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Alternative Mutual Fund Timing Models: an Extensive Integrated Review

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ABSTRACT

The main purpose of the paper is to review and extend the existing mutual fund timing research models. This paper represents the first attempt to bring together all of the biases affecting traditional timing models that have been identified by the literature and also all of the corrective measures applied to solve the spurious coefficient problem caused by these biases. Moreover, we correct the Merton & Henriksson timing model including the option cost. To examine the precision of alternative mutual fund timing models we find that this model is subject to least bias in testing timing ability of mutual fund managers.

Keywords: Mutual Funds; Options; Spurious Coefficients; Timing Models.

JEL Classification: G12, G23.

Modelos alternativos de sincronización con el mercado para los fondos de inversión: una revisión extensiva integrada

RESUMEN

El objetivo principal del trabajo consiste en revisar y extender los modelos de investigación sobre sincronización con el mercado de los fondos de inversión que existen en la actualidad. Este trabajo representa un primer intento de reunir todos los sesgos que afectan a los modelos tradicionales de sincronización con el mercado que han sido identificados por la literatura así como las medidas correctivas aplicadas para solventar el problema de coeficientes espurios causado por estos sesgos. Además, corregimos el modelo de sincronización de Merton y Henriksson incluyendo el coste de la opción. Al examinar la precisión de los modelos alternativos de sincronización con el mercado de los fondos de inversión encontramos que este último modelo está sujeto a menos sesgos en la evaluación de la habilidad de los gestores de fondos de inversión para sincronizarse con el mercado.

Palabras Clave: Fondos de Inversión; Opciones; Coeficientes Espurios; Modelos de Sincronización con el Mercado.

Clasificación JEL: G12, G23

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1. INTRODUCTION

It has traditionally been supposed that a manager's success is determined by his/her ability to choose stocks that outperform other securities with a similar level of non-diversifiable risk. This strategy is known as "stock-picking." The other strategy employed by managers to improve their results is to seek to change their exposure to the market at the right moment. Specifically, a good manager will maintain a higher beta in a bull market and a lower beta in bear market. This is the "market timing" strategy. Market timing involves swapping securities with different betas or changing the proportion of the portfolio invested in different stocks.

In any event, overall performance can be broken down into stock-picking and market timing. The split between these components of performance is an issue that has been widely discussed in the financial literature. There are useful reasons to break performance down into its constituent parts. First, the difference between timing and stock-picking throws light on the functioning of investment funds, and second, the resulting distribution of returns on assets may differ depending whether more private information is available concerning the aggregate market than individual companies or vice versa.

In general, it has proven far from easy to break performance down into its two constituent parts. Some scholars, such as Rubio (1993), consider the distinction to be conceptually inappropriate because the two strategies are not statistically independent. Gallagher, Swan, and Ross (2007), however, propose a measure to assess the timing ability of a manager in relation to an individual security. This allows them to break stock-picking skill down into its two basic components: security selection and security timing.

On the other hand, the empirical evidence suggests that the correlation between stock-picking and market timing is usually negative. For example, the findings of Bollen and Busse (2001) based on a sample of 230 equity funds reveal an inverse relationship between timing coefficients and alphas. Fung, Xo, and Yau (2002) also find this inverse relationship in their study of global hedge funds. Meanwhile, Somasundaram (2007) examines the relative performance of a group of actively managed Indian equity funds and another group of passively managed index funds. The results support fund managers' stock selection ability but find that they have negative market timing skill. This hypothesis of a negative correlation between timing and selectivity is also supported by Lhabitant (2001).

Strangely, managers who are skilled at picking the right stocks for their portfolios seem less able to anticipate market movement and vice versa. Furthermore, negative timing coefficients are easily found in the financial literature. However, as Matallín, Moreno, and Rodríguez (2007) point out, it is hard to imagine that managers would systematically synchronize their risks against the correct trend. These two rather counterintuitive results suggest that the parameter measuring timing may not adequately reflect managers' true skills but a spurious coefficient.

A number of scholars have sought to explain the possible causes of such a spurious timing coefficient. For example, Jagannathan and Korajczyk (1986) argue that it may be the result of a nonlinear payoffs structure due to the inclusion of options or leveraged assets in funds. Meanwhile, Matallín (2006) points to the effect of the omission of benchmark portfolios as a possible cause of the spurious timing coefficient. Pastor and Stambaugh (2002) argue that bias might continue to exist even if the number of benchmark portfolios were sufficiently increased to represent assets of any class due to the different weightings of the investment fund considered and the benchmark portfolios utilized.

Ferson and Warther (1996) and Ferson and Schadt (1996) argue that a conditional assessment of results might help to estimate the timing ability of managers more accurately, while Edelen (1999) considers that the bias is caused by the impact of investor cash flows on the fund's beta. However, Matallín et al. (2007) argue that negative timing could be due to the asymmetric behavior of individual stocks held in the fund.

In this paper, our objective is to review the existing market timing models by first analyzing the traditional timing models by Treynor and Mazuy (1966) and Merton and Henriksson (1981). Then, we discuss the biases inherent in these models, which have been identified by the literature. We also examine the corrections proposed by literature and obtain

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a more reliable measurement of timing ability by proposing an alternative correction connected with volatility timing. Finally, we introduce a correction into the Merton and Herniksson model that includes the cost of the option, and we demonstrate that this model is subject to least bias in testing timing ability.

The paper makes various contributions to the financial literature on market timing. First, we provide an extensive review of existing timing models, focusing on their biases documented in the financial literature. We conduct an empirical analysis that allows us to measure the impact of applying the corrective measures proposed by the literature (and some proposed here) to overcome these biases. Furthermore, we avoid the data snooping bias resulting from the repeated analysis of the US and UK markets and instead analyze data from the Spanish markets.[1] Finally, and following Connor and Korajczyk –(1991) we include the options price in the Merton and Henriksson model (1981). The impact of this correction was measured by Connor and Korajczyk (1991) but for the US mutual funds. This impact hasn't been measured for the Spanish market yet.

The rest of this paper is organized as follows. In section 2, we review the traditional timing models in such a way that we divide this section in several sub-sections, each evaluating one kind of bias affecting traditional timing models, and we also revise the proposed corrections implemented by literature to overcome these biases. Moreover, in this second section, following Connor and Korajczyk (1991), we include the option cost in the Merton and Henriksson model as a way of correcting the misspecification of the model. Moreover, we propose a new model to analyze volatility timing. Section 3 describes the data base analyzed and briefly refers to the rapid growth in the Spanish investment fund industry in recent years. In section , we conduct empirical analysis in order to assess and compare all the corrections proposed by literature of timing models and our own proposals. We provide summary and concluding remarks in section V.

2. REVIEW OF CORRECTIONS TO IMPROVE TIMING MODELS

In this section, we review the possible causes for the emergence of spurious timing coefficients in the traditional timing models that have been identified by the existing literature, and we also expose the corrections proposed to improve the measurement of timing ability. We propose an alternative correction related to volatility timing.

2.1. Market Return and Volatility Timing

Existing market timing measures, such as those proposed by Treynor and Mazuy (1966) and Merton and Henriksson (1981), focus on the convexity of the portfolio return with respect to the market return, but they ignore the reaction of the portfolio to changes in market volatility. The timing models of Treynor and Mazuy (1966) and Merton and Henriksson (1981) can be expressed in the following generic form:

$$r_{p,t+1} = \alpha_p + \sum_{j=1}^{k} \beta_j r_{j,t+1} + \gamma r_{m,t+1} S_{t+1} + \varepsilon_{t+1}, \quad (1)$$

where β_j is the loading to factor j. The timing term is $S_{t+1} = r_{m,t+1}$ in the Treynor and Mazuy model and $S_{t+1} = I(r_{m,t+1} > 0)$ in the Merton and Henriksson model. The coefficient γ measures return timing. K equals 1 for the single-market factor model. $r_{p,t+1}(r_{m,t+1})$ represents

[1] In this regard, Ayadi and Kryzanowski (2004) and Hallahan and Faff (2001) maintain that the analysis of less intensely explored markets than allows academics and professionals to analyze markets with different institutional features and, therefore, to make an original contribution to the financial literature.

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the excess return on portfolio p (the market) with respect to the return on one month Treasury Bills at month $t+1$; β_p is the portfolio beta, which varies with the timing signal received by the fund manager at time t; and ε_{t+1} is the idiosyncrasic risk.

These models describe how a fund manager with superior information should modify the portfolio beta given signals indicating a shift in future market returns. Assuming that a fund's return is generated by the following model:

$$r_{p,t+1} = \alpha_p + \beta_p r_{m,t+1} + \varepsilon_{t+1}, t = 0, ..., T-1. \quad (2)$$

Assuming that $E(\varepsilon_{t+1}) = 0$ and $Cov(r_{m,t+1}, \varepsilon_{t+1}) = 0$, if the portfolio beta β_p is constant, the intercept is Jensen's α, which measures stock-picking or micro-prediction ability (Jensen, 1968; Fama, 1972). However Jensen (1972) shows that if fund managers follow market timing strategies, then the intercept of a model for which the beta is constant will not be capable of measuring either stock picking ability or overall stock-picking and market timing ability.

Assuming that market exposure is variable over time, Admati, Bhattacharya, Pfleiderer, and Ross (1986) show that a utility-maximizing manager should display the following beta:

$$\beta_p = \frac{E\left(r_{m,t+1}\left|s_t\right.\right)}{\theta * Var\left(r_{m,t+1}\left|s_t\right.\right)}, \quad (3)$$

where θ, which is assumed to be constant, represents Rubinstein's (1973) measure of risk aversion; s_t is the timing signal received by the manager. Equation (3) shows how a manager following market timing strategies incorporates information into the management of the portfolio. Thus, beta should increase with the expected return on the market portfolio (i.e., $E\left(r_{m,t+1}\left|s_t\right.\right)$ and decrease with the rise in the expected market variance (i.e., $Var\left(r_{m,t+1}\left|s_t\right.\right)$, allowing the fund manager to increase the expected utility of his investments and thereby raise the performance of the portfolio. In this light, it would seem necessary to examine market timing skill from two dimensions: market return and volatility.

In fact, in the same way as a manager may implement market timing strategies when receiving signals of changes in the market return, he/she may also implement timing strategies given a shift in market volatility. Indeed, signals indicating a change in market volatility are more likely to exist than signs of a switch in the direction of the market.[2]

A fund manager may modify his/her exposure to the market on the basis of his/her perceptions of market returns and risk. Even where he/she predicts a high level of returns on the market, she may refrain from taking significant positions without considering volatility, and vice versa. It is plausible to suppose that a fund manager would reduce the portfolio beta not only in the face of a market downturn but also in the presence of significantly anomalous returns. Consequently, if the attitude to risk aversion is rational, timing may be based on the expected volatility of returns. Taking this into account, we may conclude that expression (3) is consistent with the reality.

In this paper, we apply the Busse (1999) model to measure fund managers' market timing ability in terms of both volatility and returns.[3]

$$r_{p,t+1} = \alpha_p + \beta_p r_{m,t+1} + \gamma r_{m,t+1}^2 + \lambda r_{m,t+1}\left(\sigma_{m,t+1} - \overline{\sigma}_m\right) + \varepsilon_{t+1}, \quad (4)$$

[2] Any assessment of volatility timing necessarily involves analysis of the robustness of results obtained with regard to the return timing. Indeed, Volkman (1999) finds evidence for contrary volatility and return timing in periods of high volatility.

[3] Busse (1999) uses a Taylor series expansion to express market beta as linear function of the difference between market volatility and its time series mean.

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where $\sigma_{m,t+1}$represents market volatility at $t+1$ and $\overline{\sigma}_m$the mean for the period analyzed.[4] Hence, the third component in the right-hand side of (4) $\gamma r^2_{m,t+1}$) represents timing ability with regard to the market return, and the fourth component $\lambda r_{m,t+1}(\sigma_{m,t+1}-\overline{\sigma}_m)$ represents volatility timing ability. We note here that a positive gamma indicates successful timing in terms of market return, and a negative lambda indicates successful timing in terms of market volatility because it represents a lower exposure to the market in scenarios of increased volatility.

It is clear that Busse (1999) constructs his measure of volatility timing on the basis of the Treynor and Mazuy (1966) model, substituting $S_{t+1}=r_{m,t+1}$ for $S_{t+1}=(\sigma_{m,t+1}-\overline{\sigma}_m)$. We propose an alternative measure based on the Merton and Henriksson (1981) model. This model is based on the option of portfolio restructuring. It assumes that the manager is only able to distinguish between a bull market ($r_{m,t+1}>0$), in which case beta will be high, and a bear market ($r_{m,t+1}<0$) when the portfolio will have a lower beta. Consequently, the relationship between the portfolio and the market return is reflected by the two straight lines with differing slopes that depend whether or not a bull market prevails. This nonlinear relationship can be estimated with two different regressions, or a single regression represented by an indicator function $I\{r_{m,t+1}>0\}$, which is equal to 1 if $r_{m,t+1}>0$ and is otherwise equal to zero.

Following this reasoning, we now assume that the manager does not perceive any signals with regard to market returns but is only able to predict market volatility. Consequently, the manager will increase his/her exposure to the market when it is less volatile (i.e., when $\sigma_{m,t+1}<\overline{\sigma}_m$) and will maintain his/her beta when the market is more volatile. Hence, the indicator function is now based on market volatility: $I\{\sigma_{m,t+1}\text{-}\overline{\sigma}_m<0\}$. In this case, the function will be equal to 1 if $\sigma_{m,t+1}$-$\overline{\sigma}_m$<0 and zero otherwise. Our proposal for the measure of volatility timing may therefore be expressed as follows:

$$r_{p,t+1}=\alpha_p+\beta_p r_{m,t+1}+\delta r_{m,t+1}\left|\sigma_{m,t+1}-\overline{\sigma_m}\right|\Big|_{\sigma_{m,t+1}-\overline{\sigma}_m<0}+\varepsilon_{t+1}, \quad (5)$$

such that δ multiplies $r_{m,t+1}$ and the absolute value of the demeaned market volatility, with the condition of low market volatility ($\sigma_{m,t+1}-\overline{\sigma}_m<0$). A positive δ would indicate successful market volatility timing on the part of the fund manager, indicating an increase in market exposure in a low volatility scenario. Of course, managers can make mistakes in terms of returns, which would result in losses due to higher exposure in relatively stable markets or the loss of gains due to reduced exposure to the market in a more volatile scenario. However, it is not the objective of this model to determine market timing in terms of returns but of risk. Furthermore, it is plausible, as argued above, that a fund manager might reduce the portfolio beta not only in the face of a market downturn but also in the presence of significantly anomalous returns.

We obtain our proposal of a joint market return and volatility timing measure that we shall apply in this paper by including (4) in the Merton and Henriksson (1981) model:

$$r_{p,t+1}=\alpha_p+\beta_p r_{m,t+1}+\gamma r_{m,t+1}I\left(r_{m,t+1}>0\right))+\delta r_{m,t+1}\left|\sigma_{m,t+1}-\overline{\sigma_m}\right|\Big|_{\sigma_{m,t+1}-\overline{\sigma}_m<0}+\varepsilon_{t+1}, \quad (6)$$

where γ measures market return timing and δ volatility timing ability.

2.2. Availability of Public Information

The Treynor and Mazuy (1966) model is based on the existence of a convex relationship between the return on the fund and the market return, provided that the manager increases (decreases) the

[4]In this paper, following Chen and Liang (2007), we use two proxies for market volatility, the implied volatility and the realized market volatility. Moreover, following Busse (1999), we also consider estimating market volatility from conditional volatility models (EGARCH). We obtain the same inferences with the three proxies, so we only report in the results section the findings obtained when using the realized market volatility.

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exposure of the portfolio to the market (specific risk) prior to increases (decreases) in the market itself (i.e., the benchmark index). This is what is known as market timing. Nevertheless, this convex relationship may appear for reasons other than the actual timing activity. One possible cause could be a common time variation in the portfolio beta and the expected market risk premium due to public information (i.e., information known by investors) about the economic cycle.

Traditional timing models fail to consider this possibility. Ferson and Schadt (1996) and Ferson and Quian (2004), however, propose a conditional version of traditional timing models expressed as follows:

$$r_{p,t+1} = \alpha_p + \beta_p r_{m,t+1} + \beta_p'(Z_t r_{m,t+1}) + \gamma r_{m,t+1} S_{t+1} + \varepsilon_{t+1}, \tag{7}$$

where Z_t is a vector of economic cycle information variables, which can predict the market risk premium, and $\beta_p'(Z_t r_{m,t+1})$ controls for the common time variation in the risk premium and the portfolio beta due to public economic information.

Furthermore, the timing coefficient also varies over time. Indeed, it can be shown that this variable depends both on the accuracy of the signal the manager receives and his/her aversion to risk. The accuracy of the signal varies over time because it depends on economic conditions, and it would therefore appear reasonable to assume that the manager will receive information with a greater or lesser degree of uncertainty. Risk aversion may also change over time, and it tends to increase in adverse economic circumstances and decrease in more buoyant times. Hence, model (7) may be expanded to allow the timing coefficient to vary with the economic cycle:

$$r_{p,t+1} = \alpha_p + \beta_p r_{m,t+1} + \beta_p'(Z_t r_{m,t+1}) + \gamma r_{m,t+1} S_{t+1} + \gamma_p'(Z_t r_{m,t+1} S_{t+1}) + \varepsilon_{t+1}, \tag{8}$$

where the term $\gamma_p'(Z_t r_{m,t+1} S_{t+1})$ captures the variability of the manager's timing ability over the economic cycle due to the use of public information.

Conditional models, then, separate fund management results into the component that is due to the use of public information accessible to the market as a whole and that which is the value-added by the manager as a result of the possession and use of superior information that is not available to any investor. Empirical evidence supports the use of specification (8). Furthermore, allowing time variations in conditional timing ability reveals that managers following timing strategies tend to do better when: the slope of the interest rate curve is high (i.e., higher long term than short term interest rates; future economic expansion); short term corporate debt markets are relatively more liquid; and aggregate liquidity in equities is higher. In fact, higher liquidity reduces the cost of timing activities.

2.3. Dynamic Trading Effect

Most studies on timing, including this one, are based on monthly data. However, this data frequency might fail to capture the contribution of a manager's timing activities to fund returns. Indeed, as Bollen and Busse (2001) have shown, it is possible that decisions regarding market exposure are likely made more frequently than monthly for most funds.

Goetzmann, Ingersoll, Ivkovich (2000) show that measures based on returns are biased downward when funds engage in active timing and trade between the observation dates of fund returns. For example, when funds engage in daily timing, return timing measures that use monthly fund returns tend to underestimate timing ability. Jiang et al. (2005) call this the "dynamic trading effect", arguing that it may introduce an artificial timing bias in returns-based tests.

To illustrate this effect, let us consider a case where a fund trades in each period, but returns are observed every two periods. Suppose a manager has no active timing ability but adjusts the fund beta during the second period conditional on the realized market return in the first period. This leads to a correlation between the fund beta in the second period and the market

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return over the first, and this further induces a seemingly contemporaneous nonlinear relation between the realized two-period fund and market returns. For example, a positive feedback manager who increases his/her market exposure after a market run-up would display positive artificial timing. Consequently, certain common, and apparently innocuous, trading strategies may generate nonlinear relationships between fund and market returns.

This effect is also known in the literature as "interim trading" because it is the result of fund trading activities between the return observation dates. It may also cause return-based tests to underestimate the true market timing ability, and Goetzmann et al. (2000) in fact perform simulations to show that Merton's and Henriksson's measure based on monthly fund returns presents a downward bias and loses explanatory power when funds engage in daily market timing strategies.

Goetzmann et al. (2000) propose a simple solution to the problem of timing measurement based on monthly returns for a manager engaged in daily timing activities. They solve this problem without the need of collecting daily returns. The solution is to take the daily returns to an index that is correlated to the timer's risky asset. Values of a daily put on the index are cumulated over each month to form a regressor that captures timing skill. This factor is expressed as follows:

$$P_{m,t} = \left(\prod_{\tau=1}^{N} \max\left\{1 + R_{m,\tau}, 1 + R_{f,\tau}\right\} \right) - 1 - R_{m,t}, \tag{9}$$

where $P_{m,t}$ represents the value added by perfect daily timing per monetary unit of assets in the fund. Even though the daily returns on the risky assets by the timer are not available, as long as the returns on the assets considered to construct the factor $P_{m,t}$ are highly correlated with them, $P_{m,t}$ thus captures daily timing. N is the number of days in month t, $R_{m,\tau}$ is the market return on day τ, and $R_{f,\tau}$ is the return on the risk-free asset on the day in question.

We can capture the correlation between the monthly return on the fund and the monthly value of daily timing by including this factor in the following regression, which employs monthly returns:

$$r_{p,t+1} = \alpha_p + \beta_p r_{m,t+1} + \gamma_p P_{m,t+1} + \varepsilon_{p,t+1} \tag{10}$$

In short, then, the value of a monthly put on the market (i.e., the Merton and Henriksson model) is substituted by a rolling account through the month of the gains to obtain a sequence of daily market puts. These sequential put contracts are known as "tandem options." Tandem options are defined as a sequence of options in which the strike price is reset daily to the product of the present value of the risky asset and the gross daily return on the risk-free asset for the day in question.

The accumulation of daily puts requires the behavioral assumption about the strategy followed by the perfect daily timer. Every day, the perfect daily timer will take the proceeds from the payoff from the daily put option that expires on that day (being the option ITM, or "in the money") and will invest these amounts in the same way as the rest of the portfolio. Thus, if the timer predicts positive excess returns, he/she will take a 100% position (investing both the "old" funds and the new payoff obtained from the daily put) in the risky asset. In contrast, a timer who forecasts a negative excess return will take a 100% position in the risk-free asset. This assumption is in line with the notion that the least a perfect daily timer could do with the proceeds from the daily put is to invest it in the risk-less asset and thus earn zero excess return.

Ferson et al. (2006) also seek a solution to interim trading bias.To this end, they employ a continuous-time asset pricing model because a continuous-time model should, in theory, price portfolio strategies that do not employ private information. Specifically, these scholars include time-average state variables suggested by the pricing model as additional control factors.

They show that time aggregation of state variables in an asset pricing model for discrete returns measured over the period from month t to $t+1$ leads to the following stochastic discount factor:

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$$_tm_{t+1} = \exp\left(a + b' A^x_{t+1} + c' \left[x_{t+1} - x_t\right]\right), \tag{11}$$

where x is the vector of state variables in the model and $A^x_{t+1} = \sum_{i=1\ldots 1/\Delta} x(t + (i-1)\Delta)\Delta$ represents the time-averaged levels of the state variables over the return measurement period. The measurement period is divided into periods of length D, which is equal to one trading day. Hence, the empirical factors suggested by the stochastic discount factor are the discrete monthly changes in the state variables and their time averages within the month, i.e., $x_{t+1} - x_t$ and A^x_{t+1}, respectively. In this context, if the state variable is proxied by the logarithm of the market price level (i.e., $x_t = \ln(P_t)$), it would be possible to control for the problem of interim trading using the within-month average of the state variable.

Following Ferson et al. (2006) and Chen and Liang (2007), we have therefore included the monthly average of the logarithm of the market price level in the market timing regressions.

2.4. The Option Implied in Timing Activities and the Passive Timing Effect

Both the Treynor and Mazuy and the Merton and Henriksson timing models are option motivated. The quadratic regression employed by Treynor and Mazuy indicates that the portfolio beta fluctuates depending on the size of the market excess return. Thus, the slope is continually increasing from left (bear market) to right (bull market). On the other hand, the Merton and Henriksson model shows that the portfolio beta fluctuates between two values depending whether the market return is larger or lower than the risk-free rate. Both models thus rest on the notion of nonlinear payoff structures. Indeed, the quadratic regression exaggerates the option-like characteristics of the Merton and Henriksson model.

However, the timing ability considered by these models can be understood as a free option. Thus, if we invest in options, we will have the same payoff structure as if we apply a market timing strategy, but the options have a non-negative cost. This implies that if funds invest in options (or similar instruments), the fall in returns as a result of the cost of the options will be transferred to the alpha coefficient. Since a positive timing coefficient in the Merton and Henriksson model is equivalent to purchasing a market put option without paying the price of the option, the reduction in the return from the cash paid for the purchase will show up as a negative alpha.

Similarly, a negative timing coefficient is equivalent to selling a market put option without receiving the price for the option. Consequently, an increase in the return from the cash generated from the sale will show up as a positive alpha. Hence, a negative correlation should be expected between timing and selectivity measures when funds include options in their portfolios.

In light of this, it is essential to recognize the cost of the option implied in timing models. To achieve this, we take the Merton and Henriksson model and consider the case of both the purchase and the sale of a put option (positive or negative timing coefficients, respectively). Following Connor and Korajczyk (1991), we assume that the (positive or negative) cash flow generated is invested (borrowed) in Treasury Bills at the risk-free rate. Hence, the new explanatory variable included would be as follows:

$$Put' = \max\left(0, R_{f,t+1} - R_{m,t+1}\right) - (1 + R_{f,t+1})P, \tag{12}$$

where P is the price of the European market put with a strike price equal to the risk-free rate.

Thus, where the usual specification is

$$r_{p,t+1} = \alpha_p + \beta_p r_{m,t+1} + \gamma_p Put + \varepsilon_{p,t+1}, \tag{13}$$

and with $Put = max(0, R_{f,t+1} - R_{m,t+1})$, the new model will be

$$r_{p,t+1} = \alpha'_p + \beta_p r_{m,t+1} + \gamma_p Put' + \varepsilon_{p,t+1}. \tag{14}$$

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The new model (14) will correctly predict $\alpha'_p = 0$, while specification (13) implies $\alpha_p = \alpha'_p - \gamma_p \left(1 + R_{f,t+1}\right) P$. Hence, when $\alpha'_p = 0$, the alpha in the usual specification is $\alpha_p = -\gamma_p \left(1 + R_{f,t+1}\right) P$, which explains the negative correlation between the alphas and the timing coefficients estimated using (13).

The cost of the option (implied in timing) required to apply specification (14) is obtained based on the Black-Scholes options pricing formula.[5] Even if the funds do not invest in options, they may display a similar payoffs structure, and options may be replicated by means of dynamic strategies between cash and stocks. If funds trade more frequently than the measurement of returns, they would be replicating the functioning of an option without the need to perceive a timing signal. This would create false evidence of timing.

Furthermore, equity in a leveraged firm is just a call option on the firm's assets with a striking price equal to the face value of debt. In addition, the debt may be equivalent to holding a risk-free zero coupon bond and to the sale of a put option on the value of the company with a striking price equal to the face value of the debt. Whenever funds buy debt and equity of leveraged companies, then their payoffs will be affected by these implicit options. The alpha and gamma coefficients in timing models for funds of this type will be negatively correlated and the models will display spurious evidence of timing.

The returns on a passive portfolio investing in assets of this kind may also have a convex or concave relation with market returns even though the fund does not follow any timing strategy. This phenomenon is referred to in the financial literature as the passive timing effect.

Jagannathan and Korajczyk (1986) argue that a fund manager holding options or assets with similar payoff structures to these could be misinterpreted as a market timer due to the options nonlinear payoff. Likewise, Brown, Gallagher, Steenbeek, and Swann (2005) argue that portfolio payoffs may exhibit concavity to the benchmark when the manager engages in "information-less investing." In keeping with the proposal made by Jagannathan and Korajczyk (1986), we include various nonlinear functions of the market index, as "exclusion restrictions" in the timing regressions in order to test for model misspecification. Thus, significant coefficients on such nonlinear terms would indicate misspecification of the timing models. These nonlinear functions of the market index are $\ln(|r_{m,t+1}|)$ and $1/r_{m,t+1}$:

$$r_{p,t+1} = \alpha + \beta r_{m,t+1} + \gamma r_{m,t+1} S_{t+1} + \Omega \ln\left(|r_{m,t+1}|\right) + \lambda \frac{1}{r_{m,t+1}} \tag{15}$$

2.5. *Thin Trading Effect*

Chen, Ferson, and Peters (2005) show that systematic thin trading may also generate spurious evidence of timing ability. This is because thin or non-synchronous trading may bias the estimates of the portfolio beta. These scholars show that when the thinness of trading is systematically related to market conditions, it results in systematic stale pricing, which would create spurious concavity or convexity and, therefore, spurious evidence of market timing ability. Infrequent trading usually occurs in relation to certain illiquid assets, and many funds hold them, as noted by Asness, Krail, and Liew (2001) and Getmansky, Lo, and Makarov (2004).

In order to mitigate the problem of infrequent trading of some assets (also known as the stale pricing problem), Chen et al. (2005) consider the true return on an asset as the

[5] According to the Black-Scholes formula, the option value $V = S\Phi(x_1) - Xe^{-rT}\Phi(x_2)$, where $x_1 = \left[\ln\left(S/X\right) + \left(r + 0.5\sigma^2\right) T\right] / \sigma\sqrt{T}$, $x_2 = x_1 - \sigma\sqrt{T}$, $\Phi\left(x_1\right)$ is the cumulative normal distribution function; S is the underlying stock price; X is the strike price; r is the instantaneous rate of interest; T is the expiration period; and s is the return volatility per period (month, here). We follow Merton's (1981) assumptions: $S = 1$, $X = R_f$, and $e^{-}rT = 1/R_f$. Under these assumptions, it is straightforward to show that $V = 2\Phi\left[0.5\sigma\sqrt{T}\right] - 1$. From our data, we use the volatility implied in the at-the-money Spanish options on the Spanish equity market as s, set T = 12 for a year, and obtain V = 0.07.

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difference between the natural log of the fund's "true" net asset value per share, with the last period's dividends reinvested at period t and the same natural log for the preceding period. Thus, $r_t = p_t - p_{t-1}$. This true return would be the observed return if no prices were stale.

The measured price p_t^* is given by $\delta_t p_{t-1} + (1-\delta_t)p_t$, where $\delta_t \ \varepsilon \ [0,1]$ measures the extent of stale pricing in period t. Hence, the measured return on fund r_t^* will be given by:

$$r_t^* = \delta_{t-1} r_{t-1} + (1-\delta_t) r_t. \quad (16)$$

The authors model systematic stale pricing based on a regression of the extent of stale pricing at time t on the market factor:

$$\delta_t = \delta_0 + \delta_1 \left(r_{m,t} - \mu_m\right) + \varepsilon_t, \quad (17)$$

where μ_m is the mean return on the market, and ε_t is the error term, which is assumed to be independent of the remaining factors in the model.

Chen et al. (2005) look at the moments of the true return, e.g., $Cov(r_t), r_{m,t}^2)$, that measures timing ability. Based on straightforward calculations, they relate the moments of the observable variables to the moments of unobservable variables. Let us focus on the moment measuring timing ability:

$$Cov\left(r_t^*, r_{m,t}^2\right) + Cov\left(r_t^*, r_{m,t-1}^2\right) = Cov\left(r, r_m^2\right). \quad (18)$$

Expression (17) provides a straightforward way to control for a biased market timing coefficient due to stale prices. The sum of the covariances of the measured return with the squared market factor and the lagged squared factor equals the true covariance or timing coefficient. Thus, Chen et al. (2005) conclude that this potential bias can be mitigated by including lagged terms of the benchmark as additional factors in the timing models. Following Chen and Liang (2007), we include two lagged market returns and their square terms to alleviate the thin trading effect in the Treynor and Mazuy model:
[6]

$$r_{p,t+1} = \alpha_p + \beta_p r_{m,t+1} + \beta_p^{'} r_{m,t} + \beta_p^{''} r_{m,t-1} + \gamma_p r_{m,t+1}^2 + \gamma_p^{'} r_{m,t}^2 + \gamma_p^{''} r_{m,t-1}^2 + \varepsilon_{p,t+1}. \quad (19)$$

2.6. Changes in Market Conditions

Investment fund managers may receive different timing signals ahead of different market conditions. For example, a fund may be expected to time the market level better in a bear market than in a bull market. It is difficult to outperform a soaring market, while a bear market may leave a room for the manager to improve. Furthermore, a manager following volatility timing strategy needs to avoid the market in volatile periods. In this light, we estimate return timing separately for bull and bear markets, and we estimate volatility timing separately for volatile and stable markets. Finally, joint market timing is measured separately for high and low Sharpe ratio market conditions. These separations are motivated by the fact that different timing abilities focus on different market moments.

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[6] We add more lagged terms to check robustness, and the inference is unchanged.

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3. DATA

In this section, we describe the data used in our analyses and provide background on the Spanish mutual funds.

3.1. Mutual Fund Data

Our database comprises a total of 180 Spanish mutual funds investing in domestic equities. We select all Spanish funds in the domestic equities categories that have data for at least three years during the interval considered in the study (June 1994 to December 2006). The reason for this three-year requirement is the need to consider a minimum period to guarantee the statistical validity of our results. The aim is to ensure that our sample is free of "survivorship bias." However, as Carhart, Carpenter, Lynch, and Musto (2002) observe, studies of this kind may be affected not only by survivorship but also by "look-ahead" bias, which arises when a certain breadth of data is required for each fund to apply the proposed methodology as is the case here.

The analysis uses monthly return data, so there are up to 151 observations. The benchmark equity index selected for the study is the MSCI-Spain. All of the data are obtained from the Spanish National Securities Market Commission (CNMV), the Spanish equivalent to the SEC in the United States. We use the monthly return obtained by one-month repos on Treasury Bills as a proxy for the risk-free rate. Table 1 shows the summary statistics for our data base.

	No. funds	Average return (%)	Return on MSCI-Spain (%)	Maximum return (%)	Minimum return (%)	St.dev.
Jun.1994/December 1994	81	-1.05	-1.87	9.60	-9.43	0.0332
Jan.1995/December 1995	86	0.97	1.32	9.16	-8.39	0.0301
Jan.1996/December 1996	98	2.08	3.32	10.63	-6.30	0.0291
Jan.1997/December 1997	134	2.53	3.31	15.71	-15.84	0.0536
Jan.1998/December 1998	155	2.39	3.23	28.76	-22.20	0.0875
Jan.1999/December 1999	160	0.66	1.74	21.04	-10.54	0.0425
Jan.2000/December 2000	160	-1.05	-0.86	27.37	-20.16	0.0510
Jan.2001/December 2001	160	-0.59	-0.51	19.82	-24.83	0.0569
Jan.2002/December 2002	156	-1.63	-2.46	24.77	-22.23	0.0696
Jan.2003/December 2003	161	1.60	2.20	12.53	-9.83	0.0366
Jan.2004/December 2004	155	1.03	1.31	9.08	-6.95	0.0234
Jan.2005/December 2005	147	1.30	1.37	9.62	-6.15	0.0269
Jan.2006/December 2006	146	1.83	2.23	8.54	-15.38	0.0253

Table 1. Summary Statistics *

***Note:** Table 1 shows the annual summary statistics of monthly returns for our sample (except for the first row where the database starts in June 1994). The first column shows the time period, and the second column provides the number of funds considered in each period. The third and fourth columns report the average return on the funds and the benchmark, respectively. Columns 5 and 6 show the maximum and minimum return on the funds analyzed. Finally, column seven contains the standard deviation of the returns on the funds.

Table 2 presents the attrition and mortality rates for the sample. The attrition rates represent the quotient between the number of funds disappearing in one year and the number of funds existing at the end of that year. The mortality rates for each year are calculated as one minus the quotient between the number of surviving funds in December 2006 that also existed

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at the end of the year analyzed and the number of funds existing at the end of that year. [7]

	Attrition rates(%)	**Mort. rates(%)**
Jun.1994/December 1994	0.00	22.22
Jan.1995/December 1995	0.00	22.09
Jan.1996/December 1996	0.00	20.41
Jan.1997/December 1997	0.00	21.64
Jan.1998/December 1998	0.00	20.00
Jan.1999/December 1999	0.00	20.00
Jan.2000/December 2000	0.00	20.00
Jan.2001/December 2001	2.50	18.13
Jan.2002/December 2002	6.41	12.82
Jan.2003/December 2003	2.48	9.32
Jan.2004/December 2004	3.87	5.81
Jan.2005/December 2005	4.76	0.68
Jan.2006/December 2006	0.68	0.00

Table 2. Attrition and Mortality Rates *

* **Note:** Table 2 presents the attrition and mortality rates for the sample. The attrition rates are calculated as the quotient between the number of funds disappearing in one year and the number of funds existing at the end of that year. The mortality rates for each year are computed as one minus the quotient of the number of surviving funds at December 2006 that also existed at the end of the year and the number of funds existing at the end of that year.

There are various reasons for analyzing the Spanish investment fund market. As mentioned in the introduction, one of these is the issue of "data snooping," which involves avoiding over-analyzing datasets. Instead, we broader the area of research by examining the previously unexplored Spanish markets. Another reason for analyzing the Spanish investment fund market is the growing significance of these products in Spain in recent years, as described in the next section.

3.2. The Mutual Fund Industry in Spain

Investment funds have been a major phenomenon in the Spanish financial market. Growth in the assets managed by Spanish funds has been among the fastest in Europe in recent years (the majority of other European markets are also young, except for the United Kingdom, Germany and France) with annual growth running at a rate of over 24%. The 2,853 currently existing Spanish funds manage assets worth 270,436€million, representing around 6.2% of all mutual funds in Europe. [8]

Mutual funds are the fourth most important instrument in Spanish private portfolios. More than 8.6 million individuals currently hold investments in Spanish funds, revealing the major impact such institutions have had on Spanish society in recent years with a net increase of 8.1 million investors since 1990.

The average number of assets managed by each Spanish fund, meanwhile, is one of the lowest in the European Union, resulting in a market in which a small number of major funds

[7] In general, attrition rates are low, especially in the early years. The highest attrition rate (6.41%) was obtained in 2002. The mortality rates follow a downward trend.

[8] Data as of November 2007.

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coexist with a plethora of small funds. This feature is indicative of the powerful influence of the leading financial groups on the market. There are in fact 114 financial groups in Spain, but the top 10 handle around 73% of the country's mutual funds.

Management companies are, of course, interested in earning management fees, and this has been the main driver behind growth in the number of Spanish investment funds. Meanwhile, the legal framework regulating the country's funds establishes ceilings on the management fees that can be charged to investors. Moreover, the favorable tax treatment of investment funds in Spain, which includes exemption for transfers between funds thereby eliminating the tax cost of such operations, is another key reason for the growth of the industry. This tax system has made investment funds into a very attractive opportunity in comparison to other forms of investment in recent years.

In the early 1990s, the Spanish funds invested mainly in domestic equities and public debt. Investment patterns have changed significantly in recent years, however, with faster growth in investment in European and US equities. Nevertheless, Spanish assets still represent the lion's share of portfolios. Table 3 reflects the rapid growth of the Spanish investment fund market in recent years, providing comparative data for the market between 1995 and 2006. We observe here that Total Net Assets (TNA) and the number of investment funds have quadrupled over the period, and that TNA/GDP (Gross Domestic Product) has almost doubled. Finally, both the number of unit holders and TNA per capita have tripled.

	1995	**2006**
TNA	€73282 mill.	€270436 mill.
Unit holders	2943714	8637781
Number of funds	751	2853
TNA/GDP (%)	16.7	27.57
Per capita TNA	1869 €	6081€

Table 3. Evolution of the Spanish Mutual Fund Market*

***Note:** Table 3 shows the evolution between 1995 and 2006 of key figures in the Spanish mutual fund market. TNA is Total Net Assets, and GDP is Gross Domestic Product.

4. EMPIRICAL RESULTS AT THE AGGREGATE LEVEL

The aim of this section is to evaluate the performance of the various methods for the correction of the bias inherent in traditional timing models as proposed in the literature. We start by reporting the results obtained by the traditional Treynor and Mazuy (1966) and Merton and Henriksson (1981) return timing models. Our purpose is to demonstrate the negative correlation between stock-picking and market timing abilities delivered by traditional timing models, and then we examine whether this negative correlation disappears when applying the different corrections proposed by literature and also when applying the model which includes the cost of the option in the Merton and Henriksson model. The results are provided at the aggregate level, i.e., for the whole the sample considered using pooled regressions.

4.1. Results Estimated by the Traditional Models

Table 4 presents the results estimated by the traditional Treynor and Mazuy return timing model (Panel A) and the Merton and Henriksson model (Panel B), as in equation (1). The table

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provides the alpha and gamma parameters, which measure the stock-picking ability of Spanish fund managers and market return timing, respectively. It also shows the beta for the model, as well as the adjusted R-squared.

All of the parameters are statistically significant at the 5% level. Overall, the Spanish domestic equity funds do exhibit the ability to time the equity market regardless of model specification. The timing coefficients across the two regressions are all positive and statistically significant at the 5% level.

Return timing of the funds is of economic significance as well. Consider the evidence from the single-factor Treynor and Mazuy model. The Spanish funds have a pooled beta of 0.723, and the pooled timing coefficient γ_{TM} is 0.244. This means that, if the timing signal forecasts a market excess return of 5% in the next month, the fund will increase market beta by about 0.0122 (= 0.244 × 0.05). Conversely, an expectation of negative market excess return would decrease the fund's market exposure, all else being equal. Results from the other model specification provide a similar impression about the economic significance of return timing. Clearly, the Spanish funds adjust market exposure to their *timing* signals in a non-trivial way.

We can also observe the economic value of timing ability from the evidence of the Merton and Henriksson model. Note that the timing term in this model, $r_m * S = max(R_m - R_f, 0)$, is equivalent to the payoff from an option. Merton (1981) shows that the value of timing ability can be calculated using the Black-Scholes formula if relevant assumptions are satisfied. Specifically, we follow Merton's assumptions on the values of the underlying stock price and strike price and find the market timing funds deliver 0.34 cents per annum from timing ability for each euro invested. [9]

Finally, we want to stress, for both models, the inverse relationship between stock-picking and timing ability, a feature already widely confirmed by the financial literature. Specifically, we may observe a negative stock-picking ability, although very close to zero (α, approximately -0.20%) and successful market timing, especially when applying the Treynor and Mazuy model, where the timing parameter γ_{TM} is as high as 24%.

In the following sub-sections of this empirical results section, we evaluate whether this negative correlation disappears when corrections proposed by literature are applied.

4.2. Results Estimated by Market Return and Volatility Timing Models

Table 5 provides the results estimated by the Busse joint volatility and return timing model (Panel A) from equation (4) and the results estimated by the joint timing model proposed in this paper (Panel B) from equation (6). The alpha coefficient indicates stock-picking ability; the gamma coefficient measures market return timing ability; and the lambda (delta) coefficient denotes market volatility timing ability in the Busse model (in the proposed measure).

All of the parameters are statistically significant at the 5% level. The alpha coefficient for both models is close to zero and is quite similar than that estimated by the traditional models. Both models also display a positive returns timing parameter (γ), which is particularly high (50%) in the case of the Busse model. Furthermore, the two models also reveal successful market volatility timing ability. [10] This is very much the case for the Busse model, where the lambda parameter is -2.21. This means that if a fund manager receives a signal where the demeaned market volatility will be in the next month but the market level is unchanged, accordingly the manager will lower the fund beta by 15.47% (= 0.07 * 2.21). We can also observe the economic value of volatility timing ability from the evidence of our proposed model. In this case, delta parameter is 0.048, which means that if a fund manager receives the same signal as the another manager, she will not change his market exposure; however if she receives another signal where

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[9]For V = 0.07 (see footnotetext 5), and for a timing coefficient 0.048 from the single-factor Merton and Herniksson regression, the added value from timing skills is 0.0034 (= 0.07 * 0.048). Of course, this value is at best an approximation, depending on the Black-Scholes conditions.

[10]The similarity between the results estimated by the Busse model and the measure proposed here confirms the correct specification of our proposal.

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Panel A: Treynor & Mazuy model			
α	β	γ_{TM}	Adjusted-R2
−0.002106 0.0000*	0.723110 0.0000*	0.243818 0.0000*	0.736487
Panel B: Merton & Henriksson model			
α	β	γ_{MH}	Adjusted-R2
−0.002276 0.0000*	0.744335 0.0000*	0.048922 0.0003*	0.735858

Table 4. Traditional Timing Models[1,2]

[1] **Note:** Table 4 shows the ability of the 180 Spanish domestic equity funds to time the market level from June 1994 to December 2006. The results are from ordinary least squares (OLS) regressions of the traditional timing models from equation (1). We consider a single-market factor model. Panel A shows the results estimated by the Treynor and Mazuy (1996) model, and Panel B shows the results estimated by the Merton and Henriksson (1981) model. Each panel reports estimated performance α, systematic risk β and the estimation of the timing parameter (γ_{TM} for the Treynor and Mazuy model and γ_{MH} for the Merton and Henriksson model). The adjusted R-squared is given in the last column. All of the parameters were obtained by means of a pooled regression. The p-value of the parameters is given in parenthesis. Standard errors are consistent with heteroskedasticity and autocorrelation problems (Newey and West, 1987).

[2] **Note:** * denotes significant at the 5% level.

the demeaned market volatility will be in the next month, other things being equal, accordingly the manager will increase the fund beta by 0.34% (=0.048 * 0.07). We may therefore conclude that, regardless of the specification considered, managers are able to be ahead of the market in terms of return and also in terms of volatility.

Our proposed measure assumes a riskier view of the manager than the Busse's measure in the sense that in our proposal the manager reacts to low volatility scenarios increasing his/her market exposure but maintains his/her position when the market volatility increases instead of reducing it as in Busse's model. This is because we consider that the manager seeks to profit from the higher volatility by getting a higher return. We can reach the same conclusion analyzing the results above. In the presence of the same volatility signal, the reaction is riskier in the case of the second manager: if the signal is positive the first manager reduces his/her exposure by 15.47%, and the second one doesn't change it; if the signal is negative the first manger increases his exposure by 15.47% and the second one by only 0.34%, given that he expects not to get big benefits in a low market volatility scenario.

Finally, note that the negative correlation between stock-picking and return timing abilities has not disappeared when considering joint timing models.

4.3. Results Estimated by Models with Public Information Variables

Data for three predetermined information variables representing the economic cycle are used to apply the conditional models represented by expression (8). Dividend yield is calculated from the dividends paid by the MSCI-Spain index in the prior twelve months divided by the current price of the index; term spread is calculated as the annualized yield spread between ten-year government bonds and the three-month interest rate on Treasury Bills; and short term interest rate is represented by the three-month interest rate on Treasury Bills. These three variables are chosen because their relevance for stock returns predictability has been proved (see Ferson and Schadt, 1996; Christopherson, Ferson, and Glassman ,1998; Cortez and Silva, 2002; and Roy and Deb, 2004).

Table 6 presents the results estimated by the conditional Treynor and Mazuy model

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Panel A: Busse's joint timing model				
α	β	γ	λ	Adjusted-R2
−0.001406	0.666075	0.501615	−2.20920	
0.0000*	0.0000∗	0.0000∗	0.0000*	0.745469
Panel B: Proposed joint timing measure				
α	β	γ	δ	Adjusted-R2
−0.002211	0.765460	0.062978	0.047681	
0.0000*	0.0000*	0.0000*	0.0000*	0.736464

Table 5. Joint Timing Models[1,2]

[1]**Note:** Table 5 shows the ability of the Spanish domestic equity funds to time the market level and volatility jointly from June 1994 to December 2006. The results are from ordinary least squares (OLS) regressions of the join timing models (4) and (6). Panel A displays the results estimated by the Busse (1999) joint timing model and Panel B the results estimated by the proposed joint timing model. Each panel reports estimated performance (α), systematic risk (β), the estimated return timing parameter (γ) and the estimated volatility timing parameter (l for the Busse model and δ for the proposed measure). We proxy market volatility by the realized volatility. The adjusted R-squared is given in the last column. All of the parameters were obtained by means of a pooled regression. The p-value of the parameters is given in parenthesis. Standard errors - Hide quoted text - are consistent with heteroskedasticity and autocorrelation problems (Newey and West, 1987).
[2]**Note:** * denotes Significant at the 5% level.

(Panel A) and those estimated by the conditional Merton and Henriksson model (Panel B). The alpha coefficient measures managers' stock-picking ability. Thus, a significant, positive alpha would indicate that the manager has made appropriate use of private information when picking the stocks to be included in the portfolio. The gamma parameter denotes conditional market timing ability. A significant, positive value for this coefficient would indicate appropriate use of private information by fund managers when timing the market in terms of return.

The table also shows the beta coefficient and the three coefficient estimates for the conditional beta function – $\beta_{DY}, \beta_{TS}, \beta_{SR}$ (associated with the dividend yield variable, the term spread variable and the short term interest rate variable, respectively). In addition, the coefficient estimates for the conditional gamma function are provided – $\gamma_{DY}, \gamma_{TS}, \gamma_{SR}$ (associated with the dividend yield variable, the term spread variable and the short term interest rate variable, respectively). Finally, the adjusted R-squared is given.

Both models display an alpha parameter very close to zero but higher than those estimated by the traditional timing models. This result is typical for mutual funds (e.g., see Ferson and Schadt, 1996), where public information can help explain the "negative" timing ability found in an unconditional model. Ferson and Warther (1996) find that a mutual fund typically experiences money inflows during a period of high expected market return based on public information. Such fund inflows reduce the fund's market exposure because the fund has to hold more cash before eventually allocating the new money to the market. Consequently, there arises a negative relationship between the expected market return and the fund's market exposure, which is consistent with negative timing ability estimated for mutual funds by an unconditional model and with better timing ability delivered by conditional models.

Gamma is positive, although it is only statistically significant when applying the Merton and Henriksson model. We, therefore, cannot draw conclusions about timing ability based on conditional Treynor and Muzy model. However, based on the conditional Merton and Henriksson model, we observe that gamma parameter is higher in this model (0.0754) than in the traditional version of the model (0.0489). We can therefore confirm that fund managers do indeed make use of superior information to anticipate movements in the market given that the conditional model removes from gamma the timing ability reached as a consequence of the manager's use of public

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information and transfers it to the dynamic gamma parameters. Consequently, gamma parameter represents only the timing ability reached by the manager's use of superior information.

Next focusing on the dynamic betas, we observe that there are two significant parameters for each model: those connected with the dividend yield (β_{DY}) and the term spread (β_{TS}) for the Treynor and Mazuy model; and those related to the dividend yield (β_{DY}) and the short term interest rate (β_{SR}) for the Merton and Henriksson model. We can therefore conclude that these variables, particularly the dividend yield, have an influence on selectivity. The results show a significant negative relation between these variables and the conditional beta, which explains why conditional alphas are higher than the unconditional ones.

In the Treynor and Mazuy model, none of the dynamic gammas are statistically significant at the 5% level. This result is not surprising, given that the average gamma (γ_{TM}) coefficient estimated by this model is not statistically significant at the 5% level. In the Merton and Henriksson model, however, the only dynamic gamma non-statistically significant at the 5% level is that associated with the term spread variable (γ_{TS}). This indicates that, as for the selectivity, the dividend yield and the short term interest rate are the two variables that influence the ability of managers to anticipate market movements. Moreover, we find a negative relationship between these two variables (γ_{DY} and γ_{SR}) and the conditional gamma (γ_{MH}), which explains why the conditional gamma is higher than the unconditional one.

Moreover, we want to stress that in both models the adjusted R-squared (0.84) is higher than in traditional models (0.74), indicating that changing information about the stance of the business cycle is relevant for managers' abilities. However, note that conditional models do not manage to remove the negative correlation between the two abilities.

4.4. Results Estimated by Models Correcting the Interim Trading Bias

Panel A of Table 7 shows the results estimated by the model proposed by Goetzmann et al. (2000) to correct the interim trading bias. Panels B and C display the results estimated by the Treynor and Mazuy model and the Merton and Henriksson model, respectively, after the inclusion of an additional regressor (Ω, the monthly average of the logarithm of the market price level) proposed by Ferson et al. (2006) and Chen and Liang (2007) to correct for the interim trading bias.

In Panel A, we observe that the alpha (-0.004519, representing stock-picking ability) and gamma (0.47438, which captures daily timing) parameters are both statistically significant at the 5% level. In this case, alpha remains close to zero. However gamma is positive and higher than in traditional models, which indicates that surely the manager is engaged in daily timing activities, and thus this is not captured in our monthly data analysis.

Panels B and C display significant timing parameters and a non-significant coefficient (Ω) for the variable controlling for interim trading. The findings of timing ability are therefore unlikely due to model misspecification. Most notable from these results is that stock-picking ability continues to be negative and significant, although it is close to zero. Furthermore, the negative correlation between selectivity and timing persists.

4.5. Results Estimated by Models Controlling for Options

Panel A of Table 8 shows the results estimated by the Merton and Henriksson model, which is modified in order to include the cost of the option implied in timing activities. All of the parameters are significant at the 5% level. Notice that the correction made to the traditional Merton and Henriksson model makes possible the elimination of the negative correlation between alpha and gamma parameters. In fact the selectivity skill (α) becomes positive and high (10.14%), while market return timing ability (γ) is also positive and very high (0.122), which demonstrates the fund managers' successful anticipation to market movements and his ability to choose the best stocks to include in his portfolio. We are, therefore, proving the need of including the cost of the option in traditional timing models in order to get well specified models with non-spurious coefficients.

Panels B and C in Table 8 display the results estimated by the model proposed by Jagannathan and Korajczyk (1986), which includes two exclusion restrictions to control for the

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Table 6. Conditional Timing Models[1,2]

Panel A: Conditional Treynor-Mazuy model									
α	β_m	γ_{TM}	β_{DY}	β_{TS}	β_{SR}	γ_{DY}	γ_{TS}	γ_{SR}	Adj-R2
−0.001604	0.705786	0.026771	−3.72822	−2.905875	−0.406124	−34.94642	−13.20249	6.672194	
(0.0000)*	(0.0000)*	(0.6684)	(0.0000)*	(0.0001)*	(0.0597)	(0.1006)	(0.0700)	(0.1131)	0.838607
Panel B: Conditional Merton-Henriksson model									
α	β_m	γ_{MH}	β_{DY}	β_{TS}	β_{SR}	γ_{DY}	γ_{TS}	γ_{SR}	Adj-R2
−0.001355	0.730903	0.075426	−3.578828	−1.680909	−0.597209	−3.143116	0.591464	−1.533433	
(0.0000)*	(0.0000)*	(0.0000)*	(0.0000)*	(0.1090)	(0.0274)*	(0.0145)*	(0.6832)	(0.0006)*	0.837548

[1]**Note:** Table 6 shows the results from ordinary least squares (OLS) regressions of the conditional versions of the Treynor and Mazuy model (Panel A) and the Merton and Henriksson model (Panel B), equation (8). The sample contains 180 Spanish domestic equity funds during the period of June 1994 to December 2006. Each panel reports the estimated conditional performance (α), the average conditional beta (β_m), the conditional estimation of return timing term (γ_{TM} for the Treynor and Mazuy model and γ_{MH} for the Merton and Henriksson model), the estimated coefficients for the conditional beta function. β_{DY}, β_{TS} and β_{SR} represent the beta coefficient associated with the dividend yield, term spread and short term interest rate variables, respectively. The Table also shows the estimated coefficients for the conditional timing function. γ_{DY}, γ_{TS}, γ_{SR} represent the gamma coefficient associated with the dividend yield, term spread and short term interest rate variables, respectively. The adjusted R-squared is given in the last column. All of the parameters were obtained using a pooled regression. The p-value of the parameters is given in parenthesis.
[2]**Note:** * denotes Significant at the 5% level. Standard errors are consistent with heteroskedasticity and autocorrelation problems (Newey and West, 1987).

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Panel A: Goetzmann et al model (2000)				
α	βm	γ		Adjusted-R2
−0.004519	0.690217	0.47438		
(0.0000)*	(0.0000)*	(0.0000)*		0.757089
Panel B: Treynor-Mazuy model including Ferson et al (2006) and Chen & Liang (2007) factor				
α	β	γ_{TM}	$\mathbf{\Omega}$	Adjusted-R2
−0.013744	0.725543	0.084556	0.001444	
(0.0001)*	(0.0000)*	(0.0002)*	(0.0887)	0.749796
Panel C: Merton-Henriksson model including Ferson et al (2006) and Chen & Liang (2007) factor				
α	β	γ_{MH}	$\mathbf{\Omega}$	Adjusted-R
−0.014265	0.735084	0.020567	0.001485	
(0.0000)*	(0.0000)*	(0.0001)*	(0.1280)	0.749751

Table 7. Timing Ability and Dynamic Trading Effect[1,2]

[1] **Note:** Table 7 presents the results from ordinary least squares (OLS) regressions of the three models proposed to solve the problem of dynamic trading bias (interim trading bias). The sample includes 180 Spanish domestic equity funds during the period of June 1994 to December 2006. Panel A reports the results from the proposal made by Goetzmann et al. (2000), equation (10),, and Panel B reports the results from the Treynor and Mazuy model with the factor proposed by Ferson et al. (2006) and Chen and Liang (2007) to correct this bias. Likewise, Panel C reports the results from the Merton and Henriksson model with the factor proposed by Ferson et al. (2006) and Chen and Liang (2007) to correct the bias. This additional factor consists of the monthly average of the logarithm of the market price level. Each panel reflects estimated performance (α), the systematic risk (β), the estimated return timing parameter (γ for the Goetzmann et al. (2000) model; γ_{TM} for the modified Treynor and Mazuy model; and γ_{MH} for the modified Merton and Henriksson model), and the adjusted R-squared. Panels B and C also show the W coefficient associated with the factor proposed by Ferson et al. (2006) and Chen and Liang (2007) to correct the dynamic trading effect. All of the parameters were obtained using a pooled regression. The p-value of the parameters is given in parenthesis.
[2] **Note:** * Significant at the 5% level. Standard errors are consistent with heteroskedasticity and autocorrelation problems (Newey and West, 1987).

nonlinearity of options payoffs. Thus, the Ω parameter represents the coefficient on $\ln(r_{m,t+1})$, and λ represents the coefficient on $1/r_{m,t+1}$. In Panel B, these nonlinear terms are included in the Treynor and Mazuy model, and Panel C provides them for the the Merton and Henriksson model.

The nonlinear terms are significant in both models, which indicate that the traditional timing models are incorrectly specified. These parameters are positive suggesting that timing ability is lower here than in the traditional models. This result is consistent with the literature intuition, which points out that a fund manager simply holding options might be misinterpreted as a market timer because of the options' nonlinear payoff. But it is not necessary to hold options; if the manager engages in "information-less investing," the portfolio payoffs can exhibit also concavity to the benchmark. Furthermore, timing ability is non-significant in the Merton and Henriksson model with option factors as can be seen in the γ_{MH} of Panel C, which is not statistically significant.

The parameter measuring stock-picking ability (α) is significant for both models, and it remains negative for the Treynor and Mazuy model with option factors (-0.006974), but it becomes positive for the Merton and Henriksson model with option factors (0.005984) Consequently, the negative correlation between selectivity and timing holds in the first model and disappears in the second one. However we want to stress the superiority of the corrected Merton and Henriksson model, proposed by Connor and Korajczyk (1991) which is shown in Table 7

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Panel A: Merton-Henriksson model including the cost of the option					
α	β	γ			Adjusted-R2
0.101445 (0.0000)*	0.775771 (0.0000)*	0.122271 (0.0000)*			0.737353
Panel B: Treynor-Mazuy model including Jagannathan & Korajczyk (1986) factors					
α	β	γ_{TM}	$\mathbf{\Omega}$	λ	Adjusted-R2
-0.006974 (0.0000)*	0.727659 (0.0000)*	0.004020 (0.0000)*	0.001375 (0.0000)*	$9.03E-06$ (0.0000)*	0.737614
Panel C: Merton-Henriksson model including Jagannathan & Korajczyk (1986) factors					
α	β	γ_{MH}	$\mathbf{\Omega}$	λ	Adjusted-R2
0.005984 (0.0050)*	0.759002 (0.0000)*	0.073422 (0.1105)	0.000997 (0.0245)*	$7.77E-06$ (0.0000)*	0.736729

Table 8. Timing Ability and Options[1,2]

[1]**Note:** Table 8 shows the results from ordinary least squares (OLS) regressions of the three models proposed to control for the options included in the fund and for option-like payoff structure assets. The sample contains 180 Spanish domestic equity funds during the period of June 1994 to December 2006. Panel A reflects the results estimated by the modified version of the Merton and Henriksson model proposed by Connor and Korajczyk (1991), which recognizes the cost of the option implied in timing activities (equation 14). Panels B and C respectively show the results estimated by the Treynor and Mazuy and Merton and Henriksson models, respectively, including the two factors proposed by Jagannathan and Koraczyk (1986) to correct the passive timing effect generated by fund assets with nonlinear payoff structures (equation 15). Each panel reflects estimated performance (α), systematic risk (β), the estimated return timing parameter (γ for the Merton and Henriksson model, including the cost of the option implied in timing activities, γ_{TM} for the Treynor and Mazuy model, which includes the exclusion restrictions proposed by Jagannathan and Korajczyk (1986), and γ_{MH} for the Merton and Henriksson model, which includes the exclusion restrictions proposed by Jagannathan and Korajczyk (1986)), as well as the adjusted R-squared. Panels B and C also include the W and l coefficients associated with the nonlinear functions of the benchmark proposed by Jagannathan and Korajczyk (1986), which is to say $\ln(r_{m,t+1})$ and $1/r_{m,t+1}$, respectively. All of the parameters were obtained using a pooled regression. The p-value of the parameters is given in parenthesis.
[2]**Note:** * denotes significant at the 5% level. Standard errors are consistent with heteroskedasticity and autocorrelation problems (Newey and West, 1987).

given that it not only removes this negative correlation but delivers significant coefficients, while in the Merton and Henriksson model including option factors from Jagannathan and Korajczyk the timing parameter is non-significant.

4.6. Results Estimated by Models Controlling for the Thin-trading Effect

Table 9 shows the results estimated from the model proposed by Chen and Liang (2007) to control for illiquid holdings, which consists of the inclusion of lagged terms of the market returns and their square terms as additional regressors, resulting in additional betas with one and two lags. The model also specifies additional gamma coefficients with one and two lags.

Stock-picking ability is again close to zero (α, -0.002822), while successful market timing is observable once more (γ, 0.286742). These results are quite similar to those obtained with the traditional model. Furthermore, we observe that the estimate of contemporaneous timing ability is still significantly different from zero, although the second lagged market return and its square term pick up some explanatory power. This seems to suggest a certain level of thin trading with the timing funds, but the extent of thinness does not severely affect the inference

Treynor-Mazuy model including Chen & Liang (2007) factors							
α	β	γ	β	γ	β"	γ"	Adjusted-R2
−0.002822	0.719453	0.286742	−0.003348	−0.557805	0.048762	0.610592	0.748641
(0.0000)∗	(0.0000)∗	(0.0000)∗	(0.3952)	(0.3058)	(0.0000)∗	(0.0000)∗	

Table 9. Timing Ability and Thin-trading effect[1,2]

[1]**Note:** Table 9 presents the results from ordinary least squares (OLS) regressions of the modified version of the Treynor and Mazuy model including the factors proposed by Chen and Liang (2007) to correct the thin trading effect (equation 19). These factors consist of two lagged market returns and their square terms. The sample includes 180 Spanish domestic equity funds during the period of June 1994 to December 2006. The table reflects the estimated performance α, the systematic risk β , the estimated return timing parameter γ , and the adjusted R-squared. It also shows the beta parameter with one and two lags (β' and β") and the timing parameter with one and two lags (γ' and γ"). All of the parameters were obtained using a pooled regression. The p-value of the parameters is given in parenthesis.

[2]**Note:** * denotes Significant at the 5% level. Standard errors are consistent with heteroskedasticity and autocorrelation problems (Newey and West, 1987).

about their timing skills. Finally, note that the negative relation between selectivity and timing has not disappeared.

4.7. Results Estimated by Models Controlling for Changes in Market Conditions

Panel A of Table 10 displays the results estimated by the Treynor and Mazuy model for bull and bear market scenarios. [11] We observe that return timing (γ_{TM}) is more apparent during bear markets than during bull markets. In bear markets, the timing coefficient is 1.44 and significant, while it is -1.159 for bull markets. This result is as expected given that is easier for the manager to beat a bear market. Stock-picking ability (α) is close to zero for both scenarios, although it is slightly positive when the market gets gains (0.002391) and slightly negative (-0.003975) in the case of losses. The negative relation between selectivity and timing appears again in both scenarios.

Panel B of Table 10 reports the results estimated by the Busse model measuring volatility timing both for a volatile scenario and for stable market conditions.[12] We find that volatility timing is significant in volatile market states and negative (λ, -6.52135), indicating successful ability because the manager reduces his market exposure when it becomes more volatile. Stock-picking ability is negative but close to zero (α, -0.001329) in high volatile scenarios, and it is and positive, although close to zero (α, 0.000513), in less volatile conditions. [13] We therefore can conclude that timing ability appears especially strong during bear markets or when the market is more volatile, suggesting that the Spanish fund provide investors with protection against unfavorable market states.

Finally, Panel C of Table 10 reports the results estimated by the Busse volatility and return timing model for high and low performance scenarios, as indicated by the Sharpe ratio. We see that there is no evidence of difference in return and volatility timing between the high Sharpe ratio and the low Sharpe ratio states, as neither the gamma nor the lambda parameters are statistically significant at the 5% level. Selectivity is significant and close to zero in both states.[14]

[11]This analysis has not been performed for the Merton and Henriksson model, because given its specification, it makes no sense to apply it for a bear market scenario.

[12]This model is obtained on the basis of expression (3), but eliminating the third term on the right side, which represents the fund manager's return timing ability.

[13]Results are similar when the measure (4) of volatility timing proposed in this paper is applied. These results are not given here for reasons of space, although they are available to interested readers upon request.

[14]The results estimated by measure (5) of volatility and return timing, proposed in this paper, are very similar.

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Panel A: Treynor & Mazuy model				
Bull Market				
α	β	γ_{TM}		Adjusted-R2
0.002391	0.568487	-1.158598		0.511268
(0.0000)*	(0.0000)*	(0.3400)		
Bear Market				
α	β	γ_{TM}		Adjusted-R2
-0.003975	0.732913	1.437012		0.596829
(0.0000)*	(0.0000)*	(0.0020)*		
Panel B: Busse's volatility timing model				
Volatile Market				
α	β	λ		Adjusted-R2
-0.001329	0.594484	-6.52135		0.755964
(0.0003)*	(0.0000)*	(0.0000)*		
Stable Market				
α	β	λ		Adjusted-R2
0.000513	0.669631	3.304975		0.681249
(0.0077)*	(0.0000)*	(0.1959)		
Panel C: Busse's joint timing model				
High Sharpe Ratio Market				
α	β	γ	λ	Adjusted-R2
0.001047	0.716392	1.381635	3.98206	0.527146
(0.0236)*	(0.0000)*	(0.0511)	(0.0800)	
Low Sharpe Ratio Market				
α	β	γ	λ	Adjusted-R2
-0.007255	0.600860	1.018421	3.04780	0.628688
(0.0000)*	(0.0000)*	(0.0550)	(0.4721)	

Table 10. Timing Ability in Different Market *Conditions*[1,2]

[1]**Note:** Table 10 presents the results from ordinary least squares (OLS) regressions of the Treynor and Mazuy model (equation 1) for both bull and bear market scenarios (Panel A), the Busse (1999) volatility timing model for volatile and stable market scenarios (Panel B), and the Busse (1999) joint timing model (equation 44) for high and low performance scenarios (Panel C). The sample includes 180 Spanish domestic equity funds during the period of June 1994 to December 2006. Each panel reports estimated performance α, the systematic risk β), and the adjusted R-squared. Panels A and C show the estimated return timing parameter γ_{TM} for the Treynor and Mazuy model and g for the Busse joint timing model). Panels B and C show the estimated volatility timing parameter (λ). All of the parameters were obtained using a pooled regression. The p-value of the parameters is given in parenthesis.
[2]**Note:** * denotes Significant at the 5% level. Standard errors are consistent with heteroskedasticity and autocorrelation problems (Newey and West, 1987).

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In a high Sharpe ratio framework, the negative correlation between both abilities disappears, but this result lacks interest because the timing parameter is non-significant.

All the findings are summarized in the figure 1, which highlights the superiority of the model including the option cost in the Merton and Henriksson model.

5. CONCLUSIONS

This paper takes the traditional timing models of Treynor and Mazuy (1966) and Merton and Henriksson (1981) as its starting point, focusing on the frequent results evidenced by the financial literature suggesting that the traditional models are affected by a series of biases that generate spurious coefficients. These results indicate the existence of a negative correlation between timing and stock-picking, which is counterintuitive because it is difficult to imagine a fund manager who is skilled at picking the right stock but is not able to anticipate correct stock market movement and vice versa .

Taking this idea as starting point, the aim of this paper is to bring together all the proposals of correction of traditional timing models addressed by literature and to propose alternative corrections in order to overcome this negative correlation between both abilities. To do this, we conduct an empirical analysis using a Spanish sample of equity funds in order to analyze whether these proposals manage to overcome this situation. Each one of the proposals of correction focuses on a different weak spot of traditional timing models that has been identified by the literature.

In this sense, the first bias analyzed in this paper is related with the failure of the traditional models to consider the reaction of fund managers in the face of changes in market volatility. We consider the Busse volatility timing model as a proposal of correction of this bias, and we also propose an alternative model, which takes a riskier view of the manager.

The second bias consists of the failure of the traditional models to not take account of shifts in investors' expectations due to changes in the available information concerning the economic cycle. The third bias analyzed in this paper refers to the dynamic trading or interim trading effect, i.e., the underestimation of return timing measures when funds follow timing strategies and trade between the observation dates.

The next bias examined in the paper is related with the option implied in timing activities. Both the Treynor and Mazuy and the Merton and Henriksson models are option motivated in that both rest on the notion of nonlinear payoff structures, and timing ability as considered by these models may be understood as a free option. This implies that a positive (negative) timing coefficient in the Merton and Henriksson model is equivalent to the purchase (sale) of a market put option without paying (receiving) the price. Hence, the decrease (increase) in the return from the cash paid (obtained) for the purchase (from the sale) of the option will show up as a negative (positive) alpha coefficient. Thus, a negative correlation will be observed between timing and stock-picking measures where funds include options, or option-like instruments, in their portfolios. Then, following Connor and Korajczyk (1991) we include the cost of the option in the timing models.

We also seek to correct the passive timing effect, continuing with the concept of the option implied in timing activities. The returns on a passive portfolio investing in assets with an option-like payoff structure (for example, equity in a leveraged company) may have a convex or concave relation with market returns, even where the fund manager does not follow any timing strategies.

The next bias considered in the study is the *thin-trading effect*, i.e., systematic thin trading may generate spurious evidence of timing ability. This results in systematic stale pricing of assets, creating a spurious concavity or convexity.

These results are not given here for reasons of space, they are available to interested readers on request.

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Model	Table	Description	Selectivity (Alpha)	Return Timing (Gamma)	Volatility Timing (Lambda, Delta)	Relation Alpha-Gamma
Treynor-Mazuy	4	return timing model (traditional)	negative	positive		negative
Proposed joint timing	4	return timing model (traditional)	negative	positive		negative
Busse joint timing	5	return+volatility timing model	negative	positive	negative-successful	negative
Proposed joint timing	5	return+volatility timing model	negative	positive	positive-successful	negative
Conditional Treynor-Mazuy	6	includes public information	negative	non-significant		
Conditional Merton-Henriksson	6	includes public information	negative	positive		negative
Goetzmann et al	7	controls for dynamic trading effect	negative	positive		negative
TM with Ferson et al and Chen & Liang factors	7	controls for dynamic trading effect	non significant			
MH with Ferson et al and Chen & Liang factors	7	controls for dynamic trading effect	non significant			
MH with option cost	8	controls for the option cost	positive	positive		positive
TM with Jagannathan & Korajczyk factors	8	controls for options	negative	positive		negative
MH with Jagannathan & Korajczyk factors	8	controls for options	positive	non-significant		
TM with Chen & Liang factors	9	control for thin-trading effect	negative	positive		negative
TM bull market	10	controls for market conditions	positive	non-significant		
TM bear market	10	controls for market conditions	negative	positive		negative
Busse volatile market	10	controls for market conditions	negative		negative-successful	
Busse stable market	10	controls for market conditions	positive		non-significant	
Busse High Sharpe Ratio market	10	controls for market conditions	positive	non-significant	non-significant	
Busse Low Sharpe Ratio market	10	controls for market conditions	negative	non-significant	non-significant	

Table 11. Summary Findings from the Different Models[1].

[1] **Note:** This table reports a comparison between the findings from the different models considered in the paper. The two first rows refer to the traditional timing models, and the rest of the rows refer to different proposals made by literature in order to improve the traditional models. Rows 4 and 10 refer to models proposed here. Column 1 identifies the model; column 2 contains the number of table where the findings of the model are reported. In the third column it is shown a description of the model. Columns 4 and 5 indicate whether the manager has a positive (successful), negative (perverse) or non-significant selectivity and return timing ability, respectively. Column 6 shows whether the manager has a successful, perverse or non-significant volatility timing ability. Finally column 7 shows the sign of the relationship between selectivity and return timing abilities. From this table, we can conclude that the only model that manages to remove the negative relation between both abilities existing in traditional model is the model including the cost of the option in MH model.

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Finally, we look at the bias caused in traditional timing models by changes in market conditions. We assume that investment fund managers may receive a variety of different timing signals ahead of the different market conditions. An inverse relationship between timing and stock-picking is observed for the traditional models, as noted in the introduction to this paper. As explained in the literature, this inverse relationship is indicative of the possible existence of bias in the traditional timing models. However, when the proposed bias corrections are applied, we find that the negative correlation between timing and stock-picking ability does not disappear except for the Merton and Henriksson model including the cost of the option, which demonstrates this model is subject to the least bias in testing the timing ability of managers.

In general, our results indicate that the stock picking ability of the Spanish fund managers is not evident, but that they display positive market return timing ability and successful volatility timing ability. We therefore can conclude that timing ability generates significant economic value to investors, and this finding is robust to alternative explanations, including public-information-based strategies, options trading, illiquid holdings.

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