# INFLATION HEDGING: A DYNAMIC APPROACH USING ONLINE PRICES*

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**Abstract**

A vast literature, spanning back more than four decades, explores the relationship between inflation and asset prices. Most studies focus on the inflation hedging properties of stocks, bonds, or commodities assuming they are held in a static, buy-and-hold portfolio. Few have examined the inflation hedging properties of actively managed strategies. In this paper, we use high-frequency inflation indices derived from millions of product prices scraped from the websites of multi-channel retailers in 21 countries. We first show that these series contain forward-looking information with respect to official government inflation releases, and find that online inflation indices can predict changes in the breakeven inflation spread between nominal and inflation-linked Treasury bond yields in the United States. We then test an investment strategy to exploit this market inefficiency by allocating dynamically between Treasury Inflation Protected Securities (TIPS) and nominal Treasury bonds. A dynamic strategy offers investors the potential to capture the price appreciation of nominal bonds when realized inflation is below market expectations and the price appreciation of TIPS when realized inflation is above market expectations.


**Disclosure: Alberto Cavallo is a co-founder and has an ownership stake in PriceStats LLC, a private company that uses scraped online data to compute inflation indices.*

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A vast literature, spanning back more than four decades, explores the relationship between inflation and asset prices. Most studies focus on the inflation hedging properties of stocks, bonds, or commodities assuming they are held in a static, buy-and-hold portfolio. Few have examined the inflation hedging properties of actively managed strategies. In this paper, we use high-frequency inflation indices derived from millions of product prices scraped from the websites of multi-channel retailers in 21 countries. We first show that these series contain forward-looking information with respect to official government inflation releases, and find that online inflation indices can predict changes in the breakeven inflation spread between nominal and inflation-linked Treasury bond yields in the United States. We then test an investment strategy to exploit this market inefficiency by allocating dynamically between Treasury Inflation Protected Securities (TIPS) and nominal Treasury bonds. A dynamic strategy offers investors the potential to capture the price appreciation of nominal bonds when realized inflation is below market expectations and the price appreciation of TIPS when realized inflation is above market expectations.

We organize the paper as follows. First, we present a selective review of the literature related to inflation forecasting and hedging. We then describe the online inflation series we use in this analysis and how they are calculated. Next, we present regression results for 21 countries as well as a dynamic inflation hedging application using U.S. Treasury Inflation Protected Securities (TIPS). We conclude with a summary.

## Literature Review

Most early studies of inflation and asset prices focus on equity and fixed income at the asset class level. Fama and Schwert (1977) decompose the inflation rate into expected and unexpected components and find that Treasury bonds and bills were an effective hedge against expected inflation during the 1953-1971 period, whereas private residential real estate hedged against both expected and unexpected inflation. However, monthly stock returns were negatively correlated to both expected and unexpected inflation. Sharpe (1999) finds that this negative correlation arises because higher expected inflation coincides with lower expected real earnings growth and higher required real returns, which cause stock prices to drop. Taking a longer term perspective, Boudoukh and Richardson (1993) compile 200 years of returns data for stocks, bonds, and inflation in the United States and United Kingdom. Their results suggest that nominal stock returns are positively correlated to inflation over the long-term. Ang et al. (2012) find that while equities as an asset class are a poor inflation hedge, individual stocks can have strong inflation-hedging abilities, particularly in the technology and energy sectors. However, stock inflation betas are difficult to forecast in advance.

More recent studies have moved beyond stocks and bonds to look at the inflation hedging prospects of other asset classes. Ang (2012) challenges the notion that so-called real assets offer a hedge against inflation. He finds that inflation-linked bonds and most commodities, including gold, are poor inflation hedges and that real estate is a mediocre inflation hedge. Of the assets he evaluates, only energy commodities and cash (short-term Treasury bills) offer compelling inflation hedging characteristics. Erb and Harvey (2005) find that commodity futures are, at best, an inconsistent inflation hedge. Erb and Harvey (2018) also find that gold is a poor inflation hedge over periods of up to 20 years, although it may hedge inflation over much longer periods. Kinlaw et al. (2022) apply a Hidden Markov Model to identify four distinct inflation regimes using Consumer Price Index (CPI) data from 1960 to 2022. On average, they find that stocks, bonds and cash have the lowest real returns during periods where inflation is rising and volatile. Stocks have the highest real returns during periods where inflation is rising and stable whereas government bonds have the highest real returns during disinflation periods, which are often associated with recessions where investors flee to safety.

Few studies look at the potential of actively managed strategies to hedge inflation. Neville et al. (2021) analyze active as well as passive strategies for various asset classes across the United States, United Kingdom and Japan over a 95-year period. They find that commodities and active trend-following strategies have positive returns during inflation surges. Andonov et al. (2018) confirm the persistence of well-documented inefficiencies in the TIPS market and find that estimates generated by the Survey of Professional Forecasters or forecasts derived from an inflation-forecasting model lead to excess returns relative to a buy-and-hold strategy.

A small but growing literature has focused on informativeness and forecasting power of online prices. In a seminal study, Cavallo (2013) constructs inflation indices for five Latin American countries using price data scraped from the websites of online retailers; he shows that the series approximate official inflation data in each country except Argentina, where the online inflation rate was three times higher than the official estimate. These results validated the widespread distrust of Argentina’s official inflation statistics at the time. Cavallo and Rigobon (2016) introduce the Billion Prices Project, created at MIT and Harvard in 2008 to gather unstructured price data from online retailers, describe the methodology they use to compute online price indices, and show how these daily measures co-move with official CPI data in most countries. Extending this work, Cavallo (2017) deploys a large number of freelancers to gather data for the first large-scale comparison of online and in-store prices, at the level of individual products, for 56 multi-channel retailers in ten countries including the United States, China, United Kingdom, Japan and Germany. He finds that online and offline price levels are identical about 72 percent of the time, with significant heterogeneity at the country, sector and retailer level. Aparicio and Bertolotto (2020) build on this literature by using online price indices to forecast the CPI in ten countries. They find that online prices predict CPI trends more than one month in advance on average. Their forecasts outperform regression-based, statistical forecasts as well as survey-based estimates from professional forecasters. As inputs to an investment strategy, online prices offer potential advantages over survey-based forecasts: they are higher frequency, available in near real-time, and can be used to forecast shorter-term inflation dynamics as opposed to surveys, which tend to focus on inflation rates that pertain to 12-month periods. Perhaps most important, they are derived from data rather than opinions which may be subject to bias.

Our contribution to the literature is twofold. First, we present evidence that online prices forecast realized CPI inflation in 21 countries using a simple linear regression framework that controls for historical inflation, including food and fuel prices, as well as seasonality. We document the strength of these results using a composite panel regression, and we also report the extent to which online prices and the other control factors relate to future inflation in each individual country using separate time series regressions. Second, we show that online inflation forecasts the relative performance of TIPS and nominal Treasury bonds in the U.S. and we introduce a trading rule to manage this exposure dynamically.

**Measuring Online Inflation**

We use global and country-level inflation series from PriceStats®, an economic data science company connected to the Billion Prices Project.[1] PriceStats uses web scraping technology to compile prices for millions of consumer products sold by hundreds of online retailers around the world and produces aggregate inflation series from these data. Cavallo and Rigobon (2016) provide a detailed description of the scraping methodology as well as key differences in how official government statistics and online series are calculated. Exhibit 1 shows some of the major differences between the measures of inflation produced by government agencies and those that are derived from online price data. The two major advantages of online inflation series relative to the official series are that they are available 1) at a daily frequency as opposed to monthly and 2) available in near real-time with a three-day lag as opposed to a 15-day (or ) lag. These advantages enable the online series to reflect changes in inflation trends sooner than the official series. However, the online series also have one disadvantage: the relevant prices for some consumption categories, such as shelter, health services and education, are not readily observable online. For these categories, the online series rely on models to estimate inflation using proxies that are available online. Overall, the series directly capture about 45 to 60 percent of the CPI basket using online prices, depending on the country. This represents the majority of prices outside of the shelter category, which makes up more than 40 percent of the consumption basket in the United States.

Exhibit 1: Differences Between Online and Official Inflation Series

| | **Official Inflation** | **Online Inflation** |
|---|---|---|
| Source of price data | Physical stores | Websites of multi-line retailers who also have physical stores |
| Release frequency | Monthly | Daily |
| Publication lag | 15 days* | 3 days |
| CPI product categories captured | 100%** | 45% to 60% |
| Products within each category | Fewer | More |
| Overall products captured | Fewer | More |

* In most countries, the CPI for each month is relased on our about the 15th of the following month. ** By definition, the official CPI series captures all categories of products and services in its consumption basket.

The process for computing online inflation series consists of two major steps:

1. Obtain information about each product using web-scraping technology, including price, brand, description, size, and unique product identifier.
2. Aggregate price changes across all retailers within a given country into narrowly defined categories that align with the CPI consumption basket, weighting each product equally. Then, aggregate the categories using official CPI weights to arrive at an overall country inflation series.

Cavallo (2016) presents a detailed description of how this methodology handles product substitutions and categories that are not available online. Additional points regarding the construction of the online inflation series are as follows:

- The series include data from large retailers that sell products both online and in physical stores. Retailers that only sell products online may exhibit price trends that are not representative of the broader market, because product composition is distorted by aggregating multiple sellers, or for other reasons.
- New retailers are incorporated into the series only after they have been tested for a period of time to ensure data quality. If the quality of data from a retailer deteriorates, it is removed or replaced in the sample.
- When online data is not available for a given product category, those products may be represented using online data from other related categories or from CPI data. For example, the prices of health services can be proxied by combining over-the-counter drug prices (which are available online) with information on the observed relationship between these two categories in historical CPI data.
- To aggregate product changes across categories or sub-sectors, the series use official weights as a point of reference. In addition, they rely on a proprietary model to estimate the impact of those sub-sectors for which data is unavailable and to compensate for methodology differences with official CPIs.
- Whereas the CPI requires hedonic adjustment models to approximate changes in the quality of goods sold over time, the online inflation series have the advantage of observing a large quantity of overlapping measurements for old and new products which reflects changing qualities directly. In the case of clothing, the series rely on a methodology that mimics the quality adjustments that official statistics use (when a new item is introduced, they look for the closest item sold by the same retailer and replace it).

To understand how the online series behave in practice, it is informative to look at inflation turning points in recent history. Exhibit 2 shows the U.S. CPI and the online series during the Global Financial Crisis of 2008 and 2009. It is evident from this chart that the online series began to plummet in September of 2008, as consumer demand collapsed, more than a month before the trend was captured in the official data. It also reached its nadir and began to rise again in late 2008, ahead of the official series.

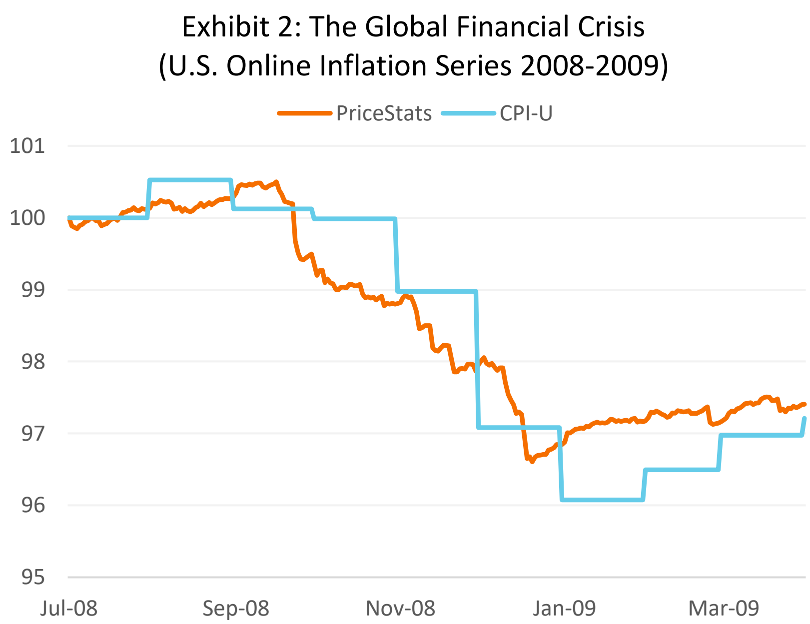
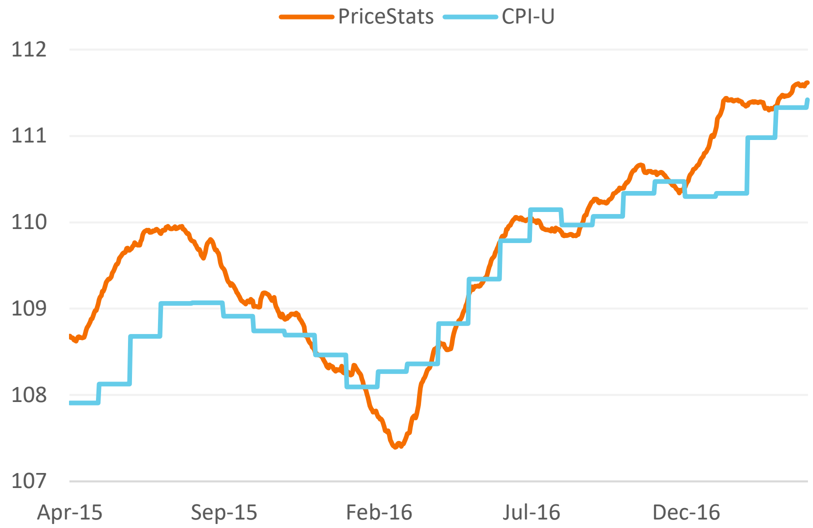


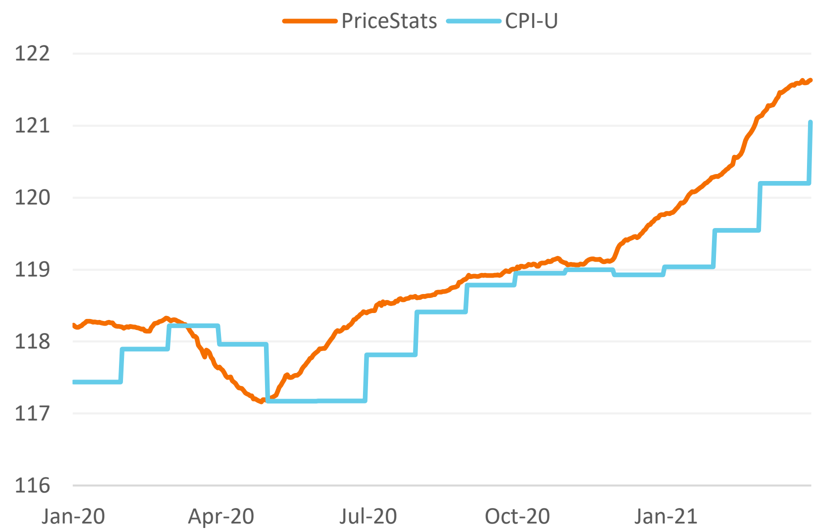

Exhibit 3 shows the period from 2015 to 2017, when the U.S. Federal Reserve Bank began to raise interest rates above zero for the first time since the crisis. There are notable inflection points in the online inflation series that foretell similar trends in the official data: the decline in consumer prices in the later part of 2015, the sharp increase in the first half of 2016, and the sharp increase in November and December of 2016.

Exhibit 3: The Fed Raises Interest Rates
(U.S. Online Inflation Series 2015-2017)




The online series were also informative during 2020 and 2021 as the world grappled with the Covid-19 pandemic and its economic fallout. The online series moved ahead of the official series in early 2020 as consumer demand flagged due to lockdowns, but then accelerated sharply in mid 2020 and again in early 2021, signaling the start of the dramatic surge in inflation that is happening presently.

Exhibit 4: The Covid-19 Pandemic
(U.S Online Inflation Series, 2020-2021)




**Predicting CPI Inflation**

Aparicio and Bertolotto (2017) undertake an extensive statistical study of the predictive power of online inflation indices relative to official inflation. They use impulse response functions, assuming a one percent shock to the online inflation index, to measure the degree and timing of subsequent changes in official inflation. For ten countries, they find a positive impulse response in official inflation ranging from 0.5 to one percent over the following one to six months. Surprisingly, their forecasts using online data remain accurate even after the timing advantage (i.e., the 15-day lead in release date) is removed. They summarize the literature to identify four potential reasons for this:

1. It is less expensive for retailers to change prices online as opposed to in stores; they may therefore adjust online prices first.

2. The way that statistical offices introduce substitutes for items that are unavailable, and adjust their price change using a regression to control for quality differences, may make the official series less reactive to price changes. The online indices do not need to introduce substitutions because they capture such a large number of products in each category.
3. When a product is not available at the time of collection, statistical offices may use prices up to one week old. If a spike has recently occurred, it would not be captured until the next collection date. The online indices do not use stale prices.
4. Statistical offices collect some prices less often than others, particularly in areas that are less densely populated, introducing a potential lag. Online indices capture prices each day.

We use a panel regression framework to further establish the robust predictive relationship between online prices and subsequent official inflation. Researchers and investors have long recognized that CPI changes are autocorrelated in most countries. To determine whether online inflation predicts official inflation, we must therefore control for past changes in the CPI itself. For 21 countries, we compile the following data for each month during the period March 2009 to March 2022[2]:

- the country's average historical CPI inflation rate for the current calendar month (to control for seasonality),
- the country's CPI inflation rate for the prior calendar month, and
- the country's online inflation rate for the prior month.

The country-specific relationship between online and official inflation is less interesting in the panel regression context if each country's inflation is driven by the same broad global trends in the most volatile categories of goods: fuel and food. Thus, we also compile the following global variables for the same period, which are common to all countries:

- online global fuel aggregate inflation rate for the prior month,
- CPI global food aggregate inflation rate for the prior month, and
- online global food aggregate inflation rate for the prior month.

In addition to serving as controls to isolate local market price relationships in each country, we may also observe interesting trends in each country's sensitivity to these global factors. We include both online and CPI global food aggregates, as it is interesting to distinguish between their effects. In contrast, fuel prices are easily observed online and they do not differ much from CPI estimates, so we rely exclusively on online fuel inflation in our analysis.

Prior studies, such as Aparicio and Bertolotto (2020), show that survey-based inflation forecasts have predictive power with respect to future inflation. We do not use these forecasts in our analysis, since they are focused on the next year (or, at best, next quarter) and our goal is to analyze the forecasting power of high-frequency online inflation data with respect to month-over-month inflation changes. For similar reasons, we exclude Australia and New Zealand from our analysis because they release inflation data quarterly rather than monthly.

We perform a panel regression to forecast CPI each month using the six independent variables outlined above.[3] Exhibit 5 shows the results from this regression and Exhibit 6 shows the t-statistics for each country.

Exhibit 5: Country Panel, Predicting Monthly CPI Inflation
(March 2009 to March 2022)

| | t-statistic | Coefficient |
|---|---|---|
| Country Seasonality | 25.66 | 0.92 |
| Global Fuel (Online) | 1.27 | 0.01 |
| Global Food CPI | 0.98 | 0.10 |
| Global Food Online | 1.56 | 0.23 |
| Country CPI | 4.02 | 0.10 |
| Country Online | 16.97 | 0.42 |

We observe from Exhibit 5 that, unsurprisingly, seasonality is the most significant variable in explaining month-to-month variation in the rate of inflation. However, the prior month's online inflation rate is the next most significant variable with a t-statistic of nearly 17. The prior month's CPI change is also significant, reflecting the fact that inflation is autocorrelated. On the other hand, the food and fuel variables, which are more volatile and less autocorrelated, have lower t-statistics. However, we do observe that lagged online food inflation is marginally more robust than lagged in-store food inflation. We note also that all of the coefficients have the expected sign.

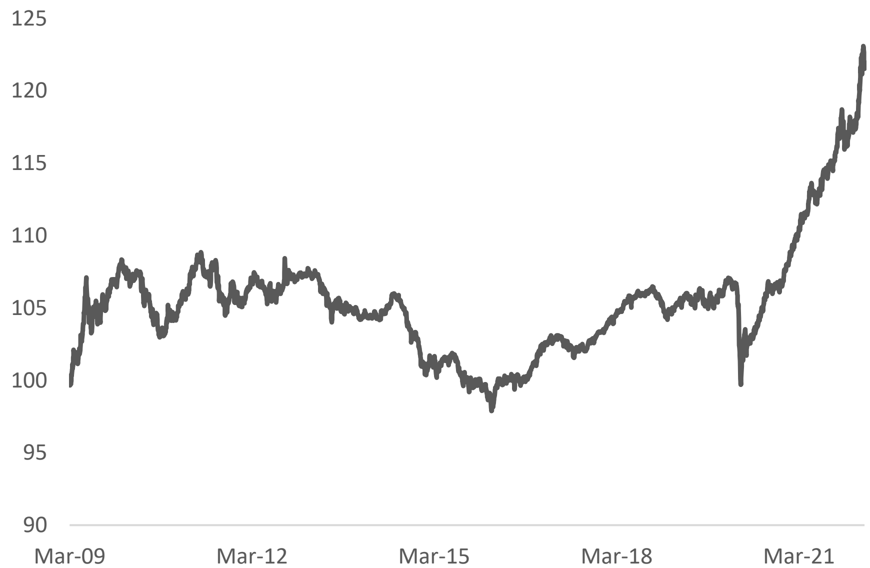
Next, we repeat the same regressions independently for each country. This narrower approach within countries has the advantage that it allows the size of each effect to differ, which it cannot in the cross-country panel. The disadvantage is that the country-specific tests have less statistical power than the composite panel. Exhibit 6 shows the independent variable t-statistics for each country individually. We observe that seasonality is significant for all countries but is most significant for Italy, Spain, Greece and France. This likely reflects the way clothing and other highly seasonal goods are captured by the official statistics in these countries. Last month’s fuel inflation is significant in about half of the countries whereas last month’s food inflation is only significant in a handful. Last month’s online inflation (the full consumption basket) is significant in about half of the countries. However, 17 countries have at least one online variable (food, fuel or full basket) that is robust in forecasting inflation one month ahead. In all but five countries, the online inflation index is more positively significant than the official CPI.

Exhibit 6: Country Panel t-Statistics

Thus far, our analysis has not included market-based inflation variables which should, in an efficient market, reflect investors' collective expectations of future inflation. Will a market-based inflation variable explain away the predictive power of online inflation? In other words, is this information already widely known by the market and therefore priced into assets? To answer this question, we turn our attention to the United States which has a $1.6 trillion market for inflation-linked bonds (TIPS).[4] We focus on the breakeven inflation rate, which is equal to the yield on nominal Treasury bonds minus the yield on TIPS with the same duration. The breakeven yield spread depends primarily on the expected level of future inflation and the premium investors demand as compensation for the uncertainty risk surrounding future inflation. Market participants refer to this spread as breakeven inflation because it is the future inflation rate at which an investor who was long an inflation-linked bond and short a nominal Treasury bond of the same duration would "break even" on her trade. The additional compensation from the inflation adjustments in the long position would be precisely offset by its higher price (lower yield) at the start of the period, such that its total holding period return would be equal to that of the nominal Treasury bond. Thus, the breakeven yield spread embeds three components. First, it reflects the market's aggregate expectation for future inflation. Second, investors generally demand a higher yield from nominal Treasury bonds relative to TIPS to compensate them for the risk of unanticipated changes in inflation, which widens the spread. Third, investors generally demand a higher yield from TIPS relative to nominal Treasury bonds because TIPS are less liquid and therefore more costly to trade, which narrows the spread. Though the illiquidity effect is typically small, during periods of market turmoil, such as the global financial crisis of 2008-2009, investors flee to the relative safety of nominal Treasury bonds and the liquidity imbalance can lead breakeven inflation to turn negative, even if investors expect future inflation to be positive. For our analysis, we focus on changes in the breakeven spread, rather than its level, and whether these changes can predict future inflation. Given this focus, and because our sample starts in March 2009 as financial markets were beginning to recover from the global financial crisis, we assume that changes in the breakeven spread are driven by changes in inflation expectations rather than the illiquidity premium. Setting illiquidity aside, the breakeven inflation trade (long TIPS and short duration-matched nominal Treasury bonds) should generate profits in a given period to the extent that 1) realized inflation exceeds expected inflation, 2) the market's expectation for future inflation rises, or 3) the premium the market demands as compensation for inflation risk falls. The opposite effects will cause a loss in the breakeven trade. We expect the first two components to exert a much larger influence than the third component, and it is the first two components that relate to the anticipation of future inflation trends.

We begin by augmenting our previous inflation forecasting regression for the United States with prior-month breakeven inflation as an additional independent variable. Rather than using the breakeven spread itself, we use the total return of the Bloomberg U.S. 5-year Breakeven Index, which captures the return of a simultaneous long position in on-the-run[5] 5-year TIPS and a short position in comparable nominal U.S. treasury bonds.[6] In order to minimize exposure to real yields, the index scales the total returns of the nominal bonds by a ratio equal to the duration of the TIPS to the duration of the nominal Treasury bonds. Exhibit 7 shows the returns of the breakeven strategy during our sample period.

Exhibit 7: US Breakeven Strategy Returns
(March 2009 to March 2022)




The left column of Exhibit 8 repeats the same results as the previous section while the right column shows the t-statistics for each variable when we include breakeven inflation.

Exhibit 8: Predicting US Monthly CPI Inflation With and Without Breakeven Inflation
(Regression t-statistics, March 2009 to March 2022)

| | Original Regression | Including Breakeven | Without Global Variables | Without CPI Variables |
|---|---|---|---|---|
| U.S. Seasonality | 6.46 | 7.77 | 9.09 | 9.35 |
| Global Fuel (Online) | 3.23 | 1.39 | | 2.18 |
| Global Food CPI | 3.03 | 1.75 | | |
| Global Food Online | 1.48 | 2.00 | | 3.08 |
| U.S. CPI | 0.55 | 1.29 | 2.34 | |
| U.S. Online | 2.05 | 2.20 | 4.21 | 2.10 |
| Breakeven Strategy Returns | | 5.33 | 6.43 | 5.83 |

We conclude from Exhibit 8 that breakeven inflation is a statistically significant variable in forecasting next-month inflation in the U.S. It explains away most of the significance of food and fuel prices, which may be more readily available information for most investors. However, it has almost no effect on the significance of online inflation which retains a t-statistic of approximately 2.

**Predicting Breakeven Inflation**

We now turn to the question of whether online inflation can forecast breakeven inflation itself, and therefore be used in a dynamic investment strategy. To do this, we adjust our regression setup as follows:

1. Rather than predicting changes in CPI, we predict the returns of the breakeven inflation trade (total return of the of the Bloomberg U.S. 5-year Breakeven Index, as described previously) as our dependent variable.

2. We account for publication lags in the CPI data (which lags that data an additional month). We also impose a four-day lag on the online inflation variable to account for lags in its publication and to allow for time to implement the strategy.[7]

3. We introduce a variable designed to capture inflection points in online inflation trends. This variable, which we first introduced and calibrated in early 2012 for this purpose and have not changed since, is equal to the one-year percentile rank of rolling 60-day median online inflation.[8] We smooth inflation over a trailing window due to the noisy nature of daily online price changes. Moreover, to reduce the impact of extreme one-day price changes, we use a rolling median rather than a rolling mean. Finally, we

normalize the rolling 60-day median as a percentile rank in order to determine where it falls relative to short-term inflation trends over the prior year.[9]

Exhibit 9 presents the results from this regression. We observe that seasonality is no longer significant because the breakeven inflation strategy return, as a market variable, generally anticipates recurring seasonal patterns, as is reasonable to expect. Because we are now forecasting securities prices in a relatively liquid market, rather than forecasting an economic data release, our independent variables are less robust as predictors. However, we observe that the online trend signal is highly significant with a t-statistic equal to 3.7.

Exhibit 9: Predicting Breakeven Strategy Returns
(Regression t-statistics)

| | t-statistic |
|---|---|
| Country Seasonality | -1.57 |
| Global Fuel (Online) | -0.60 |
| Global Food CPI | 1.55 |
| Global Food Online | 1.95 |
| U.S. CPI | -0.37 |
| U.S. Online | -0.77 |
| U.S. Online Trend Signal | 3.65 |
| Breakeven Strategy Returns | 0.96 |

**Investment Strategy**

Having established that online inflation can forecast an investable breakeven strategy, we now put forward a simple trading strategy based on our online inflation trend variable. Specifically, the model takes the following positions:[10]

| | |
|---|---|
| Online Inflation Trend > 80% | Long breakeven index (long TIPS, short nominal Treasuries) |
| Online Inflation Trend < 20% | Short breakeven index (long nominal Treasuries, short TIPS |
| Otherwise | Neutral (zero exposure) |

Exhibit 10 shows the performance of this strategy from January 2009 through April 2022 as well as that of a static breakeven strategy that is constantly long TIPS and short treasuries. It shows the performance for the strategies using bonds with both five- and ten-year maturities. The dynamic strategy has a superior risk-adjusted return, as measured by the information ratio, as well as lower drawdowns than the static strategy. We also report the annual turnover of the strategy (five times) as well as the transaction cost level at which the excess returns of the strategy would be reduced to zero.

Exhibit 10: Dynamic Inflation Hedging Strategy Performance (January 2009 to April 2022)

| | 5-year Breakeven | | 10-year Breakeven | |
|---|---|---|---|---|
| | Static | Dynamic | Static | Dynamic |
| Return (annualized) | 1.6% | 2.6% | 2.2% | 4.0% |
| Risk (annualized) | 2.7% | 2.4% | 4.8% | 4.3% |
| Information Ratio | 0.58 | 1.11 | 0.45 | 0.93 |
| Max Drawdown | -10.1% | -3.7% | -16.7% | -7.4% |
| Turnover (annualized) | n/a | 5 | n/a | 5 |
| Breakeven T-cost (bps)* | n/a | 53.2 | n/a | 80.5 |

*Breakeven t-cost relative to strategy with Information Ratio of 0.

Exhibits 11 shows the historical performance of the dynamic and static strategies for the five- and ten-year maturities. The dark grey lines show the performance of the dynamic strategies with the flat lines representing periods where the model was neutral. The light grey lines represent the static strategies which are always long the breakeven spread. The shaded areas represent periods where the online inflation trend signal was either long the breakeven strategy, short the breakeven strategy, or neutral (white). We note that the benchmark for the strategy, which is a self-funding long-short strategy, should be cash rather than static exposure to the long side. We show the static exposure merely as a reference. It is not surprising that the dynamic strategy performs best during periods where inflation is more volatile, most notably, the recovery period following the global financial crisis of 2008 and the recent surge in inflation following the Covid-19 pandemic.

Exhibit 11A: Cumulative Performance of Five-Year Breakeven Strategies
(January 2009 through April 2022)

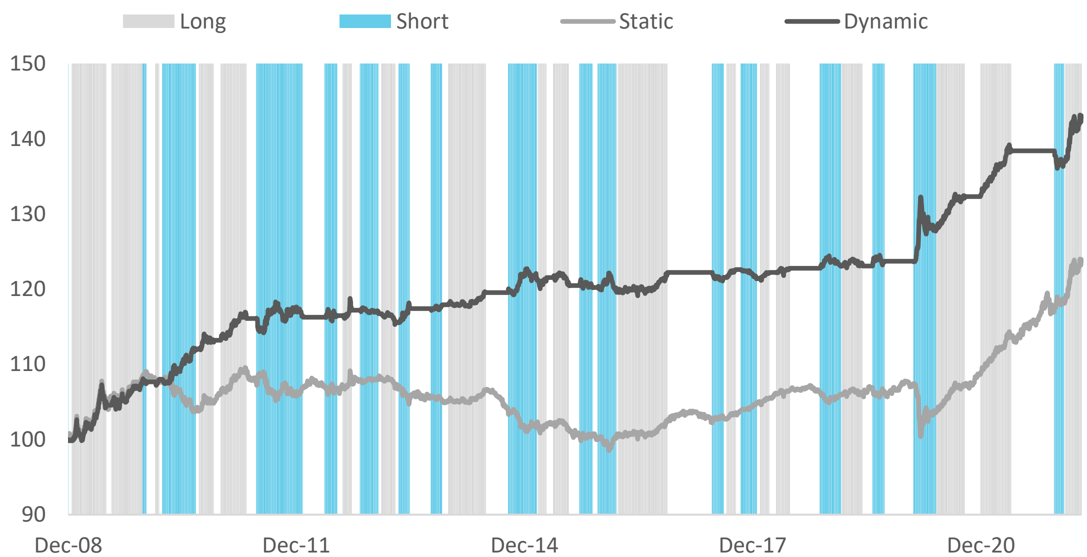
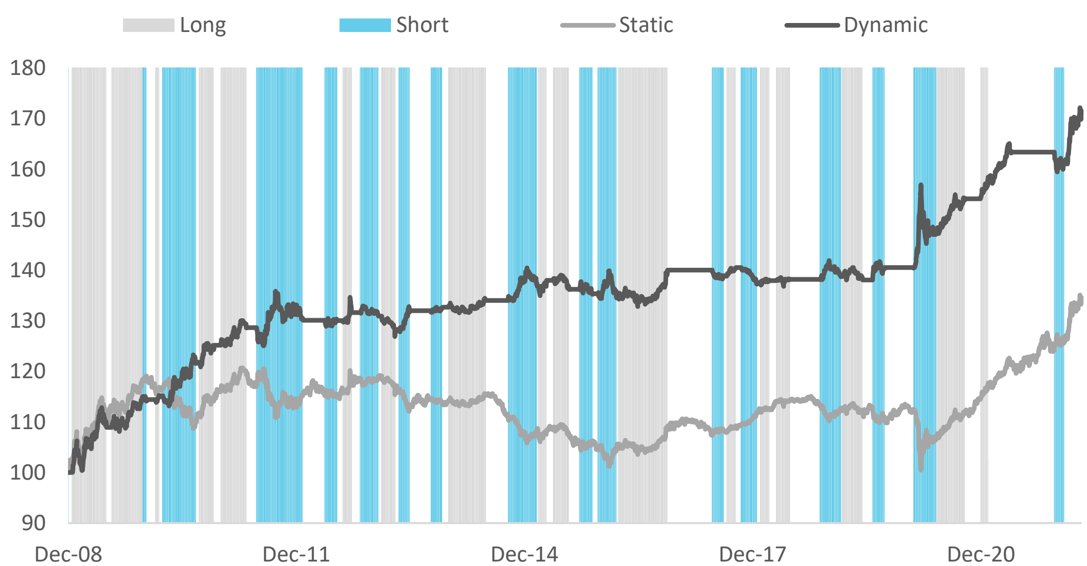



Exhibit 11B: Cumulative Performance of Ten-Year Breakeven Strategies
(January 2009 through April 2022)



**Summary**

We describe a set of online inflation indices that are derived from the websites of multi-channel retailers around the world. We confirm that these series are robust predictors of official CPI inflation using controlled regressions, and show that online inflation predicts changes in the breakeven inflation spread between nominal treasury bonds and TIPS in the U.S. This result builds upon prior studies which have found the market for TIPS to be inefficient with respect to surveys of professional forecasters. Finally, we introduce a simple investment strategy to allocate dynamically between TIPS and treasury bonds with the goal of earning a higher yield during periods of low inflation and benefiting from inflation protection during periods of high inflation.

The investment implications of these results are twofold. First, they demonstrate that online prices contain information regarding future inflation that is not fully priced into assets. Our results focus on TIPS, where the price of the security is linked explicitly to inflation. The degree to which online prices can predict price movements in other inflation-sensitive assets (equities, currencies, fixed income, etc.) is an area for future research. Second, our results suggest that investors may benefit from a dynamic, rather than static, approach to hedging inflation risk. A static approach is challenging to implement due to the scarcity of asset classes that offer both attractive expected returns and consistent inflation-hedging properties. By contrast, a dynamic strategy offers the potential to capture the price appreciation of nominal bonds when realized inflation is below market expectations and the price appreciation of TIPS when realized inflation is above market expectations.

**Notes**

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**References**

Andonov, A., F. Bardong and T. Lehnert. 2018. "TIPS, Inflation Expectations, and the Financial Crisis." Financial Analysts Journal, vol. 66, no. 6: 27-39.

Ang, A. 2012. "'Real' Assets" Columbia Business School Research Paper No. 12-60, Available at SSRN: https://ssrn.com/abstract=2161124.

Ang, A., M. Brière and O. Signori. 2012. "Inflation and Individual Equities." Financial Analysts Journal, vol. 68, no. 4: 36-55.

Aparicio, D. and M. Bertolotto. 2020. "Forecasting Inflation With Online Prices." International Journal of Forecasting, vol. 36, no. 2: 232-247 (April-June).

Boudoukh, J. and M. Richardson. 1993. "Stock Returns and Inflation: A Long-Horizon Perspective." The American Economic Review, vol. 83, no. 5: 1346-1355.

Cavallo, A. 2013. "Online and Official Price Indexes: Measuring Argentina's Inflation." Journal of Monetary Economics, vol. 60, no. 2:152-165.

Cavallo, A. 2017. "Are Online and Offline Prices Similar? Evidence From Large Multi-Channel Retailers." The American Economic Review, vol. 107, no. 1: 283-303.

Cavallo A. and R. Rigobon. 2016. "The Billion Prices Project: Using Online Prices for Measurement and Research." The Journal of Economic Perspectives, vol. 30, no. 2:151-178.

Erb, C., and C. Harvey. 2005. "The Tactical and Strategic Value of Commodity Futures." NBER Working Paper No. w11222.

Erb, C. and C. Harvey. 2018. "The Golden Dilemma." Financial Analysts Journal, vol. 69, no. 4: 10-42.

Fama, E. and G. Schwert. 1977. "Asset Returns and Inflation." Journal of Financial Economics, vol. 5, no. 2: 115-146.

Fama, E. 1981. "Stock Returns, Real Activity, Inflation, and Money." The American Economic Review, vol. 71, no. 4: 545-565.

Kinlaw, W., M. Kritzman, M. Metcalfe and D. Turkington. 2022. "The Determinants of Inflation." MIT Sloan Research Paper No. 6730, Available at SSRN: https://ssrn.com/abstract=4137861.

Neville, H., T. Draaisma, B. Funnell, C.R. Harvey, and O. Van Hemert. 2021. "The Best Strategies for Inflationary Times." Journal of Portfolio Management, vol. 47, no. 8: 8-37.

Sharpe, S. 1999. "Stock Prices, Expected Returns, and Inflation." Finance and Economics Discussion Series, 1999-02, Board of Governors of the Federal Reserve System (U.S.).

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[1] For details on the Billion Prices Project see http://bpp.mit.edu. For details on PriceStats® see http://www.pricestats.com.

[2] We start our analysis in March 2009 because this is when data for the PriceStats global aggregate series are first available.

[3] We obtain PriceStats data from State Street Global Markets and CPI data from Datastream. We correct the panel t-statistics for correlated errors across countries.

[4] Source: https://www.bloomberg.com/news/articles/2021-05-15/inflation-angst-turns-tips-into-must-watch-1-6-trillion-market.

[5] On-the-run securities are those most recently issued by the U.S. government. On-the-run securities tend to be more liquid than those from older issuances (off-the-run securities).

[6] The Bloomberg index models the short position in nominal U.S. Treasury bonds as if it is facilitated by a reverse repo agreement whereby cash is lent to a repo seller in exchange for U.S. Treasury bonds with an agreement to sell the bonds back to the repo seller at a future date. The cash lent is assumed to earn a general collateral repo rate. Therefore, the total return of the breakeven index equals the total return of TIPS minus the total return of nominal Treasury bonds plus the return on the cash collateral.

[7] At the end of a given month, we take online inflation information from t-4 days prior, so the signal is equal to the value of our rolling daily signal 4 days prior. Our month-over-month inflation rates are computed from t-4 versus t-1mo-4, so it could be for example the inflation from the 26th of a 30-day month to the 27th of the following 31-day month. This lag has minimal impact on the results.

[8] We first introduced this variable at the annual State Street Research Retreat which was held in in May 2012 in Cambridge Massachusetts. We have not changed this calibration in the decade since.

[9] Alternatively, we could normalize the rolling 60-day median as a one-year z-score. However, we use a percentile rank because it is simpler, robust to outliers, and suggests a clean choice of thresholds for identifying changes in inflation trends.

[10] In order to reduce turnover, we include a trading buffer such that if the model is long the breakeven index, the inflation trend signal must fall below 50% to return to neutral. Similarly, if the model is short the breakeven index, the inflation trend signal must rise above 50% to return to neutral.