from the benchmark are equivalent to a zero-investment portfolio (DeMiguel et al., 2017; Dichtl et al., 2019).

4.3.3 Empirical results

Table X shows estimation results and performance statistics for six news-related factor tilting allocations based on univariate parametric portfolio policies. Across the models for the benchmark equity factor portfolio (cf. Panel B), the only significant coefficients obtain for the tilting characteristics $SENT_1$ and $SENT_3$, suggesting a short-term sentiment effect among equity factors. Hence, factors with positive sentiment are overweighted relative to the equal-weighted benchmark while factors with negative sentiment are underweighted. The annualized returns of the corresponding parametric portfolio policy using $SENT_1$ and $SENT_3$ are 0.83 and 0.94 percentage points higher than the one for the equal-weighted benchmark, whereas the volatility is increased by 0.42 and 0.14 percentage points. These figures correspond to an information ratio of 0.50 and 0.56.

While statistically weak the news sentiment-related characteristics with longer horizon yet have positive information ratios as well: $SENT_6$, $wSENT_{td,6}$, $wSENT_{pt,6}$, and SIG_6 with information ratios of 0.56. 0.40, 0.40 and 0.58, respectively. Moreover, capturing news sentiment over longer horizon seem to be more profitable: The $SENT_6$ tilting portfolio has a higher Sharpe ratio than the $SENT_1$ tilting portfolio and than the equal-weighted benchmark (1.84 vs. 1.43 vs. 1.33). After accounting for transaction costs the $SENT_6$ strategy's return and Sharpe ratio are reduced to 3.08% and 1.32 compared to 2.24% and 0.92 for the equal-weighted benchmark. This reduction in (risk-adjusted) return is equivalent to an information ratio of 0.44 net transaction costs. Notably, news sentiment-related tilting allocations show similar performance statistics to allocations using common tilting characteristics such as factor crowding and factor spread and seem to be more profitable than those for factor momentum and factor valuation allocations.

[Table X about here]

While some news-related factor characteristics show predictability in this portfolio utility context for the benchmark equity factor portfolio, this turns when adding news-based equity factors to equity factor portfolio (cf. Panel C): none of the news sentiment-related factor characteristics exhibit significant coefficients if information from news flow data is directly incorporated in the equity factor portfolio. Yet, all news-related tilting allocations show positive information ratios, even after accounting for transaction costs. The economic relevance of news flow data is corroborated by overall higher (risk-adjusted) returns compared to the benchmark equity factor portfolio.

In a nutshell, our empirical evidence suggests that news sentiment information is valuable for constructing multi-factor allocation strategies. Thus, our findings are in line with Uhl et al. (2015) and Tetlock (2007) who document that news sentiment is useful for predicting future return movements.

5 Conclusion

This paper contributes to the literature on news analytics by investigating both its effects on the cross-section of stock returns and its ability to enhance multi-factor investment strategies. Studying the cross-sectional characteristics of a broad set of indicators generated from news flow data suggests that the insights gathered from firm-specific news sentiment analysis can find their way into implementable trading strategies in a manner that adds over and above common drivers of equity returns. Long-short portfolios based on news sentiment indicators seem to be particularly profitable in global and European stock universes, while results for the US and Japanese equity markets are rather moderate.

Assessing the information embedded in news flow data in risk-based and forecasting-based factor allocation strategies reveals interesting insights. An equally weighted portfolio as well as minimum-variance and risk parity strategies benefit from adding news sentiment-related equity factors to a portfolio of representative global equity factors. Building on these insights, we explore the benefits of active factor allocation when incorporating information from news flow data. Factor timing using fundamental and technical time-series predictors generates statistically significant and economically relevant results. Similarly, a factor tilting strategy that exploits cross-sectional news-related information outperforms an equally weighted benchmark portfolio. As both strategies require substantial turnover to follow the embedded information in the timing predictors or characteristics used, we experience a performance drag which is more pronounced for the factor timing than the factor tilting strategies.

References

Arnott, R., N. Beck, V. Kalesnik, and J. West (2016). How can 'smart beta' go horribly wrong? *Research Affiliates, February*.

Asness, C. S. (2016). The siren song of factor timing aka "smart beta timing" aka "style timing". *Journal of Portfolio Management 42*(5), 1–6.

Baker, M. and J. Wurgler (2006). Investor sentiment and the cross-section of stock returns. *Journal of Finance 61*(4), 1645–1680.

Banz, R. W. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics 9*(1), 3–18.

Barber, B. M. and T. Odean (2007). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *Review of Financial Studies 21*(2), 785–818.

Bender, J., X. Sun, R. Thomas, and V. Zdorovtsov (2018). The promises and pitfalls of factor timing. *Journal of Portfolio Management 44*(4), 79–92.

Brandt, M. W. and P. Santa-Clara (2006). Dynamic portfolio selection by augmenting the asset space. *Journal of Finance 61*(5), 2187–2217.

Brandt, M. W., P. Santa-Clara, and R. Valkanov (2009). Parametric portfolio policies: Exploiting characteristics in the cross-section of equity returns. *Review of Financial Studies 22*(9), 3411–3447.

Chan, W. S. (2003). Stock price reaction to news and no-news: drift and reversal after headlines. *Journal of Financial Economics 70*(2), 223–260.

Cohen, R. B., P. A. Gompers, and T. Vuolteenaho (2002). Who underreacts to cash-flow news? Evidence from trading between individuals and institutions. *Journal of Financial Economics 66*(2), 409–462.

Coqueret, G. (2018). The economic value of firm-specific news sentiment. *SSRN Working Paper*.

Da, Z., J. Engelberg, and P. Gao (2011). In search of attention. *Journal of Finance 66*(5), 1461–1499.

Da, Z. and M. C. Warachka (2009). Cashflow risk, systematic earnings revisions, and the cross-section of stock returns. *Journal of Financial Economics 94*(3), 448–468.

Dang, T. L., F. Moshirian, and B. Zhang (2015). Commonality in news around the world. *Journal of Financial Economics 116*(1), 82–110.

Daniel, K., S. Titman, and K. J. Wei (2001). Explaining the cross-section of stock returns in japan: factors or characteristics? *The Journal of Finance 56*(2), 743–766.

DeMiguel, V., L. Garlappi, and R. Uppal (2009). Optimal versus naive diversification: How inefficient is the 1/N portfolio strategy? *Review of Financial Studies 22*(5), 1915–1953.

DeMiguel, V., A. Martin-Utrera, F. J. Nogales, and R. Uppal (2017). A portfolio perspective on the multitude of firm characteristics. *Available at SSRN: 2912819*.

Dichtl, H., W. Drobetz, H. Lohre, C. Rother, and P. Vosskamp (2019). Optimal timing and tilting of equity factors. *Financial Analysts Journal, forthcoming*.

Fama, E. F. and K. R. French (1992). The cross-section of expected stock returns. *Journal of Finance 47*(2), 427–465.

Fama, E. F. and K. R. French (2006). Profitability, investment and average returns. *Journal of Financial Economics 82*(3), 491–518.

Fama, E. F. and K. R. French (2016). Dissecting anomalies with a five-factor model. *Review of Financial Studies 29*(1), 69–103.

Fang, L. and J. Peress (2009). Media coverage and the cross-section of stock returns. *Journal of Finance 64*(5), 2023–2052.

Hafez, P. A. (2010). News beta - a new measure for risk & stock analysis. *RavenPack Research Paper*.

Hafez, P. A., J. A. Guerrero-Colon, and S. Duprey (2015). Thematic alpha streams improve equity portfolio performance. *RavenPack Research Paper*.

Hammerschmid, R. and H. Lohre (2018). Regime shifts and stock return predictability. *International Review of Economics & Finance, forthcoming*.

Hanauer, M. (2014). Is japan different? evidence on momentum and market dynamics. *International Review of Finance 14*(1), 141–160.

Haugen, R. A. and N. L. Baker (1996). Commonality in the determinants of expected stock returns. *Journal of Financial Economics 41*(3), 401–439.

Heston, S. L. and N. R. Sinha (2017). News versus sentiment: Predicting stock returns from news stories. *Financial Analysts Journal 73*(3), 67–83.

Hillert, A., H. Jacobs, and S. Müller (2014). Media makes momentum. *Review of Financial Studies 27*(12), 3467–3501.

Hou, K., G. A. Karolyi, and B.-C. Kho (2011). What factors drive global stock returns? *Review of Financial Studies 24*(8), 2527–2574.

Jacobs, H. and S. Müller (2020). Anomalies across the globe: Once public, no longer existent? *Journal of Financial Economics 135*(1), 213–230.

Jegadeesh, N. (1990). Evidence of predictable behavior of security returns. *Journal of Finance 45*(3), 881–898.

Jegadeesh, N. and S. Titman (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance 48*(1), 65–91.

Kan, R. and G. Zhou (2012). Tests of mean-variance spanning. *Annals of Economics and Finance 13*(1), 139–187.

Ke, Z. T., B. T. Kelly, and D. Xiu (2019). Predicting returns with text data. *University of Chicago, Becker Friedman Institute for Economics Working Paper* (2019-69).

Kolasinski, A. C., A. V. Reed, and M. C. Ringgenberg (2013). A multiple lender approach to understanding supply and search in the equity lending market. *Journal of Finance 68*(2), 559–595.

Lee, W. (2017). Factors timing factors. *Journal of Portfolio Management 43*(5), 66–71.

Lehmann, B. N. (1990). Fads, martingales, and market efficiency. *Quarterly Journal of Economics 105*(1), 1–28.

Leinweber, D. and J. Sisk (2011). Event driven trading and the 'new news'. *Journal of Portfolio Management 38*(1).

Ludvigson, S. and S. Ng (2007). The empirical risk-return relation: A factor analysis approach. *Journal of Financial Economics 83*(1), 171–222.

Ludvigson, S. and S. Ng (2009). Macro factors in bond risk premia. *Review of Financial Studies 22*(12), 5027–5067.

Malkiel, B. G. and E. F. Fama (1970). Efficient capital markets: A review of theory and empirical work. *The journal of Finance 25*(2), 383–417.

McLean, R. D. and J. Pontiff (2016). Does academic research destroy stock return predictability? *Journal of Finance 71*(1), 5–32.

Neely, C. J., D. E. Rapach, J. Tu, and G. Zhou (2014). Forecasting the equity risk premium: The role of technical indicators. *Management Science 60*(7), 1772–1791.

Novy-Marx, R. (2013). The other side of value: The gross profitability premium. *Journal of Financial Economics 108*(1), 1–28.

Rapach, D. E., J. K. Strauss, and G. Zhou (2013). International stock return predictability: What is the role of the united states? *Journal of Finance 68*(4), 1633–1662.

Sloan, R. (1996). Do stock prices fully reflect information in accruals and cash flows about future earnings? *Accounting Review 71*(3), 289–315.

Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *Journal of Finance 62*(3), 1139–1168.

Tetlock, P. C., M. Saar-Tsechansky, and S. Macskassy (2008). More than words: Quantifying language to measure firms' fundamentals. *Journal of Finance 63*(3), 1437–1467.

Tversky, A. and D. Kahneman (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty 5*(4), 297–323.

Uhl, M. W., M. Pedersen, and O. Malitius (2015). What's in the news? using news sentiment momentum for tactical asset allocation. *Journal of Portfolio Management 41*(2), 100.

von Beschwitz, B., D. B. Keim, and M. Massa (2017). First to "read" the news: News analytics and algorithmic trading. *INSEAD Working Paper*.

Wang, Y., B. Zhang, and X. Zhu (2018). The momentum of news. *SSRN Working Paper*.

Welch, I. and A. Goyal (2008). A comprehensive look at the empirical performance of equity premium prediction. *Review of Financial Studies 21*(4), 1455–1508.

Appendix A The set of news indicators

This section describes in detail how we construct indicators exploiting the news flow data from RavenPack News Analytics. All indicators are filtered using the relevance score (REL), the event relevance score (EVR) and the event similarity days score (ESD). Unless otherwise indicated, we require all scores to be above 90.

Let E_i be the i-th news event for a specific firm in a given time horizon, as classified by the RavenPack taxonomy. The publication time of a news event is denoted as $\tau(\cdot)$. Then, the news volume indicator at time t, VOL_t, is computed as the number of news events within time horizon h, i.e.

$$VOL_{t,h} = \sum_{i \in I} \mathbb{1}_{\{\tau(E_i) \in [t-h,t]\}}, \tag{9}$$

where $I \subset \mathbb{N}$ is the number of all news events for a specific firm. In the empirical study, we calculate VOL using two filter settings: A less restrictive setting (REL > 75) to cover a firm's overall media presence and the standard setting (REL > 90, EVR > 90, ESD > 90) to restrict to the major events and thus only analyze a firm's meaningful media presence.

Let further $ESS(\cdot)$ be the event sentiment score of a news event. Then, the average firm-specific news sentiment indicator $SENT$ is given by

$$SENT_{t,h} = \frac{\sum_{i \in I} \mathbb{1}_{\{\tau(E_i) \in [t-h,t]\}} ESS(E_i)}{\sum_{i \in I} \mathbb{1}_{\{\tau(E_i) \in [t-h,t]\}}}. \tag{10}$$

The robust version of the news sentiment indicator, $rSENT$, is calculated as follows

$$rSENT_{t,h} = \frac{\sum_{i \in I} \mathbb{1}_{\{\tau(E_i) \in [t-h,t] \,|\, ESS(E_i) > u\}} - \sum_{i \in I} \mathbb{1}_{\{\tau(E_i) \in [t-h,t] \,|\, ESS(E_i) < l\}}}{\sum_{i \in I} \mathbb{1}_{\{\tau(E_i) \in [t-h,t] \,|\, ESS(E_i) > u,\, ESS(E_i) < l\}}}, \tag{11}$$

where l and u are lower and upper thresholds defining the range for the ESS. In the empirical analysis, we use two threshold settings: first, we differentiate between positive and negative news by setting $u = l = 0$. Second, we further exclude sentiment scores that are close to zero, i.e. $u = 0.1$ and $l = -0.1$.

To construct the weighted sentiment indicator $wSENT$, we denote the weight given to news event E_i by w_i. Consequently, this indicator is calculated as

$$wSENT_{t,h} = \frac{\sum_{i \in I} \mathbb{1}_{\{\tau(E_i) \in [t-h,t]\}} w_i ESS(E_i)}{\sum_{i \in I} \mathbb{1}_{\{\tau(E_i) \in [t-h,t]\}}}. \tag{12}$$

In the empirical study, we use two different weighting scheme: temporal decay and prospect theory. The former puts larger weight on sentiment scores closer to the end of time horizon h. This implies that the indicator is more reactive to recent news events and the corresponding news sentiment. The latter gives different weights to positive and negative news following evidence from prospect theory.

The news sentiment momentum indicator *SENTMOM* is constructed similar to the methodology of Uhl et al. (2015). Based on the SENT indicator, we first calculate crossing moving average time series of different time horizons (i.e. for $h = 1$ and $h = 12$ we get $SENT_{t,1} - SENT_{t,12}$) using a rolling window approach. Subsequently, we apply the cumulative sum (CUSUM) filter to this time series. See Uhl et al. (2015) for details on the CUSUM filter. Finally, the indicator series is normalized between -1 and 1.

Another way to calculate a trend indicator for news sentiment is to standardize a crossing moving average time series (e.g. for $h = 1$ and $h = 3$, see previous paragraph) by its sample standard error instead of applying the CUSUM filter. Specifically, the *aSENTMOM* indicator is computed as follows

$$aSENTMOM_{t,h} = \frac{SENT_{t,1} - SENT_{t-h}}{\sqrt{\sigma^2_{t,1}/VOL_{t,1} - \sigma^2_{t,h}/VOL_{t,h}}}, \tag{13}$$

where the sample variance $\sigma^2_{t,h}$ is given by

$$\sigma^2_{t,h} = \frac{\sum_{i \in I} \mathbb{1}_{\{\tau(E_i) \in [t-h,t]\}} \left(ESS(E_i) - SENT_{t,h}\right)^2}{\left(\sum_{i \in I} \mathbb{1}_{\{\tau(E_i) \in [t-h,t]\}}\right) - 1}. \tag{14}$$

The third news trend indicator, *REG*, is simply based on the t-statistic from regressing the cumulative sum of the ESS on the time index within time horizon h.

Among the alternative news concept indicators, *NEWSBETA* measures the responsiveness of a firm's stock return to an aggregate market news sentiment within a specific horizon. Specifically, the indicator value is calculated as the t-statistic from regressing a firm's stock return on a market capitalization-weighted average of the ESS across all firms in the universe.

The news significance indicator *SIG* measures the significance of the ESS (similar to a t-statistic) and thus captures mean and variation in the ESS. Specifically, it is given by

$$SIG_{t,h} = \frac{SENT_{t,h}}{\sqrt{\sigma^2_{t,h}/VOL_{t,h}}}. \tag{15}$$

The news dispersion indicator measures the variation in the ESS and is computed as

$$DISP_{t,h} = \frac{\sqrt{\sigma^2_{t,h}}}{SENT_{t,h}}. \tag{16}$$

All indicators except *SENTMOM* and the regression-based indicators are computed for $h = 1, 3, 6$, where h is measured in months. While *SENTMOM* uses multiple time horizons by definition, *REG* is calculated for $h = 6$, 12 and *NEWSBETA* for $h = 12$, 36, 60 due to sample size requirements for time-series regressions. In a final step, we standardize all indicators by company size and industry classification.

Table I
Descriptive statistics of news data

This table shows the descriptive statistics of news volume (Panel A) and the average event sentiment score (Panel B) per month and firm. For news volume, i.e. the number of news events per month, we require a relevance score above 75. For the ESS we require an (according to the RavenPack taxonomy) assigned and non-neutral ESS score as well as a relevance, event relevance and event similarity score above 90. For each panel, we show the overall statistics as well as statistics for the regions USA, Japan, Europe, rest of the world (RES) and emerging markets (EM) and for large, medium-sized and small firms. We show the following statistics: mean, median, minimum (Min), maximum (Max), variance (Var), standard deviation (Sd), skewness (Skew) and kurtosis (Kurt). Obs is the total number of observations and # Firms gives the average number of firms per month. The time period spans from January 2000 to December 2017.

	Mean	Median	Min	Max	Var	Sd	Skew	Kurt	Obs	# Firms
Panel A: News Events										
Overall	93.95	19	1	57,528	273,704	523.17	33.22	1,739	1,155,342	5349
USA	223.41	75	1	57,528	902,447	949.97	20.51	617	272,781	1263
Japan	41.53	10	1	24,704	49,800	223.16	32.97	2,398	106,144	491
Europe	85.11	23	1	41,395	143,970	379.43	27.62	1,383	280,823	1300
RES	55.63	13	1	12,207	35,348	188.01	17.51	542	158,896	736
EM	31.03	9	1	26,325	36,437	190.88	53.95	4,169	336,698	1559
Large	208.35	57	1	57,528	738,327	859.26	20.99	685	385,191	1783
Medium	52.83	19	1	22,643	48,775	220.85	51.52	3,538	385,038	1783
Small	20.62	7	1	18,684	13,717	117.12	92.88	11,454	385,113	1783
Panel B: ESS										
Overall	0.17	0.23	-1.0	1.0	0.15	0.39	-0.52	-0.30	851,220	3941
USA	0.16	0.18	-1.0	1.0	0.11	0.34	-0.34	-0.13	250,088	1158
Japan	0.18	0.27	-1.0	1.0	0.16	0.40	-0.60	-0.44	74,719	346
Europe	0.19	0.27	-1.0	1.0	0.15	0.39	-0.63	-0.11	199,378	923
RES	0.16	0.23	-1.0	1.0	0.18	0.42	-0.48	-0.51	104,366	483
EMM	0.17	0.27	-1.0	1.0	0.17	0.41	-0.55	-0.51	222,669	1031
Large	0.19	0.22	-1.0	1.0	0.11	0.33	-0.56	0.24	283,806	1314
Medium	0.16	0.22	-1.0	1.0	0.15	0.39	-0.45	-0.38	283,667	1313
Small	0.16	0.27	-1.0	1.0	0.18	0.43	-0.50	-0.67	283,747	1314

Table VII
Risk-based factor allocation

This table shows performance statistics of risk-based factor allocation strategies for the set of benchmark factors (Panel A) and the set of benchmark factors augmented by the news-based equity factors $SENT_1$, $SENT_6$ and $wSENT_{pt,6}$ (Panel B). Specifically, we examine an equally weighted portfolio (1/N), a minimum-variance portfolio (MVP) and a risk parity portfolio (RP). Annualized excess returns are calculated using the arithmetic average of simple returns. Standard deviation (Sd) and Sharpe ratio (SR) are annualized through multiplication by $\sqrt{12}$. Min and Max denote the lowest and highest monthly excess return in the sample period. MDD is the maximum drawdown. Excess return, Sd, Min, Max and MDD are given in percentage points. t-stat is the t-statistic for testing against the Null of a zero return effect. The performance statistics are based on the out-of-sample period from January 2007 to September 2017.

Strategy	Excess Return	Sd	Min	Max	SR	MDD	t-stat
Panel A: Benchmark factors							
1/N	3.26	2.45	-1.68	2.19	1.33	3.51	4.18
MVP	2.16	1.22	-0.50	1.37	1.77	0.94	5.55
RP	2.67	1.38	-0.79	1.74	1.94	1.27	6.07
Panel B: Benchmark + news factors							
1/N	3.47	2.18	-1.66	2.03	1.60	3.94	4.81
MVP	2.53	1.19	-0.49	1.55	2.13	0.85	6.42
RP	2.94	1.30	-0.66	1.56	2.25	1.14	6.79

Table VIII
News Factor Timing: Coefficients

This table shows the θ-coefficients for the fundamental ($FUN1$) and technical ($TECH1$) PCA factors that obtain in the parametric portfolio policy (PPP) for factor timing. We consider the PPP for the set of benchmark equity factors and the PPP for the set of benchmark factors augmented by the news-based equity factors $SENT_1$, $SENT_6$ and $wSENT_{pt,6}$. The coefficients are in bold-face if significant at the 5%-level. S.E. denotes the standard error of the coefficients. The sample period is from January 2002 to September 2017.

	Benchmark factors				Benchmark + news factors			
Predictor variable	$FUN1$	S.E.	$TECH1$	S.E.	$FUN1$	S.E.	$TECH1$	S.E.
$PROF$	-0.07	0.55	-1.68	1.47	-0.82	0.59	-1.56	1.47
CFY	0.98	0.94	0.74	1.26	1.96*	0.97	0.54	1.29
ACC	-1.99	1.09	-1.42	1.88	-1.73	1.11	-0.67	1.85
DY	-0.31	0.60	1.31	0.83	0.35	0.67	1.34	0.86
AT	-0.06	1.02	-2.10	1.16	-0.72	1.08	-0.66	1.17
BTM	-0.82	1.18	-0.88	1.58	-1.23	1.22	-0.09	1.63
$MOM12$	0.24	0.24	-0.66	0.43	-0.33	0.28	0.11	0.61
STR	-0.29	0.25	**-1.35**	0.53	-0.21	0.25	**-1.85**	0.54
LTR	0.03	0.55	**-1.36**	0.57	0.42	0.56	**-2.18**	0.62
$DLTD$	**-4.31**	1.41	-3.08	2.63	**-6.17**	1.56	-3.17	2.64
DSO	**-2.12**	0.82	1.02	1.62	-0.65	0.88	0.44	1.74
$SIZE$	**-0.80**	0.33	**-1.05**	0.46	**-0.98**	0.34	**-1.10**	0.47
AG	2.53	1.33	0.74	1.82	2.70	1.49	1.51	1.80
CP	**-2.62**	1.20	-1.56	2.06	**-4.51**	1.23	-1.61	2.10
PM	**-3.37**	1.04	1.61	1.28	**-4.30**	1.09	2.54	1.34
EY	**4.15**	1.02	**-3.83**	1.09	**4.80**	1.06	**-3.69**	1.16
LEV	-0.40	0.77	-0.11	0.91	-1.24	0.77	-0.49	0.92
ROA	-0.67	1.21	-2.60	1.44	**-2.91**	1.26	-2.11	1.53
STC	0.93	0.91	0.67	1.24	0.83	0.93	-0.27	1.23
STI	-0.92	0.69	-0.51	1.37	**-1.62**	0.68	-0.46	1.42
$SENT_1$	–	–	–	–	-0.91	0.93	-3.53	2.27
$SENT_6$	–	–	–	–	2.75	1.45	-1.12	2.38
$wSENT_{pt,6}$	–	–	–	–	1.59	1.21	-2.47	1.80

Table IX
News Factor Timing: Performance statistics

This table gives performance statistics of parametric portfolio policies (PPP) for factor timing. We use the first principal components of fundamental ($FUN1$) and technical ($TECH1$) predictor variables in the PPP. Panel A gives the PPP for the set of benchmark equity factors and Panel B gives the PPP for the set of benchmark factors augmented by the news-based equity factors $SENT_1$, $SENT_6$ and $wSENT_{pt,6}$. We include an equally weighted portfolio (1/N) as benchmark strategy for both sets. The performance statistics are based on the out-of-sample period from January 2007 to September 2017. Annualized excess returns are calculated using the arithmetic average of simple returns. Standard deviation (Sd) and Sharpe ratio (SR) are annualized through multiplication by $\sqrt{12}$. The information ratio (IR) uses arithmetic active returns of factor timing over the 1/N benchmark. Annualized turnover is stated as two-way turnover. All performance statistics are given in percentage points, except for Sharpe ratio.

	Excess Return			SR		IR		
Strategy	*gross*	*net*	Sd	*gross*	*net*	*gross*	*net*	Turnover
Panel A: Timing model with benchmark factors								
1/N	3.26	2.24	2.45	1.33	0.92	–	–	–
FUN1 + TECH1	3.75	1.12	3.36	1.12	0.33	0.29	-0.66	8.36
Panel B: Timing model with benchmark + news factors								
1/N	3.47	2.45	2.18	1.58	1.09	–	–	–
FUN1 + TECH1	3.91	0.96	3.08	1.27	0.31	0.35	-0.79	9.92

Table X
News factor tilting

The table gives estimation results and performance statistics of parametric portfolio policies (PPP) for factor tilting based on cross-sectional factor characteristics. We consider six news sentiment-related and four benchmark characteristics. Panel A gives the PPP for the set of benchmark equity factors and Panel B gives the PPP for the set of benchmark factors augmented by the news-based equity factors $SENT_1$, $SENT_6$ and $wSENT_{pt,6}$. We include an equally weighted portfolio (1/N) as benchmark strategy for both sets. The performance statistics are based on the out-of-sample period from January 2007 to September 2017. The second column gives the estimated coefficients of the PPP, marked in boldface if significant at a 5% level or better. Annualized returns are calculated using the arithmetic average of simple returns. Standard deviation and Sharpe ratio are annualized through multiplication by $\sqrt{12}$. The information ratio uses arithmetic active returns of factor timing over the 1/N benchmark. Annualized turnover is stated as two-way turnover. All performance statistics are given in percentage points, except for Sharpe ratio and t-statistic.

Characteristic	$\hat{\phi}$	Return p.a.		SD p.a.	Sharpe ratio		Maximum drawdown		t-statistic		Tracking error	Information ratio		Turnover p.a.
		gross	*net*		*gross*	*net*	*gross*	*net*	*gross*	*net*		*gross*	*net*	*two-way*
Panel A: Tilting model with benchmark factors														
1/N		3.26	2.24	2.45	1.33	0.92	3.51	4.01	4.18	2.87	–	–	–	
$SENT_1$	**5.03**	4.09	2.13	2.87	1.43	0.74	4.38	5.05	4.47	2.33	1.67	0.50	-0.07	5.02
$SENT_3$	**3.72**	4.20	2.80	2.59	1.62	1.08	5.32	5.92	5.09	3.39	1.69	0.56	0.33	2.21
$SENT_6$	2.85	4.31	3.08	2.34	1.84	1.32	4.67	5.20	5.78	4.14	1.77	0.56	0.44	1.39
$wSENT_{td,6}$	2.39	3.93	2.72	2.44	1.61	1.12	4.61	5.17	5.04	3.50	1.64	0.40	0.29	1.21
$wSENT_{pt,6}$	2.34	3.92	2.73	2.48	1.58	1.10	4.66	5.21	4.95	3.45	1.64	0.40	0.30	1.13
SIG_6	3.16	4.27	2.98	2.67	1.60	1.11	4.94	5.51	5.02	3.50	1.75	0.58	0.42	1.68
Crowding	**6.09**	4.87	3.34	3.29	1.48	1.02	3.85	4.51	4.64	3.19	1.83	0.88	0.60	2.89
Momentum	1.37	4.08	2.20	3.04	1.34	0.72	3.12	3.88	4.22	2.26	1.47	0.56	-0.03	4.61
Spread	**16.35**	4.01	2.73	3.07	1.30	0.88	3.55	4.07	4.09	2.75	1.83	0.41	0.26	1.59
Valuation	-1.51	3.72	2.50	2.41	1.54	1.04	4.12	4.67	4.84	3.26	1.72	0.27	0.15	1.30
Panel B: Tilting model with benchmark + news factors														
1/N	–	3.47	2.45	2.18	1.60	1.13	3.94	4.44	4.81	3.39	–	–	–	–
$SENT_1$	5.12	4.15	2.61	2.23	1.86	1.18	4.27	4.81	5.83	3.70	1.72	0.48	0.18	2.88
$SENT_3$	3.26	4.35	3.07	2.30	1.89	1.34	4.60	5.13	5.92	4.19	1.75	0.59	0.44	1.63
$SENT_6$	2.73	4.07	2.80	2.51	1.62	1.11	5.07	5.63	5.08	3.49	1.69	0.48	0.33	1.53
$wSENT_{td,6}$	2.49	4.29	3.07	2.36	1.82	1.30	4.67	5.21	5.70	4.07	1.72	0.56	0.44	1.31
$wSENT_{pt,6}$	2.46	4.26	3.05	2.36	1.80	1.29	4.70	5.24	5.65	4.04	1.70	0.55	0.44	1.26
SIG_6	3.17	4.40	3.16	2.39	1.84	1.32	4.74	5.27	5.78	4.15	1.75	0.62	0.49	1.41
Crowding	**6.53**	5.18	3.62	3.14	1.65	1.16	4.21	4.90	5.18	3.65	1.97	0.94	0.68	3.03
Momentum	1.12	3.93	2.04	2.65	1.49	0.77	2.84	3.55	4.66	2.40	1.39	0.44	-0.18	4.62
Spread	**15.62**	3.95	2.70	2.78	1.42	0.96	3.08	3.59	4.47	3.01	1.78	0.36	0.22	1.47
Valuation	-1.36	3.74	2.54	2.38	1.57	1.07	4.68	5.39	4.92	3.34	1.68	0.25	0.14	1.24

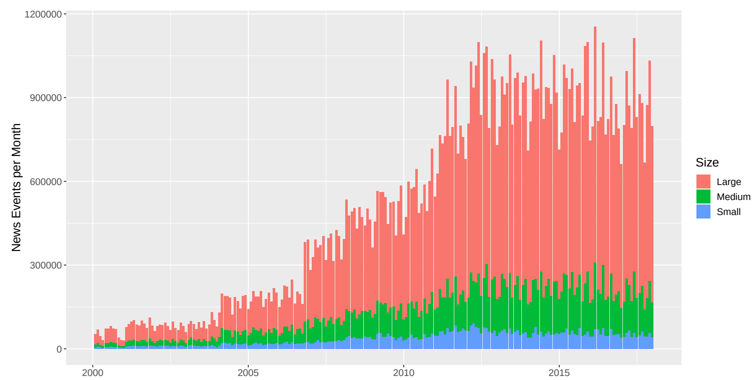
Table XI
Equity Factor Description

This table describes how we define common equity factors. The necessary data are sourced from the Worldscope database.

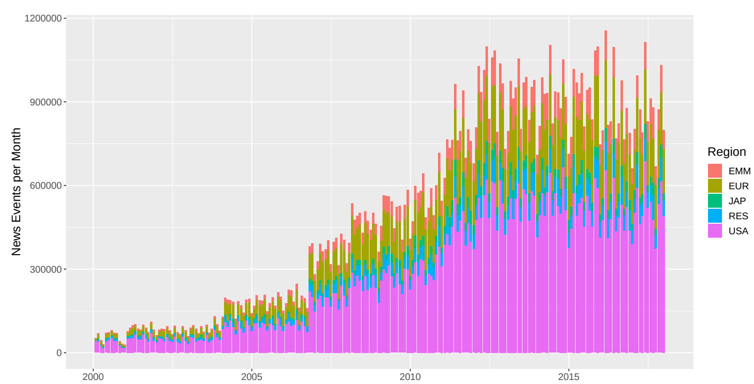
Factor	Description	Related studies
Value	We use cashflow yield as value factor. It captures the excess return of going long stocks with a high cashflow-to-price ratio and short those with a low cashflow-to-price ratio. Cashflows are measured as the sum of funds from operations, extraordinary items and funds from other operating activities	Sloan (1996); Da and Warachka (2009); Hou et al. (2011)
Quality	We use profitability as quality factor. This factor is long stocks with robust operating profitability and short stocks with weak profitability. Profitability is calculated as annual revenues less cost of goods sold and interest and other expenses, divided by book value for the last fiscal year-end.	Haugen and Baker (1996); Cohen et al. (2002); Fama and French (2006); Novy-Marx (2013); Fama and French (2016)
Momentum	We employ 12-month momentum that captures a medium-term continuation effect in returns by buying recent winners and selling recent losers. We control for the short-term reversal effect by excluding the most recent month $(t-1)$ at time t.	Jegadeesh (1990); Jegadeesh and Titman (1993)
Size	The size factors builds on the observation that stocks with a larger market capitalization tend to underperform stocks with smaller market capitalizations. The factor is going long stocks with the smallest market capitalization and short stocks with the highest market capitalizations.	Banz (1981); Fama and French (1992); Sloan (1996); Da and Warachka (2009); Hou et al. (2011)
Short-term reversal	This factor captures the short-term reversal effect in the cross-section of stock returns. The factor is long stocks with a weak previous month performance and short stocks with a high one.	Jegadeesh (1990); Lehmann (1990)

Figure 1. Characteristics of news volume

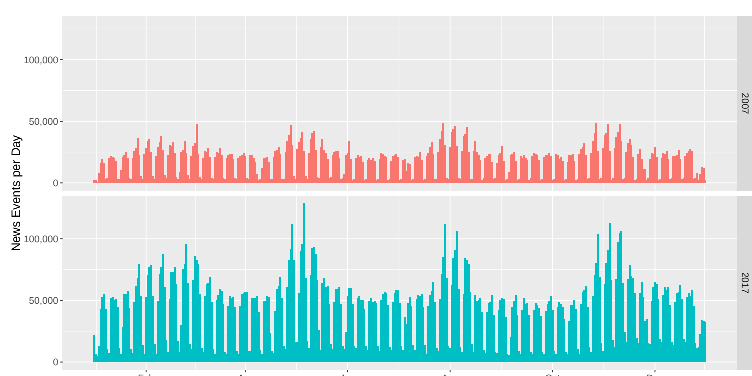
This figure illustrates various characteristics of news volume over the sample period from January 2001 to December 2017. Panel (a) shows monthly news events allocated to the following regions: United States (USA), Japan (JAP), Europe (EUR), emerging markets (EM) and rest of the world (RES). Panel (b) shows news volume per market capitalization (large, medium-sized and small companies). Panel (c) illustrates the yearly pattern of daily news events for the years 2007 and 2017.



(a) News volume per size



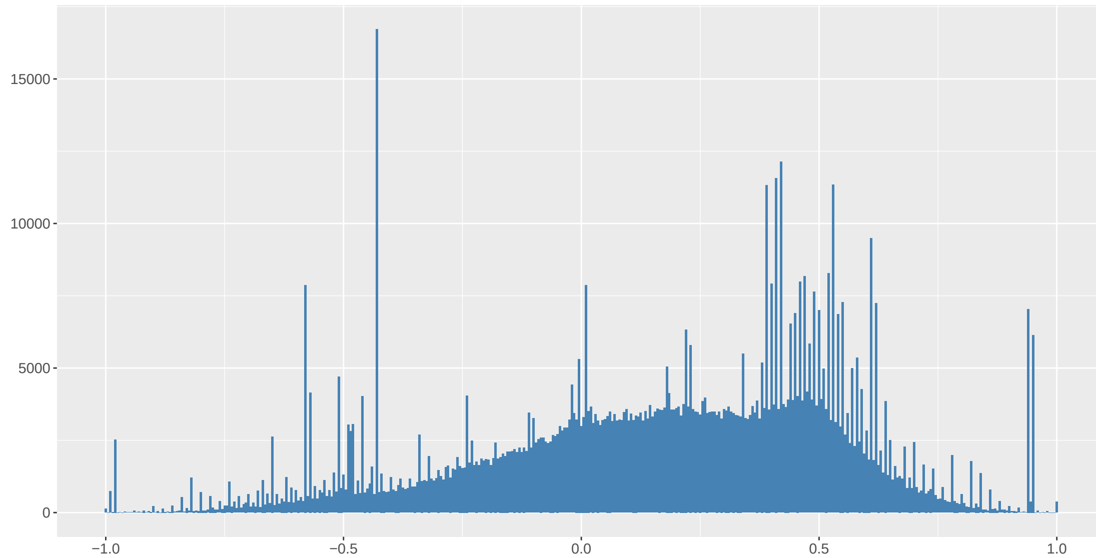
(b) News volume per region



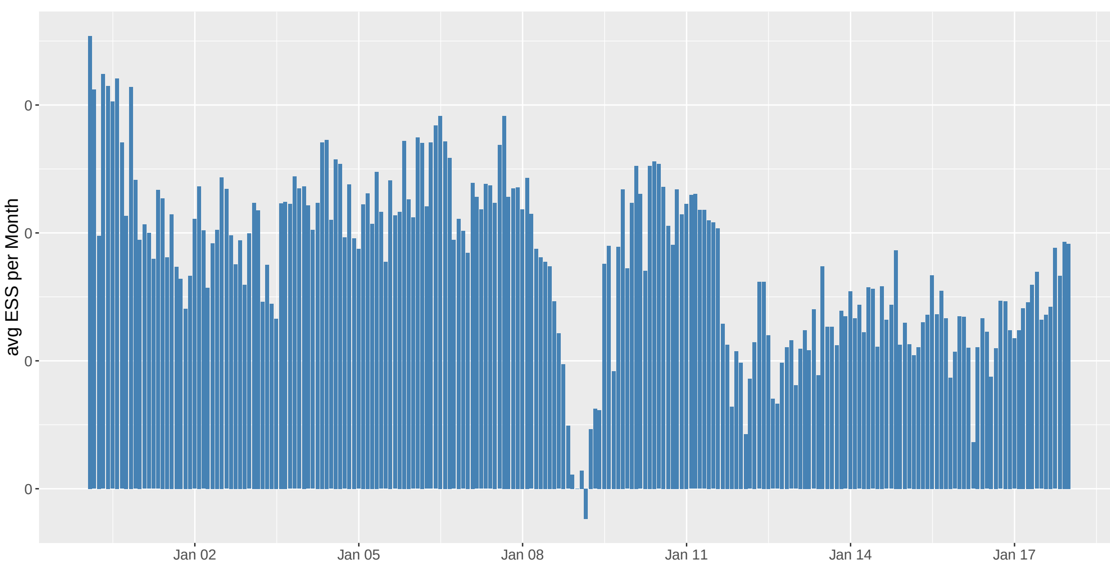
(c) Seasonality of news volume

Figure 2. Characteristics of news sentiment

Panel (a) shows the histogram of the ESS, whereas Panel (b) shows the monthly average event sentiment score across all firms. The sample period goes from January 2000 to December 2017.



(a) Histogram of ESS



(b) ESS over the sample period

Figure 3. Return correlation of news equity factors

This figure shows the correlation among news equity factors and traditional equity factors. Equity factors are derived from monthly return data for the global stock universe over the sample period from January 2001 to December 2017 and are grouped according to their concept category: news volume (A), news sentiment (B), news trend (c), alternative news concepts (D) and traditional equity factors (E).

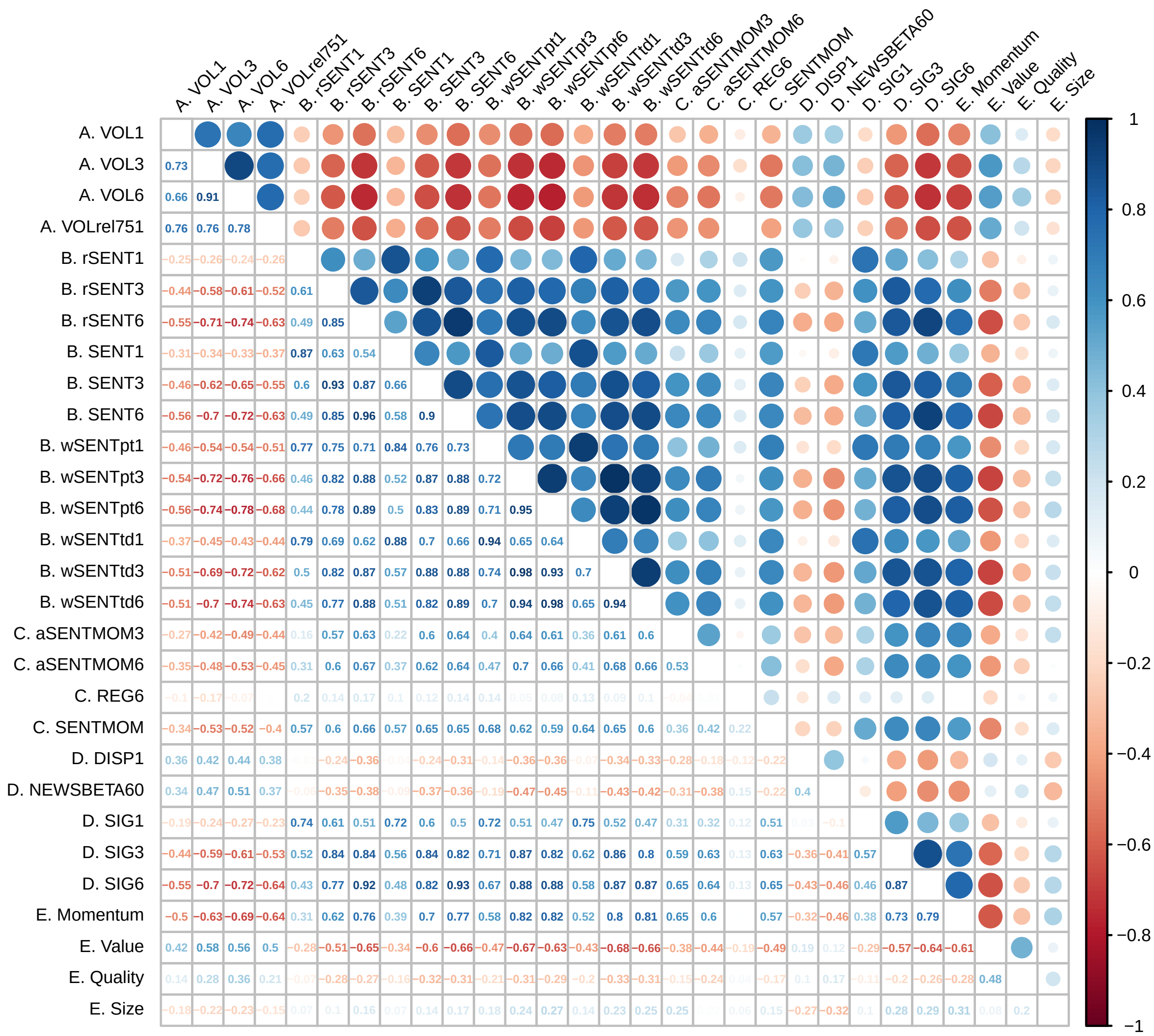
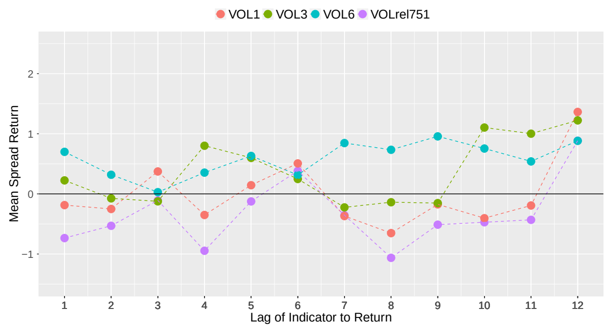
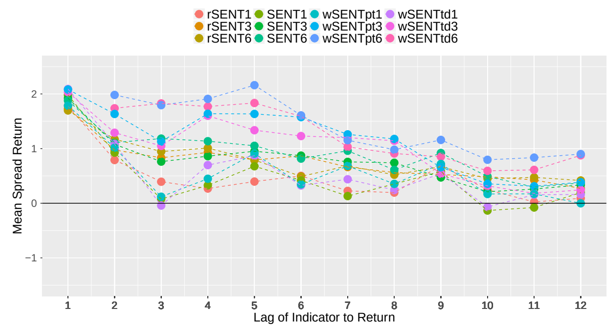


Figure 4. News equity factors: Long-horizon effects

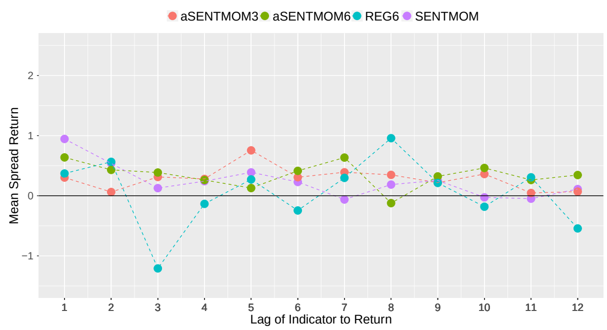
This figure shows the returns of cross-sectional long-short portfolios based on news volume (Panel A), news sentiment (Panel B), news trend (Panel C) and alternative news concepts (Panel D) indicators for the global stock universe from January 2001 to December 2017.



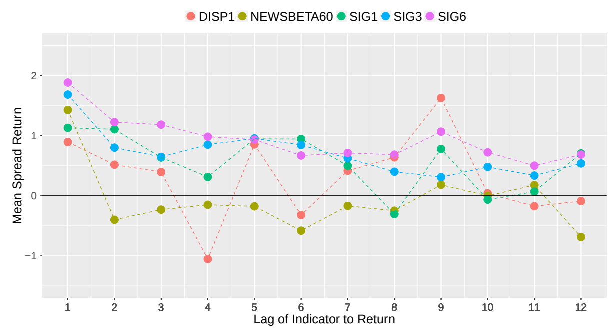
(a) News volume



(b) News Sentiment



(c) News Trend



(d) Alternative News Concepts