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ORIGINAL ARTICLE

The market timing ability of bond mutual funds

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Abstract

We apply the nonparametric methodology of Jiang (Journal of Empirical Finance 10:399–425, 2003) to examine whether bond mutual funds can time the bond market by adjusting their portfolios' market exposure based on anticipated market movement. This approach offers several advantages over the widely used regression-based tests such as Treynor and Mazuy (Harvard Business Review 44(4):131–136, 1966) and Henriksson and Merton (The Journal of Business 54(4):513–533, 1981). In a comprehensive study covering the USA, UK, and China, we find some evidence of positive market timing of bond funds at the individual fund level. On average, bond funds show neutral to slightly negative market timing abilities. After controlling for public information, we find that a smaller number of bond funds successfully time the market based on private timing signals. In terms of categories, we find strong evidence of positive market timing for Government bond funds as a group, consistent with the findings of Huang and Wang (Management Science 60:2091–2109, 2014).

Keywords Mutual fund performance · Bond funds · Market timing · Nonparametric test

JEL Classification G11 · G12 · G15 · G23

Introduction

There is an extensive established literature evaluating the performance of mutual funds. A central debate in the mutual fund literature is whether funds truly add value to investors by generating abnormal returns. Several studies have examined fund performance attributable to two abilities: security selection and market timing. The former refers to using security-specific information to pick individual securities, while the latter refers to changes in the portfolio composition in anticipation of aggregate market movements.

On market timing, the timing ability of equity mutual funds has been extensively discussed in the literature (Treynor and Mazuy 1966; Henriksson and Merton 1981; Chang and Lewellen 1984; Admati et al. 1986; Graham and Harvey 1996; Ferson and Schadt 1996; Bollen and Busse 2001; Jiang et al. 2007). However, significantly less work has been undertaken on the timing ability of bond mutual funds, although bond funds account for a large part of many investors' portfolios. When approaching retirement, many investment experts suggest shifting a substantial portion of an individual's portfolio into bond funds. Investment in bond mutual funds has grown from $2.6 trillion in 2010 to $5.2 trillion in 2020 due to net inflows from investors according to Collins and Antoniewicz (2021). With the increasing number of active bond mutual funds, it is important to understand the timing performance of bond funds since investors are allocating their resources to such funds to save for the future. Further study of bond fund timing performance is warranted given their economic importance.

Studies have shown that bond mutual funds underperform index benchmarks in risk-adjusted terms (e.g., Blake et al. 1993; Ferson et al. 2006), suggesting poor security selection by bond fund managers. Thus, investors may instead gain value from the active management of bond fund managers through their timing abilities rather than asset selection skills. The majority of studies indicate that equity mutual funds lack market timing ability. However, a small but growing literature (Chen et al. 2010; Cici and Gibson 2012; Huang and Wang 2014; Moneta 2015) suggests that some groups of bond fund managers exhibit market timing skills, specifically when portfolio-holding data and appropriate extensions of traditional timing models are employed.

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Market timing strategy often involves either tactical asset allocation that allocates money among different asset classes or rotating a fund's holdings to change the fund's market exposure (beta) in response to the anticipated market movement. Accordingly, market timing can be measured using either a holdings-based or return-based method. In this paper, we apply the nonparametric procedure of Jiang (2003) to examine the market timing ability of bond mutual funds. Its main advantage over traditional parametric (regression-based) return-based approaches is that the nonparametric approach separates the quality of private information (ability) from the aggressiveness of the fund manager's response. An investor is more interested in the quality of timing information because investors can adjust the aggressiveness of managed portfolios on their own account, and the value added by portfolio managers depends on the accuracy of the timing information they provide.

In this paper, we undertake a comprehensive investigation of bond mutual funds' market timing ability in the USA, UK, and China. We select these different markets for an interesting comparison of results. This paper distinguishes itself from previous literature in the following four ways. First, we are the first to apply a set of nonparametric tests to examine the market timing ability of bond funds in the USA, UK, and China. To our knowledge, the Jiang (2003) nonparametric market timing test has never been previously applied to the open-ended bond mutual fund industry in the USA, UK, and China. This is also the first paper to test the market timing ability of bond funds in the UK and China. Second, our paper is more comprehensive in terms of the sample length and size. We examine a total of over 2000 bond funds (including dead funds to avoid survivorship bias) from the USA, the UK, and China. The period covered by this study is one of the longest in the field, with over 30 years of data. Third, using sub-group analysis, we examine the difference in timing skills between funds with different investment styles and locations. Finally, conditional market timing performance is examined to investigate the private timing ability of fund managers.

This paper is organized as follows: Section "Literature review" briefly reviews the existing literature related to market timing. Section "Methodology" outlines the nonparametric testing methodology. The data and the empirical results are reported in Section "Data" and Section "Empirical results," respectively. Section "Conclusion" concludes.

Literature review

The majority of empirical evidence on US equity mutual funds shows zero market timing or perverse negative market timing (Becker et al. 1999; Ferson and Schadt 1996; Goetzmann et al. 2000; Wermers 2000; Jiang 2003)[1]. Bond mutual funds' market timing is rarely investigated despite their growing importance in investor portfolios. Bond timing studies employ performance models and testing methods similar to those used in equity fund studies.

Market timing can be measured using either a holdings-based or return-based method. The former method measures whether fund managers increase returns during a rising market (minimize loss during a market downturn) by allocating money among different assets (Grinblatt and Titman 1989; Graham and Harvey 1996; Daniel et al. 1997; Wermers 2000; Jiang et al. 2007). By comparing mutual fund portfolio composition with observed returns at the same frequency, we can examine whether portfolio holdings anticipate moves in the market and infer the fund's market timing ability. For example, Graham and Harvey (1996) study market timing empirically using asset allocation recommendations from investment newsletters. Using observed mutual fund holding data, Jiang et al. (2007) estimate the beta of a mutual fund as the weighted average of the betas of individual stocks in its portfolio and measure whether the fund's beta at the beginning of a holding period is significantly associated with the holding period market return.

A few recent papers use portfolio holdings to study bond mutual fund performance and find some evidence of positive market timing for various groups of bond mutual funds. Adapting the methodology of Wermers (2000) applied to equity funds, Cici and Gibson (2012) use the holdings of corporate bonds to examine whether fund managers could time bond characteristics such as credit rating. They find neutral to weakly positive evidence of characteristic timing. Huang and Wang (2014) use the measure of Jiang et al. (2007) and holdings of Treasury securities to examine the market timing ability of a sample of government bond funds. They provide evidence of some positive timing ability for government bond funds but only at the one-month forecasting horizon. Using the approach of Daniel et al. (1997), Moneta (2015) uses asset class weights (rather than individual security weights) to decompose the mutual fund returns into characteristic timing and selectivity components. The holdings-based approach has advantages over returns-based analyses because it avoids the bias caused by the nonlinearities and option-like characteristics of bond funds. The author finds evidence of a neutral ability to time different portfolio allocations (sector, credit quality, and portfolio maturity allocations), and only multi-asset bond funds exhibit successful timing ability by rebalancing a portfolio across different asset classes.

[1] Bollen and Busse (2001) and Jiang et al. (2007), however, find supportive evidence of market return timing ability in mutual funds by using daily return data and portfolio holding data, respectively, which indicates that timing results may be affected by the frequency or type of data.

Alternatively, the return-based method measures whether a fund's beta is conditional on a benchmark portfolio, which requires only information about the fund’s ex-post return and the returns of the relevant market benchmark. The two well-established regression-based models along this line are proposed by Treynor and Mazuy (1966) (henceforth, TM) and Henriksson and Merton (1981) (henceforth, HM).

Most of the work on timing performance extends these two models into a multi-factor framework (including their conditional versions in some cases). Boney et al. (2009) apply the HM models with the quadratic programming technique pioneered by Sharpe (1992) to test the market timing performance of corporate bond funds focusing on the investment-grade securities market. They find strong evidence of perverse negative market timing ability of these corporate bonds–fund managers tend to allocate more to cash when investment grade bonds of all maturities outperform the Treasury bills. After controlling for nontiming-related nonlinearity in the TM framework, Chen et al. (2010) examine whether bond funds have the ability to time nine common factors associated with the bond market. The cross-sectional distribution of the timing coefficient is neutral to slightly positive at the individual fund level. However, many funds with significantly positive timing on a before-cost basis appear significantly negative after taking transaction costs into account. Clare et al. (2019) apply the TM model to test the market timing performance of individual US bond mutual funds using both gross returns and net returns. Although there are a number of statistically positive market timers among intermediate-term and long-term funds, they find perverse timing ability of bond mutual funds on average, where the number of significantly negative timers is greater than significantly positive ones, and the mean value of timing statistics is negative.

There are several weaknesses with the TM and HM tests. Breen et al. (1986) find that the HM regression may exhibit heteroscedasticity. Jagannathan and Korajczyk (1986) and Goetzmann et al. (2000) show the bias of HM measures because of skewness. Ignoring these issues may lead to rejecting the true null hypothesis of no market timing or accepting the false null hypothesis.

In addition, the TM and HM tests fail to distinguish abnormal performance attributed to market timing from performance due to security selection skills (Admati et al. 1986; Grinblatt and Titman 1989) since selectivity skills and market timing are negatively correlated (Jagannathan and Korajczyk 1986; Coggin et al. 1993; Goetzmann et al. 2000; Jiang 2003). Jagannathan and Korajczyk (1986) suggest that such an artificial negative correlation might be attributed to nonlinear payoff structures in options and option-like securities in fund portfolios. Jiang (2003) reports simulation results showing a significant negative correlation between the selectivity measures and the TM and HM models' timing measures. The negative correlation between timing estimates and selectivity may also be due to negatively correlated sampling errors (Coggin et al. 1993).

Another specification issue is that the standard parametric timing tests (i.e., the TM and HM tests) may be biased if the data sampling frequency differs from the actual timing frequency of funds. Goetzmann et al. (2000) find that the monthly HM measure displays a significant downward bias when used to assess daily timers, and a significant component of timing skills is mistakenly credited to selectivity skills. Additionally, they provide an adjustment model for the bias without relying on daily fund information. Bollen and Busse (2001) show that TH and HM timing tests are sensitive to the frequency of observed return data. Standard return-based methods based on daily return data produce a greater number of significant estimates compared to monthly return data. Ferson and Khang (2002) suggest using portfolio weights with conditional information to address interim trading bias in returns-based measures when managers trade between observation dates and expect returns to vary over time.

The nonparametric return-based approach of Jiang (2003) addresses specification issues in parametric tests discussed above, based on the simple idea that a successful market timer's fund rises significantly in a bull market and falls slightly in a bear market. The nonparametric method has the following advantages: (i) fund managers' timing information is separated from the aggressiveness of their response to the information as the test statistic is not affected by managers' risk aversion; (ii) the result is robust and accurate in terms of the test statistic and standard error (even for small sample size) as its asymptotic distribution is unaffected by heteroscedasticity or skewness; (iii) the nonparametric method distinguishes the timing measure from selectivity measures as there is little correlation between the two estimates; (iv) the nonparametric measure is more robust than regression-based method when there are differences between timing frequency and sampling frequency because it does not rely on a regression that requires all variables measured at the right frequency. The nonparametric analysis, however, has its limitations. The model does not address two common situations in market timing: (i) maintaining overweight positions and (ii) limiting the aggressiveness of funds regardless of the manager's belief.

Methodology

Nonparametric market timing

Jiang (2003) proposes a nonparametric method for testing mutual funds' timing ability because of the difficulties in the above parametric market timing tests. The nonparametric method has been applied to equity mutual funds across countries, e.g., the USA (Jiang 2003), the UK (Cuthbertson et al. 2010), and China (Sherman et al. 2017). Here, for the first time, we extend the nonparametric method to bond mutual funds to examine whether bond mutual fund managers time the bond market return. The single-factor model (CAPM) of bond fund returns is:

$$r_{i,t+1} = \alpha_i + \beta_{i,t} r_{m,t+1} + \varepsilon_{i,t+1} \tag{1}$$

where $r_{i,t+1}$ is the expected excess return on fund i and $r_{m,t+1}$ represents the expected market excess return. α_i measures the return attributed to security selectivity, assuming that the fund manager's timing ability is independent of security selection skills. The fund beta, $\beta_{i,t}$ is assumed to vary with the information that fund managers possess at time t. The successful market timer is signaled by correctly anticipating market movements.

Let $\hat{r}_{m,t+1} = E\left(r_{m,t+1}|I_t\right)$ be the manager forecast for the time t + 1 based on the information set (both public and private) I_t at time t. The parameter v, which measures the time information, is defined as:

$$\begin{aligned} v &= \Pr(\hat{r}_{m,t_2+1} > \hat{r}_{m,t_1+1}|r_{m,t_2+1} > r_{m,t_1+1}) - \Pr(\hat{r}_{m,t_2+1} < \hat{r}_{m,t_1+1}|r_{m,t_2+1} > r_{m,t_1+1}) \\ &= 2\Pr(\hat{r}_{m,t_2+1} > \hat{r}_{m,t_1+1}|r_{m,t_2+1} > r_{m,t_1+1}) - 1 \end{aligned} \tag{2}$$

The parameter v is equal to zero if no market timing ability exists since the probability of correct prediction offsets the probability of incorrect prediction. Therefore, $v \in [-1, 1]$ represents the timing ability, where $v = -1$ represents perfectly negative (i.e., false) market timing and $v = 1$ indicates perfectly positive (i.e., successful) market timing.

The next step connects the manager's prediction of the market return $\left(\hat{r}_{m,t+1}\right)$ with their response $\left(\beta_{i,t}\right)$. Here, the beta reflects both the precision of the forecast and the aggressiveness of the manager's response to informed information. Grinblatt and Titman (1989) suggest that fund managers with independent timing and selectivity information and nonincreasing absolute risk aversion would increase the market exposure, β_t, when the market return is favorable, that is, $\frac{\partial \beta_t}{\partial \hat{r}_{m,t+1}} > 0$.[2] Combining the information, $\frac{\partial \beta_t}{\partial \hat{r}_{m,t+1}} > 0$, Eq. (2) becomes:

$$v = 2 * \Pr\left(\beta_{t2} > \beta_{t1}|r_{m,t_2+1} > r_{m,t_1+1}\right) - 1 \tag{3}$$

For any trio of observations of market return sampled from any three periods where $r_{m,t_1} < r_{m,t_2} < r_{m,t_3}$, in scale, an informed market timer should keep the average beta at a higher level over the $\left[r_{m,t_2}, r_{m,t_3}\right]$ range than the $\left[r_{m,t_1}, r_{m,t_2}\right]$ range. The nonparametric beta estimates for these two ranges are $\beta_{t_1} = \left(r_{i,t_2} - r_{i,t_1}\right)/\left(r_{m,t_2} - r_{m,t_1}\right)$ and $\beta_{t_2} = \left(r_{i,t_3} - r_{i,t_2}\right)/\left(r_{m,t_3} - r_{m,t_2}\right)$, thus yielding a convex relationship between the fund and market return:

$$\frac{r_{i,t_3} - r_{i,t_2}}{r_{m,t_3} - r_{m,t_2}} > \frac{r_{i,t_2} - r_{i,t_1}}{r_{m,t_2} - r_{m,t_1}}$$

Assume θ measures the probability that fund returns hold a convex relationship with market returns:

$$\theta = 2 * \Pr\left(\frac{r_{i,t_3} - r_{i,t_2}}{r_{m,t_3} - r_{m,t_2}} > \frac{r_{i,t_2} - r_{i,t_1}}{r_{m,t_2} - r_{m,t_1}}\right) - 1 \tag{4}$$

Here, θ is a valid proxy for v, and superior timing information $v > 0$ is approximately equal to $\theta > 0$. That is, the probability that the manager adjusts the fund's exposure to the market in the correct direction is greater than zero. θ mainly reflects probability rather than the magnitude, which separates the information quality (related to probability) from risk aversion (related to magnitude).

The sample statistic of θ is constructed as:

$$\hat{\theta}_n = \binom{n}{3}^{-1} \sum_{r_{m,t_1} < r_{m,t_2} < r_{m,t_3}} \operatorname{sign}\left(\frac{r_{i,t_3} - r_{i,t_2}}{r_{m,t_3} - r_{m,t_2}} > \frac{r_{i,t_2} - r_{i,t_1}}{r_{m,t_2} - r_{m,t_1}}\right) \tag{5}$$

The sample statistic is a U-statistic with the kernel of order three. $\hat{\theta}_n$ is a $\sqrt{n}$-consistent and asymptotically normal estimator for θ. Therefore, $\sqrt{n}\left(\hat{\theta}_n - \theta\right) \rightarrow N\left(0, \sigma^2_{\hat{\theta}_n}\right)$. $\hat{\theta}$ is

[2] The nonparametric analysis does not account for the following two scenarios of market timing. First, this model only considers an increase in β as indicative of market timing, while it ignores a decrease in β. Second, it does not address scenarios where β remains unchanged. A manager who maintains their β greater than 1 (indicating positive expectations) or less than 1 (indicating negative expectations) can still be making a market timing decision. We thank an anonymous referee for highlighting these points.

the least variance estimator for the population coefficient θ in the set of all unbiased estimators.

The kernel function of $\hat{\theta}_n$ is defined as:

where $[r_{m,t+1}]^{+}$ is defined as $\max(0, r_{m,t+1})$, which is interpreted as the payoff to a call option on the market portfolio with the exercise price equal to the risk-free rate.

$$h(z_{t_1}, z_{t_2}, z_{t_3}) = \operatorname{sign}\left(\frac{r_{i,t_3}-r_{i,t_2}}{r_{m,t_3}-r_{m,t_2}} > \frac{r_{i,t_2}-r_{i,t_1}}{r_{m,t_2}-r_{m,t_1}} \middle| r_{m,t_1} < r_{m,t_2} < r_{m,t_3}\right) \tag{6}$$

A consistent estimator of the standard error, $\hat{\sigma}_{\hat{\theta}_n}$, is defined as follows (Abrevaya and Jiang 2005):

$$\hat{\sigma}^2_{\hat{\theta}_n} = \frac{9}{n}\sum_{t_1=1}^{n}\left(\binom{n}{2}^{-1}\sum_{t_2,t_3} h(z_{t_1}, z_{t_2}, z_{t_3}) - \hat{\theta}_n\right)^2 \tag{7}$$

Abrevaya and Jiang (2005) show that the size of the test is very accurate when using the asymptotic formula for large sample sizes.

Generally, timing measures suffer from biases due to the difference between timing frequency and sampling frequency. Goetzmann et al. (2000) show that using the HM measure, the evaluation of daily timers at the monthly frequency is severely biased downward. Jiang (2003) examines the issue of measuring returns at a monthly frequency when the true timing frequency is unknown, which can be daily or weekly. The author simulates the monthly returns of a daily timer and a monthly timer using nine combinations of information quality and manager aggressiveness. The simulation shows the coefficients for the daily timer and the monthly timer have the same sign and similar magnitude. Therefore, the results of nonparametric measures are still accurate when the timing frequency and sample frequency are different.

The TM and HM models

As Jiang (2003) suggested, we also apply the widely used regression-based models, i.e., TM and HM models, to examine market timing for comparison. Compared with the nonparametric method, the TM and HM measures reflect both the quality and aggressiveness of market timing. This would provide a complete picture of fund managers' market timing performance.

Treynor and Mazuy (1966) specify a conditional beta model of market timing as:

$$r_{i,t+1} = \alpha_i + \beta_1 r_{m,t+1} + \gamma_1 (r_{m,t+1})^2 + \varepsilon_{i,t+1} \tag{8}$$

Henriksson and Merton (1981) specify the market timing regression as:

$$r_{i,t+1} = \alpha_i + \beta_1 r_{m,t+1} + \gamma_2 [r_{m,t+1}]^{+} + \varepsilon_{i,t+1} \tag{9}$$

A positive and significant γ_1 and γ_2 may be interpreted as timing ability for market return. A fund manager successfully times the market return by increasing the market beta when the market return is expected to increase in the next period.

Conditional nonparametric market timing

The literature on conditional performance highlights the importance of distinguishing performance attributable to publicly available information from performance due to private information (Ferson and Schadt 1996; Becker et al. 1999; Ferson and Khang 2002). It is natural to ask whether fund managers can time the market after taking public information into account, i.e., private timing ability that is superior to timing ability attributable to publicly available information.

The nonparametric measure can be extended to a conditional market timing test. We calculate the residuals from the regression of market returns on lagged public information (instrumental) variables as well as the residuals from the regression of fund returns on the instrumental variables. These public information variables include (i) the short-term interest rate, (ii) the monthly dividend yield of the overall stock market index,; (iii) term spread, (iv) the quality/default spread in the corporate bond market, and (v) the monthly bond-to-equity return ratio. All these variables have a one-month lag.

These residuals represent the variation of the market returns and fund returns not explained by available public information. The nonparametric test statistic is then applied to the market and fund returns residuals, yielding a conditional nonparametric timing measure.

$$\tilde{\theta}_n = \binom{n}{3}^{-1}\sum_{\tilde{r}_{m,t_1} < \tilde{r}_{m,t_2} < \tilde{r}_{m,t_3}} \operatorname{sign}\left(\frac{\tilde{r}_{i,t_3}-\tilde{r}_{i,t_2}}{\tilde{r}_{m,t_3}-\tilde{r}_{m,t_2}} > \frac{\tilde{r}_{i,t_2}-\tilde{r}_{i,t_1}}{\tilde{r}_{m,t_2}-\tilde{r}_{m,t_1}}\right) \tag{10}$$

Table 1 Definition of bond fund categories

	Bond fund definitions
USA	
Corporate bond	Corporate bond portfolios concentrate on investment-grade bonds issued by corporations in US dollars, which tend to have more credit risk than government or agency-backed bonds.
High-Yield bond	High-yield bond portfolios concentrate on lower-quality bonds, which are riskier than those of higher-quality companies. These portfolios generally offer higher yields than other types of portfolios, but they are also more vulnerable to economic and credit risk. These portfolios primarily invest in US high-income debt securities where at least 65% or more of bond assets are not rated or are rated by a major agency.
Mortgage-Backed bond	Mortgage-backed portfolios invest the majority of assets in mortgage-backed securities from a wide variety of issuers and with a wide range of maturities. These funds are exposed to both credit quality and interest rate risk, leading to both high risk and high return potential.
Inflation-Linked bond	Inflation-protected bond portfolios invest primarily in debt securities that adjust their principal values in line with the rate of inflation. These bonds can be issued by any organization, but the US Treasury is currently the largest issuer of these types of securities
Government bond	Government portfolios have at least 90% of their bond holdings invested in bonds backed by the US government or by government-linked agencies. This backing minimizes the credit risk of these portfolios, as the US government is unlikely to default on its debt.
Broad-Basket bond	Portfolios from this group focus on bond issues rated AA or higher. Typically, these funds will have exposure to both corporate and government securities. Because high-quality bonds are usually more creditworthy, the primary investment risk comes from interest-rate sensitivity
Other	Bond funds that do not fit into any of the existing sector categories.
UK	
GBP corporate bond	GBP corporate bond funds invest principally in investment grade corporate-issued bonds denominated in or hedged into GBP
GBP diversified bond	GBP diversified bond funds invest principally in investment-grade corporate and government-issued bonds denominated in or hedged into GBP. These funds do not focus on a single sector. This category includes funds investing principally in UK-domiciled issuers, global funds that invest exclusively in GBP-denominated issuance and single currency offerings that hedge all their exposure back to GBP.
GBP flexible bond	GBP flexible bond funds have the flexibility to invest across a range of bond types and can exhibit significant risk concentrations. Such concentrations may include but are not limited to, large exposures to noninvestment grade securities and some moderate exposure to emerging-markets debt. The funds are optimized for GBP-based investors but may take limited foreign currency exposure as part of their investment strategy. These funds may also use derivatives extensively to take long and short market and security-level positions; to credit, sectors, currency, or interest-rate sensitivity, though we expect them to remain directional in nature.
GBP government bond	GBP government bond funds invest principally in government or explicitly government-backed agency securities denominated in or hedged into GBP.
GBP high-yield bond	GBP high-yield bond funds invest principally in sub-investment grade securities with a credit quality equivalent to BB, or lower and denominated in or hedged into GBP.
GBP inflation-linked bond	GBP inflation-linked bond funds invest principally in inflation-linked bonds denominated in or hedged into GBP.
China	
Aggressive bond	Funds mainly invest in bonds; fixed-income investments comprise at least 80% of assets, pure-stock investments are no more than 20% of net assets, and equity-type investments are no less than 10%
Normal bond	Funds mainly invest in bonds and do not meet the criteria of short-term bond funds; fixed-income investments comprise at least 80% of assets, and equity-type investments are less than 10% of net assets and do not belong to the short-term bond category.
Pure bond	Funds invest no less than 80% of their assets into bonds, without investing in equities, convertible bonds (except pure bonds' parts of warrant bonds), or nonstandardized bonds.
Government and policy bank bond	Funds invest no less than 80% of their assets into bonds, without investing in equities, convertible bonds (except pure bonds' parts of warrant bonds), or nonstandardized bonds and invest principally in government bonds and policy bank bonds.
Corporate bond	Funds invest no less than 80% of their assets into bonds, without investing in equities, convertible bonds (except pure bonds' parts of warrant bonds), or nonstandardized bonds, and invest principally in corporate bonds, which tend to have more credit risk than government bonds or policy bank bonds
Short-term bond	Funds mainly invest in bonds and can hold only fixed-income assets with a duration of no more than 3 years.

This table presents the definitions of the bond fund categories in the USA, UK, and China

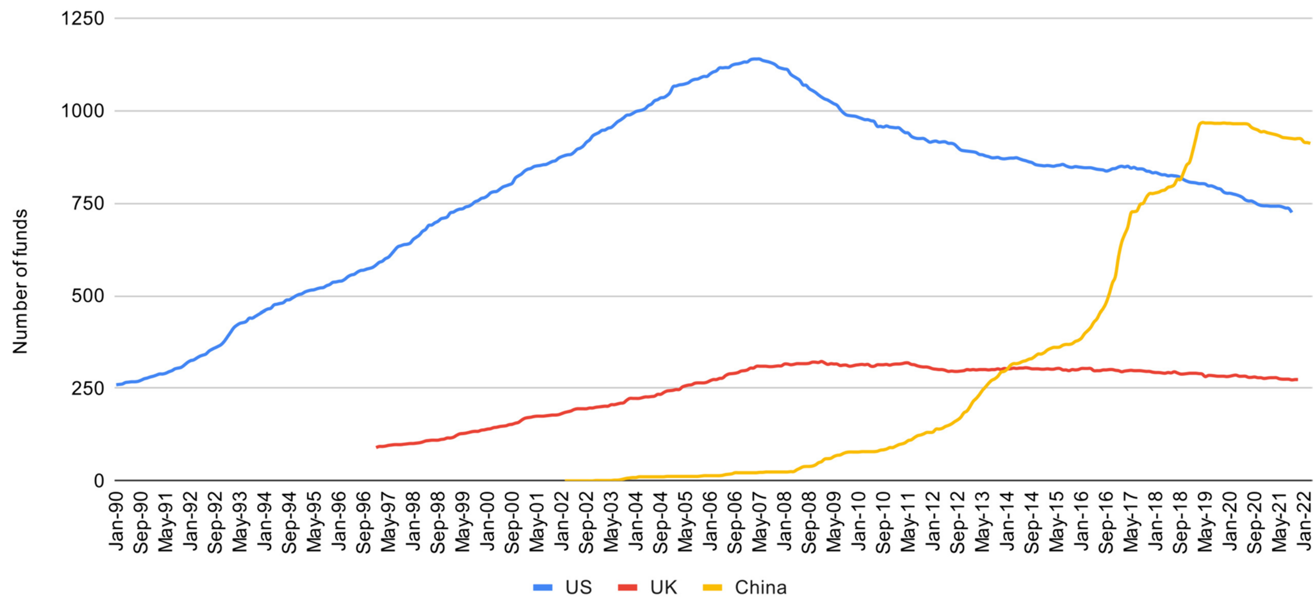

Fig. 1 The number of bond mutual funds by country. Note: This figure shows the number of bond mutual funds in each month from January 1990 to February 2022

where $\tilde{r}_{i,t}$ and $\tilde{r}_{m,t}$ are the fund return residual and market return residual, respectively, at time t. $\tilde{\theta}_n$ represents the conditional probability that fund managers increase market beta when the market return is higher, controlling for public information in both market and fund returns. $\tilde{\theta}$ in Eq. (10) may be different from $\hat{\theta}$ in Eq. (5) in terms of magnitudes or even signs because these probabilities are conditional on different assumptions. A fund with $\hat{\theta} > 0$ and $\tilde{\theta} \leq 0$ has marketing ability that is solely attributable to public information.

Data

Bond fund data

Data on bond mutual funds are from Morningstar. We remove duplicate funds by screening for the oldest share classes and exclude money market funds. Funds in the sample are required to have a minimum of 36 monthly observations. Table 1 presents the definitions of the bond fund categories in the USA, UK, and China.

Data on US bond mutual funds consist of the monthly returns on 1310 funds from January 1990 to September 2021. We exclude municipal bond funds in our US sample. Our data include both surviving funds (725) and nonsurviving funds (585) to control for survivorship bias. We group the US funds into the following seven categories, Corporate, Government, Mortgage-Backed, Inflation-Linked, Broad-Basket, High-Yield, and other funds.[3] The broad-basket category is the largest group in our sample with 503 funds. The following three categories are Corporate bond funds (268), High-Yield bond funds (221), and Government bond funds (162), respectively. These four categories account for nearly 90% of the US bond funds in our dataset. We also subcategorize funds based on their location, although all funds invest in US bonds–onshore funds are domiciled in the USA, while offshore funds are domiciled outside the USA, such as in European and Asian countries. There are 850 onshore funds and 460 offshore funds.

Data on UK bond mutual funds consist of 470 funds from January 1997 to February 2022. We select open-ended funds that declare themselves as GBP fixed-income (bond) funds. Our data include both surviving funds (249) and nonsurviving funds (221) to control for survivorship bias. These funds are grouped into the following Morningstar categories: Corporate, Diversified, Flexible, Government, High-Yield, and Inflation-Linked funds. The Corporate bond fund category is the largest group in our UK sample, with 180 funds in total. The following three categories are Diversified bond funds (120), Government bond funds (99), and Inflation-linked bond funds (43), respectively. These four categories account for nearly 95% of the UK bond funds in our dataset. We also form subgroups of bond funds based on their location, although all funds invest in sterling bonds. Onshore

[3] The broad basket funds focus on higher-quality bonds such as government or investment-grade corporate bonds. Other funds are bond funds that do not fit into any of existing sector categories.

Table 2 Bond market index

Fund group	Nobs	Benchmark index	Index source
Panel A: USA			
All funds	1310	The Bloomberg US Aggregate Index/Bloomberg US Universal Index	Morningstar
Corporate	268	The Bloomberg US Corporate Bond Index	Morningstar
High-Yield	221	The Bloomberg US Corporate High Yield Index	Morningstar
Government	162	The Bloomberg US Government Index	Morningstar
Mortgage-Backed	40	The Bloomberg US Mortgage-Backed Securities (MBS) Index	Morningstar
Inflation-Linked	40	The Bloomberg US Treasury Inflation-Protected Securities (TIPS) index	Morningstar
Broad-basket	503	The Bloomberg US Aggregate Index	Morningstar
Other	76	The Bloomberg US Aggregate Index	Morningstar
Dead funds	585	The Bloomberg US Aggregate Index	Morningstar
Live funds	725	The Bloomberg US Aggregate Index	Morningstar
Onshore funds	850	The Bloomberg US Aggregate Index	Morningstar
Offshore funds	460	The Bloomberg US Aggregate Index	Morningstar
Panel B: UK			
All funds	470	The ICE BofA Sterling Broad Market Index/Bloomberg Sterling Aggregate Bond Index	Morningstar
Corporate	180	The ICE BofA Sterling Non-Gilt Index	Morningstar
Diversified	120	The ICE BofA Sterling Broad Market Index	Morningstar
Flexible	16	The ICE BofA Sterling Broad Market Index	Morningstar
Government	99	The ICE BofA UK Gilt Index	Morningstar
High-Yield	12	The ICE BofA Sterling High-Yield Index	Morningstar
Inflation-Linked	43	The ICE BofA UK Inflation-Linked Gilt Index	Morningstar
Dead funds	221	The ICE BofA Sterling Broad Market Index	Morningstar
Live funds	249	The ICE BofA Sterling Broad Market Index	Morningstar
Onshore funds	330	The ICE BofA Sterling Broad Market Index	Morningstar
Offshore funds	140	The ICE BofA Sterling Broad Market Index	Morningstar
Panel C: China			
All funds	1001	The China Bond Composite Index/CSI aggregate bond index	Datastream
Aggressive	277	The China Bond Composite Index	Datastream
Normal	162	The China Bond Composite Index	Datastream
Pure	255	The China Bond Composite Index	Datastream
Government and policy bank	72	The S&P Government Bond Index	Datastream
Corporate	139	The S&P China Corporate Bond Index	Datastream
Short term	96	The S&P China Corporate 0–3 Years Bond Index	Datastream
Dead funds	89	The China Bond Composite Index	Datastream
Live funds	912	The China Bond Composite Index	Datastream

This table summarizes the number of funds, the benchmark index, and the corresponding data source. The first column lists the number of funds within the group. The second column describes the benchmark index for each fund group. The last column presents the data source for the relevant benchmark index

funds are domiciled in the UK, while offshore funds are domiciled outside the UK. There are 330 onshore funds and 140 offshore funds.

Data on China bond mutual funds consist of 1001 funds from January 2002 to February 2022. We select the oldest share classes of open-ended funds that declare themselves Chinese fixed-income funds. Our data include both surviving funds (912) and nonsurviving funds (89). We group the funds into six categories: Aggressive, Normal, Pure, Government and Policy Bank, Corporate, and Short-Term bond funds. The Aggressive category is the largest group in our sample, with 277 funds in total. The following three categories are Pure bond funds (255), Normal bond funds (162), and Corporate bond funds (139), respectively. These four categories account for over 80% of the bond funds in our dataset.

In Fig. 1, we plot the number of funds in each month for the full sample of USA, UK, and China bond funds from January 1990 to February 2022. The number of funds in these three countries has increased significantly over time. The USA has the largest number of bond funds among the three countries since the 1990s, followed by the UK. As of 2008, the number of US funds reached its peak and then began to decline. The China bond fund industry emerged in 2002 and grew substantially post-2016. The number of bond funds in China exceeded the UK in 2014 and the USA in 2018.

Bond market indices

We obtain the bond fund indices from Morningstar and Datastream. Table 2 summarizes the bond benchmark indices and their sources in the three regions under analysis. All of the bond indices measure monthly total returns (i.e., including reinvested dividends).

In the US market, the Bloomberg US Aggregate Index is used to proxy the bond market benchmark portfolio since it is a broad-based benchmark index that measures the investment grade, US dollar-denominated, fixed-rate taxable bond market.[4] The bond market excess return is the difference between the monthly returns on the Bloomberg US Aggregate Index and the one-month Treasury bill rate, a proxy for the risk-free rate. The Bloomberg US Aggregate Index is taken from Morningstar. The one-month Treasury bill rate is obtained from Kenneth French's website[5]. We use the Bloomberg Universal Index as an alternative market return benchmark in robustness tests, which is also taken from Morningstar.

In the UK market, the Intercontinental Exchange (ICE) Bank of America (BofA) Sterling Broad Market Index is used to proxy the bond market benchmark portfolio. This index tracks the performance of GBP-denominated investment grade debt publicly issued in the Eurobond or UK domestic market, including Gilts, quasi-government, corporate, securitized, and collateralized securities. The bond market excess return is the difference between the monthly returns of the ICE BofA Sterling Broad Market Index and the UK one-month Treasury Bill rate, a proxy for the risk-free rate. The ICE BofA Sterling Broad Market Index is taken from Morningstar. The one-month Treasury bill rate is obtained from Datastream. We use the Bloomberg Sterling Aggregate Index as an alternative market return benchmark in robustness tests, which is also taken from Morningstar.

In the China market, the bond market benchmark portfolio is the China Bond Composite Index. The bond market excess return is the difference between the monthly returns on the China Bond Composite Index and the China three-month deposit rate, a proxy for the risk-free rate. The China Bond Composite Index and three-month deposit rate are obtained from Datastream. We use the China Securities Index (CSI) Aggregate Bond Index as an alternative market return benchmark in robustness tests, which is also taken from Datastream.

We also examine the timing ability of bond funds for a specific style (sector)-related benchmark. Sector benchmarks are chosen based on the category of the fund.

For US funds, Corporate funds are paired with the Bloomberg US Corporate Bond Index. Government funds are paired with the Bloomberg US Government Index. High-Yield funds are paired with the Bloomberg US Corporate High Yield Index. Mortgage-Backed bond funds are paired with the Bloomberg US MBS Index. Inflation-Linked funds are paired with Bloomberg US Treasury Inflation-Protected Securities (TIPS) Index. These indices are sourced from Morningstar.

For UK funds, Corporate bond funds are benchmarked against the ICE BofA Sterling Non-Gilt Index, and Government funds are evaluated against the ICE BofA UK Gilt Index. High-yield funds are paired with the ICE BofA Sterling High-Yield Index. Inflation-linked funds are related to the ICE BofA UK Inflation-Linked Gilt Index. These indices are sourced from Morningstar. Given that the Diversified bond fund and Flexible bond fund invest in the broad bond market, we omit the sector-related analysis for these funds.

For China funds, Corporate bond funds are benchmarked against the S&P China Corporate Bond Index, Government and Policy Bank bond funds are paired with the S&P Government Bond Index, and Short-term funds are paired with the S&P China Corporate 0–3 Years Bond Index. These indices are sourced from Datastream. Given that Aggressive, Normal, and Pure bond funds invest in the broad bond market, we omit the sector-related analysis for these funds.

Public variables

We use a range of instrumental variables in our conditional market timing test, similar to those used by Ferson and Schadt (1996) and Cuthbertson et al. (2010). In the US analysis, these variables are as follows: (i) the short-term interest rate, measured as the one-month Treasury bill rate, (ii) the monthly dividend yield of the S&P 500 Index, sourced from Datastream, (iii) the term spread, which is the ten-year Treasury bond yields minus the three-month Treasury bill yields. The bond yields are monthly averages of daily yields from Datastream. We also include (iv) the quality spread in the corporate bond market, which is Moody's BAA-rated corporate bond monthly yield less the Moody's AAA-rated corporate bond monthly yield. Data on monthly yields are retrieved from Federal Reserve Economic Data (FRED). Finally, we include (v) the monthly bond-to-equity return

[4] This includes Treasuries, government-related and corporate securities, mortgage-backed securities, asset-backed securities, and collateralized mortgage-backed securities.

[5] Available at https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Table 3 Nonparametric market timing performance

Fund group	N	Mean $\hat{\theta}_n$	Mean z_t	$\#\hat{\theta}_n > 0$	$\#\hat{\theta}_n < 0$	$\%\hat{\theta}_n > 0$ sig 5%	$\%\hat{\theta}_n < 0$ sig 5%
USA	1310	−1.244	−0.381	491	819	9.16	21.45
UK	470	−1.817	−0.514	171	299	3.40	21.91
China	1001	−0.132	0.082	515	506	6.29	3.62

This table summarizes the unconditional nonparametric timing measures of bond mutual funds using the relevant broad market benchmarks. The first column lists the number of funds within the group. The second column lists the average value of $\hat{\theta}_n$ (in percentage) of all funds in the group. The mean value of nonparametric test statistic z_t is reported in the third column. The fourth (fifth) column shows the number of funds that have $\hat{\theta}_n > 0\left(\hat{\theta}_n < 0\right)$. The sixth (seventh) column reports the percentage of funds in each group that have $\hat{\theta}_n > 0\left(\hat{\theta}_n < 0\right)$ at a 5% significance level

ratio, measured by the monthly returns of the Bloomberg US Aggregate Index (from Morningstar) divided by the monthly returns of the S&P 500 Index (from Datastream).

In the UK analysis, these variables are as follows: (i) the short-term interest rate, measured as the UK one-month Treasury Bill rate, (ii) the monthly dividend yield of the Financial Times Stock Exchange (FTSE) All Share Index, sourced from Datastream, (iii) the term spread, measured as the 30-year UK Treasury Bond yield minus the one-month Treasury Bill yield, (iv) the default premium in the corporate bond market, measured as the difference between the monthly returns of the ICE BofA Sterling High-Yield (total return) Index and ICE BofA 1–10-Year UK Gilt (total return) Index, (v) the monthly bond-to-equity return ratio, measured by the monthly returns of ICE BofA Sterling Broad Market Index (from Morningstar) divided by the monthly returns of the FTSE All Share Index (from Datastream).

Due to a shortage of public variables in the sample period, we use the lagged market returns (2 lags) as public variables in the conditional nonparametric test for China bond funds.

Empirical results

Basic results

In this section, we describe our baseline empirical results. Table 3 shows the empirical results of the unconditional nonparametric market timing test. We display the test results for funds with a minimum of 36 monthly observations, which leaves 1310 US funds, 470 UK funds, and 1001 China bond mutual funds in our sample. The market-timing coefficients, $\hat{\theta}_n$, can be interpreted as the likelihood that a fund manager will take more systematic risk during a period of high returns than during a period of low returns. Under the null hypothesis of no market timing, the test z-statistic, $z = \sqrt{n}\hat{\theta}_n / \hat{\sigma}_{\hat{\theta}_n}$, is asymptotically distributed as N (0, 1). We use the 5% significance level (one-tail test) in the following analysis.

We begin here with the US results. For the full sample of all US bond funds, around 120 funds demonstrate statistically significant positive timing skills at a 5% significance level, around 9% of the sample of funds. However, funds are found to be negatively timing the market on average. The cross-sectional average $\hat{\theta}$ is −1.24%, suggesting that the probability, on average, that the manager adjusts the fund's exposure to the market in the correct direction is 1.24% lower than the probability of a move in the wrong direction. The proportion of negative market timing is greater than those of positive timing. Around 63% of funds possess negative market timing skills at the individual fund level, with 21% being statistically significant. The cross-sectional average test statistic (z-statistic) is negative (−0.38). As a robustness check, we also perform the nonparametric test using the Bloomberg US Universal Index as the benchmark return (results are available upon request). Here, we find broadly similar results where 11% of funds demonstrate positive market timing skills at a 5% significance level. Figure 2 plots the cross-sectional distribution of test statistics of US funds using the Bloomberg US Aggregate Index. The distribution is positively skewed, and top funds in the extreme right tail exhibit statistically significant positive timing ability. The mean of the distribution is less than zero, indicating slightly negative market-timing ability on average.

We now turn our attention to the UK market timing results in Table 3. For the full sample of all UK funds, we find the top 16 (47) funds demonstrate statistically significant positive timing skills at a 5% (10%) significance level, representing around 3.4% (10%) of the sample of funds. However, funds are found to be negatively timing the market on average. The cross-sectional average $\hat{\theta}$ for UK bond funds is equal to −1.82%. Therefore on average, the probability that the manager moves the fund's market beta in the correct direction is 1.82% lower than the probability of a move in the wrong direction. The cross-sectional average z-statistic is equal to −0.51. About 64% of funds possess negative market timing skills at the individual fund level, with 22% being statistically significant. As a robustness test, we perform the nonparametric test using the Bloomberg Sterling Aggregate Bond Index as the benchmark return. We find a

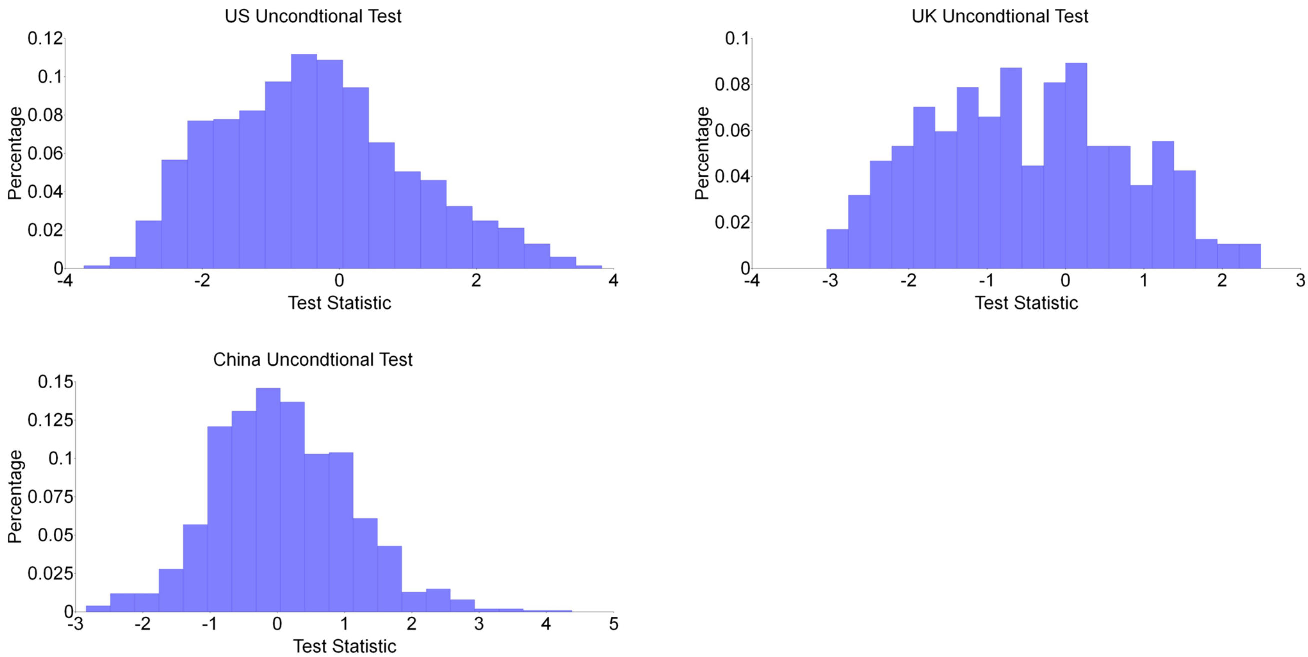

Fig. 2 Distribution of the unconditional market timing test statistic. Note: The figure shows the histograms of the cross section of unconditional market timing test statistics based on 1310 US bond mutual funds 470 UK bond mutual funds and 1001 China bond mutual funds with at least 36 monthly observations

Table 4 Market timing performance: TM and HM tests

Fund group	N	Mean $\hat{\gamma}_n$	Mean t	$\#\hat{\gamma}_n > 0$	$\#\hat{\gamma}_n < 0$	$\%\hat{\gamma}_n > 0$ sig 5%	$\%\hat{\gamma}_n < 0$ sig 5%
Panel A: *TM test*							
USA	1310	−0.075	−0.569	392	918	5.95	29.92
UK	470	−0.007	−0.256	269	201	3.82	11.06
China	1001	0.080	0.098	521	500	10.48	5.48
Panel B: *HM test*							
USA	1310	−0.375	−0.593	388	922	7.63	23.36
UK	470	−0.099	−0.430	177	293	2.98	17.02
China	1001	0.169	0.055	524	497	8.52	5.19

This table summarizes the TM and HM market timing measures of bond mutual funds using the relevant broad market benchmarks. The first column lists the number of funds within the group. The second column lists the average value of the timing coefficients $\hat{\gamma}_n$ of all funds in the group. The mean value of the t-statistics is reported in the third column. The fourth (fifth) column shows the number of funds that have $\hat{\gamma}_n > 0\left(\hat{\gamma}_n < 0\right)$. The sixth (seventh) column reports the percentage of funds in each group that have $\hat{\gamma}_n > 0(\hat{\gamma}_n < 0)$ at a 5% significance level

similar number of significant positive market timers with 3.6% (10%) of funds demonstrating positive market timing skills at a 5% (10%) significance level. As shown in Fig. 2, the cross-sectional distribution of test statistics of UK funds is slightly positively skewed, with several positive market timers in the right tail.

We then report the unconditional nonparametric market timing results for China bond funds. Around 63 funds demonstrate statistically significant positive timing skills at a 5% significance level, which is around 6% of the sample of funds. Funds are found to be neutrally timing the market on average. The cross-sectional average $\hat{\theta}$ is equal to −0.13%. However, the cross-sectional average of the *z*-statistic is equal to 0.08. About 49% of funds exhibit negative market timing at the individual fund level, with 3.62% being statistically significant. In the robustness test, we perform the nonparametric test using the CSI China Aggregate Index as an alternative benchmark return. We find a similar number of significant positive market timers where 5.5% of funds demonstrate positive liquidity timing skills at a 5% significance level. Figure 2 provides the cross-sectional distribution of test statistics of China funds using the China Bond Composite Index. The distribution is slightly positively skewed, and top funds in the extreme right tail exhibit statistically significant positive timing ability.

In summary, we find some evidence of market timing among bond mutual funds. A small number of bond mutual funds demonstrate significant positive market timing skills in the USA, UK, and China. On average, market timing coefficients are all negative for the three countries, suggesting bond funds mistime the market. That is, as groups, bond funds tend to time the market in the wrong direction rather than the right direction.

The HM and TM models

For comparison, we conduct the TM and HM tests and report their market timing coefficients and t-statistics in Table 4. Overall, we find similar evidence of market timing compared with the nonparametric test. On average, we find that US and UK funds negatively time the markets with negative mean timing coefficients and t-statistics. China bond funds tend to neutrally time the market with small positive values. At the individual fund level, we find that a small percentage of funds (below 11%) show positive market timing skills across three countries, similar to the nonparametric test. The percentage of funds with positive significant market timing varies in the TM and HM tests. Specifically, for US funds, the percentage of significant positive market timing is 5.95% and 7.63% for the TM and HM tests, respectively, which is slightly less than the nonparametric test. For UK funds, there is a similar amount of successful market timers from the TM and HM tests compared with the nonparametric test. The percentage of significantly positive market timing funds is 3.82% and 2.98% for the TM and HM tests, respectively. For China bond funds, we find slightly more evidence of successful market timers from the TM and HM tests compared with the nonparametric test. The percentage of significantly positive market timing is 10.48% and 8.52% for the TM and HM tests, respectively.

The difference in market timing results between the nonparametric and parametric tests may be due to two effects. First, the regression-based methods reflect the aggressiveness of market timing response as well as the quality of fund managers' timing information. In contrast, the nonparametric method only reflects the information quality of market prediction leading to several funds with significant TM or HM measures being insignificant in the nonparametric test. Second, the parametric methods assume the residuals of the regressions are independently and identically normally distributed (i.i.d.). If the residuals of the regressions are not normally distributed, they may produce biased results for timing ability. The more flexible assumption of the nonparametric method does not rely on the normality of fund returns, which allows it to find more significant market timers in the sample.

Table 5 Contingency table for market timing tests

Country	Test	Significance	Nonparametric test		
			# sig	# insig	Total
USA	TM test	# sig	40	38	78
		# insig	80	1152	1232
		Total	120	1190	1310
	HM test	# sig	72	28	100
		# insig	48	1162	1210
		Total	120	1190	1310
UK	TM test	# sig	1	17	18
		# insig	15	437	452
		Total	16	454	470
	HM test	# sig	4	10	14
		# insig	12	444	456
		Total	16	454	470
China	TM test	# sig	37	68	105
		# insig	26	870	896
		Total	63	938	1001
	HM test	# sig	40	47	87
		# insig	23	891	914
		Total	63	938	1001

This table compares the unconditional nonparametric timing measurement with the TM/HM test. "# sig" and "# insig" represent the number of funds that produce a positive significant test statistic and insignificant test statistic, respectively, at a 5% significance level

Table 5 is a contingency table that compares the nonparametric test results with the TM and HM tests in the three countries. For example, in the US results, 38 (28) funds with significant TM (HM) measures are found to be insignificant in the nonparametric method. Here, 80 (48) US funds with insignificant TM (HM) estimates in the parametric model are found to be significant in the nonparametric test, and 77 of 80 US funds (45 of 48 US funds) are not normally distributed using the Jarque-Bera test. In the UK results, 17 funds (10) with significant TM (HM) measures are found to be insignificant in the nonparametric test. We find that 15 (12) funds with insignificant TM (HM) estimates are found to be significant in the nonparametric test, and all 15 (12) funds are not normally distributed using the Jarque-Bera test. In the China results, 68 (47) funds with significant TM (HM) measures are found to be insignificant in the nonparametric test. Conversely, 26 (23) funds with insignificant TM (HM) estimates are found to be significant in the nonparametric test, and 22 of 26 funds (20 of 23 funds) are found to have non-normally distributed returns using the Jarque-Bera test.

Table 6 Nonparametric market timing performance-by fund categories

Fund Group	N	Mean $\hat{\theta}_n$	Mean z_t	$\#\hat{\theta}_n > 0$	$\#\hat{\theta}_n < 0$	$\%\hat{\theta}_n > 0$ sig 5%	$\%\hat{\theta}_n < 0$ sig 5%
Panel A: USA							
Corporate	268	−2.183	−0.648	68	200	2.99	16.42
High-Yield	221	−5.410	−1.771	5	217	0.00	67.87
Government	162	3.635	1.232	134	28	39.51	0.00
Mortgage-Backed	40	−0.595	−0.236	14	26	2.50	2.50
Inflation-Linked	40	−0.240	−0.025	18	22	2.50	2.50
Broad-Basket	503	−0.118	−0.038	245	258	9.15	10.54
Other	76	−4.541	−1.366	7	69	0.00	43.42
Dead funds	585	−0.718	−0.172	259	326	9.06	14.36
Live funds	725	−1.668	−0.549	232	493	9.24	27.17
Onshore funds	850	−1.193	−0.392	316	534	10.00	22.35
Offshore funds	460	−1.337	−0.361	175	285	7.61	19.78
Panel B: UK							
Corporate	180	−4.302	−1.209	18	162	0.00	33.33
Diversified	120	−2.395	−0.646	36	84	3.33	24.17
Flexible	16	−3.460	−1.091	4	12	0.00	43.75
Government	99	2.997	0.862	86	13	12.12	0.00
High-Yield	12	−5.146	−1.782	0	12	0.00	58.33
Inflation-Linked	43	0.651	0.169	27	16	0.00	0.00
Dead funds	221	−1.641	−0.387	93	128	2.71	18.10
Live funds	249	−1.974	−0.626	78	171	4.02	25.30
Onshore funds	330	−2.111	−0.613	107	223	3.03	23.94
Offshore funds	140	−1.127	−0.279	64	76	4.29	17.14
Panel C: China							
Aggressive	277	−0.320	0.079	145	132	5.42	5.78
Normal	162	0.931	0.250	93	69	8.02	2.47
Pure	255	−0.529	−0.035	111	144	5.10	4.31
Government and policy bank	72	−2.776	−0.274	24	48	2.78	0.00
Corporate	139	0.547	0.127	79	60	3.60	2.16
Short-Term	96	0.515	0.322	51	45	15.63	2.08
Dead funds	102	0.678	0.174	51	51	8.82	0.98
Live funds	919	−0.222	0.072	464	455	5.88	3.92

This table summarizes the unconditional nonparametric timing measures of bond mutual funds using the relevant broad market benchmark. Panels A, B, and C report the nonparametric test results for the USA, UK, and China, respectively. The first column lists the number of funds within the group. The second column lists the average value of $\hat{\theta}_n$ (in percentage) of all funds in the group. The mean value of nonparametric test statistic z_t is reported in the third column. The fourth (fifth) column shows the number of funds that have $\hat{\theta}_n > 0\left(\hat{\theta}_n < 0\right)$. The sixth (seventh) column reports the percentage of funds in each group that have $\hat{\theta}_n > 0\left(\hat{\theta}_n < 0\right)$ at a 5% significance level

Subgroup analysis

Our next step is to examine possible timing differences for subgroups of bond funds. In each country, we start our subgroup analysis using the relevant overall market index. In Table 6, Panels A, B, and C report the nonparametric test results for the USA, UK, and China, respectively. For comparison, we also investigate fund performance in timing sector benchmarks as bond funds may attempt to time a specific bond sector where appropriate. Ignoring the specific benchmarks might lead to potential spurious timing across funds. Finally, we report the timing performance of dead (live) funds and onshore (offshore) funds using the overall market benchmark index.

US results

We start our subgroup analysis with US results. Table 6 Panel A shows the cross-sectional timing performance of funds by fund groups, using the Bloomberg US Aggregate Index as the benchmark return. At the individual fund level, there are several skilled market timers among

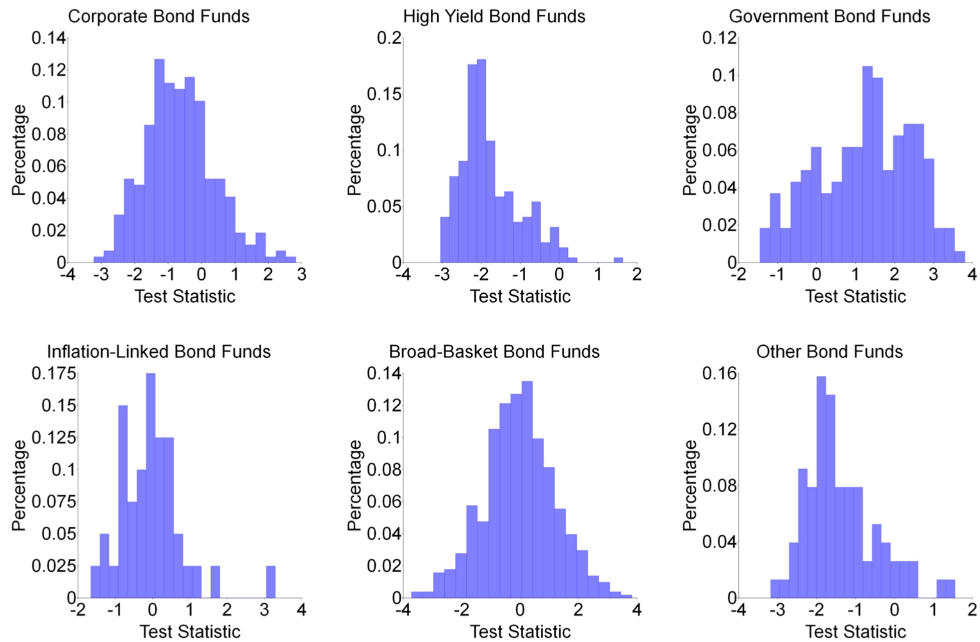

Fig. 3 Distribution of the unconditional market timing test statistic—by US bond fund type. Note: The figure shows the histograms of the cross-section unconditional market timing test statistics by US bond fund type. The analysis covers funds with a minimum of 36 monthly observations from 1990M1 to 2021M9, leaving 268 Corporate bond funds, 221 High-Yield bond funds, 162 Government bond funds, 40 Mortgage-Backed bond funds, 40 Inflation-Linked bond funds, 503 Broad-Basket bond funds, and 76 Other funds

Corporate, Government, Mortgage-Backed, Inflation-Linked, and Broad-Basket bond funds. In detail, the percentage of funds with significant positive market timings is 3.0%, 39.5%, 2.5%, 2.5%, and 9.2% for Corporate, Government, Mortgage-Backed, Inflation-Linked, and Broad-Basket bond funds, respectively. In contrast, no High-Yield or Other bond funds demonstrate statistically significant positive market timing. As groups, however, Corporate, Mortgage-Backed, Inflation-Linked, and Broad-Basket funds perform poorly on average, with negative mean $\hat{\theta}_n$ and z-statistics. Government bond funds perform well as a group, with positive timing coefficients and test z-statistics on average. Figure 3 illustrates these findings graphically. The distribution of government bond funds is negatively skewed, with a significant number of market timers in the right tail. The distributions of Corporate, Mortgage-Backed, Inflation-Linked, and Broad-Basket bond funds show a small number of skilled timers in the extreme right tails. The distributions of High-Yield and Other funds are positively skewed, with mean values less than zero.

We then investigate fund performance in timing sector benchmarks, as bond funds may attempt to time a specific bond sector where appropriate. Ignoring the specific benchmarks might lead to spurious timing across funds. As Broad-Basket funds invest in a broad universe of investment-grade bonds similar to the aggregate bond index, we do not evaluate these funds against a sector-specific bond index. In results not tabulated, we find that only six corporate bond funds show significant positive timing ability against the Bloomberg US Corporate Bond Index, which aligns with the result from the aggregate market index. High-yield funds are found to have no significant positive market timers, evaluated against the Bloomberg US Corporate High Yield Index, with an average negative test statistic (−1.38)—a similar result when this subcategory of the fund is evaluated against the broad market benchmark. Government funds are less successful at timing a sector-specific benchmark (the Bloomberg Government Index) than the market-wide aggregate benchmark. The cross-sectional average test statistic turns negative (−0.21) with a small number of statistically significant positive market timers. Specifically, only nine government funds successfully time the government bond index, with considerably more statistically significant negative market timers. There are no statistically significant market timers for Mortgage-backed and Inflation-linked funds for sector-specific benchmarks.

Of the 1310 US funds examined, 585 are dead funds. In Table 6, the rows denoted "Dead funds" and "Live funds" indicate whether the funds are dead or surviving, respectively. Dead funds generally tend to be less successful at market timing. The percentage of positive statistically significant market timers among live funds (9.24%) is slightly higher than the percentage among dead funds (9.06%). In the right tail of the performance distribution, 53 of the top

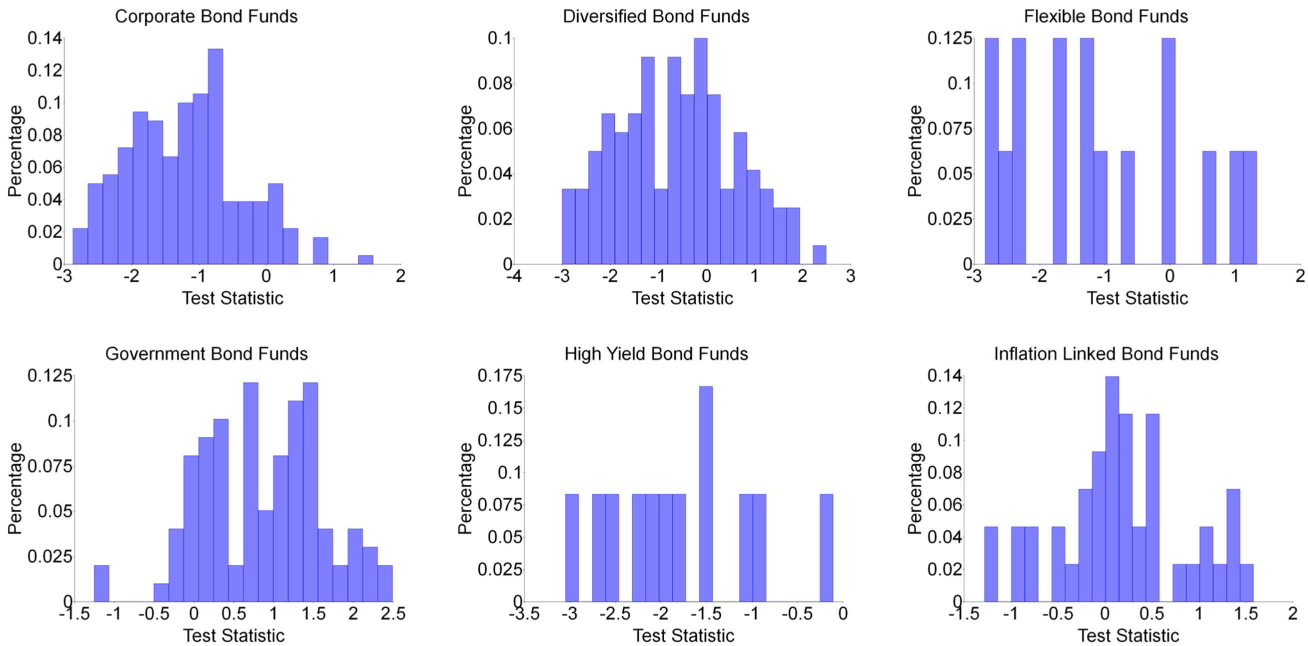

Fig. 4 Distribution of the unconditional market timing test statistic—by UK bond fund type. Note: The figure shows the histograms of the cross-section unconditional market timing test statistics by UK bond fund type. The analysis covers funds with a minimum of 36 monthly observations from 1997M1 to 2022M2, leaving 180 Corporate bond funds, 120 Diversified bond funds, 16 Flexible bond funds, 99 Government bond funds, 12 High-Yield bond funds, 43 Inflation-Linked bond funds

120 funds showing statistically significant positive timing ability are dead funds.

We examine the timing performance of 850 onshore and 460 offshore funds separately. Our question is whether geographic location causes information asymmetry and, thus, differences in fund timing performance. In Table 6 Panel A, we find onshore funds near US financial centers slightly outperform in terms of market timing at the individual fund level. Around 10% of onshore funds show significant positive timing ability compared to 7% of offshore funds, although onshore funds also exhibit a higher proportion (22%) of significantly negative market timing relative to 20% of offshore funds. As a group, both onshore and offshore funds mistime the market on average with negative cross-sectional average timing coefficients and z-statistics.

UK results

We then examine possible timing differences for subgroups of UK funds. There are six categories: Corporate, Diversified, Flexible, Government, High-Yield, and Inflation-Linked. The timing performance of each subgroup is evaluated relative to the aggregate bond market index, i.e., the ICE BofA Sterling Broad Market Index.

In Table 6, Panel B shows the cross-sectional timing performance of subgroups of UK funds. Overall, there is evidence of positive timing ability among Diversified bond funds and Government bond funds. 12.1% (3.3%) of the sample of Government bonds (Diversified bonds) successfully time the broad bond market index. The cross-sectional average timing coefficients (test z-statistics) are 3.0% (0.86) and −2.4% (−0.65) for Government bond and Diversified bond funds, respectively. Thus, Diversified funds perform poorly on average, despite a few positive market timers. Government bond funds perform well as a group with positive average test statistics compared to other types of funds. In contrast, no Corporate bond funds, Flexible bond funds, High-Yield bond funds, and Inflation-Linked bond funds demonstrate statistically significant positive market timing. There is no significant market timer among the group of Inflation-Linked bonds, but as a group, the fund at least times the market in the correct direction (mean $\hat{\theta} = 0.65\%$).

Figure 4 illustrates these findings graphically. The distributions of Diversified and Government bond funds show a number of skilled timers in the extreme right tails. The distribution of Diversified bond funds is positively skewed, with its mean value less than zero, while the Government bond fund distribution is negatively skewed, with its mean above zero. There is no significant positive market timing in the distributions of Corporate, Flexible, High-Yield, and Inflation-Linked bond funds.

We also investigate fund performance in timing-specific sector benchmarks. For Diversified and Flexible bond funds, we do not evaluate timing against a style-specific index since these two types of funds allocate their money across a broad

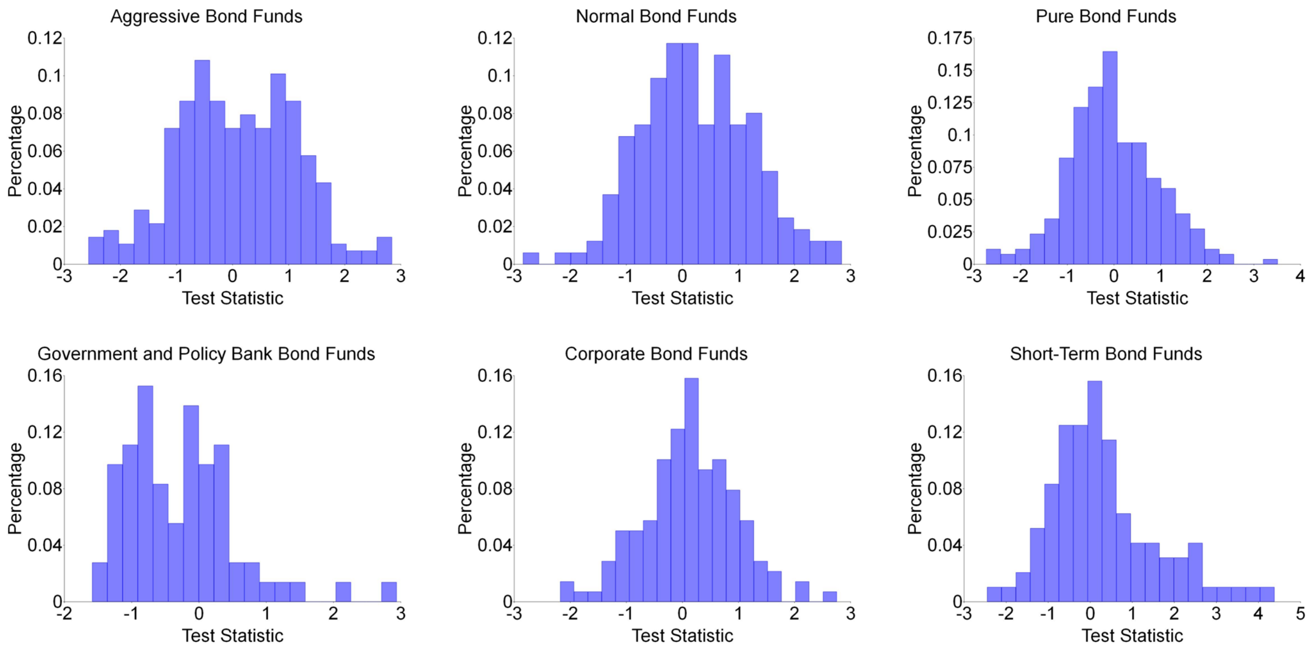

Fig. 5 Distribution of the unconditional market timing test statistic—by China bond fund type. Note: The figure shows the histograms of the cross-section unconditional market timing test statistics by China bond fund type. The analysis covers funds with a minimum of 36 monthly observations from 2002M1 to 2022M2, leaving 277 Aggressive bond funds, 162 Normal bond funds, 255 Pure bond funds, 72 Government and Policy Bank bond funds, 139 Corporate bond funds, 96 Short-Term bond funds

bond market rather than a specific sector. In the results not tabulated, Corporate bond funds are more successful market timers for the sector benchmark, i.e., the ICE BofA Sterling Non-Gilt Index, than the broad market index. In detail, four Corporate bond funds show positive market timing ability for the sector index, around 2.22% of the corporate bond fund sample. Government funds are less successful at timing a sector-specific benchmark than the market-wide benchmark. Only 4% of government bond funds show statistically significant positive market timing for the ICE BofA UK Gilts Index. The cross-sectional average test statistic turns negative (−0.10), with more statistically significant negative market timers. For the Inflation-Linked bond funds, we evaluate their market timing ability relative to the ICE BofA UK Inflation-Linked Gilt Index. Five funds successfully time the sector index. The cross-sectional average of the timing coefficients is 1.12%, suggesting these funds time the Inflation-Linked Gilt market in the correct direction on average. We find the High-Yield bond funds show no significant positive market timing ability for the sector index (ICE BofA Sterling High Yield Index), a similar result compared to the broad market index.

Of the 470 funds examined, 221 are dead funds. Dead funds tend to be less successful at market timing. The percentage of positive statistically significant market timers among live funds (4.02%) is higher than the percentage among dead funds (2.71%). In the right tail of the performance distribution, only 6 dead funds show statistically significant positive timing ability.

There are 330 onshore UK funds and 140 offshore funds. From Table 6 Panel B, we find, as groups, both onshore and offshore funds mistime the market with negative mean timing coefficients and z-statistics. Onshore funds exhibit a higher proportion (24%) of significantly negative market timing relative to 17% of offshore funds.

China results

We finally examine possible timing differences of subgroups of bond funds in China. There are six categories: Aggressive, Normal, Pure, Government and Policy Bank, Corporate, and Short-Term bond funds. The timing performance of each category is evaluated relative to the aggregate bond index.

Table 6 Panel C shows the cross-sectional timing performance of funds by their investment sector where each row shows the market timing result for the specific fund group, using the China Bond Composite Index as the benchmark return. Overall, there is evidence of positive timing ability among all subgroups of bond funds, especially for Short-Term bond funds. The percentage of statistically positive market timers is 5.42%, 8.02%, 5.10%, 2.78%, 3.60%, and 15.63% for Aggressive, Normal, Pure, Government and Policy Bank, Corporate, and Short-Term bond funds,

Table 7 Conditional nonparametric market timing performance

Fund Group	N	Mean $\tilde{\theta}_n$	Mean z_t	$\#\tilde{\theta}_n > 0$	$\#\tilde{\theta}_n < 0$	$\%\tilde{\theta}_n > 0$ sig 5%	$\%\tilde{\theta}_n < 0$ sig 5%
USA	1310	−2.208	−0.664	356	954	4.27	23.51
UK	383	−1.146	−0.350	191	279	2.98	13.40
China	1001	0.436	0.146	547	454	4.80	3.00

This table summarizes the conditional nonparametric timing measures of bond mutual funds using the relevant broad market benchmark. The first column lists the number of funds within the group. The second column lists the average value of $\tilde{\theta}$ (in percentage) of all funds in the group. The mean value of nonparametric test statistic z_t is reported in the third column. The fourth (fifth) column shows the number of funds that have $\tilde{\theta}_n > 0\left(\tilde{\theta}_n < 0\right)$. The sixth (seventh) column reports the percentage of funds in each group that have $\tilde{\theta}_n > 0(\tilde{\theta}_n < 0)$ at a 5% significance level

respectively. As a group, Normal, Corporate, and Short-Term bond funds perform well with positive timing statistics on average compared to other types of funds. Aggressive, Pure, Government and Policy Bank, and Corporate bond funds perform poorly on average with negative timing coefficients, even though there are few positive market timers. Figure 5 illustrates these findings graphically. The distributions of all subgroups of funds show a number of skilled market timers in the extreme right tails. In the Normal and Short-Term funds group, there are more skilled market timers in the right tails of the distribution than those in other subgroups of funds.

We also investigate fund performance in timing-specific sector benchmarks. As Aggressive, Pure, and Normal bond funds invest in a broad universe of investment-grade bonds, we do not evaluate these funds against sector-specific bond indices. We examine three subcategories in total: Government and Policy Bank, Corporate, and Short-Term bond funds. In the results not tabulated, two government funds are successful at timing the government bond index, and there are considerably more statistically significant negative market timers compared to the results of the broad bond market index. Five corporate funds show significant positive timing ability against the S&P China Corporate Bond Index, which is similar to the result from the China Bond Composite Index. 12.5% of Short-Term funds are found to have significant positive market timing with a positive test statistic (0.32) on average, a lower prevalence result compared to the composite market benchmark.

Of the 1001 funds examined, 102 are dead funds. Dead funds tend to be less successful at market timing. As expected, the number of live funds is higher than the number of dead funds among statistically significant market timers. In the right tail of the performance distribution, only 9 of the top 63 funds showing statistically significant positive timing ability are dead funds.

Conditional market timing

In this section, we examine conditional market timing using the nonparametric approach. In this context, a fund manager's real contribution would be the successful timing of market returns that are not predictable from public information.

Table 7 shows the empirical results of the conditional nonparametric market timing test. We find similar evidence that US and UK funds show negative market timing abilities, consistent with the unconditional test. On average, the mean value of timing coefficients for US and UK funds is all negative. In contrast, the China bond funds tend to show positive market timing abilities, with mean $\tilde{\theta}_n$ and z_t both greater than zero. At the individual fund level, compared with the unconditional test, we find a smaller number of funds successfully time the market after controlling for the full set of public information variables in all countries (in Section "Basic results"). Specifically, the percentages of significant positive market timing are 4.3%, 3.0%, and 4.8% for the USA, UK, and China bond funds, respectively, in the conditional test. In terms of negative market timing, compared with the unconditional test, there are a bigger number of significant negative market timers in the USA, while a smaller number of significant negative market timers in the UK and China. The greater prevalence of significant positive timing found by the unconditional test may be attributed to the publicly available information. Overall, our results still indicate some evidence of successful market timing attributed to private information.

Figure 6 shows the cross-sectional distributions of conditional market timing tests for the three countries. Compared with the unconditional test, for US funds, the distribution remains positively skewed. We observe a smaller number of significant positive market timers in the right tail of the distribution but a larger number of negative timers in the left tail. For UK funds, the cross-sectional distribution of conditional z-statistics is slightly positively skewed with fewer good performers and bad performers. For China bond funds, there are fewer significant positive and negative market timers in both the left and right tails of the distribution.

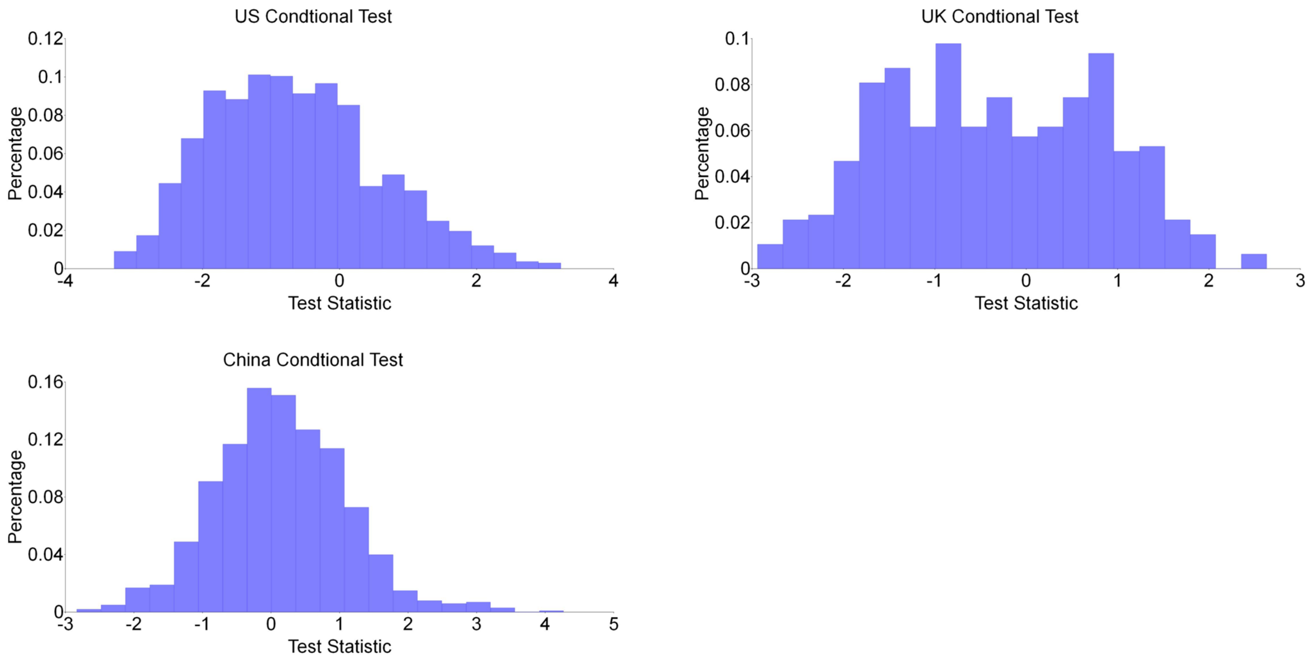

Fig. 6 Distribution of the conditional market timing test statistic. Note: the figure shows the histograms of the cross section of conditional market timing test statistics based on 1310 US bond mutual funds, 470 UK bond mutual funds, and 1001 China bond mutual funds with at least 36 monthly observations

Table 8 Nonparametric market timing subperiod performance

Fund Group	N	Mean $\hat{\theta}_n$	Mean z_t	$\#\hat{\theta}_n > 0$	$\#\hat{\theta}_n < 0$	$\%\hat{\theta}_n > 0$ sig 5%	$\%\hat{\theta}_n < 0$ sig 5%	Period
Panel A: Subsample 1								
USA	932	0.860	0.164	424	508	10.30	5.90	Jan 1990–Nov 2005
UK	286	−1.492	-0.205	120	166	4.20	9.44	Jan 1997–Jul 2009
China	59	3.141	0.546	48	11	8.47	1.69	Jan 2002–Jan 2012
Panel B: Subsample 2								
USA	1204	−2.111	-0.489	793	411	8.72	23.42	Dec 2005–ep 2021
UK	383	−2.176	-0.581	119	264	1.83	18.80	Aug 2009–Feb 2022
China	1001	−0.222	0.050	490	511	5.59	4.00	Feb 2012–Feb 2022

This table summarizes the unconditional nonparametric timing measures of subsamples of mutual funds using the relevant broad market benchmark. The first column lists the number of funds within the group. The second column lists the average value of $\hat{\theta}_n$ (in percentage) of all funds in the group. The mean value of nonparametric test statistic z_t is reported in the third column. The fourth (fifth) column shows the number of funds that have $\hat{\theta}_n > 0(\hat{\theta}_n < 0)$. The sixth (seventh) column reports the percentage of funds in each group that have $\hat{\theta}_n > 0(\hat{\theta}_n < 0)$ at a 5% significance level. The last column shows the subsample period. The analysis covers funds with a minimum of 36 monthly observations.

Subperiod test

In this section, we conduct subperiod market timing tests to examine how market timing ability varies over time, given our long observation period. We divide the full sample into two equal subsamples representing early and later periods for each country. The nonparametric market timing tests, as detailed in Section "Nonparametric market timing," are then applied to these subsamples of bond funds.

Table 8 presents the market timing results of subsamples of bond mutual funds in each country. Panels A and B display the market timing test results for the early and later periods, respectively. We find the mean values of timing coefficients and test statistics ($\hat{\theta}_n$ and z_t) in early periods are greater than those in later periods. At the individual fund level, the percentages of significant market timing in the early period are slightly higher than the percentages in later periods for all three countries. For example, the percentages of significant market timing for US funds are 10.3%

in the early period and 8.72% in the later period. The lower prevalence of market timing ability in later periods may be attributed to the variation in compositions of the fund samples, i.e., comparison bias. As shown in Fig. 1, the majority of funds emerged in the latter half of the evaluation period, particularly in the US and China bond fund industries. This variation in fund composition may bias the market timing results, although we require each fund to at least have a 3-year history at the individual fund level.

However, compared to the full sample results in Section "Basic results," we consistently find a small number of positive significant market timing in all subsamples for each country. While the percentages of significant market timing vary in subsamples, they are close to the percentage of significant market timing in the full sample. For example, there are similar percentages of significant market timing in US fund sub-samples (10.3% and 8.72% in the early and later periods, respectively) and the full sample (9.16%). This suggests that our main conclusion remains consistent, despite changes in the compositions of the fund samples.

Conclusion

This paper evaluates the market timing performance of the fixed-income mutual fund industry which has attracted little academic research despite its growing economic importance.

Using a large survivorship bias-free database of over 2500 funds, we measure the market timing performance of bond mutual funds individually in the USA, UK, and China for the first time using the nonparametric method of Jiang (2003). Our nonparametric test suggests some evidence of market timing among bond mutual funds. The evidence is more pronounced in the USA where 9% of bond funds possess significant positive market timing skills (compared to 3% and 6% for the UK and China, respectively). However, as a group, bond funds slightly negatively time the market on average. After controlling for lagged publicly available information, we find less evidence of successful private market timing among bond funds.

In the subgroup analysis, we find government bond mutual funds successfully time the market in both the USA and UK. There is evidence of positive market timing for Government bond funds as a group in the two countries. In contrast, no High-yield funds show market timing skills in either country. This result indicates that government bond funds are concerned about the overall bond market fluctuations, while high-yield funds are not. In China, we find some (about 15%) short-term bond funds demonstrate significant positive market timing skills. This may be because short-term funds are more sensitive to market movement. Finally, the market timing performance of offshore funds is similar to the performance of onshore funds, while live funds tend to be more successful market timers than dead funds.

Our nonparametric results are robust to variations in timing frequencies, underlying distributions, and data bias, such as survivorship and composition biases, as well as to alternative benchmark indices. Overall, the nonparametric approach implies some evidence of successful market timers among bond mutual funds at the individual fund level. There are a small number of truly skilled bond fund managers with market timing skills in the USA, UK, and China. The market timing ability is more evident in government bond funds, which is consistent with Huang and Wang (2014). Our findings have direct implications for the performance evaluation of active bond fund managers and individual investors.

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Declarations

Conflict of interest The authors have no conflicts of interest to declare.

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