Financial Conduct Authority

MS15/2.2: Annex 4

Market Study

Asset Management Market Study

Interim Report: Annex 4 – Retail Econometric Analysis

November 2016

Annex 4: Retail econometric analysis

Introduction

1. A key aim of this market study is to establish whether competition is working effectively in the asset management industry. We consider that an important first step in assessing this is to understand the nature of competition in the asset management industry. This annex is split into two sections. In the first section we have sought to understand the factors over which asset managers compete for the supply of services to retail investors. The second section (from paragraph 60) sets out outcomes for retail investors using different tools to help them identify outperforming asset managers.

Drivers of retail net flows

2. Commercial asset managers typically charge investors using an ad valorem fee, set as a fixed percentage of AUM. While there are occasional departures from this fee model in the form of asymmetric performance fees, these performance fees are ultimately applied as a percentage of AUM.[1]

3. An ad valorem fee structure provides asset managers with an incentive to compete for net inflows of assets, and subsequently retain those assets. This is because an additional £ in assets under management represents additional revenues to the asset management firm. So long as the marginal revenue from additional AUM exceeds the marginal cost of servicing that additional AUM, we would expect asset management firms to continue competing for assets and seeking to retain those assets.[2]

4. Ad valorem fees should also provide firms with an incentive to perform well, as this (i) will raise the value of a fund manager's AUM and therefore revenues to the asset manager, even if this does not lead to an increase in inflows; (ii) may subsequently lead to additional inflows of money attracted by the better performance; and (iii) may improve the likelihood of retaining existing client assets. However, given that asset managers continue to be paid at the same rate (percentage of AUM) under an ad valorem fee structure, even if they deliver poor performance, this last incentive may not be strong if assets do not flow out in response to below average performance.[3]

5. We consider that this fee structure gives asset managers an incentive to focus on delivering aspects of performance to investors that result in greater inflows of assets, and that improve the likelihood of retaining assets. These aspects could include, for example, high returns, brand awareness, appearance on distributors' best buy lists and inclusion in adviser recommendations.

[1] Performance fees are typically a fixed percentage applied to a measure of outperformance.

[2] These costs may not be captured fully by accounting measures of costs.

[3] To the extent that there is a convex and increasing relationship between fund flows and performance (see paragraph 1.19), this could lead to asset management firms facing perverse incentives. For example, if this relationship existed then rational firms could have an incentive to encourage their fund managers to focus their efforts and resources on the current winning fund(s) at the expense of other funds that are currently underperforming. A convex and increasing relationship between fund flows and performance could therefore explain a finding that there exist funds with negative (excess) performance persistence.

6. In this annex we have sought to understand (i) which variables drive net flows of assets into retail funds, with particular emphasis on best buy lists and ratings (see Annex 6 for the equivalent analysis on the drivers of institutional net flows); and (ii) whether these lists and ratings add value for investors.[4] We have used econometric techniques to identify these variables.

7. The evidence from this econometric analysis sits alongside other evidence we have collected on the drivers of net flows, which includes questionnaires sent to a large sample of asset managers with a UK presence, surveys of retail and institutional end investors, existing studies on the asset management industry, and statistical analysis. This other evidence is summarised in Chapter 4.

Background

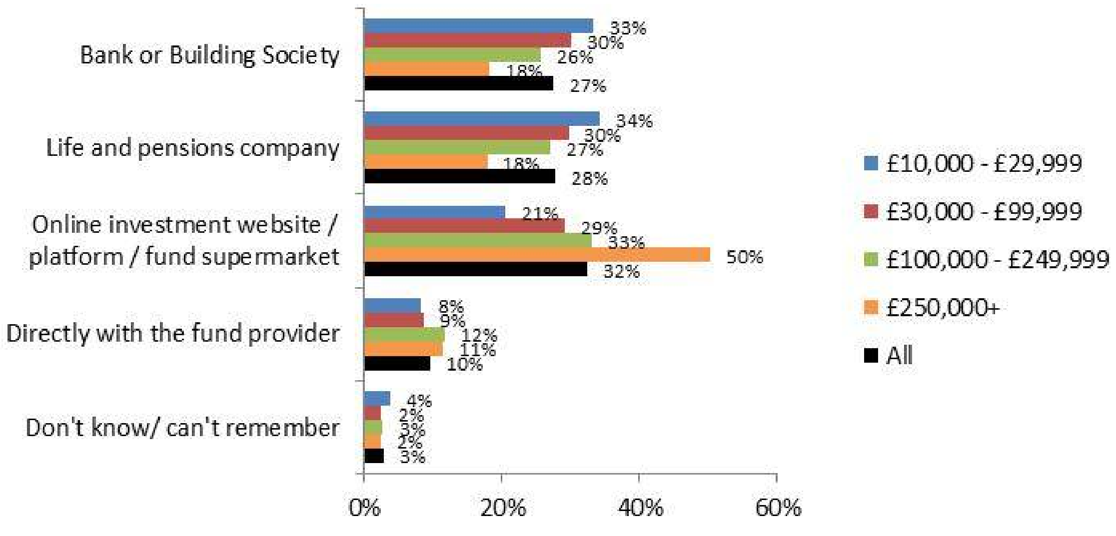
8. Retail investors can access asset management services through two routes: advised (by a financial adviser) or non-advised (execution-only). In 2015, around 78% of the sales of retail investment management services, by assets under management, were made through the advised route, with the remaining 22% made through non-advised channels, such as D2C platforms, other intermediaries, and direct sales.

9. Retail investors who access funds with the help of their financial advisor may receive a review of their risk appetite, advice on their asset allocation and choice of manager(s). Their financial advisor may also help with wider financial planning.

10. Non-advised (direct) investors access asset management services through a wide range of intermediaries. Our retail investor survey results set out in Annex 3 showed that across all non-advised (direct) respondents, direct-to-consumer (D2C) platforms[5] were the most popular distribution channel, used by 32% of respondents for their latest fund investment. Other popular channels include banks and building societies (27%) and life and pensions companies (28%).

11. The results on the choice of investment channel are summarised in Figure 1.

Figure 1: Choice of investment channel, by total investable assets



[4] Net flows are inflows less outflows of assets into investment products. Performance is therefore not reflected in this measure.

[5] We have chosen to use this term to describe online investment websites / platforms / fund supermarkets.

Source: Consumer Survey. Weighted sample sizes: £10k-£30k (606), £30k-£100k (922), £100k-£250k (429), £250+ (543).

12. Non-advised retail investors in the UK face a very large choice of investment products offered by asset managers. For example, focusing on open-ended funds available for sale in the UK, there were approximately five thousand funds operating at the end of 2015 that had at least one GBP-denominated share class.[6]

13. Investors seeking to navigate their way through this large range of funds and make better investment decisions have access to a variety of fund-specific information. This includes the following:
    - third party fund ratings;
    - platform best buy lists for users of D2C platforms;
    - fund characteristics such as past performance and charges, made available in fund factsheets, the KIID, and summarised by D2C platforms;
    - fund recommendations by media commentators;
    - recommendations from advisers if using advisers; and
    - marketing information produced by asset managers.

14. In practice, investors could rely on some or all of the above information sources when selecting a fund. In the remainder of this annex we explain our approach to identifying the factors investors use to select funds. In particular, we have focused on the potential role played by platform best buy lists in driving assets between rival funds, controlling for other factors that are also likely to drive fund flows.

15. Academic literature already exists which examines the empirical relationship between fund flows and various measures of performance, third party ratings, and charges. However, our understanding is that there is little or no research on the effect of platform best buy lists on fund flows. We consider it is important to understand the role played by platforms in allocating retail investors' assets given the increasing use of D2C platforms by retail investors in the UK (see Chapter 5).

Existing research findings

16. A large literature exists which examines the relationship between fund flows and various potential drivers of these flows. The majority of this research has focused on measuring the empirical relationship between investor fund flows and different measures of past performance.

17. For example, Ippolito (1992)[7], Patel, Zeckhauer, and Hendricks (1994)[8], Gruber (1996)[9], Chevalier and Ellison (1997)[10], and Sirri and Tufano (1998)[11] found, using cross-sectional analysis, that several performance measures are simultaneously statistically related to fund flows.

18. The performance measures that have been assessed in the above literature include raw returns, excess returns, one-factor alpha, four-factor alpha, the Sharpe ratio,

[6] Sourced from Morningstar Direct.

[7] Ippolito, R., 1992, Consumer reaction to measures of poor quality, Journal of Law and Economics 35, 45–70.

[8] Patel, J.; R. Zeckhauser; and D. Hendricks. "Investment Flows and Performance: Evidence from Mutual Funds, Cross-Border Investments and New Issues." In Japan, Europe and the International Financial Markets: Analytical and Empirical Perspectives, R. Satl, R. Levitch, and R. Ramachandran, eds. New York NY: Cambridge University Press (1994).

[9] Gruber, M., 2004, Another Puzzle: The Growth in Actively Managed Mutual Funds. Journal of Finance, 51, 783-810.

[10] Chevalier, Judith, and Glenn Ellison, 1997, Risk taking by mutual funds as a response to incentives, Journal of Political Economy 105, 1167–1200.

[11] Sirri, Erik, and Peter Tufano, 1998, Costly search and mutual fund flows, Journal of Finance 53, 1589–1622.

and whether the fund is advertised. However, the correlation between these different performance measures means that it is difficult to isolate the incremental effect of a single performance measure on fund flows.

19. Academic research on the relationship between fund flows and past performance also suggests that there is a convex link between these two variables. Put differently, funds that perform worse suffer modest outflows of assets, while the best performing funds receive a large amount of inflows. This result has been found by Sirri and Tufano (1998), and Chevalier and Ellison (1997). There are a number of reasons why flows could be convex in fund performance. These include:

- Lynch and Musto (2003)[12] show that investors may not leave poorly performing funds because they expect the fund manager to be replaced if they do poorly. Therefore the authors argue that investors do not switch poorly performing funds because they expect the fund's performance to improve over time.
- Huang, Wei and Yan (2007)[13] use search costs to explain convexity.
- Goetzman and Peles (1997)[14] use cognitive dissonance to explain convexity in the flow performance relation.
- An alternative explanation is that when a fund performs well the entire universe of investors can choose to react by investing money in that fund. However, when a fund performs poorly, only existing investors in that fund can withdraw money (because it is not possible to short a fund, but it is possible to short a stock). As a result, money in poor-performing funds may not be as sensitive to past performance as well-performing funds.

20. More recently, academics have examined the empirical relationship between investor flows and other potential drivers, such as third party ratings. For example, Del Guercio and Tkac (2002)[15], Bergstresser and Poterba (2002)[16], and Ivkovic and Weisbenner (2006)[17] found that Morningstar star ratings are significantly related to fund flows.

21. In 2008, Del Guercio and Tkac[18] published findings on the effect of *changes* in Morningstar ratings on fund flows. In contrast to previous literature, Del Guercio and Tkac used an event-study methodology in an attempt to isolate the effect of ratings changes on fund flows. Del Guercio and Tkac observed that the backward-looking Morningstar Rating (i.e. star ratings) has substantial independent influence on the investment decisions of retail mutual fund investors. In particular, Del Guercio and Tkac identified economically and statistically significant positive flows following fund rating upgrades, and negative flows following fund rating downgrades.

22. In 2015, Armstrong, Genc and Verbeek analysed the effect of Morningstar Analyst Ratings.[19] These ratings are produced by a team of analysts following processes that

[12] Lynch, Anthony W., and David K. Musto., 2003, How Investors Interpret Past Fund Returns., Journal of Finance 58 (October): 2033–58.

[13] Huang, J.; K. D. Wei; and H. Yan., 2007, Participation Costs and the Sensitivity of Fund Flows to Past Performance, Journal of Finance, 62, 1273-1311.

[14] Goetzmann, W.N., Peles, N., 2007, Cognitive dissonance and mutual fund investors, Journal of financial Research 20(2), 145-158.

[15] Del Guercio, D., and P. A. Tkac., 2002, The Determinants of the Flow of Funds of Managed Portfolios: Mutual Funds versus Pension Funds, Journal of Financial and Quantitative Analysis, 37, 523-557.

[16] Bergstresser, D., and J. Poterba., 2002, Do After-Tax Returns Affect Mutual Fund Inflows?, Journal of Financial Economics, 63, 381-414.

[17] Ivkovic, Z., and S. Weisbenner., 2006, 'Old' Money Matters: The Sensitivity of Mutual Fund Redemption Decisions to Past Performance, Working Paper, University of Illinois.

[18] Del Guercio, Diane, and Paula A. Tkac., 2008, Star power: The effect of Morningstar ratings on mutual fund flow, Journal of Financial and Quantitative Analysis" 43: 907-936.

[19] Armstrong, Will J., Egemen Genc, and Marno Verbeek., 2015, Going for gold: An analysis of Morningstar analyst ratings, SSRN 2419669.

are similar to those used by investment consultants. Armstrong et al showed that these ratings have a significant impact on fund flows, and that this impact is separate from the impact of the Morningstar Rating (i.e. star ratings).

23. Academic research has also examined the relationship between flows and charges. Barber, Odean and Zheng (2005)[20] examined the relationship between flows and fees in the US. They find that flows are negatively related to front-end loads (i.e. initial charges) but are not sensitive to annual fees (expense ratios). Keswani and Stolin (2008)[21] look at flows into UK funds by distribution channel and examine how they depend on front-end and annual fees. Fund inflows increase the higher the annual fees but decrease the higher the initial fees. Institutional investors have flows that are decreasing in both annual fees and front-end fees. Retail investors have inflows that are unaffected by initial fees and are actually increasing in annual fees. The authors consider that this latter finding could be due to funds with greater annual fees spending more on marketing their funds.

24. We are not aware of past research on the effect of platform best buy lists on fund flows. We focus our attention in this annex on examining the relationship between a fund's inclusion on a platform's best buy list and fund flows, controlling for other factors that have previously been identified as having a statistical relationship with fund flows in the literature.

Role of platform best buy lists in driving fund flows

25. The results of our retail investor survey showed that across all non-advised (direct) respondents, D2C platforms were the most popular distribution channel, used by 32% of respondents for their most recent fund investment. D2C platform usage has also been increasing over the last few years (see Chapter 5). Therefore, we consider that D2C platforms are an important sales channel in the UK for asset managers.

26. Users of D2C platforms are provided with a range of information to help them select a suitable fund given their circumstances. As well as providing users with factual information on funds, such as past performance and charges (shown separately, and by accessing the KIID and/or fund factsheet), platforms often display next to funds the results of fund analysis such as third party ratings.

27. Some D2C platforms also present on their website a 'select' or 'best buy' list which is regularly updated. These best buy lists typically contain a relatively short list of funds, sometimes grouped into different investment categories, which the platform highlights to potential investors. These lists are often described by platforms as offering their view of the 'best' funds, or their 'highest conviction' funds available to UK investors.

28. Table 1 shows a selection of some of the larger UK D2C platforms, and the analytical information available on funds. The table also presents information on the size of the D2C platform in terms of assets under administration (AUA). The table shows that of the nine D2C platforms shown in the table, five provide a best buy list. These five D2C platforms represent over 60 per cent of AUA by D2C platforms as of 30 September 2015. Therefore, we consider that best buy lists have the potential to drive a substantial amount of net flows if investors use these lists for their investment decisions.

[20] Barber, B.M., Odean, T., and Zheng, L., 2005, Out of sight, out of mind: the effects of expenses on mutual fund flows, Journal of Business, 78, 2095-2120.

[21] Keswani, A., Stolin, D., 2008, Which money is smart? Mutual fund buys and sells of individual and institutional investors, The Journal of Finance, 63(1), 85-118.

29. The framework and techniques used by these platforms to compile these best buy lists may affect whether an asset manager's fund will be invested in by UK retail investors. For example, if some platforms only present active funds in their best buy lists then investors relying on these lists to select funds may only invest in active products, and therefore may not consider tracker funds.

30. Platforms are not required to disclose their past best buy lists publicly in a manner that would allow investors to scrutinise the ability of these lists to predict 'winning' funds. Nor are we are aware of any platforms producing their own calculations of the value added of their best buy lists.

Table 1: Analytical information available on a selection of UK D2C platforms

D2C Platform	Analytical information provided to investors	AUA (£bn)	Share (%)
Hargreaves Lansdown	Platform best buy lists (Wealth 150 and 150+)	51.9	35.9
Barclays Stockbrokers	Platform best buy list (Barclays Stockbrokers), Citywire best buy list, and FE Crown Rating	14.4	9.9
TD Direct Investing	Platform best buy list (TD Direct combined with Morningstar research) Morningstar Rating and Morningstar Analyst Rating	12.4	8.6
Fidelity Personal Investing	Platform best buy list (Select 50) and Morningstar Rating	11.3	7.8
Alliance Trust Savings	Morningstar Rating and Morningstar Analyst Rating	6.1	4.2
AJ Bell	Morningstar Rating and Morningstar Analyst Rating	3.3	2.3
Interactive Investor	Platform Top 10 performing funds, Interactive Investor star rating	2.9	2.0
Bestinvest	Platform Top 10 performing funds, Bestinvest rating	1.9	1.3
Charles Stanley Direct	Platform best buy list (Foundation Fundlist). No ratings information provided	1.5	1.1
Other	-	38.8	26.9
Total	**-**	**144.5**	**100%**

Source: D2C platform websites, Platforum (March 2016) for AUA as of 30 September 2015

31. Given the potential importance of platform best buy lists in determining which funds are allocated money, we have sought to understand the following:

- whether platform best buy lists actually drive fund flows, controlling for other potential drivers of flows; and
- if platform best buy lists do drive fund flows, whether they add value for investors.

Data

32. We have used four sources of data for our analysis of the drivers of fund flows.

33. The first source of data is a monthly history over ten years of those share classes that featured in D2C platform best buy lists, for a sample of four large D2C platforms. This information was provided to the FCA as part of an information request sent to D2C platforms that have a presence in the UK.

34. This data source allows us to identify, for each platform, when a share class appeared in their best buy list, the period over which it remained on the list, and (if applicable) the date when the share class was removed from the best buy list. The platforms in our sample have provided us with data across a range of asset classes, covering multiple geographies.

35. The second is Morningstar Direct, a third party source for fund and share class information from Morningstar Inc. We have sourced data for the 2003-2015 period on the following variables:

- returns of funds and share classes available for sale in the UK with a GBP denominated share class;

- manager-specified benchmarks (as represented by the Primary Prospectus Benchmark variable in Morningstar Direct), and Morningstar Category benchmarks for these products;
- assets under management for these products;
- net flows of assets for these products; and
- charges data for these products (OCF and AMC).[22]

36. The third source is charges data (OCF and AMC) from a sample of asset management firms. We requested this information to complement the charges data available in Morningstar. This step was taken to improve the coverage of charges information that managers have self-reported to Morningstar Direct over time.

37. The fourth source of data is information from several D2C platforms on (i) their annual core platform charges over time; and (ii) the annual commission rates received by these platforms over time, by share class, for bundled share classes. We requested this information in order to analyse over time net returns for bundled and clean share classes on a like-for-like basis from the perspective of D2C platform users (see later discussion for details).

38. We have obtained Morningstar data on returns, assets under management and net flows at a monthly level, and data on charges at an annual level.

39. The Morningstar database contains information that is self-reported by fund managers. The database contains both currently operating and closed/merged funds.

40. In order to assess whether platform best buy lists drive fund flows, we matched the best buy list information into Morningstar using each share class's ISIN code, a unique identifier of a share class. This allowed us to identify which of the share classes in Morningstar appeared on a best buy list, for each platform, over time.

Methodology

41. Henceforth we use the term 'recommendation' to describe a share class that appears in a platform best buy list.

42. In this annex we explore the impact of platforms' recommendations (and changes in those recommendations) on flows into and out of share classes. We examine this by taking a standard flow-performance regression (see, for instance, Ippolito (1992), Chevalier and Ellison (1997), and Sirri and Tufano (1998)) and include additional variables that capture changes in recommendations by D2C platforms.

43. We therefore examine the relationship between fund flows at the share class level on the one hand, and platform best buy lists on the other, controlling for the past performance of the share class and a set of other attributes of the share class which could affect flows and best buy lists.

44. We define net flows in two ways. First, we define them as the change in the GBP amount of assets flowing in to and out of a share class, minus appreciation:

$$Flow_{i,t} = TNA_{i,t} - TNA_{i,t-1} * (1 + r_{i,t})$$

[22] The OCF represents the ongoing costs to the funds, which includes the AMC and other charges for services such as keeping a register of investors, calculating the price of the fund's units or shares and keeping the fund's assets safe. The OCF must be displayed in the KIID.

In the expression above $TNA_{i,t}$ is the total net assets for share class i at time period t, and $r_{i,t}$ is the return on share class i between time periods t-1 and t. Therefore, this measure of net flows reflects the change in size of a share class in excess of the amount of growth that would have occurred had no new assets flowed in, but dividends had been reinvested.

45. Second, we measure the percentage flow relative to the total net assets invested in the share class two years previously:

$$\%Flow_{i,t} = {}^{\$Flow_{i,t}}\!\big/_{TNA_{i,t-2.}}$$

46. In the expression above we have divided by *TNA* at t-2 owing to the persistence of the recommendation effect (see Results section below). Dividing by lagged TNA is a means of scaling the flow variable. We could have used a one year lag, but we chose to use a two year lag because the effects of best buy lists appear to be relatively long-lived. An additional reason for choosing a lag greater than one year is that it makes the interpretation of coefficients on best buy list recommendations in a regression easier to interpret. Adding pound measures of flows is straightforward: the coefficients of different lagged variables can be summed to arrive at a total effect. This becomes more complicated with a relative flows measure as the dependent variable. If the impact of additions (or removals) to best buy lists is persistent, this would affect flows, but also the TNA. And therefore both the numerator and the denominator in the expression above would change. A lag of greater than one year alleviates this problem.

47. We estimate the response of flows to platforms' recommendations with yearly data using the following regression:

$$Flow_{i,t} = \alpha_t + \beta 1 f(PlatformBBL_{i,t-1\ to\ t-3}) + \beta 2 PastPerf_{i,t-1} + \gamma Controls_{i,t-1} + \varepsilon_{i,t}$$

48. The variables in the regression above are as follows.

- $Flow_{i,t}$ is the GBP or percentage net flow of share class i between period t-1 and period t. We have examined net flows of GBP denominated share classes that were available for sale to UK investors. This allows us to make clear comparisons between share classes.
- $f(PlatformBBL_{i,t-1\ to\ t-3})$ is a function (or a number of alternative functions) of the number of recommendations share class *i* received between time period t-1 and t-3. The functions we use include the number of recommendations received at the end of the previous year (t-1), the number of additions and deletions from the platforms' recommendations lists in any of the three previous years (captured by different dummy variables), or the net number of additions and deletions to platforms' recommendations lists over the previous three years (captured by different dummy variables).
- In particular, we have examined the following variables. List captures the level of the number of recommendations received by a share class from platforms. Chg in List captures the change in the number of recommendations received by a share class from platforms. Add to List captures additions to the number of recommendations received by a share class from platforms, while Rem from List captures reductions to the number of recommendations received by a share class from platforms.
- The control variables are as follows: the performance percentile rank compared to all other funds in the same Morningstar Category; the performance percentile

rank compared to all other funds; an indicator variable which is 1 if the share class was given a 5-star Morningstar rating in time t-1; an indicator variable that equals 1 if the share class was given a Gold, Silver or Bronze Morningstar Analyst rating in time t-1; a percentile fee rank of the share class in question in relation to all other share classes in the same Morningstar Category; an indicator variable that equals 1 if the share class was in the top 50% of high fee share classes in its Morningstar Category; return volatility between time period t-3 and t-1; the total net assets at t-1 (for the relative flow regressions we use the log of this number instead); and a full set of time dummies. For the relative flow regressions we impose the additional restriction that funds/products should have TNA at time t-2 > GBP10 million.

49. The data set used in this analysis includes both bundled and clean share classes. To control for the impact of the RDR, where the net return and charges of share classes shown in Morningstar's database includes the distribution fee for bundled[23] but not for clean[24] share classes, we took the following approach. We included bundled share classes for the whole period (2003-2015) and included clean share classes from 2012. Since bundled share classes incorporate distribution fees in their charge and return variables, we adjusted clean share classes to also include a distribution fee in their returns and charges. Specifically, we adjusted returns and charges to include a representative average core platform charge of 0.375 per cent.[25] This allows us to compare bundled and clean share classes on a like-for-like basis.

Results

50. Table 2 reports the results from estimating the above regressions, using a pooled time-series of cross-sectional data. Each column in this table represents the results from a separate regression. The table presents the magnitude and sign of the coefficients of the variables in each regression.

51. Column 1 of Table 2 shows the impact of platforms' recommendations in year t-1 on total net assets in year t. The coefficient associated with List (t-1) shows the yearly impact of being in one of the recommendation lists of one of the platforms in our sample. This impact is an average impact of different platforms and share classes in different asset classes. Column 4 shows the impact of platforms' recommendations as the percentage change in total net assets between year t-2 and year t.[26]

52. Columns 2 and 5 show a recommendation level variable (as in columns 1 and 4) plus the change in the number of recommendations. Thus the row Chg in List (t-1) shows the change in total net assets for a share class at time t for one extra recommendation from the platforms in our sample at time t-1. In this case the change leads to a change of GBP51m in assets, or to an increase of 29%. We also run regressions for the effect of recommendation changes from t-2 to t-3. However,

[23] Bundled share classes include distribution fees (such as adviser commission or platform commission) within the Annual Management Charge (AMC). We identified bundled share classes using data from Morningstar Direct, enriched with information we received from a sample of asset managers. These indicated the charging structure of the share classes in our sample.

[24] Clean share classes do not include any form of distribution fee within the AMC. We identified clean share classes using data from Morningstar Direct, enriched with information we received from a sample of asset managers. These indicated the charging structure of the share classes in our sample.

[25] This figure is based on data received from four platforms for an asset pot size of £50,000.

[26] In each regression t-statistics are based on clustered standard errors, which are White heteroskedastic-consistent standard errors corrected for possible correlation across observations of a given investment product (White, 1980; and Rogers, 1993). This method seems sensible given the size of the data panel (see Petersen, 2009).

only the coefficient up to t-1 is statistically significant and economically important for regression (2). For regression (4) though (relative net flows) the coefficient up to t-2 is significant; the effect of an additional recommendation in year t-2 is an increase of 18% of total net assets in year t. To understand the full impact of a recommendation on flows it is necessary to include the impact of all the lags.

53. Columns 3 and 6 break down the changes in recommendations into additions to and deletions from the list of recommendations. The signs of the coefficients show that flows (where statistically significant) are in the direction of the recommendation change. For regression (3) we do not find a significant effect from an addition to the list of recommendations, but there is a significant effect from removal from the list of recommendations. However, for regression (6) which examines the effect on relative net flows, we find a significant effect from an addition to the list as well as removal from the list. The results suggest there is a stronger effect from being added to a list compared to removal from the list. The lag of up to three years in the effect of recommendation changes on flows (which is more significant for removals than additions) could be explained by a delay in the response of asset owners to such changes.[27]

[27] It is also possible this result is due to the platforms in our sample not being the only distributors to provide recommendations of investment products. For example, we do not include all D2C platforms, or the recommendations of advisers, and therefore will not cover all possible best buy lists or recommendations. However, we have included variables such as Morningstar star ratings, Morningstar Analyst ratings (as well as past performance and charges), which we understand are often used by other distributors when they put together recommendations and best buy lists to clients.

Table 2: Retail net flows regression results: annual

Variables	(1)	(2)	(3)	(4)	(5)	(6)
		Net flows			Relative net flows	
List (t-1)	56.57***	44.30*	48.75*	0.32***	0.16***	0.07
	(3.37)	(1.95)	(1.95)	(4.65)	(2.95)	(1.36)
Chg in List (t-1)		50.93***			0.29***	
		(3.12)			(3.90)	
Chg in List (t-2)		27.01*			0.18***	
		(1.95)			(3.86)	
Chg in List (t-3)		5.05			0.08	
		(0.42)			(1.27)	
Add to List (t-1)			43.48			0.67***
			(1.64)			(2.59)
Add to List (t-2)			0.88			0.31*
			(0.04)			(1.86)
Add to List (t-3)			0.82			0.11
			(0.04)			(0.69)
Rem. from List. (t-1)			-51.12***			-0.15***
			(-3.32)			(-4.24)
Rem. from List. (t-2)			-36.46***			-0.17***
			(-2.84)			(-4.36)
Rem. from List. (t-3)			-6.14			-0.08**
			(-0.58)			(-2.07)
Perf. Rank by Cat - Return (t-1)	14.35***	14.33***	14.40***	0.27***	0.22***	0.22***
	(6.70)	(6.14)	(6.18)	(6.37)	(5.63)	(5.66)
Perf. Rank All - Return (t-1)	2.16	2.63	2.48	0.06	0.04	0.05
	(1.12)	(1.18)	(1.13)	(1.46)	(1.11)	(1.20)
Morningstar Star Rating (t-1)	29.36***	30.93***	30.91***	0.28***	0.31***	0.31***
	(4.17)	(4.43)	(4.42)	(4.26)	(4.84)	(4.84)
Morningstar Analyst Rating (t-1)	1.02	0.90	1.25	0.11**	0.09*	0.08*
	(0.16)	(0.14)	(0.19)	(2.30)	(1.93)	(1.69)
Fee Rank (t-1)	-25.84***	-25.41***	-25.48***	-0.48***	-0.40***	-0.40***
	(-4.22)	(-3.44)	(-3.44)	(-6.56)	(-5.54)	(-5.48)
Top Half Fee Rank Indicator (t-1)	0.87	1.64	1.64	0.04	0.02	0.02
	(0.32)	(0.53)	(0.52)	(0.91)	(0.44)	(0.45)
Return volatility (t-1)	-156.79***	-141.67***	-141.23***	-2.96***	-2.44***	-2.45***
	(-3.93)	(-2.85)	(-2.85)	(-4.53)	(-3.75)	(-3.79)
Total Net Assets (t-1)	-0.14***	-0.14***	-0.14***	-0.03***	-0.03***	-0.03***
	(-3.11)	(-2.82)	(-2.82)	(-5.48)	(-4.38)	(-4.45)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26,204	21,952	21,952	11,740	11,245	11,245
R-squared	0.12	0.12	0.12	0.03	0.03	0.04

Source: Morningstar Direct data on net flows, returns, AUM. Fees data sourced from a sample of asset managers and Morningstar Direct. Recommendations data sourced from a sample of D2C platforms. Robust t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1

54. The results also indicate that better past performance (relative to other funds in the same Morningstar Category) has a statistically significant positive effect on asset flows, which is consistent with previous research.

55. The results also show that share classes with a five-star Morningstar rating were associated with higher net flows.

56. We have also found that other things equal, more expensive share classes experience relative falls in total net assets. This suggests that some investors

respond to prices in the UK asset management industry. However, this may be restricted to those share classes that have above average prices. We intend to explore this area further following the publication of the interim report.

57. We performed a sensitivity in which we ran the regression above only for bundled share classes, and restricted to the pre-2012 period. This sensitivity allows us to examine whether the drivers of flows identified above hold over just the pre-RDR period. This sensitivity also allows us to assess whether our methodology for controlling for the impact of the RDR is robust, or whether our chosen methodology is inadvertently driving some of the results. We find that the results in our sensitivity are qualitatively the same as the results shown in Table 2.

Drivers of retail net flows - conclusions

58. We have found that changes in inclusion of share classes on platforms' best buy lists have a large and statistically significant effect on net flows into those share classes. For example, when analysing annual net flows we have found that an additional recommendation from one of the D2C platforms in our sample at time t-1 leads to an increase in assets of GBP51m in assets, or to an increase of 29%.

59. Better relative past performance is associated with higher net flows into funds, and share classes with a five-star Morningstar rating were also associated with higher net flows. We have also found that other things equal, more expensive share classes experience relative falls in total net assets.

Retail outcomes analysis

60. In this section we compare the performance of share classes in best buy lists (i.e. those share classes that feature in at least one platform's best buy list) with those share classes not in best buy lists that were in the wider Morningstar universe, as well as those in the same Morningstar Category as a share class in a best buy list.[28]

61. We consider that the above test is a valid means of assessing whether platform best buy lists add value to end investors. From the perspective of a retail investor a best buy list represents that platform's view on the 'best' funds, out of the range of funds that are available to invest in on that platform. Therefore, we consider it reasonable for end investors to expect that on average the best buy list would be able to identify these 'winners' relative to the other funds.

Methodology

62. We assess the outcome of following platforms' recommendations by comparing the performance of the products which they recommend with the performance of non-recommended products and with benchmarks.

63. We start with a time series analysis of the net returns of recommended and non-recommended products in excess of Morningstar Category benchmarks. Our net returns reflect distribution fees as well as management fees.[29] We then conduct a

[28] By 'full Morningstar universe' we refer to all open-ended mutual funds available for sale in the UK and which have a GBP-denominated share class.

[29] Our analysis uses net returns data from Morningstar Direct over the 2003-2015 period. For bundled share classes the net returns data from Morningstar reflects both management and distribution fees. For clean share classes net returns data from Morningstar Direct reflect management fees only. For clean share classes we have therefore adjusted net returns by the average platform fee so that returns data for different share classes are presented on a like-for-like basis i.e. both include management and distribution fees.

similar analysis, but this time comparing the performance of recommended share classes with non-recommended share classes available for sale in the UK, and against a subset of non-recommended share classes available for sale in the UK and in the same Morningstar Category as a recommended share class.

Results

64. Table 3 assesses the performance of recommended products based on net excess returns over benchmark (top panel). The results shown in the top panel for recommended products assume that investors invest only in those funds that appear in best buy lists, and update their portfolios in accordance with changes to those best buy lists. By contrast, the bottom panel of the same table shows the equivalent results but assumes investors buy and hold funds listed in best buys lists for three or five years.

Table 3: Retail best buy list monthly performance results: simple comparison

Variables	(1) Not recommended	(2) Recommended	(3) Recommended weighted	(2) less (1)	(3) less (1)
Net monthly excess returns over benchmarks					
Constant	-0.10**	0.01	0.02	0.11***	0.12***
	(-2.09)	(0.25)	(0.31)	(5.69)	(5.76)
Observations	144	144	144	144	144
Net monthly excess returns over benchmarks – alternative holding periods	**(1) Not recommended**	**(2) Recommended (3 year holding period)**	**(3) Recommended (5 year holding period)**	**(2) less (1)**	**(3) less (1)**
Constant	-0.10**	-0.01	0.01	0.09***	0.11***
	(-2.09)	(-0.08)	(0.29)	(3.48)	(5.68)
Observations	144	144	144	144	144

Source: Morningstar Direct data on net flows, returns, AUM. Fees data sourced from a sample of asset managers and Morningstar Direct. Recommendations data sourced from a sample of D2C platforms. Robust t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1 For recommended products we take a simple average and also a weighted average (giving more weight to products receiving more recommendations). The number of observations reflects the number of time periods (months) in our analysis. Returns expressed in percentage points.

65. In the top panel of Table 3, column 1 shows the average excess monthly net return in terms of monthly percentage points of all non-recommended products in the sample over their respective Morningstar Category benchmarks. For example, a monthly figure of 0.01 in the table equates to a net excess return of approximately 12 basis points on an annualized basis. Column 2 shows a simple average of the excess net returns over benchmark of recommended products. Column 3 shows a

weighted average of the performance of recommended products, in which each product is weighted by the number of recommendations received.[30]

66. The results show that non-recommended share classes underperformed their benchmarks significantly, while recommended products did not significantly outperform their benchmarks. Columns 4 and 5 show that there is a significant and positive difference between the performance of recommended and non-recommended products, meaning that recommended products outperformed non-recommended products.

67. The bottom panel of Table 3 shows the equivalent results but assumes a different holding period for recommended share classes.[31] In the top panel it is assumed that investors hold recommended share classes for as long as they appear in platform best buy lists, and update their portfolios to reflect the contents of these lists. In the bottom panel we assume that investors invest in share classes when they first appear in a best buy list, and hold onto the investment for either three or five years, irrespective of whether the share classes in question are de-listed over this horizon. We find qualitatively similar results in the bottom panel as for the top panel.

68. We have performed a sensitivity in which we assessed the performance of recommended products only for bundled share classes, and restricted to the pre-2012 period. This sensitivity allows us to examine whether the results shown in Table 3 hold over just the pre-RDR period. This sensitivity also allows us to assess whether our methodology for controlling for the impact of the RDR is robust (see footnote 29), or whether our chosen methodology is inadvertently driving some of the results. We find that the results in our sensitivity are qualitatively the same (and quantitatively almost identical) as the results shown in Table 3.

69. Table 4 presents the results of an analysis in which, for each recommended product and month, we compute the average return (or excess return over benchmark) of all non-recommended products *in the same* Morningstar Category. We then calculate a time series of the difference in returns (or excess returns over benchmarks) between recommended products and all non-recommended products in the same Morningstar Category, and report the average of this time series together with t-stats based on Newey-West standard errors. Table 4 shows the analysis on a net basis.

Table 4: Retail best buy list monthly performance results: matched comparison

Variables	(1) Return difference	(2) Excess return difference	(3) Return difference weighted	(4) Excess return difference weighted
Net monthly return differences (to funds/products in the same category)				
Constant	0.06***	0.07***	0.07***	0.07***
	(4.13)	(4.23)	(4.38)	(4.47)
Observations	144	144	144	144

[30] We adopt a simple comparison in this table in which we do not condition on recommended and non-recommended products being in the same Morningstar Category. We perform a matched comparison in Table 4.

[31] These sensitivities were run in case in practice investors choose not to regularly update their investment portfolios by switching between funds. The costs of switching would act to erode potential gains from switching between funds, and these costs are not taken into account in the top panel of Table 3.

Variables	(1)	(2)	(3)	(4)
	0.06***	0.07***	0.07***	0.07***

Source: Morningstar Direct data on net flows, returns, AUM. Fees data sourced from a sample of asset managers and Morningstar Direct. Recommendations data sourced from a sample of D2C platforms. Robust t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1 For recommended products we take a simple average and also a weighted average (giving more weight to products receiving more recommendations). The number of observations reflects the number of time periods (months) in our analysis. Returns expressed in percentage points.

70. Column 1 of Table 4 shows the difference in returns between recommended and non-recommended products, while column 2 shows the difference in excess returns in the performance of these categories (the result of 0.07 per month in column 2 can be compared with the relative performance of 0.11 in column 4 of Table 3; the divergence is explained by the fact that, in Table 4, recommended products are being compared only with other products *in the same* Morningstar Category). Columns 3 and 4 of Table 4 show the same analysis as 1 and 2, respectively, except that in 3 and 4 we weight the recommended products by the number of times they were recommended. These findings confirm those of Table 3 that recommended products outperform non-recommended products.

71. In addition to assessing the performance of best buy lists, we have also examined the performance of Morningstar star ratings and Morningstar Analyst ratings.

72. Table 5 shows the performance of 5-star rated share classes based on net excess returns over benchmark (top panel). The bottom panel of the same table shows the equivalent results but for different assumed holding periods.

73. In the top panel of Table 5, column 1 shows the average excess monthly net return of all non-5-star share classes in the sample over their respective Morningstar Category benchmarks. Column 2 shows a simple average of the excess net returns over benchmark of 5-star rated share classes. The results show that non-5-star share classes underperformed their benchmarks significantly, while 5-star rated share classes did not significantly outperform their benchmarks. Column 3 shows that there is a significant and positive difference between the performance of 5-star and non-5-star rated share classes, meaning that 5-star rated share classes outperformed other share classes.

74. The bottom panel of Table 5 shows the equivalent results but assumes a different holding period for 5-star share classes. We find qualitatively similar results in the bottom panel as for the top panel.

Table 5: Retail Morningstar star rating monthly performance results: simple comparison

Variables	(1) Not five star	(2) Five star	(2) less (1)		
Net monthly excess returns over benchmarks					
Constant	-0.10**	0.00	0.10**		
	(-2.14)	(0.04)	(2.45)		
Observations	144	144	144		
Net monthly excess returns over benchmarks – alternative holding periods	**(1) Not five star**	**(2) Five star (3 year holding period)**	**(3) Five star (5 year holding period)**	**(2) less (1)**	**(3) less (1)**
Constant	-0.10**	-0.03	-0.04	0.07***	0.07***
	(-2.14)	(-0.67)	(-0.70)	(4.15)	(4.44)
Observations	144	144	144	144	144
	-0.10**	-0.03	-0.04	0.07***	0.07***

Source: Morningstar Direct data on net flows, returns, AUM. Fees data sourced from a sample of asset managers and Morningstar Direct. Recommendations data sourced from a sample of D2C platforms. Robust t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1. The number of observations reflects the number of time periods (months) in our analysis. Returns expressed in percentage points.

75. Table 6 shows the performance of Bronze, Silver and Gold Analyst (BSG) rated share classes based on net excess returns over benchmark (top panel). The bottom panel of the same table shows the equivalent results but for different assumed holding periods.

Table 6: Retail Morningstar Analyst rating monthly performance results: simple comparison

Variables	(1) Not BSG	(2) BSG	(2) less (1)		
Net monthly excess returns over benchmarks					
Constant	-0.10*	0.02	0.08**		
	(-1.70)	(-0.18)	(1.12)		
Observations	86	86	86		
Net monthly excess returns over benchmarks – alternative holding periods	**(1) Not BSG**	**(2) BSG (3 year holding period)**	**(3) BSG (5 year holding period)**	**(2) less (1)**	**(3) less (1)**
Constant	-0.10*	-0.02	-0.02	0.08	0.07
	(-1.70)	(-0.22)	(-0.24)	(1.08)	(1.05)
Observations	86	86	86	86	86

Source: Morningstar Direct data on net flows, returns, AUM. Fees data sourced from a sample of asset managers and Morningstar Direct. Recommendations data sourced from a sample of D2C platforms. Robust t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1. The number of observations reflects the number of time periods (months) in our analysis. Returns expressed in percentage points.

76. In the top panel of Table 6, column 1 shows the average excess monthly net return of all non-BSG share classes in the sample over their respective Morningstar Category benchmarks. Column 2 shows a simple average of the excess net returns over benchmark of BSG rated share classes. The results show that non-BSG share classes underperformed their benchmarks significantly, while BSG rated share classes did not significantly outperform their benchmarks. Column 3 shows that there is a significant and positive difference between the performance of BSG and non-BSG rated share classes, meaning that BSG rated share classes outperformed other share classes.

77. The bottom panel of Table 6 shows the equivalent results but assumes a different holding period for BSG share classes. We find that BSG share classes did not significantly outperform non-BSG share classes over 3 or 5 year horizons.

Retail outcomes analysis - conclusions

78. Our analysis of the performance of share classes on best buy lists of D2C platforms shows that, across all categories taken together, they perform better than non-recommended products (i.e. share classes not on platform best buy lists). This finding holds across different assumed holding periods. However, the average net excess returns of share classes on D2C platform best buy lists were not greater than their benchmarks; share classes on these lists on average achieved a net performance with little or no significant excess return over benchmarks.

79. We have found mixed results for the performance of other fund ratings systems:

- We have found that 5-star Morningstar share classes do not significantly outperform their benchmarks net of charges; net-of-fees excess returns are statistically indistinguishable from zero. However, the difference in net excess returns between 5-star rated share classes and not-5-star rated share classes is positive and significant, meaning that 5-star share classes earned greater net excess returns than other share classes. This finding holds if we assume different holding periods of 3 and 5 years; and
- we have found that Gold, Silver or Bronze (BSG) Morningstar Analyst rated share classes do not significantly outperform their benchmarks net of charges; net-of-fees excess returns are statistically indistinguishable from zero over various different holding periods. While we have found that the difference in net excess returns between BSG Morningstar Analyst rated share classes and non-BSG rated share classes is positive and significant (meaning that 5-star share classes earned greater net excess returns than other share classes), this finding does not hold when we examine 3 or 5 year holding periods.

80. Our analysis indicates that best buy lists contain funds that tend to do better than funds not on those lists. Following the publication of the interim report we intend to perform a more complete risk-adjustment analysis to provide a more conclusive view on best buy lists. We also intend to perform a sensitivity in which we compare the added value of best buy lists against other funds listed on a platform, rather than the entire Morningstar universe.

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