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The Power of Narrative Attention:
Linking Geopolitical and Economic Storylines to Currency Risk and Return Predictability

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Lee joined State Street in February 2008 and in addition to more than 20 years of experience as a macro strategist, he has also worked as a proprietary trader. Lee has a Bachelor of Science degree in economics and business economics and a master's degree in quantitative finance. He is a frequent commentator in the financial press—both written and TV—and has written articles for numerous industry publications. He has extensive experience as a keynote presenter, panel participant and host of industry conferences. State Street was ranked the World's Best FX Bank for Research in 2024.

Michael Guidi

Michael Guidi is a Managing Director and Head of Alternative Data as at State Street Associates (SSA). Michael's team focuses on generating quantitative investment research that utilizes SSA's proprietary datasets developed in conjunction with academic partners. This research and data includes indicators focused on a range of economic topics such as investor behavior, media sentiment, inflation, and geopolitics. Michael holds a Bachelor of Science in electrical and computer engineering from University of Florida, a MS in mathematical finance from Boston University, and the CFA designation.

William Kinlaw

William (Will) Kinlaw is executive vice president and head of Investor Data Products and Analytics at State Street. Will leads a firm-wide initiative that empowers clients to distill actionable insights from proprietary and third-party datasets. Drawing on State Street's technology and data infrastructure, as well as State Street Associates—our hub for partnerships with academics and fintech data companies—the team develops products that enhance clients' investment, trading, operations and distribution capabilities.

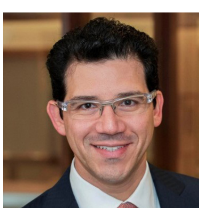
Will joined State Street in 2002. Previously, Will was head of Research for State Street Global Markets, where he led a strategic expansion of its award-winning research capabilities. This global team of data scientists, quantitative researchers, and economists delivers research directly to decision makers overseeing the world's largest institutional asset pools.

Will's published research, spanning more than a dozen peer-reviewed journal articles over 15 years, has focused on how investors can use data and quantitative models to improve outcomes. He has received six research awards, including the Harry M. Markowitz award, which was awarded to Will and his co-authors by a panel of Nobel laureates in 2023 for their research on the drivers of inflation. His book, "Asset Allocation: From Theory to Practice and Beyond," co-authored with Mark Kritzman and David Turkington, was published in 2021.

Will serves on the editorial boards of *The Journal of Portfolio Management* and *The Journal of Alternative Investments* and is a frequent presenter at investment conferences around the world. He holds a Master of Science in finance from Boston College, a Bachelor of Arts in economics from Tufts University, and a Chartered Financial Analyst designation.

Gideon Ozik

Dr. Gideon Ozik is founder and managing partner of MKT MediaStats, LLC, a technology and data analytics company, which combines expertise in data science and financial economics to extract financial markets insights from unique sets of untapped big data sources. Prior to MKT Gideon led investment solutions at Nexar Capital (acquired by UBP), managed hedge funds at Société Générale and developed quantitative derivatives strategies at NISA Investment Advisors. His prior academic experience includes teaching machine learning, alternative data, data analytics, financial derivatives, investments theory and quantitative research at HEC Paris, Dauphine University and EDHEC Business School where he is currently an affiliate professor. His research has been published at academic and practitioner journals including the *Journal of Financial Economics*, *Review of Financial Studies*, *Journal of Finance and Quantitative Analysis*, *Financial Analyst Journal*, *The Journal of Portfolio Management*, and *The Journal of Fixed Income*. Dr. Ozik earned B.Sc from the Technion - Israel Institute of Technology, MBA from Washington University, and PhD in Finance from EDHEC Business School, France.



Ronnie Sadka

Professor Ronnie Sadka Senior Associate Dean and chairperson of the Finance Department at the Carroll School of Management, Boston College. His research focuses on the liquidity in financial markets, the role of the media, and retail trading. More recently, he has been developing alternative data driven investment applications through MKT MediaStats, LLC. Sadka is a frequent speaker at academic and practitioner conferences; his work has been published in leading academic and professional journals, and has been covered by various media outlets. Prior academic experience includes teaching at the University of Chicago (Booth), New York University (Stern), Northwestern University (Kellogg), and the University of Washington (Foster). Industry experience includes Goldman Sachs Asset Management and Lehman Brothers (quantitative strategies), the economic advisory board of NASDAQ OMX, and State Street Associates (academic partner). Professor Sadka earned a B.Sc. (Magna Cum Laude) in industrial engineering and a M.Sc. (Summa Cum Laude) in operations research, both from Tel-Aviv University. He received a Ph.D. in finance from Northwestern University (Kellogg).

The Power of Narrative Attention: Linking Geopolitical and Economic Storylines to Currency Risk and Return Predictability

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KEY FINDINGS

- Drawing on a large pool of articles published over nearly a decade, the authors introduce a textual analysis framework to measure media attention to more than 100 narratives related to global economics, geopolitics and FX markets. The model captures the volume of coverage for each particular narrative as well as the prevailing tone.
- Fluctuations in emerging and developed currencies exhibit significant, time-varying exposure to these narratives, including themes like recession, inflation and trade wars.
- Narrative shocks are not fully priced immediately into FX markets and gradually impact future returns over a period of several weeks. The results highlight the importance of considering narratives in explaining risk in FX markets.
- Quantified narratives may capture novel sources of risk in the foreign exchange market.

ABSTRACT

A growing body of research studies the channels through which geopolitical and macroeconomic narratives, such as trade tensions, elections, civil unrest, and economic risks, can influence investors and asset prices. This article uses textual analysis of digital media to quantify attention to over 100 narratives. Regressions of currency returns on the variation in narrative attention are employed to compute narrative risk exposures, showing that currencies exhibit significant narrative exposures. Taken together, temporal narrative shocks and narrative exposures can predict currency returns, even after controlling for past return and institutional flow. The results are robust across developed and emerging markets and alternative model specifications. Overall, the article advances quantified narratives as novel sources of risk in the foreign exchange market.

The macroeconomics literature has long studied the channels through which geopolitical and macroeconomic topics, such as trade tensions, civil unrest, and economic risks, influence investors and asset prices. Instead of directly examining the mechanism underpinning these channels using standard economic variables, which are often difficult to measure, this article offers an alternative approach based on narrative economics by measuring attention to narratives.

Shiller (2019) introduces the concept whereby economic narratives can potentially “go viral” and drive asset prices over long periods of time. Indeed, Bhargava et al. (2023) quantify attention to narratives from a large set of media sources and demonstrate some implications for asset allocation and portfolio management use cases. We posit that media coverage offers a way of measuring attention to a large set of narratives and test their asset pricing implications on currency returns.

Most prior works that use media coverage do so to gauge overall sentiment and to demonstrate its impact on equity markets (e.g., Tetlock 2007; Manela and Moreira 2017; Calomiris and Mamaysky 2019), while some recent works studying narratives focus primarily on equity markets (e.g., Engle et al. 2020; Mai and Pukthuanthong 2021; Blanqué et al. 2022; Bybee et al. 2023; and Lee et al. 2024). Two exceptions are by Froot et al. (2017) and Filippou, Taylor, and Wang (2024), who study interactions of general media sentiment (rather than specific narratives) and short-term return reversals in currency markets.

The purpose of this study is to demonstrate that quantified narratives have a significant role in the pricing of currencies. The hypothesis is straightforward: Economic narratives contemporaneously drive currency prices, but they can also have a lasting effect, leading to currency return predictability. Following Bhargava et al. (2023), textual analysis of digital financial media is used to quantify attention to narratives. We find that foreign exchange rates are shown to exhibit significant and economically meaningful time-varying exposures to narrative attention. A model that forecasts future returns of narrative-sensitive currencies based on their exposures to contemporaneously high-varying narratives performs well (about 220 basis points per year, with a t-statistic above 3). Finally, various tests verify the robustness of the findings, and implications for foreign exchange risk modeling are discussed.

DATA

The analysis includes 53 developed and emerging markets currencies, which are listed in Exhibit 1. For each currency, we compile daily spot exchange rate data from Refinitiv WMR for the sample period of January 2015–April 2024. Of the foreign exchange rates, 32 are quoted relative to the US dollar, 20 are non-USD cross-currency pairs, and the US dollar is represented by the DXY Index, which measures the value of the dollar relative to a trade-weighted basket of major currencies including the euro, Japanese yen, British pound, Canadian dollar, Swedish krona, and Swiss franc. We convert exchange rates (and DXY values) to daily, monthly, or weekly returns for our analysis.

We use media coverage to derive time series proxies for the degree of attention that market participants allocate to specific narratives at a given point in time. For each day in the sample, narrative attention proxies are derived from articles published by approximately 150,000 global digital media sources.[1] Each article is assigned to one or more article collections (“reservoirs”) based on its content and source type. We consider four reservoirs: general media, corporate, foreign exchange, and country equity. The contributing sources comprise global English language media, including general news sources (such as CNN and the *Wall Street Journal*), local business publications (e.g., *Boston Business Journal* and *Chicago Business Journal*), news services (e.g., Reuters and PR Wire), industry publications (e.g., *PC Mag*), business and investing publications, corporate communications, and others.

The textual content of each article is evaluated for relevance to a set of predefined economic and financial narratives. This is done using proprietary algorithms that rely on keyword searches and specific textual conditions. Articles deemed relevant to specific narratives are tagged accordingly.

[1] The data are sourced from www.mktmediastats.com.

EXHIBIT 1
Global Currencies and Code

Currency	Code	Currency	Code
Argentine Peso	ARS	Japanese Yen	JPY
Australian Dollar	AUD	Malaysian Ringgit	MYR
Brazilian Real	BRL	Mexican Peso	MXN
British Pound	GBP	New Zealand Dollar	NZD
Canadian Dollar	CAD	Norwegian Krone	NOK
Chilean Peso	CLP	Philippine Peso	PHP
Chinese Yuan	CNY	Polish Zloty	PLN
Colombian Peso	COP	Singapore Dollar	SGD
Czech Koruna	CZK	South African Rand	ZAR
Danish Krone	DKK	South Korean Won	KRW
Euro	EUR	Swedish Krona	SEK
Hong Kong Dollar	HKD	Swiss Franc	CHF
Hungarian Forint	HUF	Taiwan Dollar	TWD
Indian Rupee	INR	Thai Baht	THB
Indonesian Rupiah	IDR	Turkish Lira	TRY
Israeli Shekel	ILS	US Dollar	USD
EUR per 1 GBP	EUR:GBP	Slovak Koruna	SKK
EUR per 1 CHF	EUR:CHF	AUD per 1 CAD	AUD:CAD
EUR per 1 SEK	EUR:SEK	AUD per 1 JPY	AUD:JPY
EUR per 1 AUD	EUR:AUD	GBP per 1 AUD	GBP:AUD
EUR per 1 CAD	EUR:CAD	GBP per 1 JPY	GBP:JPY
EUR per 1 JPY	EUR:JPY	GBP per 1 CHF	GBP:CHF
EUR per 1 NOK	EUR:NOK	GBP per 1 CAD	GBP:CAD
EUR per 1 SGD	EUR:SGD	CAD per 1 JPY	CAD:JPY
EUR per 1 NZD	EUR:NZD	CAD per 1 CHF	CAD:CHF
EUR per 1 CZK	EUR:CZK	EUR per 1 HUF	EUR:HUF
EUR per 1 PLN	EUR:PLN		

QUANTIFIED NARRATIVES

Narratives that have the potential to affect currency markets are identified as follows. We begin with 55 core, evergreen narratives and supplement this universe with additional narratives based on our discussions with investors and industry analysts. Through this process, we identify a set of 103 narratives, which are categorized in Exhibit 2.

The 55 evergreen narratives are identified as follows. MKT MediaStats has built an extensive library of narratives from multiple sources of news tags, including Reuters, IPTC, Bloomberg's macroeconomic announcement news tags, and analyst interest (through interactions since 2018). This library includes more than a thousand narratives. A core subset of 55 evergreen narratives that are long lasting in nature are identified by intersecting the narratives library with themes included in the *Journal of Economic Literature* (JEL) classification system, with a focus on the (E) Macroeconomics & Monetary Economics, (D) Microeconomics, (G) Financial Economics, (R) Urban, Rural, Regional, Real-Estate, and Transportation Economics in particular, R21, (F) International Economics, (J) Labor and Demographic Economics, (I) Health Education and Welfare, and (Q) Agricultural and Natural Resource Economics; Environmental and Ecological Economics classification branches.[2]

[2] The JEL Codes Guide can be found online at https://www.aeaweb.org/jel/guide/jel.php.

EXHIBIT 2
Quantified Media Narratives

Asset Classes. Commodity
Asset Classes. Derivative Securities
Asset Classes. Emerging Markets
Asset Classes. Equity Investing
Asset Classes. ETF
Asset Classes. FX
Asset Classes. Government & Corp Debt
Asset Classes. Interest Rates
Asset Classes. Money Market
Asset classes. Treasury Bonds
Asset classes. US Stocks
Brexit
Commodities. Gold
Commodities. Oil
Consumer Savings
Consumer Spending
COVID19. General
COVID19. Hospital Beds
COVID19. Subsequent Waves
COVID19. Tests
Cryptos. Bitcoin
Debt Ceiling
Demographics
Donald Trump
Economic Conditions. Business Cycles
Economic Conditions. China Growth
Economic Conditions. China Reopening
Economic Conditions. GDP
Economic Conditions. Global Growth
Economic Conditions. Goldilocks Economy
Economic Conditions. Housing Market
Economic Conditions. Inflation
Economic Conditions. Labor Market
Economic Conditions. Manufacturing
Economic Conditions. Recession
Economic Conditions. Stagflation
Economic Conditions. US Growth
Economic Conditions. US Growth Slowdown
Environmental Regulation
Fin Markets. Crowded Trades
Fin Markets. Investor Sentiment
Fin Markets. Liquidity
Fin Markets. Market Crash
Fin Markets. Risk
Fin Markets. Volatility
Financial Conditions
Financial Regulation
Firms. Bankruptcy
Firms. Buybacks
Firms. Earning Season
Firms. Earnings
Firms. Financing
Firms. Governance
Firms. Industry
Firms. Investment
Firms. M&A
Firms. Profitability
Fiscal Sustainability
Govt. Federal Reserve
Govt. Fiscal
Govt. International Trade
Govt. Money
Govt. Trade War
Households. Personal Consumption
Households. Personal Finance
Joe Biden
Nations. Globalization
Nations. International Conflicts
Nations. International Organizations
Nations. Political Elections
Nature. Natural Disasters
Offshoring
Onshoring
Participants. Commercial Banking
Participants. Fund & Asset Management
Participants. Investment Banking
Participants. Retail Investors
Policy Divergence
Quantitative Easing
Quantitative Tightening
Shortages
Social Issues. Civil Unrest
Social Issues. Crime
Social Issues. Environment
Social Issues. Health
Social Issues. Healthcare
Social Issues. Immigration
Social Issues. Inequality
Social issues. Privacy
Social Issues. Race
Styles. Carry
Styles. Dividends Factor
Styles. ESG
Styles. Minimum Volatility
Styles. Momentum
Styles. Passive Investing
Styles. Profitability
Styles. Size
Styles. Smart Beta
Styles. Value Investing
Worker Hiring
Worker Layoffs
Yield Curve

For each article, we create a sentiment score that is adjusted for the overall daily tone of the articles in the reservoir from which it is extracted. Article sentiment is measured based on a dictionary approach (Loughran and McDonald 2011) on a scale of –1 (most negative) to +1 (most positive). An article's sentiment of a given narrative in a particular reservoir is measured as the article sentiment, minus the average sentiment of all articles in that reservoir that day (this is done to adjust for systematic temporal variations in the overall sentiment expressed in each reservoir). We compute $A_{r,t}^{narr} = \frac{C_{r,t}^{narr}}{C_{r,t}}$ as the measure of attention allocated to narrative *narr* in reservoir *r* at day *t*, where $C_{r,t}^{narr}$ is the count of narrative *narr*-relevant articles in reservoir *r* at day *t* and $C_{r,t}$ is the total count of articles in reservoir *r*, irrespective of a narrative, at time *t*.

A related measure, $A^{narr}_{r,s<0,t} = \frac{C^{nar}_{r,s<0,t}}{C_{r,t}}$, considers only those narrative *narr*-relevant articles whose adjusted sentiment is negative. Its numerator $C^{narr}_{r,s<0,t}$ captures articles only if their sentiment scores are negative. We compute $A^{narr}_{r,t}$ and $A^{narr}_{r,s<0,t}$ for each reservoir separately and then average across the four individual reservoirs as follows:

$$A^{narr}_{t} = \frac{\sum_{r=1}^{4} A^{narr}_{r,t}}{4} \tag{1}$$

$$A^{narr}_{s<0,t} = \frac{\sum_{r=1}^{4} A^{narr}_{r,s<0,t}}{4}. \tag{2}$$

In our analysis to follow, we use $A^{narr}_{s<0,t}$ (condition on negative sentiment) because this measure captures both the tone (sentiment sign) and the quantity (intensity) of narrative coverage and refer to $A^{narr}_{s<0,t}$ as negative intensity. This calibration enables us to study how currencies respond to shifts in the tone and quantity of narrative coverage, recognizing that larger amounts of coverage are likely to exert greater influence on markets than smaller amounts. Our approach is similar to that of Engle et al. (2020), who construct a negative sentiment climate change news index using the fraction of media articles that relate to climate change and have a negative sentiment score.

To develop intuition for negative intensity, we focus initially on three narratives: inflation, recession, and trade. Exhibit 3 shows the number of articles used in this study that are narrative-relevant, covering the period from January 2015 through April 2024. Exhibit 4 shows the negative intensity series for the recession narrative along with selected headlines (from our sample of 591,933 articles) that coincided with historical spikes in negative coverage related to recession risk. Recession fears peaked in 2020 as the world grappled with economic fallout from the Covid-19 pandemic and again in 2022 as central banks around the world began increasing interest rates to fight rising inflation.

Exhibits 5 and 6 present the same information for the inflation and trade war narratives, respectively. Negative intensity for the inflation narrative was relatively benign until mid-2021 when consumer price increases began to accelerate. The negative inflation intensity continued to rise through the second half of 2021 as the Federal Reserve adopted a relaxed stance, arguing that price pressures would prove "transitory." It was only in early 2022 when the Federal Reserve rhetoric shifted to a more hawkish tone and it subsequently delivered a 25 basis point (bp) increase

EXHIBIT 3

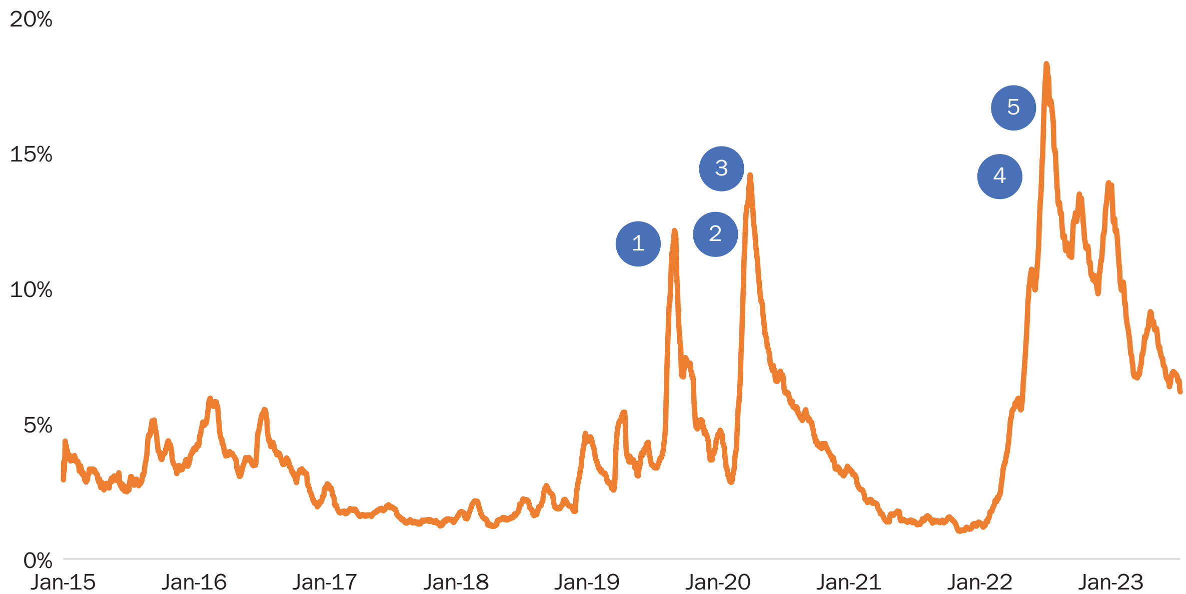
Sample Size of Relevant Articles for Three Major Narratives, January 2015 through April 2024

	Overall	Sentiment > 0	Sentiment < 0
Inflation	1,319,134	407,848	911,286
Recession	591,933	126,564	465,369
Trade War	614,586	154,394	460,192

NOTE: This exhibit displays the number of articles used to calculate negative intensity values for three major narratives over the sample period.

EXHIBIT 4

Negative Intensity for the Recession Narrative and Select Articles



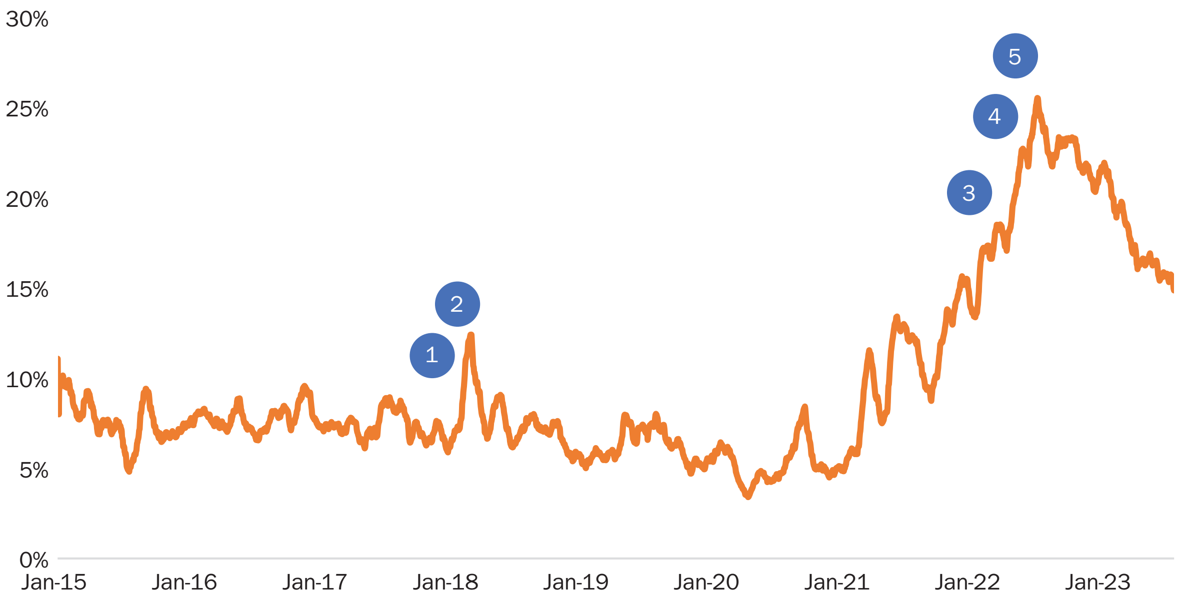
#	Article Title	Relevant Text	Date	Source
1	Inverted curve proves White House has won its rate battle with the Fed	"inverted yield curve is a classic signal of a looming **recession**—in the US, the curve has inverted ahead of every **recession** over the past 50 years…"	8/14/2019	*The Guardian*
2	As Trump acknowledges United States "may be" headed for **recession**, House passes coronavirus aid package	"President Donald Trump acknowledged Monday that the US economy 'may be' heading toward a **recession** because of the coronavirus…"	3/16/2020	*USA Today*
3	Coronavirus has plunged the world into a **recession**, according to S&P	"The coronavirus outbreak has plunged the world's economy into a global **recession**, according to S&P Global."	3/17/2020	CNN
4	How to prepare for a possible **recession**	"During a **recession**, a country's overall economic output declines, the unemployment rate goes up, retail sales fall, businesses cut their spending and manufacturers produce less goods."	6/17/2022	ABC News
5	Mortgage rates held in check as **recession** fears mount	"The rapid rise in mortgage rates has finally paused, largely due to the countervailing forces of high inflation and the increasing possibility of an economic **recession**…"	6/30/2022	*Washington Post*

in interest rates in March 2022, followed by a further 50 bps tightening in May and another 75 bps in June, that negative intensity around the inflation narrative began to recede.

The trade war narrative peaked in 2018 and 2019 as President Donald Trump sought to impose tariffs on US imports from China. The trade war narrative spiked higher (from a low base) in January 2018 as President Trump imposed tariffs on solar panels and washing machine imports from China of 30% and 20%, respectively. It spiked still higher in March 2018 as Trump imposed tariffs on steel and

EXHIBIT 5

Negative Intensity for the Inflation Narrative and Select Articles

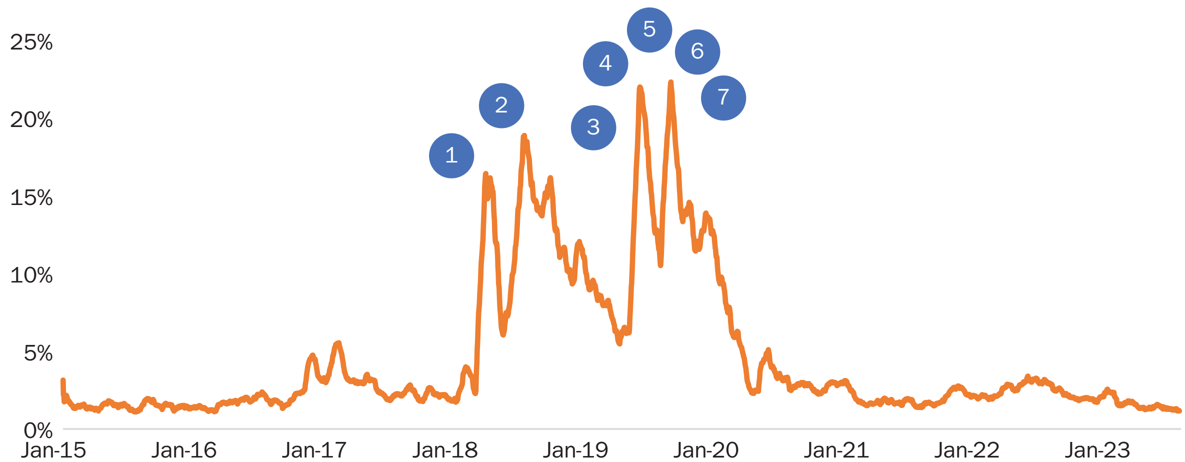


#	Article Title	Relevant Text	Date	Source
1	Fed's Powell sworn in, greeted with market turbulence	"This followed Friday's 666 point decline as bond yields rose after the January US jobs report suggested higher **inflation** ahead."	2/5/2018	Fox Business
2	FTSE and European stock markets fall after US and Asia rout	"For several weeks, economists and analysts have warned that **inflation** levels in major economies could increase this year beyond the 2% to 3%..."	2/6/2018	The Guardian
3	Stocks dive to another losing week as **inflation** worsens	"Wall Street's shuddering realization that **inflation** got worse last month, not better as hoped, sent markets reeling on Friday."	6/10/2022	*LA Times*
4	Fears mount over health of UK economy after sharp sell-off in markets	"Fears are mounting over the health of the UK economy after it unexpectedly shrank in April, as concerns over soaring **inflation** and slowing global growth triggered a sharp sell-off in financial markets."	6/13/2022	*The Guardian*
5	Fed raises key interest rate by 0.75% as it hardens fight against **inflation**	"The expected effect of these changes is that consumers will spend less and the heightened demand for goods—one of the drivers of **inflation**—will slow down."	6/15/2022	NBC News

aluminum imports from all trading partners of 25% and 10%, respectively. Further peaks were witnessed in the second half of 2019 as the United States announced a further 10% tariff on $200 billion of Chinese products and China responded with tariffs of their own on US imports. This tit-for-tat process continued through the remainder of 2019 until the US and China signed the Phase One Trade Agreement in January 2020, which saw negative intensity around the narrative fall back sharply, close to pre-2018 levels.

EXHIBIT 6

Negative Intensity for the Trade War Narrative and Select Articles



#	Article Title	Relevant Text	Date	Source
1	With just two days to go, countries have no clue whether they'll be affected by Trump's **tariffs**	"Just two days before **tariffs** on foreign-made steel and aluminum are scheduled to take effect, the Trump administration has yet to make public its plans for how the import levies will work in practice."	3/21/2018	Washington Post
2	China steps in to keep currency stable after trade fears spook markets	"…in a trip to Shanghai last week, he 'detected increasing alarm over **trade tensions** and a lot of nervousness about a full blown **trade war**,' which comes at a bad time for China."	7/3/2018	CNN Money
3	Why the US economy may have already peaked for the year	"But the gravest perceived threat may be the escalating **trade war** between the United States and China, the world's two largest economies."	5/30/2019	Fox Business
4	Rare earths could be the next front in the US-China **trade war**. Here's what you should know	"As the **trade war** between the United States and China escalates, Beijing may be preparing to play a new card: its control of rare earth minerals. Chinese state media…"	5/30/2019	CNN
5	US hiring slows sharply as Trump's **trade war** starts to bite	"The slowdown is really coming from the sectors that are most susceptible to **trade tensions** like manufacturing, construction, mining and logging. That does make me worried,…"	6/7/2019	Washington Post
6	Stock markets drop on new Trump China **tariffs**	"US stock markets have fallen for a second day following a decision by Donald Trump to impose new **tariffs** on a further $300bn of Chinese imports."	8/2/2019	BBC
7	Global **trade fights** will keep markets on edge	"The world's three largest economies are engaged in **trade conflicts.** Two more heavyweights could soon have major trade issues of their own Japan (the world's No. 3 economy) last week escalated its **trade spat**…"	8/4/2019	CNN

NARRATIVE EXPOSURES AND CURRENCY PRICING

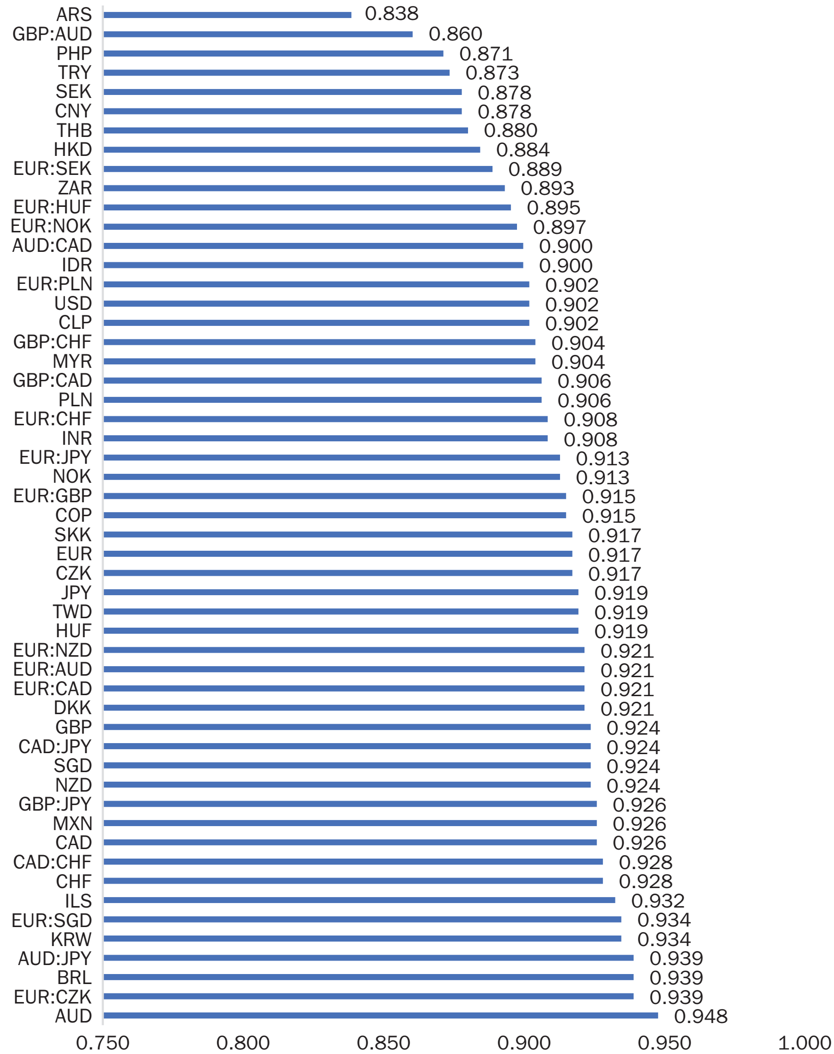
We regress each of the 53 currencies in our sample against changes in negative intensity for the 103 narratives presented in Exhibit 2. Our regression model is defined as

$$R_{c,t} = \alpha + \beta_{c,narr,t} * Z_{narr,t} + e_{c,t}, \tag{3}$$

where $R_{c,t}$ is the one-week (Tuesday to Tuesday, 11am ET) currency return of currency c, α is a constant, and $Z_{narr,t}$ is a standardized weekly shock in the negative intensity

EXHIBIT 7

Percentage of Weeks Where Each Currency Exhibits Significant Exposure to At Least One Active Narrative



NOTES: A currency exhibits a significant exposure to a narrative if its six-month exposure carries a *t*-statistic with an absolute value greater than 1.5. A narrative is considered active if its four-week change in negative intensity is in the top quintile of its historical four-week changes in negative intensity. We examine each currency pair in the 458 weeks between July 14, 2015, and April 16, 2024. For each currency pair, we determine whether it has a significant exposure to at least one active narrative for each of these 458 weeks. The value presented with each currency pair in the chart is the proportion of the 458 weeks in which these conditions are met. For example, ARS presents a value of 0.838; that is, ARS has a significant exposure to an active narrative for approximately 83.8% of the sample. The average displayed proportion of the chart is 90.98%.

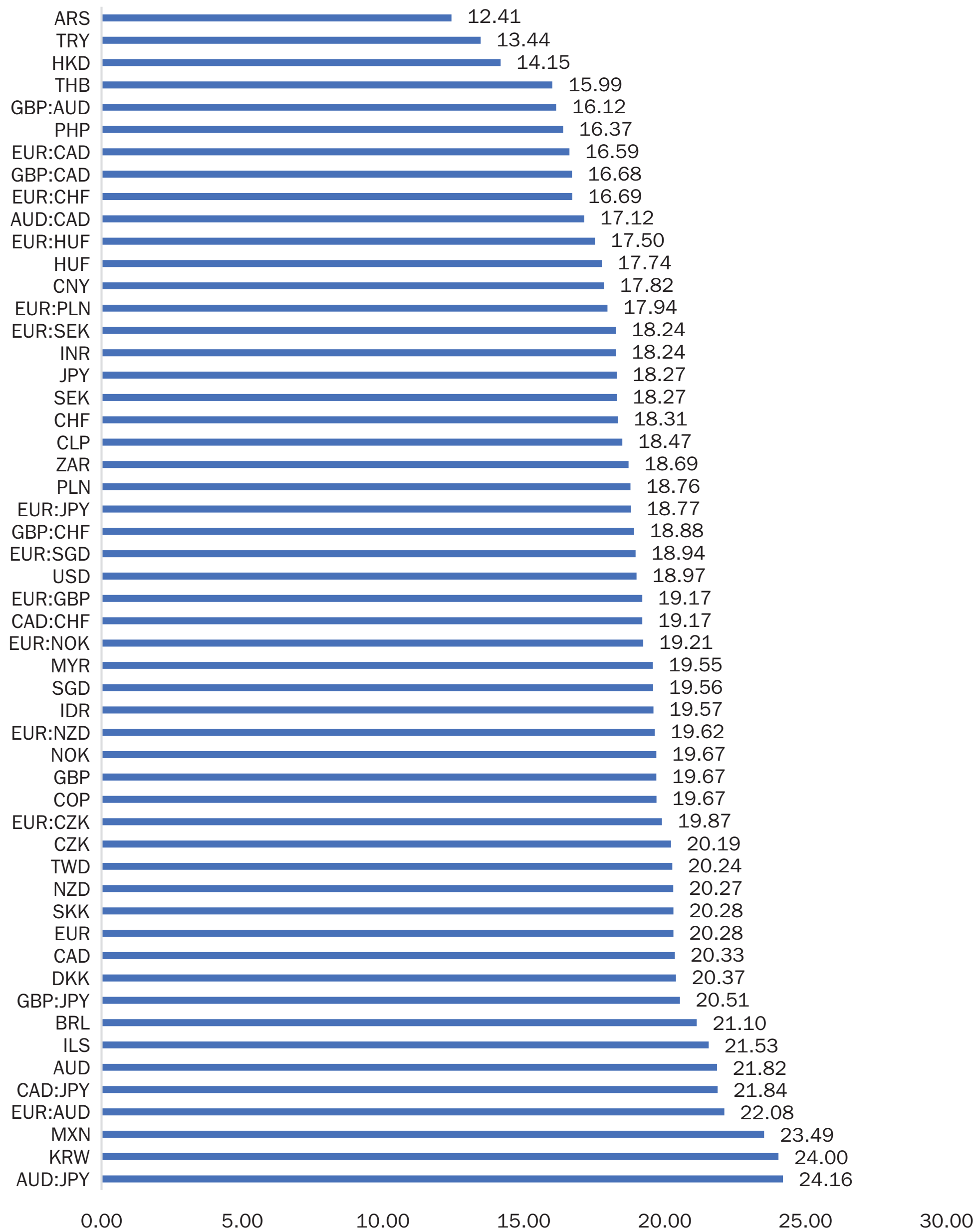
of narrative *narr*.[3] We then estimate the weekly regression using a six-month rolling window whereby currency weekly returns are regressed on weekly nonoverlapping changes in negative intensity. The sample period is July 10, 2015, through April 14, 2024.

Exhibits 7, 8, and 9 provide some summary statistics of narrative exposures. Exhibit 7 reports the percentage of weeks with significant exposures to at least one narrative per currency. The percentage ranges between 84% (ARS) and 95% (AUD),

[3] Standardized weekly shocks in negative intensity of narrative *narr* are calculated as the one-week (Tuesday to Tuesday) change, minus the historical mean one-week change, divided by the standard deviation of one-week changes. We compute the mean and standard deviation using all available data prior to date *t*.

EXHIBIT 8

Mean Number Narratives to Which Each Currency Is Exposed Each Day

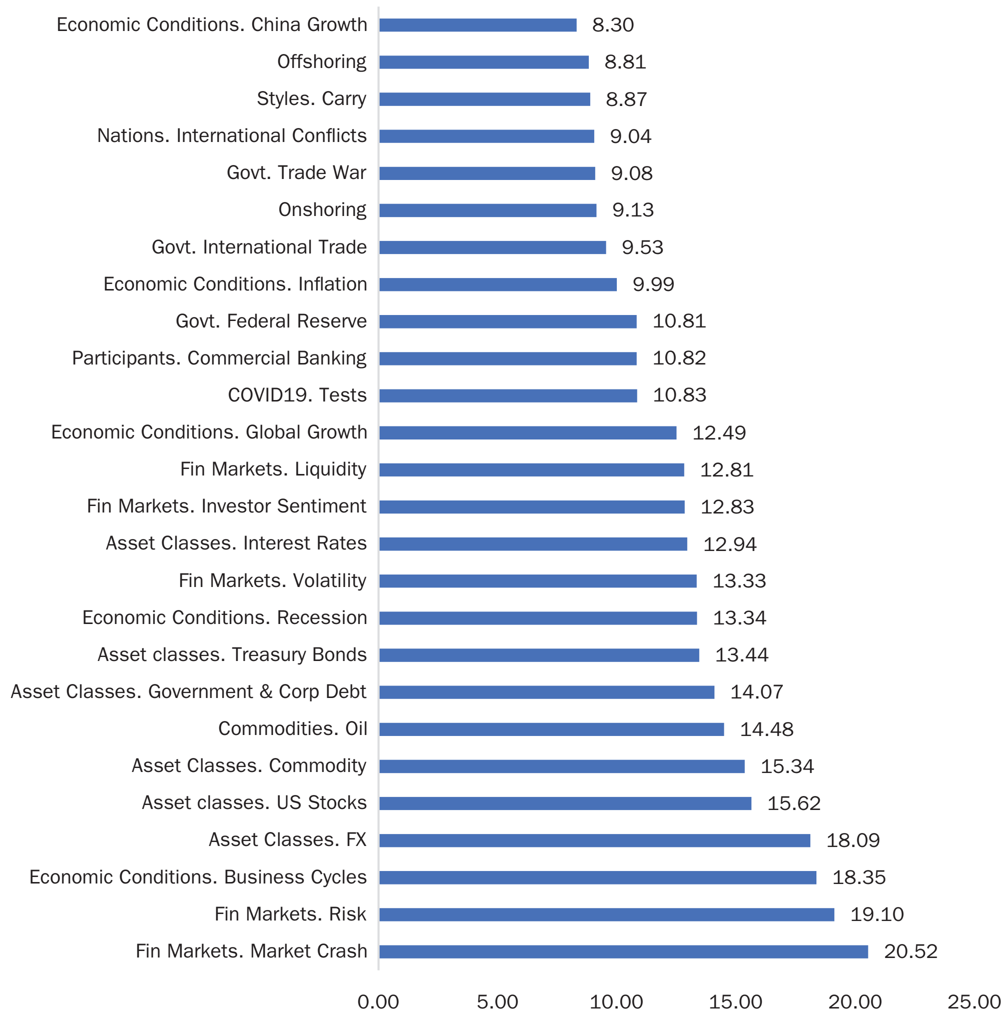


NOTES: A currency exhibits a significant exposure to a narrative if its six-month exposure carries a *t*-statistic with an absolute value greater than 1.5. We examine each currency pair in the 458 weeks between July 14, 2015, and April 16, 2024. The value presented with each currency pair in the chart is the mean number of themes per week that the currency has a significant exposure. For example, ARS presents a value of 12.41; that is, on average, ARS is significantly exposed to 12.41 narratives (out of 103 possible narratives in the dataset) per week. The average displayed value of the chart is 18.992.

with an average of 91% across all currencies. This demonstrates that most of the time, currency returns are significantly correlated with variations of at least one of the 103 narratives included in our sample, suggesting that the set of narratives used in this study is adequately defined. In fact, Exhibit 8 shows that the average currency is significantly exposed to 19 narratives at any given point in time, ranging from 12 (ARS) to 24 (AUD:JPY). Therefore, each currency pair is significantly exposed to several narratives each week; however, they are not consistently exposed to so many narratives that significant exposure is meaningless. From the perspective of a given

EXHIBIT 9

Mean Number of Currencies with Exposure to Each Narrative Each Day



NOTES: Similar to the analysis to Exhibit 8, we now determine the number of currencies per week that have a significant exposure to a given theme. We examine each narrative in the 458 weeks between July 14, 2015, and April 16, 2024. The value presented with each narrative in the chart is the mean number of currency pairs per week that has a significant exposure to the given narrative. For example, "offshoring" carries a value of 8.81; that is, this narrative has an average of 8.81 currency pairs with a significant exposure to it on any given week. For brevity, the exhibit does not report the results for all themes, rather a selected handful with an intuitive relationship to foreign exchange. The mean value for all 103 themes is 9.876.

narrative, Exhibit 9 shows that, on average, about 10 currency pairs are exposed to a narrative on any given day.

In Exhibit 10, we show some examples of significant currency exposures to popular narratives to provide the reader with better intuition. Panel A in Exhibit 10 depicts the narrative beta of the Chinese yuan to the "trade war" narrative. In 2018, US President Donald Trump imposed tariffs on Chinese goods and the Chinese government retaliated with its own set of tariffs. The yuan exhibited negative narrative beta exposure to the trade war narrative starting in 2019 and a subsequent spike in that narrative coincided with a deprecation of the yuan relative to the US dollar. Panel B reveals that the Japanese yen exhibited a positive exposure to the same trade war narrative during much of the same period. Japanese investors hold substantial foreign assets and tend to repatriate funds during periods of global risk aversion, such as during a Trade War. Consistent with this, we observe that the Yen appreciated as attention to the trade war narrative spiked in 2019 and began to depreciate after the

EXHIBIT 10

Examples of Significant Currency Exposures to Popular Narratives

NOTES: The panels show four separate currency pair time series along with the negative intensity time series of a narrative in which the currency pair displays a significant exposure during the displayed sample. The purpose is to display how currency pair exchange rates change in accordance with the narrative negative intensity before, during, and after a significant currency pair exposure to the narrative is calculated. The dark blue time series in each chart is the currency-pair exchange rate with its axis on the left-hand side. The orange time series is the negative intensity of the corresponding narrative with its axis displayed on the right-hand side. The units of this axis are the standard negative intensity unit (the proportion of negative sentiment articles pertaining to the narrative to the total number of articles). The portions of the time series with green background shading occur when the currency pair has an exposure to the corresponding narrative with a *t*-statistic greater than 1.5. The portions of the time series with red background shading occur when the currency pair has an exposure to the corresponding narrative with a *t*-statistic less than –1.5.

narrative peaked. Panel C shows, intuitively, that the British pound had a negative narrative beta to the Brexit narrative throughout most of 2016 and 2017. When negative coverage of the Brexit narrative spiked in 2016, the pound depreciated. Finally, Panel D shows the narrative beta of the Mexican peso to the “onshoring” narrative attention during 2021–2023. This could be explained, at least phatically, by concerns about the war in Ukraine and the potential for armed conflicts in other regions, driving many US companies to transfer operations to the western hemisphere. We observe that the Peso exhibited positive narrative beta to that narrative (positively correlated with increased negative attention) during parts of this period and indeed appreciated as negative coverage from the narrative picked up.

Next, we study the impact of narrative shocks on currency returns. Specifically, we estimate a panel regression model across narratives and currencies (time fixed effects are included), with results shown in Exhibit 11.[4] Panel A reports the results

[4] The Slovak Koruna (SKK) is excluded from the regressions reported in Exhibits 11, 12, and 13 due to lack of investor flow data.

EXHIBIT 11

Regressions of Currency Returns on Past Narrative Shocks and Exposures (sample period: January 2015–March 2024)

Panel A: $Y = R_{c,t}$

Variable	1	2	3	4	5
α	3.953	3.92	3.931	3.925	3.901
	[1.361]	[1.342]	[1.352]	[1.346]	[1.336]
$F_{c,t-1}$	–3.127			–3.141	–3.181
	[–0.905]			[–0.915]	[–0.928]
$R_{c,t-1}$		–62.764		–65.04	–81.513
		[–0.349]		[–0.362]	[–0.454]
$sign(\beta_{narr,c,t-2})NI_{narr,t-1}$			6.643		6.764
			[3.559]		[3.659]
N	99,479	99,479	99,479	99,479	99,479
R^2	0.186	0.186	0.187	0.186	0.187

Panel B: $Y = R_{c,t}$ Decomposed by Week

Variable	R1W(t)	R1W(t+1w)	R1W(t+2w)	R1W(t+3w)
α	6.442	7.391	–8.209	–1.313
	[3.829]	[3.501]	[–4.626]	[–1.097]
$F_{c,t-1}$	–1.022	–0.238	–1.985	0.16
	[–0.743]	[–0.176]	[–1.432]	[0.087]
$R_{c,t-1}$	38.225	–503.254	483.351	–116.366
	[0.334]	[–4.486]	[3.718]	[–0.772]
$sign(\beta_{narr,c,t-2})NI_{narr,t-1}$	2.633	1.859	0.55	1.78
	[3.026]	[1.742]	[0.662]	[2.451]
N	99,479	99,479	99,479	99,479
R^2	0.147	0.183	0.167	0.142

NOTES: This exhibit shows the predictiveness of narrative negative intensity changes on the future returns of a currency pair when that currency pair has a significant exposure to a given narrative. The dataset is first narrowed to monthly currency-pair-narrative observations keeping only exposure observations from the last Tuesday of every month, to avoid overlaps in monthly return, flow, and narrative observations. The sample is further narrowed to include only currency pairs to narrative observations in which the currency pair exposure to the narrative is significant (abs(t-stat) ≥ 1.5). For the remaining observations in our sample, we compute the one-month future return of the currency pair starting at observation t and label this variable $R_{c,t}$. We lag this variable by one month to compute $R_{c,t-1}$. We also compute the one-month future return of the currency pair starting at observation $t + 1$ and label this variable $R_{c,t+1}$. For Panel B, we further decompose this variable into four one-week returns: R1W(t), R1W(t + 1w), R1W(t + 2w), R1W(t + 3w). To construct currency flow at month t, we sum the daily published indicator flow values over the next month for each currency pair. We then normalize this monthly flow sum by each currency pair's six-month standard deviation of monthly flow sum. The flow indicator series used in this analysis is the FX Flow Indicator AllPort MA AUM Wtd All, available from State Street. This computation results in the variable $F_{c,t}$. We lag this variable by one month to compute $F_{c,t-1}$. To construct the narrative at month t, we compute the future one-month change in negative intensity for the given narrative. This change is further normalized by the six-month standard deviation of negative intensity change for each narrative. The negative intensity changes are multiplied by –1 for negative narrative exposures. The resulting computation is the $NI_{narr,t}$ variable. Panel A reports the results of six OLS regressions. Covariances are clustered at the currency and narrative level with a time-fixed effect. Panel B repeats Regression 5 of Panel A while decomposing the target one-month return into four non-overlapping one-week returns.

$$R_{c,t} = \alpha + \beta_0 * F_{c,t-1} + \beta_1 * R_{c,t-1} + \beta_2 * sign(\beta_{narr,c,t-2})NI_{narr,t-1} + e_{c,t}$$

of regressing monthly currency returns on prior weekly narrative intensity change scaled by the standard deviation of the weekly narrative intensity change.[5] Past monthly return and currency flow are used as control variables. The regression only pools currency-narrative pair observations at a given week if the corresponding narrative beta exhibit a significant t-statistic (above 1.5 in absolute value). Standardized

[5] Standard deviations are calculated point-in-time, that is, using the distribution of the six months of prior values up to that point.

EXHIBIT 12

Regressions on All Currency Pairs with Negative Shock Dummy *Var* (sample period: January 2015–March 2024)

Panel A: $Y = R_{c,t}$

Variable	1	2	3	4	5	6	7
α	3.953	3.92	3.931	2.907	3.925	3.901	3.204
	[1.361]	[1.342]	[1.352]	[1.007]	[1.346]	[1.336]	[1.109]
$F_{c,t-1}$	–3.127				–3.141	–3.181	–3.202
	[–0.905]				[–0.915]	[–0.928]	[–0.934]
$R_{c,t-1}$		–62.764			–65.04	–81.513	–78.064
		[–0.349]			[–0.362]	[–0.454]	[–0.435]
$sign(\beta_{narr,c,t-2})NI_{narr,t-1}$			6.643			6.764	3.622
			[3.559]			[3.659]	[1.978]
$sign(\beta_{narr,c,t-2})NI_{narr,t-1}Dummy$				11.122			7.558
				[3.95]			[2.707]
N	99,479	99,479	99,479	99,479	99,479	99,479	99,479
R^2	0.186	0.186	0.187	0.187	0.186	0.187	0.187

Panel B: $Y = R_{c,t}$ Decomposed by Week

Variable	R1W(t)	R1W(t+1w)	R1W(t+2w)	R1W(t+3w)
α	6.143	6.878	–7.82	–1.58
	[3.706]	[3.29]	[–4.603]	[–1.344]
$F_{c,t-1}$	–1.031	–0.253	–1.973	0.152
	[–0.75]	[–0.187]	[–1.43]	[0.082]
$R_{c,t-1}$	39.702	–500.715	481.429	–115.046
	[0.347]	[–4.501]	[3.702]	[–0.762]
$sign(\beta_{narr,c,t-2})NI_{narr,t-1}$	1.287	–0.454	2.301	0.577
	[1.174]	[–0.418]	[2.149]	[0.543]
$sign(\beta_{narr,c,t-2})NI_{narr,t-1}Dummy$	3.237	5.564	–4.211	2.893
	[1.668]	[2.069]	[–2.526]	[1.815]
N	99,479	99,479	99,479	99,479
R^2	0.147	0.184	0.168	0.142

NOTE: This exhibit repeats the analysis in Exhibit 11 with an additional variable: the original sign of beta and narrative shock interaction variable, interacted with a dummy variable that takes on the value of 1 if the narrative shock is negative and 0 otherwise.

$$R_{c,t} = \alpha + \beta_0 * F_{c,t-1} + \beta_1 * R_{c,t-1} + \beta_2 * sign(\beta_{narr,c,t-2})NI_{narr,t-1} + \beta_3 * sign(\beta_{narr,c,t-2})NI_{narr,t-1}Dummy + e_{c,t}$$

narrative attention shocks are multiplied by the sign of the corresponding narrative beta; that is, for the currencies with a negative narrative beta, we multiply the narrative shock by –1 such that the product of narrative beta and the sign is aligned with the direction of the expected impact on return.

The results in this panel indicate that the product of narrative shocks and sign of narrative beta significantly predict future returns of currencies that have displayed significant exposures to those narratives, with *t*-statistics exceeding 3 for all regression specifications considered. Using the product of standardized narrative shock (*z*-score) and the sign of narrative beta allows the interpretation of the coefficient as a monthly return per unit of standard deviation of narrative attention shock. Therefore, the coefficient of 6.76 in Exhibit 11, Panel A, column 5, can be interpreted as 6.76 bps, translating to roughly 2.4% annually spread between top and bottom currency deciles (roughly three times standard deviation). In unreported results, we also perform the analysis using other variable specifications, such as the product of narrative shock sign and narrative beta, as well as the product of narrative attention shock and narrative beta. All specifications yield significant coefficients.

EXHIBIT 13

$Y = R_{c,t}$ on Different Currency Samples (sample period: January 2015–March 2024)

Variable	All Currency Pairs	DM Currencies USD Pairs	EM Currencies USD Pairs
Panel A: Base Regression			
α	3.901	6.169	–1.906
	[1.336]	[1.884]	[–0.286]
$F_{c,t-1}$	–3.181	–0.988	–5.135
	[–0.928]	[–0.127]	[–1.156]
$R_{c,t-1}$	–81.513	115.091	–333.658
	[–0.454]	[0.445]	[–0.931]
$sign(\beta_{narr,c,t-2})NI_{narr,t-1}$	6.764	3.717	4.19
	[3.659]	[2.342]	[2.192]
N	99,479	22,132	38,415
R^2	0.188	0.477	0.398
Panel B: Negative Shock Dummy Included			
α	3.204	5.385	–2.662
	[1.109]	[1.661]	[–0.393]
$F_{c,t-1}$	–3.202	–0.953	–5.143
	[–0.934]	[–0.122]	[–1.159]
$R_{c,t-1}$	–78.064	117.773	–333.75
	[–0.435]	[0.455]	[–0.932]
$sign(\beta_{narr,c,t-2})NI_{narr,t-1}$	3.622	0.742	2.26
	[1.978]	[0.324]	[1.536]
$sign(\beta_{narr,c,t-2})NI_{narr,t-1}Dummy$	7.558	7.278	4.588
	[2.707]	[1.522]	[1.426]
N	99,479	22,132	38,415
R^2	0.188	0.477	0.398

NOTES: This exhibit repeats the exercise shown in Panel A of Exhibits 11 and 12 for three different currency universes. The set "All Currency Pairs" refers to the currency pairs outlined in Exhibit 1. The set "DM Currencies USD Pairs" includes USD crosses with GBP, EUR, CHF, NOK, SEK, CAD, JPY, SGD, JPY, AUD, NZD, as well as DXY. The set "EM Currencies USD Pairs" includes USD crosses with CNY, INR, IDR, MYR, PHP, THB, TWD, HKD, KRW, ZAR, TRY, CZK, HUF, PLN, COP, ARS, BRL, CLP, and MXN.

Panel B of Exhibit 11 repeats the analysis using future weekly returns, up to four weeks post narrative attention shock. The results indicate a positive impact of narrative shock on future currency returns for all four weeks (where weeks 1, 2, and 4 are statistically significant). Overall, the results in Exhibit 11 demonstrate that narrative attention shocks not only impact currency returns contemporaneously, but they also display a predictable, continued effect during the following month.

Robustness tests are provided in Exhibits 12 and 13. In Exhibit 12, a term is added to account for negative narrative shocks using a dummy variable multiplied by the product of narrative attention shock and the sign of narrative beta. The results in Exhibit 12, column 7, show that both positive and negative shocks to narrative attention have significant coefficients, yet the impact of a negative narrative attention shock is roughly double that of a positive shock. These results suggest that future currency returns are more sensitive to declining attention than rising attention.

Separating developed versus emerging market currencies in Exhibit 13 shows that regression coefficient pertaining to the main variable remains significant for both currency types. However, the impact of negative narrative shocks is far larger than such positive shocks for developed currencies, while the impacts of positive versus negative narrative shocks is similar among emerging currencies.

NARRATIVE AND RISK IMPLICATIONS

The previous discussion demonstrates that narratives may be used to predict currency returns. Quantified narratives can also aid portfolio and risk managers in understanding unique sources of risk in the foreign exchange market. For example, a manager may desire to estimate a portfolio's exposures to narratives and decide whether to hedge such risks by transacting in currencies with high/low narrative-beta exposures as appropriate. Such narratives may provide a differentiated perspective relative to traditional risk factors.

To test the hypothesis that incorporating narratives could enhance risk understanding, we perform a regression analysis in which returns of the trade-weighted US dollar index (DXY) are regressed on traditional currency risk factors (value, momentum, and carry are available from the AQR data library), and the added inclusion of narratives in this framework results in a meaningful marginal regression r-square.

EXHIBIT 14

Contribution of Media Narratives to Explaining Variations of US Dollar (DXY)

2015–2017

Factor/Narrative		R^2: 3 Traditional Factors and a Single Narrative	Incremental R^2: Due to Adding a Single Narrative to 3 Traditional Factors	Cumulative R^2: 3 Traditional Factors and Varying Number of Narratives
Traditional Factors	*3 AQR*			0.071
Narrative 1	*Personal Consumption*	0.151	0.081	0.151
Narrative 2	*M&A*	0.133	0.062	0.217
Narrative 3	*GDP*	0.133	0.062	0.233
Narrative 4	*Consumer Spending*	0.125	0.054	0.234
Narrative 5	*Earnings*	0.122	0.051	0.293

2016–2018

Factor/Narrative		R^2: 3 Traditional Factors and a Single Narrative	Incremental R^2: Due to Adding a Single Narrative to 3 Traditional Factors	Cumulative R^2: 3 Traditional Factors and Varying Number of Narratives
Traditional Factors	*3 AQR*			0.091
Narrative 1	*Recession*	0.183	0.093	0.183
Narrative 2	*Fiscal*	0.171	0.080	0.245
Narrative 3	*Business Cycles*	0.170	0.080	0.250
Narrative 4	*Environment*	0.166	0.075	0.294
Narrative 5	*Natural Disasters*	0.138	0.048	0.298

2017–2019

Factor/Narrative		R^2: 3 Traditional Factors and a Single Narrative	Incremental R^2: Due to Adding a Single Narrative to 3 Traditional Factors	Cumulative R^2: 3 Traditional Factors and Varying Number of Narratives
Traditional Factors	*3 AQR*			0.064
Narrative 1	*Business Cycles*	0.160	0.096	0.160
Narrative 2	*Political Elections*	0.157	0.094	0.203
Narrative 3	*Fiscal*	0.147	0.084	0.249
Narrative 4	*Government & Corp Debt*	0.140	0.077	0.256
Narrative 5	*International Organizations*	0.133	0.070	0.275

2018–2020

Factor/Narrative		R^2: 3 Traditional Factors and a Single Narrative	Incremental R^2: Due to Adding a Single Narrative to 3 Traditional Factors	Cumulative R^2: 3 Traditional Factors and Varying Number of Narratives
Traditional Factors	*3 AQR*			0.113
Narrative 1	*Business Cycles*	0.268	0.155	0.268
Narrative 2	*International Organizations*	0.267	0.154	0.386
Narrative 3	*Risk*	0.247	0.134	0.387
Narrative 4	*Oil*	0.225	0.112	0.456
Narrative 5	*Manufacturing*	0.208	0.095	0.470

(continued)

EXHIBIT 14 *(continued)*

Contribution of Media Narratives to Explaining Variations of US Dollar (DXY)

2019–2021

Factor/ Narrative		R^2: 3 Traditional Factors and a Single Narrative	Incremental R^2: Due to Adding a Single Narrative to 3 Traditional Factors	Cumulative R^2: 3 Traditional Factors and Varying Number of Narratives
Traditional Factors	*3 AQR*			0.129
Narrative 1	*Risk*	0.372	0.243	0.372
Narrative 2	*Market Crash*	0.304	0.176	0.380
Narrative 3	*Volatility*	0.284	0.155	0.381
Narrative 4	*Investor Sentiment*	0.259	0.130	0.437
Narrative 5	*Equity Investing*	0.259	0.130	0.495

2020–2022

Factor/ Narrative		R^2: 3 Traditional Factors and a Single Narrative	Incremental R^2: Due to Adding a Single Narrative to 3 Traditional Factors	Cumulative R^2: 3 Traditional Factors and Varying Number of Narratives
Traditional Factors	*3 AQR*			0.138
Narrative 1	*Market Crash*	0.300	0.162	0.300
Narrative 2	*Business Cycles*	0.290	0.152	0.342
Narrative 3	*Bitcoin*	0.285	0.146	0.480
Narrative 4	*FX*	0.255	0.117	0.484
Narrative 5	*Fiscal*	0.225	0.087	0.484

2021–2023

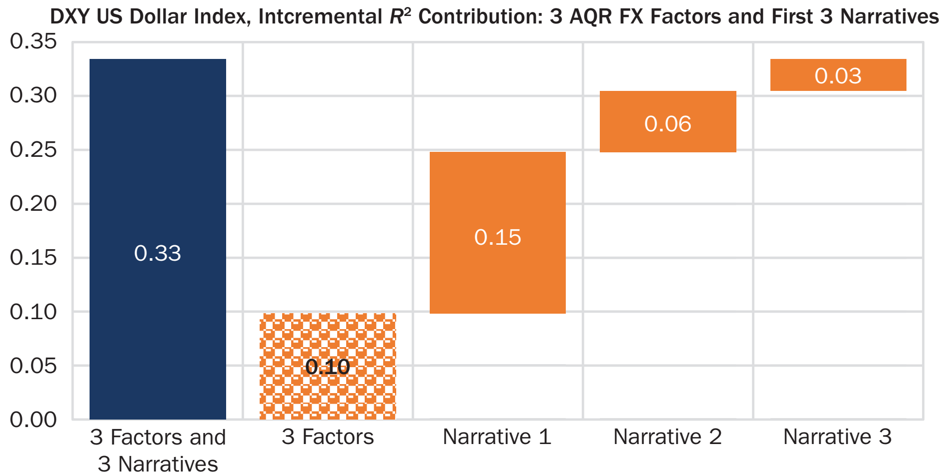
Factor/ Narrative		R^2: 3 Traditional Factors and a Single Narrative	Incremental R^2: Due to Adding a Single Narrative to 3 Traditional Factors	Cumulative R^2: 3 Traditional Factors and Varying Number of Narratives
Traditional Factors	*3 AQR*			0.082
Narrative 1	*Market Crash*	0.301	0.218	0.301
Narrative 2	*Treasury Bonds*	0.297	0.215	0.360
Narrative 3	*Government & Corp Debt*	0.288	0.206	0.360
Narrative 4	*FX*	0.234	0.152	0.376
Narrative 5	*Political Elections*	0.231	0.149	0.514

NOTES: This exhibit shows the results of a new analysis to determine whether narratives can help explain variations in exchange rates. Using the DXY and the set of narratives previously introduced, we now consider one-month currency returns, one-month AQR FX factor* returns (factors considered are value, momentum, and carry), and one-month change in negative intensity for the narratives. (Changes in negative intensity are *z*-scored by historical means and deviations for the given narrative, using the same methodology employed for narrative exposure calculations in the text.) We index these observations at the end of each month over the period 2015–2024. For all regressions, we use three-year windows: 2015–17, 2016–18, 2017–19, etc. In each window, we first regress the AQR FX factors against DXY returns and then repeat using both the AQR FX factors and negative intensity changes against DXY returns, calculating the incremental R^2 between the two regressions (using the regression equation: $DXY_t = \alpha + \beta_{AQR}AQR_t + \beta_{Narr}Narr_t$). We repeat this process for each narrative in the dataset, individually inspecting that narrative's incremental R^2 over the AQR FX factors. In each three-year window, we select the five narratives with the highest incremental R^2 (to be considered one of the top five narratives, a narrative must also have an average negative intensity greater than 2% within the window being analyzed). We repeat the regressions, except this time first add the largest incremental R^2 narrative to the regression and progressively add the other narratives to build a cumulative R^2 contribution curve.

For example, Exhibit 14 shows that over the period 2015–2017 variation in DXY returns is driven by personal consumption, M&A, GDP, consumer spending, and earnings (marginal R^2 of 22.2%), while over the period 2021–2023 the driving narratives are political elections, FX, government & corporate debt, treasury bonds, and market crash (marginal R^2 of 43.2%). In general, it seems that DXY is more narrative-driven post-2020.

EXHIBIT 15

Incremental Contribution of Media Narratives in Explaining US Dollar (DXY) Variation



NOTES: This exhibit plots the average marginal R^2s computed by the inclusion of narratives in a model that explains DXY over a three-year period, as in Exhibit 14. The baseline model includes the AQR FX factors and the first three narratives with the highest marginal R^2 individually (relative to the base model) are progressively added to the model. The process is repeated for each three-year period over 2015–2024 (there are eight such periods).

To further gauge the potential contribution of narratives to risk modeling of DXY, Exhibit 15 reports the marginal regression R^2s computed by adding three narratives to a baseline model that includes three AQR factors. While the baseline model can explain roughly 10% of risk, one additional narrative can explain an additional 15%; with three narratives, the overall regression R^2 increases to 33%, on average, essentially tripling the fraction of explained risk. These results demonstrate the significant potential added value of quantified narratives to risk modeling.

CONCLUSION

The purpose of this article is to demonstrate the impact of narratives on currency markets. While narratives are often intangible and difficult to measure, we offer an approach to quantify attention to narratives and estimate the impact of narratives on currencies through regressions. The approach demonstrates both a significant contemporaneous effect and the ability to predict future currency returns over several weeks and highlights the importance of considering narratives in explaining risk in foreign exchange markets.

REFERENCES

Bhargava, R., X. Lou, G. Ozik, R. Sadka, and T. Whitmore. 2023. "Quantifying Narratives and Their Impact on Financial Markets." *The Journal of Portfolio Management* 49 (5): 82–95.

Blanqué, P., M. Ben Slimane, A. Cherief, T. Le Guenedal, T. Sekine, and L. Stagnol. 2022. "The Benefit of Narratives for the Prediction of the S&P 500 Index." *The Journal of Financial Data Science* 4 (4): 72–94.

Bybee, L., B. Kelly, and Y. Su. 2023. "Narrative Asset Pricing: Interpretable Systematic Risk Factors from News Text." *The Review of Financial Studies* 36 (12): 4759–4787.

Calomiris, C. W., and H. Mamaysky. 2019. “How News and Its Context Drive Risk and Returns around the World.” *Journal of Financial Economics* 133 (2): 299–336.

Engle, R., S. Giglio, B. Kelly, H. Lee, and J. Stroebel. 2020. “Hedging Climate Change News.” *The Review of Financial Studies* 33 (3): 1184–1216.

Filippou, I., M. P. Taylor, and Z. Wang. 2024. “Media Sentiment and Currency Reversals.” *Journal of Financial and Quantitative Analysis* 59 (3): 1401–1429.

Froot, K., R. Bhargava, E. Cuipa, and J. Arabadjis. 2014. “Multi-Asset Sentiment and Institutional Investor Behavior: A Cross-Asset Perspective.” *The Journal of Portfolio Management* 40 (4): 144–156.

Froot, K., X. Lou, G. Ozik, R. Sadka, and S. Shen. 2017. “Media Reinforcement in International Financial Markets.” Working paper (March).

Lee, H., X. Lou, G. Ozik, and R. Sadka. 2024. “Narrative Momentum.” Working paper.

Loughran, T., and B. McDonald. 2011. “When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks.” *The Journal of Finance* 66 (1): 35–65.

Mai, D., and K. Pukthuanthong. 2021. “Economic Narratives and Market Outcomes: A Semi-Supervised Topic Modeling Approach.” Working paper, SSRN.

Manela, A., and A. Moreira. 2017. “News Implied Volatility and Disaster Concerns.” *Journal of Financial Economics* 123 (1): 137–162.

Shiller, R. J. 2019. *Narrative Economics: How Stories Go Viral & Drive Major Economic Events*. Princeton: Princeton University Press.

Tetlock, P. 2007. “Giving Content to Investor Sentiment: The Role of Media in the Stock Market.” *The Journal of Finance* 62 (3): 1139–1168.