Sentiment Risk Premia in the Cross-Section of Global Equity *

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Abstract

This paper introduces a new sentiment-augmented asset pricing model in order to provide a comprehensive understanding of the role of this new type of risk factors. We find that news and social media search-based indicators are significantly related to international stocks' excess returns. Adding sentiment factors to both, classical and more recent pricing models, leads to a significant increase in model performance. Following the Fama-MacBeth procedure, our modified pricing model obtains positive estimates of the risk premium for positive sentiment, while being negative for negative sentiment. Our results contribute to the explanation of the cross-section of average, international excess returns and are robust for fundamental asset pricing factors, idiosyncratic volatility, skewness, and kurtosis.

JEL Classification Codes: $C53$, $G12$, $G41$

Key Words: *Asset pricing*; *behavioral finance*; *financial markets*; *investor sentiment*; *sentiment risk premium.*

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1 Introduction

Classical finance theories rest upon the assumption that investors are rational and form their return expectations based on fundamental values and hard-fact news. These models work well in "normal" times but fail to capture deviations of prices from their intrinsic values in both volatile and high-sentiment market phases (see, e.g., Yu and Yuan, 2011). The observed over- and under-reaction of asset prices to news announcements (see, e.g., Abarbanell and Bernard, 1992; Veronesi, 1999; Frazzini, 2006; Sinha, 2016), often followed by sudden plunges in states of financial turmoil, cannot be entirely explained by rational behavior based on fundamental factors. Instead, these abnormal price dynamics have been traced back to irrational investor sentiment like fear and panicking or greed and overconfidence that influence human decision-making (see, e.g., Barberis et al., 1998; Ottaviani and Sørensen, 2015; Ben-Rephael et al., 2017). Hence, these investors' moods that generally fail to be related to objective, fundamental features of the traded assets drive asset prices via supply and demand (see, e.g., Bushee and Friedman, 2016).

In this paper, we test this hypothesis by estimating sentiment risk premia in international stock markets based on a set of novel, direct search-based investor sentiment indicators. This new type of measure is derived from human language processing and distilled from newly available bases of data that collect asset-specific information as it circulates through public news and social media channels (see, e.g., Chen et al., 2014). By adding these investor-based mood factors to classical asset pricing models, we find that positive and negative deviations of sentiment from its long-term mean, as commonly observed to occur in extreme market situations and in the presence of tail events, adds significant explanatory power to asset pricing models.

We introduce a novel investor- rather than an asset-related sentiment-risk factor and establish a robust relationship between excess asset returns, several known systematic risk factors, and our novel sentiment factor. We find that our global sentiment factors contain additional explanatory power over standard factors and contribute to partially resolving the long-standing puzzle of the cross-sectional equity premia in the international dimension. Exploiting the fact that global equity indices each represent a diversified equity portfolio, we show that their excess returns can be better explained by adding investor-based sentiment factors to asset pricing models. These models contain otherwise well-known factors that relate to the largely understood mean-variance, risk-return trade-off logic, or to profitability, investment, and value. We also provide an explanation to the occurrence of persistent mispricing during bubbles and financial crashes by separating the effect of sentiment into measures that reflect the structure of its differential time-variation relative to economic and financial market cycles.

Our empirical analyses are based on a measure of micro-grounded, bottom-up news and social media sentiment. The findings derived from portfolio sorts and linear factor models support the hypothesis that sentiment represents an aggregate measure of investor beliefs (whether rational or not) on the outlook of cash flows and future asset values. We uncover a significant relationship between abnormal sentiment shifts and realized returns. In particular, a standard sorting of equity indices into portfolios provides empirical evidence that high (low) sentiment scores relate to very large, positive (negative) realized average excess returns. We show that positive (negative) deviations of sentiment from its long-term mean, i.e. positive (negative) *abnormal sentiment*, explains positive (negative) excess stock returns, while *average sentiment* has no significant effect. Interestingly, this result differs from the finding by Baker and Wurgler (2006, 2007), who report positive (negative) returns after negative (positive) sentiment. We argue that our sentiment indicator captures a different life-cycle of the emotional process of investors and therefore may serve as a leading indicator that pre-runs a composite index of fundamental variables as in Baker and Wurgler (2006, 2007). Furthermore, under the hypothesis that sentiment is a direct measure of investor mood, it must affect individual stocks and regional markets differently, to reflect their heterogeneous exposures to the unavoidable swings in the *relative* moods for different assets, and across geographies. A sentiment breakdown based on the underlying indices proves that there are sentiment-sensitive assets and others, which retain instead a prevailing correlation to classical risk factors. We relate this heterogeneity to the overall level of market efficiency. We use sub-samples of our data to explore sentiment during alternative bull and bear market phases, and our main results still hold.

As a by-product of our empirical analysis, we open a further avenue of inquiry to explain a number of asset pricing anomalies, based on the introduction of a novel, global sentiment risk factor. However, due to the complexity of the dynamics of sentiment as a risk factor, we demonstrate that a simple "positive-minus-negative sentiment" (PMNSNT) factor in the style of Fama and French (1993) cannot fully capture the priced contribution of sentiment to asset pricing relationships. We therefore split the global sentiment factor into negative, neutral, and positive sentiment portfolios, respectively, to cover the plane of human emotion along the arousal-valence framework more holistically. Using the excess returns of those specific portfolios as factor-mimicking representations, the results confirm that negative, neutral, and positive sentiment is differently priced. Negative sentiment leads to statistically significant and sizable under-performance compared to standard models, while positive sentiment bears a significant positive risk premium. These findings provide the empirical link to the theoretical model of Shefrin and Belotti (2008) who argues that sentiment is best understood as a distribution rather than as a scalar. Netting only excessively bullish and only excessively bearish emotions in a market sentiment can result in an oversimplified characterization.

We use these insights to benchmark different sentiment-augmented linear factor models against the standard CAPM and more recent asset pricing models. In this process, we resort to both the estimation of simple time series models and to the more sophisticated two-stage approach introduced by Fama and MacBeth (1973). The Fama-MacBeth method (FMB henceforth) provides estimates of the price of risk of the sentiment factor(s) in our cross-section of international stock index returns that allows us to perform comparisons with the downside risk CAPM (DR-CAPM henceforth) proposed by Lettau et al. (2014) and the Fama-French five factor model (FF5 henceforth). Based on the FMB specification, we show that a sentiment-augmented pricing model outperforms the CAPM, the DR-CAPM, and the FF5. We argue that our sentiment indicators and, in particular, the positive and negative deviations from its long-term mean, capture a new notion of pure investor sentiment that usefully separate fear-driven, neutral, and bullish mood dynamics. In contrast, Lettau et al. (2014) use market returns as a proxy for downside risk which takes only the perspective on the left tail of the objective, backward-looking distribution, and hence can only capture (presumably rational) aversion to left-skewness, i.e., losses from the extreme left tail. We therefore contribute to the literature by adding another key piece to the mosaic explaining the cross-section of international asset excess returns recently investigated by a number of papers (see, e.g., Lettau et al., 2014; Hou et al., 2017).

The paper is organized as follows. Section 2 provides a literature review on behavioral asset pricing and, based on this, derives a sentiment-augmented asset pricing framework. Section 3 describes the data. In particular, it gives a detailed description of our novel sentiment indicators and points out their advantages compared to existing sentiment proxies. In Section 4, we bridge our framework to empirical asset pricing models and show that sentiment, as captured by our novel indicators, leads to remarkable excess returns by means of portfolio sorting. Section 5 benchmarks different sentiment-augmented linear factor models against the standard CAPM and more recent asset pricing models using time-series regression. This section also applies the two-stage FMB method to estimate sentiment risk premia in the cross-section of global equity indices. Section 6 reports the results of a variety of robustness checks. Section 7 concludes.

2 Is Sentiment a Price Risk Factor

2.1 Related Literature

The Capital Asset Pricing Model (CAPM) proposed by Sharpe (1964), Lintner (1965) and Mossin (1966) relates the expected return of an asset to its sensitivity (beta) to the market risk premium. The single-factor CAPM was subsequently extended by including additional systematic risk factors, as represented by shocks to state variables correlated with the marginal utility of investors' wealth.[1] However, it is now well-established that (I)CAPM-style models tend to break down in abnormal times (i.e., during financial crises as well as in periods of massive overvaluation, often imputed to alleged bubbles) when asset prices significantly deviate from their intrinsic values (see, e.g., Russell and Thaler, 1985; Lakonishok et al., 1994; Daniel and Titman, 1997; Finter et al., 2012). Keynes (1936) and Livermore (1940) had already emphasized that fluctuations in asset prices might also be due to the influence of investors' "animal spirits" like greed, fear, ignorance, and hope. These non-fundamental, arguably not completely rational factors, could move asset prices by massive amounts away from their fundamental, intrinsic value. Such a recurring pattern of irrationality has led to detect widely debated and hence investigated phenomena such as fads, bubbles, and panics. In this regard, the prospect theory proposed by Kahneman and Tversky (1979) may provide a more accurate description of decision making compared to standard expected utility theory based on rational preferences (see, e.g., De Bondt, 1998; Bradshaw, 2002, 2004). Because people base their decisions not purely on rational expectations about the final outcome, but rather use heuristics to evaluate potential risks and losses of risky choices, decision making cannot be disconnected from human sentiment (see, e.g., Damasio, 1994; Dolan, 2002; Nofsinger, 2003; Peterson, 2011). For instance, seminal work by De Long et al. (1990) and more recently by Shu (2010) finds that sentiment affects equilibrium asset prices, and thus may cause magnified market fluctuations and excess volatility. Accordingly, there is now an increasing consensus that sentiment should be

[1] See, e.g., Basu (1977, 1983), Banz (1981), Jaffe et al. (1989), Fama and French (1993, 2015), Jegadeesh and Titman (1993), Carhart (1997), and Pastor and Stambaugh (2003).

considered as an integral part of asset pricing theory (see, e.g., Brown and Cliff, 2005; Da et al., 2015).

Because of the growing awareness of the importance of irrational trading and pricing motives, there is a growing literature that has explored the role of news, social media, and sentiment in asset pricing. Tetlock (2007) suggests that the frequency of negative words in a Wall Street Journal column is a proxy of the journalist's mood and that this has predictive power for stock returns. Ahern and Sosyura (2015) study the stock market impact of the accuracy of rumor articles concerning mergers and report that it has a significant impact, even though investors overestimate the accuracy of the average rumor. Da et al. (2011) show that individual investors prefer stocks with attention-grabbing news and this would obviously be reflected as a risk premium in the equity cross-section. In fact, evidence in Engelberg and Parsons (2011) shows that investors trade stocks based on narratives in newspaper articles, despite easy access to firms' press releases and analysts' reports. Da et al. (2015) use daily Google Internet searches by households to construct an aggregate indicator of sentiment, the Financial and Economic Attitudes Revealed by Search (FEARS) indicator. They find that this measure predicts short-term return reversals, temporary volatility spikes, and mutual fund flows out of equity and into bond funds. They argue that search-based methods bear advantages compared to survey-based techniques: online news and social media data are available in real time and reveal rather than just inquire about attitudes when the incentive to answer surveys or questionnaires honestly and truthfully is unclear. Furthermore, Da et al. (2015) find that an increase in a search volume indicator (SVI) made public by GoogleTrends, of the terms "recession" and "bankruptcy" on average leads a decline in the University of Michigan Consumer Sentiment Index (MCSI) by one month. In a previous study, Da et al. (2011) associated the SVI changes with trading by less sophisticated individual investors, a finding that has been confirmed by other researchers (see, e.g., Joseph et al., 2011). Ben-Rephael et al. (2017) propose a related (yet distinct) measure of institutional investor attention using the news searching and reading activity at Bloomberg terminals. They report that announcements accompanied with abnormal institutional attention experience larger returns (in absolute terms) and very little subsequent price drift. When institutional investors fail to pay sufficient attention, prices initially underreact to information, resulting in a drift.

Besides search- and survey-based methods, also indicators that are based on fundamentals are often treated as proxies for sentiment. For instance, Baker and Wurgler (2006) build a composite indicator (BW henceforth) using principal component analysis applied to a vector of fundamental variables.[2] Empirically, they show that depending on the value of this proxy indicator at the beginning of a period, the subsequent returns of hard-to-value shares like small, young, or unprofitable stocks are high (low) in low- (high-) sentiment states. This finding is further supported by the theoretical model in Baker and Wurgler (2007) using a top-down approach. They maintain that the existing bottom-up models of equity markets are too complicated to be summarized by a few selected biases and trading frictions. In their top-down approach, Baker and Wurgler (2007) focus on aggregate sentiment and trace its effects on market and individual stock returns back to two central forces showcased by modern behavioral finance: sentiment and limits to arbitrage. Brealey et al. (2017) show that sentiment measured by the BW indicator and meant to proxy for the trading activities of arbitrageurs, predicts the reversion of share prices to their fundamental value, while retail sentiment, expressed by a naïve trend-following metric, has some short-term explanatory power for return momentum. Laborda and Olmo (2014) and Hillert et al. (2014) aggregate similar indicators to those in Baker and Wurgler (2006) to build a single market sentiment factor in order to predict the risk premium on U.S. sovereign bonds. The forecasting performance of such a sentiment index turns out to be time-varying and is generally stronger during recessions.

2.2 Theoretical Framework

Although the main contribution of this paper is empirical, we embed our model in a simplified theoretical framework to depict the relationship between investor sentiment and asset pricing. In this chapter, we develop a formal definition of market sentiment and how it fits to our empirical specification with international equity indices. By doing so, we formulate the theoretical foundation why sentiment should be treated as a risk factor in asset pricing models and why it is applicable in aggregate states. Our argumentation hereby closely follows Shefrin and Belotti (2008).

In his keynote speech at a behavioral finance conference at Northwestern University in 2000, Daniel Kahnemann suggests to see the market as a stereotypical investor with thoughts, beliefs, moods, and emotions (see, e.g., Shefrin and Belotti, 2008). He encourages to think of a market as a representative agent who acts as if he sets market prices, but does not require Gorman

[2] To isolate the common sentiment component of sentiment proxies from fundamental variables, the BW index is based on the mutual variation in six underlying proxies for sentiment: the closed-end fund discount, the NYSE share turnover, the number of and the average first-day returns on IPOs, the equity share out of new security issuance activity, and the dividend premium.

aggregation[3] to form a uniform set of assumptions. Agents are not all alike and the differences among them surely matter. As such, this representative investor must reflect the heterogeneity in beliefs, coefficients of relative risk tolerance, and time discount factors. Failing to do so, would lead to oversimplification and an “illusion of intentionality and continuity”. Consequently, Shefrin and Belotti (2008) formulates that in a market involving a single representative investor, the equilibrium price ν at any point in time t and under consideration of all date-event pairs[4] $\chi_t|t = 0, ..., T$ follows:

$$\nu(\chi t) = \delta^t_{R,t} P_R(x_t) g(x_t)^{-\gamma_R(x_t)}, \tag{1}$$

where $\delta_R(t)$ is the representative investor's time preference function, $P_R(t)$ are the representative investor's beliefs, $g(x_t)$ is the equilibrium growth trajectory for aggregate consumption, and $-\gamma_R(x_t)$ is the representative investor's risk aversion.

In line with the existing view in finance literature of sentiment being synonymous with error, Shefrin and Belotti (2008) formally defines sentiment Λ as a proxy for distorted probabilities stemming from deviations in beliefs of a representative investor P_R, called the “market's beliefs” relative to objective beliefs Π, and deviations from the representative investor's equilibrium time discount factor δ_R relative to the objective discount factor when all investors hold correct beliefs δ_Π:

$$\Lambda = ln(P_{R,t}/\Pi_t) + ln(\delta_{R,t}/\delta_{\Pi,t}). \tag{2}$$

As such, sentiment is time-varying and can be described as a stochastic process. Sentiment should be modeled as a distribution and not only as a scalar in terms of first moments, because market participants are not only excessively bullish or bearish but subject to a great trajectory of human emotions. The first moment is unable to capture all investors' emotions and errors. Second moments may describe errors how investors perceive risks. Third moments capture whether investors are concerned about a price reversals and fourth moments may find that investors attach high probabilities to extreme events such as stock market crashes. As such, sentiment is much more complex than purely assigning erroneous probabilities to very positive or negative events.

[3] Gorman aggregation limits the impact of heterogeneity on aggregate demand and therefore equilibrium prices. Brennan and Kraus (1978) argue that a necessary condition for (Gorman) aggregation is that investors either have constant absolute risk aversion (CARA utility), or have homogeneous beliefs and homogeneous CRRA coefficients (constant relative risk aversion).

[4] At each time t there is an information structure in the market common to all investors with elements called events E. An ordered pair (t, E) is called date-event pair.

The individual investor's emotions aggregate to a market sentiment as a collage of different investors' beliefs, attitudes toward risk, and time preferences. As long as the aggregate investor's errors are non-zero, the market sentiment function will be non-zero. Shefrin and Belotti (2008) describe various scenarios of how overconfidence and representativeness, two commonly applied behavioral phenomena, affect the aggregate sentiment function in terms of first (representativeness) and second (overconfidence) moments. The quintessence of his exploration is that sentiment typically does not average to the zero function but rather leads to time varying oscillations in probabilities assigned to different market events.

Shefrin and Belotti (2008) also stipulates that the risk premium for any security is the sum of a fundamental premium and a sentiment premium. When the sentiment premium is large relative to the fundamental, risk premia reflect both mispricing and compensation for bearing sentiment-based risk. However, if sentiment is zero, the risk premium is fully determined by the fundamental one. We denote the fundamental based pricing kernel M_t as a stochastic discount factor (SDF) to measure the state price per unit probability. As such, for any (gross) return $r(Z)$ for a security Z the pricing kernel M_t satisfies $E_t(M_{t+1}r_{t+1}(Z)) = 1$. If we define the log-SDF as $m = ln(M)$ and combine Eq. 1 and Eq. 2 the log-SDF can be expressed as a sum of sentiment and a fundamental process based on aggregate consumption growth:

$$m = \Lambda - \gamma_R ln(g) + ln(\delta_{R,\Pi}). \tag{3}$$

It follows that the risk premium of security Z is determined by the covariance of its return with the SDF $-cov(r(Z), M)$.[5] Due to covariance decomposition into a fundamental and sentiment part we get:

$$\begin{aligned} E_t[r_{t+1}(Z)] &= -cov(r(Z), \Lambda M_{t+1}) \\ &= -E_t[\Lambda]cov(M_{t+1}, r(Z)) - E_t[M_{t+1}]cov(\lambda, r(Z)) \\ &- E_t[(M_{z+1})(\Lambda - E[\Lambda])(r(Z) - E[r(Z)])], \end{aligned} \tag{4}$$

where $cov(M_{t+1}, r(Z))$ denotes the fundamental risk premium and $cov(\lambda, r(Z))$ the sentiment risk premium. Given that a single sentiment factor is not able to fully capture the oscillation of

[5]The interested reader is referred to Shefrin and Belotti (2008) for a full quantitative derivation.

the sentiment function with heterogeneity in beliefs, risk aversion, and time discount factors as described above, we further break-down the sentiment risk premium $cov(\lambda, r(Z))$ into negative $cov(\lambda^{-}, r(Z))$, neutral $cov(\lambda^{0}, r(Z))$, and positive $cov(\lambda^{+}, r(Z))$. By doing so, we aim to capture the different investors' errors in probability estimation for positive and negative tail events, as well as midrange events.

The shape of the market sentiment function is affected by the wealth weighted aggregated mixture of sentiments of the individual investors. We argue that this aggregation best manifests in the sentiment for international equity market indices and affect global equity risk premia. In any other case, erroneous beliefs or sentiment may be diversified away or any mispricing eliminated by arbitrageurs. As stated by Kozak et al. (2018) arbitrageurs neutralize components of sentiment-driven asset demand that are orthogonal to common factor covariances as long as they do not expose themselves to factor risk. Only in the latter case can the sentiment-driven demand have a substantial impact on expected returns. In their model they impose a "near-arbitrage" opportunity restriction and exclude high levels of leverage and unbounded short sales as implausible assumptions. Sentiment investors may still construct strong tilts in their portfolio but these restrictions prevent the most extreme cases. The authors argue that those deviations must be caused by sentiment with sentiment either being orthogonal to existing factor exposures or being correlated with them. Arbitrageurs' trading largely eliminates the effects of the orthogonal components of sentiment-driven asset demand, but those that are correlated with common factor exposures survive because arbitrageurs are not willing to accommodate these demands without compensation for the factor risk exposure. This understanding contradicts the previous elaboration of our theoretical framework and would lead to the conclusion that sentiment may change the pricing of existing common factors instead of being treated as an individual risk factor. Kozak et al. (2018) do not extend their model into this direction but if heterogeneity in beliefs pertains in aggregate state as outlined by the theoretical framework above, arbitrageurs would be reluctant to trade and expose themselves to a sentiment risk factor. We thus do not see that the findings of Kozak et al. (2018) eliminate the treatment of sentiment as a risk factor and postulate that sentiment should be part of asset pricing models and have its own risk premia. However, whether these sentiment premia are small or large relative to the fundamental component is an empirical question.

Despite the breakdown of sentiment risk into three sentiment premia, we are aware that this approach is still an approximation of the time-varying sentiment risk premium driven by the oscillating sentiment function, but it is a much more sophisticated specification than in the existing theoretical or empirical behavioral finance literature. So far, empirical models limit sentiment to positive or negative events. However, our theoretical framework based on the work of Shefrin and Belotti (2008) suggests that sentiment captured as excessive optimism or pessimism is overly simplified but more complex treats of sentiment have been traditionally hard to measure in empirical specifications. Researchers are thus motivated to explore new sources of sentiment and the next section will describe how MarketPsych's sentiment data capture these various behavioral phenomena and how it can be used for an empirical asset pricing model.

3 Data

In this section, we introduce our sentiment indicators and discuss their differences with respect to the proxies in Baker and Wurgler (2006, 2007). This step is important as understanding the sources of differences compared to earlier literature is a crucial step in interpreting our empirical findings.

3.1 Sentiment Indicators

Our search-based sentiment index is the Refinitiv MarketPsych indicator (RMI) for *Sentiment*. The automatic language processing system from MarketPsych uses a human-made lexicon, which associates words and word groups to different kinds of indicators related to the performance of financial assets. Words and word groups in a message are annotated with so-called "Psych Words" (e.g., volatility, conflict, safety, etc.), defining a novel, different conceptual space. To define groups of words and create relationships, the lexicon distance is assessed by applying weights on a scale from 0.0 to 1.0 to account for proximity in the text, but also punctuation and additional structures are taken into account. This process results in tuples, which are then recorded as sentiment indicators. Tuples referring to the same subject are aggregated into a score. The scores are again divided by the total of the scores for all psych categories. The resulting total is called the *Buzz*, i.e., the weight of all messages and phrases of interest over a certain period. This ratio gives an indication of how important (or commonly discussed) a subject is (or was) over a given interval of time. This normalization allows equally weighted comparisons among numerous topics and nouns. Because of this construction method, MarketPsych's approach goes far beyond the often used bag-of-words or similar techniques applied in previous studies (see, e.g., Jiang et al., 2019; Tetlock, 2007).[6]

In our empirical analysis, we use aggregate, RMI investor sentiment for a range of international stock market indices for the period from 1998 to 2017. The MarketPsych *Sentiment* indicator captures the net positive versus negative references in the media and press news related to an asset. It can be interpreted as an overall market sentiment proxy, absent of any insights on the fundamental reasons for why references to a security may be positive or negative. MarketPsych language processing engine hereby goes way beyond traditional textual sentiment analysis with a one-dimensional output of positive or negative sentiment and a notion of neutrality, but exploits a broad range of human emotions. A common classification system of human emotions uses two dimensions known as valence and arousal, and psychological research has demonstrated that more than just one dimension has predictable effects on investor behavior. MarketPsych uses this classification system following the affective circumplex model of sentiment by Russell (1980) and constructs RMI indicators spanning the entire plane of human emotions. Figure 3 depicts several of the RMI sentiments that are described in detail in Table A.1 of the Internet Appendix on the affective circumplex. Each dot hereby corresponds to the emotion's location on the circumplex, whereby RMI indicators are themselves hybrids of multiple emotions according to the original framework. The thin grey line connects the positive and negative poles of matching indicators. The RMI *Sentiment* indicator itself spans the entire plane of circumplex as described in detail in Table A.1 of the Internet Appendix. It shows that the construction of *Sentiment* is tilted towards capturing negative statements as MarketPsych research on business and financial language has found more concepts on negative than positive valence. As a result, the *Sentiment* indicator is usually net negative.

Figure [3] about here

To provide more intuition of the construction mechanism, MarketPsych has provided an example about the complex language processing system that indicates how MarketPsych addresses some common pitfalls in news and social media sentiment analysis. Figure 4 evaluates the opinion of a Goldman Sachs' analyst about his expectations of tomorrow's quarterly call of Apple Inc.

[6]Compared to other sentiment providers like RavenPack (see, e.g., Audrino et al., 2019; Shi et al., 2016), MarketPsych indicators have not been calibrated to financial markets using a training sample. Hence, we can use back-fitted time-series without any concern for the existence of hindsight biases.

and increasing profit margins. MarketPsych is able to differentiate between forward-looking statements and general chatter by breaking down concepts into forecasts (future tense) versus present or past observations. PriceForecast is a future-tense subset of PriceDirection. "The price of Apple rose last week." is a PriceDirection-only reference while "The price of Apple will rise." would be attributed to both PriceDirection and PriceForecast. In order to have a correct attribution of articles to the right time window MarketPsych also limits article consumption to those less than 2,500 words as longer articles usually take longer to write and are unlikely to be timely. In order to avoid the impact of stale news, content that was published more than 24 hours previously, is excluded, and all content drops out of the 24 hours averages when it has been more than 24 hours since publication. Articles that are more than 98% similar to articles received in the past 24 hours are removed from analysis to avoid double-counting. For social media with concepts of re-tweets, re-posts and commenting, MarketPsych employs a tailored and rigorous approach to cleanse the data. The RMI indicators do not include retweets, unless those retweets include additional commentary or observations about the original tweet. RMI does not include comments with the same title that are repeated multiple times, however, do include the comment text if it changes from post to post.

Figure [4] about here

Various sources are used to inform the data feed of the language processing system used by MarketPsych. This includes news publishers like Refinitiv and Bloomberg, electronic databases like the U.S. Securities and Exchange Commission's Edgar repository of company filings, direct press releases by companies, transcripts of conference calls, websites, blogs, and especially posts in social media like Twitter and Yahoo's stock message boards. We use the aggregate measure that reflects activities through all types of channels, news and social media. The indicators are updated at a one-minute frequency and the system works 24/7 continuously scanning all the tracked sources. For daily records the last 24 hours or 1440 minutes are aggregated. If no records are found for the constituents of a specific stock index, a "N/A" is returned and the observation is not stored. This implies that the retrievable time series of each individual sentiment indicator are not equally spaced over the time axis. In practical terms, if no observation is found, no Buzz is recorded and the time series fails to be updated. Crucially, such a case needs to be differentiated from true "0" values, where positive and negative statements concerning an asset exactly balance each other.[7]

[7]Positive and negative references that net each other out may still signal increased uncertainty in the market and disagreement between investors and potentially lead to higher trading activity. However, MarketPsych has

For the purposes of our investigation, we accumulate the RMI index at a lower frequency versus the original, daily frequency, by aggregating the indicators to weekly observations using Equation (5). A weekly frequency appears to strike a reasonable balance between sufficient granularity of the data and a need to control for the risk of using a noisy estimator of *Sentiment*.[8] Let $Buzz_0$, $Buzz_{-1}$, $Buzz_{-(T-1)}$ and RMI_0, RMI_{-1}, $RMI_{-(T-1)}$ represent the corresponding Buzz RMI data for a given asset class or security, content source, and timestamp over the past T days. The Buzz-weighted average RMI over the trailing T-day window length is then computed as[9]:

$$\frac{(Buzz_0 * RMI_0 + Buzz_{-1} * RMI_{-1} + ... + Buzz_{-(T-1)} * RMI_{-(T-1)})}{(Buzz_0 + Buzz_{-1} + ... + Buzz_{-(T-1)})}. \tag{5}$$

For illustrative purposes of the empirical results of this approach in terms of dynamics of the *Sentiment* variable over time, MarketPsych illustrates the results of an in-depth data analysis for the S&P 500 U.S. equity index. Figure 5 shows for a period of January 2007 to January 2015 how *Sentiment* falling below the long-term average creates selling pressure with negative returns, while when *Sentiment* rises above the long-term average a phase of rising market with increasing returns is indicated.

Figure [5] about here

3.2 Comparison of Sentiment Indicators

The current academic standard in the matter of sentiment indicators, the BW index, extracts sentiment from fundamental variables that reflect trading volumes, issuance activity, and hence, directly or indirectly also asset prices. It thus only captures a specific type of sentiment, namely the one after market participants have taken trading or investment actions as reflected by the price and traded quantities of securities. For instance, Baker and Stein (2004) suggest that turnover and liquidity in general are proxies for investor sentiment. In a market subject to short-sales

confirmed that the primary relationship is that *Sentiment* RMI variability rises as the overall *Buzz* decreases. So *Buzz* is the primary determinant of *Sentiment* dispersion

[8] In an unreported explorative data analysis, we verify that *Sentiment* fluctuates rather massively at higher frequencies, whereas at a lower frequency it suffers from a loss of valuable information that however appears to be manageable. This analysis is available upon request.

[9] Additionally, this definition ensures comparability of *Sentiment* between different assets as outlined by MarketPsych in their research guidelines. The interested reader is referred to the MarketPsych user guide, accessible at `https://old.marketpsych.com/guide/`.

constraints, retail investors participate only when they are optimistic, and thereby add liquidity to the market. Hence, high liquidity can also be seen as an indicator of overvalued stock prices. The BW indicator captures such an above-average liquidity, maps it in the overvaluation of stocks, and refers to it as contribution to positive sentiment. Moreover, and also differently from the traditional view, DeVault et al. (2019) find that these commonly used measures of investor sentiment capture the demand shocks of institutional rather than individual investors. Nofsinger (2003) confirms that emotions and moods have a severe impact on financial decision-making. Due to its nature as an emotional barometer, the stock market itself can be interpreted as an indicator of social mood. However, business activities tend to follow, rather than lead, social mood.

On the opposite, the index used in our paper extracts sentiment directly from news and social media posts, which are expected to at least partially anticipate investors' actions. Kahneman and Tversky (1979), Damasio (1994), and Dolan (2002) investigate how emotions affect parts of the human brain and influence the decision-making process. More recent research in Peterson (2011) exploits advanced neuroimaging techniques, which gives information about psychological processes in the human brain and their connection to financial decisions. Peterson's work offers the foundations to the MarketPsych indicators. The academic literature however just stands at the beginning of exploring this novel data set with only very few papers published or in progress (see, e.g., Hu and Wang, 2012; Crone and Koeppel, 2014; Daszynska-Zygadlo et al., 2014; Audrino and Tetereva, 2017).

In the stylized model of Figure 1, we assume that BW (dashed line) and RMI (solid line) are simply initialized at zero in $t-2$. There is no sentiment-driven signal in the market, and consequently, also no significant excess returns (measured by the grey bars) in the subsequent period, $t-1$. However, in $t-1$ a positive shock affects RMI, while BW remains unaffected. For instance, think of the case in which investors become optimistic about the general economic outlook and enter the market according to the theoretical foundations discussed in Baker and Stein (2004). Their actions drive excess equity returns up in t. We argue that our sentiment index is able to detect such a surge in positive sentiment in the period before retail investors enter the market and increase liquidity as well as share prices. In contrast to the BW indicator that reflects the sentiment shock only later, a positive sentiment shock to RMI is associated with an immediate price increase and predicts positive stock returns. At time t fundamental factors such as liquidity and volume reflect trading activities in the previous period, that are instead interpreted by BW as positive sentiment. However, we argue that on many occasions investors may perceive these very dynamics in liquidity, volume, and prices just as a manifestation of ongoing overvaluation of the market at the time when this is disclosed in the news and social media. It may therefore even be recorded as a negative RMI mood shock, originating a more pessimistic outlook. RMI would capture this turn of events as negative sentiment and we would observe a decline in prices deriving from negative excess returns in period $t + 1$. Also, in this case, BW would record the dynamics in observable trading activities with a delay and characterize these as a downturn in sentiment. Hence true but unobserved sentiment carries a positive relationship with stock returns as the measurement gap between true sentiment dynamics and realized return increases.

One of the key empirical contributions of our paper consists in showing that there is a significant wedge in explanatory power in favor of search-based news and social media RMI sentiment measures over more traditional, market outcome-based ones, especially when the rebalancing horizon is of one week. Moreover, we shall maintain that sentiment is a temporary state variable that only provides additional explanatory power (over standard asset pricing models) in the short-term, which represents another important difference compared to the BW indicator that has been traditionally constructed and used at a lower, monthly frequency. To provide support to these conjectures on the different dynamics of search-based versus market outcome-based sentiment measures, we compute the correlation between BW and RMI, when the latter is sampled at a monthly frequency, well-aware of the potential loss of information that this causes to such a high-frequency indicator as RMI. We find that the BW and RMI US stock market sentiment indices carry a significantly negative correlation of -0.13. However, when we lag the variables according to the conceptual framework in Figure 1, the correlation switches to positive +0.11. When we increase the lag between the two series, the correlation climbs even higher until the lead-lag difference is increased up to six months. It then remains stable at a highly significant +0.22 and starts declining back towards zero when the lead-lag differential exceeds ten months. As Figure 2 shows, such a dynamic cross-serial relationship varies over time and we can identify three phases. The first phase spans the sub-sample from 1998 to 2002 and is characterized by a high and significant negative correlation of the contemporaneous data equal to -0.37. However, when the RMI index is lagged, the correlation is +0.20 and consistent with the full sample statistic reported above. In the second phase, between 2003 and 2011, the estimated correlations turn positive, at +0.15 and +0.24, respectively, for the contemporaneous and lagged series. The strength of the linear association declines in the last sub-sample, between 2012 and 2017, when the correlations are +0.08 and +0.1 only, without and with lags.

Figure [1] about here

Figure [2] about here

3.3 Asset Markets

We consider global equity markets over the period January 1998 to December 2017. In total, we cover 21 different international equity indices.[10] As a prediction target variable, we choose weekly excess returns. To be consistent with the aggregation methodology applied to the *Sentiment* indicators, we first compute the average equity performance index level per week and then the return scaled by the previous week's mean index level. In so doing, we avoid any day-of-the-week effects. We choose the one-month U.S. Treasury Bill rate as the risk-free asset from the publicly available data repository maintained by Fama and French (1993, 2015). This choice is appropriate because all indices are expressed in U.S. dollars. As a proxy for the unobservable market portfolio return, we use the excess return on the MSCI World performance index from the Fama-French data repository due to the international set-up of our study.[11]

4 Sentiment in the Cross-section of Portfolio Sorts

It is well known that empirical tests of standard asset pricing models based on traditional, fundamental-based and theoretical risk factors generally fail to explain price deviations from the intrinsic value of assets (see, e.g., Ferson and Korajczyk, 2002). One source of these mispricings may be traced back to the existence of irrational components in investors' beliefs. If our sentiment indicator represents an aggregate measure of investor beliefs on an asset, we expect that the fit of otherwise traditional asset pricing models may improve when a new factor driven by the RMI *Buzz*

[10]See Table A.3 in the Internet Appendix B for the complete list of stock market indices.

[11]`https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`. The MSCI World index is a capital-weighted total return index that includes the largest companies from all developed markets. The constituents list overlaps greatly with the indices for which RMI *Sentiment* indicators are available, i.e., Australia, Canada, France, Germany, Hong Kong, Japan, Russia, Spain, Switzerland, the UK, and the US. The following countries are instead represented in the MSCI World index but are simply consolidated as a Eurozone overall index by RMI: Austria, Belgium, Denmark, Finland, Ireland, the Netherlands, Norway, Portugal, and Sweden and included in this way on our RMI buzz series. RMI indicators are also available for Brazil, China, India, and Russia but not for Israel or New Zealand, two further constituents of the MSCI World index. In light of such a considerable overlap, we consider the MSCI World index an appropriate proxy for the market portfolio in our application.

scores is added to the empirical framework. In this section, we show that the RMI *Sentiment* indicator is priced in the cross-section of portfolio sorts. We proceed to form portfolios based on the exposure of assets to deviations of *Sentiment* from its long-term mean. This is a common approach (see, e.g., Fama and MacBeth, 1973; Fama and French, 2015; Lettau et al., 2014; Borochin and Zhao, 2017) to show that the portfolios created in this way yield significant positive/negative average excess returns.

More precisely, we sort our assets into sentiment-based portfolios: on a weekly basis, we rank the international equity indices on the basis of the corresponding, aggregate *Sentiment* measure. Therefore, we use investor-related rather than (or in addition to) asset (systematic) market-based risk factors. Psychological and cultural traits suggest that sentiment has no common definition and as such it may be not comparable in terms of its level across markets, even when measured on a common scale of values. Inconsistencies may also occur because MarketPsych is only able to evaluate English-written content. Thus, we sort the indices at every time step t according to the deviation of *Sentiment* from its long-term mean until t.[12] As a result, the change in *Sentiment* is comparable across indices only if we account for local differences by scaling the variation by standard deviations.[13] We apply three alternative sorts based on negative, neutral, and positive *Sentiment*. For each week t, we determine whether an equity index belongs to the lower ($s(-)$), middle ($s(0)$), or upper ($s(+)$) quantile of assets sorted based on previous week's *Sentiment*. This is motivated by Shefrin and Belotti (2008) who argues that sentiment is best understood as a distribution rather than as a scalar. Describing market sentiment as being either only excessively bullish or only excessively bearish can result in an oversimplified characterization.

Following DeVault et al. (2019) our first goal is to examine correlation rather than causal effects. However, we acknowledge the dynamic relationship between financial markets and sentiment by using one-week lagged *Sentiment* to avoid a potential reverse causality problem. In Panel A of Table 1, we present the results of Welch's (Welch, 1947) two-sample t-test of equality of average weekly excess percentage returns across these sorts. The first column gives the average weekly percentage excess returns sorted in accordance to average weekly sentiment reported in the third

[12] Such long-term mean is estimated and updated on a recursive basis to avoid any hindsight biases, i.e. the mean is computed since inception of the *Sentiment* index until t, not the entire period T.

[13] This approach is backed by the literature and relates changes in sentiment to demand shocks. DeVault et al. (2019) identify whether the trades explained by sentiment metrics are, in the aggregate, initiated by individual or institutional investors exploiting the fact that changes in sentiment will be positively related to changes in sentiment traders' demand (i.e., demand shocks) in the case of speculative stocks and inversely related to demand shocks in the case of safe stocks.

column. Sort $s(-)$ implies a large, negative mean excess return of -0.15%, while $s(0)$ leads to a small positive mean excess return of 0.06%. This difference is highly significant at a 10% level. Portfolio $s(+)$ implies a significantly positive, large mean excess return of 0.19% corresponding to positive *Sentiment* of 7.4%. The *Sentiment* level of sort $s(-)$ is instead deeply negative with -7.4% and practically zero for $s(0)$. The standard deviation of *Sentiment* across the sorts however does not differ greatly and lies between 3.4% ($s(0)$) and 4.0% ($s(+)$). The standard deviation of excess equity returns is the highest with 2.5% for $s(-)$, compared to 2.1% and 2.2% for $s(0)$ and $s(+)$, respectively. As a result, positive deviations of sentiment from its long-term mean are associated to high, positive excess returns with the modest standard deviation across equity market indices return. The standard deviation of excess returns allows us to conclude, however, that returns are highly volatile in each sort. Columns 5 through 7 report the p-values associated to Welch t-tests, indicating that the differences in mean excess return across sorts are often significantly different from zero. Conceptually, negative *Sentiment* is associated to negative excess returns. Even though this makes intuitive sense, this is at odds with earlier findings by Baker and Wurgler (2006, 2007) based on the BW index, by which high sentiment predicts low returns in the cross-section. However, as we have argued in Sub-section 3.1, the BW proxies measured sentiment when this has already been reflected in equilibrium financial prices and quantities by conscious decisions, whereas our RMI *Buzz* indicator captures emotions that investors consciously or unconsciously express through their news and social media activity.

Table [1] about here

Crucially, sentiment behaves differently among the three different portfolio sorts. Although the average sentiment level itself has no critical explanatory power for (excess) returns, prices react to changes in investor sentiment measured in terms of its deviation from the long-term mean. We have reported that positive (negative) sentiment change is followed by positive (negative) returns.

In the next section, we first use the sentiment-based mimicking portfolio to enrich standard asset pricing models like the CAPM to demonstrate that sentiment significantly increases the explained variation in excess returns and may represent a priced risk factor. Second, we additionally account for the Fama and French's five factor model and a momentum factor to empirically estimate the additional contribution of our new sentiment factor. Third, we use these findings to compute the sentiment risk premia and compare it to a recent model by Lettau et al. (2014) that is based on a downside risk specification as well as to Fama-French's five factor model.

5 Sentiment-Augmented Asset Pricing Models

5.1 Linear Factor Models Including Sentiment

Based on our earlier finding that the change in sentiment is a priced factor, we further investigate whether the sentiment-based mimicking portfolios can be used to enhance traditional asset pricing models. We test different linear factor models including the capital asset pricing model (CAPM), the downside risk capital asset pricing model (DR-CAPM) of Lettau et al. (2014), a CAPM-augmented model that includes a positive-minus-negative sentiment portfolio (PMNSNT-CAPM), and a CAPM-augmented model for negative, neutral, and positive sentiment deviation (SNT-CAPM).[14] We select Lettau, Maggiori, and Weber's model because they also investigate international cross-sectional data for equity markets and report a remarkable outperformance of their downside risk model (DR-CAPM) over the CAPM. We estimate linear models for international stock indices, and compare their coefficients and their goodness-of-fit with the standard CAPM and the DR-CAPM.[15] In the following, all standard errors of the estimates are adjusted to account for time-series correlation and heteroscedasticity by using Newey-West corrected standard errors. Given the multiple testing set-up, we also correct the p-values for multiple testing bias and to counteract the problem of multiple comparison between markets by applying the Holm-Bonferroni correction proposed by Holm (1979).

The first model, the traditional CAPM, projects the excess returns of each index on the excess market return of the MSCI world:

$$r_i^e = \alpha_i + \beta_{CAPM,i} r_m^e + \epsilon_i, \tag{6}$$

where $\beta_{CAPM,i}$ is the standard CAPM beta for index i and r_m^e is the market excess return.

For the DR-CAPM we appropriately modify the methodology of Lettau et al. (2014). In a first stage, we perform two regressions by separately estimating the CAPM and DR-CAPM betas:

[14] In robustness checks, we also control for the global five factors proposed in Fama and French (2015) and include a momentum factor to address concerns that our sentiment indicators may capture news that are already incorporated in traditional risk factors or may reflect momentum. The results are qualitatively the same.

[15] To save space, we limit the assets used in these tests to the most important indices, while the remaining ones serve for robustness checks. From the list of equity indices in Table A.3 we remove the Dow Jones Industrial Index (US30), the Russell 2000 (USMID2000) and the Nasdaq 100 (USNAS100), so that the U.S. market is represented by the S&P500 (US500) only. We also exclude the MSCI 50 index emerging market index (EM50), the EURO STOXX 50 (EU50), the FTSE Mid 250 (GBMID250), so that we are left with 15 country equity indices.

$$r^e_{i,t} = \alpha_i + \hat{\beta}_i r^e_{m,t} + \epsilon_{i,t}, \text{for all } t \in T \tag{7}$$

and

$$r^e_{i,t} = \alpha^-_i + \hat{\beta}^-_i r^e_{m,t} + \epsilon^-_{i,t}, \text{ whenever } r^e_{m,t} \leq \bar{r^e_{m,t}} - \sigma_{r^e_{m,t}}, \tag{8}$$

where $r^e_{i,t}$ and $r^e_{m,t}$ are excess returns on the test assets and the market in the period ending in t over the risk-free rate, respectively. $\bar{r}^e_{m,t}$ and $\sigma_{r^e_{m,t}}$ are the sample mean and the sample standard deviation of the market excess return, respectively. More precisely, the second regression is estimated on a sub-sample, based on the condition $r^e_{m,t} \leq \bar{r^e_{m,t}} - \sigma_{r^e_{m,t}}$. This is equivalent to the joint model in Equation (9). We compare the regression coefficients of the CAPM and the DR-CAPM to test the null hypothesis $H_0 : \hat{\beta}_i = \hat{\beta}^-$, where $\hat{\beta}_i$ and $\hat{\beta}^-$ are the regression coefficients for the CAPM and the DR-CAPM. To perform this analysis, we first create a dummy variable DR that equals 1 when the downside risk condition is met and 0 otherwise, and a variable $DR \times MRP$ that is the product of DR and the market risk premium (MRP) $r^e_{m,t}$:

$$r^e_i = \alpha_i + DR_i + \beta_{CAPM,i} r^e_m + \beta_{DR \times MRP,i} DR \times MRP + \epsilon_i, \tag{9}$$

where α_i is the alpha in Equation (7). Adding α_i to the estimation of DR leads to the intercept in Equation (8). The CAPM factor $\beta_{CAPM,i} r^e_m$ is equal to the same expression as in Equation (7). We test the null hypothesis of whether $\hat{\beta}_i$ equals $\hat{\beta}$. The significance of the coefficient $\beta_{DR \times MRP,i}$ of $DR \times MRP$ indicates a rejection of this hypothesis. Note that adding $\beta_{CAPM,i}$ to $\beta_{DR \times MRP,i}$ results in the estimation of $\hat{\beta}^-$ in Equation (8).

As for the third model, we form a single sentiment risk factor as the excess return on a portfolio of long-positive/short-negative sentiment-sensitive indices. We test whether sentiment represents an additional, priced risk factor. The estimated model is

$$r^e_i = \beta_{CAPM,i} r^e_m + \beta_{PMNSNT,i} \Delta r^e_{PMNSNT} + \epsilon_i, \tag{10}$$

where the benchmark CAPM is nested under the restriction $\beta_{PMNSNT,i} = 0$. $\beta_{PMNSNT,i}$ is the beta on the excess return Δr^e_{PMNSNT} of a long-positive/short-negative sentiment portfolio formed by difference between the first and third sentiment-ranked portfolios defined above. Due to multicollinearity with the market risk premium, we orthogonalize this factor in the same manner described in the following for the extended Sentiment-CAPM.

Additionally, we also split the long-positive/short-negative portfolio and use the excess returns of the sorts directly. We estimate the sensitivity of assets to the portfolio returns mimicking the reaction of international stock markets to negative, neutral, and positive changes in investor sentiment. We allow for a more complex (composite) hypothesis by assuming that different amplitudes of change in sentiment may be priced differently based on the "sign" of sentiment fluctuations, so that there does not exist a single sentiment risk factor. The model is specified as

$$r_i^e = \beta_{CAPM,i} r_m^e + \beta_{s(-),i} r_{s(-)}^e + \beta_{s(0),i} r_{s(0)}^e + \beta_{s(+),i} r_{S3(+)}^e + \epsilon_i, \tag{11}$$

where $\beta_{CAPM,i}$ is the standard CAPM beta for asset i, r_m^e is the market excess return, $\beta_{s(-),i}$, $\beta_{s(0),i}$, and $\beta_{s(+),i}$ are the betas on the excess returns of the negative, neutral, and positive sentiment portfolios, respectively.

Because our portfolio sorts use the average returns of the constituents, there may be concerns about the existence of multicollinearity between our sentiment variables and market excess returns. The correlation analysis in Table A.2 of the Internet Appendix shows indeed the existence of highly significant correlations uniformly above 0.7 between the three sentiment sorts. The correlation to market returns is also highly significant with values greater than 0.5. In order to address such a potential multicollinearity, we orthogonalize the variables in a stepwise approach and use the residuals for the last model estimated. In particular, we first orthogonalize negative sentiment by regressing its mimicking excess portfolio returns on market returns:

$$r_{s(-)}^e = \beta_{CAPM} r_m^e + \epsilon_{s(-)}. \tag{12}$$

Next, we orthogonalize neutral sentiment by regressing the mimicking returns on market excess returns and the residuals from Equation (12):

$$r_{s(0)}^e = \beta_{CAPM} r_m^e + \beta_{\epsilon_{s(-)}} \epsilon_{s(-)} + \epsilon_{s(0)}. \tag{13}$$

Third, we orthogonalize the positive sentiment portfolio indicator in the same manner relative to market excess returns and the residuals of the previous two equations used as explanatory variables. This results in four distinct variables with zero correlation with each other:

$$r^e_{s(+)} = \beta_{CAPM} r^e_m + \beta_{\epsilon_{s(-)}} \epsilon_{s(-)} + \beta_{\epsilon_{s(0)}} \epsilon_{s(0)} + \epsilon_{s(+)}. \tag{14}$$

Finally, we use excess market returns and the residuals from the regressions above to estimate negative, neutral, and positive sentiment betas in a cross-sectional model that explains the excess returns of each target asset as follows:

$$E(r^e_i) = \beta_{CAPM,i} r^e_m + \beta_{\epsilon_{s(-),i}} \epsilon_{s(-)} + \beta_{\epsilon_{s(0),i}} \epsilon_{s(0)} + \beta_{\epsilon_{s(+),i}} \epsilon_{s(+)}. \tag{15}$$

While this approach yields unbiased coefficient estimates, it often complicates their economic interpretation. For models containing sentiment risk factors, we also provide information about the relative importance of each coefficient by presenting the estimated relative importance index (RI). RI allows to estimate the contribution of each factor to the total explained variation and practically proceeds to decompose the coefficient of determination to estimate the contribution of each risk factor to the overall model fit. We follow the methodology in Lindeman et al. (1980) and report the absolute contribution to the R^2 to represent such a characterization.

Panel A of Table 2 reports the estimated coefficients for each equity index along with Newey-West corrected standard errors. P-values are corrected for multiple testing bias using Holm-Bonferroni's method. For most of the equity indices (excluding the China CN300), the estimated CAPM coefficients are highly significant at the 1% level. The intercepts α are small and insignificant. If an asset pricing model is able to completely capture the variation in expected excess returns, the intercept should be close to zero. Given that we use well-diversified stock market indices this makes intuitive sense. One can argue whether these results justify adding another risk factor but as we are interested in the relative, not absolute performance of sentiment-augmented models compared to benchmarks and the explained variation of the CAPM is not very high, we still see a justification for adding sentiment to our model.[16] The R^2 ranges from a high 53.8% for the S&P500 (US500), to a moderate 36.7% for the German DAX (DE30), to a low 0.0% for the Chinese (CN300) equity index.

In Panel B, we estimate the DR-CAPM and note that the market risk factor remains significant at the 1% level for all indices (excluding the Chinese CN300), while the downside risk factor is only significant in the case of Australia (AU500), Canada (CA250), Spain (ES35), France (FR40), and

[16]The low absolute and insignificant intercepts make any more sophisticated method like the GRS statistic from Gibbons et al. (1989) redundant and we will limit our discussion to absolute α.

India (IN50). In fact, in overall terms, the downside risk model does not seem to be applicable to aggregate equity indices and downside risk has only a marginal contribution to the overall model performance. This again can be argued by the diversification effect aggregated stock market indices and may look different in factor-mimicking portfolios or individual assets.

In Panel C, we extend the CAPM by including a single sentiment risk factor based on a portfolio of long-positive/short-negative sentiment assets (PMNSNT-CAPM). The results show that sentiment is seldom statistically significant, and if, the contribution of sentiment to the overall explained variation hardly exceeds 5%. We conjecture that this first sentiment indicator may lack the power to capture domestic sentiment in aggregated equity indices. Absolute intercepts are either equal or higher compared to the CAPM model, i.e. that our sentiment-augmented model fails to capture additional variation in excess returns. The adjusted R^2 shows a small improvement compared to Panels A and B for models with significant single sentiment factor. We conclude that sentiment as a single risk factor based on a long-positive/short-negative sentiment portfolio does not provide a meaningful improvement of fit over the traditional CAPM.

In Panel D, we estimate the time series regressions using three distinct sentiment factors representing mimicking portfolios of assets with negative, neutral, and positive sentiment (SNT-CAPM). The three sentiment factors are mostly significant at the 1% level. The absolute intercepts are smaller or equal to CAPM, indicating the sentiment-augmented model is able to capture variation in excess returns left unexplained by the traditional model. The intercepts are all insignificant and indistinguishable from zero as required by well-specified asset-pricing models (see, e.g., Merton, 1973; Fama and French, 1993). The R^2 increases substantially for all indices reaching 85.9% for the U.S. market. We plot the total explained variation benchmarked against the CAPM in Figure 6 and visualize the improved model fit when the three novel sentiment factors are added. The estimated betas of all sentiment variables are generally positive. These coefficients can be interpreted as the sensitivity of the equity indices to portfolios of negative, neutral, and positive sentiment assets conditioning out the effects of the market risk factor according to our orthogonalization procedure. The relative importance analysis also emphasizes that negative sentiment provides the highest contribution, after market risk.

Table [2] about here

Figure [6] about here

Table 2 also reveals that sentiment seems more important in emerging than in developed markets, which are known to be (more) efficient in overall terms (see, e.g., Griffin et al., 2010). In order to support this claim, we apply two tests: a simple comparison of the CAPM-implied R^2 coefficients and the variance ratio test proposed by Lo and MacKinlay (1988). The R^2 of the market model is often seen as a naïve metric for stock price informational efficiency.[17] If we compute the correlation[18] between the relative importance of sentiment over the market risk premium and the R^2 of the CAPM market model, we obtain a strongly negative and highly significant estimate of -0.96: the higher the R^2 from the CAPM, i.e., the more efficient the market, the less important are the sentiment factor-mimicking portfolios. The second, more sophisticated approach to the measurement of market efficiency employs the variance ratio test under the null hypothesis of a random walk with homoskedastic ($M1$) or heteroskedastic increments ($M2$).[19] A high value of the variance ratio statistic leads to a rejection of the null of market informational efficiency. We perform variance ratio tests at lags $k = 2, 5, 10$ as suggested in Morck et al. (2000) and Bramante et al. (2013a,b). Next, we compute the correlations between the aggregated, relative importance of all sentiment variables above the market risk premium against all sample values of the variance ratio metrics $M1(k)$ and $M2(k)$ at different lags. The correlations peak at a positive value of 0.29 for the $M2$ statistic at lag 2 ($M2(2)$). The results support our conjecture that sentiment risk matters more for the less efficient markets.[20]

Next, we estimate a Fama-French five factor, sentiment-augmented linear pricing model to check whether any additional factors may reduce the explanatory power of the RMI sentiment portfolio mimicking returns. To address any concerns that our RMI indicators may actually fail to measure sentiment and instead just reflect market information contained in news that may be captured by more traditional variables, we also employ a Fama-French five factor model (FF5) as in Fama and French (2015, 2017), augmented with our sentiment indicators. These concerns are grounded in the way *Sentiment* is constructed, including references to fundamental topics like accounting results, earning expectations and economic outlooks. Another model extension also

[17] See Morck et al. (2000); Bramante et al. (2013a,b) for comprehensive studies and details about the use of R^2 as a price efficiency measure.

[18] Due to the non-normality of our data we apply Spearman's rank correlation coefficient. We also winsorize the data in order to reduce the effect of possibly spurious outliers.

[19] Under the null hypothesis, the associated test statistic has an asymptotic standard normal distribution with finite variance for all the time series. As argued by Lo and MacKinlay (1988), this test is more suitable to weekly observations to avoid the biases associated with infrequent trading, bid-ask spread bounce, and asynchronous prices typical of daily time series.

[20] See Table A.1 in Internet Appendix A for details on the correlation coefficients using alternative metrics and at different lags.

includes a relative strength factor to address a concern that our sentiment proxies may simply capture price momentum, also in the light of the empirical evidence on the relationship between news coverage and momentum.

In addition to market excess returns, the Fama-French factors are:

- SMB (Small Minus Big), the average return on a portfolio of small stocks minus the average return on a portfolio of large stocks, under rules of formation detailed in Fama and French (2017).

- HML (High Minus Low), the average return on the two top decile portfolios sorted by book-to-market (value) minus the average return on the bottom two portfolios sorted by book-to-market (growth).

- RMW (Robust Minus Weak) is the average return on the two top deciles sorted by a measure of operating profitability portfolios (robust) minus the average return on the bottom two decile portfolios sorted by operating profitability (weak).

- CMA (Conservative Minus Aggressive) is the average return on the two most conservative portfolios as sorted by relative investment outlays minus the average return on the top two deciles portfolios (aggressive).

Note that the applicability of the FF5 model to aggregate international equity indices is debatable (see, e.g., Cakici, 2015), given that these assets represent already diversified vehicles. On the one hand, any sensitivity to traditional company-specific attributes should be averaged out and removed in the aggregation stage and we do not expect that such a rich factor structure may interfere with our findings nor that the FF factors may offer a significant contribution to explaining cross-sectional returns. On the other hand, the equity indices themselves reflect by construction a strong selection bias because only the largest and most successful companies are the constituents of the country factors distilled by Fama and French. Similarly to the methodology followed above, we orthogonalize all variables to avoid multicollinearity. We emphasize that we first orthogonalize the FF factors and then proceed on to the sentiment factors to be able to disentangle any sentiment effects after any other (by now) classical FF5 factors have been considered. Table A.2 of the Internet Appendix presents a preliminary correlation analysis that reveals that the relationships between sentiment and the profitability (RMW) and investment (CMA) factors are statistically significant with estimated negative correlations in excess of -0.3. All other correlations are negligibly small or insignificant.

On these grounds, we proceed with the orthogonalization procedure in a similar fashion as in Equation (12) of Sub-section 5.1. All Fama-French factors as well as the sentiment indicators are treated accordingly. Finally, to address a concern that sentiment may just be a proxy for momentum, we augment the linear five-factor model by including a relative strength indicator (RSI) computed as the ratio of recent upward price movements and the absolute price movement over a 52-week window, as in Wilder (1978).[21] We add this additional factor to estimate the ultimate SNT-RSI-FF5 model:

$$\begin{aligned}E(r_i^e) = \beta_{CAPM,i} r_m^e + \beta_{SMB,i}\epsilon_{SMB} + \beta_{HML,i}\epsilon_{HML} + \beta_{RMW,i}\epsilon_{RMW} + \beta_{RSI,i}\epsilon_{RSI} \\ + \beta_{\epsilon_{s(-)},i}\epsilon_{s(-)} + \beta_{\epsilon_{s(0)},i}\epsilon_{s(0)} + \beta_{\epsilon_{s(+)},i}\epsilon_{s(+)},\end{aligned} \tag{16}$$

where $\beta_{CAPM,i}$ measures the sensitivity of asset i to the market factor, $\beta_{SMB,i}$ to the size factor, $\beta_{HML,i}$ to the value premium, $\beta_{RMW,i}$ to the profitability factor, and $\beta_{RSI,i}$ to the momentum factor. The remaining terms refer to the orthogonalized sentiment indicators as previously included in the linear factor models.

Table 3 reports the estimation results for this model in Panels A and C. The coefficients attached to the sentiment mimicking returns remain unchanged in terms of sign, estimated coefficient size, and relative significance when the additional variables are added. Although the Fama-French factors, in particular SMB and CMA, turn out to matter in various equity markets, no clear pattern emerges. SMB is often precisely estimated, which can be explained by the selection bias for the large companies which represent the constituents of the major equity indices. In these cases, when SMB is significant, the adjusted R^2 increases consistently but the market remains the most relevant factor. Our RMI indicators turn out to provide the largest contributions to the explained variation after the CAPM component, which is a robust finding.

In addition to the three portfolio sorts based on positive, neutral, and negative deviations of sentiment from its long-term mean, we also estimate a model for the single sentiment factor in Panel

[21] We compute the indicator using the RSI function of the R-package TTR, which defines $RSI = 100 - 100/(1+RS)$, where RS is the smoothed ratio of "average" gains over "average" losses. The "averages" are not true averages, since they are divided by the value of n, i.e. sample size, and not by the number of periods in which the gains/losses occur.

B. The PMNSNT-CAPM model confirms that a single sentiment factor is unable to capture the variability in market sentiment and remains mostly insignificant when the Fama-French factors are added. If we also include a momentum factor, which is (despite considerable debate) still missing from the Fama-French five factor model, no significant increase is recorded. Panel D of each of Table 3 shows that this factor is mostly insignificant and, when it turns out to be precisely estimated, its contribution to the explained variation is only marginal. We conclude that a single sentiment factor measured as the return of a long-positive/short-negative sentiment portfolio loses significance if traditional variables based on the Fama-French five factor model are included in the empirical model. However, the separate sentiment mimicking portfolios, which distinguish between positive and negative sentiment shocks, are accurately estimated and economically significant when applied in our specifications. We also learn that none of the sentiment sorts simply captures momentum and that momentum is not relevant to explain the excess returns on international equity indices.

Table [3] about here

5.2 Sentiment Risk Premia

In previous analyses, we have shown that sentiment depending on its directional deviation from its long-term mean can lead to positive or negative excess performance in international indices. We have further shown that sentiment-augmented linear pricing models carry higher explanatory power than the standard CAPM or the DR-CAPM. In addition, the stronger performance of sentiment-sorted portfolios can be traced back to the sensitivity of individual assets to sentiment. In order to quantify the additional return demanded by investors for investments in sentiment-responsive assets, in this section we proceed to estimate the price of sentiment risk. In fact, we compute a separate risk premium for negative, neutral, and positive changes in sentiment. We follow the two-stage regression methodology of Fama and MacBeth (1973) (henceforth, FMB) to compute the sentiment price of risk and systematically compare our approach with the in-sample fit of the CAPM, DR-CAPM and FF5 using standard error corrections to account for cross-asset correlation. Lettau's downside risk model is motivated by Ang et al. (2006), who argue that investors who place higher weight on downside risk demand additional compensation for holding stocks with high sensitivities to downward market price shifts. As Ang et al. (2006) state "the reward for bearing downside risk is not simply compensation for regular market beta, nor is it explained by co-skewness or liquidity risk, or by size, value, and momentum characteristics." In line with Ang et al. (2006), we argue that in times of increased uncertainty and fear, investors expect to be compensated for the additional risk from investing in sentiment-sensitive assets. We also conjecture that investors fear over-optimism and market overheating, and hence also demand a positive risk premium in the case of good sentiment-exposed assets. In fact, the correlation between our negative sentiment-based portfolio and the downside risk implied by the MSCI World index is a statistically significant and positive 0.56.[22]

The time series regressions of the first stage in FMB procedure yield the point estimates of the market $\hat{\beta}_i$ and downside risk betas $\hat{\beta}_i^-$ as per Equation (9). These are then used as explanatory variables in a second stage, cross-sectional regression of the average return of the assets on their market and downside risk betas.[23] This two-stage approach of using estimated betas of the first stage as variables in the second introduces a generated regressor bias which we correct with the Shanken (1992) adjustment for the standard errors:

$$\bar{r}_i^e = \hat{\beta}_i \bar{r}_m^e + \hat{\beta}_i^- \lambda^- + \epsilon_i \text{ for } i = 1, 2, ..., N, \tag{17}$$

where $\bar{r}_i^e$ and $\bar{r}_m^e$ are the average excess returns of the test assets and the market, respectively. ϵ_i are the pricing errors and N is the number of test assets. $\hat{\beta}_i^-$ is the relative importance of downside risk from the first-stage regression and λ^- is the downside risk conditional risk premium. This regression is estimated at each time t. As pointed out by Cochrane (2009), large sampling errors, resulting from cross-sectional correlation of asset returns, are a key obstacle when producing inferences in cross-sectional analysis. Performing the recursive estimation on sub-samples and averaging the statistics accounts for this cross-sectional correlation and reduces the sampling error. The FMB approach takes this idea to the extreme and computes the cross-sectional regression for each period t. The second stage regression for our sentiment model is

$$r_{i,t}^e = \hat{\beta}_i \bar{r}_m^e + \hat{\beta}_{s(-),i}\lambda_{s(-)} + \hat{\beta}_{s(0),i}\lambda_{s(0)} + \hat{\beta}_{s(+),i}\lambda_{s(+)} + \epsilon_{SNT,i,t}, \forall t \in T, \tag{18}$$

[22]Lettau et al. (2014) report that their extension of the CAPM to account for a downside risk beta leads to more precise predictions of cross-sectional excess returns across markets and asset classes. However, as they also discuss, their method lacks a structural interpretation. We extend their work and test whether their results can be rationalized by an estimate of the price of sentiment risk derived from a search-based market sentiment measure such as the RMI indicator.

[23]We use an adjusted version due to the simultaneous estimation in the first stage. Lettau et al. (2014) use two separate estimations for $\hat{\beta}_i$ and $\hat{\beta}_i^-$, while we estimate them jointly for better comparison with the sentiment-based approach.

where $r^e_{i,t}$ is the asset excess return, $\alpha_{SNT,i}$ is a constant, $\hat{\beta}_{s(-),i}$, $\hat{\beta}_{s(0),i}$, and $\hat{\beta}_{s(+),i}$ are the betas on the excess return of the negative, neutral, and positive sentiment portfolios at time t, respectively. $\lambda_{s(-)}$, $\lambda_{s(0)}$, and $\lambda_{s(+)}$ are the prices of risk for negative, neutral, and positive sentiment. Of course, this framework is easy to adapt to the PMNSNT-CAPM, which would yield a unique estimate of the price of sentiment risk, λ_{PMNSNT}.

We jointly estimate the first stage betas for the CAPM, $s(-)$, $s(0)$, and $s(+)$ factors.[24] Following Lettau et al. (2014), we assume the market price of risk to be correctly priced and equal to the sample period mean excess return of the MSCI market index. Importantly, we choose not to include an intercept term, and thus impose that an asset with zero beta has a zero excess return. As in Fama and French (1992), we regress the indices directly on the factors, not sorted mimicking portfolios. This is justified by the indices representing a diversified portfolio by definition, even though it is biased towards large caps that tend to be included in each country's main stock market index. This procedure will presumably lead to more noisy estimators with higher standard errors, but it seems more appropriate in the case of our model, in which sentiment is index-specific and so are their betas.

In order to address concerns that sentiment might only measure statistical properties like idiosyncratic volatility $iv_{i,t}$, skewness $is_{i,t}$, or kurtosis $ik_{i,t}$ left unexplained by the fundamental variables of either the CAPM or FF5, we additionally control for them in the FMB procedure. Following Boyer et al. (2010), we define these control variables as:

$$iv_{i,t} = \left(\frac{1}{N(t)} \sum_{d \in S(t)} \epsilon^2_{i,d}\right)^{\frac{1}{2}}, \tag{19}$$

$$is_{i,t} = \frac{1}{N(t)} \frac{\sum_{d \in S(t)} \epsilon^3_{i,d}}{iv^3_{i,t}}, \tag{20}$$

$$ik_{i,t} = \frac{1}{N(t)} \frac{\sum_{d \in S(t)} \epsilon^4_{i,d}}{iv^4_{i,t}}, \tag{21}$$

where $\epsilon_{i,d}$ is the residual of a CAPM or FF5 model. Given the international set-up of our study, we also control for major global currencies, EUR, GBP, and JPY to the USD base.

[24] Lettau et al. (2014) use separate regressions for the first stage to avoid multicollinearity among downside risk and the overall market risk due the fact that both, the market and the downside risk factor are based on excess global market returns. This is not a concern in our case, because of the orthogonalization that has been applied to the factors.

Overall, we compare ten different models: i) a standard CAPM as a naïve benchmark, ii) a DR-CAPM model to price the downside risk premium following Lettau et al. (2014), iii) a PMNSNT-CAPM model, enriching the CAPM model with a long-positive / short-negative sentiment factor, iv) a PMNSNT-CAPMx model that also controls for idiosyncratic volatility, skewness, kurtosis and major currencies, v) a PMNSNT-FF5 which adds the PMNSNT factor to a Fama-French five factor specification, vi) a PMNSNT-FF5x model that additionally controls for $iv_{i,t}$, $is_{i,t}$, $ik_{i,t}$, EUR, GBP, and JPY, vii) a SNT-CAPM that prices positive, neutral, and negative sentiment separately, viii) a SNT-CAPMx with controls for idiosyncratic volatility, skewness, kurtosis, and currencies, iv) a SNT-FF5 Fama-French five factor specification with three sentiment factors, as well as x) a SNT-FF5x model that also incorporates all the control variables.

Table 4 reports the results for the international equity indices. The R^2 of the CAPM is 40.45%, supported by a price of weekly market risk of 0.11%, i.e. the average weekly excess percentage return, for the MSCI world. The downside risk premium is estimated to be 0.10% that is highly significant. This result is much smaller than highlighted by the original authors but may be explained by the diversification effect of stock market indices compared to single stocks or other asset classes. Major international equity indices are themselves diversified and downside risk as measured by Lettau et al. (2014) may already be hedged and/or incorporated into the global market risk premium associated to the MSCI world index. The explained variation is however very small with 3.01% and as such much worse than the simple CAPM. The single sentiment-augmented CAPM (PMNSNT-CAPM) produces a positive estimate of 0.65% and performs also worse than the CAPM with a R^2 of 13.27%. If we add the control variables the premium halves to 0.32% but increases R^2 to 25.01%. That means that the control variables explain additional variation in index returns as well as (partially) absorbs our single sentiment factor which remains significant. If we add PMNSNT to a FF5 specification we observe a slight increase in R^2 to 16.45%, respectively 27.43% if controlled for volatility, skewness, kurtosis, and currencies. This comes along with a decreased sentiment risk premium of 0.44% or 0.36%, respectively. It clearly indicates that our PMNSNT sentiment loses explanatory power in the cross-section if we control for fundamental factors like size, value, profitability, and investment as well as statistical properties. The 3-factor Sentiment-CAPM (SNT-CAPM) however performs remarkably better than a CAPM, DR-CAPM, PMNSNT-CAPM, or PMNSNT-FF5 model with a significantly negative sentiment risk premium of -0.43% for negative sentiment and with a low standard error of 0.0004%. The negative sentiment risk premium for negative sentiment is in line with our results from the portfolios sorts. Neutral sentiment appears to be significantly positively priced with a 0.17% premium and standard error of 0.0002%. This is contrary to our expectations of a close-to-zero premium for neutral sentiment and might capture other effects. However, if we control for fundamental or statistical properties the premium remains robust between 0.12% and 0.19%. On the other hand, positive sentiment is as expected positively priced with a risk premium of 0.40% with a low standard error of 0.0004%. This result is robust, in fact increasing, if we add control variables to the CAPM specification (0.47%), Fama-French factors (0.42%) or both (0.70%). As such, investors expect to be compensated for holding assets, which are highly sensitive to positive sentiment. The variability as well as absolute size in risk premia is very similar between positive and negative sentiment. In terms of explained variation we observe a true jump when the three sentiment factors are added. Additional fundamental and control variables do only have a marginal effect. As such the adjusted R^2 increases from 56.72% for the simple SNT-CAPM model over 57.67% for the SNT-CAPM with controls and 57.18% for the SNT-FF5% to 57.53% for the fully-specified SNT-FF5 with controls. Overall, the results for positive and negative sentiment are in line with our previous findings and support the addition of sentiment factors to asset pricing models.

Table [4] about here

6 Robustness Checks

In this section, we conduct various robustness checks. First, we extend our empirical tests by considering additional equity indices. Second, we divide the 1998-2015 period in sub-samples to validate our initial intuition that sentiment is more important during crises periods, because classical CAPM models are well-known to fail in extreme, turbulent market regimes (see, e.g., Yu and Yuan, 2011; Hillert et al., 2014). Third, we split the sentiment data based on the two different sources, social media and news, in order to investigate which channel may be more relevant for the pricing of risk. Given the efficient market hypothesis that all information is instantaneously reflected in market prices, the weekly granularity of our observations and the orthogonalization of the variables, we expect that social media based sentiment either contains more novel information or proxies private investors who are more exposed to sentiment and exuberance, compared to widely available public news. Fourth, we re-run the Fama-MacBeth procedure, but this time abstain from any orthogonalization in order to address concerns that the risk premia may not be easily interpreted if done so.

Tests on an Extended Set of Equity Indices. While earlier we have used only the major global equity indices, we extend the estimation of our time series models to additional assets to show that our results are generally applicable. First, we use a range of alternative U.S. stock indices and compare them with our previous regression results for the S&P500. The findings, summarized in Table B.1 of the Internet Appendix B, emphasize that all of our key results hold for the Dow Jones Industrial Average, the Russell 2000 (that includes mid-size companies), and the technology-oriented Nasdaq 100. The R^2 is slightly lower than for our earlier findings and we interpret this as confirmation that the model is also applicable to smaller companies. The reduction can be explained with the lower media coverage of smaller companies. We also extend the analysis to aggregate indices like the Top 50 emerging markets companies, measured by the MSCI 50 (EM50), and the Top 50 pan-European companies, covered by the EURO STOXX 50 (EU50). The significance level and sign of the estimated coefficients confirm our previous, strong finding that sentiment plays an important role in explaining the cross-section of excess equity returns. For the index ranking the 101st-350th size-ranked, UK-based, and LSE-listed companies ($GBMID250$), the findings are similar to the FTSE100 with comparable size and significance of the estimated coefficients. Overall, these robustness analyses on equity indices confirm our findings and even yield evidence of additional explanatory power of our novel sentiment measure for a wider set of equity indices including medium- and small-sized companies. Additionally, the results remain essentially unchanged when the analysis is applied to aggregate indices for both the Eurozone and emerging markets. The absolute intercepts of the models decline when sentiment is added but as for our core indices they are already close to zero for a simple CAPM.

Sub-samples Analysis. We also evaluate our models on sub-samples by splitting the data into the 1998-2001, 2002-2006, 2007-2011, and 2012-2017 periods. The splits were motivated economically to differentiate between alternative bull-bear cycles in international financial markets. As such, we focus on sub-periods that span both bull market regimes like the 2002-2006 and 2012-2017 periods, as well as crisis regimes like 1998-2001 (the Dot.Com crisis) and of course 2007-2011 (the Global Financial crisis, encompassing also the European sovereign debt crisis). The aggregate regression results are reported in Table B.2 of the Internet Appendix B. The results demonstrate that adding the three novel sentiment factors to both a CAPM or FF5 specification about doubles the average R^2 in all market phases. The single sentiment models, either PMNSNT-CAPM or PMNSNT-FF5, only lead to marginal contribution across all sub-periods. The absolute intercepts are reduced when the separate sentiment factors are added to both CAPM and FF5 specifications. The period 2007-2011 is marked by a high average R^2 across all national markets. This confirms our hypothesis that sentiment is a priced risk factor, which tends to become stronger in financial crises. This result is consistent with earlier evidence in García (2013) on the impact of news on stock returns. However, the highest contribution of sentiment to the R^2 emerges in the last, 2012-2017 sub-sample. Yet, given that our sentiment sorts exhibit higher average excess returns for positive sentiment, this is not surprising. Moreover, in relative terms, adding sentiment to the pricing model increases the explanatory power in correspondence to all market phases. The best model across all categories is the sentiment-augmented FF5. Adding momentum does not further improve the performance metrics, neither in terms of a reduced intercepts nor in an increase in explanatory power. Overall, it seems that sentiment became more relevant to pricing the international cross section of equities in the recent years which we trace back to both the occurrence of improvements in the precision of the algorithms applied by the MarketPsych's human-language processing engine as well as a better coverage of financial markets in both the news and social media channels.

Separating the Effects of News from Social Media Channels. So far, we have used sentiment indicators that aggregate the signals from both news and social media channels. However, MarketPsych also disentangles the two types of sources. We hypothesize that social media may be more used by retail investors, whereas news may be preferred by both retail and institutional traders for their investment decisions, because they are generally presumed to be less volatile and more reliable. Therefore, we have also estimated our linear factor models separately for news versus social media sentiment risk in order to investigate whether we observe a different effect on asset returns. If we split sentiment into news- and social media-driven signals, we observe that social-media based models perform slightly better than news-based or aggregated models of both sources. Minimum, maximum, average, and median R^2 for sentiment-augmented models are uniformly better for social media-only sentiment than for the combined measure or news-only. The increase in average R^2 is marginal though. The absolute intercepts do not show a difference in these statistics. The same is true for the relative importance of sentiment. Social media-only sentiment carries the highest average coefficient of determination when compared to news-only sentiment. This does not only apply to the three-factor Sentiment CAPM and FF5 specification but also to the single factor sentiment-augmented models. However, the absolute effect of the PMNSNT factor is still negligible. The overall results are shown in Table B.3 of the Internet Appendix B and appear to be in line with previous findings on similarly classified sentiment data, e.g., by Nooijen (2013). Even though the improvements are marginal, we see our hypothesis confirmed while we acknowledge that additional research on the differing asset pricing implications for news versus social media seems to be required from an economic perspective.

Fama-MacBeth without orthogonalization of variables. When computing the sentiment risk premia we used orthogonalized variables in order to address concern of correlations between variables. Other reviews claimed that those risk premia are no longer easily interpretable. In this robustness check we proof that those concerns are unfounded and the results remain robust. The findings are summarized in Table B.4 in the Internet Appendix B. CAPM and DR-CAPM remain identical as they were not affected by the orthogonalization. For the PMNSNT-based models the risk premium is either slightly reduced for the CAPM models, e.g. from 0.32% to 0.31% for the extended PMNSNT-CAPMx with control variables, or increased for the FF5-based models, e.g. from 0.36% to 0.40% for the extended PMNSNT-CAPMx including the controls. The results remain similarly robust for models with three sentiment variables. The risk premia for all three sentiment variables are consistently reduced in absolute terms. All sentiment risk premia remain significant at the 1% level. We highlight two interesting observations. First, we observe a steep decrease for positive sentiment in the SNT-FF5x model from 0.70% to 0.53% in weekly average percentage return. Second, neutral sentiment becomes very small and switches to negative as soon as we control for idiosyncratic risks and currencies. The risk premium for the SNT-FF5x model changes from 0.19% to -0.08%. Overall, we treat these robust findings as confirmation for our previous results.

7 Conclusion

Using newly created sentiment measures based on MarketPsych's human-language processing engine applied to news and social media feeds, this paper proves the existence of a strong empirical relationship between sentiment and the excess returns of a number of international stock market indices. Moreover, we uncover strong evidence that sentiment is a priced risk factor. We show that long/short portfolios constructed according to Fama and French (1993, 2015, 2017), based on sorting the test assets into quartiles according to the deviation of their sentiment score from its asset-specific long-term average, generate a significant outperformance over the market. The outperformance is positive for positive deviations of sentiment from its long-term average, and negative for negative deviations. This represents a new finding, qualitatively different from the existing evidence in Baker and Wurgler (2006, 2007), by which positive excess returns are accompanied by negative sentiment shocks. While the Baker-Wurgler index captures investment activities like increased turnover, our sentiment anticipates investors' actions and is hereby in line with psychological evidence, where business activities tend to follow, rather than lead, social mood.

These insights are used to benchmark multiple linear regression models including sentiment as a priced risk factor against the standard CAPM, a downside risk capital asset pricing model, and a Fama-French five factor model. Our specifications consistently yield a better goodness-of-fit for sentiment-augmented models. Moreover, we report that sentiment cannot be fully captured by a single risk factor because negative, neutral, and positive deviations in sentiment are differently priced by the cross section of international stock indices. Our time series regressions emphasize that sentiment is asset-specific and has more explanatory power for assets in less efficient markets and with lower correlation with traditional factors. Using the FMB technique applied to sentiment-augmented models, we compute a positive conditional sentiment risk premium for positive changes in sentiment, while the estimated risk premium turns out to be negative and significant for negative sentiment in global equity markets. Compared to the standard CAPM, Lettau et al.'s downside risk approach, and a Fama-French five factor specification, our sentiment-augmented model significantly improves the explanatory power even if further controlled for idiosyncratic volatility, skewness and kurtosis.

A rich set of robustness checks confirms our results and provides valuable insights about the mechanics of sentiment formation and of its relationships to asset prices. First, in yielding precisely estimated coefficients sentiment is also and even more relevant in the case of inefficient markets and exotic assets as well as for aggregate equity indices in the Eurozone and emerging markets. This confirms our conjecture that sentiment is more prevalent in informationally inefficient markets. Second, social media-driven sentiment provides stronger signals than a news-only or joint indicator that reflects both, indicating a sentiment bias by retail investors. Third, sentiment provides additional explanatory power for the cross-section of excess asset returns during all market phases and is not limited to crisis periods. Recent technological enhancements and wider news and social media coverage increase however the measurable contribution of sentiment to the explained variation of various asset-pricing models. And fourth, the sentiment risk premia are confirmed under additional controls for idiosyncratic risks and currencies as well as if the variables are not orthogonalized.

A Appendix

Table A.1: Construction of TRMI Sentiment Index

This table provides the construction details for the TRMI Sentiment indicator as the net of positive and negative references along the valence-arousal sentiment classification system.

Positive References	Negative References
Positive	Negative
AccountingGood	AccountingBad
Upgrade	Downgrade
EconomicPositive	EconomicNegative
EconomistPositive	EconomistNegative
EconomicActorsPositive	EconomicActorsNegative
ManagementGood	ManagementBad
BullVerbs	BearVerbs
ExcitementPos	
FearDown	FearUp
AngerDown	AngerUp
HappyUp	HappyDown
GloomDown	GloomUp
OptimismUp	OptimismDown
PessimismDown	PessimismUp
LoveUp	LoveDown
HateDown	HateUp
InnovativeUp	InnovativeDown
EarningsSurprisePos	EarningsSurpriseNeg
EarningsUp	EarningsDown
EarningsExpectationsUp	EarningsExpectationsDown
EarningsGuidanceUp	EarningsGuidanceDown
GuidanceUp	GuidanceDown
	ProfitWarning
	CatastropheConcept
	DeclareBankruptcy

Figure A.1: Description of MarketPsych Indicators

This table provides a detailed description of RMI indicators to better understand the aggregated sentiment measure.

TRMI COMMON NAME	ANTICIPATED MARKET IMPACT
Sentiment	There are several important research findings related to sentiment and price movement. Based on academic research on Thomson Reuters News Analytics sentiment scores, positive and negative sentiment in the news about individual stocks extend price momentum,[25] which is supported by additional evidence that traders collectively under-react to negative sentiment in news reports.[26] Another study finds that market sentiment improves factor weighting in some models.[27] In foreign exchange, news sentiment was found to influence volatility.[28]
Optimism	There is empirical evidence that proxies for optimism correlate with positive price behavior[29] and that bullish comments in financial social media precede higher trading volume.[30] Optimism in earnings press releases was found correlated with future stock price activity.[31]
Fear	Academic researchers who aggregated search terms they deemed reflective of economic fear found short-term mean reversion in prices when fear-related search terms spiked in volume.[32] In experimental markets, fear was found to decrease bid and increase ask prices, leading to less overall trading activity.[33] As a result, we expect wider bid-ask spreads when fear is high.
Joy	Joy is a marker of exuberance. Experimental markets demonstrate higher price peaks and larger collapses during bubble simulations if traders watched a positively exciting movie clip before trading begins.[34]
Trust	Trust was designed specifically for nations and banking and financial groups. Economists have found that national interpersonal Trust levels correlate with future economic growth.[35,36]
Conflict	The Conflict TRMI, which is intended to capture disagreement and dispute, is anticipated to correlate with price volatility. A study of international markets found that global conflicts significantly impact asset prices.[37]
Stress[*] and Urgency	Urgency and Stress are high-arousal indices that vary in valence. Based on evidence that arousal drives cognitive performance in an inverse-U shaped curve, we infer that pricing anomalies are more likely to emerge at low or high arousal values, as seen with both high positive and high negative arousal during research into experimental market bubbles.[38]
Uncertainty	Researchers found that high-uncertainty equities and country indices on average outperform their low-uncertainty peers.[39] In contrast, during speculative bubbles uncertainty amplifies the price momentum of positive sentiment.[40] In emerging fixed income markets, releases of macroeconomic data decrease future volatility.[41]
Gloom[*]	Traders in an experimental market offered lower ask and high bid prices when "sadness" was induced prior to trading, leading to increased transaction volume.[42] If this result transfers into larger market behavior, we expect increased trading volume during periods of high Gloom.[43] Researchers speculate that identified semi-annual variations in country stock index returns - which scale by latitude and reverse from northern to southern hemispheres - may be caused by seasonal changes in affect (the "winter blues") among local traders.[44]
Anger[*]	Traders induced to feel anger in an experimental market decrease both average ask and bid prices.[45] As a result, we speculate that higher TRMI Anger readings should lead to increased selling and reduced buying in associated assets, leading to downward pressure on prices during high Anger periods.

Table A.2: Pearson Correlation Analysis between Predictor Variables

This Table shows the Pearson correlation between the return based variables in Panel A and their corresponding p-values in Panel B. The correlation is computed for the market risk premium (MRP), the three portfolio sorts based on negative, neutral, and positive deviation of sentiment from the long-term mean as well as the additional four global Fama-French factors.

Panel A: Pearson Correlation

	MRP	s(-)	s(0)	s(+)	SMB	HML	RMW	CMA
MRP	1.0000	0.5670	0.6578	0.5623	-0.3323	-0.0316	-0.3743	-0.4507
s(-)		1.0000	0.7988	0.7383	0.0112	0.0419	-0.2847	-0.3213
s(0)			1.0000	0.8479	-0.0022	0.0022	-0.3544	-0.3692
s(+)				1.0000	0.0790	0.0331	-0.3093	-0.3150
SMB					1.0000	0.0131	-0.1008	0.0906
HML						1.0000	0.0093	0.5818
RMW							1.0000	0.2466
CMA								1.0000

Panel B: p-Values

	MRP	s1(-)	s2(0)	s3(+)	SMB	HML	RMW	CMA
MRP		0.0000***	0.0000***	0.0000***	0.0000***	0.3525	0.0000***	0.0000***
s1(-)			0.0000***	0.0000***	0.7420	0.2177	0.0000***	0.0000***
s2(0)				0.0000***	0.9481	0.9487	0.0000***	0.0000***
s3(+)					0.0201**	0.3306	0.0000***	0.0000***
SMB						0.6994	0.0030***	0.0076***
HML							0.7846	0.0000***
RMW								0.0000***
CMA								

* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Table A.3: Stock Market Indices List

This list contains the full set of stock market indices, the respective asset code and as short description.

Asset Code	Description	Resembling Index
MPTRXUS30	Top 30 US-based companies	Dow Jones Industrial Average
MPTRXUS500	Top 500 US-based companies	S&P 500
MPTRXUSMID2000	Ranks 2001-3000 of US-based companies	Russell 2000
MPTRXUSS100	Top 100 Nasdaq-based companies	Nasdaq 100
MPTRXAU500	Top 500 Australia-based companies	ASX All Ordinaries
MPTRXBR50	Top 50 Brazil-based companies	IBRX 50
MPTRXCA250	Top 250 Canada-based & Toronto-listed companies	S&P/TSX Composite
MPTRXCH20	Top 20 Switzerland-based companies	Swiss Market
MPTRXCN300	Top 300 China-based companies	CSI 300
MPTRXDE30	Top 30 Germany-based companies	Deutsche BÃ¶rse DAX 30
MPTRXEM50	Top 50 emerging markets companies	MSCI 50
MPTRXES35	Top 35 Spain-based companies	IBEX 35
MPTRXEU50	Top 50 pan-European companies	EURO STOXX 50
MPTRXFR40	Top 40 France-based companies	CAC 40
MPTRXGB100	Top 100 UK-based & LSE-listed companies	FTSE 100
MPTRXGBMID250	Ranks 101-350 of UK-based & LSE-listed companies	FTSE Mid 250
MPTRXHK50	Top 50 Hong Kong-listed companies	Hang Seng
MPTRXIN50	Top 50 India-based companies	Nifty 50
MPTRXJP225	Top 225 Japan-based companies	Nikkei 225
MPTRXRU50	Top 50 Russia-based companies	RTS
MPTRXSG30	Top 30 Singapore-based companies	FTSE Straits Times

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B Figures and Tables

Figure 1: Schematic Differences between RMI and BW

This chart visualizes the differences between the RMI and BW indices, showing that RMI leads BW by construction. To ease the comparison, we initialize both RMI (solid line) and BW (dashed line) index at zero in $t-2$. A sentiment signal for RMI is measured by its deviation from the long-term mean, while we use the level of the BW as in Baker and Wurgler (2007). The grey bars show excess returns of an index at a specific point in time t.

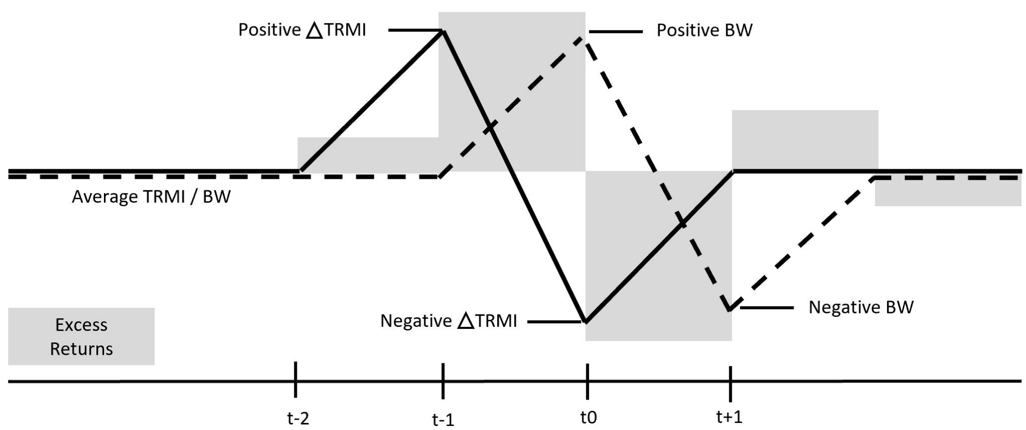


Figure 2: Time Series Plot of BW and RMI Indices for the United States

This chart plots the monthly time series of the BW and the RMI sentiment indices for the U.S. stock market. The data are re-based to equal 1 at the beginning of the period for better visualization.

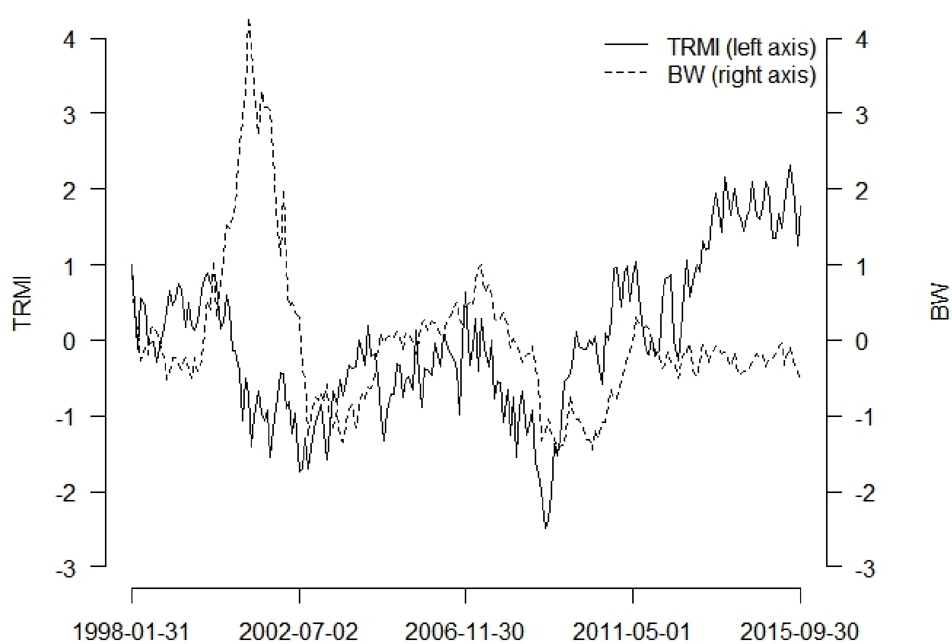
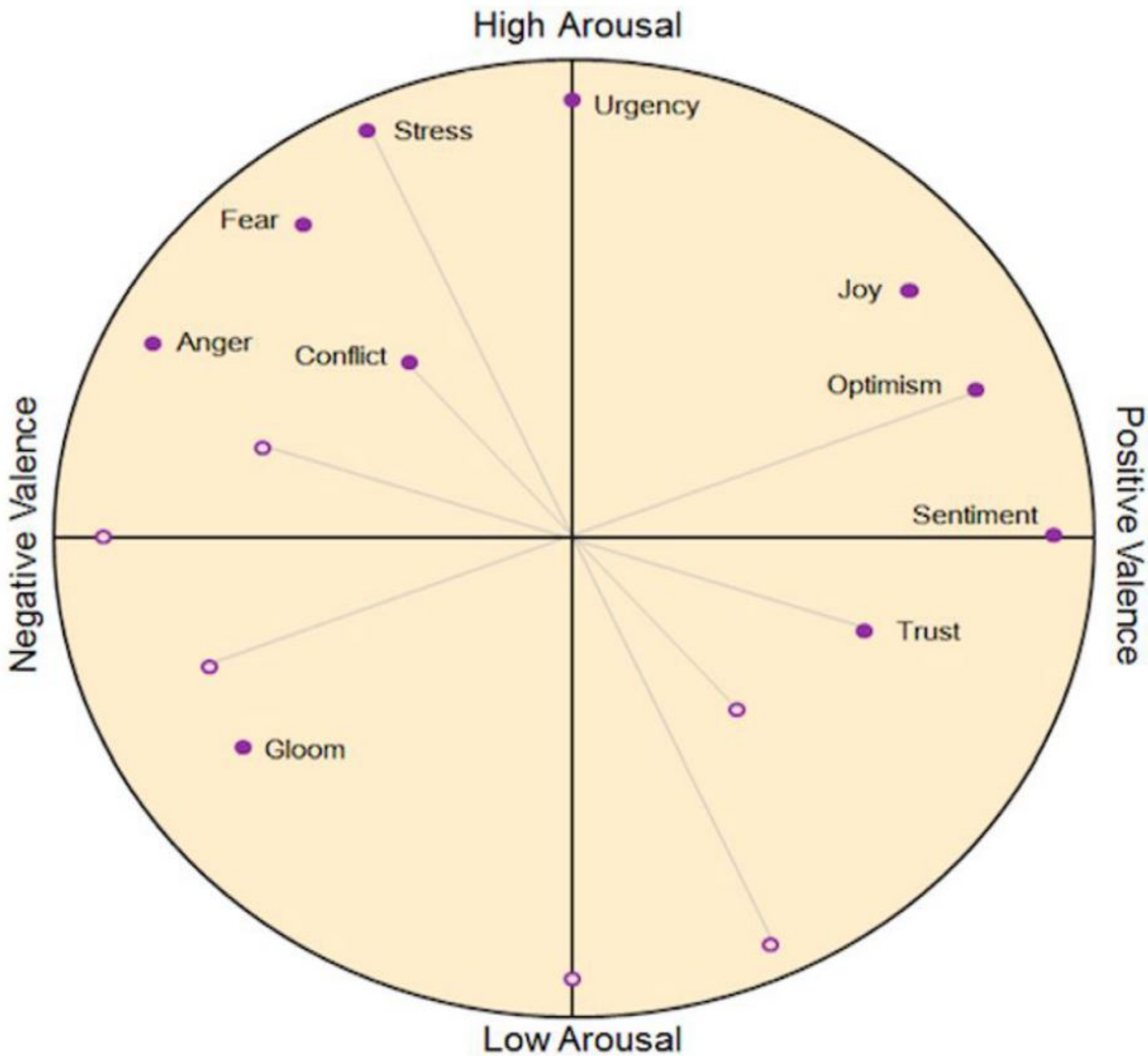


Figure 3: Sentiment Classification System: Valence and Arousal

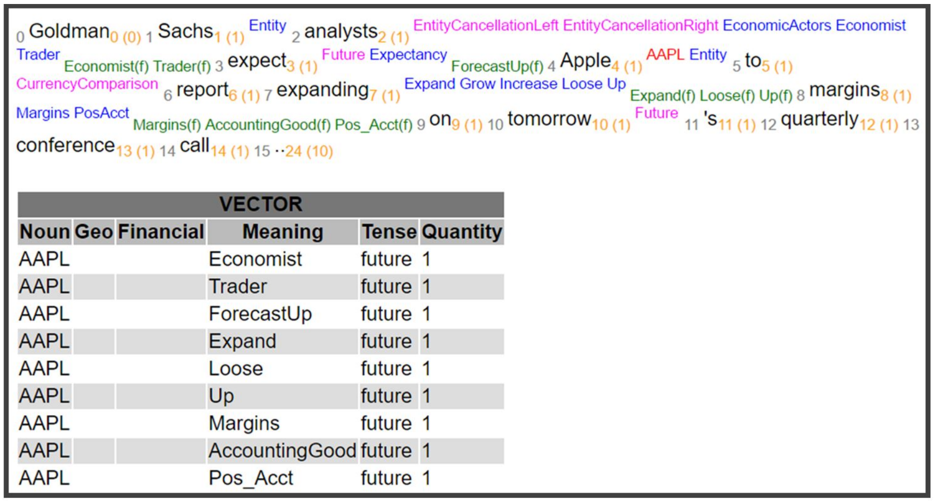
This chart plots a common classification system for human emotions along two dimensions: valence and arousal. MarketPsych uses this classification system following the affective circumplex model of sentiment by Russell (1980) and constructs RMI indicators spanning the entire plane of human emotions. The figure depicts several of the RMI sentiments on the affective circumplex. Each dot hereby corresponds to the emotion's location on the circumplex, whereby RMI indicators are themselves hybrids of multiple emotions according to the original framework. The thin grey line connects the positive and negative poles of matching indicators.



Source: MarketPsych

Figure 4: Example of MarketPsych's Human Language Processing System

This chart depicts an example of how MarketPsych processes news and evaluates the human emotions. Each term is annotated by MarketPsych. Complex meanings such as $AccountingGood_f$ are extracted. This is a future looking assessment based on the attribute "tomorrow". "Goldman Sachs" is ignored as an irrelevant entity related to the analyst. MarketPsych differentiates between value-adding statement as above versus irrelevant terms. Those irrelevant terms are excluded from the score vector, and they are not used in RMI calculations.

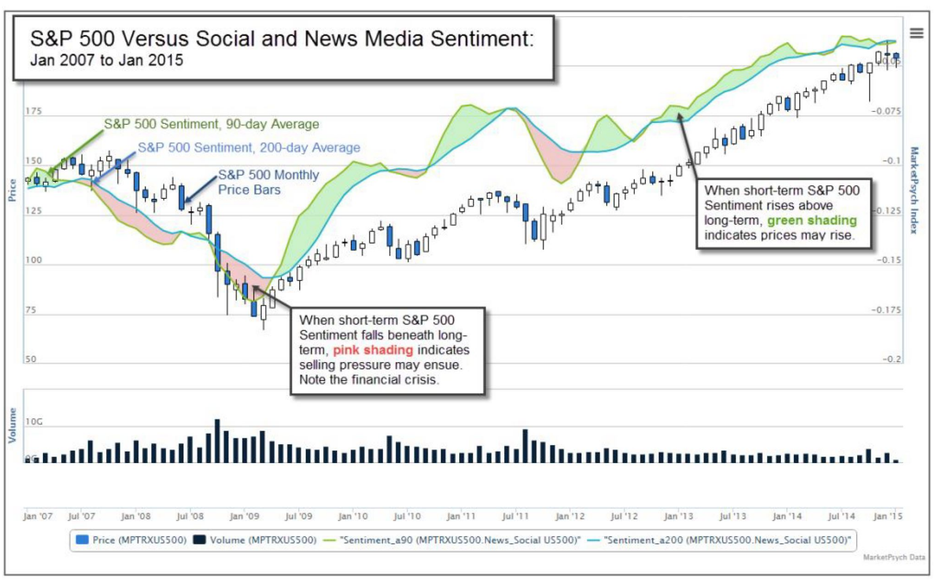


VECTOR					
Noun	Geo	Financial	Meaning	Tense	Quantity
AAPL			Economist	future	1
AAPL			Trader	future	1
AAPL			ForecastUp	future	1
AAPL			Expand	future	1
AAPL			Loose	future	1
AAPL			Up	future	1
AAPL			Margins	future	1
AAPL			AccountingGood	future	1
AAPL			Pos_Acct	future	1

Source: MarketPsych

Figure 5: RMI Sentiment Indicator on S&P 500)

This chart depicts how the RMI indicator provides technical signals for price increases or decreases for the S&P500 stock market index.



Source: MarketPsych

Figure 6: Comparing the R^2 of the CAPM to the Sentiment-CAPM

The figure displays the adjusted R^2 for various sentiment-augmented linear factor models (light grey), benchmarked against the standard CAPM (black). Panel A shows the CAPM and Panel B the DR-CAPM of Lettau et al. (2014). Panel C is a CAPM extension with a single sentiment risk factor based on the excess return of a long-positive/short-negative portfolio (PMNSNT-CAPM). Panel D uses the excess returns of all portfolio sorts based on negative, neutral, and positive sentiment (SNT-CAPM). The sample period is from January 1998 to December 2017. All plots use the same scale to favor direct visual comparisons.

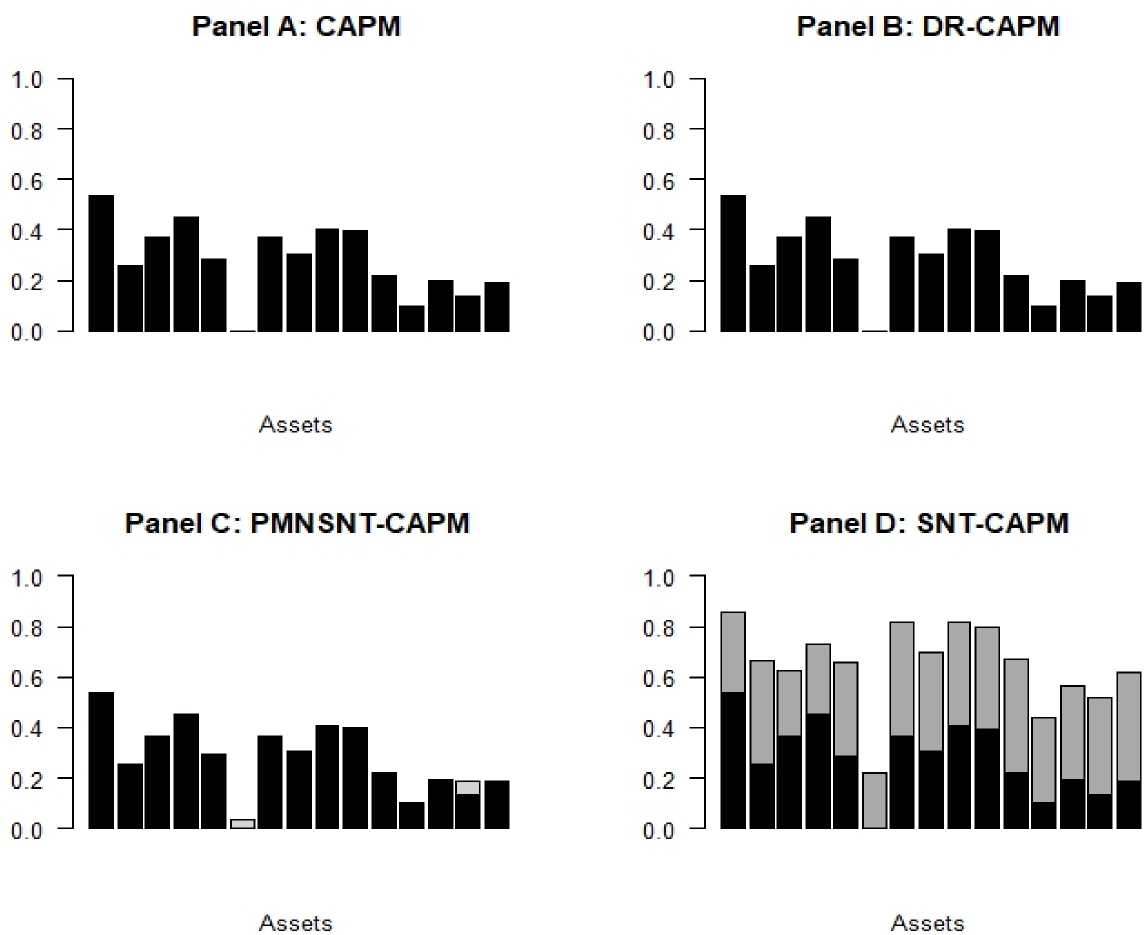


Table 1: Portfolios Sorted by Sentiment

The table shows the descriptive statistics of the portfolio sorts and the results of the Welch two-sample t-test of equality of the average weekly excess percentage returns across three sorts. For each time interval $[t, t-1]$, the asset is either in the lower ($s(-)$), middle ($s(0)$), or upper ($s(+)$) quartile of instruments sorted based on the previous week's sentiment. The table reports the average excess return and its standard deviation for each sort in columns 1 and 2 along with the corresponding average sentiment in column 3 and the standard deviation of sentiment in column 4. Sort $s(-)$ contains the assets with the most negative sentiment, which increases subsequently up to sort $s(+)$. Columns 5 through 7 report the results of a Welch's two-sample t-test of the null hypothesis that the difference in means between two sorts is zero. ***, **, and * indicate significance at the 0.1%, 1%, and 5% level, respectively. The sample period is from January 1998 to December 2017 and portfolio rebalancing is weekly.

	Mean Return	Return SD	Mean Sentiment	Sentiment SD	Sort $s(-)$	Sort $s(0)$	Sort $s(+)$
$s(-)$	-0.1505	2.5414	-7.3877	3.9408		0.0604*	0.0029***
$s(0)$	0.0598	2.0940	0.0879	3.3592			0.2116
$s(+)$	0.1880	2.1743	7.4373	4.0135			

* p $\leq$ 0.1, ** p $\leq$ 0.05, *** p $\leq$ 0.01

Table 2: Comparing the CAPM to Alternative Sentiment-Augmented CAPM Models

The table compares the standard CAPM to a number of sentiment-augmented linear factor models. Panel A concerns results for the standard CAPM based on the market risk premium (MRP) as its single priced factor. Panel B reports results for the DR-CAPM as in Lettau et al. (2014). Panel C is the extension of the CAPM to include the return of a long-positive/short-negative sentiment portfolio as a single sentiment risk factor (PMNSNT-CAPM). Panel D uses three separate sentiment risk factors based on the returns of portfolios mimicking negative, neutral, and positive sentiment (SNT-CAPM). The table reports the coefficient estimates, Newey-West corrected standard errors to adjust for autocorrelation and heteroscedasticity in returns in parentheses as well as the adjusted R^2. For models including sentiment, we also report the relative importance indicator for each coefficient which estimates its contribution to the total explained variation. The regressions are estimated for each equity index individually on weekly returns from 1998 to 2017.

	US500	AU500	BR50	CA250	CH20	CN300	DE30	ES35	FR40	GB100	HK50	IN50	JP225	RU50	SG30
Panel A: CAPM															
Intercept	-0.0002	-0.0003	0.0008	0.0000	-0.0006	0.0021	-0.0007	-0.0001	-0.0005	-0.0006	-0.0013	0.0013	-0.0015	-0.0013	-0.0001
	(0.0005)	(0.0006)	(0.0011)	(0.0006)	(0.0007)	(0.0022)	(0.0007)	(0.0008)	(0.0006)	(0.0004)	(0.0010)	(0.0013)	(0.0011)	(0.0021)	(0.0009)
MRP	0.6193***	0.3605***	0.7283***	0.5647***	0.4879***	0.0423	0.7008***	0.6032***	0.6767***	0.5276***	0.5708***	0.4285***	0.5074***	0.8182***	0.4096***
	(0.0249)	(0.0241)	(0.0527)	(0.0376)	(0.0474)	(0.1033)	(0.0423)	(0.0544)	(0.0454)	(0.0323)	(0.0434)	(0.0640)	(0.0631)	(0.1317)	(0.0444)
Adj. R^2	0.5382	0.2537	0.3663	0.4515	0.2843	-0.0015	0.3669	0.3039	0.4049	0.3944	0.2170	0.0993	0.1970	0.1351	0.1892
Panel B: DR-CAPM															
Intercept	-0.0005	0.0002	0.0001	0.0003	-0.0003	0.0014	-0.0004	0.0000	-0.0001	-0.0004	-0.0016	0.0018	-0.0008	-0.0012	0.0006
	(0.0006)	(0.0006)	(0.0013)	(0.0007)	(0.0008)	(0.0022)	(0.0009)	(0.0009)	(0.0007)	(0.0006)	(0.0012)	(0.0014)	(0.0013)	(0.0023)	(0.0010)
DR-Intercept	0.0041	0.0031	0.0064	0.0058**	-0.0053	-0.0058	-0.0077**	-0.0088*	-0.0091***	-0.0031	0.0065	0.0174*	0.0005	0.0019	0.0065
	(0.0025)	(0.0030)	(0.0057)	(0.0028)	(0.0034)	(0.0121)	(0.0039)	(0.0047)	(0.0035)	(0.0030)	(0.0074)	(0.0094)	(0.0061)	(0.0160)	(0.0072)
MRP	0.6384***	0.3001***	0.7740***	0.5185***	0.4817***	0.1053	0.6978***	0.6160***	0.6759***	0.5263***	0.5861***	0.3460***	0.4344***	0.8071***	0.3391***
	(0.0411)	(0.0420)	(0.0906)	(0.0477)	(0.0584)	(0.1073)	(0.0611)	(0.0559)	(0.0515)	(0.0424)	(0.0617)	(0.0995)	(0.0936)	(0.1487)	(0.0610)
$DR \times MRP$	0.0348	0.1713*	0.0238	0.1930***	-0.0861	-0.2590	-0.1352	-0.1804*	-0.1644**	-0.0524	0.1105	0.5582**	0.1428	0.0638	0.2862
	(0.0609)	(0.0877)	(0.1282)	(0.0745)	(0.0715)	(0.2786)	(0.0933)	(0.1087)	(0.0715)	(0.0618)	(0.1980)	(0.2635)	(0.1714)	(0.3976)	(0.2406)
Adj. R^2	0.5383	0.2583	0.3657	0.4554	0.2844	-0.0039	0.3680	0.3063	0.4078	0.3936	0.2157	0.1073	0.1968	0.1326	0.1938
RI-DR-Int	0.1095	0.0652	0.0732	0.0990	0.0755	0.0002	0.0958	0.0791	0.1076	0.0951	0.0459	0.0239	0.0515	0.0317	0.0522
RI-MRP	0.4309	0.1901	0.2969	0.3533	0.2108	0.0010	0.2732	0.2270	0.2999	0.3005	0.1732	0.0771	0.1479	0.1047	0.1392
$RI - DR \times MRP$	0.0002	0.0059	0.0000	0.0056	0.0009	0.0018	0.0014	0.0029	0.0025	0.0004	0.0005	0.0112	0.0018	0.0001	0.0064
Panel C: PMNSNT-CAPM															
Intercept	-0.0002	-0.0003	0.0008	0.0000	-0.0006	0.0025	-0.0008	-0.0001	-0.0005	-0.0005	-0.0013	0.0013	-0.0015	-0.0012	-0.0002
	(0.0004)	(0.0006)	(0.0011)	(0.0007)	(0.0007)	(0.0020)	(0.0007)	(0.0008)	(0.0006)	(0.0004)	(0.0010)	(0.0013)	(0.0011)	(0.0019)	(0.0009)
MRP	0.6193***	0.3612***	0.7347***	0.5644***	0.4890***	0.0124	0.7012***	0.6037***	0.6777***	0.5276***	0.5701***	0.4289***	0.5073***	0.8016***	0.4115***
	(0.0253)	(0.0258)	(0.0529)	(0.0394)	(0.0407)	(0.0954)	(0.0388)	(0.0536)	(0.0399)	(0.0321)	(0.0425)	(0.0670)	(0.0628)	(0.1072)	(0.0434)
PMNSNT	-0.0019	0.0510	-0.0702	-0.0390	-0.1556**	0.4444**	-0.0984	-0.1275**	-0.0930	-0.0646	-0.0669	0.0132	0.0031	-0.6054***	-0.0494
	(0.0468)	(0.0372)	(0.1721)	(0.0418)	(0.0775)	(0.1755)	(0.0688)	(0.0642)	(0.0688)	(0.0449)	(0.0910)	(0.1084)	(0.0571)	(0.2017)	(0.0820)
Adj. R^2	0.5375	0.2549	0.3657	0.4516	0.2958	0.0314	0.3693	0.3091	0.4072	0.3962	0.2172	0.0977	0.1955	0.1840	0.1887
RI-MRP	0.5387	0.2551	0.3648	0.4521	0.2859	0.0004	0.3679	0.3051	0.4062	0.3952	0.2181	0.1010	0.1983	0.1336	0.1909
RI-PMNSNT	0.0003	0.0018	0.0038	0.0012	0.0118	0.0354	0.0029	0.0058	0.0025	0.0026	0.0018	0.0000	0.0001	0.0528	0.0004
Panel D: SNT-CAPM															
Intercept	0.0000	-0.0002	0.0002	0.0001	-0.0003	0.0022	-0.0006	0.0002	-0.0002	-0.0003	-0.0007	0.0020**	-0.0010	-0.0019	-0.0003
	(0.0004)	(0.0004)	(0.0010)	(0.0005)	(0.0006)	(0.0020)	(0.0005)	(0.0006)	(0.0005)	(0.0004)	(0.0007)	(0.0010)	(0.0009)	(0.0016)	(0.0006)
MRP	0.6246***	0.3542***	0.7560***	0.5693***	0.4912***	0.0321	0.7013***	0.5950***	0.6753***	0.5268***	0.5488***	0.4456***	0.5029***	0.8141***	0.4293***
	(0.0139)	(0.0201)	(0.0333)	(0.0287)	(0.0362)	(0.1034)	(0.0310)	(0.0422)	(0.0351)	(0.0231)	(0.0304)	(0.0644)	(0.0504)	(0.0967)	(0.0345)
$s(-)$	0.3839***	0.3831***	0.7499***	0.4183***	0.5571***	0.4469***	0.7166***	0.6756***	0.6531***	0.4979***	0.7813***	0.6605***	0.5705***	1.3594***	0.6445***
	(0.0264)	(0.0287)	(0.1049)	(0.0234)	(0.0564)	(0.0985)	(0.0429)	(0.0432)	(0.0418)	(0.0244)	(0.0596)	(0.0733)	(0.0444)	(0.1191)	(0.0518)
$s(0)$	0.7531***	0.6260***	0.3758*	0.5391***	0.5901***	0.9465***	0.9436***	0.7473***	0.7612***	0.6180***	0.7217***	0.7657***	0.8525***	0.6358***	0.5190***
	(0.0373)	(0.0494)	(0.1934)	(0.0582)	(0.0935)	(0.2025)	(0.0620)	(0.0734)	(0.0589)	(0.0436)	(0.1118)	(0.1219)	(0.0728)	(0.1752)	(0.0772)
$s(+)$	0.0844*	0.2341***	0.3278***	0.1871***	0.0881	0.6902***	0.1738***	0.2489***	0.1998***	0.1555***	0.3685***	0.4486***	0.2735***	0.3775**	0.3382***
	(0.0488)	(0.0389)	(0.1241)	(0.0463)	(0.0631)	(0.1750)	(0.0631)	(0.0664)	(0.0664)	(0.0475)	(0.0850)	(0.1410)	(0.0841)	(0.1736)	(0.0679)
Adj. R^2	0.8588	0.6650	0.6223	0.7308	0.6549	0.2188	0.8150	0.6943	0.8196	0.7952	0.6725	0.4387	0.5650	0.5198	0.6205
RI-MRP	0.5435	0.2501	0.3729	0.4560	0.2872	0.0008	0.3679	0.3006	0.4046	0.3943	0.2097	0.1049	0.1963	0.1355	0.1991
RI-$s(-)$	0.1567	0.2213	0.1726	0.1856	0.2709	0.0748	0.2886	0.2772	0.2775	0.2700	0.3361	0.2222	0.2039	0.3615	0.2853
RI-$s(0)$	0.1579	0.1711	0.0341	0.0773	0.0954	0.0932	0.1517	0.1078	0.1268	0.1204	0.1008	0.0807	0.1562	0.0192	0.1096
RI-$s(+)$	0.0016	0.0242	0.0462	0.0137	0.0033	0.0572	0.0077	0.0104	0.0115	0.0117	0.0281	0.0350	0.0118	0.0064	0.0290

* p ≤ 0.1, ** p ≤ 0.05, *** p ≤ 0.01

Table 3: Comparing Fama French Factor and Momentum with Sentiment CAPM

This table compares the Fama-French Five Factor (FF5) model with different sentiment-augmented linear factor models. Panel A concerns results for the traditional FF5 model. Panel B reports the FF5 model with an extension by the long-positive/short-negative sentiment portfolio (PMNSNT-FF5). Pan). Panel C extends the FF5 model with three sentiment risk factors based on the returns of portfolios mimicking negative, neutral, and positive sentiment (SNT-FF5). Pan). Panel D incorporates a momentum factor RSI (SNT-RSI-FF5). The). The table shows the coefficient estimates, Newey-West corrected standard errors to adjust for autocorrelation and heteroscedasticity in returns in parentheses as well as the adjusted R^2. For models including sentiment, we also report the relative importance indicator for each coefficient which estimates its contribution to the total explained variation. The regressions are estimated for each equity index individually on weekly returns from 1998 to 2015. The table is shortened to the important variables for better accessibility.

	US500	AU500	BR50	CA250	CH20	CN300	DE30	ES35	FR40	GB100	HK50	IN50	JP225	RU50	SG30
Panel A: FF5															
Intercept	-0.0001	-0.0001	0.0006	-0.0001	-0.0005	0.0020	-0.0007	0.0000	-0.0004	-0.0005	-0.0015	0.0011	-0.0015	-0.0013	-0.0002
	(0.0004)	(0.0005)	(0.0010)	(0.0005)	(0.0007)	(0.0023)	(0.0007)	(0.0008)	(0.0005)	(0.0004)	(0.0009)	(0.0012)	(0.0010)	(0.0019)	(0.0008)
MRP	0.6170***	0.3598***	0.6784***	0.5582***	0.4887***	0.0673	0.7016***	0.6004***	0.6756***	0.5278***	0.5805***	0.4212***	0.5188***	0.8474***	0.4086***
	(0.0238)	(0.0265)	(0.0569)	(0.0331)	(0.0506)	(0.1039)	(0.0415)	(0.0539)	(0.0487)	(0.0359)	(0.0451)	(0.0629)	(0.0627)	(0.0998)	(0.0449)
SMB	0.1881**	0.4993***	0.5732***	0.4822***	0.2314**	1.0072***	0.5493***	0.5257***	0.4096***	0.2127***	0.7724***	0.9559***	0.9019***	0.9546***	0.6495***
	(0.0855)	(0.0542)	(0.1573)	(0.0706)	(0.0948)	(0.1964)	(0.0941)	(0.0895)	(0.0739)	(0.0633)	(0.1266)	(0.1280)	(0.1143)	(0.2043)	(0.1377)
HML	0.0394	0.1313**	0.2887	-0.0532	0.1537*	-0.2165	-0.0024	0.2455**	0.1022	0.1013	0.0641	-0.1715	0.1723	0.3824**	0.1564
	(0.0807)	(0.0539)	(0.1912)	(0.0823)	(0.0828)	(0.2835)	(0.1044)	(0.0953)	(0.0915)	(0.0670)	(0.1081)	(0.1157)	(0.1686)	(0.1837)	(0.1027)
RMW	-0.1188	0.1489*	0.0023	-0.0341	-0.0027	-0.4095	-0.3754***	-0.3875***	-0.1935*	0.0541	-0.3084*	0.1247	-0.3039	-0.0952	-0.0031
	(0.1161)	(0.0832)	(0.2300)	(0.1120)	(0.1208)	(0.4575)	(0.1424)	(0.1478)	(0.1169)	(0.0963)	(0.1662)	(0.1770)	(0.1884)	(0.2631)	(0.1570)
CMA	-0.2152**	-0.2713**	-0.5950**	-0.6152***	-0.1516	-0.2435	-0.4209***	-0.3614**	-0.3139**	-0.2259**	-0.5298***	-0.1801	-0.3697*	-1.5701***	-0.4800***
	(0.0892)	(0.1065)	(0.2586)	(0.1053)	(0.1973)	(0.3669)	(0.1596)	(0.1585)	(0.1586)	(0.1089)	(0.1222)	(0.2515)	(0.1956)	(0.4027)	(0.1568)
Adj. R^2	0.5477	0.3333	0.4018	0.5283	0.2959	0.0334	0.4094	0.3553	0.4318	0.4072	0.2817	0.1774	0.2991	0.1995	0.2726
Panel B: PMNSNT-FF5															
Intercept	-0.0001	-0.0001	0.0006	-0.0001	-0.0006	0.0026	-0.0007	0.0000	-0.0004	-0.0005	-0.0015	0.0011	-0.0015	-0.0012	-0.0003
	(0.0004)	(0.0005)	(0.0010)	(0.0005)	(0.0007)	(0.0021)	(0.0007)	(0.0008)	(0.0006)	(0.0004)	(0.0009)	(0.0012)	(0.0010)	(0.0018)	(0.0008)
PMNSNT	-0.0017	-0.0501	0.0716	0.0376	0.1556**	-0.4131***	0.1034	0.1266**	0.0900	0.0634	0.0754	0.0132	0.0070	0.5844***	0.0782
	(0.0489)	(0.0346)	(0.1356)	(0.0434)	(0.0774)	(0.1386)	(0.0712)	(0.0641)	(0.0704)	(0.0469)	(0.0830)	(0.0936)	(0.0577)	(0.2190)	(0.0743)
Adj. R^2	0.5469	0.3345	0.4013	0.5285	0.3074	0.0609	0.4121	0.3605	0.4340	0.4089	0.2824	0.1759	0.2978	0.2450	0.2735
RI-PMNSNT	0.0002	0.0016	0.0033	0.0011	0.0117	0.0317	0.0033	0.0060	0.0025	0.0025	0.0022	0.0002	0.0000	0.0505	0.0009
Panel C: SNT-FF5															
Intercept	-0.0001	-0.0002	0.0003	0.0001	-0.0004	0.0019	-0.0006	0.0002	-0.0002	-0.0004	-0.0008	0.0019**	-0.0009	-0.0018	-0.0003
	(0.0003)	(0.0004)	(0.0010)	(0.0005)	(0.0005)	(0.0020)	(0.0005)	(0.0006)	(0.0005)	(0.0003)	(0.0007)	(0.0010)	(0.0008)	(0.0015)	(0.0005)
$s(-)$	0.3942***	0.3428***	0.7286***	0.3696***	0.5750***	0.4011***	0.7004***	0.6480***	0.6514***	0.5120***	0.7380***	0.6060***	0.5078***	1.2950***	0.5942***
	(0.0235)	(0.0232)	(0.1076)	(0.0267)	(0.0593)	(0.0977)	(0.0408)	(0.0451)	(0.0430)	(0.0232)	(0.0641)	(0.0740)	(0.0444)	(0.1148)	(0.0505)
$s(0)$	0.7998***	0.6196***	0.3836**	0.5019***	0.6388***	0.9192***	0.9510***	0.7506***	0.7842***	0.6755***	0.6980***	0.6972***	0.8052***	0.6304***	0.4976***
	(0.0406)	(0.0416)	(0.1889)	(0.0581)	(0.0934)	(0.2080)	(0.0587)	(0.0741)	(0.0597)	(0.0421)	(0.1116)	(0.1198)	(0.0696)	(0.1809)	(0.0723)
$s(+)$	0.1195***	0.2170***	0.3442***	0.1683***	0.1235**	0.6461***	0.1964***	0.2543***	0.2264***	0.1899***	0.3629***	0.4228***	0.2317***	0.3585**	0.3107***
	(0.0395)	(0.0377)	(0.1221)	(0.0425)	(0.0586)	(0.1726)	(0.0569)	(0.0629)	(0.0587)	(0.0428)	(0.0860)	(0.1380)	(0.0873)	(0.1787)	(0.0664)
Adj. R^2	0.8720	0.6777	0.6230	0.7439	0.6730	0.2174	0.8182	0.7029	0.8253	0.8170	0.6716	0.4498	0.5706	0.5260	0.6265
RI-$s(-)$	0.1439	0.1624	0.1312	0.1291	0.2610	0.0562	0.2503	0.2306	0.2485	0.2581	0.2781	0.1733	0.1445	0.3047	0.2111
RI-$s(0)$	0.1677	0.1602	0.0321	0.0634	0.1075	0.0848	0.1472	0.1027	0.1279	0.1362	0.0925	0.0655	0.1339	0.0182	0.0978
RI-$s(+)$	0.0031	0.0201	0.0388	0.0111	0.0057	0.0528	0.0092	0.0105	0.0137	0.0160	0.0281	0.0304	0.0081	0.0060	0.0239
Panel D: SNT-RSI-FF5															
Intercept	-1e-04	-2e-04	-2e-04	1e-04	-4e-04	1e-04	-6e-04	2e-04	-2e-04	-4e-04	-7e-04	0.0018*	-9e-04	-0.0018	-7e-04
	(3e-04)	(4e-04)	(0.0012)	(5e-04)	(5e-04)	(0.0027)	(5e-04)	(6e-04)	(4e-04)	(3e-04)	(6e-04)	(0.0010)	(9e-04)	(0.0015)	(5e-04)
RSI	0.0000	0.0000	1e-04	1e-04**	1e-04	1e-04	1e-04**	0.0000	0.0000	0.0000	2e-04**	2e-04**	0.0000	6e-04**	1e-04***
	(0.0000)	(1e-04)	(1e-04)	(0.0000)	(1e-04)	(1e-04)	(1e-04)	(1e-04)	(1e-04)	(0.0000)	(1e-04)	(1e-04)	(1e-04)	(2e-04)	(1e-04)
$s(-)$	0.4013***	0.3446***	0.7277***	0.3671***	0.5780***	0.4035***	0.7017***	0.6557***	0.6630***	0.5175***	0.7266***	0.6008***	0.5113***	1.2772***	0.5965***
	(0.0266)	(0.0223)	(0.1017)	(0.0277)	(0.0569)	(0.1001)	(0.0384)	(0.0437)	(0.0372)	(0.0267)	(0.0652)	(0.0739)	(0.0408)	(0.1105)	(0.0521)
$s(0)$	0.7989***	0.6192***	0.3786**	0.5047***	0.6382***	0.9113***	0.9508***	0.7463***	0.7803***	0.6736***	0.7052***	0.6927***	0.8056***	0.6264***	0.4885***
	(0.0390)	(0.0426)	(0.1825)	(0.0563)	(0.0913)	(0.2110)	(0.0557)	(0.0728)	(0.0507)	(0.0439)	(0.1087)	(0.1196)	(0.0688)	(0.1915)	(0.0678)
$s(+)$	0.1127***	0.2178***	0.3470***	0.1734***	0.1219**	0.6443***	0.1986***	0.2470***	0.2166***	0.1848***	0.3763***	0.4419***	0.2286***	0.4076**	0.3114***
	(0.0430)	(0.0368)	(0.1172)	(0.0441)	(0.0575)	(0.1748)	(0.0562)	(0.0609)	(0.0482)	(0.0438)	(0.0832)	(0.1394)	(0.0870)	(0.1723)	(0.0637)
Adj. R^2	0.8725	0.6773	0.6227	0.7447	0.6726	0.2184	0.8180	0.7031	0.8267	0.8173	0.6737	0.4536	0.5699	0.5351	0.6297
RI-$s(-)$	0.1443	0.1614	0.1304	0.1251	0.2599	0.0551	0.2479	0.2323	0.2522	0.2602	0.2653	0.1674	0.1449	0.2910	0.2086
RI-$s(0)$	0.1674	0.1599	0.0319	0.0640	0.1073	0.0843	0.1471	0.1018	0.1269	0.1353	0.0940	0.0653	0.1336	0.0183	0.0971
RI-$s(+)$	0.0029	0.0202	0.0387	0.0119	0.0055	0.0529	0.0092	0.0098	0.0127	0.0151	0.0304	0.0324	0.0077	0.0076	0.0242

* p ≤ 0.1, ** p ≤ 0.05, *** p ≤ 0.01

Table 4: Cross-Sectional Pricing Comparison of CAPM, the DR-CAPM, and the SNT-CAPM

The table shows the results of a comparison between ten different models: i) a standard CAPM as a naive benchmark, ii) a DR-CAPM model to price the downside risk premium following Lettau et al. (2014), iii) a PMNSNT-CAPM model, enriching the CAPM model with a long-positive / short-negative sentiment factor, iv) a PMNSNT-CAPMx model that also controls for idiosyncratic volatility, skewness, and kurtosis, v) a PMNSNT-FF5 which adds the PMNSNT factor to a Fama-French five factor specification, vi) a PMNSNT-FF5x model that additionally controls for $iv_{i,t}$, $is_{i,t}$, and $ik_{i,t}$, vii) a SNT-CAPM that prices positive, neutral, and negative sentiment separately, viii) a SNT-CAPMx with controls for idiosyncratic volatility, skewness, and kurtosis, iv) a SNT-FF5 Fama-French five factor specification with three sentiment factors as well as x) a SNT-FF5x model that also incorporates the control variables. Displayed is the market risk premium, which is assumed to be priced correctly and hence equal the average excess returns on the MSCI World market portfolio. Thus, no standard errors of the estimates are provided. λ^{-} is the price for downside risk and λ_{PMNSNT} the price for the single sentiment risk factor PMNSNT. The three estimates $\lambda_{s(-)}$, $\lambda_{s(0)}$, and $\lambda_{s(+)}$ are the sentiment premia for negative, neutral, and positive sentiment, respectively. Additional rows indicate whether we also control for the change in idiosyncratic volatility $iv_{i,t}$ (dVol), skewness $is_{i,t}$ (dSkew), kurtosis $ik_{i,t}$ (dKurt), jointly for the Fama French factors for size, value, profitability and investment or jointly for the global currencies EUR, GBP, JPY to the USD base. Standard errors of the estimates are provided in parentheses and incorporate the Shanken (1992) errors-in-variables correction. The last row reports the adjusted R^2 of each model for the cross-section.

	CAPM	DR-CAPM	PMNSNT-CAPM	PMNSNT-CAPMx	PMNSNT-FF5	PMNSNT-FF5x	SNT-CAPM	SNT-CAPMx	SNT-FF5	SNT-FF5x
λ	0.1050	0.1050	0.1050	0.1050	0.1050	0.1050	0.1050	0.1050	0.1050	0.1050
λ^{-}		0.0993***								
		(0.0002)								
λ_{PMNSNT}			0.6455***	0.3184***	0.4374***	0.3556***				
			(0.0009)	(0.0007)	(0.0012)	(0.0011)				
$\lambda_{s(-)}$							-0.4306***	-0.4695***	-0.3219***	-0.6309***
							(0.0004)	(0.0005)	(0.0003)	(0.0008)
$\lambda_{s(0)}$							0.1695***	0.1731***	0.1215***	0.1857***
							(0.0002)	(0.0002)	(0.0001)	(0.0002)
$\lambda_{s(+)}$							0.3967***	0.4765***	0.4168***	0.7002***
							(0.0004)	(0.0007)	(0.0005)	(0.0008)
dVol				YES		YES		YES		YES
dSkew				YES		YES		YES		YES
dKurt				YES		YES		YES		YES
FF5 Factors					YES	YES			YES	YES
Currencies				YES		YES		YES		YES
Adj. R2	40.4481	3.0078	13.2726	25.0103	16.4464	27.4324	56.7172	57.6661	57.1788	57.5292

* p ≤ 0.1, ** p ≤ 0.05, *** p ≤ 0.01

Internet Appendix for
Sentiment Risk Premia in the Cross-Section of Global Equity *

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Abstract

This paper introduces a new sentiment-augmented asset pricing model in order to provide a comprehensive understanding of the role of this new type of risk factors. We find that news and social media search-based indicators are significantly related to international stocks' excess returns. Adding sentiment factors to both, classical and more recent pricing models, leads to a significant increase in model performance. Following the Fama-MacBeth procedure, our modified pricing model obtains positive estimates of the risk premium for positive sentiment, while being negative for negative sentiment. Our results contribute to the explanation of the cross-section of average, international excess returns and are robust for fundamental asset pricing factors, idiosyncratic volatility, skewness, and kurtosis.

JEL Classification Codes: $C53$, $G12$, $G41$

Key Words: *Asset pricing*; *behavioral finance*; *financial markets*; *investor sentiment*; *sentiment risk premium.*

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Internet Appendix for

Sentiment Risk Premia in the Cross-Section of Global Equity

In this appendix we present several descriptive statistics, additional tests and robustness checks. The Internet appendix has the following structure:

Appendix A: Market Efficiency Test

Appendix B: Robustness Checks

A Market Efficiency Test

Table A.1: Market Efficiency Tests

This table provide the Spearman rank correlation coefficient between the aggregated relative importance of all sentiment variables of the third regression on sentiment for stock market indices against the R^2 of the CAPM market model as well as the Lo-MacKinlay variance ratio tests for lags $k = 2, 5, 10$. $M1(k)$ refers to the null hypothesis of homoskedastic increments random walk while $M2(k)$ describes the heteroskedastic increments random walk hypothesis.

Test	Equity Indices
Correl R^2	-0.9600***
Correl LoMac M1(2)	-0.0201
Correl LoMac M1(5)	-0.0208
Correl LoMac M1(10)	0.0075
Correl LoMac M2(2)	0.2968
Correl LoMac M2(5)	0.0644
Correl LoMac M5(10)	0.1673

* p ≤ 0.1, ** p ≤ 0.05, *** p ≤ 0.01

B Robustness Checks

Table B.1: Global Stock Markets: Comparing the CAPM to different sentiment-augmented CAPM for Additional Indices

This table compares the standard CAPM with different sentiment-augmented linear factor models for equity market indices. Panel A concerns results for the standard CAPM on the market risk premium (MRP). Panel B reports the DR-CAPM from Lettau et al. (2014). Panel C is the extension of the CAPM to include the return of a long-positive/short-negative sentiment portfolio as a single sentiment risk factor (PMNSNT-CAPM). Panel D uses three sentiment risk factors based on the returns of portfolios mimicking negative, neutral, and positive sentiment (SNT-CAPM). The table shows the coefficient estimates, Newey-West corrected standard errors to adjust for autocorrelation and heteroscedasticity in returns in parentheses as well as the adjusted R^2. For models including sentiment, we also report the relative importance indicator for each coefficient which estimates its contribution to the total explained variation. The regressions are estimated for each equity index individually on weekly returns from 1998 to 2015.

	US30	USMID2000	USNAS100	EM50	EU50	GBMID250
Panel A: CAPM						
Intercept	0.0003	-0.0009	-0.0001	0.0007	-0.0008	-0.0002
	(0.0004)	(0.0007)	(0.0010)	(0.0009)	(0.0006)	(0.0007)
vwretd	0.5663***	0.7281***	0.7097***	0.6372***	0.6795***	0.4935***
	(0.0225)	(0.0324)	(0.0448)	(0.0526)	(0.0488)	(0.0247)
Adj. R^2	0.4982	0.4693	0.3649	0.3165	0.4053	0.3216
Panel B: DR-CAPM						
Intercept	0.0003	-0.0003	-0.0006	0.0011	-0.0002	0.0008
	(0.0005)	(0.0009)	(0.0012)	(0.0010)	(0.0007)	(0.0007)
DR-Intercept	0.0013	0.0038	-0.0007	0.0097**	-0.0108***	-0.0022
	(0.0022)	(0.0033)	(0.0038)	(0.0046)	(0.0039)	(0.0037)
MRP	0.5620***	0.6649***	0.7629***	0.5680***	0.6599***	0.4120***
	(0.0344)	(0.0591)	(0.0804)	(0.0655)	(0.0548)	(0.0493)
$DR \times MRP$	0.0331	0.1794**	-0.1090	0.3106**	-0.1551**	0.1154
	(0.0682)	(0.0845)	(0.1015)	(0.1306)	(0.0746)	(0.0956)
Adj. R^2	0.4971	0.4709	0.3641	0.3227	0.4098	0.3260
RI-DR-Int	0.1125	0.1108	0.0759	0.0687	0.1152	0.0943
RI-MRP	0.3863	0.3595	0.2905	0.2486	0.2949	0.2325
$RI - DR \times MRP$	0.0002	0.0032	0.0010	0.0078	0.0023	0.0019
Panel C: PMNSNT-CAPM						
Intercept	0.0003	-0.0009	-0.0001	0.0007	-0.0009	-0.0002
	(0.0004)	(0.0007)	(0.0010)	(0.0009)	(0.0006)	(0.0007)
MRP	0.5663***	0.7295***	0.7089***	0.6348***	0.6820***	0.4935***
	(0.0221)	(0.0338)	(0.0474)	(0.0530)	(0.0497)	(0.0252)
PMNSNT	-0.0114	0.0688	0.0287	0.0583	-0.0884	-0.0053
	(0.0332)	(0.0697)	(0.0899)	(0.0712)	(0.1002)	(0.0482)
Adj. R^2	0.4976	0.4701	0.3640	0.3167	0.4063	0.3207
RI-MRP	0.4988	0.4708	0.3652	0.3154	0.4070	0.3225
RI-PMNSNT	0.0001	0.0010	0.0010	0.0030	0.0010	0.0000
Panel D: SNT-CAPM						
Intercept	0.0004	-0.0006	-0.0003	0.0003	-0.0011**	0.0001
	(0.0004)	(0.0006)	(0.0008)	(0.0006)	(0.0004)	(0.0005)
MRP	0.5676***	0.7364***	0.7184***	0.6555***	0.6873***	0.4928***
	(0.0156)	(0.0212)	(0.0345)	(0.0480)	(0.0422)	(0.0220)
$s(-)$	0.3487***	0.4717***	0.4896***	0.7133***	0.7512***	0.4857***
	(0.0223)	(0.0261)	(0.0522)	(0.0344)	(0.0444)	(0.0288)
$s(0)$	0.5821***	0.9103***	1.1424***	0.8694***	0.8114***	0.6929***
	(0.0385)	(0.0759)	(0.1537)	(0.0523)	(0.0570)	(0.0500)
$s(+)$	0.0631	0.2829***	0.0641	0.4663***	0.0815	0.2162***
	(0.0513)	(0.0610)	(0.0924)	(0.0569)	(0.0630)	(0.0592)
Adj. R^2	0.7660	0.7820	0.6828	0.7951	0.8526	0.7208
RI-MRP	0.5000	0.4754	0.3699	0.3255	0.4099	0.3218
RI-$s(-)$	0.1407	0.1509	0.1181	0.2687	0.2764	0.2421
RI-$s(0)$	0.1247	0.1448	0.1962	0.1625	0.1615	0.1401
RI-$s(+)$	0.0018	0.0124	0.0007	0.0395	0.0056	0.0183

* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Table B.2: Equity indices - Sub-samples Comparisons

This table depicts the results of the sub-samples of stock market indices. The columns show the different model with a pure CAPM (CAPM), the DR-CAPM, the extension with a single sentiment risk factor based on a long-positive/short-negative sentiment portfolio (PMNSNT-CAPM), and the 3-factor sentiment-augmented CAPM (SNT-CAPM). We provide the average, minimum, maximum and median adjusted R^2 as well as relative importance of the sentiment coefficients as the sum of of negative, neutral, and positive sentiment. Panel A shows the full sample from 1998-2017 as comparison, Panel B the dot-com crisis 1998-2001, Panel C the pre-crisis period 2002-2006, Panel D the financial crisis period 2007-2011, Panel E the post-crisis period 2012-2017.

Panel A: Full Sample 1998-2017							
	CAPM	PMNSNT-CAPM	SNT-CAPM	FF5	PMNSNT-FF5	SNT-FF5	SNT-RSI-FF5
Abs. Alpha							
Mean	0.0007	0.0007	0.0006	0.0006	0.0007	0.0006	0.0005
Min	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0001
Max	0.0021	0.0025	0.0022	0.0020	0.0026	0.0019	0.0018
Median	0.0006	0.0006	0.0003	0.0005	0.0005	0.0004	0.0004
Adj. R^2							
Mean	0.3131	0.3180	0.6805	0.3776	0.3821	0.6961	0.6971
Min	-0.0015	0.0314	0.2188	0.0334	0.0609	0.2174	0.2184
Max	0.5382	0.5375	0.8588	0.6061	0.6062	0.8720	0.8725
Median	0.3216	0.3207	0.6943	0.4072	0.4089	0.7348	0.7344
RI-SNT							
Mean		0.0062	0.3671		0.0058	0.3149	0.3128
Min		0.0000	0.2252		0.0000	0.1938	0.1923
Max		0.0528	0.4707		0.0505	0.4252	0.4227
Median		0.0018	0.3871		0.0016	0.3289	0.3169
Panel B: Sub-sample 1998-2001							
Abs. Alpha							
Mean	0.0024	0.0026	0.0027	0.0023	0.0026	0.0025	0.0025
Min	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
Max	0.0086	0.0094	0.0094	0.0081	0.0090	0.0088	0.0090
Median	0.0014	0.0014	0.0015	0.0015	0.0017	0.0015	0.0015
Adj. R^2							
Mean	0.2422	0.2552	0.6457	0.3639	0.3746	0.6787	0.6655
Min	0.0865	0.0902	0.3890	0.1844	0.1770	0.4078	0.4171
Max	0.4553	0.5053	0.9342	0.5825	0.5868	0.9441	0.8451
Median	0.2274	0.2244	0.6527	0.3402	0.3445	0.6577	0.6616
RI-SNT							
Mean		0.0200	0.4042		0.0141	0.3064	0.2998
Min		0.0003	0.2524		0.0001	0.1676	0.1709
Max		0.1230	0.6071		0.0910	0.4150	0.3940
Median		0.0085	0.4227		0.0043	0.2942	0.2945
Panel C: Sub-sample 2002-2006							
Abs. Alpha							
Mean	0.0017	0.0017	0.0016	0.0019	0.0019	0.0018	0.0017
Min	0.0001	0.0001	0.0003	0.0001	0.0001	0.0002	0.0001
Max	0.0076	0.0076	0.0064	0.0082	0.0084	0.0078	0.0068
Median	0.0011	0.0011	0.0010	0.0012	0.0012	0.0011	0.0011
Adj. R^2							
Mean	0.2816	0.2877	0.6717	0.3458	0.3537	0.6894	0.6915
Min	-0.0152	-0.0319	0.0467	-0.0319	-0.0498	0.0726	0.1005
Max	0.4716	0.4769	0.8799	0.5752	0.5796	0.8922	0.8917
Median	0.3093	0.3087	0.7412	0.3996	0.4042	0.7867	0.7856
RI-SNT							
Mean		0.0142	0.3945		0.0160	0.3407	0.3351
Min		0.0005	0.1021		0.0000	0.1149	0.0980
Max		0.0792	0.5180		0.0516	0.5170	0.5013
Median		0.0078	0.4029		0.0132	0.3498	0.3352
Panel D: Sub-sample 2007-2011							
Abs. Alpha							
Mean	0.0015	0.0015	0.0012	0.0013	0.0014	0.0011	0.0011
Min	0.0002	0.0002	0.0001	0.0001	0.0001	0.0000	0.0000
Max	0.0064	0.0064	0.0049	0.0066	0.0066	0.0050	0.0049
Median	0.0009	0.0009	0.0008	0.0008	0.0008	0.0007	0.0007
Adj. R^2							
Mean	0.4244	0.4290	0.7753	0.4797	0.4873	0.7869	0.7870
Min	-0.0049	0.0239	0.2079	0.0204	0.0465	0.2009	0.2044
Max	0.6585	0.6572	0.9312	0.7030	0.7010	0.9367	0.9379
Median	0.4604	0.4794	0.8106	0.5207	0.5299	0.8135	0.8128
RI-SNT							
Mean		0.0082	0.3536		0.0102	0.3028	0.3023
Min		0.0000	0.1971		0.0004	0.1534	0.1531
Max		0.0343	0.4926		0.0323	0.4151	0.4153
Median		0.0054	0.3684		0.0097	0.3365	0.3365
Panel E: Sub-sample 2012-2017							
Abs. Alpha							
Mean	0.0011	0.0010	0.0012	0.0011	0.0010	0.0012	0.0012
Min	0.0001	0.0001	0.0002	0.0001	0.0001	0.0001	0.0001
Max	0.0033	0.0031	0.0031	0.0031	0.0029	0.0030	0.0030
Median	0.0008	0.0008	0.0011	0.0008	0.0008	0.0010	0.0010
Adj. R^2							
Mean	0.2140	0.2323	0.6391	0.2686	0.2840	0.6522	0.6530
Min	-0.0050	0.0416	0.2925	0.0358	0.0775	0.2854	0.2902
Max	0.3975	0.4096	0.8159	0.5196	0.5343	0.8246	0.8240
Median	0.2050	0.2480	0.6647	0.2808	0.2905	0.6762	0.6752
RI-SNT							
Mean		0.0229	0.4242		0.0200	0.3754	0.3750
Min		0.0002	0.2737		0.0001	0.2150	0.2155
Max		0.1511	0.5402		0.1475	0.4942	0.4938
Median		0.0026	0.4166		0.0017	0.3760	0.3768

Table B.3: Comparison between News & Social Media, News-only and Social Media-only Models

This table depicts the results for equity indices for different sentiment channels differentiating between news-and social media-driven sentiment compared to the default combined sentiment. The columns show the different model with a pure PMNSNT-CAPM, the 3-factor sentiment-augmented CAPM (SNT-CAPM), the Fama-French based PMNSNT-FF5, and , and the SNT-FF5 with with three sentiment factors. We provide the average, minimum, maximum and median adjusted R^2 as well as relative importance of sentiment (in case of the SNT-CAPM this is the aggregated importance of negative, neutral, and positive sentiment). Panel A shows the combined news and social media models, Panel B news only, and Panel C social media only. The time period is January 1998 - December 2017.

Panel A: Combined News & Social Media

	CAPM	PMNSNT-CAPM	SNT-CAPM	FF5	PMNSNT-FF5	SNT-FF5	SNT-RSI-FF5
Abs. Alpha							
Mean	0.0007	0.0007	0.0006	0.0006	0.0007	0.0006	0.0005
Min	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0001
Max	0.0021	0.0025	0.0022	0.0020	0.0026	0.0019	0.0018
Median	0.0006	0.0006	0.0003	0.0005	0.0005	0.0004	0.0004
Adj. R^2							
Mean	0.3131	0.3180	0.6805	0.3776	0.3821	0.6961	0.6971
Min	-0.0015	0.0314	0.2188	0.0334	0.0609	0.2174	0.2184
Max	0.5382	0.5375	0.8588	0.6061	0.6062	0.8720	0.8725
Median	0.3216	0.3207	0.6943	0.4072	0.4089	0.7348	0.7344
RI-SNT							
Mean		0.0062	0.3671		0.0058	0.3149	0.3128
Min		0.0000	0.2252		0.0000	0.1938	0.1923
Max		0.0528	0.4707		0.0505	0.4252	0.4227
Median		0.0018	0.3871		0.0016	0.3289	0.3169

Panel B: News only

	CAPM	PMNSNT-CAPM	SNT-CAPM	FF5	PMNSNT-FF5	SNT-FF5	SNT-RSI-FF5
Abs. Alpha							
Mean	0.0006	0.0006	0.0006	0.0006	0.0006	0.0005	0.0005
Min	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Max	0.0019	0.0023	0.0020	0.0019	0.0023	0.0018	0.0017
Median	0.0005	0.0005	0.0003	0.0004	0.0004	0.0004	0.0004
Adj. R^2							
Mean	0.3126	0.3163	0.6782	0.3781	0.3816	0.6947	0.6954
Min	-0.0017	0.0257	0.2213	0.0336	0.0552	0.2199	0.2214
Max	0.5361	0.5354	0.8527	0.6075	0.6072	0.8662	0.8660
Median	0.3213	0.3209	0.6957	0.4090	0.4083	0.7367	0.7363
RI-SNT							
Mean		0.0049	0.3656		0.0046	0.3131	0.3115
Min		0.0000	0.2277		0.0000	0.1933	0.1920
Max		0.0438	0.4726		0.0404	0.4280	0.4258
Median		0.0011	0.3798		0.0010	0.3190	0.3103

Panel C: Social Media only

	CAPM	PMNSNT-CAPM	SNT-CAPM	FF5	PMNSNT-FF5	SNT-FF5	SNT-RSI-FF5
Abs. Alpha							
Mean	0.0006	0.0007	0.0006	0.0006	0.0006	0.0006	0.0006
Min	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Max	0.0019	0.0019	0.0024	0.0019	0.0019	0.0023	0.0022
Median	0.0005	0.0005	0.0003	0.0004	0.0005	0.0003	0.0004
Adj. R^2							
Mean	0.3148	0.3155	0.6875	0.3794	0.3803	0.7035	0.7041
Min	-0.0015	-0.0037	0.2319	0.0314	0.0291	0.2339	0.2364
Max	0.5370	0.5362	0.8803	0.6049	0.6050	0.8934	0.8935
Median	0.3279	0.3293	0.7072	0.4078	0.4071	0.7348	0.7344
RI-SNT							
Mean		0.0024	0.3709		0.0027	0.3210	0.3191
Min		0.0000	0.2369		0.0000	0.2083	0.2053
Max		0.0161	0.4704		0.0130	0.4296	0.4279
Median		0.0006	0.3814		0.0005	0.3362	0.3361

Table B.4: Cross-Sectional Pricing Comparison of CAPM, the DR-CAPM, and the SNT-CAPM without Orgonalization

The table shows the results of a comparison between ten different models where the variables are not orthogonalized: i) a standard CAPM as a naive benchmark, ii) a DR-CAPM model to price the downside risk premium following Lettau et al. (2014), iii) a PMNSNT-CAPM model, enriching the CAPM model with a long-positive / short-negative sentiment factor, iv) a PMNSNT-CAPMx model that also controls for idiosyncratic volatility, skewness, and kurtosis, v) a PMNSNT-FF5 which adds the PMNSNT factor to a Fama-French five factor specification, vi) a PMNSNT-FF5x model that additionally controls for $iv_{i,t}$, $is_{i,t}$, and $ik_{i,t}$, vii) a SNT-CAPM that prices positive, neutral, and negative sentiment separately, viii) a SNT-CAPMx with controls for idiosyncratic volatility, skewness, and kurtosis, iv) a SNT-FF5 Fama-French five factor specification with three sentiment factors as well as x) a SNT-FF5x model that also incorporates the control variables. Displayed is the market risk premium, which is assumed to be priced correctly and hence equal the average excess returns on the MSCI World market portfolio. Thus, no standard errors of the estimates are provided. λ^{-} is the price for downside risk and λ_{PMNSNT} the price for the single sentiment risk factor PMNSNT. The three estimates $\lambda_{s(-)}$, $\lambda_{s(0)}$, and $\lambda_{s(+)}$ are the sentiment premia for negative, neutral, and positive sentiment, respectively. Additional rows indicate whether we also control for the change in idiosyncratic volatility $iv_{i,t}$ (dVol), skewness $is_{i,t}$ (dSkew), kurtosis $ik_{i,t}$ (dKurt), jointly for the Fama French factors for size, value, profitability and investment or jointly for the global currencies EUR, GBP, JPY to the USD base. Standard errors of the estimates are provided in parentheses and incorporate the Shanken (1992) errors-in-variables correction. The last row reports the adjusted R^2 of each model for the cross-section.

	CAPM	DR-CAPM	PMNSNT-CAPM	PMNSNT-CAPMx	PMNSNT-FF5	PMNSNT-FF5x	SNT-CAPM	SNT-CAPMx	SNT-FF5	SNT-FF5x
λ	0.1050	0.1050	0.1050	0.1050	0.1050	0.1050	0.1050	0.1050	0.1050	0.1050
λ^{-}		0.0993***								
		(0.0002)								
λ_{PMNSNT}			0.6357***	0.3086***	0.5032***	0.4030***				
			(0.0009)	(0.0007)	(0.0012)	(0.0011)				
$\lambda_{s1(-)}$							-0.3660***	-0.4063***	-0.2967***	-0.6133***
							(0.0004)	(0.0005)	(0.0003)	(0.0008)
$\lambda_{s2(0)}$							0.0086***	-0.0069***	0.0065***	-0.0809***
							(0.0001)	(0.0001)	(0.0001)	(0.0001)
$\lambda_{s3(+)}$							0.3497***	0.4105***	0.3483***	0.5313***
							(0.0003)	(0.0004)	(0.0004)	(0.0005)
dVol				YES		YES		YES		YES
dSkew				YES		YES		YES		YES
dKurt				YES		YES		YES		YES
FF5 Factors					YES	YES			YES	YES
Currencies				YES		YES		YES		YES
Adj. R2	40.4481	3.0078	13.2769	25.0141	16.4315	27.4103	57.0742	57.9751	57.3466	57.6804

* p ≤ 0.1, ** p ≤ 0.05, *** p ≤ 0.01