Meshram, Vedprakash; Lalwani, Vaibhav

Article

Inflation hedging via tracking portfolios in the BRICS markets

Cogent Economics & Finance

Provided in Cooperation with:
Taylor & Francis Group

Suggested Citation: Meshram, Vedprakash; Lalwani, Vaibhav (2024) : Inflation hedging via tracking portfolios in the BRICS markets, Cogent Economics & Finance, ISSN 2332-2039, Taylor & Francis, Abingdon, Vol. 12, Iss. 1, pp. 1-16, https://doi.org/10.1080/23322039.2024.2431525

This Version is available at:
https://hdl.handle.net/10419/321679

Cogent Economics & Finance

ISSN: 2332-2039 (Online) Journal homepage: www.tandfonline.com/journals/oaef20

Inflation hedging via tracking portfolios in the BRICS markets

Vedprakash Meshram & Vaibhav Lalwani

To cite this article: Vedprakash Meshram & Vaibhav Lalwani (2024) Inflation hedging via tracking portfolios in the BRICS markets, Cogent Economics & Finance, 12:1, 2431525, DOI: 10.1080/23322039.2024.2431525

To link to this article: https://doi.org/10.1080/23322039.2024.2431525

Published online: 01 Dec 2024.

COGENT ECONOMICS & FINANCE
2024, VOL. 12, NO. 1, 2431525
https://doi.org/10.1080/23322039.2024.2431525

FINANCIAL ECONOMICS | RESEARCH ARTICLE

OPEN ACCESS Check for updates

Inflation hedging via tracking portfolios in the BRICS markets

Vedprakash Meshram[a] and Vaibhav Lalwani[b]

[a]Goa Institute of Management, Goa, India; [b]XLRI Xavier School of Management Delhi-NCR, Jhajjar, India

ABSTRACT

This study investigates the creation of portfolios that effectively hedge against inflation in the context of the stock markets of Brazil, Russia, India, China, and South Africa (BRICS). Utilizing Ordinary Least Squares (OLS), Ridge, MM, and Quantile regressions, we construct portfolios that closely track the unexpected changes in Consumer Price Index (CPI) inflation. Our empirical analysis, based on data from spanning 2005 to 2023, demonstrates that statistical tracking portfolios outperform benchmark portfolios in tracking inflation, particularly during periods of low inflation uncertainty. Among all the methods, Quantile regression generally shows good tracking performance, though not universally. The findings suggest that these tracking portfolios can assist investors who are seeking to mitigate inflationary risks in volatile emerging markets. This research contributes to the literature by demonstrating out-of-sample performance of tracking portfolios and their application in less stable economic environments.

IMPACT STATEMENT

This study provides a critical analysis of constructing inflation-hedging portfolios tailored for the BRICS stock markets, utilizing advanced regression techniques such as OLS, Ridge, MM, and Quantile regressions. The results highlight the superior performance of statistical tracking portfolios in mitigating inflation risks compared to benchmark portfolios, particularly under low inflation uncertainty conditions. By addressing the challenge of inflation hedging in less stable economic environments, this study offers valuable insights for investors and contributes significantly to the field of portfolio management in emerging economies.

ARTICLE HISTORY
Received 27 July 2024
Revised 7 October 2024
Accepted 14 November 2024

KEYWORDS
Inflation hedging; tracking portfolios; inflation; out-of-sample; BRICS; emerging markets; inflation uncertainty

SUBJECTS
Economics; Finance; Investment & Securities

JEL CODES
G11; G12; G17

1. Introduction

Since the COVID pandemic, Inflation around the world has exceeded its highest levels since 1995 (Ha et al., 2023). While increased prices affect everyone, they also pose a serious challenge to savers, as inflation shocks threaten to erode the real values of their investments. Even a modest inflation rate of 4% can erode the purchasing power of cash by about half in 17 years. Uncontrolled inflation can rapidly erode the purchasing power of money, lead to macroeconomic instability, and create an uncertain business environment. Given such extreme consequences, protection from inflationary risks is crucial for investors (Bekaert & Wang, 2010). Therefore, investors need to understand how to invest their money strategically so as to outpace the rate of inflation.

There is no universal approach by which investors can protect themselves from inflation (Attié & Roache, 2009). However, the core principle of inflation hedging is to invest in assets whose returns move in tandem with inflation. In other words, investments with returns (cash flows) linked to real assets can act as inflation hedges. Other assets that tend to rise during bad economic times, such as gold and real estate, have also been pitted as inflation hedges (Shahzad et al., 2019; Salisu et al., 2020).

Academics and practitioners have been studying inflation hedging for a long time. Research on asset allocation strategies proposes the inclusion of Inflation-protection bonds (e.g. Kothari & Shanken, 2004) and other alternative asset classes such as real estate, commodities, and hedge funds (e.g. Hoevenaars et al., 2008). Regardless of the number and type of asset classes, the weights of constituents in

CONTACT Vaibhav Lalwani vaibhavlalwani@outlook.com XLRI Xavier School of Management Delhi-NCR Campus, Jhajjar, Haryana, India

an inflation-hedging portfolio need to be dynamically adjusted due to changing market conditions. The tracking portfolio approach as in Engle et al. (2020) can be used to achieve this objective.

In this study, we use the tracking portfolio approach to explore investment strategies that can be used to hedge inflationary risks. Tracking portfolios closely tracks a particular indicator. Therefore, a tracking portfolio that invests in assets highly correlated with inflation can help investors hedge inflation. In simple terms, if a portfolio is correlated with inflation, its returns increase when inflation is high, thus providing an appropriate hedge against inflationary risk.

Although the concept is simple to understand, creating portfolios that are correlated with inflation can be quite challenging. Economic tracking portfolios are popular in the literature ((Lamont, 2001; Vassalou, 2003), etc.); however, much of the existing literature uses in-sample tracking portfolios. Creating tracking portfolios that work outside the original sample is an even more daunting task. We address this challenge in our study.

As discussed, the concept of an economic-tracking portfolio is not novel. However, its application in hedging inflationary risks in emerging markets is relatively unchartered. Emerging markets are characterized by their high growth potential, which often comes hand-in-hand with heightened volatility and susceptibility to inflationary pressure. While effective in developed economies, traditional investment strategies may not suffice in such dynamic markets. Thus, there is a paramount need for a specialized approach that accounts for the unique challenges faced by these economies. The average inflation rate in advanced economies from 2000 to 2023 is 2.15%. During the same period, the average monthly inflation in emerging markets and developing economies was 6.27% or around three times the inflation in developed markets.[1] Therefore, the current state of the literature does not tell us whether tracking portfolios can successfully hedge inflationary risks in emerging markets out-of-sample.

This study attempts to fill this research gap. We do so by testing whether out-of-sample tracking portfolios do a better job of tracking inflation than an equally weighted benchmark. Based on the data of Brazil, Russia, India, China, and South Africa (BRICS countries) from 2005 to 2023, our results show that it is possible to develop dynamic asset allocation strategies that result in portfolios that efficiently track inflation. The BRICS countries account for more than 40% of the world's population and the four BRIC countries account for a similar proportion of the world stock-market capitalization (Mensi et al., 2016). We concur with (McIver & Kang, 2020) in suggesting that global investors must better understand how the BRICS markets work. Therefore, our study adds to the literature by showing whether and how investors in emerging markets like BRICS can hedge inflationary risks by creating portfolios with the explicit objective of tracking inflation.

The remainder of this paper is organized as follows. We discuss the existing literature in Section 2. Section 3 describes the statistical methodology used to track the portfolio creation. Section 4 explains the data and Section 5 discusses the empirical findings. We conclude our study in Section 6.

2. Literature review

The relationship between inflation and asset prices has interested financial economists as far back as (Fisher, 1912). Later, Bodie (1976), (Fama, 1981), and (Bernard & Frecka, 1983) explored how inflation and asset prices interact. The famous (Fisher, 1930) expresses a formal baseline hypothesis of the relationship between price rise (inflation) and asset prices. Fama and Schwert (1977) show that in the following regression of asset returns on the change in the inflation rate, the estimate of the beta of expected inflation shows the relationship between nominal asset returns and inflation:

$$R_{jt} = \alpha_j + \beta_j * E_{t-1}(\pi_t) + \varepsilon_{jt} \tag{1}$$

An asset whose β_j is statistically indistinguishable from zero acts as a perfect hedge for the expected inflation (Arnold & Auer, 2015). Fama and Schwert (1977) augment Equation 1 with unexpected inflation, leading to the following expression:

$$R_{jt} = \alpha_j + \beta_j * E_{t-1}(\pi_t) + \gamma_j * \left[\pi_t - E_{t-1}(\pi_t)\right] + \varepsilon_{jt} \tag{2}$$

In this augmented version of Fischer's hypothesis, an asset for which the γ_j is statistically indistinguishable from 1.0, is a perfect hedge against unexpected inflation. A coefficient between 0 and 1

signifies a partial hedge, whereas a negative coefficient indicates that an asset can be shorted to hedge inflation.

The versions of Equations 1 and 2 have been extensively used to test whether a particular asset serves as an inflation hedge. A priori, some assets are expected to work as better inflation hedges than others. In Fisher's model, assets such as stocks and real estate, which represent claims against real assets, are more likely to move in tandem with inflation. A nominal income asset such as a treasury bill cannot provide a hedge for any unexpected inflation until its maturity.

As discussed, common stocks, backed by the real assets of the underlying corporations, are expected to act as effective hedges against inflation. However, initial studies ((Bodie, 1976; Nelson, 1976; Fama & Schwert, 1977), among others) observed that there is often a negative or negligible relationship between stock returns and inflation. Fama and Schwert (1977) rightly call this "the most anomalous result" in their study. However, subsequent research rationalizes the counterintuitive relationship between stock returns and inflation. Fama (1981) notes that high inflation is also correlated with lower real activity. In other words, the negative relationship between stock returns and inflation is due to the positive relationship between stock prices and real economic activities. Once real activity is controlled for, the relationship between inflation and stock returns becomes positive. Geske and Roll (1983) provided a similar explanation. They refer to an empirical illusion due to the spurious causality induced by variables linked to debt monetization.

Another set of studies provided a different line of thought. They argue that the hypothesized relationship is for the long run, whereas the empirical tests in previous studies use short-run data. Boudoukh and Richardson (1993) tested the relationship between inflation and stock returns in the U.S. and the U.K. using almost 190 years of data from 1802 to 1990 to provide a clearer picture of the long-run dynamics between stock returns and inflation. They reported a significantly positive long-term relationship between inflation and stock returns. Evans and Lewis (1995), Engsted and Tanggaard (2002), and Anari and Kolari (2001) confirm that the long-run Fisher elasticities of stock prices exceed 1. Therefore, stocks are expected to be good hedges against inflation in the long run. More recent analyses by Illeditsch (2018), Boons et al. (2020), and Campbell et al. (2020) also confirm that risks related to inflation are prices in stocks; that is, equity is positively correlated with inflation.

While our focus is predominantly on equities, we also discuss some studies that explore the inflation-hedging potential of other assets. The list of studies is, by no means, comprehensive. We refer the reader to Arnold and Auer (2015) for a broader list of relevant studies. Beginning with (Fama, 1981), real estate has been shown as a hedge against inflation, both expected and unexpected. While (Bond & Seiler, 1998; Salisu et al., 2020) also show that real estate provides security against inflationary risk, (Fang et al., 2008) show that it does not work, at least in Taiwan, in their sample.

Gold is another prominent asset in discussions of inflation hedging. While contradictory evidence exists for all assets, the evidence of the inflation-hedging properties of gold appears to be quite divided. The initial results from Mahdavi and Zhou (1997) and Taylor (1998) do not support the inflation hedging hypothesis for gold. However, Lucey et al. (2017) and Aye et al. (2016) state that gold can act as an inflation hedge only in certain countries and during certain periods. In summary, there appears to be a time-varying relationship between asset prices and inflation, and the same asset mix cannot be expected to work at all times.

As the nature of the relationship between assets and inflation changes over time, asset allocation strategies should also be sufficiently dynamic to reflect the changing market conditions. How can we develop a dynamic asset allocation strategy that hedges inflationary risk over time? In this study, we use a tracking portfolio approach to develop such a strategy.

While we discuss the statistical methodology of tracking portfolios in the next section, we also discuss the core ideas in order. Simply defined, a tracking portfolio closely tracks an underlying variable of interest. For example, an inflation-tracking portfolio should be composed so that the resulting portfolio returns are highly correlated with some specified inflation proxies. These portfolios can be used to test asset pricing models, such as those in Breeden et al. (1989), Vassalou (2003), and Kapadia (2011). However, if used in an out-of-sample setting, the application of tracking portfolios extends far beyond model testing. Intuitively, a portfolio correlated with an economic indicator can be used to hedge risks arising from changes in the aforementioned indicators. For example, an investor concerned about the erosion of purchasing power due to a rise in inflation can invest in an inflation-tracking portfolio. Therefore, if inflation increases, the value of the investor's portfolio also increases, offsetting the impact

of the rise in inflation. The extent to which the impact of inflation is compensated for depends on the extent of the correlation with the economic indicator. A portfolio perfectly correlated with inflation would fully hedge risk. However, developing such portfolios is challenging, especially for out-of-sample portfolios. Chan et al. (1998) and others later show that portfolios that mimic economic factors perform poorly and are indistinguishable from randomly formed portfolios.

To the best of our knowledge, Lamont (2001) is one of the first studies to empirically explore the creation of tracking portfolios. Using vector autoregressions (VAR), he creates economic tracking portfolios to track various economic variables such as industrial production, real consumption growth, and inflation. This study shows that tracking portfolios track the underlying economic variables. However, the tracking performance deteriorates considerably out of the sample. Portfolios that track an indicator in-sample can be constructed efficiently. The jury is still out of question whether in-sample success can be carried out in out-of-sample testing. However, the recent advances in this area are promising. Jurczenko and Teiletche (2022) showed that using machine learning estimators improves the performance of tracking portfolios. Luo et al. (2022) use a regularization approach to improve the out-of-sample performance of forecasts and thus create portfolios with lower tracking errors. Similarly, De Nard et al. (2023) propose a new mimicking portfolio approach that takes into account recent developments in the estimation of large-dimensional covariance matrices in short samples (Engle et al., 2019).

To summarize, the literature can be categorized into two strands: the first strand explores whether selected assets (e.g. precious metals, stocks, bonds, real estate, etc.) can hedge inflation. The second strand, which is of our interest, relates to systematic portfolio strategies to generate portfolios that track an indicator. There are two key takeaways from the literature survey. First, it is difficult to create tracking portfolios that work out of samples. Second, much of the literature focuses on the developed markets. Even in developed markets, much of the evidence is from the U.S., with limited research coming from other countries (see (Neville et al., 2021) and (Nakagawa & Suimon, 2022) for exceptions). However, as previously argued, there is substantial heterogeneity in the dynamics of inflation in developing and developed countries. First, the average inflation in emerging markets is much higher than in advanced economies (Ha, Ivanova, Ohnsorge, et al., 2019). Second, emerging and low-income countries are more susceptive to external inflationary shocks and have much higher inflation volatility than developed economies (Ha, Ivanova, Montiel, et al., 2019). Therefore, tracking portfolio methods have been tested under more stable regimes. We need to know if the same methodologies hold in smaller economies, where economic conditions are relatively unstable. This study aims to fill this gap in the literature. We used the BRICS markets as the laboratory for our experiments. Using 13 broad diversified portfolios as our base assets, we test whether it is possible to develop portfolios that track expected and unexpected inflation. We find it possible to create portfolios that do a good job of tracking inflation out of sample. Detailed methods, data sources, and results are presented in the following sections.

3. Tracking portfolio methodology

To fix the ideas, a tracking portfolio can be expressed in the form of a linear regression of the following form:

$$Y_t = \alpha + \beta * X + \varepsilon_t \tag{3}$$

Where Y_t is inflation at time t, and X is the matrix of asset returns over time. The choice of X is determined by the investor and depends on the type of asset they would like to invest in. The estimates of β are the weights of the maximum correlational portfolio, that is, the portfolio with the maximum (in-sample) correlation with inflation. The ordinary least squares (OLS) solution is the most popular estimation technique for tracking portfolios:

$$\hat{\beta}_{OLS} = (X^T X)^{-1} X^T y \tag{4}$$

However, the regularization/shrinkage of beta coefficients has been shown to yield better out-of-sample forecasts (Luo et al., 2022). Because our goal is out-of-sample forecasting, we use an alternative estimator that uses the ridge penalty to shrink the estimates. The solution for the ridge regression is given by:

$$\hat{\beta}_{ridge} = (X^T X + \lambda I)^{-1} X^T y \tag{5}$$

where λ is a shrinkage parameter provided by the user. We use 10^{-4} as the value for the shrinkage parameter.

Further, we also use the robust MM-regression of Yohai (1987) to estimate the tracking portfolio weights. The MM-regressions use the following objective function:

$$\text{Minimize} \sum_{i=1}^{n} \rho\left(\frac{y_i - x_i^T \beta}{s_{MM}}\right) \tag{6}$$

Where parameter s_{MM} is the scale estimate obtained from the initial S-estimation. The MM regression gives less weight to outliers compared to the OLS, a property that can be very useful when dealing with financial market data.

We also used the quantile regression of Koenker and Bassett (1978) to estimate the weights of the tracking portfolio. Instead of estimating the conditional mean as in OLS, Quantile regressions estimate the conditional quantiles of the dependent variable. Quantile regression uses the following objective function:

$$\text{Minimize} \sum_{i=1}^{n} \rho_\tau (y_i - x_i^T \beta) \tag{7}$$

where parameter ρ_τ (Tau) represents the quantile of interest to be specified by the user. A value of 0.5 denotes the median, whereas 0.75 would indicate the 75th percentile value.

Quantile regression-based tracking offers various benefits compared with other estimators. First, Quantile regression is more robust to outliers and can accommodate heavy-tailed distributions (Koenker & Hallock, 2001; Billah Dar et al., 2014). As asset returns are inherently asymmetric and fat-tailed, quantile regression tracking can yield weights robust to extreme values. Second, Quantile regression allows users to focus on specific parts of the distribution. Therefore, assigning weights to higher inflation levels can help create portfolios that do a better job of tracking an economic indicator, particularly when its value is high. Therefore, using a tau greater than 0.5, we can create portfolios that perform better when inflation is high. In our study, we used tau values of 0.5 and 0.75.

Furthermore, tracking portfolio regression can impose additional constraints on the estimated parameters. We used the following three constraints in our study:

1. $\alpha = 0$. This was imposed to ensure that there was no intercept in the regression.
2. $\sum_{i=1}^{k} \beta_k = 1$. This constraint is imposed to ensure that the sum of all the weights is equal to one.
3. All $\beta_i > 0$. This long-only constraint ensures that all assets have non-negative weights in the portfolio. In our study, we assume that shorting of the factors used as base assets is not allowed.

The first two constraints jointly ensure that the betas obtained from the regressions can be interpreted as weights of assets in a fully invested tracking portfolio. The last constraint ensures that all weights are greater than 0.

Equation (3) estimates the maximum correlation weights using the in-sample data. We use a rolling window of five years (60 months) of data for the out-of-sample tracking portfolios. We estimate the initial set of portfolio weights using the first five years of inflation and return data. The resultant tracking portfolio is held for one month and is rebalanced every month using updated weights from the rolling window estimation. While our baseline results use monthly rebalancing, we also create additional portfolios that are rebalanced every six months.

As previously discussed, the out-of-sample performance of tracking portfolios is often much worse than that of in-sample tracking portfolios. For better performance, we incorporate some improvements in the portfolio creation process using the following insights from the literature:

First, unexpected inflation is used as a measure of inflation. As asset prices already incorporate the expected component of inflation, subsequent price movements are expected to be due to unexpected inflation. Thus, the literature uses unexpected inflation as a proxy for inflation news in the market. The estimation of unexpected inflation involves subtracting the inflation forecast from the actual inflation.

However, Neville et al. (2021) show that the difference between the current and previous months' inflation works, as well as other sophisticated measures of unexpected inflation. Therefore, we use the monthly difference in inflation as the metric we want to track.

Further, Downing et al. (2012) show that using one-month-ahead inflation instead of the current month's inflation as a dependent variable enhances the performance of the tracking portfolio. Therefore, we create tracking portfolios using one-month-ahead unexpected inflation instead of contemporaneous inflation. We skip the last three months of data in our rolling window to ensure that we use only the information available to an investor at the time of portfolio creation. For example, suppose our rolling window spans five years from January 2000 to December 2004. In this case, we do not consider the data from October 2004 to December 2004, assuming that the inflation data for these months will not be available until January 2005. This step enhances the practical feasibility of our analysis.

4. Data

This study was conducted using data from January 2005 to July 2023. We use Data for monthly CPI Inflation of the BRICS countries from the FRED Database. We have used 13 diversified anomaly portfolios from Jensen et al. (2023) as our base assets to construct an inflation-tracking portfolio. These assets constitute a diverse set of portfolios (factors) that are created from multiple cross-sectional indicators, and therefore, these assets demonstrate substantial cross-sectional heterogeneity. The data for these factors can be obtained from the website www.jkpfactors.com. Our choice of assets is similar to Lamont (2001) and Downing et al. (2012), who use a broad set of diversified portfolios for their study. We do not consider other asset classes (gold and real estate) in our tracking portfolio. Our main objective is to test whether an equity-only investment is sufficient to create a workable tracking portfolio. Our results show that equities are sufficient for creating a portfolio that closely tracks inflation. We leave the inclusion of other asset classes to future studies.

The details of the base assets and their summary statistics are in Table 1. As shown in the table, our choice of base assets consists of a diverse set of assets composed of broad-based portfolios that reflect various investment themes such as value, accruals, momentum, profitability, quality, etc. The mean, volatility, skewness, and kurtosis of assets vary from each other. We emphasize diversity because an ideal asset base for portfolio creation should consist of assets with different statistical behaviors. Our asset choice seems to fulfill this criterion.

We now discuss the creation of the tracking portfolios discussed above. In the next section, we report the results and the overall performance of our tracking portfolios.

5. Results

We created ten types of inflation-tracking portfolios. The portfolios correspond to the four choices of estimators – OLS, Ridge, MM, and Quantile Regression (with Tau of 0.5 and 0.75) and two rebalancing frequencies – monthly and half-annually. As a naïve benchmark, we create an equally weighted portfolio for all the base assets.

We report the performance of each portfolio on four metrics: Sharpe Ratio (S.R.), average monthly portfolio turnover (ATO), and cumulative tracking error (T.E.). The calculation of these metrics is as follows:

The Sharpe ratio is calculated as the average monthly return of the portfolio divided by the standard deviation of the monthly returns.

The average monthly turnover of a portfolio is calculated using the following formula:

$$\frac{100}{N-1}\sum_{t=2}^{N}\sum_{i=1}^{S}\left|w_{i,t}-w_{i,t-1}\right|$$

Here, N refers to the number of months for which the portfolio returns are estimated, S is the number of assets in the portfolio, and $w_{i,t}$ is the weight for the asset' i' in the month 't' in the tracking portfolio. A lower turnover is generally preferred because it signifies that the portfolio strategy does not involve

Table 1. Descriptive statistics of inflation and base asset returns.

Brazil				
Indicator	Mean	Std. Dev.	Skewness	Kurtosis
CPI inflation	0.47	0.17	0.70	0.05
Accruals	0.02	3.34	−0.05	3.59
Debt issuance	0.07	2.25	0.06	2.65
Investment	0.20	2.69	0.25	5.08
Low leverage	−0.18	2.39	−0.04	3.06
Low risk	0.15	3.45	−0.40	1.29
Momentum	0.71	4.11	−0.89	3.59
Profit growth	0.11	1.67	−0.59	1.23
Profitability	0.22	2.92	−0.19	1.64
Quality	0.27	2.77	−0.30	0.36
Seasonality	0.07	1.62	0.12	2.58
Short term reversal	−0.14	2.33	1.54	8.58
Size	0.10	3.26	1.08	5.59
Value	0.35	2.89	0.56	1.06
Russia				
Indicator	Mean	Std. Dev.	Skewness	Kurtosis
CPI inflation	0.64	0.30	0.46	−0.71
Accruals	0.19	3.24	0.21	3.55
Debt issuance	0.14	2.19	0.00	1.78
Investment	0.12	2.42	0.24	3.96
Low leverage	0.05	2.26	−1.09	8.10
Low risk	−0.08	2.61	−0.56	4.47
Momentum	0.83	4.16	−0.54	3.06
Profit growth	0.42	2.08	0.21	2.80
Profitability	0.36	2.88	−0.37	1.94
Quality	0.56	3.00	0.01	1.60
Seasonality	−0.14	1.83	−1.18	6.86
Short term reversal	−0.03	3.04	0.21	3.56
Size	0.01	3.62	0.53	4.29
Value	0.57	2.46	0.40	1.51
India				
Indicator	Mean	Std. Dev.	Skewness	Kurtosis
CPI inflation	0.56	0.22	0.64	0.31
Accruals	0.03	1.90	0.44	3.28
Debt issuance	0.18	1.35	0.01	0.93
Investment	0.24	1.84	−0.63	5.74
Low leverage	0.03	2.11	−0.25	1.45
Low risk	0.17	3.49	−2.06	12.69
Momentum	0.46	4.18	−1.98	16.00
Profit growth	0.17	1.39	−0.73	3.77
Profitability	0.12	2.65	−0.58	1.59
Quality	0.28	3.45	−0.73	1.73
Seasonality	0.05	0.86	0.30	0.61
Short term reversal	−0.19	1.93	−2.06	11.45
Size	0.27	2.77	0.23	1.56
Value	0.19	2.34	−0.13	1.64
China				
Indicator	Mean	Std. Dev.	Skewness	Kurtosis
CPI inflation	0.20	0.15	0.82	1.24
Accruals	0.14	1.67	−0.23	0.23
Debt issuance	0.07	0.95	−0.46	1.05
Investment	0.08	2.06	−0.18	1.19
Low leverage	−0.03	2.36	−0.42	1.66
Low risk	0.44	3.04	−0.24	0.22
Momentum	−0.06	3.52	−0.16	0.46
Profit growth	0.27	1.36	−0.03	1.05
Profitability	0.07	2.94	0.15	2.76
Quality	0.15	2.68	−0.15	1.72
Seasonality	0.11	0.88	0.62	3.01
Short term reversal	0.34	1.91	−0.70	4.90
Size	0.80	4.09	−0.36	2.18
Value	0.36	3.23	0.21	1.90
South Africa				
Indicator	Mean	Std. Dev.	Skewness	Kurtosis
CPI inflation	0.00	0.03	0.02	0.55
Accruals	0.03	2.96	0.40	2.53

(*continued*)

Table 1. Continued.

Brazil				
Indicator	Mean	Std. Dev.	Skewness	Kurtosis
Debt issuance	0.17	1.72	0.54	1.64
Investment	−0.05	2.48	0.63	2.86
Low leverage	−0.01	2.39	0.01	2.41
Low risk	−0.03	2.24	−1.00	5.65
Momentum	0.40	3.46	−0.86	3.56
Profit growth	0.31	1.84	−0.60	2.18
Profitability	0.22	2.67	0.25	4.25
Quality	0.16	2.64	−0.31	2.41
Seasonality	0.03	1.37	−0.37	4.74
Short term reversal	0.11	1.85	0.83	2.71
Size	−0.13	2.83	−0.25	0.82
Value	0.12	2.38	0.90	4.48

Notes: This table reports the country-wise monthly mean, standard deviation, skewness, and kurtosis of the CPI inflation and returns of base assets used for the portfolio construction.

frequent buying and selling. The portfolio turnover can be controlled by rebalancing the portfolios less frequently (e.g. every six months instead of every month).

The cumulative tracking error is calculated as follows:

$$TE = \sum_{i=1}^{N} (R_p - Inf)^2$$

Here, R_p is the return of the tracking portfolio, and *Inf* is the inflation rate. The tracking error highlights how closely the cumulative returns of the tracking portfolio mimic cumulative inflation. The lower the tracking error, the better the portfolio tracks inflation.

Table 2 reports the results of portfolios that track total inflation. The results in Table 2 show that statistical tracking portfolios perform well at tracking overall inflation, except in Brazil and India. Tracking portfolios generally have lower tracking errors than the equally weighted benchmark portfolios. At first glance, the poor performance in a couple of countries may seem surprising. Diversified portfolios (such as our benchmark) usually deliver good risk-adjusted returns (DeMiguel et al., 2009b), while tracking portfolios are supposed to do a good job of tracking the underlying (and possibly deliver only modest returns in the process). We observed an opposite trend in our results. Tracking portfolios delivers superior returns and often better Sharpe Ratios. This may seem counterintuitive, but there is an economic rationale behind what we observe. Studies on inflation hedging and tracking (see (Fama, 1981; Neville et al., 2021) for example) argue that asset prices do not react to overall inflation but only to the unexpected component of inflation. If we create portfolios that track overall inflation (as in Table 2), our portfolios are not optimized to correlate with inflation surprises. Because overall inflation is more stable compared to inflation surprises, tracking portfolios yield portfolios with extremely stable weights, which leads to better performance because weight stability is correlated with portfolio performance (DeMiguel et al., 2009a). Regardless, as Neville et al. (2021) argue, inflation hedging concerns the ability to hedge unexpected inflation and not the expected component. Therefore, in the next set of results, we used unexpected inflation as our tracking objective.

Table 3 contains the results for portfolios that track unexpected inflation (one month ahead). Despite using future inflation, our portfolios are fully out-of-sample because we only use the information available at the time of portfolio creation.

The results in Table 3 show that, barring India, statistical tracking portfolios that track unexpected inflation deliver lower tracking errors. Quantile regression portfolios deliver the low tracking errors and the high Sharpe Ratios in Brazil, China, and South Africa. In Russia, OLS and Ridge appear to do well. While statistical portfolios have higher monthly turnovers (∼30% vs. 1.7% for the benchmark), this excess turnover can be substantially reduced by rebalancing the portfolio every six months instead of every month. This infrequent rebalancing has a negligible effect on portfolio performance. While quantile regression portfolios perform better, even simpler OLS or Ridge portfolios often have lower tracking errors than the benchmark. Therefore, tracking portfolios can be successfully utilized to hedge

Table 2. Performance of benchmark and tracking portfolios when tracking overall inflation.

Brazil							
Portfolio	Rebalancing	Sharpe ratio	Sharpe ratio rank	Turnover	Turnover rank	Tracking error	Tracking error rank
Benchmark	Monthly	0.21	1	1.8%	1	0.27	1
OLS	Monthly	0.13	4	21.0%	7	0.37	4
Quantile Reg – 0.5	Monthly	0.08	6	37.8%	11	0.40	6
Quantile Reg – 0.75	Monthly	0.09	5	32.2%	10	0.38	5
Ridge	Monthly	0.13	2	21.0%	9	0.37	2
Robust MM	Monthly	0.13	3	21.0%	8	0.37	3
OLS	Half-annually	0.08	7	7.7%	2	0.45	9
Quantile Reg – 0.5	Half-annually	0.02	11	11.2%	6	0.50	11
Quantile Reg – 0.75	Half-annually	0.07	10	10.7%	5	0.43	7
Ridge	Half-annually	0.08	9	7.7%	4	0.45	8
Robust MM	Half-annually	0.08	8	7.7%	3	0.45	10
Russia							
Portfolio	Rebalancing	Sharpe ratio	Sharpe ratio rank	Turnover	Turnover rank	Tracking error	Tracking error rank
Benchmark	Monthly	0.26	1	1.5%	1	0.38	11
OLS	Monthly	0.18	4	17.9%	8	0.33	3
Quantile Reg – 0.5	Monthly	0.14	11	22.0%	10	0.37	10
Quantile Reg – 0.75	Monthly	0.16	5	24.6%	11	0.36	5
Ridge	Monthly	0.18	2	17.9%	9	0.33	1
Robust MM	Monthly	0.18	3	17.9%	7	0.33	2
OLS	Half-annually	0.14	10	8.3%	2	0.36	9
Quantile Reg – 0.5	Half-annually	0.16	6	9.4%	6	0.36	6
Quantile Reg – 0.75	Half-annually	0.15	7	9.0%	5	0.35	4
Ridge	Half-annually	0.14	8	8.3%	4	0.36	7
Robust MM	Half-annually	0.14	9	8.3%	3	0.36	8
India							
Portfolio	Rebalancing	Sharpe ratio	Sharpe ratio rank	Turnover	Turnover rank	Tracking error	Tracking error rank
Benchmark	Monthly	0.26	4	1.4%	1	0.45	1
OLS	Monthly	0.24	11	15.5%	8	0.50	10
Quantile Reg – 0.5	Monthly	0.26	2	28.0%	11	0.49	3
Quantile Reg – 0.75	Monthly	0.24	8	20.3%	10	0.50	11
Ridge	Monthly	0.24	9	15.5%	7	0.50	8
Robust MM	Monthly	0.24	10	15.5%	9	0.50	9
OLS	Half-annually	0.25	6	6.0%	3	0.49	6
Quantile Reg – 0.5	Half-annually	0.30	1	8.8%	6	0.46	2
Quantile Reg – 0.75	Half-annually	0.26	3	6.0%	2	0.49	4
Ridge	Half-annually	0.25	7	6.0%	5	0.49	7
Robust MM	Half-annually	0.25	5	6.0%	4	0.49	5
China							
Portfolio	Rebalancing	Sharpe ratio	Sharpe ratio rank	Turnover	Turnover rank	Tracking error	Tracking error rank
Benchmark	Monthly	0.40	11	1.6%	1	0.05	10
OLS	Monthly	0.50	5	11.7%	7	0.04	4
Quantile Reg – 0.5	Monthly	0.48	10	18.2%	11	0.02	1
Quantile Reg – 0.75	Monthly	0.50	3	17.3%	10	0.04	6
Ridge	Monthly	0.50	4	11.7%	9	0.04	5
Robust MM	Monthly	0.50	6	11.7%	8	0.04	3
OLS	Half-annually	0.48	8	4.7%	2	0.05	7
Quantile Reg – 0.5	Half-annually	0.51	2	6.5%	5	0.03	2
Quantile Reg – 0.75	Half-annually	0.51	1	6.7%	6	0.06	11
Ridge	Half-annually	0.48	7	4.7%	4	0.05	9
Robust MM	Half-annually	0.48	8	4.7%	2	0.05	7
South Africa							
Portfolio	Rebalancing	Sharpe ratio	Sharpe ratio rank	Turnover	Turnover rank	Tracking error	Tracking error rank
Benchmark	Monthly	0.19	11	1.6%	1	0.30	11
OLS	Monthly	0.27	1	15.1%	8	0.21	2
Quantile Reg – 0.5	Monthly	0.26	5	25.7%	11	0.22	6
Quantile Reg – 0.75	Monthly	0.27	4	22.1%	10	0.22	4
Ridge	Monthly	0.27	3	15.1%	9	0.21	1
Robust MM	Monthly	0.27	2	15.1%	7	0.21	3
OLS	Half-annually	0.25	7	6.3%	2	0.22	9
Quantile Reg – 0.5	Half-annually	0.23	10	8.4%	6	0.22	5
Quantile Reg – 0.75	Half-annually	0.24	9	8.0%	5	0.23	10
Ridge	Half-annually	0.25	8	6.3%	4	0.22	7
Robust MM	Half-annually	0.25	6	6.3%	3	0.22	8

Notes: This table reports the country-wise Sharpe Ratio, monthly average turnover, and the cumulative tracking error of benchmark and regression-based tracking portfolios. The portfolios are designed to track overall CPI inflation.

Table 3. Performance of benchmark and tracking portfolios when tracking unexpected inflation.

Brazil							
Portfolio	Rebalancing	Sharpe ratio	Sharpe ratio rank	Turnover	Turnover rank	Tracking error	Tracking error rank
Benchmark	Monthly	0.20	2	1.7%	1	0.30	4
OLS	Monthly	0.13	8	23.1%	7	0.33	8
Quantile Reg – 0.5	Monthly	0.26	1	41.2%	11	0.24	1
Quantile Reg – 0.75	Monthly	0.20	4	32.6%	10	0.25	2
Ridge	Monthly	0.13	6	23.3%	9	0.32	5
Robust MM	Monthly	0.13	7	23.2%	8	0.33	7
OLS	Half-annually	0.10	10	10.4%	2	0.35	11
Quantile Reg – 0.5	Half-annually	0.20	3	12.1%	6	0.27	3
Quantile Reg – 0.75	Half-annually	0.16	5	10.9%	5	0.32	6
Ridge	Half-annually	0.10	9	10.4%	4	0.35	9
Robust MM	Half-annually	0.10	11	10.4%	3	0.35	10
Russia							
Portfolio	Rebalancing	Sharpe ratio	Sharpe ratio rank	Turnover	Turnover rank	Tracking error	Tracking error rank
Benchmark	Monthly	0.27	1	1.5%	1	0.37	9
OLS	Monthly	0.19	4	15.7%	7	0.26	3
Quantile Reg – 0.5	Monthly	0.10	10	30.1%	10	0.43	10
Quantile Reg – 0.75	Monthly	0.19	5	31.1%	11	0.32	7
Ridge	Monthly	0.19	2	15.8%	9	0.26	1
Robust MM	Monthly	0.19	3	15.7%	8	0.26	2
OLS	Half-annually	0.16	8	7.4%	3	0.30	6
Quantile Reg – 0.5	Half-annually	0.10	11	9.8%	5	0.45	11
Quantile Reg – 0.75	Half-annually	0.12	9	12.9%	6	0.37	8
Ridge	Half-annually	0.16	6	7.4%	2	0.30	4
Robust MM	Half-annually	0.16	7	7.4%	4	0.30	5
India							
Portfolio	Rebalancing	Sharpe ratio	Sharpe ratio rank	Turnover	Turnover rank	Tracking error	Tracking error rank
Benchmark	Monthly	0.26	1	1.4%	1	0.44	1
OLS	Monthly	0.14	10	18.3%	7	0.60	11
Quantile Reg – 0.5	Monthly	0.14	8	34.6%	11	0.59	8
Quantile Reg – 0.75	Monthly	0.21	2	27.7%	10	0.54	2
Ridge	Monthly	0.14	11	18.3%	9	0.60	9
Robust MM	Monthly	0.14	9	18.3%	8	0.60	10
OLS	Half-annually	0.18	4	8.4%	3	0.56	4
Quantile Reg – 0.5	Half-annually	0.17	6	10.0%	6	0.57	7
Quantile Reg – 0.75	Half-annually	0.15	7	8.7%	5	0.56	6
Ridge	Half-annually	0.18	5	8.4%	2	0.56	5
Robust MM	Half-annually	0.18	3	8.4%	4	0.56	3
China							
Portfolio	Rebalancing	Sharpe ratio	Sharpe ratio rank	Turnover	Turnover rank	Tracking error	Tracking error rank
Benchmark	Monthly	0.40	3	1.6%	1	0.04	3
OLS	Monthly	0.28	4	18.1%	8	0.05	6
Quantile Reg – 0.5	Monthly	0.24	11	27.5%	11	0.06	10
Quantile Reg – 0.75	Monthly	0.44	1	26.3%	10	0.04	1
Ridge	Monthly	0.28	6	18.3%	9	0.05	4
Robust MM	Monthly	0.28	5	18.1%	7	0.05	7
OLS	Half-annually	0.27	8	7.8%	2	0.05	9
Quantile Reg – 0.5	Half-annually	0.27	10	9.7%	6	0.07	11
Quantile Reg – 0.75	Half-annually	0.44	2	8.4%	5	0.04	2
Ridge	Half-annually	0.27	9	8.0%	4	0.05	5
Robust MM	Half-annually	0.27	7	7.8%	3	0.05	8
South Africa							
Portfolio	Rebalancing	Sharpe ratio	Sharpe ratio rank	Turnover	Turnover rank	Tracking error	Tracking error rank
Benchmark	Monthly	0.19	11	1.6%	1	0.30	11
OLS	Monthly	0.25	9	21.8%	7	0.22	9
Quantile Reg – 0.5	Monthly	0.22	10	38.6%	11	0.22	10
Quantile Reg – 0.75	Monthly	0.28	2	30.1%	10	0.18	3
Ridge	Monthly	0.25	7	22.0%	9	0.21	7
Robust MM	Monthly	0.25	8	21.8%	8	0.22	8
OLS	Half-annually	0.27	4	9.2%	2	0.20	6
Quantile Reg – 0.5	Half-annually	0.26	6	13.7%	6	0.15	1
Quantile Reg – 0.75	Half-annually	0.30	1	9.5%	5	0.17	2
Ridge	Half-annually	0.27	3	9.2%	4	0.19	4
Robust MM	Half-annually	0.27	5	9.2%	3	0.20	5

Notes: This table reports the Sharpe Ratio, monthly average turnover, and the cumulative tracking error of benchmark and regression-based tracking portfolios. The portfolios are designed to track unexpected CPI inflation.

Table 4. Performance of benchmark and tracking portfolios when tracking unexpected inflation in phases on low inflation uncertainty.

Brazil					
Portfolio	Rebalancing	Sharpe ratio	Sharpe ratio rank	Tracking error	Tracking error rank
Benchmark	Monthly	0.26	7	0.06	10
OLS	Monthly	0.33	6	0.04	6
Quantile Reg – 0.5	Monthly	0.26	8	0.05	8
Quantile Reg – 0.75	Monthly	0.24	9	0.04	7
Ridge	Monthly	0.34	4	0.04	1
Robust MM	Monthly	0.33	5	0.04	5
OLS	Half-annually	0.34	3	0.04	4
Quantile Reg – 0.5	Half-annually	0.19	10	0.06	9
Quantile Reg – 0.75	Half-annually	0.15	11	0.08	11
Ridge	Half-annually	0.34	1	0.04	2
Robust MM	Half-annually	0.34	2	0.04	3
Russia					
Portfolio	Rebalancing	Sharpe ratio	Sharpe ratio rank	Tracking error	Tracking error rank
Benchmark	Monthly	0.19	5	0.12	11
OLS	Monthly	0.22	4	0.06	4
Quantile Reg – 0.5	Monthly	0.16	6	0.09	9
Quantile Reg – 0.75	Monthly	0.24	1	0.06	1
Ridge	Monthly	0.22	2	0.06	2
Robust MM	Monthly	0.22	3	0.06	3
OLS	Half-annually	0.16	9	0.08	7
Quantile Reg – 0.5	Half-annually	0.13	11	0.11	10
Quantile Reg – 0.75	Half-annually	0.14	10	0.09	8
Ridge	Half-annually	0.16	7	0.08	5
Robust MM	Half-annually	0.16	8	0.08	6
India					
Portfolio	Rebalancing	Sharpe ratio	Sharpe ratio rank	Tracking error	Tracking error rank
Benchmark	Monthly	0.12	11	0.19	10
OLS	Monthly	0.25	8	0.16	8
Quantile Reg – 0.5	Monthly	0.29	5	0.10	1
Quantile Reg – 0.75	Monthly	0.25	6	0.17	9
Ridge	Monthly	0.24	9	0.16	6
Robust MM	Monthly	0.25	7	0.16	7
OLS	Half-annually	0.29	3	0.12	4
Quantile Reg – 0.5	Half-annually	0.33	1	0.10	2
Quantile Reg – 0.75	Half-annually	0.13	10	0.20	11
Ridge	Half-annually	0.29	4	0.12	5
Robust MM	Half-annually	0.29	2	0.12	3
China					
Portfolio	Rebalancing	Sharpe ratio	Sharpe ratio rank	Tracking error	Tracking error rank
Benchmark	Monthly	0.48	3	0.06	9
OLS	Monthly	0.33	7	0.01	2
Quantile Reg – 0.5	Monthly	0.23	11	0.02	7
Quantile Reg – 0.75	Monthly	0.49	2	0.07	10
Ridge	Monthly	0.33	9	0.01	3
Robust MM	Monthly	0.33	8	0.01	1
OLS	Half-annually	0.40	4	0.01	4
Quantile Reg – 0.5	Half-annually	0.28	10	0.02	8
Quantile Reg – 0.75	Half-annually	0.59	1	0.08	11
Ridge	Half-annually	0.40	6	0.02	6
Robust MM	Half-annually	0.40	5	0.01	5
South Africa					
Portfolio	Rebalancing	Sharpe ratio	Sharpe ratio rank	Tracking error	Tracking error rank
Benchmark	Monthly	0.24	9	0.16	10
OLS	Monthly	0.27	6	0.12	9
Quantile Reg – 0.5	Monthly	0.17	11	0.16	11
Quantile Reg – 0.75	Monthly	0.24	10	0.12	7
Ridge	Monthly	0.27	4	0.12	6
Robust MM	Monthly	0.27	5	0.12	8
OLS	Half-annually	0.28	2	0.11	4
Quantile Reg – 0.5	Half-annually	0.25	8	0.09	1
Quantile Reg – 0.75	Half-annually	0.26	7	0.09	2
Ridge	Half-annually	0.29	1	0.11	3
Robust MM	Half-annually	0.28	3	0.11	5

Notes: This table reports the Sharpe Ratio and the cumulative tracking error of benchmark and regression-based tracking portfolios across periods of low uncertainty around Inflation. The portfolios are designed to track unexpected CPI inflation.

Table 5. Performance of benchmark and tracking portfolios when tracking unexpected inflation in phases on high inflation uncertainty.

Brazil					
Portfolio	Rebalancing	Sharpe ratio	Sharpe ratio rank	Tracking error	Tracking error rank
Benchmark	Monthly	0.15	5	0.21	5
OLS	Monthly	−0.04	6	0.31	6
Quantile Reg – 0.5	Monthly	0.27	1	0.15	1
Quantile Reg – 0.75	Monthly	0.17	3	0.18	3
Ridge	Monthly	−0.05	8	0.31	8
Robust MM	Monthly	−0.04	7	0.31	7
OLS	Half-annually	−0.09	10	0.33	9
Quantile Reg – 0.5	Half-annually	0.20	2	0.17	2
Quantile Reg – 0.75	Half-annually	0.16	4	0.20	4
Ridge	Half-annually	−0.08	9	0.33	11
Robust MM	Half-annually	−0.09	11	0.33	10
Russia					
Portfolio	Rebalancing	Sharpe ratio	Sharpe ratio rank	Tracking error	Tracking error rank
Benchmark	Monthly	0.37	1	0.20	7
OLS	Monthly	0.18	3	0.16	2
Quantile Reg – 0.5	Monthly	0.07	11	0.25	11
Quantile Reg – 0.75	Monthly	0.15	8	0.21	8
Ridge	Monthly	0.18	4	0.16	3
Robust MM	Monthly	0.18	2	0.16	1
OLS	Half-annually	0.16	5	0.17	6
Quantile Reg – 0.5	Half-annually	0.09	10	0.24	10
Quantile Reg – 0.75	Half-annually	0.12	9	0.22	9
Ridge	Half-annually	0.16	7	0.17	4
Robust MM	Half-annually	0.16	6	0.17	5
India					
Portfolio	Rebalancing	Sharpe ratio	Sharpe ratio rank	Tracking error	Tracking error rank
Benchmark	Monthly	0.41	1	0.18	1
OLS	Monthly	0.01	8	0.30	8
Quantile Reg – 0.5	Monthly	−0.03	11	0.33	11
Quantile Reg – 0.75	Monthly	0.14	3	0.25	2
Ridge	Monthly	0.00	10	0.30	9
Robust MM	Monthly	0.01	9	0.30	7
OLS	Half-annually	0.03	5	0.30	5
Quantile Reg – 0.5	Half-annually	0.01	7	0.31	10
Quantile Reg – 0.75	Half-annually	0.17	2	0.25	3
Ridge	Half-annually	0.03	6	0.30	6
Robust MM	Half-annually	0.03	4	0.30	4
China					
Portfolio	Rebalancing	Sharpe ratio	Sharpe ratio rank	Tracking error	Tracking error rank
Benchmark	Monthly	0.29	3	0.04	2
OLS	Monthly	0.24	7	0.05	5
Quantile Reg – 0.5	Monthly	0.25	5	0.05	8
Quantile Reg – 0.75	Monthly	0.39	1	0.04	3
Ridge	Monthly	0.24	6	0.05	4
Robust MM	Monthly	0.24	8	0.05	6
OLS	Half-annually	0.20	10	0.06	11
Quantile Reg – 0.5	Half-annually	0.25	4	0.05	7
Quantile Reg – 0.75	Half-annually	0.33	2	0.04	1
Ridge	Half-annually	0.19	11	0.06	9
Robust MM	Half-annually	0.20	9	0.06	10
South Africa					
Portfolio	Rebalancing	Sharpe ratio	Sharpe ratio rank	Tracking error	Tracking error rank
Benchmark	Monthly	0.14	11	0.12	11
OLS	Monthly	0.23	9	0.08	10
Quantile Reg – 0.5	Monthly	0.28	3	0.05	1
Quantile Reg – 0.75	Monthly	0.33	2	0.06	3
Ridge	Monthly	0.23	8	0.08	8
Robust MM	Monthly	0.23	10	0.08	9
OLS	Half-annually	0.25	6	0.07	7
Quantile Reg – 0.5	Half-annually	0.26	4	0.05	2
Quantile Reg – 0.75	Half-annually	0.34	1	0.06	4
Ridge	Half-annually	0.25	7	0.07	5
Robust MM	Half-annually	0.25	5	0.07	6

Notes: This table reports the Sharpe Ratio and the cumulative tracking error of benchmark and regression-based tracking portfolios across periods of high uncertainty around Inflation. The portfolios are designed to track unexpected CPI inflation.

inflationary risks. We also corroborate the findings of Downing et al. (2012) findings and recommend that tracking portfolios use unexpected future inflation to identify portfolio weights.

We now extend our analysis to subperiods to ensure that the results are robust across different economic regimes. To do this, we divide the overall sample period into two parts based on high and low uncertainty regarding inflation. We estimate inflation uncertainty as the 36-month rolling standard deviation of the inflation. The months in which this inflation uncertainty was above the median were classified as high uncertainty, while others were classified as low uncertainty.

These sub-sample-wise results are in Tables 4 and 5. Table 4 reports the performance of the tracking portfolio in periods of low uncertainty (i.e. stable prices) whereas Table 5 contains the results for periods of high inflation uncertainty. We do not report the turnover for these portfolios as portfolio turnover is meaningful only for continuously held portfolios.

The results in Table 4 highlight some crucial aspects of the relationship between inflation uncertainty and portfolio-tracking performance. In times of low inflation uncertainty, tracking portfolios deliver superior performance by a large margin across all countries. While quantile regression does well in India, Russia, and South Africa, most tracking methods have similarly low tracking errors in other countries. The main takeaway from this set of results appears to be that while some methods may outperform others at tracking, in a majority of cases, any tracking portfolio is superior to the benchmark.

We now discuss the performance of tracking portfolios in a highly uncertain inflationary environment. Statistical tracking portfolios perform well in Brazil, Russia, and South Africa, despite the challenges of tracking inflation in a highly uncertain environment. These results are quite encouraging as our prior expectation was of low tracking ability in uncertain periods.

In China, benchmark portfolios deliver similar tracking performance compared to tracking portfolios. Only in India does the performance of the benchmark exceed that of tracking portfolios substantially. This finding is unsurprising because tracking portfolios perform better in a stable environment. It is challenging for any particular strategy to operate during periods of highly volatile inflation (or uncertainty in general). Therefore, tracking portfolios work, but they need a relatively stable inflation regime to perform at their best.

Overall, we report that statistical inflation-tracking portfolios can deliver gains to investors who aim to hedge unexpected inflation. These findings pave the way for future research on the efficacy of portfolio tracking in emerging markets. We provide concluding comments and some overall learnings for inflation hedging strategies in the next section.

6. Conclusion

Assets that are highly correlated with inflation can be used to hedge against unexpected inflation risks. This study tests whether statistical tools can be utilized to create portfolios that track inflation. We used the BRICS Stock Markets as a Laboratory for our experiment. Using data from January 2005 to July 2023, we created out-of-sample tracking portfolios using OLS, Ridge, MM, and Quantile Regressions to estimate the weights of assets in portfolios.

As part of our findings, we report that tracking portfolios created using statistical methods deliver better tracking performance than benchmarks. The superior tracking ability of statistical portfolios derives from their performance during periods of low inflation uncertainty. Based on our observations, we also provide a set of best practices for creating tracking portfolios, particularly for inflation. The observations are as follows:

1. It is advisable to use regression-based tracking portfolios to hedge inflation, especially in periods of relative price stability.
2. Better tracking performance can be obtained using one month ahead of unexpected inflation as the target for tracking instead of overall inflation.
3. Methods that are robust to outliers and incorporate asymmetric loss functions (e.g. quantile regression) yield better tracking performance.
4. Rebalancing portfolios infrequently reduces turnover while imposing little cost in terms of performance metrics (either Sharpe ratio or Tracking error).

Note

1. Source: Authors' calculations based on Data from IMF's World Economic Outlook Database.

Author contributions

Vaibhav Lalwani: conceptualization, formal analysis, investigation, methodology, supervision, writing – original draft. Vedprakash Meshram: software, validation, writing – review & editing.

Disclosure statement

No potential competing interest was reported by the author(s).

Funding

No funding was received

About the authors

Vedprakash Meshram is an Assistant Professor at the Goa Institute of Management. He holds a PhD from the Indian Institute of Management Lucknow. His research work has been published in several journals, including the Journal of International Accounting, Auditing and Taxation, Applied Economics, and the Journal of Prediction Markets, among others. He has presented his research at several leading international and national conferences.

Vaibhav Lalwani is an Assistant Professor at the at the Xavier Labour Relations Institute's (XLRI) Delhi NCR Campus. He holds a PhD from the Indian Institute of Management Lucknow. His research work has been published in several journals, including Economics Letters, Finance Research Letters, Applied Economics, Managerial Finance, Applied Finance Letters, and Journal of Prediction Markets, among others. He has presented his research at several leading international and national conferences.

ORCID

Vaibhav Lalwani http://orcid.org/0000-0001-7476-5311

Data availability statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

References

Anari, A., & Kolari, J. (2001). Stock prices and inflation. *Journal of Financial Research*, *24*(4), 587–602. https://doi.org/10.1111/j.1475-6803.2001.tb00832.x

Arnold, S., & Auer, B. R. (2015). What do scientists know about inflation hedging? *The North American Journal of Economics and Finance*, *34*, 187–214. https://doi.org/10.1016/j.najef.2015.08.005

Attié, A. P., & Roache, S. K. (2009). *Inflation hedging for long-term investors*. International Monetary Fund, Finance Department.

Aye, G. C., Chang, T., & Gupta, R. (2016). Is gold an inflation-hedge? Evidence from an interrupted Markov-switching cointegration model. *Resources Policy*, *48*, 77–84. https://doi.org/10.1016/j.resourpol.2016.02.011

Bekaert, G., & Wang, X. (2010). Inflation risk and the inflation risk premium. *Economic Policy*, *25*(64), 755–806. https://doi.org/10.1111/j.1468-0327.2010.00253.x

Bernard, V. L., & Frecka, T. J. (1983). Evidence on the existence of common stock inflation hedges. *Journal of Financial Research*, *6*(4), 301–312. https://doi.org/10.1111/j.1475-6803.1983.tb00340.x

Billah Dar, A., Shah, A., Bhanja, N., & Samantaraya, A. (2014). The relationship between stock prices and exchange rates in Asian markets: A wavelet based correlation and quantile regression approach. *South Asian Journal of Global Business Research*, *3*(2), 209–224. https://doi.org/10.1108/SAJGBR-07-2013-0061

Bodie, Z. (1976). Common stocks as a hedge against inflation. *The Journal of Finance*, *31*(2), 459–470. https://doi.org/10.1111/j.1540-6261.1976.tb01899.x

Bond, M., & Seiler, M. (1998). Real estate returns and inflation: An added variable approach. *Journal of Real Estate Research*, *15*(3), 327–338. https://doi.org/10.1080/10835547.1998.12090932
Boons, M., Duarte, F., de Roon, F., & Szymanowska, M. (2020). Time-varying inflation risk and stock returns. *Journal of Financial Economics*, *136*(2), 444–470. https://doi.org/10.1016/j.jfineco.2019.09.012
Boudoukh, J., & Richardson, M. (1993). Stock returns and inflation: A long-horizon perspective. *The American Economic Review* (Vol. 83 No. 5. pp. 1346–1355) JSTOR.
Breeden, D. T., Gibbons, M. R., & Litzenberger, R. H. (1989). Empirical tests of the consumption-oriented CAPM. *The Journal of Finance*, *44*(2), 231–262. https://doi.org/10.1111/j.1540-6261.1989.tb05056.x
Campbell, J. Y., Pflueger, C., & Viceira, L. M. (2020). Macroeconomic drivers of bond and equity risks. *Journal of Political Economy*, *128*(8), 3148–3185. https://doi.org/10.1086/707766
Chan, L. K., Karceski, J., & Lakonishok, J. (1998). The risk and return from factors. *The Journal of Financial and Quantitative Analysis*, *33*(2), 159–188. https://doi.org/10.2307/2331306
De Nard, G., Engle, R. F., & Kelly, B. T. (2023). Factor mimicking portfolios for climate risk. University of Zurich, Department of Economics, Working Paper No. 429.
DeMiguel, V., Garlappi, L., Nogales, F. J., & Uppal, R. (2009a). A generalized approach to portfolio optimization: Improving performance by constraining portfolio norms. *Management Science*, *55*(5), 798–812. https://doi.org/10.1287/mnsc.1080.0986
DeMiguel, V., Garlappi, L., & Uppal, R. (2009b). Optimal versus naive diversification: How inefficient is the 1/N portfolio strategy? *Review of Financial Studies*, *22*(5), 1915–1953. https://doi.org/10.1093/rfs/hhm075
Downing, C. T., Longstaff, F. A., & Rierson, M. A. (2012). Inflation Tracking Portfolios. Working Paper, National Bureau of Economic Research. https://doi.org/10.3386/w18135
Engle, R. F., Giglio, S., Kelly, B., Lee, H., & Stroebel, J. (2020). Hedging climate change news. *The Review of Financial Studies*, *33*(3), 1184–1216. https://doi.org/10.1093/rfs/hhz072
Engle, R. F., Ledoit, O., & Wolf, M. (2019). Large dynamic covariance matrices. *Journal of Business & Economic Statistics*, *37*(2), 363–375. https://doi.org/10.1080/07350015.2017.1345683
Engsted, T., & Tanggaard, C. (2002). The relation between asset returns and inflation at short and long horizons. *Journal of International Financial Markets, Institutions and Money*, *12*(2), 101–118. https://doi.org/10.1016/S1042-4431(01)00052-X
Evans, M. D. D., & Lewis, K. K. (1995). Do expected shifts in inflation affect estimates of the long-run fisher relation? *The Journal of Finance*, *50*(1), 225–253. https://doi.org/10.1111/j.1540-6261.1995.tb05172.x
Fama, E. F. (1981). Stock returns, real activity, inflation, and money. *The American Economic Review*, *71*(4), 545–565.
Fama, E. F., & Schwert, G. W. (1977). Asset returns and inflation. *Journal of Financial Economics*, *5*(2), 115–146. https://doi.org/10.1016/0304-405X(77)90014-9
Fang, W.-S., Wang, K.-M., & Nguyen, T.-B. T. (2008). Is real estate really an inflation hedge? Evidence from Taiwan*. *Asian Economic Journal*, *22*(2), 209–224. https://doi.org/10.1111/j.1467-8381.2008.00275.x
Fisher, I. (1912). *How to invest when prices are rising: A scientific method of providing for the increasing cost of living*. G. Lynn Sumner.
Fisher, I. (1930). *The theory of interest*. New York: Macmillan.
Geske, R., & Roll, R. (1983). The fiscal and monetary linkage between stock returns and inflation. *The Journal of Finance*, *38*(1), 1–33. https://doi.org/10.1111/j.1540-6261.1983.tb03623.x
Ha, J., Ivanova, A., Montiel, P. J., & Pedroni, P. (2019). *Inflation in low-income countries*. SSRN Scholarly Paper.
Ha, J., Ivanova, A., Ohnsorge, F., & Unsal, D. F. (2019). *Inflation: Concepts, evolution, and correlates*. SSRN Scholarly Paper.
Ha, J., Kose, M. A., & Ohnsorge, F. (2023). One-stop source: A global database of inflation. *Journal of International Money and Finance*, *137*, 102896. https://doi.org/10.1016/j.jimonfin.2023.102896
Hoevenaars, R. P. M. M., Molenaar, R. D. J., Schotman, P. C., & Steenkamp, T. B. M. (2008). Strategic asset allocation with liabilities: Beyond stocks and bonds. *Journal of Economic Dynamics and Control*, *32*(9), 2939–2970. https://doi.org/10.1016/j.jedc.2007.11.003
Illeditsch, P. K. (2018). Residual inflation risk. *Management Science*, *64*(11), 5289–5314. https://doi.org/10.1287/mnsc.2017.2803
Jensen, T. I., Kelly, B., & Pedersen, L. H. (2023). Is there a replication crisis in finance? *The Journal of Finance*, *78*(5), 2465–2518. https://doi.org/10.1111/jofi.13249
Jurczenko, E., & Teiletche, J. (2022). Macro factor-mimicking portfolios. Available at SSRN 3363598.
Kapadia, N. (2011). Tracking down distress risk. *Journal of Financial Economics*, *102*(1), 167–182. elsevier,https://doi.org/10.1016/j.jfineco.2011.05.004
Koenker, R., & Bassett, G. (1978). Regression quantiles. *Econometrica: Journal of the Econometric Society*, *46*(1), 33–50. https://doi.org/10.2307/1913643
Koenker, R., & Hallock, K. F. (2001). Quantile regression. *Journal of Economic Perspectives*, *15*(4), 143–156. https://doi.org/10.1257/jep.15.4.143
Kothari, S. P., & Shanken, J. (2004). Asset allocation with inflation-protected bonds. *Financial Analysts Journal*, *60*(1), 54–70. https://doi.org/10.2469/faj.v60.n1.2592

Lamont, O. A. (2001). Economic tracking portfolios. *Journal of Econometrics*, *105*(1), 161–184. https://doi.org/10.1016/S0304-4076(01)00074-4

Lucey, B. M., Sharma, S. S., & Vigne, S. A. (2017). Gold and inflation(s) – a time-varying relationship. *Economic Modelling*, *67*, 88–101. https://doi.org/10.1016/j.econmod.2016.10.008

Luo, D., Rytchkov, O., & Zhong, X. (2022). Regularized mimicking portfolios. SSRN Scholarly Paper, Rochester, NY, 18 February. https://doi.org/10.2139/ssrn.4038417

Mahdavi, S., & Zhou, S. (1997). Gold and commodity prices as leading indicators of inflation: Tests of long-run relationship and predictive performance. *Journal of Economics and Business*, *49*(5), 475–489. https://doi.org/10.1016/S0148-6195(97)00034-9

McIver, R. P., & Kang, S. H. (2020). Financial crises and the dynamics of the spillovers between the U.S. and BRICS stock markets. *Research in International Business and Finance*, *54*, 101276. https://doi.org/10.1016/j.ribaf.2020.101276

Mensi, W., Hammoudeh, S., Nguyen, D. K., & Kang, S. H. (2016). Global financial crisis and spillover effects among the U.S. and BRICS stock markets. *International Review of Economics & Finance*, *42*, 257–276. https://doi.org/10.1016/j.iref.2015.11.005

Nakagawa, K., & Suimon, Y. (2022). Inflation rate tracking portfolio optimization method: Evidence from Japan. *Finance Research Letters*, *49*, 103130. https://doi.org/10.1016/j.frl.2022.103130

Nelson, C. R. (1976). Inflation and rates of return on common stocks. *The Journal of Finance*, *31*(2), 471–483. https://doi.org/10.1111/j.1540-6261.1976.tb01900.x

Neville, H., Draaisma, T., Funnell, B., Harvey, C. R., & Hemert, O. V. (2021). The best strategies for inflationary times. *The Journal of Portfolio Management*, *47*(8), 8–37. https://doi.org/10.3905/jpm.2021.1.274

Salisu, A. A., Raheem, I. D., & Ndako, U. B. (2020). The inflation hedging properties of gold, stocks and real estate: A comparative analysis. *Resources Policy*, *66*, 101605. https://doi.org/10.1016/j.resourpol.2020.101605

Shahzad, S. J. H., Mensi, W., Hammoudeh, S., Sohail, A., & Al-Yahyaee, K. H. (2019). Does gold act as a hedge against different nuances of inflation? Evidence from quantile-on-quantile and causality-in- quantiles approaches. *Resources Policy*, *62*, 602–615. https://doi.org/10.1016/j.resourpol.2018.11.008

Taylor, N. J. (1998). Precious metals and inflation. *Applied Financial Economics*, *8*(2), 201–210. https://doi.org/10.1080/096031098333186

Vassalou, M. (2003). News related to future GDP growth as a risk factor in equity returns. *Journal of Financial Economics*, *68*(1), 47–73. https://doi.org/10.1016/S0304-405X(02)00248-9

Yohai, V. J. (1987). High breakdown-point and high efficiency robust estimates for regression. *The Annals of Statistics*, *15*(2), 642–656. https://doi.org/10.1214/aos/1176350366