How Smart is 'Smart Money'?
An extended investigation of the smart money effect.

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1. Introduction

Are investors smart? There is a growing amount of recent literature debating whether investors are intelligent enough to invest in funds that outperform the market. In the light of academic scholars favoring the weak form of efficient market hypothesis and financial practitioners actively searching for ways to consistently beat the market, Gruber (1996) and Zheng (1999) first documented the smart money effect, suggesting that money flows disproportionately to funds exhibiting superior future returns and hinting that some investors are smart. This was subsequently disputed by Sapp and Tiwari (2004), claiming that outperformance was a result of the momentum effect rather than the intelligence of investors. Keswani and Stolin (2008) re-examined the case and provided strong evidence for the smart money effect using UK mutual funds even after controlling for return momentum. They ascribed the insignificance of the results in Sapp and Tiwari (2004) to their use of low-frequency (quarterly) data and the weight they placed on the pre-1991 period.

This leads us to our second question. How smart are smart investors if they exist? Do they possess ability to predict performance or are they simply naively chasing star funds? Chen and Qin (2012) believe that it is the latter. Based on prior studies by Gebhardt, Hvidkjaer, and Swaminathan (2005) and Gutierrez, Maxwell, and Xu (2009) demonstrating that corporate bond mutual funds do not exhibit return momentum, Chen and Qin (2012) went further to test for and reaffirm the smart money effect in the unique and unexplored setting free of momentum. They proceed to conjecture that investors are smart largely to the extent that they chase past performance, rather than using superior information to make investment decisions since momentum is unlikely to be the cause.

In their extensive study, Chen and Qin (2012) infer the smart money effect by taking the payoffs from four portfolios featuring different flow patterns. They conducted comparisons between small and large funds, finding that small funds for high-yield bonds have more dominant smart money effect. They compared between different sub-periods, discovering that the effect is significant in all but during the financial crisis in 2008-2009. They compared different time periods, finding that smart money is only significant within four months for high-yield bonds.

They continued to propose various explanations for the smart money phenomenon. Given the widely held belief that retail investors are often less sophisticated than institutional investors according to previous research by Barber and Odean (2000) and having learnt a stronger smart money effect among bond funds managing assets for retail investors, they readily rejected the proposition that smart money reflects investor sophistication. They also found no positive evidence supporting the possibility that fund expenses are the drivers for differences in fund performance and hence smart money.

Also in Chen and Qin's analysis, smart money effect was related with past performance, which demonstrates performance persistence. Lastly, they examined arguments by Wermers (2003) and Lou (2011) which suggests smart money as a consequence of temporary flow-induced price pressure. They argue that the case to be less than plausible for small funds as it would be for large funds to influence market movements. Chen and Qin (2012) concludes with smart investors being only smart in identifying and chasing winners and not possessing any higher sophistication than the rest of the market.

This finding is contrary to several research papers. Yu (2011) providing evidence from equity mutual funds, asserts that smart investors are smart because they possess superior market timing ability to distinguish themselves from momentum-style investors. I believe that market timing being an aspect that was possibly overlooked in their explanation by Chen and Qin (2012). In addition, in another recent paper by Peng, Chen, Shyu and Wei (2011), they present significant smart money effect in only bull markets but not bear markets for Taiwan equity. This contradicts the effect's supposed non-existence in Chen and Qin's data during the global financial crisis.

In this report, I will seek to replicate the main results in the published paper by Chen and Qin (2012) using a similar and slightly more recent dataset of corporate bond mutual funds and attempt to reconcile the gaps and offer the most comprehensive review of the smart money effect in the broad literature.

2. Data and Samples

The data was collected from the Center for Research in Security Prices (CRSP) Survivor-Bias Free U.S. Mutual Fund database[1]. Reproducing the results of the paper, the sample includes domestic corporate bond funds that existed during the period from June 1994 to December 2012, from which I obtain fund data at a monthly frequency. The sample has a total of 1860 fund entries and 215,473 fund month observations. The sample consists of 1239 high-quality corporate bond funds and 621 high-yield corporate bond funds, of which containing bonds with a credit rating lower than investment grade. Of those, there were 886 retail funds and 631 institutional funds. Index funds are removed. Outliers like very small and young funds (with a TNA < $1 million or fund age < 1 year) are excluded. Funds with more than 30% government bonds and equities combined are also excluded due to different risk exposure.

[Table 1]

Table 2.1 presents the descriptive statistics for the required sample. Fund size is skewed by large funds with a mean TNA of $594.8 million and a median TNA of $64.95 million. Following the convention of previous studies as in Sirri and Tufano (1998), net money flow[2] for a fund is defined simply as the change in TNA for the month where $TNA_{i,t}$ is the total net asset value of fund i at the end of month t and $R_{i,t}$ is the fund's return over the month t. Taking the fund size into account, the money flow ratio is subsequently evaluated.

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

$$FlowRatio_{i,t} = Flow_{i,t} \,/\, TNA_{i,t}$$

The sample of funds has an average money flow (flow ratio) of $2.12 million (2.91%) with a median of $1.94 million (1.94%). The average turnover is 151% and the average expense ratio is 1.03% per month. The funds attained an average return of 0.49% per month, with an average return of 0.55% for high-yield funds and 0.46% for high-quality funds respectively.

[1] I selected only corporate bond mutual funds with the strategic insight objective code CHY, CHQ, CGN, CIM, CMQ or CSM during 1994-1998 or the Lipper objective code HY, A, BBB, IID, SID or SII during 1999-2012. I went on to group funds with objective codes CHY or HY as high yield funds and others as high quality funds.

[2] The effect of fund mergers is ignored in my analysis due to an unavailability of merger data.

3. Methodology

To begin the investigation, I will measure the risk-adjusted fund performance for corporate bonds. Following the proposed models by Elton, Gruber and Blake (1995) and Gutierrez, Maxwell and Xu (2009), I will construct a modified three-factor model that fits my data availability. I have used proxies[3] where appropriate.

$$R_{i,t} - R_{ft} = \alpha + \beta_1 \mathrm{STK}_t + \beta_2 \mathrm{BOND}_t + \beta_3 \mathrm{DEF}_t + \epsilon_t$$

where STK is the excess return on the CRSP value-weighted stock index, BOND is the excess return on Vanguard Total Bond Market Index Fund, DEF is the return spread between the Merrill Lynch US High-Yield index and Vanguard Intermediate-Term Government Bond Index Fund. Summary statistics of the three variables are listed in Table 1.

[Table 2]

Table 2 depicts the regression results[4] from the model for the value-weighted portfolios of the whole sample of corporate bond funds and two subsamples of high-yield and high-quality funds respectively. As noted, all factors in each of the three regressions are each individually significant at 5% significance level, with t-statistic greater than 1.96.They have p-values less than 1% significance level, which imply that the variables are jointly significant in each of the regressions. However, there exists a discrepancy with the dataset as the corporate bond funds did not underperform the benchmarks after fees and expenses as expected in the literature. The bias might be attributed to the incompleteness of the risk factors in explaining the bond returns and the consequence of not taking into account the effect merger funds as above.

Nevertheless, I will move on to the next step to build four hypothetical trading strategies, each consisting of a portfolio of mutual funds as follows to illustrate the intuition behind the approach and to see where this might lead.

[3] Since I was unable to obtain access to the conventionally used Barclays Capital bond indices, I have used the pure index funds 'Vanguard Total Bond Market Index Fund', 'Vanguard Scottsdale Funds: Vanguard Intermediate-Term Government Bond Index Fund' and the alternative 'Merrill Lynch US High Yield Master II' to proxy the Barclays Aggregate Bond Index, the Barclays Intermediate Government Bond Index and the Barclays High-Yield Index respectively.

[4] Running regression diagnostics suggest that there is a strong multi-collinearity effect between the risk factors. Principal component analysis can be conducted to improve the results. See Appendix A.

Portfolio A: All available funds with positive money flows, equally weighted.
Portfolio B: All available funds with negative money flows, equally weighted.
Portfolio C: All available funds with positive money flows, weighted in proportion to new money flows.
Portfolio D: All available funds with negative money flows, weighted in proportion to new money flows.

$$R_{pt} - R_{ft} = \alpha + \beta_1 \mathrm{STK_t} + \beta_2 \mathrm{BOND_t} + \beta_3 \mathrm{DEF_t} + \epsilon_t$$
$$R_{pt} - R_{nt} = \alpha + \beta_1 \mathrm{STK_t} + \beta_2 \mathrm{BOND_t} + \beta_3 \mathrm{DEF_t} + \epsilon_t$$

Two separate regressions are used to capture the excess return of the positive new-money portfolio over the risk-free rate in the former and the return spread between the positive new-money portfolio and negative new-money portfolio. Through comparisons, I will deduce the smart money effect.

4. Empirical Results and Extension

[Table 3]

Table 3 provides clear evidence of the smart money effect for both equally-weighted and flow-weighted new money portfolios. The return spread between Portfolios A and B is 0.245% (with t-statistic of 8.97) and the return spread between Portfolios C and D is 0.357% (with t-statistic of 6.21). There is significant outperformance of Portfolios A and C relative to Portfolios B and D respectively. This is largely consistent with prior research that smart money effect exists in the case of corporate bonds.

Following up on what was discovered by Chen and Qin (2012) that smart money effect is insignificant during the financial crisis in 2008, I will apply part of the methodology used by Peng, Chen, Shyu and Wei (2011) to shed light on this validity of this finding. In the paper researching the Taiwanese equity market, Peng, Chen, Shyu and Wei separated the market into UP and DOWN states and investigated the extent of smart money for UP and DOWN periods. Following their definition, the UP and DOWN states of a market at time *t* is only when the lagged 36-month market return are nonnegative and negative respectively. I will use the CRSP value-weighted NYSE stock index as the broad generalized market return of the US economy.

Noting the results in Table 3, I found that the return spread between Portfolios C and D for the UP market is 0.360% (with t-statistic of 5.85). For the regression of the return spread between Portfolios C and D for the DOWN market, the p-value of the F-test is 0.235, which is larger than the significance level of 5% and the variables are jointly insignificant. This result (despite the several potential inaccuracies in its dataset) provides at least a brief supporting evidence of Chen and Qin (2012)'s finding that smart money effect is only observed during bull periods but not bear periods of the economy.

Considering the explanation proposed in Peng, Chen, Shyu and Wei's paper to suggest otherwise, they argue based on several financial behavioural studies that adverse market conditions tend to evoke negative emotions in investors and hence resulting in the decreasing reliance in heuristics. They believe that investors tend to more careful and rational and are smarter in their decision making and found that their findings in the equity market that supports this perspective. The interesting question is to ask why the inconsistencies as observed in the bond and equity markets. Are investors not more logical in bond investments?

5. Conclusion

It seems that there can be a potential all-encompassing answer to the gaps notably created by Chen and Qin (2012)'s paper. Where Chen and Qin fail to mention the possibility of market timing ability of bond investors, there are suggestions by Boney, Comer and Kelly (2008) finding evidence for perverse market timing ability between cash and investment grade securities and also perverse market timing across the bond maturity spectrum. They present a plausible explanation that the survival of bond funds despite its known continued negative performance is due to the value investors place on their portfolio for its diversification benefits. This meant that investors are possibly less likely to be affected by a need for rigorous decision making for bond funds. From this, I might postulate that the behaviour and the smart money effect of investors for bond funds differ fundamentally from that in equity.

In the wider perspective, it has certainly become exciting and yet confusing as we discover more contradictory findings in the literature. Similarly when Frazzini and Lomont (2008) uses mutual fund flows to measure investment sentiment, they found that high investor sentiment predicts low future returns and are dumb money in the long run. They relate this to value effect where investors tend to buy growth stocks and sell value stocks. They argue that non-financial institutions often take advantage of investors by selling growth stocks and buying value stocks. They also argue that smart money as demonstrated by Grubb (1996) and Zheng (1999) was only relevant in the short run.

Blanchett (2010) explores the controversy and examines active and passive investors separately. He discovers that while actively managed equity styles that receive larger inflows are likely to outperform their peers in the short run (three to six months), they tend to underperform in the long run (three years). In contrast, passively managed equity style funds that receive large inflows are likely to outperform both on a short-term and long-term basis. Consistent with previous studies, he suggests that both groups are smart in the short term, with passive investors being smart and active investors being dumb in making long term asset allocation decisions. And that is also implied that our search for profitable corporate bond funds is in vain, or is it not?

The smart money effect has generated an overwhelming interest in itself as its implications can be far-reaching in its related efficient market hypothesis. I shall speculate the direction of future research to develop a unifying theory encompassing inter-disciplinary models to describe financial return predictability and player interactions.

Table 1 Summary Statistics

The sample used is from June 1994 to December 2012. Various fund characteristics and risk factors data are collected and their statistics are described.

PANEL A: US Corporate Bond Funds	Total		High-Yield		High-Quality	
	Mean	Median	Mean	Median	Mean	Median
TNA ($ million)	594.80	64.95	455.22	72.90	664.75	58.20
Money flow ($million/month)	2.12	1.94	0.87	1.26	2.76	2.23
Money flow ratio (%/month)	2.91%	2.45%	3.36%	2.72%	2.71%	2.10%
Turnover (%/month)	151%	83%	81%	65%	186%	105%
Expense ratio (%/month)	1.03%	0.90%	1.21%	1.10%	0.94%	0.83%

PANEL B: Equal-Weighted Fund Returns (%/month)	Mean	Median	SD	Max	Min
All funds	0.49%	0.61%	1.25%	4.28%	-7.80%
High-yield funds	0.55%	0.87%	2.43%	9.09%	-15.52%
High-quality funds	0.46%	0.50%	0.95%	3.31%	-4.09%

PANEL C: Risk Factors (%/month)	Mean	Median	SD	Max	Min
STK	0.92%	0.92%	4.32%	-18.92%	11.50%
BOND	0.27%	0.31%	1.04%	-3.41%	3.62%
DEF	0.06%	0.38%	2.57%	-16.44%	9.71%

Table 2 Risk-adjusted Fund Performance

The table reports the risk-adjusted performance estimated from factor regressions for value-weighted portfolios of corporate bond funds using a three-factor model below.

$$R_{i,t} - R_{ft} = \alpha + \beta_1 \mathrm{STK}_t + \beta_2 \mathrm{BOND}_t + \beta_3 \mathrm{DEF}_t + \epsilon_t$$

	All Funds	High-Yield	High-Quality
α	0.0026	0.2557	0.0403
	(8.17)	(8.49)	(5.67)
β1	0.0932	0.6939	0.0403
	(20.04)	(6.45)	(35.42)
β2	0.8175	0.4274	0.9015
	(7.78)	(8.02)	(5.80)
β3	0.1570	0.0026	0.0730
	(6.43)	(2.40)	(9.67)
Adjusted R^2	0.7538	0.6227	0.8699

Table 3 Performance of Portfolios in Different Conditions

The table displays the various portfolio performances and some statistics from their regression models.

	α	t-stat	Adjusted R^2		
All funds, value weighted	0.0026	8.17	0.7538	F(3, 219) = 227.55	Prob > F = 0.0000
Portfolio A	0.0033869	7.68	0.7094	F(3, 218) = 180.81	Prob > F = 0.0000
Portfolio B	0.0009341	1.87	0.7091	F(3, 218) = 180.57	Prob > F = 0.0000
Portfolio C	0.0039599	7.82	0.6506	F(3, 218) = 138.81	Prob > F = 0.0000
Portfolio D	0.0003919	0.69	0.6582	F(3, 218) = 142.85	Prob > F = 0.0000
Portfolio A - Portfolio B	0.0024528	8.97	0.1536	F(3, 218) = 14.37	Prob > F = 0.0000
Portfolio C - Portfolio D	0.003568	6.21	0.0525	F(3, 218) = 5.08	Prob > F = 0.0020
When market state is UP					
Portfolio C	0.0050409	7.53	0.3054	F(3, 164) = 25.48	Prob > F = 0.0000
Portfolio D	0.0014433	1.8	0.3001	F(3, 164) = 24.87	Prob > F = 0.0000
Portfolio C - Portfolio D	0.0035977	5.85	0.0995	F(3, 164) = 7.15	Prob > F = 0.0002
When market state is DOWN					
Portfolio C	0.0020923	1.25	0.6422	F(3, 49) = 32.11	Prob > F = 0.0000
Portfolio D	-0.001475	-1	0.7559	F(3, 49) = 54.68	Prob > F = 0.0000
Portfolio C - Portfolio D	0.0035673	2.45	0.0263	F(3, 49) = 1.47	Prob > F = 0.2345

Appendix A Regression Diagnostics of Three-Factor Model

We will examine the regression that we used initially for the value-weighted portfolio of all corporate bond funds and suggest improvements.

$$R_{i,t} - R_{ft} = \alpha + \beta_1 STK_t + \beta_2 BOND_t + \beta_3 DEF_t + \epsilon_t$$

1) Test for multi-collinearity
Correlation between STK and BOND: 0.0180
Correlation between DEF and STK: 0.5785 (High, suggesting multi-collinearity)
Correlation between DEF and BOND: -0.3126
Variance Inflation Factor (VIF) for DEF, STK and BOND are 1.78, 1.61 and 1.19 respectively, with a mean VIF of 1.53 > 1, suggesting that there exists multi-collinearity.

Solution: To conduct a Principal Component Analysis such that correlations between new factors become zero. The first 2 factors are chosen to cumulatively explain 88.8% of total variance.

2) Test for overall model specification (Ramsey RESET)
$F(3, 216) = 2.06 <$ critical value of 2.65, Prob > F = 0.1066
Therefore, accepting the null hypothesis at 5% significance level and concluding that the original model is well-specified.

3) Test for heteroskedasticity (Breusch-Pagan test)
$Chi2(1) = 0.29 <$ critical value of 3.84, Prob > chi2 = 0.5883
Therefore, accepting the null hypothesis at 5% significance level and concluding that the original model has constant variance.

4) Test for normality
Chi2(2) for STK, BOND and DEF are 25.73, 6.31 and 68.68 respectively.
All of which are more than the critical value of 5.99 at 5% significance level.
Normality assumption is not valid for residuals.

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