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SENTIMENT RISK PREMIA IN THE CROSS-SECTION OF GLOBAL EQUITY

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WORKING PAPERS ON FINANCE NO. 2019/13

SWISS INSTITUTE OF BANKING AND FINANCE (S/BF – HSG)

AUGUST 28, 2019
THIS VERSION: MAY 16, 2020

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 excess returns of international equity indices. 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 global cross-sectional average excess returns and are robust for fundamental factors, momentum, idiosyncratic volatility, skewness, kurtosis, and international currencies.

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

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

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*We are grateful to Richard Peterson from MarketPsych and Elijah DePalma from Refinitiv for granting access to the MarketPsych indicators as well as to Claudius Ulmer from Refinitiv for providing the financial market data. We also thank Martin Brown, Francesco Audrino, Steffen Meyer (19th Cologne Colloquium on Financial Markets), as well as the discussants and participants of the 6th PFMC conference in Paris, the PiF seminar at the University of St. Gallen and the Finance Research Seminar at University of Liechtenstein for their helpful comments and suggestions.

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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, all of which 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 equity 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). In particular, we hypothesize according to Shefrin and Belotti (2008) that sentiment is priced differently depending on the type of tail event. Given that sentiment covers a spectrum of moods rather an aggregated level, sentiment risk divides into risk premia for positive, negative, and neutral events. By adding these 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 sentiment-risk factor and establish a robust relationship between excess asset returns, several known systematic risk factors (e.g., market, size, value, profitability, investment, momentum), and our novel global sentiment factor. To circumvent any concerns about endogeneity or reverse causality, we use lagged sentiment in line with Nofsinger (2003) who find that business activities tend to follow, rather than lead social mood. We find that our international 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 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 positive and negative 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 international equity indices into portfolios provides empirical evidence that high (low) abnormal 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 equity index 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. Based on a lead/ lag correlation analysis and a conceptual interpretation, 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 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 markets 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 subsamples of our data to explore sentiment during alternative bull and bear market phases following a naïve classification of bull and bear markets as well as the categorization of recessions by the National Bureau of Economic Research (NBER), and our main results still hold.

With 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 confirm our hypothesis 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 positive, negative, and neutral 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 demonstrate that positive, negative, and neutral 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 argue 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 equity index returns. As sentiment is suspected to proxy downside risk or fundamental risk factors we 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. To reduce the omitted variable bias, we further control for international currencies, statistical properties like idiosyncratic volatility, skewness, or kurtosis as well as momentum. 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 Priced 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, represented by shocks to state variables correlated with the marginal utility of investors' wealth.[1] However, it is now well-known 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

[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 Pástor and Stambaugh (2003).

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. For instance, 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 security payoffs, 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, 2007). 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 is able to magnify market fluctuations and cause excess volatility. Accordingly, there is now an increasing consensus that sentiment should be 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 famed Wall Street Journal column may be 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 covered by attention-grabbing news and this would obviously be reflected by 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 whilst 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 an earlier 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 by abnormal institutional attention experience larger returns (in absolute terms) and modest, 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 have often been 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 the 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 the 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]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.

2.2 Theoretical Framework

Although the main contribution of this paper is empirical, we embed our empirical analysis in a simple theoretical framework to rigorously pin down the relationship between investor sentiment and asset pricing. In this sub-section, we develop a formal definition of market sentiment and show how it fits with our empirical specification involving the cross-section of international equity indices. By doing so, we formulate the theoretical foundation for why sentiment, if decomposed into positive, negative, and neutral specifications, should be treated as a risk factor in asset pricing models and why such a factor is likely to be applicable to international equity index returns. Following closely the arguments of Shefrin and Belotti (2008), we hypothesize that positive, neutral, and negative sentiment is priced differently and that a global sentiment factor in the spirit of Fama and French (1993) cannot fully capture the entire dimension of sentiment pricing.

In his keynote speech at a behavioral finance conference at Northwestern University in 2000, Daniel Kahnemann suggested to investigate the stock market as a stereotypical investor with thoughts, beliefs, moods, and emotions (see, e.g., Shefrin and Belotti, 2008). He encouraged to think of a market as a representative agent who acts as if he may set market prices, but does not require Gorman aggregation[3] to form a uniform set of assumptions. However, in reality, agents are not all alike and the differences among them surely matter. As such, Kahnemann's 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) posits that in a market involving a single representative investor, the equilibrium price ν at any point in time t under consideration of all date-event $\{\chi_t | t = 0, ..., T\}$ pairs follows :[4]

$$\nu(\chi_t) = \delta_{R,t}^t P_R(x_t) g(x_t)^{-\gamma_R(x_t)}, \tag{1}$$

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

[3]Gorman aggregation limits the impact of heterogeneity on aggregate demand and therefore equilibrium prices. Brennan and Kraus (1978) prove 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]We assume that 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.

In line with the existing view in the finance literature that depicts sentiment as being synonymous with error, Shefrin and Belotti (2008) formally defines sentiment Λ_t as a proxy for distorted probabilities in time t stemming from: (i) deviations in the beliefs of a representative investor P_R, called the "market's beliefs", relative to the objective beliefs Π; and (ii) deviations of the representative investor's equilibrium time discount factor δ_R relative to the objective discount factor, that would apply under the condition that all investors held correct beliefs, δ_Π:

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

As a result, sentiment is time-varying and can be described as a stochastic process. Moreover, sentiment should be modeled as a distribution and not only as a scalar or in terms of first moments of Λ_t, because market participants are not only excessively bullish or bearish but subject to a great variety of potential trajectory of human emotions. While the first moment of Λ_t is unable to capture all investors' emotions and errors, the second moment may describe errors in how investors perceive risks, the third moment would capture whether investors are concerned about a price reversals, and the fourth moment may render the idea that investors attach high probabilities to extreme events such as stock market crashes. As such, sentiment is much more complex than simply assigning erroneous probabilities to very positive or negative events. The individual investors' emotions aggregate into a market sentiment as a collage of different investors' beliefs, attitudes toward risk, and time preferences. As long as the representative investor's errors in beliefs are non-zero, the market sentiment function Λ_t will be non-zero. Shefrin and Belotti (2008) describe various scenarios of how overconfidence and representativeness, two commonly invoked behavioral phenomena, affect the aggregate sentiment function in terms of first (representativeness) and second (overconfidence) moments. The key aspect of his analysis is that sentiment typically does not average to the zero function but rather leads to time-varying oscillations in the probabilities assigned to different payoff-relevant 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 will 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, a standard stochastic discount factor (SDF) that measures the state price per unit probability. Therefore, 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 Equation (1) and Equation (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] Because it is possible to decompose such covariance into a fundamental and sentiment part, we obtain:

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

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 the sentiment function in the presence of heterogeneity in beliefs, risk aversion, and time discount factors as described above, we further empirically 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 at capturing the errors in probability estimation by different investors in the case of positive vs. negative tail events, as well as for mid-range events. We therefore hypothesize that the priced contribution of sentiment may factor into positive, neutral, and negative risk premia according to the spectrum of human emotions.

The shape of the market sentiment function is affected by the wealth weighted aggregated mixture of individual investors' sentiment. We argue that such an aggregation best manifests in the sentiment for international equity indices and hence will affect global equity risk premia. In any other application, erroneous beliefs or sentiment may be diversified away and any mispricing easily eliminated by arbitrageurs. As stated by Kozak et al. (2018), arbitrageurs can 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 case of aggregate international stock

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

markets 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 portfolios but the restrictions imposed prevent the most extreme cases. Kozak et al. (2018) argue that those deviations must be caused by sentiment either being orthogonal to existing factor exposures or being correlated with them. The trading by the arbitrageurs largely eliminates the effects of the orthogonal components of sentiment-driven asset demand, but those that are correlated with common factor exposures may survive because arbitrageurs are not willing to accommodate these demands without a compensation for factor risk exposures. This model contrasts with 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 additional risk factor on its own. Kozak et al. (2018) do not extend their model into this direction but if heterogeneity in beliefs persists in aggregate as implied by our theoretical framework, arbitrageurs would be reluctant to trade and expose themselves to the sentiment risk factor. Therefore, in the following we postulate that sentiment should be part of asset pricing models and be able to command a risk premium of its own. However, whether these sentiment premia are small or large relative to the fundamental component remains an empirical question that we shall address below. Despite our hypothesis on the breakdown of sentiment risk into three sentiment premia, we are aware that this approach still represents at best an approximation of the time-varying sentiment risk premium driven by the oscillating sentiment function. Yet, the framework represents a more sophisticated specification than in the existing theoretical and empirical behavioral finance literature because, thus far, empirical models have limited sentiment to capture either positive or negative events. In Section 3 we shall therefore describe how MarketPsych's sentiment data may capture these complex behavioral phenomena and how it can be used to support estimation and testing of 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 departures from the earlier literature is crucial in interpreting our empirical findings.

3.1 Sentiment Indicators

Our search-based sentiment index is the Refinitiv MarketPsych sentiment indicator (RMI). 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 time interval. 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 aggregated, RMI investor sentiment for 21 international equity indices for the period 1998-2017. The MarketPsych sentiment indicator captures the net positive versus negative references in the social media and in the press news related to a given equity market. It can be interpreted as an overall market sentiment proxy, void of any insights on the fundamental reasons for why references to a security may be positive or negative. MarketPsych's language processing engine goes way beyond traditional textual sentiment analysis based on 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[7], and psychological research has demonstrated that more than just one dimension has predictable effects on investor behavior (see, e.g., Peterson, 2007; Shu, 2010). Besides positivity or negativity in terms of valence, the level of arousal has been shown to map directly to cognitive performance through an inverse U-curve relationship, the Yerkes-Dodson

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

[7]Valence hereby refers to the positive or negative affectivity, while arousal measures the level of calmness or excitement of information.

Law, capturing either the reduction in complex problem solving skills when stress levels are high or the reduction in attention and reaction times when arousal levels are low (see, e.g., Yerkes and Dodson, 1908; Diamond et al., 2007).

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. Among others, the aggregated sentiment reflects notions of fear, optimism, and joy. According to Shen et al. (2017), those are the three most commonly documented emotions in the finance literature. Optimism is generally defined as the tendency to overestimate/the overconfidence of investors about the future payoffs of a financial asset that may result in deviations of asset prices from intrinsic values as observed during extreme bullish or overheated markets. Odean (1998) finds that overconfidence leads to the entry in the market by retail investors, driving up liquidity. Ciccone (2003) reports lower returns for firms characterized by optimistic vs. those driven by pessimistic expectations. Fear, on the other hand, leads to demand shocks, driven by investors' emotional stress, increasing market uncertainty and volatility. Da et al. (2015) establish a daily fear index based on the online searches of U.S. households, predicting return reversals and volatility. Strongly negative emotions like anger, fear, and gloom, all of which are captured by RMI, bias human decision making and lead to various behaviors like herding or panic and affect trading activities with either under- or over-reactions (see, e.g., Daniel et al., 1998; Lerner and Keltner, 2001; Lerner et al., 2004; Winkielman et al., 2005, 2007). Wright and Bower (1992) found that pleasant emotions like bliss, joy, and optimism affect the subjective probability assessments of uncertain outcomes and therefore influence investors' decision-making as documented by Dolan (2002). Figure 1 depicts several among the RMI sentiments that are described in detail in Table A.2 of the Appendix on the affective circumplex. Each dot in the figure 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 the circumplex as described in detail in Table A.1 of the Appendix. The table shows that RMI's construction of sentiment is tilted towards capturing negative statements because, as confirmed in private exchanges, MarketPsych research on business and financial language has found a prevalence of concepts with negative vs. positive valence. As a result, the sentiment indicator is usually measured to be negative in net terms.

Figure [1] about here

To provide more intuition on the mechanism of index construction, MarketPsych provides an example on the complex language processing system that reveals they address some common pitfalls in news and social media sentiment analysis. Figure 2 evaluates the opinion of a Goldman Sachs' analyst about his expectations of tomorrow's quarterly call of Apple Inc. and of 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. For instance, the PriceForecast category 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 has been published more than 24 hours before a given time t, is excluded and all content drops out of the 24 hours averages when it has been more than 24 hours since its publication. Articles that are more than 98% similar to articles recorded in the previous 24 hours are removed from analysis to avoid double-counting.[8]

Figure [2] about here

Various sources, though limited to English, 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. In order to construct a daily record, 24 hours or 1440 minutes are aggregated. If no records are found for the constituents of a specific equity 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 time. In practical terms, if no observa-

[8]In the case of social media for which the concepts of re-tweeting, re-posting, and commenting are defined, 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 remarks about the original tweet. RMI does not include comments with the same title that are repeated multiple times; however, they do include commentary text when it changes from post to post.

tion 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.[9]

For the purposes of our investigation, we accumulate the RMI index at a lower, weekly frequency versus the original, higher 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.[10] As we have international equity indices and aggregate the sentiment indicators to weekly data, there are no observations missing in our dataset. 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 equity market, 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:[11]

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

For illustrative purposes of the 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. With reference to a period from January 2007 - January 2015, Figure 3 shows that 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 prices and increasing returns ensues. In the case of our indicators, we use the deviation of sentiment from the long-term rolling mean.

Figure [3] about here

[9]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, in private exchanges, MarketPsych has confirmed to us that the primary relationship is that sentiment RMI variability rises as the overall *Buzz* decreases. So *Buzz* is the primary determinant of sentiment dispersion.

[10]In an unreported exploratory analysis, we checked that sentiment fluctuates massively at higher daily frequencies, whereas at a lower monthly frequency it suffers from a loss of valuable information that, however, appears to be manageable. This analysis is available upon request.

[11]Additionally, this definition ensures comparability of sentiment between different markets as outlined by MarketPsych in their research guidelines, accessible at `https://old.marketpsych.com/guide/`.

3.2 Comparison of Sentiment Indicators

The current academic standard in the matter of sentiment indicators, Baker and Wurgler (2006)'s (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 that emerges after market participants have taken trading or investment actions as reflected by prices and trades. For instance, Baker and Stein (2004) suggest that turnover and liquidity are proxies for investor sentiment. In a market subject to short-sales 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 we use in this 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 (2007) 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 MarketPsych's 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).

Figure [4] about here

In the stylized model in Figure 4, 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 a prediction of positive equity market 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 equity market returns as the measurement gap between true sentiment dynamics and realized return increases.

To provide support to these conjectures on the different dynamics of search-based versus market outcome-based sentiment measures, we compute the lead-lag 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 a higher-frequency indicator such as RMI. We find that the BW and RMI U.S. equity market sentiment indices carry a significantly negative correlation of -0.13. However, when we lag the variables according to the conceptual framework in Figure 4, 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 5 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 [5] about here

3.3 Equity Markets

We analyze weekly excess returns for global equity markets over a sample January 1998 - December 2017. In total, we cover 21 different international equity indices.[12] 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 by scaling the index 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 yield as the risk-free rate 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.[13]

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 investors' 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* scores is added to the empirical framework. In this section, we show that the RMI sentiment

[12]See Table A.4 in the Internet Appendix B for the complete list of equity indices.

[13]`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 in RMI indices: Austria, Belgium, Denmark, Finland, Ireland, the Netherlands, Norway, Portugal, and Sweden. RMI indicators are also available for Brazil, China, India, and Russia but not for Israel and 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.

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 market sentiment measure. 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 historical, expanding window mean up to time t.[14] As a result, the change in sentiment is comparable across indices only if we account for local differences by scaling the variation by its standard deviation.[15] We apply three alternative sorts based on positive, negative, and neutral sentiment. For each week t, we determine whether an equity index belongs to the lower ($s(-)$), middle ($s(0)$), or upper ($s(+)$) quantile of equity indices sorted based on previous week's sentiment. This is motivated by Shefrin and Belotti (2008) who argue 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, see Section 2 for an extensive discussion.

Following DeVault et al. (2019) our first goal is to examine correlation patterns rather than testing for causal effects. However, we acknowledge the existence of dynamic relationships between financial returns and sentiment by using one-week lagged sentiment to avoid a potential reverse causality problem, in the sense that it might be returns to lead sentiment shifts and not the opposite. 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 the average weekly

[14] Such 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.

[15] This approach is backed by the literature and relates changes in sentiment to demand shocks. DeVault et al. (2019) identify whether trades explained by sentiment metrics are, in the aggregate, initiated by individual or institutional investors. Such a differentiation exploits 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".

sentiment reported in the third column. Sort $s(-)$ implies a small, negative mean excess return of -0.0019%, while $s(0)$ leads to a small positive weekly mean excess return of 0.1186%, or 6.36% annually. As such, this portfolio has a similar return as the market index MSCI Worlds with 6.57%. Portfolio $s(+)$ implies a significantly positive, large mean excess return of 0.2731%, or 15.24% when annualized. The sentiment level of sort $s(-)$ is deeply negative with -7.70%, practically zero for $s(0)$ and deeply positive with 6.9% for $s(+)$. The standard deviation of sentiment across the sorts however does not differ much and lies between 3.49% ($s(0)$) and 4.52% ($s(+)$). The weekly standard deviation of excess equity returns is the highest with 2.23% for $s(-)$, compared to 2.01% and 2.16% 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. 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 more often than not 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 Section 3.1, BW's proxy measures sentiment when this has already been reflected in equilibrium stock prices and quantities by conscious decisions, whereas our RMI indicator captures emotions that investors consciously or unconsciously express through their news and social media activity and that are likely to lead to and hence precede decisions.

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 found indeed that positive (negative) sentiment change is followed by positive (negative) returns.

In the next section, we first use sentiment-based mimicking portfolios 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 Fama-French like CAPM-augmented model that includes a positive-minus-negative sentiment portfolio (PMNSNT-CAPM), and a CAPM-augmented model for positive, negative, and neutral sentiment deviations (SNT-CAPM).[16] We select as a benchmark 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 equity indices, and compare their coefficients and their goodness-of-fit with the standard CAPM and the DR-CAPM.[17] In the following, all standard errors of the estimates are adjusted to account for time-series correlation and heteroscedasticity by using Newey-West corrections. Given the multiple testing set-up, we also correct the p-values for multiple testing bias and to deal with the problem of multiple comparisons across 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:

$$r_{i,t}^e = \alpha_i + \beta_{CAPM,i} r_{m,t}^e + \epsilon_{i,t}, \text{for all } t \in T, \tag{6}$$

[16] In robustness checks in Section 6, 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.

[17] 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.4 in the Appendix 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. The excluded indices serve as our sample in robustness checks.

where $\beta_{CAPM,i}$ is the standard CAPM beta for index i and $r^e_{m,t}$ is the market excess return for time t.

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:

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

and

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

where $r^e_{i,t}$ and $r^e_{m,t}$ are the 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) $r^e_{m,t}$:

$$r^e_{i,t} = \alpha_i + DR_{i,t} + \beta_{CAPM,i} r^e_{m,t} + \beta_{DR\times MRP,i} DR \times MRP + \epsilon_{i,t}, \tag{9}$$

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 $\beta_{CAPM,i} r^e_{m,t}$ 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

$$r^e_{i,t} = \beta_{CAPM,i} r^e_{m,t} + \beta_{PMNSNT,i} r^e_{PMNSNT,t} + \epsilon_{i,t}, \tag{10}$$

where the benchmark CAPM is nested under the restriction $\beta_{PMNSNT,i} = 0$. $\beta_{PMNSNT,i}$ is the beta on the excess return r^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 equity markets to positive, negative, and neutral changes in investor sentiment. According to our hypothesis in Section 2.2, 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

$$r^e_{i,t} = \beta_{CAPM,i} r^e_{m,t} + \beta_{s(-),i} r^e_{s(-),t} + \beta_{s(0),i} r^e_{s(0),t} + \beta_{s(+),i} r^e_{s(+),t} + \epsilon_{i,t}, \tag{11}$$

where $\beta_{CAPM,i}$ is the standard CAPM beta for asset i, $r^e_{m,t}$ 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 positive, negative, and neutral sentiment portfolios, respectively.

Because our portfolio sorts use the average weekly returns of the constituents so that the daily extremes used to sort equity indices based on sentiment and the alternative equity portfolio returns may overlap, there may be concerns about the existence of multicollinearity between our sentiment variables and market excess returns. The correlation analysis in Table A.3 in the Appendix shows indeed the existence of highly significant correlations uniformly above 0.7 between the three sentiment sorts. The correlation with market returns is also highly significant yielding estimates in excess of 0.5. In order to address such a potential multicollinearity, we orthogonalize the variables following a stepwise regression approach and use the residuals for the last model estimated. Given the results in Section 4, positive abnormal sentiment are likely to contain most information, followed by negative abnormal sentiment and average sentiment. This finding dictates the sequence of our orthogonalization.[18] In particular, we first orthogonalize positive sentiment by regressing its mimicking excess portfolio returns on market returns:

[18]While the sequence described below makes intuitive sense, we acknowledge a concern that it might remain somewhat arbitrary. In unreported results, we try various permutations of the orthogonalization sequence. The main results hold as long as the resulting variables are uncorrelated to each other.

$$r^e_{s(+),t} = \beta_{CAPM} r^e_{m,t} + \epsilon_{s(+),t}. \tag{12}$$

The residuals represent our positive sentiment indicator when excess market returns are accounted for. Next, we orthogonalize negative sentiment by regressing the mimicking returns on market excess returns and the residuals from Equation (12):

$$r^e_{s(-),t} = \beta_{CAPM} r^e_{m,t} + \beta_{\epsilon_{s(+)}} \hat{\epsilon}_{s(+),t} + \epsilon_{s(-),t}. \tag{13}$$

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

$$r^e_{s(0),t} = \beta_{CAPM} r^e_{m,t} + \beta_{\epsilon_{s(+)}} \hat{\epsilon}_{s(+),t} + \beta_{\epsilon_{s(-)}} \hat{\epsilon}_{s(-),t} + \epsilon_{s(0),t}. \tag{14}$$

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

$$r^e_i = \beta_{CAPM,i} r^e_{m,t} + \beta_{\epsilon_{s(-),i}} \hat{\epsilon}_{s(-),t} + \beta_{\epsilon_{s(0),i}} \hat{\epsilon}_{s(0),t} + \beta_{\epsilon_{s(+),i}} \hat{\epsilon}_{s(+),t} + \epsilon_i. \tag{15}$$

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 estimating the relative contribution of each regressor to the total explained variation and 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 relative 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 Chinese index CN300), the estimated CAPM coefficients are highly significant at the 1% level. The intercepts α are small and mostly 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 equity indices this makes intuitive sense. One can debate 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 by the CAPM is not very high, we still see a justification for adding sentiment to our model.[19] The R^2 ranges from a high of 55.9% for the S&P500 (US500) - the main contributor to the MSCI World, to a moderate 37.7% for the German DAX (DE30), to a low of 0.1% for the Chinese (CN300) 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 index), while the downside risk factor is only significant in the case of Australia (AU500), Canada (CA250), India (IN50), and Singapore (SG30). In fact, in overall terms, the downside risk model does not seem to be applicable to aggregate equity indices and downside risk gives only a marginal contribution to the overall model performance. This can also be understood in the light that equity indices are aggregated and any downside risk is reduced by the diversification effect. In Panel C, we extend the CAPM to include a single sentiment risk factor based on a portfolio of long-positive/short-negative sentiment indices (PMNSNT-CAPM). The results show that sentiment is seldom statistically significant (apart from the cases of Brazil BR50, Switzerland CH20, and Spain ES35), and when it is, the contribution of sentiment to the overall explained variation hardly exceeds 5%. The exception is China CN300 which shows a high relative contribution of 71.2% despite being insignificant and resulting in a negligible R^2 of 0.4%. 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., our sentiment-augmented model fails to capture any additional variation in excess returns. The adjusted R^2 shows a small improvement compared to Panels A and B for models implying a precisely estimated sentiment factor. We conclude that sentiment as a single risk factor based on a long-positive/short-negative sentiment-sorting of equity indices fails to provide a meaningful improvement of the fit vs. a traditional CAPM.

Table [2] about here

In Panel D, we estimate the time series regressions using three distinct uncorrelated sentiment factors representing mimicking portfolios of equities with positive, negative, and neutral sentiment (SNT-CAPM). The three sentiment factors are mostly significant at the 1% level. The absolute

[19] The low absolute and insignificant intercepts make more sophisticated methods like GRS tests proposed in Gibbons et al. (1989) redundant and we will limit our discussion to the estimates of absolute α.

alphas are smaller or equal vs. the CAPM, indicating that the sentiment-augmented model is able to capture variation in excess returns left unexplained by the traditional model. The intercepts are all insignificant (except for the Indian IN50 index) 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 85.2% 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 uncorrelated portfolios of positive, negative, and neutral sentiment assets conditioning out the effects of the market risk factor according to our orthogonalization procedure. The relative importance analysis also emphasizes that positive sentiment provides the highest relative contribution, after market risk.[20]

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.[21] If we compute the correlation 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 -0.63: the higher the R^2 from the CAPM, i.e., the more efficient the market, the less important are the sentiment factor-mimicking portfolios.[22] 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 ($M2$).[23] A high value of the variance ratio statistic leads to a rejection of the null of market informational efficiency. We apply variance ratio tests at lags $k = 2, 5, 10$ as suggested in Morck et al. (2000) and Bramante et al.

[20] This is of course partially due to the sequence of orthogonalization with positive abnormal sentiment being the primary factor.

[21] 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.

[22] Due to the non-normality of our data we apply Spearman's rank correlation coefficient.

[23] 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.

(2013a,b). Next, we compute the correlations between the aggregated, relative importance of all sentiment variables on top of the market risk premium against all sample values of the variance ratio metrics $M1(k)$ and $M2(k)$ at different lags. All correlations are positive and peak at a value of 0.39 for the $M2$ statistic at lag 2 ($M2(2)$). This correlation is significant at the 10% level. The results support our conjecture that sentiment risk matters more for less efficient markets.[24]

Next, we estimate a Fama-French five-factor, sentiment-augmented 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 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 the portfolio formation rules 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

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

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 are already generously diversified portfolios. On the one hand, any sensitivity to traditional company-specific attributes should be averaged out and removed at 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 with the sentiment factors to be able to disentangle any sentiment effects after any other (by now) classical FF5 factors have been considered. Table A.3 in the 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 (13) 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 5-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).[25] We add this additional factor to estimate the ultimate SNT-RSI-FF5 model:

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

where $\beta_{CAPM,i}$ measures the sensitivity of asset i to the market factor, $\beta_{SMB,i}$ to the size factor,

[25] 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., the sample size, and not by the number of periods in which the gains/losses occur.

$\beta_{HML,i}$ 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 defined.

Table 3 reports the estimation results for the Fama-French five-factor models with and without sentiment according to Equation (16) in Panels A and C, respectively. The coefficients attached to the sentiment mimicking returns remain mostly 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 B. The PMNSNT-CAPM model confirms that a single sentiment factor is unable to capture the variability in market sentiment and hence 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, a significant increase in the model's fit is recorded. Panel D of Table 3 shows that this factor is always significant and its contribution to the explained variation is usually slightly lower than sentiment. We conclude that a single sentiment factor measured as the return of a long-positive/short-negative sentiment portfolio further 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 used in our linear specifications. The range of valence with average, abnormal positive and abnormal negative sentiment, is captured by significant positive coefficients associated to single-sorted factor mimicking portfolios. We also learn that none of the sentiment sorts simply captures momentum, as they all remain significant with estimated coefficients mostly unchanged, but that momentum represents a meaningful addition 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, depending on its directional deviation from its long-term mean, sentiment can lead to positive or negative excess performance in international equity 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 global sentiment risk. In fact, we compute a separate risk premium for positive, negative, and neutral changes in sentiment. We follow the two-stage regression methodology in 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 and heteroscedasticity. 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 sample correlation between our negative sentiment-based portfolio and the downside risk implied by the MSCI World index is statistically significant and positive at 0.56.[26]

To replicate Lettau's model, the time series regressions of the first stage in the FMB procedure yield the point estimates of the market $\hat{\beta}_i$ and downside risk betas $\hat{\beta}_i^-$ as in 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.[27] This two-stage approach of using

[26]Lettau et al. (2014) report that their extension of the CAPM to account for the 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 estimating the price of sentiment risk derived from a search-based market sentiment measure such as the RMI indicator.

[27]We use an adjusted version due to simultaneous estimation in the first stage. Lettau et al. (2014) use two

estimated betas of the first stage as variables in the second introduces a generated regressor bias which we correct using the adjustment for the standard errors in Shanken (1992):

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

where $\bar{r}_i^e$ and $\bar{r}_m^e$ are the average excess returns of the test assets and of the market, respectively. ϵ_i are the pricing errors and N is the number of test assets. $\hat{\beta_i^-}$ is the exposure to downside risk estimated 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 analyses. 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.

For our sentiment-augmented model, the second stage regression is

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

where $r_{i,t}^e$ 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 positive, negative, and neutral sentiment mimicking portfolios at time t, respectively. $\lambda_{s(-)}$, $\lambda_{s(0)}$, and $\lambda_{s(+)}$ are the prices of risk for positive, negative, and neutral 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, full-sample betas for the market, $s(-)$, $s(0)$, and the $s(+)$ factors.[28] We deviate from Lettau et al. (2014), who assume the price of market risk to be correctly priced and to equal the sample period mean excess return of the MSCI global index. In fact, we also price the market return in the second-stage regression. However, we deviate from Lettau's approach by including an intercept term and thus we do not impose the restriction that an asset with zero beta has a zero excess return. We find this rather restricting hypothesis of Lettau is not

separate estimations for $\hat{\beta}_i$ and $\hat{\beta_i^-}$, while we estimate them jointly for better comparison with the sentiment-based approach.

[28] Lettau et al. (2014) use separate regressions for the first stage to avoid multicollinearity among downside risk and overall market risk that is made likely by the fact that both the market and the downside risk factors are measured by transformations of excess global market returns. This is not a concern in the case of our sentiment factors, because of the orthogonalization that has been applied to them.

backed by the literature (see, e.g., Cochrane, 2009). As in Fama and French (1992), we regress the indices directly on the factors, not on the long-short mimicking portfolios. This is justified by the fact that the indices represent diversified portfolios by definition, even though they tend to be inevitably biased towards large caps. This procedure may presumably lead to more noisy estimators with higher standard errors, but it seems more appropriate in the case of our empirical exercise.

In order to reduce the omitted variable bias and address a concern that sentiment might only measure omitted statistical properties of excess equity returns, such as idiosyncratic volatility $iv_{i,t}$, skewness $is_{i,t}$, or kurtosis $ik_{i,t}$ that are left unexplained by the "fundamental" factors in either the CAPM or FF5, we additionally control for such statistical features in our implementation of the FMB methodology.[29] Following Boyer et al. (2010), we define these control variables as:

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

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

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

where $\epsilon_{i,d}$ is the residual of either the CAPM or the FF5 model. Given that our study contains an application to international equity returns, we also control for the effects of major global currencies. We therefore use the U.S. Dollar index returns, which represents a basket of currencies like EUR, JPY, GBP, CAD, SEK, and CHF to the USD base. The full specification also controls for momentum.

All in all, we compare ten different models: i) a standard CAPM, used as a naive benchmark, ii) a DR-CAPM model to price the downside risk premium following Lettau et al. (2014), iii) a standard Fama-French five-factor model FF5, iv) a PMNSNT-CAPM model, that augments the CAPM model by adding a long-positive/short-negative sentiment factor, v) a PMNSNT-FF5 which includes the PMNSNT factor to a Fama-French five-factor specification, vi) a PMNSNT-FF5x model that additionally controls for $iv_{i,t}$, $is_{i,t}$, $ik_{i,t}$, and the USD index, vii) a SNT-CAPM

[29] Because these properties are idiosyncratic factors that should not be priced in the cross-section, we do not include them in the second-stage, but only in the time-series regression. A similar rationale applies to momentum which is why we abstain from estimating a separate model.

that prices positive, neutral, and negative sentiment separately, viii) a SNT-FF5 Fama-French five-factor specification including three sentiment factors, ix) a SNT-FF5x model that also incorporates the control variables, and finally x) a SNT-RSI-FF5x model that encompasses all fundamental, control variables, disaggregated sentiment and also momentum factors.

In Table 4, the R^2 of the CAPM is 25.42%, supported by a price of market risk of 0.12%, i.e. the average weekly excess percentage return for the MSCI world.[30] The downside risk premium is estimated to be 0.09% and it is highly significant. This result is much smaller than what reported by Lettau et al. (2014), but this may be explained by the diversification effect of equity indices compared to single stocks and other asset classes. Major international equity indices are themselves aggregated and downside risk might already be reduced by diversification. We are also employing a different estimation window vs. Lettau et al. (2014), and this may cause some discrepancy. The explained variation is 28.27%, slightly higher than the CAPM. Estimates of the Fama-French model show that the size (SMB) and investment (CMA) factors do not yield a positive risk premium in contrast to the market, value (HML) and profitability (RMW) factors. Global equity indices select the largest companies with the largest investment outlays and because these companies represent the majority of the indices, the related size and investment factors may not be separately priced. We also observe that the market premium is 0.22%, implying a higher price in the cross-section vs. the average weekly excess return on the MSCI World. The explained variation is 38.46% and it is significantly higher than the CAPM-based benchmarks. With 41.63%, the PMNSNT-CAPM model exceeds the cross-sectional R^2 of the FF5 model, which remains stable if the five Fama-French factors are added. Market risk is more highly priced in the cross-section as already observed for the FF5 model. We note the positive and significant risk premia of the PMNSNT factor at 0.15%. If we add the control variables, the estimated premium and explained variation remain both stable. Those, the proposed, mostly idiosyncratic, control variables are not priced in the cross-section but also do not change the effect of our global sentiment factor. Yet, the Sentiment-CAPM including disaggregated sentiment indicators (SNT-CAPM), performs remarkably better than the CAPM, DR-CAPM, FF5, PMNSNT-CAPM, and PMNSNT-FF5(x) models and imply a significantly negative sentiment risk premium of -0.03% for negative sentiment. The negative risk premium for negative sentiment is in line with our results from the portfolios sorts. Negative sentiment does not seem to be a compensated factor for investors. Positive sentiment however

[30]The market risk premium is assumed to be correctly priced.

returns a weekly average excess return of 0.06% and, as such, compensates investors for bearing such a risk. Neutral sentiment appears to be also negatively priced with a -0.02% premium. This is contrary to our expectations of an insignificant price although the estimated premium is effectively close to zero in economic terms. If we control for the usual "fundamental factors" or for factors that reflect the statistical properties of returns, the estimated sentiment premia keep the same sign. Interestingly, with the introduction of the higher moment factors in the first stage, the absolute values of the estimated premia increase for all the sentiment factors that increase to levels similar to the market risk premium. In terms of explained variation, we observe a real jump to 56.84% when the three sentiment factors are added. Additional fundamental and control variables do not have a significant effect, neither does momentum. The adjusted R^2 increases from 56.84% for the simple SNT-CAPM model to 57.18% for both the SNT-FF5 and for the fully-specified SNT-FF5 with controls. The adjusted R^2 even decreases slightly to 56.16% when momentum is included and both negative and neutral sentiment are priced negatively with a premium of -0.07%, while momentum itself is positively priced, as expected. 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.[31]

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 1998-2017 period in sub-samples to validate our initial intuition that sentiment is more important during crisis periods, because classical asset pricing 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

[31]For robustness, we also estimated the SNT-FF5x model with each sentiment factor separately, i.e., when the second stage FMB regression only accounts for one single sentiment factor at the time. When we only price positive sentiment, the risk premia remains the same at 0.11% with a reduced R^2 of 46.50%; when we only consider neutral sentiment, the coefficient remains negative with -0.02% and cross-sectional R^2 of 46.90%. Pricing negative sentiment in isolation, leads to a switch in the sign of the premium to positive 0.04% with R^2 of 43.20%. That means that negative sentiment bears some positive risk premia if positive sentiment is neglected. We trace this back to the high variability in the negative sentiment factor mimicking portfolio and to a significant correlation between the time series of negative and positive sentiment beta of 0.68 from the first-stage regression of the SNT-CAPM model. This correlation increases to 0.78 in the case of the SNT-FF5x model. Other pairwise correlations are insignificant at the conventional 5% level.

two different sources covered by MarketPsych, i.e., social media and news, in order to investigate which channel may be more relevant to the pricing of risk. Given the efficient market hypothesis by which all information is instantaneously reflected in market prices, the weekly granularity of our observations, and the orthogonalization of the variables that we have enforced, we expect that social media based sentiment may either contain more novel information or proxy for the prevalence of private investors who are more exposed to sentiment and exuberance, compared to widely available public news. Fourth, we apply afresh the Fama-MacBeth procedure but refrain from any orthogonalization in order to prove that this procedure was indeed needed to support a correct interpretation of the risk premia due to the considerable collinearity between sentiment factors.

Tests on an Extended Set of Equity Indices. While earlier we used only 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. equity indices and compare them to 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 (US30), the Russell 2000 (USMID2000), that includes mid-size companies, and the technology-oriented NASDAQ 100 (USNAS100). The R^2 is slightly lower than in our earlier findings. Overall, we interpret this as confirmation that the model is also applicable to smaller companies. The reduction in the reported R^2 can be explained by 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 particular, we note the high exposure of emerging markets companies to positive sentiment which further supports our hypothesis that sentiment is more applicable to inefficient markets. For the index ranking the 101st-350th size-ranked, UK-based, London stock exchange (LSE) listed companies ($GBMID250$), the findings are similar to the FTSE100 (GB100) with comparable size and significance of the estimated coefficients. Overall, these robustness analyses for equity indices confirm our main findings and in fact occasionally 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.

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 but also have a similar number of observations in each phase. 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 approximately doubles the average R^2 in all market phases. The single sentiment models, either PMNSNT-CAPM or PMNSNT-FF5, only reveals marginal contribution of sentiment across all sub-periods. The period 2007-2011 is marked by a high average R^2 across all international markets. This confirms our hypothesis that sentiment is a priced risk factor, which tends to become stronger during financial crises. This result is consistent with earlier evidence in García (2013) on the impact of news on stock returns. We also note a very high contribution of sentiment to the R^2 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 models increases the explanatory power in correspondence to all market phases. The best model across all categories is the sentiment-augmented FF5. It seems that sentiment became more relevant in 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 to a better coverage of financial markets in both the news and social media channels.

In addition to our naïve classification of bull and bear markets and in consideration of the dominance of the U.S. stock markets in international equity trading, we also apply the classical categorization of recessions offered by the National Bureau of Economic Research (NBER) and show the results in Table B.3. NBER defines a recession as a significant decline in economic activity spread across the economy, lasting for at least two consecutive quarters, normally observable in real GDP, real income, employment, industrial production, and wholesale-retail sales. According to this methodology, our dataset comprises three expansionary/bull markets in Panel A (Jan 1998 - Feb 2001), Panel C (2001 Dec - Nov 2007) and Panel E (Jul 2009 - Dec 2017) as well as two recession/bear markets in Panel B (Mar 2001 - Nov 2001) and Panel D (Dec 2007 - Jun 2009). First, improvements in the model performance measures are achieved by splitting sentiment into its positive, negative, and neutral notion, independently of market cycle classification. This means that disaggregated sentiment improves standard asset pricing models in both bullish and bearish markets. Second, if we compare the two recessions, we observe that while the overall goodness-of-fit measures are on similar levels, the relative importance of sentiment significantly increases during the financial crisis in 2007-2009. This confirms previous findings of improved sentiment measures with the introduction of social media in 2006 that have increased news coverage and have led to enhancements in the language processing engine applied by MarketPsych. Interestingly, if we apply the same comparison to the three bull markets subperiods, the relative importance of sentiment diminishes in the recent bull cycles. These findings suggest that the pricing effect of sentiment may change over time. Third, if we consequently compare the latest bull-bear phases pair with the previous one, we observe that the effect of sentiment seems to have changed. While sentiment was more dominant in the 2001 - 2007 bull market compared to the previous, arguably short bear market over 8 months in 2001, this relationship changes for the financial crisis and the subsequent long bull 2009-2017 regime. These remarks motivate additional research on the time-varying pricing dynamic effects of sentiment. In unreported results (available upon request from the authors), we observe that the pricing of positive and negative sentiment is distorted during recessions, indicating that the pricing mechanism of sentiment turns in such a way so that neither positive nor negative sentiment is compensated while it remains true that there is a reward to investing in a long-positive/ short-negative sentiment portfolio. Moreover, in bull markets the findings from the full-sample analysis are even more pronounced with negative sentiment being even more negatively and positive sentiment even more positively priced. As such, especially in bull markets it seems beneficial for investors to be long in positive and short in negative sentiment assets/markets.

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 conjecture that social media may be more used by retail investors, whereas news may be preferred by institutional traders for their investment decisions, because they are generally presumed to be less volatile and more reliable. Therefore, we also estimate our linear factor models separately for news versus social media sentiment risk in order to investigate whether there is 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 modest, though. The absolute intercepts do not show any major differences in these statistics. The average relative importance of sentiment is higher for social media-only sentiment. Social media-only sentiment also carries the highest average coefficient of determination when compared to news-only sentiment. This does not only apply to the 3-factor sentiment CAPM and FF5 specifications but also to the single factor sentiment-augmented models. However, the absolute effect of the PMNSNT factor remains negligible. The overall results are shown in Table B.4 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, these findings are consistent with our hypothesis, although we acknowledge that additional research on the differing asset pricing implications of news vs. social media appears to be called for.

Fama-MacBeth without Orthogonalization of factors. When computing the sentiment risk premia we orthogonalized all factors in order to address a concern on correlations between variables. However, this comes with a cost that the resulting estimated risk premia may no longer be easily interpretable. We therefore checked that the orthogonalization is on the contrary essential to a correct interpretation of our results. The findings are summarized in Table B.5 in the Internet Appendix B. The empirical findings concerning the CAPM, DR-CAPM, and FF5 models remain identical as they were not affected by the orthogonalization. In the case of the PMNSNT-based models, the estimated risk premium is slightly reduced, e.g., from 0.23% to 0.21% for the extended PMNSNT-FF5x that includes control variables. Therefore, earlier results are confirmed. The estimates for models with three sentiment variables, however, change as expected, due to the correlation between the returns on the sentiment factor-mimicking portfolios. The risk premia on all the three sentiment variables turn now positive with positive sentiment risk premia being much higher than both the negative and neutral sentiment premia. We therefore emphasize that the orthogonalization of the factors is essential to capture the marginal effects of the sentiment portfolios as outlined in the theoretical framework. Overall, we treat these findings as confirmation of the importance of the orthogonalization.

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 equity 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 Baker and Wurgler's index captures investment activities like increased turnover, our sentiment anticipates investors' actions and is therefore 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 Fama and French's five-factor model. Our specifications consistently yield a better goodness-of-fit for sentiment-augmented models vs. the benchmarks. Moreover, we report that sentiment cannot be fully captured by a single risk factor, because positive, negative, and neutral deviations in sentiment are differently priced by the cross-section of international equity indices. Our time series regressions emphasize that sentiment is asset-specific and has more explanatory power for assets in less efficient markets and 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 in the presence of additional controls for idiosyncratic volatility, skewness, kurtosis, and a basket of international currencies. In summary, we report empirical evidence supporting our main hypothesis that different breadths of change in sentiment are priced differently with a positive (negative) premium for positive (negative) sentiment.

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, while yielding precisely estimated coefficients, sentiment is more relevant as a priced risk factor in the case of inefficient markets and for aggregate equity indices in the Eurozone and emerging markets. This confirms our conjecture that sentiment may play a more prevalent role in informationally inefficient markets. Second, social media-driven sentiment provides stronger signals than news-only or aggregate indicators that reflect both, indicating a potentially stronger 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 have increased however the measurable contribution of sentiment to the explained variation of various asset-pricing models. Finally, the existence of sentiment risk premia is robust to modelling additional controls for idiosyncratic risks, currency returns, and momentum.

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

Source: MarketPsych

Table A.2: 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, which is supported by additional evidence that traders collectively under-react to negative sentiment in news reports. Another study finds that market sentiment improves factor weighting in some models. In foreign exchange, news sentiment was found to influence volatility.
Optimism	There is empirical evidence that proxies for optimism correlate with positive price behavior and that bullish comments in financial social media precede higher trading volume. Optimism in earnings press releases was found correlated with future stock price activity.
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. In experimental markets, fear was found to decrease bid and increase ask prices, leading to less overall trading activity. 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.
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.
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.
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.
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. In emerging fixed income markets, releases of macroeconomic data decrease future volatility.
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. If this result transfers into larger market behavior, we expect increased trading volume during periods of high Gloom. 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.
Anger	Traders induced to feel anger in an experimental market decrease both average ask and bid prices. 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.

Source: MarketPsych

Table A.3: 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.4: Equity Indices List

This list contains the full set of international equity indices, the respective asset code and a 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 Börse 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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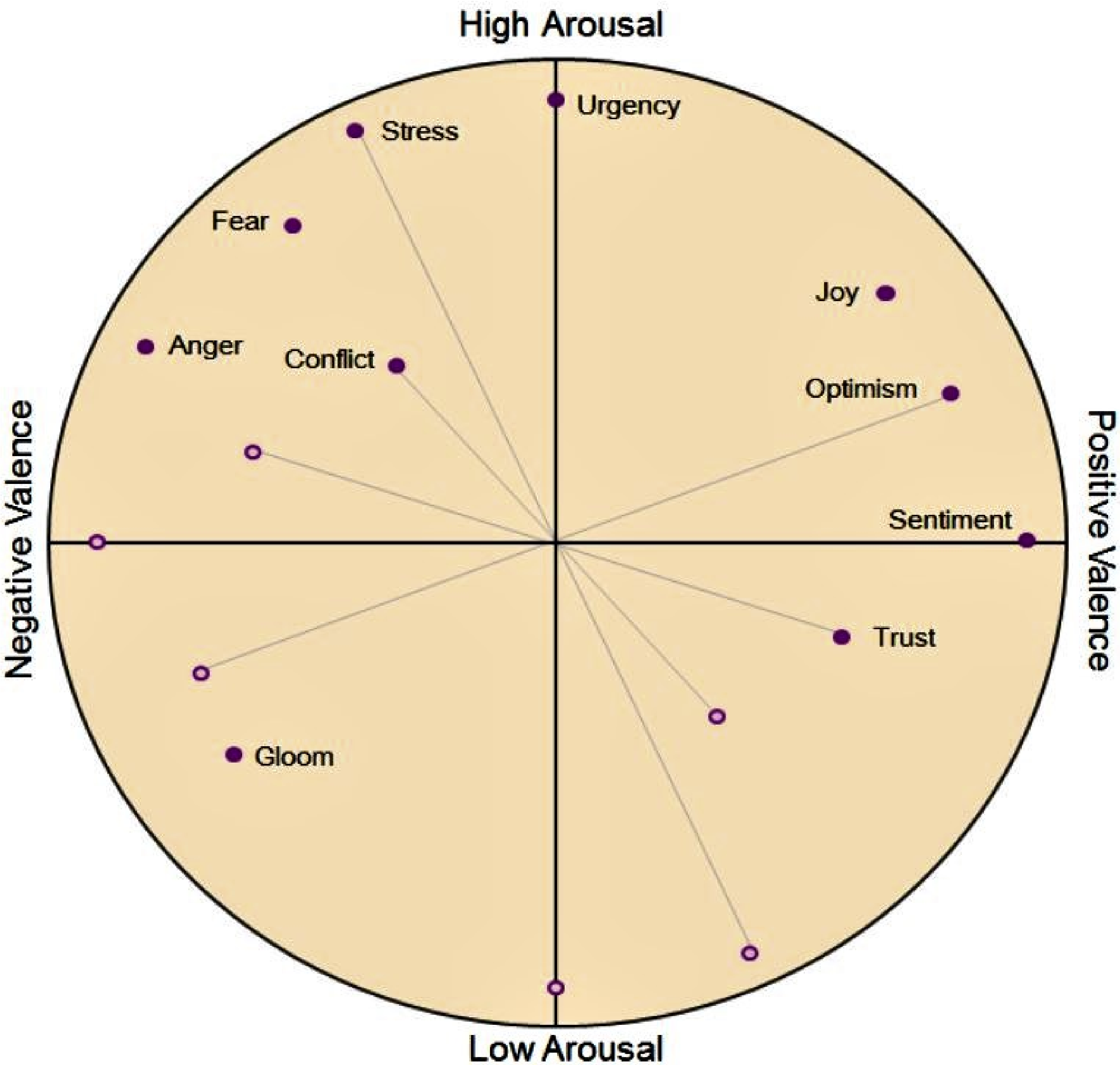
B Figures and Tables

Figure 1: 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 sentiment indicators on the affective circumplex. Each dot corresponds to the emotion's location on the circumplex, whereby RMI indicators are themselves hybrids of multiple emotions according to the original framework. The grey lines connect the positive and negative poles of matching indicators.



Source: MarketPsych

Figure 2: Example of MarketPsych's Human Language Processing System

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

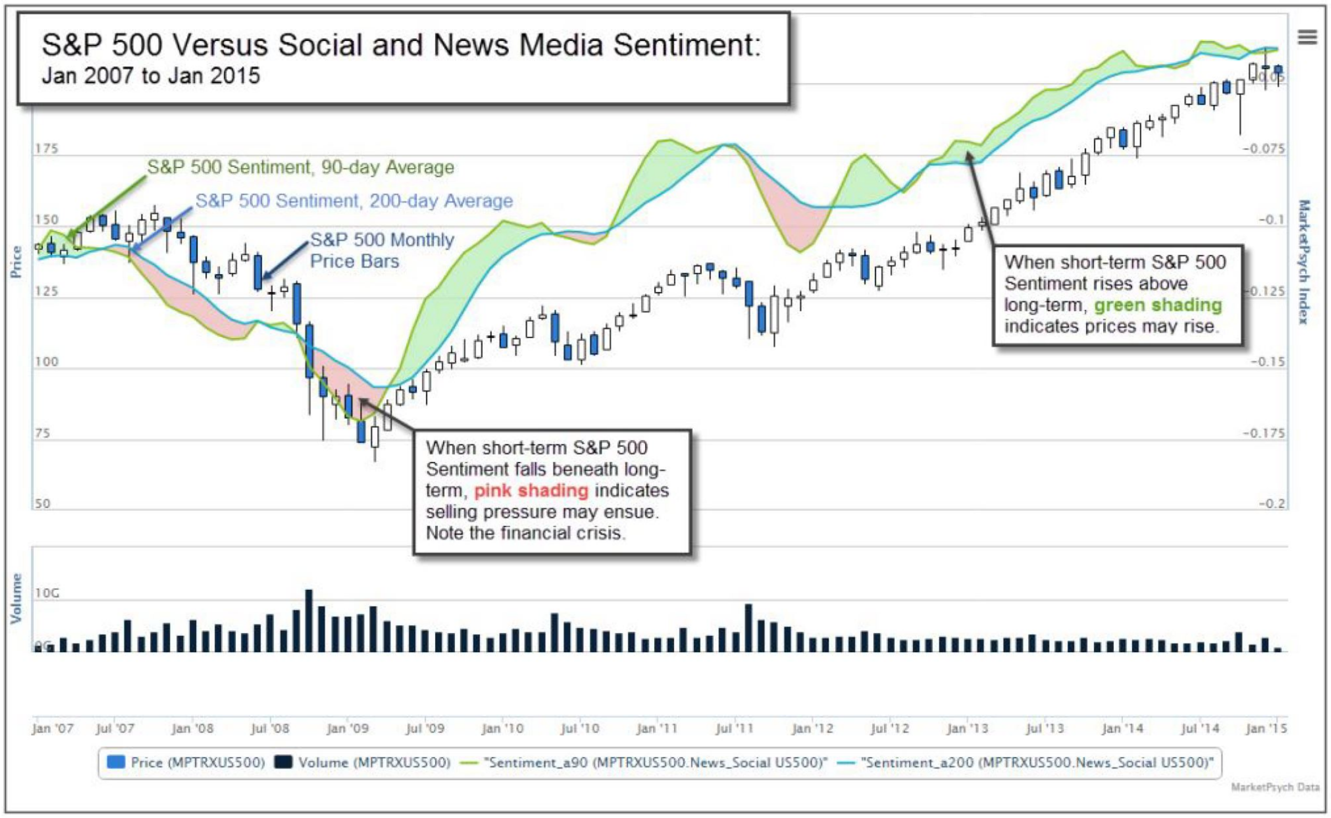
$_0$ Goldman$_{0\ (0)}$ 1 Sachs$_{1\ (1)}$ Entity 2 analysts$_{2\ (1)}$ EntityCancellationLeft EntityCancellationRight EconomicActors Economist Trader Economist(f) Trader(f) 3 expect$_{3\ (1)}$ Future Expectancy ForecastUp(f) 4 Apple$_{4\ (1)}$ AAPL Entity 5 to$_{5\ (1)}$ CurrencyComparison 6 report$_{6\ (1)}$ 7 expanding$_{7\ (1)}$ Expand Grow Increase Loose Up Expand(f) Loose(f) Up(f) 8 margins$_{8\ (1)}$ Margins PosAcct Margins(f) AccountingGood(f) Pos_Acct(f) 9 on$_{9\ (1)}$ 10 tomorrow$_{10\ (1)}$ Future 11 's$_{11\ (1)}$ 12 quarterly$_{12\ (1)}$ 13 conference$_{13\ (1)}$ 14 call$_{14\ (1)}$ 15 ··24 (10)

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 3: RMI Sentiment Indicator on S&P 500

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



Source: MarketPsych

-

Figure 4: Schematic Differences between Refinitiv MarketPsych and Baker and Wurgler

This figure visualizes the differences between the Refinitiv MarketPsych (RMI) and the Baker and Wurgler (BW) indices, showing that RMI leads BW by construction. To ease the comparison, we initialize both the RMI (solid line) and the BW (dashed line) indices at zero at $t-2$. 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 on an index at a point in time t.

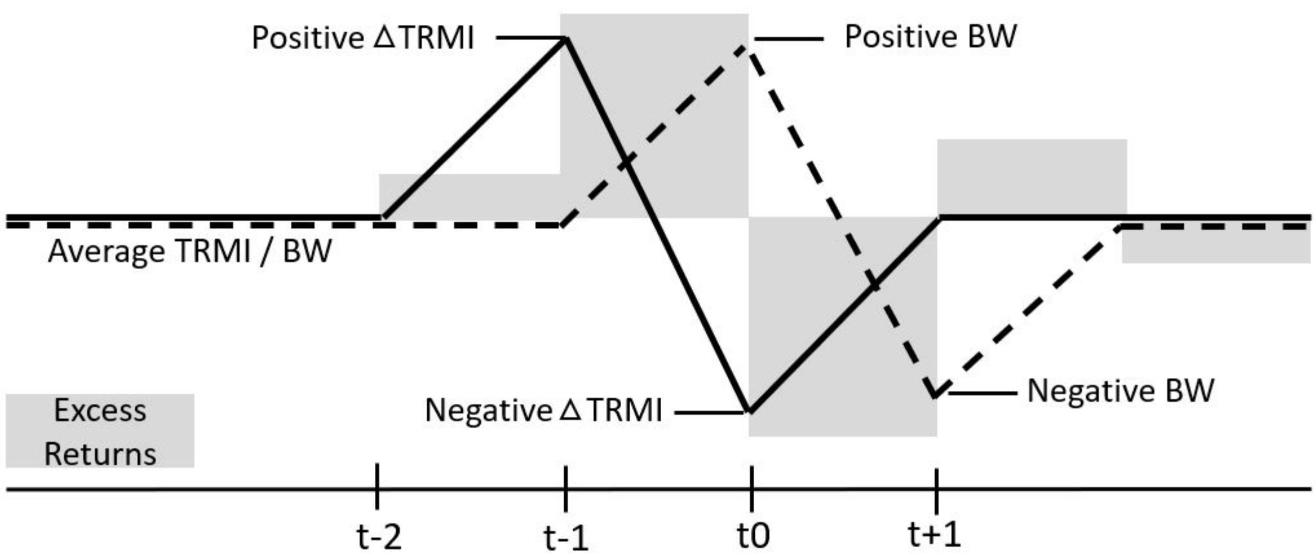


Figure 5: Time Series Plot of Refinitiv MarketPsych and Baker and Wurgler Indices for the United States

This figure plots the monthly time series of the Refinitiv MarketPsych (RMI) and Baker and Wurgler (BW) 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.

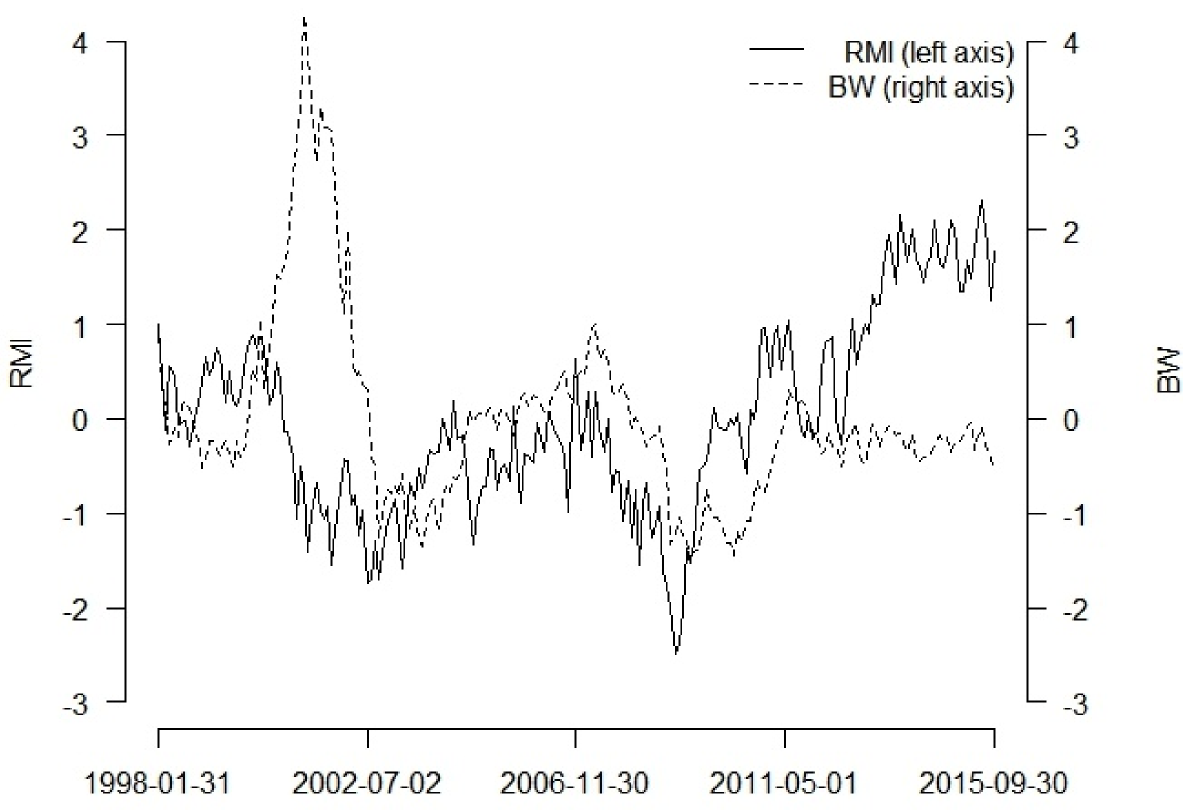


Figure 6: Comparing the R^2 of the CAPM to the Sentiment-CAPM

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 results for the CAPM and Panel B for 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.

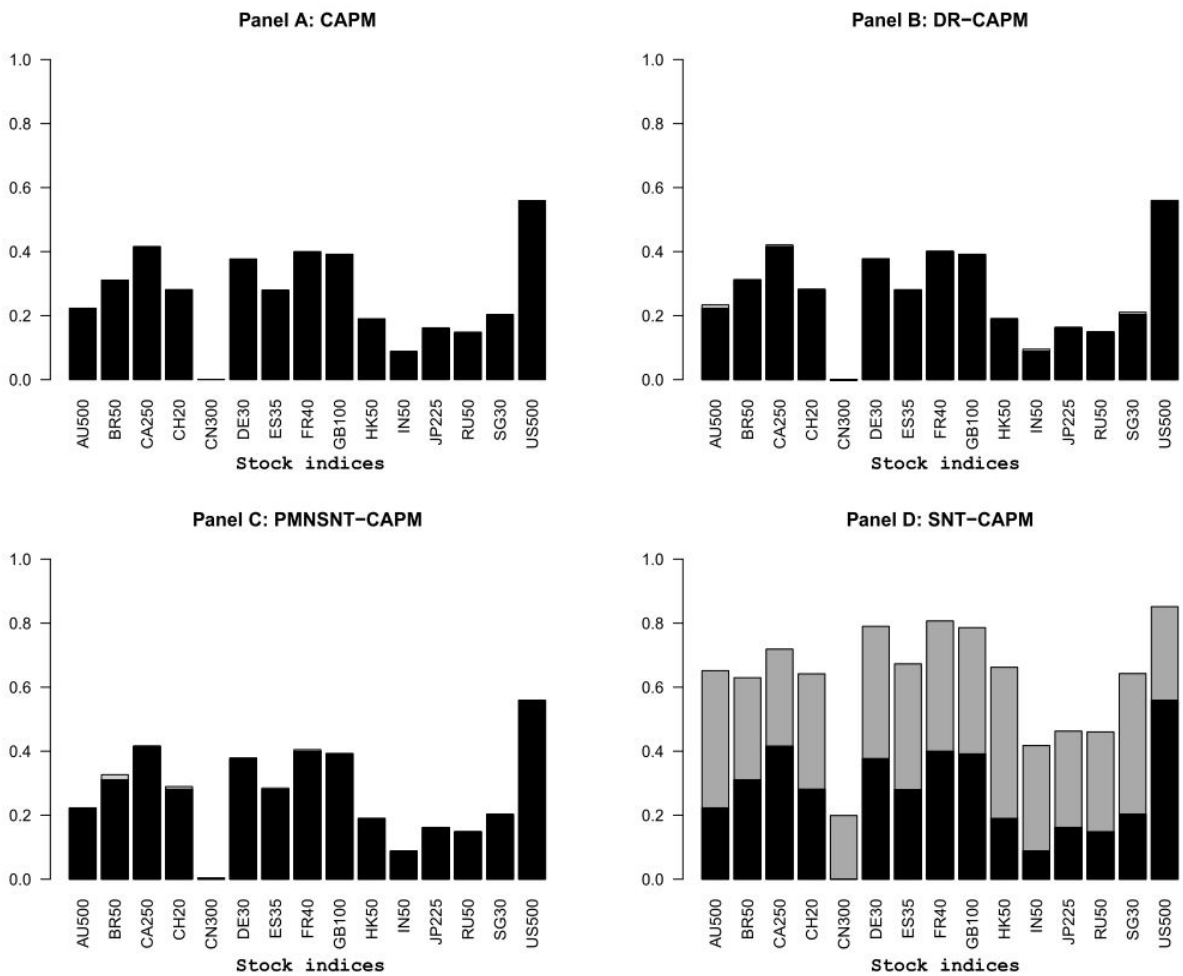


Table 1: Portfolios Sorted by Sentiment

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 stocck indices sorted based on the previous week's sentiment change. The table reports the average weekly excess percentage return and its standard deviation for each sort in columns 1 and 2 along with the corresponding average sentiment level in column 3 and the related standard deviation in column 4. Sort $s(-)$ ($s(+)$) contains the indices with the most negative (positive) sentiment change. 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.

	Return Mean	Return SD	Sentiment Mean	Sentiment SD	$s(-)$	$s(0)$	$s(+)$
$s1(-)$	-0.0019	2.2264	-7.6984	3.7282		0.1952	0.0043***
$s2(0)$	0.1186	2.0102	-0.6543	3.4942			0.0914*
$s3(+)$	0.2731	2.1644	6.9015	4.5243			

* 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 and the adjusted R^2. In the case of models including sentiment, we also report the relative importance indicator for each coefficient, which estimates its relative contribution to the total explained variation. The regressions are estimated for each equity index individually on weekly returns from 1998 to 2017.

	AU500	BR50	CA250	CH20	CN300	DE30	ES35	FR40	GB100	HK50	IN50	JP225	RU50	SG30	US500
Panel A: CAPM															
Intercept	0.0002	0.0016*	0.0005	0.0001	0.0024	0.0002	0.0002	0.0002	0.0002	0.0004	0.0018*	0.0002	0.0007	-0.0001	0.0004
	(0.0004)	(0.0009)	(0.0004)	(0.0005)	(0.0019)	(0.0006)	(0.0006)	(0.0005)	(0.0003)	(0.0008)	(0.0009)	(0.0008)	(0.0018)	(0.0006)	(0.0003)
MRP	0.3447***	0.6933***	0.5391***	0.4938***	0.0749	0.7184***	0.5977***	0.6753***	0.5340***	0.5406***	0.3724***	0.4942***	0.8444***	0.4306***	0.6335***
	(0.0217)	(0.0417)	(0.0285)	(0.0510)	(0.1175)	(0.0427)	(0.0602)	(0.0476)	(0.0307)	(0.0395)	(0.0445)	(0.0361)	(0.0880)	(0.0344)	(0.0229)
Adj. R^2	22.30	31.09	41.60	28.13	0.08	37.69	27.96	40.00	39.16	19.01	8.78	16.18	14.83	20.27	55.90
Panel B: DR-CAPM															
Intercept	0.0010	0.0021	0.0010	0.0007	0.0021	0.0006	0.0008	0.0008	0.0004	0.0001	0.0026**	0.0008	0.0012	0.0002	0.0007
	(0.0006)	(0.0011)	(0.0005)	(0.0006)	(0.0020)	(0.0008)	(0.0009)	(0.0007)	(0.0005)	(0.0010)	(0.0011)	(0.0009)	(0.0020)	(0.0008)	(0.0004)
DR.Intercept	0.0038	0.0053	0.0044	-0.0031	0.0015	-0.0049	-0.0074	-0.0061	-0.0004	0.0065	0.0091*	0.0050	0.0122	0.0098***	0.0023
	(0.0030)	(0.0049)	(0.0032)	(0.0035)	(0.0121)	(0.0036)	(0.0041)	(0.0033)	(0.0028)	(0.0042)	(0.0047)	(0.0051)	(0.0123)	(0.0031)	(0.0025)
MRP	0.2660***	0.6314***	0.4813***	0.4464***	0.0951	0.6894***	0.5647***	0.6409***	0.5169***	0.5533***	0.2738***	0.4286***	0.7675***	0.3781***	0.6029***
	(0.0505)	(0.0920)	(0.0518)	(0.0671)	(0.1191)	(0.0580)	(0.0788)	(0.0640)	(0.0465)	(0.0933)	(0.0876)	(0.0834)	(0.1210)	(0.0802)	(0.0369)
$DR \times MRP$	0.2393**	0.2283	0.2082**	0.0364	-0.0121	-0.0383	-0.0816	-0.0511	0.0284	0.1054	0.3887**	0.2370	0.4047	0.3018*	0.1096
	(0.0987)	(0.1314)	(0.0843)	(0.0868)	(0.3156)	(0.0944)	(0.1266)	(0.0814)	(0.0621)	(0.1615)	(0.1630)	(0.1744)	(0.3513)	(0.1398)	(0.0676)
Adj. R^2	23.35	31.26	42.09	28.24	-0.22	37.70	28.11	40.13	39.08	19.01	9.51	16.38	14.97	21.05	55.98
RI-DR-Int	26.49	21.87	23.45	26.96	13.44	25.00	26.98	25.94	23.21	18.73	23.23	23.71	21.20	19.80	22.71
RI-MRP	69.45	77.07	75.24	72.99	86.41	74.98	72.86	74.01	76.76	80.94	67.97	74.29	76.78	75.85	77.02
$RI - DR \times MRP$	4.07	1.06	1.31	0.05	0.14	0.03	0.16	0.05	0.03	0.34	8.80	2.00	2.01	4.35	0.27
Panel C: PMNSNT-CAPM															
Intercept	0.0002	0.0015*	0.0005	0.0001	0.0025	0.0002	0.0003	0.0003	0.0002	0.0004	0.0018*	0.0002	0.0007	-0.0001	0.0004
	(0.0004)	(0.0009)	(0.0005)	(0.0005)	(0.0019)	(0.0006)	(0.0006)	(0.0005)	(0.0003)	(0.0008)	(0.0009)	(0.0008)	(0.0020)	(0.0007)	(0.0003)
MRP	0.3448***	0.7080***	0.5390***	0.4932***	0.0653	0.7180***	0.5971***	0.6747***	0.5338***	0.5407***	0.3722***	0.4943***	0.8436***	0.4306***	0.6335***
	(0.0211)	(0.0427)	(0.0285)	(0.0430)	(0.1194)	(0.0401)	(0.0572)	(0.0443)	(0.0298)	(0.0402)	(0.0467)	(0.0347)	(0.1035)	(0.0342)	(0.0231)
PMNSNT	0.0096	-0.3286**	-0.0070	-0.1490*	0.2197	-0.0980	-0.1486*	-0.1317	-0.0620	0.0127	-0.0534	0.0286	-0.1099	0.0230	0.0087
	(0.0456)	(0.1274)	(0.0370)	(0.0734)	(0.2053)	(0.0703)	(0.0756)	(0.0704)	(0.0485)	(0.0976)	(0.0967)	(0.1241)	(0.2136)	(0.0832)	(0.0487)
Adj. R^2	22.23	32.66	41.54	28.95	0.42	37.87	28.49	40.47	39.28	18.93	8.76	16.12	14.83	20.21	55.86
RI-MRP	99.98	96.56	99.99	96.84	28.82	99.31	97.82	98.63	99.49	99.99	99.24	99.91	99.32	99.93	100.00
RI-PMNSNT	0.02	3.44	0.01	3.16	71.18	0.69	2.18	1.37	0.51	0.01	0.76	0.09	0.68	0.07	0.00
Panel D: SNT-CAPM															
Intercept	0.0002	0.0013	0.0005	0.0001	0.0024	0.0002	0.0003	0.0003	0.0002	0.0005	0.0018**	0.0003	0.0008	-0.0001	0.0004
	(0.0003)	(0.0007)	(0.0003)	(0.0005)	(0.0017)	(0.0005)	(0.0005)	(0.0004)	(0.0003)	(0.0006)	(0.0007)	(0.0007)	(0.0015)	(0.0004)	(0.0003)
MRP	0.3421***	0.7002***	0.5361***	0.4899***	0.1164	0.7134***	0.5936***	0.6707***	0.5305***	0.5368***	0.3691***	0.4913***	0.8373***	0.4386***	0.6303***
	(0.0173)	(0.0308)	(0.0192)	(0.0312)	(0.1027)	(0.0253)	(0.0400)	(0.0274)	(0.0164)	(0.0242)	(0.0427)	(0.0321)	(0.0940)	(0.0264)	(0.0161)
$s(+)$	0.5676***	0.8416***	0.5267***	0.6008***	0.8317***	0.8425***	0.8111***	0.7551***	0.6031***	1.0429***	0.8694***	0.8335***	1.4830***	0.8124***	0.5073***
	(0.0296)	(0.0494)	(0.0180)	(0.0309)	(0.1336)	(0.0422)	(0.0321)	(0.0269)	(0.0193)	(0.0409)	(0.0716)	(0.0409)	(0.0975)	(0.0336)	(0.0196)
$s(-)$	0.2845***	0.7150***	0.2820***	0.4818***	0.0974	0.5497***	0.5910***	0.5425***	0.3843***	0.5285***	0.5134***	0.4015***	0.8925***	0.3862***	0.2540***
	(0.0334)	(0.0944)	(0.0296)	(0.0653)	(0.1654)	(0.0666)	(0.0533)	(0.0524)	(0.0344)	(0.0652)	(0.0925)	(0.1301)	(0.2004)	(0.0528)	(0.0354)
$s(0)$	0.4361***	0.1348	0.5242***	0.5959***	0.8826***	0.8127***	0.4860***	0.6929***	0.5780***	0.4524***	0.3062**	0.3117	0.2558	0.2788***	0.6311***
	(0.0521)	(0.1293)	(0.0540)	(0.0697)	(0.2620)	(0.0580)	(0.0691)	(0.0549)	(0.0541)	(0.1003)	(0.1491)	(0.2133)	(0.2842)	(0.0848)	(0.0521)
Adj. R^2	65.16	62.95	71.89	64.17	19.90	79.01	67.28	80.69	78.61	66.21	41.75	46.27	46.02	64.25	85.16
RI-MRP	34.00	49.61	57.55	43.50	2.09	47.40	41.30	49.27	49.51	28.57	20.95	34.80	31.98	32.21	65.32
RI-$s(+)$	52.96	38.20	31.44	36.81	77.12	37.32	43.61	35.25	36.15	61.21	65.80	56.95	56.98	59.11	23.94
RI-$s(-)$	6.78	11.91	4.66	12.32	2.00	8.22	11.98	9.45	7.59	7.99	11.71	6.72	10.74	6.99	3.11
RI-$s(0)$	6.25	0.28	6.35	7.36	18.78	7.05	3.12	6.03	6.75	2.23	1.54	1.53	0.29	1.69	7.63

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

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). 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). Panel D incorporates a momentum factor RSI (SNT-RSI-FF5). 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. We also report the relative importance indicator for each coefficient, which estimates its relative contribution to the total explained variation. The regressions are estimated for each equity index individually on weekly returns from 1998 to 2017. The table is shortened to the important variables for better accessibility.

	AU500	BR50	CA250	CH20	CN300	DE30	ES35	FR40	GB100	HK50	IN50	JP225	RU50	SG30	US500
Panel A: FF5															
Intercept	0.0002	0.0017	0.0005	0.0001	0.0027	0.0002	0.0002	0.0003	0.0002	0.0005	0.0018	0.0002	0.0008	-0.0001	0.0004
	(0.0004)	(0.0008)	(0.0004)	(0.0005)	(0.0018)	(0.0006)	(0.0006)	(0.0005)	(0.0004)	(0.0007)	(0.0009)	(0.0007)	(0.0016)	(0.0006)	(0.0003)
MRP	0.3476***	0.6464***	0.5389***	0.4957***	0.0483	0.7182***	0.5999***	0.6762***	0.5350***	0.5423***	0.3764***	0.4979***	0.8514***	0.4325***	0.6333***
	(0.0232)	(0.0460)	(0.0290)	(0.0498)	(0.1090)	(0.0448)	(0.0627)	(0.0510)	(0.0325)	(0.0416)	(0.0424)	(0.0359)	(0.0726)	(0.0350)	(0.0222)
SMB	0.4896***	0.5997***	0.4549***	0.1685	0.9096***	0.4141***	0.4412***	0.3115***	0.1690***	0.7049***	0.7773***	0.7841***	1.0597***	0.6394***	0.1737**
	(0.0531)	(0.1242)	(0.0454)	(0.0789)	(0.1735)	(0.0776)	(0.0779)	(0.0666)	(0.0538)	(0.1099)	(0.1036)	(0.0954)	(0.1640)	(0.0987)	(0.0643)
HML	0.1228**	0.2728	-0.0294	0.1145	0.0203	0.0001	0.2128**	0.0793	0.0509	0.0697	0.1383	0.1622	0.2932	0.1738	-0.0090
	(0.0448)	(0.1655)	(0.0601)	(0.0770)	(0.2560)	(0.0910)	(0.0747)	(0.0767)	(0.0548)	(0.1028)	(0.1368)	(0.1015)	(0.1681)	(0.0883)	(0.0600)
RMW	0.1081	0.0768	-0.0568	-0.0288	-0.1425	-0.2953*	-0.4332**	-0.1766	0.0845	-0.2306	-0.0475	-0.1125	-0.1566	-0.0278	-0.1296
	(0.0906)	(0.1940)	(0.0833)	(0.1152)	(0.3792)	(0.1353)	(0.1575)	(0.1201)	(0.0912)	(0.1704)	(0.1532)	(0.1355)	(0.2337)	(0.1182)	(0.0830)
CMA	-0.2885***	-0.5191	-0.5826***	-0.0538	-0.1656	-0.4634***	-0.4574**	-0.3638*	-0.2321*	-0.5057**	-0.1336	-0.3428	-1.4687***	-0.5347***	-0.1608
	(0.0738)	(0.2349)	(0.0929)	(0.1723)	(0.3840)	(0.1491)	(0.1560)	(0.1498)	(0.0973)	(0.1718)	(0.1648)	(0.1566)	(0.2932)	(0.1415)	(0.0777)
Adj. R^2	30.38	34.85	48.96	28.68	2.99	40.79	32.76	42.09	40.11	24.91	14.50	22.85	21.21	28.65	56.76
RI-MRP	73.40	75.43	84.59	97.48	3.97	91.83	84.99	94.64	97.20	75.72	60.10	70.51	69.53	70.40	98.12
RI-SMB	21.28	9.47	8.67	1.56	93.08	4.36	6.68	2.84	1.33	18.69	37.85	25.68	15.69	21.68	1.01
RI-HML	1.58	11.11	0.16	0.82	0.76	0.04	1.79	0.16	0.10	0.15	1.41	1.26	1.25	2.02	0.06
RI-RMW	0.41	1.97	0.11	0.04	0.57	1.21	3.28	0.53	0.13	1.11	0.11	0.33	0.24	0.02	0.35
RI-CMA	3.32	2.02	6.47	0.09	1.61	2.55	3.26	1.84	1.24	4.33	0.52	2.22	13.29	5.88	0.46
Panel B: PMNSNT-FF5															
Intercept	0.0002	0.0016	0.0005	0.0001	0.0028	0.0002	0.0003	0.0003	0.0002	0.0005	0.0018	0.0002	0.0008	-0.0001	0.0004
	(0.0004)	(0.0008)	(0.0004)	(0.0005)	(0.0019)	(0.0006)	(0.0006)	(0.0005)	(0.0004)	(0.0007)	(0.0008)	(0.0007)	(0.0018)	(0.0006)	(0.0003)
PMNSNT	-0.0235	-0.3430**	-0.0318	-0.1643	0.2501	-0.1212	-0.1814**	-0.1531	-0.0748	-0.0289	-0.1031	-0.0214	-0.1859	-0.0420	-0.0001
	(0.0402)	(0.1197)	(0.0383)	(0.0747)	(0.1953)	(0.0739)	(0.0752)	(0.0726)	(0.0512)	(0.0927)	(0.0884)	(0.1221)	(0.2000)	(0.0777)	(0.0459)
Adj. R^2	30.35	36.58	48.96	29.68	3.47	41.11	33.58	42.74	40.32	24.86	14.65	22.79	21.39	28.62	56.72
RI-PMNSNT	0.13	3.89	0.12	3.61	10.85	0.93	2.65	1.69	0.69	0.09	1.56	0.05	1.20	0.13	0.00
Panel C: SNT-FF5															
Intercept	0.0002	0.0014	0.0005	0.0001	0.0024	0.0002	0.0003	0.0003	0.0002	0.0005	0.0018**	0.0003	0.0008	-0.0001	0.0004
	(0.0003)	(0.0007)	(0.0003)	(0.0004)	(0.0017)	(0.0005)	(0.0005)	(0.0004)	(0.0003)	(0.0006)	(0.0007)	(0.0007)	(0.0014)	(0.0004)	(0.0002)
$s3(+)$	0.5430***	0.8255***	0.4948***	0.6549***	0.8066***	0.8696***	0.8125***	0.7906***	0.6551***	1.0392***	0.8396***	0.7841***	1.4293***	0.7779***	0.5458***
	(0.0296)	(0.0550)	(0.0200)	(0.0318)	(0.1357)	(0.0461)	(0.0359)	(0.0307)	(0.0179)	(0.0430)	(0.0722)	(0.0431)	(0.0977)	(0.0307)	(0.0202)
$s1(-)$	0.2840***	0.7115***	0.2705***	0.4962***	0.0834	0.5494***	0.5902***	0.5478***	0.3951***	0.5254***	0.5146***	0.3959**	0.8765***	0.3866***	0.2590***
	(0.0335)	(0.0920)	(0.0291)	(0.0628)	(0.1635)	(0.0631)	(0.0510)	(0.0496)	(0.0319)	(0.0648)	(0.0912)	(0.1304)	(0.1831)	(0.0497)	(0.0317)
$s2(0)$	0.4678***	0.1331	0.4946***	0.6497***	0.8975***	0.8033***	0.4954***	0.7100***	0.6105***	0.4426***	0.3430	0.3293	0.2134	0.2951***	0.6418***
	(0.0532)	(0.1237)	(0.0526)	(0.0676)	(0.2579)	(0.0583)	(0.0690)	(0.0563)	(0.0527)	(0.1014)	(0.1556)	(0.2132)	(0.2984)	(0.0819)	(0.0571)
Adj. R^2	66.37	63.18	72.94	66.42	20.14	79.37	68.08	81.39	80.76	66.10	42.21	46.64	46.88	64.77	86.06
RI-$s3(+)$	40.95	30.52	23.62	36.42	61.58	34.15	37.25	33.06	35.83	52.39	52.00	42.94	44.57	46.12	23.71
RI-$s1(-)$	6.58	11.72	4.21	12.48	1.70	8.11	11.70	9.47	7.74	7.84	11.50	6.41	10.10	6.82	3.16
RI-$s2(0)$	6.72	0.37	5.28	7.99	18.47	6.49	3.00	5.92	6.92	2.00	1.81	1.59	0.17	1.77	7.38
Panel D: SNT-RSI-FF5															
Intercept	-0.0017***	0.0001	-0.0006	0.0046***	0.0138***	0.0019***	-0.0013**	-0.0015***	0.0002	-0.0033***	-0.0009	-0.0056***	0.0076***	0.0007	0.0022***
	(0.0004)	(0.0008)	(0.0004)	(0.0005)	(0.0020)	(0.0005)	(0.0005)	(0.0004)	(0.0003)	(0.0009)	(0.0008)	(0.0011)	(0.0016)	(0.0005)	(0.0004)
RSI	0.0540***	0.0986***	0.0602***	0.0800***	0.1555***	0.0780***	0.1030***	0.0719***	0.0622***	0.0738***	0.1098***	0.1648***	0.2163***	0.0615***	0.0493***
	(0.0025)	(0.0034)	(0.0027)	(0.0031)	(0.0062)	(0.0033)	(0.0043)	(0.0029)	(0.0022)	(0.0053)	(0.0053)	(0.0245)	(0.0147)	(0.0037)	(0.0035)
$s3(+)$	0.4968***	0.7296***	0.4631***	0.5587***	0.4994***	0.8071***	0.6922***	0.7388***	0.5948***	0.9140***	0.6997***	0.6711***	1.1326***	0.6646***	0.5287***
	(0.0288)	(0.0474)	(0.0215)	(0.0340)	(0.1188)	(0.0444)	(0.0323)	(0.0243)	(0.0176)	(0.0425)	(0.0552)	(0.0480)	(0.0860)	(0.0319)	(0.0186)
$s1(-)$	0.2383***	0.6389***	0.2264***	0.3907***	-0.0385	0.5016***	0.5558***	0.4977***	0.3527***	0.4605***	0.3841***	0.3303**	0.5035***	0.3255***	0.2516***
	(0.0329)	(0.0756)	(0.0328)	(0.0500)	(0.1550)	(0.0606)	(0.0446)	(0.0435)	(0.0331)	(0.0660)	(0.0936)	(0.1174)	(0.1355)	(0.0533)	(0.0314)
$s2(0)$	0.3703***	0.1750	0.3756***	0.4970***	0.5429**	0.7066***	0.3794***	0.6285***	0.5535***	0.4146***	0.1678	0.1605	0.2128	0.2387***	0.5742***
	(0.0527)	(0.1111)	(0.0503)	(0.0659)	(0.1839)	(0.0617)	(0.0618)	(0.0539)	(0.0488)	(0.0831)	(0.1488)	(0.2338)	(0.2190)	(0.0783)	(0.0460)
Adj. R^2	72.96	73.66	77.16	74.57	43.04	82.36	74.05	85.31	84.14	72.16	56.84	58.80	56.14	68.88	88.24
RI-RSI	22.12	29.43	16.33	25.91	70.52	17.02	19.44	16.28	17.81	18.40	40.49	22.27	27.38	21.01	11.10
RI-$s3(+)$	28.22	17.23	17.57	23.66	12.31	25.26	25.35	25.09	25.63	36.80	26.05	27.50	28.54	29.90	18.92
RI-$s1(-)$	3.58	6.54	2.37	7.00	0.08	5.61	9.48	6.54	5.10	5.13	4.04	3.78	3.43	4.43	2.32
RI-$s2(0)$	3.46	0.22	2.67	4.50	3.85	4.43	1.64	4.08	5.08	1.54	0.17	0.49	0.16	1.04	5.07

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

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

The table shows the results of a comparison between ten different models: i) a standard CAPM, used as a benchmark, ii) a DR-CAPM model to price the downside risk premium following Lettau et al. (2014), iii) a standard Fama-French five-factor model FF5, iv) a PMNSNT-CAPM model that extends the CAPM model to include a long-positive/short-negative sentiment factor, 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 $iv_{i,t}$, $is_{i,t}$, $ik_{i,t}$, and the USD index, vii) a SNT-CAPM that prices positive, neutral, and negative sentiment separately, viii) a SNT-FF5 Fama-French five-factor specification with three sentiment factors, ix) a SNT-FF5x model that also incorporates the control variables, and x) a SNT-RSI-FF5x model that includes all fundamental variables, control variables, disaggregated sentiment factors and also momentum. We report the market risk premium as λ and its standard error. For the CAPM and DR-CAPM we assume market risk to be priced correctly and hence equal to the average weekly excess return on the MSCI World portfolio, so that no standard error of the estimate is provided. λ^{-} is the price of downside risk and λ_{PMNSNT} the price of the single sentiment risk factor PMNSNT. The three estimates $\lambda_{s(+)}$, $\lambda_{s(-)}$ and $\lambda_{s(0)}$ are the sentiment premia for positive, negative, and neutral sentiment change, respectively. Additional rows indicate whether we also control jointly for the Fama-French factors for size, value, profitability and investment, the change in idiosyncratic volatility $iv_{i,t}$ (dVol), skewness $is_{i,t}$ (dSkew), kurtosis $ik_{i,t}$ (dKurt), the log returns on U.S. Dollar index computed as a basket of international currencies vs. USD base, or momentum. Standard errors of the estimates are provided in parentheses and incorporate the Shanken (1992) errors-in-variables correction as well as the Newey-West correction for heteroscedasticity. P-values are corrected by the Bonferroni-Holm method for multiple testing bias. The last row reports the adjusted R^2 of each model for the cross-section of returns.

	Baseline			Aggregated Sentiment Factor			Disaggregated Sentiment Factors			
	CAPM	DR-CAPM	FF5	PMNSNT-CAPM	PMNSNT-FF5	PMNSNT-FF5x	SNT-CAPM	SNT-FF5	SNT-FF5x	SNT-RSI-FF5x
λ	0.1225	0.1225	0.2174***	0.2164***	0.2729***	0.2613***	0.1714***	0.3552***	0.2626***	0.0858***
			(0.0031)	(0.0030)	(0.0070)	(0.0061)	(0.0012)	(0.0077)	(0.0032)	(0.0005)
λ^{-}		0.0887***								
		(0.0003)								
λ_{PMNSNT}				0.1502***	0.2282***	0.2369***				
				(0.0010)	(0.0021)	(0.0023)				
$\lambda_{s(+)}$							0.0630***	0.0056***	0.1133***	0.1300***
							(0.0003)	(0.0003)	(0.0005)	(0.0007)
$\lambda_{s(-)}$							-0.0302***	-0.0364***	-0.1199***	-0.0720***
							(0.0004)	(0.0004)	(0.0007)	(0.0005)
$\lambda_{s(0)}$							-0.0187***	-0.0993***	-0.0836***	-0.0720***
							(0.0002)	(0.0004)	(0.0004)	(0.0005)
FF5 Factors					Yes	Yes		Yes	Yes	Yes
dVol						Yes			Yes	Yes
dSkew						Yes			Yes	Yes
dKurt						Yes			Yes	Yes
USD Index						Yes			Yes	Yes
Momentum										Yes
Adj. R2	25.42	28.27	38.46	41.63	41.00	41.27	56.84	57.18	57.18	56.16

* 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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This Version: May 16, 2020

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 excess returns of international equity indices. 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 global cross-sectional average excess returns and are robust for fundamental factors, momentum, idiosyncratic volatility, skewness, kurtosis, and international currencies.

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

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

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*We are grateful to Richard Peterson from MarketPsych and Elijah DePalma from Refinitiv for granting access to the MarketPsych indicators as well as to Claudius Ulmer from Refinitiv for providing the financial market data. We also thank Martin Brown, Francesco Audrino, Steffen Meyer (19th Cologne Colloquium on Financial Markets), as well as the discussants and participants of the 6th PFMC conference in Paris, the PiF seminar at the University of St. Gallen and the Finance Research Seminar at University of Liechtenstein for their helpful comments and suggestions.

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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:

A Market Efficiency Test

Table A.1: Market Efficiency Tests

This table shows results for the Spearman rank correlation coefficients for two tests. First we correlate the aggregated relative importance of all sentiment variables of the SNT-CAPM model with the R^2 of the CAPM market model. This is known as a naïve market efficiency test. Second, we correlate the same aggregated importance of sentiment with the results of the Lo-MacKinlay variance ratio tests for lags $k = 2, 5, 10$. $M1(k)$ refers to the null hypothesis of a random walk with homoskedastic increments while $M2(k)$ concerns the heteroskedastic increments random walk hypothesis.

M	k	Correlation	p-value
CAPM		-0.63	0.00
M1	2	0.20	0.37
M1	5	0.22	0.33
M1	10	0.14	0.55
M2	2	0.39	0.09
M2	5	0.34	0.13
M2	10	0.27	0.24

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

B Robustness Checks

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

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 and the adjusted R^2. In the case of models including sentiment, we also report the relative importance indicator for each coefficient, which estimates its relative contribution to the total explained variation. The regressions are estimated for each equity index individually on weekly returns from 1998 to 2017.

	EM50	EU50	GBMID250	US30	USMID2000	USNAS100
Panel A: CAPM						
Intercept	0.0012	-0.0004	0.0012**	0.0006**	0.0005	0.0005
	(0.0008)	(0.0005)	(0.0005)	(0.0003)	(0.0004)	(0.0008)
MRP	0.6077***	0.6819***	0.4834***	0.5685***	0.7367***	0.7918***
	(0.0414)	(0.0542)	(0.0275)	(0.0219)	(0.0238)	(0.0496)
Adj. R^2	28.70	40.20	29.72	49.65	46.47	40.31
Panel B: DR-CAPM						
Intercept	0.0018**	0.0004	0.0021***	0.0009	0.0014*	0.0008
	(0.0009)	(0.0007)	(0.0007)	(0.0004)	(0.0006)	(0.0010)
DR.Intercept	0.0135***	-0.0076	0.0012	0.0026	0.0032	-0.0026
	(0.0044)	(0.0038)	(0.0034)	(0.0026)	(0.0029)	(0.0045)
MRP	0.5129***	0.6317***	0.3961***	0.5416***	0.6524***	0.7730***
	(0.0748)	(0.0711)	(0.0626)	(0.0339)	(0.0562)	(0.0760)
$DR \times MRP$	0.4644**	-0.0448	0.2051*	0.1076	0.2404**	-0.0124
	(0.1732)	(0.0920)	(0.0985)	(0.0717)	(0.0872)	(0.1227)
Adj. R^2	30.09	40.48	30.42	49.72	46.95	40.22
RI-DR-Int	20.76	27.21	27.55	22.46	24.70	23.52
RI-MRP	74.17	72.75	70.90	77.22	74.36	76.48
$RI - DR \times MRP$	5.07	0.04	1.56	0.32	0.94	0.00
Panel C: PMNSNT-CAPM						
Intercept	0.0012	-0.0005	0.0012**	0.0006*	0.0005	0.0005
	(0.0008)	(0.0005)	(0.0005)	(0.0003)	(0.0004)	(0.0007)
MRP	0.6075***	0.6819***	0.4833***	0.5685***	0.7369***	0.7918***
	(0.0486)	(0.0487)	(0.0276)	(0.0221)	(0.0241)	(0.0473)
PMNSNT	0.0507	-0.2247**	-0.0132	0.0147	0.0384	0.0139
	(0.1119)	(0.0883)	(0.0541)	(0.0511)	(0.0525)	(0.0817)
Adj. R^2	28.68	41.26	29.66	49.61	46.46	40.25
RI-MRP	99.77	97.27	99.96	99.98	99.92	99.99
RI-PMNSNT	0.23	2.73	0.04	0.02	0.08	0.01
Panel D: SNT-CAPM						
Intercept	0.0010**	-0.0005	0.0012***	0.0007**	0.0005	0.0004
	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0004)	(0.0007)
MRP	0.6215***	0.6807***	0.4803***	0.5658***	0.7332***	0.7967***
	(0.0350)	(0.0302)	(0.0181)	(0.0160)	(0.0196)	(0.0455)
$s(+)$	1.0492***	0.8024***	0.6958***	0.4718***	0.6712***	0.6774***
	(0.0281)	(0.0324)	(0.0284)	(0.0217)	(0.0302)	(0.0532)
$s(-)$	0.4920***	0.5948***	0.3772***	0.2287***	0.3056***	0.3380***
	(0.0653)	(0.0620)	(0.0413)	(0.0408)	(0.0397)	(0.0699)
$s(0)$	0.4116***	0.7937***	0.4408***	0.5266***	0.6764***	1.0845***
	(0.0719)	(0.0596)	(0.0430)	(0.0501)	(0.0862)	(0.1629)
Adj. R^2	82.04	83.55	72.83	76.21	75.12	66.33
RI-MRP	35.83	48.07	40.59	64.82	61.55	61.10
RI-$s(+)$	56.12	34.82	48.29	25.54	29.25	23.90
RI-$s(-)$	6.10	10.39	7.27	3.11	3.12	2.93
RI-$s(0)$	1.95	6.72	3.86	6.53	6.07	12.07

* p ≤ 0.1, ** p ≤ 0.05, *** p ≤ 0.01

Table B.2: Sub-samples Comparisons

This table reports the results for a number of asset pricing models on different subsets of the data for various business cycles. The columns show a CAPM, a long-positive/short-negative sentiment CAPM (PMNSNT-CAPM), a 3-factor sentiment CAPM (SNT-CAPM), a 5-factor Fama-French model (FF5), a long-positive/short-negative sentiment FF5 model (PMNSNT-FF5), and 3-factor sentiment FF5 model (SNT-FF5). Panel A shows results concerning 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. We provide the average, minimum, and maximum absolute alpha and adjusted R^2 as well as the relative importance of sentiment as the sum of of negative, neutral, and positive sentiment.

	CAPM	PMNSNT-CAPM	SNT-CAPM	FF5	PMNSNT-FF5	SNT-FF5
Panel A: Full Sample 1998-2017						
Abs. Alpha						
Max	0.2422	0.2498	0.2360	0.2381	0.2817	0.2368
Mean	0.0651	0.0653	0.0656	0.0679	0.0684	0.0662
Min	0.0057	0.0050	0.0083	0.0033	0.0107	0.0108
Adj. R^2						
Max	55.9000	55.8600	85.1600	60.0900	60.0500	86.0600
Mean	30.3800	30.6000	66.4500	36.2400	36.5500	68.1300
Min	0.0800	0.4200	19.9000	2.9900	3.4700	20.1400
RI-SNT						
Max		71.1800	97.9000		10.8500	81.7500
Mean		4.1600	57.1400		1.4900	48.8000
Min		0.0000	34.6800		0.0000	24.8500
Panel B: Sub-sample 1998-2001						
Abs. Alpha						
Max	0.2232	0.2390	0.2378	0.3409	0.2602	0.2207
Mean	0.0692	0.0665	0.0903	0.0899	0.0863	0.1039
Min	0.0087	0.0053	0.0014	0.0000	0.0056	0.0016
Adj. R^2						
Max	52.3800	53.8900	85.9400	62.9600	63.0600	89.8600
Mean	26.9200	27.4900	62.2900	37.6900	38.1800	65.4400
Min	1.1500	1.1800	24.4800	8.5900	8.3800	25.9800
RI-SNT						
Max		24.9400	92.8400		10.9200	68.5300
Mean		5.3200	60.9300		2.2500	47.4900
Min		0.2100	38.2600		0.1100	23.5200
Panel C: Sub-sample 2002-2006						
Abs. Alpha						
Max	0.6258	0.6216	0.5136	0.5219	0.6959	0.6608
Mean	0.1713	0.1654	0.1338	0.1141	0.1269	0.1222
Min	0.0095	0.0026	0.0003	0.0007	0.0076	0.0055
Adj. R^2						
Max	50.8700	52.2900	85.8400	59.5600	59.9800	87.3500
Mean	29.1900	29.8800	65.2300	34.7400	35.7200	67.2900
Min	-0.2600	-1.4200	2.9400	-0.6700	-1.6400	3.5700
RI-SNT						
Max		25.4900	85.1000		23.8600	71.5200
Mean		9.8900	64.8000		8.6300	54.1800
Min		2.1200	40.7000		2.2500	30.4900
Panel D: Sub-sample 2007-2011						
Abs. Alpha						
Max	0.1362	0.1415	0.1996	0.1949	0.1790	0.1568
Mean	0.0714	0.0706	0.0865	0.0939	0.0885	0.0793
Min	0.0024	0.0016	0.0087	0.0055	0.0130	0.0054
Adj. R^2						
Max	63.9400	63.8200	91.5200	66.7100	66.7200	92.0500
Mean	37.7200	38.1800	76.2500	43.7200	43.9900	77.2500
Min	-0.2800	-0.5600	20.2300	2.2200	1.8500	20.5100
RI-SNT						
Max		40.1200	97.6600		16.1400	83.9900
Mean		5.3300	52.1700		2.4600	43.6200
Min		1.5800	30.4800		0.6400	23.3500
Panel E: Sub-sample 2012-2017						
Abs. Alpha						
Max	0.2659	0.2850	0.2815	0.2537	0.3146	0.2976
Mean	0.0861	0.0956	0.0927	0.0915	0.1190	0.0838
Min	0.0017	0.0027	0.0047	0.0077	0.0175	0.0016
Adj. R^2						
Max	48.5300	49.0700	86.0700	57.1300	57.9200	86.6900
Mean	27.3600	28.2900	66.2900	31.9500	32.7100	67.1300
Min	0.8100	5.4300	23.6800	5.0100	8.9500	24.1600
RI-SNT						
Max		82.8900	94.5900		40.8400	73.2900
Mean		7.5100	59.2000		4.9100	51.6400
Min		0.0600	39.8100		0.0600	26.7200

Table B.3: Sub-samples Comparisons - NBER Recession Dates

This table reports the results for a number of asset pricing models on different subsets of the data following the classification of recessions by the National Bureau of Economic Research (NBER). The columns show a CAPM, a long-positive/short-negative sentiment CAPM (PMNSNT-CAPM), a 3-factor sentiment CAPM (SNT-CAPM), a 5-factor Fama-French model (FF5), a long-positive/short-negative sentiment FF5 model (PMNSNT-FF5), and 3-factor sentiment FF5 model (SNT-FF5). The dataset comprises three bull markets in Panel A (Jan 1998 - Feb 2001), Panel C (2001 Dec - Nov 2007) and Panel E (Jul 2009 - Dec 2017) as well as two recessions in Panel B (Mar 2001 - Nov 2001) and Panel D (Dec 2007 - Jun 2009). We provide the average, minimum, and maximum absolute alpha and adjusted R^2 as well as the relative importance of sentiment as the sum of of negative, neutral, and positive sentiment.

	CAPM	PMNSNT-CAPM	SNT-CAPM	FF5	PMNSNT-FF5	SNT-FF5	SNT-RSI-FF5
Panel A: Jan 1998 - Feb 2001 Bull Market							
Abs. Alpha							
Max	0.4099	0.3891	0.3216	0.4004	0.4056	0.3831	0.3831
Mean	0.1089	0.1015	0.1279	0.1207	0.1154	0.1412	0.1412
Min	0.0080	0.0127	0.0171	0.0017	0.0199	0.0182	0.0182
Adj. R^2							
Max	46.5000	47.1900	76.7200	64.3600	64.9700	84.1500	88.6500
Mean	21.6100	22.1900	58.3300	32.8000	33.4500	61.7500	68.4400
Min	-0.5400	-0.7800	22.1800	3.6900	3.3600	21.8000	45.4000
RI-SNT							
Max		81.8900	99.4500		18.4700	73.9000	52.4000
Mean		11.5600	65.3400		3.5200	50.1900	32.6600
Min		0.0300	42.3300		0.0600	20.9600	11.8100
Panel B: Mar 2001 - Nov 2001 Bear Market							
Abs. Alpha							
Max	0.8674	0.9150	1.2035	1.1939	1.1779	1.4048	1.4048
Mean	0.2414	0.2509	0.1908	0.2814	0.2525	0.2331	0.2331
Min	0.0184	0.0157	0.0049	0.0119	0.0302	0.0543	0.0543
Adj. R^2							
Max	64.6400	63.6900	90.0800	74.8700	74.1100	93.2500	93.6200
Mean	36.7800	37.2100	72.6000	49.9700	51.0400	75.3800	80.6900
Min	-0.8200	2.7700	31.6600	23.0900	23.8900	27.2700	48.8200
RI-SNT							
Max		61.9800	92.0200		22.5300	55.8300	33.4100
Mean		12.2900	55.7300		6.7800	40.0400	22.3100
Min		2.6500	31.7300		0.6900	24.1300	8.2400
Panel C: 2001 Dec - Nov 2007 Bull Market							
Abs. Alpha							
Max	1.0985	1.0132	0.9133	1.1527	1.0360	0.9823	0.9823
Mean	0.1948	0.1834	0.1559	0.1783	0.1656	0.1509	0.1509
Min	0.0029	0.0032	0.0304	0.0044	0.0011	0.0155	0.0155
Adj. R^2							
Max	51.8000	53.0700	85.3600	59.6600	60.1400	85.9300	88.3500
Mean	28.9700	29.6300	65.0000	35.3100	36.2800	67.0400	74.4000
Min	-0.3800	1.5400	8.4800	-2.4800	-0.0400	6.2400	42.7700
RI-SNT							
Max		85.8200	94.0100		56.0000	81.4200	44.7600
Mean		10.7400	63.6200		8.8400	53.9100	30.6200
Min		1.4000	42.9400		0.7500	31.9800	10.3600
Panel D: Dec 2007 - Jun 2009 Bear Market							
Abs. Alpha							
Max	0.4175	0.4450	0.4950	0.3977	0.3538	0.3795	0.3795
Mean	0.1823	0.2053	0.1418	0.1592	0.1334	0.1414	0.1414
Min	0.0120	0.0293	0.0076	0.0244	0.0020	0.0006	0.0006
Adj. R^2							
Max	70.1900	69.9500	92.9900	72.9900	72.6300	93.9100	94.2100
Mean	39.8800	41.9600	80.8300	46.0800	46.8800	81.9100	84.5100
Min	2.0000	4.7600	32.4100	5.9500	6.8600	31.7600	45.6300
RI-SNT							
Max		68.4000	95.1800		28.5700	78.9700	42.1800
Mean		10.6500	53.2300		5.6000	43.3000	29.0400
Min		4.7400	27.2500		2.0600	18.6300	11.9900
Panel E: Jul 2009 - Dec 2017 Bull Market							
Abs. Alpha							
Max	0.2262	0.2394	0.2157	0.2119	0.2345	0.2248	0.2248
Mean	0.0870	0.0916	0.0824	0.0826	0.1092	0.0767	0.0767
Min	0.0098	0.0073	0.0001	0.0014	0.0035	0.0048	0.0048
Adj. R^2							
Max	50.5800	50.9000	87.5500	55.8900	56.5500	88.0600	89.2200
Mean	29.9600	30.6500	68.2300	33.7300	34.3300	68.9000	74.8300
Min	3.1000	5.5900	22.2800	5.2000	7.6100	21.9800	43.8100
RI-SNT							
Max		45.7100	83.8500		27.8600	68.7800	43.2000
Mean		4.7800	56.6000		3.7000	49.2000	30.9600
Min		0.0200	39.6200		0.0900	27.9500	16.490

Table B.4: Comparison between News- and Social Media-Driven Sentiment Indicators

This table depicts the results for various asset pricing models based on different sentiment channels differentiating between news-only and social media-only driven sentiment compared to the default combined (news and social media) sentiment. The columns show a CAPM, a long-positive/short-negative sentiment CAPM (PMNSNT-CAPM), a 3-factor sentiment CAPM (SNT-CAPM), a 5-factor Fama-French model (FF5), a long-positive/short-negative sentiment FF5 model (PMNSNT-FF5), and 3-factor sentiment FF5 model (SNT-FF5). We provide the average, minimum, maximum and median absolute alpha and adjusted R^2 as well as the relative importance of sentiment as the sum of 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.

	CAPM	PMNSNT-CAPM	SNT-CAPM	FF5	PMNSNT-FF5	SNT-FF5
Panel A: Combined News & Social Media						
Abs. Alpha						
Max	0.2422	0.2498	0.2360	0.2381	0.2817	0.2368
Mean	0.0651	0.0653	0.0656	0.0679	0.0684	0.0662
Median	0.0449	0.0453	0.0496	0.0483	0.0492	0.0497
Min	0.0057	0.0050	0.0083	0.0033	0.0107	0.0108
Adj. R^2						
Max	55.9000	55.8600	85.1600	60.0900	60.0500	86.0600
Mean	30.3800	30.6000	66.4500	36.2400	36.5500	68.1300
Median	29.7200	29.6600	67.2800	40.1100	40.3200	72.9400
Min	0.0800	0.4200	19.9000	2.9900	3.4700	20.1400
RI-SNT						
Max		71.1800	97.9000		10.8500	81.7500
Mean		4.1600	57.1400		1.4900	48.8000
Median		0.2300	56.4900		0.4000	50.4900
Min		0.0000	34.6800		0.0000	24.8500
Panel B: News only						
Abs. Alpha						
Max	0.2422	0.2506	0.2451	0.2381	0.2795	0.2459
Mean	0.0651	0.0652	0.0653	0.0679	0.0681	0.0661
Median	0.0449	0.0480	0.0493	0.0483	0.0496	0.0494
Min	0.0057	0.0076	0.0055	0.0033	0.0113	0.0086
Adj. R^2						
Max	55.9000	55.8600	84.1300	60.0900	60.0600	85.2100
Mean	30.3800	30.9100	66.1200	36.2400	36.9200	67.9000
Median	29.7200	29.8100	67.1300	40.1100	40.6100	72.7000
Min	0.0800	0.2200	19.8000	2.9900	3.1400	19.8700
RI-SNT						
Max		59.3800	98.1200		7.3400	81.8100
Mean		4.8000	56.8200		2.4200	48.5900
Median		0.8600	56.2500		1.2900	50.3200
Min		0.0000	33.7800		0.0100	24.3800
Panel C: Social Media only						
Abs. Alpha						
Max	0.2422	0.2491	0.2229	0.2381	0.2660	0.2095
Mean	0.0651	0.0653	0.0650	0.0679	0.0674	0.0647
Median	0.0449	0.0446	0.0498	0.0483	0.0464	0.0500
Min	0.0057	0.0074	0.0123	0.0033	0.0094	0.0111
Adj. R^2						
Max	55.9000	55.9600	87.0100	60.0900	60.0700	88.2700
Mean	30.3800	30.8800	67.0100	36.2400	36.7100	68.6600
Median	29.7200	30.2300	70.7000	40.1100	40.4600	73.5900
Min	0.0800	0.5500	20.1900	2.9900	3.3300	20.2100
RI-SNT						
Max		74.5500	97.5400		12.8400	81.9600
Mean		6.0300	57.6200		2.3400	49.2300
Median		1.2600	56.5200		1.1000	50.6600
Min		0.0100	35.9800		0.0200	26.3500

Table B.5: Cross-Sectional Pricing Comparison of the 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, used as a naïve benchmark, ii) a DR-CAPM model to price the downside risk premium following Lettau et al. (2014), iii) a standard Fama-French five-factor model FF5, iv) a PMNSNT-CAPM model that extends the CAPM model to include a long-positive/short-negative sentiment factor, 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 $iv_{i,t}$, $is_{i,t}$, $ik_{i,t}$, and the USD index, vii) a SNT-CAPM that prices positive, neutral, and negative sentiment separately, viii) a SNT-FF5 Fama-French five-factor specification with three sentiment factors, ix) a SNT-FF5x model that also incorporates the control variables, and x) a SNT-RSI-FF5x model that includes all fundamental variables, control variables, disaggregated sentiment factors and also momentum. We report the market risk premium as λ and its standard error. For the CAPM and DR-CAPM we assume market risk to be priced correctly and hence equal to the average weekly excess return on the MSCI World portfolio, so that no standard error of the estimate is provided. λ^{-} is the price of downside risk and λ_{PMNSNT} the price of the single sentiment risk factor PMNSNT. The three estimates $\lambda_{s(+)}$, $\lambda_{s(-)}$ and $\lambda_{s(0)}$ are the sentiment premia for positive, negative, and neutral sentiment change, respectively. Additional rows indicate whether we also control jointly for the Fama-French factors for size, value, profitability and investment, the change in idiosyncratic volatility $iv_{i,t}$ (dVol), skewness $is_{i,t}$ (dSkew), kurtosis $ik_{i,t}$ (dKurt), the log returns on U.S. Dollar index computed as a basket of international currencies vs. USD base, or momentum. Standard errors of the estimates are provided in parentheses and incorporate the Shanken (1992) errors-in-variables correction as well as the Newey-West correction for heteroscedasticity. P-values are corrected by the Bonferroni-Holm method for multiple testing bias. The last row reports the adjusted R^2 of each model for the cross-section of returns.

	Baseline			Aggregated Sentiment Factor			Disaggregated Sentiment Factors			
	CAPM	DR-CAPM	FF5	PMNSNT-CAPM	PMNSNT-FF5	PMNSNT-FF5x	SNT-CAPM	SNT-FF5	SNT-FF5x	SNT-RSI-FF5x
λ	0.1225	0.1225	0.2174***	0.2164***	0.2483***	0.2338***	0.1714***	0.1418***	0.0281***	0.0604***
			(0.0031)	(0.0030)	(0.0050)	(0.0041)	(0.0012)	(0.0008)	(0.0003)	(0.0004)
λ^{-}		0.0887***								
		(0.0003)								
λ_{PMNSNT}				0.1466***	0.2140***	0.2147***				
				(0.0009)	(0.0018)	(0.0018)				
$\lambda_{s3(+)}$							0.1587***	0.2067***	0.2109***	0.2259***
							(0.0010)	(0.0019)	(0.0020)	(0.0024)
$\lambda_{s1(-)}$							0.1148***	0.0326***	-0.0122***	0.0583***
							(0.0006)	(0.0003)	(0.0002)	(0.0003)
$\lambda_{s2(0)}$							0.1116***	0.1330***	0.1519***	0.1208***
							(0.0005)	(0.0008)	(0.0012)	(0.0006)
FF5 Factors					Yes	Yes		Yes	Yes	Yes
dVol						Yes			Yes	Yes
dSkew						Yes			Yes	Yes
dKurt						Yes			Yes	Yes
USD Index						Yes			Yes	Yes
Momentum										Yes
Adj. R2	25.42	28.27	38.46	41.63	41.65	41.80	56.84	56.78	56.85	56.10

* p ≤ 0.1, ** p ≤ 0.05, *** p ≤ 0.01