Inflation Concerns and Stock Market Returns

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Abstract

This study introduces a novel measure of inflation concerns, derived from media coverage and Internet searches by households on inflation-related topics. We document that inflation concerns negatively predict future aggregate stock market returns. This predictive effect surpasses that of conventional inflation risk proxies in the short term and remains robust over longer horizons, when considering conventional measures. The predictive effect of inflation concerns is complementary to that of conventional inflation risk measures: integrating inflation concerns with conventional measures significantly enhances the explanatory power of the predictive regressions. We further demonstrate that the predictive ability of inflation concerns on stock returns can be explained by their capacity to forecast future macroeconomic conditions.

Keywords: Inflation, concerns, stock market returns, return predictability, macroeconomic conditions

JEL classification: G11, G12

1. Introduction

Inflation is a subject of enduring importance, particularly in an imperfectly indexed monetary world where it stands as one of the most significant economic risks faced by consumers and investors alike. However, hedging against inflation risk cannot be easily achieved in financial markets using standard bonds and well-diversified equity indices (Bekaert and Wang, 2010). Instead, investors often form their own perceptions of inflation risk—which captured not only their explicit expectation of inflation rate but also their cognitive 'inflation concerns'—through various information channels. Similar to other types of concerns that are found to influence stock market movements, such as rare disasters, tail risk, and climate changes (e.g., Manela and Moreira, 2017; Gao, Lu, and Song, 2019; Ardia, Bluteau, Boudt, and Inghelbrecht, 2023), it is natural to expect that inflation concerns would affect equity returns since they influence investment, as well as borrowing decisions for households, companies, and governments. Despite a rich and fruitful literature on inflation risk such as expected inflation, there remains a gap in the direct link between cognitive inflation concerns and their association with stock market returns.

Motivated by the idea that time variation in the topics covered by news media and searched by households on the Internet are good proxies for the evolution of investors' concerns regarding these topics (Gentzkow and Shapiro, 2006; Da et al., 2015; Manela and Moreira, 2017), we construct a novel measure of inflation concerns. We refer to our measure as the Inflation Concern Index (hereafter, ICIX) that is derived from the news coverage in the *Wall Street Journal* (WSJ) and Google search volume of inflation-related topics. The underlying premise is that heightened concerns about inflation lead to a corresponding increase in news coverage and internet searches of inflation-related topics.

ICIX offers advantageous features that enhance our understanding of the relationship between cognitive inflation concerns and expected stock market returns. Unlike widely-used measures of inflation risk based on realized inflation, ICIX is immediately accessible without any reporting lags, making it a responsive measure. Furthermore, "inflation concerns" differ from "inflation expectation". Specifically, inflation expectation denotes explicit forecasts about future inflation rates held by individuals, businesses, or market participants. On the other hand, inflation concerns delve deeper into cognitive worries, fears, or perceived risks related to potential inflationary scenarios. Such concerns stem from current information and a subjective understanding of prevailing economic conditions, encompassing apprehensions about how high inflation could erode purchasing power, impact savings, influence investments, or even affect the broader economic landscape. While expected inflation can be quantified based on the predictions of a particular professional group or the rates of specific inflation-related instruments, gauging cognitive inflation concerns is inherently challenging. ICIX provides a unique aspect in measuring these concerns. With its interpretable variation, ICIX enables us to study how investors' subjective inflation concerns, as reflected in newspaper coverage and Internet searches, fluctuate over time and allows us to identify how the stock market reacts to these cognitive inflation concerns.

We take into account both media coverage and Internet search by households, as media coverage reflects public information and the media's emphasis on inflationary developments, while the latter represents households' perception and awareness of inflation risk, influencing their economic decisions. Specifically, we measure media coverage of inflation as the 12-month moving average of direct coverage on inflation-related topics reported by the *Wall Street Journal* (WSJ) and measure households' concerns as the 12-month moving average of Google searches on inflation-related topics. We define ICIX as the average of these two. The implementation of a moving average mitigates potential biases that may arise in the news article counts and internet searching during critical inflation-related events such as the Federal Open Market Committee (FOMC) meetings. Additionally, it better accounts for the reaction time of investors, considering their tendency to respond slowly to adverse news (Hong and Stein, 1999; Hong et al., 2000). Consequently, ICIX reflects investors' concerns regarding inflation as indicated by high (or low) index levels.[1]

First, we utilize our newly-constructed ICIX to investigate the predictive effects of inflation concerns on aggregate stock market returns within univariate predictive regressions. The empirical analysis reveals that the ICIX has a strong negative predictive power on aggregate stock market returns over both monthly and longer forecast horizons. Its predictability is statistically and economically significant. On an economical scale, one-standard-deviation increase in ICIX predicts a 1.06% lower monthly return in the following month.

Despite that ICIX captures cognitive concerns, it is closely related to inflation, which is commonly considered as a macroeconomic variable. Considering typical macroeconomic predictors such as realized inflation are reported to fail in effectively predicting the stock market returns (Goyal and Welch, 2008), we compare the predictive effects of ICIX with those variables. We employ 13 macroeconomic variables studied by Goyal and Welch (2008) that are not directly related to inflation and find consistent results showing that none of them presents an in-sample predictive effect within univariate regressions over our sample period. The results from bivariate predictive regressions depict that the predictive effects of ICIX remains robust when these typical economic variables are considered. In a cross-sectional

[1] While concerns about inflation could arise during both high- and low-inflation periods, it is noteworthy that the data reveals ICIX primarily captures the concerns about high inflation. Particularly, for the terms used for article researching in WSJ and Google search, we also consider screening out terms such as “deflation” and “low inflation” and find consistent results as with ICIX. Details are presented in Appendix III.

analysis, the predictive effects of ICIX remain significant. Stocks that are small, distressed (high BtM ratio), or past losers are more predictable by ICIX.

We then compare ICIX with a group of typical measures for inflation risk including both realized and expected inflation, such as one-month Treasury bill rate, break-even rates of Treasury Inflation-Protected Securities (TIPS) and expected inflation rate reported by University of Michigan Surveys of Consumers. We document that ICIX outperforms these conventional inflation risk measures dramatically particularly in predicting short-term aggregate stock market returns both in sample and out of sample. Specifically, ICIX has significant predictive effects with an in-sample R^2 of 5.44% and an out-of-sample R^2 of 4.17% with an MSFE *t*-statistic of 2.45 on a monthly forecast horizon. In a long term, the predictive effect of ICIX remain significant when conventional measures are included in the predictive regressions. Moreover, the predictive effect of ICIX is complementary to those of conventional measures, evidenced by the largely improved explanatory power of predictive regressions. These findings suggest that cognitive inflation concerns diverge from economic statistics, such as realized and expected inflation rates. Such concerns encompass a broader array of information that is at least not fully captured by the explicit rates.

To better understand the economic mechanisms underlying the predictability of the ICIX, which distinguishes it from other types of inflation risk measures, we investigate its links to macroeconomic conditions. We find that ICIX predicts poor macroeconomic conditions, whereas traditional measures exhibit much weaker—and in most of the cases, opposite—predictive effects on macroeconomy. To further support this explanation, we explore the correlation between ICIX and mutual fund flows. Our findings reveal that an increase in ICIX is associated with outflows from the equity market and high-yield bonds, and inflows into money market funds. These findings suggest that investors tend to withdraw from riskier capital market and gravitate towards short-term and secure instruments when they have heightened concerns about inflation. This evidence is consistent with the notion of "flight-to-safety" during economic downturns, affirming that the ICIX is indeed an indicator of expected macroeconomic conditions and aligning with our empirical findings on return predictability.

Our study is closely related to the literature analyzing the relationship between inflation risk and stock returns. In the literature, expected inflation is widely used as a proxy for inflation risk. Fama and Schwert (1977) used the nominal yield of Treasury bills as a measure of inflation risk and examined its correlation with stock market returns, and reported an anomalous negative relationship. Fama (1981) found that this negative relation largely disappeared when future real activity measures were considered, especially when including a base growth rate variable highly correlated with inflation risk. Gultekin (1983) and Hasbrouck (1984) also found a negative association between expected inflation and expected stock market returns. Modigliani and Cohn (1979) attributed this to the inflation illusion causing market mispricing, which should dissipate over time. Their hypothesis was later tested by studies such as Campbell and Vuolteenaho (2004), Cohen, Polk, and Vuolteenaho (2005), and Lee (2010). Stulz (1986) and Ritter and Warr (2002) also identified a negative relationship, attributing it to decreased wealth from higher inflation expectations and money outflows from stocks when nominal interest rates are high. Bhamra et al. (2023) reported a contemporaneous negative relationship between inflation and stock returns within an asset pricing model with endogenous corporate policies. On the other hand, Boudoukh and Richardson (1993) suggested that stocks can serve as superior inflation hedges over five-year periods rather than one-year periods. Campbell and Vuolteenaho (2004) found high inflation positively correlated with expected long-run real dividend growth, implying a positive relationship, which is empirically supported by Schmeling and Schrimpf (2011). Several studies, including Hess and Lee (1999), Boons et al. (2020), and Campbell, Pflueger, and Viceira (2020), suggested a time-varying relationship between stock market returns and expected inflation. There exists a robust body of research that investigates the pricing effects of inflation risk in the cross-section of stock market returns (e.g., Chen et al.,1986; Ferson and Harvey, 1991; Ang et al., 2012; Konchitchki and Xie, 2023). Our study contributes to the rich literature by focusing on cognitive inflation concerns rather than using realized or expected inflation rates to proxy inflation risk, highlighting the importance of considering investors' cognitive feelings.

Our study also aligns with existing literature that investigates the relationship between specific risk concerns and stock market returns. Manela and Moreira (2017), for example, constructed a text-based uncertainty measure from 1890 using front-page articles of the *Wall Street Journal*. Their objective was to gauge disaster concerns, and they found that their measure can predict not only stock returns but also actual disasters. Meanwhile, Gao, Lu, and Song (2019) delve into the pricing effects of tail risk concerns across diverse asset classes such as international equity indices, foreign currencies, and government bond futures. In a contemporary twist, Ardia, Bluteau, Boudt, and Inghelbrecht (2023) formulate a climate change concerns index, sourcing news about climate change from major U.S. newspapers and newswires. Their focus was on discerning the impact of these concerns on green and brown stocks. Central to these studies is the longstanding notion that investors' concerns regarding a specific issue mirror the perceived risks associated with that issue (e.g., Slovic, 1987, Lerner et al., 2001; Barberis and Richard, 2002; Shefrin, 2002; Tetlock, 2007). Following a similar approach to Manela and Moreira (2017) and Ardia et al. (2023), we introduce the ICIX, an innovative measure specifically designed to capture inflation concerns.

Additionally, our study relates to previous research analyzing stock return predictability and economic conditions. Merton (1973) provides theoretical guidance through the Intertemporal Capital Asset Pricing Model (ICAPM), which posits that state variables indicating changes in the future investment opportunity set are crucial determinants of agents' current consumption decisions. These state variables embody fundamental risks and are intricately linked with the risk premium. Rapach et al. (2010) find that combining individual economic variables offers better forecasts of the equity premium, as these combinations more closely reflect real economic conditions. Bybee, Kelly, and Su (2023) report that news text from the *Wall Street Journal* closely relates to economic states, capturing investors' concerns about future investment opportunities and driving the pricing kernel. Similarly, Chen et al. (2023) show that news extracted by ChatGPT from the front pages of the *Wall Street Journal* can predict the stock market, with the predictive effect explained by the extracted information's reflection of underlying macroeconomic fundamentals. In light of this perspective, we document that the predictive effect of inflation concerns, as measured by our ICIX, can be attributed to its indication of underlying macroeconomic conditions.

The remainder of the paper is structured as follows: Section 2 outlines our data and measures of inflation concerns. Section 3 presents the main empirical results, and Section 4 concludes.

2. Data and Variables

Our sample covers the period from October 2004 to December 2021, encompassing the global financial crisis of 2007-2008 (GFC) and the COVID-19 pandemic.[2] In this section, we will discuss the construction of ICIX, along with two widely used proxies for inflation risk.

2.1. Construction of ICIX

[2] Our sample period is subject to the data availability of Google search volume, which is available since January 2004. We start from October 2004 to ensure that there are at least ten observations in regressions used to identify the highest inflation-related terms (see more details in Section 2.1.2.). Additionally, a sample starting from 2004 allows ICIX to be more comparable to some other instrument-based inflation risk proxies, as the breakeven rates based on TIPS that are only available since then. More details are discussed in section 2.2.

As previously discussed, our ICIX index is designed to capture the shared variation between media coverage and household search on inflation-related topics. To achieve this, we calculate the ICIX as the average of these two distinct types of concerns. In the subsequent two sub-sections, we separately discuss the metrics used for both components: media inflation concerns and household inflation concerns.

2.1.1. Media coverage

Previous studies have reported the significant impact of news of inflation on the yield curve (e.g., Duffee, 2018; Gomez-Cram and Yaron, 2021). Larsen, Thorsrud, and Zhulanova (2021) demonstrate that various news topics covered in the media (e.g., education, trading) can predict inflation and reflect inflation concerns. Taking into consideration the important role of news as the primary source of information for investors to learn about inflation risk (Nimark and Pitschner, 2019), we construct a news-based concern index to reflect the direct media coverage of inflation-related topics. Intuitively, when investors are concerned about rising inflation, the news coverage regarding inflation should also increase, effectively reflecting heightened inflation risk perceived by investors.[3] We capture investors' concerns to inflation by using articles from the main source of market-wide news, the *Wall Street Journal*. We develop our news-based inflation concern index by first counting the articles in the WSJ that contain the word "inflation" or other inflation-related terms.[4] Such a simple and direct word choice allows us to limit the degree of freedom effectively. The news data of matched articles is sourced from Dow Jones Factiva. Then the monthly count of matched articles in the WSJ is divided by the respective monthly total number of articles.[5] We standardize the resulting

[3] Such a relationship is also consistent with Robinson (2007) and Trussler and Soroka (2014), who suggest news tends to focus on negative events.
[4] In addition to "inflation", other terms include "CPI", "PPI", "consumer price index", and "producer price index". A matched article in the WSJ needs to pertain to at least one of those search terms.
[5] We report the monthly original count on inflation-related news articles (over total article number) from WSJ in Appendix II.

monthly series and re-normalize it to an average value of one to obtain a raw monthly count index.

However, the above-mentioned raw concern index is vulnerable to potential bias in the monthly count of articles, particularly during critical events pertaining to inflation. One such instance is the regularly scheduled meetings of the Federal Open Market Committee (FOMC), which typically take place eight times per annum. During these meetings, the Committee assesses the current economic and financial conditions and determines an appropriate monetary policy stance aimed at achieving long-term goals of price stability and sustainable economic growth. Given that inflation is a core topic of discussion, it is expected that the number of articles related to inflation will be higher during these months, leading to a skewed estimation of inflation concerns for that month. To mitigate these, we utilize a 12-month moving average of the monthly raw index to account for the, approximately, eight most recent FOMC meetings.[6] A moving-average approach also better takes into account the reaction time of investors, given their tendency to respond to adverse news, such as rising inflation, more slowly (Hong and Stein, 1999; Hong et al., 2000). We refer to this index as the news-based inflation concern (*NBIC*) index.

2.1.2. Internet search by households

To more effectively capture the market-wide cognitive inflation concerns, we also consider concerns of households. Adapting the approach of Da et al. (2015), we construct an index based on internet searches of inflation-related topics to gauge household concerns. We

[6] As robustness tests, we apply alternative moving-average windows varying between one month to 24 months for both media concerns and household concerns to estimate ICIX. The results remain consistent and are reported in Appendix IV. It is noteworthy that ICIX constructed within very short (less than three months) or very long (greater than 14 months) moving-average windows shows slightly weaker predictive effects in terms of statistical significance. This is not surprising. A too short window is more susceptible to potential biases associated with critical inflation-related events, while a too long window includes articles published and online searches conducted long ago, which may have limited impact on current and future market conditions.

employ the text analytics methodology from the literature, which utilizes the Harvard IV-4 Dictionary and the Lasswell Value Dictionary (e.g., Tetlock, 2007; Tetlock, Saar-Tsechansky, and Macskassy, 2008; Da et al., 2015). To measure household concerns about inflation, we select a set of inflation-related words and examine their search frequency in Google by households. We input each word into Google Trends, which returns ten "top searches" for each word. We then remove terms with insufficient data or irrelevant to high inflation, resulting in a list of 17 search terms.[7] We obtain the monthly search volume (*SV*) data for these terms from Google Trends for the U.S. region. Appendix II, Panel B shows an example of the original monthly search volume for the term "inflation". To address seasonality and heteroscedasticity, we regress the *SV* data of each term on month dummies and retain the residuals. We standardize each time series by scaling them with their standard deviation, resulting in an adjusted (de-seasonalized and standardized) monthly search volume data for our 17 inflation-related terms.

Adopting the approach of Da et al. (2015), we allow the data to identify the most crucial search terms related to realized inflation, as opposed to market returns, which is the focus in their study. We run expanding backward rolling regressions of adjusted search volume on lagged realized inflation every month to establish the historical relationship between search and inflation for all 17 terms.[8] The relationship is almost always positive for search terms with a strong connection to inflation. We select the five terms with the largest positive *t*-statistic on search volume to create a raw searching-based inflation concern index (*SBIC_raw*):

$$SBIC\_raw_t = \sum_{i=1}^{5} Rank^i\,(SV_t). \tag{1}$$

[7] Our search terms include terms such as “inflation”, “inflation rate”, “consumer price index”, “CPI”, “hyperinflation”. In comparison to the 118 search terms used by Da et al. (2015), our list is significantly shorter. This difference is expected, as their study encompasses all aspects of the economy, while our focus is specifically on inflation.

[8] We use lagged realized inflation to account for the delay in CPI releases. To clarify, the realized inflation for month *t* is not reported until month *t*+1.

$Rank^i(SV)$ denotes the adjusted search volume for the search term with a *t*-statistic rank of *i* from October 2004 through the last month, where ranks range from most positive (*i*=1) to most negative (*i*=17). For instance, at the end of June 2012, we run a regression of *SV* on contemporaneously reported inflation (i.e., realized inflation for May 2012) from October 2004–June 2012 for each of the 17 search terms. We rank the *t*-statistics on *SV* from this regression, selecting the five most positive terms to form our *SBIC_raw* index for July 2009.[9] The terms that historically have the largest monthly correlation with realized inflation include "inflation" (*t*-statistic = 5.31), "inflation rate" (*t*-statistic = 4.20), "real estate price" (*t*-statistic = 2.31), "value of money" (*t*-statistic = 1.33), and "consumer price index" (*t*-statistic = 1.32).

Similar to *NBIC*, we apply a 12-month moving average on the raw searching-based inflation concern index (*SBIC_raw*) to address potential bias caused by critical inflation events such as FOMC meetings. We refer to the final index as the searching-based inflation concern (*SBIC*) index capturing household concerns on inflation.

Finally, we construct ICIX as the average of the news-based inflation concern (*NBIC*) index and searching-based inflation concern (*SBIC*) index.[10] For robustness tests, we also consider an alternative measure ($ICIX^{PC}$) calculated as the first principal component of *NBIC* and *SBIC*. Additionally, we consider another alternative measure, $ICIX^{\perp}$, defined as ICIX orthogonalized to the common systematic expected inflation (*EIPC*), the details of which are discussed in the next section.[11]

[9] Our results are robustness to alternative cut-off choices (e.g., top three or top seven).

[10] In addition to our main results with *ICIX*, we also report the test results for *NBIC* and *SBIC* separately in Appendix V. It is worth noting that *ICIX*, which combines *NBIC* and *SBIC*, provides significantly improved explanatory power, as reflected by the higher adjusted R^2.

[11] The principal component analysis shows that $ICIX^{PC}$ accounts for 74.3% of the sample variation of *NBIC* and *SBIC*. It is noteworthy that the key difference between *ICIX* and $ICIX^{PC}$ is that *ICIX* is not subject to potential forward-looking basis whereas the latter is. The test results for $ICIX^{PC}$ are reported in Appendix VI.

2.2. Typical inflation risk measures

To highlight the capabilities of ICIX in forecasting stock market returns, we compare it with multiple conventional inflation risk measures. The first typical measure of inflation risk we consider is realized inflation (*INFL*), which has been widely used in precious studies. In addition to realized inflation, we use the one-month Treasury bill rate (*TBL*) as in Fama and Schwert (1977). In the remainder of this section, we discuss other conventional measures.

2.2.1. Break-even inflation rate of TIPS

Accordingly, TIPS are fixed-income securities whose coupons and principal payments are indexed to the non-seasonally adjusted consumer price index (CPI) for all urban consumers (Sack and Elsasser, 2004). The market for TIPS has expanded substantially since its inception in 1997. By the end of 2021, the market for TIPS had a total outstanding notional amount of $1,579 billion, taking up around 7.5% of all marketable debt issued by the Treasury (Anderson, Christensen and Riddell, 2021). As the coupons and principal payments of TIPS are adjusted for inflation, the yield of TIPS is often thought of as a measure for the real interest rate. Similarly, the break-even inflation rate that is implied from the yields of TIPS has been widely used as a proxy for expected inflation (D'Amico, Kim, and Wei, 2018). Following the literature, we consider the break-even inflation rate (*BRKE*) as one proxy for expected inflation. We apply the two-year break-even inflation rate available since October 2004 and collect the monthly data from Bloomberg. [12]

[12] We use the two-year break-even inflation rate rather than the one-year rate, because the later presents less data availability. Nevertheless, we use one-year break-even inflation rates for robustness tests and find consistent results.

2.2.2. Inflation swap rate

The inflation swap rate based on "zero-coupon inflation swaps", one of the most liquid over-the-counter market inflation derivative products, provides an alternative measure of expected inflation. Since their inception together with TIPS in 1997, inflation swaps have become widely used among institutional investors (Fleckenstein, Longstaff, and Lustig, 2014). Accordingly, zero-coupon inflation swaps are forward contracts. Investors taking long positions in contracts (i.e., inflation buyers) pays a predetermined fixed nominal rate and receives from the inflation sellers an inflation-linked payment. Haubrich, Pennacchi, and Ritchken (2012) apply the inflation swap rate as an alternative proxy for expected inflation. They show that inflation-indexed yields computed as the difference between equivalent-maturity nominal Treasury yields and inflation swap rates are less prone to liquidity shocks, and therefore provide more reliable estimation in nominal and real bond yield curves.[13] The one-year inflation swap rate (*ISWAP*) data, available since 2003, is obtained from Bloomberg.

2.2.3. Survey-based and model-based expected inflation

Given consumers react to surveys on expected inflation (Armantier et al. 2015), we use the well-known University of Michigan Surveys of Consumers (UMSC) and the Survey of Professional Forecasters (SPF) as the two survey-based measures for expected inflation. The survey data on the expected inflation of UMSC and SPF have been widely used in the inflation literature (e.g., Chernov and Mueller,2012; Ehling, Gallmeyer Heyerdahl-Larsen, and Illeditsch, 2018; Breach, D'Amico, and Orphanides, 2020; Bhamra et al., 2023). Accordingly, the UMSC surveys ask a sample of U.S. households about the future change in prices they expect on a monthly basis. The Survey of Professional Forecasters asks a panel of professional

[13] A large number of studies investigate TIPS and inflation swap rates (e.g., Haubrich, Pennacchi, and Ritchken, 2012; Christensen, Lopez, and Rudebusch, 2010; Pflueger and Viceira, 2016; D'Amico, Kim, and Wei, 2018).

forecasters for their expected inflation on a quarterly basis. In our study, we apply one-year expected inflation from both surveys and collect the data from DataStream. Additionally, we employ the expected inflation estimated within an ARIMA (0,1,1) model (EI^{ARIMA}) as in Gultekin (1983).

2.2.4. Other inflation risk measures

It is important to note that these survey- and instrument-based forward-looking measures of expected inflation, used as proxies for inflation risk, are not without controversy. They are sourced from specific groups of investors (e.g., households, professionals, or investors in particular instruments), making them susceptible to group biases. For instance, trading-based proxies carry significant liquidity risk due to the low trading volumes and longer turnaround times of underlying instruments like TIPS and inflation swaps (Sack and Elsasser, 2004; Campbell, Shiller, and Viceira, 2009; Dudley, Roush, and Ezer, 2009; Gurkaynak, Sack, and Wright, 2010; Andreasen, Christensen, and Riddell, 2021).

To achieve a more precise forward-looking proxy for inflation risk, we eliminate the idiosyncratic noise present in these forward-looking level measures, such as group bias and liquidity risk. Specifically, we utilize five forward-looking proxies for inflation risk, namely, *BRKE*, *ISWAP*, *UMSC*, *SPF*, and EI^{ARIMA} which provide direct estimates of the expected inflation rate and compute the first principal component of these five measures to obtain a common systematic measure for expected inflation (*EIPC*). This procedure leads to a parsimonious index:

$$EIPC_t = 0.451BRKE_t + 0.486ISWAP_t + 0.401UMSC_t + 0.437SPF_t + 0.457EI_t^{ARIMA} .$$

Our analysis indicates that *EIPC* explains 73.2% of the sample variation.

Additionally, we consider inflation uncertainty as another perspective to measure inflation risk. To this end, we apply the 12-month rolling standard deviation of realized inflation (*INFUN*).

Fig. 1 depicts the historical levels of the ICIX index and other inflation risk measures. As shown in Panel A, the ICIX index presents a big decline during the GFC period for the first time over the sample period due to the low interest rate that provided additional liquidity to financial markets and institutions. The latest apparent drop that the ICIX experienced is accompanied by the outbreak of COVID-19, but then a large rally during the post-pandemic period, triggered by excessive debt growth of the government in 2020–2021 to finance aid schemes.

FIG. 1 HERE

2.3. Other variables

Following previous studies on stock market return predictability (e.g., Huang et al. (2015). Rapach et al., 2016; Jiang et al., 2019), we include 13 typical economic variables apart from realized inflation in the predictive regression model: dividend-price ratio, *DP*, defined as the difference between the log of a 12-month moving sum of dividends paid on the S&P 500 index and the log of the S&P 500 index price; dividend yield, *DY,* defined as the difference between the log of S&P 500 dividends and the log of lagged S&P 500 prices; earnings-price ratio, *EP*, defined as the difference between the log of earnings on the S&P 500 index and the log of prices; dividend-payout ratio, *DE,* defined as the difference between the log of dividends and the log of earnings on the S&P 500 index; stock return variance, *SVAR*, calculated as the sum of squared daily returns on the S&P 500 index; book-to-market ratio, *BM*, defined as the ratio of book value to market value for the Dow Jones Industrial Average; net equity expansion, *NTIS*, calculated as the 12-month moving sums of net issues by stocks listed on the NYSE divided by the total end-of-year market capitalization of NYSE stocks; Treasury bill rate, *TBR*, defined as the yield of a 3-month T-bill; long-term yield, *LTY*, which is the long-term government bond yield; long-term return, *LTR*, defined as the return on long-term government bonds; term spread, *TMS*, calculated as the long-term yield minus the T-bill rate; default yield spread, *DFY*, defined as the difference between BAA- and AAA-rated bond yields; default return spread, *DFR*, calculated as the difference between the long-term corporate bond return and the long-term government bond return. The data for all 13 economic variables above are available and updated at Goyal's website.[14]

For robustness test, we compare ICIX with established predictors that predict stock market returns on top of business cycle variables. These predictors include the well-known sentiment measures presented in Baker and Wurgler (2006), Huang et al. (2015) and Jiang et al. (2019). In addition to sentiment, we test with another market-wide measure that is closely relative to the interest rate, namely the Short Interest Index (SII) by Rapach, Ringgenberg and Zhou (2016). The sentiment index data by Baker and Wurgler (2006) is sourced from Jeffrey Wurgler's personal website. The aligned sentiment, manager sentiment and SII data is retrieved from Guofu Zhou's research website.

The data on the S&P 500 index are sourced from Bloomberg. For the sake of brevity, we list the description and sources of all the variables mentioned in Appendix I. The descriptive statistics and correlation matrix of the main variables employed in our study are summarized in Table 1. For all the regression analysis, we report the Newey-West *t*-statistics with the

[14] See https://sites.google.com/view/agoyal145.

number of lags equal to the forecast horizon. We also test the variance inflation factors to ensure that our results are not subject to any multicollinearity problems.

TABLE 1 HERE

3. Empirical analysis

3.1. Forecasting the market returns

In this section, we scrutinize the predictive effects of the ICIX on aggregate stock market returns. We consider the following regression:

$$\frac{1}{h}\sum_{j=1}^{h} r_{t+(j-1),t+j} = \alpha + \beta \cdot ICIX_t + \varepsilon_{t+h}, \tag{2}$$

where the dependent variable is the cumulative monthly returns of the S&P 500 index over the next *h* months (*h*=0, 1,3,6,9,12 or 24). *ICIX* is our measure of inflation concerns, calculated as the average the news-based inflation concern (*NBIC*) index and searching-based inflation concern (*SBIC*) index.

[TABLE 2 HERE]

Table 2 reports the basic univariate predictive regressions with *ICIX* as the independent variable over the sample period 2004 to 2021. As noted, *ICIX* manifests strong predictive effects on the stock market returns over all the forecast horizons. The adjusted R^2 ranges from 5.44% (for monthly forecast) to 33.34% (for the 12-month forecast horizon) and the predictability is statistically significant across all the specifications. The predictive effects of *ICIX* are also economically significant. For example, the coefficient of *ICIX* in column (1) suggests a one-standard-deviation increase in *ICIX* predicts a 1.06% lower monthly return in the following month. Moreover, it is worth noting that *ICIX*'s explanatory power is most pronounced over relatively shorter-term horizons. The adjusted R square for the 24-month forecast horizon is 25.7%, which is less than the 33.34% for the 12-month forecast horizon. To address potential overlapping-observation issues for horizons exceeding one month, we adopt the method from Jiang et al. (2019), computing the wild bootstrapped empirical *p*-value, which accounts for factors like predictor persistence and correlations between market returns and predictor innovations. Furthermore, we consider Hodrick's (1992) *t*-statistics, and our results remain robust.

To deal with the concern that market return predictability of inflation concerns may source from the information associated with other factors reflected by typical economic variables, we compare the predictive power of ICIX with 13 economic variables applied by Goyal and Welch (2008) which are not directly related to inflation. We first consider the monthly predictive regression with a single predictor:

$$R_{t+1}^{m} = \alpha + \varphi \cdot Z_{t}^{k} + \varepsilon_{t+1}, \tag{3}$$

where R_{t+1}^{m} is the monthly aggregate stock market return, and Z_{t}^{k} is the one of the 13 individual economic predictors or their first principal component (*ECON*). Panel A Table 3 reports the in-sample estimation results for the predictive regressions of the monthly market return on one of the lagged individual predictors (Eq. (3)). Over our sample period, only long-term yield (*LTY*) out of the 13 individual predictors exhibits significant predictive effects on the market returns at the 5% significance levels. *LTY* also presents the highest adjusted R^2 of 1.95%. Based on the results presented in Table 2, it is evident that the *ICIX* outperforms all the 13 individual predictors in the ability to forecast the monthly market returns in-sample.

[TABLE 3 HERE]

Next, we investigate whether the forecasting power of *ICIX* remains significant after controlling for those typical predictors tested in Panel A. To examine the incremental forecasting power of *ICIX*, we conduct the following monthly bivariate predictive regressions:

$$R_{t+1}^{m} = \alpha + \beta \cdot ICIX_t + \varphi \cdot Z_t^k + \varepsilon_{t+1}. \tag{4}$$

The coefficient of interest is the regression slope β on *ICIX*. Panel B of Table 3 shows that the estimates of the slope β in Eq. (4) are all statistically significant and economically large with a negative sign, confirming our results reported in Table 2. The adjusted R^2 in Panel B Table 3 ranges from 5.1% to 6.2%, which are substantially greater than those reported in Panel A based on those typical economic predictors alone. Notably, when the *ICIX* is incorporated into the predictive regression, none of the macroeconomic variables remain significant. These findings indicate that the return predictability of the *ICIX* is not driven by information captured by those economic variables. As robustness tests, we use two alternative measures: $ICIX^{PC}$, defined as the first principal component of *NBIC* and *SBIC*, and $ICIX^{\perp}$, defined as *ICIX* orthogonalized to the common systematic expected inflation (*EIPC*). The results, presented in Appendix VI, are consistent with those reported previously.

3.2. Forecasting characteristic portfolios

Considering inflation could have different impacts on different stocks (Boudoukh, Richardson, and Whitelaw, 1994; Boyd, Levine, and Smith, 2001; Horstmeyer, 2022), in this subsection, we investigate the monthly predictive effects of ICIX on the returns of Fama-French portfolios sorted by size, book-to-market ratio, and momentum. This would help test the consistency of our previous findings on aggregate stock market predictability, and shed light on the economic sources of return predictability (e.g., Cohen and Frazzini, 2008; Menzly and Ozbas, 2010; Huang et al., 2015).

[TABLE 4 HERE]

Panels A, B and C of Table 4 present the results for univariate predictive regressions for size, book-to-market ratio, and momentum portfolios, respectively. Overall, the results are consistently significant across all the specifications— *ICIX* forecasts the monthly returns of all the 10 characteristic proportions sorted by size, book-to-market ratio, and momentum. Stocks that are small, distressed (high *BtM* ratio), or past losers are more predictable by ICIX.

3.3. Comparison with other inflation risk measures

In this subsection, we provide a comprehensive analysis by comparing the forecasting power of *ICIX* with other widely-used conventional inflation risk measures. In Table 5, we report the estimation results for the predictive regressions as following:

$$R_{t+1}^{m} = \alpha + \beta ICIX_t + \varphi IR_t^k + \varepsilon_{t+1} \, , \tag{5}$$

where *X* is one of the nine conventional inflation risk measures (i.e., *INFL, TBL, BRKE, ISWAP*, *UMSC, SPF,* EI^{ARIMA}, *EIPC, INFUN*).

[TABLE 5 HERE]

As shown, among typical inflation risk measures, only *SPF* has a coefficient significant at a 10% significance level, while the other proxies lack notable predictive power on monthly aggregate stock market returns. However, even when incorporating other inflation risk measures, *ICIX* consistently shows significant monthly predictive impacts on aggregate stock market returns. Additionally, the adjusted R-squares of the monthly predictive regressions are substantially enhanced by 3.69% to 6.63% when *ICIX* is included. The significant monthly predictive effect of *ICIX*, along with the improved explanatory power, suggests that cognitive inflation concerns provide complementary and valuable information for future stock returns, which is not captured by standard inflation risk measures that denote realized or expected inflation rates.

As additional tests, we run predictive regressions similar to Eq. (5) but for longer forecast horizons. The results are reported in Appendix VII. Columns (1) to (9) present the estimates for univariate predictive regressions with one typical inflation risk measure, while Columns (10) to (18) report the results for bivariate predictive regressions that include *ICIX* alongside a conventional measure. It is noteworthy that over longer forecast horizons, traditional inflation measures such as realized inflation and expected inflation also exhibit negatively predictive effects, consistent with previous studies (e.g., Fama and Schwert, 1977; Gultekin, 1983; Stulz, 1986; Ritter and Warr, 2002). Conversely, inflation uncertainty shows a positively predictive effect on aggregate stock market returns over six to 12-month forecast horizons. More importantly, the predictive power of *ICIX* remains consistently significant across various forecast horizons, and including *ICIX* in predictive regressions dramatically improves their explanatory power as reflected by enhanced adjusted R-squares. These findings align with the results reported in Table 5 and further affirm the complementary and significant predictive effects of inflation concerns.

For robustness tests, we incorporate *ICIX* alongside investor sentiment measures from Baker and Wurgler (2006), Huang et al. (2015) and Jiang et al. (2019), as well as the short interest index from Rapach et al. (2016) into the predictive regressions. Our aim is to determine whether *ICIX's* predictive ability remains significant in the presence of other established predictors. The results of these tests are reported in Appendix VIII, which affirms the predictive robustness of *ICIX* even when investor sentiment and short interest are considered. Additionally, to mitigate the concerns that our results are mainly driven the post-COVID19 periods after the quantitative easing of the U.S. government, we conduct sub-sample tests by only considering the pre-pandemic sample period, 2004-2019. The results are presented in Panel A of Appendix IX, which yield consistent findings.

3.4. Out-of-sample forecasts

In light of the argument presented by Goyal and Welch (2008) that predictors such as realized inflation lack out-of-sample predictability, we evaluate the out-of-sample predictive capacity of ICIX and the typical inflation risk measures. Out-of-sample tests are less susceptible to econometric issues such as small-sample size distortion, overfitting, and the Stambaugh bias (Jiang et al., 2019), which alleviate concerns related to the relatively short sample period of our study. To this end, we adopt an expanding window following Liu and Matthies (2022) for coefficient estimation, which allows the use of more available data. To ensure a sufficient number of monthly observations for initial in-sample training and a relatively long out-of-sample period for forecast evaluation, we started coefficient estimation for the out-of-sample test with at least 96 months (eight years) of data.

Following Goyal and Welch (2008), we estimate the out-of-sample forecasts at time *t* only using information available up to *t* and forecast aggregate stock market returns over the next month. Specifically, we calculate the out-of-sample R^2 as:

$$R_{OOS}^2 = 1 - \frac{\sum_{t=p}^{T-1}\left(r_{t+1} - \hat{r}_{t+1}\right)^2}{\sum_{t=p}^{T-1}\left(r_{t+1} - \bar{r}_{t+1}\right)^2}, \tag{6}$$

where $\hat{r}_{t+1}$ is the forecasted one-month-ahead aggregate stock market return, which is estimated using information up to time *t*. $\bar{r}_{t+1}$ denotes the historical mean of one-month-ahead stock market return up to time *t*, and T represents the sample size. If a given inflation risk measure proves to be a robust predictor, we anticipate obtaining an out-of-sample R^2 that is statistically greater than zero. To further validate the statistical significance of the out-of-sample R^2, we apply the mean squared forecast error (MSFE)-adjusted statistic of Clark and West (2007).[15]

[TABLE 6 HERE]

Table 6 presents the outcomes of the out-of-sample analysis. It is evident that *ICIX* exhibits the highest positive out-of-sample R^2 of 4.2% on the monthly forecast horizon, which is comparable to its in-sample adjusted R^2 reported in Table 2. The MSFE-adjusted *t*-statistic of 2.45 suggests that the out-of-sample monthly predictive effect of *ICIX* is statistically significant. Such out-of-sample R^2 and MSFE-adjusted *t*-statistic surpasses those of conventional inflation risk measures, indicating that *ICIX* also outperforms typical inflation risk measures in out-of-sample predictability. In consistent with the findings of Goyal and Welch (2008), our results suggest that realized inflation (*INFL*) has poor out-of-sample predictive effects on stock market returns. Additionally, the out-of-sample R^2 of *TBL* (1.05%) is found to be significantly positive at the monthly forecast horizon, although only at a 10% significance level with an MSFE *t*-statistic of 1.71. However, this finding contradicts its in-sample forecast result reported in Table 5. Given *TBL* might not be an accurate measure for the inflation risk (Geske and Roll, 1983), its out-of-sample test results should be interpreted with caution. Furthermore, the forward-looking proxies for inflation risk, derived from the expected inflation rate (i.e., *BRKE*, *ISWAP*, *UMSC*, *SPF*, EI^{ARIMA}, *EIPC*), and inflation uncertainty measure (*INFUN*), fail to exhibit significant out-of-sample predictive prowess for monthly forecast horizons.

[15] Accordingly, the MSFE-adjusted statistic tests the null hypothesis that the historical average MSFE does not surpass the predictive regression forecast MSFE against the one-sided alternative hypothesis that the historical average MSFE exceeds the predictive regression forecast MSFE.

3.5. Source of predictability

As discussed in the preceding section, the significant monthly predictive effect demonstrated by *ICIX* suggests that investors' cognitive inflation concerns capture invaluable information for future aggregate stock market, which is not detected by the traditional inflation risk measures. To better understand the *ICIX's* predictive effect, in this subsection, we explore the potential economic explanation underlying the observed evidence.

The Intertemporal Capital Asset Pricing Model (ICAPM), as posited by Merton (1973), suggests that macroeconomic state variables signal shifts in the future investment opportunity set, which are critical in shaping agents' current consumption choices. These state variables, encapsulating fundamental risks, are closely intertwined with future stock market returns. Empirical support from Rapach et al. (2010) reinforces this model, demonstrating that forecasts closely linked with macroeconomic activities consistently outperform others. Building on this theoretical foundation, we propose that investors' cognitive concerns regarding inflation, a crucial metric of macroeconomic conditions, may reflect underlying economic fundamentals, thereby potentially enabling these concerns to serve as a predictor of aggregate stock market dynamics and returns.

To test this conjecture, we examine a range of monthly proxies for macroeconomic conditions. These proxies include Industrial Production Growth (*IPG*), the Chicago Fed National Activity Index (*CFNAI*), Total Non-farm Payroll Growth (*PRG*), the Aruoba-Diebold-Scotti Business Conditions Index (*ADSI*), the CBOE Volatility Index (*VIX*), the Kansas City Financial Stress Index (*KCFSI*), and Smoothed Recession Probability (*SRP*).[16]

[16] We do not include macroeconomic condition variables such as GDP growth, which is available only on a quarterly basis, in our main results. However, we apply GDP growth in a robustness check and find consistent results, which are available upon request.

Data for these monthly macroeconomic state variables is obtained from the Federal Reserve Bank of St. Louis. We apply the following regressions:

$$Y_{t+1}^{K} = \alpha + \beta \cdot ICIX_{t}^{N} + \varepsilon_{t+1}, \tag{7}$$

where Y^{K} is one of the proxies of the macroeconomic conditions; $ICIX^{N}$ is either *ICIX*, or $ICIX^{\perp}$. We include $ICIX^{\perp}$ in the predictive regressions above to better demonstrate how the cognitive concerns, which are not reflected by expected inflation rates, indicate the macroeconomic conditions.

[TABLE 7 HERE]

As evidenced in Table 7, both *ICIX* and $ICIX^{\perp}$ significantly predict macroeconomic conditions. Specifically, the coefficients are negatively significant for *IPG*, *CFNAI*, *PRG*, and *ADSI*, indicating that heightened inflation concerns predict lower industrial production, employment growth, and worsening business conditions. Conversely, coefficients are positive for *VIX*, *KCFSI*, and *SRP*, suggesting that such concerns also predict increased market volatility, financial stress, and higher recession probabilities. Notably, apart from the coefficient of *ICIX* on *IPG*, which is significant at the 5% level, all other coefficients are significant at the 1% level. As robustness, we present the coefficient estimates for Eq. (7) within a pre-pandemic subsample period before 2020 in Panel B, Appendix IX and document consistent results.

In contrast, when evaluating the predictive capabilities of conventional inflation risk measures (as shown in Appendix X), we find that these proxies exhibit significantly weaker and often contrary effects on macroeconomic states. Collectively, these results suggest that investors' cognitive concerns about inflation encapsulate their perceptions and valuable insights into macroeconomic conditions, whereas traditional inflation risk measures, such as realized and expected inflation rates, fail to capture such information.

After examining the link of inflation concerns to macroeconomic conditions, we conduct an additional set of empirical tests to examine how inflation concerns correlates with mutual fund flows to U.S. capital market and money market securities. We obtain fund flow data from the Investment Company Institute. To account for any potential trends in mutual fund flows over time, we detrend the original fund flow data. Subsequently, we perform predictive regressions for *k*-month-ahead fund flows (*Flow*) as follows:

$$Flow_{t+k}^{n} = \alpha + \gamma \cdot ICIX_t + \sum \theta^j \cdot Control_t^j + \varepsilon_{t+k}, \quad (8)$$

where *Control* is the set of control variables including the lagged fund flow, monthly stock market return and realized volatility of daily market returns in a given month.

[TABLE 8 HERE]

Table 8 presents the estimation results. We observe that *ICIX* maintains a negative and significant correlation with the net fund flow to U.S. equities for up to six months. This implies that heightened inflation concerns push investors away from the equity market. The strongest predictive impact is seen at the monthly forecast horizon, diminishing progressively over the subsequent six months. The results also reveal that *ICIX* predicts a fund outflow from high-yield bonds, another class of relatively risky long-term assets, while it predicts inflows to the more secure, short-term money market funds. Collectively, these findings suggest that escalating inflation concerns induce investors to withdraw from capital market securities and gravitate towards money market instruments. This pattern aligns with the of “flight-to-safety” phenomenon, where investors seek to protect their capital from anticipated economic downturns. This evidence further affirms that the ICIX effectively indicates macroeconomic conditions and supports our empirical findings on return predictability.[17]

4. Conclusion

In this study, we introduce a new method to measure cognitive inflation concerns. This method captures investors' perceptions of inflation risk using media coverage and households' Internet searches on inflation-related topics. Compared to typical inflation risk measures such as the backward-looking realized inflation and forward-looking expected inflation rates, this approach offers a more immediate and effective measure of perceived inflation risk which impacts investment decisions, borrowing costs for households, companies, and governments, and consequently, stock returns. Using our inflation concerns index, we conduct a comprehensive analysis of the relationship between the inflation concerns and stock market returns.

Our results show that inflation concerns significantly and negatively predict aggregate stock market returns across various forecasting horizons. Notably, the predictive power of inflation concerns complements conventional inflation risk measures, showing dominant performance in monthly forecasts. Furthermore, we analyze the relationship between inflation concerns and macroeconomic conditions, demonstrating that inflation concerns' predictive ability stems from their capacity to indicate macroeconomic conditions, which conventional inflation risk proxies fail to capture. Moreover, our exploration of the link between inflation concerns and mutual fund flows reveals that such concerns prompt investors to shift from

[17] To further support the economic mechanism discussed in Section 3.5., we employ a simple equilibrium model whose implications align with our empirical evidence. The model is discussed in Appendix XI with the proof reported in Appendix XII.

capital market securities to money market instruments. This aligns with a "flight-to-safety" notation, confirming the economic mechanisms underlying return predictability.

Our paper makes several significant contributions. Firstly, we fill a gap in the existing literature by developing a market-wide cognitive inflation concerns index and analyzing its relationship with expected stock market returns. Secondly, our findings suggest that cognitive inflation concerns are distinct from economic statistics such as realized and expected inflation rates. Our results suggest that inflation concerns capture a broader range of macroeconomic information not fully reflected in explicit inflation rates. Thirdly, we highlight the pivotal role of news media and household Internet searches as reliable indicators of evolving investor concerns. These factors significantly impact investment decisions and market fluctuations. Additionally, our results underscore the value of using media coverage and Internet searches related to inflation for monitoring market concerns, providing valuable insights for policymakers and market participants to better anticipate and respond to perceived inflation risks.

References

Andreasen, M.M., Christensen, J.H., Riddell, S., 2021. The TIPS liquidity premium. Review of Finance 25, 1639-1675

Ardia, D., Bluteau, K., Boudt, K. and Inghelbrecht, K., 2023. Climate change concerns and the performance of green vs. brown stocks. Management Science, Forthcoming.

Baker, M., Wurgler, J., 2006. Investor sentiment and the cross‐section of stock returns. The Journal of Finance, 61, 1645-1680.

Bansal, R. and Yaron, A., 2004. Risks for the long run: A potential resolution of asset pricing puzzles. The Journal of Finance, 59(4), 1481-1509.

Barberis, N. and Thaler, R., 2003. A survey of behavioral finance. Handbook of the Economics of Finance, 1, 1053-1128.

Bekaert, G. and Wang, X., 2010. Inflation risk and the inflation risk premium. Economic Policy, 25(64), 755-806.

Benzoni, L., Collin-Dufresne, P. and Goldstein, R.S., 2011. Explaining asset pricing puzzles associated with the 1987 market crash. Journal of Financial Economics, 101(3), 552-573.

Bollerslev, T., Tauchen, G., Zhou, H., 2009. Expected stock returns and variance risk premia. The Review of Financial Studies, 22, 4463-4492.

Boons, M., Duarte, F., De Roon, F., Szymanowska, M., 2020. Time-varying inflation risk and stock returns. Journal of Financial Economics, 136, 444-470.

Boudoukh, J., Richardson, M., Whitelaw, R.F., 1994. Industry returns and the Fisher effect. The Journal of Finance, 49, 1595-1615.

Boyd, J.H., Levine, R., Smith, B.D., 2001. The impact of inflation on financial sector performance. Journal of Monetary Economics, 47, 221-248.

Campbell, J.Y., Shiller, R.J., Viceira, L.M., 2009. Understanding inflation-indexed bond markets. National Bureau of Economic Research

Campbell, J.Y., Vuolteenaho, T., 2004. Inflation illusion and stock prices. American Economic Review, 94, 19-23.

Cen, L., Wei, K.J., Yang, L., 2017. Disagreement, underreaction, and stock returns. Management Science, 63, 1214-1231.

Chen, N.F., Roll, R. and Ross, S.A., 1986. Economic forces and the stock market. Journal of Business, 383-403.

Christensen, J.H., Lopez, J.A. and Rudebusch, G.D., 2010. Inflation expectations and risk premiums in an arbitrage‐free model of nominal and real bond yields. Journal of Money, Credit and Banking, 42, 143-178.

Clark, T.E., West, K.D., 2007. Approximately normal tests for equal predictive accuracy in nested models. Journal of econometrics, 138, 291-311.

Cohen, L. and Frazzini, A., 2008. Economic links and predictable returns. The Journal of Finance, 63(4), 1977-2011.

D’Amico, S., Kim, D.H., Wei, M., 2018. Tips from TIPS: the informational content of Treasury Inflation-Protected Security prices. Journal of Financial and Quantitative Analysis, 53, 395-436.

Da, Z., Engelberg, J., Gao, P., 2015. The sum of all FEARS investor sentiment and asset prices. The Review of Financial Studies, 28, 1-32.

Dudley, W., Roush, J.E., Steinberg, M., 2009. The case for TIPS: An examination of the costs and benefits. Economic Policy Review 15

Duffee, G.R., 2018. Expected inflation and other determinants of Treasury yields. The Journal of Finance, 73, 2139-2180.

Easley, D., O'hara, M., 2004. Information and the cost of capital. The Journal of Finance, 59, 1553-1583.

Fama, E.F., 1981. Stock returns, real activity, inflation, and money. The American Economic Review, 71, 545-565.

Fama, E.F., Schwert, G.W., 1977. Asset returns and inflation. Journal of Financial Economics, 5, 115-146.

Ferson, W.E. and Harvey, C.R., 1991. The variation of economic risk premiums. Journal of Political Economy, 99(2), 385-415.

Gao, G.P., Lu, X. and Song, Z., 2019. Tail risk concerns everywhere. Management Science, 65(7), 3111-3130.

Gentzkow, M. and Shapiro, J.M., 2006. Media bias and reputation. Journal of Political Economy, 114(2), 280-316.

Geske, R. and Roll, R., 1983. The fiscal and monetary linkage between stock returns and inflation. The Journal of Finance, 38(1), pp.1-33.

Goldstein, I., Yang, L., 2015. Information diversity and complementarities in trading and information acquisition. The Journal of Finance 70(4), 1723-1765.

Gomez-Cram, R., Yaron, A., 2021. How important are inflation expectations for the nominal yield curve? The Review of Financial Studies, 34, 985-1045.

Goyal, A., Welch, I., 2008. A comprehensive look at the empirical performance of equity premium prediction. The Review of Financial Studies, 21, 1455-1508.

Gultekin, N.B., 1983. Stock market returns and inflation forecasts. The Journal of Finance 38, 663-673.

Gürkaynak, R.S., Sack, B., Wright, J.H., 2010. The TIPS yield curve and inflation compensation. American Economic Journal: Macroeconomics, 2, 70-92.

Hasbrouck, J., 1984. Stock returns, inflation, and economic activity: The survey evidence. The Journal of Finance, 39(5), 1293-1310.

Haubrich, J., Pennacchi, G., Ritchken, P., 2012. Inflation expectations, real rates, and risk premia: Evidence from inflation swaps. The Review of Financial Studies 25, 1588-1629.

Hong, H., Lim, T., Stein, J.C., 2000. Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. The Journal of Finance, 55, 265-295.

Hong, H., Stein, J.C., 1999. A unified theory of underreaction, momentum trading, and overreaction in asset markets. The Journal of Finance, 54, 2143-2184.

Horstmeyer, D., 2022. Which Stocks Do Best During High Inflation? In: The Wall Street Journal

Huang, D., Jiang, F., Tu, J., Zhou, G., 2015. Investor sentiment aligned: A powerful predictor of stock returns. The Review of Financial Studies, 28, 791-837.

Hodrick, R.J., 1992. Dividend yields and expected stock returns: Alternative procedures for inference and measurement. The Review of Financial Studies, 5(3), 357-386.

Jiang, F., Lee, J., Martin, X. and Zhou, G., 2019. Manager sentiment and stock returns. Journal of Financial Economics, 132(1), 126-149.

Kang, J. and Pflueger, C.E., 2015. Inflation risk in corporate bonds. The Journal of Finance, 70(1), 115-162.

Konchitchki, Y. and Xie, J., 2023. Undisclosed material inflation risk. Journal of Monetary Economics, Forthcoming.

Larsen, V.H., Thorsrud, L.A., Zhulanova, J., 2021. News-driven inflation expectations and information rigidities. Journal of Monetary Economics, 117, 507-520.

Lerner, J.S. and Keltner, D., 2001. Fear, anger, and risk. Journal of Personality and Social Psychology, 81(1), p.146.

Liu, Y., Matthies, B., 2022. Long‐Run Risk: Is It There? The Journal of Finance, 77(3), 1587-1633.

Manela, A. and Moreira, A., 2017. News implied volatility and disaster concerns. Journal of Financial Economics, 123(1), 137-162.

Mehra, R. and Prescott, E.C., 1985. The equity premium: A puzzle. Journal of Monetary Economics, 15(2), 145-161.

Menzly, L. and Ozbas, O., 2010. Market segmentation and cross‐predictability of returns. The Journal of Finance, 65(4), 1555-1580.

Nimark, K.P., Pitschner, S., 2019. News media and delegated information choice. Journal of Economic Theory, 181, 160-196.

Ritter, J.R., Warr, R.S., 2002. The decline of inflation and the bull market of 1982–1999. Journal of Financial and Quantitative Analysis 37, 29-61

Robinson, M.J., 2007. Two decades of American news preferences. Pew Research Center

Sack, B.P., Elsasser, R., 2004. Treasury inflation-indexed debt: a review of the US experience. Economic Policy Review 10

Shefrin, H., 2002. Beyond greed and fear: Understanding behavioral finance and the psychology of investing. Oxford University Press.

Slovic, P., 1987. Perception of Bisk. Science, 236(4799), 280-285.

Tetlock, P.C., 2007. Giving content to investor sentiment: The role of media in the stock market. The Journal of Finance, 62(3), 1139-1168.

Tetlock, P.C., Saar‐Tsechansky, M. and Macskassy, S., 2008. More than words: Quantifying language to measure firms' fundamentals. The Journal of Finance, 63(3), 1437-1467.

Trussler, M., Soroka, S., 2014. Consumer demand for cynical and negative news frames. The International Journal of Press/Politics, 19, 360-379.

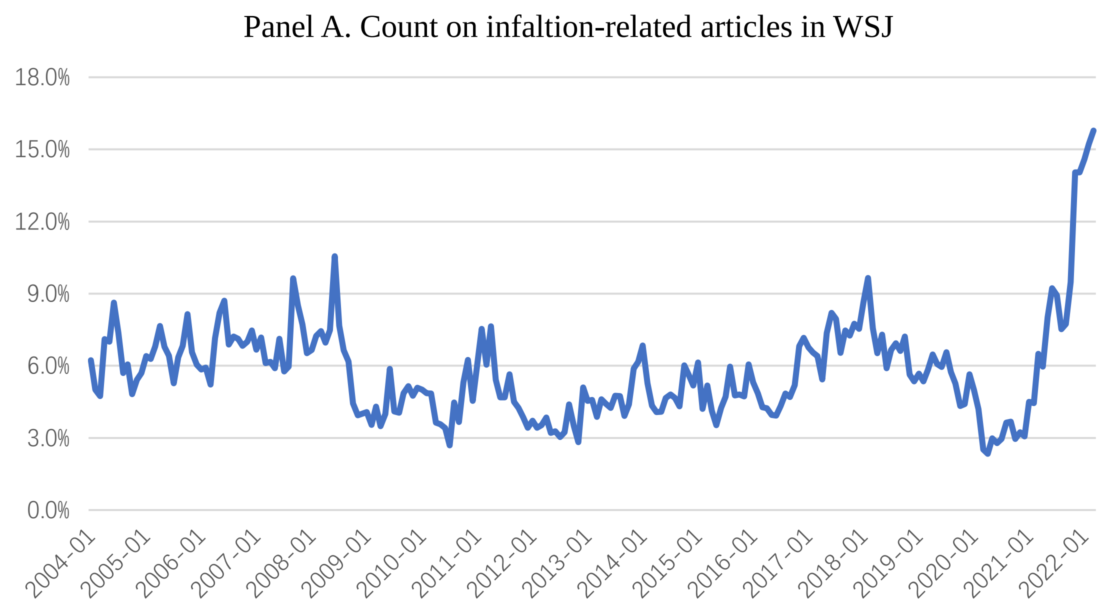
Appendix I: Variable Description

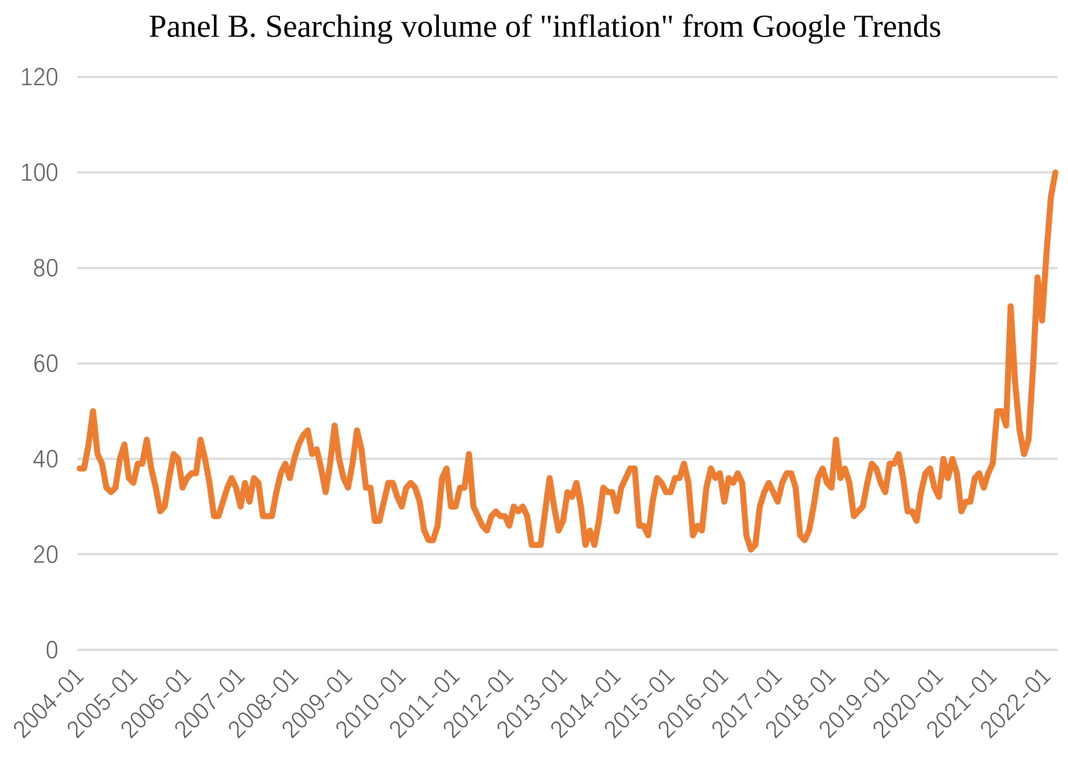
Variable	Description
ICIX	The Inflation Concern Index defined as the average of the news-based inflation concern (*NBIC*) index and searching-based inflation concern (*SBIC*) index
$ICIX^{PC}$	Alternative inflation concern index defined as the first principal component of the news-based inflation concerns (*NBIC*) index and searching-based inflation concerns (*SBIC*) index
$ICIX^{\perp}$	*ICIX* orthogonalized to the common systematic expected inflation, *EIPC*
NBIC	The news-based inflation concern index, calculated as the 12-month moving average of the monthly count of inflation-related articles in the *Wall Street Journal*
SBIC	The searching-based index of inflation concern, which captures household concerns. It is calculated as the 12-month moving average of the searching volume of inflation-related terms in Google Trend
TBL	Treasury bill rate as a classic proxy for expected inflation, defined as the yield of a one-month T-bill
INFL	Lagged realized inflation, calculated based on the Consumer Price Index (CPI) by Welch and Goyal (2008)
BRKE	Break-even inflation rate that is implied from the yields of TIPS
ISWAP	One-year inflation swap rate
UMSC	Expected inflation based on the University of Michigan Surveys of Consumers
SPF	Expected inflation based on Survey of Professional Forecasters
EI^{ARIMA}	Expected inflation estimated within an ARIMA(0,1,1) model
EIPC	Common systematic expected inflation defined as the first principal component of *BRKE*, *ISWAP*, *UMSC*, *SPF*, and EI^{ARIMA} to measure
INFUN	Inflation uncertainty defined as the 12-month standard deviation of *INFL*
DP	Dividend-price ratio, defined as the difference between the log of a 12-month moving sum of dividends paid on the S&P 500 index and the log of S&P 500 index price
DY	Dividend yield, defined as the difference between the log of S&P 500 dividends and the log of lagged S&P 500 prices
EP	Earnings-price ratio, defined as the difference between the log of earnings on the S&P 500 index and the log of prices
DE	Dividend-payout ratio, defined as the difference between the log of dividends and the log of earnings on the S&P 500 index
SVAR	Stock return variance, calculated as the sum of squared daily returns on the S&P 500 index
BM	Book-to-market ratio, defined as the ratio of book value to market value for the Dow Jones Industrial Average
NTIS	Net equity expansion, calculated as the 12-month moving sums of net issues by stocks listed on NYSE divided by the total end-of-year market capitalization of NYSE stocks
TBR	Treasury bill rate, defined as the yield of a 3-month T-bill;
LTY	Long-term yield, which is the long-term government bond yield
LTR	Long-term return, defined as the return on long-term government bonds

TMS	Term spread, calculated as the long-term yield minus the T-bill rate
DFY	Default yield spread, defined as the difference between BAA- and AAA-rated bond yields
DFR	Default return spread, calculated as the difference between the long-term corporate bond return and the long-term government bond return
IPG	Industrial Production Growth
CFNAI	the Chicago Fed National Activity Index
PRG	Total Non-farm Payroll Growth
ADSI	Aruoba-Diebold-Scotti Business Conditions Index
VIX	CBOE Volatility Index
KCFSI	Kansas City Financial Stress Index
SRP	Smoothed Recession Probability

Appendix II: Raw monthly article counts and Internet searching volume

Fig. A1





Panel A shows the original monthly percentage of inflation-related news articles out of the total number of articles from WSJ. Panel B presents the original monthly search volume for the term "inflation" from Google Trends as an example of all search terms. We observe a significant increase in both the article counts and search volumes following the implementation of quantitative easing measures in response to the COVID-19 pandemic.

Appendix III: Concerns about high inflation or low inflation?

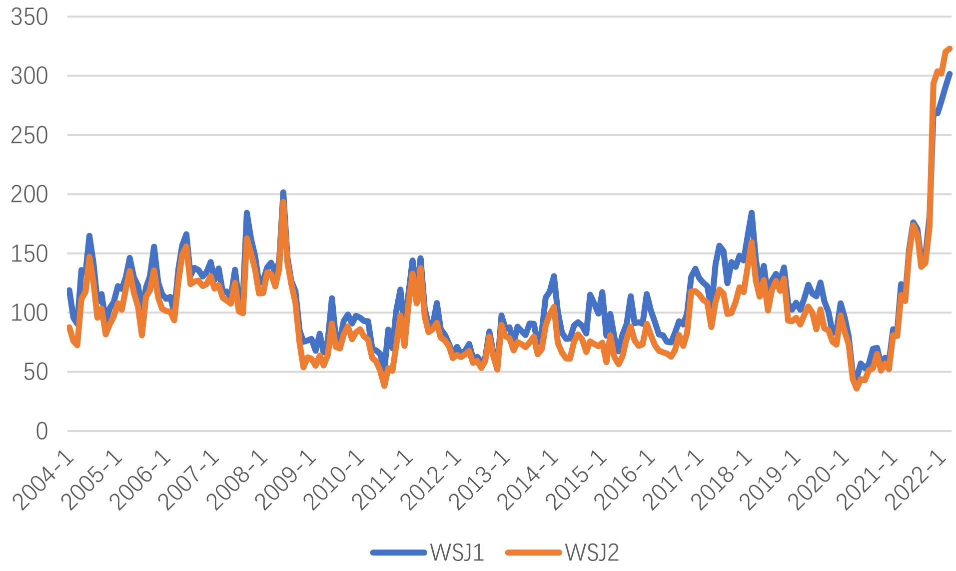
One aspect unique to inflation is that investors' concern may stem not only from inflation being too high but also too low. Inflation remained relatively low and stable throughout most of the sample period until after the onset of the COVID-19 crisis. While researchers argue that investors may be concerned about high in inflation even during periods of low and stable prices, there might also be reasons to expect that investor concern, corresponding news coverage and Internet search, may have also been focused on deflation during this particular period.

In this Appendix section, we examine whether ICIX mainly reflects concerns about high inflation. To do so, we delve into the two components of ICIX: the news-based inflation concern (*NBIC*) index and the searching-based inflation concern (*SBIC*) index, analyzing each separately.

For the NBIC index, a straightforward strategy to address potential concerns about low inflation is to exclude terms like "deflation" and "low inflation" when searching WSJ articles. Fig. A2 depicts two time series of standardized inflation concern indices derived from the WSJ: *WSJ1* represents the original raw index obtained by searching for inflation-related terms such as "inflation", "CPI", "PPI", "consumer price index", and "producer price index"; *WSJ2*, on the other hand, is an alternative index. While it includes the same set of inflation-related terms as *WSJ1*, it also specifically screens out terms like "deflation" and "low inflation".

A comparison reveals that these two time series are highly correlated. This suggests that the NBIC index, which is a component of ICIX, predominantly reflects concerns about high inflation rather than low inflation. Furthermore, substituting the original *WSJ1* with *WSJ2* in the ICIX construction process doesn't compromise the robustness of our tests.

Fig. A2

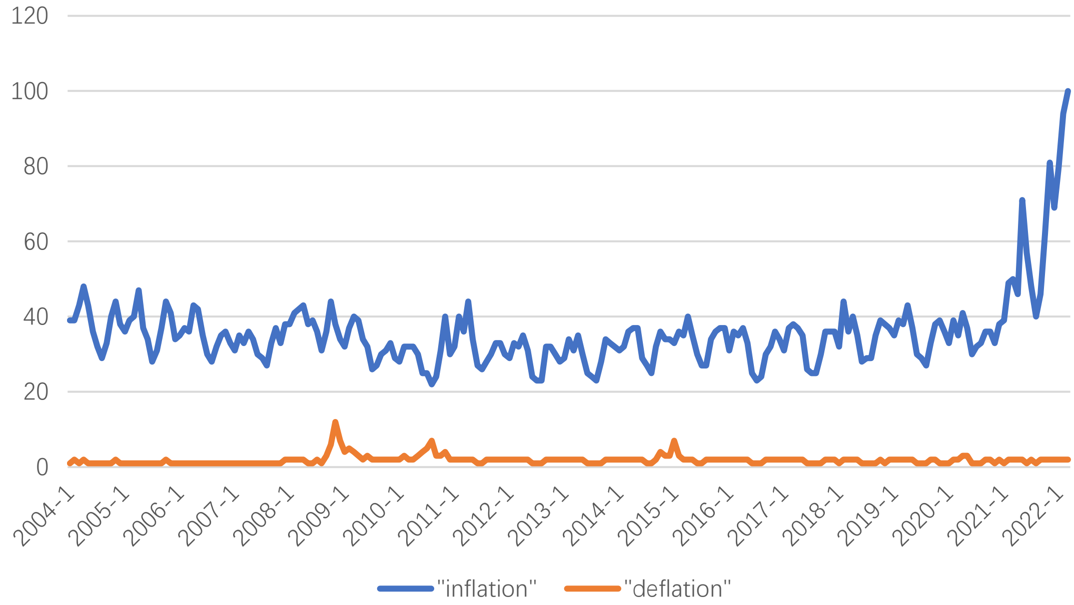


Regarding the SBIC index, the second component of ICIX, its design naturally minimizes the impact of low inflation. For instance, during a period of low inflation, should there be a surge in Internet searches for inflation-related terms, the result would be a juxtaposition of low realized inflation alongside high search volumes for those terms. By regressing these search volumes against lagged realized inflation, the resulting *t*-statistics are likely to be negative. This makes these terms less likely to be selected among the top five inflation-related terms, which are characterized by positive *t*-statistics.

To further reinforce the idea that terms such as “deflation” or “low inflation” are scarcely included in the SBIC index's construction, we present a comparison in Fig. A3. This presents the search volumes of “inflation” against “deflation”, and it is evident that the SBIC seldom captures concerns regarding deflation or low inflation.

Overall, both the NBIC and SBIC components provide compelling evidence. Taken together, they underscore the inclination of ICIX to reflect concerns about high inflation over those of low inflation.

Fig. A3



120
100
80
60
40
20
0
2004-1
2005-1
2006-1
2007-1
2008-1
2009-1
2010-1
2011-1
2012-1
2013-1
2014-1
2015-1
2016-1
2017-1
2018-1
2019-1
2020-1
2021-1
2022-1
"inflation"
"deflation"

Appendix IV: Predictive regressions with alternative rolling window for ICIX

Rolling window	β	t-stat	Adj. R^2	Rolling window	β	t-stat	Adj. R^2
n=1	-0.021**	(-2.20)	2.28%	n=13	-0.048***	(-2.63)	5.45%
n=2	-0.022**	(-2.41)	2.12%	n=14	-0.047**	(-2.47)	4.99%
n=3	-0.027**	(-2.49)	2.90%	n=15	-0.047**	(-2.41)	4.94%
n=4	-0.034***	(-2.67)	4.13%	n=16	-0.048**	(-2.36)	4.86%
n=5	-0.036***	(-2.80)	4.52%	n=17	-0.048**	(-2.31)	4.71%
n=6	-0.037***	(-2.78)	4.34%	n=18	-0.048**	(-2.25)	4.54%
n=7	-0.038***	(-2.74)	4.54%	n=19	-0.048**	(-2.19)	4.47%
n=8	-0.042***	(-2.84)	5.17%	n=20	-0.048**	(-2.13)	4.36%
n=9	-0.042***	(-2.75)	4.96%	n=21	-0.047**	(-2.02)	4.05%
n=10	-0.043***	(-2.74)	5.02%	n=22	-0.047*	(-1.97)	3.87%
n=11	-0.044***	(-2.72)	5.06%	n=23	-0.047*	(-1.96)	3.82%
n=12	-0.047***	(-2.72)	5.44%	n=24	-0.048*	(-1.96)	3.79%

This table reports the coefficient estimation of the univariate predictive regressions for alternative inflation concern indices constructed using various moving-average windows ($ICIX_t^n$). *T*he dependent variable is the one-month ahead aggregate stock market return. $ICIX_t^n$ is the inflation concern index calculated as the average of *n*-month moving average of the monthly raw news-based concern index and monthly raw Internet-search-based concern index. Newey-West *t*-statistics and adjusted R^2 are reported. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix V: Predictive regressions for ICIX components

Panel A: NBIC

Horizon	β	t	γ	t	Adj. R^2
1	-0.040^{***}	(-2.61)	-0.065	(-0.22)	3.71%
3	-0.038^{***}	(-2.61)	0.013	(0.05)	11.84%
6	-0.033^{**}	(-2.35)	0.125	(0.73)	19.73%
9	-0.029^{**}	(-2.33)	0.154	(1.31)	24.55%
12	-0.025^{**}	(-2.36)	0.153^{**}	(2.12)	26.73%
24	-0.017^{*}	(-1.86)	0.188^{***}	(3.59)	32.07%

Panel B: SBIC

Horizon	β	t	γ	t	Adj. R^2
1	-0.031^{***}	(-2.63)	0.199	(0.76)	3.36%
3	-0.031^{***}	(-2.76)	0.272	(1.30)	12.53%
6	-0.031^{**}	(-2.56)	0.380^{***}	(2.64)	25.81%
9	-0.032^{***}	(-2.98)	0.414^{***}	(3.54)	38.81%
12	-0.031^{***}	(-3.81)	0.418^{***}	(4.96)	48.95%
24	-0.022^{***}	(-6.84)	0.387^{***}	(6.45)	58.81%

Panel C: ICIX

Horizon	β	t	γ	t	Adj. R^2
1	-0.048^{***}	(-2.89)	0.102	(0.38)	5.17%
3	-0.047^{***}	(-3.06)	0.172	(0.79)	16.85%
6	-0.045^{***}	(-2.90)	0.278^{*}	(1.82)	30.78%
9	-0.043^{***}	(-3.25)	0.304^{**}	(2.52)	42.06%
12	-0.040^{***}	(-3.81)	0.297^{***}	(3.38)	49.08%
24	-0.027^{***}	(-4.29)	0.289^{***}	(4.44)	53.98%

This table reports the coefficient estimation of the following predictive regression:

$$\frac{1}{h}\sum_{j=1}^{h} r_{t+(j-1),t+j} = \alpha + \beta IC_t^j + \gamma ECON_t + \varepsilon_{t+h}$$

The dependent variable is the average monthly stock market return over the h month. IC^j could be either the news-based inflation concern (*NBIC*) index in Panel A, the searching-based inflation concern (*SBIC*) index in Panel B or the inflation concern index (*ICIX*), which is defined as the average of *NBIC* and *SBIC* in Panel C. *ECON* is included as the control variable, which is defined as the first principal component of the 13 individual economic predictors. See Appendix I for detailed definitions of those individual predictors. Newey-West standard errors are estimated and t-statistics are reported. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix VI: Robustness tests with alternative measures

Panel A

Horizon	β	t	γ	t	Adj. R^2
1	-0.009***	(-2.90)	0.080	(0.30)	5.22%
3	-0.009***	(-3.05)	0.151	(0.68)	16.87%
6	-0.008***	(-2.88)	0.257*	(1.67)	30.38%
9	-0.008***	(-3.17)	0.282**	(2.34)	40.98%
12	-0.007***	(-3.62)	0.276***	(3.15)	47.36%
24	-0.005***	(-3.81)	0.273***	(4.18)	52.03%

Panel B

Horizon	β	t	γ	t	Adj. R^2
1	-0.051***	(-2.98)	0.274	(1.14)	4.70%
3	-0.046***	(-2.88)	0.323	(1.65)	13.33%
6	-0.041***	(-2.64)	0.406***	(2.76)	22.86%
9	-0.040***	(-2.85)	0.423***	(3.38)	32.71%
12	-0.038***	(-3.22)	0.412***	(4.02)	40.73%
24	-0.027***	(-3.25)	0.371***	(3.90)	49.05%

These table report the coefficient estimation of the predictive regression with alternative measures for *ICIX*:

$$R_{t+1}^{m} = \alpha + \beta \cdot ICIX_t^{alt} + \gamma ECON_t + \varepsilon_{t+1}.$$

The dependent variable is the stock market return over the next month. $ICIX^{alt}$ is the alternative measure of inflation concerns, that could be either $ICIX^{PC}$, defined as the first principal component of *NBIC* and *SBIC*, in Panel A or $ICIX^{\perp}$, defined as *ICIX* orthogonalized to the common systematic expected inflation (*EIPC*) in Panel B. *ECON* is included as the control variable, which is defined as the first principal component of the 13 individual economic predictors. See Appendix I for detailed definitions of those individual predictors. Newey-West t-statistics with lag numbers equivalent to the forecast horizons are reported. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix VII: Complementary predictive effects of ICIX over multiple forecast horizons

Panel A: Three-month forecast

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IR	-0.004	-0.002	-0.000	-0.003	-0.014***	-0.028***	-0.066**	-0.004*	0.022
	(-0.33)	(-1.57)	(-0.02)	(-0.75)	(-2.62)	(-2.70)	(-2.54)	(-1.71)	(1.33)
IR measure	INFL	TBL	BRKE	ISWAP	UMSC	SPF	EI^{ARIMA}	EIPC	INFUN
Adj. R^2	-0.27%	1.05%	-0.49%	1.48%	11.84%	8.18%	11.12%	6.34%	1.48%

	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
ICIX	-0.045***	-0.048**	-0.045***	-0.045***	-0.036**	-0.038**	-0.037**	-0.041**	-0.051***
	(-2.91)	(-2.54)	(-3.02)	(-2.77)	(-2.60)	(-2.16)	(-2.56)	(-2.41)	(-3.55)
IR	-0.001	0.001	-0.001	-0.003	-0.009**	-0.015	-0.046*	-0.002	0.038**
	(-0.17)	(0.53)	(-0.27)	(-0.84)	(-2.07)	(-1.28)	(-1.84)	(-1.30)	(2.25)
IR measure	INFL	TBL	BRKE	ISWAP	UMSC	SPF	EI^{ARIMA}	EIPC	INFUN
Adj. R^2	15.24%	15.55%	15.37%	16.78%	20.40%	17.53%	20.27%	18.29%	20.86%

Panel B: Six-month forecast

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IR	-0.010*	-0.002*	-0.003	-0.005**	-0.016***	-0.027**	-0.071***	-0.005***	0.026**
	(-1.68)	(-1.85)	(-1.48)	(-2.53)	(-2.86)	(-2.25)	(-2.80)	(-3.03)	(2.19)
IR measure	INFL	TBL	BRKE	ISWAP	UMSC	SPF	EI^{ARIMA}	EIPC	INFUN
Adj. R^2	2.46%	3.65%	3.52%	9.73%	27.21%	14.38%	22.39%	19.72%	4.50%

	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
ICIX	-0.041***	-0.043**	-0.044***	-0.041***	-0.031***	-0.034**	-0.033***	-0.036***	-0.049***
	(-2.85)	(-2.18)	(-2.98)	(-2.94)	(-3.06)	(-2.33)	(-2.81)	(-2.89)	(-3.76)
IR	-0.009**	0.000	-0.004**	-0.005***	-0.012***	-0.017	-0.055**	-0.004***	0.042***
	(-2.11)	(0.19)	(-2.52)	(-2.93)	(-2.79)	(-1.36)	(-2.30)	(-2.92)	(2.63)
IR measure	INFL	TBL	BRKE	ISWAP	UMSC	SPF	EI^{ARIMA}	EIPC	INFUN
Adj. R^2	25.43%	23.17%	30.03%	33.48%	38.96%	28.18%	36.02%	36.68%	35.35%

Panel C: Nine-month forecast

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IR	-0.010**	-0.003*	-0.004***	-0.005***	-0.014***	-0.024**	-0.064***	-0.005***	0.022**
	(-2.18)	(-1.90)	(-2.75)	(-3.39)	(-3.09)	(-2.00)	(-2.75)	(-3.12)	(2.15)
IR measure	INFL	TBL	BRKE	ISWAP	UMSC	SPF	EI^{ARIMA}	EIPC	INFUN
Adj. R^2	4.46%	7.34%	8.07%	15.64%	29.27%	16.56%	24.95%	25.86%	4.81%

	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
ICIX	-0.038***	-0.038**	-0.042***	-0.039***	-0.030***	-0.032**	-0.031***	-0.033***	-0.045***
	(-3.04)	(-2.12)	(-3.53)	(-3.60)	(-2.80)	(-2.46)	(-2.96)	(-3.60)	(-4.16)
IR	-0.010**	-0.000	-0.005***	-0.006***	-0.011***	-0.015	-0.050**	-0.004***	0.037**
	(-2.34)	(-0.14)	(-3.59)	(-3.62)	(-3.31)	(-1.21)	(-2.32)	(-3.15)	(2.48)
IR measure	INFL	TBL	BRKE	ISWAP	UMSC	SPF	EI^{ARIMA}	EIPC	INFUN
Adj. R^2	33.33%	29.14%	43.02%	46.34%	45.69%	34.75%	43.37%	47.80%	43.01%

Panel D: One-year forecast

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IR	-0.011**	-0.003*	-0.004***	-0.005***	-0.011***	-0.022**	-0.053**	-0.004***	0.017**
	(-2.21)	(-1.96)	(-2.89)	(-3.22)	(-3.02)	(-2.07)	(-2.37)	(-2.93)	(2.05)
IR measure	INFL	TBL	BRKE	ISWAP	UMSC	SPF	EI^{ARIMA}	EIPC	INFUN
Adj. R^2	6.01%	12.43%	9.99%	18.10%	22.49%	17.64%	21.14%	25.78%	3.66%

	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
ICIX	-0.035***	-0.032**	-0.039***	-0.036***	-0.029**	-0.030**	-0.030***	-0.031***	-0.041***
	(-3.21)	(-2.21)	(-4.16)	(-4.22)	(-2.49)	(-2.50)	(-2.89)	(-3.80)	(-4.09)
IR	-0.010**	-0.001	-0.005***	-0.005***	-0.008***	-0.013	-0.038**	-0.003***	0.030***
	(-2.53)	(-0.63)	(-4.02)	(-4.02)	(-2.99)	(-1.27)	(-1.99)	(-3.12)	(2.61)
IR measure	INFL	TBL	BRKE	ISWAP	UMSC	SPF	EI^{ARIMA}	EIPC	INFUN
Adj. R^2	38.71%	33.83%	49.93%	53.00%	43.36%	38.66%	43.61%	51.06%	45.57%

Panel F: Two-year forecast

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IR	-0.006**	-0.004***	-0.003***	-0.004***	-0.007***	-0.019**	-0.036***	-0.003***	-0.002
	(-2.17)	(-3.02)	(-2.99)	(-3.60)	(-2.91)	(-2.46)	(-2.70)	(-3.65)	(-0.14)
IR measure	INFL	TBL	BRKE	ISWAP	UMSC	SPF	EI^{ARIMA}	EIPC	INFUN
Adj. R^2	3.58%	33.04%	15.19%	23.52%	15.81%	25.34%	17.21%	28.83%	-0.42%

	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
ICIX	-0.023**	-0.014**	-0.026***	-0.024***	-0.019*	-0.017**	-0.019**	-0.020***	-0.025***
	(-2.59)	(-2.16)	(-3.96)	(-3.79)	(-1.85)	(-2.35)	(-2.05)	(-2.92)	(-3.23)
IR	-0.006**	-0.003***	-0.004***	-0.004***	-0.005**	-0.014**	-0.026*	-0.003***	0.007
	(-2.00)	(-2.71)	(-5.42)	(-6.10)	(-2.05)	(-2.27)	(-1.87)	(-4.81)	(0.49)
IR measure	INFL	TBL	BRKE	ISWAP	UMSC	SPF	EI^{ARIMA}	EIPC	INFUN
Adj. R^2	28.61%	40.39%	47.49%	50.44%	32.26%	37.96%	34.23%	46.98%	26.70%

This table reports the coefficient estimations for the predictive regressions over one-month, three-month, six-month, nine-month, 12-month, and 24-month forecast horizons in Panels A, B, C, D, E, and F, respectively. The dependent variable R_{t+h}^{m} in each panel is the average monthly aggregate stock market return over next *h* months. Columns (1) to (9) reports the estimation results for the univariate predictive regressions:

$$\frac{1}{h}\sum_{j=1}^{h} r_{t+(j-1),t+j} = \alpha + \varphi \cdot IR_t^k + \varepsilon_{t+h}.$$

Columns (10) to (18) reports the estimation results for the bivariate predictive:

$$\frac{1}{h}\sum_{j=1}^{h} r_{t+(j-1),t+j} = \alpha + \beta \cdot ICIX_t + \varphi \cdot IR_t^k + \varepsilon_{t+h}.$$

IR^k is one of the typical inflation risk measures including: *INFL*, the lagged realized inflation; *TBL*, the one-month Treasury bill rate; *BRKE*, the break-even inflation rate that is implied from the yields of TIPS; *ISWAP*, the one-year inflation swap rate; *UMSC*, the expected inflation based on the University of Michigan Surveys of Consumers; *SPF*, the expected inflation based on Survey of Professional Forecasters, and EI^{ARIMA}, the expected inflation estimated within an ARIMA(0,1,1) model. *EIPC* is the first principal component of *BRKE*, *ISWAP*, *UMSC*, *SPF*, and EI^{ARIMA} to measure common systematic expected inflation. *INFUN* is the measures of inflation uncertainty, defined as the 12-month standard deviation of *INFL*. *ICIX* is our inflation concern index defined as the average of the news-based inflation concern (*NBIC*) index and searching-based inflation concern (*SBIC*) index. Newey-West t-statistics with lag numbers equivalent to the forecast horizons and adjusted R2 are reported. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix IX: Pre-pandemic Subsample Tests

Panel A: Return predictability

Horizon	β	t-stat	Adj. R^2
1	-0.045**	(-2.57)	4.94%
3	-0.044***	(-2.63)	14.99%
6	-0.042**	(-2.51)	29.57%
9	-0.039***	(-2.84)	41.28%
12	-0.036***	(-3.40)	49.59%
24	-0.027***	(-4.26)	54.99%

Panel B: Link to macroeconomic conditions

Y_{t+1}^{K}	β	t-stat	Adj. R^2
IPG	-1.018***	(-2.67)	9.29%
CFNAI	-1.284***	(-4.04)	24.75%
PRG	-0.537***	(-5.94)	36.06%
ADSI	-1.683***	(-3.91)	27.49%
VIX	0.174***	(3.56)	19.56%
KCFSI	3.440***	(4.53)	34.66%
SRP	0.771***	(4.81)	42.18%

These table reports the coefficient estimation of the predictive regression over a pre-pandemic sub-sample period as robustness tests. In Panel A, the dependent variable is the average monthly stock market return over the next h months. In Panel B, the dependent variable is of one of the macroeconomic condition variables one-month ahead, including the the Industrial Production Growth (*IPG*), the Chicago Fed National Activity Index (*CFNAI*), Total Non-farm Payroll Growth (*PRG*), the Aruoba-Diebold-Scotti Business Conditions Index (*ADSI*), the CBOE Volatility Index (*VIX*), the Kansas City Financial Stress Index (*KCFSI*) and Smoothed Recession Probability (*SRP*). *ICIX* is the key independent variable, defined as the average of the news-based inflation concern (*NBIC*) index and searching-based inflation concern (*SBIC*) index. In panel, *ECON* is included as the control variable for robustness, which is defined as the first principal component of the 13 individual economic predictors. Newey-West t-statistics with lag numbers equivalent to the forecast horizons and adjusted R2 are reported. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix VIII: Additional tests with other established predictors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ICIX	-0.048***		-0.056***		-0.052***		-0.042**		-0.043***
	(-2.89)		(-3.32)		(-3.05)		(-2.47)		(-2.65)
$SENT^{BW}$		-0.001	0.012*						
		(-0.07)	(1.69)						
$SENT^{PLS}$				-0.026	-0.029*				
				(-1.64)	(-1.93)				
$SENT^{manager}$						-0.008	-0.002		
						(-1.42)	(-0.42)		
SII								-0.005**	-0.002
								(-1.97)	(-0.85)
Adj. R^2	5.17%	-0.95%	5.66%	1.70%	7.99%	0.77%	4.95%	1.24%	4.98%

These table report the coefficient estimation of the predictive regression including both *ICIX* and another well-established predictor:

$$R_{t+1}^{m} = \alpha + \beta ICIX_t^{alt} + \mu Predictor_t^{K} + \gamma ECON_t + \varepsilon_{t+1}.$$

ICIX is our inflation concern index defined as the average of the news-based inflation concern (*NBIC*) index and searching-based inflation concern (*SBIC*) index. $Predictor^K$ could be either the sentiment index ($SENT^{BW}$) of Baker and Wugler (2006); the aligned sentiment ($SENT^{PLS}$) from Huang et al. (2015), the manager sentiment ($SENT^{manager}$) from Jiang et al. (2019), or the short interest index (*SII*) from Rapach et al. (2016). *ECON* is included as the control variable, which is defined as the first principal component of the 13 individual economic predictors. The sample period for columns (6) and (7) is 2004-2017 due to the data availability of $SENT^{manager}$, while for other columns, it is 2004-2021. Newey-West t-statistics with lag numbers equivalent to the forecast horizons and adjusted R2 are reported. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix X: Conventional inflation risk measures and macroeconomy

	INFL			TBL			BRKE		
	β	t-stat	Adj. R^2	β	t-stat	Adj. R^2	β	t-stat	Adj. R^2
IPG	0.106	(0.20)	-0.41%	-0.005	(-0.13)	-0.47%	0.287**	(2.57)	5.82%
CFNAI	0.119	(0.22)	-0.41%	0.011	(0.27)	-0.46%	0.361***	(2.70)	7.09%
PRG	-0.059	(-0.22)	-0.44%	-0.005	(-0.20)	-0.46%	0.170	(1.52)	2.62%
ADSI	0.580	(0.93)	0.22%	0.015	(0.21)	-0.46%	0.547**	(2.35)	7.71%
VIX	-0.053*	(-1.76)	3.13%	-0.013***	(-3.79)	4.18%	-0.044***	(-7.77)	33.18%
KCFSI	-1.024	(-1.60)	6.67%	-0.108**	(-2.13)	1.33%	-0.732***	(-7.62)	48.61%
SRP	-0.108	(-0.82)	1.30%	-0.008	(-0.88)	-0.25%	-0.108***	(-4.63)	23.04%

	ISWAP			UMSC			SPF		
	β	t-stat	Adj. R^2	β	t-stat	Adj. R^2	β	t-stat	Adj. R^2
IPG	0.306**	(2.00)	6.31%	0.156	(0.70)	0.06%	-0.260	(-0.80)	-0.20%
CFNAI	0.378**	(1.99)	7.37%	0.168	(0.69)	0.00%	-0.085	(-0.24)	-0.45%
PRG	0.198	(1.28)	3.51%	0.154	(0.97)	0.25%	-0.064	(-0.38)	-0.45%
ADSI	0.635**	(1.97)	9.95%	0.425	(1.01)	0.93%	-0.094	(-0.19)	-0.46%
VIX	-0.042***	(-7.68)	27.84%	0.002	(0.10)	-0.46%	-0.100***	(-3.13)	8.23%
KCFSI	-0.667***	(-5.01)	38.05%	0.045	(0.15)	-0.42%	-1.128*	(-1.83)	5.56%
SRP	-0.094***	(-2.91)	16.40%	0.073	(0.99)	2.58%	-0.012	(-0.08)	-0.46%

	EI^{ARIMA}			EIPC			INFUN		
	β	t-stat	Adj. R^2	β	t-stat	Adj. R^2	β	t-stat	Adj. R^2
IPG	-0.322	(-0.30)	-0.38%	0.096	(1.18)	1.13%	0.067	(0.10)	-0.47%
CFNAI	-0.096	(-0.09)	-0.46%	0.133	(1.48)	1.84%	-0.480	(-0.65)	-0.23%
PRG	-0.080	(-0.16)	-0.46%	0.070	(1.19)	0.72%	-0.155	(-0.36)	-0.42%
ADSI	0.012	(0.01)	-0.47%	0.228	(1.56)	2.74%	-0.332	(-0.29)	-0.42%
VIX	-0.073	(-0.72)	0.54%	-0.019***	(-3.59)	13.77%	0.185***	(3.34)	9.99%
KCFSI	-1.631	(-0.92)	2.25%	-0.301**	(-2.57)	18.29%	3.751***	(3.70)	22.71%
SRP	-0.046	(-0.12)	-0.42%	-0.030	(-1.05)	3.55%	0.545**	(2.30)	10.34%

This table reports the coefficient estimation for the monthly univariate predictive regression for macroeconomic states with conventional inflation risk measures:

$$Y_{t+1}^{K} = \alpha + \beta \cdot IR_t^k + \varepsilon_{t+1},$$

where Y^K is one of the macroeconomic condition proxies, including the the Industrial Production Growth (*IPG*), the Chicago Fed National Activity Index (*CFNAI*), Total Non-farm Payroll Growth (*PRG*), the Aruoba-Diebold-Scotti Business Conditions Index (*ADSI*), the CBOE Volatility Index (*VIX*), the Kansas City Financial Stress Index (*KCFSI*) and Smoothed Recession Probability (*SRP*). IR^k is one of the typical inflation risk measures including: *INFL*, the lagged realized inflation; *TBL*, the one-month Treasury bill rate; *BRKE*, the break-even inflation rate that is implied from the yields of TIPS; *ISWAP*, the one-year inflation swap rate; *UMSC*, the expected inflation based on the University of Michigan Surveys of Consumers; *SPF*, the expected inflation based on Survey of Professional Forecasters, and

EI^{ARIMA}, the expected inflation estimated within an ARIMA(0,1,1) model. *EIPC* is the first principal component of *BRKE*, *ISWAP*, *UMSC*, *SPF*, and EI^{ARIMA} to measure common systematic expected inflation. *INFUN* is the measures of inflation uncertainty, defined as the 12-month standard deviation of *INFL*. Newey-West standard errors are estimated and *t*-statistics are reported. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix XI: A Conceptual Model

In this appendix, we present a parsimonious model to explore the economic mechanism of our empirical findings. The proof is provided in the Appendix XII. Following Easley and O'hara (2004) and Cen et al. (2017), we consider a two-period model: Day zero when investors choose portfolios, and Day one when cash flows are realized and all investors consume. There are two assets traded in the financial market: one riskless asset (i.e., bond) and one risky asset (i.e., stock). The bond is in unlimited supply; its payoff is one and its price is normalized to one. The stock has a total supply of one unit; it has a price of $\tilde{p}$, endogenously determined in the financial market, and it pays a dividend.

$$\tilde{v} = \bar{v} - \tilde{\pi} + \tilde{\varepsilon}, \tag{A1}$$

where parameter $\bar{v} > 0$ is a constant representing the unconditional mean of the representative firm's cash flow $\tilde{v}$, the random variable $\tilde{\pi} \sim N(0,1/\tau_\pi)$ represents any negative macroeconomic shocks such as inflation shocks that can harm the economy, and the random variable $\tilde{\varepsilon} \sim N(0,1)$ is the residual uncertainty of the firm's cash flow.

Boons et al. (2020) use a consumption-based asset pricing model to suggest that the negative risk premium of inflation risk in the cross-section of stock returns can be attributed to the fact that inflation can negatively predict real consumption growth. When the market clears, all consumption should source from dividends (Mehra and Prescott, 1985; Bansal and Yaron, 2004; Benzoni et al., 2011). Our model has the same nature as theirs; that is, negative macroeconomic shocks negatively predict the economy, and therefore negatively predicts the equity risk premium.

However, negative macroeconomic shocks $\tilde{\pi}$ cannot be directly observed ex-ante. For investors, they form their concerns (denoted $\tilde{s}$) about negative macroeconomic shocks via media news and Internet resources on specific topics. We further assume that there are two groups of optimizing traders; that is, informed and uninformed traders who have a constant absolute risk aversion (CARA) utility function with the same risk aversion parameter $\gamma > 0$. There is a fraction λ of informed traders, where $0 \leq \lambda \leq 1$. The uninformed traders optimize their utility by observing the current stock price $\tilde{p}$. The informed traders cannot observe $\tilde{\pi}$; instead, in addition to $\tilde{p}$, they perceive negative macroeconomic shocks via their concerns on these shocks,

$$\tilde{s} = \tilde{\pi} + \tilde{\delta}, \tag{A2}$$

where the random variable $\tilde{\delta} \sim N(0,1/\tau_{\delta})$.

Finally, to prevent fully revealing prices, we assume that there are noise traders who trade a random amount $\tilde{x} \sim N(0,1/\tau_x)$ of the stock.

As is well known, the CARA-normal setup assumed here implies that the demand function of the traders of type $j = I, U$ is

$$D(\mathcal{F}_j) = \frac{E(\tilde{v}|\mathcal{F}_j) - \tilde{p}}{\gamma Var(\tilde{v}|\mathcal{F}_j)}, \tag{A3}$$

where $\mathcal{F}_j$ is the traders' information set,

$$\mathcal{F}_I = \{\tilde{s}, \tilde{p}\}, \quad \mathcal{F}_U = \{\tilde{p}\}. \tag{A4}$$

The equilibrium price is determined by the market-clearing condition for the risky asset:

$$\lambda D(\tilde{s}, \tilde{p}) + (1 - \lambda) D(\tilde{p}) + \tilde{x} = 1 \tag{A5}$$

We assume that all random variables are independent of each other. As in most of the literature, we consider a linear equilibrium, where the price $\tilde{p}$ linearly depends on the signals and the noisy trading,

$$\tilde{p} = \bar{v} - \alpha_0 - \alpha_s \tilde{s} - \alpha_x \tilde{x}, \tag{A6}$$

where α_0, α_s, and α_x are solved in Appendix XII. In particular, we show that $0 < \alpha_s < 1$ and $\alpha_x < 0$.

We define the (dollar) return $\tilde{R} = \tilde{v} - \tilde{p}$, which could be rewritten as:

$$\tilde{R} = \alpha_0 + (\alpha_s \tilde{s} - \tilde{\pi}) + \alpha_x \tilde{x} + \tilde{\varepsilon} = \alpha_0 + (\alpha_s - 1)\tilde{s} + \tilde{\delta} + \alpha_x \tilde{x} + \tilde{\varepsilon}. \tag{A7}$$

Then, using $0 < \alpha_s < 1$, the regression coefficient of $\tilde{s}$ used to forecast return $\tilde{R}$ is

$$\beta = \frac{Cov(\tilde{R}, \tilde{s})}{Var(\tilde{s})} = \frac{(\alpha_s - 1)}{Var(\tilde{s})} < 0. \tag{A8}$$

The negative regression coefficient of $\tilde{s}$ suggests that concerns on negative macroeconomic shocks such as inflation concerns can negatively predict market stock returns. Our model reveals that the negative relationship between concerns on negative macroeconomic shocks and the future market return empirically documented in this paper can be attributed to the fact that negative macroeconomic shocks would harm the economy, for example, firms' future cash flow.

Furthermore, according to Goldstein and Yang (2015), the aggregate trading intensity of informed traders (i.e., traders with concerns on negative macroeconomic shocks) could be defined as

$$I = \lambda \frac{\partial D(\tilde{s}, \tilde{p})}{\partial \tilde{s}} = \frac{\alpha_s}{\alpha_x} < 0. \tag{A9}$$

The above equation generally shows that a unit increase in $\tilde{s}$ will cause the traders with concerns on negative macroeconomic shocks to buy I more stocks. In other words, due to the fact that negative macroeconomic shocks decrease the firms' future cash flow, informed traders will sell stocks with increase in $\tilde{s}$. This is consistent with our findings of mutual fund flows: investors facing high inflation concerns tend to withdraw from capital market securities and lean more towards money market instruments, leading to lower market returns the following month.

Appendix XII: Proof

The information contained in the price $\tilde{p}$ is equivalent to the following signal,

$$\tilde{s}_p = \frac{\tilde{p} - \bar{v} + \alpha_0}{-\alpha_\pi} = \tilde{s} + m^{-1}\tilde{x},$$

with precision $\tau_p = m^2\tau_x$ and $m = \frac{\alpha_s}{\alpha_x}$.

By Bayes's rule, we can compute the conditional moments as follows:

$$\begin{aligned} E(\tilde{v}|\tilde{s},\tilde{p}) &= \bar{v} - \frac{\tau_\delta \tilde{s}}{\tau_\pi + \tau_\delta}, \quad Var(\tilde{v}|\tilde{s},\tilde{p}) = \frac{1 + \tau_\pi + \tau_\delta}{\tau_\pi + \tau_\delta}, \\ E(\tilde{v}|\tilde{p}) &= \bar{v} - \frac{\tau_\delta \tau_p \tilde{s}_p}{\tau_\delta\tau_\pi + \tau_\delta\tau_p + \tau_\pi\tau_p}, \quad Var(\tilde{v}|\tilde{p}) = \frac{\tau_\delta\tau_\pi + \tau_\delta\tau_p + \tau_\pi\tau_p + \tau_\delta + \tau_p}{\tau_\delta\tau_\pi + \tau_\delta\tau_p + \tau_\pi\tau_p}. \end{aligned}$$

The demands of traders are

$$\begin{aligned} D(\tilde{v}|\tilde{s},\tilde{p}) &= \frac{(\bar{v} - \tilde{p})(\tau_\pi + \tau_\delta) - \tau_\delta \tilde{s}}{\gamma(1 + \tau_\pi + \tau_\delta)}, \\ D(\tilde{v}|\tilde{p}) &= \frac{(\bar{v} - \tilde{p})\left(\tau_\delta\tau_\pi + \tau_\delta\tau_p + \tau_\pi\tau_p\right) - \tau_\delta\tau_p\tilde{s}_p}{\gamma\left(\tau_\delta\tau_\pi + \tau_\delta\tau_p + \tau_\pi\tau_p + \tau_\delta + \tau_p\right)}. \end{aligned}$$

Plugging into market clear condition, we have

$$\begin{aligned} \tilde{p} &= \bar{v} - \frac{\gamma(1 + \tau_\pi + \tau_\delta)\left(\tau_\delta\tau_\pi + \tau_\delta\tau_p + \tau_\pi\tau_p + \tau_\delta + \tau_p\right)}{\lambda\left(\tau_\delta\tau_\pi + \tau_\delta\tau_p + \tau_\pi\tau_p + \tau_\delta + \tau_p\right)(\tau_\pi + \tau_\delta) + (1 - \lambda)(1 + \tau_\pi + \tau_\delta)\left(\tau_\delta\tau_\pi + \tau_\delta\tau_p + \tau_\pi\tau_p\right)} \\ &\quad - \frac{\lambda\left(\tau_\delta\tau_\pi + \tau_\delta\tau_p + \tau_\pi\tau_p + \tau_\delta + \tau_p\right)\tau_\delta + (1 - \lambda)(1 + \tau_\pi + \tau_\delta)\tau_\delta\tau_p}{\lambda\left(\tau_\delta\tau_\pi + \tau_\delta\tau_p + \tau_\pi\tau_p + \tau_\delta + \tau_p\right)(\tau_\pi + \tau_\delta) + (1 - \lambda)(1 + \tau_\pi + \tau_\delta)\left(\tau_\delta\tau_\pi + \tau_\delta\tau_p + \tau_\pi\tau_p\right)}\tilde{s} \\ &\quad - \frac{(1 - \lambda)(1 + \tau_\pi + \tau_\delta)\tau_\delta\tau_p m^{-1} - \gamma(1 + \tau_\pi + \tau_\delta)\left(\tau_\delta\tau_\pi + \tau_\delta\tau_p + \tau_\pi\tau_p + \tau_\delta + \tau_p\right)}{\lambda\left(\tau_\delta\tau_\pi + \tau_\delta\tau_p + \tau_\pi\tau_p + \tau_\delta + \tau_p\right)(\tau_\pi + \tau_\delta) + (1 - \lambda)(1 + \tau_\pi + \tau_\delta)\left(\tau_\delta\tau_\pi + \tau_\delta\tau_p + \tau_\pi\tau_p\right)}\tilde{x}. \end{aligned}$$

It leads to

$$m^{-1} = \frac{(1 - \lambda)(1 + \tau_\pi + \tau_\delta)\tau_\delta\tau_p m^{-1} - \gamma(1 + \tau_\pi + \tau_\delta)\left(\tau_\delta\tau_\pi + \tau_\delta\tau_p + \tau_\pi\tau_p + \tau_\delta + \tau_p\right)}{\lambda\left(\tau_\delta\tau_\pi + \tau_\delta\tau_p + \tau_\pi\tau_p + \tau_\delta + \tau_p\right)\tau_\delta + (1 - \lambda)(1 + \tau_\pi + \tau_\delta)\tau_\delta\tau_p}.$$

Then m could be solved as

$$m = -\frac{\lambda\tau_\delta}{\gamma(1 + \tau_\pi + \tau_\delta)}.$$

Finally, we get

$$
\begin{aligned}
\alpha_0 &= \frac{\gamma(1+\tau_\pi+\tau_\delta)\left(\tau_\delta\tau_\pi+\tau_\delta\tau_p+\tau_\pi\tau_p+\tau_\delta+\tau_p\right)}{\lambda\left(\tau_\delta\tau_\pi+\tau_\delta\tau_p+\tau_\pi\tau_p+\tau_\delta+\tau_p\right)(\tau_\pi+\tau_\delta)+(1-\lambda)(1+\tau_\pi+\tau_\delta)\left(\tau_\delta\tau_\pi+\tau_\delta\tau_p+\tau_\pi\tau_p\right)} \\
\alpha_s &= \frac{\lambda\left(\tau_\delta\tau_\pi+\tau_\delta\tau_p+\tau_\pi\tau_p+\tau_\delta+\tau_p\right)\tau_\delta+(1-\lambda)(1+\tau_\pi+\tau_\delta)\tau_\delta\tau_p}{\lambda\left(\tau_\delta\tau_\pi+\tau_\delta\tau_p+\tau_\pi\tau_p+\tau_\delta+\tau_p\right)(\tau_\pi+\tau_\delta)+(1-\lambda)(1+\tau_\pi+\tau_\delta)\left(\tau_\delta\tau_\pi+\tau_\delta\tau_p+\tau_\pi\tau_p\right)} \\
\alpha_x &= \frac{(1-\lambda)(1+\tau_\pi+\tau_\delta)\tau_\delta\tau_p m^{-1}-\gamma(1+\tau_\pi+\tau_\delta)\left(\tau_\delta\tau_\pi+\tau_\delta\tau_p+\tau_\pi\tau_p+\tau_\delta+\tau_p\right)}{\lambda\left(\tau_\delta\tau_\pi+\tau_\delta\tau_p+\tau_\pi\tau_p+\tau_\delta+\tau_p\right)(\tau_\pi+\tau_\delta)+(1-\lambda)(1+\tau_\pi+\tau_\delta)\left(\tau_\delta\tau_\pi+\tau_\delta\tau_p+\tau_\pi\tau_p\right)}.
\end{aligned}
$$

The solution of α_s implies that $0<\alpha_s<1$ and the solution of α_x implies that $\alpha_x<0$.

Fig. 1

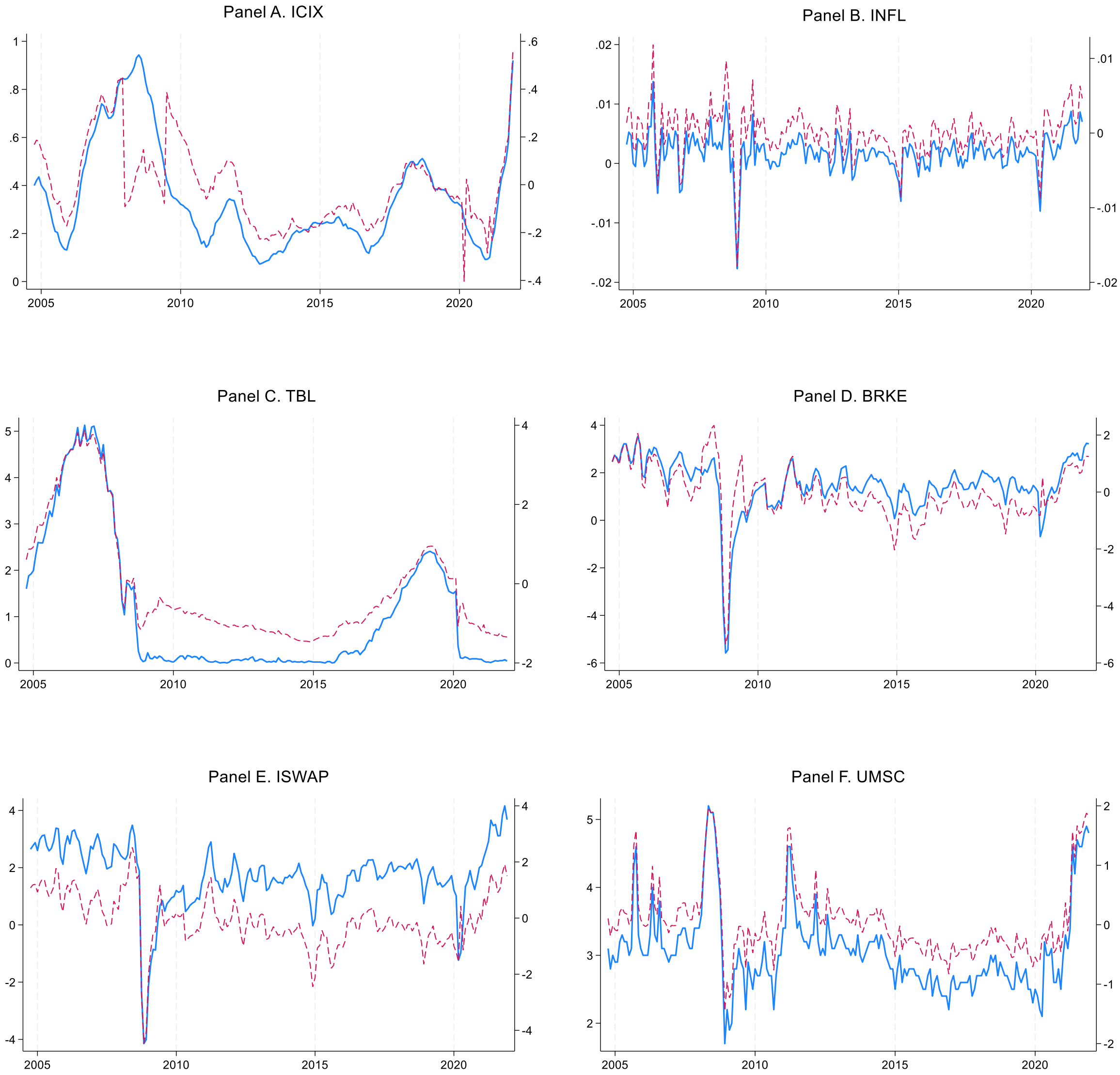

Panel A. ICIX
Panel B. INFL
Panel C. TBL
Panel D. BRKE
Panel E. ISWAP
Panel F. UMSC

Fig. 1 displays the historical trends of inflation risk measures. Specifically, *ICIX* is our inflation concerns index capturing perceived inflation risk; *INFL* and *TBL* are typical inflation risk measures defined as the lagged realized inflation and the one-month Treasury bill rate, respectively. *INFL* is the lagged realized inflation; *TBL*, the one-month Treasury bill rate; *BRKE* is the break-even inflation rate that is implied from the yields of TIPS; *ISWAP*, the one-year inflation swap rate; *UMSC* is the expected inflation based on the University of Michigan Surveys of Consumers; *SPF* is the expected inflation based on Survey of Professional Forecasters; EI^{ARIMA} is the expected inflation estimated within an ARIMA(0,1,1) model; *EIPC* is the first principal component of *BRKE*, *ISWAP*, *UMSC*, *SPF*, and EI^{ARIMA} to measure common systematic expected inflation. *INFUN* is the measures of inflation uncertainty, defined as the 12-month standard deviation of *INFL*. The solid lines (left axis) are the original data, whereas the dash lines (right axis) illustrate the values orthogonalized to the industrial production index, consumption growth, and recession indicator.

Table 1 Statistic summary

Panel A	Mean	SD	Min	Max	5^{th} pctl	Median	95^{th} pctl
R_m	0.0076	0.0421	-0.1694	0.1268	0.0126	-0.0718	0.0691
ICIX	0.3482	0.2180	0.0729	0.9434	0.2854	0.1057	0.8423
INFL	0.1875	0.3207	-1.7706	1.3768	0.1981	-0.2812	0.6387
TBL	1.1257	1.5267	0.0000	5.1300	0.1500	0.0200	4.7100
BRKE	1.4888	1.1749	-5.5812	3.5268	1.5434	-0.0749	2.9920
ISWAP	1.7236	1.1430	-4.1480	4.1600	1.7900	0.0950	3.2700
UMSC	3.0802	0.6320	1.7000	5.2000	3.0000	2.4000	4.6000
SPF	2.1299	0.2613	1.5551	2.6651	2.1304	1.7069	2.6146
EI^{ARIMA}	0.1858	0.1266	-0.2778	0.5779	0.1761	-0.0235	0.4114
EIPC	-0.0858	1.7863	-7.6373	4.5883	-0.2464	-2.4815	3.0666
INFUN	0.0026	0.0015	0.0007	0.0079	0.0020	0.0012	0.0069

This table presents the statistical summary of the key variables. *ICIX* is our inflation concern index defined as the average of the news-based inflation concern (*NBIC*) index and searching-based inflation concern (*SBIC*) index. $ICIX^{PC}$ is an alternative measure of inflation concerns estimated as the first principal component of *NBIC* and *SBIC*. *INFL* is the lagged realized inflation; *TBL*, the one-month Treasury bill rate; *BRKE* is the break-even inflation rate that is implied from the yields of TIPS; *ISWAP*, the one-year inflation swap rate; *UMSC* is the expected inflation based on the University of Michigan Surveys of Consumers; *SPF* is the expected inflation based on Survey of Professional Forecasters; EI^{ARIMA} is the expected inflation estimated within an ARIMA(0,1,1) model; *EIPC* is the first principal component of *BRKE*, *ISWAP*, *UMSC*, *SPF*, and EI^{ARIMA} to measure common systematic expected inflation. *INFUN* is the measures of inflation uncertainty, defined as the 12-month standard deviation of *INFL*.

Table 2 Baseline simple-factor predictive regressions

Horizon	β	t	Adj. R^2
1	-0.047***	(-2.72)	5.44%
3	-0.045***	(-2.92)	15.63%
6	-0.041***	(-2.70)	23.47%
9	-0.038***	(-2.77)	29.45%
12	-0.035***	(-2.84)	33.34%
24	-0.023**	(-2.49)	25.72%

This table reports the coefficient estimation of the baseline predictive regression:

$$\frac{1}{h}\sum_{j=1}^{h} r_{t+(j-1),t+j} = \alpha + \beta \cdot ICIX_t + \varepsilon_{t+h}.$$

The dependent variable is the average monthly stock market return over the next *h* months. *ICIX* is our inflation concern index defined as the average of the news-based inflation concern (*NBIC*) index and searching-based inflation concern (*SBIC*) index. Newey-West standard errors are estimated and *t*-statistics are reported. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3 Comparison with economic variables

	Panel A: Univariate regressions $R^m_{t+1} = \alpha + \varphi Z^k_t + \varepsilon_{t+1}$			*Panel B: Bivariate regressions* $R^m_{t+1} = \alpha + \beta ICIX_t + \varphi Z^k_t + \varepsilon_{t+1}$				
	φ	t-stat	Adj. R^2	β	t-stat	φ	t-stat	Adj. R^2
DP	0.008	(0.25)	-0.41%	-0.048***	(-2.92)	0.016	(0.58)	5.34%
DY	0.013	(0.43)	-0.28%	-0.048***	(-2.81)	0.018	(0.62)	5.37%
EP	-0.005	(-0.45)	-0.30%	-0.051***	(-3.02)	-0.011	(-1.14)	6.00%
DE	0.004	(0.41)	-0.29%	-0.052***	(-3.08)	0.009	(1.06)	6.03%
SVAR	-0.036	(-0.04)	-0.48%	-0.050***	(-3.01)	0.319	(0.38)	5.28%
BM	0.028	(0.48)	-0.37%	-0.051**	(-2.55)	-0.047	(-0.68)	5.28%
NTIS	0.333	(1.40)	1.39%	-0.044***	(-2.93)	0.065	(0.33)	5.03%
TBR	-0.216	(-1.48)	0.14%	-0.050**	(-2.38)	0.091	(0.44)	5.07%
LTY	-0.540**	(-2.16)	1.95%	-0.042**	(-2.34)	-0.225	(-0.95)	5.32%
LTR	0.110	(0.97)	0.20%	-0.049***	(-2.79)	0.141	(1.33)	6.11%
TMS	-0.169	(-0.66)	-0.22%	-0.049***	(-2.74)	-0.275	(-1.01)	5.68%
DFY	-0.440	(-0.36)	-0.26%	-0.049***	(-3.14)	0.347	(0.31)	5.10%
DFR	0.156	(0.59)	0.13%	-0.046***	(-2.82)	0.086	(0.36)	5.16%
ECON	0.037	(0.13)	-0.46%	-0.048***	(-2.89)	0.102	(0.38)	5.17%

This table reports the coefficient estimation of typical economic predictors. Panel A reports the in-sample estimation results for the univariate predictive regressions of the monthly market return on one of the lagged economic variables, Z^k_t,

$$R^m_{t+1} = \alpha + \varphi \cdot Z^k_t + \varepsilon_{t+1},$$

where R^m_{t+1} is the monthly aggregate stock market return, and Z^k_t is one of the 13 individual economic predictors or their first principal component (*ECON*). See Appendix I for detailed definitions of those individual predictors. Panel B reports the estimation results for the bivariate predictive regressions on both the lagged inflation concern index $ICIX_t$ and Z^k_t,

$$R^m_{t+1} = \alpha + \beta \cdot ICIX_t + \varphi \cdot Z^k_t + \varepsilon_{t+1}.$$

ICIX is our inflation concern index defined as the average of the news-based inflation concern (*NBIC*) index and searching-based inflation concern (*SBIC*) index. Newey-West *t*-statistics and adjusted R^2 are reported. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4 Portfolio return predictability

Panel A: Size Portfolios	Small	2	3	4	5	6	7	8	9	Big
β	-0.076***	-0.071***	-0.066***	-0.055**	-0.058***	-0.053**	-0.057***	-0.058***	-0.053***	-0.045***
	(-3.31)	(-3.07)	(-2.94)	(-2.50)	(-2.62)	(-2.53)	(-2.70)	(-2.83)	(-2.61)	(-2.86)
Adj. R^2	6.83%	5.15%	4.95%	3.71%	4.25%	4.09%	4.91%	5.93%	5.72%	5.37%

Panel B: BtM Portfolios	Low	2	3	4	5	6	7	8	9	High
β	-0.043**	-0.041**	-0.049***	-0.046***	-0.047***	-0.052***	-0.071***	-0.057**	-0.050**	-0.067**
	(-2.23)	(-2.57)	(-3.03)	(-2.62)	(-2.86)	(-2.66)	(-3.09)	(-2.21)	(-2.33)	(-2.29)
Adj. R^2	3.83%	4.00%	6.25%	4.49%	4.91%	4.96%	8.59%	4.47%	2.92%	3.22%

Panel C: Momentum Portfolios	Loser	2	3	4	5	6	7	8	9	Winner
β	-0.086**	-0.062**	-0.050*	-0.049**	-0.042**	-0.040**	-0.035**	-0.042***	-0.053***	-0.061***
	(-2.14)	(-2.04)	(-1.90)	(-2.32)	(-2.23)	(-2.30)	(-2.42)	(-2.70)	(-3.02)	(-2.67)
Adj. R^2	2.93%	3.02%	2.82%	3.66%	3.27%	3.36%	2.72%	4.28%	6.26%	4.95%

This table reports the coefficient estimation for the following predictive regression:

$$PR_{t+1}^{k} = \alpha + \beta \cdot ICIX_t + \varepsilon_{t+1},$$

where the dependent variable is the one-month head monthly returns of univariate sorted Fama-French size, BtM and momentum portfolios in Panels A, B, and C, respectively. *ICIX* is our inflation concern index defined as the average of the news-based inflation concern (*NBIC*) index and searching-based inflation concern (*SBIC*) index. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5 Comparison with typical inflation risk measures

	Panel A: Univariate regressions $R^m_{t+1} = \alpha + \varphi IR^k_t + \varepsilon_{t+1}$			Panel B: Bivariate regressions $R^m_{t+1} = \alpha + \beta ICIX_t + \varphi IR^k_t + \varepsilon_{t+1}$				
	φ	t-stat	Adj. R^2	β	t-stat	φ	t-stat	Adj. R^2
INFL	0.904	(0.75)	-0.01%	-0.048***	(-2.80)	1.162	(1.24)	5.76%
TBL	-0.196	(-1.32)	0.02%	-0.051**	(-2.39)	0.119	(0.55)	5.13%
BRKE	0.002	(0.47)	-0.21%	-0.046***	(-2.84)	0.001	(0.34)	5.08%
ISWAP	-0.001	(-0.24)	-0.41%	-0.047***	(-2.65)	-0.001	(-0.19)	5.01%
UMSC	-0.010	(-1.53)	1.57%	-0.042**	(-2.35)	-0.005	(-0.75)	5.38%
SPF	-0.023*	(-1.79)	1.59%	-0.043**	(-2.11)	-0.010	(-0.64)	5.28%
EI^{ARIMA}	-0.047	(-1.28)	1.54%	-0.043**	(-2.19)	-0.024	(-0.65)	5.44%
EIPC	-0.002	(-0.82)	0.36%	-0.045**	(-2.35)	-0.001	(-0.37)	5.12%
INFUN	1.394	(0.51)	-0.22%	-0.052***	(-3.11)	3.038	(1.20)	6.17%

This table reports the coefficient estimation of typical inflation risk measures. The dependent variable is the monthly stock market return over next month. Panel A reports the estimation results for the univariate predictive regressions:

$$R^m_{t+1} = \alpha + \varphi \cdot IR^k_t + \varepsilon_{t+1}.$$

Panel B reports the estimation results for the bivariate predictive:

$$R^m_{t+1} = \alpha + \beta \cdot ICIX_t + \varphi \cdot IR^k_t + \varepsilon_{t+1}.$$

ICIX is our inflation concern index defined as the average of the news-based inflation concern (*NBIC*) index and searching-based inflation concern (*SBIC*) index. IR^k is one of the typical inflation risk measures including: *INFL*, the lagged realized inflation; *TBL*, the one-month Treasury bill rate; *BRKE*, the break-even inflation rate that is implied from the yields of TIPS; *ISWAP*, the one-year inflation swap rate; *UMSC*, the expected inflation based on the University of Michigan Surveys of Consumers; *SPF*, the expected inflation based on Survey of Professional Forecasters, and EI^{ARIMA}, the expected inflation estimated within an ARIMA(0,1,1) model. *EIPC* is the first principal component of *BRKE*, *ISWAP*, *UMSC*, *SPF*, and EI^{ARIMA} to measure common systematic expected inflation. *INFUN* is the measures of inflation uncertainty, defined as the 12-month standard deviation of *INFL*. Newey-West standard errors are estimated and *t*-statistics are reported. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6 Out-of-sample forecast

	R^2_{OOS}	MSFE t-stat		R^2_{OOS}	MSFE t-stat
ICIX	4.17%	2.453	UMSC	-2.88%	0.294
INFL	-2.18%	-1.116	SPF	0.06%	0.659
TBL	1.05%	1.707	EI^{ARIMA}	-0.32%	0.866
BRKE	-1.14%	-0.700	EIPC	0.53%	0.721
ISWAP	-0.25%	-0.545	INFUN	-0.60%	-0.902

This table reports the R-square of the out-of-sample predictability on stock market return over different horizons. *ICIX* is our inflation concern index defined as the average of the news-based inflation concern (*NBIC*) index and searching-based inflation concern (*SBIC*) index. We also report the results for typical inflation risk measures including *INFL*, the lagged realized inflation; *TBL*, the one-month Treasury bill rate; *BRKE*, the break-even inflation rate that is implied from the yields of TIPS; *ISWAP*, the one-year inflation swap rate; *UMSC*, the expected inflation based on the University of Michigan Surveys of Consumers; *SPF*, the expected inflation based on Survey of Professional Forecasters, and EI^{ARIMA}, the expected inflation estimated within an ARIMA(0,1,1) model. *EIPC* is the first principal component of *BRKE*, *ISWAP*, *UMSC*, *SPF*, and EI^{ARIMA} to measure common systematic expected inflation. *INFUN* is the measures of inflation uncertainty, defined as the 12-month standard deviation of *INFL*. The *t*-statistics based on the MSFE-adjusted statistic of Clark and West (2007) are reported.

Table 7 Inflation concerns and macroeconomic conditions

	Panel A: ICIX			Panel B: ICIX$^{\perp}$		
	β	t-stat	Adj. R^2	β	t-stat	Adj. R^2
IPG	-1.031**	(-2.51)	2.28%	-1.345***	(-3.70)	4.15%
CFNAI	-1.291***	(-3.48)	2.82%	-1.702***	(-5.59)	5.14%
PRG	-0.515***	(-2.98)	0.51%	-0.739***	(-7.97)	1.48%
ADSI	-1.603***	(-2.79)	1.92%	-2.330***	(-5.63)	4.47%
VIX	0.141***	(2.95)	10.86%	0.200***	(4.49)	22.50%
KCFSI	3.090***	(4.20)	28.99%	4.051***	(5.60)	49.78%
SRP	0.709***	(4.58)	33.80%	0.809***	(5.70)	43.61%

This table reports the coefficient estimation for the following monthly univariate predictive regression for macroeconomic states:

$$Y_{t+1}^{K} = \alpha + \beta \cdot ICIX_t^N + \varepsilon_{t+1},$$

where Y^K is one of the macroeconomic condition proxies, including the the Industrial Production Growth (*IPG*), the Chicago Fed National Activity Index (*CFNAI*), Total Non-farm Payroll Growth (*PRG*), the Aruoba-Diebold-Scotti Business Conditions Index (*ADSI*), the CBOE Volatility Index (*VIX*), the Kansas City Financial Stress Index (*KCFSI*) and Smoothed Recession Probability (*SRP*). $ICIX^N$ is either *ICIX*, defined as the average of the news-based inflation concern (*NBIC*) index and searching-based inflation concern (*SBIC*) index (in Panel A) or $ICIX^{\perp}$, defined as *ICIX* orthogonalized to the common systematic expected inflation, *EIPC* (in Panel B). Newey-West standard errors are estimated and *t*-statistics are reported. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8 Inflation concerns and mutual fund flow

Panel A: Equity fund flow

	$Flow_{(t+1)}$	$Flow_{(t+3)}$	$Flow_{(t+6)}$	$Flow_{(t+9)}$	$Flow_{(t+12)}$	$Flow_{(t+24)}$
γ	-0.013***	-0.013**	-0.013**	-0.012	-0.009	-0.010
	(-3.01)	(-2.47)	(-2.23)	(-1.62)	(-1.11)	(-1.20)
Controls	YES	YES	YES	YES	YES	YES
Adj. R^2	55.46%	50.26%	47.29%	46.00%	50.14%	43.93%

Panel B: High-yield bond fund flow

	$Flow_{(t+1)}$	$Flow_{(t+3)}$	$Flow_{(t+6)}$	$Flow_{(t+9)}$	$Flow_{(t+12)}$	$Flow_{(t+24)}$
γ	-0.004***	-0.005***	-0.004**	-0.003	-0.001	0.004**
	(-3.21)	(-3.13)	(-2.14)	(-1.36)	(-0.62)	(1.98)
Controls	YES	YES	YES	YES	YES	YES
Adj. R^2	19.60%	14.28%	8.06%	3.27%	1.97%	6.99%

Panel C: Money market fund flow

	$Flow_{(t+1)}$	$Flow_{(t+3)}$	$Flow_{(t+6)}$	$Flow_{(t+9)}$	$Flow_{(t+12)}$	$Flow_{(t+24)}$
γ	0.043**	0.109***	0.096***	0.059*	0.024	-0.062
	(2.27)	(3.65)	(3.55)	(1.85)	(0.62)	(-1.36)
Controls	YES	YES	YES	YES	YES	YES
Adj. R^2	23.65%	13.65%	12.28%	8.31%	11.18%	1.93%

This table reports the coefficient estimation for the following predictive regression for fund flow:

$$Flow_{t+k}^{n} = \alpha + \gamma \cdot ICIX_t + \sum \theta^j \cdot Control_t^j + \varepsilon_{t+k}.$$

The dependent variables in Panel A, B, C are the detrended monthly net fund flow to the U.S. equity funds, high-yield bond funds and money market funds in month $t+k$ (k=1,3,6,9,12,24), respectively. *ICIX* is our inflation concern index defined as the average of the news-based inflation concern (*NBIC*) index and searching-based inflation concern (*SBIC*) index. Control variables include lagged fund flow, stock market return and realized volatility of daily stock market returns in each month. Newey-West standard errors are estimated and *t*-statistics are reported. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.