# Fear, Anger, and the Price of Risk

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This version: November 6, 2026

Most updated version available **here**

**Abstract**

Experimental evidence shows that fear makes people more risk averse and anger makes them more risk seeking, but the sentiment measures used in finance treat both as negative. This paper asks whether the two emotions, as expressed in economic news, move the market price of risk differently. I measure daily fear and anger with dictionary word shares in 9.83 million UK newspaper articles from 2003 to 2022 and relate them to the next day's price of risk on the FTSE 100, proxied by a model-motivated mean–variance ratio. Because the same events can shape both news and markets, I instrument emotions in economic news with the same emotions in non-economic and sports news. The two emotions do move the price of risk in opposite directions, but against the experimental evidence. A one-standard-deviation increase in anger raises the proxy by 28.3 per cent of its mean with non-economic-news instruments and by 27.9 per cent with sports-news instruments, while fear lowers it by 21.0 per cent with non-economic-news instruments and is imprecise with sports-news instruments. When investors are myopic, these estimates point to lower risk appetite after angry coverage and higher risk appetite after fearful coverage.

**Keywords:** Asset Pricing, Behavioural Finance, Sentiment Analysis, Textual Analysis.

**JEL Classification:** G12, G41, C55, E71

*I am grateful to Roger Farmer, Christine Braun, and Leonardo Melosi for their helpful guidance, and Roberto Pancrazi, Johannes Zahner, Juri Marcucci, and Thijs van Rens for their advice and feedback.

# 1 Introduction

Fear and anger push people in opposite directions when facing risk. In experiments, fearful people make pessimistic risk estimates and risk-averse choices, while angry people make optimistic estimates and risk-seeking choices, because the two emotions carry different appraisals of certainty and control (Lerner and Keltner, 2001). More generally, emotions that are both negative can lead to different choices (Raghunathan and Pham, 1999; Pertl et al., 2024). Evidence from finance points the same way for fear: financial professionals primed with a market bust become more fearful and more risk averse (Cohn et al., 2015), and investors' risk aversion rose after the 2008 crisis in a way consistent with a fear-based explanation (Guiso et al., 2018). Yet the sentiment measures used in applied work on news and markets score text on a single positive–negative scale (García, 2013; Young and Soroka, 2012), which places these two negative emotions on the same side. This paper asks whether the distinction matters for asset prices: do fear and anger in economic news move the price of risk differently?

Whether individual-level effects of this kind reach market prices is an open question. The idea that emotions move markets has a long history: Keynes (1936) describes investment as driven by "animal spirits", Graham (1949) personifies the market as the manic-depressive Mr. Market, and Shiller (2000) documents waves of optimism and pessimism that move prices away from fundamentals. For emotions to reach prices, they need a route to investors. Central bank communication is one route that has been studied: the emotional, vocal, and facial cues of central bankers move markets (Gorodnichenko et al., 2023; Kanelis and Siklos, 2026; Barry et al., 2025). Newspapers are another, and the one this paper studies. News providers select, simplify, and frame economic information, and in doing so may change what reaches investors and how they act on it (Dougal et al., 2012).

I measure fear and anger in 9.83 million articles published by four UK newspapers between 2003 and 2022, counting words associated with each emotion in the NRC Word–Emotion Association Lexicon (Mohammad and Turney, 2010, 2013). Dictionaries also classify each article as economic, non-economic, or sports news. The price

of risk comes from a partial-equilibrium portfolio-choice model in which a time-varying price of risk links the conditional mean of FTSE 100 excess returns to their conditional variance; I estimate it as an AR(1)–GARCH(1,1) mean–variance ratio. The main obstacle to identification is that the same events can shape both the tone of economic reporting and the market. I therefore instrument emotions in economic news with the same emotions in non-economic news and in sports news. These sections share a news day and a newsroom with economic coverage, and I assume that they affect the price of risk only through economic news. Because publication and trading overlap within the day, I relate emotions at $t$ to the price-of-risk state at $t + 1$. Because the proxy is itself estimated and both returns and news are serially dependent, inference uses a moving-block bootstrap that re-estimates the proxy in every draw.

Fear and anger do move the price of risk in opposite directions, but not in the directions the experiments predict. A one-standard-deviation increase in anger in economic news raises the price of risk on the next trading day by 28.3 per cent of its mean with non-economic-news instruments and by 27.9 per cent with sports-news instruments. Fear lowers it by 21.0 per cent of its mean with non-economic-news instruments; the sports-news estimate is imprecise. In the portfolio-choice model, the price of risk is the expected return investors require per unit of variance; when investors are myopic, it rises with risk aversion. Read this way, anger reduces investors' willingness to bear risk, and fear, where precisely estimated, increases it. Decomposing the proxy shows that both effects operate through expected volatility. The results are consistent with emotions changing risk aversion in a way that alters later volatility, or with emotions changing perceived risk and trading (Lerner et al., 2003; Da et al., 2015).

This paper adds to three literatures. First, it brings the emotional content of public information into the empirical study of time-varying risk prices. Asset-pricing models explain this variation through external habit (Campbell and Cochrane, 1999), long-run growth and volatility risks (Bansal and Yaron, 2004), rare disasters (Barro, 2009), and learning about uncertain mean returns (Brennan, 1998), but the state variables

they rely on are often latent. Emotion measures from news provide observable proxies for the shifts in beliefs that drive asset prices and economic activity in the general-equilibrium models of Farmer (2012, 2018) and Farmer and Platonov (2019). Second, it contributes to research on emotions and financial-market behaviour (Ackert et al., 2003; Breaban and Noussair, 2018; Consoli et al., 2021; Da et al., 2015) by studying whether emotions embedded in broad newspaper coverage affect the market price of risk over a long daily sample. Third, it connects sentiment-based text analysis in economic and financial news (Tetlock, 2007; Shapiro et al., 2022) to research on discrete emotions in news content (Soroka et al., 2015), and shows that two emotions a sentiment score treats alike move the price of risk in opposite directions. Two papers are closest to this one. Manela and Moreira (2017) estimate a news-implied volatility index from front-page *Wall Street Journal* text and option-implied volatility, and show that high values predict above-average stock returns over the following one to two years, which they attribute to time-varying concerns about rare disasters. Consoli et al. (2021) measure fear-related emotions of varying intensity in Italian and Spanish macroeconomic news and show that they help forecast sovereign bond spreads during distressed periods, beyond a measure of negative tone. This paper relates two negative emotions with opposite predicted effects on risk taking to the equity price of risk and instruments them with the same emotions in other sections of the newspaper. It also covers twenty years of daily UK newspaper coverage, compared with four and a half years in Consoli et al. (2021).

Because institutional messages reach investors partly through the press, these findings suggest that financial stability authorities could monitor how their communications are reframed in the news. Emotion measures derived from news could complement market stress indicators. Authorities could also track emotional responses to announcements to review how their messages were interpreted and adjust their approach if necessary.

The paper is structured as follows: Section 2 derives the price-of-risk relation used in the empirical work; Section 3 describes the newspaper corpus, emotion measures,

financial data, and the price-of-risk proxy; Section 4 explains the empirical specifications; Section 5 reports the results of the estimations and provides robustness checks; Section 6 concludes.

# 2 Model Setup

This section derives the price-of-risk measure used in the empirical analysis. A price-taking investor chooses consumption and exposure to a risky asset. For small one-period shocks, the portfolio first-order condition links the expected excess return to its conditional second moment through a time-varying price of risk. Under projection bias, this price of risk is proportional to current risk aversion, scaled by the wealth elasticity of future consumption and by an intertemporal hedging term. When consumption is a fixed share of wealth, the hedging term disappears and the investor is myopic. Market clearing then sets the price of risk equal to current risk aversion divided by the safe gross return.

## 2.1 The Investor's Problem

At date $t$, the investor observes $\mathcal{F}_t$ and chooses consumption $c_t$ and the share $\pi_t$ of investable wealth $a_t = w_t - c_t > 0$ held in a risky asset with gross return $R_{t+1}$. The remaining wealth earns the safe gross return $R_f > 0$, known at $t$. With excess return $x_{t+1} = R_{t+1} - R_f$, next-period wealth is

$$w_{t+1} = a_t(R_f + \pi_t x_{t+1}). \tag{1}$$

Preferences are CRRA with time-varying curvature $\rho_t > 0$, $u(c;\rho_t) = c^{1-\rho_t}/(1-\rho_t)$, with $u = \log c$ for $\rho_t = 1$. Write $\mathbb{E}_t[\cdot] = \mathbb{E}[\cdot \mid \mathcal{F}_t]$ and

$$\mu_{t+1} = \mathbb{E}_t[x_{t+1}], \qquad h_{t+1} = \mathbb{E}_t[x_{t+1}^2], \tag{2}$$

so $h_{t+1}$ is the conditional second moment. The states of the return process are its conditional mean and second moment, $z_t = (\mu_{t+1}, h_{t+1})$, with steady-state value $\bar{z} = (\bar{\mu}, \bar{h})$. The investor takes the return distribution as given.

**Assumption 1 (projection bias).** At date $t$, the investor values all future outcomes with the current risk aversion $\rho_t$.

This is full projection bias in the sense of Loewenstein et al. (2003): the investor acts as if risk aversion in every future period equals risk aversion at $t$. For a given $\rho$, let $V(w, z; \rho)$ denote the value function of the problem in which risk aversion stays at $\rho$ in every period,

$$V(w_t, z_t; \rho) = \max_{c_t, \pi_t} \left\{ u(c_t; \rho) + \beta \, \mathbb{E}_t\big[V(w_{t+1}, z_{t+1}; \rho)\big] \right\}, \tag{3}$$

subject to (1), with consumption policy $c(w, z; \rho)$. Under Assumption 1, the date-$t$ choice solves (3) with $\rho = \rho_t$. The portfolio first-order condition and the envelope condition give (Appendix A.1)

$$\mathbb{E}_t\big[c(w_{t+1}, z_{t+1}; \rho_t)^{-\rho_t} x_{t+1}\big] = 0. \tag{4}$$

Because $c(w_{t+1}, z_{t+1}; \rho_t)$ can covary with $x_{t+1}$ through the return-process states, the condition generally contains intertemporal hedging terms.

Assumption 1 lets the investor's emotional state at the time of the decision govern the valuation of outcomes. This is consistent with evidence that feelings experienced at the moment of decision affect choices under risk (Loewenstein et al., 2001).

## 2.2 Price of Risk

I approximate (4) around a zero excess return and the steady state of the return-process states. A second-order expansion (Appendix A.2) gives

$$\mathbb{E}_t[x_{t+1}] \approx \lambda_t \, \mathbb{E}_t[x_{t+1}^2], \tag{5}$$

that is, $\mu_{t+1} \approx \lambda_t h_{t+1}$, with

$$\lambda_t = \frac{\rho_t \pi_t}{R_f} \frac{\varepsilon_{c,t}}{\kappa_{H,t}}, \qquad \kappa_{H,t} = 1 + \kappa_{\mu,t} + \kappa_{h,t}. \tag{6}$$

Here $\varepsilon_{c,t}$ is the elasticity of the consumption policy $c(\cdot; \rho_t)$ with respect to wealth. The terms $\kappa_{\mu,t}$ and $\kappa_{h,t}$ reflect the covariance between the excess return and next period's conditional mean and second moment, and so capture the intertemporal hedging demand.

The price of risk $\lambda_t$ is therefore not equivalent to the risk-aversion parameter $\rho_t$. It combines current risk aversion, the investor's risky-asset position, the wealth elasticity of future consumption, and the hedging term. A higher $\lambda_t$ means that the investor requires a higher expected excess return for a given amount of conditional risk. The price of risk can therefore move because fundamentals change, because willingness to bear risk changes, or because both change.

**Assumption 2 (fixed consumption share).** $c(w, z; \rho_t) = \theta w$, with a constant $\theta \in (0, 1]$.

Under Assumptions 1 and 2, (4) reduces exactly to

$$\mathbb{E}_t\left[x_{t+1}(R_f + \pi_t x_{t+1})^{-\rho_t}\right] = 0, \tag{7}$$

the first-order condition of a one-period problem (Appendix A.2). In (6), Assumption 2 sets $\kappa_{\mu,t} = \kappa_{h,t} = 0$ and $\varepsilon_{c,t} = 1$. A second-order expansion of (7) around a zero excess return gives (5) with

$$\lambda_t = \frac{\rho_t \pi_t}{R_f}. \tag{8}$$

I refer to this as the myopic case: the investor's portfolio rule coincides with the solution of a one-period problem, with no intertemporal hedging demand (Samuelson, 1969; Merton, 1971).

The resulting relation has the form used in the empirical risk–return literature, where Merton (1980) treats the expected excess market return as proportional to its

conditional variance, with a coefficient equal to the relative risk aversion of a representative investor, as an approximation to the intertemporal capital asset pricing model.

For a representative investor holding the aggregate risky asset, with the safe asset in zero net supply, market clearing gives $\pi_t = 1$. With $R_f \approx 1$ at daily frequency, $\lambda_t \approx \rho_t$. Therefore, if Assumptions 1 and 2 hold, the price-of-risk proxy is approximately identified by risk aversion $\rho_t$.

### 2.3 Empirical Counterpart

Equation (5) implies

$$\lambda_t \approx \frac{\mu_{t+1}}{h_{t+1}}. \tag{9}$$

The empirical proxy is estimated with an AR(1)–GARCH(1,1) model, which gives the conditional mean $\mu_{t+1}$ and the conditional variance $\mathrm{Var}_t(x_{t+1}) = h_{t+1} - \mu_{t+1}^2$. For small shocks, $\mu_{t+1}^2$ is of smaller order than $\mathrm{Var}_t(x_{t+1})$, so the ratio of the conditional mean to the conditional variance approximates $\lambda_t$ to the same order. The empirical proxy uses this mean–variance ratio: the AR(1) specification conditions the estimated mean on the lagged excess return, while a GARCH(1,1) specification updates the conditional variance using the previous squared return innovation and the previous conditional variance. The observed return history therefore provides an empirical approximation to the return-relevant information in $\mathcal{F}_t$.

## 3 Data

The data combine UK newspaper articles published between 2003 and 2022 with daily FTSE 100 total-return, risk-free-yield, and trading-volume series. The unit of observation in the text data is an article; the unit of observation in the regressions is a trading day. I use the article data to construct daily measures of emotions in economic, non-economic, and sports news, and I merge those measures with financial data used to measure the market price of risk.

## 3.1 Financial Data

Financial-market data come from the London Stock Exchange Group (LSEG) and span 1 July 2003 to 31 December 2022. The risky asset is the FTSE 100 Total Return Index, which measures the performance of the 100 most highly capitalised blue-chip companies listed on the London Stock Exchange and includes capital gains and reinvested dividends. I calculate the excess returns of the stock market as the return on the risky asset minus the two-year UK gilt yield, which proxies for the risk-free rate. I also construct the ten-year minus two-year gilt spread as a control for the slope of the yield curve.

### 3.1.1 The Price-of-Risk Proxy

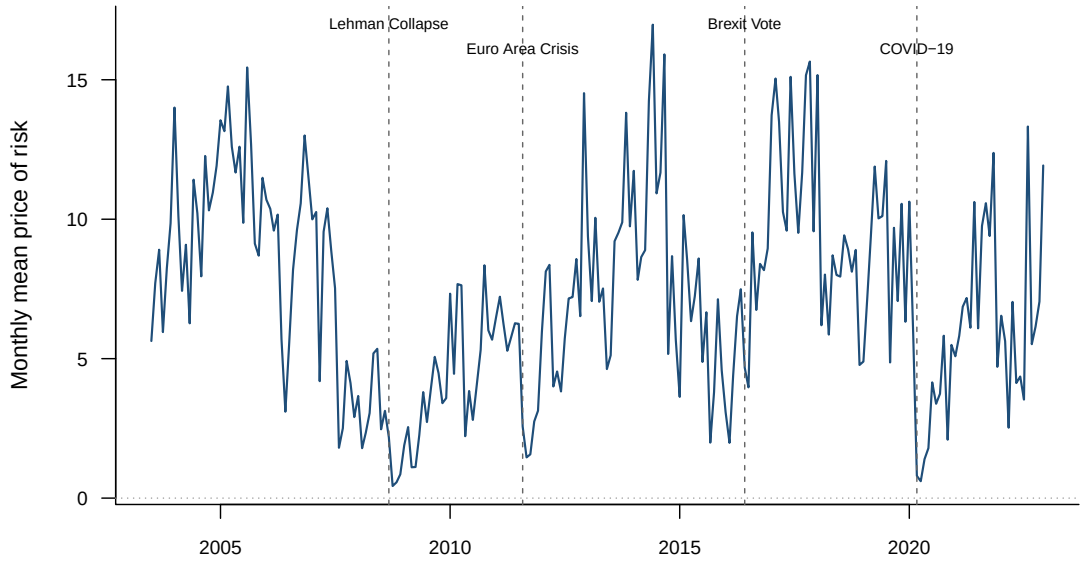
Figure 1 describes the price-of-risk proxy used as the outcome in the regressions. The proxy is the ratio of the conditional mean to the conditional variance of the excess return implied by Equation (5), estimated with an AR(1)–GARCH(1,1) model on the full sample of daily FTSE 100 excess returns.

In the main regression sample, the proxy has a mean of 7.35 and a standard deviation of 5.14. It is negative on 5.4 per cent of days, when the fitted conditional mean of the excess return is negative. The proxy moves more closely with the conditional variance than with the conditional mean: its correlation with the log conditional variance is $-0.72$, compared with 0.42 for the conditional mean. This is consistent with evidence that changes in volatility are not matched by proportional changes in expected returns (Moreira and Muir, 2017). The proxy is also persistent, with a first-order autocorrelation of 0.61.

The proxy is lowest during periods of market stress: its monthly averages reach their minimum in late 2008, after the collapse of Lehman Brothers, and in March and April 2020 (Figure 1). In these periods the conditional variance rises sharply while the conditional mean barely changes. The pattern is consistent with evidence that the market risk premium rises less than market variance in recessions, so that the premium per unit of variance is procyclical, unlike the Sharpe ratio (Jensen and Lazarus, 2025).

Interpreted through the model, it implies that risk aversion falls when volatility is high. This differs from survey and experimental evidence, in which risk aversion rises after market downturns (Guiso et al., 2018; Cohn et al., 2015). The two need not coincide: the proxy is inferred from market returns, whereas surveys and experiments elicit the attitudes of individual investors.

Figure 1: Monthly Average of the Price-of-Risk Proxy, 2003–2022




*Notes*: The line is the monthly mean of the daily price-of-risk proxy $\hat{\lambda}_t = \hat{\mu}_{t+1|t}/\hat{h}_{t+1|t}$ over the main regression sample, indexed by the date $t$ of the price-of-risk state. The conditional moments come from an AR(1)–GARCH(1,1) model of daily FTSE 100 total-return excess returns over the two-year gilt yield. Dashed lines mark September 2008, August 2011, June 2016, and March 2020.

## 3.2 Text Data

The newspaper corpus comes from the online editions of four major UK newspapers: The Daily Mail, The Guardian, The Independent, and Metro. These outlets cover a substantial segment of UK print and online newspaper readership (Ofcom, 2025)[1]. The raw corpus contains 9,832,307 articles between 2003 and 2022, spanning the Global Financial Crisis, the European sovereign debt crisis, the Brexit referendum, the COVID-19 pandemic, and the subsequent inflationary episode. Table 1 reports the raw number of articles by newspaper and year. The Daily Mail contributes the largest

[1]Ofcom's 2025 News Consumption Survey reports that, among adults using print or online newsbrands, The Daily Mail/Mail on Sunday and Guardian/Observer were the two most widely used newsbrands, reaching 33 and 31 per cent, respectively; Metro reached 17 per cent and The Independent 7 per cent.

share of articles, followed by The Guardian, The Independent, and Metro. I then retain articles that contain at least 100 words and were published during the trading week, and align the resulting sample period with that of the financial data. The filtered corpus contains 7,709,678 articles.

Table 1: UK Newspaper Articles by Outlet and Year, 2003–2022

| Year | Daily Mail | Guardian | Independent | Metro | Total |
|---|---|---|---|---|---|
| 2003 | 23,142 | 70,334 | 38,312 | 0 | 131,788 |
| 2004 | 29,372 | 74,361 | 41,771 | 0 | 145,504 |
| 2005 | 25,799 | 74,013 | 43,283 | 2,160 | 145,255 |
| 2006 | 38,077 | 79,165 | 42,481 | 14,376 | 174,099 |
| 2007 | 68,394 | 91,029 | 23,089 | 45,036 | 227,548 |
| 2008 | 92,777 | 102,048 | 45,468 | 58,397 | 298,690 |
| 2009 | 89,081 | 91,883 | 61,596 | 56,193 | 298,753 |
| 2010 | 103,065 | 83,049 | 78,807 | 43,189 | 308,110 |
| 2011 | 130,081 | 89,246 | 76,891 | 34,785 | 331,003 |
| 2012 | 167,026 | 87,417 | 80,700 | 36,862 | 372,005 |
| 2013 | 181,050 | 89,575 | 78,130 | 48,272 | 397,027 |
| 2014 | 334,974 | 99,427 | 73,775 | 44,458 | 552,634 |
| 2015 | 468,409 | 115,887 | 83,010 | 55,881 | 723,187 |
| 2016 | 555,385 | 107,980 | 72,670 | 70,562 | 806,597 |
| 2017 | 549,941 | 83,480 | 71,714 | 79,753 | 784,888 |
| 2018 | 606,307 | 78,095 | 64,312 | 87,359 | 836,073 |
| 2019 | 571,000 | 76,905 | 65,533 | 92,184 | 805,622 |
| 2020 | 545,428 | 77,082 | 78,029 | 87,295 | 787,834 |
| 2021 | 597,590 | 75,149 | 144,331 | 79,779 | 896,849 |
| 2022 | 468,995 | 77,124 | 181,962 | 80,760 | 808,841 |
| **Total** | **5,645,893** | **1,723,249** | **1,445,864** | **1,017,301** | **9,832,307** |

*Notes*: Cells count articles collected from the online editions of the Daily Mail, The Guardian, The Independent, and Metro in each calendar year. These are raw corpus counts before any filter is applied to the corpus. The Metro series begins in 2005. The final row sums articles across 2003–2022.

### 3.2.1 Emotion Measures and News Classification

I extract emotions using the NRC Word–Emotion Association Lexicon (EmoLex) developed by Mohammad and Turney (2010) and Mohammad and Turney (2013). I construct article-level shares for fear and anger, defined as the fraction of words associated with each category relative to the total number of words in an article. I also use the Harvard-IV4 (HIV4) sentiment lexicon as a benchmark for broad sentiment. HIV4 is a word list that classifies terms into positive, negative, and related categories. For each article, I construct a measure of polarity as $(P - N)/(P + N)$, where $P$ and $N$ are the article's counts of HIV4 positive and negative words. The measure ranges

from −1 to 1: higher (lower) values indicate more (less) positive sentiment.

I classify articles as economic or sports news using the dictionaries in Table 2. An article is classified as economic if it contains at least one economy term. The sports rule is narrower: an article is classified as sports if it contains a competition phrase, or if it contains one of the listed venue names together with at least one sports-context term within 15 tokens. This narrower rule prevents generic terms such as *manager*, *game*, or *club* from being misclassified. Using these labels, I average the article-level emotion shares by trading day to construct separate dictionary emotion indices for economic news, non-economic news, and sports news. The economic-news indices are the regressors of interest. The non-economic and sports-news indices supply the excluded instruments in the IV specifications.

Table 2: Dictionary Rules Used to Classify Economic and Sports News

| Dictionary component | Terms and phrases |
|---|---|
| Economy terms | GDP; inflation; interest rate; interest rates; monetary policy; central bank; BoE; bank of england; Federal Reserve; Fed; ECB. |
| Sports competitions | Premier League; Champions League; FA Cup; League Cup; World Cup; European Championship; Euros; Test match; Ashes; Wimbledon; Grand Prix; Formula 1; Six Nations; Premiership. |
| Sports venues | Old Trafford; Anfield; Wembley. |
| Sports context | football; cricket; rugby; tennis; match; game; fixture; final; semifinal; semifinal; goal; goals; score; scored; manager; coach; club; team; league; season; stadium; fans; captain; striker; midfielder; defender; tournament; cup; championship. |

*Notes*: The table defines the dictionary rules used to classify newspaper articles before constructing the dictionary emotion measures. Matching is case-insensitive. An article is classified as economic news when it contains any economy term. It is classified as sports news when it contains any sports-competition phrase, or when a sports-venue phrase appears within 15 tokens of a sports-context term.

Table 3 reports the differences in dictionary fear and anger shares, in percentage points, between economic and non-economic news and between sports and non-sports news. Economic articles have higher fear and anger shares than non-economic articles, and sports articles have lower fear and anger shares than non-sports articles. The greater concentration of negative emotional language in economic news is consistent with evidence that negative news elicits stronger and more sustained reactions (Soroka and McAdams, 2015) and that negative headline words can increase online news consumption (Robertson et al., 2023). Table 4 reports mean fear and anger shares in

economic news by newspaper. The Daily Mail, The Guardian, and The Independent have similar shares, with The Independent slightly highest for both emotions (2.61 per cent of words for fear and 1.84 for anger). Metro's shares are lower, at 2.17 and 1.58.

Table 3: Mean Fear and Anger Share Differences Across News Types

| Emotion | Economic − non-economic | Sports − non-sports |
|---|---|---|
| Fear | 0.369*** | -0.593*** |
| | (0.003) | (0.002) |
| Anger | 0.195*** | -0.323*** |
| | (0.002) | (0.002) |

*Notes*: Cells report percentage-point differences in raw mean emotion shares, with publication-date-clustered standard errors in parentheses. The first column subtracts the non-economic-news mean from the economic-news mean; the second subtracts the non-sports-news mean from the sports-news mean. Economic news uses the rule-based economy indicator; outcomes are NRC emotion-word shares. The sports classification is rule-based. The sample contains articles with at least 100 words published Monday–Friday from 1 July 2003 to 31 December 2022. ***, **, and * denote significance at the 1, 5, and 10 per cent levels.

Table 4: Mean Fear and Anger Shares in Economic News by Newspaper

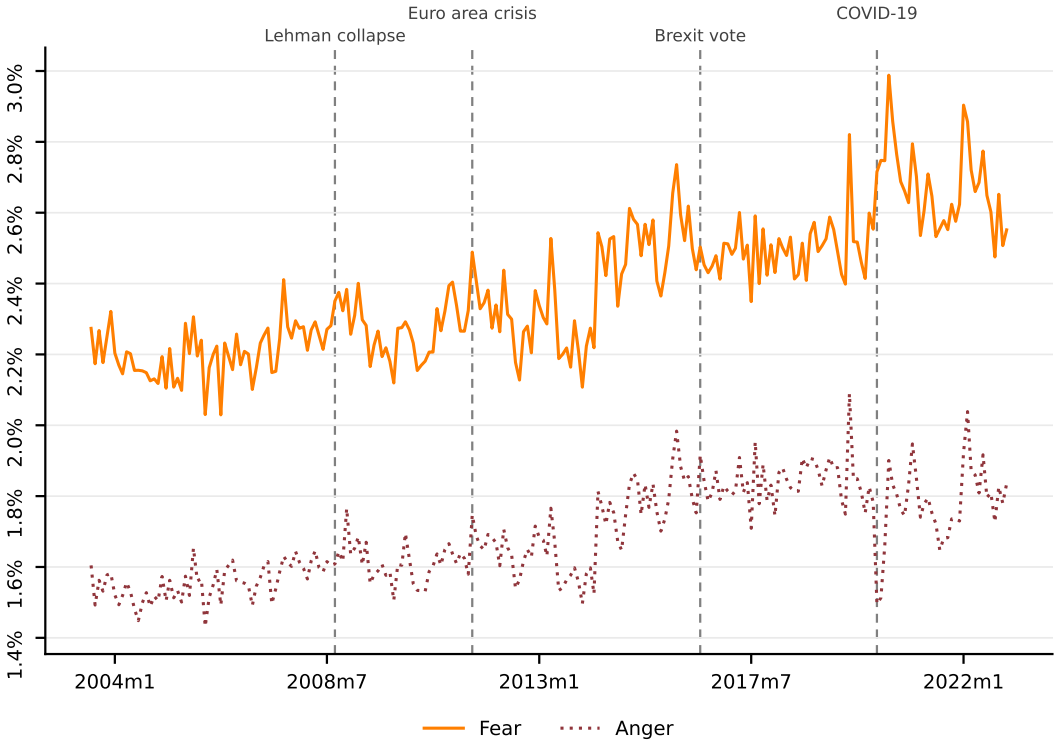
| Emotion | Daily Mail | Guardian | Independent | Metro |
|---|---|---|---|---|
| Fear | 2.540 | 2.464 | 2.608 | 2.171 |
| | (0.004) | (0.004) | (0.009) | (0.010) |
| Anger | 1.781 | 1.691 | 1.841 | 1.575 |
| | (0.003) | (0.003) | (0.006) | (0.008) |
| Articles | 681,061 | 209,937 | 142,225 | 42,171 |

*Notes*: Cells report mean NRC emotion-word shares in economic news, in per cent of words, with publication-date-clustered standard errors in parentheses. For each article, an emotion share equals the number of words associated with that NRC emotion category divided by the article's total word count. Economic news uses the rule-based economy indicator. The sample contains articles with at least 100 words published Monday–Friday from 1 July 2003 to 31 December 2022.

Figure 2 shows the monthly evolution of dictionary fear and anger shares in economic news. Emotional content varies over time. Relative to the preceding twelve months, fear is higher in the three months starting with the collapse of Lehman Brothers, with the escalation of the euro area crisis in August 2011, and with the onset of

the COVID-19 pandemic, but not around the Brexit referendum. Anger rises most around August 2011 and is lower around the onset of the pandemic. The levels also shift: from 2015 to 2022, fear and anger shares are higher than from 2003 to 2013. The shift coincides with a change in the corpus. The number of Daily Mail economic articles more than doubled between 2013 and 2014 and their average length fell, while their fear and anger shares rose; most of the 2013–2014 increase comes from within the Daily Mail rather than from its larger weight in the sample.

Figure 2: Monthly Average Fear and Anger Word Shares in UK Economic News, 2003–2022




*Notes*: Each line is the monthly mean, over trading days, of the daily average article-level dictionary emotion share in economic news. Economic news uses the rule-based economy indicator, and articles have at least 100 words. For each article and emotion, the share equals the number of words associated with that NRC emotion category divided by the article's total word count. Values are in per cent of words. Dashed lines mark September 2008, August 2011, June 2016, and March 2020.

# 4 Empirical Setup

The empirical analysis asks whether emotions in economic news are related to short-run movements in the market price of risk using the daily dictionary-based emotion indices from economic news. The main specification focuses on fear and anger because

they are both negative emotions but conceptually different categories; focusing on two emotions also keeps the regressions parsimonious.

The main specification is organised around three threats to inference and identification. First, the outcome variable is constructed rather than directly observed. Conventional standard errors would not account for the uncertainty in the generated variables or the serial dependence in returns and news. I therefore use a moving-block bootstrap that preserves short-run dependence and, within every draw, reconstructs the proxy, returns, and controls before re-estimating the OLS and IV models. Second, publication and trading overlap within the day, creating temporal ambiguity and the possibility of same-day feedback from markets to reporting. The chosen specification therefore relates emotions, excluded instruments, the return control, and the remaining controls at $t$ to the price-of-risk state at $t+1$, represented by the conditional mean–variance ratio for the return at $t+2$. Third, common macroeconomic or financial shocks can move both reporting and the price of risk, thus making the economic-news emotions endogenous to market returns. I address this concern with two instrument sets, discussed in Section 4.1.

Let $x_t$ denote the daily FTSE 100 excess return over the two-year gilt yield. Equation (5) implies that the price-of-risk state at $t+1$ is approximated by the conditional mean–variance ratio for the return at $t+2$:

$$\hat{\lambda}_{t+1} = \frac{\hat{\mu}_{t+2|t+1}}{\hat{h}_{t+2|t+1}}.$$

A higher (lower) value indicates a higher (lower) price of risk, which through the lens of the model implies a lower (higher) risk appetite.

The regression specification is

$$\hat{\lambda}_{t+1} = \alpha + \boldsymbol{E}_t'\boldsymbol{\beta} + \delta_t + X_t'\boldsymbol{\gamma} + u_{t+1}, \tag{10}$$

where $\boldsymbol{E}_t$ contains fear and anger. The term $\delta_t$ captures day-of-week fixed effects. The vector $X_t$ includes the excess return at $t$, log article count, log trading volume,

inflation- and monetary-policy-announcement dummies, the ten-year minus two-year gilt spread, log UK Economic Policy Uncertainty from Baker et al. (2016), and HIV4 polarity. Table 5 describes the variables used in the regressions.

Table 5: Description of Variables

| Variable | Role | Construction |
|---|---|---|
| $\hat{\lambda}_{t+1}$ | GARCH price-of-risk outcome | Price-of-risk state at $t+1$, represented by the AR(1)–GARCH(1,1) conditional mean–variance ratio $\hat{\mu}_{t+2\|t+1}/\hat{h}_{t+2\|t+1}$ for the return at $t+2$. |
| $\boldsymbol{E}_t$ | Dictionary emotions | Daily dictionary-based fear and anger indices in economic news. |
| $\boldsymbol{Z}_t^{NE}$ | Non-economic instruments | Matching dictionary emotions measured in non-economic news. |
| $\boldsymbol{Z}_t^{SP}$ | Sports-news instruments | Matching sports-news dictionary emotions. |
| $X_t$ | Controls | Excess return, log article count, log trading volume, Bank of England and CPI announcement dummies, ten-year minus two-year gilt spread, log UK Economic Policy Uncertainty, and HIV4 polarity. |
| $\delta_t$ | Calendar controls | Day-of-week fixed effects. |

*Notes*: The table defines the dependent variable, endogenous emotion measures, excluded instruments, controls, and fixed effects in the daily regressions in Equation (10). The sample runs from 2 July 2003 to 30 December 2022. HIV4 polarity is $(P-N)/(P+N)$, where $P$ and $N$ are the article's counts of HIV4 positive and negative words. HIV4 polarity is computed for dictionary-classified economic articles. Newspaper variables come from the four-outlet article corpus; dictionary variables use the NRC emotion and HIV4 sentiment lexicons. FTSE 100 total-return prices, trading volume, and gilt yields come from LSEG. Bank of England and CPI announcement indicators come from the event calendar merged to the trading-day data. The UK Economic Policy Uncertainty index comes from Baker et al. (2016). All regression emotion variables are standardised.

These controls absorb observable variation in market conditions, the information environment, the yield curve, and broad sentiment. To interpret $\boldsymbol{\beta}$, write the price of risk in Equation (6) as $\lambda_{t+1} = \rho_{t+1}\, g_{t+1}$, where $g_{t+1} = \pi_{t+1}\varepsilon_{c,t+1}/(R_f \kappa_{H,t+1})$ collects the investor's risky-asset position, the wealth elasticity of future consumption, and the hedging term. A change in emotions at $t$ then affects the price of risk through two terms:

$$\frac{\partial \lambda_{t+1}}{\partial \boldsymbol{E}_t} = g_{t+1}\,\frac{\partial \rho_{t+1}}{\partial \boldsymbol{E}_t} + \rho_{t+1}\,\frac{\partial g_{t+1}}{\partial \boldsymbol{E}_t}. \tag{11}$$

The first term is the direct effect of a change in risk aversion, holding $g_{t+1}$ fixed. The second term captures changes in the risky position, future consumption, and hedging; because the consumption policy and the hedging term depend on risk aversion, part of it can itself result from a change in $\rho_{t+1}$. $\boldsymbol{\beta}$ therefore measures the effect of emotions on the price of risk, and it cannot be mapped one to one into an effect on risk aversion. In the myopic case with market clearing, $g_{t+1} = 1/R_f$, so the second term is zero and $\boldsymbol{\beta}$ estimates a weighted average of $R_f^{-1}\,\partial\rho_{t+1}/\partial \boldsymbol{E}_t$. With $R_f \approx 1$ at daily frequency, $\boldsymbol{\beta}$ then measures the effect of emotions on risk aversion.

The emotional variables have been standardised, meaning that the coefficients mea-

sure the change in risk pricing associated with an increase of one standard deviation in the relevant emotional index. In the IV specifications, the interpretation applies to the part of economic-news emotions predicted by the excluded instruments. A positive (negative) coefficient implies a higher (lower) price of risk and lower (higher) risk appetite. I refer to coefficients as a percentage of the estimation-sample mean of the outcome to make them more interpretable.

## 4.1 Identification

The IV specifications instrument fear and anger in economic news with the same emotions measured in other news published on the same day. IV–NE uses fear and anger in non-economic news, and IV–Sports uses fear and anger in sports news. Each instrument set has to satisfy two conditions: relevance and exclusion.

The instruments are relevant if emotional language in economic news shares a daily component with emotional language elsewhere in the newspaper. Such a component can arise because the same events are reported across sections and because the same newsrooms shape the tone of a day's coverage. The first stages support relevance: the minimum Sanderson–Windmeijer conditional first-stage statistic across the two endogenous emotions is 372.0 under IV–NE and 93.3 under IV–Sports (Table 6). The IV coefficients therefore measure the effect of the part of economic-news fear and anger that moves with emotional language in the rest of the newspaper.

The exclusion restriction requires that, conditional on the controls, fear and anger in non-economic or sports news affect the price of risk at $t + 1$ only through fear and anger in economic news. Two threats are most relevant. The first is events that are reported across all sections and also move markets directly, such as terrorist attacks or the onset of the COVID-19 pandemic. Such events can raise fear in non-economic news and move the price of risk through channels other than economic reporting. The controls absorb part of this variation: log UK Economic Policy Uncertainty, a newspaper-based index, captures policy-related uncertainty; the Bank of England and CPI dummies remove scheduled releases; and the excess return and trading volume at

$t$ capture same-day market conditions. The threat is larger for non-economic news, which includes political, international, and health coverage, than for sports news. Sporting results and coverage are plausibly unrelated to economic conditions, which makes IV–Sports the stricter instrument set.

The second threat is feedback from markets to reporting. If returns shape the emotional tone of non-economic or sports coverage, the instruments would carry market information. Regressions of fear and anger in non-economic and sports news at $t + 1$ on returns at $t$, conditional on the main controls, show no significant response in any of the four coefficients (Appendix Table B.5).

# 5 Results

Table 6 reports the daily estimates. Dictionary anger rises from 0.51 in OLS (6.9 per cent of the mean outcome) to 2.08 under IV–NE (28.3 per cent) and 2.05 under IV–Sports (27.9 per cent). The two IV estimates are almost identical, so the anger result holds under the stricter sports-news instruments. Dictionary fear is negative: the IV–NE coefficient is $-1.55$ ($-21.0$ per cent of the mean), while the imprecise IV–Sports estimate is $-0.83$ ($-11.3$ per cent).

The regression table also reports the minimum Sanderson–Windmeijer conditional first-stage statistic across the endogenous emotions for each IV specification. In the main two-emotion model, the minimum ranges from 93.3 to 372.0.

Table 6: Price-of-Risk Regressions

| | (1) OLS | (2) IV–NE | (3) IV–Sports |
|---|---|---|---|
| *Dictionary emotions* | | | |
| Fear | -0.716*** | -1.547*** | -0.833 |
| | [-1.244, -0.300] | [-2.681, -0.625] | [-2.076, 0.264] |
| Anger | 0.510*** | 2.080*** | 2.054** |
| | [0.141, 0.997] | [0.592, 4.114] | [0.340, 4.353] |
| Controls | Yes | Yes | Yes |
| Min. SW $F$ | – | 372.03 | 93.34 |
| Mean of proxy | 7.354 | 7.354 | 7.354 |
| Observations | 4,927 | 4,927 | 4,927 |
| Bootstrap replications | 5,000 | 5,000 | 5,000 |

*Notes*: The table reports daily OLS and IV regressions for the estimation sample, 2 July 2003–30 December 2022. The dependent variable is an AR(1)–GARCH(1,1) conditional-mean-to-variance ratio. Emotion measures are NRC dictionary word shares. The dependent price-of-risk state is dated $t + 1$ and is represented by the conditional mean–variance ratio for the return at $t + 2$; emotions, excluded instruments, and the other controls are dated $t$. Emotion indices are standardised. Coefficients are estimated using OLS and IV. NE denotes non-economic news. IV–NE instruments economic-news emotions with matching non-economic-news emotions. IV–Sports instruments economic-news dictionary emotions with sports-news dictionary emotions. Controls are the excess return, log article count, log trading volume, Bank of England and CPI announcement indicators, the ten-year minus two-year gilt spread, log UK Economic Policy Uncertainty, HIV4 polarity, and day-of-week effects. The minimum SW $F$ is the minimum Sanderson–Windmeijer conditional first-stage statistic across the endogenous emotions; it is undefined for OLS. HIV4 polarity is $(P - N)/(P + N)$, where $P$ and $N$ are the article's counts of HIV4 positive and negative words. Each moving-block draw reconstructs the generated proxy and lagged controls. Point estimates are bootstrap means; brackets are 95 per cent percentile intervals. ***, **, and * denote significance at the 1, 5, and 10 per cent levels, respectively.

## 5.1 Interpreting the Results

Both main estimates have the opposite sign to the individual-level predictions that motivate the focus on fear and anger. In the appraisal-tendency framework, fear is associated with pessimistic risk estimates and risk-averse choices, and anger with optimistic risk estimates and risk-seeking choices (Lerner and Keltner, 2000, 2001), and evidence from finance links fear to higher risk aversion (Cohn et al., 2015; Guiso et al., 2018). In the myopic case, these effects would raise the price of risk after fearful news and lower it after angry news. The estimates show the reverse: fear lowers the price-of-risk proxy, and anger raises it. The individual-level evidence on anger is, however, less uniform: anger has been found to raise or lower risk taking depending on the context of the decision (Baumann and DeSteno, 2012).

Because the proxy is a ratio, a change in it can come from its numerator, the conditional mean, or from its denominator, the conditional variance. Table B.4 reports the main OLS and IV specifications with the AR(1) conditional mean and the GARCH(1,1) conditional variance of the return at $t+2$ as separate outcomes. Neither

emotion has a precise effect on the conditional mean. Both affect the conditional variance, in opposite directions: anger lowers it under both instrument sets, and fear raises it under IV–NE, with an imprecise estimate of the same sign under IV–Sports. Both results therefore operate through expected volatility. This matches the behaviour of the proxy as a whole (Section 3.1.1), which moves more closely with the conditional variance than with the conditional mean, consistent with evidence that expected returns do not rise in proportion to volatility (Moreira and Muir, 2017; Jensen and Lazarus, 2025).

One reading works through beliefs about risk and trading. Fear raises risk estimates and plans for precautionary measures, and anger lowers them (Lerner et al., 2003). In financial markets, the FEARS index of Da et al. (2015), built from household internet search volume, predicts temporary increases in volatility and flows out of equity funds into bond funds. Angry news could therefore be followed by less selling and calmer markets, and fearful news by more selling and larger price moves. This would move the conditional variance in the observed directions.

Outside the myopic case, emotions could in addition move the hedging term in Equation (11) if they signal changes in future investment opportunities.

## 5.2 Robustness

I test the results from Section 5 against a series of alternative data, measurements, and specifications. First, I look at a broader decomposition of emotional content using the six basic emotions from Ekman and Friesen (1971) and Ekman (1992): in addition to fear and anger, I construct sadness, disgust, happiness, and surprise shares in the same way from the NRC lexicon. The results are qualitatively similar for fear and anger. Appendix Table B.2 reports the results of this specification.

Second, the price-of-risk proxy may be persistent and thus affect estimation. Therefore, I estimate a separate specification that adds a lag of the proxy as a control. Relative to the main estimates, controlling for persistence reduces dictionary anger by 66–69 per cent. Dictionary anger retains its sign and significance under IV–NE, while

its IV–Sports interval includes zero. Appendix Table B.3 reports the estimates.

Third, I test for feedback from markets to the instruments, the second threat to exclusion discussed in Section 4.1. I regress fear and anger in non-economic news and in sports news at $t+1$ on the FTSE 100 excess return at $t$. If market movements shaped the emotional tone of these sections, the instruments would carry market information and the return coefficient would differ from zero. None of the four coefficients does: all 95 per cent bootstrap intervals include zero, and the Holm-adjusted $p$-values, which correct jointly across the four regressions, range from 0.35 to 1.00 (Appendix Table B.5).

Fourth, the full-sample estimation of the GARCH parameters may introduce look-ahead bias by allowing later returns to influence the proxy at earlier dates. I therefore reconstruct the proxy using an expanding window, and each moving-block bootstrap repeats this construction within each draw[2]. Dictionary anger remains positive under both instrument sets, significant at the 5 per cent level under IV–NE and at the 10 per cent level under IV–Sports. Dictionary fear remains negative under IV–NE. These estimates retain the qualitative patterns of the main specification. Appendix Table B.6 reports the estimates.

Fifth, the Daily Mail contributes the largest share of articles in the corpus (Section 3.2), so its reporting could skew the results. I therefore remove Daily Mail articles, reconstruct the economic-, non-economic-, and sports-news measures from the remaining three newspapers, and re-estimate the main specification. Dictionary anger is unchanged under IV–NE at 2.08 (28.3 per cent of the mean), while the IV–Sports estimate falls to 1.24 and is less precisely estimated. Dictionary fear remains negative under both instrument sets: $-1.98$ under IV–NE ($-27.0$ per cent of the mean) and $-0.95$ under IV–Sports, significant at the 10 per cent level. Appendix Table B.1 reports the estimates.

[2]I estimate the model using a 1,008-day initial window, which is approximately four trading years. I use fewer bootstrap replications to keep the estimation feasible.

# 6 Conclusions

This paper examines whether fear and anger in economic news move the market price of risk. It combines 9.83 million newspaper articles with daily FTSE 100 returns from 2003 to 2022 and measures emotions in reporting using dictionary methods. The main regressions relate emotions and controls at $t$ to the price of risk at $t+1$. I instrument economic-news emotions with matching emotions in non-economic and sports news.

A one-standard-deviation increase in anger raises the price-of-risk proxy by 28.3 per cent of its mean under non-economic-news instruments and by 27.9 per cent under sports-news instruments. Fear lowers it under non-economic-news instruments and is imprecise under sports-news instruments. When investors are myopic, a higher price of risk reflects higher risk aversion, so these estimates point to lower risk appetite after angry coverage and, where precisely estimated, higher risk appetite after fearful coverage. Both signs are opposite to the individual-level evidence on fear, anger, and risk taking. Decomposing the proxy shows that both effects operate through the conditional variance of returns, with no precise effect on the conditional mean.

The robustness checks narrow the scope of these findings. Dictionary anger remains positive under both instrument sets in the six-emotion model, with lower precision under IV–Sports. Controlling for the price-of-risk state at $t$ attenuates the emotion coefficients: IV–NE continues to support positive dictionary anger, while the IV–Sports emotion estimates become imprecise. Re-estimating the GARCH model on an expanding window, which removes look-ahead bias from the proxy, leaves dictionary anger positive under both instrument sets, at the 10 per cent level under IV–Sports, and dictionary fear negative under IV–NE. Excluding the Daily Mail, the largest contributor to the corpus, leaves dictionary anger unchanged under IV–NE and dictionary fear negative under both instrument sets, while the IV–Sports anger estimate becomes imprecise. Regressions of the instrument emotions on the previous day's return show no significant response of non-economic or sports coverage to market returns. Under the identifying assumptions, the evidence therefore shows that emotional content in public economic news, anger in particular, moves the next day's inferred price of risk.

Finally, these findings suggest that news-based emotion measures may play a role in monitoring financial stability. Authorities could use these measures alongside market stress indicators to track the emotional tone of coverage following a major announcement, allowing them to monitor how their messages are interpreted.

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# Appendix

# A Model Derivation

## A.1 The Investor's Problem

Under Assumption 1, the investor at date $t$ holds risk aversion at its current value $\rho_t$ in every future period and chooses consumption $c_t$ and the risky share $\pi_t$ to solve

$$V(w_t, z_t; \rho_t) = \max_{c_t, \pi_t} \left\{ \frac{c_t^{1-\rho_t}}{1-\rho_t} + \beta\, \mathbb{E}_t\big[V(w_{t+1}, z_{t+1}; \rho_t)\big] \right\}$$

subject to the budget constraint

$$w_{t+1} = (w_t - c_t)(R_f + \pi_t x_{t+1}),$$

with $u = \log c_t$ for $\rho_t = 1$. Substituting the budget constraint and assuming an interior optimum, the first-order conditions with respect to $c_t$ and $\pi_t$ are

$$c_t^{-\rho_t} = \beta\, \mathbb{E}_t\big[V_w(w_{t+1}, z_{t+1}; \rho_t)(R_f + \pi_t x_{t+1})\big], \qquad \mathbb{E}_t\big[V_w(w_{t+1}, z_{t+1}; \rho_t)\, x_{t+1}\big] = 0. \tag{A.1}$$

The envelope condition $V_w(w, z; \rho_t) = c(w, z; \rho_t)^{-\rho_t}$ turns the portfolio condition into (4).

## A.2 Price of Risk

Holding $\rho_t$ fixed, expand the product $x_{t+1} V_w(w_{t+1}, z_{t+1}; \rho_t)$ to second order around $(a_t R_f, \bar{z})$, where $\bar{z} = (\bar{\mu}, \bar{h})$ is the steady-state value of the state vector $z_t = (\mu_{t+1}, h_{t+1})$ of conditional moments of the excess return, with $\Delta\mu_{t+2} = \mu_{t+2} - \bar{\mu}$ and $\Delta h_{t+2} = h_{t+2} - \bar{h}$. Wealth deviates from $a_t R_f$ by $a_t \pi_t x_{t+1}$. Every term carries the factor $x_{t+1}$, so

$$0 \approx A_t \mu_{t+1} + B_t a_t \pi_t h_{t+1} + D_t\, \mathbb{E}_t[\Delta\mu_{t+2} x_{t+1}] + H_t\, \mathbb{E}_t[\Delta h_{t+2} x_{t+1}], \tag{A.2}$$

where $A_t = V_w$, $B_t = V_{ww}$, $D_t = V_{w\mu}$, and $H_t = V_{wh}$, all evaluated at $(a_t R_f, \bar{z}; \rho_t)$. The omitted terms are $x_{t+1}$ times products of two deviations. Define the hedging terms

$$\kappa_{\mu,t} = \frac{D_t}{A_t} \frac{\mathbb{E}_t[\Delta\mu_{t+2} x_{t+1}]}{\mu_{t+1}}, \qquad \kappa_{h,t} = \frac{H_t}{A_t} \frac{\mathbb{E}_t[\Delta h_{t+2} x_{t+1}]}{\mu_{t+1}}, \tag{A.3}$$

and let $\kappa_{H,t} = 1 + \kappa_{\mu,t} + \kappa_{h,t}$. The local portfolio condition becomes

$$0 \approx A_t \mu_{t+1} \kappa_{H,t} + a_t \pi_t B_t h_{t+1},$$

so $\mu_{t+1} \approx \lambda_t h_{t+1}$ with $\lambda_t = -a_t \pi_t B_t/(A_t \kappa_{H,t})$. The envelope condition gives $V_{ww} = -\rho_t\, c^{-\rho_t - 1} c_w$, so $-a_t R_f B_t / A_t = \rho_t \varepsilon_{c,t}$, where $\varepsilon_{c,t} = a_t R_f\, c_w / c$ with $c$ and $c_w$ evaluated at $(a_t R_f, \bar{z}; \rho_t)$. Hence $\lambda_t$ takes the form (6). Since, for $s \in \{\mu, h\}$, $\mathbb{E}_t[\Delta s_{t+2} x_{t+1}] = \mathrm{Cov}_t(s_{t+2}, x_{t+1}) + (\mathbb{E}_t[s_{t+2}] - \bar{s})\mu_{t+1}$, the terms $\kappa_{\mu,t}$ and $\kappa_{h,t}$ contain the covariances between the return and next period's conditional mean and second moment, which capture the intertemporal hedging demand.

The curvature in $\lambda_t$ is $\rho_t$ because the expansion holds risk aversion at its current value. Without Assumption 1, (4) contains $\rho_{t+1}$, which is random at $t$ and cannot be held fixed in the expansion; its effect on the coefficient on $h_{t+1}$ then appears only through terms in $x_{t+1}^2(\rho_{t+1} - \bar{\rho})$, which are of third order.

**Assumption 2 (fixed consumption share).** Under Assumptions 1 and 2, $V_w(w_{t+1}, z_{t+1}; \rho_t) = \theta^{-\rho_t} w_{t+1}^{-\rho_t}$, so

$$\theta^{-\rho_t} a_t^{-\rho_t}\, \mathbb{E}_t\big[x_{t+1}(R_f + \pi_t x_{t+1})^{-\rho_t}\big] = 0. \tag{A.4}$$

The first two factors are positive and known at $t$, which yields (7). This is the first-order condition of $\max_{\pi_t} \mathbb{E}_t[u(w_{t+1}; \rho_t)]$, whose second derivative $-\rho_t a_t^{1-\rho_t} \mathbb{E}_t[x_{t+1}^2 (R_f + \pi_t x_{t+1})^{-\rho_t - 1}]$ is negative, so the interior solution is unique.

Define $G_t(x) = x(R_f + \pi_t x)^{-\rho_t}$, so (7) reads $\mathbb{E}_t[G_t(x_{t+1})] = 0$. Expand around $x = 0$, holding $\pi_t$, $R_f$, and $\rho_t$ fixed, at the optimal $\pi_t$; the actual mean $\mu_{t+1}$ is unrestricted. Then $G_t(0) = 0$, $G_t'(0) = R_f^{-\rho_t}$, and $G_t''(0) = -2\rho_t \pi_t R_f^{-\rho_t - 1}$, so

$$G_t(x) = R_f^{-\rho_t} \left[ x - \frac{\rho_t \pi_t}{R_f} x^2 \right] + \mathcal{R}_t(x). \tag{A.5}$$

Taking conditional expectations and multiplying by $R_f^{\rho_t}$,

$$\mu_{t+1} = \frac{\rho_t \pi_t}{R_f} h_{t+1} - R_f^{\rho_t}\, \mathbb{E}_t[\mathcal{R}_t(x_{t+1})]. \tag{A.6}$$

Dropping the expected remainder gives (5) with (8). The definition of $\lambda_t$ is exact; its identification with $\mu_{t+1}/h_{t+1}$ uses the approximation.

Because $V_w$ does not depend on $\mu$ or $h$, $D_t = H_t = 0$ and $\kappa_{\mu,t} = \kappa_{h,t} = 0$, and $c_w = \theta = c/w$ gives $\varepsilon_{c,t} = 1$. Equation (6) then reduces to $\lambda_t = \rho_t \pi_t / R_f$.

Both assumptions are needed. Without Assumption 1, (4) contains $\rho_{t+1}$ and averages over future curvatures. Without Assumption 2, or if $\theta$ depended on $z_{t+1}$ or covaried with $x_{t+1}$, a hedging term would remain. With constant risk aversion and independent and identically distributed returns, the CRRA problem is homothetic, so optimal consumption is linear in wealth and Assumption 2 holds; in that case the optimal risky share is the same in every period and equals the one-period solution (Samuelson, 1969). With time-varying return moments, Assumption 2 is an assump-

tion on the policy of (3).

# B Robustness Checks

Table B.1: Price-of-Risk Regressions, Daily Mail Excluded

| | OLS | IV–NE | IV–Sports |
|---|---|---|---|
| *Dictionary emotions* | | | |
| Fear | -0.728*** | -1.982*** | -0.954* |
| | [-1.284, -0.280] | [-3.577, -0.746] | [-2.178, 0.164] |
| Anger | 0.514*** | 2.080** | 1.243 |
| | [0.132, 1.000] | [0.409, 4.327] | [-0.485, 3.348] |
| Controls | Yes | Yes | Yes |
| Min. SW $F$ | – | 325.42 | 119.96 |
| Mean of proxy | 7.354 | 7.354 | 7.354 |
| Observations | 4,927 | 4,927 | 4,927 |

*Notes*: The table reports daily OLS and IV regressions after removing Daily Mail articles before reconstructing economic-, non-economic-, and sports-news dictionary measures. The estimation sample runs from 2 July 2003 to 30 December 2022. The dependent price-of-risk state is dated $t + 1$ and is represented by the conditional mean–variance ratio for the return at $t + 2$; emotions, excluded instruments, and the other controls are dated $t$. The dependent variable is an AR(1)–GARCH(1,1) conditional-mean-to-variance ratio. Emotion measures are NRC dictionary word shares. Each specification jointly includes fear and anger. Emotion indices are standardised. NE denotes non-economic news. IV–NE instruments economic-news emotions with matching non-economic-news emotions. IV–Sports instruments economic-news dictionary emotions with sports-news dictionary emotions. Controls are the excess return, log article count, log trading volume, Bank of England and CPI announcement indicators, the ten-year minus two-year gilt spread, HIV4 polarity, log UK Economic Policy Uncertainty, and day-of-week effects. The minimum SW $F$ is the minimum Sanderson–Windmeijer conditional first-stage statistic across the endogenous emotions; it is undefined for OLS. HIV4 polarity is $(P - N)/(P + N)$, where $P$ and $N$ are the article's counts of HIV4 positive and negative words. Each moving-block draw reconstructs the generated proxy and constructed controls. Point estimates are bootstrap means; brackets are 95 per cent percentile intervals. ***, **, and * denote significance at the 1, 5, and 10 per cent levels, respectively.

Table B.2: Price-of-Risk Regressions, Six Emotions

| | (1) OLS | (2) IV–NE | (3) IV–Sports |
|---|---|---|---|
| *Dictionary emotions* | | | |
| Fear | -0.448*** | -1.412** | -1.848* |
| | [-0.893, -0.104] | [-3.206, -0.011] | [-4.706, 0.329] |
| Anger | 0.567*** | 1.888** | 1.723* |
| | [0.141, 1.124] | [0.238, 4.094] | [-0.165, 4.195] |
| Sadness | -0.442*** | -0.355 | -0.171 |
| | [-0.818, -0.141] | [-1.392, 0.644] | [-1.576, 1.274] |
| Happiness | 0.035 | 0.516 | -1.187 |
| | [-0.241, 0.338] | [-1.037, 2.329] | [-3.977, 1.234] |
| Surprise | -0.151 | -1.623*** | -0.468 |
| | [-0.388, 0.046] | [-3.007, -0.573] | [-1.786, 0.755] |
| Disgust | -0.016 | -0.192 | 0.656 |
| | [-0.255, 0.213] | [-1.390, 0.913] | [-0.783, 2.367] |
| Controls | Yes | Yes | Yes |
| Min. SW $F$ | – | 168.42 | 54.18 |
| Mean of proxy | 7.354 | 7.354 | 7.354 |
| Observations | 4,927 | 4,927 | 4,927 |
| Bootstrap replications | 5,000 | 5,000 | 5,000 |

*Notes*: The table reports daily OLS and IV regressions for the estimation sample, 2 July 2003–30 December 2022. The dependent variable is an AR(1)–GARCH(1,1) conditional-mean-to-variance ratio. Emotion measures are NRC dictionary word shares. The dependent price-of-risk state is dated $t + 1$ and is represented by the conditional mean–variance ratio for the return at $t + 2$; emotions, excluded instruments, and the other controls are dated $t$. Emotion indices are standardised. Coefficients are estimated using OLS and IV. NE denotes non-economic news. IV–NE instruments economic-news emotions with matching non-economic-news emotions. IV–Sports instruments economic-news dictionary emotions with sports-news dictionary emotions. Controls are the excess return, log article count, log trading volume, Bank of England and CPI announcement indicators, the ten-year minus two-year gilt spread, log UK Economic Policy Uncertainty, HIV4 polarity, and day-of-week effects. The minimum SW $F$ is the minimum Sanderson–Windmeijer conditional first-stage statistic across the endogenous emotions; it is undefined for OLS. HIV4 polarity is $(P - N)/(P + N)$, where $P$ and $N$ are the article's counts of HIV4 positive and negative words. Each moving-block draw reconstructs the generated proxy and lagged controls. Point estimates are bootstrap means; brackets are 95 per cent percentile intervals. ***, **, and * denote significance at the 1, 5, and 10 per cent levels, respectively.

Table B.3: Price-of-Risk Regressions, Lagged Price-of-Risk Control

| | (1) OLS | (2) IV–NE | (3) IV–Sports |
|---|---|---|---|
| *Dictionary emotions* | | | |
| Fear | -0.339*** | -0.659*** | -0.330 |
| | [-0.724, -0.072] | [-1.439, -0.105] | [-1.034, 0.276] |
| Anger | 0.207** | 0.646** | 0.694 |
| | [0.020, 0.527] | [0.046, 1.674] | [-0.190, 2.109] |
| Controls | Yes | Yes | Yes |
| Min. SW $F$ | – | 373.03 | 94.33 |
| Mean of proxy | 7.354 | 7.354 | 7.354 |
| Observations | 4,927 | 4,927 | 4,927 |
| Bootstrap replications | 5,000 | 5,000 | 5,000 |

*Notes*: The table reports daily OLS and IV regressions for the estimation sample, 2 July 2003–30 December 2022. The dependent variable is an AR(1)–GARCH(1,1) conditional-mean-to-variance ratio. Emotion measures are NRC dictionary word shares. The dependent price-of-risk state is dated $t+1$ and is represented by the conditional mean–variance ratio for the return at $t+2$; emotions, excluded instruments, and the other controls are dated $t$. Each specification also includes the GARCH price-of-risk state at $t$, the first lag of the dependent state. Emotion indices are standardised. Coefficients are estimated using OLS and IV. NE denotes non-economic news. IV–NE instruments economic-news emotions with matching non-economic-news emotions. IV–Sports instruments economic-news dictionary emotions with sports-news dictionary emotions. Controls are the excess return, log article count, log trading volume, Bank of England and CPI announcement indicators, the ten-year minus two-year gilt spread, log UK Economic Policy Uncertainty, HIV4 polarity, and day-of-week effects. The minimum SW $F$ is the minimum Sanderson–Windmeijer conditional first-stage statistic across the endogenous emotions; it is undefined for OLS. HIV4 polarity is $(P-N)/(P+N)$, where $P$ and $N$ are the article's counts of HIV4 positive and negative words. Each moving-block draw reconstructs the generated proxy and lagged controls. Point estimates are bootstrap means; brackets are 95 per cent percentile intervals. ***, **, and * denote significance at the 1, 5, and 10 per cent levels, respectively.

Table B.4: Conditional Mean and Conditional Variance Regressions

| | (1) OLS | (2) IV–NE | (3) IV–Sports |
|---|---|---|---|
| *Panel A: Conditional mean* $\hat{\mu}_{t+2\|t+1}$ | | | |
| Fear | -0.007 | -0.218 | 0.067 |
| | [-0.207, 0.193] | [-0.862, 0.189] | [-0.587, 0.868] |
| Anger | -0.167 | -0.242 | 0.055 |
| | [-0.519, 0.035] | [-1.049, 0.284] | [-1.104, 1.299] |
| Mean of outcome ($\times 10^4$) | 4.904 | 4.904 | 4.904 |
| *Panel B: Conditional variance* $\hat{h}_{t+2\|t+1}$ | | | |
| Fear | 0.479*** | 1.066*** | 0.828 |
| | [0.138, 0.950] | [0.234, 2.241] | [-0.164, 2.177] |
| Anger | -0.477*** | -1.208*** | -1.058** |
| | [-0.990, -0.109] | [-2.318, -0.316] | [-2.144, -0.115] |
| Mean of outcome ($\times 10^4$) | 1.229 | 1.229 | 1.229 |
| Controls | Yes | Yes | Yes |
| Observations | 4,927 | 4,927 | 4,927 |
| Bootstrap replications | 5,000 | 5,000 | 5,000 |

*Notes*: The table re-estimates the specifications in Table 6 with the two components of the price-of-risk proxy as separate dependent variables: the AR(1) conditional mean (Panel A) and the GARCH(1,1) conditional variance (Panel B) of the excess return at $t+2$, conditional on information at $t+1$. Returns are in decimal units, so the variance is in squared decimal units. Coefficients and outcome means are multiplied by $10^4$. Emotions, excluded instruments, and controls are dated $t$ and are the same as in the main table; emotion indices are standardised. The two component regressions are not an additive decomposition of the coefficient on the ratio. Each moving-block draw (block length 22) refits the AR(1)–GARCH(1,1) model and rebuilds the controls. The sample runs from 2 July 2003 to 30 December 2022. Point estimates are bootstrap means; brackets are 95 per cent percentile intervals. ***, **, and * denote significance at the 1, 5, and 10 per cent levels, respectively.

Table B.5: Feedback from Market Returns to Instrument Emotions

| | Fear | Anger |
|---|---|---|
| *Panel A: Non-economic-news instrument emotions* | | |
| Return at $t$ | 0.117 | 1.839 |
| | [-1.798, 1.941] | [-0.385, 4.182] |
| Holm-adjusted $p$-value | 1.000 | 0.346 |
| *Panel B: Sports-news instrument emotions* | | |
| Return at $t$ | 0.363 | 1.227 |
| | [-2.193, 3.104] | [-1.080, 3.529] |
| Holm-adjusted $p$-value | 1.000 | 0.888 |
| Main controls | Yes | Yes |
| EPU | Yes | Yes |
| Observations | 4,928 | 4,928 |
| Bootstrap replications | 5,000 | 5,000 |

*Notes*: Each column reports a separate daily OLS regression of a dictionary instrument-emotion measure at $t + 1$ on the FTSE 100 excess return at $t$. Panel A uses emotions in non-economic news. Panel B uses emotions in sports news. All regressions control for log article count, log trading volume, Bank of England and CPI announcement indicators, the ten-year minus two-year gilt spread, HIV4 polarity, log EPU, and day-of-week effects. Emotion indices are standardised. Point estimates are bootstrap means; brackets contain 95 per cent moving-block-bootstrap percentile intervals. Holm-adjusted $p$-values correct jointly across the four feedback regressions. The block length is 22 trading observations.

Table B.6: Price-of-Risk Regressions, Expanding-Window GARCH

| | (1) OLS | (2) IV–NE | (3) IV–Sports |
|---|---|---|---|
| *Dictionary emotions* | | | |
| Fear | -0.725*** | -1.579*** | -0.843 |
| | [-1.423, -0.236] | [-3.122, -0.354] | [-2.358, 0.509] |
| Anger | 0.512** | 2.103** | 2.015* |
| | [0.051, 1.118] | [0.087, 4.782] | [-0.110, 4.956] |
| Controls | Yes | Yes | Yes |
| Min. SW $F$ | – | 499.99 | 102.34 |
| Mean of proxy | 7.689 | 7.689 | 7.689 |
| Observations | 3,921 | 3,921 | 3,921 |
| Bootstrap replications | 1,000 | 1,000 | 1,000 |

*Notes*: The table reports daily OLS and IV regressions for 25 June 2007–28 December 2022. Emotion measures are NRC dictionary word shares. Emotion indices are standardised. The dependent variable is the price-of-risk state at $t+1$, represented by the one-step conditional-mean-to-variance forecast for the return at $t + 2$. An AR(1)–GARCH(1,1) model is fitted to an initial 1,008-return window and re-estimated at every step. IV–NE uses matching non-economic-news emotions; IV–Sports uses sports-news dictionary emotions. Controls are the excess return, log article count, log trading volume, Bank of England and CPI announcement indicators, the ten-year minus two-year gilt spread, log UK Economic Policy Uncertainty, HIV4 polarity and day-of-week effects. The minimum SW $F$ is the minimum Sanderson–Windmeijer conditional first-stage statistic across the endogenous emotions; it is undefined for OLS. Point estimates are bootstrap means; brackets are 95 per cent percentile intervals. ***, **, and * denote significance at the 1, 5, and 10 per cent levels, respectively.