Fund (mis)classification
Evidence based on Style Analysis V2.0

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"The best way to win a contest for the largest tomato...
...is to paint a cantaloupe red...
...and hope the judges don’t notice."

Motivation

- One must be able to evaluate active managers if one is to hire them.
  - Finding the correct peer group for an investment strategy is the most important step in doing this.
  - If a fund is not being compared to the correct peer group the active returns and historic alpha & IR are misleading.
  - If a fund is mis-classified it may not be as diversifying in the context of other holdings as the investor may think.
- Checking fund classification can be a very simple & practical due diligence measure / selection criterion.
  - if a fund is misclassified, what else could be wrong with its management?
  - If a fund is misclassified and there’s a comparable fund that is classified correctly why not choose the fund with the correct label?
V1.0 Summary

  - Covered 748 funds
  - 6 peer groups: aggressive growth; growth; growth-income; income; international, and; small cap.
  - 298 or 40% of all funds were found to have their greatest style analysis weight in a peer group other than their classification.
  - About 60% wound up being less risky than they said they were
  - About 40% wound up being more risky than they said they were
– When fund issuers were observed in aggregate, however there was evidence of systematic misclassification:
  ▪ “…although misclassification appears to take place in both directions (into more and less aggressive categories), among seriously misclassified funds, the ratio of funds misclassified was nearly 2/1. The result allows us to reject the null hypothesis that an equal number of funds is misclassified upward and downward.
  ▪ “…probit analysis reveals that misclassification is not random, but related to fund size and assets under management to a statistically significant degree.”
What is Style Analysis?

- Developed by Bill Sharpe in 1984, style analysis is best described as an OLS regression where the all independent variables $B_n$ are constrained:
  - $Y = B_nX + \varepsilon$
  - $0 < B_n < 1$
  - $\Sigma B_n = 1$

- Since style weights add up to one they can be thought of as percentage weights.
- The greatest style weight will be assigned to the independent variable that explains most of the behavior of the dependent variable.
- In the specific case of fund classification, the fund returns are the dependent variable and peer group index returns are the independent variables
What’s Unique about Northfield’s Style Analysis

- We’ve implemented this methodology & only apply results that are approximately significant at the 5% level.
What’s different in V2.0?

• Now using the TR Lipper fund DB. Over 20,000 US funds equity and fixed income in dataset.
• 169 initial fund classifications.
• Each fund is also assigned to one of 11 “Broad Allocations” and 4 “Asset Classes”.
• Using Style Analysis we can see frequency of “misclassification” at 3 levels of granularity.
• We reclassify funds and recalculate peer group indices iteratively, until classifications converge.
• We apply the CUSUM method to determine the relevant lookback period.
• We calculate Precision Weighted Excess Returns (PWER) for each fund using Bayes Law with the peer group return as the prior – these can be useful in a manager selection process.
What is CUSUM? Magellan case study…

Cumulative IR – Magellan vs. S&P
Magellan Case Study – cont’d…

• What happened in the mid 80’s? Nascent technology boom… Peter Lynch, practicing what he preached (“buy what you know”) began withdrawing from the management of Magellan.

• When considering Magellan now… which one do we want to analyze? The whole history? They glory years? The current reality?

• Using the CUSUM method to find the most recent major inflection point in the historic plot of cumulative IRs is a useful way to set a relevant look-back period for peer group classification and manager selection purposes.
CUSUM details...

• Calculate active returns to peer group
• Calculate mean and standard deviation (we use a rolling window of 24 months by default)
• Use Mean and Standard Deviation to get the Information Ratio
• Calculate the cumulative sum of the information ratio, i.e. \( \text{CUSUM}_n = \text{CUSUM}_{n-1} + \text{IR}_n \)
• Calculate critical date point
  – Create series: \( \text{ABS}(\text{ER}_n - \text{ER}_{n-1}) \times \sqrt{N - n} \)
    ▪ \( \text{ER} \) = excess return
    ▪ \( N \) = total number of periods
    ▪ \( n \) = current period
  – Find maximum in above series – the corresponding date is the pivot – bias towards the start of the series. Magellan CD = 09/83
Method - P1 – winnowing classifications

- 169 classifications are too many to provide enough depth, even with 20,000 funds, to build peer group indices.
- So we rank each classification according to 2 parameters:
  - (1) The number of funds in the classification
  - (2) The average correlation in returns between funds
- and build a third ranking (3) composed of 40%(1) + 60%(2)
- we add the first two sectors by ranking (3) from each broad allocation
- then add all classifications in the “sector equity” & “diversified equity” broad allocation – these are all very deep and need to be represented
- add the next 40 sectors by ranking (3)
- Distribute the displaced funds amongst the remaining 69 sectors by finding the highest correlation to the corresponding equally weighted sector index return.
Method - P2 – find grossly misclassified funds

- In addition to belonging to one of 169 fund sectors, each fund belongs to one of 11 “broad allocations” and one of 4 “asset classes”.
- We set up a style analysis where fund returns are the dependent variable and the asset class indices are the independent variables.
- If the primary style analysis weight is a different asset class than the one the fund is assigned to & it is significant (TVal >=2.0) we consider the fund to be “grossly misclassified”.
- Transition matrix - 309 in the lower triangular – 107 in the upper - 416 total...

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Method – P2 – Broad Allocation Level

- After removing the “Asset Class” level mis-classifications from the data set, we do the same process for the “Broad Allocation” level. This time we have 350 out of 395 in the upper triangular – the vast majority of which are Mixed Asset transitions to riskier “broad allocations”.

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- 395
Method – P3 – Sector Level…

• There’s too many sectors, even after the winnowing process, 63, to use all of them as independent variables – so we limit the independent variables to the ones that belong to the same “broad allocation” as the dependent variable fund.

• In some cases there may not be enough history – especially after applying the CUSUM critical date, to allow enough degrees of freedom to run the style analysis (any regression needs more observation than independent variables)

• The resultant table is too big to print here… but out of 23,853 funds that met the screening criteria, 6,796 funds were reclassified by the process – or about 28%. Of those, 3,577 transitioned to less risky sectors and 3219 transitioned to more risky sectors.

• But what happens if we break this result down further and look at individual “Broad Allocations”
Method P4 – Sector level Cont’d

• What happens when we break it down further & look at just the funds in the Equity broad allocations?
  – 224 out of 1369 or 16% of funds changed classification in the “Sector Equity” broad allocation.
  – 3094 out of 6606 or 46% of funds changed classification within the “Diversified Equity” broad allocation
  
  ▪ There were 6796 transitions in the entire dataset – nearly half of them took place within the “Diversified Equity” slice of data.
  ▪ Diversified Equity is actually the closest dataset for comparison to V1.0 of this study where there were 6 peer groups based on growth/value style criteria – this broad allocation contains 18 peer groups also based on growth/value criteria, just breaking things out further by capitalization
    o V1.0 classifications: agg growth, growth, growth-income, income, international & small cap.
    o V2.0 classifications: large cap growth, large cap core, large cap value, mid cap growth, mid cap core, mid cap value, etc..
Method P4 – Sector level Cont’d (2)

- In “Diversified Equity” we find a comparable level of misclassification to the V1.0 of this study, done 18 years ago. It’s apples & oranges since the classification schemes are different, or maybe we should call it “apples and pears” as the classification criteria are similar, even though the current study is 3 times more granular.
  - I wouldn’t give the 6% increase much thought – it could just be down to the increased granularity of the peer group buckets.
  - It could also be down to the increased coverage of smaller funds with relatively low AUM
Method P4 – Sector level Cont’d (3)

- How about the other sectors, broken down by broad allocation?

- In general, less risky classifications are at the top of the table with some notable exceptions all the way at the bottom of the table
  - Municipal Money Market
  - Money Market
  - General Municipal Fixed Income

- Here, the intuition is that the cross sectional dispersion within the peer group is so tight & the correlation between style analysis independent variables is so great that the process breaks down.
Conclusions

• Anecdotally – it seems things haven’t changed much in the 18 years since V1.0 of this study was published.
  – The classification scheme is different here, but it’s reasonable to assume that this doesn’t really matter:
    ▪ the classification criteria are similar…
    ▪ if the motivation exists to misclassify people would continue to misclassify regardless of the label on the bucket.
• The overwhelming majority of misclassification at the “broad allocation” level was in the “mixed assets” category. This makes total sense as that category purposefully includes anything & is therefore pretty useless as a descriptor of a strategy.
• The validity of this approach for Money Markets & low risk fixed income strategies is questionable & needs to be verified.
Possible further directions

- Try this approach on an international dataset – Is fund misclassification as prevalent in Europe as it is in the USA? Fund misclassification was a big deal in the USA during the late 90s. It seems not much has changed since then. How about Europe & other regions?
- Apply fund issuer data & probit analysis as discussed in diBartolomeo & Witkowski to determine whether fund size & AUM
- Is the split between reclassification to more and less aggressive categories really equal? Use fund size & AUM data to weigh the split.
- Rank fund issuers according to % of funds under management that are misclassified – a sort of due-diligence or “trustworthy” index on issuer policy...