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Abstract

This study complements the scarce literature on conditional market timing in the mutual fund industry by assessing determinants of market timing throughout the distribution of market exposure. It builds on the intuition that the degree of responsiveness by fund managers to investigated factors (aggregate liquidity, information asymmetry, volatility and market excess return) is contingent on their levels of market exposure. To this end, we use a panel of 1467 active open-end mutual funds for the period 2004-2013. Fund-specific time-dynamic beta is employed and we avail room for more policy implications by disaggregating the dataset into market fundamentals of: equity, fixed income, allocation and tax preferred. The empirical evidence is based on Quantile regressions. The following findings are established. First, there is consistent positive threshold evidence of volatility and market return in market timing, with the slim exception of allocation funds for which the pattern of volatility is either U- or S-shaped. Second, the effect of volatility and market return are consistently positive and negative respectively in the bottom and top quintiles of market exposure, but for allocation funds. Third, the effects of information asymmetry and aggregate liquidity are positive and negative, contingent on specifications, level of market exposure and market fundamentals. The findings broadly suggest that blanket responses of market exposures to investigated factors are unlikely to represent feasible strategies for fund managers unless they are contingent on initial levels of market exposure and tailored differently across 'highly exposed'-fund managers and 'lowly exposed'-fund managers. Implications for investors and fund managers are discussed.

Key words: Mutual funds; Market timing; Thresholds; Quantile regression
JEL Classification: C52; G12; G14; G18.

1. Introduction

Over the past decades, the popularity of mutual funds has grown rapidly. Hence, instead of getting into equity markets directly, investors have tended to prefer mutual funds (Wu, 2011). Though, the performance of active mutual funds has been widely explored in the literature. In other to deliver high performance, investment managers use different means like quantitative methods, quantitative models plus additional information such as information on managers; press articles or investment analysts (Bassett Jr & Chen, 2001). The assessment of the performance is sometimes contingent on the market timing skills of managers of active mutual funds.

Market timing is a situation where a timer seizes the opportunity of market fluctuations. He or she can rebalance portfolio or switch asset allocations. Should the timer's forecast market expected return be accurate, he/she would be rewarded with a better performance relative to benchmark portfolio characterised with a constant beta that is equivalent to the timer's portfolio average beta. Starting with the fundamental study of Trenor and Mazuy (1966), several authors have worked on the ability of active mutual funds managers to time the market. Trenor and Mazuy (1966) used a sample of 57 funds between 1957 and 1962 and found evidence of timing ability only in one fund. They reached the conclusion that investment managers cannot outguess the market. Considerable studies reached the same conclusion of little evidence of market timing in the mutual fund industry. For instance, (1) Kon (1983) found evidence of market timing at the individual fund level but no evidence when funds are grouped; (2) Chang and Lewellen (1984) studied a sample of 67 monthly mutual funds and found that only few fund managers seem to exhibit some ability to time the market ; (3) Henriksson (1984) found evidence of market timing in only 3 funds out of the 118 studied and (4) Mansor et al. (2015) analysed 106 Malaysian equity funds and found that evidence of market timing disappeared when employing panel regressions.

However, inquiries by Bollen and Busse (2001) have found evidence of market forecast among managers of active mutual funds. Bollen and Busse (2001) emphasised the importance of the frequency of data. Using daily data of 230 mutual funds, they found evidence of market timing skill in a substantial numbers of funds. Applying holding-based measures, Jiang et al. (2007) found a positive timing ability of mutual fund managers. It is important to note that their sample is only made of equity funds.

Every fund managers do not time the market exactly the same way since they do not have access to the same information. Therefore, the market timing may be contingent on the set of information each fund manager has. Some studies in the existing literature have employed conditional market timing to assess the performance of funds in terms of market timing skill.

The concept of conditional market timing has been explored in different perspectives, but mostly conditioned on public versus private information. Ferson and Schadt (1996) advocate the conditional performance evaluation of mutual funds, conditioned on public information. They use a sample of 67 monthly mutual funds for the period 1968-1990 and their findings reveal statistical and economical results when applying conditional information. Therefore, the responsiveness of funds to public information changes with risk exposure. More recently, Dahr and Mandal (2014) have also employed the conditional performance evaluation to investigate the performance of Indian mutual funds with respect to the ability of fund managers to forecast the market. Using 80 mutual funds schemes over the period 2000-2012, they found that the conditioning on public information improves the coefficient of determination when applying the unconditional Henriksson-Merton and Treynor-Mazuy models under the same period.

The findings of Dahr and Mandal run counter to those earlier established by Becker et al. (1999) on the evidence of market timing skills from active mutual fund managers. They made a distinction between timing based on publicly available information which can be captured by some instrumental variables and timing based on better information. They call the latter "*Conditional market timing*". Analysing a sample of 400 U.S. mutual funds over 1976 – 1994 period, with conditioning based on public information, they find that mutual funds are highly risk averse and no evidence of a significant timing ability in the market. Taking into account the conditional perspective, Saez (2008) and Holmes and Faff (2004) also found very little evidence of market timing ability.

The engaged literature clearly leaves room for improvement on two fronts, namely: the need to assess market timing in the mutual fund industry beyond equity funds on the one hand and on the other hand, assess how market factors affect market timing when existing levels of market timing are considered. To put the above points into more perspective, as discussed above, the concept of market timing has been more studied with equity funds for the most part. However, the timing ability of funds managers should not be limited only to equity funds (Elton et al., 2011). Hence, we complement equity funds with fixed income, allocation, tax preferred funds.

This study contributes to the literature by investigating the roles of information asymmetry and other factors on market timing throughout the conditional distribution of market timing. This second contribution builds on the fact that the degree of responsiveness by fund managers with low market exposure to the conditioning information set (aggregate liquidity; information asymmetry and volatility) should intuitively be different from managers that are characterised with higher market exposure. Moreover, it is very likely that fund managers with low market exposure are associated with a higher level of information asymmetry and vice versa. Hence, from logic and intuition, the response of fund managers to information asymmetry is very likely to be contingent on the level of market exposure fund managers are acquainted with.

The rest article is organised as follows. Data, methodology and estimation procedure are presented in section 2. Section 3 documents the empirical analysis and results. Section 4 presents concluding implications and future research directions.

2. Data and methodology

2.1 Data

We analyse annual open-end mutual fund returns from the Morningstar Direct database for the period 2004 to 2013. We divide our sample into four sub-samples based on the Global Broad Category Group of Morningstar: equity, fixed-income, allocation and tax-preferred funds. We study each sub-sample in detail to compare the responsiveness of fund managers to each type of fund on the conditional distribution of market exposure.

We apply a filter to remove all missing values due to methodological constraint and end-up with a strongly balanced panel dataset of 882 equity funds, 243 fixed-income funds, 156 allocation funds and 186 tax-preferred funds. As result, we have 1467 active mutual funds for 10 years. The definitions of variables and fund categories are provided in Appendix 1.

Table 1

Summary statistics

This table presents the Summary statistics of variables used in our analysis in panel A and fund categories in panel B. Std. Dev.: Standard Deviation. Min.: Minimum. Max. : Maximum. Obs.: Observations.

Panel A : Variables					
	Obs.	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Beta	8928	-0.018	0.932	-4.502	4.571
Info. Asymmetry	8928	19.467	15.245	0.000	93.425
Volatility	7440	19.467	12.115	0.691	64.902
Mkt Excess Return	14880	8.578	19.038	-38.39	35.15
Aggregate Liquidity	14880	-0.025	0.028	-0.098	0.010
SMB	14880	3.003	7.485	-7.01	17.74
HML	14880	2.411	12.342	-21.55	23.66
Panel B: Fund categories					
Equity	14880	0.592	0.491	0	1
Fixed income	14880	0.163	0.369	0	1
Allocation	14880	0.104	0.306	0	1
Tax preferred	14880	0.125	0.330	0	1

SMB: Size. HML: Book to market. Std. Dev.: Standard Deviation. Min.: Minimum. Max. : Maximum. Obs.: Observations.

The summary statistics for various types of mutual fund and variables are discussed in Panel A and Panel B respectively of Table 1. Two motivations underpin the summary statistics. One on the hand, it is apparent that the variables are comparable from the perspective of mean values. On the other hand, corresponding variations from the standard deviations is an indication that we can be confident that reasonable estimated linkages will result from the empirical analysis.

Table 2 discloses the correlation matrix. It enables the study to avoid concerns about multicollinearity that could lead to variables with a high degree of substitution entering into conflict and reflecting unexpected signs in the estimation output. Therefore, in specifications of the main equation, 'aggregate liquidity' and 'market excess return' are not involved the same estimation owing their high degree of substitution. This is consistent with a caution from Cao et al. (2013, p. 285) that high market return is strongly associated with market liquidity. In accordance with Bodson et al. (2013), book-to-market and market size are entered into the same equation when estimating the beta variable for market timing.

Table 2
Correlation matrix

This table presents the correlation matrix of variables used in our analysis

Info. Asymmetry	Volatility	Mkt Excess Return	SMB	HML	Aggregate Liquidity	Beta	
1.0000	0.1868	-0.0125	-0.0413	-0.0307	0.0137	0.0186	Info. Asymmetry
	1.0000	-0.0418	-0.0308	-0.0090	0.0337	0.0050	Volatility
		1.0000	0.5516	0.5184	0.7498	0.0231	Mkt Excess Return
			1.0000	0.7186	0.0298	-0.0201	SMB
				1.0000	0.2964	0.0123	HML
					1.0000	0.0512	Aggregate Liquidity
						1.0000	Beta

SMB: Size. HML: Book to market.

2.2 Methodology

2.2.1 Estimation of volatility, beta and information asymmetry

Various measurements for information asymmetry have been proposed in the literature. Tchamyou and Asongu (2017), Asongu et al. (2016) have used private credit bureaus and public credit registries as proxies for 'reducing information asymmetry' in the banking industry. Dai et al. (2013) have employed the standard deviation of return's idiosyncratic risk to investigate how mutual fund ownership and information asymmetry affect the management of earnings by listed companies. In accordance with the same definition, the cost originating from information asymmetry between elements of a syndicated bank loan has been examined by Ivashina (2009). Dierken (1991) has used four indicators to appreciate information asymmetry between the market and firm managers within the context of equity. What is common among these studies is the fact that information asymmetry is proxied as the difference between realised and expected returns. This study is in line with the underlying intuition for the estimation of uncertainty in information as well as asymmetric information. Therefore, we compute information asymmetry as the standard deviation of the idiosyncratic risk of returns[1]. Within this context, asymmetric information corresponds to the standard deviations of individual returns' residuals, in which case standard errors are equal to the standard deviation of residuals. Accordingly, whereas the Capital Asset Pricing Model (CAPM) augmented with the Fama-French 3-factor model (here after FF) (see Eq.2 below) is employed for the computation of asymmetric information, a stochastic modelling estimation process is used to derive volatility or uncertainty. The approach we adopt

[1] The idiosyncratic risk of return is similar to abnormal returns. This corresponds to the variation between the realized return and expected return.

for the of estimation volatility, beta and information asymmetry is consistent with Tchamyou et al. (2017).

Returns' volatility is estimated as the standard errors corresponding to the first order auto-regressive processes of the returns. In accordance with Kangoye (2013), owing to the low frequency nature of our data, volatilities or uncertainties cannot be computed with GARCH (Generalized Auto-Regressive Conditional Heteroskedasticity) models. Hence, auto-regressive estimations are employed. It follows that the Kangoye (2013) estimation process is employed to estimate volatility because the dataset consists of open-end mutual funds of annual periodicity. Therefore, uncertainty corresponds to the saved RMSE[2] (Root-Mean_Square Error) of each return obtained from the first autoregressive processes. The computation process is summarised in the following equation.

$$R_{i,t} = \alpha + \varphi R_{i,t-1} + \kappa T + \varepsilon_{i,t} \quad , \tag{1}$$

where $R_{i,t}$ is the return of fund i at time t; $R_{i,t-1}$ the return of fund i at time $t-1$; T the time trend; α the constant ; φ the parameter and $\varepsilon_{i,t}$ the error term.

We model mutual fund returns with the FF three factors model to estimate fund-specific systematic risk.

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{MKT,i,t} MKT_t + \beta_{SMB,i} SMB_t + \beta_{HML,i} HML_t + \varepsilon_{i,t} \quad , \tag{2}$$

where R_f is the risk free rate. MKT is the market excess return, SMB Small [market capitalization] Minus Big and HML High [book-to-market ratio] Minus Low. The previous 3 factors are taken from the Kenneth French's website[3].

A simple view of information asymmetry can then be modelled as follows:

$$IA_{i,t} = \sigma\left(R_{i,t} - \hat{R}_{i,t} \right) \tag{3}$$

Where IA is Information Asymmetry; σ the standard deviation; $R_{i,t}$ the realised return of fund i at time t; $\hat{R}_{i,t}$ the expected return computed using the FF 3 factor model.

The dynamic beta corresponding to each mutual fund is estimated as a proxy for market exposure or market time. The advantage of employing betas is that it captures more market heterogeneities because in each year a distinct beta is computed for each fund. It is important to note that time-

[2] The RMSE (Root-Mean-Square Error) can be employed as a measure of uncertainty or as the standard deviation of residuals (see Kitagawa & Okuda, 2013).

[3] Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

static beta have the shortcoming of failing to capture some inherent variations that could substantially help in the elucidation of the market timing ability of fund managers. In essence, the mainstream literature has cautioned that assets' betas may vary over time (see Ferson & Schadt, 1996, p. 428). Using the Rollreg Stata command, we estimate the time-varying beta and RMSE for asymmetric information in Equation 2. Considering that there is a time-window that is higher than the number of independent indictors by at least one degree of freedom, a five-year moving-window is adopted because four missing observations are apparent in each fund. It is important to note that four observations are automatically missing because we are using four independent variables of interest.

In order to estimate the indicator of liquidity, the aggregate liquidity factors from an updated series by Pástor and Stambaugh (2003) are used. Consistent with Bodson et al. (2013), all factors are retrieved from the website of Robert Stambaugh[4]. Given that liquidity data is in months, whereas the mutual fund data is annual, annual averages are computed with the monthly data.

2.2.2. Estimation technique

Consistent with the motivation of the study, estimation techniques that are based on mean values of market timing can only result in blanket practical implications for fund managers. Hence, approaches based on mean values of the dependent variable like Ordinary Least Squares (OLS) and the Generalised Method of Moments (see Tchamyou et al., 2017) reflect the underlying shortcoming. Accordingly, they estimate the linear conditional mean functions and articulate the central trend of the dependent variables. Consequently, they do not take into account the distribution of the tails. Hence, a Quantile Regression (QR) approach is applied in this study to address the discussed shortcomings from estimation techniques that are based on mean values of the market timing's distribution. In essence, the QR is employed in this study to investigate the determinants of market exposure throughout the conditional distribution of market timing (Keonker & Hallock, 2001). The QR is based on median regression and was developed by Koenker and Bassett (1978). While the OLS supposes the normal distribution between the error term and the dependent variables, the QR is not established on this hypothesis. According to Lee and Saltoglu (2001), the main advantage of the QR technique is its capacity of producing more robust estimates (Koenker & Basett, 1982). The application of QR is increasing in the finance literature, notably in: (i) analysing risk in mutual funds (Wang

[4] Robert Stambaugh's Website: http://finance.wharton.upenn.edu/~stambaugh/

et al., 2015) and (ii) examining the relationship between fund governance and performance (Chen & Huang, 2011).

In accordance with recent QR literature (Efobi & Asongu, 2016; Asongu et al., 2017), the θ^{th} quintile estimator of market timing is obtained by solving for the following optimization problem, which is presented without subscripts in Eq. (3) for ease of presentation.

$$\min_{\beta \in R^k} \left[\sum_{i \in \{i: y_i \geq x_i' \beta\}} \theta \left| y_i - x_i' \beta \right| + \sum_{i \in \{i: y_i \geq x_i' \beta\}} (1-\theta) \left| y_i - x_i' \beta \right| \right], \quad (4)$$

where $\theta \in (0,1)$. Contrary to OLS that is fundamentally based on minimizing the sum of squared residuals, with QR, we minimize the weighted sum of absolute deviations. For instance the 10$^{\text{th}}$ or 90$^{\text{th}}$ quintiles (with θ=0.10 or 0.90 respectively) by approximately weighing the residuals. The conditional quintile of market timing or y_i given x_i is:

$$Q_y(\theta / x_i) = x_i' \beta_\theta , \quad (5)$$

where unique slope parameters are modelled for each θ^{th} specific quintiles. This formulation is analogous to $E(y/x) = x_i' \beta$ in the OLS slope where parameters are examined only at the mean of the conditional distribution of market timing. For the model in Eq. (5), the dependent variable y_i is the market timing indicator, while x_i contains a constant term, *information asymmetry*, *market excess return and aggregate liquidity*.

3. Empirical results

While Table 3 presents findings corresponding to the full sample, the results of the remaining tables pertain to sub-samples. Accordingly, Table 4, Table 5, Table 6 and Table 7 respectively correspond to equity funds, fixed income funds, tax-preferred funds and allocation funds. There are two main specifications corresponding to each table: one specification without aggregate liquidity and another specification without market excess return. The two specifications are used to address the apparent concern of multicollinearity or high degree of substitution between market excess return and aggregate liquidity.

For all tables disclosing the empirical results, consistent difference in estimates from market exposure determinants between OLS and quintiles (in terms of sign, significance and magnitude of significance) justify the relevance of adopted empirical strategy. Since, the effect of the independent variables are investigated through the conditional distribution of market exposure, the corresponding trend in tendencies could take several patterns, *inter alia*: S-shaped, U-shaped, inverted U-shaped and positive or negative threshold shapes. The notion of threshold adopted in this study is consistent with Asongu (2014). In essence, a positive threshold is apparent when throughout the distribution of market exposure, the estimates consistently display decreasing negative magnitudes and/or increasing positive magnitudes. In the same vein, a negative threshold is established when an estimated coefficient consistently displays decreasing positive and/or increasing negative magnitudes throughout the conditional distribution of market exposure. In other words, a positive threshold denotes consistent incremental effects of the underlying estimate on market exposure.

The following findings can be established from Table 3 which shows results of the full sample. First, information asymmetry significantly affects market exposure in the bottom quintiles, with a negative (positive) effect (s) in the 10^{th} (25^{th} and 50^{th}) quintile(s). Second, positive thresholds are apparent from the effects of volatility and market excess return. Third, aggregate liquidity has a positive effect on market exposure in the top quintiles.

In Table 4 which shows results of the equity funds sub-sample, the findings of the full sample are broadly confirmed with the exception that the positive effect from aggregate liquidity is now also significant in the 25^{th} and 50^{th} quintiles. Looking at Table 5 which shows results of the fixed-income funds sub-sample, the findings of the full sample are broadly confirmed with the exception that the effect of information asymmetry is consistently negative in the top quintiles of the market exposure distribution. From Table 6 on the results of the tax-preferred funds sub-sample, findings of the full sample are broadly confirmed with the exception that the effect of aggregate liquidity is not negative (positive) in the top quintiles of market exposure. In Table 7 which presents findings of the sub-sample corresponding to allocation funds: (i) information asymmetry positively affects market exposure from the 10^{th} to the 50^{th} quintiles; (ii) the incidence of volatility is U-shaped on the left-hand-side and S-shaped in the right-hand-side; (iii) market excess return displays a positive threshold effect from the 25^{th} to the 90^{th} quintiles whereas aggregate liquidity positively (negatively) affects market exposure in the 90^{th} (10^{th}, 25^{th} and 75^{th}) quintile (s).

Table 3

Quantile regression based on full sample

This table presents the quantile regression of the determinants of market timing.
*, **, ***: significance levels of 10%, 5% and 1% respectively. P-values are in brackets. OLS: Ordinary Least Squares. R^2 is for OLS and Pseudo R^2 for Quantile regression. I.A: Information Asymmetry. MKT: Market Excess Return. AggLiq: Aggregate Liquidity. Lower quantiles (e.g., Q 0.10) signify fund where market exposure is least.

	Dependent variable: Beta											
	Specifications with MKT						Specifications with AggLig					
	OLS	Q.10	Q.25	Q.50	Q.75	Q.90	OLS	Q.10	Q.25	Q.50	Q.75	Q.90
Constant	-0.000	-0.030	-0.105**	0.050	0.059**	0.133***	0.001	-0.552***	-0.317***	0.010	0.302***	0.674***
	(0.999)	(0.386)	(0.020)	(0.208)	(0.032)	(0.004)	(0.964)	(0.000)	(0.000)	(0.733)	(0.000)	(0.000)
I.A	0.001**	-0.003***	0.001	0.002***	0.000	-0.000	0.001**	0.001	0.002**	0.002***	-0.000	-0.001
	(0.041)	(0.000)	(0.215)	(0.003)	(0.149)	(0.683)	(0.027)	(0.115)	(0.046)	(0.001)	(0.769)	(0.233)
Volatility	-0.000	-0.026***	-0.013***	-0.001	0.015***	0.023***	-0.000	-0.023***	-0.013***	-0.001	0.014***	0.022***
	(0.968)	(0.000)	(0.000)	(0.146)	(0.000)	(0.000)	(0.905)	(0.000)	(0.000)	(0.129)	(0.000)	(0.000)
MKT	-0.001	-0.020***	-0.010***	-0.002***	0.006***	0.021***	---	---	---	---	---	---
	(0.105)	(0.000)	(0.000)	(0.008)	(0.000)	(0.000)						
AggLiq.	---	---	---	---	---	---	2.630***	-0.881	-1.395	0.761	6.090***	10.219***
							(0.000)	(0.194)	(0.108)	(0.267)	(0.000)	(0.000)
R^2/ Pseudo R^2	0.001	0.089	0.024	0.001	0.029	0.078	0.002	0.0403	0.0144	0.001	0.032	0.043
Fisher	2.56*						9.00***					
	(0.053)						(0.000)					
Observations	7440	7440	7440	7440	7440	7440	7440	7440	7440	7440	7440	7440

Table 4

Quantile regression based on equity funds

This table presents the quantile regression of the determinants of market timing based on equity funds.
*, **, ***: significance levels of 10%, 5% and 1% respectively. P-values are in brackets. OLS: Ordinary Least Squares. R^2 is for OLS and Pseudo R^2 for Quantile regression. I.A: Information Asymmetry. MKT: Market Excess Return. AggLiq: Aggregate Liquidity. Lower quantiles (e.g., Q 0.10) signify fund where market exposure is least.

	Dependent variable: Beta											
	Specifications with MKT						Specifications with AggLig					
	OLS	Q.10	Q.25	Q.50	Q.75	Q.90	OLS	Q.10	Q.25	Q.50	Q.75	Q.90
Constant	0.157***	-0.078	0.024	0.283***	0.188***	0.272***	0.072*	-0.683***	-0.275***	0.131***	0.356***	0.711***
	(0.001)	(0.135)	(0.621)	(0.000)	(0.000)	(0.000)	(0.057)	(0.000)	(0.000)	(0.007)	(0.000)	(0.000)
I.A	0.001*	-0.004***	0.001	0.002**	0.000	-0.000	0.002**	0.002	0.002*	0.002*	-0.000	0.000
	(0.096)	(0.000)	(0.139)	(0.019)	(0.669)	(0.717)	(0.022)	(0.313)	(0.054)	(0.052)	(0.426)	(0.617)
Volatility	-0.003**	-0.023***	-0.019***	-0.003**	0.016***	0.020***	-0.003**	-0.024***	-0.018***	-0.004***	0.015***	0.020***
	(0.020)	(0.000)	(0.000)	(0.010)	(0.000)	(0.000)	(0.012)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)
MKT	-0.007***	-0.024***	-0.016***	-0.011***	0.002*	0.022***	---	---	---	---	---	---
	(0.000)	(0.000)	(0.000)	(0.000)	(0.060)	(0.000)						
AggLiq.	---	---	---	---	---	---	4.562***	-0.883	3.076***	0.131***	6.573***	7.035***
							(0.000)	(0.589)	(0.001)	(0.007)	(0.000)	(0.000)
R^2/ Pseudo R^2	0.008	0.111	0.042	0.011	0.018	0.067	0.007	0.036	0.023	0.003	0.025	0.031
Fisher	9.67***						14.20***					
	(0.000)						(0.000)					
Observations	4410	4410	4410	4410	4410	4410	4410	4410	4410	4410	4410	4410

Table 5

Quantile regression based on fixed-income funds

This table presents the quantile regression of the determinants of market timing based on fixed-income funds.
*, **, ***: significance levels of 10%, 5% and 1% respectively. P-values are in brackets. OLS: Ordinary Least Squares. R² is for OLS and Pseudo R² for Quantile regression. IA: Information Asymmetry. MKT: Market Excess Return. AggLiq: Aggregate Liquidity. Lower quantiles (e.g., Q 0.10) signify fund where market exposure is least.

	Dependent variable: Beta											
	Specifications with MKT						Specifications with AggLig					
	OLS	**Q.10**	**Q.25**	**Q.50**	**Q.75**	**Q.90**	**OLS**	**Q.10**	**Q.25**	**Q.50**	**Q.75**	**Q.90**
Constant	**-0.206*****	-0.067	-0.035	-0.012	-0.080	-0.111	0.042	**-0.256*****	-0.048	**0.113*****	**0.321*****	**0.878*****
	(0.007)	(0.401)	(0.544)	(0.819)	(0.197)	(0.356)	(0.406)	(0.000)	(0.285)	(0.001)	(0.000)	(0.000)
I.A	**-0.003***	0.004	0.002	-0.001	**-0.004****	**-0.008*****	**-0.004***	0.005	**0.003***	-0.000	**-0.007*****	**-0.009*****
	(0.087)	(0.126)	(0.116)	(0.271)	(0.012)	(0.004)	(0.056)	(0.101)	(0.085)	(0.572)	(0.000)	(0.000)
Volatility	0.002	**-0.029*****	**-0.025*****	**-0.009*****	**0.014*****	**0.032*****	0.002	**-0.029*****	**-0.024*****	**-0.010*****	**0.013*****	**0.022*****
	(0.385)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.459)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
MKT	**0.009*****	**-0.011*****	0.000	**0.008*****	**0.013*****	**0.025*****	---	---	---	---	---	---
	(0.000)	(0.000)	(0.829)	(0.000)	(0.000)	(0.000)						
AggLiq.	---	---	---	---	---	---	**4.077*****	2.396	-0.706	-0.781	**5.885*****	**17.681*****
							(0.001)	(0.184)	(0.557)	(0.351)	(0.000)	(0.000)
R²/ Pseudo R²	0.016	0.108	0.055	0.023	0.061	0.166	0.008	0.088	0.055	0.015	0.048	0.113
Fisher	**5.16*****						**3.98*****					
	(0.001)						(0.007)					
Observations	1215	1215	1215	1215	1215	1215	1215	1215	1215	1215	1215	1215

Table 6

Quantile regression based on tax-preferred funds

This table presents the quantile regression of the determinants of market timing based on tax-preferred funds.
*, **, ***: significance levels of 10%, 5% and 1% respectively. P-values are in brackets. OLS: Ordinary Least Squares. R² is for OLS and Pseudo R² for Quantile regression. I.A: Information Asymmetry. MKT: Market Excess Return. AggLiq: Aggregate Liquidity. Lower quantiles (e.g., Q 0.10) signify fund where market exposure is least.

	Dependent variable: Beta											
	Specifications with MKT						Specifications with AggLig					
	OLS	**Q.10**	**Q.25**	**Q.50**	**Q.75**	**Q.90**	**OLS**	**Q.10**	**Q.25**	**Q.50**	**Q.75**	**Q.90**
Constant	0.005	**-0.411*****	-0.051	0.004	**0.187****	**0.373*****	0.079	**-0.810*****	**-0.283*****	0.011	**0.349*****	**1.077*****
	(0.932)	(0.000)	(0.404)	(0.975)	(0.022)	(0.000)	(0.256)	(0.000)	(0.000)	(0.902)	(0.000)	(0.000)
I.A	0.000	0.005	**-0.003****	-0.002	0.000	-0.001	0.000	0.001	-0.000	0.001	0.000	0.001
	(0.947)	(0.126)	(0.028)	(0.535)	(0.894)	(0.740)	(0.915)	(0.630)	(0.408)	(0.688)	(0.930)	(0.669)
Volatility	-0.001	**-0.010*****	**-0.007*****	-0.0015	**0.007*****	**0.007*****	-0.001	**-0.006****	**-0.008*****	-0.001	**0.007*****	-0.000
	(0.338)	(0.000)	(0.000)	(0.639)	(0.000)	(0.002)	(0.329)	(0.039)	(0.000)	(0.594)	(0.000)	(0.982)
MKT	**0.004****	**-0.012*****	**-0.003****	0.003	**0.006****	**0.025*****	---	---	---	---	---	---
	(0.042)	(0.001)	(0.027)	(0.242)	(0.011)	(0.000)						
AggLiq.	---	---	---	---	---	---	-1.735	**-12.609*****	**-7.148*****	-1.968	**3.477****	**11.222*****
							(0.200)	(0.000)	(0.000)	(0.346)	(0.011)	(0.000)
R²/ Pseudo R²	0.006	0.0330	0.0211	0.0014	0.0195	0.0715	0.002	0.0609	0.0424	0.0014	0.0179	0.0374
Fisher	1.67						0.89					
	(0.171)						(0.443)					
Observations	930	930	930	930	930	930	930	930	930	930	930	930

Table 7

Quantile regression based on allocation funds

This table presents the quantile regression of the determinants of market timing based on allocation funds.
*, **, ***: significance levels of 10%, 5% and 1% respectively. P-values are in brackets. OLS: Ordinary Least Squares. R^2 is for OLS and Pseudo R^2 for Quantile regression. I.A: Information Asymmetry. MKT: Market Excess Return. AggLiq: Aggregate Liquidity. Lower quantiles (e.g., Q 0.10) signify fund where market exposure is least.

	Dependent variable: Beta											
	Specifications with MKT						**Specifications with AggLig**					
	OLS	**Q.10**	**Q.25**	**Q.50**	**Q.75**	**Q.90**	**OLS**	**Q.10**	**Q.25**	**Q.50**	**Q.75**	**Q.90**
Constant	**-0.534*** **	**-1.263*** **	**-0.645*** **	**-0.324*** **	-0.157	0.018	**-0.512*** **	**-1.311*** **	**-1.118*** **	**-0.381*** **	-0.077	**0.310*** **
	(0.000)	(0.000)	(0.000)	(0.000)	(0.152)	(0.868)	(0.000)	(0.000)	(0.000)	(0.000)	(0.229)	(0.000)
I.A	**0.006*** **	**0.012*** **	**0.011*** **	**0.006*** **	0.000	-0.000	**0.006*** **	**0.014*** **	**0.010*** **	**0.007*** **	0.000	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.648)	(0.849)	(0.000)	(0.000)	(0.000)	(0.000)	(0.708)	(0.728)
Volatility	**0.017*** **	**0.013*** **	**0.011*** **	**0.009*** **	**0.021*** **	**0.033*** **	**0.017*** **	**0.010*** **	**0.018*** **	**0.010*** **	**0.024*** **	**0.034*** **
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)
MKT	0.003	-0.001	**-0.010*** **	**0.004*** **	**0.008*** **	**0.013*** **	---	---	---	---	---	---
	(0.169)	(0.558)	(0.000)	(0.003)	(0.003)	(0.000)						
AggLiq.	---	---	---	---	---	---	**-3.795** **	**-5.651** **	**-7.974*** **	-2.117	**-2.611* **	**6.583** **
							(0.013)	(0.016)	(0.000)	(0.186)	(0.054)	(0.012)
R^2/ Pseudo R^2	0.092	0.045	0.076	0.059	0.080	0.117	0.096	0.052	0.085	0.057	0.072	0.094
Fisher	**32.04*** **						**27.78*** **					
	(0.000)						(0.000)					
Observations	780	780	780	780	780	780	780	780	780	780	780	780

4. Concluding implications and future research direction

This study has complemented the scarce literature on conditional market timing in the mutual fund industry by assessing determinants of market timing throughout the conditional distribution of market exposure. It builds on the intuition that the degree of responsiveness by fund managers to investigated factors (aggregate liquidity, information asymmetry, volatility and market excess return) is contingent on their levels of market exposure. To this end, we have used a panel of 1467 active open-end mutual funds for the period 2004-2013. Fund-specific time-dynamic beta has been employed and we have availed room for more policy implications by disaggregating the dataset into market fundamentals of: equity, fixed income, allocation, tax preferred. The empirical evidence is based on Quantile Regressions.

The following findings have been established. First, there is a consistent positive threshold evidence of volatility and market return in market timing, with the slim exception of allocation funds for which the pattern of volatility is either U- or S-shaped. Second, the effect of volatility and market return are consistently positive and negative respectively in the bottom and top quintiles of market exposure, with the exception of allocation funds. Third, the effects of information asymmetry and aggregate liquidity are positive and negative, contingent on specifications, level of market exposure and market fundamentals.

The notion of threshold adopted in the study is such that, a positive threshold is apparent when throughout the distribution of market exposure, the estimates consistently display decreasing negative magnitudes and/or increasing positive magnitudes. In the same vein, a negative threshold is established when an estimated coefficient consistently displays decreasing positive and/or increasing negative magnitudes throughout the conditional distribution of market exposure. In other words, positive thresholds denote consistent incremental effects of the underlying estimate on market exposure.

Our findings, especially threshold evidence have confirmed the fact that the effect of information asymmetry and other determinants of market exposure are contingent on existing levels of market exposure. Hence, ceteris paribus, with the same information on volatility and market excess return, a fund manager who is already comparatively more exposed to the market is very likely to increase his/her market exposure at a higher rate compared to his/her counterpart who is less exposed to the market. Hence, the degree of sensitivity to market exposure from market excess return and market volatility is a positive function to exiting levels in market exposure.

In the light of the above, the degree of responsiveness by fund managers with low market exposure to the investigated factors (aggregate liquidity; information asymmetry and volatility) should intuitively be different from those from their counterparts with higher market exposure. This information is critical in the understanding of fund managers' behaviour towards or reaction to common market information. Hence, policy makers who have been viewing fund managers' market exposure reactions to market information regardless of their initial levels of market exposure may be getting their dynamics badly wrong.

The findings related to market volatility and market excess return have implications for arbitrage and portfolio diversification in the perspective that, with information on market excess return and market volatility if an investor judges that the returns to more market exposure outweigh potential risks, everything being equal; engaging with fund managers that are more exposed to the market is more likely to reward the underlying investors. Conversely, if the investor judges that the risk/return advantage associated with more market exposure is great, with the same information on market excess return and market volatility, the investor is more likely to engage with fund managers that have less exposure to the market compared to their counterparts that are more exposed. The underlying patterns from our findings could enable a market timer to switch asset allocations and/or rebalance portfolios depending on his/her forecast of market fluctuations.

The above policy implications should also be contingent on the following trends: (i) the effect of information asymmetry is driven by the equity funds sub-sample; (ii) the impact of market volatility and market excess return are driven by equity and fixed-income sub-samples for the most part while (iii) the effect of aggregate liquidity is driven by the fixed income funds sub-sample. Moreover, the fact that the incidences of market return and volatility are consistently negative and positive respectively in the top and bottom quintiles of market exposure further substantiate the suggested practical recommendations in arbitrage and portfolio diversification. Overall, the findings broadly suggest that blanket responses of market exposure to investigated factors are unlikely to represent feasible strategies for fund managers unless they are contingent on initial levels of market exposure and tailored differently across 'highly exposed'-fund managers and 'lowly exposed'-fund managers.

Future studies can focus on assessing thresholds at which various determinants of market timing influence fund managers' market timing ability both at the conditional mean and conditional distribution of market exposure. This future direction will provide insights into whether the signs of the determinant change when certain levels of the underlying determinants are reached.

Appendices

Appendix 1

Definition of Variables

Variables	**Signs**	**Definitions**	**Sources**
Market timing	Beta	Measure of systematic risk.	Computed
Information Asymmetry	Info. Asymmetry (IA)	Standard deviation of the idiosyncratic risk of individual return.	Computed
Volatility	Vol.	Measure of dispersion of return (or uncertainty) of a security.	Computed
Market Excess Return	Mkt Excess Return	Difference between the return of the market and the risk free rate.	
Size	SMB	Small [market capitalization] Minus Big.	Kenneth French's website
Book-to-market	HML	High [book-to-market ratio] Minus Low.	
Aggregate Liquidity	Agg.Liq.	"*Our monthly aggregate liquidity measure is a cross-sectional average of individual- stock liquidity measures"* (Pástor and Stambaugh, 2003, p.643).	Robert Stambaugh's Website

Mutual fund categories

Variables	**Definitions**	**Source**
Equity	"*Global equity portfolios invest in companies domiciled in developed countries throughout the world. Some of these portfolios may include emerging market countries".*(p.9)	
Fixed-income	"*Global fixed income portfolios invest in fixed income securities from countries domiciled in developed countries throughout the world. Some of these portfolios may include fixed income securities of emerging market countries*".(p.20)	Morningstar
Allocation	"*Allocation portfolios seek to provide both capital appreciation and income by investing in three major areas: stocks, bonds, and cash. While these portfolios explore the whole world, most of them focus on the U.S., Canada, Japan, and the larger markets in Europe. These portfolios typically have at least 10% of assets in bonds and less than 70% of assets in stocks."*(p.15)	
Tax-preferred	"*US municipal fixed income portfolios invest in US municipal bond securities. These funds may invest nationally, or they may invest primarily in one single state*". (p.25)	

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