Portfolio Managment: Homework 8

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B.1. Estimating E and V by the sample estimates.

stuff

B.2. Estimating the Performance-Flow Relation.

We write the function '`EVALperformancetoflow`' that computes our desired question answers:

```
EVAL_performance_to_flow <- function(year, graph = FALSE, ...){
    data <- transpose(rbind(rets[Date == year], flows[Date == year + 1]))
    colnames(data) <- c("returns", "inflows")
    data <- na.omit(data[-1, ]) # remove year and remove NAs

    data <- data[order(returns, decreasing = TRUE)]
    data[ ,group_interval := cut_number(returns, n = 10)]
    data[, decile := as.integer(group_interval)]
    data[ ,avg_returns := mean(returns), by = group_interval]
    data[ ,avg_flows := mean(inflows), by = group_interval]

    data_per_decile <- data[!duplicated(avg_returns)]
    linear <- lm(avg_flows ~ avg_returns + I(avg_returns ^ 2), data = data_per_decile)

    data_per_decile[ ,hat_avg_flows := linear$fitted][ ,c("returns", "inflows") := NULL]

    estimates <- rbind(
                alpha_hat = summary(linear)$coefficients[,'Estimate'][1],
                beta_hat = summary(linear)$coefficients[,'Estimate'][2],
                charlie_hat = summary(linear)$coefficients[,'Estimate'][3],

                alpha_se  = summary(linear)$coefficients[,'Std. Error'][1],
                beta_se   = summary(linear)$coefficients[,'Std. Error'][2],
                charlie_se  = summary(linear)$coefficients[,'Std. Error'][3]
    ); colnames(estimates) <- year

    data <- merge(data, data_per_decile)

    if(graph){

        p <- ggplot(data = data, aes(decile, group = 1)) +
                geom_point(aes(y = avg_flows), color = "black") +
                geom_line(aes(y = avg_flows)) +
                geom_line(aes(y = hat_avg_flows), color = "darkgrey", linetype = "dotted", size = 1.3) +
                ggtitle(paste("Performance(", year, ") to Fund Flows(", year + 1, ")", sep = "")) +
                labs(x = "Performance Deciles", y = "Average Fund Flow (t+1)")
```

```
        print(p)
    }

    return(list(data = data_per_decile, estimates = estimates))
}
```

a) i - iv.

We evaluate the performance-fund for 2001 and observe a convex pattern. As expected, the better performing the fund in the previous year, the more new funds flow into it. Further, our estimates (fitted_values) are highly correlated with the real values. This linear model explains much of the variation (in-sample, of course). All three of the coefficients appear to be highly significant.

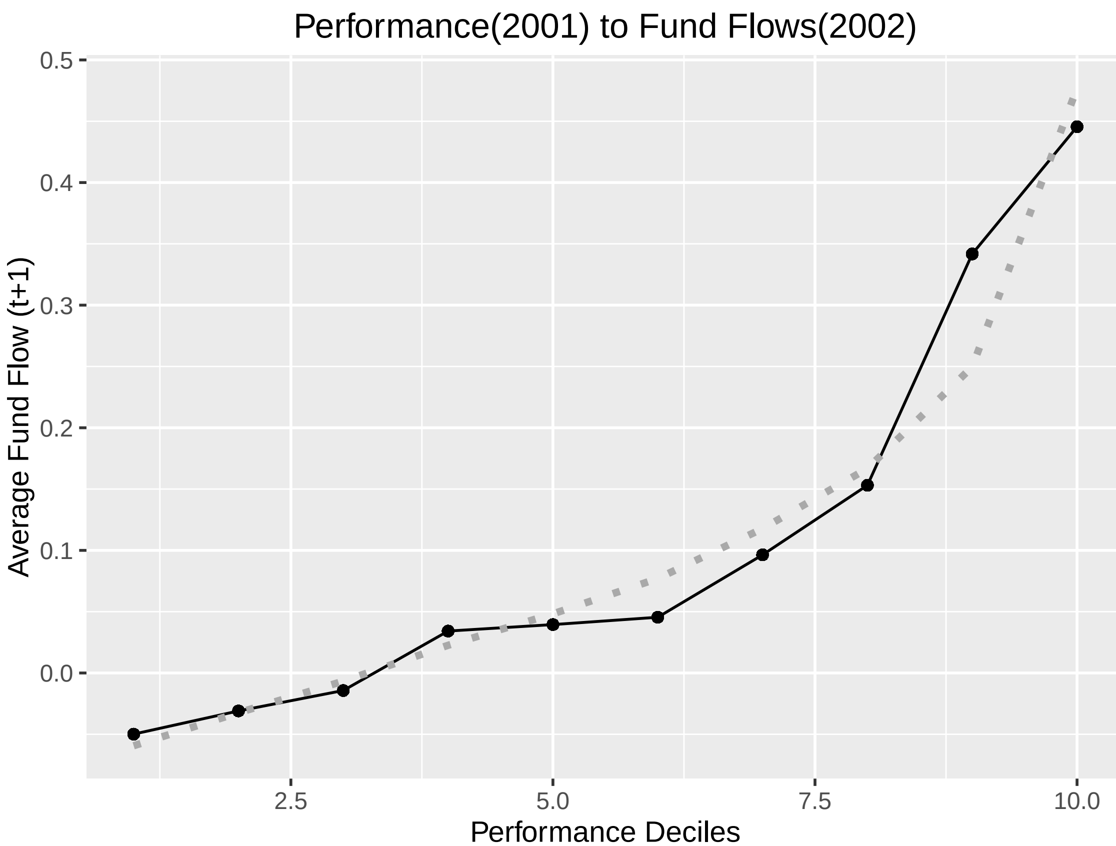


Table 1: Average: Returns, Flows, Fitted Values by Decile

group_interval	decile	avg_returns	avg_flows	hat_avg_flows
(0.0877,0.735]	10	0.1781	0.4455	0.4770
(0.00687,0.0877]	9	0.0426	0.3418	0.2497
(-0.041,0.00687]	8	-0.0191	0.1531	0.1667
(-0.0813,-0.041]	7	-0.0610	0.0963	0.1178
(-0.118,-0.0813]	6	-0.1005	0.0454	0.0771
(-0.146,-0.118]	5	-0.1322	0.0395	0.0482
(-0.185,-0.146]	4	-0.1642	0.0342	0.0226
(-0.23,-0.185]	3	-0.2077	-0.0143	-0.0067

group_interval	decile	avg_returns	avg_flows	hat_avg_flows
(-0.294,-0.23]	2	-0.2577	-0.0310	-0.0324
[-0.722,-0.294]	1	-0.3717	-0.0499	-0.0594

Table 2: Coefficients and Standard Errors

	alpha_hat	beta_hat	charlie_hat	alpha_se	beta_se	charlie_se
2001	0.191	1.3	1.7	0.017	0.124	0.46

b) i.

We write the function ‘`getStatSignif`’ and compute our Fama-MacBeth estimates:

```
years <- as.numeric(unlist(rets[,'Date'][-11])) # remove 2002
performance <- lapply(years, EVAL_performance_to_flow)

getStatSignif <- function(coef, ...){
    FM_alpha_hat <- do.call(sum, lapply(performance, function(x)
                        x$estimates[paste(coef, "_hat", sep = ""),])) / 10
    FM_alpha_se  <- sd(unlist(lapply(performance, function(x)
                        x$estimates[paste(coef, "_se", sep = ""),]))) / sqrt(10)
    summary_stat <- cbind(FM_alpha_hat, FM_alpha_se)
    colnames(summary_stat) <- NULL; rownames(summary_stat) <- coef
    return(summary_stat)
}
```

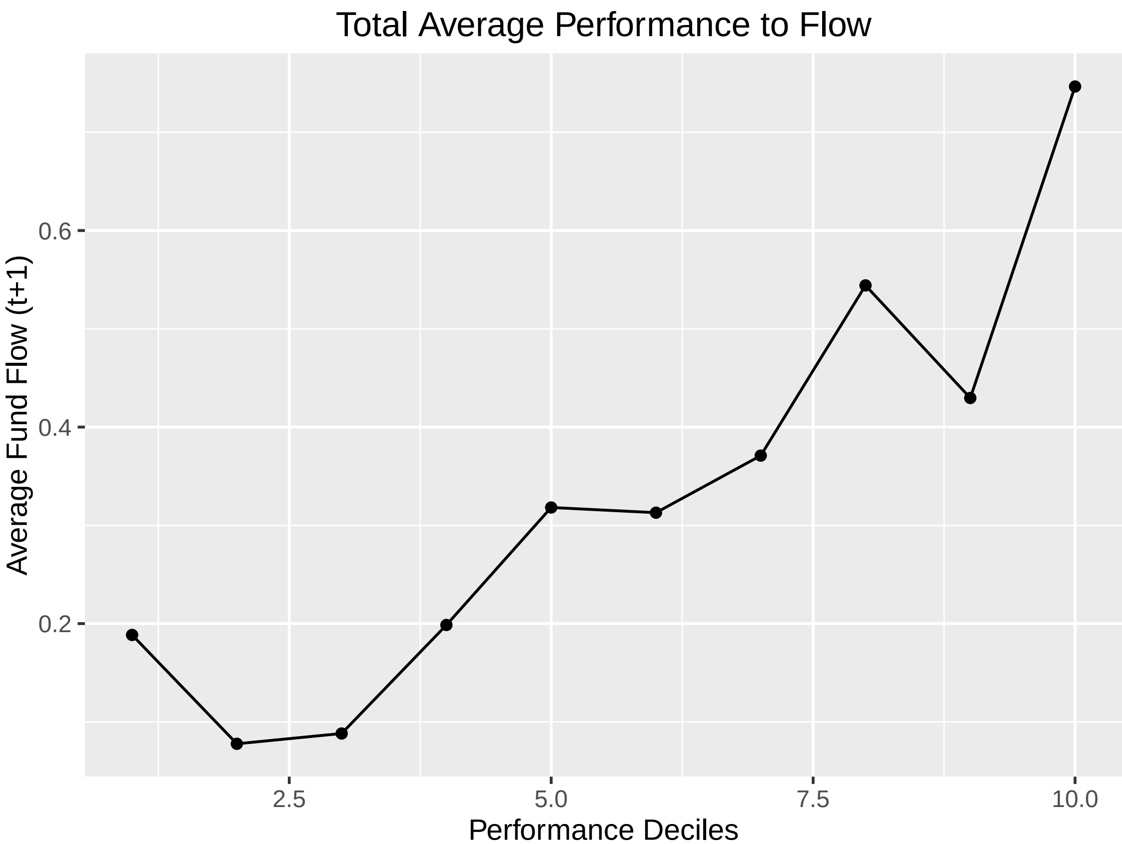
Confirming our results from above, the Fama-Macbeth approach is significant for all three coefficients, implying that the convexity pattern(charlie) is statistically signficant as well.

Table 3: Fama-MacBeth Estimates

	Estimate	Standard Error
alpha	0.0433	0.0094
beta	1.5640	0.0936
charlie	4.4437	0.4863

b) ii

Next, we average the performance-flow per decile across years. We, again, observe a convex pattern:



c) i.

$\mathbb{E}$(A) = 1(0.01) + 0(0) = 0.01
$\mathbb{E}$(B) = -0.25(0.60) + 0.25(0.40) = -0.05

Thus, choose A.

c) ii.

Given,

Initial investment size = 100M
$\hat{a}$ = 0.04
$\hat{b}$ = 1.56
$\hat{c}$ = 4.44

Scenario A:
$\hat{F_A}$ = 0.04 + 1.56 * 0.01 + 4.44(0.01^2) = 0.05
Year-end investment size = 105.6
$\mathbb{E}_{\mathbb{A}}$(A) = 1.05M

Scenario B:
$\hat{F_B}$ = 0.04 + 1.56 * 0.25 + 4.44(0.25^2) = 0.7075
Year-end investment size = 170.75
Fee(good) = 1.70M

$\hat{F_B}$ = 0.04 + 1.56 * -0.25 + 4.44(-0.25^2) = -0.0725
Year-end investment size = 92.75 Fee(bad) = 9.275M

$\mathbb{E}(B) = 0.40(1.70) + 0.60(0.92) = 1.23$

Thus, choose B.

c) iii.

Due to the quadractic term and incentive(1% fee after inflows) structure, the potential upside for investment B, even after factoring in the investment's riskyness (-0.25), is greater ($1.23 > 1.05$). Thus, a short term looking money manger would have greater incentives to take risky bets given their expected payoff.

d)

New money chases hot money.
There holds a strong quadratic relationship between a funds past return and its future inflows. Although it may be that these well-performing funds continue to perform well into the future (more analysis needed), given our class discussion, notes, and referenced papers, this seems unlikely. And, noting that incentives are tied not only to raw return performance but also fund inflows, it appears that money managers stand to gain, in expectation, significant upside on risky investments.