Does social media sentiment matter in the pricing of U.S. stocks?*

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Abstract

This paper applies a recently developed social media-based sentiment proxy for the construction of a new risk factor for sentiment-augmented asset pricing models on U.S. equities. Accounting for endogeneity, autocorrelation and heteroskedasticity in a GMM framework, we find that the inclusion of sentiment significantly improves the performance of the five-factor model from Fama and French (2015, 2017) for different industry and style portfolios like size, value, profitability, investment. The sentiment risk premium provides the missing component in the behavioral asset pricing theory of Shefrin and Belotti (2008) and (partially) resolves the pricing puzzles of small extreme growth, small extreme investment stocks and small stocks that invest heavily despite low profitability.

JEL Classification Codes: *C*32, *C*53, *G*12, *G*41

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

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1. Introduction

Shefrin and Belotti (2008) stipulate that the price of any security is determined by the sum of a fundamental and sentiment premium. In their latest seminal work, Fama and French (2015) add profitability (RMW) and investment (CMA) to the market, size (SMB) and value (HML) factors[3] of the famous Fama-French three-factor asset pricing model (FF3 henceforth) to describe average stock returns. The formation of this new five-factor model (FF5 henceforth) is a response to the findings of Titman et al. (2004), Aharoni et al. (2013), and Novy-Marx (2013) and justified by the dividend discount model. Using the Modigliani-Miller theorem from Modigliani and Miller (1958) they formulate the relationship of a share's expected return to its size, price-to-book ratio and expectations of its future profitability and investment.

These possible explanations were, however, constrained by the paradigms of neoclassical finance and traditional asset pricing models, which neglect the contribution of the sentiment premium as postulated by Shefrin and Belotti (2008). Those classical models assume that their predictions are the same, whether the price behavior is rational or irrational, and constant over time. Thus, the results show that even the FF5 model only partially describes an asset's expected return and, in particular, fails for presumably irrational situations. Asset pricing puzzles of hard-to-value stocks, i.e. in explaining average returns of small stocks or companies which invest heavily despite low profitability, remain unsolved. When supply and demand determine market prices, those firms' evaluations seem to deviate from their fundamentally explainable values and could be driven by irrational investors. Such behavior cannot be captured by any fundamental pricing model that assumes rational agents in perfect markets. In fact, investors do not necessarily act completely reasonable nor do they only pursue the maximization of their personal utility function. Likewise, they are not even unexceptionally risk-averse. They do not have perfect data nor the unlimited cognitive capabilities to gather, absorb and interpret all information immediately and correctly to derive fully rational and optimal decisions. Neither are the markets strongly efficient nor free of arbitrage as widely assumed by traditional finance. In contrast, behavioral theories consider human biases and market imperfections in the analysis of

[3]SMB: Mimicking portfolio of small-minus-big market capitalization (*size*) firms; HML: Mimicking portfolio of high-minus-low book-to-market ratio (B/M) firms; RMW: Mimicking portfolio of robust-minus-week profitability (OP) firms; CMA: Mimicking portfolio of conservative-minus-aggressive investment (Inv) firms

risk and return, and the decision-making process for investments. In addition to the risk-free rate and a fundamental risk premium, the intrinsic value of an asset is further described by sentiment, forming a joint stochastic discount factor for future cash flows. Due to the lack of other sources, the sentiment risk premium has been often estimated as the dispersion of analyst's forecasts.

In this paper, we add the sentiment premium to asset pricing, to particularly address anomalies of hard-to-value portfolios of extreme growth, extreme investment, and small stocks that invest heavily despite weak profitability. We test Shefrin and Belotti's hypothesis by constructing a novel sentiment risk factor based on a set of recently developed, direct search-based investor sentiment indicators provided by MarketPsych. This new type of measure is derived from a proprietary human language processing that analyzes asset-specific information as it circulates through social media channels (see, e.g., Chen et al., 2014). This study shows that this indicator captures and quantifies investors' sentiment, making it the ideal factor to model the sentiment risk premium in the cross-section of U.S. equity markets.

Our key results can be summarized as follows: By using search-based and bottom-up sentiment indicators to construct a new risk factor, we reveal patterns in average returns related to investors' mood. The sentiment score augments the existing fundamental asset pricing model by Fama and French (2015) for the U.S. equity market and adds the sentiment premium to the pricing paradigm from Shefrin and Belotti (2008). We trace back the significant performance improvements for different factor-mimicking and industry portfolios to investors' activities in social media. The same effect is not found exploiting sentiment extracted from public news channels. Different notions of human mood are expressed in social media and can be used to form a monthly-rebalanced sentiment risk factor which is orthogonal to underlying macroeconomic or business cycle-related developments. It is also unrelated to existing fundamental pricing factors and independent of momentum.

In two sets of portfolio sorts with either 25 or 36 portfolios using 5x5 double-sorting or 2x2x3x3 quadruple-sorting, we show a high average excess return spread between stocks with positive and securities with negative sentiment. This spread is significantly higher than for other style tilts like size, value, profitability, or investment. We use those factor-mimicking portfolios in a sentiment-augmented asset pricing model to show that the inclusion of sentiment reduces the intercepts and improves the explained variation. Our model accounts for endogeneity, autocorrelation of returns and heteroskedasticity by mapping it to the GMM framework and generating robust standard errors. We show that similar to the five-factor model from Fama and French (2015), the GRS test rejects our sentiment-augmented model to fully explain the cross-section of expected returns for different style or industry portfolios. However, it improves the five-factor model in the cross-section along various dimensions and provides an additional piece to solve the pricing mosaic for portfolios of hard-to-value securities like small extreme growth and extreme investment stocks. Sentiment reduces the (absolute) intercepts by 13-17%.

We also directly address the research challenge put forward by Fama and French (2015) regarding behavioral stories for stocks that invest heavily despite low profitability. Sentiment has an indirect contribution by modifying the slopes of other factors. We also report a very poor performance of the five-factor model for sentiment-tilted portfolios. Unsurprisingly, the inclusion of the sentiment risk factor here is particularly beneficial as it is targeted to explain the excess returns of those style portfolios. Judged on regression slopes, both largecaps and smallcaps with negative sentiment seem to behave like stocks with weak profitability.

Section 2 introduces the stock and sentiment dataset with detailed descriptions and summary statistics. We begin our analysis in Section 3 with the formation of factor-mimicking portfolios in order to extract return patterns of the known existing fundamental stock properties and our novel sentiment risk factor. In Section 4, we construct both the fundamental and sentiment factors which are used in Section 5 for our sentiment-augmented GMM pricing model and the five-factor benchmark model from Fama and French (2015). In Section 6, we explore the relation between sentiment and fundamental factors before we go into the detailed regression analysis on intercepts and slopes for well-known asset pricing puzzles of hard-to-value stocks. Section 8 juxtaposes our findings with the same results for sentiment extracted from news instead of social media. Section 9 concludes.

2. U.S. equity stocks and sentiment indicators

Following Fama and French (2015), our dataset comprises all New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and National Association of Securities Dealers

Automated Quotations (NASDAQ) stocks on both CRSP and Compustat with share codes 10 or 11 for the period from January 1998 - December 2017.[4] The data traditionally excludes Financial Services, i.e. banks, insurance companies, broker/dealers, real estate and other financial services. We use monthly data as in the original paper of Fama and French (2015).

Our search-based sentiment index is the Refinitiv-MarketPsych social media-based sentiment indicator (RMI) available more than 12.000 U.S. stocks. The automatic language processing system from MarketPsych uses a human-developed 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 conceptual space. To define groups of words and create relationships, the lexical distance is assessed by applying weights on a scale from 0.0 to 1.0 to account for proximity in the text, although punctuation and additional structures are also taken into account. This process results in tuples, which are then recorded and aggregated as sentiment indicators. The scores are again divided by the total of the scores for all psych categories, 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 was over a given time interval in social media channels. This normalization allows equally weighted comparisons among numerous topics and nouns. Compared to other sentiment providers like RavenPack (see, e.g., Audrino et al., 2020; 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. 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). The interested reader is referred to the Internet Appendix Appendix A for further details about the construction of the RMI sentiment indicators.

In our empirical analysis, we use the aggregated sentiment indicator Snt from MarketPsych which captures the net positive versus negative references in the social media concerning a given stock. It can be interpreted as an overall sentiment proxy, void of any insight into the fundamental

[4]The time period is very limited for an asset pricing study which is due to the unavailability of sentiment data before 1998.

reasons for why references to a security may be positive or negative.[5] It comprises among others, the three most commonly documented emotions in the existing finance literature according to Shen et al. (2017): optimism, joy, and fear. Optimism is defined as the overestimation or overconfidence of investors about the future payoff of a financial asset, and may result in deviations of asset prices from intrinsic values as observed during extreme bullish or overheated markets. Overconfidence leads to the entry of retail investors, driving up liquidity (Odean, 1998). Wright and Bower (1992) find that pleasant emotions like bliss, joy and optimism affect the subjective probability assessments of uncertain outcomes, and thus, influence investors' decision-making as documented by Dolan (2002).[6] Ciccone (2003) reports lower returns for firms with optimistic compared to those with 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 rehearsals and volatility.

Weighted by *Buzz*, we refer to abnormally high-positive or high-negative sentiment. Since the level of sentiment shows trend behavior and is non-stationary, we compute the change to the long-term mean since inception ("sentiment changes"). Such an average is estimated and updated on a recursive basis to avoid any hindsight biases, i.e., the mean is computed on an expanding window since inception of the sentiment index until t, not the entire period T. As a result, the change in sentiment is comparable across stocks as we account for differences of sentiment perception.[7] This approach is advantageous over a monthly change since it allows us to consider time-varying perception of sentiment and thus better reflects the time-oscillation of sentiment as postulated by Shefrin and Belotti (2008). We treat the sentiment change for each individual company as a property of that particular stock and use it in Section **??** for the construction of Fama-French-like factor-mimicking portfolios and a sentiment risk factor PMN.

[5]The interested reader is referred to Internet Appendix Appendix A for further details about the construction of the RMI sentiment indicators.

[6]In unreported results we also used the individual indicators for optimism, joy, and fear but the results did not justify the higher model complexity.

[7]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 classification 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".

PMN is the difference between the returns on diversified portfolios comprised of stocks with positive and negative deviation of previous month's sentiment from the expanding window mean from inception up to time t.

In order to resolve concerns that sentiment from social media may still only proxy underlying rational economic and business activities, we regress our constructed risk factor PMN against various economic indicators for the U.S. market. This analysis addresses the hypothesis whether the RMI sentiment indicator only captures fundamental, rational references to the business and economic cycles instead of true sentiment. Table 1 provides an overview of the seven most relevant economic and business factors which go beyond those used in Baker and Wurgler (2006) to orthogonalize their sentiment proxy. The list comprises labor statistics, production and consumption indices, price and inflation indicators, as well as a proxy for the developments in the U.S. housing market. The choice of indicators is motivated by those which most likely affect the mood and sentiment of retail investors, i.e. the same group who is most active in social media channels. The results in Table 2 show that the economic indicators only explain a negligible portion in terms of adjusted R^2 of 0.03 of the PMN variance. The unemployment rate from the U.S. Bureau of Labor Statistics is significant at the 5% confidence level with a small coefficient of 0.05. The same applies for the order of durable goods from the U.S. Census Bureau with a higher estimate of 0.44. Personal consumption from the Bureau of Economic Analysis (BEA) is the last relevant factor at the 10% confidence level, respectively, and a high negative estimation of -1.68. The remaining four economic indicators are not significant at any meaningful level. We conclude that the RMI factor truly captures sentiment and cannot be explained by economic or business activities, making any orthogonalization unnecessary.

Table [2] about here

Table 3 shows detailed summary statistics of the sentiment level across sectors, liquidity, size, and stock exchanges. For each category we display the mean, median, and standard deviation (SD). Panel A differentiates sentiment across various industries using the NAICS (North American Industry Classification) from the Compustat and CRSP databases. We see a heterogeneous picture for sentiment with values ranging from 3.09 for Arts, Entertainment, and Recreation to 8.50 for Professional, Scientific, and Technical Services. We also observe that the mean is skewed by outliers as the median tends to lie much lower with very high standard deviation. The median ranges from -1.46 for Other Services (except Public Administration) to 5.71 for Wholesale Trade. Panel B shows the sentiment across five liquidity quintiles. We use the ratio of trading volume over shares outstanding as a naïve proxy for liquidity. The breakpoints only use NYSE securities[8] in order to prevent the bias of data with micro stocks. Sentiment is lowest for very liquid and highest for illiquid stocks. Low-liquidity assets are also most diverse with a standard deviation twice as large as for highly liquid securities. It seems that less liquid stocks are more sensitive to sentiment. Panel C differentiates firms by size using market equity from the CRSP database. Small firms tend to have lower sentiment than large companies but with a higher variance. Panel D differentiates sentiment across the three exchanges NYSE, AMEX, and NASDAQ. While NYSE and AMEX seem to behave very similarly, the mean, median, and standard deviation of sentiment is higher for the NASDAQ.

Table [3] about here

3. Factor-mimicking portfolios

Our empirical tests apply the sentiment-augmented asset pricing models to portfolios designed to produce large excess return spreads in size, value, profitability, investment, and sentiment. The sorting mechanism for the non-sentiment related portfolios closely follows the original methodology of Fama and French (2015).[9] For sentiment portfolios we apply the sorting more frequently to exploit the higher frequency. In contrast to fundamental data, our sentiment sorts are rebalanced on a monthly basis. Table 4 shows average monthly excess returns over the one-month U.S. treasury bill rate for 25 value-weighted (VW henceforth) portfolios from independent sorts of stocks into five size groups and an additional variable of interest. In Panels A-C, we first examine whether the well-known Fama-French patterns are also shown in our dataset. In Panel D, we apply the sorting with our social media-based sentiment variable which measures the deviation of sentiment in the previous month from the long-term mean since

[8] As mentioned by Fama and French (1992) the use of NYSE stocks only prevents that breakpoints are biased by the large variability in characteristics of microcaps which comprise more than 60% of the investable universe but only 3% of total market value.

[9] The interested reader is referred to the third chapter in Fama and French (2015) for a detailed description of the applied methods.

inception.

Panel A of Table 4 sorts the stocks into five $Size$ and five B/M groups, called 5x5 $Size-B/M$ portfolios.[10] The data exhibits the size effect, for which the average return for each column of B/M falls from small to big stocks. As in the original paper of Fama and French (1993) the first column of low B/M stocks, also known as extreme growth stocks, is an exception and does not show a clear relation between $Size$ and B/M. Extreme growth stocks traditionally pose an asset pricing challenge which we address in details later. The average monthly return of microcaps is smaller than for large stocks. The portfolios also show the value effect where average returns tend to increase from low to high B/M portfolios per each $Size$ row. However, this relation is not as clear for the two largest size quintiles.[11] Panel B shows the results for 25 VW portfolios based on stocks sorted into five $Size$ and five $Profitability$ quantiles.[12] Without any exception, we observe the $Size$ effect with decreasing returns. We also find the effect of Novy-Marx (2013) and Fama and French (2015) with increasing average returns from low to high profitability OP for each $Size$ row. The effect is primarily driven by the small (large) returns for low (high) profitability firms. In Panel C, we sort the stocks into five $Size$ and five $Investment$ portfolios.[13] The size effect is consistently confirmed. The investment factor shows itself decreasing returns, if $Size$ is kept rather stable and investment activities are reduced from aggressively to conservatively investing firms. This suggests that average excess returns are lower for firms that invest more heavily. High Inv portfolios usually display significantly lower average returns. Firms with extremely high investment activities have comparatively small returns as investors might relate these to weak cash flows or dividend outlooks. Similar to

[10]The $Size$ and B/M quintile breakpoints use only stocks listed on the NYSE. However, the stock sample is all NYSE, AMEX, and NASDAQ stocks on both CRSP and Compustat with share codes 10 or 11 and data for $Size$ and B/M. As mentioned by Fama and French (1992) the use of NYSE stocks only prevents that breakpoints are biased by the large variability in characteristics of microcaps which comprise more than 60% of the investable universe but only 3% of total market value. We use the same methodology of NYSE breakpoints for sentiment as the approach ensures consistency and social media coverage also tends to be better for larger companies.

[11]Similar disturbances in the value effect are shown in the original monthly 5x5 portfolios from Kenneth's homepage for the reduced observation period January 1998 - December 2017.

[12]The operating profitability measure, OP, is computed every June of year t based on accounting data for the fiscal year ending in $t-1$ as annual revenues minus cost of goods sold, interest expense, and selling, general, and administrative expenses, divided by book equity at the end of fiscal year $t-1$. Breakpoints use only NYSE firms.

[13]Investment Inv is computed in June of year t as the growth of total assets for the fiscal year ending in $t-1$ divided by total assets at the end of $t-2$. We acknowledge that the Miller-Modigliani theorem refers to growth of equity instead of growth of assets, but we follow the rationale of Fama and French (2015) that the lagged growth of assets might be a better proxy for the infinite growth in book equity. It may also produce slightly larger spreads in average returns.

extreme growth stocks, extreme investment firms are one of the most difficult conundrums for asset pricing models and we will look at this phenomenon in detail later.

With Panel A-C, we are able to reproduce and confirm most of the results of Fama and French (2015) regarding size, value, profitability, and investment, whereas Panel D shows the real contribution with portfolio sorts on size and sentiment change in the previous month calculated as the deviation of sentiment from the long-term mean since inception. The 25 VW portfolios still confirm the size effect with decreasing returns when sentiment is kept roughly constant. The sentiment effect shows increasing returns from negative to positive sentiment in each $Size$ row. The positive relationship means that stocks for which the investors have a positive (negative) view, have a higher (lower) return. The spreads are much larger than in any of the three other panels. In concrete figures, small firms with positive sentiment outperform their peers with negative by 58.6bps per month (177.22 - 118.61). The effect becomes smaller with bigger firms and diminishes for large caps. Here, low and high sentiment firms have similar small excess returns. We argue that this is due to strong fundamentals while smaller firms seem to be more sensitive to sentiment change.

Table [4] about here

Given that this double-sorting does not jointly control for multiple fundamental variables, we are unable to disentangle the impact of value, profitability, or investment on each other and jointly on sentiment. Previous studies show that the Fama-French variables are indeed correlated (see, e.g., Fama and French, 1995, 2015). It may also be argued that our social media-based sentiment indicator purely reflects the information in prices and publicly available news. In order to isolate the various effects and to particularly resolve concerns that our sentiment indicator only measures fundamental information that is contained in the other variables, we choose another sorting approach. We compromise on the FF3 factors, $Size$ and B/M, which we split into two groups, and use each additional FF5 factor, profitability OP and investment Inv, to disentangle the sentiment effect. In order to manage the complexity, we use low, medium, and high quantiles for each variable. While we apply the same logic to sentiment (Negative $s(-)$, Neutral $s(0)$, and Positive $s(+)$), we form 2x2x3x3 = 36 portfolios.[14] Each sort is independent of

[14]Due to our focus on sentiment, we only report sorts containing sentiment. Additional results for the other factors are available upon request.

the other for a cleaner distribution of stocks across the portfolios. However, this does not imply zero correlation.

Panel A of Table 5 shows the so called $Size-B/M-OP-Snt$ portfolios, sorting for size and value using the NYSE median and three clusters of each profitability and sentiment. For Panel B, we replace the third term, profitability OP, with investment Inv to form 36 $Size-B/M-Inv-Snt$ portfolios. First, size (small versus big) and value portfolios (low versus high B/M) monthly average excess returns increase from negative to positive sentiment. The spread is higher for smaller and growth companies in both panels. Small growth stocks which tend to be hard to estimate with traditional asset pricing models show clear sentiment patterns. Second, there is a material difference in returns between small and large stocks with the latter having significantly smaller returns for the size effect. This confirms the previous findings that small stocks are more susceptible to sentiment. The value effect on the other hand, is again disturbed, such that firms with high B/M ratio do not necessarily outperform their peers with low B/M. The profitability effect is mostly confirmed. Robust firms with high profitability outperform weak firms with low OP even if controlled for the other factors including sentiment. Exceptions occur for the group of small growth stocks where weak profitability firms outperform their peers with robust OP, another asset pricing puzzle we explore later. In Panel B, we evaluate the relationship between investment and sentiment. The investment effect states that conservative firms have higher returns than aggressively investing companies. In terms of sentiment, the results confirm a clear pattern of primarily increasing returns with positive sentiment. Even if controlled for fundamental factors, portfolios formed on stocks with positive sentiment relate to higher returns than peers with negative sentiment.

Table [5] about here

4. Risk factor construction and summary statistics

Fama and French (2015) examine the sensitivity of risk factors to the specifics of factor construction. The authors state that the original 2x3 sorts for the size and value factors have been an arbitrary choice. This sorting mechanism weights small and big stocks equally, i.e. they are roughly neutral with respect to size. However, if the model is extended by the additional variables profitability and investment, the constructed factors HML, RMW, and CMA do not control for the other aspects. For example, HML is neutral in terms of size but does not control for operating profitability nor investment. That means that the average HML return combines the premia of value, profitability and investment. Analogous remarks apply to the construction of RMW and CMA. In order to overcome this challenge, we jointly control for all factors and isolate the premia in average returns related to value, profitability, investment, and sentiment. We rely on five sorts which jointly control for all variables including sentiment. Even a minimalistic sorting of each variable into low and high using the median of all observations, results in a high number of portfolios (2x2x2x2x2 = 32). To be more precise, we form two groups of $Size$ for small and big stocks, two groups on low and high book-to-market ratio B/M, two groups on robust and week profitability OP, two groups on conservative and aggressive investments Inv, and finally two groups on positive $s(+)$ and negative $s(-)$ sentiment Snt. Overall, the intersections of these groups form 32 VW portfolios and the returns of the relevant factors are the difference of the averages of the two groups the factors account for. The average return of the SMB factor, for example, is the average of the 16 small portfolios minus the average of the 16 big portfolios. In terms of sentiment, PMN is the average of 16 positive sentiment portfolio minus 16 negative.[15] Further details can be found in Table 6. As the individual portfolios tend to be poorly diversified, we also choose the 2x3 sorts to achieve better diversification and allow for benchmarking with Fama and French (2015) at the expense that the average returns of factors may not entirely control for other variables.

Table [6] about here

Table 7 shows summary statistics for factor returns. The average market return above the risk-free rate $Mkt - RF$ is 55.16bps per year with a high dispersion of 446.16bps. These values match the statistics given by Fama and French (2015). The average return of SMB is 20.27bps for the 2x3 sorts, 49.71bps respectively for the more granular approach. With more than 2.4 standard errors, it is only in the latter case significantly different from zero. The dispersion is higher than in the original paper which is due to the reduced dataset between 1998 and 2017. This also applies to the other three Fama/French factors which are, at most, less than

[15]Sentiment refers here to the positive and negative deviation of previous month's sentiment from the long-term mean since inception until time t.

1.8 standard errors away from zero. Extremely poor, and posing a challenge as in Fama and French (2015), are the small average HML returns of 14.39bps, -3.07bps respectively, with high standard deviations of 344.94bps and 262.95bps. This also applies for average RMW and CMA returns with 4.08 and 6.82bps for the 2x2x2x2x2 sorts. The dispersion of the factors is overall smaller than in the 2x3 sorts due to a better diversification effect. The 2x3 sorts neglect the stocks in the middle 40%. This applies to the fundamental factors only. In fact, the standard deviation of the PMN factor is comparable with 172.61 (2x2x2x2x2) to 166.49 (2x3). Overall, the dispersion is also the lowest of all factors which indicates that stocks sorted along the change of sentiment perform similarly. Average PMN returns are 22.28bps and 30.43bps for the two sorting approaches and more than 2.0, respectively 2.7, standard errors away from zero.

Table [7] about here

The correlations between the 2x3 Fama-French factors are mostly in line with the original version in terms of value and sign. Exception to this is the high correlation between the market risk premium and RMW of -0.54 compared to -0.21 in Fama and French (2015). Our sentiment factor, PMN, is significantly negatively correlated with -0.32 to the market and -0.16 to HML. The relation to RMW is significantly positive at 0.24. The alternative 2x2x2x2x2 sorting approach effectively neutralizes the factors and also reduces the correlation despite not being perfectly orthogonal. While the 2x3 sorts only control for size and one other factor, the 2x2x2x2x2 jointly neutralize for size, value, profitability, and investment with the largest impact on the PMN factor. The correlation of this factor between the 2x3 and the 2x2x2x2x2 approach is with 0.71 the lowest, followed by CMA with 0.77 and RMW with 0.80. The correlation for different versions of SMB and HML are above 0.90. Within the 2x2x2x2x2 sorts, the correlation between PMN and RMW is no longer significant and reduced to a negative relation of -0.02. The remaining correlations of sentiment to the FF5 factors remain similar in value and sign as for the 2x3 sorts, all below 0.25. The correlations between the fundamental factors are similar to the most granular sorting of 2x2x2x2 in the original paper by Fama and French (2015). SMB is positively related to the market, confirming that small stocks tend to have higher market betas than big. The correlation of HML to RMW is positive and significant confirming the original authors who explicitly outline the high correlation between RMW and HML as a negative feature of factors constructed by joint controls. This is due to the extraordinarily high return of small stocks with low B/M, weak OP, and low or high Inv which are held short in the HML and RMW factor. Overall, the results of the correlation analysis show beneficial properties for linear regressions as sentiment seems to capture different information than the fundamental factors.

In Figure 1 we plot the cumulative returns of the risk factors based on the 2x2x2x2x2 sorts from January 1998 - December 2017. During this period investors with exposure to the size factor had gained the highest yield, followed by the market and sentiment factor. For sentiment we observe spikes shortly before the Dotcom crisis in the late 90s as well as during and after the great financial crisis occurring in 2008. Outside these windows, the sentiment premium was relatively stable compared to the other factors and most importantly always positive. The value factor has a negative cumulative return, while investment and profitability exposure gained small positive returns. This provides further guidance for incorporating sentiment into the asset pricing models in the following section.

5. Sentiment-augmented asset pricing models

In this section we turn our focus to pricing models that include our novel sentiment risk factor. The baseline is the FF5 model that is designed to model the fundamental and rational relations between average stock excess returns and market, size SMB (market capitalization in terms of price time shares outstanding), value HML (book-to-market ratio), profitability RMW (operating profit), and investment CMA (growth in book equity) factors. We add the sentiment factor based on a positive-minus-negative sentiment sorts of stocks to Equation (1) in order to cover the sentiment premium for excess returns of stock portfolios:

$$R_{i,t} - R_{f,t} = a_i + b_i(R_{m,t} - R_{f,t}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + p_i PMN_t + e_{i,t} \quad (1)$$

where $R_{i,t}$ is the return on security or portfolio i for period t, $R_{f,t}$ is the risk-free return, $R_{m,t}$ is the excess return on the value-weighted (VW) market portfolio, SMB_t is the return on a diversified portfolio of small stocks minus the return of a diversified portfolio of big stocks, HML_t is the difference between the returns of diversified portfolios of high and low B/M stocks, RMW_t is the spread between the returns of diversified portfolios with robust and weak operating profitability, CMA_t is the return difference between firms with conservative and aggressive investment activities, and $e_{i,t}$ is a zero-mean residual. The additional sentiment factor PMN_t is the difference between the returns on diversified portfolios comprised of stocks with positive and negative deviation of previous month's sentiment from the long-term mean since inception until time t.

We map the above OLS regression to the GMM framework to correct the standard errors for autocorrelation and conditional heteroskedasticity and account for potential endogeneity. The objective of GMM matches our goal to minimize the sum of squared pricing errors without the usual distributional assumptions of i.i.d., normal distribution, or homoskedasticity of the OLS framework. It also accounts for risks of endogeneity between sentiment and returns. Both the portfolio and factor sorts are based on the change in sentiment of individual securities and are rebalanced on a monthly basis. The factor-mimicking portfolio and sentiment factor PMN are thus constructed at a higher frequency than the fundamental FF5 factors. We cannot completely rule out that a sentiment shock may have an impact on the existing risk factors and change their pricing which leads back to the perpetual debate on whether sentiment can be truly seen as an independent risk factor or rather as an instrumental or state variable that affects the fundamental pricing factors. As previously outlined, we follow the theoretical framework of Shefrin and Belotti (2008) who argue in favor of a sentiment-based risk premium. Both this theoretical evidence as well as our empirical specification elevate the GMM framework with an individual sentiment risk factor. In line with Cochrane (2009), our factor-mimicking portfolios are predestined for the GMM estimator as those portfolios are more stationary than individual stocks. Statistical characteristics of portfolio returns are more constant than the properties of individual securities which are selected and dropped from the portfolios at each rebalancing step. With sentiment-mimicking portfolios we achieve a smoothing effect which is particularly important for our specification with sentiment of individual stocks that changes very frequently, may rise steeply and drop immediately for the next rebalancing window.

We use the new sentiment risk factor to explain average excess returns of factor-mimicking and industry portfolios and benchmark our model against the FF5 model. We consider the following pricing models: i) the standard FF5 model with $R_m - R_f$, SMB, HML, RMW, CMA,

ii) a modified FF5 (FF5-SNT) including aggregate sentiment PMN. The two models are applied to the 25 VW portfolios of Table 4 and 36 VW portfolios of Table 5 as well as to the ten and 30 industry portfolios from Kenneth's homepage as an additional robustness check.

Following Fama and French (2015), we apply these test statistics:[16] i) the average absolute intercept $A|\alpha_i|$ to have a relative measure for the dispersion of intercepts. We are interested in relative performance improvements if sentiment is added to the FF5 model and test whether sentiment adds explanatory power to traditional asset pricing models. ii) The GRS statistic of Gibbons et al. (1989) to test for the hypothesis of a zero intercept.[17] If an asset pricing model is able to completely capture the variation in expected excess returns, the intercept should be close to zero. Thus, a lower GRS score of a model points towards a comparative advantage of that particular specification over the benchmark. iii) We compute a ratio $\frac{A|\alpha_i|}{A|\bar{r}_i|}$ to estimate the unexplained proportion in the cross-section of returns. The numerator is the mean absolute intercept. The denominator measures the dispersion of dependent expected returns. We compute the difference of the time-series mean excess return on portfolio i and the cross-sectional mean of excess returns. A value greater than one suggests that intercepts are more dispersed than average returns. iv) We use the squared versions of the previous metric $\frac{M|\alpha_i^2|}{A|\bar{r}_i^2|}$, following Fama and French (2015), in order to account for biases due to measurement errors which inflate both the median absolute intercept $M|\alpha_i|$ and the average absolute deviation $A|\bar{r}_i|$. As stated by Fama and French (2015) this metric is similar to an adjusted version of $1-R^2$ and as such a goodness-of-fit measure.[18] We use the median over the mean for the absolute intercepts considering the remarks by Fama and French (2015) that the results are distorted by extreme alphas from hard-to-value portfolios (for more details see Section 7).

Table [8] about here

Table 8 shows the results of this analysis for different factor-mimicking and industry port-

[16]Given that R^2 is not applicable in the GMM framework, none is provided. Also no J-test is provided as our model specification has an exact identification with as many instruments as endogenous variables, i.e. the J-test is zero by definition.

[17]We are aware that the GRS test assumes normally distributed error terms, that are homoskedastic and serially uncorrelated but it is provided for comparative reasons and relative assessment of the two models. We do not show the p-value of getting a GRS statistic larger than the one observed if the true intercepts are all zero to avoid false inferences due to aforementioned assumptions. We are less interested whether the GRS test assesses that our models are complete descriptions of expected returns than their relative performance to the FF5 model.

[18]The interested reader is referred to Section 6 in Fama and French (2015) for an in-depth discussion of the last two metrics, their construction and motivation.

folios on the left-hand side (LHS). The sentiment-augmented model generates lower absolute intercepts than the FF5 model for all LHS portfolios except the $Size - B/M$ portfolios in Panel A. The intercepts are unsurprisingly lowest for the FF5 factor-mimicking portfolios for which the right-hand side (RHS) factors are targeted. They are sensitive to the factor construction and 30-50% higher for the 2x2x2x2x2 sorts which contradicts the pattern shown by Fama and French (2015). In their study, the more granular factors tend to outperform the 2x3 sorts. We thus lead this back to the inclusion of sentiment in the extended 2x2x2x2x2 sorting. The improvement of the sentiment-augmented model is also larger for the more granular approach compared to 2x3. The highest intercepts are shown for the sentiment-mimicking portfolio which suggests that the FF5 performs particularly poorly for portfolios with a sentiment tilt. These portfolios are also the only ones for which the neutralization of the fundamental factors of the 2x2x2x2x2 sort is beneficial for the results. The reduction in average absolute intercepts amounts to 25-30%. The 36 factor-mimicking portfolios of the quadruple 2x2x3x3 sorts show intercepts of similar values as the industry portfolios. Here, sentiment achieves improvements between 5-20%. The GRS score is better for the sentiment-augmented models for all factor-mimicking portfolios but not for the two industry portfolios. Table 8 also shows that intercepts are more dispersed than average returns for the two industry portfolios. When we exclude those for the different 5x5 factor-mimicking portfolios, the FF5 factors based on 2x3 sorts leave between 39-65% of the average returns unexplained. This ratio is higher for the 2x2x2x2x2 sort with 49-105%.

The addition of sentiment is able to achieve remarkable improvements. The minimum of the range reduces to 26% for the 2x3, respectively 37% for the 2x2x2x2x2. Interesting is the higher value of the FF5-SNT model for the $Size - SNT$ portfolios of 71% compared to 52%. This is, however, only the case if the factors are not neutralized to each other. In fact, if we correct for estimation errors we observe the lowest ratio of only 8% for the $Size - SNT$ portfolios using the FF5-SNT model. Also the two sets of 36 factor-mimicking portfolios including sentiment show very low values of 24-30%. In general, the correction for estimation errors tend to significantly improve the evaluation and is in favor of the sentiment-augmented model. That means that the added value of the FF5-SNT model is even higher if the metric accounts for estimation errors.

6. Relation between fundamental factors and sentiment

Previously, we elaborated on the idea that the addition of sentiment benefits the FF5 asset pricing model. In order to better understand the relation between fundamental factors and sentiment, we now run linear regressions for each factor against the five others. This should particularly answer the question whether sentiment (partially) captures existing information in fundamental variables (and vice versa) or indeed contains novel information. In case of the excess market return, $Mkt - Rf$, the explanatory factors are SMB, HML, RMW, CMA, and PMN. Further regressions swap the dependent with one of the explanatory variables. In Panel A of Table 9, we observe that for the 2x3 sorts, PMN is, with a coefficient of -0.68, significantly negatively related to the market. PMN has a positive relation to the size factor with a coefficient of 0.32. The relation to HML is negative with -0.31. In line with the results from Fama and French (2015), HML seems to be a redundant factor as the other factors can explain around 60% of its variation, driven by the positive slopes of RMW and CMA.[19] Interesting is the high R^2 of 63% for RMW, which is clearly above the 21% given by Fama and French (2015). This is not driven by the inclusion of PMN with an estimate of 0.14 and a t-statistic of 1.83 but rather by the chosen time period of January 1998 - December 2017 and the high slope of the HML factor. If we exclude PMN from the regression, the R^2 does not change to the third decimal. For our variable of interest, PMN, the results show low coefficients smaller than 0.20. The FF5 factors only explain 17% of the PMN variation, the lowest value across all regressions. It means that stocks with positive sentiment behave fundamentally different which cannot be explained by traditional security properties like size, value, profitability, or investment. In Panel B with the neutralized risk factors of the 2x2x2x2x2 sort, the coefficients, t-statistics, and goodness-of-fit measures tend to be even smaller. The neutralization of PMN reduces the correlation to RMW at the expense of increasing the one to CMA. The overall R^2 is with 19% on a similar level. The more granular sorting approach has a higher effect on SMB and CMA for which the R^2 levels are now even below the ones outlined by Fama and French (2015) in their 2x2x2x2 sort.

These results raise the question if there are other relevant factors that may impact the

[19]The interested reader is referred to Section 7 from Fama and French (2015) for an in-depth discussion of the HML factor.

contribution of sentiment. Fama and French (2015) discuss that neither the addition of the momentum factor from Carhart (1997) nor the liquidity factor from Pástor and Stambaugh (2003) lead to significant performance improvements of the FF5 model. However, due to concerns that sentiment, in particular positive mood, may only proxy stock momentum, we extend the factor analysis accordingly in Table C.1 in the Internet Appendix. The results show that the average return of the momentum factor UMD[20] does not significantly differ from zero. The t-statistic reports 1.12 standard deviation for the 2x3 sort, respectively 0.53 for the 2x2x2x2x2 approach, with high dispersion of returns of 5.27% or 3.26%. The correlation to sentiment is moderately significant with 0.56 and 0.48 if the factors are neutralized to each other. If we include sentiment in the regression of PMN, the coefficient is with 0.14 similarly low as for other factors.

We further investigate the relation between sentiment and liquidity given that overconfidence leads to the entry of retail investors, driving up liquidity, as shown by Odean (1998). In this case, our indicator may only be a proxy for the change in liquidity. As above we construct liquidity (LMI) as the difference between two groups of liquid and illiquid stocks, measured as the change in monthly trade volume in relation to shares outstanding. Table C.2 in the Internet Appendix shows that for both factor constructions the average return of the LMI factor is not significantly different from zero (2x3: 31.05, t=0.97, 2x2x2x2x2: 22.07, t=1.64). The correlation to sentiment is close to zero. Along Fama and French (2015), those results do not suggest the addition of momentum or liquidity to the pricing models.

7. Regression details of hard-to-value stock portfolios

We now turn to a detailed discussion of the regression details from Section 5 and in particular examine the intercepts and coefficient estimations of the sentiment-augmented pricing model. To keep the analysis clear, we hereby focus on the well-known pricing puzzles of hard-to-value stocks. These comprise extreme growth and extreme investment portfolios as outlined in Fama and French (1993, 2015), small stocks that invest heavily despite low profitability, and sentiment-

[20] Up-minus-down (UMD) captures the return spread between firms with high prior returns over the last twelve months (up) and low prior returns (down). The monthly prior (2-12) return breakpoints are the 30th and 70th NYSE percentiles as described on Kenneth's homepage. The sorts comprise all NYSE, AMEX, and NASDAQ stocks with clean price history for the end of month $t-13$ to $t-2$.

mimicking portfolios. Our research hypothesis states that sentiment can help to (partially) solve these puzzles that all seem to be related to irrational investor behavior.

7.1. *Extreme growth stocks*

Fama and French (2015) report that the FF5 model helps to explain the returns of extreme growth stocks, but cannot provide all the missing pieces to resolve the puzzle. Both in the FF3 model as well as in the FF5 model the intercepts for small extreme growth stocks are significantly negative while being positive for large extreme growth stocks. In Panel A of Table 10, we clearly depict the significantly negative intercepts for small extreme growth stocks and the positive alphas of large extreme growth firms of the 25 $Size - B/M$ portfolios for the FF5 model. The large negative intercept of the growth smallcap portfolio is sufficient to reject the FF5 model to describe the expected returns of the 25 $Size - B/M$ portfolios overall. The sentiment-augmented model reduces the problem by increasing the intercept by 10bps from -0.79 to -0.69. It also increases the intercepts for the next two size quintiles of extreme growth portfolios but cannot completely explain the negative intercept for growth smallcaps and positive for growth largecaps. Panel B shows the further coefficients of the FF5-SNT model. The market slope is always close to one. As in Fama and French (2015) the SMB slope is positive for small (1.21, t=11.74) and negative for big stocks (-0.19, t=-8.98). The HML (-0.53, t=-2.13) and CMA (-0.38, t=-2.58) slopes are comparable across all growth portfolios but the RMW is steepest for growth smallcaps (-0.49, t=-2.32) and positive for growth largecaps (0.20, t=4.12). In terms of sentiment, the small growth portfolio has the most negative slope (-0.29, t=-2.53). This suggests that the returns of this portfolio are driven by smallcaps which behave like unprofitable, aggressively investing firms for which investors have a negative sentiment outlook. The sentiment coefficient for growth largecaps is zero and insignificant to further prove our point.

Table [10] about here

7.2. *Extreme investment stocks*

Fama and French (2015) describe the FF5 asset pricing problem of negative intercepts for high investment small stock and positive intercepts for high investment big stock portfolios. Table 8 indicates that sentiment generally improves the model performance for the 25 $Size - Inv$

portfolios. Panel A of Table 11 shows the problem of highly significant negative intercepts for the three small stock portfolios in the highest investment quintile (Small: -0.59, t=-4.49; S2: -0.40, t=-3.22; S3: -0.29, t=-2.09). The FF5-SNT model increases the intercepts by 10bps, 7bps, and 4bps (Small: -0.49, t=-4.81; S2: -0.33, t=-2.81; S3: -0.25, t=-1.67). This represents a reduction of 13-18% and can be traced back to the negative slopes for PMN, in particular for smallcaps (-0.33, t=-3.45). This estimate is the lowest for all high investment portfolios. Similar to extreme growth stocks the addition of sentiment to pricing models cannot fully explain the mechanisms behind these extreme investments but add at least further knowledge to better understand them.

Table [11] about here

7.3. Small stocks that invest heavily despite weak profitability

Fama and French (2015) describe the FF5 asset pricing problem of negative intercepts for portfolios of stocks that invest heavily despite low profitability for the 36 $Size - B/M - OP - Inv$ portfolios. Panel A of Table 12 shows the problem of highly significant negative intercepts for small growth (-0.82, t=-5.61) and small value stocks (-0.29, t=-3.09). Both portfolios contain firms that invest heavily (aggressive) despite low (weak) profitability. The coefficients are most negative if size and value is kept stable. The FF5-SNT model increases the intercepts by 10bps for small growth stocks (-0.72, t=-4.17), respectively 7bps for small value stocks (-0.22, t=-1.88). This represents an absolute reduction of 12-23%. However, the slopes for PMN are not significant. This is an interesting result as for both portfolios the slopes of the other factors change drastically. It appears that in this asset pricing puzzle, the inclusion of a sentiment factor is indirectly beneficial by changing the pricing of the existing factors. Similar to other hard-to-value stocks the addition of sentiment to pricing models cannot resolve but significantly reduce the problem of negative intercepts of firms that invest heavily despite low profitability.

Table [12] about here

7.4. Sentiment-mimicking portfolios

We now evaluate the model performance on sentiment-mimicking portfolios. Table 8 shows that the 25 $Size - Snt$ portfolios are much more difficult to price than the other factor-mimicking portfolios and that the inclusion of sentiment is greatly beneficial. This is not surprising since the sentiment factor PMN is targeted to explain the returns of such portfolios. In Panel A of Table 13, the intercepts of the FF5 model show that the fundamental factors do a surprisingly good job for portfolios with a negative sentiment tilt. The portion of expected returns left unexplained is close to zero and ranges from -0.08 (t=0.69) to 0.23 (t=1.81). Only the intercept for largecaps with negative sentiment is significant. Portfolios with a positive sentiment tilt are, however, more difficult to value and the intercepts range from 0.07 (t=0.59) to 0.74 (t=4.24). Smaller stocks with positive sentiment outlook are harder to price than bigger stocks. The inclusion of sentiment improves the results with less significant intercepts across all 25 $Size - Snt$ portfolios. A portfolio of small stocks with positive sentiment only has a significant exposure to the size (1.08, t=13.52), sentiment (-0.33, t=-0.45) and investment factor (-0.41, t=-5.02). Large stocks with a positive sentiment tilt are negatively exposed to the size factor (-0.20, t=-6.27), value (-0.42, t=-3.86), profitability (0.19, t=2.07), and investment (-0.61, t=-5.11). This suggests that this portfolio is fundamental- and not sentiment-driven which is similar for big stocks with a negative sentiment tilt (SMB: -0.22, t=-4.60; HML: 0.39, t=3.55; CMA: 0.66, t=3.87). Different is the slope of RMW (-0.30, t=-2.33), i.e., that this portfolio of big stocks with negative sentiment behaves like big stocks with weak profitability. The coefficient to sentiment is insignificant (-0.06, t=-0.49). Small stocks with negative sentiment are surprisingly not susceptible to PMN either (0.01, t=0.05), but have a significant positive slope for SMB (1.29, t=10.69) and negative to RMW (-0.58, t=-4.26). Similar to big stocks, smallcaps with low sentiment behave like small stocks with weak profitability. Overall, portfolios with sentiment tilt are a challenge to price, even when a factor that particularly targets this portfolio style is included.

Table [13] about here

8. News-based sentiment

In our last section, we investigate whether sentiment from social media offers unique and more suitable results than other sentiment factors. During the introduction of the RMI indicators, we differentiated between social media- and news-based sentiment. In this section, we re-run most of the analysis, but this time with sentiment extracted from public news. We hypothesize that this source of sentiment captures more factual information than investors' mood.

The 5x5 sentiment-mimicking portfolios in Table B.1 of the Internet Appendix do not show the same return spreads between positive and negative sentiment-tilted stocks. For smallcaps, the portfolio with positive sentiment returns on average 24.87bps per month less than the portfolio with negative stocks. For largecaps the difference amounts still to 5.34bps. The more granular 2x2x3x3 portfolios in Table B.2 of the Internet Appendix show an even more disturbed picture where negatively-tilted sometimes outperform portfolios with positive sentiment, and sometimes vice versa. That means that if the sentiment is neutralized for other fundamental factors, no clear pattern for a sentiment effect can be distinguished.

The factor analysis in Table B.3 reveals that the average return of PMN is not significantly different from zero for neither the 2x3 (3.80bps, t=0.27) nor the 2x2x2x2x2 approach (6.69bps, t=0.69). 2x3 PMN is negatively related to the market (-0.25) and HML (-0.11) at the 10% confidence level, while the 2x2x2x2x2 PMN is negatively related to all factors except SMB. The correlation between different versions of PMN is only 0.66 and as such more dependent on the sorting approach.

Table B.4 of the Internet Appendix summarizes the statistics of regressions with the same LHS portfolios from Table 8, though sentiment-mimicking portfolios are based on news-based sentiment as are the PMN factors. We observe that the FF5-SNT model has a marginally better explanatory power than the FF5 model. Comparing its performance with the social media-based regressions, the news-based model falls short in all categories. First, the FF5 model itself does a better job on news-based sentiment-mimicking portfolios in terms of lower intercepts than for the social-media based portfolios. That means that fundamental factors from the FF5 framework leave less variance in expected returns unexplained. This points into the direction that those sentiment-tilted stocks behave more like fundamental-driven stocks. Second, the improvement of the FF5-SNT over the FF5 is still marginal, even though the PMN factor is explicitly targeted for those portfolios. Adding sentiment to the pricing model only marginally changes its performance.

One may still be concerned that social media-based sentiment measures fundamental information instead of pure sentiment. In order to purify sentiment, we orthogonalize the social media-based risk factor against the news-based and show the results of the regressions in Table B.5. Compared to Table 8 orthogonalization worsens the results marginally. The outperformance of the sentiment-augmented FF5-SNT over the traditional FF5 model becomes smaller in terms of absolute alphas, GRS scores, and the two measures of dispersion of the intercepts. Only for $Size - B/M - Inv - SNT$ portfolios in Panel F, the variation of alphas is now higher than for the FF5 model. We acknowledge that the social media-based sentiment indicator does capture some notions of the fundamental news flow. However, the differences are marginal and do not motivate further studies. We conclude that there is not sufficient evidence to reject our hypothesis that social media-based sentiment contains more novel information about investors' moods than news-based and is thus more suitable to capture the sentiment risk premium from Shefrin and Belotti (2008).

9. Conclusion

By using the recently developed search-based and bottom-up sentiment indicator from MarketPsych, we construct a novel risk factor from a positive-minus-negative sentiment-portfolio sorts and reveal patterns in average returns related to investors' mood. The sentiment score is beneficial in augmenting the existing fundamental asset pricing model by Fama and French (2015) for the U.S. equity market and add the sentiment premium to the pricing paradigm from Shefrin and Belotti (2008). We can trace back the significant performance improvements for different factor-mimicking and industry portfolios to investors' activities in social media. The same effect is not found exploiting sentiment extracted from public news channels. Different notions of human mood are expressed in social media and can be used to form a monthly-rebalanced sentiment risk factor which is orthogonal to underlying macroeconomic or business cycle-related developments. It is also unrelated to existing fundamental pricing factors and independent of momentum. Therefore, we believe that this novel risk factor successfully captures and quantifies investor sentiment.

In two sets of portfolio sorts with either 25 or 36 portfolios using 5x5 double-sorting or 2x2x3x3 quadruple-sorting, we show a high average excess return spread between stocks with positive and securities with negative sentiment. This spread is significantly higher than for other style tilts like size, value, profitability or investment. We use those factor-mimicking portfolios in a sentiment-augmented asset pricing model to show that the inclusion of sentiment reduces the intercepts and improves the model performance. We explore two different versions of the sentiment factor, one using the original 2x3 double-sorting from Fama and French (2015) and the other a more granular 2x2x2x2x2 sorting which effectively neutralizes all five factors against each other. While the latter produces cleaner risk premia for the various factors, the more granular approach suffers from less diversified portfolios. This becomes more challenging when the list of factors grows, e.g., by adding a momentum or liquidity factor. However, the performance improvement by sentiment is independent of the sorting approach on the factor.

Our models account for endogeneity, autocorrelation of returns and heteroskedasticity by mapping them to the GMM framework and generating robust standard errors. We show that similar to the five-factor model from Fama and French (2015), the GRS test rejects our sentiment-augmented model to fully explain the cross-section of expected returns for different style or industry portfolios. However, it improves the five-factor model in the cross-section along various dimensions and provides an explanation, at least partially, for asset pricing puzzles of hard-to-value stocks. Our sentiment-augmented models supply an additional component for solving the pricing mosaic for portfolios of small extreme growth and extreme investment stocks. Sentiment increases the negative intercept by 13-17%. For another pricing puzzle of small stocks that invest heavily despite low profitability, sentiment has an indirect contribution by modifying the slopes of the other factors. We also report a very poor performance of the five-factor model for sentiment-tilted portfolios. Unsurprisingly, the inclusion of the sentiment factor here is particularly beneficial as it is targeted to explain the excess returns of those style portfolios. Judged on regression slopes, both largecaps and smallcaps with negative sentiment seem to behave like stocks with weak profitability. The study's findings contribute to finally overcome the research challenges put forward by Fama and French (2015) regarding behavioral stories for stocks that invest heavily despite low profitability. Investor sentiment on stock outlooks expressed in social media channels can add crucial knowledge to answer this question. As such, the wisdom of the crowd seems to matter in U.S. equity pricing.

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Figures and tables

Table 1: List of economic indicators

This table shows the list of economic indicators. We provide the name and source as well as a short description of the data. This is typically taken directly from the source. For each indicator we compute the month-on-month percentage change from January 1998 - December 2017.

Name and Source	Description
Unemployment rate from the U.S. Bureau of Labor Statistics	Seasonally adjusted monthly change in the U.S. national unemployment rate. The unemployment rate represents the number unemployed as a percent of the labor force. Persons are classified as unemployed if they do not have a job, have actively looked for work in the prior 4 weeks, and are currently available for work.
Industrial Production from the Federal Reserve Bank of St. Louis	Seasonally adjusted monthly change in the U.S. industrial production index. The Industrial Production Index (INDPRO) is an economic indicator that measures real output for all facilities located in the United States manufacturing, mining, and electric, and gas utilities (excluding those in U.S. territories).
Consumption from the BEA - Bureau of Economic Analysis, U.S. Department of Commerce	Seasonally adjusted monthly change in the U.S. household consumption. Consumer spending, or personal consumption expenditures (PCE), is the value of the goods and services purchased by, or on the behalf of, U.S. residents.
Consumer price index from the U.S. Bureau of Labor Statistics	Monthly change in the U.S. consumer price index for all urban consumers. The Consumer Price Index (CPI) is a measure of the average change over time in the prices paid by urban consumers for a market basket of consumer goods and services.
Durable goods from the U.S. Census Bureau	Seasonally adjusted monthly change in the U.S. durable goods orders. The Manufacturers' Shipments, Inventories, and Orders (M3) survey provides broad-based, monthly statistical data on economic conditions in the domestic manufacturing sector. The survey measures current industrial activity and provides an indication of future business trends.
House price index from the Office of Federal Housing Enterprise Oversight	Seasonally adjusted monthly change in the U.S. FHFA house price index. The house price indexes measure changes in single-family home values based on data from all 50 states and over 400 American cities. The methodology based upon a weighted, repeat-sales statistical technique to analyze house price transaction data.
Non/farm payrolls from the U.S. Bureau of Labor Statistics	Seasonally adjusted monthly change in the U.S. non-farm payroll. Non-farm payrolls is the measure of the number of workers in the U.S. excluding farm workers surveyed from private and government entities throughout the U.S.

Table 2: Regressions of social media-based sentiment against economic indicators

This table shows the output of a regression of the social media-based sentiment factor PMN against well-known economic indicators. We show the coefficient estimates, standard errors, t-statistics and p-values for each variable as well as the overall goodness of fit in terms of adjusted R^2. The details of the economic indicators can be found in Table 1.

	estimate	std.error	t-statistic	p-value
Unemployment_Rate	0.05	0.02	2.23	0.03
Industrial_Production	0.00	0.00	1.08	0.28
Personal_Consumption	-1.68	0.92	-1.83	0.07
CPI_MM	0.79	0.51	1.56	0.12
Durable_Goods	0.44	0.21	2.13	0.03
Home_Prices	0.04	0.25	0.16	0.87
Non.farm_Payrolls	-0.73	0.99	-0.74	0.46
Adj. R^2	0.03			

Table 3: Descriptive statistics of social media-based sentiment by groups

This table shows simple summary statistics of social media-based sentiment for different categories. Panel A differentiates sentiment across various industries using the NAICS (North American Industry Classification) used in the Compustat and CRSP databases. Panel B shows the sentiment across five liquidity quantiles. We use the ratio of trading volume over shares outstanding as a naïve proxy for liquidity. The breakpoints only use NYSE in order not to bias the data with small stocks that only comprise a small portion of the traded volume. Panel C clusters sentiment by size using market capitalization with NYSE breakpoints from the CRSP database. Panel D differentiates sentiment across the three exchanges NYSE, AMEX, and NASDAQ. For each panel, we display the mean, median, and standard deviation of sentiment for stocks forming this group. The data covers the full time horizon January 1998 - December 2017 with rolling classifications and mappings to accomodate for changes over time. Values are scaled by a factor 100 for better visualization, now forming a range between -100 and 100.

Name	Mean	Median	SD
Panel A: Sentiment by Industries			
Agriculture, Forestry, Fishing and Hunting	4.05	0.52	26.96
Mining, Quarrying, and Oil and Gas Extraction	5.64	2.94	22.79
Utilities	4.84	2.20	29.49
Construction	7.59	3.53	28.12
Manufacturing	6.65	3.66	26.83
Wholesale Trade	8.00	5.71	32.50
Retail Trade	5.17	2.43	24.75
Transportation & Warehousing	4.70	1.21	28.59
Information	7.02	3.39	27.16
Finance and Insurance	6.66	3.33	34.39
Real Estate and Rental and Leasing	6.61	2.76	29.84
Professional, Scientific, and Technical Services	8.50	5.26	29.43
Admin. & Support & Waster Mgmt & Remediation Svcs	5.23	2.33	30.12
Educational Services	4.20	0.00	31.82
Health Care and Social Assistance	5.77	2.96	30.19
Arts, Entertainment, and Recreation	3.09	1.14	25.34
Accommodation and Food Services	6.55	4.35	23.81
Other Services (except Public Administration)	3.12	-1.46	33.45
Panel B: Sentiment by Liquidity			
Liquid	3.77	1.62	20.02
Q2	8.60	5.56	34.56
Q3	7.47	4.28	29.98
Q4	6.53	3.87	26.46
Illiquid	8.66	6.52	40.99
Panel C: Sentiment by Size			
Big	5.01	2.22	22.07
Q2	7.21	4.17	34.13
Q3	8.01	4.93	32.87
Q4	7.46	4.60	30.14
Small	3.46	1.12	30.38
Panel D: Sentiment by Exchange			
NYSE	5.65	2.42	26.94
AMEX	5.92	3.42	28.20
NASDAQ	7.35	4.40	29.88

Table 4: 5x5 portfolios using social media-based sentiment

This table shows average monthly excess returns in basis points (bps) for portfolios formed on $Size$ and book-to-market ratio B/M, operating profitability OP, investment Inv, and sentiment Snt for January 1998 - December 2017. The sorting follows Fama and French (2015) using only NYSE breakpoints: at the end of each June, stocks are allocated to five Size groups (Small to Big) or five B/M groups (Low to High). The intersections produce 25 value-weight $Size - B/M$ portfolios. The $Size - OP$ and $Size - Inv$ portfolios are formed analogously with the second sort variable being either operating profitability or investment. For the sentiment-mimicking sorts $Size - Snt$, we sort the stocks more frequently based on the previous month's deviation of social media-based sentiment from the long-term mean since inception until time t.

	Low / Negative	2	3	4	High / Positive
Panel A: Size-B/M Portfolios					
Small	41.30	84.62	86.76	99.36	97.74
2	68.13	85.71	87.60	77.67	81.32
3	68.69	78.87	77.99	72.23	100.23
4	82.18	75.32	85.20	74.84	76.81
Big	55.49	62.21	64.02	43.65	47.28
Panel B: Size-OP Portfolios					
Small	72.47	100.82	93.69	85.76	89.46
2	58.91	74.33	92.54	98.08	102.98
3	58.42	74.51	76.16	76.70	102.52
4	51.56	80.21	83.33	80.88	95.99
Big	21.58	44.21	49.36	56.75	58.80
Panel C: Size-Inv Portfolios					
Small	108.60	100.96	108.55	80.54	47.44
2	76.58	85.91	95.16	92.71	65.09
3	80.28	84.28	90.45	86.79	62.29
4	74.51	84.89	78.75	94.17	69.18
Big	63.35	52.43	59.90	59.74	49.92
Panel D: Size-SNT Portfolios					
Small	118.61	169.04	192.82	251.76	177.22
2	84.30	123.55	112.67	144.17	127.37
3	80.71	91.67	120.53	94.43	109.19
4	76.33	71.49	93.62	118.87	78.19
Big	66.78	32.77	48.14	64.62	61.66

Table 5: 2x2x3x3 portfolios using social media-based sentiment

This table shows average monthly excess returns in basis points (bps) for portfolios formed on $Size$ and book-to-market ratio B/M, operating profitability OP, investment Inv, and sentiment Snt for January 1998 - December 2017. The sorting follows Fama and French (2015) using only NYSE breakpoints: at the end of each June, stocks are allocated to two Size groups (Small and Big), two B/M groups (Low and High), three groups of either profitability or investment (Low, Medium, and High) and three groups of Snt (negative s(-), neutral s(0), and positive s(+)). For sentiment, we sort the stocks based on the previous month's deviation of social media-based sentiment from the long-term mean since inception until time t. The intersections produce 36 portfolios.

	Small						Large					
	Low B/M			High B/M			Low B/M			High B/M		
	$s(-)$	$s(0)$	$s(+)$	$s(-)$	$s(0)$	$s(+)$	$s(-)$	$s(0)$	$s(+)$	$s(-)$	$s(0)$	$s(+)$
Panel A: Size-B/M-OP-SNT Portfolios												
Low	128.12	110.97	140.50	79.19	143.59	131.55	42.32	85.18	16.04	22.28	49.45	79.17
Medium	100.45	104.48	121.21	78.13	143.32	99.98	66.23	46.36	86.54	81.40	66.33	77.34
High	104.55	128.69	156.78	90.68	114.08	146.29	55.78	54.70	69.29	69.16	97.89	104.84
Panel B: Size-B/M-Inv-SNT Portfolios												
Low	132.23	126.10	199.97	72.19	179.22	114.13	68.36	64.54	56.10	33.27	70.73	74.50
Medium	86.01	95.22	120.62	78.43	117.90	146.15	69.63	49.02	74.82	67.92	64.48	92.73
High	114.07	118.54	120.75	85.96	123.80	118.79	45.49	58.41	66.08	25.88	31.77	92.36

Table 6: Factor construction

This table shows the construction of size, value, profitability, investment, and sentiment factors. We use independent sorts to assign stocks to two size, value (B/M), operating profitability (OP), investment (Inv), and sentiment (SNT) groups. The value-weighted portfolios defined by the intersections of the groups are the building blocks for the factors, comprising in total 32 value-weighted portfolios. We label these portfolios with five letters. The first always describes the size, small (S) or big (B), the second the value, high (H) or low (L), the third the profitability, robust (R) or weak (W), or fourth the investment, conservative (C) or aggressive (A), and the fifth the sentiment group, positive (P) or negative (N). The building blocks then form the factors for size (SMB), value (HML), profitability (RMW), investment (CMA), and sentiment (PMN). Those are constructed as the difference between the 16 building blocks of one property minus the other 16. Exemplary for SMB these are all 16 portfolios with S for small stocks minus 16 portfolios with B for big stocks.

Breakpoints		Construction
Panel A: 2x3 sorts on $Size$ and B/M, OP, Inv, or PMN		
Size: NYSE median	$SMB_{B/M}$ =	(SH + SN + SL)/3 - (BH + BN + BL)/3)
	SMB_{OP} =	(SR + SN + SW)/3 - (BR + BN + BW)/3)
	SMB_{Inv} =	(SC + SN + SA)/3 - (BC + BN + BA)/3)
	SMB =	($SMB_{B/M}$ + SMB_{OP} + SMB_{Inv})/3)
Value: 30th and 70th NYSE percentiles	HML =	(SH + BH)/2 - (SL + BL)/2
Profitability: 30th and 70th NYSE percentiles	RMW =	(SR + BR)/2 - (SW + BW)/2
Investment: 30th and 70th NYSE percentiles	CMA =	(SC + BC)/2 - (SA + BA)/2
Sentiment: 30th and 70th NYSE percentiles	PMN =	(SP + BP)/2 - (SN + BN)/2
Panel A: 2x2x2x2x2 sorts on $Size$, B/M, OP, Inv, and PMN		
Size: NYSE median	SMB =	(SHRCP + SHRCN + SHRAP + SHRAN + SHWCP + SHWCN + SHWAP + SHWAN + SLRCP + SLRCN + SLRAP + SLRAN + SLWCP + SLWCN + SLWAP + SLWAN) / 16 -(BHRCP + BHRCN + BHRAP + BHRAN + BHWCP + BHWCN + BHWAP + BHWAN + BLRCP + BLRCN + BLRAP + BLRAN + BLWCP + BLWCN + BLWAP + BLWAN) / 16
Value: NYSE median	HML =	(SHRCP + SHRCN + SHRAP + SHRAN + SHWCP + SHWCN + SHWAP + SHWAN + BHRCP + BHRCN + BHRAP + BHRAN + BHWCP + BHWCN + BHWAP + BHWAN) / 16 -(SLRCP + SLRCN + SLRAP + SLRAN + SLWCP + SLWCN + SLWAP + SLWAN + BLRCP + BLRCN + BLRAP + BLRAN + BLWCP + BLWCN + BLWAP + BLWAN) / 16
Profitability: NYSE median	RMW =	(SHRCP + SHRCN + SHRAP + SHRAN + BHRCP + BHRCN + BHRAP + BHRAN + SLRCP + SLRCN + SLRAP + SLRAN + BLRCP + BLRCN + BLRAP + BLRAN) / 16 -(SHWCP + SHWCN + SHWAP + SHWAN + BHWCP + BHWCN + BHWAP + BHWAN + SLWCP + SLWCN + SLWAP + SLWAN + BLWCP + BLWCN + BLWAP + BLWAN) / 16
Investment: NYSE median	CMA =	(SHRCN + BHRCN + SLWCN + BLWCN + SHRCN + BHRCN + SLWCN + BLWCN + SHRCP + BHRCP + SLWCP + BLWCP + SHRCP + BHRCP + SLWCP + BLWCP) / 16 -SHRAN + BHRAN + SLWAN + BLWAN + SHRAN + BHRAN + SLWAN + BLWAN + SHRAP + BHRAP + SLWAP + BLWAP + SHRAP + BHRAP + SLWAP + BLWAP) / 16
Sentiment: NYSE median	PMN =	(SHRCP + SHRAP + BLRCP + BLRAP + SHWCP + SHWAP+ BLWCP + BLWAP + SHRCP + SHRAP+ BLRCP + BLRAP + SHWCP + SHWAP+ BLWCP + BLWAP) / 16 -(SHRCN + SHRAN + BLRCN + BLRAN + SHWCN + SHWAN + BLWCN + BLWAN + SHRCN + SHRAN + BLRCN + BLRAN + SHWCN + SHWAN + BLWCN + BLWAN) / 16

Table 7: Summary statistics for factor returns using social media-based sentiment

This table shows the summary statistics for monthly factor returns in bps using the 2x3 and 2x2x2x2x2 sorting approach for January 1998 - December 2017. $MktRF$ is the value-weighted return on the market portfolio of all sample stocks minus the one-month Treasury bill rate. For the five Fama French factors SMB, HML, RMW, and CMA we follow their exact methodology. At the end of each June, stocks are assigned to two $Size$ groups using the NYSE median market capitalization as the breakpoint. Stocks are also assigned independently to two book-to-market equity (B/M), operating profitability (OP), and investment (Inv) groups, using NYSE medians of B/M, OP, and Inv. Sentiment is constructed as the social media sentiment change compared to the rolling mean. As such, this sort is more frequently constructed than those on fundamental factors, given the higher frequency of changes in sentiment. Panel A of the table shows average monthly returns (Mean), the standard deviations of monthly returns (Std dev.) and the t-statistics for the average returns. Panel B shows the correlations between factors and Panel C the corresponding p-values. Panel D demonstrates the correlation between the different versions of the same factor from the 2x3 and 2x2x2x2x2x2 sorts.

	2x3						2x2x2x2x2					
	$Mkt-Rf$	SMB	HML	RMW	CMA	PMN	$Mkt-Rf$	SMB	HML	RMW	CMA	PMN
Panel A: Average, standard deviation and one-sample t-statistics for monthly returns												
Mean	55.16	20.27	14.39	33.27	19.38	22.28	55.16	49.71	-3.07	4.08	6.82	30.43
Std. dev	446.16	344.94	338.16	298.61	185.66	166.49	446.16	312.03	262.95	205.87	142.74	172.61
t-Statistic	1.92	0.91	0.66	1.73	1.62	2.07	1.92	2.47	-0.18	0.31	0.74	2.73
Panel B: Correlation between different factors												
$Mkt-Rf$	1.00	0.29	-0.23	-0.47	-0.28	-0.29	1.00	0.24	-0.23	-0.36	-0.19	-0.13
SMB		1.00	-0.34	-0.62	-0.03	0.11		1.00	-0.14	-0.34	0.13	0.15
HML			1.00	0.58	0.56	-0.19			1.00	0.73	0.14	-0.35
RMW				1.00	0.15	0.02				1.00	-0.03	-0.23
CMA					1.00	-0.03					1.00	-0.09
PMN						1.00						1.00
Panel C: P-value of correlations between different factors in Panel B												
$Mkt-Rf$		0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.04
SMB			0.00	0.00	0.67	0.08			0.04	0.00	0.04	0.02
HML				0.00	0.00	0.00				0.00	0.03	0.00
RMW					0.02	0.71					0.68	0.00
CMA						0.68						0.17
PMN												
Panel D: Correlation between different versions of the same factor												
2x3							1.00	0.92	0.91	0.80	0.77	0.71

Table 8: Summary statistics for regressions using social media-based sentiment

This table shows the summary statistics for tests of the sentiment-augmented model benchmarked against the FF5 for January 1998 - December 2017. We test the ability of the models to explain monthly excess returns on 25 $Size - B/M$ portfolios (Panel A), 25 $Size - OP$ portfolios (Panel B), 25 $Size - Inv$ portfolios (Panel C), 25 $Size - Snt$ portfolios (Panel D), 36 $Size - B/M - OP - SNT$ Portfolios (Panel E), 36 $Size - B/M - Inv - SNT$ Portfolios (Panel F), 10 Fama-French Industry Portfolios (Panel G), and 30 Fama-French Industry Portfolios (Panel H). We show the average absolute value of the intercepts, the GRS statistic testing whether the expected values of all intercept estimates are zero, $A|\alpha_i|$, the median absolute value of the intercept over the mean absolute return on portfolio i minus the mean of the cross-sectional portfolio returns $\frac{M|\alpha_i|}{A|\bar{r}_i|}$, and the squared version of the previous ratio $\frac{M|\alpha_i|^2}{A|\bar{r}_i^2|}$ to account for biases due to measurement errors.

	2x3				2x2x2x2x2			
	$A\|\alpha_i\|$	GRS	$\frac{M\|\alpha_i\|}{A\|\bar{r}_i\|}$	$\frac{M\|\alpha_i\|^2}{\bar{r}_i^2}$	$A\|\alpha_i\|$	GRS	$\frac{M\|\alpha_i\|}{\bar{r}_i}$	$\frac{M\|\alpha_i^2\|}{A\|\bar{r}_i^2\|}$
Panel A: Size-B/M portfolios								
FF5	10.43	1.96	0.65	0.26	15.33	2.34	1.05	0.66
FF5-SNT	10.65	1.83	0.79	0.38	15.67	2.11	1.02	0.63
Panel B: Size-OP portfolios								
FF5	7.20	1.10	0.39	0.10	15.26	1.68	0.82	0.44
FF5-SNT	6.74	1.09	0.26	0.04	13.95	1.53	0.69	0.31
Panel C: Size-Inv portfolios								
FF5	10.91	1.69	0.54	0.20	15.07	2.26	0.80	0.45
FF5-SNT	9.18	1.47	0.46	0.15	13.79	1.89	0.68	0.33
Panel D: Size-SNT portfolios								
FF5	35.70	2.72	0.52	0.16	26.74	2.86	0.49	0.14
FF5-SNT	30.88	2.45	0.71	0.30	22.08	2.45	0.37	0.08
Panel E: Size-B/M-OP-SNT Portfolios								
FF5	25.63	1.81	0.59	0.24	24.50	1.71	0.85	0.50
FF5-SNT	23.53	1.65	0.60	0.24	23.17	1.47	0.66	0.30
Panel F: Size-B/M-Inv-SNT Portfolios								
FF5	24.92	1.47	0.64	0.27	23.55	1.35	0.64	0.27
FF5-SNT	20.94	1.30	0.44	0.13	21.14	1.10	0.60	0.24
Panel G: 10 Industry Portfolios								
FF5	24.25	4.58	2.27	3.79	32.39	6.28	2.77	4.98
FF5-SNT	22.86	4.91	1.91	2.60	30.79	6.67	2.78	5.02
Panel H: 30 Industry Portfolios								
FF5	23.20	1.66	0.95	0.54	33.20	2.14	1.50	1.35
FF5-SNT	22.02	1.89	1.03	0.64	33.63	2.49	1.60	1.54

Table 9: Regressions on factors using social media-based sentiment

This table shows the coefficients and t-statistics for using five factors in regressions to explain average monthly returns on the sixth for January 1998 - December 2017. $Mkt - RF$ is the value-weighted return on the market portfolio of all sample stocks minus the one-month Treasury bill rate; SMB (small minus big) is the size factor; HML (high minus low book-to-market ratio B/M) is the value factor; RMW (robust minus weak operating profitability OP) is the profitability factor; CMA (conservative minus aggressive investment Inv) is the investment factor. PMN (positive minus negative sentiment Snt) is the social media-based sentiment factor. Panel A shows the 2x3 factors from two Size groups and 3 groups of the other variable of interest. Panel B shows the 2x2x2x2x2 factors which are constructed using separate sorts of stocks into two Size groups, two B/M groups (HML), two OP groups (RMW), two Inv groups (CMA), and two Snt groups (PMN).

	α	$Mkt - Rf$	SMB	HML	RMW	CMA	PMN	R^2
Panel A: 2x3 sorts								
MktRf								
Coef	0.01		0.10	0.28	-0.73	-0.78	-0.68	0.35
t-statistic	4.35		1.20	2.57	-6.11	-4.94	-4.62	
SMB								
Coef	0.00	0.06		0.01	-0.70	0.16	0.32	0.40
t-statistic	1.63	1.20		0.08	-8.24	1.26	2.81	
HML								
Coef	-0.00	0.10	0.00		0.64	0.93	-0.31	0.60
t-statistic	-1.60	2.57	0.08		10.02	11.81	-3.46	
RMW								
Coef	0.00	-0.19	-0.32	0.47		-0.37	0.14	0.63
t-statistic	3.90	-6.11	-8.24	10.02		-4.63	1.83	
CMA								
Coef	0.00	-0.12	0.04	0.40	-0.22		0.03	0.42
t-statistic	2.72	-4.94	1.26	11.81	-4.63		0.52	
PMN								
Coef	0.00	-0.12	0.10	-0.16	0.10	0.04		0.17
t-statistic	2.43	-4.62	2.81	-3.46	1.83	0.52		
Panel B: 2x2x2x2x2 sorts								
MktRf								
Coef	0.01		0.26	0.02	-0.80	-0.79	-0.68	0.24
t-statistic	2.76		2.98	0.11	-4.12	-4.31	-4.32	
SMB								
Coef	0.00	0.14		0.29	-0.61	0.31	0.32	0.18
t-statistic	1.76	2.98		2.69	-4.31	2.26	2.76	
HML								
Coef	-0.00	0.00	0.10		0.94	0.24	-0.29	0.60
t-statistic	-0.44	0.11	2.69		15.45	2.97	-4.27	
RMW								
Coef	0.00	-0.08	-0.12	0.54		-0.19	0.00	0.63
t-statistic	2.08	-4.12	-4.31	15.45		-3.22	0.05	
CMA								
Coef	0.00	-0.09	0.07	0.15	-0.22		-0.10	0.12
t-statistic	1.44	-4.31	2.26	2.97	-3.22		-1.80	
PMN								
Coef	0.00	-0.11	0.10	-0.25	0.00	-0.14		0.19
t-statistic	3.08	-4.32	2.76	-4.27	0.05	-1.80		

Table 10: Regressions on Size-B/M portfolios using social media-based sentiment

This table shows the coefficients and t-statistics of the GMM estimator using the independent 2x2x2x2x2 factors on 25 $Size - B/M$ portfolios constructed by the 5x5 sorts. The left-hand side (LHS) variables are the monthly excess returns on the 25 $Size - B/M$ portfolios which sorts the stocks at the end of June each year into five size groups (Small to Big) and five B/M groups (Low B/M to High B/M). The right-hand side (RHS) variables are the excess market return, $Mkt - Rf$, the size factor, SMB, the value factor, HML, the profitability factor, RMW, the investment factor, CMA, and the sentiment factor, PMN, constructed using independent 2x2x2x2x2 sorts on $Size$ and each of book-to-market ratio B/M, operating profitability OP, investment Inv, and sentiment Snt. Table A shows the intercepts from the five-factor model, Panel B the intercepts and coefficients of the sentiment-augmented FF5-SNT model of the form: $R(t) - R_f(t) = a + b(Mkt - Rf) + sSMB + hHML + rRMW + cCMA + pPMN + \epsilon(t)$. The market beta is not shown to save space.

	Low	P2	P3	P4	High	Low	P2	P3	P4	High
Panel A: FF5 intercepts										
			a					**t(a)**		
Small	-0.79	-0.28	-0.09	0.03	0.01	-3.46	-1.55	-0.66	0.22	0.04
S2	-0.40	-0.13	-0.02	-0.16	-0.19	-2.87	-1.22	-0.15	-1.79	-1.58
S3	-0.27	-0.07	0.01	-0.05	0.18	-2.14	-0.58	0.12	-0.41	1.27
S4	0.00	0.05	0.20	0.13	0.11	0.03	0.40	1.44	0.96	0.73
Big	0.10	0.19	0.24	0.00	0.14	1.63	2.16	2.12	0.01	0.79
Panel B: FF5-SNT coefficients										
			a					**t(a)**		
Small	-0.69	-0.25	-0.04	-0.01	0.06	-4.96	-2.68	-0.49	-0.06	0.43
S2	-0.33	-0.12	0.01	-0.13	-0.15	-2.07	-1.31	0.15	-1.55	-1.75
S3	-0.24	-0.05	0.06	-0.03	0.24	-1.70	-0.61	0.60	-0.32	1.56
S4	-0.02	0.09	0.21	0.12	0.19	-0.22	0.99	1.67	0.93	1.31
Big	0.10	0.21	0.27	0.05	0.24	1.82	3.21	1.76	0.34	1.83
			s					**t(s)**		
Small	1.21	1.25	0.97	0.99	0.90	11.74	14.07	20.70	25.87	27.95
S2	1.01	0.96	0.76	0.85	0.89	17.70	20.12	18.73	28.31	20.38
S3	0.74	0.59	0.44	0.46	0.49	12.79	20.31	9.42	9.69	9.29
S4	0.48	0.24	0.16	0.20	0.19	9.66	5.64	3.59	3.92	7.08
Big	-0.19	-0.21	-0.22	-0.11	-0.25	-8.98	-7.52	-8.69	-4.01	-3.74
			h					**t(h)**		
Small	-0.53	-0.22	0.20	0.34	0.60	-2.13	-1.53	2.56	3.56	3.79
S2	-0.40	0.03	0.42	0.60	0.81	-6.65	0.51	6.32	13.91	8.45
S3	-0.65	0.10	0.48	0.80	0.77	-8.71	0.88	3.55	6.77	9.74
S4	-0.52	0.23	0.57	0.76	0.98	-10.67	2.07	4.74	4.87	8.98
Big	-0.40	0.14	0.62	1.01	1.20	-8.74	1.70	4.36	6.23	8.99
			r					**t(r)**		
Small	-0.49	-0.43	-0.24	-0.13	-0.19	-2.32	-4.73	-2.20	-1.62	-1.28
S2	-0.40	-0.03	0.00	0.00	-0.13	-5.60	-0.23	-0.02	0.00	-1.02
S3	-0.06	0.08	0.07	-0.13	0.04	-0.96	0.93	1.09	-1.38	0.28
S4	-0.07	0.11	0.01	-0.28	-0.21	-1.14	0.90	0.07	-3.05	-1.86
Big	0.20	0.08	-0.25	-0.23	-0.93	4.12	1.56	-2.07	-2.37	-6.68
			c					**t(c)**		
Small	-0.38	-0.22	-0.03	0.13	0.18	-2.58	-1.79	-0.39	1.72	2.02
S2	-0.38	-0.23	-0.05	0.13	0.12	-2.59	-1.86	-0.65	2.10	1.02
S3	-0.39	-0.09	-0.03	0.27	0.25	-2.52	-1.32	-0.43	3.58	2.08
S4	-0.34	0.05	0.07	0.14	0.24	-2.11	0.71	0.87	1.50	2.04
Big	-0.09	0.21	0.07	0.01	0.30	-2.68	1.97	0.82	0.12	2.06
			p					**t(p)**		
Small	-0.29	-0.10	-0.14	0.11	-0.16	-2.53	-0.87	-3.18	1.46	-2.24
S2	-0.20	-0.04	-0.09	-0.09	-0.14	-1.96	-0.76	-1.17	-1.64	-3.47
S3	-0.08	-0.05	-0.15	-0.05	-0.17	-1.13	-0.77	-2.01	-0.76	-1.52
S4	0.07	-0.12	-0.05	0.01	-0.25	1.07	-1.83	-0.60	0.12	-2.98
Big	0.00	-0.05	-0.09	-0.15	-0.31	0.03	-0.82	-0.92	-1.14	-2.46

Table 11: Regressions on Size-Inv portfolios using social media-based sentiment

This table shows the coefficients and *t*-statistics of the regressions using the independent 2x2x2x2x2 factors on 25 $Size - Inv$ portfolios constructed by the 5x5 sorts. The left-hand side (LHS) variables are the monthly excess returns on the 25 $Size - Inv$ portfolios which sorts the stocks at the end of June each year into five size groups (Small to Big) and five investment groups (Low Inv to high Inv). The right-hand side (RHS) variables are the excess market return, $Mkt - Rf$, the Size factor, SMB, the value factor, HML, the profitability factor, RMW, the investment factor, CMA, and the social media-based sentiment factor, PMN, constructed using independent 2x2x2x2x2 sorts on $Size$ and each of book-to-market ratio B/M, operating profitability OP, investment Inv, and sentiment Snt. Table A shows the intercepts from the five-factor model, Panel B the intercepts and coefficients of the sentiment-augmented FF5-SNT model of the form: $R(t) - R_f(t) = a + b(Mkt - Rf) + sSMB + hHML + rRMW + cCMA + pPMN + \epsilon(t)$. The market beta is not shown to save space.

	Low	P2	P3	P4	High	Low	P2	P3	P4	High
Panel A: FF5 intercepts										
			a					**t(a)**		
Small	-0.15	0.04	0.16	-0.11	-0.59	-0.95	0.46	1.52	-1.07	-4.49
S2	-0.35	-0.05	0.07	-0.03	-0.40	-3.29	-0.72	0.97	-0.30	-3.22
S3	-0.09	0.03	0.10	0.03	-0.29	-0.70	0.37	0.90	0.29	-2.09
S4	0.02	0.20	0.15	0.26	-0.10	0.21	1.41	1.50	1.64	-0.70
Big	0.19	0.08	0.15	0.15	0.01	1.98	1.03	1.50	0.99	0.15
Panel B: FF5-SNT coefficients										
			a					**t(a)**		
Small	-0.15	0.04	0.16	-0.10	-0.49	-0.61	0.38	1.23	-0.88	-4.81
S2	-0.31	-0.01	0.08	-0.03	-0.33	-3.66	-0.09	1.29	-0.28	-2.81
S3	-0.01	0.03	0.10	-0.01	-0.25	-0.05	0.36	0.79	-0.14	-1.67
S4	0.10	0.27	0.16	0.19	-0.09	0.87	1.61	1.39	1.23	-0.61
Big	0.21	0.08	0.12	0.10	0.03	2.18	0.87	1.48	0.72	0.25
			s			t(s)				
Small	1.29	0.97	0.93	0.92	1.08	10.69	17.37	22.64	26.05	13.52
S2	0.98	0.73	0.83	0.89	1.01	18.44	12.88	32.96	38.36	18.09
S3	0.55	0.60	0.50	0.59	0.71	9.73	12.82	13.41	12.87	12.23
S4	0.19	0.12	0.22	0.34	0.42	3.48	2.00	7.87	5.62	8.44
Big	-0.22	-0.13	-0.16	-0.16	-0.20	-4.60	-3.79	-5.55	-2.77	-6.27
			h			t(h)				
Small	0.00	0.39	0.26	0.28	-0.08	0.01	3.62	1.94	1.86	-0.45
S2	0.38	0.34	0.37	0.39	-0.09	6.66	6.05	9.60	6.64	-1.44
S3	0.29	0.43	0.22	0.26	-0.08	3.44	4.58	3.11	2.39	-1.05
S4	0.40	0.37	0.37	0.27	-0.04	6.76	2.81	5.12	2.23	-0.77
Big	0.39	0.12	0.29	0.10	-0.42	3.55	2.07	3.23	1.34	-3.86
			r			t(r)				
Small	-0.58	-0.24	-0.03	-0.18	-0.11	-4.26	-2.81	-0.20	-1.09	-0.55
S2	-0.41	0.11	-0.05	0.05	-0.14	-5.35	0.85	-0.52	0.50	-1.13
S3	-0.27	-0.12	0.23	0.03	-0.07	-3.37	-1.66	2.42	0.41	-0.65
S4	-0.11	0.09	0.05	-0.09	-0.24	-0.87	0.64	0.46	-0.87	-3.52
Big	-0.30	0.05	0.02	-0.02	0.19	-2.33	1.04	0.53	-0.27	2.07
			c			t(c)				
Small	0.19	0.30	0.18	-0.02	-0.41	1.21	3.74	1.47	-0.20	-5.02
S2	0.34	0.34	0.11	-0.18	-0.48	3.77	3.53	1.74	-1.61	-4.24
S3	0.42	0.35	0.27	-0.12	-0.41	5.80	4.22	3.30	-1.59	-2.63
S4	0.40	0.32	0.17	-0.03	-0.59	5.23	2.76	2.58	-0.22	-5.08
Big	0.66	0.31	0.34	0.04	-0.61	3.87	4.03	3.12	0.35	-5.11
			p			t(p)				
Small	0.01	-0.01	-0.01	-0.06	-0.33	0.05	-0.13	-0.10	-0.67	-3.45
S2	-0.12	-0.13	-0.06	0.01	-0.20	-1.49	-1.57	-1.66	0.14	-1.33
S3	-0.26	0.01	0.00	0.13	-0.11	-3.50	0.15	0.01	2.48	-0.98
S4	-0.24	-0.22	-0.04	0.20	-0.03	-3.07	-2.12	-0.60	1.74	-0.34
Big	-0.06	0.00	0.08	0.14	-0.06	-0.49	-0.07	0.82	1.32	-0.60

Table 12: Regressions on Size-B/M-OP-Inv portfolios using social media-based sentiment

This table shows the coefficients and t-statistics (in parentheses to save space) of the regressions using the independent 2x2x2x2x2 factors on 36 $Size - B/M - OP - Inv$ portfolios constructed by the 2x2x3x3 sorts. The left-hand side (LHS) variables are the monthly excess returns on the 25 $Size - B/M - OP - Inv$ portfolios which sorts the stocks at the end of June each year into two size groups (Small to Big), two value groups (Low to High), three profitability groups (Weak to Robust), and three investment groups (Conservative to Aggressive). The right-hand side (RHS) variables are the excess market return, $Mkt - Rf$, the size factor, SMB, the value factor, HML, the profitability factor, RMW, the investment factor, CMA, and the social media-based sentiment factor, PMN, constructed using independent 2x2x2x2x2 sorts on $Size$ and each of book-to-market ratio B/M, operating profitability OP, investment Inv, and sentiment Snt. Table A shows the intercepts from the five-factor model, Panel B the intercepts and coefficients for PMN of the sentiment-augmented FF5-SNT model of the form: $R(t) - R_f(t) = a + b(Mkt - Rf) + sSMB + hHML + rRMW + cCMA + pPMN + \epsilon(t)$. The market beta is not shown to save space.

Size	Small						Big					
Value	Low			High			Low			High		
Investment / Profitability	Weak	P2	Robust	Weak	P2	Robust	Weak	P2	Robust	Weak	P2	Robust
Panel A: FF5 intercepts												
a												
Conservative	-0.39	-0.12	0.09	-0.14	-0.08	-0.24	-0.08	0.03	0.20	0.04	0.40	-0.04
	(-2.06)	*(-0.81)*	*(0.82)*	*(-1.46)*	*(-0.8)*	*(-1.21)*	*(-0.23)*	*(0.16)*	*(1.43)*	*(0.24)*	*(3.2)*	*(-0.16)*
S2	-0.06	0.06	0.11	0.09	0.08	-0.03	-0.06	0.18	0.14	0.27	0.29	0.26
	(-0.29)	*(0.89)*	*(0.96)*	*(0.8)*	*(1.04)*	*(-0.15)*	*(-0.22)*	*(1.64)*	*(1.84)*	*(2.3)*	*(2.44)*	*(1.16)*
Aggressive	-0.82	-0.14	-0.20	-0.29	-0.07	0.04	-0.14	-0.08	0.14	-0.05	0.02	0.02
	(-5.61)	*(-0.87)*	*(-3.59)*	*(-3.09)*	*(-0.65)*	*(0.19)*	*(-0.99)*	*(-0.99)*	*(1.54)*	*(-0.39)*	*(0.12)*	*(0.07)*
Panel B: FF5-SNT coefficients												
a												
Conservative	-0.36	-0.10	0.18	-0.16	-0.01	-0.11	0.03	-0.01	0.27	0.11	0.41	0.03
	(-1.91)	*(-0.64)*	*(1.35)*	*(-1.39)*	*(-0.11)*	*(-0.53)*	*(0.14)*	*(-0.08)*	*(2.43)*	*(0.75)*	*(2.63)*	*(0.11)*
S2	-0.07	0.09	0.16	0.07	0.09	0.01	-0.05	0.17	0.10	0.23	0.28	0.21
	(-0.36)	*(0.9)*	*(1.3)*	*(0.7)*	*(0.96)*	*(0.08)*	*(-0.17)*	*(1.43)*	*(1.18)*	*(1.72)*	*(1.99)*	*(0.86)*
Aggressive	-0.72	-0.13	-0.17	-0.22	-0.05	0.07	-0.01	-0.09	0.12	0.05	0.00	0.07
	(-4.17)	*(-1.1)*	*(-1.49)*	*(-1.88)*	*(-0.44)*	*(0.32)*	*(-0.03)*	*(-0.8)*	*(1.21)*	*(0.32)*	*(0.01)*	*(0.29)*
p												
Conservative	-0.76	-0.27	-0.32	-0.25	-0.10	-0.61	-1.21	-0.16	-0.41	-0.01	-0.68	-0.86
	(-4.4)	*(-3.45)*	*(-3.54)*	*(-2.14)*	*(-0.96)*	*(-4.13)*	*(-5.73)*	*(-2.00)*	*(-3.44)*	*(-0.09)*	*(-3.62)*	*(-5.07)*
S2	-0.11	-0.04	-0.28	0.06	-0.23	-0.41	-0.36	0.13	-0.21	-0.24	-0.06	-0.22
	(-0.59)	*(-0.36)*	*(-2.33)*	*(0.59)*	*(-2.82)*	*(-2.9)*	*(-1.49)*	*(0.85)*	*(-2.39)*	*(-2.32)*	*(-0.55)*	*(-1.01)*
Aggressive	0.03	-0.10	-0.16	0.05	-0.04	-0.14	-0.05	0.01	0.13	0.12	0.05	0.15
	(0.23)	*(-1.32)*	*(-1.99)*	*(0.71)*	*(-0.51)*	*(-0.87)*	*(-0.22)*	*(0.1)*	*(2.06)*	*(0.99)*	*(0.44)*	*(1.1)*

Table 13: Regressions on Size-Snt portfolios using social media-based sentiment

This table shows the coefficients and t-statistics of the regressions using the independent 2x2x2x2x2 factors on 25 $Size-Snt$ portfolios constructed by the 5x5 sorts. The left-hand side (LHS) variables are the monthly excess returns on the 25 $Size-Snt$ portfolios which sorts the stocks at the end of June each year into five size groups (Small to Big) and on a monthly basis into five sentiment groups (Positive to Negative Snt). The right-hand side (RHS) variables are the excess market return, $Mkt-Rf$, the size factor, SMB, the value factor, HML, the profitability factor, RMW, the investment factor, CMA, and the social media-based sentiment factor, PMN, constructed using independent 2x2x2x2x2 sorts on $Size$ and each of book-to-market ratio B/M, operating profitability OP, investment Inv, and sentiment Snt. Table A shows the intercepts from the five-factor model, Panel B the intercepts and coefficients of the sentiment-augmented FF5-SNT model of the form: $R(t)-R_f(t) = a + b(Mkt-Rf) + sSMB + hHML + rRMW + cCMA + pPMN + \epsilon(t)$. The market beta is not shown to save space.

	Negative	P2	P3	P4	Positive	Negative	P2	P3	P4	Positive
Panel A: FF5 intercepts										
			a					**t(a)**		
Small	0.09	0.43	0.81	1.16	0.74	0.69	2.03	2.53	4.25	4.24
S2	-0.08	0.15	0.21	0.32	0.33	-0.61	0.82	1.35	2.32	3.50
S3	0.03	0.00	0.21	0.07	0.33	0.24	-0.02	1.16	0.62	2.10
S4	0.09	-0.06	0.18	0.45	0.07	0.78	-0.51	1.35	4.14	0.59
Big	0.23	-0.16	0.05	0.24	0.18	1.81	-1.50	0.73	3.43	2.10
Panel B: FF5-SNT coefficients										
			a					**t(a)**		
Small	-0.15	0.04	0.16	-0.10	-0.49	-0.61	0.38	1.23	-0.88	-4.81
S2	-0.31	-0.01	0.08	-0.03	-0.33	-3.66	-0.09	1.29	-0.28	-2.81
S3	-0.01	0.03	0.10	-0.01	-0.25	-0.05	0.36	0.79	-0.14	-1.67
S4	0.10	0.27	0.16	0.19	-0.09	0.87	1.61	1.39	1.23	-0.61
Big	0.21	0.08	0.12	0.10	0.03	2.18	0.87	1.48	0.72	0.25
			s					**t(s)**		
Small	1.29	0.97	0.93	0.92	1.08	10.69	17.37	22.64	26.05	13.52
S2	0.98	0.73	0.83	0.89	1.01	18.44	12.88	32.96	38.36	18.09
S3	0.55	0.60	0.50	0.59	0.71	9.73	12.82	13.41	12.87	12.23
S4	0.19	0.12	0.22	0.34	0.42	3.48	2.00	7.87	5.62	8.44
Big	-0.22	-0.13	-0.16	-0.16	-0.20	-4.60	-3.79	-5.55	-2.77	-6.27
			h					**t(h)**		
Small	0.00	0.39	0.26	0.28	-0.08	0.01	3.62	1.94	1.86	-0.45
S2	0.38	0.34	0.37	0.39	-0.09	6.66	6.05	9.60	6.64	-1.44
S3	0.29	0.43	0.22	0.26	-0.08	3.44	4.58	3.11	2.39	-1.05
S4	0.40	0.37	0.37	0.27	-0.04	6.76	2.81	5.12	2.23	-0.77
Big	0.39	0.12	0.29	0.10	-0.42	3.55	2.07	3.23	1.34	-3.86
			r					**t(r)**		
Small	-0.58	-0.24	-0.03	-0.18	-0.11	-4.26	-2.81	-0.20	-1.09	-0.55
S2	-0.41	0.11	-0.05	0.05	-0.14	-5.35	0.85	-0.52	0.50	-1.13
S3	-0.27	-0.12	0.23	0.03	-0.07	-3.37	-1.66	2.42	0.41	-0.65
S4	-0.11	0.09	0.05	-0.09	-0.24	-0.87	0.64	0.46	-0.87	-3.52
Big	-0.30	0.05	0.02	-0.02	0.19	-2.33	1.04	0.53	-0.27	2.07
			c					**t(c)**		
Small	0.19	0.30	0.18	-0.02	-0.41	1.21	3.74	1.47	-0.20	-5.02
S2	0.34	0.34	0.11	-0.18	-0.48	3.77	3.53	1.74	-1.61	-4.24
S3	0.42	0.35	0.27	-0.12	-0.41	5.80	4.22	3.30	-1.59	-2.63
S4	0.40	0.32	0.17	-0.03	-0.59	5.23	2.76	2.58	-0.22	-5.08
Big	0.66	0.31	0.34	0.04	-0.61	3.87	4.03	3.12	0.35	-5.11
			p					**t(p)**		
Small	0.01	-0.01	-0.01	-0.06	-0.33	0.05	-0.13	-0.10	-0.67	-3.45
S2	-0.12	-0.13	-0.06	0.01	-0.20	-1.49	-1.57	-1.66	0.14	-1.33
S3	-0.26	0.01	0.00	0.13	-0.11	-3.50	0.15	0.01	2.48	-0.98
S4	-0.24	-0.22	-0.04	0.20	-0.03	-3.07	-2.12	-0.60	1.74	-0.34
Big	-0.06	0.00	0.08	0.14	-0.06	-0.49	-0.07	0.82	1.32	-0.60

Figure 1: Sentiment classification system: Valence and arousal

This figure plots the cumulative returns of the Fama-French and sentiment risk factors constructed by the 2x2x2x2x2 sorts from January 1998 - December 2017. SMB (small minus big market capitalization) is the size factor; HML (high minus low book-to-market ratio B/M) is the value factor; RMW (robust minus weak operating profitability OP) is the profitability factor; CMA (conservative minus aggressive investment Inv) is the investment factor. PMN (positive minus negative sentiment Snt) is the social media-based sentiment factor.

Internet Appendix for
Does social media sentiment matter in the pricing of U.S. stocks?

This version: January 22, 2021

Abstract

This paper applies a recently developed social media-based sentiment proxy for the construction of a new risk factor for sentiment-augmented asset pricing models on U.S. equities. Accounting for endogeneity, autocorrelation and heteroskedasticity in a GMM framework, we find that the inclusion of sentiment significantly improves the performance of the five-factor model from Fama and French (2015, 2017) for different industry and style portfolios like size, value, profitability, investment. The sentiment risk premium provides the missing component in the behavioral asset pricing theory of Shefrin and Belotti (2008) and (partially) resolves the pricing puzzles of small extreme growth, small extreme investment stocks and small stocks that invest heavily despite low profitability.

JEL Classification Codes: *C*32, *C*53, *G*12, *G*41

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

Declarations of interest: none

Internet Appendix for

Does social media sentiment matter in the pricing of U.S. stocks?

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

Appendix A. Details on Refinitiv-MarketPsych's sentiment construction

MarketPsych's language processing engine goes 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[1] as 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 so-called Yerkes-Dodson's Law, capturing both the reduction in complex problem solving skills when stress levels are high and 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, their aggregated sentiment reflects notions of fear, optimism, and joy. As argued by 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 future payoffs of a financial asset. Such an overconfidence from investors 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 versus 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 a range of behaviors like herding or panic and affect trading activities, for instance by triggering either under- or over-reactions (see, e.g., Daniel et al., 1998; Lerner and Keltner, 2001; Lerner et al., 2004; Winkielman et al., 2005,

[1]Valence refers to the positive or negative affectivity, while arousal measures the level of calmness or excitement of a statement or news item.

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 A.1 depicts several among the RMI sentiments that are described in detail in Table **??** devoted to explaining 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. The table shows that RMI's construction of the sentiment indicator 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 versus positive valence. As a result, the sentiment indicator is usually negative in net terms.

To provide insights about the mechanism of sentiment indicator construction, MarketPsych provides an example on the complex language processing system that reveals how they address some common pitfalls in news and social media sentiment analysis. Figure A.2 evaluates the opinion of a Goldman Sachs' analyst about his expectations of the following day's quarterly call of Apple Inc. 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.[2]

[2]In the case of social media for which the concepts of re-tweeting, re-posting, and commenting are defined,

Table A.1: Construction of the Refinitiv-MarketPsych sentiment indicator

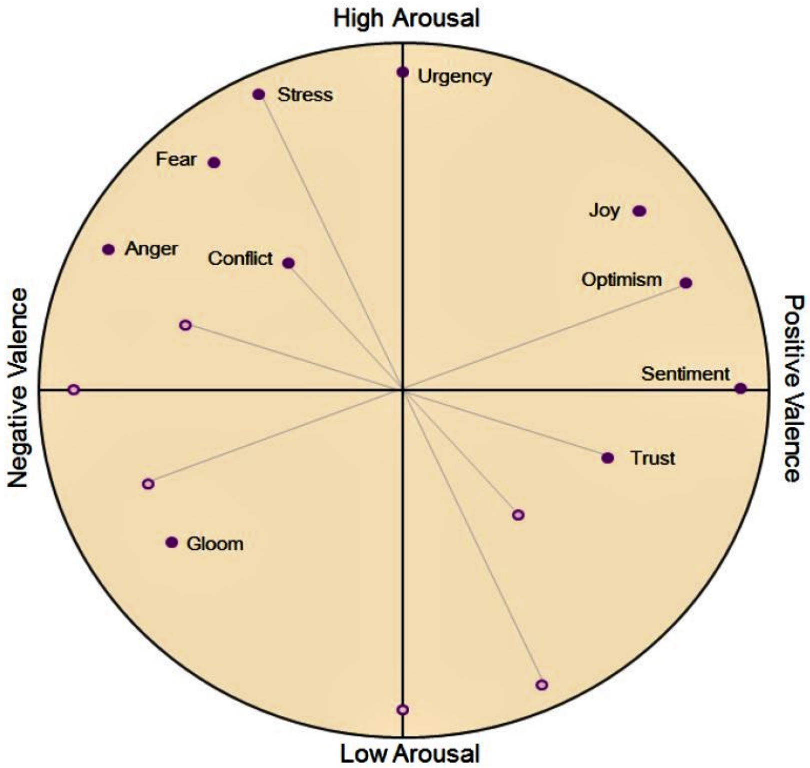
This table provides the construction details for the Refinitiv-MarketPsych (RMI) Sentiment indicator as the net of positive and negative references along the valence-arousal sentiment classification system.

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

Figure A.1: Sentiment classification system: valence and arousal

This figure 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 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

Table A.2: Description of Refinitiv-MarketPsych indicators

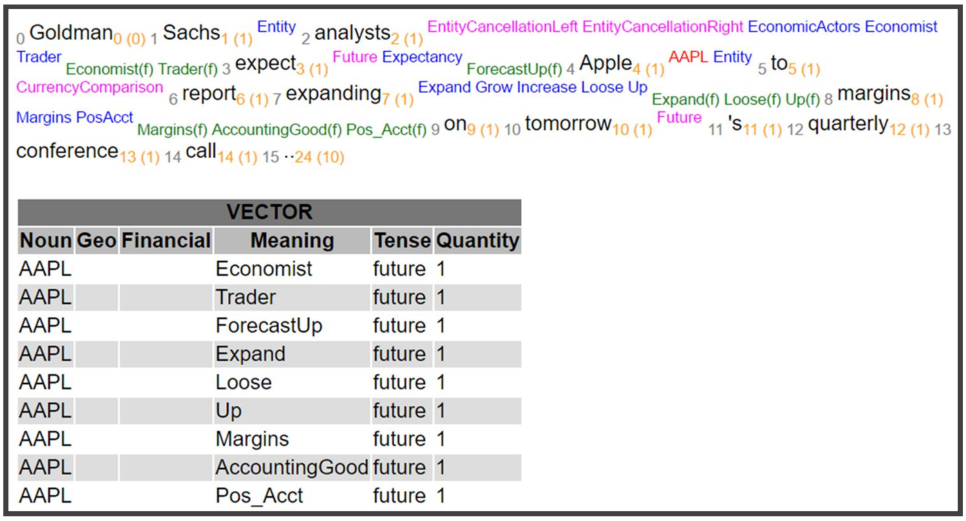
This table provides a detailed description of Refinitiv-MarketPsych (RMI) indicators to better understand the aggregated sentiment measure.

RMI 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 RMI, 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 RMI 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

Figure A.2: Example of MarketPsych's human language processing system

This figure 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.



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

Various sources, though limited to English, are used to inform the data feed of the language processing system used by MarketPsych. These include 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 on 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 into one daily observation. 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 observation is found, no *Buzz* is recorded and the time

MarketPsych employs a rigorous approach to cleanse the data. RMI indicators do not include re-tweets, unless they 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.

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.[3]

For the purposes of our investigation, we cumulate the RMI index at a lower, weekly frequency thus aggregating the original, higher daily frequency using Equation (A.1). A weekly frequency appears to strike a reasonable balance between a sufficient granularity of the data and a need to control for the risk of using a noisy estimator of sentiment.[4] As we aim to study the sentiment exposure of international equity indices in weekly data, there are no missing observations in our sample. 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:[5]

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

[3]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.

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

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

Appendix B. News-based sentiment

Table B.1: 5x5 portfolios using news-based sentiment

This table shows average monthly excess returns in bps for portfolios formed on $Size$ and Snt for January 1998 - December 2017. The sorting follows Fama and French (2015) using only NYSE breakpoints: at the end of each June, stocks are allocated to five Size groups (Small to Big). For sentiment we sort the stocks into five sentiment groups (Positive to Negative) based on the previous month's deviation of news-based sentiment from the long-term rolling mean. The intersections produce 25 value-weight $Size - Snt$ portfolios.

	Negative	2	3	4	Positive
Small	180.42	138.86	176.08	184.48	155.55
2	121.87	125.20	119.29	100.75	112.12
3	115.98	106.60	75.35	92.48	106.31
4	66.37	78.95	84.21	89.09	121.99
Big	59.23	36.75	62.10	59.23	64.57

Table B.2: 2x2x3x3 portfolios using news-based sentiment

This table shows average monthly excess returns in bps for portfolios formed on *size* and B/M, OP, Inv, Snt for January 1998 - December 2017. The sorting follows Fama and French (2015) using only NYSE breakpoints: at the end of each June, stocks are allocated to two Size groups (Small and Big), two B/M groups (Low and High), three groups of either profitability or investment and three groups of Snt. For sentiment we sort the stocks based on the previous month's deviation of news-based sentiment from the long-term rolling mean. The intersections produce 36 portfolios.

	Small						Large					
	Low B/M			High B/M			Low B/M			High B/M		
	$s(-)$	$s(0)$	$s(+)$	$s(-)$	$s(0)$	$s(+)$	$s(-)$	$s(0)$	$s(+)$	$s(-)$	$s(0)$	$s(+)$
Panel A: Size-B/M-OP-SNT Portfolios												
Low	159.69	88.39	152.47	110.88	110.39	70.26	18.87	65.67	106.79	30.42	65.52	62.49
Medium	122.76	79.88	96.50	88.05	100.42	111.64	47.79	66.51	71.00	43.86	84.84	78.17
High	159.64	85.86	122.48	96.09	87.35	166.49	55.53	64.91	67.53	89.08	79.23	80.63
Panel B: Size-B/M-Inv-SNT Portfolios												
Low	127.86	166.58	151.54	87.12	92.08	96.22	82.74	59.29	71.55	52.00	76.10	63.80
Medium	138.04	83.01	92.64	106.22	104.89	105.73	59.91	69.00	46.09	59.35	78.14	106.39
High	126.70	65.07	120.24	92.65	97.07	89.79	32.62	64.12	86.91	38.77	53.48	50.64

Table B.3: Summary statistics for factor returns using news-based sentiment

This table shows the summary statistics for monthly factor returns in bps using the 2x3 and 2x2x2x2x2 sorting approach for January 1998 - December 2017. $MktRF$ is the value-weighted return on the market portfolio of all sample stocks minus the one-month Treasury bill rate. For the five Fama French factors SMB, HML, RMW, and CMA we follow their exact methodology. At the end of each June, stocks are assigned to two $Size$ groups using the NYSE median market cap as the breakpoint. Stocks are also assigned independently to two book-to-market equity (B/M), operating profitability (OP), and investment (Inv) groups, using NYSE medians of B/M, OP, and Inv. Sentiment is constructed as the the news-based sentiment change compared to the rolling mean. As such, this sort is more frequently constructed than those on fundamental factors, given the higher frequency of changes in sentiment. Panel A of the table shows average monthly returns (Mean), the standard deviations of monthly returns (Std dev.) and the t-statistics for the average returns. Panel B shows the correlations between factors and Panel C the corresponding **p**-values. Panel D demonstrates the correlation between the different versions of the same factor from the 2x3 and 2x2x2x2x2x2 sorts.

	2x3						2x2x2x2x2					
	$Mkt-Rf$	SMB	HML	RMW	CMA	PMN	$Mkt-Rf$	SMB	HML	RMW	CMA	PMN
Panel A: Average, standard deviation and one-sample t-statistics for monthly returns												
Mean	55.16	20.27	14.39	33.27	19.38	3.80	55.16	42.84	-9.63	4.98	7.69	6.69
Std. dev	446.16	344.94	338.16	298.61	185.66	216.08	446.16	304.79	278.18	219.74	151.18	163.52
t-Statistic	1.92	0.91	0.66	1.73	1.62	0.27	1.92	2.18	-0.54	0.35	0.79	0.63
Panel B: Correlation between different factors												
$Mkt-Rf$	1.00	0.29	-0.23	-0.47	-0.28	-0.25	1.00	0.23	-0.24	-0.34	-0.23	-0.18
SMB		1.00	-0.34	-0.62	-0.03	0.06		1.00	-0.16	-0.33	0.11	-0.03
HML			1.00	0.58	0.56	-0.11			1.00	0.71	0.24	-0.16
RMW				1.00	0.15	0.00				1.00	0.06	-0.12
CMA					1.00	-0.01					1.00	-0.11
PMN						1.00						1.00
Panel C: P-value of correlations between different factors in Panel B												
$Mkt-Rf$		0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00
SMB			0.00	0.00	0.67	0.36			0.01	0.00	0.09	0.60
HML				0.00	0.00	0.09				0.00	0.00	0.01
RMW					0.02	0.99					0.37	0.06
CMA						0.88						0.10
PMN												
Panel D: Correlation between different versions of the same factor												
2x3							1.00	0.90	0.92	0.81	0.72	0.66

Table B.4: Summary statistics for regressions using news-based sentiment

This table shows the summary statistics for tests of the sentiment-augmented model benchmarked against the FF5 for January 1998 - December 2017. We test the ability of the models to explain monthly excess returns on 25 $Size - B/M$ portfolios (Panel A), 25 $Size - OP$ portfolios (Panel B), 25 $Size - Inv$ portfolios (Panel C), 25 $Size - Snt$ portfolios (Panel D), 36 $Size - B/M - OP - SNT$ Portfolios (Panel E), 36 $Size - B/M - Inv - SNT$ Portfolios (Panel F), 10 Fama-French Industry Portfolios (Panel G), and 30 Fama-French Industry Portfolios. We show the average absolute value of the intercepts, the GRS statistic testing whether the expected values of all intercept estimates are zero, $A|\alpha_i|$, the median absolute value of the intercept over the mean absolute return on portfolio i minus the mean of the cross-sectional portfolio returns $\frac{M|\alpha_i|}{A|\bar{r}_i|}$, and the squared version of the previous ratio $\frac{M|\alpha_i|^2}{A|\bar{r}_i^2|}$ to account for biases due to measurement errors.

	2x3				2x2x2x2x2			
	$A\|\alpha_i\|$	GRS	$\frac{A\|\alpha_i\|}{\bar{r}_i}$	$\frac{A\|\alpha_i\|^2}{\bar{r}_i^2}$	$A\|\alpha_i\|$	GRS	$\frac{A\|\alpha_i\|}{\bar{r}_i}$	$\frac{A\|\alpha_i^2\|}{\bar{r}_i^2}$
Panel A: Size-B/M portfolios								
FF5	10.43	1.96	0.65	0.26	14.58	2.13	0.86	0.44
FF5-SNT	10.72	1.98	0.75	0.34	14.90	2.15	1.03	0.64
Panel B: Size-OP portfolios								
FF5	7.20	1.10	0.39	0.10	15.35	1.54	0.71	0.33
FF5-SNT	6.74	1.07	0.37	0.09	14.87	1.51	0.79	0.41
Panel C: Size-Inv portfolios								
FF5	10.91	1.69	0.54	0.20	14.35	2.21	0.89	0.55
FF5-SNT	10.54	1.65	0.52	0.19	13.87	2.15	0.87	0.53
Panel D: Size-SNT portfolios								
FF5	31.32	2.19	0.68	0.30	26.27	2.45	0.68	0.30
FF5-SNT	30.20	2.16	0.56	0.20	26.21	2.40	0.60	0.23
Panel E: Size-B/M-OP-SNT Portfolios								
FF5	24.51	1.24	0.67	0.26	24.14	1.22	0.89	0.45
FF5-SNT	23.21	1.23	0.64	0.23	24.47	1.18	0.89	0.45
Panel F: Size-B/M-Inv-SNT Portfolios								
FF5	20.71	1.63	0.57	0.21	21.21	1.47	0.70	0.31
FF5-SNT	20.56	1.60	0.68	0.29	21.45	1.42	0.77	0.38
Panel G: 10 Industry Portfolios								
FF5	24.25	4.58	2.27	3.79	32.53	6.35	2.77	4.97
FF5-SNT	23.11	4.74	2.02	2.94	31.56	6.62	2.73	4.84
Panel H: 30 Industry Portfolios								
FF5	23.20	1.66	0.95	0.54	33.89	2.19	1.44	1.25
FF5-SNT	22.47	1.79	1.04	0.65	32.91	2.30	1.51	1.37

Table B.5: Summary statistics for regressions using orthogonalized social media-based sentiment

This table shows the summary statistics for tests of the sentiment-augmented model benchmarked against the FF5 for January 1998 - December 2017. We test the ability of the models to explain monthly excess returns on 25 $Size - B/M$ portfolios (Panel A), 25 $Size - OP$ portfolios (Panel B), 25 $Size - Inv$ portfolios (Panel C), 25 $Size - Snt$ portfolios (Panel D), 36 $Size - B/M - OP - SNT$ Portfolios (Panel E), 36 $Size - B/M - Inv - SNT$ Portfolios (Panel F), 10 Fama-French Industry Portfolios (Panel G), and 30 Fama-French Industry Portfolios. Social media-based sentiment is orthogonalized against the news-based sentiment. We show the average absolute value of the intercepts, the GRS statistic testing whether the expected values of all intercept estimates are zero, $A|\alpha_i|$, the median absolute value of the intercept over the mean absolute return on portfolio i minus the mean of the cross-sectional portfolio returns $\frac{M|\alpha_i|}{A|\bar{r}_i|}$, and the squared version of the previous ratio $\frac{M|\alpha_i|^2}{A|\bar{r}_i^2|}$ to account for biases due to measurement errors.

	2x3				2x2x2x2x2			
	$A\|\alpha_i\|$	GRS	$\frac{A\|\alpha_i\|}{A\|\bar{r}_i\|}$	$\frac{A\|\alpha_i\|^2}{\bar{r}_i^2}$	$A\|\alpha_i\|$	GRS	$\frac{A\|\alpha_i\|}{\bar{r}_i}$	$\frac{A\|\alpha_i^2\|}{A\|\bar{r}_i^2\|}$
Panel A: Size-B/M portfolios								
FF5	10.43	1.96	0.65	0.26	15.33	2.34	1.05	0.66
FF5-SNT	10.30	1.83	0.80	0.39	15.73	2.11	1.00	0.61
Panel B: Size-OP portfolios								
FF5	7.20	1.10	0.39	0.10	15.26	1.68	0.82	0.44
FF5-SNT	6.75	1.09	0.27	0.05	14.55	1.53	0.69	0.31
Panel C: Size-Inv portfolios								
FF5	10.91	1.69	0.54	0.20	15.07	2.26	0.80	0.45
FF5-SNT	9.43	1.47	0.44	0.14	14.44	1.89	0.74	0.38
Panel D: Size-SNT portfolios								
FF5	35.70	2.72	0.52	0.16	26.74	2.86	0.49	0.14
FF5-SNT	30.96	2.45	0.71	0.29	22.46	2.45	0.47	0.13
Panel E: Size-B/M-OP-SNT Portfolios								
FF5	25.63	1.81	0.59	0.24	24.50	1.71	0.85	0.50
FF5-SNT	23.88	1.65	0.62	0.26	23.54	1.47	0.74	0.37
Panel F: Size-B/M-Inv-SNT Portfolios								
FF5	24.92	1.47	0.64	0.27	23.55	1.35	0.64	0.27
FF5-SNT	21.41	1.30	0.48	0.15	21.33	1.10	0.69	0.31
Panel G: 10 Industry Portfolios								
FF5	24.25	4.58	2.27	3.79	32.39	6.28	2.77	4.98
FF5-SNT	23.69	4.91	2.20	3.63	32.16	6.67	2.82	5.15
Panel H: 30 Industry Portfolios								
FF5	23.20	1.66	0.95	0.54	33.20	2.14	1.50	1.35
FF5-SNT	22.73	1.89	1.01	0.61	34.90	2.49	1.62	1.58

Appendix C. Sentiment, momentum, and liquidity

Table C.1: Summary statistics for factor returns including momentum using social media-based sentiment

This table shows the summary statistics for monthly factor returns in bps using the 2x3 and 2x2x2x2x2 sorting approach for January 1998 - December 2017. $MktRF$ is the value-weighted return on the market portfolio of all sample stocks minus the one-month Treasury bill rate. For the five Fama French factors SMB, HML, RMW, and CMA we follow their exact methodology. At the end of each June, stocks are assigned to two $Size$ groups using the NYSE median market cap as the breakpoint. Stocks are also assigned independently to two book-to-market equity (B/M), operating profitability (OP), and investment (Inv) groups, using NYSE medians of B/M, OP, and Inv. Momentum (UMD) are two groups of ood performers and bad performers, monthly measured as prior (2-12) cumulative returns. Sentiment is constructed as the social media-based sentiment change compared to the rolling mean. As such, this sort is more frequently constructed than those on fundamental factors, given the higher frequency of changes in sentiment. Panel A of the table shows average monthly returns (Mean), the standard deviations of monthly returns (Std dev.) and the t-statistics for the average returns. Panel B shows the correlations between factors and Panel C the corresponding **p**-values. Panel D demonstrates the correlation between the different versions of the same factor from the 2x3 and 2x2x2x2x2x2 sorts.

	2x3							2x2x2x2x2						
	$Mkt-Rf$	SMB	HML	RMW	CMA	UMD	PMN	$Mkt-Rf$	SMB	HML	RMW	CMA	UMD	PMN
Panel A: Average, standard deviation and one-sample t-statistics for monthly returns														
Mean	55.16	20.27	14.39	33.27	19.38	38.02	22.28	55.16	32.15	4.53	11.21	5.06	11.24	22.48
Std. dev	446.16	344.94	338.16	298.61	185.66	526.72	166.49	446.16	280.56	235.30	180.86	128.92	325.62	114.97
t-Statistic	1.92	0.91	0.66	1.73	1.62	1.12	2.07	1.92	1.78	0.30	0.96	0.61	0.53	3.03
Panel B: Correlation between different factors														
$Mkt-Rf$	1.00	0.29	-0.23	-0.47	-0.28	-0.31	-0.29	1.00	0.19	-0.22	-0.35	-0.27	-0.30	-0.23
SMB		1.00	-0.34	-0.62	-0.03	0.06	0.11		1.00	-0.16	-0.35	0.01	0.04	0.13
HML			1.00	0.58	0.56	-0.18	-0.19			1.00	0.75	0.29	-0.22	-0.21
RMW				1.00	0.15	0.04	0.02				1.00	0.18	-0.17	-0.16
CMA					1.00	0.03	-0.03					1.00	-0.04	-0.06
UMD						1.00	0.56						1.00	0.48
PMN							1.00							1.00
Panel C: P-value of correlations between different factors in Panel B														
$Mkt-Rf$		0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00	0.00
SMB			0.00	0.00	0.67	0.34	0.08			0.01	0.00	0.88	0.54	0.04
HML				0.00	0.00	0.01	0.00				0.00	0.00	0.00	0.00
RMW					0.02	0.57	0.71					0.01	0.01	0.01
CMA						0.65	0.68						0.50	0.39
UMD							0.00							0.00
PMN														
Panel D: Correlation between different versions of the same factor														
2x3								1.00	0.94	0.94	0.84	0.77	0.96	0.69

Table C.2: Summary statistics for factor returns including liquidity using social media-based sentiment

This table shows the summary statistics for monthly factor returns in bps using the 2x3 and 2x2x2x2x2 sorting approach for January 1998 - December 2017. $MktRF$ is the value-weighted return on the market portfolio of all sample stocks minus the one-month Treasury bill rate. For the five Fama French factors SMB, HML, RMW, and CMA we follow their exact methodology. At the end of each June, stocks are assigned to two $Size$ groups using the NYSE median market cap as the breakpoint. Stocks are also assigned independently to two book-to-market equity (B/M), operating profitability (OP), and investment (Inv) groups, using NYSE medians of B/M, OP, and Inv. Liquidity (LMI) are two groups of liquid and illiquid stocks, measured as monthly traded volume in relation to shares outstanding. Sentiment is constructed as the social media-based sentiment change compared to the rolling mean. As such, this sort is more frequently constructed than those on fundamental factors, given the higher frequency of changes in sentiment. Panel A of the table shows average monthly returns (Mean), the standard deviations of monthly returns (Std dev.) and the t-statistics for the average returns. Panel B shows the correlations between factors and Panel C the corresponding **p**-values. Panel D demonstrates the correlation between the different versions of the same factor from the 2x3 and 2x2x2x2x2x2 sorts.

	2x3							2x2x2x2x2						
	$Mkt-Rf$	SMB	HML	RMW	CMA	LMI	PMN	$Mkt-Rf$	SMB	HML	RMW	CMA	LMI	PMN
Panel A: Average, standard deviation and one-sample t-statistics for monthly returns														
Mean	55.16	20.27	14.39	33.27	19.38	31.05	22.28	55.16	26.74	1.17	16.51	1.58	22.07	22.36
Std. dev	446.16	344.94	338.16	298.61	185.66	493.71	166.49	446.16	279.36	153.95	158.87	119.43	207.93	113.51
t-Statistic	1.92	0.91	0.66	1.73	1.62	0.97	2.07	1.92	1.48	0.12	1.61	0.20	1.64	3.05
Panel B: Correlation between different factors														
$Mkt-Rf$	1.00	0.29	-0.23	-0.47	-0.28	0.67	-0.29	1.00	0.21	-0.39	-0.33	-0.15	0.66	-0.19
SMB		1.00	-0.34	-0.62	-0.03	0.66	0.11		1.00	-0.11	-0.23	0.13	0.41	0.05
HML			1.00	0.58	0.56	-0.55	-0.19			1.00	0.73	0.23	-0.65	-0.22
RMW				1.00	0.15	-0.78	0.02				1.00	0.00	-0.52	-0.15
CMA					1.00	-0.33	-0.03					1.00	-0.14	-0.16
LMI						1.00	-0.03						1.00	0.02
PMN							1.00							1.00
Panel C: P-value of correlations between different factors in Panel B														
$Mkt-Rf$		0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.02	0.00	0.00
SMB			0.00	0.00	0.67	0.00	0.08			0.08	0.00	0.05	0.00	0.44
HML				0.00	0.00	0.00	0.00				0.00	0.00	0.00	0.00
RMW					0.02	0.00	0.71					0.95	0.00	0.02
CMA						0.00	0.68						0.03	0.02
LMI							0.68							0.74
PMN														
Panel D: Correlation between different versions of the same factor														
2x3								1.00	0.93	0.90	0.81	0.77	0.94	0.69