Navigating Inflation Risk in Corporate Bond Markets

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Abstract

The global inflation surge has refocused attention on the impact of inflation risks in financial markets. We investigate whether mutual fund managers time the inflation risks in the corporate bond market. Our findings reveal a significant and robust timing ability among managers in different investment subcategories, translating into a sizable fund performance of around 4% per annum. Timing is associated with managers adjusting portfolio holdings to bet on future risks rather than past realizations. Cross-sectional evidence suggests that over 40% of individual funds exhibit strong inflation risk timing ability, controlling alternative timing abilities, factor structures, and monetary policy shocks. The bootstrapping exercise further validates managerial skills rather than pure luck. Our results provide important policy implications for monetary policy transmission in corporate bond markets.

Keywords: Inflation risk, corporate bonds, mutual funds, timing ability

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1 Introduction

The global surge in inflation has refocused attention on the impacts of inflation risks. Central banks adjust interest rates to tame inflation risks, whose efficiency depends on investors' transactions in the fixed-income market, for instance, mutual funds.[1] Thus, whether fund managers bet on future inflation risks and actively trade bond securities are essential for monetary policy transmission. In this paper, we provide novel evidence on the inflation-risk timing abilities of mutual funds investing in the U.S. corporate bond market and emphasize that managers revise their bond portfolio exposures to inflation risks.

Growing evidence suggests inflation risk is priced in the corporate bond market, and mutual fund performance should tie to their exposure to this source of risk.[2] Managers forecast and time inflation risk to boost their performance. Using a large sample of around 4,000 mutual funds that invest primarily in the corporate bond market, we find that fund managers exhibit the ability to time on market inflation risk in the period 2003 − 2022. We define the time series of inflation risk as the inflation volatility risk factor ($IVRF$), following the procedure in Ceballos (2022). Specifically, in each month, we create quintile double-sorted portfolios based on inflation exposure beta (β^{π}) and credit risk, measured by credit ratings from Moody's and S&P. $IVRF$ is the value-weighted average return spread between the highest- and lowest-β^{π} portfolios across the credit rating portfolios.

We start with estimating a return-based model to capture managerial inflation-risk timing ability in the corporate bond mutual fund industry. We document a positive and significant timing coefficient ($\gamma = 0.03$ with t-statistic $= 4.55$), indicating that in a given month, when $IVRF$ is one standard deviation above its historical mean, the average mutual fund portfolio's market beta increases by 7%. This evidence suggests that fund managers correctly anticipate high (low) market inflation risk and increase (reduce) market exposure accordingly. Moreover, we show that timing ability is more prevalent in periods of high inflation, which indicates that inflation risk is an essential source of risk for portfolio managers in an environment of elevated inflation uncertainty.

To contextualize our findings in economic terms, we focus on whether the timing ability adds

[1] In the FOMC meeting on July 25–26, 2023, the Federal Reserve expressed worries about upside risk in inflation. See Fang et al. (2022); Cieslak and Pflueger (2023) for further discussions about the impacts of inflation on financial markets.

[2] In the corporate bond market, Ceballos (2022) shows a negative relation between inflation risk exposure and individual corporate bond returns. There is also evidence of the inflation risk premium embedded in the government bond market (Gürkaynak and Wright, 2012; Grishchenko and Huang, 2013; Bekaert and Wang, 2014; Kupfer, 2018). Moreover, in the equity market, Boons et al. (2020) document a significant and time-varying inflation risk premium, defined as the exposure to inflation innovations. Bhamra et al. (2022) also finds a negative relationship between expected inflation and both equity valuation and default risk, conditioning on firm leverage.

economic value to fund performance. Specifically, we construct portfolios sorted by each fund's estimated inflation-risk timing coefficient in our sample. Then, we form portfolios and hold them for three to 36 months. Comparing returns of two extreme deciles, we document a sizable and significant economic value between 0.30% and 0.37% per month, depending on the holding period. That is, funds managed by successful inflation-risk timers outperform funds with incorrect timing managers by 3.6% to 4.4% per year on a risk-adjusted basis. This evidence supports that inflation-risk timing reflects managerial skills in mutual funds, and the timing ability is priced in portfolio performance.

We distinguish the inflation-risk timing from the reaction, which captures a manager's ability to change the exposure based on the observed inflation risk in the previous month. Up to a 12-month holding period, there is no economic value, where top reactors marginally deliver larger αs than bottom reactors in out-of-sample tests. We argue that corporate bond mutual fund managers benefit from forecast inflation risks (timing ability) rather than react to existing public information (reaction). To further validate that our findings are not driven by latent variables or statistical luck, we focus on a subsample of inflation-protected corporate bond mutual funds. As these funds protect investors from the eroding effect of inflation risks by investing primarily in securities that seek to provide a "real" return, the prediction is that the reaction, not timing, coefficient should provide economically large and statistically significant value. We find that the economic value of reaction among inflation-protected funds is 1.7% per year in a three-month holding period, compared to a -0.7% per year for timing ability. Thus, inflation-risk timing ability measures the proper skill set among bond mutual fund managers.

To address the concerns that the results are driven by funds focused on specific assets or with a particular investment style, we analyze the timing ability in funds with various credit-rating portfolios and investor types. First, the timing ability coefficient is positive and significant at 1% with an estimate of 0.03 for investment-grade bonds, while for high-yield bonds, the timing coefficient is 0.01 and statistically insignificant. Second, we analyze funds oriented to different investors, including retail and institutional shares. The timing coefficients for retail and institutional shares are positive and statistically significant, with a point estimate between 0.02 and 0.03. Lastly, we explore inflation-risk timing in index funds. As these funds hold most of the portfolio with weightings close to those in the benchmark index, we predict that managers have no inflation-risk timing ability. We document that the timing coefficient is positive but significantly smaller than the estimated ability in other types of (active) bond mutual funds.

Next, we analyze the inflation-risk timing ability at the individual fund level. In particular, we examine the cross-sectional distribution of t-statistics, focusing on the coefficient that captures timing skills at the fund level. We show that the right tail is thicker than the left tail, supporting the evidence of the positive coefficient based on aggregate portfolio fund returns. Indeed, funds that exceed the t-statistics cutoff of 2.33 range between 32.6% to 42.1% depending on the funds (excluding index funds). In contrast, a small fraction of funds around 4% exhibit a t-statistics lower than the cutoffs of the left tail. This evidence is consistent across all funds in the sample and also by focusing on funds based on investment style (investment grade, high yields) or different pools of investors (retail and institutional). Therefore, the evidence indicates that most funds have a positive inflation-risk timing coefficient.

Inflation risks affect bond market returns and are closely related to market fluctuation. To migrate the effect of alternative timing ability, we control market and volatility timing abilities in the corporate bond market. We extend our baseline timing model to include the square of bond market returns to address whether inflation risk timing is correlated with aggregate bond market timing. For volatility timing ability, we adopt three volatility measures: (1) bond market return volatility, (2) stock market return volatility, and (3) the CBOE S&P 500 index option implied volatility (VIX). The evidence suggests that after controlling for market and volatility timing abilities, the number of funds with significant inflation-risk timing coefficients remains similar. The results above indicate that the significant inflation-risk timing coefficients are not due to the correlation between market returns or volatility and inflation risks.

We also control additional factors that can affect timing ability in the corporate bond market. First, we include the terms spread and default spread as relevant factors explaining the expected return in the bond market. Second, we add different measures of uncertainty, such as the macroeconomic uncertainty index from Jurado et al. (2015) and the economic uncertainty measure from Baker et al. (2018). Third, as inflation risk is closely related to monetary policy shocks, spurious timing ability could exist if fund managers target exposure to monetary policy variations or surprises. Thus, we include measures of monetary policy shocks to investigate whether inflation-risk timing ability among corporate bond mutual fund managers is diminished due to monetary policies. We show that our baseline results are robust to controlling for these potential sources affecting risk inflation timing ability.

In addition, to avoid the issue that conventional inference can yield misleading results under non-normality returns, we evaluate fund managers' inflation risk timing ability at the individual fund level using a bootstrap approach (Kosowski et al., 2006). We simulate a sample of pseudo-individual funds without pre-determined timing ability and compare the empirical distribution of t-statistics for timing ability among pseudo funds with actual t-statistic. The bootstrapped distribution of t-statistics for top 1%- to 10%-performing funds in the sample suggests that the significant inflation-risk timing ability is robust and does not inherit from statistical luck. In particular, comparing t-statistics from actual fund returns versus t-statistics from pseudo fund returns with no timing ability, almost all top 10% performers exhibit statistically strong timing ability. The results remain similar to portfolio-level analysis and in subsamples with different credit ratings, investor orientations, and indexing.

Jiang et al. (2007) argue that return-based timing suffers from biases induced by the interim trading or dynamic trading effect since returns only contain ex-post information without discussing how managers prepare for inflation risks by changing portfolio holdings. To address the concern, we analyze timing ability using a portfolio-holding-based approach using a portfolio-level measure of inflation risk exposure (β^{π}). For all corporate bonds in the fund portfolio, we aggregate the individual bond's inflation risk beta using portfolio holding weights. The sensitivity between current portfolio-level inflation risk exposure to future inflation risks, $IVRF$, indicates how well managers time the inflation risks. We rely on the bootstrapping exercise to migrate the concerns for misleading traditional statistical inference.

We highlight three main findings from the holding-based timing ability method. First, corporate bond fund managers can successfully time the inflation volatility risk factor, $IVRF$, for a three-month forecasting horizon. For example, the actual t-statistic of top 10%-timers' coefficient (t-statistics = 3.10) has a p-value of 0.06, suggesting that the holding-based timing ability does not inherit from statistical randomness. Second, the economic value for the fund managers with average timing ability is 0.68% per year, based on the idea that inflation-risk timing is equivalent to a contingent claim on the $IVRF$. Similarly, top 10% timing performers can add value up to 2.6% per year, indicating that inflation-risk timing can be an essential investment strategy for corporate bond mutual funds. Lastly, we show that managers' inflation-risk timing ability stems from their activeness in adjusting to their portfolios. We consider the one-period difference in portfolio-level inflation risk beta and estimate the sensitivity of the "active beta" to forecasting three-month $IVRF$. The estimation is statistically and economically significant by comparing the inflation beta between an actively adjusted portfolio according to the inflation risks with a passively owned portfolio, suggesting that managers pre-allocate corporate bonds according to their prediction about future inflation risks.

We contribute to the literature on the relevance of inflation risk. A growing body of literature has documented the relevance of inflation risk in corporate bonds. For instance, Kang and Pflueger (2015) documents that inflation risk, defined as inflation volatility and cyclicality, significantly impacts aggregate credit spreads for a panel of developed economies while controlling for equity volatility. They argue that the transmission channel is that high inflation volatility increases the ex-ante likelihood of default, affecting credit spreads. Similarly, Illeditsch (2018) states that the component of inflation risk correlated with real assets and risky cash flows is priced in corporate bonds. More recently, Bhamra et al. (2022) documents a negative relationship between expected inflation and both equity valuation and default risk, and such a relationship varies with firm leverage. Recent evidence suggests that inflation volatility risk is a relevant priced factor in the corporate market, which yields a significant excess return in the cross-section of U.S. corporate bonds. For example, Ceballos (2022) shows that the portfolio spread between corporate bonds with a higher exposure to inflation uncertainty relative to bonds with a lower inflation risk exposure command a negative premium, a phenomenon widely reported in the literature on volatility risk factors.

We complement this literature in two ways. First, we report significant inflation risk timing ability in the time-series and cross-sectional of mutual funds. Indeed, we show that the timing ability is higher during periods of high inflation uncertainty, which indicates that institutional investors can bet on or hedge against future inflation risks and affect the effectiveness of the transmission of monetary policies. The strong inflation risk timing ability implies that the mutual fund industry could help with policy implementation through expectation formation. Second, we examine the relevance of inflation risk in mutual funds that invest primarily in the corporate bond market. Based upon the aforementioned evidence on the pricing of inflation risk in corporate bond markets, mutual fund performance can be driven by their portfolio exposure to inflation risk. We find significant value creation in top-timer mutual funds.

Our paper contributes to the mutual fund timing ability literature by analyzing the ability of forecasting inflation risk information. Literature has documented multiple timing abilities in equity and bond mutual funds. For example, Chen et al. (2010) show that bond mutual fund managers exhibit strong market timing ability, conditioning on non-linearity in bond market returns. The seminal paper by Treynor and Mazuy (1966) proposes the return-based method to study market timing ability among equity fund managers, and Jiang et al. (2007) further suggest a portfolio holding-based model to uncover the source of market timing ability. Huang and Wang (2014) document that government bond mutual funds have market timing ability, and managers alter the portfolio holdings to bet on the future direction of the government bond market. Busse (1999) starts to focus on additional future market conditions, i.e., the market return volatility, which could change the market risk exposure of mutual funds. Moreover, equity fund managers also target future liquidity and downside risks, contributing to superior performance among top timers (Cao et al., 2013; Bodnaruk et al., 2019). Our paper focuses on the current concern about how inflation affects the financial markets and how institutional investors tackle the rising inflation risks. We show that managers can prepare for the direction of inflation risks.

The rest of the paper is organized as follows. Section 2 describes the data and the measure of inflation volatility risk. Section 3 documents the main analysis at the portfolio level and Section 4 presents the results using cross-sectional individual fund-level regressions. In Section 5 we show evidence of inflation risk timing ability from a holding-based approach. Section 6 concludes the paper.

2 Data and Methodology

2.1 Data

For corporate bond returns, we use transaction records reported in the enhanced version of the TRACE for the sample period July 2002 to September 2022, reported by the WRDS Corporate Bond Database. The WRDS Corporate Bond Database is a unique clean database for U.S. Corporate Bond research. It incorporates two feeds: FINRA's TRACE (Trade Reporting and Compliance Engine) data for bond transactions and Mergent FISD data for bond issue and issuer characteristics. The database reports monthly bond returns following the data cleaning procedures outlined in Dick-Nielsen (2009, 2014) to clean TRACE Enhanced and Standard databases.

We use the Mergent Fixed Income Securities Database (FISD) for bond characteristics. The database is a comprehensive database of publicly-offered United States bonds encompassing over 140,000 corporate, corporate medium-term note (MTN), and other debt securities. We proxy credit quality measures by credit ratings assigned by leading credit rating agencies (such as S&P and Moody's). A numerical rating is assigned historically to each bond (AAA = 1, ..., BBB− = 10, ..., D = 21) according to the information collected at the bond level from the Mergent Fixed Income Securities Database (FISD). Thus, we measure credit rating (Rating) as the average rating between the numerical rating provided by Moody's and S&P credit rating agencies.

For mutual funds, we obtain the sample of bond funds from the CRSP Survivor-Bias-Free Mutual

Fund Database that invests primarily in corporate bonds. We focus only on funds classified as corporate bonds or general funds based on their CRSP fund styles following Choi and Kronlund (2018) classification of fund style. The final sample consists of around 4,500 unique funds classified as corporate or general bond funds (i.e., CRSP style categories I, ICQH, ICQM, ICQY, ICDI, ICDS, or IC).

2.2 Inflation Volatility Risk Factor (***IVRF***)

2.2.1 A measure of inflation volatility risk

We measure inflation volatility risk (denoted as IVR) as the six-month rolling volatility of the unexpected inflation component captured by an ARMA(1,1) model.[3] The monthly inflation (π_t) is calculated as the percentage change in the seasonally adjusted Consumer Price Index for All Urban Consumers (CPI) available from the U.S. Bureau of Labor Statistics and then filter out these innovations using an ARMA(1,1)-model. Finally, to account for the available information for investors each month, we use the lagged monthly CPI.

(Insert Figure 1)

Figure 1 presents the time series of the inflation volatility risk measure and compares it with alternative inflation volatility risk measures commonly used in the literature: the inflation dispersion from the Michigan Survey of Consumer (MSC) and the Survey of Professional Forecasters (SPF).[4] The top Panel plots the monthly time series of the *IVR*. As expected, relatively high inflation risk was observed during the global financial crisis of 2008 to 2009 and the recent COVID-19 period in 2020. It also shows other episodes with relevant jumps in the IVR measure before and after the financial crisis. The bottom Panel presents alternative survey-based measures of inflation volatility risk. MSC and SPF measures capture the dispersion in inflation forecasts, showing that this dispersion varies substantially. Both measures exhibit a high correlation of 0.45 and 0.56 in 2002-2022, respectively.

[3] Similar approach is used by Kang and Pflueger (2015).

[4] Hong et al. (2017) use the interquartile range in monthly inflation forecasts from the Michigan Survey of Consumer (MSC) to show that government bond excess returns increase with inflation dispersion. Similarly, Soderlind (2011) explores the inflation risk uncertainty from the Survey of Professional Forecasters (SPF) at a lower (quarterly) frequency.

2.2.2 Inflation volatility risk factor ($IVRF$)

We construct a time series measure of the inflation volatility risk factor based on double-sorted portfolios between credit risk and the risk exposure to inflation volatility risk beta (β^{π}) (Ceballos, 2022). Specifically, in each month of the sample, quintile portfolios are formed based on inflation beta (β^{π}) and quintile portfolios based on credit risk (Rating).

The inflation volatility risk beta (β^{π}) is defined as the exposure of each excess bond return on the IVR measure and obtained by regressing excess bond returns on the IVR measure using a rolling window of 36 months with at least 24 non-missing observations as follows:

$$R_{i,t} = \alpha_i + \beta^{\pi}_{i,t} IVR_t + \beta^{MKT}_{i,t} MKT_t + \epsilon_t \tag{1}$$

where $R_{i,t}$ is the excess return of bond i in month t, IVR_t captures the inflation volatility risk measure in each month t and the regression controls by the bond market return (MKT_t) measured by the weighted average returns for all corporate bonds traded in the market in each month t of the sample.

To obtain the inflation volatility risk factor ($IVRF$), we follow the procedure described in Ceballos (2022) to obtain a time-series measure of the inflation volatility risk factor based on a double-sorted portfolio between credit risk and inflation risk exposure (β^{π}). Each month, we create quintile portfolios based on inflation beta (β^{π}) and quintile portfolios based on credit risk. The inflation volatility risk factor is the value-weighted average return spread between the highest-β^{π} and lowest-β^{π} portfolio across the credit rating portfolios. Figure 2 depicts the time series of the inflation volatility risk factor ($IVRF$).

(Insert Figure 2)

In Appendix, we present detailed evidence on the pricing of inflation volatility risk in the cross-section of corporate bonds. Table A.1 presents the alpha return from asset pricing models that control for equity risk factors following Fama and French (2015) and bond risk factors following Dickerson et al. (2023). We show a significant inflation volatility risk pricing in the cross-section of corporate bond returns using quintile portfolios based on β^{π}. As each quintile portfolio shows significant differences in credit risk, size, maturity, and liquidity, we extend the analysis and show that the inflation volatility risk premium remains after controlling for bivariate characteristics, as shown in Table A.2.

2.3 Summary Statistics

Panel A in Table 1 reports the summary statistics for mutual funds that invest primarily in the bond market. Age is defined as the number of years between the last return date in the database and the first date when the fund was offered, and averaged across funds within each fund category. Size ($millions) is the total net asset value (TNA). Expense ratios, turnover rates, and monthly flows (percentages of total net assets (TNAs)) and returns are in percentages. Maturity is the weighted maturity within each fund (in years). The last four rows report the average portfolio allocation within each fund category in corporate bonds, treasury bonds, cash and equity, respectively. The first column reports the characteristics of all bond funds in the sample. Columns (2) – (8) report the characteristics of funds in subcategories based on credit ratings, investor-oriented types, surviving and non-surviving.

(Insert Table 1)

On average, bond mutual funds have an age of 18.2 years, total net assets of $692 million, a monthly expense ratio of 0.01%, a turnover rate of 1.45%, monthly flows of 0.39%, and invest 42.6% of the fund in corporate bonds. Among funds with different categories, funds based on credit ratings exhibit higher returns for investment-grade funds (IG) than high-yield funds (HY). Funds based on investor-oriented types have higher returns for retail shares (Retail) than institutional shares (Inst.). The average return for index funds is -0.03%. As expected, index funds present the larger size and lowest expense ratio. Finally, compared with non-survivors, survivors are, on average, larger funds with longer histories, higher flows, and heavily invested in corporate bonds.

Panel B in Table 1 exhibits the descriptive statistics for the inflation volatility risk factors ($IVRF$), as well as common risk factors in the bond and equity markets. We consider the revised corporate bond risk factors in Dickerson et al. (2023), which measures the bond market, downside, liquidity, and credit risks. The downside risk factor (DRF) captures the expected decline of bond returns over a given time horizon and probability. We also obtain the credit risk factor (CRF) and the liquidity risk factor (LRF) that capture common risks beyond the DRF.[5] For equity market

[5] Bai et al. (2019) constructs risk factors based on characteristics of corporate bonds: downside risk, credit risk, and liquidity risk. They show that these factors have statistically significant risk premia and outperform other bond pricing models in explaining the corporate bond returns. However, Dickerson et al. (2023) reveals an error in the data used by the earlier paper that consists of temporal misalignment of different data series. Dickerson et al. (2023)

risk factors, we include the size factor (SMB), the value factor (HML), and the momentum factor (UMD), which are significantly exposed among equity mutual funds, as documented in Carhart (1997).

The mean (median) of the inflation volatility risk factor ($IVRF$) is -0.27 (-0.13) and a dispersion varying from -2.19 (percentile 5$^{\text{th}}$) to 2.24 (percentile 95$^{\text{th}}$). The mean (median) corporate bond return in the sample exhibits a monthly excess return of 33 (38) basis points. The average return for bond risk factors oscillates between 21 bps (CRF) to 34 bps (DRF). For equity risk factors, we document that the mean returns for SMB, HML, and UMD are 8, -2, and 8 bps, respectively.

2.4 Inflation-risk timing model

This section discusses a common measure of timing ability captured by the following specification:

$$R_{p,t+1} = \alpha_p + \beta_{MKT} MKT_{t+1}^{Bond} + \sum_{m=1}^{M} \beta_m f_{m,t+1} + u_{p,t+1} \tag{2}$$

Classic timing models, for example, Treynor and Mazuy (1966), Ferson and Schadt (1996), and Busse (1999), construct the timing ability as the conditional information contributed to fund market exposures. In this setting, inflation-volatility-risk timing behavior arises as a function of the market conditions, that is, the expected inflation volatility risk. Specifically, the timing model assumes the following linear specification:

$$\beta_{m,t} = \beta_m + \gamma_p (IVRF_{t+1} - \overline{IVRF}) + \epsilon_{t+1} \tag{3}$$

We obtain the following inflation-risk timing model by substituting Eq. (3) in Eq. (2) as follows:

$$R_{p,t+1} = \alpha_p + \beta_p MKT_{t+1}^{Bond} + \gamma_p MKT_{t+1}^{Bond} (IVRF_{t+1} - \overline{IVRF}) + \sum_{m=1}^{M} \beta_m f_{m,t+1} + \upsilon_{p,t+1} \tag{4}$$

where $R_{p,t+1}$ is the excess return on each individual fund p in month $t+1$. The explanatory risk factor variables from the bond market (f^{Bond}) include the bond market excess return (MKT^{Bond}), the credit risk factor (CRF), the liquidity factor (LRF), and the downside risk factor (DRF). In addition, we control for risk factors from the equity market (f^{Equity}), such as the size factor (SMB), the value factor (HML), and the momentum factor (UMD). The $IVRF_{p,t+1}$ is the market inflation

find that in data that do not exhibit this error, the factors identified in Bai et al. (2019) do not have incremental explanatory power over the aggregate corporate bond market return. Thus, we adopt the revised list of factors. In later section, we also use alternative factors in Fama and French (1993) and the results are similar.

risk measure in month $t+1$, and $\overline{IVRF}$ is the mean level of inflation risk measure over the previous 12 months ($t-12$ to t).

The coefficient γ measures the inflation-risk timing ability of fund managers. A significant and positive γ coefficient indicates that mutual fund managers correctly anticipate high (low) market inflation volatility risk and increase (reduce) market exposure accordingly. When γ is significant and negative, mutual fund managers incorrectly forecast market inflation volatility risk or, perversely, increase market exposure when market inflation volatility risk is higher.

3 Empirical analysis: Portfolio level

This section estimates inflation-risk timing ability among corporate bond mutual fund managers at the aggregate portfolio level. We first examine the inflation-risk timing ability using the whole sample. We also investigate the economic value of inflation-risk timing ability. Then, we check whether the results are robust to subcategories, separated based on style into investment-grade and high-yield bond investment, based on investor orientation into retail and institutional shares, whether a fund survives until the end of the sample, and active versus index mutual funds. We also distinguish managers' inflation-risk timing ability with reaction to past inflation risks. Finally, using inflation-protected funds, we verify that the inflation-risk timing ability is unique to those managers who alter portfolio exposures according to inflation risks.

3.1 Evidence from aggregate funds

We first estimate the inflation-risk timing model Eq. (4) using aggregate (equal-weighted) fund portfolios. Due to the extraordinary volatility in asset prices after the onset of COVID-19, we exclude from the sample March and April 2020.[6]

(Insert Table 2)

Table 2 reports the coefficients from Eq. (4) using corporate bond mutual fund managers in the sample. We report all coefficients estimated for both bond and equity market risk factors. The t-statistics in parentheses are calculated using Newey and West (1987) heteroscedasticity and

[6] In particular, the period is characterized by the stock and the bond market crashes, two of the largest increases in market volatility (captured by VIX) after the global financial crisis of 2008. Furthermore, the policy reactions of Federal Open Market Committee with extraordinary meetings during those days, along with the high demand for U.S dollar liquidity, induce noise in our identification of the inflation risk premium in the corporate bond market.

autocorrelation-consistent standard errors with twelve lags.

Column (1) reports the estimated inflation-risk timing ability, γ, using all funds in the sample. Corporate bond mutual fund managers exhibit a positive and statistically significant estimate at the 1% level for the inflation-risk timing coefficient, suggesting that bond fund managers have strong timing ability on average. The timing coefficient γ of 0.03 indicates that in a given month, when market inflation risk, *IVRF*, is one standard deviation (STD=1.86) above its sample mean, the average mutual fund portfolio's market beta is higher by 0.055 (i.e., $\gamma \times (IVRF_{t+1} - \overline{IVRF}) = 0.03 \times 1.86$), which is up to 7.1% of the bond market beta ($\beta_{MKT} = 0.77$) if the aggregate inflation risk is at its average level.

To analyze the variation of fund managers' timing ability across different regimes of inflation risks, we consider periods of elevated inflation uncertainty. Based on dispersion for expected inflation from the Survey of Professional Forecasters (SPF) between 2003 and 2022, we identify high-inflation-uncertainty regimes as the periods when inflation dispersion was higher than 90% or 95% percentiles of their historical values. We define a dummy variable for the high-uncertainty periods.

We multiply the high-inflation-uncertainty regime dummy with the interaction of the *IVRF* measure and the bond market returns to capture the timing ability in such an inflation environment. That is, we add a term, $\gamma_p^{D(High\ \pi)} \times D(High\ \pi) \times MKT_{t+1}^{Bond} \times (IVRF_{t+1} - \overline{IVRF})$, in Eq. (4), where $\gamma^{D(High\ \pi)}$ estimates how fund managers allocate portfolio exposure to inflation risks differently across high uncertainty regimes.

Columns (2) and (3) in Table 2 report the high-uncertainty regime timing coefficient in the second row. Both coefficients are positive and statistically significant at a 1% level. The magnitude of $\gamma^{D(High\ \pi)}$ is more than two times above the timing ability coefficient γ observed in the whole sample. The coefficient estimated in the top 90% uncertainty is 0.07 (t-statistic = 22.3), and the number increases to 0.08 (t-statistic = 19.1) under the top 95% inflation environment. Thus, managers exhibit even more vital timing ability under a more uncertain inflation risk regime.

The evidence from the aggregate portfolio-level analysis suggests that corporate bond mutual fund managers can successfully time inflation risks. We examine the economic value of timing ability to explore whether the estimated timing coefficient reflects managerial skills.

3.2 Economic value of inflation-risk timing ability

Does inflation-risk timing ability add value to fund investors? We investigate the investment value of selecting top inflation-risk timers to gauge the economic significance of our inflation-risk timing γ.

In each month starting from January 2006, we estimate the timing coefficient γ for each fund using the past 36-month estimation period and then form ten portfolios based on their estimated timing coefficients. We hold these portfolios subsequently for three, six, 12 months, 18 months, 24 months, and 36 months. This method yields six different time series of portfolio returns based on the sorted fund timing ability from 2006 to 2022. We include a fund return until it disappears during the holding period. The portfolio is rebalanced going forward. The spread portfolio between top and bottom timers, which measures the economic value of inflation-risk timing ability, is defined as the return difference between two extreme deciles. Lastly, we estimate and report the portfolios' out-of-sample αs using bond and equity factors.

(Insert Table 3)

Table 3 presents evidence of the economic value of inflation-risk timing ability. The top decile portfolio of inflation-risk timers delivers economically and statistically significant αs in the next three-month to 36-month post-ranking periods. For a 12-month holding period in Column (3), the top timer portfolio's α is 0.41% per month (4.9% per year) with a t-statistic of 3.14. Yet, the bottom timers only provide 0.08% per month (0.96% per year) risk-adjusted returns. The spread portfolio between the top and bottom timers yields a significant α of 0.3% per month. That means, on average, successful inflation-risk timing fund managers can gain at least 4.0% per year higher abnormal returns than incorrect timing managers.

Top timers can continuously deliver positive and non-diminishing profits to their investors in the following three years at a 1% significance level, whereas bottom timers only marginally beat factor models and provide insignificant abnormal returns for up to two years. Top-timer portfolios also generate significantly higher out-of-sample αs than the bottom-timer portfolios over the next three-year holding period. The αs of the spreads between the top and the bottom timers range from 0.30% (36-month in Column (6)) to 0.37% (three-month in Column (1)) per month, depending on the holding periods, and remain significant three years after the ranking period. That is, successful inflation-risk timing funds outperform incorrect timing funds by 3.5 – 4.4% per year on a risk-adjusted basis. This result is both economically and statistically significant.

(Insert Figure 3)

The economic value of inflation risk timing skill can be seen more directly from Figure 3, which shows cumulative returns on the portfolios of top and bottom inflation-risk timing funds, respectively, for a three-month holding period. Holding the top-decile of successful timing funds yields a cumulative return of 109.7% from July 2006 to December 2022, and holding the bottom-decile of incorrect timing managers generates a cumulative return of only 16.4% over the same period. It illustrates that top timers deliver an average higher economic value that of bottom timers in post-ranking periods.

To summarize, we find strong evidence that inflation-risk timing skill adds economic value to investors. Our economic value results further confirm that inflation-risk timing reflects managerial skill and can be one of the sources for bond mutual fund α.

3.3 Timing versus reaction to inflation risks: Evidence from inflation-protected funds

The literature on timing ability examines whether fund managers could *forecast* the level of market conditions. If market conditions such as inflation risks are serially correlated, their values in month $t+1$ contain information from prior months. Thus, a fund manager may adjust market exposure based on lagged values of market conditions. As noted by Ferson and Schadt (1996), lagged market conditions are public information, and adjusting fund betas based on public information does not reflect actual timing skill.

The *IVRF* measure has a mild serial (first lag) autocorrelation of 0.32 (See Fig. 2). Suppose a fund manager uses observed inflation risk in month t to derive a predictable inflation risk component and adjusts his fund beta accordingly. In that case, she has no timing skill but reacts to past inflation risk conditions. This observation highlights a primary difference between inflation-risk timing and inflation-risk reaction: Inflation-risk reactors adjust fund exposures based on observed inflation risk in month t, and inflation-risk timers manage bond market exposures based on their forecasts of inflation risk in month $t+1$. To distinguish inflation-risk timing ability with reaction to past inflation shocks, we replace the inflation risk factor in $t+1$ with the factor value in time t; that is, the reaction to inflation risk model is specified as

$$R_{p,t+1} = \alpha_p + \beta_p MKT^{Bond}_{t+1} + \gamma_p^{Reaction} MKT^{Bond}_{t+1}(IVRF_t - \overline{IVRF}) + \sum_{m=1}^{M} \beta_m f_{m,t+1} + \upsilon_{p,t+1} \quad (5)$$

where $IVRF_t$ represents the observed public inflation risk factor in month t and $\gamma_p^{Reaction}$ is the coefficient of reaction to inflation risks. All other variables are the same as are defined in Eq. (4).

The logic of the reaction coefficient, $\gamma^{Reaction}$, is that if a fund manager observes a public signal of inflation risks in the past, then she will alter her portfolio's exposures to the past inflation risk factor in a corresponding way. The manager herself does not necessarily have any prior forecast about future levels of inflation risk. Thus, there should be an economic value for fund managers who only react to, rather than time, inflation risks. We re-examine the economic value test as in the previous section but replace the future inflation risk factors with past inflation risk factors. Lastly, we sort fund performance using the estimated reaction coefficient, $\gamma^{Reaction}$. We document the magnitudes and significance levels of portfolio abnormal returns in Table 4.

(Insert Table 4)

Our results suggest that the economic value of reaction to inflation risks is mixed with timing ability. Both top and bottom reactors generally produce economically and significantly large αs, suggesting that reaction to inflation risk contributes equally to different reactors to inflation risks. In Column (2), with the post-ranking holding period as six months, the top reactor decile delivers 0.20% per month abnormal returns, and the α of the bottom reactor decile is 0.17%, with corresponding t-statistics as 1.48 and 1.74. Top-timer portfolios generate marginally lower out-of-sample αs than the bottom-timer portfolios over the three-month holding period in Column (1). The spread between top and bottom timers is -0.01% per month with the t-statistic as -0.06. The results imply that reaction to inflation risk does not have additional value to bond fund manager's performance.

From Column (2) to Column (6), successful managers regain advantageous positions relative to incorrect reactors in the portfolios with longer holding periods since the inflation risk factor may accumulate future information. The αs of the spreads between the top and the bottom reactors range from 0.03% to 0.17% per month or 1.4% to 2.1% per year if the holding period is over six months.

Compared with the economic value of timing ability among bond mutual fund managers, reaction delivers consistently and significantly lower premium than timing ability. For example, if the holding period is 18 months (Column (4)), the economic value of reaction to inflation risk is 0.12% per month with t-statistic as 1.74; yet, the economic value of timing ability is 0.34% per month with t-statistic as 3.55 in Table 3.

One possible explanation for the significant economic value of timing ability rather than reaction is that inflation risk coincides with either latent variables or statistical errors. Bond fund managers thus inherit timing ability, even though they do not forecast inflation risks. We focus on a subsample of inflation-protected corporate bond mutual funds to show that inflation-risk timing ability is not driven by either latent variables or pure "luck". To tease out the alternative explanation, we focus on fund managers who are not required to have any inflation risk timing ability.

Inflation-protected funds are designed to protect investors from the eroding effect of inflation risks by investing primarily in securities that seek to provide a "real" return. The funds focus on investments in inflation-protected bonds backed by the federal government's full faith and credit and whose principal is adjusted based on inflation, which adjust their valuations in response to inflation. Hence, the funds' performance fluctuates in response to both changes in interest rates and the rate of publicly observed inflation. Inflation-protected funds should react to, rather than time, inflation risks. Suppose there still exists the economic value of timing ability rather than a reaction to past information. In that case, the inflation risk timing ability is spurious. Bond mutual fund managers do not necessarily have the ability and benefits from forecasting inflation risks.

We examine the economic value of the inflation-risk timing and inflation-risk reaction among inflation-protected funds using the same approach to valuing other bond mutual funds. To estimate timing and reaction, we include $IVRF_{t+1}$ in Eq. (4) or $IVRF_t$ in Eq. (5) and repeat the analysis of economic value. Inflation-protected corporate bond mutual funds are identified by searching for keywords in the fund names, including abbreviations of "inflation" and "protect." There are 361 inflation-protected funds in our sample. Thus, we form three portfolios and obtain out-of-sample αs of each inflation-risk timing and reaction portfolio and the spread between the top and bottom portfolios.

(Insert Table 5)

Panel A and B in Table 5 document the portfolio abnormal returns based on fund managers' inflation-risk timing ability and reaction to inflation risks. The results show that inflation-risk reaction, rather than timing ability, generates economically and statistically large economic value for fund investors.

For the sample of inflation-protected funds, the out-of-sample α for the portfolio consisting of top timer is 0.12% for a three-month holding period, and the α for the bottom timer is 0.18%

for the same holding period. The spread between the out-of-sample performance of the top and bottom timers among inflation-protected funds is negative and insignificant for all the three holding periods considered, i.e., three, 24, and 36 months. Nevertheless, inflation-protected funds' reaction to inflation risk is large and significant. For example, focusing on the same three-month holding period, the top reactors receive 0.23% premium and the bottom reactors only have 0.09%. The spread is up to 0.15% per month over the next three-month holding period. The significance level remains large if we hold the top reactor-versus-bottom reaction portfolio for the next 24 to 36 months.

In conclusion, we show that inflation-risk timing ability is truly distinguishing among corporate bond mutual fund managers, which cannot be subsumed or explained by lagged public information or latent variables.

3.4 Evidence from subcategories

This section presents evidence of the timing ability in subcategories of corporate bond mutual funds based on credit ratings, investor-oriented types, survival or not until the end of the sample, and active versus index funds.

Credit ratings and maturities Since the credit rating is a critical component in determining corporate bond prices, Ceballos (2022) shows that the inflation volatility risk premium in high-yield bonds yields at least twice as large as the premium using investment-grade bonds in quintile sorting portfolios.[7] Thus, corporate bonds with worse credit ratings tend to carry more inflation risk.

(Insert Table 6)

Columns (1) and (6) in Table 6 report the regression results for any mutual funds whose investment objectives focus on investment-grade (IG) and high-yield (HY) corporate bonds. Then, for mutual funds concentrated on IG bonds, we further separate the sample based on detailed credit ratings and time to maturity. Funds are separated by credit rating into "A or higher" and "BBB or higher" in Columns (2) and (3). By looking at the maturity of invested bonds, we partition IG funds into short-maturity (less than five years) and long-maturity (five to ten years) groups in Columns (4) and (5).

[7] In Appendix Table A.2 we replicate evidence in Ceballos (2022) and show that the pricing of inflation volatility risk in high-yield bonds is 80% higher than the pricing in investment-grade bonds.

Overall, the timing coefficient is positive and significant at 1% with a coefficient estimate of 0.03 for all investment-grade bonds (t-statistic = 9.2). In addition, the timing coefficients among subcategories (A or higher versus BBB or higher) suggest that mutual fund managers exhibit stronger skills in portfolios with bonds of better credit quality.

In contrast, we document no timing ability among mutual funds concentrated on high-yield bonds in Column (6). For high-yield bonds, the timing coefficient is 0.01 (t-statistic = 1.3), while the portfolio exhibits a higher exposure to bond market risk (β_{MKT}) and credit risk factor (β_{CRF}) than those for IG bond funds. For example, the exposure on credit risk factor for HY bond funds is 0.56% at a 1% significance level, and the number decreases to -0.03 with a 10% significance level for IG bond funds.

The estimated timing ability coefficients within IG bond funds are statistically significant but with some variations. In Columns (2) and (3), we find that when a fund manager invests in bonds with highest credit ratings (A or higher), she generates marginally better performance in terms of higher timing ability than other manager who transacts BBB or higher bonds (0.04 versus 0.03). In Columns (4) and (5), the results also indicate that a fund manager investing in bonds with longer time to maturity (five to ten years) contains greater timing ability than those with shorter maturity (one to five years).

Subcategories and placebo tests We now investigate fund shares oriented to different investors, i.e., retail and institutional investors. Institutional shares of mutual funds are designed to cater to institutional investors, including retirement plans, foundations, and endowments. They differ from retail shares in sophistication and investment constraints; for example, fund managers communicate directly with institutional investors to attract a large inflow of funds and ask for higher minimum initial/subsequent investment. On the other hand, retail shares may free-ride on the sophisticated skills of institutional shares. Managers of retail shares are sometimes the same as those of institutional shares, thus exerting some inflation-risk timing ability.

To distinguish inflation-risk timing ability between institutional and retail shares, we first identify the investor-oriented types based on the institutional versus retail share flags in the CRSP Survivor-Bias-Free Mutual Fund Database. We then estimate and report γs in Columns (1) and (2) of Table 7. The timing coefficient for retail shares is 0.02 with a t-statistic of 4.4, and the estimation of institutional investors is 0.03 (t-statistic = 4.7). Moreover, the risk exposures on bond and equity factors are similar in retail and institutional shares. For example, the factor loading on bond market returns is of similar positive magnitude (0.76 versus 0.77) and statistically significant with t-statistics as 16.4 and 16.6, respectively. Thus, managers of retail shares share similar timing skill sets with those of institutional shares.

(Insert Table 7)

We focus on whether inflation-risk timing ability vanish among managers of disappeared mutual funds. Mutual funds exit the market either because their performance is very poor over a period of time or because their total market value is too small to pay to maintain the fund. The latter reason for closing a fund is usually associated with the former reason: poor performance.

Empirical evidence has shown evidence of how survivorship funds induce a performance bias (Carhart et al., 2002). In the context of our paper, non-surviving funds may offset the inflation volatility risk timing of live funds. Therefore, we address the concern of whether the timing ability documented is due to survivorship bias in our sample. Columns (5) and (6) of Table 7 document the timing ability for survived and non-survived mutual bond funds until the end of the sample period (i.e., September 2022). In both cases, the timing coefficient is of similar magnitude as the timing coefficient γ estimated using all funds (coefficients of 0.02 – 0.03). Thus, survivorship bias will not affect the main results.

Lastly, we perform a placebo test by exploring inflation-risk timing by the most passive mutual funds: index funds. The index funds aim to match the total investment performance of a publicly recognized index. The fund will hold virtually all securities in the noted index with weightings close to those in the index. Thus, index fund managers may have little inflation-risk timing ability. In Column (5) of Table 7, the timing coefficient γ for index funds is positive but smaller than the estimated ability in other types of (active) bond mutual funds. In particular.

Table 7 generally supports the robustness of our main results, that is, corporate bond mutual funds have inflation timing ability. Nevertheless, the evidence raises two subsequent questions: why do we observe the indifference of estimated timing ability between retail and institutional fund shares and why do we have statistically significant timing ability among index funds? The answer these questions calls for individual fund level analysis to uncover the distribution of inflation-risk timing ability.

4 Empirical analysis: Fund level

This section estimates the inflation-risk timing ability at the fund level. In particular, for each category analyzed, we evaluate the inflation-risk timing skill using Eq. (4) for individual funds. Then, we examine the cross-sectional distribution of t-statistics, focusing on the γ coefficient that captures timing skills for a subset of funds reported in the previous section.

4.1 Cross-sectional distribution of t-statistics for inflation-risk timing

Table 8 reports the cross-sectional distribution of t-statistics for inflation-risk timing coefficients across individual funds. Numbers in Columns (3) to (10) show the percentage of t-statistics computed from all funds that exceed the indicated cutoff values of t-distribution. For example, the first row represents the t-statistic distribution of all funds in the sample. The evidence shows that the right tails appear thicker than the left tails: At least 46.8% of all corporate bond mutual funds have t-statistics greater than 1.28 (at 10% significance level). More importantly, up to 33% of managers are top-timers whose timing ability estimate is above the 1% significance level, i.e., t-statistic = 2.33. Meanwhile, about 11.7% of the funds have t-statistics smaller than -1.28, indicating that a limited amount of funds have negative timing ability (466 bottom timers out of 3986 mutual funds).

(Insert Table 8)

Managers in bond funds with different risk characteristics may incorporate different timing abilities. Thus, we investigate inflation-risk timing ability among corporate bond mutual funds with different credit ratings, investor-oriented types, survivorship, and index investment. The following rows in Table 8 document similar distributions for subcategories of mutual funds. First, more than 50% of managers in funds focusing on investment-grade corporate bonds and 40% of managers specializing in high-yield bond investment, have significant inflation-risk timing ability. In particular, the number of investment-grade bond funds with significant inflation-risk timing ability is roughly three times larger than that of high-yield bond funds. The results are consistent with portfolio-level evidence that funds investing in bonds with higher than BBB corporate bonds illustrate stronger inflation-risk timing ability than those investing in high-yield bonds.

The portfolio-level evidence shows a marginal difference between the retail and institutional funds' significant inflation-risk timing abilities. Yet the distribution of individual funds provides a detailed comparison in Rows (4) and (5) of Table 8. For example, more than 50% or 969 of managers who are in charge of the institutional shares in bond funds illustrate strong timing ability at a 10% significance level, whereas the number decreases to 36.2% or 630 among retail shares. Comparing managers with negative γs, we also find that institutional shares have fewer incorrect timing cases than retail shares (3.0% versus 5.1% at 1% significance level). Even though the inflation-risk timing γs are significant in Table 7, institutional fund managers illustrate more robust timers.

If we separate bonds into survivor versus non-survivor groups, the distributions of estimated γs are consistent with the whole sample results in Rows (6) and (7). In particular, managers of survived funds have marginally similar pattern as the all fund results. Yet non-survived funds have a relatively heavy right tail, indicating that there are more successful inflation-risk timers, as well as less incorrect timers. The detailed comparison between survived versus non-survived funds highlights that even though at the portfolio level, survivors illustrate a larger magnitude of timing ability (i.e., larger estimated γ), there are more robust and correct inflation-risk timers among non-survived funds, who may have closed before they suffer from unexpected spikes in inflation.

In contrast to Table 7, Rows (8) and (9) in Table 8 show that only 25%, or 69 managers of index bond funds, exhibit a positive inflation-risk timing ability with t-statistics greater than 1.28, while there are 48.5%, or 1799 managers have significant inflation-risk timing ability among non-index funds. Although the amount of inflation-risk sensitive managers among index funds becomes realistic, the question is whether the remaining index funds with timing ability are due to pure "luck" or the actual capacity of resilience to inflation risks. We will investigate index funds using bootstrap methods in the next section.

Lastly, a key finding is that the right tail (positive timing ability) is thicker than the left tail (negative timing ability). Indeed, funds that exceed the t-statistics cutoff of 2.33 range between 19.9% to 42.1%, depending on the fund investment objectives and categories. In contrast, less than 5.5% of funds have a t-statistics lower than -2.33. Therefore, the evidence indicates that most funds (except "Index" funds) have a positive inflation-risk timing coefficient.

In summary, the distribution of individual funds' inflation-timing ability is consistent with the portfolio-level evidence. We also get better insights into the differences in bonds with various credit ratings or investor orientations, which reinforces the portfolio-level evidence. We further provide robustness evidence in the following subsections to investigate whether inflation-risk timing is alleviated by alternative timing abilities, risk factors, or monetary policy changes.

4.1.1 Controlling for market timing and volatility timing

Inflation risk is negatively correlated with contemporaneous bond market returns and market volatility (Ceballos, 2022). Fund managers could time market returns and volatility as well. Thus, the evidence on inflation-risk timing may manifest the market or volatility timing abilities. To address this concern, we explicitly control for alternative timing abilities in our inflation-risk timing model in the specification

$$\begin{aligned} R_{p,t+1} &= \alpha_p + \beta_p MKT_{t+1}^{Bond} + \gamma_p MKT_{t+1}^{Bond}(IVRF_{t+1} - \overline{IVRF}) \\ &\quad + \underbrace{\lambda_p MKT_{t+1}^{Bond} \times Var_{t+1}}_{\text{Market or Volatility timing}} + \sum_{m=1}^{M} \beta_m f_{m,t+1}^{Bond} + \sum_{n=1}^{N} \beta_n f_{n,t+1}^{Equity} + \upsilon_{p,t+1} \end{aligned} \tag{6}$$

where $R_{p,t+1}$ is the excess return on each individual fund p in month $t+1$. In addition to inflation risk measure and factors described in Eq. (4), we consider market timing or volatility timing abilities in the term $MKT_{t+1}^{Bond} \times Var_{t+1}$. For market timing ability, we follow the seminal paper by Treynor and Mazuy (1966), who includes the square of market return, $(MKT_{t+1}^{Bond})^2$, to approximate managers' projection about the future performance of the market. When the market is up, the successful market-timing fund will be up by a disproportionate amount. When the market is down, the fund will be down by a lesser amount. Thus, we estimate market timing ability by using bond market returns as Var_{t+1}.

In addition, market volatility is predictable because it is more persistent than market returns and moves closely with macroeconomic risks, i.e., inflation risk. Managers may identify the public or macroeconomic signals about future fluctuation of the market and adjusts the risk exposure of the portfolio. To address the concern that volatility timing ability may overlap with inflation risks, we include volatility timing ability term by defining Var_{t+1} as $(Vol_{t+1} - \overline{Vol})$, the difference between monthly volatility measure and the mean level of volatility measure over the previous 12 months (t-12 to t).. We adopt three volatility measures. The first measure is bond market return volatility (Bond vol.), defined as the standard deviation of 36-month bond market returns. The second measure is stock market return volatility (Equity vol.), defined as the standard deviation of 36-month S&P 500 index returns. The last measure is month-end CBOE S&P 500 index option implied volatility (i.e., the VIX) from the CBOE website.

The correlation between bond market returns and the inflation risk measure is -0.28 over the sample period 2003–2022, and the correlation between the bond market return volatility, equity market return volatility, and VIX and the inflation risk measure are -0.24, -0.19, and -0.52 over the same period at 1% significance levels.

(Insert Table 9)

Table 9 shows the distributions of estimated γs of inflation-risk timing ability with either market or volatility timing ability in the first two panels and both alternative abilities in Panel C.[8]

We find that after controlling for market timing and volatility timing, the number of funds with significant inflation-risk timing coefficients γs, remain similar to the number of significant γ in Table 8. For example, after controlling for market timing and volatility timing (Bond vol.) abilities, we observe significant evidence of inflation-risk timing ability. Specifically, 40.4% of bond fund managers, compared to 46.8% of all funds in Table 8, have strong inflation-risk timing ability at a 10% significance level. Moreover, in Appendix Table A.3, the fraction of significant market-timing coefficients are no higher than 14%, whereas there are up to 48.9% of managers who have incorrect market timing ability, suggesting that there is no evidence of market timing. The volatility-timing coefficients are significant and negative. This result is consistent with the evidence of volatility timing among equity mutual funds in Busse (1999).

Taken together, these results indicate that the significant inflation-risk timing coefficients are not due to the correlation between market returns or market volatility and inflation risks. Inflation-risk timing is therefore an important component of the strategies of actively managed corporate bond mutual funds.

4.1.2 Controlling for alternative factors and monetary policy shocks

In addition to bond market factors documented in Bai et al. (2019) and Dickerson et al. (2023), there are alternative factor models that explain the risk premium structure in the bond market. For example, Fama and French (1993) show that default and term spreads are important factors that affect expected returns on corporate bonds. Managers may adjust the inflation risk exposure of the portfolio to time changes in macroeconomic conditions. They may vary the allocation to asset classes differing in credit or duration risks and adjust the portfolio's exposure according to other economic factors (i.e., term and default spreads). Since default and term spread represent macroeconomic conditions and are negatively correlated with inflation, managers may oversee inflation risks if they

[8] We also report estimated market or volatility timing abilities, λs, in Appendix Table A.3.

rely on default and term spreads factors. Bali et al. (2021) also find that economic uncertainty risk is negatively correlated with corporate bond returns.

We adopt following bond factors. The first factor is the term spread ($TERM$), defined as the difference between the monthly long-term government bond return and the one-month Treasury bill rate measured at the end of the previous month. $TERM$ captures the unexpected changes in interest rates. The second factor is the default spread (DEF), defined as the difference between the corporate bond market return and the long-term government bond return. DEF captures the change of the likelihood of default.

To measure uncertainty, we first use the macroeconomic uncertainty index (UNC) from Jurado et al. (2015), which is a factor-based estimate of economic uncertainty. They estimate the conditional volatility of the unpredictable component of the future value using a rich set of time series that represent broad categories of macroeconomic activities, then aggregate individual conditional volatilities into a macro uncertainty index. The second measure is the economic uncertainty measure (EPU) based on newspaper coverage frequency in Baker et al. (2018). EPU captures uncertainty about the timing and effects of economic policy decisions and policy actions, which helps to address the possibility that inflation risks are relevant to uncertainties about the economic ramifications of policy matters.

(Insert Table 10)

We replace these alternative bond factors in Eq. (4) with aforementioned factors and report the distributions of estimated γs in Panel A and Panel B in Table 10. Using Fama-French bond factors, the distributions of inflation-risk timing ability are similar. For example, by using changes in default spread (Row (1)), 46.6% of bond fund managers have significant inflation-risk timing ability. The distributions move right compared to ones in Table 8 using changes in uncertainty measures, where at least half of bond managers illustrate strong inflation-risk timing ability (Rows (3) and (4)). In general, the results suggest that using alternative bond market risk factors does not materially affect the distributions of significant inflation-risk timing coefficients.

Inflation risk is also closely related to monetary policy shocks. Central banks has been implementing "inflation targeting" after the efforts to reduce inflation in the 1980s. This monetary policy is characterized by the announcement of official target ranges for the inflation rate at one or more horizons, and by explicit acknowledgment that low and stable inflation is the overriding goal of monetary policy. Inflation targeting also aims to increase communication with the public about the plans and objectives of the monetary policymakers. Monetary policy surprises also have strong effects on the corporate bond credit risk premium (Bernanke and Mishkin, 1997; Kashyap and Stein, 2023). Thus, spurious inflation-risk timing ability could exist if fund managers target on exposure to variation in monetary policies. To alleviate the impacts of policies, we include monetary policy shock variables to Eq. (4) to investigate whether inflation-risk timing ability among corporate bond mutual fund managers is diminished due to monetary policies.

We focus on days with the Federal Open Market Committee (FOMC) announcements, and adopt three well-known monetary shocks. The first measure is defined by high-frequent news policy shock in Nakamura and Steinsson (2018), which estimate changes in expectations about the Fed funds rate using tick-by-tick data on Fed funds futures and eurodollar futures. They argue that monetary policy announcements convey information about the Fed's internal forecasts for unemployment or GDP, which in turn, affects investors' (including fund managers) beliefs about economic fundamentals and causes asset prices to move.

The second measure is defined as the current federal funds rate target factor and the future path of policy factor in Gürkaynak et al. (2005). The target factor is similar to the measure of federal funds target surprises and drives unexpected change in the current target for the federal funds rate. The path factor represents all other aspects of FOMC announcements that move futures rates fur the upcoming period without changing the current federal funds rate, which includes any information that affects the expected path for monetary policy. They show that both factors have large impacts on Treasury yields.

The last measure is the unexpected changes in interest rates in a 30-minute window surrounding scheduled Federal Reserve announcements arise from news about monetary policy.[9]

Rows (5) to (7) in Table 10 report the distribution of estimated γ by including three different monetary policy shock variables. The results are similar to those in Table 8; in particular, the right tails of successful inflation-risk timers perform marginally better than the cases where we ignore the effects of monetary policy shocks. For example, use Nakamura and Steinsson (2018)'s measure, more than 35% of bond fund managers are top-timers after taking policy surprises into consideration.

After including both alternative bond factors and monetary policy shocks (Row (8), "All

[9] Macro uncertainty index (UNC) is downloaded directly from Sydney Ludvigson's website `https://www.sydneyludvigson.com/data-and-appendixes`. Economic policy uncertainty (EPU) index is downloaded from `https://www.policyuncertainty.com/research.html`. FOMC meeting calendar is collected from Board of Governors of the Federal Reserve System.

alternative factors and shock"), the distribution of estimated inflation-risk timing coefficients, γs, are similar to the main evidence. Collectively, the findings do not suggest that our inflation-risk timing model is misspecified or subsumed by alternative explanations.

4.2 Evidence from individual funds: Bootstrap analysis

Using parametric estimation using individual funds, the cross-sectional distributions of t-statistics suggest that there generally exists inflation-risk timing ability based on the significance levels defined under the normality assumption. However, the conclusion is inconsistent in some cases; for example, inflation-risk timing ability is indifferent between survived funds and other subcategories. Index funds also yield unexpected significance. We argue that the conventional parametric inference can yield misleading results for several reasons.

First, for majority of our sample funds, the distributions of their estimated residuals and the distributions of timing coefficients using Eq. (4) are non-normal. Second, corporate bonds in the mutual fund portfolios are illiquid and exhibit non-normal and correlated returns. The estimated timing ability spuriously depends on the cross-sectional distributions of fund returns. Hence, managerial skill for a large number of funds may have significant t-statistics under the conventional levels even if none of the funds has true timing ability (pure "luck"). Finally, the number of corporate bond mutual funds changes over time and many funds exist in the history, making it difficult to estimate the covariance matrix of fund returns. To isolate true managerial timing ability with statistical variations, we employ bootstrap procedure similar to that in Kosowski et al. (2006); Jiang et al. (2007); Cao et al. (2013).

4.2.1 Bootstrap procedure

We describe the bootstrap procedure used to assess the statistical significance of inflation-risk timing coefficients for individual funds. The basic idea of the bootstrap analysis is that we randomly resample data (e.g., regression residuals) to generate hypothetical pseudo-funds that, by construction, have the same factor loadings as the actual funds but have zero loading on inflation-risk timing ability (that is, imposing $\gamma = 0$). Presumably, these pseudo-funds should have no timing ability. Then, we evaluate if the t-statistics of the estimated timing coefficients γ for the actual funds are different from the bootstrapped distribution that assumes no timing ability.

The underlying assumption is that the variation of estimated γs using pseudo-funds comes from statistical randomness, which measures pure "luck" for fund managers to achieve good performance.

If the actual t-statistics is higher than the percentile cutoffs using empirical distribution of timing ability coefficients of pseudo-funds, we conclude that these managers do have inflation-risk timing skills rather than pure "luck." Our bootstrap procedure has following five steps.

Step 1. Estimate the inflation-risk timing model for each fund p:

$$R_{p,t+1} = \alpha_p + \beta_p MKT^{Bond}_{t+1} + \gamma_p MKT^{Bond}_{t+1}(IVRF_{t+1} - \overline{IVRF}) + \sum_{m=1}^{M} \beta_m f_{m,t+1} + \upsilon_{p,t+1}$$

where $R_{p,t+1}$ is the excess return on each individual fund p in month $t+1$ and independent variables are defined as in the previous section. We save the estimated coefficients $\{\hat{\alpha}_p$, $\hat{\beta}_p$, $\hat{\beta}_1$, $\cdots$, $\hat{\beta}_M\}$ and the time series of estimated residuals, $\{\hat{\upsilon}\}_{t=1}^{T}$, where T is the current observation period.

Step 2. For the b^{th} iteration, we re-sample the estimated residuals with replacement and obtain a randomly re-sampled residual time series $\{\hat{\upsilon^b}\}$, where b is the index of bootstrap iteration (b = 1, 2, $\cdots$, B). We then construct the time series of monthly excess returns for a pseudo-fund, R^b_p, which has no timing skill by construction (i.e., $\gamma_p = 0$). That is,

$$R^b_{p,t+1} = \hat{\alpha_p} + \hat{\beta}_p MKT^{Bond}_{t+1} + \sum_{m=1}^{M} \hat{\beta}_m f_{m,t+1} + \hat{\upsilon^b}_{p,t+1}$$

The pseudo-funds have exactly the same risk exposures to common risk factors and latent variables, except for timing ability.

Step 3. Using a time series of pseudo-fund excess returns from Step 2, we estimate the timing model from Step 1 and store the estimation of the timing coefficient, γ^b_p, and its t-statistic. Since the pseudo-fund has a true γ^b_p of zero by construction, any nonzero timing coefficient is due to sampling variation.

Step 4. Run Steps 1 to 3 across all individual funds. The cross-sectional distribution of the estimated timing coefficients and their t-statistics across all sample funds can be observed. For the estimated distribution in the b^{th} iteration, we record the bootstrapped cutoffs at the top and bottom 1%, 3%, 5%, and 10% percentiles.

Step 5. Repeat Steps 1 to 4 for B iterations to generate the list of time series for cross-sectional statistics of t-statistics estimated using all individual pseudo-funds. The output of the exercise above is a set of bootstrapped cutoffs as the empirical distributions to evaluate managerial skills. We set the number of bootstrap simulations B to 10,000.

The bootstrap analysis helps to investigate whether a significant estimated inflation-risk timing coefficient is the result of pure "luck" or managerial skills. For each cross-sectional statistic of the timing coefficient (or its t-statistic), we compare the actual estimate with the corresponding distribution of estimates based on bootstrapped pseudo-funds, and we determine whether the inflation-risk timing coefficient can be explained by random sampling variation (i.e., the source of pure luck). We conduct our bootstrap analysis mainly for t-statistics of the timing coefficient γ.

4.2.2 Bootstrap estimation results

Table 11 reports the empirical p-values corresponding to the t-statistics of inflation-risk timing coefficients at different extreme percentiles from the bootstrap analysis. For all extreme percentiles considered (from the top and bottom 1% to 10% percentiles), the evidence suggests that the top inflation-risk timers are unlikely to be attributed to pure "luck," i.e., the random sample variation. Specifically, for the full sample of 3,524 corporate bond mutual funds, the t-statistics of timing coefficient γ for the top 1%, 3%, 5%, and 10% successful timing funds are 3.42, 2.60, 2.23, and 1.69, respectively, with empirical p-values all close to zero.

(Insert Table 11)

We also summarize the results of bootstrap analyses for bond funds in subcategories. We find low empirical p-values for the top percentiles of t-statistics for subcategory groups, consistent with parametric estimation using aggregate portfolios. The subcategories include investment-grade funds, retail and institutional shares, survived and non-survived funds, and non-index funds. The results support the conclusion that successful inflation-risk timing managers do have relevant skills that are not due to random variations. Moreover, the t-statistic of timing coefficients among index fund managers are indifferent from sample variation. The evidence shows that managers pa construct the portfolios based on index compositions and do not necessarily determine the exposure on predicted inflation risks.

The negative timing coefficients cannot be attributed to random chance neither. For example, the empirical p-values associated with bottom 1% t-statistic of timing coefficients are close to zero for the sample of all subcategories, suggesting that managers incorrectly time the inflation risks, which leads to significantly under-performance in corporate bond funds.

(Insert Figure 4)

Figure 4 further presents the kernel density distributions of bootstrapped 10^{th} percentile t-statistics in blue solid line and the actual t-statistics of the timing coefficients as described in the horizontal red dash line. For example, the top-left panel in Figure 4 presents the bootstrapped distribution of t-statistics for all funds in the sample. For the estimated t-statistic of 4.0, its bootstrapped distribution is around 2.5, suggesting that all funds in the sample show significant inflation-risk timing ability. For the other funds we document similar findings. Index fund graph suggest that inflation-risk timing ability is not significant as it is expected.

5 Empirical analysis: Holding-based timing ability

Holdings-based timing measures have several advantages over the traditional returns-based measures Jiang et al. (2007); in particular, holding-based measures do not suffer from biases induced by the interim trading or dynamic trading effect because they use only *ex-ante* information on portfolio holdings. They are also robust to the passive timing effect, which could be an essential concern for government bond funds, given the convexity of bond prices to interest rate changes. In this section, we extend our examination of inflation-risk timing ability using corporate bond portfolio holdings and security level estimated inflation risk exposures.

5.1 Holdings-based timing measures

Following Ceballos (2022), we start with estimating corporate bond j's inflation-risk exposure at time t, $\beta^{\pi}_{j,t}$. We compute the beta of each fund's corporate bond portfolio p at time t, $\beta^{\pi}_{p,t}$,

$$\beta^{\pi}_{p,t} = \sum_{j=1}^{N_{p,t}} w_{p,j,t} \beta^{\pi}_{j,t} \tag{7}$$

where $w_{p,j,t}$ is the normalized portfolio weight of corporate bond j in fund's corporate bond portfolio p at time t, such that $\sum_{j=1}^{N_{p,t}} w_{p,j,t} = 1$, and $N_{p,t}$ is the total number of corporate bond securities held by fund's portfolio p at time t. $\beta^{\pi}_{j,t}$ is the beta estimate of corporate bond security j.

Then we construct the holding-based timing measure, γ^H, as in Jiang et al. (2007) and Huang and Wang (2014) from the following regression,

$$\beta^{\pi}_{p,t} \quad = \quad \alpha_p + \gamma^H_p \left(IVRF_{t+h} - \overline{IVRF} \right) + \eta_{p,t} \tag{8}$$

where $IVRF_{t+h}$ is the inflation volatility risk factor over the period $[t,\ t+h]$ with a forecasting horizon h periods, $h = \{1,\ 3,\ 6\}$. If managers possess positive inflation-risk timing ability, we expect the γ^H_p coefficient to be significantly positive. Similar to return-based timing ability estimation, γ^H is also associated with biases in statistical inference using t-statistics. First, corporate bond inflation risk exposure estimation may incur measurement errors and heterogeneity, violating the independent and identically distributed assumption across funds. Second, our corporate bond fund sample with sufficient holding information is relatively small (1778 funds), so the finite sample property may differ from their asymptotic statistics.

Thus, we modify the bootstrap approach described above to derive statistical inference for holding-based timing ability. In each bootstrapping round b, we randomly resample a time series of inflation volatility risk factor with replacement, $IVRF^{Random}_b$. At the same time, we fix each fund's inflation-risk exposure $\beta^{\pi}_{p,t}$. Then we re-estimate each fund's holding-based timing coefficient and obtain a bootstrapped sample of each individual fund's γ^H_bs and corresponding t-statistics for the b^{th} bootstrapping round,

$$\beta^{\pi}_{p,t} \quad = \quad \alpha_b + \gamma^H_b \left(IVRF^{Random}_{t+h,b} - \overline{IVRF}_b \right) + \eta_{t,b} \tag{9}$$

where $IVRF^{Random}_{t+h,b}$ is the randomly sampled inflation volatility risk factor at the b^{th} round bootstrapping, and $\beta^{\pi}_{p,t}$ is the fixed inflation risk exposure at the fund level. We repeat this procedure 2,000 times to obtain the empirical distributions of bootstrapped statistics, γ^H_b and $t(\gamma^H_b)$, and calculate the bootstrapped p-values, $b = 1,\ \cdots,\ 2000$. If the estimated timing measures or their t-statistics ("actual") from Eq. (8) are consistently higher than their bootstrapped values ("bootstrapped") from Eq. (9), we conclude that fund managers have significantly positive inflation-risk timing ability rather than due to pure luck.

(Insert Table 12)

Panel A of Table 12 presents the results of our bootstrap analysis. The table reports the cross-sectional statistics of holdings-based inflation-risk timing measure, γ^H in Eq. (9), with a three-month forecasting horizon and their Newey-West t-statistics, as well as the corresponding bootstrapped p-values. The bootstrapped p-values for the estimated γ^H are below 1% for the 97% percentile and below 5% for the 90%, the 95%, and the 99% percentiles. For the t-statistics of γ^H, we also find that p-values are below 10% for the 90th and 99th percentiles. Notice that the standard p-values and their bootstrapped counterparts can be different at some percentiles due to the non-normal empirical distribution of γ^H. For example, at 95% percentile, the t-statistic is 3.88, much higher than the threshold under normal distribution assumption, whereas the bootstrapped p-value is 0.16. The results are consistent with return-based timing ability and suggest that non-normality does not change the conclusion.

(Insert Figure 5)

We also illustrate the kernel density distributions of the bootstrapped t-statistics of estimated holding-based measures, γ^H, at different forecasting horizons in the left panels of Figure 5 and at multiple performance percentiles for one-month ahead prediction in the left panels of Figure 6. Figure 5 suggests that at various forecasting horizons, top 10% corporate bond fund managers have significant inflation-risk timing ability based on their portfolio holdings.

(Insert Figure 6)

In the top left panel of Figure 6, the actual t-statistic lies at the tail of the distribution of the bootstrapped t-statistics of the top 1% funds, suggesting a statistically significant timing ability among top 1% performed mutual fund managers. The bootstrapped distributions reject the null hypothesis of no significantly positive timing ability for managers, showing that significantly positive timing ability at the one-month horizon cannot simply be attributed to luck.

5.2 Economic value of inflation-risk timing

Following Jiang et al. (2007) and Huang and Wang (2014), inflation-risk timing is equivalent to a contingent claim on the inflation volatility risk factor. We follow this intuition to quantify the economic value of the inflation-risk timing ability of corporate bond mutual funds in our sample. Specifically, given the fund return process in Eq. (8), inflation-risk timing generates an additional terminal payoff $\gamma^H \left(IVRF_{t+1} - \overline{IVRF} \right)$ to a fund with the maturity of the payoff equal to the forecasting horizon, where $IVRF_{t+1} - \overline{IVRF}$ is the inflation volatility risk factor, *IVRF*, in excess of the average of *IVRF*. Assume that the excess inflation volatility risk factor, $P_{ivrf} = IVRF_{t+1} - \overline{IVRF}$, follows a geometric Brownian motion,

$$\frac{dP_{ivrf}}{P_{ivrf}} = \mu_{ivrf}dt + \sigma_{ivrf}dW$$

where μ_{ivrf} and σ_{ivrf} represent mean and standard deviation of the excess *IVRF*, and dW is the standard Brownian motion. Then the value of inflation-risk timing V can be derived as the expected present value of $\gamma^H \left(IVRF_{t+1} - \overline{IVRF}\right)$ under the risk-neutral measure (Q):

$$\begin{aligned} V &= \frac{1}{1+r_f} E^Q \left[\gamma^H \left(IVRF_{t+1} - \overline{IVRF}\right)\right] \\ &= (1+r_f)\gamma^H \left(e^{\sigma^2_{ivrf}} - 1\right) \end{aligned} \tag{10}$$

At the three-month horizon, the median (mean) timing measure is 0.35% (0.27%), estimated using the holding-based method in Eq. (8). The annual risk-free rate is 3%, and the monthly variance of *IVRF* is 1.86% in Table 1. Thus, the economic value of inflation-risk timing is 0.68% (0.52%) per year. For top 1% to 10% successful inflation-risk timers, the economic values of correct timing ability range from 2.62% to 15.21%[10]. These values are economically significant, indicating that inflation-risk timing can be an important investment strategy for corporate bond mutual funds.

The value numbers are not directly interpreted as the realized contribution to corporate bond fund performance. The underlying assumptions require that fund managers trade continuously with zero transaction costs. In addition, the timing coefficient, γ^H, used in computing the economic values are the holdings-based measures that capture only active timing without adjusting for the negative passive timing effect in fund returns. In the next section, we discuss whether corporate bond mutual fund managers successfully time inflation volatility risk factors by comparing active versus passive portfolio weights.

5.3 Changes in active fund betas

Variations in fund betas can be driven by active fund trading activities and passive portfolio weight changes due to non-proportional changes in corporate bond prices. Changes in fund beta due to active trading are more relevant when measuring active inflation-risk timing. To examine the effect of active trading on inflation-risk timing, we calculate the fund beta changes induced by active

[10] For example, a top-10% performed corporate bond mutual fund manager has estimated $\gamma^H = 1.35\%$. We can calculate the economic value of the timing ability as $V = (1 + 3\%) \times 1.35\% \times \left(e^{1.86\%} - 1\right) = 2.62\%$.

trading of fund managers from month $t-3$ to month t, $\Delta\beta^{\pi}_{p,t}$:

$$\Delta\beta^{\pi}_{p,t} = \beta^{\pi}_{p,t} - \beta^{\pi}_{p,t-3} = \sum_{j=1}^{N_{p,t}} w_{p,j,t}\beta^{\pi}_{j,t} - \sum_{j'=1}^{N_{p,t-3}} w_{p,j',t-3}\beta^{\pi}_{j',t} \quad (11)$$

where $\beta^{\pi}_{p,t}$ is the fund portfolio p's inflation risk exposure at the end of the month t and $\beta^{\pi}_{p,t-3}$ is the fund portfolio p's inflation risk exposure assuming that the fund passively holds all corporate bonds from three months ago to current month t. $N_{p,t}$ and $N_{p,t-3}$ are the number of corporate bonds the fund holds at the end of month t and $t-3$. $\beta^{\pi}_{j,t}$ is estimated inflation risk exposure at the corporate bond level. $w_{p,j,t}$ is the fund portfolio weight of corporate bond j at month t. $w_{p,j,t-3}$ is the hypothetical portfolio weight of corporate bond j in month $t-3$, assuming that a fund passively holds corporate bonds from the previous month to the current month t,

$$w_{p,j',t-3} = \frac{n_{p,j',t-3} \times P_{j',t}}{\sum_{j'=1}^{N_{p,t-3}} \left(n_{p,j',t-3} \times P_{j',t}\right)} \quad (12)$$

where $n_{p,j',t-3}$ is the number shares held in fund portfolio p for each corporate bond j' in month $t-3$, and $P_{j',t}$ is the price of corporate bond j' at the end of month t from WRDS Corporate Bond Return database. Note that the components of fund portfolio p in month $t-3$ are not necessarily the same as those in month t, i.e., $j' \neq j$. We perform the holding-based timing tests in Eq. (8) using changes in active fund betas, $\Delta\beta^{\pi}_{p,t}$. We focus on one- to six-month forecasting horizons (h = 1, 3, and 6). Similar to the tests using fund beta levels, we require that a fund have at least ten security holding observations to ensure the robustness of inference for holding-based measures.

Panel B of Table 12 reports the cross-sectional statistics of the holdings-based measures, γ^H, using active changes in fund beta, as well as the t-statistics and bootstrapped p-values. The t-statistic of γ^H is computed following the Newey-West method with a twelve-month lag. Despite that, the power of the tests based on $\Delta\widehat{\beta^{\pi}}_{p,t}$ is limited by the number of available observations of portfolio betas' active changes, at three-month forecasting horizons, the 90$^{\text{th}}$ and 95$^{\text{th}}$ percentiles of the t-statistics are significantly higher than the bootstrapped ones, indicating strong timing ability by some funds. These results suggest that fund betas' active changes are significantly correlated with forecasting inflation volatility risk factor, providing further evidence of positive timing ability by mutual funds.

Similarly, the estimated holding-based timing ability, γ^H, using active changes in fund betas, is consistent with return-based and holding-based estimations. For example, in the right panels of Figure 5, we plot the kernel density functions of the distributions of bootstrapped t-statistics for funds at the next one- to six-month forecasting horizons. The right panels of Figure 6 further illustrate the kernel densities of bootstrapped t-statistics for funds, estimated with a one-month ahead horizon, at various percentiles in the cross-section, as well as the actual t-statistics of timing measures.

We can see that the actual top 1% fund t-statistic of 9.27 (the dashed line in the top right panel) lies well within the right-tail rejection region of the bootstrapped distribution, indicating that the significantly positive timing ability of the fund is not purely due to luck. Similarly, at the 90^{th}, 95^{th}, and 97^{th} percentiles, the bootstrapped distributions reject the null hypothesis of no significantly positive timing ability for managers. In general, the results suggest that corporate bond fund managers exhibit significantly positive timing ability at the one-month horizon and that the timing ability of top fund managers cannot simply be attributed to luck. The results suggest managers rebalancing the portfolio to time the forecasted inflation risks.

6 Concluding Remarks

This paper has delved into the issue of inflation risk and its impact on financial markets, focusing on the corporate bond market and the timing abilities of mutual fund managers. The global surge in inflation has heightened concerns among researchers, policymakers, and investors about the implications of inflation risk for financial portfolios. Building upon a substantial body of literature that has identified the relevance of inflation risk in various markets, this paper contributes by shedding light on how mutual fund managers navigate the challenges posed by inflation risk in the corporate bond market.

We document significant timing abilities among mutual fund managers to market inflation risk. The positive inflation risk timing coefficient indicates that fund managers are adept at adjusting their portfolios in response to changes in inflation volatility. This ability is particularly pronounced during periods of high inflation, underlining the significance of inflation risk as a source of portfolio risk for corporate bond investors.

Furthermore, we show that the timing ability of mutual fund managers adds substantial economic value to fund performance. Our evidence indicates that top-timing funds consistently outperform bottom-timing funds by a considerable margin on a risk-adjusted basis. The timing ability persists after controlling for factors that could affect timing abilities, such as market volatility, monetary policy shocks, and other macroeconomic variables. After accounting for these factors, the robustness of the findings reinforces the significance of inflation-risk timing as a distinct skill among mutual fund managers.

Our study has important practical implications for the transmission of monetary policy. It is well-documented that monetary policy reacts to episodes of significant inflation deviation from its target, particularly in periods of elevated uncertainty of future inflation. As mutual funds are active traders in the corporate bond market, the significant inflation risk timing ability documented in our paper has at least two policy implications. First, the forecasting ability of top-timer mutual funds can help understand the contemporaneous effect of monetary policy transmission. Second, the mutual fund transactions in episodes of inflation uncertainty may contribute to the time-varying bond-equity return correlation (Song, 2017). Future research could provide evidence of the efficiency of the monetary policy by considering the active ex-ante inflation risk timing behavior of mutual funds.

In summary, we provide valuable insights into the role of inflation risk in the corporate bond market and the timing abilities of mutual fund managers. It contributes to understanding how portfolio managers navigate this risk and highlights the economic value of their timing skills. These findings have important implications for investors, fund managers, and policymakers as they grapple with the challenges of inflation in today's financial landscape.

References

Amihud, Y. (2002): "Illiquidity and Stock Returns: Cross-Section and Time-Series Effects," *Journal of Financial Markets*, 5, 31–56.

Bai, J., T. Bali, and Q. Wen (2019): "Common Risk Factors in the Cross Section of Corporate Bond Returns," *Journal of Financial Economics*, 131, 619–642.

Baker, S. R., N. Bloom, and S. J. Davis (2018): "Measuring Economic Policy Uncertainty," *Quarterly Journal of Economics*, 131, 1593–1636.

Bali, T. G., A. Subrahmanyam, and Q. Wen (2021): "The Macroeconomic Uncertainty Premium in the Corporate Bond Market," *Journal of Financial and Quantitative Analysis*, 56, 1653–1678.

Bekaert, G. and X. Wang (2014): "Inflation Risk and the Inflation Risk Premium," *Economic Policy*, 25, 755–806.

Bernanke, B. S. and F. S. Mishkin (1997): "Inflation Targeting: A New Framework for Monetary Policy?" *Journal of Economic Perspectives*, 11, 97–116.

Bhamra, H. S., C. Dorion, A. Jeanneret, and M. Weber (2022): "High Inflation: Low Default Risk and Low Equity Valuations," *The Review of Financial Studies*.

Bodnaruk, A., B. Chokaev, and A. Simonov (2019): "Downside Risk Timing by Mutual Funds," *Review of Asset Pricing Studies*, 9, 171–196.

Boons, M., F. Duarte, F. DeRoon, and M. Szymanowska (2020): "Time Varying Inflation Risk and Stock Returns," *Journal of Financial Economics*, 136, 444–470.

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

Cao, C., T. Simin, and Y. Wang (2013): "Do Mutual Fund Managers Time Market Liquidity," *Journal of Financial Markets*, 16, 279–307.

Carhart, M. (1997): "On Persistence in Mutual Fund Performance," *Journal of Finance*, 52, 57–82.

Carhart, M. M., J. N. Carpenter, A. W. Lynch, and D. K. Musto (2002): "Mutual Fund Survivorship," *The Review of Financial Studies*, 15, 1439–1463.

Ceballos, L. (2022): "Inflation Volatility Risk and the Cross-section of Corporate Bond Returns," *Pennsylvania State University, Working Paper.*

Chen, Y., W. Ferson, and H. Peters (2010): “Measuring the Timing Ability and Performance of Bond Mutual Funds,” *Journal of Financial Economics*, 98, 72–89.

Choi, J. and M. Kronlund (2018): “Reaching for Yield in Corporate Bond Mutual Funds,” *Review of Financial Studies*, 31, 1930–1965.

Cieslak, A. and C. Pflueger (2023): “Inflation and Asset Returns,” Working Paper 30982, National Bureau of Economic Research.

Dick-Nielsen, J. (2009): “Liquidity Biases in TRACE,” *Journal of Fixed Income*, 19, 43–55.

——— (2014): “How to Clean Enhanced TRACE Data,” *Working paper*, SSRN.

Dickerson, A., P. Mueller, and C. Robotti (2023): “Priced Risk in Corporate Bonds,” *Journal of Financial Economics*, 150, 103707.

Fama, E. and K. French (1993): “Common Risk Factors in the Returns on Stocks and Bonds,” *Journal of Financial Economics*, 33, 3–56.

——— (2015): “A Five-Factor Asset Pricing Model,” *Journal of Financial Economics*, 116, 1–22.

Fang, X., Y. Liu, and N. Roussanov (2022): “Getting to the Core: Inflation Risks Within and Across Asset Classes,” Working Paper 30169, National Bureau of Economic Research.

Ferson, W. and R. Schadt (1996): “Measuring Fund Strategy and Performance in Changing Economic Conditions,” *Journal of Finance*, 51, 425–461.

Grishchenko, O. V. and J.-Z. Huang (2013): “The Inflation Risk Premium: Evidence from the TIPS Market,” *Journal of Fixed Income*, 22, 5–30.

Gürkaynak, R., B. Sackb, and E. Swansonc (2005): “Do Actions Speak Louder Than Words? The Response of Asset Prices to Monetary Policy Actions and Statements,” *International Journal of Central Banking*.

Gürkaynak, R. S. and J. H. Wright (2012): “Macroeconomics and the Term Structure,” *Journal of Economic Literature*, 50, 331–367.

Hong, H., D. Sraer, and J. Yu (2017): “Inflation Bets on the Long Bond,” *Review of Financial Studies*, 30, 900–947.

Huang, J.-Z. and Y. Wang (2014): “Timing Ability of Government Bond Fund Managers: Evidence from Portfolio Holdings,” *Management Science*, 60, 2091–2109.

Illeditsch, P. K. (2018): “Residual Inflation Risk,” *Management Science*, 64, 5289–5314.

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

Jurado, K., S. Ludvigson, and S. Ng (2015): “Measuring Uncertainty,” *American Economic Review*, 105, 1177–1216.

Kang, J. and C. Pflueger (2015): “Inflation Risk in Corporate Bonds,” *Journal of Finance*, LXX, 115–162.

Kashyap, A. K. and J. C. Stein (2023): “Monetary Policy When the Central Bank Shapes Financial-Market Sentiment,” *Journal of Economic Perspectives*, 37, 53–76.

Kosowski, R., A. Timmermann, R. Wermers, and H. White (2006): “Can Mutual Fund ”Stars” Really Pick Stocks? New Evidence from a Bootstrap Analysis,” *Journal of Finance*, 61, 2551–2595.

Kupfer, A. (2018): “Estimating Inflation Risk Premia Using Inflation-Linked Bonds: A Review,” *Journal of Economic Surveys*, 32, 1326–1354.

Nakamura, E. and J. Steinsson (2018): “High-Frequency Identification of Monetary Non-Neutrality: The Information Effect,” *Quarterly Journal of Economics*, 133, 1283–1330.

Newey, W. and K. West (1987): “A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix,” *Econometrica*, 55, 703–708.

Soderlind, P. (2011): “Inflation Risk Premia and Survey Evidence on Macroeconomic Uncertainty,” *International Journal of Central Banking*, 7, 113–133.

Song, D. (2017): “Bond Market Exposures to Macroeconomic and Monetary Policy Risks,” *The Review of Financial Studies*, 30, 2761–2817.

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

Figure 1: Inflation volatility risk

The figure depicts the time series of the inflation risk measure and compares it with other measures of inflation uncertainty. The top Panel plots the monthly time series of inflation risk (six-month volatility of inflation innovations). The bottom Panel presents two alternative survey-based measures, including the interquartile range in monthly inflation forecasts from the Michigan Survey of Consumers (MSC) and the inflation risk uncertainty from the Survey of Professional Forecasters (SPF) at a lower (quarterly) frequency. The shadow area denotes the recession period reported by NBER. The period covered spans from July 2002 to September 2022. Values are reported in percent.

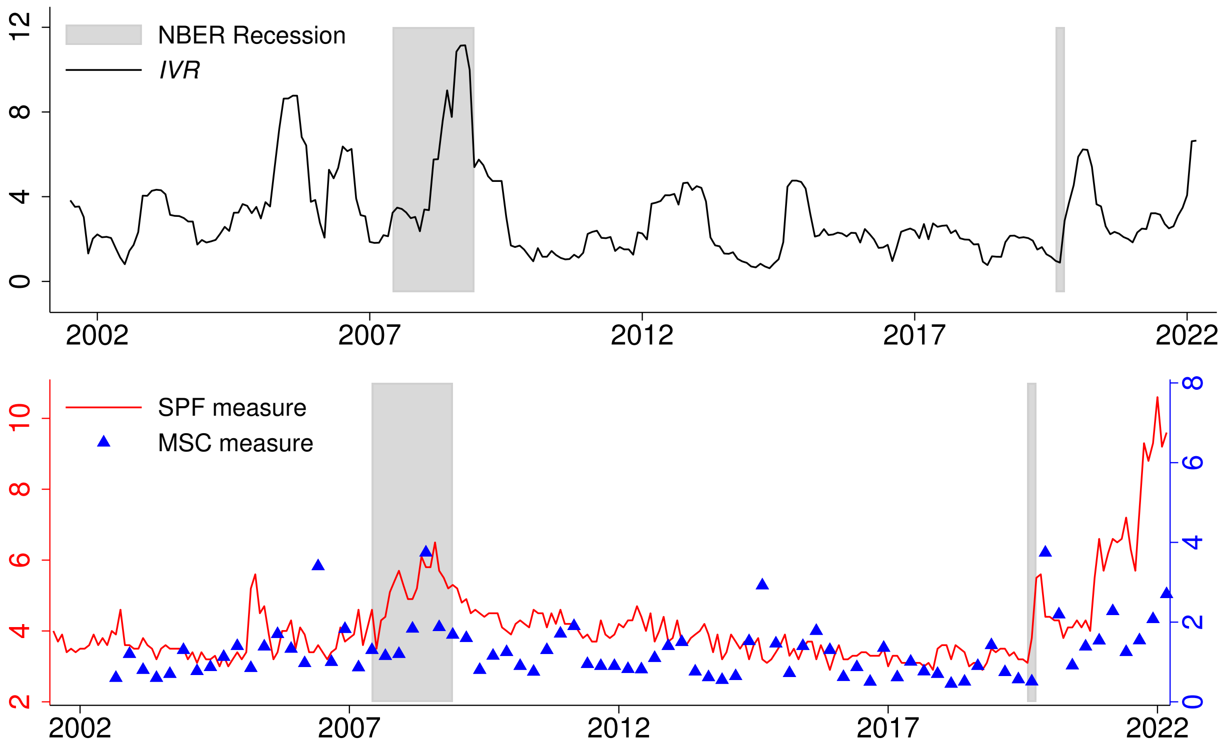

Figure 2: Inflation volatility risk factor (*IVRF*)

The figure depicts the time series of the inflation volatility risk factor. We compute the time series measure of the inflation volatility risk factor ($IVRF$) based on a double-sorted portfolio between credit risk and inflation risk exposure (β^{π}). Specifically, each month, we create quintile portfolios based on inflation beta (β^{π}) and quintile portfolios based on credit risk (measured by credit ratings from Moody's and S&P). $IVRF$ is the value-weighted average return spreads between the highest-β^{π} and lowest-β^{π} portfolio across the credit rating portfolios. The period covered spans from July 2004 to September 2022. Values are reported in percent.

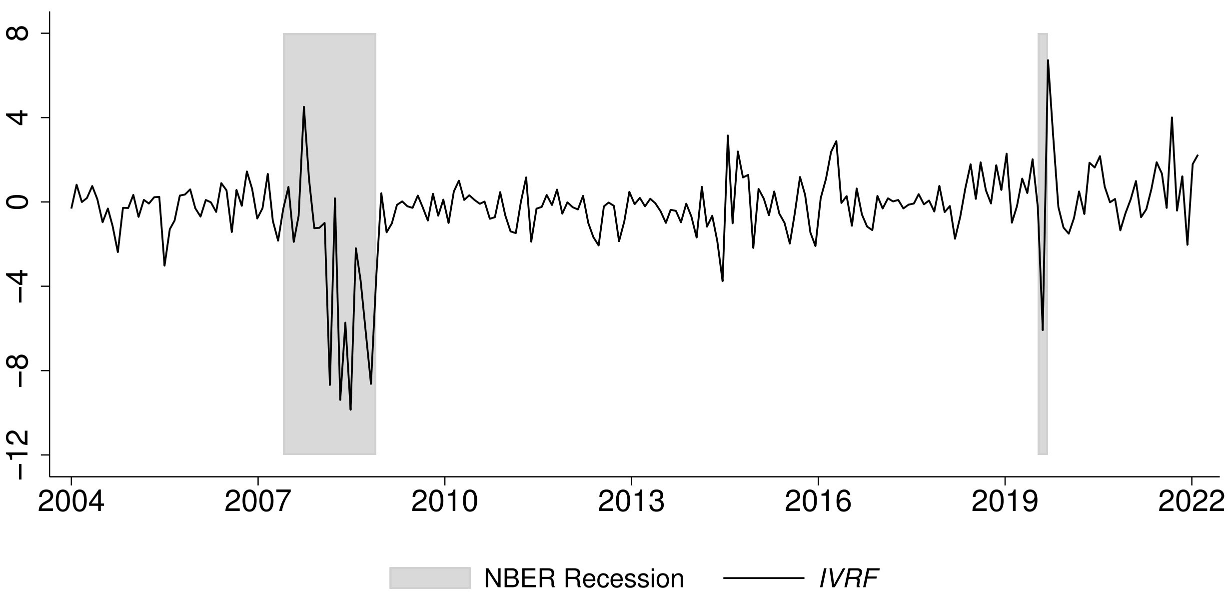

Figure 3: Cumulative returns of investing in fund portfolios with successful timers (top decile) verses incorrect timers (bottom decile).

This figure plots cumulative out-of-sample fund portfolio returns of successful versus incorrect inflation-risk timing managers of corporate bond mutual funds for a three-month holding period. In each month, we form the portfolios based on estimated inflation-risk timing coefficients in Eq. (4) using the past 36 months. These portfolios are held for three months subsequently.

Figure 4: Bootstrapped versus actual t-statistics of the inflation-risk timing coefficients

The figure presents the kernel density distributions of bootstrapped 10^{th} percentile t-statistics as blue solid lines and the actual t-statistics of the timing coefficients as red dash lines across funds. For each fund in the sample, we estimate the factor loadings based on regression Eq. (**??**). Next, a random sample of residuals is chosen to generate hypothetical fund returns that, by construction, have the same factor loadings as the actual funds but have no timing ability (that is, imposing $\gamma_p = 0$). Finally, Eq. (7) is estimated using these hypothetical returns, in which, significant γ_p are due to random sample variation. This procedure is repeated 10,000 iterations to get a distribution of t-statistic for the inflation-risk timing coefficient at the 10^{th} percentile. The period covered spans from January 2003 to September 2022.

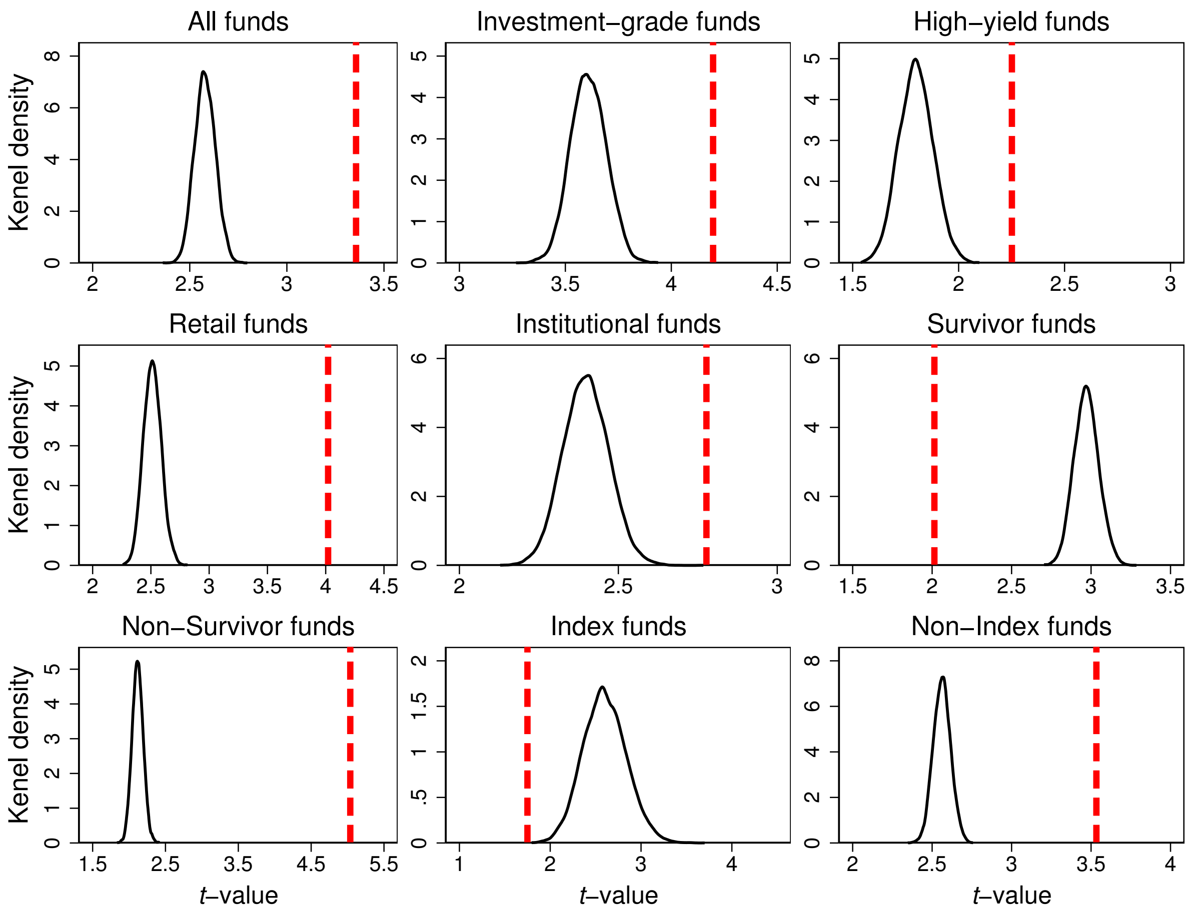

Figure 5: Bootstrapped versus actual t-statistics of the holdings-based and active-beta estimated inflation-risk timing coefficients at various forecasting horizons

The figure plots kernel density distributions of the bootstrapped top 10th percentile t-statistics of holdings-based inflation-risk timing measures (solid lines) using Eq. (9) and the actual t-statistics of timing measures (dashed red lines) using Eq. (8), as well as active-beta based timing measure using Eq. (11), for individual funds with forecasting horizon for one, three, and six months. Corporate bond inflation-risk betas are estimated using the past 36-month returns. The estimation sample is spanning from January 2003 to September 2022.

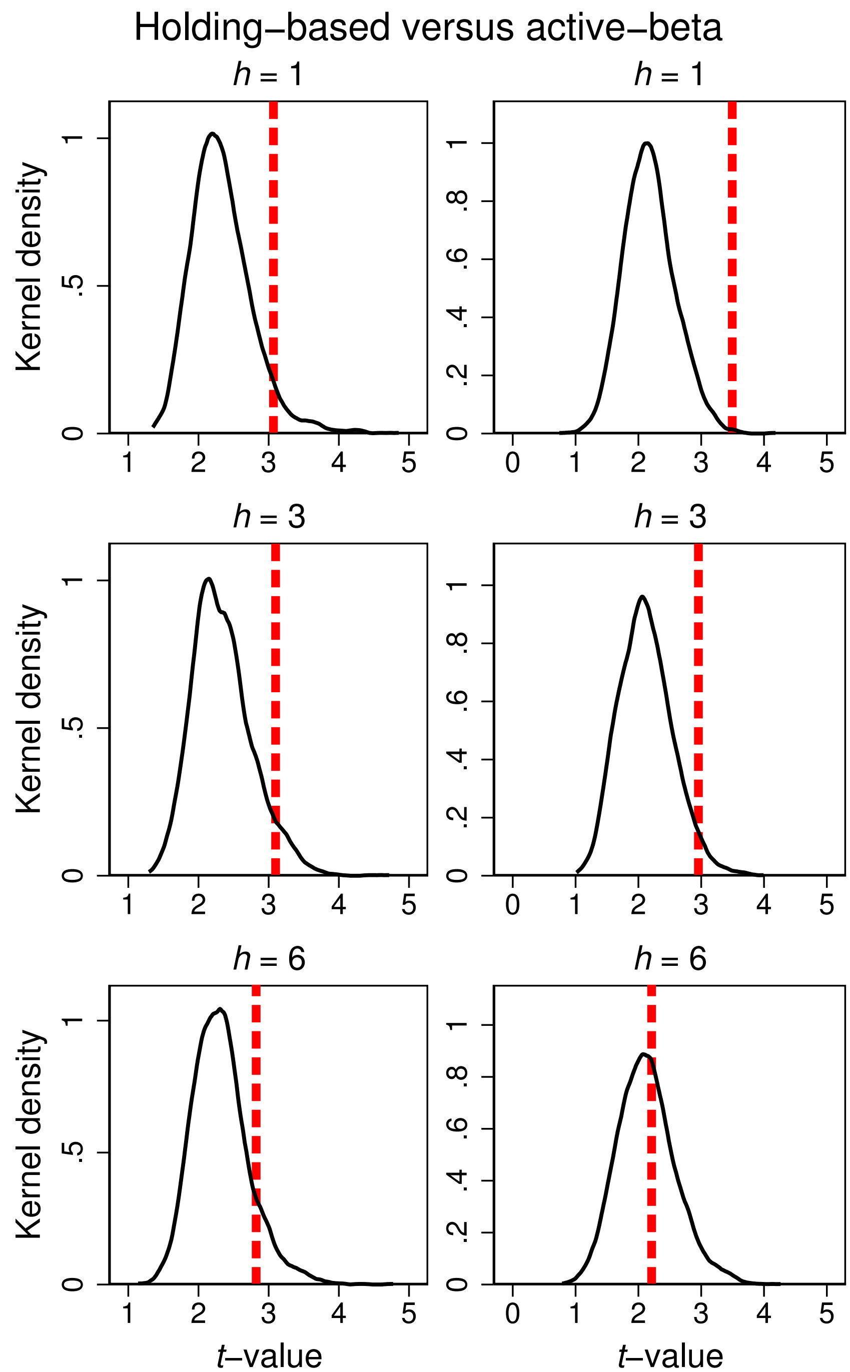

Figure 6: Bootstrapped versus actual t-statistics of the holdings-based and active-beta estimated inflation-risk timing coefficients at various percentiles

The figure plots kernel density distributions of the bootstrapped top 1^{th}, 3^{th}, 5^{th}, and 10^{th} percentile t-statistics of holdings-based inflation-risk timing measures (solid lines) using Eq. (9) and the actual t-statistics of timing measures (dashed red lines) using Eq. (8), as well as active-beta based timing measure using Eq. (11), for individual funds with one-month forecasting horizon. Corporate bond inflation-risk betas are estimated using the past 36-month returns. The estimation sample is spanning from January 2003 to September 2022.

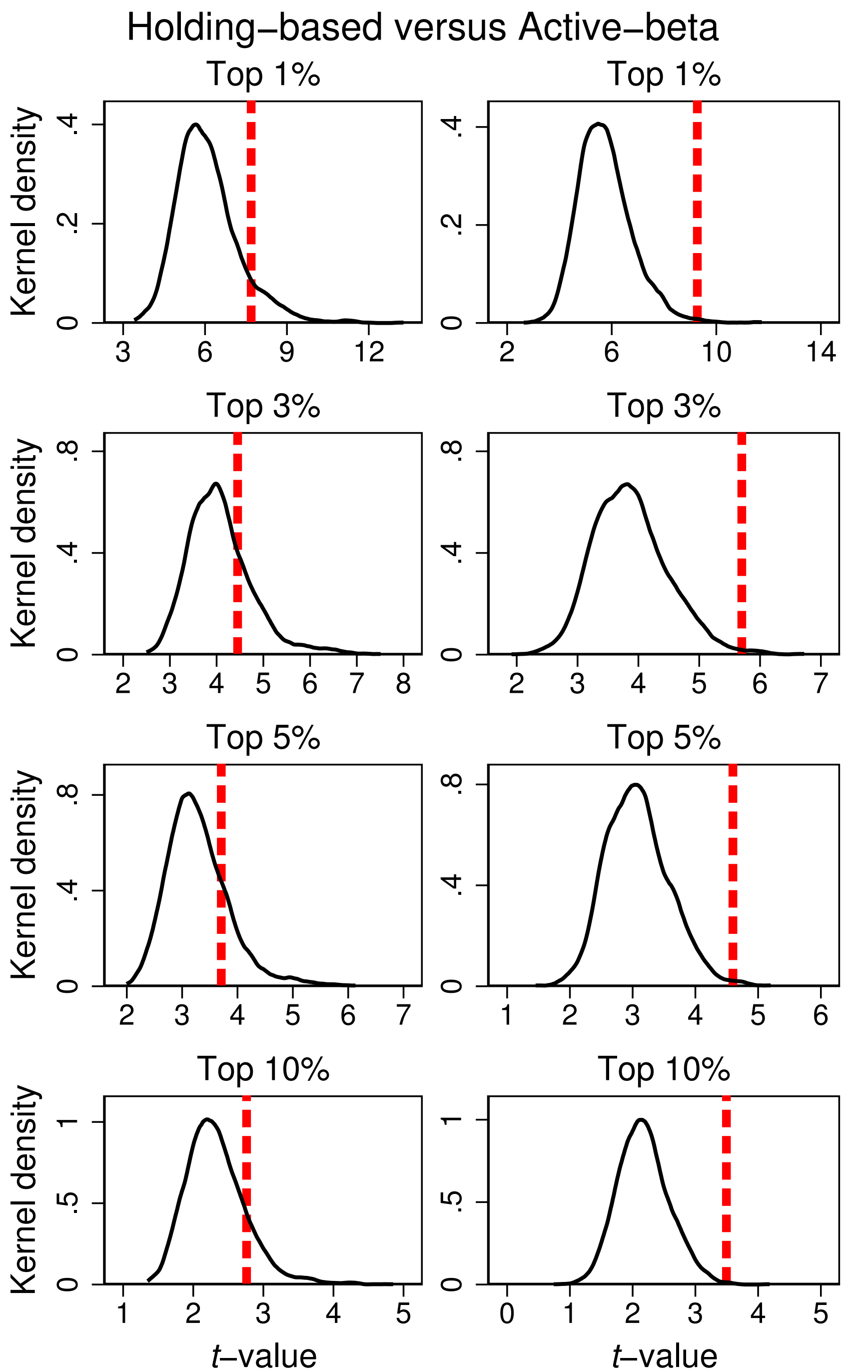

Table 1: Summary statistics

The table reports the summary statistics of fund characteristics from January 2003 to September 2022. Funds classified as either corporate bond funds or general funds based on their CRSP fund styles following Choi and Kronlund (2018). Age is defined as the number of years between the last return date in the database and the first date when the fund was offered, and averaged across funds within each fund category. Size ($millions) is the total net asset value (TNA). Expense ratios, turnover rates, monthly flows (percentages of total net assets), and returns are in percentages. Maturity is the weighted maturity within each fund (in years). The last four rows report the average portfolio allocation weights in corporate bonds, Treasury bonds, cash, and equity. The first column reports the characteristics of all bond funds in the sample. Columns (2) – (8) report the characteristics of funds based on credit ratings, investor-oriented types, surviving and non-surviving, and index funds. In Panel B, we report the statistics for corporate bond risk factors, including the bond market returns, downside, credit, and liquidity risk factors from Dickerson et al. (2023). We also summarize equity risk factors such as size factor (SMB), the value factor (HML), and the momentum factor (UMD).

(a) Summary Statistics

		Credit ratings		Investor style			Survival	
	All funds	IG	HY	Inst.	Retail	Index	Yes	No
Number funds	4516	2802	1375	2073	2165	289	2366	2147
Return (%)	0.32	0.14	0.10	0.09	0.16	-0.03	0.07	0.24
Age (years)	18.2	18.6	18.3	15.9	19.9	13.9	20.2	14.5
Flow (monthly %)	0.39	0.46	-0.02	0.75	-0.02	1.88	0.72	-0.41
Size ($ millions)	691.8	858.6	381.7	889.5	549.8	3942.5	972.8	164.0
Maturity (years)	10.2	12.1	6.5	10.2	10.1	10.4	10.2	10.0
Expense ratio	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.01
Turnover	1.45	1.79	0.83	1.46	1.44	0.74	1.42	1.52
Weight Corporate bonds (%)	42.6	32.9	62.7	47.2	37.2	50.6	48.7	29.2
Weight Treasury bonds (%)	11.1	15.2	1.6	11.8	8.6	24.5	12.5	8.0
Weight Cash (%)	-0.5	-3.3	4.2	-0.3	-1.2	2.0	1.2	-4.4
Weight Equity (%)	0.6	0.2	1.1	0.5	0.8	0.0	0.5	1.0

(b) Inflation Volatility Risk Factor and Risk Factors

	Mean	Median	SD	P5	P10	P25	P75	P90	P95
Inflation volatility risk factor ($IVRF$)	-0.27	-0.13	1.86	-2.19	-1.84	-0.88	0.50	1.45	2.24
Bond market return (MKT^{Bond})	0.33	0.38	1.86	-2.29	-1.64	-0.49	1.12	2.16	2.75
Credit risk factor (CRF)	0.21	0.32	2.63	-3.40	-2.65	-0.82	1.47	2.63	3.69
Liquidity risk factor (LRF)	0.22	0.12	1.08	-1.09	-0.69	-0.33	0.57	1.17	1.94
Downside risk factor (DRF)	0.34	0.39	2.83	-3.66	-2.64	-0.95	1.55	2.68	4.66
Small minus big (SMB)	0.08	0.11	2.43	-3.82	-3.01	-1.77	1.64	3.08	4.46
High minus low (HML)	-0.02	-0.21	3.14	-4.19	-3.13	-1.78	1.43	3.52	6.17
Momentum factor (UMD)	0.08	0.43	4.32	-6.81	-4.62	-1.84	2.56	4.27	5.98

Table 2: Estimates of inflation risk timing ability among corporate bond mutual fund managers

The table reports the coefficients from the following inflation risk timing ability regression:

$$R_{p,t+1} = \alpha_p + \beta_p MKT^{Bond}_{t+1} + \gamma_p MKT^{Bond}_{t+1}(IVRF_{t+1} - \overline{IVRF}) + \sum_{m=1}^{M} \beta_m f_{m,t+1} + \upsilon_{p,t+1}$$

where $R_{p,t+1}$ is the excess return on each individual fund p in month $t+1$. The risk factor variables (f) include risk factors in the corporate bond market such as the bond market excess return (MKT^{Bond}), a credit risk factor (CRF), a liquidity factor (LRF) and a downside risk factor (DRF). We include risk factors from the equity market such as the size factor (SMB), the value factor (HML), and the momentum factor (UMD). $IVRF_{p,t+1}$ is the inflation volatility risk factor in month $t+1$, and $\overline{IVRF}$ is the average of the inflation volatility risk factor over the previous 12 months (t-12 to $t-1$). The coefficient of interest, γ, measures the inflation volatility risk timing ability among fund managers. The t-statistics in parentheses are calculated using Newey and West (1987) heteroscedasticity and autocorrelation-consistent standard errors with twelve lags. *, ** and *** are statistical significance at the 1, 5 and 10% levels. Column (1) includes all mutual fund managers in the sample period, and Columns (2) and (3) report the timing ability interaction with a dummy (High$^{\pi}$) that equals to 1 in periods of high inflation uncertainty, based on dispersion for expected inflation from the Survey of Professional Forecasters (SPF). The sample period is from 1/2003 to 9/2022.

	Full Sample	Inflation Environment	
		Top 90%	Top 95%
γ	0.03***	0.01***	0.01***
	(4.55)	(5.57)	(5.37)
$\gamma^{D(High\ \pi)}$		0.07***	0.08***
		(22.32)	(19.07)
β_{MKT}	0.77***	0.85***	0.85***
	(16.28)	(40.40)	(40.86)
β_{CRF}	0.15***	0.15***	0.15***
	(18.46)	(22.32)	(23.36)
β_{DRF}	-0.11***	-0.13***	-0.13***
	(-5.52)	(-7.36)	(-7.54)
β_{LRF}	0.09*	0.02	0.02
	(1.78)	(1.17)	(1.15)
β_{SMB}	-0.01	-0.01	-0.01
	(-1.32)	(-1.33)	(-1.29)
β_{HML}	-0.01	-0.00	0.00
	(-0.77)	(-0.11)	(0.04)
β_{MOM}	0.01**	0.01***	0.01***
	(2.42)	(2.74)	(2.92)
Constant	-0.03	-0.03*	-0.03
	(-1.13)	(-1.78)	(-1.61)
Observations	199	199	199
Adj. R^2	0.950	0.971	0.972

Table 3: Economic value of inflation risk timing ability: Evidence from out-of-sample portfolios sorted by estimated γs

The table reports the α of out-of-sample fund portfolios sorted by the inflation risk timing ability. In each month, we form ten portfolios sorted by fund inflation risk timing coefficients, γ, estimated from past 36 months, and hold these portfolios for K months, where K = 3, 6, 12, 18, 24, and 36. The table reports the out-of-sample αs (in percentage per month) estimated from the post-ranking portfolio returns using bond and equity factors. The t-statistics (in parentheses) are calculated using Newey and West (1987) heteroscedasticity and autocorrelation-consistent standard errors with one lag. *, ** and *** denote statistical significance at the 1, 5 and 10% levels, respectively.

	Alpha return					
	K=3	K=6	K=12	K=18	K=24	K=36
Portfolio 1 (bottom timers)	-0.014	0.021	0.081	0.097	0.120	0.189
	-(0.082)	(0.146)	(0.682)	(0.971)	(1.380)	(3.763)
Portfolio 2	0.079	0.120	0.170	0.186	0.206	0.252
	(0.576)	(1.102)	(1.946)	(2.559)	(3.273)	(6.941)
Portfolio 3	0.080	0.121	0.174	0.191	0.211	0.255
	(0.645)	(1.211)	(2.126)	(2.854)	(3.647)	(7.990)
Portfolio 4	0.136	0.170	0.221	0.239	0.257	0.289
	(1.444)	(2.153)	(3.241)	(4.263)	(5.270)	(9.982)
Portfolio 5	0.147	0.180	0.229	0.249	0.267	0.297
	(1.640)	(2.378)	(3.464)	(4.520)	(5.536)	(9.991)
Portfolio 6	0.187	0.213	0.264	0.285	0.302	0.332
	(2.208)	(2.865)	(3.858)	(4.997)	(5.971)	(9.862)
Portfolio 7	0.250	0.270	0.322	0.347	0.362	0.388
	(3.274)	(3.882)	(4.647)	(5.782)	(6.731)	(9.904)
Portfolio 8	0.275	0.289	0.336	0.362	0.376	0.405
	(3.464)	(3.989)	(4.754)	(5.768)	(6.666)	(9.440)
Portfolio 9	0.316	0.319	0.363	0.383	0.391	0.422
	(3.815)	(4.139)	(5.059)	(5.978)	(6.722)	(9.045)
Portfolio 10 (top timers)	0.353	0.347	0.409	0.438	0.451	0.486
	(3.524)	(3.749)	(4.467)	(5.361)	(6.257)	(9.166)
Portfolio 10 − Portfolio 1	0.367	0.326	0.328	0.341	0.331	0.297
	(2.450)	(2.741)	(3.137)	(3.554)	(3.692)	(3.957)

Table 4: Economic value of reaction to inflation risks: Evidence from out-of-sample portfolios sorted by estimated $\gamma^{Reaction}$s

The table reports the α of out-of-sample fund portfolios sorted by the inflation-risk reaction to lagged *IVRF*. In each month, we form ten portfolios sorted by estimated coefficients on lagged *IVRF*, γ, estimated from past 36 months, and hold these portfolios for K months, where K = 3, 6, 12, 18, 24, and 36. The table reports the out-of-sample αs (in percentage per month) estimated from the post-ranking portfolio returns using bond and equity factors. The t-statistics (in parentheses) are calculated using Newey and West (1987) heteroscedasticity and autocorrelation-consistent standard errors with one lag. *, ** and *** denote statistical significance at the 1, 5 and 10% levels, respectively.

	Alpha return					
	K=3	K=6	K=12	K=18	K=24	K=36
Portfolio 1 (bottom reactors)	0.160	0.172	0.209	0.214	0.230	0.271
	(1.391)	(1.742)	(2.617)	(3.190)	(3.910)	(7.019)
Portfolio 2	0.164	0.181	0.213	0.221	0.234	0.258
	(1.886)	(2.381)	(3.452)	(4.277)	(5.126)	(7.951)
Portfolio 3	0.153	0.171	0.206	0.215	0.228	0.256
	(1.852)	(2.375)	(3.448)	(4.344)	(5.215)	(8.794)
Portfolio 4	0.161	0.182	0.221	0.234	0.250	0.275
	(2.080)	(2.695)	(3.839)	(4.933)	(6.005)	(10.622)
Portfolio 5	0.173	0.199	0.244	0.261	0.278	0.306
	(2.176)	(2.836)	(3.899)	(5.027)	(6.195)	(11.118)
Portfolio 6	0.189	0.217	0.266	0.287	0.305	0.332
	(2.398)	(3.108)	(4.142)	(5.374)	(6.592)	(11.278)
Portfolio 7	0.189	0.220	0.277	0.301	0.320	0.353
	(2.087)	(2.793)	(3.744)	(4.860)	(5.925)	(10.237)
Portfolio 8	0.225	0.259	0.328	0.357	0.377	0.415
	(1.990)	(2.742)	(3.625)	(4.615)	(5.644)	(9.305)
Portfolio 9	0.205	0.241	0.322	0.357	0.378	0.427
	(1.581)	(2.287)	(3.341)	(4.381)	(5.344)	(9.465)
Portfolio 10 (top reactors)	0.154	0.198	0.293	0.337	0.366	0.437
	(0.999)	(1.483)	(2.316)	(3.129)	(4.051)	(9.258)
Portfolio 10 − Portfolio 1	-0.005	0.026	0.084	0.123	0.136	0.166
	(-0.062)	(0.365)	(1.091)	(1.739)	(2.231)	(3.952)

Table 5: Economic value of inflation-risk timing ability versus reaction using inflation-protected funds: Evidence from out-of-sample portfolios sorted by estimated γs or $\gamma^{Reaction}$s

The table reports the α of out-of-sample fund portfolios sorted by the inflation risk timing ability versus reaction using inflation-protected bond mutual funds. In each month, we form three portfolios sorted by fund inflation risk timing coefficients, γ (Panel A), or reaction coefficients, $\gamma^{Reaction}$ (Panel B), estimated from past 36 months and hold these portfolios for K months, where $K = 3$, 24, and 36. The table reports the out-of-sample αs (in percentage per month) estimated from the post-ranking portfolio returns using bond and equity factors. The t-statistics (in parentheses) are calculated using Newey and West (1987) heteroscedasticity and autocorrelation-consistent standard errors with one lag. *, ** and *** denote statistical significance at the 1, 5 and 10% levels, respectively.

	Panel A: Inflation-risk timing			Panel B: Inflation-risk reaction		
	K=3	K=24	K=36	K=3	K=24	K=36
Portfolio 1 (bottom)	0.180	0.195	0.165	0.088	0.115	0.087
	(2.221)	(2.723)	(3.042)	(0.898)	(1.543)	(1.726)
Portfolio 2	0.183	0.159	0.130	0.203	0.201	0.172
	(2.324)	(2.390)	(2.571)	(2.569)	(2.989)	(3.331)
Portfolio 3 (Top)	0.123	0.168	0.145	0.233	0.224	0.199
	(1.169)	(2.303)	(2.572)	(2.837)	(2.770)	(2.768)
Portfolio 3 − Portfolio 1	-0.057	-0.027	-0.019	0.145	0.109	0.112
	(-0.848)	(-1.085)	(-1.129)	(1.844)	(1.766)	(2.173)

Table 6: Estimates of inflation risk timing ability by credit rating

The table reports the coefficients from the following inflation risk timing ability regression:

$$R_{p,t+1} = \alpha_p + \beta_p MKT^{Bond}_{t+1} + \gamma_p MKT^{Bond}_{t+1}(IVRF_{t+1} - \overline{IVRF}) + \sum_{m=1}^{M} \beta_m f_{m,t+1} + \upsilon_{p,t+1}$$

where $R_{p,t+1}$ is the excess return on each individual fund p in month $t+1$. The risk factor variables (f) include risk factors in the corporate bond market such as the bond market excess return (MKT^{Bond}), a credit risk factor (CRF), a liquidity factor (LRF) and a downside risk factor (DRF) (Bai et al., 2019). We include risk factors from the equity market such as the size factor (SMB), the value factor (HML), and the momentum factor (UMD). $IVRF_{p,t+1}$ is the inflation volatility risk factor in month $t+1$, and $\overline{IVRF}$ is the average of the inflation volatility risk factor over the previous 12 months (t-12 to t). The coefficient of interest, γ, measures the inflation volatility risk timing ability among fund managers. The t-statistics in parentheses are calculated using Newey and West (1987) heteroscedasticity and autocorrelation-consistent standard errors with twelve lags. *, ** and *** are statistical significance at the 1, 5 and 10% levels. We separate funds into investment grade (IG) and high yield (HY) subcategories based on credit ratings. Column (1) reports the estimation result for all mutual funds concentrating on investment-grade bonds. Columns (2) to (5) separate IG type funds into more detailed subgroups based on credit ratings (A higher or BBB higher) and maturity (short versus long). Column (6) shows the estimation for funds with high-yield bonds. The sample period is from 1/2003 to 9/2022.

	Investment Grade (IG)					High Yield (HY)
		Credit rating		Maturity		
	All	A or higher	BBB or higher	Short (1-5y)	Long (5-10y)	
γ	0.03***	0.04***	0.03***	0.01***	0.03***	0.01
	(9.16)	(11.21)	(4.91)	(2.83)	(10.72)	(1.32)
β_{MKT}	0.72***	0.81***	0.99***	0.40***	0.75***	0.90***
	(15.79)	(16.91)	(22.97)	(7.92)	(13.94)	(12.55)
β_{CRF}	-0.03*	-0.06*	-0.01	0.01	-0.05**	0.56***
	(-1.91)	(-1.88)	(-0.73)	(1.09)	(-2.47)	(27.10)
β_{DRF}	-0.15***	-0.18***	-0.16***	-0.13***	-0.16***	-0.05
	(-9.21)	(-6.81)	(-4.28)	(-4.94)	(-7.96)	(-0.91)
β_{LRF}	0.18***	0.24***	0.18**	0.15***	0.19***	-0.11
	(4.54)	(4.04)	(2.55)	(6.69)	(4.65)	(-1.14)
β_{SMB}	-0.02	-0.03*	-0.02*	-0.01	-0.02	0.00
	(-1.51)	(-1.69)	(-1.66)	(-0.97)	(-1.51)	(0.00)
β_{HML}	-0.01*	-0.03***	0.00	-0.01	-0.02**	-0.01
	(-1.82)	(-2.62)	(0.27)	(-0.71)	(-2.07)	(-0.21)
β_{MOM}	0.00	0.01	0.02**	-0.01	-0.00	0.03***
	(0.30)	(1.07)	(2.12)	(-1.08)	(-0.04)	(2.67)
Constant	-0.04	-0.05	-0.06	-0.02	-0.05*	-0.01
	(-1.63)	(-1.45)	(-1.41)	(-1.31)	(-1.82)	(-0.33)
Observations	199	199	199	199	199	199
Adj. R^2	0.891	0.869	0.910	0.811	0.871	0.649

Table 7: Estimates of inflation risk timing ability by subgroups

The table reports the coefficients from the following inflation risk timing ability regression:

$$R_{p,t+1} = \alpha_p + \beta_p MKT^{Bond}_{t+1} + \gamma_p MKT^{Bond}_{t+1}(IVRF_{t+1} - \overline{IVRF}) + \sum_{m=1}^{M} \beta_m f_{m,t+1} + \upsilon_{p,t+1}$$

where $R_{p,t+1}$ is the excess return on each individual fund p in month $t+1$. The risk factor variables (f) include risk factors in the corporate bond market such as the bond market excess return (MKT^{Bond}), a credit risk factor (CRF), a liquidity factor (LRF) and a downside risk factor (DRF). We include risk factors from the equity market such as the size factor (SMB), the value factor (HML), and the momentum factor (UMD). $IVRF_{p,t+1}$ is the inflation volatility risk factor in month $t+1$, and $\overline{IVRF}$ is the average of the inflation volatility risk factor over the previous 12 months (t-12 to t). The coefficient of interest, γ, measures the inflation volatility risk timing ability among fund managers. The t-statistics in parentheses are calculated using Newey and West (1987) heteroscedasticity and autocorrelation-consistent standard errors with twelve lags. *, ** and *** are statistical significance at the 1, 5 and 10% levels. We separate funds into retail and institutional fund shares in Columns (1) and (2) are identified based on the institutional share flag in the CRSP database. In Columns (3) and (4) we define survival funds if a fund appears until the end of the sample, it belongs to survival group; otherwise it is in non-survival group. We define index funds in Column (5) based on pure index funds where the investment objective is to match the total investment performance of a publicly recognized securities market index. The sample period is from 1/2003 to 9/2022.

	Investor		Survival		Index fund	
	Retail	Institutional	Yes	No	Yes	No
γ	0.02***	0.03***	0.03***	0.02***	0.02***	0.03***
	(4.43)	(4.72)	(4.38)	(4.51)	(5.95)	(4.43)
β_{MKT}	0.76***	0.77***	0.79***	0.74***	0.84***	0.76***
	(16.36)	(16.63)	(16.52)	(16.88)	(28.90)	(15.94)
β_{CRF}	0.17***	0.14***	0.16***	0.15***	-0.11***	0.16***
	(22.41)	(14.74)	(20.18)	(17.41)	(-8.07)	(20.12)
β_{DRF}	-0.11***	-0.11***	-0.12***	-0.11***	-0.18***	-0.11***
	(-4.70)	(-5.72)	(-5.65)	(-5.32)	(-6.99)	(-5.10)
β_{LRF}	0.08	0.10**	0.10*	0.07	0.12***	0.08
	(1.49)	(2.08)	(1.93)	(1.51)	(3.11)	(1.65)
β_{SMB}	-0.01	-0.02	-0.01	-0.02*	-0.02	-0.01
	(-1.11)	(-1.46)	(-1.32)	(-1.74)	(-1.48)	(-1.22)
β_{HML}	-0.01	-0.01	-0.01	-0.01	0.00	-0.01
	(-0.70)	(-0.75)	(-0.74)	(-0.80)	(0.03)	(-0.72)
β_{MOM}	0.01**	0.01*	0.01**	0.01**	-0.01	0.01**
	(2.58)	(1.84)	(2.25)	(2.25)	(-0.83)	(2.44)
Constant	-0.04	-0.01	-0.01	-0.07**	-0.01	-0.03
	(-1.58)	(-0.44)	(-0.52)	(-2.27)	(-0.25)	(-1.06)
Observations	199	199	199	199	199	199
Adj. R^2	0.825	0.842	0.838	0.822	0.848	0.827

Table 8: Cross-sectional distribution of t-statistics for the inflation-risk-timing coefficient across funds

The table presents the cross-sectional distribution of t-statistics for the inflation-risk-timing coefficient γ. For each fund with at least 36 non-missing observations, we estimate the following timing model:

$$R_{p,t+1} = \alpha_p + \beta_p MKT^{Bond}_{t+1} + \gamma_p MKT^{Bond}_{t+1}(IVRF_{t+1} - \overline{IVRF}) + \sum_{m=1}^{M} \beta_m f_{m,t+1} + \upsilon_{p,t+1}$$

where $R_{p,t+1}$ is the excess return on each individual fund p in month $t+1$. The risk factor variables (f) include risk factors in the corporate bond market such as the bond market excess return (MKT^{Bond}), a credit risk factor (CRF), a liquidity factor (LRF) and a downside risk factor (DRF). We include risk factors from the equity market such as the size factor (SMB), the value factor (HML), and the momentum factor (UMD). $IVRF_{p,t+1}$ is the inflation volatility risk factor in month $t+1$, and $\overline{IVRF}$ is the average of the inflation volatility risk factor over the previous 12 months (t-12 to t). The coefficient of interest, γ, measures the inflation volatility risk timing ability among fund managers. Fund categories are described in table 1. We separate the full sample based on credit ratings (Rows (2) and (3)), investor-oriented types (Rows (4) and (5)), survivalship (Rows (6) and (7)), and index funds (Row (8)). The numbers in Columns (2) to (9) of the table report the percentage of funds with t-statistics of the timing coefficient exceeding the indicated t-statistic values at 1%, 5%, and 10% significance levels.

		Percentage of funds							
Category	# of funds	$t \leq$-2.326	$t \leq$-1.96	$t \leq$-1.645	$t \leq$-1.282	$t \geq$1.282	$t \geq$1.645	$t \geq$1.96	$t \geq$2.326
All funds	3,986	3.7	6.2	8.1	11.7	46.8	41.7	37.2	32.6
Investment grade	2,418	3.4	5.3	7.0	10.4	50.6	47.7	45.3	42.1
High yields	1,239	4.1	8.4	10.3	14.1	39.7	31.1	22.5	15.3
Retail	1,740	5.1	8.1	10.9	15.4	36.2	32.6	28.5	24.5
Institutional	1,892	3.0	5.1	6.4	9.8	51.2	44.2	38.9	34.1
Survivors	2,356	3.9	7.3	9.6	14.1	41.9	39.1	34.8	31.3
Non survivors	1,630	3.3	4.7	6.0	8.2	53.9	45.5	40.7	34.4
Index	276	5.4	9.1	11.2	15.2	25.0	22.8	21.4	19.9
Non index	3,709	3.6	6.1	7.8	11.3	48.5	43.2	38.4	33.6

Table 9: Cross-sectional distribution of t-statistics of γ: Controlling for market and volatility timing abilities

The table presents the cross-sectional distribution of t-statistics for the inflation-risk-timing coefficient γ. For each fund with at least 36 non-missing observations, we estimate the following timing model:

$$R_{p,t+1} = \alpha_p + \beta_p MKT^{Bond}_{t+1} + \gamma_p MKT^{Bond}_{t+1}(IVRF_{t+1} - \overline{IVRF}) + \sum_{m=1}^{M} \beta_m f_{m,t+1} + \upsilon_{p,t+1}$$

where $R_{p,t+1}$ is the excess return on each individual fund p in month $t+1$. The risk factor variables (f) include risk factors in the corporate bond market such as the bond market excess return (MKT^{Bond}), a credit risk factor (CRF), a liquidity factor (LRF) and a downside risk factor (DRF). We include risk factors from the equity market such as the size factor (SMB), the value factor (HML), and the momentum factor (UMD). $IVRF_{p,t+1}$ is the inflation volatility risk factor in month $t+1$, and $\overline{IVRF}$ is the average of the inflation volatility risk factor over the previous 12 months (t-12 to t). The coefficient of interest, γ, measures the inflation volatility risk timing ability among fund managers. Fund categories are described in table 1. Panel A includes market timing ability using squared bond market returns. Panel B controls for volatility timing ability using three volatility measures, bond return volatility using lagged 12-month bond market returns, equity return volatility using lagged 12-month S&P 500 index returns, and month-end VIX. Panel C investigates different combinations of market and volatility timing abilities. The numbers in Columns (2) to (9) of the table report the percentage of funds with t-statistics of the timing coefficient exceeding the indicated t-statistic values at 1%, 5%, and 10% significance levels.

		Percentage of funds							
Category	# of funds	$t \leq$-2.326	$t \leq$-1.96	$t \leq$-1.645	$t \leq$-1.282	$t \geq$1.282	$t \geq$1.645	$t \geq$1.96	$t \geq$2.326
Panel A: Market timing									
MKT^2_{Bond}	3,986	4.3	5.7	8.5	13.4	42.9	37.7	34.3	31.8
Panel B: Volatility timing									
Bond vol.	3,986	4.3	6.5	9.0	13.2	38.6	33.5	30.1	26.3
Equity vol.	3,986	4.8	6.8	9.8	14.1	34.2	31.0	27.6	24.6
VIX	3,986	4.6	6.5	9.5	14.2	34.4	30.9	27.9	24.9
Panel C: Market + Volatility timing									
MKT^2_{Bond} + Bond vol.	3,986	5.1	7.4	10.0	14.6	40.4	35.8	32.8	29.4
MKT^2_{Bond} + Equity vol.	3,986	5.3	7.0	8.9	13.5	37.6	33.1	29.3	25.9
MKT^2_{Bond} + VIX	3,986	4.9	7.8	10.4	15.0	38.2	33.0	29.1	25.3

Table 10: Cross-sectional distribution of t-statistics of γ: Controlling for alternative factors and monetary policy shocks

The table presents the cross-sectional distribution of t-statistics for the inflation-risk-timing coefficient γ. For each fund with at least 36 non-missing observations, we estimate the following timing model:

$$R_{p,t+1} = \alpha_p + \beta_p MKT^{Bond}_{t+1} + \gamma_p MKT^{Bond}_{t+1}(IVRF_{t+1} - \overline{IVRF}) + \sum_{m=1}^{M} \beta_m f_{m,t+1} + \upsilon_{p,t+1}$$

where $R_{p,t+1}$ is the excess return on each individual fund p in month $t+1$. The risk factor variables (f) include risk factors in the corporate bond market such as the bond market excess return (MKT^{Bond}), a credit risk factor (CRF), a liquidity factor (LRF) and a downside risk factor (DRF). We include risk factors from the equity market such as the size factor (SMB), the value factor (HML), and the momentum factor (UMD). $IVRF_{p,t+1}$ is the inflation volatility risk factor in month $t+1$, and $\overline{IVRF}$ is the average of the inflation volatility risk factor over the previous 12 months (t-12 to t). The coefficient of interest, γ, measures the inflation volatility risk timing ability among fund managers. Fund categories are described in table 1. Panel A includes changes of default spreads (ΔDEF) and changes of term spreads ($\Delta TERM$). Panel B includes changes of uncertainty measure (ΔUNC) and changes of economic policy uncertainty (ΔEPU). Panel C focuses days with the Federal Open Market Committee announcements, and includes monetary shocks defined by high-frequent news policy shock in Nakamura and Steinsson (2018), the current federal funds rate target factor and the future path of policy factor in Gürkaynak et al. (2005), and unexpected changes in interest rates in a 30-minute window surrounding scheduled Federal Reserve announcements arise from news about monetary policy. The numbers in Columns (2) to (9) of the table report the percentage of funds with t-statistics of the timing coefficient exceeding the indicated t-statistic values at 1%, 5%, and 10% significance levels.

		Percentage of funds							
Category	# of funds	$t \leq$-2.326	$t \leq$-1.96	$t \leq$-1.645	$t \leq$-1.282	$t \geq$1.282	$t \geq$1.645	$t \geq$1.96	$t \geq$2.326
Panel A: Alternative bond factors									
ΔDEF	3,986	4.3	6.5	9.8	14.5	46.6	41.5	37.9	33.0
$\Delta TERM$	3,986	3.9	6.3	9.0	13.1	45.7	40.9	36.6	31.1
Panel B: Additional uncertainty factors									
ΔUNC	3,986	3.7	5.6	8.2	12.1	50.4	45.1	40.8	35.2
ΔEPU	3,986	3.4	5.4	7.4	12.1	50.1	44.7	39.7	33.6
Panel C: Monetary policy shocks									
Nakamura and Steinsson (2018)	3,986	3.7	5.6	8.0	11.7	49.2	44.1	39.1	35.7
Gürkaynak et al. (2005)	3,986	3.8	5.3	7.5	11.5	46.2	40.0	36.5	32.3
Δexpectations of Federal Funds rate	3,986	4.1	5.4	7.7	11.6	47.2	41.2	37.1	32.7
All alternative factors and shock	3,986	4.2	6.8	10.2	14.6	43.9	38.4	34.0	29.9

Table 11: Bootstrap estimates of inflation-risk timing ability: t-statistics of γ

The table reports the results of the bootstrap analysis of inflation-risk timing. For each fund with 36-month return observations, we estimate the coefficients from the following inflation-risk timing regression:

$$R_{p,t+1} = \alpha_p + \beta_p MKT^{Bond}_{t+1} + \gamma_p MKT^{Bond}_{t+1}(IVRF_{t+1} - \overline{IVRF}) + \sum_{m=1}^{M} \beta_m f_{m,t+1} + \upsilon_{p,t+1}$$

where $R_{p,t+1}$ is the excess return on each individual fund p in month $t+1$. The risk factor variables (f) include risk factors in the corporate bond market such as the bond market excess return (MKT^{Bond}), a credit risk factor (CRF), a liquidity factor (LRF) and a downside risk factor (DRF) (Bai et al., 2019). We include risk factors from the equity market such as the size factor (SMB), the value factor (HML), and the momentum factor (UMD). $IVRF_{p,t+1}$ is the inflation volatility risk factor in month $t+1$, and $\overline{IVRF}$ is the average of the inflation volatility risk factor over the previous 12 months (t-12 to t). Next, a random sample of residuals is chosen to generate hypothetical fund returns that, by construction, have the same factor loadings as the actual funds but have no timing ability (that is, imposing $\gamma_p = 0$). Finally, we re-estimate the regression above using these hypothetical fund returns. The coefficient of interest, γ, measures the inflation volatility risk timing ability among fund managers. Fund categories are described in table 1. In the table, the odd rows report the sorted t-statistics of timing coefficients across individual funds, and the even rows are the empirical p-values from bootstrap simulations. The number of resampling iterations is 10,000.

	Number		Bottom performers (γ)				Top performers (γ)			
Category	of funds		1%	3%	5%	10%	10%	5%	3%	1%
All funds	3,986	t-statistic	-9.63	-6.97	-5.61	-3.72	3.36	4.96	6.41	8.44
		p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Investment grade	2,418	t-statistic	-9.71	-7.20	-5.60	-3.65	4.20	6.13	7.18	8.57
		p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
High yields	1,239	t-statistic	-9.35	-6.91	-6.13	-3.84	2.25	2.86	3.34	4.97
		p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.01)
Retail	1,740	t-statistic	-9.59	-6.82	-5.29	-3.06	4.02	5.62	6.76	8.44
		p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Institutional	1,892	t-statistic	-10.15	-7.53	-6.56	-4.66	2.78	4.32	6.24	8.49
		p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Survivors	2,356	t-statistic	-10.54	-7.94	-6.69	-4.87	2.01	2.66	2.87	7.66
		p-value	(0.00)	(0.00)	(0.00)	(0.00)	(1.00)	(1.00)	(1.00)	(0.29)
Non survivors	1,630	t-statistic	-7.16	-3.62	-2.70	-1.68	5.04	6.57	7.18	8.54
		p-value	(0.00)	(0.00)	(0.05)	(0.96)	(0.00)	(0.00)	(0.00)	(0.00)
Index	276	t-statistic	-8.59	-7.01	-6.56	-4.76	1.75	3.62	4.27	5.47
		p-value	(0.04)	(0.00)	(0.00)	(0.00)	(1.00)	(0.86)	(0.95)	(0.99)
Non index	3,709	t-statistic	-9.63	-6.84	-5.51	-3.64	3.53	5.04	6.53	8.45
		p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Table 12: Bootstrap estimates of holdings-based and active-beta inflation-risk timing ability

The figure plots kernel density distributions of the bootstrapped top and bottom 1^{th}, 3^{th}, 5^{th}, and 10^{th} percentiles t-statistics of holdings-based inflation-risk timing measures (solid lines) using Eq. (9), as well as active-beta based timing measure using Eq. (11), for individual funds with three-month forecasting horizon. Corporate bond inflation-risk betas are estimated using the past 36-month returns. The estimation sample is spanning from January 2003 to September 2022.

	Bottom performers (γ^H)				Top performers (γ^H)			
	1%	3%	5%	10%	10%	5%	3%	1%
	Panel A: Three-month forecasting horizon							
	$\beta^{\pi}_{p,t} = \alpha + \gamma^H(IVRF_{t+3} - \overline{IVRF}) + \eta_t$							
γ^H	-0.09	-0.06	-0.04	-0.03	0.03	0.05	0.08	0.11
$p(\gamma^H)$-value	(0.13)	(0.09)	(0.12)	(0.13)	(0.05)	(0.04)	(0.00)	(0.03)
t-statistic	-4.67	-3.40	-2.80	-1.92	3.10	3.88	4.69	7.69
$p(t)$-value	(0.94)	(0.89)	(0.87)	(0.87)	(0.06)	(0.16)	(0.18)	(0.08)
	Panel B: Three-month forecasting horizon controlling for passive funds							
	$\Delta\beta^{\pi}_{p,t} = \beta^{\pi}_{p,t} - \beta^{\pi}_{p,t-3} = \alpha + \gamma^H(IVRF_{t+3} - \overline{IVRF}) + \eta_t$							
γ^H	-0.01	0.00	0.00	0.00	0.00	0.01	0.01	0.02
$p(\gamma^H)$-value	(0.23)	(0.64)	(0.39)	(0.49)	(0.01)	(0.01)	(0.01)	(0.04)
t-statistic	-4.91	-2.84	-2.45	-1.60	2.96	3.78	4.51	5.89
$p(t)$-value	(0.70)	(0.93)	(0.86)	(0.90)	(0.04)	(0.09)	(0.11)	(0.32)

Appendix

A Additional Analysis

Table A.1: Univariate portfolio analysis

The table reports the portfolio, alpha return and bond characteristics for the univariate portfolio sorted by β^{π}. The portfolio sorting is based on the inflation beta (β^{π}). Quintile 1 (Low-β^{π}) is the portfolio with the lowest inflation beta and Quintile 5 (High-β^{π}) is the portfolio with the highest inflation beta. Panel A reports the portfolio average inflation-beta (Average β^{π}), and alpha returns (in percent) based on the 5-factor (MKT, SMB, HML+UMD+LIQ) denoted as FF5 risk factor model, a 6-factor model (+ market bond return from Dickerson et al. (2023)) denoted FF5+DRM1 risk model, and a 9-factor model (+ credit, liquidity and downside risk factors from Dickerson et al. (2023) denoted as FF5+DRM4. Panel B reports the portfolio bond characteristics in each quintile such as maturity (time to maturity), credit rating (Rating), the Amihud (2002) bond liquidity measure (Illiquid), bond outstanding amount (Size), bond market beta (β^{MKT}). The sample spans from July 2002 to September 2022. Newey-West adjusted t-statistics are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

		Panel A: Alpha return			Panel B: Portfolio characteristics				
Quintile	Average β^{π}	FF5	FF5+DRM1	FF5+DRM4	Rating	Size	Maturity	Liquidity	β^{MKT}
Low-β^{π}	-0.41	0.50**	0.33***	0.29***	8.41	708.8	13.72	0.21	1.29
		(2.42)	(2.78)	(2.71)					
2	-0.12	0.22**	0.11***	0.11***	7.62	777.2	7.51	0.12	0.87
		(2.23)	(3.36)	(3.42)					
3	-0.03	0.15*	0.03	0.04*	7.69	785.0	5.68	0.10	0.75
		(1.80)	(0.80)	(1.66)					
4	0.08	0.05	-0.09	-0.09*	8.79	699.6	6.77	0.11	0.91
		(0.56)	(-1.27)	(-1.92)					
High-β^{π}	0.56	0.00	-0.25*	-0.21*	11.41	609.1	9.58	0.22	1.60
		(0.02)	(-1.94)	(-1.93)					
High-Low	0.97	-0.50**	-0.57***	-0.50**	3.00	-99.6	-4.13	0.00	0.31
		(-2.11)	(-2.89)	(-2.38)					

Table A.2: Bivariate portfolio analysis

The Table reports the alpha return based on the 9-factor risk model by double-sorting portfolios in quintiles based on the inflation beta (β^{π}) and bond characteristics. In each month from July 2002 to September 2022, quintile portfolios are formed based on bond characteristics. Within each quintile bond portfolio, a new quintile-sorted portfolios are formed based on (β^{π}). This procedure creates quintile portfolios with dispersion on inflation beta (β^{π}) while controlling for bond-characteristics. Low-β^{π} (High-β^{π}) represents the lowest (highest) β^{π}-sorted portfolio within each bond characteristics. Panel A reports the result for quintile portfolios sorted by credit rating. Panel B reports the alpha return for bivariate-sorted quintile portfolios for inflation beta (β^{π}) controlling for time to maturity (Maturity). Panel C presents the bivariate results from size and the inflation beta (β^{π}). Panel D presents the bivariate analysis controlling for bond liquidity based on Amihud (2002). Alphas are reported in percent. Newey-West adjusted t-statistics are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Panel A: Credit rating			Panel B: Maturity		
Quintiles	All bonds	IG	NIG	All bonds	Short	Long
Low-β^{π}	0.20***	0.18***	0.25***	0.36***	0.37***	0.32***
	(2.87)	(2.80)	(2.65)	(2.75)	(2.62)	(2.73)
2	0.09***	0.08***	0.09	0.08***	0.09**	0.06
	(3.01)	(2.89)	(1.24)	(2.80)	(2.33)	(1.60)
3	0.02	0.04***	0.02	0.00	0.03	-0.03
	(1.17)	(2.66)	(0.42)	(0.07)	(0.64)	(-0.96)
4	0.01	0.00	0.07	-0.12**	-0.07	-0.14**
	(0.28)	(0.08)	(0.86)	(-2.39)	(-1.09)	(-2.51)
High-β^{π}	-0.18**	-0.12*	-0.28**	-0.23**	-0.17	-0.33***
	(-2.30)	(-1.70)	(-2.16)	(-2.09)	(-1.39)	(-2.73)
High-Low	-0.39***	-0.30**	-0.53**	-0.59**	-0.54**	-0.64***
	(-2.63)	(-2.34)	(-2.57)	(-2.50)	(-2.24)	(-2.83)
	Panel C: Size			**Panel D: Illiquid**		
Quintiles	All bonds	Small	Large	All bonds	Low	High
Low-β^{π}	0.25***	0.23***	0.24***	0.24***	0.28**	0.31**
	(2.77)	(2.67)	(2.60)	(2.80)	(2.13)	(2.13)
2	0.10***	0.09***	0.11***	0.11***	0.14***	0.13***
	(3.19)	(3.01)	(3.63)	(3.51)	(3.73)	(3.83)
3	0.04**	0.03	0.04	0.06**	0.05*	0.04
	(2.14)	(1.48)	(1.47)	(2.34)	(1.69)	(1.41)
4	-0.06	-0.05	-0.06	-0.08*	-0.06	-0.04
	(-1.39)	(-0.99)	(-1.30)	(-1.95)	(-1.11)	(-0.80)
High-β^{π}	-0.21**	-0.21**	-0.20**	-0.21**	-0.28**	-0.31**
	(-2.19)	(-2.18)	(-1.97)	(-2.09)	(-2.46)	(-2.52)
High-Low	-0.47**	-0.45**	-0.44**	-0.46**	-0.55**	-0.62**
	(-2.53)	(-2.49)	(-2.35)	(-2.46)	(-2.39)	(-2.40)

Table A.3: Cross-sectional distribution of t-statistics of γ: Controlling for market and volatility timing abilities

The table presents the cross-sectional distribution of t-statistics for the inflation-risk-timing coefficient γ. For each fund with at least 36 non-missing observations, we estimate the following timing model:

$$R_{p,t+1} = \alpha_p + \beta_p MKT^{Bond}_{t+1} + \gamma_p MKT^{Bond}_{t+1}(IVRF_{t+1} - \overline{IVRF}) + \sum_{m=1}^{M} \beta_m f_{m,t+1} + \upsilon_{p,t+1}$$

where $R_{p,t+1}$ is the excess return on each individual fund p in month $t+1$. The risk factor variables (f) include risk factors in the corporate bond market such as the bond market excess return (MKT^{Bond}), a credit risk factor (CRF), a liquidity factor (LRF) and a downside risk factor (DRF). We include risk factors from the equity market such as the size factor (SMB), the value factor (HML), and the momentum factor (UMD). $IVRF_{p,t+1}$ is the inflation volatility risk factor in month $t+1$, and $\overline{IVRF}$ is the average of the inflation volatility risk factor over the previous 12 months (t-12 to t). The coefficient of interest, γ, measures the inflation volatility risk timing ability among fund managers. Fund categories are described in table 1. Panel A includes market timing ability using squared bond market returns. Panel B controls for volatility timing ability using three volatility measures, bond return volatility using lagged 12-month bond market returns, equity return volatility using lagged 12-month S&P 500 index returns, and month-end VIX. Panel C investigates different combinations of market and volatility timing abilities. The numbers in Columns (2) to (9) of the table report the percentage of funds with t-statistics of the timing coefficient exceeding the indicated t-statistic values at 1%, 5%, and 10% significance levels.

			Percentage of funds							
Category		# of funds	$t \leq$-2.326	$t \leq$-1.96	$t \leq$-1.645	$t \leq$-1.282	$t \geq$1.282	$t \geq$1.645	$t \geq$1.96	$t \geq$2.326
Panel A: Market timing										
MKT^2_{Bond}		3986	39.0	44.0	48.9	54.7	7.9	5.5	4.2	3.1
Panel B: Volatility timing										
Bond vol.		3,982	18.3	24.0	30.4	38.5	13.8	10.7	8.3	5.9
Equity vol.		3,927	29.7	36.7	43.1	50.1	9.1	6.9	5.4	3.8
VIX		3,857	20.9	28.4	36.0	44.0	13.4	10.6	8.2	6.0
Panel C: Market + Volatility timing										
	MKT^2_{Bond} + Bond vol.	3,982	27.8	32.9	37.8	44.9	10.1	7.4	5.8	4.1
MKT	MKT^2_{Bond} + Equity vol.	3,927	19.8	24.0	28.9	35.7	13.8	10.0	7.5	5.6
	MKT^2_{Bond} + VIX	3,857	36.4	43.2	49.2	56.6	7.3	5.6	4.4	3.2
	MKT^2_{Bond} + Bond vol.	3,982	12.0	16.2	20.5	27.0	13.7	10.3	7.7	5.4
VOL	MKT^2_{Bond} + Equity vol.	3,927	17.3	23.0	28.4	36.3	8.8	6.9	5.2	3.9
	MKT^2_{Bond} + VIX	3,857	20.8	26.5	32.3	39.1	13.3	9.7	7.4	5.7