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The dynamics of mutual fund management*

García, Andrés
Ortiz, Cristina
Población, Javier
Sarto, José Luis

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Abstract

This paper investigates the time-varying properties of mutual fund betas. The study demonstrates that the fund beta is not constant and proposes various models to determine the underlying structure of the daily time-series. These methods include the Kalman filter technique. In addition to the results of the model, we draw conclusions on additional factors affecting the variability of the beta. The seasonality of betas is confirmed and so the relationship between money flows and the variations in fund betas. A significant inflow of money in the mutual fund entails a decrease in its beta value.

Keywords:

Fund beta, Kalman filter, Seasonality, Money flows, Active management.

JEL classification:

G23, G11.

García, A. IES Juan del Enzina, c/ Ramón y Cajal 2, 24002 León, Spain. ✆ +34987208390.
E-mail: andres_g@telecable.es

Ortiz, C. Facultad de Economía y Empresa. Universidad de Zaragoza. Gran Vía 2, 50005 Zaragoza, Spain. ✆+34876554652.
E-mail: cortiz@unizar.es

Población, J. ✉ D.G.A. Supervisión, Banco de España, c/ Alcalá 48, 28014, Madrid, Spain. ✆+34913385812.
E-mail: javier.poblacion@bde.es

Sarto, J.L. Facultad de Economía y Empresa. Universidad de Zaragoza. Gran Vía 2, 50005 Zaragoza, Spain. ✆+34976762308.
E-mail: jlsarto@unizar.es

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La dinámica de **la gestión de los fondos de inversión**

García, Andrés
Ortiz, Cristina
Población, Javier
Sarto, José Luis

Resumen
Este artículo trata sobre cómo varían en el tiempo las betas de los fondos de inversión. Este estudio demuestra que la beta de los fondos de inversión no es constante y propone varios modelos para determinar la estructura subyacente de la serie diaria. Estos modelos incluyen la técnica del filtro de Kalman. Adicionalmente a los resultados de los modelos, se extraen conclusiones sobre factores adicionales que afectan a la variabilidad de la beta. Se confirma la existencia de estacionalidad en las betas y también su relación con los flujos de dinero que entran y salen del fondo de inversión. Un flujo de dinero entrante, significativo, en el fondo de inversión conlleva un decremento en el valor de la beta.

Palabras clave:
Betas de los fondos de inversión, filtro de Kalman, estacionalidad, flujos monetarios, gestión activa.

1. Introduction

This paper investigates the time-varying properties displayed by market model betas in mutual funds. Systematic risk has long been assumed to be constant, but recent empirical studies show that this systematic risk varies through time.

The goal of researchers is modeling and forecasting volatility, that is, the covariance structure of asset returns. Capturing the dynamics of beta risks is more important than might be suspected. In fact, Ghysels (1998) concludes that the misspecification of beta risk may introduce pricing errors that are larger than would occur with a constant traditional beta model.

The underlying structure of the models used to evaluate individual securities and mutual funds has long relied on a linear factor model with constant coefficients. This modeling is especially important in mutual funds because managers are assumed to actively respond to market oscillations and rebalance their portfolios accordingly. The dynamics of active portfolio management makes it difficult to assume constant levels of risk in mutual funds.

The best way to know the investment strategy of a portfolio is to observe portfolio holdings, but different techniques for estimating time-varying betas with return information have been used in the literature.

Which model better describes the time-varying behavior of betas is not a trivial question and has been the focus of several previous works. The results of Brooks *et al.* (1998) for Australian industry portfolios overwhelmingly support the Kalman filter approach as the optimal technique by which time-varying betas should be generated. Similarly, Mergner and Bulla (2008) analyze the systematic risk for eighteen pan-European industry portfolios and find that the random walk process, estimated by the use of the Kalman filter, shows a better ability to explain sector returns relative to movements of the overall market. Some of the alternative techniques used in these studies are a variety of GARCH models and a bivariate stochastic volatility model.

The advantages in the time-series adjustment used in the Kalman filter for mutual funds has also been shown in Swinkels and Van der Sluis (2006) who estimate mutual fund styles by return-based style analysis. Mamaysky *et al.* (2008) calculate US mutual fund alpha and beta with Kalman filter model. Both studies find differences with traditional estimation techniques. Additionally, Holmes and Faff (2008) include Kalman filtering to examine selectivity and market timing in a sample of Australian multi-sector trusts.

Within the fund industry, the study of the dynamics of systematic risk is especially interesting for hedge funds due to the dynamic strategies they follow (Fung and Hsieh, 1997) and to the range of investments available. The Kalman Filter is a broadly used methodology in modeling the hedge fund dynamics, for instance, in Bollen and Whaley (2006) and in Racicot and Théoret (2007).

Using daily net asset values of Spanish domestic equity funds, we estimate time-varying betas using the OLS model, rolling windows and a Kalman filter procedure. Matallín-Sáez (2006) also applied the Kalman filter technique in the Spanish mutual fund industry to make more accurate timing measurements.

The primary contributions of the paper are threefold. First, we evaluate whether the daily beta of our sample can be considered constant, a result we do not expect based on previous literature of other international markets. Second, we propose different alternatives to approach the underlying structure of the beta series. Third, we test for factors that could cause betas to be time-dependent.

Therefore, the findings of the model specification are not the sole objective of this paper. The Kalman filter procedure is a powerful technique for estimating unobservable variables in time, but it may not be suitable in selecting the most appropriate model.

This paper also reports the patterns in the distribution of estimated daily betas. Several tests are performed to search for seasonal and other patterns in fund characteristics. The calculation of a monthly effect allows us to draw conclusions on the seasonal variability of betas throughout the year. January seems to be a very active month for managers, which could be related to the January effect (Ortiz *et al.*, 2010) and to the well-known managers' strategy of closing-up portfolios at the end of the year. Fund managers who have exhibited strong performance by mid-year have incentives to minimize the risk of their portfolios and to reduce the activity of their trading, as described by the tournament hypothesis (Brown *et al.,* 1996).

Finally, we investigate whether time-varying betas can be related only to investment managers' decisions or whether time-dependence results from factors external to the managers' direct control can also affect betas. In particular, this study focuses on the potential impact of abnormal flows into or out of the fund. Portfolio allocation is based on assets that are under management. Portfolios must be continuously rebalanced due to the inflow of new money and money that leaves the fund from redemptions. In the event of abnormal inflows or outflows of money, managers might need some time to reallocate the portfolio. During that time, portfolio holdings might not necessarily be in accordance with the expected investment strategy the manager would normally follow. In this case, a significant shock in the asset allocation of the fund would imply distortions in the series of betas.

The paper is organized as follows, section 2 describes the data used, section 3 develops the methodology of the study, section 4 reports the main results of the model, section 5 examines the seasonality effects, section 6 develops the relationship between fund flows and the variation of fund betas, and the final section concludes the paper.

2. Data and the market model

2.1. Data

We have collected data from Spanish domestic equity funds from the database of the Spanish Stock Exchange (CNMV) during the time period between May 1999 and December 2009. Inclusion in the sample is revised monthly according to the official classification of funds. Additionally, quarterly portfolio holdings are revised to detect potential inconsistencies in fund categories.[1] The final sample includes 179 Spanish domestic equity funds.

Our database is free of survivorship bias; however, new funds launched to the market can follow strategies that do not correspond to their investment goals in the future, which could lead to a potential inception bias. We have addressed this source of bias by analyzing outliers in the first portfolios in operation and by deleting those portfolios from the included sample.[2]

The database includes monthly information on the size and number of investors, quarterly information on fees and daily information on net asset values (NAV). The calculation of return using the difference in NAV provides net return to investors. The purpose of this study is detecting the variability in risk exposure from manager decisions. In this sense, the addition of fees should be essential to meeting our goals. Specifically, gross return in our study includes deposit and management fees. These fees are assumed to be constant through the quarter, and the equivalent daily cumulative fees is computed and added to the daily net return.

[1] *Some authors demonstrate the misclassification of mutual funds, such as diBartolomeo and Witkowski (1997) and Kim* et al. *(2000).*

[2] *It is customary that new funds invest primarily in fixed-returns during the first months in operation due to the importance of money flows when the fund is listed in the market.*

Table 1. Descriptive statistics of the Spanish domestic equity fund sample

This table shows the mean, median and standard deviation of some typical characteristics of mutual funds. Panel A presents information as of the end of December 2006 for the 96 surviving funds. Panel B shows the cross-section time-averaged characteristics of the entire sample. A total of 180 funds are included in the analysis.

Panel A: Data on December 2006

	Mean	Median	Std. deviation
Size (€ thousand)	89,809.95	46,991	125,659.58
# investors	2,783.15	1,171	4,476.15
Age (years)	9.20	9.11	4.99
Custodial fee	0.010%	0.008%	0.005%
Management fee	0.140%	0.159%	0.048%
Monthly net return	2.07%	2.02%	0.54%

Panel B: Cross-section time-series average characteristics of the entire sample

	Mean	Median	Std. deviation
Size (€ thousand)	57,833.31	26,974.99	79,237.30
# investors	2,505.73	714.45	4,095.09
# of observations	1,520.94	1,409.00	870.54
Custodial fee	0.011%	0.010%	0.007%
Management fee	0.134%	0.144%	0.047%
Monthly net return	0.40%	0.74%	5.29%

The descriptive statistics in Table 1 show that the Spanish domestic equity fund industry is made up of funds with different scales because of the high standard deviations of the size and the number of investors.

2.2. Market model

The market model serves as the benchmark for the models to compute the systematic risk of the portfolio. The market model is defined as:

$$R_{it} = \alpha_i + \beta_i R_{Mt} + \varepsilon_{it} \quad (1)$$

where R_{it} denotes the daily excess return of the fund i, and R_{Mt} is the daily excess return of the benchmark for period $t = 1, ..., T$. The 1-day repo is used as the fixed-return index, and the return of Ibex-35 is used as the benchmark.[3] The Ibex-35 series includes dividends. The model is estimated using OLS and assumes that β_i is constant for every fund i during the given time horizon.

[3] *McKenzie* et al. *(2000) show the relevance of using a domestic market index rather than a worldwide market index to estimate betas in the Australian industry.*

Mutual fund performance literature has repeatedly shown doubts about the advantages of active fund management, including Gruber (1996). In a preliminary descriptive exploration, we confirm this insight for Spanish domestic equity fund investors. The alpha excess net return of the pooled regression of equation 1 of our sample is 9.09E-06, which is insignificantly different from zero. The individual regressions show that 94 out of 180 funds of the study achieve negative alpha.

Our paper focuses on analyzing the levels of risk rather than the performance. In particular, it focuses on the dynamics of mutual fund management and the adjustment of fund risk to the market. This scope led us to concentrate on fund beta results. As expected, due to the nature of domestic funds, the beta coefficient of the pooled regression is close to one (0.863) and is significantly different from one at a 1% significance level. Nine funds have a beta that is significantly higher than one, which indicates very aggressive behavior during the horizon of the study. However, the vast majority of the funds (163) show a beta significantly lower than one.

Our first concern is to test whether fund managers modify the risk level of Spanish portfolios or if they establish a strategy over a beta range and rebalance their portfolios accordingly. To accomplish this, we split fund observations into two equal subsamples. One outstanding result is that, based on the *t*-test of mean and variance equality, we cannot accept the null hypothesis of equality at the 5% level for 137 funds. This result is in line with previous studies that address time-varying betas (i.e., Mamaysky *et al.*, 2008) and that make further analysis necessary to investigate the dynamics of mutual fund management.

3. Methodology and measurements

3.1. Methodologies

3.1.1. Rolling windows

Prior studies on the variability of fund betas have applied rolling windows to test whether beta is constant and we proceed similarly.

When a rolling window analysis is carried out, we first determine the window length using the rolling window methodology. In this approach, a fixed number of N observations is set using the weighted least-squares method. The whole sample is used in the estimation, but each observation weight, λ^{t-I}, depends on the time between this observation (i) and the last one (t). In this sense, we choose N such that the weights sum in both cases to be equal: $\sum_{i=-\infty}^{t}\lambda^{t-I} = \sum_{i=t-N}^{t} 1$, which implies that $N=\frac{1}{1-\lambda}$.

Broadly speaking, then, the Kalman filter methodology, which is presented in the following section, clearly assigns a weight to each observation with the following relationship: $\lambda = \frac{1}{1+\sigma}$, where σ is the standard deviation of the measurement equation error ($v_{i,t-1}$).

Consequently, as the average of the σ estimates should be around 0.09, $\lambda = \frac{1}{1+0.09} = 0.947$, which implies that $N = \frac{1}{1-0.947} = 11.47$. That is, the window length for conducting an empirical analysis of rolling windows will be 11 observations, consisting of five data points before and after the central point.

3.1.2. Kalman filter

Another well-known approach for beta dynamics is the Kalman Filter, which has the advantage of considering more information than the rolling window methodology.

The primary relationship is the market model of equation 1 with the assumption that the beta is time-dependent. We are going to propose a general beta dynamics (see, for example, Hamilton 1994):

$$\beta_{it} = \bar{\beta}_i + \phi_i \left(\beta_{i,t-1} - \bar{\beta}_i \right) + v_{i,t-1} \qquad (2)$$

where β_{it} is the fund i at time t beta, and $\bar{\beta}_i$ are the long-term beta mean and mean reverting speed for fund i, respectively, and v_{it} is the measurement error, which is normally distributed with a mean of zero and a standard deviation of σ.

The primary difficulty in estimating the model parameters is the fact that the beta is not directly observable and must be estimated from the returns. The Kalman filtering methodology is a powerful technique for solving this problem because it calculates the likelihood of a data series given a particular set of model parameters and a prior distribution of the variables. Detailed descriptions of Kalman filtering are given in Harvey (1989).

The Kalman filter methodology is a recursive methodology that estimates an unobservable time series, the stated variables or factors (Z_t), based on an observable time series (Y_t), which depends on these stated variables. The relationship between the observable time series and the stated variables is described through *the measurement equation*:

$$Y_t = d_t + M_t Z_t + \eta_t \qquad t = 1, \ldots, N_t \qquad (3)$$

where Y_t, $d_t \in \Re^n$, $M_t \in \Re^{nxn}$, $Z_t \in \Re^h$ (h is the number of state variables, or factors, used in the model) and $\eta_t \in \Re^n$ is a vector of serially uncorrelated Gaussian disturbances with a mean of zero and a covariance matrix H_t.

The evolution of the stated variables is described through the *transition equation*:

$$Z_t = c_t + T_t Z_{t-1} + \psi_t \qquad t = 1, \ldots, N_t \tag{4}$$

where $c_t \in \Re^n$, $T_t \in \Re^{hxh}$ and $\psi_t \in \Re^h$ is a vector of serially uncorrelated Gaussian disturbances with a mean of zero and a covariance matrix Q_t.

Let $Y_{t|t-1}$ be the conditional expectation of Y_t, and let Ξ_t be the covariance matrix of Y_t, based on all information available at time t–1. Then, after omitting nonessential constants, the log-likelihood function can be expressed as:

$$1 = -\sum_t \ln|\Xi_t| - \sum_t (Y_t - Y_{t|t-1})' \Xi_t^{-1} (Y_t - Y_{t|t-1}) \tag{5}$$

Maximizing this expression, we obtain the whole parameter estimations, including those for the transition equation. In our case, equation 1 is the *measurement equation*, whereas equation 2 is the *transition equation*.

Alternative specifications of the model can be formulated under different assumptions on ϕ_i and $\bar{\beta}_i$. This work incorporates the following assumptions:

- The *random walk* (RW) model imposes shocks to conditional betas that persist indefinitely.
- A model in which shocks are permitted but the model is mean reverting. This structure follows a first order *autoregressive process with constant mean* (AR).

The equations of these two specifications are as follows:

$$\beta_{it}^{RW} = \beta_{t-1} + v_{i,t-1} \tag{6}$$

$$\beta_{it}^{AR} = \bar{\beta}_i + \phi_i \left(\beta_{i,t-1} - \bar{\beta}_i \right) + v_{i,t-1} \tag{7}$$

equation 7 can also be written as $\beta_{it}^{AR} = (1-\phi_i)\,\bar{\beta}_i + \phi_i\,\beta_{i,t-1} + v_{i,t-1}$. The parameters for this expression, the independent term $(1-\phi_i)\,\bar{\beta}_i$ and the slope of the equation ϕ_i, are estimated in the following section.

3.2. Accuracy Measurements

To compare the accuracy of the different models for calculating betas, we carry out in-sample forecasts of the mutual fund returns during the sample period, as it has been done in previous studies. Additionally, we present out-of-sample forecasts of mutual fund returns to assess the estimates' accuracy in a sub-sample that was not used for estimation. In this sense, we split the sample into two parts, one that will be used for estimating and another that will be used for results validation. Strictly speaking, the out-of-sample forecast is the only way to test the model performance because, by definition, the model parameters have been chosen in a way that optimized the model for in-sample predictive ability. However, the comparison between the in-sample and out-of-sample predictive abilities is useful because it highlights the true performance of the model.

We present the results for both in-sample and out-of-sample while varying the sizes of the two sub-samples. The estimated sample consists of 75% of the whole sample in one case and 25% in the other case. We also analyze 50% of the data in each subsample. The results are omitted since they are similar to the ones obtained in the former classifications, but are available to the reader upon request.

The accuracy of each forecast series is evaluated using two criteria: the bias and the root mean squared error (*RMSE*). Both of these criteria are reported in absolute and percentage terms. In this sense, the bias in absolute terms is defined as:

$$Bias = \frac{1}{N}\sum_{i=1}^{N}|Y_i - \hat{Y}_i| \qquad (8)$$

where Y_i and $\hat{Y}_i$ are the actual and estimated values, respectively. Consequently, the bias in percentage terms is:

$$Biasp = \frac{\frac{1}{N}\sum_{i=1}^{N}|Y_i - \hat{Y}_i|}{\sum_{i=1}^{N}|Y_i|} \qquad (9)$$

The *RMSE* in absolute terms is defined in equation 10 and the *RMSE* in percentage (*RMSEp*) is defined in equation 11.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Y_i - \hat{Y})^2} \qquad (10)$$

$$RMSEp = \sqrt{\frac{\sum_{i=1}^{N}(Y_i - \hat{Y})^2}{\sum_{i=1}^{N}Y_i^2}} \qquad (11)$$

3.3. Seasonality analysis

The analysis of seasonality is addressed using a similar procedure to the standard *F*-test described by Gallardo and Rubio (2009). That is, through a dummy regression with constant to avoid multicollinearity and using raw data and dummies instead of averages.

$$\beta_{it} = a + b_2 D_2 + \ldots + b_{12} D_{12} \quad (12)$$

where β_{it} is the series of betas estimated with the two models RW and $AR(1)$ and with D_2 to D_{12} as the dummy variables for the months of February to December, which takes the value of 1 in the given month or 0 otherwise. A Chi-squared test on all b_i is then also performed.

Another regression is performed on all the dummies in equation 13 to directly measure the month-related effects.

$$\beta_{it} = b_1^* D_1 + b_2^* D_2 + \ldots + b_{12}^* D_{12} \quad (13)$$

As this regression is contaminated by the mean, we calculate the mean effect (ME_i) over fund i as follows:

$$ME_i = a + \frac{b_2 + \ldots + b_{12}}{12} \quad (14)$$

Note that ME_i is defined similarly to the mean of the series, but accounts for the fact that each month has a different number of days.

For each month m, we define the absolute monthly effect as the deviation from the mean effect (i.e., $E_i^m = b_m^* - ME_i$), and we find the relative effect (e_i^m) as:

$$e_i^m = \frac{E_i^m}{ME_i} \quad (15)$$

The coefficients b_m^* are calculated using equation 13.

4. Estimation of time-varying beta

4.1. Conditional betas

This section describes the results of the Kalman filter procedure to estimate fund betas and compares the validity of the beta estimates to a constant beta or a beta calculated over rolling windows.

As explained in the previous section, we run two different models assuming that the beta dynamics are governed by a random walk or an *AR*(1) process. Table 2 shows the mean of the results of the daily estimates. Considering net returns and applying the *AR*(1) model, the results of the individual funds indicate that we cannot reject the fact that the beta-beta parameter is significantly different from 1 in 177 out of 180 funds. Only 31 of the 180 alpha-beta parameters are significantly different from zero.

Table 2. Estimates of the Kalman filter

This table shows the results of the estimation of equations 6 and 7. For the *AR*(1) model (equation 7), the figures in parentheses indicate the *p*-value of the test of the parameters different from zero for the independent term ($(1-\phi_i)\bar{\beta}_i$), and different from one for the slope (ϕ_i).

	RW model		*AR*(1) model			
	Av. Likelihood	Av. *RMSE* (%)	Independent term	ϕ_i	Av. Likelihood	Av. *RMSE* (%)
Gross return	-5.397	29.352	0.194 (0.000)	0.771 (0.000)	-5.412	28.573
Net return	-5.397	29.360	0.196 (0.000)	0.765 (0.000)	-5.413	28.752

The fitness of the two models is acceptable. The mean estimates of the parameters of the *AR*(1) model show the rejection of the null hypothesis that the independent term equals zero and that the slope of the model equals one. Therefore, we cannot reject the model *AR*(1) as the source of the beta dynamics.

Table 3 allows a comparison between the beta estimates from the constant beta, the mean conditional beta estimates using rolling windows and the two time varying models using the Kalman Filter. In the summary shown in Table 3 the beta coefficients are very similar using different estimation procedures. This is not surprising given that the results are calculated over daily average values.

These results offer a preliminary overview for comparing beta-generating models. The next section provides the evaluation of the model specifications with the in-sample and out-of-sample forecast errors.

Table 3. Estimates of fund beta

This table shows the mean conditional estimates of the fund beta using rolling windows, the auto regressive (*AR*(1)) model and the random walk (*RW*) model. Panel A reports the aggregate results. *EW* is the equally weighted portfolio and *SW* is the size-weighted portfolio. Panel B reports the results of the estimation for individual funds.

Panel A: Aggregate results

	OLS beta	R^2	Rolling window beta	*AR*(1) beta	*RW* beta
EW Gross returns	0.861	97.65%	0.861	0.861	0.862
EW Net returns	0.861	97.65%	0.861	0.862	0.862
SW Gross returns	0.901	98.05%	0.902	0.902	0.893
SW Net returns	0.901	98.04%	0.902	0.900	0.896

Panel B: Individual fund results

	OLS beta	R^2	Rolling window beta	*AR*(1) beta	*RW* beta
Gross return	0.841	88.66%	0.863	0.839	0.843
Net return	0.841	88.66%	0.863	0.834	0.843

4.2. In-sample and out-of-sample accuracy measures

We evaluate the forecasting abilities of the different specification models. We estimate the in-sample forecast errors of the beta series and determine the adequacy of the models calculating the *RMSE* and the *RMSEp*, as defined in equations 10 and 11, respectively. First, in-sample forecast errors are computed for the entire sample with the data split into different subsamples. Specifically, the estimation period is 25%, 50% and 75% of the sample, and the validation period, as the rest of the sample. The estimation period allows us to estimate the parameters of the model and the validation period updates these forecasts with new information. Similarly, out-of-sample tests are computed. The results are shown in Table 4.[4]

In general, the rolling windows method generates better forecasts. Again, we reinforce our results by showing the time-varying properties of the fund betas. The Kalman filter method has similar accuracy tests, but the refinement of the beta estimation does not allow us to significantly improve forecasts.

The objective of this paper is to show the time-varying structure that underlies the fund betas and this structure's implications. Additionally, we propose that a sophisticated tool such as the Kalman Filter should be used to define the series generator of a non-observable variable. Although providing good estimations, the two proposed alternatives may not be capturing the true dynamics of the variable. This is, undoubtedly, the starting point for further research.

Table 4. **In-sample and out-of-sample accuracy tests**

The forecast accuracy of the beta series generated with different models is tested with *RMSE* and *RMSEp* statistics defined in equations 10 and 11, respectively. Tests are carried out considering different data samples, (25%-75%) and (75%-25%). Panel A shows the results for the equally weighted portfolio (*EW*) and the size-weighted portfolio (*SW*). Panel B reports individual fund average statistics.

Panel A: Aggregate results

In-sample forecast errors (25-75%)		OLS beta	Rolling window beta	*AR*(1) beta	*RW* beta
EW Gross returns	*RMSE*	0.0017	0.0015	0.0017	0.0017
	RMSEp	0.1357	0.1230	0.1375	0.1395
SW Gross returns	*RMSE*	0.0017	0.0015	0.0016	0.0017
	RMSEp	0.1247	0.1076	0.1186	0.1200

[4] *Table 4 only reports the results for gross returns because we focus on the managers' decisions.The results for net returns are virtually the same and can be available upon request.*

In-sample forecast errors (75-25%)					
EW Gross returns	*RMSE*	0.0014	0.0012	0.0014	0.0014
	RMSEp	0.1285	0.1077	0.1252	0.1254
SW Gross returns	*RMSE*	0.0013	0.0012	0.0013	0.0013
	RMSEp	0.1135	0.0987	0.1125	0.1130
Out-of-sample forecast errors (25-75%)					
EW Gross returns	*RMSE*	0.0023	0.0021	0.0022	0.0021
	RMSEp	0.1751	0.1614	0.1677	0.1595
SW Gross returns	*RMSE*	0.0020	0.0020	0.0020	0.0021
	RMSEp	0.1449	0.1460	0.1490	0.1523
Out-of-sample forecast errors (75-25%)					
EW Gross returns	*RMSE*	0.0032	0.0030	0.0031	0.0032
	RMSEp	0.1832	0.1751	0.1811	0.1851
SW Gross returns	*RMSE*	0.0030	0.0032	0.0030	0.0032
	RMSEp	0.1692	0.1822	0.1726	0.1801

Panel B: Individual fund results

In-sample forecast errors (25-75%)		OLS beta	Rolling window beta	*AR*(1) beta	*RW* beta
Gross returns	*RMSE*	0.0031	0.0027	0.0081	0.0053
	RMSEp	0.2991	0.2610	0.7890	0.4980
In-sample forecast errors (75-25%)					
Gross returns	*RMSE*	0.0032	0.0030	0.0071	0.0037
	RMSEp	0.2846	0.2380	0.6407	0.3193
Out-of-sample forecast errors (25-75%)					
Gross returns	*RMSE*	0.0039	0.0041	0.0092	0.0053
	RMSEp	0.3186	0.3306	0.6955	0.4198
Out-of-sample forecast errors (75-25%)					
Gross returns	*RMSE*	0.0044	0.0045	0.0089	0.0048
	RMSEp	0.3210	0.3384	0.0683	0.4415

5. The underlying dynamics of the fund beta

We further investigate on the dynamics of the fund beta; specifically, we explore potential calendar effects. This section analyzes whether the movements of betas follow a seasonal pattern during the calendar year.

The existence of seasonal effects has important implications for management because it provides signs of the aggressiveness of funds relative to the market throughout the year. We run the dummy regression as expressed in equation 13 on each fund and present the results in Table 5.

According to Panel A of Table 5, we cannot accept that there is no seasonal effect on our series of betas estimated by both a random walk (*RW*) and a first-order autoregressive process *AR*(1) via Kalman filter. Even at the level of significance of 1%, 162 and 148 out of 173 funds analyzed reject the null hypothesis.

Regarding the monthly effects, the results of Panel B of Table 5 only gather the number of significant coefficients. In this case, other aggregate statistics as average coefficients could lead to biased results because positive and negative effects could mask each other.

Significant monthly effects are present in a higher degree in beta estimates using the random walk model. The number of funds with significant monthly effects is especially low in August and September, implying that there are very few funds that are actively managed during the vacation period.

Table 5. Analysis of the seasonality of fund betas

This table shows the results of equation 13. Panel A shows the number of funds with significant χ^2 statistics for the null hypothesis that all dummies together have no effect. Please note that this test has only been calculated for 173 funds given that full-year data are required. Panel B splits the results by month. E_i is the absolute monthly effect. The significance level is at 5%.

Panel A: All dummies together (χ^2 test)

	Net return-*RW*	Gross return-*RW*	Net return-*AR*(1)	Gross return-*AR*(1)
Significance 1%	162	162	148	148
Significance 5%	167	167	156	156

Panel B: Monthly effects

	E_i	E_i	E_i	E_i
January	81	84	53	57
February	80	78	61	63
March	76	76	65	65
April	70	71	56	56
May	123	122	97	93
June	81	79	71	70
July	81	83	56	57
August	58	59	52	52
September	56	56	49	48
October	68	65	57	56
November	75	75	55	57
December	73	73	61	59

The results of this section elucidate the seasonality of beta series, but we should note that we are assuming that variations in beta series are associated with the management of the fund, i.e., that this information is strictly linked to managers' decisions.

6. Influence of flows over fund beta

An increasing attention has been devoted to mutual fund flows in recent years. A first line of research focuses on the determinants of fund flows. The seminal papers of Ippolito (1992), Chevalier and Ellison (1997) and Sirri and Tufano (1998) conclude that investors clearly rely on past performance to make their investment decisions. On the other hand, Goetzmann and Peles (1997) and Berk and Green (2004) focus on the investor's perspective. While the first study analyses questionnaire responses of mutual fund investors to show the importance of past performance, the latter, Berk and Green (2004) present a model which assumes rational investors competing with each other for managers with superior abilities. The authors state that mutual funds suffer potential capacity constraints and managers present decreasing returns to scale.

A second line of research analyses the effects of fund flows on subsequent performance testing the investors' rationality also known as the smart money effect. (Zheng, 1999, and Vicente *et al*., 2011 for the Spanish market).

However, to our knowledge, this is the first study that relates the effect of fund flows to the management of the fund, specifically, we analyse the effect of flows on portfolio risk levels. This approach gains insight into managerial decisions and how they might be affected during times of special purchases or withdrawals.

The implied money flow (IMF) is defined as the monthly change in total net assets (TNA) net of fund returns for fund i in month t (R_{it}). Similarly, the percentage money flow ($IPMF$) is the implied money flow divided by the size of the fund in the previous month. In the event of a merger, the observation of implied flow of that month is considered a missing observation.

$$IPMF_{it} = \frac{TNA_{it} - TNA_{i,t-1}\,(1+R_{it})}{TNA_{i,t-1}} \qquad (16)$$

The calculation of money flows requires an assumption about the timing of these flows. As we cannot know the exact moment of investment, equation 16 assumes that the new money invested or withdrawn from the fund occurs at the end of the period in which the flows are computed.

The consideration of implied measures may bias the results because it is an approximation based on fund magnitudes. However, we are able to minimize this bias because we use monthly data instead of quarterly, as is traditionally used.

To test the relationship between fund flows and managers' decisions, we write equation 17. Note that our proxy to study the reaction of managers is the variation in the level of beta of the portfolio.

$$\Delta\beta_{i,t} = a + b\,IPMF_{i,t-1} \qquad (17)$$

As noted above, assumptions are needed for the exact time the flows occur. To control for different situations, we consider four different models:

1. The variables of equation 17 are computed monthly.

2. The variation of beta is calculated for the first 15 days of the following month.

3. The variables of equation 17 are computed daily. The monthly flow is estimated using interpolation.

4. The variation of beta is calculated as the difference between the beta average of the last 15 days and the beta average of the first 15 days of the month the flow is considered.

Our null hypothesis states that there is no relationship between fund management in terms of the level of risk measured with the beta of the portfolio and the flow of money into and out of the fund. However, in daily fund management, professionals may encounter either moments of excess of liquidity due to large inflows or moments with necessities of money because of withdrawals.

Following this reasoning, we may think that inflows of money would induce a decline in the beta. The fund has an excess of liquidity due to the time managers need to acquire assets for rebalancing their portfolios. However, the opposite relationship, that is, large outflows from the fund, can result in changes in the levels of the beta. Predictions, however, are more difficult to make because we cannot know the process by which liquidity is gained.

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Table 6. Flows influence on fund beta

This table shows the results of equation 17. Numbers 1 to 4 correspond to the four different models proposed. Panel A shows the results of the panel data regression, where b is the slope of the regression. Panel B shows the number of funds with significant b parameter both positive and negative. The significance level is at 5%.

Panel A: Aggregate results

	RW			*AR*(1)		
IMF	***b***	***p*-value**	**R^2(%)**	***b***	***p*-value**	**R^2(%)**
(1)	-3.27E-06	0.003	0.078	-3.12E-06	0.006	0.069
(2)	-3.44E-06	0.019	0.142	-2.49E-06	0.018	0.128
(3)	-2.33E-07	0.143	0.001	-3.01E-07	0.370	0.000
(4)	-6.72E-07	0.371	0.545	-2.00E-06	0.821	0.315
IPMF						
(1)	-0.259	0.001	0.104	-0.253	0.016	0.056
(2)	-0.259	0.002	0.170	-0.182	0.036	0.119
(3)	-0.018	0.324	0.000	-0.023	0.670	0.000
(4)	-0.021	0.000	0.720	-0.144	0.003	0.382

Panel B: Individual fund results

IMF	**# signif +**	**# signif –**	**# signif +**	**# signif–**
(1)	9	6	5	7
(2)	7	10	7	6
(3)	2	1	2	2
(4)	10	5	6	8
IPMF	**# signif +**	**# signif –**	**# signif +**	**# signif–**
(1)	13	3	12	4
(2)	14	6	11	3
(3)	3	2	2	1
(4)	14	4	14	6

The results of this analysis are shown in Table 6. As expected, Panel A shows that the relationship between fund money flows and the variation of the fund beta is negative in the four models proposed. The estimation of the panel data drastically reduces the levels of R^2, but upon examination of individual regressions, these levels appear acceptable. This result implies that the dynamics of individual funds can be different and they must be treated independently with regard to the estimation model that will best fit the data. A similar reasoning is needed to explain the results of Panel B of Table 6. Apparently there is no clear dominance of significant negative coefficients; however, this could be the result of the weight of the funds in the sample. The significance of these coefficients varies among the models but we cannot draw conclusive statements on the timing of the flows due to the frequency of the data.

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An additionally worthy approach is testing the asymmetry in managerial risk-taking strategies, that is, whether the beta levels change differently whether entries or withdrawals occur. In individual decisions, Sirri and Tufano (1998), among others, showed the asymmetric performance-flow relationship. We compute the following model:

$$\Delta\beta_{i,t} = a + b_1 IPMF^{+}_{i,t-1} + b_2 IPMF^{-}_{i,t-1} \quad (18)$$

where the superscript of the independent variable indicates whether it takes positive (+) or negative (-) values. The rest of the variables have been explained earlier.

Table 7 shows the results of equation 18. The results indicate that the negative coefficients found in Table 6 are mostly driven by withdrawals of money from the fund. The coefficients of negative flow measures, b_2 coefficients, are higher than the slope of positive coefficients; this finding implies that managers' response to moments of withdrawals is more pronounced than for entries of flows. The variations in beta levels are higher when the money leaves the funds, although only significant in the random walk model. In fact, as stated earlier, further analyses are required with different models to estimate beta for each fund.

Table 7. Asymmetry in flows influence on fund beta

This table shows the results of equation 18. Numbers 1 to 4 correspond to the four different models proposed. The results of the panel data regression are shown, where b_1 and b_2 are the coefficients of the regression.

Panel A: Aggregate results

	RW					AR(1)				
IMF	b_1	*p*-value	b_2	*p*-value	R^2(%)	b_1	*p*-value	b_2	*p*-value	R^2(%)
(1)	9.34E-07	0.568	-7.83E-06	0.009	0.058	1.41E-06	0.492	-8.03E-06	0.014	0.056
(2)	-9.58E-07	0.574	-6.14E-06	0.043	0.122	-1.09E-06	0.586	-4.00E-06	0.027	0.119
(3)	4.81E-08	0.932	-5.40E-07	0.057	0.002	6.86E-08	0.943	-7.05E-07	0.253	0.001
(4)	-1.36E-06	0.810	7.68E-08	0.611	0.190	-1.88E-06	0.781	-2.14E-06	0.948	0.169
IPMF										
(1)	0.004	0.009	-0.573	0.048	0.087	0.047	0.051	-0.611	0.162	0.050
(2)	-0.123	0.019	-0.420	0.055	0.160	-0.117	0.091	-0.261	0.123	0.119
(3)	0.001	0.430	-0.040	0.030	0.002	0.003	0.762	-0.053	0.289	0.001
(4)	-0.134	0.001	0.115	0.190	0.279	-0.206	0.017	-0.070	0.553	0.214

This section allows us to conclude that the risk level of the portfolio, as measured by the fund beta, can be affected by the purchases and withdrawals of fund units. This aspect must, therefore, be considered in further analyses of fund beta dynamics.

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7. Conclusions

This paper analyzes several aspects of the volatility of mutual funds, as measured by betas. The level of betas is an important source of information for the aggressiveness of the fund management with respect to its benchmark. Therefore, more information about beta dynamics will empower investors to make better decisions.

We ran preliminary analyses that clearly reject the stability of fund betas. We then estimated daily fund betas using various techniques such as the rolling windows approach and the sophisticated Kalman filter procedure. Although the Kalman filter is a powerful statistical method to estimate the dynamics of unobservable variables, it requires a previous definition of the model followed by the variable. In this sense, the models traditionally proposed in the literature (the random walk and a first-order autoregressive models) do not achieve the desired improvement in the accuracy of the forecasts. Several in-sample and out-of-sample tests were conducted to evaluate the models. The results, however, do not allow us to disregard the methodology. The models are evaluated considering one specification at a time for every fund when we may not be able to assign a single model to the entire sample of funds.

However, finding the model that best fits the beta series is not the sole objective of this paper. On the contrary, we are primarily interested in testing for factors that are causing the time-dependence of a beta.

The most immediate time-varying phenomenon to be tested is seasonality. Our tests confirm that we cannot assume constant levels of beta along the year, and we find significant monthly effects.

Finally, we test the influence of fund flows on the variation of beta. Fund managers do not have a static portfolio with which to implement their investment strategy. The size of the fund is constantly changing due to the purchases and redemptions of investors. Their strategy can, therefore, be affected by these flows of money. In fact, we find a significant relationship between money flows and the variation of fund betas. The data analysis panel draws conclusions about a negative relationship between money flows and variations in the levels of fund beta. This relationship is asymmetric and mostly driven by fund withdrawals. We also find that the reaction of fund managers is stronger when money is out of the fund than when money comes into the fund.

The findings of this study are undoubtedly the starting point of further research related to time-varying properties of fund betas and the refinement of the models to find the underlying structure of the beta time-series.

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