result of an explicit investor decision. 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 important difference between overall mutual fund flows and the 401(k) transfers studied here is that, given the contribution limits to 401(k) plans, 401(k) transfers are less likely to be dominated by the decisions of a relatively small group of wealthy individuals. In addition, investment in 401(k) plans is limited to individuals, whereas mutual fund flows include investments of both individuals and institutions.³ Finally, 401(k) transfers are free of tax implications, whereas changes in mutual fund allocations and withdrawals may lead to capital gains taxation. In summary, we would predict that 401(k) transfers should be better indicators of small-investor preferences than overall mutual fund flows, and our results support this.

Finally, we provide evidence, using a novel econometric technique, that the positive contemporaneous relation between flows and returns from the mutual fund flow literature is partly due to

² Note that a regression of S&P500 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&P500 returns.

³ Two papers highlight the differences in behavior between institutional and retail mutual fund investors: Del Guercio and Tkac (2002) and James and Karceski (2002).

the immediate response of investors to returns. This is in contrast with Edelen and Warner (2001) and Goetzmann and Massa (2003), who find evidence that causality goes exclusively from flows to return. We use the identification through heteroskedasticity methodology of Rigobon (2003) and Rigobon and Sak (2003, 2004) and find evidence that causality goes in both directions. This indicates that while some investors' decisions proxy for the demand effects that move prices (such as news, price pressure, and investor sentiment), some investors are somewhat mechanically reacting to returns through positive-feedback trading.

The paper is organized as follows. Section 2 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 VAR) that jointly models the transfers and return series. Section 4 implements a GMM estimation based on the heteroskedasticity of the transfers and returns series to determine the contemporaneous relations between the two series. Section 5 performs a simulation to evaluate the potential utility costs associated with implementing a feedback trading strategy. Section 6 concludes.

2. Data and general summary statistics

2.1. Description of the data and comparison with other studies

This study is made possible by a newly-available 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 a total of over 10 million participants. Our data set is created from a subset of this larger group of participants. Changes in the composition of individuals' existing assets can be communicated to the plan administrator until 4:00PM (ET) for execution on the same day. Changes submitted after 4:00PM are executed at the end of the following business day.

As mentioned earlier, this paper focuses specifically on transfers, or investor-initiated movements of existing monies from one fund to another. We do not look at asset flows generated from new contributions or distributions. Hewitt tracks the daily transfer activity among 12 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 12 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, and Company Stock. For each of the 12 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 discussed below, we eliminated from the main analysis four asset classes: Company Stock, the Specialty Sector, International and Emerging Markets. We eliminated Company Stock because a clear return benchmark is not available. 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, there is no way to test if transfers in and out Company Stock affect (or are affected by) prices. In addition, we exclude International and Emerging Markets, because several of the major markets where these instruments are traded close before, or soon after, the beginning of the business day in the U.S. As a result, there is little or no overlap between the times when returns are calculated, and when transfers are typically implemented. Finally, the Specialty Sector (healthcare and technology sectors) is excluded because aggregate balances are modest.

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), and our anecdotal evidence from January 22, 2008 shows a Federal Reserve Rate cut occurring on the same day as the Dow Jones Index fell, we have also collected data on 28 major macroeconomic announcements, using the

Bloomberg database, to use as controls.⁴ The announcements include: Advance Retail 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. 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 that includes 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 and wealthy individuals. 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, Mitchell, Mottola and Utkus (2006) look at trading and subsequent portfolio performance not if returns are motivating trading. Elton, Gruber and Blake (2006) use data derived from 11-k filings with an annual periodicity; while Agnew et al. (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 outstanding feature of the data studied here is that our data set has specific information on the transfer component of 401(k) flows. For the reasons outlined in the introduction, transfers should have greater information content than total flows used in most mutual fund studies that include new purchases and sales. The additional benefit of focusing on transfers only is that it 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).⁵

⁴ 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.

⁵ Further details regarding the construction of the transfer series and the treatment of outliers in this study are available from the authors upon request.

Although the focus of this paper is the reaction of retirement investors to returns, we do at times compare our findings to the mutual fund flow literature where trades represent a broader class of investors, including non-retirement investors, especially when we consider the nature of the contemporaneous relation between transfers and returns. Therefore, to conclude this section, we will distinguish our dataset from two important mutual fund flow studies that use daily mutual fund flow data most similar to ours: Edelen and Warner (2001) and Goetzmann and Massa (2003). In addition to having specific information on the transfer component of flows, our daily data set covers longer and more recent time periods: 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. Finally, 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.

2.2. Summary statistics

Table 1 provides a summary of the average daily balances, transfers, and absolute transfers within our six asset classes. Of the classes reported, the Large Equity class has the highest daily average balance of \$17.2 billion. The next most popular investment choice of the reported asset classes is the GIC asset class, with an average daily balance of \$15.5 billion. These choices may be popular because they are common offerings in 401(k) plans and because large U.S. equity and GIC funds were among the earlier choices offered to investors. In comparison, the balances of the Bond, Balanced, Medium Equity, and Small Equity asset classes are small, ranging between \$1.4 and \$7.3 billion.

The signed dollar transfer column and the absolute dollar transfer column 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 and Large Equity.⁶ 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). The Large Equity class transfers are negative (-\$2.2 million) on average; while the average absolute transfer is the second largest (\$10.4 million). The Medium Equity asset class is associated with the lowest average absolute transfer.

⁶ Recall that we are only considering transfers among a subset of the asset classes. Hence, the fact that the total daily average transfer is positive denotes that investors transferred funds from the four asset classes (International, Emerging Markets, Speciality Sector and Company Stock) not included in this study to the six asset classes considered (GIC, Bond, Balanced, Large Equity, Medium Equity and Small Equity).

To quantify the fraction of each fund that trades daily, a relative transfer measure is calculated by dividing each asset class' daily transfers by the previous day's balance.^{7,8} This transfer measure quantifies the daily percentage change in a given asset class, due exclusively to transfer activity. The last column of Table 1 reports the standard deviation of the series. The standard deviation of transfers ranges from 5.16 basis points (Balanced) to 30.05 basis points (Small Equity).

3. What is the relationship between transfers and returns?

At the same time as the stock market exhibited volatile behavior during January 2008, Hewitt Associates reported that the majority of monies that were transferred in 401(k) accounts moved from equity investments to fixed income investments. In this section, we explore whether this was an anomaly and whether a longer time series of data supports this type of trading behavior. Our goal is to determine whether market movements 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 et al. (2003) find evidence of feedback trading with a one-day lag, but weak evidence of contemporaneous feedback trading. Also, Elton et al. (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 by looking at simple correlations between asset-class transfers and asset-class returns (Section 3.1). We then explore whether the contemporaneous correlations 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 (Section 3.2). 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. We investigate the nature of the contemporaneous relation further in Section 4.

3.1. Simple correlations

We begin our analysis by looking at the transfer series and return series separately and focusing on their autocorrelations. Table 2, 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

⁷ We standardize net transfers by the previous-day balance, rather than the same-day balance, to avoid the possibility of inducing a spurious contemporaneous correlation between transfers and returns.

⁸ We actually take the log of one plus the relative transfer. This is the continuously-compounded percentage change in asset balance due to transfers.

lag vary between -19% and 27%, and only one transfers series (Bond) exhibits serial correlation above 10% beyond 5 lags. Table 2, Panel B documents the cross-correlations of transfers and shows evidence consistent with the trading observed on January 22. The fixed income classes (GIC and Bond) are all negatively related contemporaneously (see Table 2.B column header: “Lead 0”) to the Equity classes. Transfers in Balanced and Equity funds are positively related to each other. In addition, the overall lack of serial dependence extends to cross-correlation patterns. Overall, these results suggest that individuals tend to shift funds between equities and cash or bonds, and that this is driving much of the activity.

Table 3 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 in Panel A is significant at the 1% level: the lag-three coefficient for Bond returns, at -8.1%. Cross-correlations (Table 3, Panel B) highlight a similar absence of serial dependence, with only two of the non-contemporaneous coefficients significant at the 1% level. Also, 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.

Table 4 allows us to examine how returns relate to transfers. First, there is evidence of positive-feedback trading from one day’s returns to the next day’s transfers. For example, Bond returns correlate positively with next-day (column header: “Lead 1”) 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 (column headers: “Lag 1” and “Lag 2”): -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.

Finally, the contemporaneous correlations are strongest: out of 24 correlation coefficients, 19 coefficients are significant at the 1% level. Bond returns correlate significantly and positively with bond transfers (9.7%), 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 -47.7% and -42.6%, while correlations between equity returns and equity transfers range between 16.1% and 45.3%. Therefore, 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. In addition, there may be costs associated with this type of behavior. Therefore, our next section examines in more depth the nature of the contemporaneous relationship.

3.2. VAR

The contemporaneous correlations that we observe in Section 3.1 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 macro-economic events, or day-of-the-week effects. Therefore, to test this we use a VAR framework to determine the influence of these variables. Finding evidence of their significance, we then 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.

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 macro-economic 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.

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, macro-economic 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 4.

Table 5, Panel B reports results for the last four returns equations. Findings in Table 4 are once again 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 correlation patterns, 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, macro-economic events, and day-of-the-week effects. Therefore, to examine the contemporaneous correlations without the influence of these factors, we use the innovations generated from the ten VAR equations and estimate their correlation coefficients. The results in Table 6 clearly show significant contemporaneous correlations between transfers and returns. Out of 45 coefficients, 41 are significant at the 5% level or better (40 at the 1% level). From Table 6, 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%. As noted in the introduction, this means that conditioning on GIC transfers would allow us to explain more than 25% of the variation in daily S&P500 returns.

Thus, these results are consistent with the transfer behavior observed on January 22. The results also suggest that individuals are 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, before we analyze the potential costs associated with feedback trading, it is important that we confirm that feedback trading actually occurs and that it is not exclusively transfers leading returns. We do this in the next section.

4. Investigating further the contemporaneous correlations

4.1. The current debate and our contribution

The previous VAR analysis shows a strong contemporaneous relationship between returns and transfers, even when controlling for other factors like macroeconomic announcements and lagged transfers and returns. However, the VAR analysis used cannot determine the direction of the causality between transfers and returns. In addition, the existing literature does not solidly point to causality 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).

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 impact immediately 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). Since 401(k) transfers are typically not netted until the end of the day and do not result in trading activity until the next day, it is unlikely that they contribute to order imbalance on the same day. However, they may be *correlated* with the order imbalance on that day. A second possibility is that transfers 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.

In summary, existing studies do not clearly support causality going uniquely in one direction. In addition, when we reproduce the intraday tests of Edelen and Warner (2001) and Goetzmann and Massa (2003) using our data set, we find that equity transfers (especially Medium and Small Equity) correlate with *both* morning and afternoon S&P500 returns (results available upon request). For these reasons, we introduce a newly-developed identification approach to disentangle the direction of causality. This approach exploits the heteroskedasticity of the transfers and returns series and follows the analysis of Rigobon (2003), and Rigobon and Sak (2003, 2004).⁹

4.2. Identification through heteroskedasticity

For the first time in the literature on flows and returns, we use GMM to implement the identification-through-heteroskedasticity methodology. Given that this is the first time this technique has been used in this area, we include detailed explanations in Sections 4.2.B. through 4.2.C. to allow others to replicate the methodology. The goal of this section is to determine if positive-feedback trading exists.

4.2.A. Implementation

In a nutshell, the identification-through-heteroskedasticity approach uses lagged volatilities as instruments to identify the contemporaneous relation between two series. In principle, this new methodology can be implemented for several time series at a time. Yet, the analysis quickly becomes unwieldy for more than two series at a time. Hence, we use two approaches. In our first approach, we analyze the interaction between the innovations in the first principal component (PC) of the six transfers and the innovations in

⁹ Rigobon (2003) applies the approach to estimate the contemporaneous relation between returns of Latin American bonds. Rigobon and Sak (2003, 2004) estimate the contemporaneous relation between changes in U.S. short-term rates, changes in long-term rates, and stock returns.

the first PC of the four returns.¹⁰ The first PC of the correlation matrix of transfers loads with opposite signs on GIC and Bond transfers from the equity transfers. Hence, this first PC, which explains more than 48% of overall variability, captures the “polarity” factor in transfers from fixed income to equities. The first PC of returns, which explains more than 69% of overall variability, is essentially an equally-weighted average of the returns on the three equity indices. In our second approach, we examine the interaction between different pairs of transfers and returns innovations from the VAR of Section 3.2.

4.2.B. *No common factor*

In the following, we formulate a structural-form model of transfers and returns and we outline the approach to the estimation of the structural-form parameters. Let x_t denote the innovation in the transfers equation and let r_t denote the innovation in the returns equation. We formulate a structural model where transfers are affected by returns, and where returns are affected by transfers:

$$x_t = \alpha r_t + \kappa_t \quad (1)$$

$$r_t = \phi x_t + e_t. \quad (2)$$

As to the structural innovations κ_t and e_t , we assume

$$E(\kappa_t e_t | z_t) = 0, \quad (3)$$

where z_t is a vector of instruments. In other words, we assume that the residuals κ_t and e_t are orthogonal, conditional on the realization of a set of instruments. Using the law of iterated expectations, the condition above implies

$$E(\kappa_t e_t z_t) = 0. \quad (4)$$

As to the choice of instruments, we follow Rigobon (2003), and we focus on variables that capture the time-variation of volatility in x_t and r_t . Specifically, we choose as instruments in z_t dummy variables identifying different volatility regimes. In Section A.1 of the Appendix, we show how, in the exactly-identified case of two volatility regimes, imposing the orthogonality condition (4) leads to the same closed-form estimates of the structural parameters α and ϕ as in the approach outlined in Rigobon (2003).

Note that this approach corresponds to that of identification through unconditional heteroskedasticity. Rigobon (2002) implements an alternative approach based on conditional

¹⁰ This approach follows Goetzmann, Massa, and Rouwenhorst (2000), who extract PCs from mutual fund flows to use them as factors in an asset pricing model.

heteroskedasticity, where the identification assumptions place restrictions on an ARCH-GARCH process for the conditional volatilities of the reduced-form innovations. We choose to implement the unconditional approach for two main reasons. First, Rigobon (2003) demonstrates the robustness of this approach to misspecification of the volatility-regime dummies; while a similar robustness result is not available for the conditional approach. Second, the unconditional approach allows for the estimation of the effect of a common factor, whereas the conditional approach does not.

It is worth noting that our approach to the identification-through-heteroskedasticity technique has advantages relative to the implementation suggested by Rigobon (2003). Consider, for example, the case of two volatility regimes. Rigobon (2003) suggests estimating the covariance matrix for the two series in the two regimes, leading to six moment conditions: two variances for each series plus two covariances. The six moment conditions can then be met with six parameter estimates: the variances of the two structural innovations k_t and e_t in each of the two regimes (four estimates in total) and the two structural parameters α and ϕ . Our approach, on the other hand, requires only two orthogonality conditions and two parameter estimates. In general, assuming S volatility regimes, Rigobon (2003) suggests imposing $3S$ moment conditions to estimate $2S + 2$ parameters; in our approach, we need only S orthogonality conditions to estimate two parameters. This simplifies the estimation set-up and reduces the numerical burden. Our approach also makes it easy to implement the identification-through-heteroskedasticity technique using standard econometric packages.

As noted by Rigobon (2003), there are two equivalent structural representations. The first structural representation is the one presented in equations (1)-(2). The second structural representation is

$$x_t = (1/\phi)r_t + (1/\phi)e_t \quad (5)$$

$$r_t = (1/\alpha)x_t + (1/\alpha)k_t. \quad (6)$$

Hence, for any set of estimates α and ϕ , there is an equally admissible set of estimates $(1/\phi)$ and $(1/\alpha)$. We can base the selection of the relevant set of estimates on economic considerations. In our setting, for example, we choose the set of two estimates that are less than one; the other two estimates exceed one, implying responses that are too large, and hence not plausible.

Obviously, when we allow for more than two volatility regimes, the estimation problem is over-identified, and closed-form solutions are no longer available. In this case, we can test the validity of the structural form by a standard test of the over-identifying conditions.

4.2.C. Common factor

We can augment the structural form of equations (1)-(2) with a common factor f_t , which affects instantaneously both transfers and returns. In this case, we assume:

$$x_t = \alpha r_t + f_t + \kappa_t \equiv \alpha r_t + \tilde{k}_t \quad (7)$$

$$r_t = \phi x_t + \beta f_t + e_t \equiv \phi x_t + \tilde{e}_t. \quad (8)$$

The structural form above assumes that transfers and returns first react jointly to a common factor. Then, returns impact transfers and transfers impact returns. It is natural to interpret the common factor as an information effect, not captured by the macro news already included in the VAR.

If we restrict the common factor to be homoskedastic, we can implement the estimation of the structural form (7)-(8) by imposing the orthogonality condition

$$E(\tilde{k}_t \tilde{e}_t - \nu \mid z_t) = 0, \quad (9)$$

where $\nu = \beta \sigma_f$ is the constant covariance between $\tilde{k}_t$ and $\tilde{e}_t$. This implies

$$E[(\tilde{k}_t \tilde{e}_t - \nu) z_t] = 0. \quad (10)$$

Notice that, while we assume the common factor to be homoskedastic, the orthogonal innovations k_t and e_t are still allowed to exhibit heteroskedasticity. As to the instruments z_t , we now need at least three instruments to achieve identification. If the estimation is over-identified, we can test the assumption of homoskedasticity of the common factor.

Note that our specification with a common homoskedastic factor differs from the specification with a common factor considered in Rigobon (2003). Rigobon (2003) assumes the common factor to be heteroskedastic. This requires the estimation of one volatility parameter for each of the volatility regimes. Hence, as shown by Rigobon (2003), for the estimation to be identified, one needs at least three series and four volatility regimes. In Rigobon's (2003) implementation, this leads to 24 orthogonality conditions (six variances and covariances for each of the four regimes) to estimate 24 parameters: eight structural parameters, four variances of the common factor, and three variances of the structural innovations for each of the four regimes. Our homoskedasticity assumption enables us to achieve identification with only two series. Moreover, our approach means that we have to estimate only three parameters.

4.2.D. Empirical results

Table 7 presents results of the empirical analysis. In Panel A, we report results for the analysis of the interaction of the PC innovations. Panel A presents results of the estimation of the structural form (1)-(2) and then results of the estimation of the structural form (7)-(8). To facilitate the interpretation of the

economic magnitude of the estimates, we standardize the estimates using the standard deviations of the structural innovations in the series involved, and we report: $(\sigma_r / \sigma_x)\alpha$, $(\sigma_x / \sigma_r)\phi$, and $\nu/(\sigma_k \sigma_e)$.

The base set of instruments is four volatility dummies. The first dummy identifies periods when innovations in both transfers and returns experience high volatility. The second dummy identifies periods when both transfers and returns experience low volatility. The third and fourth dummies identify periods when one series is volatile and the other is not. We calculate volatility based on a 20 business-day rolling standard deviation. In the Panel A, volatility is “high” when the rolling standard deviation exceeds its median.¹¹

Additional instruments are: a dummy variable for the bull market ended in March 2000, two dummy variables identifying periods of negative transfers or return innovations, and two dummy variables identifying periods when transfers or returns innovations are large in absolute value (above the 75th percentile or below the 25th percentile). These dummy variables should capture structural breaks and non-linearities in the structural relation between transfers and returns.

Panel A shows a significant instantaneous-feedback relation between transfers and returns. The response of transfers to returns (α) ranges between 16.86% and 36.27%, while the impact of returns to transfers (ϕ) ranges between 33.83% and 50.75%. There is evidence of a common factor, affecting transfers and innovations in opposite directions: the correlation-coefficient estimate (ν) ranges between -30.28% and -19.61%. The introduction of instruments capturing regime breaks does not lead to rejection of the model; and the introduction of instruments capturing non-linearities only leads to very mild rejections. While not reported in the table, we replicated our analysis for two alternative definitions of the volatility of transfers and returns being “high:” when the rolling standard deviation exceeds its 75th or 25th, respectively. Evidence from this analysis is broadly consistent with the evidence from Panel A. Moreover, point estimates for the choice of instruments including the large/small dummies are quite close across the three definitions of volatility regime (results available upon request).

In Panels B-D, we present results for separate pairs of equity transfers and returns innovations generated from the VAR in Section 3.2 (pairs include Large Equities, Medium Equities and Small Equities). As in Panel A, the definition of a high volatility regime is based on the median of the rolling standard deviation of the innovations. Relative to the results in Panel A, we see stronger evidence of a common factor. As in Panel A, both the impact of returns on transfers and the impact of transfers on returns are positive and mainly significant. While not reported in the table, we also performed a number

¹¹ The same approach to the identification of regimes is used by Rigobon and Sak (2004).

of additional robustness checks of our analysis, with results qualitatively and quantitatively similar to those reported in the table (results available upon request).

4.2.E. Relevant conclusions from new technique

The results from the analysis above lead to a conclusion that reconciles the disparate views in the literature. The finding is that there is instantaneous feedback between transfers and returns, as transfers tend to react significantly to returns and returns tend to react significantly to transfers. Therefore, we refute both the assumption that causality flows uniquely from transfers to returns and the assumption that causality flows uniquely from returns to transfers. This is an important and new finding in itself. In addition, it suggests that examining the utility costs associated with feedback trading in retirement accounts is needed. This is accomplished in Section 6.

6. The potential costs of feedback trading

Our analysis above provides evidence of feedback trading on the part of some investors. Therefore, this section examines how inefficient such behavior may be. For this purpose, we construct a set of economies, where we take the extreme view that the correlations between transfers and returns are uniquely due to feedback trading. We then ask which of these economies generate realistic properties of individual portfolio turnover and aggregate transfers, and we measure the associated utility costs relative to an optimal policy with no feedback trading.

We consider an investor who can invest in the equity index and the risk-free asset. The investor faces i.i.d. daily lognormal returns on the index and a constant risk-free rate. We calibrate the properties of equity returns to the value-weighted CRSP return index (Center for Research in Security Prices, University of Chicago), including dividends, over the period January 1959-December 2005. The real risk-free rate is based on the three-month T-bill rate (Federal Reserve Bank of St. Louis). Inflation is based on the CPI (Bureau of Labor Statistics). The annualized mean of the continuously-compounded real equity return is 5.79%, the annualized standard deviation is 15.38%, and the annualized continuously-compounded real risk-free rate is 1.48%. The investor has a 20-year horizon, CRRA preferences defined over terminal wealth, and an RRA coefficient of 4.64. This value of the RRA coefficient is such that the optimal allocation to equities, based on the approximate solution of Campbell and Viceira (2002), is 50%.

We consider four policies, one optimal policy and three suboptimal policies:

- Optimal Policy: Continuous Rebalancing
- Suboptimal Policy 1: Infrequent Rebalancing to the Optimum
- Suboptimal Policy 2: Infrequent Rebalancing, Feedback Trading, $\frac{1}{2}$ Rule

- Suboptimal Policy 3: Infrequent Rebalancing, Feedback Trading, Extreme

The optimal policy allows for continuous rebalancing to the optimum. All suboptimal policies start at a 50-50 allocation, but then allow the allocations to deviate from the optimum. The suboptimal policy 1, “infrequent rebalancing to the optimum,” rebalances the portfolio to the optimum at random intervals, with constant probability. The “feedback” policies, suboptimal policies 2 and 3, combine infrequent rebalancing with positive-feedback trading in response to contemporaneous equity returns. Suboptimal policy 2, the “1/2 rule,” reduces by half the existing allocation to the risk-free asset (equities), if the equity return is above (below) the mean; the “extreme” rule reduces that allocation to zero. The extreme rule is supported by evidence from Agnew et al. (2003) where 401(k) investors in one plan often held portfolios that were either 100% in bonds or 100% in stocks. In Agnew et al. (2003), roughly 70% of the observations fall into this category. Moreover, Agnew et al. (2003) also document large swings in allocations, when changes in allocations take place: conditional on a change in allocation taking place, average yearly turnover is 130%. Likewise, Yamaguchi et al. (2006) find that traders taken from a sample of over one million 401(k) participants have an average portfolio turnover rate of 92% over a two-year period. We calibrate the frequency of rebalancing to the average frequency of rebalancing documented in Agnew et al. (2003): one trade every 3.85 years.

For all policies, we perform simulations to compute the average lifetime allocations, the utility costs relative to the optimal policy (the percentage of initial wealth that the suboptimal investor is willing to give up to use the optimal policy instead), and the average yearly turnover. We also compute the average daily standard deviation of percentage transfers, and the average correlations between percentage transfers and returns, for a cohort of 100 individuals. In simulating the cohort data, we assume that all investors enter each period with the same financial wealth, and we approximate percentage transfers with the percentage change in the average allocations across individuals. The four policies are simulated 100,000 times for the individual and 1,000 times for the cohort. Further details on the simulation exercise and a tabular summary of the results (Table A.1) discussed below are included in the Appendix, Section A.2.

We first investigate whether the optimal and suboptimal policies are realistic in terms of their implications for portfolio turnover, the volatility of transfers, and the correlation between transfers and returns. The yearly turnover implied by the optimal policy is too high, 48.49%, and the turnover implied by the rebalancing to optimum policies is too low, 1.43%, relative to the average yearly turnover documented by Agnew et al. (2003), 16.20%, and Mitchell et al. (2006), 9.00%. The 1/2 rule also comes short, at 6.50%, while the extreme rule, at 12.98%, is squarely between the empirical findings of Agnew et al. (2003) and Mitchell et al. (2006).

The optimal policy leads to a daily standard deviation of aggregate percentage transfers of 0.49%. Suboptimal policy 1, infrequent rebalancing to the optimum, leads to a standard deviation of 0.04%, while the suboptimal feedback policies, $\frac{1}{2}$ rule and extreme rule, lead to standard deviations of 0.18% and 0.45%, respectively. The range of standard deviations for equity transfers documented in this paper (see Table 1) is between 0.07% and 0.30%. Hence, similar to the results on turnover, the optimal policy generates too much volatility, while the infrequent-rebalancing-to-the-optimum policy generates too little volatility. The $\frac{1}{2}$ rule is in the middle of the range, whereas the extreme rule leads to a somewhat high volatility in transfers.

Finally, we consider the correlations between transfers and same-day returns. The optimal policy leads to a correlation of -1, while infrequent rebalancing to the optimum leads to a correlation of (almost) zero. Hence, both policies are unrealistic, given the correlations between equity transfers and equity returns of between 0.16 and 0.45 documented in Table 4. On the other hand, the two feedback rules generate roughly realistic correlations of 0.22 and 0.19, respectively.

We then turn to average allocations and utility costs. The average allocation ranges between 50.73% and 54.02%, for the three suboptimal strategies. The cost for the policy that infrequently rebalances to the optimum is minimal: 0.41%. The $\frac{1}{2}$ rule, on the other hand, leads to a utility cost of 6.71%, while the extreme rule leads to the highest costs of 20.21%. Hence, even though the feedback strategies lead to average allocations that do not depart significantly from the optimum, being “right on average, but always very wrong” can have substantial utility implications.

Given our extreme view that the correlation between returns and transfers is uniquely driven by feedback trading, the utility costs above should be considered upper bounds on the actual costs experienced by investors. Yet, it is instructive to compare these upper bounds to the costs of overinvestment in company stock estimated by other authors. For example, Poterba (2003) quantifies the cost of being invested in company stock, as opposed to the S&P 500 index, for a CRRA investor with an RRA coefficient of 4 and a 35-year investment horizon. He estimates the cost of having half of the 401(k) account invested in company stock between 13% and 46%, depending on the amount of non-401(k) wealth.

In summary, positive-feedback policies, by which investors infrequently rebalance by large amounts and in response to contemporaneous returns, can reproduce several features of our data and other studies looking at retirement trading. Moreover, these policies can lead to substantial utility losses, comparable to the costs of overinvestment in company stock.

Note that our results do not depend on the poor market-timing abilities of the simulated 401(k) investors. In fact, in our simulations, equity returns are i.i.d. and the utility costs arise simply because the

sub-optimal investors do not keep their allocations at the constant optimal level. On the other hand, poor market timing is at the origin of the findings of Yamaguchi et al. (2006), who study the relationship between the trading (or non-trading) activity of 401(k) participants and their subsequent portfolio performance on a risk-adjusted return basis. Studying a sample of nearly 1 million 401(k) participants over a two year period, the authors find that trading participants in the highest turnover quintile lose more than 70 basis points per year on a risk-adjusted return basis compared to the lowest turnover quintile. However, participants who invest in a lifecycle fund, which effectively allows for automatic rebalancing by the portfolio manager, perform the best overall on a risk-adjusted return basis.

6. Conclusions

This paper takes a closer look at how individuals trade in their 401(k) plans. The above-normal trading reaction recorded by the Hewitt 401(k) Index of 401(k) participants to the stock market decline in January 2008 warrants a closer look at retirement account trading relative to market returns. While previous research has demonstrated a tendency not to trade, we do 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. Given that existing research shows that when individuals trade their asset turnover is high, and that they rarely trade more than once over several years, this causes concern that a return-motivated trading strategy can have negative effects. Through a simulation that mimics a trading strategy with limited trading, high turnover, and positive-feedback behavior, we find that the utility costs are high. This type of behavior should be a concern for plan sponsors and efforts to educate plan participants against such practices should be considered. This behavior should also be a consideration when policy makers consider private accounts in the Social Security system. Introducing private Social Security accounts would increase the number of individuals with self-directed retirement accounts who may react to market shocks. The impact of transfers by a much larger group of retirement investors could have consequences on market returns and the investors' ultimate retirement savings, which should be studied in future research.

Finally, this paper concludes that some 401(k) participants make their trading decisions based on returns on the same day. Previous research has arguments supporting this view, but also the opposite claim that flows uniquely cause returns. We implement a new econometric technique that reconciles both views and demonstrates a bi-directional causality between transfers and returns. This is a contribution to the research in the mutual fund area, and it provides strong support for the assumption we used in our simulation and for the concerns that we raise over positive feedback trading in retirement accounts.

Appendix

A.1. Identification through heteroskedasticity and GMM

The connection between the orthogonality condition (4) and time variation in volatility is best seen in the case of *two* regimes. In this case, the estimation approach is *exactly identified*, and we obtain closed-form expressions for the structural-parameter estimates. Using the structural form (1)-(2) and the orthogonality condition (4), we obtain

$$(1 + \alpha\phi)E(x_t r_t z_{1,t}) - \phi E(x_t^2 z_{1,t}) - \alpha E(r_t^2 z_{1,t}) = 0 \quad (\text{A.1})$$

$$(1 + \alpha\phi)E(x_t r_t z_{2,t}) - \phi E(x_t^2 z_{2,t}) - \alpha E(r_t^2 z_{2,t}) = 0, \quad (\text{A.2})$$

where $z_{1,t}$ identifies the first volatility regime, and $z_{2,t}$ identifies the second volatility regime.

The system above leads to the same closed-form solutions presented in Rigobon (2003):¹²

$$\alpha = \frac{\phi b - a}{\phi a - c} \quad (\text{A.3})$$

$$\phi = \frac{(bf - ec) \pm \sqrt{(bf - ec)^2 - 4(bd - ae)(af - cd)}}{2(bd - ae)}, \quad (\text{A.4})$$

where

$$a = E(x_t r_t z_{1,t}), \quad b = E(x_t^2 z_{1,t}), \quad c = E(r_t^2 z_{1,t}) \quad (\text{A.5})$$

$$d = E(x_t r_t z_{2,t}), \quad e = E(x_t^2 z_{2,t}), \quad f = E(r_t^2 z_{2,t}). \quad (\text{A.6})$$

A.2. Simulation exercise

We obtain the (approximate) optimal constant equity allocation w^* as

$$w^* = \frac{\mu_e + (\sigma_e^2 / 2) - r_f}{\gamma \sigma_e^2}, \quad (\text{A.7})$$

where μ_e is the mean of the continuously-compounded equity return, σ_e^2 is the variance of the continuously-compounded equity return, r_f is the continuously-compounded risk-free rate, and γ is the relative-risk-aversion coefficient.

The utility cost of employing a suboptimal policy can be expressed in terms of the certainty-equivalent returns associated with the optimal and suboptimal policies. In turn, the certainty-equivalent

¹² Rigobon (2003) derives conditions on the relation between moments across volatility regimes for the solutions to exist.

return is that return that, if earned with certainty, would give the investor the same utility as the expected utility obtained for a given allocation policy. The certainty-equivalent return is implicitly defined as

$$\frac{[W_0(1 + CER)]^{1-\gamma}}{1-\gamma} = E\left(\frac{W_T^{1-\gamma}}{1-\gamma}\right) \quad (\text{A.8})$$

and the utility cost is given by

$$Cost = \frac{CER^* - CER}{1 + CER^*}, \quad (\text{A.9})$$

where W_0 is the initial wealth, W_T is the terminal wealth, CER is the certainty-equivalent return associated with a given policy, and CER^* is the certainty-equivalent return associated with the optimal policy. The expectation in A.8 is evaluated by simulation.

When we simulate the behavior of a cohort of investors, we assume that all investors start with the same (optimal) allocation, and the same wealth. Then, depending on the assumed investment policy, all, or only a fraction of the investors, change allocations. When allocations are not actively changed, they still vary because of returns. In this case, the current allocation to equities w_t equals the inherited allocation $\hat{w}_t$ (following Balduzzi and Lynch, 1999, we assume that all proceeds from investment in equities and bonds are reinvested in the same security),

$$w_t = \hat{w}_t = \frac{w_{t-1}(1 + R_{et})}{w_{t-1}(1 + R_{et}) + (1 - w_{t-1})(1 + R_f)}, \quad (\text{A.10})$$

where R_{et} is the rate of return on equities and R_f is the risk-free rate. Note that transfers take place only when there are “active” changes in allocations, i.e. when $w_t \neq \hat{w}_t$.

To simplify the setting, we assume that investors’ relative wealth remains equal over time. Hence, we approximate the daily percentage equity transfer as the average active change in the equity allocation across individuals, relative to the previous day’s average equity allocation.

Table A.1: Summary of Simulation Results

	Yearly Turnover	Standard Deviation of Transfers*	Correlation between Transfers and Same- Day Returns*	Average Allocations	Utility Cost
Optimal Policy					
Continuous Rebalancing	48.49%	0.49%	-1.00	50.00%	0.00%
Suboptimal Policies					
Infrequent Rebalancing to the Optimum	1.43%	0.04%	0.00	53.22%	0.41%
Infrequent Rebalancing, Feedback Trading, 1/2 Rule	6.50%	0.18%	0.22	54.02%	6.71%
Infrequent Rebalancing, Feedback Trading, Extreme	12.98%	0.45%	0.19	50.73%	20.21%
Empirical Results for Comparison					
Agnew, Balduzzi and Sunden (2003)	16.20%				
This paper		.07% to .30% (See Table 1)	.16 to .45 (See Table 4)		

* These results are generated from a simulation of a cohort of 100 individuals.

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Table 1: General Summary Statistics

The table reports: means of the aggregate daily balances; means and standard deviations of the daily signed and absolute dollar transfers; and standard deviations of the daily signed (%) transfers. Sample Period: 8/4/1997-9/30/2002

	Dollar Balances		Signed Dollar Transfers		Absolute Dollar Transfers		Signed (%) Transfers
Asset Class	Mean		Mean	Std.	Mean	Std.	Std.
GIC	\$ 15,464,711,533	\$	4,022,648	\$ 39,498,613	\$ 28,257,351	\$ 27,878,951	0.2207
Bond	\$ 1,737,737,716	\$	1,503,371	\$ 7,465,323	\$ 4,713,515	\$ 5,979,836	0.2676
Balanced	\$ 7,345,886,222	\$	(1,235,706)	\$ 7,461,950	\$ 3,531,922	\$ 6,687,651	0.0516
Large Equity	\$ 17,244,168,671	\$	(2,209,538)	\$ 15,849,741	\$ 10,432,232	\$ 12,131,943	0.0675
Medium Equity	\$ 2,966,174,488	\$	348,340	\$ 5,593,017	\$ 3,382,202	\$ 4,467,112	0.1280
Small Equity	\$ 1,362,977,809	\$	611,950	\$ 5,527,093	\$ 3,467,515	\$ 4,346,322	0.3005

Table 2: Serial Correlations and Cross-correlations of Transfers

Panel A reports serial correlation coefficients of the transfers series. Panel B reports cross-correlations between the transfers. Significance is based on standard errors adjusted for heteroskedasticity and serial correlation (five lags). Sample Period: 8/4/1997-9/30/2002

Panel A: Serial Correlations of Transfers

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*

** Significant at the .01 level. *Significant at the .05 level.

Table 2 (Continued): Serial Correlations and Cross-correlations of Transfers

Panel B: Cross-correlations of Transfers

Transfers	Lagged / Lead Transfers	Lead 5	Lead 4	Lead 3	Lead 2	Lead 1	Lead 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5
GIC	Bond	-0.001	0.034	0.047	-0.020	0.076**	0.332**	-0.066*	0.043	0.061*	0.033	-0.024
	Balanced	-0.001	-0.012	-0.031	-0.041	-0.108**	-0.251**	-0.001	-0.003	-0.017	-0.009	-0.017
	Large Equity	-0.001	-0.027	-0.027	0.001	-0.101**	-0.350**	-0.032	0.037	0.007	-0.006	-0.029
	Medium Equity	-0.029	-0.036	0.035	0.020	-0.023	-0.525**	0.069*	0.014	-0.028	-0.004	0.023
	Small Equity	0.015	-0.073*	0.011	0.062*	-0.050	-0.457**	0.138**	0.002	-0.018	-0.028	0.016
Bond	Balanced	-0.027	-0.082*	-0.096*	-0.127**	-0.155**	-0.210**	-0.159**	-0.064	-0.077*	-0.059	-0.012
	Large Equity	-0.055	-0.124**	-0.133**	-0.156**	-0.177**	-0.385**	-0.171**	-0.059	-0.089*	-0.053	-0.074*
	Medium Equity	-0.050	-0.095**	-0.125**	-0.070	-0.076*	-0.386**	-0.122**	-0.010	-0.065*	-0.061	-0.011
	Small Equity	0.009	-0.039	-0.046	-0.078*	-0.094**	-0.278**	-0.042	-0.012	-0.048	-0.041	0.008
Balanced	Large Equity	0.038	0.024	0.123**	0.103**	0.217**	0.514**	0.214**	0.090*	0.101**	0.042	0.023
	Medium Equity	0.066	0.047	0.054	0.060	0.122**	0.384**	0.170**	0.071*	0.039	0.036	0.010
	Small Equity	-0.000	0.008	0.044	0.052	0.113**	0.250**	0.197**	0.046	0.057	0.021	0.041
Large Equity	Medium Equity	0.030	0.045	0.018	0.041	0.087*	0.541**	0.167**	0.055	0.023	0.053	-0.007
	Small Equity	0.032	-0.004	0.005	-0.008	0.090**	0.304**	0.123**	0.018	0.045	0.006	0.012
Med. Equity	Small Equity	0.026	0.049	0.033	-0.019	0.116**	0.488**	0.045	-0.006	-0.022	0.041	0.061

** Significant at the .01 level. *Significant at the .05 level.

Table 3: Serial Correlations and Cross-correlations of Returns

Panel A reports serial correlation coefficients of the returns series. Panel B reports cross-correlations between the returns. Significance is based on standard errors adjusted for heteroskedasticity and serial correlation (five lags). Sample Period: 8/4/1997-9/30/2002

Panel A: 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

** Significant at the .01 level. *Significant at the .05 level.

Table 3 (Continued): Serial Correlations and Cross-correlations of Returns

Panel B: Cross-correlations of Returns

Returns	Lagged / Lead											
	Returns	Lead 5	Lead 4	Lead 3	Lead 2	Lead 1	Lead 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5
Bond	Large Equity	0.009	-0.015	-0.001	0.030	0.009	-0.139**	0.028	0.060*	-0.028	-0.026	-0.011
	Medium Equity	-0.025	-0.009	0.016	0.015	-0.016	-0.158**	0.021	0.043	-0.001	-0.029	0.001
	Small Equity	-0.018	0.003	0.026	0.007	-0.007	-0.170**	0.016	0.041	-0.007	-0.038	-0.000
Large Equity	Medium Equity	-0.023	0.009	-0.011	-0.058	0.055*	0.867**	0.022	-0.051	-0.000	-0.006	-0.042
	Small Equity	-0.020	0.026	0.010	-0.040	0.066*	0.803**	0.003	-0.069*	0.010	-0.013	-0.072*
Med. Equity	Small Equity	-0.003	0.039	0.049	-0.060	0.085**	0.924**	0.039	-0.098**	0.039	0.009	-0.045

** Significant at the .01 level. *Significant at the .05 level.

Table 4: Cross-correlations of Returns and Transfers

The table reports cross-correlations between returns and transfers at leads and lags. Significance is based on standard errors adjusted for heteroskedasticity and serial correlation (five lags). Sample Period: 8/4/1997-9/30/2002

Returns	Lagged / Lead											
	Transfers	Lead 5	Lead 4	Lead 3	Lead 2	Lead 1	Lead 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5
Bond	GIC	0.008	-0.004	0.015	-0.007	0.002	0.003	-0.003	-0.041	0.014	0.006	-0.014
	Bond	0.008	0.038	0.021	0.119**	0.135**	0.097**	-0.075**	-0.082**	-0.048	-0.004	0.002
	Balanced	-0.055*	-0.008	-0.043	-0.010	-0.039	-0.043	0.033	-0.025	-0.009	-0.029	0.020
	Large Equity	-0.036	-0.020	-0.014	-0.064*	-0.113**	-0.048	0.002	0.023	0.031	0.022	-0.035
	Medium Equity	-0.036	-0.004	-0.021	-0.018	-0.065*	-0.031	0.013	0.035	-0.011	-0.027	-0.014
	Small Equity	-0.002	0.013	-0.028	-0.074**	-0.056*	0.022	0.037	0.010	-0.008	-0.004	-0.038
Large Equity	GIC	0.017	-0.049	-0.024	0.048	0.280**	-0.477**	0.013	-0.003	0.033	0.000	0.047
	Bond	-0.045	-0.082**	-0.068*	-0.054	-0.087*	-0.211**	0.042	0.040	-0.007	0.035	0.042
	Balanced	0.066*	0.075*	0.130**	0.093**	0.268**	0.244**	-0.056	-0.050	-0.068	-0.051	-0.055
	Large Equity	0.036	0.099**	0.110**	0.114**	0.215**	0.161**	-0.040	-0.069*	-0.033	-0.039	-0.013
	Medium Equity	0.031	0.052	-0.005	0.024	0.046	0.418**	-0.081**	-0.088**	-0.034	0.006	-0.026
	Small Equity	0.007	0.094**	0.021	0.009	0.056	0.349**	-0.065*	-0.066*	-0.079**	-0.019	-0.015

** Significant at the .01 level. *Significant at the .05 level.

Table 4 (Continued): Cross-correlations of Returns and Transfers

Returns	Lagged / Lead											
	Transfers	Lead 5	Lead 4	Lead 3	Lead 2	Lead 1	Lead 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5
Medium Equity	GIC	0.008	-0.056	-0.056	0.057	0.232**	-0.438**	-0.011	0.026	0.010	0.004	0.025
	Bond	-0.052	-0.097**	-0.069*	-0.044	-0.054	-0.243**	0.053	0.069*	-0.033	0.030	0.028
	Balanced	0.079**	0.099**	0.149**	0.098**	0.253**	0.262**	-0.048	-0.026	-0.057	-0.068	-0.038
	Large Equity	0.024	0.116**	0.121**	0.117**	0.175**	0.195**	-0.025	-0.070**	-0.041	-0.032	-0.026
	Medium Equity	0.048	0.061*	0.034	0.027	0.060	0.441**	-0.059*	-0.107**	-0.006	0.008	-0.040
	Small Equity	0.049	0.099**	0.060*	0.044	0.081*	0.353**	-0.053	-0.068*	-0.062*	-0.011	-0.008
Small Equity	GIC	0.026	-0.036	-0.081**	0.046	0.223**	-0.426**	-0.032	0.031	0.010	-0.010	0.031
	Bond	-0.032	-0.086**	-0.070*	-0.045	-0.058	-0.283**	0.056	0.064*	-0.032	0.000	0.023
	Balanced	0.081**	0.098**	0.141**	0.091**	0.235**	0.254**	-0.033	-0.003	-0.030	-0.060	-0.016
	Large Equity	0.019	0.111**	0.103**	0.101**	0.150**	0.208**	-0.014	-0.054	-0.025	-0.015	-0.013
	Medium Equity	0.033	0.059*	0.058*	0.023	0.043	0.453**	-0.027	-0.099**	-0.010	0.014	-0.043
	Small Equity	0.031	0.091**	0.089**	0.067*	0.096**	0.372**	-0.009	-0.058	-0.044	-0.004	-0.012

** Significant at the .01 level. *Significant at the .05 level.

Table 5: Results from VAR

The table reports statistics for a VAR of the six 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 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.

Panel A: VAR Results, Transfers Equations

Dependent Variable:	Transfers					
	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*

** Significant at the .01 level. *Significant at the .05 level.

Panel B. VAR Results from Four Returns

Dependent Variable:	Returns			
	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

** Significant at the .01 level. *Significant at the .05 level.

Table 6: Correlations of VAR Innovations

The table reports the correlation matrix of the VAR innovations. Significance is based on standard errors adjusted for heteroskedasticity. Sample Period: 8/4/1997-9/30/2002

		Transfers						Returns			
Innovations		GIC	Bond	Balanced	Large Equity	Medium Equity	Small Equity	Bond	Large Equity	Medium Equity	Small Equity
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

** Significant at the .01 level, two-tailed test. *Significant at the .05 level, two-tailed test.

Table 7: Identification through Heteroskedasticity

The table reports estimates of the instantaneous response of transfers to returns (α), of the instantaneous response of returns to transfers (ϕ), and of the covariance between the transfers and returns shocks (ν). The estimation is implemented by GMM, where the instruments are dummy variables identifying volatility regimes (volatility), the bull/bear market periods (bull/bear), periods of positive/negative transfers and returns (positive/negative), and periods of unusually large (in absolute value) transfers and returns (large/small). Panel A models the interaction of innovations in the PCs of transfers and returns. Panels B-D model the interaction between innovations in different pairs of transfers and returns. See Section 4 for details. Sample Period: 8/4/1997-9/30/2002

Panel A: Unconditional heteroskedasticity, 50th percentile

Instruments	Chi-Square	Significance Level	α	ϕ	ν
Volatility	5.58	0.0614	0.1686*	0.3383**	
Volatility	2.14	0.1433	0.2154**	0.5075**	-0.2165
Volatility, bull/bear	2.57	0.2768	0.2368**	0.4855**	-0.2137
Volatility, positive/negative	4.87	0.1816	0.2471**	0.4605**	-0.1961
Volatility, large/small	7.79	0.0505	0.3627**	0.4451**	-0.3028**

Panel B: Large Equities

Instruments	Chi-Square	Significance Level	α	ϕ	ν
Volatility	4.03	0.1335	0.0321	0.1440	
Volatility	1.55	0.2124	0.2131*	0.2920**	-0.2861**
Volatility, bull/bear	1.58	0.4541	0.2176*	0.2872**	-0.2858**
Volatility, positive/negative	2.38	0.4973	0.2203*	0.2834**	-0.2847**
Volatility, large/small	3.21	0.3598	0.1900**	0.2170**	-0.1884**

Panel C: Medium Equities

Instruments	Chi-Square	Significance Level	α	ϕ	ν
Volatility	7.28	0.0263	0.3264**	0.1167	
Volatility	2.52	0.1126	0.4167**	0.3253**	-0.3027*
Volatility, bull/bear	2.52	0.2832	0.4179**	0.3236**	-0.3022*
Volatility, positive/negative	2.76	0.4306	0.4172**	0.3260**	-0.3039*
Volatility, large/small	2.64	0.4501	0.3951**	0.3473**	-0.3026**

Panel D: Small Equities

Instruments	Chi-Square	Significance Level	α	ϕ	ν
Volatility	10.59	0.0050	0.1351**	0.2253**	
Volatility	4.23	0.0396	0.2990**	0.4555**	-0.3719**
Volatility, bull/bear	4.72	0.0942	0.3079**	0.4478**	-0.3733**
Volatility, positive/negative	5.61	0.1324	0.3017**	0.4572**	-0.3764**
Volatility, large/small	8.36	0.0392	0.3026**	0.3707**	-0.2895**

** Significant at the .01 level. *Significant at the .05 level.