**A global approach to mutual funds market timing ability**

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**Abstract**

In this paper, we globally investigate market timing abilities of mutual fund managers from the three perspectives: market return, market-wide volatility and aggregate liquidity. We propose a new specification to study market timing. Instead of considering an average market exposure for mutual funds, we allow mutual fund market betas to follow a random walk in the absence of market timing ability. As a consequence, we capture market exposure dynamics which is really due to manager market timing skills while allowing dynamics to come from other sources than market timing. We find that on average 6% of mutual funds display return market timing abilities while this percentage amounts to respectively 13% and 14% for volatility and liquidity market timing. We also analyze market timing by investment strategies and for surviving and dead funds. Dead fund exhibit lower volatility and liquidity timing skills than live funds.

**Keywords**: Mutual fund, Market timing, market return, volatility, liquidity

Since the seminal paper of Treynor and Mazuy (1966), the market timing ability of investment funds managers has been extensively investigated. Following Treynor and Mazuy (1966), Kon (1983), Henriksson (1984), Chang and Lewellen (1984), Lee and Rahman (1990), Bollen and Busse (2001) and Jiang et al. (2007) focus on the ability of mutual fund managers to use their prediction about future market returns to deliver abnormal returns. As suggested by Cao et al (2011), the relative lack of evidence supporting mutual fund managers’ market timing skills from the return perspective may be due to the difficulty linked to the prediction of future market returns.

Besides return-timing, the literature on the market timing ability of investment fund managers has also recently developed along two other perspectives. On the one hand, the development of techniques which are relative reliable in predicting return volatility may be used by mutual fund managers to adjust their market exposure accordingly. In order to protect their performance from higher levels of volatility, they may decide to decrease (increase) their exposure to equities when the market is expected to become more (less) volatile. Using daily data, Busse (1999) shows that mutual fund managers tend to use their volatility timing ability and that this market timing ability leads to higher risk-adjusted performance.

More recently, Cao et al. (2011) have investigated the market timing ability of mutual fund managers from the market-wide liquidity perspective. They suggest that mutual fund managers may adjust their systematic risk as a function of the level of aggregate liquidity. In times of high liquidity, mutual funds would tend to increase their exposure to the market while they would reduce it when liquidity decreases. They find significant results indicating that mutual fund managers actually decrease their market exposure when aggregate is low supporting the idea that mutual fund managers have liquidity timing abilities.

In this context, the goal of our paper is to investigate all three form of market timing within a single analysis and to determine whether mutual fund managers actually possess market timing ability of any kind. In addition, we propose an alternative specification for the dynamic market exposure of mutual funds. Rather than imposing an average market exposure to each mutual fund as in previous studies, we relax this assumption and model the change in market exposure (instead of its value) as a function of forecasted returns, volatility and liquidity. Moreover, following the approach suggested by Swinkels and Van Der Sluis (2006), we further allow mutual fund market exposure to follow a random walk in the absence of market timing ability. The same idea is applied by among others Monarcha (2009) and Bodson et al. (2010) to study hedge fund style exposures. In our context, our specification allows the existence of dynamic in market exposure and changes in investment strategies even in the absence of market timing ability. We use a Kalman filter to estimate the state space representation of our model.

The paper is structured as follow. We first present the data that we use in our empirical analysis. We then define the methodology that we adopt and display the results of the analysis.

**Data**

*Mutual funds*

Mutual fund data are retrieved from the CRSP Survival Bias Free Mutual Fund Database which contains both live and dead mutual funds. We exclusively select mutual funds investing in domestic equity. Following Pastor and Stambaugh (2002), we use the Wiesenberger and Strategic Insight objective codes to classify the mutual funds into the same 4 broad investment strategies as Cao et al. (2011): Aggressive Growth (AGG), Long Term Growth (LTG), Growth and Income (GI) and Income (I). Mutual funds with Wiesenberger codes SCG, AGG and MCG and Strategic Insight codes AGG and SCG are classified as Aggressive Growth funds. Mutual funds with Wiesenberger codes G, G-S, S-G, GRO, LTG and Strategic Insight code GRO are classified as Long Term Growth funds. Mutual funds with Wiesenberger codes GCI, G-I, G-I-S, G-S-I, I-G, I-G-S, I-S-G, S-G-I, S-I-G, GRI and Strategic Insight code GRI are classified as Growth and Income funds. Mutual funds with Wiesenberger codes I, I-S, IEQ, ING and Strategic Insight code ING are classified as Income funds. We further exclude Exchange Traded Funds which do not make use of any market timing strategy as well as mutual funds with less than one year of returns and multiple share classes of the same fund. In addition, we impose that there is at any time at least 25 mutual funds in each fund category. As a result, our database consists of 2780 mutual funds (among which 1570 are dead funds) with monthly returns between January 1970 and December 2010. We create equally weighted portfolios using all the mutual funds in our dataset as well as for the 4 investment categories aforementioned. Descriptive statistics are reported in Table 1.

Table 1: Mutual funds descriptive statistics

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|   | Nb of funds | Mean | Median | St. Dev. | Min | Max |
| Total | 2780 | 0.81% | 1.08% | 3.90% | -16.90% | 13.22% |
| Surviving | 1570 | 0.87% | 1.11% | 3.87% | -16.86% | 13.42% |
| Non-surviving | 1210 | 0.71% | 1.00% | 4.02% | -17.28% | 12.96% |
| AGG | 544 | 0.99% | 1.44% | 5.33% | -23.13% | 16.51% |
| LTG | 1145 | 0.85% | 1.22% | 4.66% | -22.99% | 15.17% |
| GI | 540 | 0.81% | 1.10% | 3.79% | -16.84% | 12.54% |
| I | 551 | 0.68% | 0.77% | 2.05% | -10.43% | 7.82% |
|  |  |  |  |  |  |  |

*Risk factors, variance and liquidity measure*

To evaluate the market timing ability of mutual fund managers, we use the asset pricing model proposed by Fama and French (1992) augmented with the momentum factors of Carhart (1997). Market excess returns (MKT), risk free rates (Rf) as well as size (SMB), book-to-market (HML) and momentum (MOM) factors are retrieved from the Kenneth French’s database[[4]](#footnote-4).

As our goal is to investigate mutual funds market timing from the perspectives of return, volatility and liquidity, we need market-wide indicators of volatility and liquidity. We obtain a market-wide volatility measure by applying a GARCH(1,1) to the market return series and forecasting the conditional variance ($V\_{m,t}$) at each time period.

As an indicator of market-wide liquidity, we use the liquidity measure proposed by Pastor and Stambaugh (2003). They measure market-wide liquidity as the average of the liquidity measure of each stock on the NYSE and AMEX. For each stock and each month, they first estimate the following equation by OLS:

$r\_{i,d+1,t}^{e}=θ\_{i,t}+ϕ\_{i,t}r\_{i,d,t}+γ\_{i,t}sign\left(r\_{i,d,t}^{e}\right)\*v\_{i,d,t}+ϵ\_{i,d+1,t}$ [1]

Where $r\_{i,d,t}$ is the return on stock *i* on day *d* in month *t*, $r\_{i,d,t}^{e}$ is the excess return on stock *i* on day *d* in month *t* and $v\_{i,d,t}$ is the dollar volume for stock *i* on day *d* in month *t*.

The liquidity of stock i in month *t* is estimated as $\hat{γ}\_{i,t}$. The larger $\hat{γ}\_{i,t}$ is in absolute value, the less liquid the stock is in month *t*. A market wide liquidity measure is hence obtained as the average of the liquidity measure of each stock in the index:

$\hat{γ}\_{t}=\frac{1}{N}\sum\_{i=1}^{N}\hat{γ}\_{i,t}$ [2]

Where *N* is the number of stocks in the index.

As the size of financial markets has been significantly increased over the last decades, Pastor and Stambaugh (2003) suggest to define a scaled liquidity measure $(L\_{m,t})$ using the following adjustment:

 $L\_{m,t}=\frac{m\_{t-1}}{m\_{1}}\hat{γ}\_{t}$ [3]

Where $m\_{t-1}$ is the total market capitalization at the end of month *t-1*, $m\_{1}$ is the total market value in August 1962.

Updated series of the Pastor and Stambaugh (2003) aggregate liquidity measure is retrieved from Robert Stambaugh’s website[[5]](#footnote-5).

Table 2: Factors descriptive statistics

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|   | Mean | Median | St. Dev. | Min | Max |
| MKTt | 0.46% | 0.86% | 4.70% | -23.14% | 16.05% |
| SMBt | 0.20% | 0.05% | 3.23% | -16.67% | 22.19% |
| HMLt | 0.43% | 0.42% | 3.07% | -12.78% | 13.84% |
| MOMt | 0.69% | 0.82% | 4.56% | -34.75% | 18.39% |
| Vm,t | 2.27E-03 | 2.01E-03 | 1.16E-03 | 8.75E-04 | 7.80E-03 |
| Lm,t | -3.37% | -2.38% | 6.57% | -46.10% | 20.06% |
|  |  |  |  |  |  |

**Methodology**

The goal of this paper is to investigate in a single analysis the market timing ability of mutual fund managers from three different perspectives i.e. return-timing, volatility-timing and liquidity-timing. We use the Fama and French (1992) model augmented with the Carhart (1997) momentum factor to model mutual fund returns.

$R\_{i,t}=α\_{i}+β\_{1,i,t}MKT\_{t}+β\_{2,i}HML\_{t}+β\_{3,i}SMB\_{t}+β\_{4,i}MOM\_{t}+ϵ\_{i,t}$ [4]

Where $R\_{i,t}$ is the excess return of mutual fund *i* at time *t*.

In order to test market timing ability of mutual fund managers, we model the change in the market exposure as a linear function of changes in market returns, in market volatility and market liquidity. Unlike previous studies on market timing, we do not impose the existence of an average market exposure for mutual funds. Instead, we allow the presence of dynamics in mutual fund market exposures even in the absence of any market timing ability by letting their market beta follow a random walk when no market timing ability is detected. As a consequence, there may be dynamics in market exposure of mutual funds which may not be due to any market timing ability of funds’ managers such as changes in investment strategies or changes in the exposure of underlying assets. This allows us to detect the part of mutual funds market exposure which is truly due to the market timing ability of their managers.

$Δβ\_{1,i,t}=θ\_{1,i}ΔMKT\_{t}+θ\_{2,i}ΔV\_{m,t}+θ\_{3,i}Δ L\_{m,t}+υ\_{i,t} $ [5]

or alternatively,

$β\_{1,i,t}=β\_{1,i,t-1}+θ\_{1,i}ΔMKT\_{t}+θ\_{2,i}ΔV\_{m,t}+θ\_{3,i}Δ L\_{m,t}+υ\_{i,t}$ [6]

If market excess returns, market volatility and aggregate liquidity do not vary, we do not expect a mutual fund manager to change its exposure to the market. It may nevertheless change for reasons which are not linked to the market timing skills of the manager. This is taken into account by the error term $υ\_{i,t}$.

We estimate the state space representation composed of the measurement equations (Equation 4) and the state equation (Equation 6) using a Kalman filter with $ϵ\_{i,t} \~N(0,σ\_{ϵ\_{i}})$ and $υ\_{i,t}\~N(0,σ\_{υ\_{i}})$ .

If mutual fund managers have market timing abilities from all three perspectives, we would expect to find $θ\_{1,i}$ and $θ\_{3,i}$ being significant and positive and $θ\_{2,i}$ being significant and negative.

We first apply this methodology to the equally weighted portfolio composed of all the mutual funds in our dataset and to equally weighted portfolios for the 4 investment categories. We then implement a fund-by-fund analysis in which we apply the same methodology to each fund taken individually. We report the results of our analysis in the coming sections.

**Results**

*Global analysis*

We first study mutual fund market timing ability using the entire dataset that we have at our disposal. We create an equally-weighted portfolio composed of all the mutual funds in the dataset including surviving and non-surviving funds. We estimate the system of equations formed by Equations 4 and 6 using a Kalman filter. We also divide the dataset between surviving and non-surviving mutual funds and create two equally-weighted portfolio of respectively all the surviving and non-surviving funds. We estimate the system of equations for these two portfolios. This would enable us to determine whether there exist differences between the market timing ability of live and dead funds or in other words if the market timing skills of managers of surviving funds are significantly better than those of the managers of dead funds. Results are reported in Table 3.

Results from the global regressions show that mutual fund managers do not seem to have significant return timing abilities. For the whole dataset as well as for the two subgroups (surviving and on-surviving funds), the coefficients on the change in market return in the state equations are negative and insignificant at the 5% level. These results are consistent with those of among others Treynor and Mazuy (1966) and Chang and Lewellen (1984). From the volatility timing perspective, the global regression displays a significant volatility timing ability on the whole and even for both subgroups. Mutual fund managers would thus tend to reduce their exposure to the market when they forecast an increase in market-wide volatility. Lastly, the results show a significant liquidity-timing ability of mutual fund managers in general and for the subgroup of surviving funds while it is not significant for the group of dead funds. Managers of surviving mutual funds are more reactive to changes in aggregate liquidity than managers of dead funds. We can also notice the significantly negative alpha of non-surviving funds whereas surviving funds do not seem to be able to deliver significantly positive abnormal returns to their investors on the whole.

Table 3: Global regression results

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|   |   | Total | Surviving | Non-surviving |
|  |  |  |  |  |
| *Measurement Equation* |  |  |  |  |
|  | Constant | -0.0002 | 0.0004 | -0.0012\*\* |
|  |  | (0.0003) | (0.0003) | (0.0003) |
|  | MKT (final state) | 0.8669\*\* | 0.8594\*\* | 0.9134\*\* |
|  |  | (0.0338) | (0.0314) | (0.0394) |
|  | HML | 0.0072 | 0.0285\*\* | -0.0144 |
|  |  | (0.0076) | (0.0075) | (0.0087) |
|  | SMB | 0.1196\*\* | 0.1144\*\* | 0.1287\*\* |
|  |  | (0.0057) | (0.0057) | (0.0065) |
|  | MOM | 0.0113\* | 0.0050 | 0.0220\*\* |
|  |  | (0.0047) | (0.0051) | (0.0050) |
|  |  |  |  |  |
| *State Equation* |  |  |  |  |
|  | Δ MKT | -0.0457 | -0.0872 | -0.0399 |
|  |  | (0.0924) | (0.0948) | (0.0958) |
|  | Δ V | -14.7483\*\* | -17.8516\*\* | -11.1534\* |
|  |  | (3.8643) | (3.6045) | (4.7977) |
|  | Δ L | 0.2012\* | 0.2235\*\* | 0.1455 |
|  |  | (0.0808) | (0.0823) | (0.0865) |
|   |   |   |   |   |

Note: Standard errors between parentheses. \*\* and \* respectively denote significance at the 5% and 1% level.

*Analysis by investment categories*

We perform the same analysis as in the previous section for each of the investment categories Aggressive Growth, Long Term Growth, Growth and Income and Income. This allows us to refine our analysis and to capture potentially different market timing behavior of different investment strategies. Results are reported in Table 4.

Table 4: Regression results by investment categories

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|   |   | AGG | LTG | GI | I |
|  |  |  |  |  |  |
| *Measurement Equation* |  |  |  |  |  |
|  |  |  |  |  |  |
|  | Constant | 0.0001 | -0.0002 | -0.0003 | 0.0002 |
|  |  | (0.0005) | (0.0003) | (0.0003) | (0.0004) |
|  | MKT (final state) | 0.9953\*\* | 1.0073\*\* | 0.9065\*\* | 0.3886\*\* |
|  |  | (0.0587) | (0.0400) | (0.0336) | (0.0480) |
|  | HML | -0.0874\*\* | -0.0726\*\* | 0.0917\*\* | 0.1414\*\* |
|  |  | (0.0125) | (0.0099) | (0.0079) | (0.0169) |
|  | SMB | 0.4373\*\* | 0.1275\*\* | -0.0372\*\* | 0.0077 |
|  |  | (0.0101) | (0.0071) | (0.0053) | (0.0162) |
|  | MOM | 0.0664\*\* | 0.0249\*\* | -0.0262\*\* | -0.0301\*\* |
|  |  | (0.0082) | (0.0060) | (0.0051) | (0.0112) |
|  |  |  |  |  |  |
| *State Equation* |  |  |  |  |  |
|  |  |  |  |  |  |
|  | Δ MKT | -0.2036 | 0.0807 | 0.0025 | -0.2002 |
|  |  | (0.1686) | (0.1132) | (0.0909) | (0.1739) |
|  | Δ V | -14.2043\* | -16.9527\*\* | -14.3227\*\* | -11.1387 |
|  |  | (7.0688) | (4.7916) | (4.1494) | (8.4057) |
|  | Δ L | 0.2026 | 0.2593\*\* | 0.1365 | 0.1763 |
|  |  | (0.1349) | (0.0949) | (0.0719) | (0.1443) |
|   |   |   |   |   |   |

Note: Standard errors between parentheses. \*\* and \* respectively denote significance at the 5% and 1% level.

We find evidence of a significant return timing ability for none of the 4 investment categories. This confirms the results of the global regression. Results on volatility timing from the global regression are also confirmed by the regressions by investment strategies. We find a significant coefficient on the change of market-wide volatility in the state equation for all investment strategies except for the Income category. These results are in line with those of Busse (1999) who finds that mutual funds tend to adjust their exposure to the market in response to expected changes n market-wide volatility. From the liquidity timing perspective, only the Long Term Growth strategy displays a significant market timing ability at the 5% level (the coefficient of the Growth and Income strategy has a p-value of 5.77%). These results are consistent with those of Cao et al. (2011) who find a significant liquidity timing ability for some (but not all) of the investment strategies.

Overall, all but the Income strategy display at least one kind of market timing ability while none of the fund strategies exhibit return timing skills. The absence of significant market timing ability for the Income strategy is coupled with a lower exposure to the market than for the other three investment strategies. The lowest impact on their performance of the excess return of the market may partly explain the fact that they do not use market timing ability as much as the other investment strategies for which the exposure to the market is significantly higher.

*Fund-by-fund analysis*

In this section, we repeat the estimation procedure for each fund in our dataset on an a individual basis. This allows us to determine which funds display significant market timing abilities as well as the percentage of mutual funds’ managers which actually possess these market timing skills. We report the results of this analysis in Table 5 for the entire dataset as well as for live and dead funds and for the different investment categories.

Table: Fund-by-fund regression results

|  |  |  |  |
| --- | --- | --- | --- |
|   | % of funds with θ1 (ΔMKT) significantly positive\* | % of funds with θ2 (ΔV) significantly negative\* | % of funds with θ3 (ΔL) significantly positive\* |
|  |  |  |  |
| TOTAL | 6.04% | 14.06% | 13.38% |
| Surviving | 5.98% | 24.73% | 18.84% |
| Non-surviving | 6.10% | 5.90% | 9.21% |
| AGG | 5.33% | 19.67% | 6.62% |
| LTG | 7.77% | 10.66% | 13.97% |
| GI | 5.37% | 16.30% | 13.33% |
| I | 3.81% | 13.43% | 18.87% |
|   |   |   |   |

Note: \* significance at the 5% level of a one-sided test.

Results indicate that approximately 1 fund out of 17 exhibit significant return timing abilities. This is significantly more than the 1 out of 57 found by Treynor and Mazuy (1966). These proportions amount to around 1 out of 7 funds for volatility and liquidity timing.

Regarding surviving and non-surviving funds, there seems to be no difference in terms of the percentage of mutual funds with return timing abilities (both groups display a percentage around 6%). However, the differences are stronger for volatility and liquidity timing. While only 5.9% of non-surviving mutual funds show evidence of volatility market timing, this percentage rises up to 24.7% for surviving mutual funds. The same pattern can be observed for liquidity market timing for which the percentages are 9.2% for non-surviving funds and slightly more than twice as much for surviving funds (18.8%).

With respect to investment strategies, the proportion of mutual funds with significant return timing abilities ranges from 1 out of 13 for the Long Term growth strategy to 1 out of 26 for the income strategies. As already mentioned, this may be due to the goal of the strategy which is to provide regular streams of payments and the lower exposure to market returns. In this context, Income mutual funds may be more concerned about changes in market-wide volatility and liquidity. This is reflected in the higher percentages of funds exhibiting volatility timing abilities (13.43%) and liquidity timing abilities (18.87%). Proportions for volatility timing are the highest for the Aggressive Growth category with 1 fund out of 5 displaying significant timing abilities and the lowest for the Long Term Growth strategy with only 1 fund out 9 exhibiting the same timing skills. Lastly, liquidity timing abilities also seem to be prevailing for a part of mutual funds in our dataset. We can notice that the Aggressive Growth strategy has the lowest percentage for liquidity timing abilities (only 6.62%) while it has the highest figures from the volatility timing perspective. The highest proportion is reached by the Income strategy with 1 fund out of 5.

On the whole there seems to be a non-negligible part of mutual funds which have market timing abilities. Return timing ability is less frequently found to be significant. This should be surprising as market return is certainly more complicated to be predicted than volatility and liquidity. Though there exist discrepancies between investment categories, the most striking results is certainly the huge difference which exist between the number of surviving and non-surviving fund exhibiting volatility and liquidity timing abilities. The percentage of surviving funds displaying volatility (respectively liquidity) timing abilities is more than 4 times (respectively twice as much as) the percentage of non-surviving funds.

**Conclusion**

The goal of this paper is to develop a global investigation of mutual fund managers’ market timing abilities from the three perspectives of market return, volatility and liquidity. We offer an analysis in which these three market timing skills are tested together for a large database of equity mutual funds. A second contribution of this paper is the specification that we use to test the presence of market timing. While most previous studies make the assumption of an average market exposure to which mutual funds return in times of average market conditions, we allow the existence of a dynamic market exposure even without any market timing intervention. Specifically, we model the change in market exposure of a mutual as a function of changes in market return, market-wide liquidity and aggregate volatility. In the absence f market timing abilities, the market exposure of a fund is nevertheless allowed to evolve according to a random walk. Consequently, in our analysis, market timing is not the only source of mutual funds’ market exposure. This is consistent with the fact that the market exposure of a mutual fund may vary according to factors which are not due to any market timing ability of their managers (such as for instance changes in investment style or market exposure of underlying assets).

We study market timing for equally weighted portfolio of all the funds in the database as well as for 4 different investment strategies (Aggressive Growth, Long Term Growth, Growth and Income and Income). Global results suggest the existence of volatility and liquidity timing abilities (though not necessarily for all investment strategies) but not of return timing. We further investigate market timing on a fund-by-fund basis. We find that around 6% of mutual funds exhibit return timing abilities. These percentages are multiplied by more than two for volatility and liquidity timing. Surviving funds tend to have more volatility and liquidity timing abilities than dead funds.

**References**

Bodson, L., Coen A. and Hübner G. (2010) Dynamic Hedge Fund Style Analysis with Errors-in-Variables. *Journal of Financial Research*, 33(3): 201-221.

Bollen, N. and Busse J. (2001) On the Timing Ability of Mutual Fund Managers. *Journal of Finance*, 56(3): 1075-1094.

Busse, J. (1999) Volatility Timing in Mutual Funds: Evidence from Daily Returns. *Review of Financial Studies*, 12(5): 1009-1041.

Cao, C., Simin T. and Wang Y. (2011) Do Mutual Fund Managers Time Market Liquidity? *SSRN* *Working Paper*, April.

Carhart, M. (1997) On Persistence in Mutual Fund Performance. *Journal of Finance*, 53(1): 57-82.

Chang, E. and Lewellen W. (1984) Impact of Size and Flows on Performance for Funds of Hedge Funds. *Journal of Business*, 57(1): 57-72.

Fama, E. and French K. (1992) The Cross-Section of Expected Stock Returns. *Journal of Finance*, 47(2): 427-465.

Henriksson, R. (1984) Market Timing and Mutual Fund Investment Performance. *Journal of Business*, 57(1): 73-96.

Jiang, G., Yao T. and Yu T. (2007) Do Mutual Funds Time the Market? Evidence from Portfolio Holdings. *Journal of Financial Economics*, 86(3): 724-758.

Kon, S. (1983) The Market-Timing Performance of Mutual Fund Managers. *Journal of Business*, 56(3): 323-347.

Lee, C. and Rahman S. (1990) Market Timing, Selectivity, and Mutual Fund Performance: An Empirical Investigation. *Journal of Business*, 63(2): 261-278.

Monarcha, G. (2009) A Dynamic Style Analysis Model for Hedge Funds. *SSRN Working Paper,* October.

Pastor, L. and Stambaugh R. (2002) Do Mutual Fund Performance and Seemingly Unrelated Assets. *Journal of Financial Economics*, 63(3): 315-349.

Pastor, L. and Stambaugh R. (2003) Liquidity Risk and Expected Stock Returns. *Journal of Political Economy*, 111(3): 642-685.

Swinkels, L. and Van Der Sluis P. (2006) Return-Based Style Analysis with Time-Varying Exposures. *European Journal of Finance*, 12(6): 529-552.

Treynor, J. and Mazuy K. (1966) Can Mutual Funds Outguess the Market? *Harvard Business Review*, 44(4): 131-136.

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