Quantifying Narratives and their Impact on Financial Markets

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July 15, 2022

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Abstract

This paper introduces a media-coverage-based approach to quantify narratives and develops methodologies to explain the extent to which narratives drive financial markets and returns of investment portfolios. We show that media-derived narratives may contain predictive information for market returns beyond traditional macro indicators. Finally, we demonstrate that narrative indicators can be used to enhance asset allocation strategies and to gain or hedge exposure to narratives by constructing portfolios of narrative-sensitive assets.

Key Findings

- Narratives derived from media coverage using textual analysis can explain market-wide moves
- Narrative-conscious strategies can improve asset allocation
- Investors can gain or hedge financial exposure to a narrative by constructing portfolios of narrative-sensitive assets

Keywords

Media Sentiment, Investor Behavior, Economic Themes, Narratives, Market Drivers

Quantifying Narratives and their Impact on Financial Markets

"*We need to incorporate the contagion of narratives into economic theory. Otherwise, we remain blind to a very real, very palpable, very important mechanism for economic change, as well as a crucial element for economic forecasting*".

Robert Shiller, Narrative Economics

Shiller (2019) advocates that to improve our understandings of economy and financial markets, economists must look beyond typical economic indicators to incorporate stories that affect individual and collective economic behavior. While market participants are influenced by what they see, hear, and talk about, narratives are intangible and hard to measure. This paper seeks to further our understanding of economic and financial markets by quantifying narratives, constructing narrative indicators, studying the impact of narratives on asst prices, and demonstrating the practical implication for investment professionals.

In this paper, we apply textual analysis (Natural Language Processing (NLP)) on large reservoirs of media articles to identify media coverage intensity and sentiment expressed toward various themes and narratives[1]. In addition to quantifying attention paid to each narrative, this paper also develops an empirical framework that can help investors identify which narratives are important in explaining aggregate market returns. For example, the Market Crash narrative, a measure of how often "markets" (including SPY, NYSE, and other variants) appear textually close to "crash" (variants include bear or

[1] Theme is the subject of a discussion while narrative is a particular way of explaining or understanding subjects and events. We use the terms interchangeably.

meltdown), has the highest explanatory power in explaining US equity markets. In addition, we find that some narratives would emerge and rise to the top for a while and then fade away. For example, the tumultuous year of 2020 brought with it competing narratives such as the onset of the COVID-19 pandemic and the US elections that influenced investor perceptions.

We also show that media narratives can contain information for future market returns beyond traditional macroeconomic indicators. Specifically, in a predictive regression of future SPY returns on past market returns, VIX, and media coverage on the Market crash narrative, the coefficient for the Market Crash narrative is negative and statistically significant. Inspired by this result, we show that investors can apply the insights from the narrative indicators to improve asset allocation strategies. A narrative-based dynamic asset allocation strategy significantly outperforms the equity only, the bond only, and the 50/50 equity/bond balance strategy.

Finally, the paper demonstrates a portfolio construction methodology by which investors can select narrative-sensitive assets to achieve desired narrative exposure. Using the COVID-19 narrative as an example, we estimate individual stock sensitivities to negative coverage of COVID-19 and construct a long-short portfolio by buying the 25 stocks with the lowest exposure measure (stock prices rise when negative coverage of COVID-19 *decreases*) and shorting the 25 stocks with the highest exposure measures (stock prices decrease when negative coverage of COVID-19 *decreases*). This narrative-beta based long-short portfolio, dubbed COVID-19 recovery portfolio, had a negative return before Pfizer publicly announced that its COVID-19 vaccine is more than 90% effective on November 9, 2020. However, it earned a return of 120.74% in the period from November 2020 to December 2021. This narrative-beta based portfolio tracks the COVID recovery much better than a similar long-short portfolio that instead uses the return sensitivity to the changes of actual COVID cases: the case-count beta sorted long-short portfolio does not show a similar upward trend after November 2020.

1. Literature Review

Humanities and social sciences disciplines have long appreciated the importance that stories and narratives have in explaining historical events. Economists, however, have lagged in this regard. Economic research has primarily relied on economic modeling tools, which focus on feedback loops and multiplier effects, to explain significant economic events, but have yet to seriously incorporate or study in depth the impact that prevailing narratives have. This is despite several instances of economists arguing the case for the incorporation of narratives in the field. Recently the incorporation of narratives into economic models has gain traction, in part driven by Shiller's work in *Narrative Economics* (2019), which expands on previous work spanning decades (Shiller, 1984). This field of study has called "for a more serious quantitative analysis of narratives."

Empirically, it is challenging to study narratives that "are deeply human phenomena" (Shiller 2019) as it entails reducing complex and multi-dimensional narratives to numbers fed to statistical modeling. Due to the technical challenges in handling large amounts of unstructured datasets of texts, earlier papers tend to utilize smaller datasets, focus on a very limited number of themes, and construct simple measures such as the frequency of certain words. For example, Tetlock (2007) constructs a simple measure of media pessimism from the content of a single *Wall Street Journal* column over 1984–1999. Shiller (2019) uses the frequency at which words are used in books (Google Ngram) and news sources (ProQuest). Manela and Moreira (2017) construct a text-based measure of uncertainty starting in 1890 using front-page articles of the *Wall Street Journal*. They find that high-uncertainty periods are associated with high future stock returns.

Recently, the technology advancements in Natural Language Processing and machine learning have allowed researchers to start exploring larger unstructured text datasets. For example, Mai and

Pukthuanthong (2021) extract the Shiller (2019) narratives from nearly seven million New York Times articles over the past 150 years and find that a Panic narrative is most important in predicting market returns. Calomiris and Mamaysky (2019) group words from all Reuters News articles from 1996 to 2015 into several topic clusters (markets, governments, corporations, commodities, and credit) and demonstrate the importance of context by showing that the predictive ability of words is context-specific. Blanqué et al. (2022) show that variables from the Global Database of Events, Language, and Tone can aid the process of modeling the US equity market. Engle et al. (2020) construct a climate change news index using the fraction of media articles that are about "climate change". They then create a mimicking portfolio designed to hedge the change risk. Our goal in this paper is to contribute to the quantitative analysis of narratives by leveraging a novel dataset built from thousands of digital media articles. We construct narrative indicators for a large set of narratives and develop an empirical framework to identify which narratives are driving the financial markets. We also demonstrate how our narrative indicators can be used to improve asset allocation strategies. Finally, the paper develops an empirical methodology to construct portfolios to hedge or gain exposure to a narrative.

2. Data Construction and Methodology

Every day, articles published by over 150,000 global digital media sources are collected and assigned to reservoirs based on articles' general topic (e.g., domestic matters, international politics etc.) and the asset covered in the text (e.g., corporations, currencies, country equity indexes, etc) to generate a comprehensive set of articles. Articles are further tagged with respect to relevancy to each of a predefined set of 73 narratives using proprietary algorithms based on keyword searches and textual conditions. We identify the set of 73 narratives that can potentially affect financial markets via two channels. We start with the

Journal of Economic Literature (JEL) Classification System, which was developed for use in the Journal of Economic Literature and is a standard method of classifying scholarly literature in the field of economics. The system is used to classify articles, dissertations, books, book reviews, and working papers in EconLit and many other applications.[2] We also supplement the list of narratives from interviews with industry analysts and eventually compile a list of 73 themes, which is presented in Appendix A.

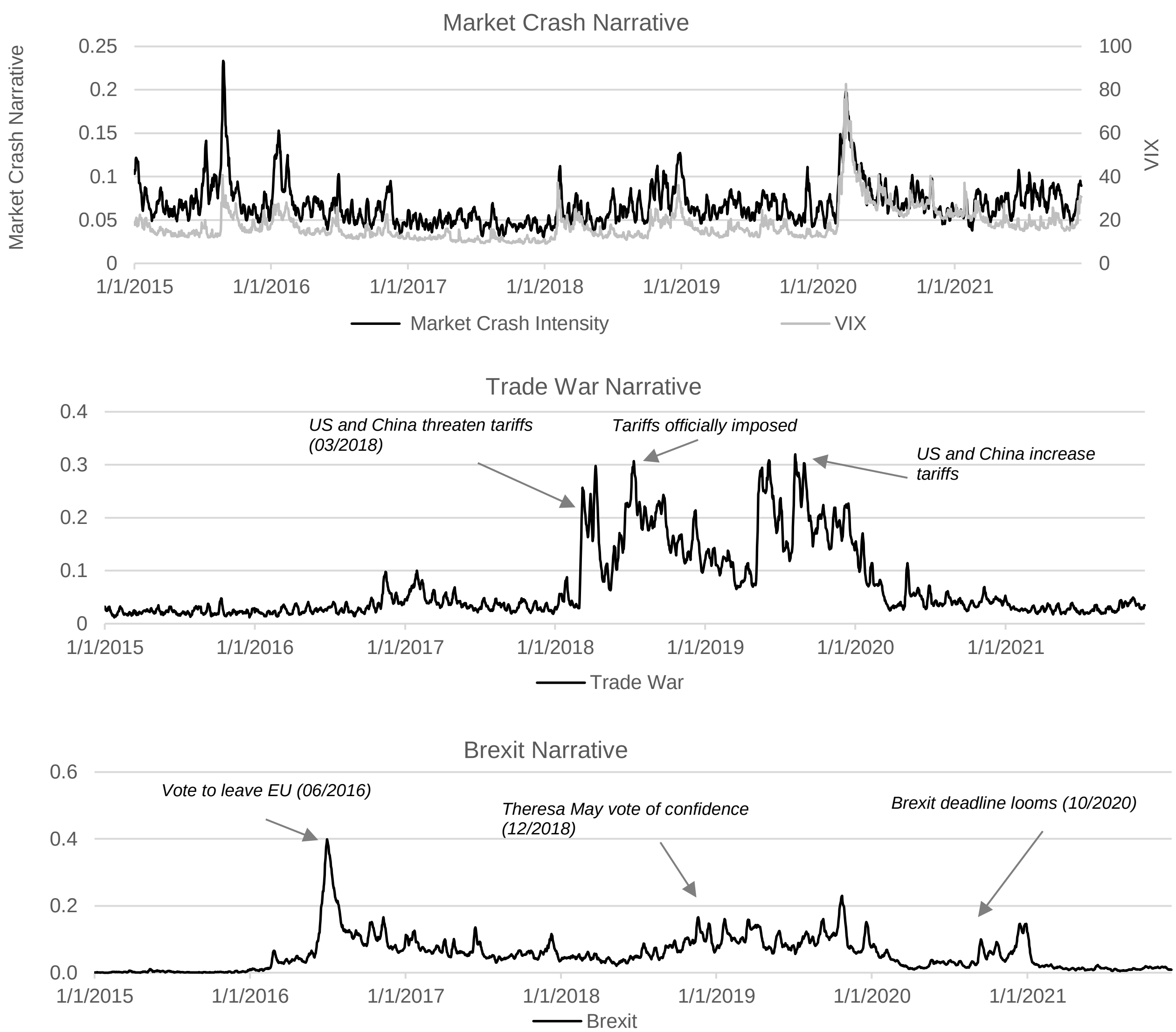
For each article, a sentiment score is assigned, which is adjusted for the overall daily tone of the articles in the reservoir from which the article is extracted. We consider two measures of intensity. *Intensity* measures the proportion of articles relevant to a narrative relative to all news articles collected in a given day in a respective reservoir, proxying for the importance that the media gives to a narrative. *Negative intensity*, as the name implies, provides a similar view but considers only articles expressing a negative tone, thus providing a view into how negative the media coverage is for a given theme. In the main analysis in Sections 3 and 4, we use *negative intensity* as it captures directionality (sign) in addition to coverage amount. This is similar to Engle et al. (2020) which constructs a negative sentiment climate change news index using the fraction of media articles that are about "climate change" and are assigned with a negative sentiment score.

Exhibit 1 plots the intensity of three selected narratives: market crash, trade war, and Brexit over time from January 2015 to November 2021. **Exhibit 1** shows that we are able to capture important changes in a narrative by measuring the tone and volume of digital media coverage. The first chart clearly shows that the intensity of digital-media coverage of the Market Crash narrative closely tracks the VIX index. Often increases in Market Crash coverage lead to increases in VIX. Spikes in the Trade War narrative illustrate periods of heightened economic tension between China and the US with the threatening and

[2] For descriptions and examples, see https://www.aeaweb.org/econlit/jelCodes.php.

eventual enactment of tariffs. For example, we see the coverage of the narrative peak when substantial duties were imposed on imports from China in July 2018. Lastly, we capture the intensity of media coverage around Brexit, which spiked leading up to the initial decision of Britain to leave the European Union and then again during Theresa May's vote of confidence in December 2018, and again when the government drew closer to negotiation deadlines with Europe. This unique, real-time view into narratives allows us to empirically study the impact of narratives on financial markets and portfolio returns.

Exhibit 1: Example Narrative Time Series: Market Crash, Trade War, and Brexit



**The exhibit plots the intensity of three selected narratives: market crash, trade war, and Brexit over time from January 2015 to November 2021.*

3. Do Narratives Drive Markets?

With our empirical measures of digital media-derived narratives, we next attempt to answer some fundamental questions about the markets and economy. For example, which narratives are important market drivers? To study this, we first develop an empirical framework to quantify the degree to which changes in the intensity of media coverage for a given narrative explain aggregate market returns. First, for each day, we construct a weekly intensity value as the average of the daily intensity values of the most recent seven days (this measure includes media coverage over weekends). We then compute weekly changes by taking the seven-day difference in the weekly intensity indicators (e.g., difference from Tuesday through Monday). Returns are generated over the same window (five trading days, e.g., Monday close to Monday close). We then run a daily rolling three-month univariate regressions with weekly market index returns regressed on weekly changes in the seven-day intensity for every narrative in our universe for the period from July 2015 to November 2021. From these regressions, we obtain a time-series of the regression R^2 for each narrative. The R^2 values give us a general sense of the degree to which changes in a certain narrative contemporaneously explain aggregate market moves.

3.1 Top Narratives

We identify top narratives that explain the largest degree of market moves by ranking narratives based on the time-series average R^2 for each narrative (**Exhibit 2**). Our analysis covers two markets: US equity (proxied by SPY) and US currency (proxied by DXY).

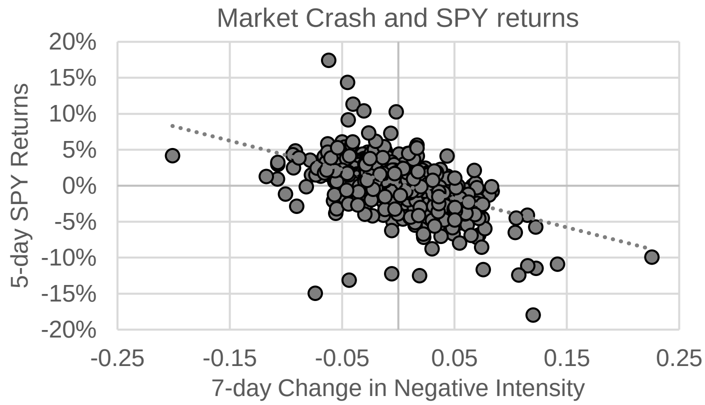
Exhibit 2: Top narratives by R^2 for SPY and DXY from 2015 – 2021

SPY Narratives	Average R^2	DXY Narratives	Average R^2
Market Crash	34%	Federal Reserve	14%
Government & Corp Debt	19%	Donald Trump	13%
Treasury Bonds	18%	Emerging Markets	12%
Global Growth	15%	Interest Rates (Global)	12%
Liquidity	15%	Labor Market	12%
Multivariate with top-5 narratives	*40%*		*29%*

**Top narratives that explain the largest degree of market moves based on the time-series average R^2 for each narrative.*

Notably, we observe that narrative intensity of Market Crash, considering articles featuring equity markets (including S&P 500, NYSE, and other variants) in close textual proximity to terms associated with crash (variants include crash, bear or meltdown), has the highest average R^2 value in equity markets. This result suggests that investors are sensitive to new economic, geopolitical, and other risks associated with market drawdowns. When investors are concerned with the market crash risk, they will adjust their portfolios accordingly and move to safter assets, which suggests that a heightened awareness of crash risk should be accompanied by a drop in the stock prices. To test this relation, we regress SPY weekly returns on weekly changes in our 7-day negative coverage (which is referred to as negative intensity) of the Market Crash narrative. The results presented in **Exhibit 3** show a negative and significant relation between Market Crash coverage and SPY returns, confirming that increases in negative coverage of this narrative coincide with lower market returns.

Exhibit 3: Negative news around Market Crash Significantly Correlate with Lower Returns



Regression Results

Dep. Variable	5-day SPY return
Ind. Variable:	7-day Change in Negative Intensity of the Market Crash narrative
Coefficient	-0.26
T-Statistic	-9.94
Covariance Type:	HAC
R^2	.30

**Result of regressing SPY weekly returns on weekly changes in our 7-day negative coverage (which is referred to as negative intensity) of the Market Crash narrative.*

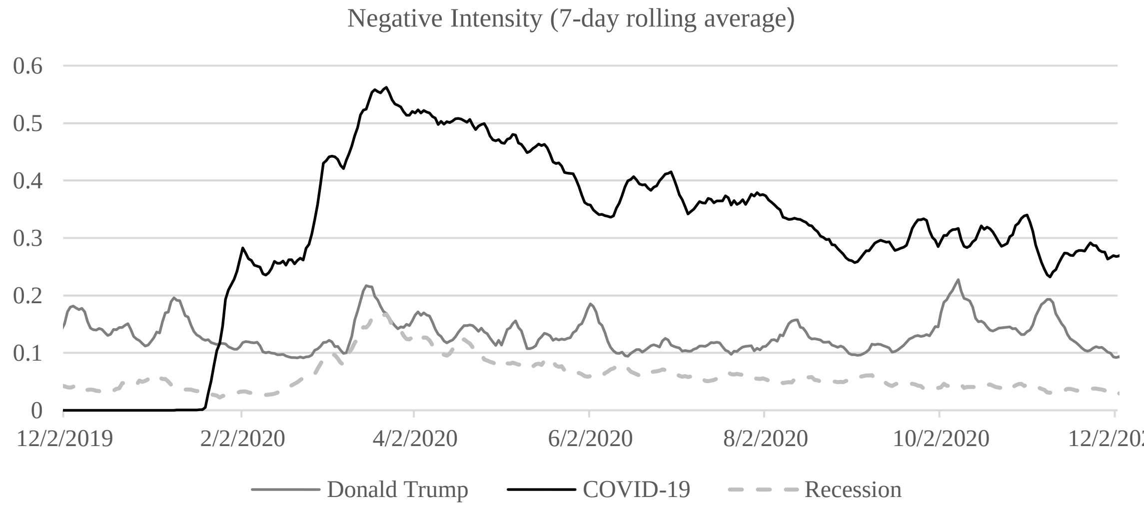
Exhibit 2 also shows that top narratives vary across markets. The topmost important narrative drivers for the US Dollar (DXY) are more aligned with what we would typically think about in currencies, such as interest rates and the policies set by the Federal Reserve and the White House (during the sample period, the Trump administration).

3.2 Topical Narratives

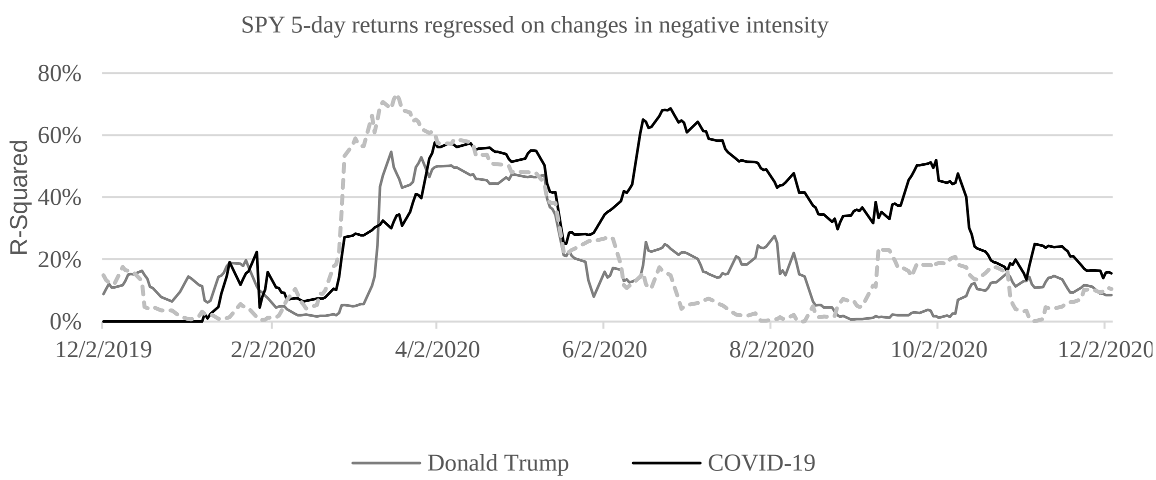
An examination of the top narratives over time reveals that some narratives would emerge and rise to the top for a while and then fade away. For example, the tumultuous year of 2020 brought with it competing narratives such as the onset of the COVID-19 pandemic and the US elections that influenced the perceptions and decisions of investors. **Exhibit 4** illustrates how the onset of the pandemic in early February thrust the COVID-19 narrative into prominence.

Exhibit 4: Prominence of Topical Narratives in 2020

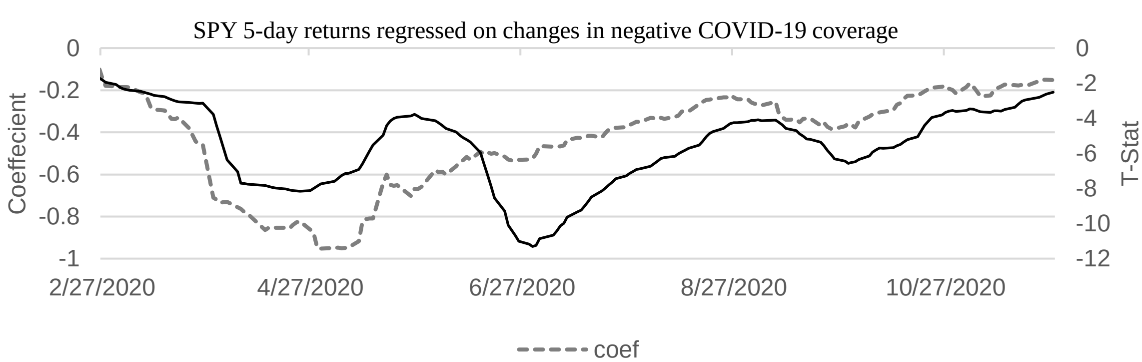
Panel A: Plot of narrative intensity



Panel B: R-squared of SPY regressed on narrative intensity



Panel C: Coefficient and T-stat of COVID-19 narrative through time



Panel A of Exhibit 4 shows that when the first case of COVID-19 was reported in early December 2019, outlets paid little attention. However, as it became clear that this may have a serious impact on public safety, the media quickly turned its full attention to it. Interestingly, as shown in Panel B, the risk of an impending recession due to the pandemic drove markets during the early onset, even more so than the actual coverage of COVID-19. This was paralleled by the importance given to the Trump administration's response. After the initial fear of recession set in, we see investors track COVID-19 related news to a greater degree. A bleaker outlook of the pandemic would likely mean reduced mobility due to voluntary actions or involuntary quarantine orders, which investors understood to have significant impacts on the economy. Panel C presents the coefficient and the associated t-statistics for the Covid-19 narrative when we conduct rolling regressions of five-day SPY returns on changes in seven-day narrative intensity. There is a significant negative relation in seven-day changes in negative coverage of the virus and contemporaneous SPY returns.

4. Predicting Market Returns

The previous section demonstrates that narratives can be quantified and are important drivers of market movements. In this section, we examine whether media narratives can enhance our ability to forecast future markets returns.

To explore the ability of our narrative indicators to predict market returns, we focus on the Market Crash narrative, which is shown to be the top one narrative for US equity markets. Exhibit 3 shows that the Market Crash narrative explains the contemporaneous market returns more than any other narrative.

In this section, we are interested in the question whether the media-derived Market Crash narrative contains predictive information for future market returns. The Market Crash narrative can in many ways be a self-fulfilling prophecy. A market correction could be more severe if a Market Crash narrative proliferates in the media, influencing investor decisions, thus turning that story into reality. After all, fear is a strong emotion (Goetzmann, Kim, and Shiller, 2016). We explore this hypothesis by conducting a regression analysis of future market returns on the Market Crash narrative measures. Our regression accounts for a one-day publication lag. In other words, the t-1 Market Crash value reflects the media coverage from t-2. The regression controls for VIX as the traditional measure of market crash risk. Our analysis therefore examines whether the Market Crash narrative contains additional market price information over and beyond VIX. The regression also includes one- and two-day lagged market returns. We standardize the daily Market Crash intensity in the time series with a rolling 60-day window to obtain a daily z-score. The results are reported in **Exhibit 5**. The coefficient for t-1 Market Crash Negative Intensity is negative with a t-statistic of -2.2, suggesting that the Market Crash narrative is informative in predicting future market returns in addition to the VIX.

Exhibit 5: Market Crash Narrative Predicting Market Returns

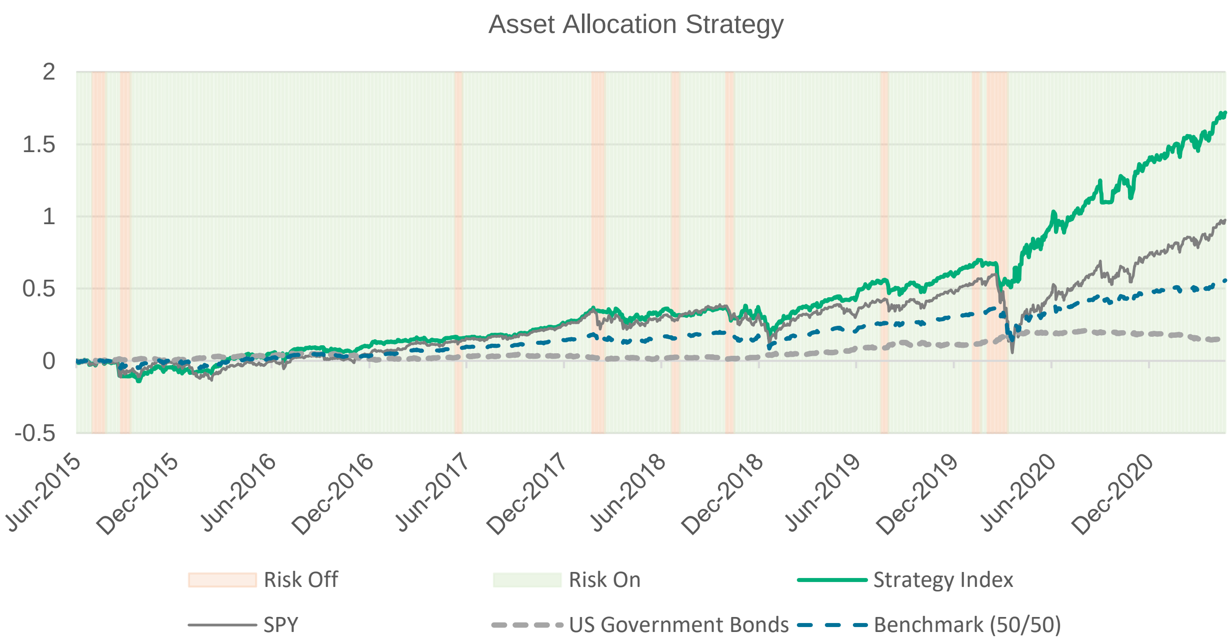
Dependent variable = SPY Returns of Day t		
	Coefficient	T-stat
Intercept	.001	
t-1 SPY	-.161	[-2.57]
t-2 SPY	.069	[0.78]
t-1 VIX	-.002	[-2.41]
t-2 VIX	.002	[1.90]
t-1 Market Crash Negative Intensity (z score)	-.011	[-2.20]
t-2 Market Crash Negative Intensity (z score)	.009	[0.27]

**Future market returns (SPY on Day t) are regressed on past Market Crash narrative measures (on Days t-1 and t-2), past stock returns, and past VIX values. The regression accounts for a one-day publication lag. In other words, the t-1 Market Crash value reflects the media coverage from t-2.*

Inspired by the regression result, we next explore how the Market Crash narrative indicator can be used to improve asset allocation strategies. The regression results indicate that a high coverage intensity of Market Crash with negative sentiment is associated with lower future stock returns, suggesting that a narrative-conscious market-timing strategy that rotates out of equity when the negative coverage on the Market Crash narrative is abnormally high might yield good performances. We identify instances of abnormally high negative coverage of the narrative when the narrative z-score breaches the threshold of 3. Accounting for a two-day publication and implementation lag, we rotate out of equities (SPY) into bonds (US Government Bonds) for two weeks when our standardized 'Market Crash' indicator breaches the threshold of 3.

Exhibit 6 plots the cumulative returns of four strategies: our narrative-based strategy, all Equity (proxied by SPY), all Bond, and 50/50 Equity/Bond. The narrative-based strategy significantly outperforms the other three strategies including the 50/50 equity/bond strategy. The information ratio of the narrative-based strategy is 1.26, which compares favorably with that of the 50/50 balance strategy (0.91). Results are consistent across different normalization windows. The plot in Exhibit 6 shows that abnormally high media coverage of Market Crash can be useful in avoiding risk-off regimes.

Exhibit 6: Avoid 'Risk-Off' Regimes with the Market Crash Narrative



Performance Metrics	Narrative-based Strategy	SPY	US Bonds	50/50 Equity/Bond
Annualized Returns	18.13%	13.38%	2.51%	7.94%
Annualized Vol	14.38%	18.66%	3.55%	8.73%
Max Drawdown	-11.57%	-13.94%	-.02%	-6.17%
Reward-to-Risk/ IR	1.26	0.71	0.71	0.91

Narrative-based Strategy vs. 50/50 Equity/Bond	
Annualized Returns	10.18%
Tracking Error	10.17%
Reward-to-Risk/ IR	1.00

**The exhibit presents the performances of four asset allocation strategies: our narrative-conscious asset allocation strategy, all Equity (proxied by SPY), all Bond, and 50/50 Equity/Bond. The narrative-bases asset allocations strategy we rotate out of equities (SPY) into bonds (US Government Bonds) for two weeks when the standardized 'Market Crash' indicator breaches the threshold of 3.*

5. Enhancing Stock Selection Performance

The previous section shows that we can use media narratives to improve asset allocations strategies. In this section, we demonstrate that investors can obtain reliable estimates of firm-level exposures to a narrative to hedge or gain exposure to a narrative by constructing portfolios using narrative-sensitive assets.

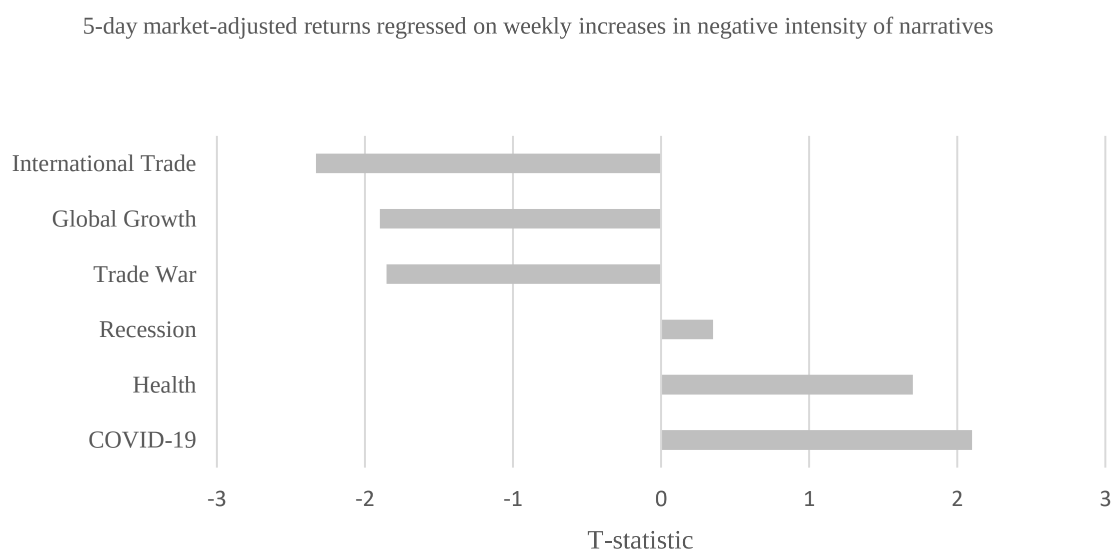
5.1 Measuring asset exposure to narratives

We first explain our procedures to estimate stock-level sensitivity measures for various narratives. Investors often have an intuition on how assets prices and market segments should respond to a given narrative but are unable to systematically quantify these relationships to more precisely estimate their sensitivities. Using Amazon as an example, we demonstrate how our narrative indicators can help measure exposures in a meaningful way. Specifically, we estimate stock sensitivities to various narratives with a relatively straightforward regression model.

First, we obtain market-adjusted stock returns by running a rolling one-year regression of weekly stock returns on weekly market returns (proxied by SPY). Market-adjusted stock returns are estimated as the difference between a given stock's return and the product of the respective stock's market beta with the return on SPY. Next, we estimate a given stock's exposure to fluctuations in various narratives by regressing five-day market-adjusted returns on changes in the negative intensity of each narrative in the same time period. The resulting beta coefficients and the associated Newey-West adjusted t-stats provide an estimate of how changes in each narrative influence the stock returns. For example, a positive coefficient suggests that stock returns respond positively to increases in negative narrative coverage. This stock can be considered as a hedge against the risk associated with the narrative.

Exhibit 7 presents the results from applying this framework to Amazon from 2015 to April 2021, providing a view into how Amazon stock prices respond to the negative intensity of various narratives: International Trade, Global Growth, Trade War, Recession, Health, and COVID-19. At the end of each month in the sample period, Amazon's market-adjusted returns are regressed on the weekly changes of the negative intensity of various narratives using the most recent one-year data. Note that the coverage of the COVID-19 narrative starts in January 2020. Plotted in the exhibit are the regression t-stats averaged over the entire sample period from 2015 to April 2021. We observe that Amazon stock price reacts positively to increases in negative news coverage in the COVID-19 narrative, suggesting that investors believe that more stay-at-home orders will lead to increased revenue for the online retailer. Yet, the negative coefficients on the Global Trade and Trade War narratives suggest that Amazon has high exposure to the deterioration in global trade conditions. Increases in the negative intensity of these narratives negatively influence Amazon's stock returns.

Exhibit 7: Amazon's Exposure to Narratives



**At the end of each month in the sample period from July 2015 to April 2021, Amazon's weekly market-adjusted returns are regressed on the weekly increases in the negative intensity of various narratives using the most recent one-year data. Plotted are the regression t-stats averaged over the entire sample period from July 2015 to April 2021. The COVID narrative data starts in January 2020.*

5.2 Accessing exposure to narratives

Building upon the insights that we glean from estimating asset exposures, we demonstrate how investors can leverage the framework to construct portfolios to achieve desired narrative exposure. This process involves systematically measuring individual asset exposures to a specified narrative and construct an equity portfolio of narrative-sensitive stocks.

As a proof-of-concept, we use a scenario in which an investor wants to achieve exposure to the COVID-19 recovery, perhaps believing the pandemic is abating. To capture this exposure, investors would wish to go long stocks that are expected to respond positively when the COVID pandemic outlook improves. One possible measure of the COVID pandemic condition is the actual case count. In this paper, we advance that the media derived COVID narrative may better capture the pandemic outlook. A given stock's COVID recovery exposure can be measured by estimating the stock's return sensitivity to our COVID narrative indicators, specifically, increases in the negative intensity of the COVID-19 narrative, caused by an increase in total coverage and/or a decrease in positive sentiment. Stocks with negative COVID narrative betas are expected to rise in the COVID recovery.

We start by estimating narrative betas for our universe of stocks—stocks in the S&P500 index. As in the previous section, we calculate the market-adjusted stock returns as the difference between a given stock's return and the product of the respective stock's beta with the market. Next, we regress market-adjusted weekly stock returns on changes in weekly negative intensity of COVID-19 to estimate stock-level exposures. Again, note that the COVID-19 narrative indicators start from January 2020.

Exhibit 8 presents the securities with positive and negative exposure to negative coverage of COVID-19 using the data up till the end of April 2020. The results are consistent with our intuition. Specifically, real estate, travel, and energy companies have low COVID narrative betas. In fact, they are negatively exposed to increases in negative coverage of COVID and their stock prices should rise during a COVID recovery. In contrast, biopharma and communication companies have positive COVID narrative betas—their stock prices rise when the negative coverage of COVID increases.

Exhibit 8: Securities by COVID-19 Narrative Exposure

Company	Sensitivity to COVID-19 Narrative (T-stat)	Company	Sensitivity to COVID-19 Narrative (T-stat)
AT&T Inc	2.58	Wynn Resorts	-2.98
Procter & Gamble Co	2.35	Walt Disney	-2.92
Johnson & Johnson	2.41	Las Vegas Sands	-2.43
Verizon Communications	2.40	Host Hotels and Resorts	-2.92
Charter Communications	2.45	Transocean	-2.47
Pfizer	3.51	Halliburton	-3.10
Citrix Systems	3.57	Live Nation Entertainment	-3.17

* *In the sample period from January 2020 to April 2020, a stock's weekly market-adjusted returns are regressed on the weekly increases in the negative intensity of the COVID narrative. The exhibit presents the regression t-stats.*

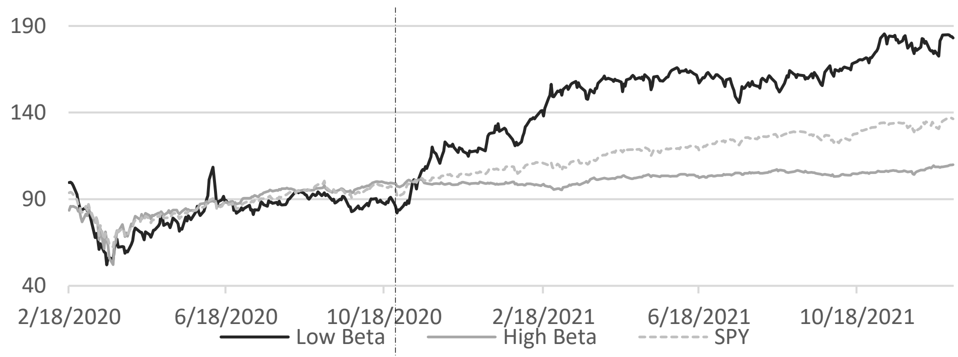
After obtaining measures of COVID-19 exposure for each stock, we construct two portfolios: the low COVID narrative beta portfolio includes the 25 stocks with the lowest exposure, measured by the t-statistics of the beta-coefficients, and is expected to outperform during a COVID recovery when negative coverage of COVID-19 decreases; the high COVID narrative beta portfolio includes the 25 stocks with the highest exposure and is expected to underperform when negative coverage of COVID-19 decreases. **Exhibit 9** illustrates the performance of these two COVID narrative beta portfolios, rebalanced monthly starting in February 2020.

Throughout most of 2020, the high Covid narrative beta portfolio outperforms the low COVID narrative beta portfolio. This reverses in early November 2020, when Pfizer publicly announces its COVID-19 vaccine is more than 90% effective. Panel C shows that a long-short portfolio that goes long on the low narrative beta portfolio and short on the high narrative beta portfolio, dubbed the COVID recovery portfolio, earns a return of 120.74% in the time period from November 2020 to December 2021.

As a comparison, we apply the same framework to investigate an alternative way of capturing exposure to a COVID-19 recovery: using confirmed Covid-19 cases as an indicator of the COVID pandemic. We calculate firm-level case-count betas and the associated t-statistics with respect to the weekly changes of confirmed COVID-19 cases and construct the low and high beta portfolios using the t-statistics of the case-count betas. Panel B plots the return spread between low case-count beta and high case-count beta portfolios and demonstrates that the long-short case-count beta portfolio does not track a COVID-19 recovery well. The outperformance of the media narrative beta-sorted portfolio over a portfolio constructed based on sensitivity to the actual number of cases suggests that the media narrative can be more influential on investor decision-making than changes in actual case statistics.

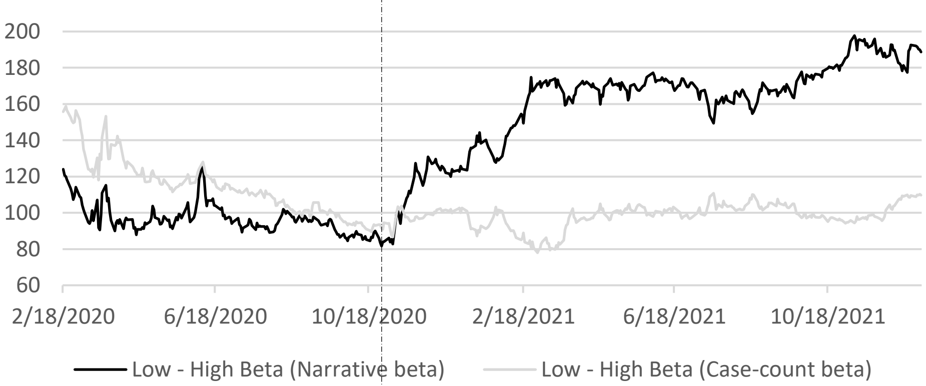
Exhibit 9: Accessing Exposure to a COVID-19 Recovery

Panel A: Low and high COVID narrative beta portfolios



Nov 9th: Pfizer and BioNTech announced that their vaccines is more than 90% effective

Panel B: Long-short portfolios (Low beta minus high beta)



Panel C: Summary Statistics

Time Period	Metric	Low narrative beta minus high narrative beta portfolios	Low case-count beta minus High case-count beta portfolios
February 18th, 2020 – October 30th 2020	Return (cumulative)	-32.25%	-39.30%
	Standard Deviation*	0.56	0.43
	Reward-to-Risk/ IR*	-0.71	-1.41
November 2nd, 2020 – December 31st 2021	Return (cumulative)	120.74%	16.55%
	Standard Deviation*	0.38	0.35
	Reward-to-Risk/ IR*	2.01	0.54

** At the end of each month from January 2020 to November 2021, a stock's weekly market-adjusted returns are regressed on the weekly changes in the negative intensity of the COVID narrative using the most recent one-year data (the Covid narrative data starts on January 4th, 2020). Low-beta stock portfolio includes the 25 stocks that have the most negative t-statistics of the beta coefficients. High-beta stock portfolios includes the 25 stocks with the most positive regression coefficient t-statistics. Portfolio levels are set to be 100 on Nov 9, 2020, the day when Pfizer and BioNTech announced that their vaccines is more than 90% effective. Standard deviation is calculated from the daily returns and annualized. Reward-to-risk ratio is the daily average returns divided by the standard deviation (annualized).*

6. Conclusions

Driven by digital media, stories, narratives, and themes, whether true or not, can quickly spread throughout the world, dictating the social discourse of a country and influencing human behavior, and affecting security prices in financial markets. Therefore, it is becoming increasingly important for investors to understand and track these narratives. In this paper, we demonstrate how media-derived measures provide economists and investors with a powerful tool to understand what narratives and themes are driving markets and how their evolution through time impacts asset prices. Ultimately, this enables investors to access desired narrative exposure and enhance portfolio returns.

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Appendix A: List of Narratives

Theme/ Narrative			
Bankruptcy	Fiscal	Joe Biden	Smart Beta
Brexit	Fund & Asset Management	Labor Market	Trade War
Business Cycles	FX	Liquidity	Treasury Bonds
Buybacks	GDP	Manufacturing	US Growth
Carry	Global Growth	Market Crash	US Growth Slowdown
China Growth	Globalization	Minimum Volatility	US Stocks
Civil Unrest	Governance	Momentum	Value Investing
Commercial Banking	Government & Corp Debt	Money	
Commodity	Health	Money Market	
COVID-19	Healthcare	Natural Disasters	
Crime	Housing Market	Passive Investing	
Derivative Securities	Immigration	Personal Consumption	
Dividends Factor	Industry	Personal Finance	
Donald Trump	Inequality	Political Elections	
Earning Season	Inflation	Privacy	
Emerging Markets	Interest Rates	Profitability	
Environment	International Conflicts	Profitability	
Equity Investing	International Organizations	Race	
ESG	International Trade	Recession	
ETF	Investment	Retail Investors	
Federal Reserve	Investment Banking	Risk	
Financing	Investor Sentiment	Size	

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