Are Financial Advisors Useful?

Evidence from Tax-Motivated Mutual Fund Flows[✧]

Gjergji Cici, Alexander Kempf, and Christoph Sorhage [*]

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ABSTRACT

This study shows that financial advisors provide useful tax advice to their clients, being the first to provide evidence of tangible benefits delivered by financial advisors in the U.S. We find that investors who purchase mutual fund shares through financial advisors exhibit a stronger tendency of avoiding taxable distributions than investors who buy shares directly. This differential is more pronounced for distributions that have large tax implications and are hard-to-predict. Furthermore, the differential gets stronger in December but only when investors face large capital losses, consistent with financial advisors helping the former investors engage in tax-loss selling.

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* Cici is from Mason School of Business, The College of William & Mary. P.O. Box 8795, Williamsburg, VA 23187-8795, United States. Email: gjergji.cici@mason.wm.edu, Phone: 757-221-1826. Cici is also a Research Fellow at the Centre for Financial Research (CFR), University of Cologne. Kempf is from Department of Finance and Centre for Financial Research (CFR), University of Cologne. Albertus-Magnus Platz, Cologne, 50923, Germany. Email: kempf@wiso.uni-koeln.de, Phone: +49 221 470 2714. Sorhage is from Department of Finance and Centre for Financial Research (CFR), University of Cologne. Albertus-Magnus Platz, Cologne, 50923, Germany. Email: sorhage@wiso.uni-koeln.de, Phone: +49 221 470 7885.

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1 Introduction

The value of advice provided by financial advisors to mutual fund investors has been the subject of an ongoing regulatory and academic debate. A critical interpretation of the extant empirical evidence suggests that financial advisors are unable to create value by helping their clients pick better-performing funds (e.g. Bergstresser, Chalmers, and Tufano (2009); Chalmers and Reuter (2012); Del Guercio and Reuter (2012) and Hackethal, Haliassos, and Jappelli (2012)), which could be because financial advisors either have limited skills or face conflicts of interest with their clients.[1] However, the possibility that financial advisors could provide services resulting in benefits other than superior investment performance to an unsophisticated investor clientele has not been ruled out. In fact, this view has been advanced by several studies even though supporting empirical evidence is lacking.[2]

Several factors complicate the process of assessing the value of financial advisors. For one, assessments based on performance comparisons between mutual funds sold through financial advisors and those sold directly are subject to a potential endogeneity in the relation between fund performance and the distribution channel. Fund families devoting fewer resources to active management might choose to sell funds through the brokered channel, making it hard for advisors to pick even average-return funds.[3] Another complicating factor in assessing the value generated by financial advisors is that in most cases there is no clear way for researchers to know each investor's objectives so that they can be compared against his or her actions that were shaped by financial advice. The final complicating factor is that for many of the investors' needs that financial advice is supposed to address there is no objective

[1] Studies that look at aspects other than performance of investments bought through the brokered channel also support this view. For example, Mullainathan, Noeth, and Schoar (2012) show that financial advisors exacerbate rather than diminish the existing biases of their investors, while Christoffersen, Evans, and Musto (2012) show that fund flows in the brokered channel are affected by financial advisors' incentives related to compensation.

[2] Although many of the studies that compare the direct and brokered investment channels touch on this idea, Del Guercio, Reuter, and Tkac (2010) and Del Guercio and Reuter (2012) are the first to fully espouse the view that unsophisticated investors from the brokered channel seek advisory services rather than portfolio management services, which could explain why fund families invest less in the performance of funds sold in the brokered channel.

[3] A similar argument is made by Del Guercio and Reuter (2012).

way of knowing ex-ante what constitutes an optimal strategy. For example, since markets are presumed to be highly efficient, it is not ex-ante obvious what constitutes an optimal strategy for picking funds with the highest risk-adjusted performance or for allocating assets in a portfolio. If such optimal strategies existed and were known to researchers, comparing their outcomes against observed investment outcomes shaped by financial advice would help assess whether financial advisors are useful to their investors.

Our paper contributes to the debate on the role of financial advisors, being the first to provide empirical evidence that financial advice creates value for investors. We do so by documenting that financial advice intended to help mutual fund investors with tax-management is valuable. Analyzing the tax-management dimension of financial advice is attractive because it circumvents the three complicating factors highlighted above. First, focusing on tax management advice from financial advisors rather than fund performance eliminates the endogeneity problem in the relation between fund performance and the distribution channel. Second, from researchers' point of view, there is no ambiguity with respect to investors' objectives as far as taxes are concerned: all investors want to minimize taxes.[4,5] Finally, ex-ante optimal tax-management strategies for mutual fund investors are relatively easy and transparent to understand.

To assess the value created by financial advisors, we compare the extent to which investors that operate under the guidance of financial advisors (hereafter, indirect channel investors) implement a better tax strategy than investors that do not rely on financial advisors (hereafter, direct channel investors). As pass-through entities, U.S. mutual funds have to

[4] For example, most investors state access to tax planning services as one of the reasons for maintaining an ongoing advisory relationship with a financial advisor (Investment Company Institute (2007)), while an overwhelming majority of mutual fund investors recognize the impact of taxes on mutual fund returns and consider tax implications when making investment decisions (Eaton Vance (2010, 2008, 2003, 2001)).

[5] Academic research also supports the view that mutual fund investors care about taxes. For example, Barclay, Pearson, and Weisbach (1998) show that investors avoid funds with large embedded unrealized capital gains that could potentially lead to taxable distributions, while Bergstresser and Poterba (2002) document investors' inflows to be smaller for funds that had higher tax-burdens in the past. Further, Ivković and Weisbenner (2009) show that mutual fund investors harvest losses and defer realization of gains consistent with the optimal tax-loss selling strategies of Constantinides (1984).

distribute dividends and realized capital gains to their investors to avoid taxation as corporations. These distributions create tax liabilities for investors even though their purchased fund shares might have declined in value since the purchase date. Thus, for investors that are considering purchasing shares in a fund around its distribution date, a tax-deferral strategy of purchasing fund shares right after rather than right before a given funds' distribution date is optimal in that it lowers the present value of the associated tax liabilities.[6,7] If financial advisors provide useful tax management advice to indirect channel investors we would expect indirect investors' flows to exhibit stronger tax-deferral patterns than direct investors (Tax Advisory Hypothesis).

We quantify tax-deferral behavior as the net flow differential between the week after and before the week of a taxable distribution made by a given mutual fund. Our findings show evidence of tax deferral in both channels. However, flows exhibit a much stronger tax-deferral pattern in the indirect channel. Specifically, the tax-deferral flow effect in the indirect channel is about 1.4 times the effect in the direct channel, suggesting that financial advice increases the tax awareness of indirect channel investors to a level that even surpasses that of their presumably more sophisticated peers from the direct channel.[8] Hereafter, for ease of exposition, we refer to the tax-deferral flow differential between indirect and direct investors as the tax-deferral differential effect.

We extend the Tax Advisory Hypothesis a step further. If financial advisors provide useful tax advice for fund investors, then financial advice ought to be more valuable with respect to timing of fund purchases around taxable distributions that matter the most for investors, that is, distributions that have greatest potential tax implications. Our results

[6] See, Johnson and Poterba (2010) for a more detailed discussion of how tax liabilities are affected by such distributions.

[7] This strategy is not only well known among financial professionals, but is also widely discussed in the financial press usually towards the end of the calendar year when most of the taxable distributions take place (e.g., Moisand (2011)).

[8] For a detailed discussion of why indirect channel investors are arguably less sophisticated than their indirect counterparts see Malloy and Zhu (2004) and Del Guercio and Reuter (2012).

support this hypothesis. Specifically, we show that the tax-deferral differential is more pronounced for distributions that are larger and have potentially larger tax liabilities (i.e., large distributions combined with higher tax rates).

We next analyze whether financial advice is more valuable when distributions are harder to predict. The rationale is that retail investors are unable to forecast hard-to-predict distributions while financial advisors are able to do so since they have access to resources that ordinary investors do not. For example, software data packages such as those provided by Morningstar to financial advisors closely track distributions made through the year as well as embedded capital gains or capital losses for each fund. After conversations with U.S.-based financial advisors, we also learned that mutual fund companies often warn affiliated financial advisors of the size of impending distributions, effectively placing financial advisors at an advantage to more accurately predict the size of capital gain distributions.

To categorize distributions by their predictability, we distinguish between dividend and capital gain distributions. Dividend distributions occur at a higher frequency, and knowing the universe of stocks that a fund invests in together with the associated dividend yields of those stocks makes dividend distributions more predictable. On the contrary, capital gain distributions depend on the trading behavior of portfolio managers and their unique preference for realizing capital gains and losses, which makes capital gains less predictable.[9] Consistent with financial advice being more valuable in the case of less predictable distributions, we find evidence of the tax-deferral differential effect being present among capital gain distributions but not among dividend distributions.

In the next step we analyze whether financial advisors are able to help their clients avoid unexpected high distributions. To do so, we decompose capital gains into expected and unexpected components employing a number of variables with explanatory power for capital

[9] Cici (2012) shows that preferences for realizing capital gains versus capital losses differ across mutual fund managers — some managers exhibit patters that are more likely to be consistent with behavioral biases such as the disposition effect — and differ through time depending on the conditions of the fund, e.g., whether the fund has experienced inflows or outflows.

gains (see Barclay, Pearson, and Weisbach (1998) and Sialm and Starks (2012)). Consistent with financial advisors assisting investors more in the face of surprisingly high distributions, the indirect channel investors react more vigorously to the unexpected component while direct channel do not react at all to the unexpected component of the capital gain distributions.

We next explore how the tax-deferral differential effect interacts with other tax-related considerations. Ivković and Weisbenner (2009) show that investors' propensity to sell fund shares that have declined in value is more pronounced in December, when investors engage in tax-loss selling to reduce tax obligations. This tax-loss selling behavior towards the end of the year could interact with the tax-deferral differential effect. Consider a group of investors who are subject to large unrealized capital gains in their shares of a fund, which is about to make a taxable distribution. The optimal strategy for these investors might be to hold onto their fund shares (and thus receive the distribution) to avoid triggering large capital gains. The optimal strategy for another group of investors who are subject to large unrealized capital losses due to their participation in the poor past performance of a given fund is to redeem their shares right before the distribution date, allowing them to harvest capital losses and avoid a taxable distribution at the same time.[10]

Our results confirm the presence of an interaction between the tax-deferral differential effect and tax-loss selling. More specifically, the tax-deferral differential effect gets stronger in December but only for mutual funds where investors are most likely to be facing capital losses in their fund shares. This finding is consistent with indirect channel investors being advised by their financial advisors to not only delay additional investments until after the distribution date but to also redeem shares that have declined in value in order to harvest losses that can be used to reduce their tax bills.

[10] This is exactly what happened during the recession following the burst of the tech bubble when many mutual funds experienced significant declines in their shares but were also forced to make large taxable distributions because investor redemptions forced them to liquidate positions with large embedded capital gains (Smith (2001)). A similar effect took place during the most recent recession.

Our paper is related to a growing number of studies that examine whether financial advice generates measurable benefits for its recipients. Bergstresser, Chalmers, and Tufano (2009); Chalmers and Reuter (2012); Del Guercio and Reuter (2012) and Hackethal, Haliassos, and Jappelli (2012) show that financial advisors are unable to help investors pick outperforming funds. Mullainathan, Noeth, and Schoar (2012) document that financial advisors fail to moderate their clients' behavioral biases. Bhattacharya, Hackethal, Kaesler, Loos, and Meyer (2012) show that investors' inattention to financial advice — even when the advice is unbiased — is a major impediment to financial advice achieving its goals. We contribute to this literature with findings suggesting that financial advisors are providing useful tax management advice to fund investors in the U.S. and that fund investors indeed act on this advice. To the best of our knowledge, ours is the first study to provide evidence of tangible benefits delivered by financial advisors to their clients in the U.S. As such, our evidence provides concrete support for the view espoused by Del Guercio and Reuter (2012) and Del Guercio, Reuter, and Tkac (2010) that indirect channel investors demand and receive financial advisory services rather than purely portfolio management services.

Our study is also related to a second group of studies that examine how tax considerations shape the decisions of individual mutual fund investors (e.g., Barclay, Pearson, and Weisbach (1998); Bergstresser and Poterba (2002); Ivković and Weisbenner (2009) and Johnson and Poterba (2010)). We contribute to this literature strand by documenting that mutual fund investors are not homogenous when responding to taxes. Instead, investors' reaction to taxes is related to the distribution channel through which they transact, whereby indirect channel investors display stronger tax awareness shaped in large part by financial advice.

The remainder of this paper is organized as follows. In Section 2, we discuss our data set and sample summary statistics. Section 3 presents our findings on mutual fund investors' avoidance of taxable distribution across the direct and indirect distribution channels. We

investigate how the tax-deferral effect is accentuated by the distributions' implicit tax liabilities in Section 4. Section 5 analyzes whether financial advice is more valuable to clients when distributions are hard-to-predict. We investigate whether advisors help their clients avoid unexpected high distribution in Section 6 and whether the tax-deferral effect interacts with tax-loss selling in Section 7. Section 8 concludes.

2 Data

2.1 Data Sources and Sample Construction

We obtain mutual fund data from four databases – Thomson Reuters Lipper Flows, Thomson Reuters Mutual Fund Holdings, Center for Research in Security Prices (CRSP) Stock Files, and CRSP Survivor-Bias Free US Mutual Fund databases.

Data on the primary distribution channels of U.S. equity fund shares as well as weekly data on net flows and assets under management are from Thompson Reuters Lipper Flows (Lipper). Lipper assigns each fund share class to one of its three distribution channel categories.[11] Share classes sold primarily through brokers and financial advisors are placed in the brokered channel (hereafter indirect channel) category while share classes sold directly to investors are placed in the direct channel category. The remaining distribution channel comprises share classes sold primarily to institutional investors.

Holdings data for U.S. equity funds are from Thomson Reuters Mutual Fund Holdings Database. The database reports the name, identifier, and number of shares for each security held by each mutual fund on each reporting date. Holdings data were supplemented with individual stock prices and other information from the CRSP Monthly and Daily Stock Files.

[11] Previous studies (e.g., Del Guercio and Reuter (2012); Del Guercio, Reuter, and Tkac (2010), and Bergstresser, Chalmers, and Tufano (2009)) have relied on the distribution channel classifications from Financial Research Corporation (FRC). However, since FRC's classification is based on Lipper's, we do not expect big differences between the two classification schemes, which was indeed confirmed by Bergstresser, Chalmers, and Tufano (2009) who show that the Lipper and FRC classifications are very similar.

Information on share class characteristics, such as funds returns, expense ratios, turnover ratios, and investment objectives was obtained from the CRSP Mutual Fund database. We estimate weekly returns for each share class by compounding daily returns. Since CRSP offers investment objectives from several data providers we combine them into a single investment style classification. For the share classes we also obtain information on distribution dates, amounts, and reinvestment prices (NAV) from CRSP. We eliminate all distributions from our sample that are tax-exempt. Similar to Sialm and Starks (2012) we normalize distribution amounts by the NAV of the respective fund share at the distribution date. The resulting distribution yields that we use to assess the size of distributions correspond to the number of shares an investor could have purchased with the distributed amount.

We analyze flows at the share class level instead of at the fund level. Two considerations make analysis at the share class level more attractive. First, most share classes are distributed primarily only through one distribution channel, and accordingly the Lipper classification of primary distribution channels is done at the share class level. Second, mutual funds allocate received dividends and realized capital gains on a pro-rata basis when making distributions and these distributions are paid net of expenses, causing distributions to differ across share classes.[12]

To arrive at our final sample, we eliminate all share classes with missing MFLINKS code and exclude shares sold through the institutional channel because we want to examine investment behavior of retail investors. In addition, since our focus is on taxable and actively managed U.S. equity funds, we take additional steps to exclude index, international, sector, balanced, fixed-income, and tax-exempt funds. We further require that each fund share has at

[12] The fact that distributions are paid net of expenses is explicitly stated on the websites of many mutual fund families (e.g., the websites of Waddel&Reed and Nicholas Company Inc. fund families, respectively, at www.waddell.com/mutual-funds/capital-gain-distributions and www.nicholasfunds.com/dividend). Also, differences in distribution amounts across share classes are directly observable in asset managements' distribution reports (e.g., the websites of Pioneer Investments and Thornburg Investment Management fund families, respectively, at us.pioneerinvestments.com/funds/distributions and www.thornburginvestments.com/funds/dividends).

least 52 weeks of flow and return data. Our final sample includes 722,280 share class-week observations. It covers 2,430 U.S. domestic equity fund shares over the period September 1999 – the first point of time for which all data is available – to June 2011.

2.2 Sample Characteristics

Table I presents summary statistics for each year and distribution channel in our dataset.

- Insert Table I approximately here -

The number of share classes increases from 363 in 1999 to 2,412 in 2011, consistent with an increase in investment choices for retail investors.[13] The indirect channel share classes represent the dominant form of distribution in the retail investment sector. About 75% of the share classes in our sample are sold through the indirect channel, which is consistent with Bergstresser, Chalmers, and Tufano (2009). In terms of assets, directly sold share classes are significantly larger in all periods of our sample and they grow at a higher rate on average. Also consistent with previous studies that examined mutual fund distribution channels, indirect channel share classes have higher expense ratios during all periods.[14] An interesting observation is that although they are more numerous, indirect share classes control a smaller amount of total assets. This is consistent with Del Guercio and Reuter (2012) who show that the total assets of indirect share classes are only about two thirds of the total assets of direct share classes.

For the direct and indirect channels we report the number and size of distributions in Table II. Summary statistics are presented by year in Panel A and by month in Panel B.

- Insert Table II approximately here -

[13] The Investment Company Institute (2012) provides a comprehensive overview on the evolution of the mutual fund industry.
[14] See, e.g., Bergstresser, Chalmers, and Tufano (2009) and Del Guercio and Reuter (2012).

There are a total of 21,055 taxable distributions in our sample that are categorized either as capital gain or dividend distributions. Overall, dividend distributions occur about twice as often as capital gain distributions.

Comparing distributions across channels shows that the number of capital gain and dividend distributions is much larger for the indirect channel than for the direct channel. This holds for the entire sample period and almost every single year and is attributable to the fact that there are more shares in the indirect than in the direct channel. On the contrary, the size of dividend distributions is significantly larger in the direct channel than in the indirect channel for all years, while the opposite holds for capital gain distributions, on average.

It is noteworthy that the number and size of distribution varies considerably over time. In particular, we see much smaller capital gain distributions in the subprime crisis (2008-2011) than in the other years. By comparison, the variation of the dividend distributions is much smaller.

Consistent with Sialm and Starks (2012), we observe that capital gains dominate dividend distributions in terms of size, being on average more than twelve times larger than dividend distributions.

Panel B shows considerable intra-year effects of distributions irrespective of the distribution channel. While most capital gain distributions occur at the turn of the year, dividend distributions occur throughout the year and mostly with quarterly frequency.

3 Tax-Deferral Differential between Direct and Indirect Channel Investors

This section explores our Tax Advisory Hypothesis: flows of indirect investors exhibit stronger tax-deferral patterns than direct investors. Our measurement of the tax-deferral flow effect is based on a two-step procedure. First, for each share class *i* around each taxable distribution event, we compute the flow change from the week before to the week after the distribution week *t* as follows,

$$(1)\ \Delta F_{i,t}=F_{i,t+1}-F_{i,t-1}\ ,$$

where $F_{i,t}$ is the net flow of fund share class *i* normalized by the share class's assets under management lagged by one week. Looking at the share class's flow change is attractive because it directly captures investors' net reaction around distribution weeks and minimizes the influence of share class- and fund-level characteristics on flows. Second, flow changes around distribution weeks are compared with flow changes around non-distribution weeks. The intuition behind our approach for measuring tax-deferral behavior is that if investors are delaying their investments in a particular share class in the week prior to the distribution week to avoid that distribution, then flows in the week before should be lower than in the week after, resulting in a higher flow change around distribution weeks compared to non-distribution weeks, all else equal.

To test our hypothesis, i.e., test for differences in the tax-deferral behavior of direct and indirect channel investors, we employ several regression specifications where the dependent variable is our flow change measure, $\Delta F_{i,t}$.[15] To avoid contamination of flow changes corresponding to non-distribution weeks by flow responses to distribution events, we exclude all observations taking place in weeks t-2, t-1, t+1 and t+2 whenever week t corresponds to a distribution week. Our base model specification is as follows:

$$(2)\ \Delta F_{i,t}=\alpha_0+\alpha_1 D_{i,t}^{Distr.}+\beta_0 D_i^{Ind}+\beta_1 D_{i,t}^{Distr.}D_i^{Ind}+\gamma\Delta R_{i,t-1}+\epsilon_{i,t}$$

Our main independent variables are the *Distribution* dummy ($D_{i,t}^{Distr.}$) which equals one if share class *i* is subject to a taxable distribution in week *t* and the *Indirect* dummy (D_i^{Ind}) which equals one if fund share *i* is sold indirectly. Our key test for the Tax Advisory Hypothesis is based on the interaction of these two variables, which is, in effect, a difference

[15] We acknowledge that $F_{i,t+1}$ is affected by net inflows in week t. As a robustness check we employ $\Delta F_{i,t} \coloneqq \frac{net\ inflows_{i,t+1}}{AUM_{i,t-2}}-\frac{net\ inflows_{i,t-1}}{AUM_{i,t-2}}$ in an alternative specification and repeat our analyses. Our results (not reported) remain qualitatively the same.

in difference test measuring how the effect of distributions on the flow change variable differs between indirect and direct channels (i.e., "tax deferral differential" effect).

To control for flows reacting to past performance, we include *Delta Return* ($\Delta R_{i,t-1}$), the differential weekly return of share class *i* between week *t* and *t-2*.[16] In further regressions we extend our baseline specification by sequentially including investment objective fixed effects, time (yearly) fixed effects as well as other fund and share class-level controls. Those controls include the one year return, expense ratio, logarithm of assets under managements, and turnover ratio. The first three control variables are measured at the share class level, while the last one, turnover ratio, is measured at the fund level. To account for possible correlations both within time periods and funds' share classes that share the same distribution channel, we cluster standard errors on both fund specific distribution channel and week (Petersen (2009)).

- Insert Table III approximately here -

Results reported in Table III confirm a general pattern of tax-deferral in fund flows around taxable distributions. In all models, the incremental effect of a distribution on the flow change in the direct channel is about 0.35 percentage points, i.e. the flow in the week after a taxable distribution is about 0.35 percentage points larger than the flow in the week before. As expected, the intercept suggests that this effect is non-existent for the non-distribution weeks.

Results from our main test based on the interaction term, i.e., testing the tax-deferral differential effect, suggest that the tax-deferral effect is significantly stronger in the indirect channel than in the direct channel. The coefficient on the interaction term of about 0.16 percentage points is significant in all models. It suggests that the incremental effect of a distribution on the flow change in the indirect channel is about 0.5 percentage points, thus 1.4 times as large as in the direct channel. This result supports our Tax Advisory Hypothesis.

[16] Flow reactions to past fund performance was first documented as an empirical regularity by Ippolito (1992); Chevalier and Ellison (1997), and Sirri and Tufano (1998) and has been confirmed by a large number of subsequent studies.

Regarding the control variables, *Delta Return* has a significantly positive impact on the flow change variable, which is consistent with flows following returns. All our results are virtually identical in the various models suggesting that the controls have no notable impact.

In summary, our results suggest that mutual fund investors exhibit behavior that is consistent with a tax-deferral motivation. Most important, the effect of tax-deferral on flows is stronger among indirect channel investors. This is consistent with financial advisors informing their clients about impending distributions and advising them accordingly to delay investments until after taxable distributions take place.

4 Tax-Deferral Differential and Magnitude of Tax Consequences

In this section we introduce additional tests of the Tax Advisory Hypothesis that explicitly take into account the associated tax implications of the underlying fund distributions. In particular, we hypothesize that if financial advisors generate value for their clients by increasing their awareness of tax effects, we ought to observe a stronger tax-deferral differential effect in exactly those cases when distributions can create larger tax liabilities. We start by exploring whether the tax-deferral differential is related to distribution size, which is expected to be positively related to the size of the associated tax liabilities. Next, distinguishing between distributions taxed at different rates, we explicitly compute associated tax liabilities for each distribution, which we then relate to the tax-deferral behavior of investors.

4.1 Stratifying Distributions by Size

We start by investigating whether the value of financial advice increases with the size of the distribution, i.e., whether the tax-deferral differential between direct and indirect channel investors increases with distribution size. We split fund distributions into three equally sized groups every year based on their magnitude. Using a similar approach as in the

previous section, we then compare investors' reactions to large, medium, and low sized distributions across the direct and indirect channel.

- Insert Table IV approximately here -

Table IV results suggest that the tax-deferral differential between indirect and direct channel investors, as hypothesized, increases with the size of the distribution. In particular, the tax-deferral differential effect among large distributions amounts to 0.54% (p-value<0.01). It suggests that the tax deferral behavior of indirect investors is 1.6 times as strong as that of direct channel investors. Moving from large to medium distributions, the tax-deferral differential, although statistically significant at the 5%-level, declines almost by a factor of two. Moving from medium to small distributions, the tax-deferral differential drops even further, becoming statistically insignificant. Interestingly, direct channel investors also exhibit tax-deferral behavior but only for the largest taxable distributions

Take all together, these results are consistent with financial advisors taking an active role in advising their clients when larger distributions with potentially larger tax implications are about to take place.

4.2 Stratifying Distributions by Their Tax Liabilities

Although avoidance of large distributions is preferable to investors, an even more attractive tax-management strategy is to avoid distributions that have the highest tax-liabilities associated with them. In this section, we investigate whether the value of financial advice increases with the tax liability of underlying distributions, i.e., whether the tax-deferral differential between direct and indirect channel investors increases with the associated tax liability.

To calculate tax liabilities we multiply each distribution with the tax rate that the distribution is subject to. Since tax rates depend on investors' income, we use tax rates that

apply to the median income of U.S. households as a proxy for a representative investor.[17] More specifically, we employ the median income of an U.S. household using U.S. Census Bureau data for each year. Then we use historical information on federal tax rates of individual income and calculate for each point of time the marginal tax rates for long-term gain distributions, short-term gain distributions, and dividends that apply to the respective median-income household.[18]

We split fund distributions into three equally sized groups every year based on the size of their associated tax liability. We then compare investors' reactions to distributions that fall in the large, medium, and low tax liability groups across the direct and indirect channel.

- Insert Table V approximately here -

Results from Table V suggest that the tax-deferral differential between indirect and direct channel investor increases with the size of the associated tax liability. In particular, the tax-deferral differential effect among distributions with large tax liabilities amounts to 0.53% (p-value<0.01). This is similar to the tax-deferral differential documented among the largest distributions in the previous section, which is most likely due to the fact that distribution size is highly correlated with tax liabilities. Moving from large-tax-liability to medium-tax-liability distributions, the tax-deferral differential, although statistically significant, declines almost by a factor of three. Moving from medium-tax-liability to small-tax-liability distributions, the tax-deferral differential drops even further and remains only marginally significant. Interestingly, direct channel investors also exhibit tax-deferral behavior but only for the largest-tax-liability. In summary, our combined results from this section suggest that financial advice becomes more valuable for large distributions and distributions with explicitly larger tax burdens.

[17] As a robustness check, we repeat this analysis using the highest income tax rates that could apply to an investor. Results (not reported) remain qualitatively the same.

[18] Information on federal individual income tax rates was taken from the Tax Foundation's website, http://taxfoundation.org/tax-basics.

5 Tax-Deferral Differential and Predictability of Fund Distributions

In this section we introduce a test of the Tax Advisory Hypothesis that takes into account the predictability of underlying fund distributions. Harder-to-predict distributions are likely to increase the variability of annual tax liabilities, which is undesirable for most investors. If financial advisors help their clients minimize the variability of their annual tax liabilities by increasing their clients' awareness of harder-to-predict distributions, then we ought to observe a stronger tax-deferral differential effect for these types of distributions. In other words, we would expect financial advisors to guide their clients to put more effort into avoiding hard-to-predict types of distributions.

We classify distributions into easier- and harder-to-predict categories by distinguishing between dividend and capital gain distributions. Dividend distributions occur at a higher and more regular frequency (usually every quarter) and are generally more stable. Furthermore, information on the dividend yields of the underlying fund portfolio stocks is generally easy to obtain. These features afford investors the opportunity to anticipate mutual funds' dividend distributions with relatively greater ease. Capital gain distributions, however, are harder to anticipate because they depend on the trading behavior of portfolio managers, the portfolio managers' unique preference for realizing capital gains and losses, as well as redemption activity, which at times might be outside the portfolio manager's control.[19] These features give capital gain distributions a higher volatility, which is undesirable for most investors.

To measure the investors' reactions around the two types of distributions we use the following baseline model:

[19] For instance, Dickson, Shoven, and Sialm (2000) document that share redemptions of fund shareholders can force portfolio managers to close positions and thus trigger capital gain distributions. Furthermore, a growing number of papers show that individual trading behavior of portfolio managers and their preferences for realizing capital gains and losses can have a considerable impact on accrued capital gains (see, e.g., Barclay, Pearson, and Weisbach (1998); Cici (2012); Gibson, Safieddine, and Titman (2000); Huddart and Narayanan (2002) and Sialm and Starks (2012)).

$$(3)\ \Delta F_{i,t} = \alpha_0 + \alpha_1 D_{i,t}^{Gains} + \alpha_2 D_{i,t}^{Div} + \beta_0 D_i^{Ind} + \beta_1 D_{i,t}^{Gains} D_i^{Ind} + \beta_2 D_{i,t}^{Div} D_i^{Ind} + \gamma_1 \Delta R_{i,t-1} + y_2 Size_{i,t} + \epsilon_{i,t},$$

where independent variables *Gain Distribution* ($D_{i,t}^{Gains}$) and *Dividend Distribution* ($D_{i,t}^{Div}$) are indicator variables that equal one if share class *i* is subject to a capital gain or dividend distribution during week *t*. We use *Delta Return* ($\Delta R_{i,t-1}$) to capture the impact of past return on flows (as in the previous regressions) and add *Distribution Size* ($Size_{i,t}$) to control for the impact of distribution size on the flow differential (as documented in Table IV).

- Insert Table VI approximately here -

Our results from Table VI show that financial advice is more valuable when the distributions are hard-to-predict. Specifically, the tax-deferral differential is statistically significant for capital gain distributions but not for dividend distributions. This suggests that financial advisors help their clients reduce the uncertainty associated with their tax liabilities.

6 Tax-Deferral Differential and Unexpected High Distributions

Having shown that financial advisors help their clients reduce the uncertainty associated with their tax liabilities, we next address whether financial advisors are also able to help their clients avoid unexpected high distributions. From an investor's perspective these are the most undesirable distributions that investors would like to avoid.

We hypothesize that because of the assistance of financial advisors, indirect channel investors are in a better position to avoid surprisingly high distributions than direct channel investors. Financial advisors could warn their clients based on their ability to come up with more precise estimates of capital gain distributions than the estimates that direct channel investors can come up with on their own. This argument is predicated on the premise that, as

service providers in the financial industry, financial advisors are presumed to have more experience and access to superior information and technologies.

Since capital gains are harder to predict and the tax-deferral differential is more pronounced for these types of distributions, in what follows we restrict our analysis to capital gain distributions. We model realized capital gains in a regression framework as a function of past share class and fund-level characteristics shown in the previous literature to have predictive power (e.g., Barclay, Pearson, and Weisbach (1998) and Sialm and Starks (2012)). The main independent variables, measured at the share class level, include past returns and past normalized net flows — both measured over short-term as well as long-term intervals — and the expense ratio. Also measured at the share class level, we include the volatility of past returns and past flows to capture the effects that share redemption activity could have on the realization of capital gains. The independent variables measured at the fund level include assets under management, age, portfolio fraction held in cash, portfolio turnover, and capital gains overhang. Finally, we add fixed effects to account for different distributions patterns of gains over time as well as across investment styles and fund families. We run the regression on a rolling basis requiring at least two years of data.[20] This provides us with a time series of regression coefficients which we use to predict out-of-sample one-step-ahead values of the capital gains. This generates both expected and unexpected capital gains. We divide the unexpected capital gain distribution by the actual capital gain distribution to get the *Surprise Ratio*.

We now explore our hypothesis that investors in the indirect channel benefit from financial advisors, which puts them in a better position to avoid unexpected high distributions. We do so by regressing the flow change variable on the *Surprise Ratio* and test whether the effect is stronger in the indirect channel. Results are provided in Table VII.

[20] Our model fits the gain distribution fairly well. The average R^2 across all regressions is 43.1%.

- Insert Table VII approximately here -

The positive and significant coefficient on the interaction term *Surprise Ratio*Indirect* in Table VII supports our hypothesis that investors in the indirect channel exhibit stronger tax-deferral behavior around capital gains with larger positive unexpected components. Thus, indirect investors seem to benefit from the warnings of financial advisors. The warnings of financial advisors targeting distributions with large positive surprise components appears to give indirect channel investors an advantage over direct channel investor when it comes to avoiding these types of distributions.

7 Interaction with Tax-Loss Selling

In this section we examine how the tax-deferral differential effect interacts with tax-loss selling, which is another important tax strategy. Ivković and Weisbenner (2009) document a greater propensity for investors in December to sell fund shares that have depreciated in value. This suggests that investors engage in tax-loss selling at the end of the year in order to reduce their tax obligations.

We hypothesize that the tax-deferral differential effect will get stronger in the presence of tax-loss selling considerations. The rationale is that by acting on advice from financial advisors investors receive the double benefit of reducing their tax liabilities by tax-loss selling and avoiding impending taxable distributions. This is perhaps best illustrated by the following example. Consider a group of investors whose fund shares — that they bought at the same point in time — are subject to large unrealized capital losses because of poor past fund performance. We also know that the underlying fund is about to make a taxable distribution. The optimal strategy for these investors is to redeem their shares right before the distribution date, allowing them to harvest capital losses and avoid a taxable distribution at the same time. Redemptions motivated by tax-loss selling from existing fund investors prior to a distribution

would add to the tax-deferral effect of other (both existing and new) investors who simply choose to delay their investments in the fund until after the distribution date. The resulting effect will be an even larger flow change, especially for funds sold to indirect investors who are alerted to engage in both tax-deferral and tax-loss selling by financial advisors.[21]

To test for the hypothesized interaction between tax-loss selling and the tax-deferral differential effect, we first identify funds whose investors are most likely to engage in tax-loss selling. Not having tax basis information for the shares held by each individual investor, we argue that funds which performed worst during the previous year while having low levels of capital gain overhang in their portfolios are most likely to be subject to tax-loss selling in December. These funds are the best candidates for tax-loss selling because they are subject to both short-term and long-term portfolio paper losses, which would suggest that the shares of the average investor in these funds are subject to capital losses (i.e., have depreciated in value).

Each week of our sample we sort share classes into terciles based on their fund's capital gains overhang at the end of the previous quarter. Within each overhang tercile, we further sort share classes into terciles based on their compounded one-year NAV-return. We use NAV-returns rather than total returns because NAV-returns best reflect appreciation or depreciation of the underlying shares, which in turn drives the tax-loss-selling decisions of investors as shown in Ivković and Weisbenner (2009). Based on this sorting, we construct a "Tax-Loss Group" which consists of all share classes that belong to the low overhang – low return group. We estimate a regression model based only on weekly observations that correspond to distribution weeks[22] as follows:

[21] Edward Jones, for instance, a leading financial advisor, points out that one key step in their approach is the strategic realization of losses to offset gains to manage tax outcomes. Similar strategies are discussed in the financial press (Diliberto (2008)).

[22] The choice to restrict the regression observations to only distribution weeks is made primarily to keep the model tractable by reducing the number of interaction terms. However, when we repeat the analysis for all

$$(4)\ \Delta F_{i,t} = \alpha_0 + \alpha_1 \mathrm{TLG_{i,t}} + \alpha_2 Dec_i + \alpha_3 \mathrm{TLG_{i,t}} Dec_i + \beta_0 D_i^{Ind} + \beta_1 \mathrm{TLG_{i,t}} D_i^{Ind} +$$
$$\beta_2 Dec_i D_i^{Ind} + \beta_3 TLG_{i,t} Dec_i D_i^{Ind} + \gamma \Delta R_{i,t-1} + \epsilon_{i,t},$$

where $TLG_{i,t}$ represents the "Tax-Loss Group", a binary variable that equals one if share class *i* belongs to the group that we consider to most likely to be subject to tax-loss selling in week *t*. Dec_i is a *December* dummy, that equals one if the observation occurs in the month of December. Our key test is based on the triple interaction, $TLG_{i,t} Dec_i D_i^{Ind}$, which measures whether the tax-deferral differential is stronger in December for funds that are candidates for tax-loss selling.

- Insert Table VIII approximately here -

Table VIII results show that there is a general December effect across all investors. Thus, investors seem to take a closer look at their investments and react more to distributions in December. However, the most interesting insight comes from the huge positive coefficient on the triple interaction term. This suggests that the tax-deferral differential between indirect and direct channel investors gets significantly stronger in December for funds that are most likely candidates for tax-loss selling. Thus, there is an interaction effect between the tax-deferral differential effect and tax-loss selling, suggesting that financial advisors alert their clients to not only avoid distributions but to also engage in tax-loss selling in December if they currently hold fund shares that have depreciated in value.

8 Conclusion

With more than 200 thousand personal financial advisors[23], the market for financial advice in the U.S. is characterized by tremendous size and activity. What happens in this market affects the investment decisions of millions of investors and shapes portfolio decisions

observations, i.e. with the entire set of required interaction terms, our results (not reported) remain qualitatively the same.

[23] Bureau of Labor Statistics: http://www.bls.gov/ooh/business-and-financial/personal-financial-advisors.htm.

that collectively cover billions of dollars. Despite this level of activity in this important market and the number of individuals that are affected by it, our understanding of the economic forces that shape the interactions among its different players is limited at best.

Recent studies have begun to address the gap between its importance and our rather limited knowledge of the market for financial advice. Using the mutual fund industry as a testing ground, most of these studies have analyzed the performance of investment choices made by mutual fund investors that were shaped by financial advice. A common finding is that outcomes from investment decisions shaped by financial advice were inferior to those that do not rely on such advice. This evidence lends itself to a natural question: If investors do not get any performance benefits from the financial advice they receive, what explains the presence of financial advisors and why are investors willing to pay for such advice?

Our paper contributes to the academic literature that seeks to understand the role of financial advisors in their clients' decision making by being the first to provide evidence of tangible benefits delivered by financial advisors. The tangible benefits we document appear in the form of useful tax management advisory services to mutual fund investors, which help them engage in tax-deferral strategies. Financial advice puts its beneficiaries, indirect channel investors, at a clear advantage over their peers who do not receive financial advice. A detailed exploration of this dimension through which investors receive assistance from financial professionals suggests that financial advice appears to target situations when investors need this advice the most. In other words, we document financial advice to be even more valuable when investors are facing situations that significantly increase the size or the uncertainty of their tax liabilities. This, taken together with our evidence that investors' tax-deferral behavior shaped by financial advisors is intensified by what appear to be tax-loss selling considerations, could suggest that financial advice comprehensively addresses not one but several facets of tax-management.

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Table I - Share Class Characteristics by Distribution Channel

This table reports descriptive statistics for our sample from 1999-2011. U.S. equity fund share classes are categorized by their primary channel of distribution. We classify a share class as belonging to the *Direct* (*Indirect*) distribution channel based on classification provided by Lipper. *Assets* represents the average assets under management per share class in million USD. *Net Flow* is the average share class net flow, which is defined as the weekly net flow per share class normalized by its assets lagged by one week; *Expense Ratio* is the average expense ratio of the share classes during the respective year. *Net Flow* and *Expense Ratio* are in percentages. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

	Number of Share Classes		Share Class Characteristics								
			Assets			Net Flow			Expense Ratio		
Year	Direct	Indirect	Direct	Indirect	Difference	Direct	Indirect	Difference	Direct	Indirect	Difference
1999	143	220	1,701.0	417.1	1,283.8 ***	-7.4%	9.7%	-17.0% ***	1.17%	1.58%	-0.42% ***
2000	180	331	1,520.6	370.9	1,149.7 ***	7.2%	14.9%	-7.7%	1.21%	1.68%	-0.47% ***
2001	210	415	1,167.2	280.1	887.1 ***	21.7%	19.4%	2.3%	1.22%	1.71%	-0.49% ***
2002	243	589	969.2	276.4	692.8 ***	12.3%	11.9%	0.3%	1.24%	1.77%	-0.53% ***
2003	269	727	911.2	249.5	661.7 ***	14.3%	19.1%	-4.9%	1.26%	1.83%	-0.57% ***
2004	297	868	1,252.9	286.9	966.0 ***	13.0%	12.4%	0.6%	1.26%	1.85%	-0.59% ***
2005	338	1,059	1,276.6	316.0	960.6 ***	11.4%	6.6%	4.8% *	1.21%	1.80%	-0.58% ***
2006	401	1,206	1,093.9	332.6	761.3 ***	6.8%	3.2%	3.6%	1.21%	1.77%	-0.55% ***
2007	462	1,307	1,214.3	371.1	843.1 ***	2.6%	-2.6%	5.1% **	1.22%	1.74%	-0.52% ***
2008	485	1,479	974.4	295.9	678.5 ***	-1.0%	-11.9%	10.9% ***	1.21%	1.72%	-0.51% ***
2009	542	1,565	825.4	200.9	624.5 ***	6.6%	-10.5%	17.1% ***	1.21%	1.76%	-0.55% ***
2010	568	1,705	956.6	225.8	730.8 ***	2.1%	-9.9%	12.0% ***	1.22%	1.80%	-0.57% ***
2011	605	1,807	1,115.0	248.7	866.3 ***	4.0%	-6.0%	10.0% ***	1.20%	1.77%	-0.58% ***
All Years	609	1,821	1,024.1	251.1	773.0 ***	7.5%	-1.1%	8.6% ***	1.22%	1.78%	-0.56% ***

Table II - Number and Size of Taxable Distributions

This table reports descriptive statistics on the *Number of Distributions* and the *Size of Distributions* across the *Indirect* and *Direct* distribution channel. The channel classification of share classes is defined as in Table I. The *Distribution Size* is in percentage points and measured as the distribution amount per share normalized by the share's NAV at the distribution date. We report the descriptive statistics by year in Panel A and by month in Panel B. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Panel A: Variation across years

	Number of Distributions				Size of Distributions					
	Capital Gains		Dividends		Capital Gains			Dividends		
Year	Direct	Indirect	Direct	Indirect	Direct	Indirect	Difference	Direct	Indirect	Difference
1999	106	191	78	136	7.43%	9.03%	-1.61% *	0.58%	0.26%	0.32% ***
2000	171	322	153	342	10.57%	11.43%	-0.86%	0.52%	0.24%	0.27% ***
2001	130	207	151	296	4.22%	3.74%	0.48%	0.44%	0.20%	0.24% ***
2002	81	83	179	465	3.15%	3.50%	-0.35%	0.39%	0.20%	0.20% ***
2003	82	117	263	663	2.78%	3.29%	-0.51%	0.41%	0.21%	0.20% ***
2004	137	339	223	668	5.45%	5.65%	-0.20%	0.40%	0.25%	0.14% ***
2005	219	673	290	854	6.70%	6.69%	0.01%	0.43%	0.25%	0.18% ***
2006	299	874	365	977	6.55%	7.23%	-0.69%	0.45%	0.29%	0.16% ***
2007	385	1,090	428	1,129	8.66%	9.98%	-1.32% ***	0.54%	0.33%	0.21% ***
2008	288	544	560	1,515	5.38%	3.64%	1.74% ***	0.69%	0.52%	0.17% ***
2009	26	21	546	1,562	0.81%	1.12%	-0.30%	0.56%	0.42%	0.13% ***
2010	68	100	537	1,440	2.50%	2.83%	-0.32%	0.48%	0.33%	0.15% ***
2011	11	12	160	499	1.31%	1.19%	0.12%	0.35%	0.25%	0.10% ***
All Years	2,003	4,573	3,933	10,546	6.43%	7.17%	-0.73% ***	0.50%	0.33%	0.17% ***

Table II - Number and Size of Taxable Distributions (continued)

Panel B: Intra-year variation

	Number of Distributions				Size of Distributions						
	Capital Gains		Dividends		Capital Gains				Dividends			
Month	Direct	Indirect	Direct	Indirect	Direct	Indirect	Difference		Direct	Indirect	Difference	
January	266	112	377	420	5.71%	4.61%	1.10%	*	0.52%	0.27%	0.25%	***
February	4	2	24	221	1.16%	1.08%	0.08%		0.07%	0.11%	-0.04%	**
March	47	139	315	1,352	1.04%	1.39%	-0.36%		0.31%	0.24%	0.07%	***
April	28	28	207	555	1.96%	1.56%	0.40%		0.28%	0.24%	0.05%	**
May	24	31	52	249	2.38%	3.27%	-0.89%		0.28%	0.15%	0.12%	***
June	47	141	408	1,407	3.91%	2.21%	1.70%	***	0.40%	0.27%	0.13%	***
July	25	77	240	561	2.23%	3.10%	-0.87%		0.38%	0.27%	0.11%	***
August	13	113	38	245	2.24%	2.70%	-0.45%		0.25%	0.14%	0.11%	***
September	24	87	277	1,255	2.82%	5.54%	-2.73%	**	0.35%	0.25%	0.11%	***
October	49	25	192	487	7.85%	6.94%	0.91%		0.31%	0.21%	0.10%	***
November	156	721	89	330	7.95%	8.70%	-0.75%		0.49%	0.29%	0.20%	***
December	1,320	3,097	1,714	3,464	7.00%	7.79%	-0.79%	***	0.67%	0.52%	0.15%	***

Table III – The Tax Effects on Fund Flows

This table presents results from a pooled OLS regression that relates flow changes with share class and fund characteristics. The analysis is done at the share class and weekly level. The dependent variable, $\Delta F_{i,t}$, denotes the difference between the normalized net flow ($F_{i,t}$) of share class *i* in weeks *t+1* and *t-1*. $F_{i,t}$ is in percentages and is the net flow of share class *i* in week *t* normalized by assets under management in *t-1*. The independent variables include: *Distribution* ($D_{i,t}^{Distr.}$), a binary variable that equals one if a share class is subject to a taxable distribution in week *t*; *Indirect* (D_i^{Ind}), a binary variable that equals one if a share class is indirectly sold; and *Delta Return* ($\Delta R_{i,t-1}$), the difference of weekly returns of a share class between weeks *t* and *t-2*. Additional independent variables include *Annual Return*, *Expense Ratio*, *Share Class Assets*, and *Portfolio Turnover*. *Annual Return* is the average return of a share class during the t-3 to t-55 interval. *Expense Ratio* is the share class' expense ratio. *Share Class Assets* represents the log of the total assets of the share class. *Portfolio Turnover* is the fund's turnover rate in percentage points. The latter three independent variables are all lagged by two weeks. Regressions are run with and without time (yearly) and investment objective fixed effects. Standard errors are clustered by funds' specific distribution channel and week. P-values are reported in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Dependent Variable: Difference in Normalized Weekly Flows around t								
Model:	1		2		3		4	
Constant	-0.0138	*	-0.0066		0.0636		0.0434	
	(0.0968)		(0.5310)		(0.6134)		(0.7412)	
Distribution	0.3534	***	0.3610	***	0.3578	***	0.3574	***
	(0.0000)		(0.0000)		(0.0000)		(0.0000)	
Indirect	0.0022		0.0030		0.0037		0.0025	
	(0.7758)		(0.6959)		(0.6170)		(0.7412)	
Distribution* Indirect	0.1558	*	0.1600	*	0.1597	*	0.1598	*
	(0.0925)		(0.0830)		(0.0830)		(0.0827)	
Delta Return	0.0205	***	0.0205	***	0.0205	***	0.0207	***
	(0.0000)		(0.0000)		(0.0000)		(0.0000)	
Annual Return							-0.0624	**
							(0.0168)	
Expense Ratio							0.0116	*
							(0.0532)	
Share Class Assets							0.0038	
							(0.1033)	
Portfolio Turnover							-0.0001	
							(0.1472)	
Style Fixed Effects	No		Yes		Yes		Yes	
Time (Yearly) Fixed Effects	No		No		Yes		Yes	
Number of Observations	722,280		722,280		722,280		722,280	
Adj.R-Squared	0.2%		0.2%		0.2%		0.2%	

Table IV – Fund Distribution Size Segments

This table presents results from a pooled OLS regression that relates flow changes with distributions stratified into terciles. The main independent variables include: *Distribution High*, *Distribution Medium*, and *Distribution Low*, which are all binary variables indicating whether a share class is subject to a taxable distribution during week *t* that belongs, respectively, to the highest, medium, and lowest terciles determined based on distribution size during that year. Other independent variables are defined in Table III. Regressions are run with and without time (yearly) and investment objective fixed effects. Standard errors are clustered by funds' specific distribution channel and week. P-values are reported in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Dependent Variable: Difference in Normalized Weekly Flows around t								
Model:	1		2		3		4	
Constant	-0.0138	*	-0.0109		0.0583		0.0542	
	(0.0968)		(0.2967)		(0.6451)		(0.6812)	
Distribution High	0.8672	***	0.8696	***	0.8678	***	0.8667	***
	(0.0000)		(0.0000)		(0.0000)		(0.0000)	
Distribution Medium	0.0218		0.0279		0.0239		0.0221	
	(0.7957)		(0.7384)		(0.7746)		(0.7918)	
Distribution Low	-0.0757		-0.0718		-0.0757		-0.0738	
	(0.2218)		(0.2477)		(0.2225)		(0.2354)	
Indirect	0.0022		0.0024		0.0032		0.0021	
	(0.7758)		(0.7486)		(0.6697)		(0.7799)	
Distribution High* Indirect	0.5435	***	0.5440	***	0.5416	***	0.5400	***
	(0.0029)		(0.0029)		(0.0030)		(0.0031)	
Distribution Medium* Indirect	0.2033	**	0.2057	**	0.2069	**	0.2069	**
	(0.0304)		(0.0287)		(0.0276)		(0.0274)	
Distribution Low* Indirect	0.1033		0.1071		0.1079		0.1075	
	(0.1645)		(0.1503)		(0.1477)		(0.1498)	
Delta Return	0.0207	***	0.0207	***	0.0207	***	0.0208	***
	(0.0000)		(0.0000)		(0.0000)		(0.0000)	
Annual Return							-0.0600	**
							(0.0206)	
Expense Ratio							0.0090	
							(0.1286)	
Share Class Assets							0.0028	
							(0.2352)	
Portfolio Turnover							-0.0001	
							(0.1058)	
Style Fixed Effects	No		Yes		Yes		Yes	
Time (Yearly) Fixed Effects	No		No		Yes		Yes	
Number of Observations	722,280		722,280		722,280		722,280	
Adj.R-Squared	0.4%		0.4%		0.4%		0.4%	

Table V - Tax Liability

This table presents results from a pooled OLS regression that relates flow changes with distributions' tax liabilities stratified into terciles. The main independent variables include: *High Tax Liability*, *Medium Tax Liability*, *Low Tax Liability*, which are all binary variables indicating whether a share class is subject to a taxable distribution during week *t* that belongs, respectively, to the highest, medium, and lowest terciles determined based on the distribution's implied tax liability during that year. Other independent variables are defined as in Table III. Regressions are run with and without time (yearly) and investment objective fixed effects. Standard errors are clustered by funds' specific distribution channel and week. P-Values are reported in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Dependent Variable: Difference in Normalized Weekly Flows around t								
Model:	1		2		3		4	
Constant	-0.0138	*	-0.0109		0.0597		0.0555	
	(0.0979)		(0.2957)		(0.6364)		(0.6734)	
High Tax Liability	0.8457	***	0.8481	***	0.8462	***	0.8451	***
	(0.0000)		(0.0000)		(0.0000)		(0.0000)	
Medium Tax Liability	0.0601		0.0665		0.0627		0.0610	
	(0.4788)		(0.4301)		(0.4561)		(0.4694)	
Low Tax Liability	-0.0928		-0.0889		-0.0932		-0.0912	
	(0.1329)		(0.1514)		(0.1331)		(0.1426)	
Indirect	0.0023		0.0025		0.0033		0.0023	
	(0.7658)		(0.7378)		(0.6586)		(0.7655)	
High Tax Liability* Indirect	0.5317	***	0.5323	***	0.5301	***	0.5284	***
	(0.0041)		(0.0040)		(0.0041)		(0.0042)	
Medium Tax Liability* Indirect	0.1750	*	0.1774	*	0.1782	*	0.1781	*
	(0.0640)		(0.0605)		(0.0590)		(0.0588)	
Low Tax Liability* Indirect	0.1213		0.1251	*	0.1263	*	0.1260	*
	(0.1095)		(0.0993)		(0.0968)		(0.0978)	
Delta Return	0.0207	***	0.0207	***	0.0207	***	0.0208	***
	(0.0000)		(0.0000)		(0.0000)		(0.0000)	
Annual Return							-0.0597	**
							(0.0214)	
Expense Ratio							0.0089	
							(0.1294)	
Share Class Assets							0.0028	
							(0.2346)	
Portfolio Turnover							-0.0001	
							(0.1025)	
Style Fixed Effects	No		Yes		Yes		Yes	
Time (Yearly) Fixed Effects	No		No		Yes		Yes	
Number of Observations	722,280		722,280		722,280		722,280	
Adj.R-Squared	0.4%		0.4%		0.4%		0.4%	

Table VI - Capital Gain versus Dividend Distributions

This table presents results from a pooled OLS regression that relates flow changes to distributions categorized as either capital gains or dividends. The main independent variables include: *Gain Distribution* ($D_{i,t}^{Gains}$), a binary variable that equals one if a share class is subject to a taxable capital gain distribution in week *t* and *Dividend Distribution* ($D_{i,t}^{Div}$), a binary variable that equals one if a share class is subject to a taxable dividend distribution in week t. *Distribution Size* ($Size_{i,t}$), represents the distribution amount per share in week *t* normalized by the share reinvestment NAV at the distribution date. The other independent variables are defined as in Table III. Regressions are run with and without time (yearly) and investment objective fixed effects. Standard errors are clustered by funds' specific distribution channel and week. P-values are reported in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Dependent Variable: Difference in Normalized Weekly Flows around t								
Model:	1		2		3		4	
Constant	-0.0139	*	-0.0151		-0.0105		-0.0148	
	(0.0938)		(0.1439)		(0.9354)		(0.9128)	
Gain Distribution	0.0790		0.0791		0.0794		0.0755	
	(0.5821)		(0.5816)		(0.5805)		(0.5986)	
Dividend Distribution	-0.1143	*	-0.1138	*	-0.1147	*	-0.1149	*
	(0.0976)		(0.0961)		(0.0936)		(0.0916)	
Indirect	0.0025		0.0023		0.0024		0.0039	
	(0.7416)		(0.7645)		(0.7504)		(0.6058)	
Gain Distribution* Indirect	0.3039	*	0.3040	*	0.3042	*	0.3032	*
	(0.0796)		(0.0795)		(0.0791)		(0.0798)	
Dividend Distribution* Indirect	0.1269		0.1274		0.1276		0.1279	
	(0.1195)		(0.1186)		(0.1182)		(0.1176)	
Distribution Size	0.1423	***	0.1423	***	0.1423	***	0.1424	***
	(0.0000)		(0.0000)		(0.0000)		(0.0000)	
Delta Return	0.0210	***	0.0210	***	0.0210	***	0.0211	***
	(0.0000)		(0.0000)		(0.0000)		(0.0000)	
Annual Return							-0.0551	**
							(0.0359)	
Expense Ratio							0.0052	
							(0.3671)	
Share Class Assets							0.0030	
							(0.1993)	
Portfolio Turnover							-0.0001	*
							(0.0878)	
Style Fixed Effects	No		Yes		Yes		Yes	
Time (Yearly) Fixed Effects	No		No		Yes		Yes	
Number of Observations	722,280		722,280		722,280		722,280	
Adj.R-Squared	0.5%		0.5%		0.5%		0.6%	

Table VII – Unexpected Capital Gain Distributions

This table presents results from a pooled OLS regression that relates flow changes to the unexpected component of capital gain distributions. The sample is restricted to the observations that are subject to capital gain distributions. The main independent variables include: *Surprise Ratio*, a continuous variable that represents the fraction of a capital gain distribution that is unexpected, defined as the difference between the actual gain distribution and the forecasted gain distribution, normalized by the actual gain distribution; *Gain Distribution Size*, is the capital gain distribution amount per share during week *t* normalized by the share reinvestment NAV at the distribution date. Other independent variables are defined as in Table III. Regressions are run with and without time (yearly) and investment objective fixed effects. Standard errors are clustered by funds' specific distribution channel and week. P-values are reported in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Dependent Variable: Difference in Normalized Weekly Flows around t								
Model:	1		2		3		4	
Constant	0.0658		0.2477		0.7580		1.8720	
	(0.7316)		(0.4523)		(0.1621)		(0.1001)	
Surprise Ratio	-0.0012		-0.0011		-0.0012		-0.0011	
	(0.1419)		(0.1892)		(0.1737)		(0.2410)	
Indirect	0.4248	*	0.4333	**	0.4236	**	0.4891	**
	(0.0512)		(0.0451)		(0.0434)		(0.0396)	
Surprise Ratio* Indirect	0.0028	**	0.0028	**	0.0027	**	0.0025	**
	(0.0105)		(0.0139)		(0.0199)		(0.0231)	
Gain Distribution Size	0.1264	***	0.1229	***	0.1214	***	0.1211	***
	(0.0000)		(0.0000)		(0.0000)		(0.0000)	
Delta Return	0.0163		0.0158		0.0153		0.0168	
	(0.6816)		(0.6904)		(0.7045)		(0.6915)	
Annual Return							-0.2904	
							(0.5345)	
Expense Ratio							-0.2367	
							(0.2065)	
Share Class Assets							-0.0577	
							(0.3177)	
Portfolio Turnover							-0.0024	
							(0.1384)	
Style Fixed Effects	No		Yes		Yes		Yes	
Time (Yearly) Fixed Effects	No		No		Yes		Yes	
Number of Observations	4,681		4,681		4,681		4,681	
Adj.R-Squared	5.7%		5.8%		5.8%		6.0%	

Table VIII – The Interaction of Tax-Deferral with Tax-Loss Selling

This table presents results from a pooled OLS regression that relates flow changes to determinants of tax-loss selling interacted with the distribution channel. The sample is restricted to the observations that are subject to fund distributions. The main independent variables include: *Tax Loss Group (*$TLG_{i,t}$*)*, a binary variable that equals one if a share class belongs to the share classes belonging to portfolios that exhibit the lowest level of capital gain overhang and the share class had the worst one-year performance as of week *t*; *December* (Dec_i), a binary variable that equals one if the observation week is in December. Other independent variables are defined as in Table III. Regressions are run with and without time (yearly) and investment objective fixed effects. Standard errors are clustered by funds' specific distribution channel and week. P-Values are reported in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Dependent Variable: Difference in Normalized Weekly Flows around t								
Model:	1		2		3		4	
Constant	0.1357		0.5924	***	1.0994	***	0.6268	
	(0.1202)		(0.0028)		(0.0003)		(0.2131)	
TLG	0.0163		0.0694		0.0226		0.0241	
	(0.9099)		(0.6215)		(0.8714)		(0.8631)	
December	0.4393	***	0.2872	*	0.2851	**	0.2776	*
	(0.0055)		(0.0671)		(0.0475)		(0.0551)	
TLG* December	-0.3324		-0.3049		-0.2104		-0.1949	
	(0.3009)		(0.3315)		(0.4979)		(0.5296)	
Indirect	0.1835		0.2462	*	0.2274	*	0.1820	
	(0.1323)		(0.0608)		(0.0716)		(0.1671)	
TLG* Indirect	-0.2876		-0.3160	*	-0.2970	*	-0.2863	*
	(0.1013)		(0.0726)		(0.0808)		(0.0908)	
December* Indirect	0.0234		0.0233		0.0125		0.0037	
	(0.8934)		(0.8956)		(0.9436)		(0.9836)	
TLG* December* Indirect	0.7199	**	0.7268	**	0.7380	**	0.7255	**
	(0.0482)		(0.0469)		(0.0398)		(0.0444)	
Delta Return	0.0080		0.0088		0.0145		0.0152	
	(0.6241)		(0.5773)		(0.2853)		(0.2774)	
Annual Return							-0.0562	
							(0.6082)	
Expense Ratio							0.1796	*
							(0.0698)	
Share Class Assets							0.0256	
							(0.2143)	
Portfolio Turnover							-0.0006	
							(0.4225)	
Style Fixed Effects	No		Yes		Yes		Yes	
Time (Yearly) Fixed Effects	No		No		Yes		Yes	
Number of Observations	18,866		18,866		18,866		18,866	
Adj.R-Squared	0.7%		1.4%		2.8%		2.8%	