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Abstract

This paper studies optimal equity portfolios with long-term horizon under heterogeneous risk aversion levels. We focus on European stocks and empirically show that contemporaneous excess returns of semi-active strategies are negatively associated with market conditions and sentiment. Consistent with our long-horizon perspective, we find that the effects of sentiment measures on semi-active portfolio returns are sizeable and economically relevant, particularly in bull (post-crisis) periods, even after controlling for the five Fama-French factors, momentum, macro indicators and political uncertainty shocks either globally or country-wise. By contrast, the effects of sentiment measures on the passive (benchmark) portfolio are negligible. The results further indicate that realized portfolio returns generated from our long-term strategies are considerably resilient to the episodes of flight-to-safety (risk-off) regimes.

Keywords: Asset Management, Portfolio choice, Investment horizons, Investor and market sentiment, Fund performance, Signal processing

JEL: C61, D81, G11, G12, G14

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1. Introduction

The periods of severe market turmoil and crisis have shifted the focus of researchers toward developing more resilient asset allocation and portfolio management strategies. In the U.S., for instance, the hedge fund and mutual fund industries experienced significant losses during the 2007-2008 mortgage crisis, which triggered downside consequences not only at the firm level idiosyncratically but also globally through systemic channels (see e.g., Billio et al., 2012 and Elliott et al., 2014). Since then, the common discussion among practitioners and within the research community has been heavily centered on critical debates with respect to active versus passive investments (e.g., French, 2008) and the role of investment horizons (Dierkes et al., 2010) in preventing large losses and jointly achieving reasonable portfolio returns.

Despite this substantial progress over the last decade, practical and academic research is still relatively limited and sparse in this direction, particularly in understanding *how* and *why* risk aversion affects asset allocation over relatively long investment horizons. In this respect, we conjecture that an optimal portfolio generates returns in excess of the return on the benchmark as long as the horizon is adjusted fairly long and risk tolerance is sufficiently reasonable for investors. If this perspective is supported by the data, then investors are likely to adopt semi-active strategies promising a certain amount of realized excess returns for a given horizon and risk aversion level without being *too much* exposed to conventional active investing (and hence associated transaction and management costs).[1] Exploring further in this direction, we aim to explain the temporal behavior of excess returns over business cycles through driving factors embedded in market sentiment and conditions. As shown by Frijns et al. (2017), investor sentiment affects not only equity returns, but also the comovements among markets. Specifically, Frijns et al. (2017) document that the observed increase in the international equity market correlations over time is driven by an increase in the correlations of the *non-fundamental* rather than the *fundamental* component of returns, and this in turn is amplified by the sentiment of investors. In this regard, we empirically investigate whether such non-fundamental regularities related to sentiment likely influence portfolio strategies and hence excess returns over a passive portfolio (benchmark) in particular.

On the methodological front, however, it is rather challenging to characterize such optimal portfolio specifications and fine-tuned risk aversion along with changing long-horizon in a unified framework. While the Markowitz mean-variance optimization remains a fundamental concept in modern portfolio theory to construct risky portfolios (Markowitz, 1991), it has shown some limitations as a single-period model (see e.g., Campbell and Viceira, 2002). To overcome this challenge, we instead

[1] Averaging over 1980 to 2006, French (2008) finds investors spend 67 basis points of the aggregate value of the market each year searching for superior returns.

utilize recent advances in digital signal processing (Jones, 2013, Jones, 2017), which follows a mean-variance-autocovariance portfolio optimization paradigm and provides greater flexibility to adjust investment horizon and tolerance towards risk either market-based or firm-specific. We outline the structure of our approach and discuss in depth how to modify the mechanics to design portfolio strategies.

In line with our conjecture, the empirical results reveal that semi-active strategies with various levels of risk tolerance generate significant excess returns over time and outperform the benchmark index. Perhaps more interestingly, we find that the realized contemporaneous excess returns of our semi-active portfolios are tightly linked to market conditions or sentiment measured by the indicators of business environment, consumer sentiment and financial condition factors, such as volatility index (henceforth VIX). The effects of sentiment measures on contemporaneous portfolio returns are negative, sizeable and economically relevant, specifically in bull periods during post-crisis spells. The results remain considerably stable even after controlling for the five Fama-French factors, momentum, macro indicators and political uncertainty shocks either globally or country-wise. In addition to these principle findings, our analysis further suggests that realized portfolio returns generated from our long-term strategies are likely to be resilient to flight-to-safety (risk-off) regimes observed in the marketplace. Studying the U.S. stock market, Baele et al. (2014) document that hedge fund returns have significantly negative exposure to flight-to-safety regimes. With a particular focus on European stocks, however, we find no evidence of significant exposure. This may in turn highlight the importance of European stocks in investment strategies compared to other markets.

On a broader perspective, our paper is closely related to studies that distinguish portfolio strategies as active versus passive investment schemes. Passive strategies consist generally in tracking the performance of a benchmark (index) by minimizing the tracking error, measured as the standard deviation of the difference between the portfolio returns and the benchmark returns (see e.g., Beasley et al., 2003, Corielli and Marcellino, 2006). By contrast, active strategies construct portfolios that are expected to outperform the benchmark while having minimum tracking error. To lie on the mean-variance frontier, which consists of portfolios with the lowest variance for various levels of expected return, a risk constraint is generally set to these active portfolios (Roll, 1992, Jorion, 2003, Alexander and Baptista, 2010). In this vein, Alford et al. (2003) further show that portfolio managers with high levels of active risk tend to generate lower risk-adjusted returns. We extend this stream of research by considering semi-active strategies, such as the enhanced index tracking, aiming at securing higher returns than those on the benchmark, while minimizing the tracking error similar to Wu et al. (2007) and Lima de Paulo et al. (2016). Unlike a pure active strategy, semi-active strategies do not necessarily require frequent intervention, but at the same time they help track the benchmark index, passively limiting potential downside risk. Furthermore, in contrast to these studies, we directly allow the risk exposure to be aggressive or conservative and examine the resulting portfolio gains/losses under various situations that are either market-based or firm-specific.

As it is well known, the classical Markowitz (1991) framework requires knowledge of both the mean returns and the covariance matrix. Kan and Zhou (2007) find that substituting sample estimates for population parameters can cause significant reduction in out-of-sample performance. Their results suggest that it is important to estimate parameters by combining the estimation with the economic objectives at hand. Departing from these studies, we use a signal processing approach that allows us to extract signals from multiple periods, short or long, and delivers optimal weights accordingly under different risk schemes (i.e., aggressive or conservative). Prior research has particularly concentrated on the question of how the optimal asset allocation varies with respect to the time horizon. First, in the context of predictable returns, both buy-and-hold and active investors invest substantially more in risky equities over long horizons, as time variation in asset returns induces mean-reversion in returns (Barberis, 2000, Ait-Sahalia and Brandt, 2001, Sanfilippo, 2003). Dierkes et al. (2010) provide further evidence that strategy attractiveness substantially depends on the investment horizon. However, the weak significance of the evidence for return predictability likely suffers from both estimation risk and model uncertainty (see e.g., Barberis, 2000). Unlike these conventional approaches, we explore the role of investment horizon directly within the optimization stage. Therefore, the model uncertainty problem and inference-related estimation constraints become fairly negligible. For a given level of horizon duration (long or short), we obtain the optimal weights under different levels of risk tolerance.[2] We particularly focus on the performance over the long term since market anomalies often arise in short horizons and disappear quickly (due to, for instance, autocorrelations in the value-weighted index, see e.g., Lo and MacKinlay, 1988). Other forms of anomalies may last longer, however (e.g., the January effect, Keim, 1983) or persist over a relatively long period of time, as may be the case for the momentum effects (see e.g., Jegadeesh and Titman, 2001).

Our empirical analysis extends and complements the studies on market sentiment in several respects. For instance, Baker and Wurgler (2006), Baker et al. (2012) and Huang et al. (2015) find that investor sentiment affects the cross-section of stock returns and performs much better than commonly used economic predictors in forecasting stock returns (either at the aggregate level or at the portfolio level). Sibley et al. (2016) show that the power of the sentiment index to predict cross-sectional stock returns is mainly driven by the component constructed from variables related to market conditions and economic fundamentals. Shen et al. (2017) examine the effect of investor sentiment on the pricing of macro risk factors and construct portfolios by sorting individual stocks on their sensitivity to macro factors. They find that high-risk portfolios earn significantly higher returns than low-risk portfolios following low-sentiment periods, whereas the exact opposite occurs following high-sentiment periods. In contrast, we consider in this paper mean-variance-autocovariance portfolio optimization and we aim to explain how sentiment proxies affect realized portfolio returns,

[2] It is worth mentioning that mean returns, volatilities and correlations between security returns vary across time periods. Analyzing the returns on a stock market portfolio and portfolios tracking size- and value effects, Guidolin and Timmermann (2008) show that regimes have a large impact on the optimal asset allocation.

considering that diversification benefits are not only a function of fundamental-based correlations, but are also a function of non-fundamental correlations mainly driven by investor sentiment (Frijns et al., 2017).

Yu and Yuan (2011) document that investors receive more compensation for bearing volatility in low sentiment periods than in high sentiment periods. Perhaps more importantly, both global and local components of investor sentiment appear to play a role in the cross-section of returns (Baker et al., 2012). Likewise, Wu et al. (2017) find that total, local, and global sentiment differences have signicantly positive relationships with the price deviations between American Depository Receipt (ADR) and its home share. With a particular focus on European equity portfolios that constitute an unprecedented contribution to this extant literature, we find that the standard fear proxy VIX index explains the variation in excess returns more than the sentiment factors proposed by Baker and Wurgler (2006) (henceforth BW factors). This result is consistent with the finding of Harju and Hussain (2011) such that equity returns and volatility are generally sensitive to the news originating in foreign markets. In particular, European stock markets react similarly to the information originating in the U.S. One financial motive behind this result could be that stock return predictability of investor sentiment stems from investors biased belief about news surprises on future cash flows rather than discount rates (Huang et al., 2015).[3] The role of VIX turns out to be crucial from asset allocation and risk tolerance perspective, lending support the global risk version and monetary policy impact hypotheses examined by Bekaert et al. (2014, 2013) and Bekaert and Hoerova (2014).[4]

The remainder of this paper is organized as follows. The next section introduces the data, outlines our methodology based on digital portfolio theory and discusses how to adjust risk aversion levels. Section 3 presents our empirical analysis and reports the results. In Section 4, we consider various robustness checks and extensions. Section 5 concludes.

[3] See also Stambaugh et al. (2012) and Stambaugh et al. (2014), who find that market anomalies should be stronger following periods of high sentiment, to the extent that the anomalies reflect mispricing. This corroborates Massa and Yadav (2015), who suggest that mutual funds implement contrarian strategies based on investor sentiment. They may choose to bet against investor sentiment in the hope that the long-term benefits from superior performance outweigh the short-term catering effects. Sentiment-based strategies appear to systematically exploit investor over-reaction to time the market or pick between winners and losers (Basu et al., 2006).

[4] In particular, prior research suggests that there are at least two financial channels through which the VIX index can affect markets. First, the VIX reveals whether market uncertainty in the U.S.—as one of the main measures of the global contagion—influences the risk aversion of investors focusing on European assets (for empirical evidence, see e.g., Bekaert et al., 2014). In addition to this channel, Bekaert et al. (2013) and Bekaert and Hoerova (2014) further document that the VIX is strongly associated with the U.S. monetary policy actions. Specifically, the periods of loose monetary policy often trigger excessive risk taking by investors resulting in elevated levels of market uncertainty captured by the VIX index. This is the second, the monetary policy channel that the VIX can influence investor decisions in constructing portfolios based on European stocks. Therefore, the VIX indicator in our regressions is consistent with this explanation such that market uncertainty in the U.S.—linked to Fed policy and risk aversion—has effects on European equity portfolio returns.

2. Data and methodology

We start by introducing our data on stocks and sentiment indicators. We next outline our methodological framework, which permits accommodating different levels of risk tolerance (aggressive versus conservative) based on the digital portfolio approach.

2.1. Data description and sample selection

We obtain data on European stocks from Thomson Reuters Eikon. Our equity portfolios consist of the securities included in the ten MSCI Europe sector indices, which capture the large and mid-cap segments across 15 developed markets in Europe.[5]

We extract our sentiment indicators and macroeconomic factors from the Bloomberg Data Analytics and Thomson Reuters EIKON. The sentiment and market condition indicators consist of the European Business Climate Sentiment Index (BUSC), the U.S. National Financial Condition Index (NFCI) and CBOE's Volatility Index (VIX). We decompose the economic factors into two categories, labeled as macro factors and price factors. These factors are (aggregated) Euro Area Unemployment (UEMP), Total Industrial Production (TIP), Core Consumer Price Index (CCPI) and the euro-dollar exchange rate (EURUSD). In addition to these economic factors, we further consider political risk proxies for both the Euro area and the U.S. We use monthly data on European and U.S. political uncertainty indices (labeled as EUPUX and USPUX, respectively). The sample matches our equity data and hence covers the period from January 1, 2000, to December 31, 2015.[6]

2.2. Portfolio construction through signal processing

To construct our various portfolios, we use the digital portfolio theory (DPT) mean-variance algorithm developed by Jones (Jones, 2001, Jones, 2013, Jones, 2017). The DPT algorithm is an extension of Markowitz's modern portfolio theory (MPT), which decomposes long-term portfolio variance using digital signal processing. The variance is represented non-parametrically with orthogonal mean-reversion components for different horizons. Unlike MPT, DPT does not require returns to be *independent and identically distributed* while returns still follow a stationary process. As in the MPT, the DPT objective is to maximize the expected return of the portfolio. The DPT algorithm has the following formulation:

$$\text{Max } E\left(\tilde{r}_p(t)\right) = \sum_{j=1}^{N} w_j \mu_j \tag{1}$$

[5] In our supplemental appendix, we provide the descriptive statistics of the ten sector indices over the full sample. We further report statistics for the crisis period (2007-2011) and the post-crisis period (2012-2015). It is natural to notice that many maximum and minimum returns are observed for the crisis period. In the same vein, non-cyclical industries (telecommunications, consumer staples, healthcare) seem to relatively better withstand the crisis. For brevity, these tables are presented in our supplemental appendix.

[6] For the regression analysis, our sample covers the period from January 1, 2004, to December 31, 2015 in order to eliminate the sharp breakdowns and missing data corresponding to periods 2000-2004.

subject to following $4K$ constraints, $k = 1, 2, 3, ..., K$ (for $K = 24$)

$$\textbf{systematic risk} \left\{ \begin{array}{l} \sum_{j=1}^{N} w_j R_{kj} cos\theta_{kmj} \leq c\beta_k, \\ \sum_{j=1}^{N} w_j R_{kj} cos\theta_{kmj} \geq -c\beta_k. \end{array} \right\} \tag{2}$$

$$\textbf{unsystematic risk} \left\{ \begin{array}{l} \sum_{j=1}^{N} w_j R_{kj} sin\theta_{kmj} \leq c\alpha_k, \\ \sum_{j=1}^{N} w_j R_{kj} sin\theta_{kmj} \geq -c\alpha_k. \end{array} \right\} \tag{3}$$

for

$$\sum_{j=1}^{N} w_j = 1, \quad w_j \geq 0, \quad j = 1, 2, 3, ..., N, \tag{4}$$

where j is the security, μ_j is the expected return for every j (security), w_j is the optimal weight for each security and N is the number of securities. In the maximization problem, R_{kj} further denotes the standard deviation of the kth periodic return. We consider that $c\beta_k$ and $c\alpha_k$ are the constants that constrain the *market risk* and *unsystematic risk* of each period k, respectively. In this representation, K indicates half a signal length T and θ_{kmj} is the phase shift (i.e., $cos\theta_{kmj}$) which represents the correlation between the return of j and the index m's k-period returns.

In our study, we choose a four-year signal, which implies $T = 48$ months and hence there are 12 mean-reversion variance components. Because there are $4K$ constraints, we have 48 constraints overall; each constraint does not change over time as all return processes are assumed to have stationary second moments. The cosine equations further help control the lower and upper bounds of the market risk (systematic risk) and the sine equations control the lower and upper bounds of the diversifiable risk (unsystematic risk). By selecting different values for the constants $c\beta_k$ and $c\alpha_k$, the signal processing model allows us to diversify independently from all the different periodic, unsystematic and systematic risk components that are part of the total portfolio variance. Compared to MPT, DPT uses a covariance structure that measures the different covariance relative to different indices m.

It is worth emphasizing that DPT allows us to consider that investors having the same risk tolerance might not end up with the same efficient portfolio in the DPT. First, the theory takes into account both sets of *systematic risk* and *unsystematic risk*. For instance, some investors might have a high tolerance of risk but might not want to select a high systematic risk. In that case, the investor might choose focusing on relatively fewer stocks and bear high unsystematic risk. Another essential aspect that differs from the MPT is about the "time difference". An investor might be tolerant towards a high portfolio variance on short time differences (i.e., high frequency components), but the same investor may prefer small variance on long-term differences (i.e., low frequency components). In this regard, our approach reveals a non-myopic (long-term) asset allocation since it explicitly takes into account information that is not restricted to the current period.

2.3. Adjusting risk aversion and implementation

When optimizing the portfolios, we follow Jones (2017) and set various constraints on systematic and unsystematic risk $c\beta_k$ and $c\alpha_k$. Extending Jones (2017) and in order to allow for potential heterogeneity in returns, we created two conservative and two aggressive portfolios based on the type of risk the investor is willing to bear. Typically, active investors can increase systematic components (exposure to market movements) and the unsystematic, diversifiable component associated with a particular security. Conservative portfolios are, however, portfolios with relatively limited exposure to either systematic or unsystematic risk.

To adjust the level of risk aggressiveness/conservativeness explicitly (i.e., within the optimization problem), we construct portfolios constituting conservative risk strategy (henceforth CRS) or aggressive risk strategy (henceforth ARS). In this specification, we further vary the degree of aggressiveness and conservativeness in terms of both systematic (market) risk and unsystematic (firm-specific) risk. To facilitate such characteristics, let superscripts (1) and (2) denote the changes in market risk exposure (for a given level of firm-specific risk) and firm-specific exposure (for a given level of market risk), respectively. For instance, as one specific scenario, we consider that the portfolio $CRS^{(1)}$ has a systematic (market) risk up to 0.25 and an unsystematic (firm-specific) risk component limited to 1.25 (regardless the time horizon). Being relatively more aggressive than $CRS^{(1)}$, the portfolio $ARS^{(1)}$ has an exposure of 2.5 to systematic (market) risk, while having the same level of firm-specific risk constraint (i.e., 1.25). Relying on this intuition, the strategies $CRS^{(2)}$ and $ARS^{(2)}$ incorporate the low and high levels of firm-specific risk exposure (i.e., 0.25, 2.5, respectively) for a given level of systematic (market) risk constraint (i.e., as we set to 1.25).[7] It is also worth mentioning that conservative portfolios will in fact most likely require more securities than the more aggressive portfolios. In the same vein, a lower unsystematic risk will require more securities in the portfolio for the same level of systematic risk.

We estimate the parameters using the equities part of the universe of the sector indices plus the benchmark (Stoxx Europe 600 index) with 16 years of monthly returns. We rely on a four-year signal length (i.e., $T = 48$ months) to estimate the variance and the cross-covariance spectrum. We then run the optimization system to identify the (fixed) weights assigned to each stock. We collect the historical dataset of portfolio returns for each risk-profile.

3. Empirical Analysis

This section presents our empirical analysis. We proceed by first discussing the properties of the constructed portfolios under different risk levels. In Section 3.2, we carry out our baseline regression

[7] Of course, from the optimization perspective, there is no (upper limit) restriction for the choice of ARS, that is, one can consider an even higher level of risk by setting, for instance, $ARS^{(2)} > 2.5$. In unreported simulations, we have assessed the realized risk-return patterns stemming from portfolios with a higher level of aggressiveness. We, however, find that portfolios with risk aggressiveness—higher than 2.5—reveal excess returns that are rather unrealistic. We therefore consider $ARS^{(2)} = 2.5$ which is fairly reasonable to represent high level of aggressive risk.

analysis to explain the variation in realized portfolio returns via sentiment factors. In Sections 3.3 and 3.4, we investigate the tracking performance of the portfolios and the excess return dynamics, respectively. Finally, Section 3.5 examines the exposure of portfolios to additional source of risk regimes stemming from flight-to-safety fund flows.

3.1. Properties of optimal portfolios: size, risk and performance

We start by assessing the risk-return characteristics and the sector allocation of the four portfolios constructed ($ARS^{(1)}$, $ARS^{(2)}$, $CRS^{(1)}$, $CRS^{(2)}$) for the full sample and the post-crisis period. Table 1 shows that aggressive portfolios $ARS^{(1)}$ and $ARS^{(2)}$ generate a higher average return and higher volatility, market beta, skewness, kurtosis and VaR than their conservative counterparts $CRS^{(1)}$ and $CRS^{(2)}$. In the same vein, conservative portfolios are more diversified in terms of number of securities included in the portfolio. A decrease in risk level often goes along with an increase in the number of securities. For each risk level, conservative portfolios appear to be less concentrated towards specific sectors compared to aggressive portfolios. We also observe that the portfolios outperform the STOXX Europe 600 index (the passive portfolio); average returns and Sharpe ratios are systematically higher for all the semi-active portfolios.

[Insert Table 1 here]

The results further indicate the impact of raising the number of the mean-reversion periods on the risk-return characteristics and the sector allocation of the four semi-active portfolios. For instance, based on the aggressive risk strategy, the patterns suggest that the consideration of shorter mean-reversion periods in the risk constraints reduces the average return, the standard deviation, the skewness, the kurtosis as well as the VaR of the active portfolio. The Sharpe ratio and the number of securities in the portfolio, however, increase during the full period. By contrast, adding more risk constraints during the post-crisis (recovery) period decreases (increases) the Sharpe ratio (kurtosis) while the impact of the standard deviation and the VaR is mixed. Financial stocks are clearly avoided for the full sample (including the crisis period), but they are over-weighted during the post-crisis period. The assigned weights fall down with the inclusion of shorter mean-reversion periods. Overall, we however note that the portfolios report more volatility and more return in the post-crisis period.[8]

3.2. Baseline regressions: full and post-crisis analysis

Having examined the unconditional portfolio characteristics, we turn to our main analysis by linking (realized) portfolio returns to market sentiment. Based on market or firm-specific risk exposure, we consider the set of aggressive-conservative strategies and regress the returns obtained from

[8]To ease the flow of the paper, these results are unreported, but they are available in our supplemental appendix.

each strategy to our sentiment proxies. We consider the following regression model

$$R_t^p = a + bBUSC_t + cNFCI_t + dVIX_t + eVIX_{t-1} + \epsilon_t, \tag{5}$$

where R_t^p denotes the monthly portfolio return, a is the constant term and (b, c, d, e) are the coefficients of the (standardized) baseline sentiment indicators that are the European Business Climate Sentiment Index ($BUSC$), U.S. National Financial Condition Index ($NFCI$) and CBOE's Volatility Index (VIX). Unlike $BUSC$ and $NFCI$, VIX index is an implied variable (i.e., forward-looking) in our model, and hence, we also control for its one-period lagged effect (i.e., VIX_{t-1}).

Table 2 reports the regression results for four different risk-exposure models from aggressive market-based (i.e., $ARS^{(1)}$) to conservative firm-specific (i.e., $CRS^{(2)}$). The results indicate that semi-active contemporaneous portfolio returns are considerably associated with sentiment and market conditions, while the benchmark returns are not sensitive at all to sentiment. Nevertheless, the VIX index, i.e. the implied volatility in the U.S., is a crucial factor in explaining the variation of the STOXX Europe 600 index returns. The estimated coefficients of Business Climate and Financial Condition indices are significantly negative for semi-active portfolios, with values of approximately -0.015 and -0.034 (first column), which are economically large in basis point terms. The negative sentiment coefficients may be interpreted as follows. When they see stocks becoming a bargain (proxied by a negative return), investors see a buying opportunity and become bullish. Thus, this "bargain shopper" effect predicts a negative relation between sentiment and contemporaneous returns[9]. More interestingly perhaps, we find no strong evidence of such a "bargain shopper" effect for the passive portfolio. Having a positive sign, the VIX index appears to influence realized semi-active returns with one-month lag (VIX_{t-1}), suggesting that higher market volatility in the U.S. leads to higher portfolio returns. Further, as the risk exposure moves from aggressive to conservative, the estimated coefficients decrease in absolute terms. These three main indicators explain approximately 14-18% of variation of realized portfolio returns over the full sample (last column in the table).

[Insert Tables 2 and 3 here]

We augment these standard regressions by including additional macro/price/political factors. These factors consist of the (aggregated) Unemployment (UEMP), Total Industrial Production (TIP), Core Consumer Price Index (CCPI) and euro-dollar exchange rate (EURUSD). The political risk proxies are the European and U.S. political uncertainty indices (EUPUX and USPUX, respectively). The estimated coefficients of market sentiment along with the economic and political factors are reported in Table 3. The main finding revealed by this table is that sentiment factors retain their significance and magnitudes for semi-active portfolios (compared to those in Tables 2) and that economic factors barely change the previous conclusions.[10] For instance, while the coefficient of

[9]This possible alternative was presented in Brown and Cliff (2004), but was not supported by these authors.

[10]The estimation results with benchmark index returns confirm quite clearly that sentiment factors are negligible in

Unemployment is significant at the 5% level (Panel A), Total Industrial Production fails to affect portfolio returns (TIP_t). Similar patterns hold for price factors, such as Consumer Prices or exchange rates (Panel B). Perhaps more interestingly, there is no evidence that political uncertainty (European or U.S.) impacts the portfolio returns (Panel C). The estimated coefficients of political factors are statistically insignificant regardless of the risk strategy, which is aggressive or conservative.

[Insert Table 4 here]

Considering aggressive strategies, we complete our initial analysis for the post-crisis period, 2012-2015. We hence regress the realized monthly portfolio returns—generated from an aggressive risk strategy ($ARS^{(1)}$) on a set of sentiment factors, controlling for economic and political factors. The estimation results provided by Table 4 are broadly consistent with the previous results. The benchmark sentiment and condition factors are statistically and economically significant. Macro factors, price levels and political indicators, however, fail to affect portfolio returns. Finally, the explanatory power of sentiment factors (i.e., R^2) is rather large, with values ranging from 0.29 to 0.37.

3.3. Tracking the benchmark

Our preliminary analysis in the previous section shows that the variation in portfolio returns can be attributed to market sentiment factors. We now turn to examine how closely our portfolios track the benchmark stock index, that is the STOXX Europe 600 index. We proceed as follows. First, we take the full sample data and construct the optimal portfolios for each category of strategy (i.e., from conservative to aggressive, with market and firm-specific risk exposures). We then obtain the realized portfolio returns and compare them with the historical returns of STOXX Europe 600 index returns.

[Insert Table 5 here]

Examining the different panels of the figure, one can observe that our signal-based portfolios track the performance of the benchmark index in a reasonable way. Certain periods, however, appear to display a larger difference between portfolio versus benchmark returns, such as in periods of 2008-2009 U.S. subprime mortgage crisis and the post-crisis (recovery) period as a whole. To better identify the return differentials, we further report in Table 5 the summary statistics for *excess* portfolio returns calculated as

$$EPR_t = R_t^p - B_t, \tag{6}$$

where, R_t^p is the realized portfolio return and B_t denotes the historical return of the benchmark index, STOXX600. As the last column of Table 5 indicates, the tracking error (i.e., the standard

explaining the passive portfolio returns. For brevity, these results are unreported here, but they are available upon request.

deviation of EPR_t) reports typical values around 0.03-0.04 for the entire (full sample) holding period, with conservative strategies reporting lower tracking error than aggressive strategies.[11]

[Insert Figure 1 here]

Next to the full sample results, we now consider a case in which the investment horizon starts after the European sovereign crisis, corresponding to the period from 2012 onward. Similar to full sample analysis, we compare in Figure 1 the realized portfolio and benchmark index returns over time for conservative versus aggressive risk strategies (labeled as CRS and ARS, respectively). One noticeable pattern revealed by the figure is that portfolio returns (solid line) are likely to be larger than those of benchmark STOXX Europe 600 index (dashed line). Interestingly, perhaps, we observe that the realized portfolio returns are particularly larger than index returns between mid-2012 and mid-2013 and early 2015.

The lower panel of Table 5 reflects such differences in terms of the properties of excess returns and tracking errors: an aggressive strategy against market risk (i.e, $ARS^{(1)}$) generates a 0.034 excess return (highest) whereas a conservative strategy against market risk ($CRS^{(1)}$) gives the lowest excess return (0.013). The corresponding tracking errors follow a similar fashion such that aggressive strategies are associated with larger tracking errors compared to conservative strategies; this regularity especially holds if the investor is exposed to market rather than firm-specific risk.

3.4. Excess portfolio returns and market sentiment

Previous results suggest that an investor with a long-term investment horizon and aggressive strategy is likely to obtain excess portfolio returns over the benchmark index in the post-crisis sample. In light of this finding, we now conjecture that such realized excess returns stem from the benchmark European and U.S. sentiment factors. Therefore, we proceed by estimating our sentiment regressions for excess returns—generated solely from the aggressive risk strategy ($ARS^{(1)}$)—and consider several sentiment proxies as explanatory variables. Our regression model takes the following form:

$$EPR_t = a + bBUSC_t + cNFCI_t + dVIX_t + eVIX_{t-1} + \epsilon_t, \tag{7}$$

where EPR_t denotes the monthly excess return over the benchmark STOXX Europe 600 index at time t, a is the constant term and (b, c, d, e) are the coefficients of the baseline sentiment indicators used in Equation (5) for portfolio returns. We construct optimal portfolios based on aggregated stocks (all European stocks), country-specific stocks (UK, France, Germany) and sector-specific stocks (Financials, Cyclicals and Non-Cyclicals). Table 6 reports the estimated coefficients of excess return regressions for the sample spanning 2012−2015.

[11] It is worth mentioning that the optimal weights on stocks are fixed over a long horizon. Therefore, this contrasts with passive strategies that often assign the same drifting weights as a broad-based index. In this regard, our strategies entail rebalancing the portfolio each month to keep the weights fixed.

[Insert Table 6 here]

The results provide clear evidence that three sentiment/condition factors significantly explain 45% of the variation in excess returns (see e.g., the R^2 values reported in the lower row of the table). The influence of the three sentiment factors on excess returns, however, varies across different portfolios depending on whether they are country- or sector-specific. Unlike Financials, for instance, excess returns from Non-Cyclicals appear to have relatively lower exposure to sentiment factors (with R^2 around 35%), particularly to European Business Climate Index (labeled as $BUSC_t$). This result is considerably intuitive and might be expected because Non-Cyclical firms often have weak association with market conditions and the environment. Therefore, business sentiment or environment fails to impact excess returns.

The estimated coefficients of the sentiment variables further show certain asymmetry across countries. For instance, excess returns from French stocks have positive and significant exposure to VIX_t (0.057), which is higher than that of UK and Germany (0.050 and 0.044, respectively). The case of France distinguishes itself from other regression results also with respect to covariates $BUSC_t$ and $NFCI_t$. The estimated coefficients of these variables for the French market excess returns are larger in absolute terms than that obtained from other country- and sector-specific regressions. In addition to these findings, the evidence also suggests that the impact of U.S. sentiment proxies ($NFCI_t$) and VIX_t) on excess portfolio returns is larger than that of European Business Climate Sentiment indicator ($BUSC_t$), irrespective of the choice of country or sector. The market sentiment and conditions in the U.S. are likely to have a direct effect on excess returns solely generated through European stocks.

[Insert Table 7 here]

To investigate the role of sentiment more comprehensively, we run a simple probit model and assess the constant and marginal effects. Using the same variables displayed in Table 6, we now consider that the binary dependent variable is the excess return dummy, which takes the value 1 if the realized portfolio return in month t exceeds the benchmark return in month t, and 0 otherwise. That is,

$$y_t = \begin{cases} 1 & \text{if } R_t^p > B_t, \\ 0 & \text{otherwise.} \end{cases}$$

Panel A of Table 7 reports the estimated coefficients of the probit model (constant effects) and the marginal effects calculated as the derivatives of probabilities based on the time-series mean of each regressor (Panel B). The marginal effects are denoted by β'_{BUSC}, β'_{NFCI} and β'_{VIX} in Panel B.

Panel B of the table indicates that the partial (marginal) effect of VIX is considerably large for France, the UK and Financials, with estimates of approximately 0.57-0.60. This finding implies that one unit change of the U.S. stock volatility index increases the probability of observing an excess return by more than 50%. As reported by the other two rows of Panel B, the marginal effects of other sentiment indicators (β'_{BUSC}, β'_{NFCI}) are significantly negative and sizeable (with estimates close to 30%) except for Germany and Non-Cyclicals (last column). The negative exposure might imply that in periods when market conditions are better than normal (i.e., an increase in $BUSC$ or $NFCI$, excess returns tend to decline in the post-crisis sample. In line with the results reported in Table 6, the marginal effects of U.S. sentiment proxies are larger (in absolute terms) than that of European Sentiment Index ($BUSC$) except for German stocks and for Non-Cyclicals.

3.5. Portfolio exposure to flight-to-safety fund flows

The evidence from our baseline regressions suggests that long term portfolio (excess) returns—constructed from European stocks—closely track market sentiment, climate and financial conditions. Despite the role of such factors, portfolio returns may be still vulnerable to other forms of risk sentiment, i.e., those particularly driven by the sudden shifts of investors' tolerance towards risk versus safety. These risk (mood) shifts are often referred to as *risk-off* trades or *flight to safety (FTS)* fund flows in markets. In FTS regimes (with horizons over trading days or weeks), investors sell risky assets (such as stocks) and buy safe assets instead (such as gold or Treasury bonds) almost instantaneously in trading platforms. Using U.S. data, Baele et al. (2014) regress historical hedge fund index returns on the identified FTS episodes and show that the FTS-beta (β_{FTS}) is significantly negative. That is, U.S. hedge funds fail to provide a hedge against FTS flows. Our aim is now to empirically assess the exposure of our portfolio returns to FTS risk regimes.

To proceed, we first identify the FTS events by using two stock indices representing *risky* securities (STOXX600 and S&P500). As is standard, we consider "safe haven" assets such as gold and 10-year U.S. Treasury government bonds. Following Baele et al. (2014), we then detect the FTS episode in the data when an (*extreme*) negative stock return and an (*extreme*) positive bond (or gold) return occur within the exact same day. That is,

$$FTS_t = I\left\{r_t^s < -z_s\right\} \times I\left\{r_t^b > z_b\right\},$$

where I is the indicator function, r_t^s and r_t^b are the daily returns at time t for the stock index and government bonds, respectively. To identify flights from stocks to gold, we replace bond returns r_t^b with gold returns r_t^g. The flights thresholds z_s and z_b (z_g for gold) are proportional to volatility of the returns given by

$$z_{s,b} = \alpha \times \sigma_{s,b}, \tag{8}$$

where α is the flight magnitude parameter indicating the number of standard deviations from the mean of returns (e.g., $\alpha = 1, 2, 3$). Panels A and B of Table 8 report the estimated coefficients of the flight-to-safety (FTS) dummy (i.e., β_{FTS}) for the full sample (2000-2015) and crisis sample (2007-2011), respectively. For each subsample, we control for the impact of Business Climate Sentiment Index ($BUSC_t$) and three standard Fama-French risk factors. We construct the optimal portfolios and hence the corresponding weights for returns accordingly.[12]

[Insert Table 8 here]

For the results based on the European benchmark index (STOXX600), we find no strong evidence in favor of FTS-type risk sensitivity (columns five to seven). The estimated FTS coefficients (β_{FTS}) are approximately -0.02 to -0.03 but are not statistically different from zero. This finding holds irrespective of the choice of flight magnitude α and even in periods of turbulence (2007-2011). Unlike the case for STOXX Europe 600, however, Panel B of the table indicates that portfolio returns have significantly negative FTS exposure when the risky assets benchmark is S&P 500 rather than STOXX Europe 600. In periods of U.S. subprime and European sovereign crisis, the (β_{FTS}) estimates range between -0.083 and -0.156 and these estimates appear to be the largest in magnitude compared to results with the full sample or those with STOXX Europe 600 index. One implication of this finding is that European stock portfolio returns are vulnerable to risk shifts linked to the U.S. risk environment (through S&P 500) whereas FTS events have relatively no significant impact on our portfolio returns even in periods of financial turmoil.

[Insert Figures 2 and 3 here]

We further display the detected FTS spells in Figures 2 and 3 for the full and crisis samples, respectively. The figures show that the majority of FTS fund flows are detected between 2007 and 2009, corresponding to period of the U.S. subprime crisis (dashed vertical lines in Figure 2). Among these periods, we further observe that the most extreme risk-off trades occur in the last quarter of 2008 following the collapse of Lehman Brothers (upper panel of Figure 3).

[Insert Table 9 here]

As a final FTS assessment, we construct optimal portfolios for Financials, Cyclicals and Non-Cyclicals. We regress the realized portfolio returns obtained from each sector on our FTS factor. We report in Table 9 the estimated coefficients of the FTS dummy together with other control variables. The findings suggest that the exposure of portfolio returns for each sector to FTS episodes is rather weak with estimated coefficients that are not statistically different from zero (β_{FTS} in Panel A), except for Financials. While our portfolio returns are rather prone to market sell-offs stemming from STOXX Europe 600 (right panels in the table), European stock investments are affected by FTS risk shifts, particularly in periods of crisis, 2007-2011.

[12] For brevity, the optimal weights are unreported here, but they are available upon request.

4. Robustness checks and extensions

In this section, we assess the robustness of our results and consider several extensions. First, we run our excess return regressions using alternative sentiment indicators. Next, we use Fama-French five factors and momentum proxy as control variables. We complete this section by comparing excess portfolio and benchmark index returns over the risk-free rate.

Alternative market sentiment proxies. In addition to the benchmark sentiment indicators we used in our main analysis ($BUSC$, VIX and $BUSC$), we now consider alternative proxies (for both U.S. and Europe), including Consumer Confidence Index ($CONC$), Economic Sentiment Indicator ($ECOS$), National Financial Condition Index ($NFCI$) and Consumer Sentiment Index (CSI). We further examine the robustness of our results to two orthogonalized and non-orthogonalized U.S. sentiment measures developed by Baker and Wurgler (2006, 2007), respectively (denoted by $BWI^{(ort)}$ and $BWI^{(nort)}$). Similar to our main regression analysis, the dependent variable is the monthly excess returns (i.e., difference between portfolio and benchmark index returns) generated from the aggressive risk strategy ($ARS^{(1)}$). Table 10 reports the estimated coefficients under each model specification (1) to (10).

[Insert Table 10 here]

The results indicate that the role of sentiment in explaining excess returns is still considerably evident regardless of the choice of sentiment proxy. The estimated coefficients of new European sentiment proxies (CONC, ECOS) are negative and statistically significant with relatively large magnitudes (see Models (2), (3), (9) and (10)). While the VIX is highly significant in each model, the U.S. sentiment proxies of Baker and Wurgler (2006, 2007) fail to influence excess returns (see $BWI^{(ort)}$ and $BWI^{(nort)}$). Overall, our results and main conclusions qualitatively remain the same, and these proxies combined together explain approximately 33-44% of the variation in our portfolio's excess returns.

Controlling for the Fama-French factors and momentum. We next extend our baseline regressions by including standard Fama-French factors for European portfolios. More specifically, we consider five different model specifications: Model (1): only benchmark sentiment indicators, Model (2): benchmark sentiment indicators and market risk premium ($Rm - Rf$), Model (3): benchmark sentiment indicators and three factors including market risk premium ($Rm - Rf$), Small-minus-Big (SMB), and High-minus-Low (HML). In Model (4), we also include two additional factors—capturing profitability and investment—that are Robust-minus-Weak (RMW) and Conservative-minus-Aggressive (CMA), respectively, as in Fama and French (2015). Finally, in Model (5), we add the Winners-minus-losers (WML) momentum factor constructed by Carhart (1997) and Fama and French (2012).

[Insert Table 11 here]

As Table 11 reveals, the coefficient estimates of the sentiment variables maintain their sign, significance and magnitudes even after controlling for these additional risk factors. The reduced-form model (i.e., Model (1)) generates 42% R^2 value which appears to be higher (53%) under the full model (i.e., Model (5)). Except for the market and size factors, these risk factors fail to statistically explain the movements in our excess returns.

[Insert Figure 4 here]

The role of risk-free rate. In our base investigation, we define excess returns as the difference between the realized returns of our portfolio and benchmark index returns. We now aim to compare the portfolio returns with benchmark returns in terms of their difference over the risk-free rates. Specifically, we construct realized European portfolio returns from our aggressive risk strategy ($ARS^{(1)}$), and the benchmark index is the STOXX Europe 600 index as before. Figure 4 shows monthly excess returns (index line) and benchmark excess returns over the risk-free rate (circle-marked) lines. The patterns display clear difference and time variation over these two forms of excess returns. The excess returns generated from our aggressive risk strategy often exceed the benchmark returns over the risk-free rate. This result is likely to be consistent with the idea that aggressive risk taking reveals a higher premium (over the risk-free asset) relative to the benchmark STOXX Europe 600 index.

5. Conclusions

It is well known that optimal asset allocation plays a pivotal role by allowing market risk exposure to be reduced. The practices based on conventional (Markowitz-type) portfolios, however, often pose tight restrictions, particularly in terms of the adjustment of investment horizon and the level of risk tolerance. This paper aims to develop an understanding of the time variation of excess returns (over the benchmark index) when the trading horizon is considerably long and when investors are reasonably risk-tolerant. For this purpose, we adopt a signal-based (digital) portfolio approach that gives us the flexibility to study the realized returns of optimal portfolios.

Our findings provide evidence of significant excess returns that are fairly sizable as long as the investment horizon is long and risk exposure is sufficiently high. To help exploit the reasons behind such patterns, we regress excess portfolio returns on a set of sentiment variables, controlling for Fama-French, macroeconomic, financial and political factors. Among all market condition indicators, U.S. volatility index (VIX) and European business sentiment index have high explanatory power for portfolios constructed from European stocks, while the passive STOXX Europe 600 index returns are not sensitive at all to sentiment. Nevertheless, the VIX index, i.e. the implied volatility in the U.S., is a crucial factor in explaining the variation of the index returns. We notice that the negative effects of sentiment measures on semi-active portfolio returns are sizeable and economically relevant particularly in bull (post-crisis) periods. The negative sentiment coefficients may suggest that when investors see the semi-active portfolios becoming a bargain (proxied by a negative return),they see a buying opportunity and become bullish .On the other hand, we show that the impact of macro and political shocks on excess returns remains relatively small in explaining the likelihood of observing excess returns over the benchmark.

Our analysis further reveals that it is possible to construct portfolios that do not suffer from flight-to-safety (FTS) risk-off fund flows, that is, when investors sell risky securities (e.g., stocks) and buy "safer" assets (i.e., gold). This result is likely to be of interest mainly because prior research shows that hedge funds in the U.S. fail to compensate FTS spells (Baele et al., 2014); in other words, the estimated coefficient of *FTS beta* in excess return regressions has been found as significantly negative. In contrast, our results with optimal portfolios present an alternative feature: sentiment-tracking optimal portfolios with a long-term view and risk tolerance appear to be immune to FTS episodes even in periods of severe market turbulence (such as in periods of European sovereign crisis and U.S. subprime mortgage crisis).

This study can be extended in at least two important directions. First, our focus is solely on the European stock market, and hence, the results can be easily compared and extended to other asset classes. Second, the question of *"why FTS events result in losses in hedge fund returns but not in optimal portfolios"* requires further in-depth investigation. In this regard, one way to cope with this assessment would be through incorporating the FTS risk factor to the optimal portfolio problem directly, that is, *ex ante* rather than ex post as is done in this paper. This adjustment may reveal different allocation weights and help explain why the fund industry is vulnerable to FTS shocks.

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Table 1: Optimal portfolio selection for conservative versus aggressive risk-taking

The table reports the descriptive characteristics of optimal portfolios for four strategies, and each strategy has a different risk tolerance from aggressive to conservative, that is, $s = ARS^{(1)}, ARS^{(2)}, CRS^{(1)}, CRS^{(2)}$. The corresponding aggressive and conservative portfolios further differ in terms of risk constraints denoted by superscripts (1) and (2). The superscript (1) represents the changes in systematic (market) risk constraint, given the same level of firm-specific risk constraint. The superscript (2) represents the changes in firm-specific risk constraint, given the same level of systematic (market) risk constraint. Relying on this specification, we set the parameter values for the two aggressive (conservative) strategies as 2.5-1.25 and 1.25-2.5 (0.25−1.25 and 1.25−0.25), respectively. The sample covers the periods from January 1, 2000 to December 31, 2015. Market exposure is estimated against the STOXX Europe 600 index.

	Full sample				**Post-crisis period**			
Panel A. Monthly Performance	ARS$^{(1)}$	ARS$^{(2)}$	CRS$^{(1)}$	CRS$^{(2)}$	ARS$^{(1)}$	ARS$^{(2)}$	CRS$^{(1)}$	CRS$^{(2)}$
Mean Return	2.56%	2.25%	1.54%	1.82%	4.29%	3.70%	2.51%	2.96%
Standard Deviation	6.28%	6.27%	4.84%	5.19%	8.05%	6.70%	5.11%	5.70%
Market Beta	0.93	0.98	0.86	0.89	1.37	1.44	1.19	1.29
Skewness	0.74	0.67	-0.47	-0.20	1.73	1.14	0.90	0.97
Kurtosis	6.44	7.37	3.11	3.81	8.99	5.42	4.41	4.89
VaR 95%	-7.03%	-7.16%	-6.50%	-6.66%	-6.60%	-6.42%	-5.87%	-5.79%
Sharpe	0.36	0.32	0.26	0.30	0.52	0.54	0.47	0.50
Portfolio Size	28	50	161	96	27	46	164	94
Panel B. Sector Allocation								
Communications	7.81%	4.02%	1.24%	2.41%	3.26%	8.20%	4.28%	3.75%
Consumer Disc.	23.20%	29.14%	20.96%	22.96%	40.53%	30.07%	23.45%	23.38%
Consumer Staples	0.16%	3.30%	13.48%	13.30%	0.16%	3.30%	8.95%	5.49%
Energy	2.18%	1.12%	3.18%	2.26%	1.40%	3.85%	0.77%	1.50%
Financials	0.65%	5.81%	12.70%	10.10%	16.63%	15.64%	22.19%	22.79%
Health Care	32.98%	25.08%	11.11%	13.73%	11.24%	9.79%	8.13%	9.35%
Industrials	12.99%	14.55%	24.26%	16.86%	13.55%	6.97%	15.39%	16.96%
Materials	12.56%	10.67%	10.11%	14.43%	0.00%	13.94%	9.60%	8.91%
Technology	7.47%	4.36%	2.56%	3.17%	13.23%	8.25%	6.85%	7.11%
Utilities	0.00%	1.95%	0.39%	0.76%	0.00%	0.00%	0.39%	0.76%
Panel C. Risk level								
Systematic (Market) Risk	2.5	1.25	0.25	1.25	2.5	1.25	0.25	1.25
Unsystematic (Firm-Specific) Risk	1.25	2.5	1.25	0.25	1.25	2.5	1.25	0.25

Table 2: Realized portfolio returns and market sentiment

The table reports the regression results of portfolio returns on several baseline sentiment proxies. The dependent variables (given in the first row) are realized monthly returns obtained from the benchmark (the STOXX Europe 600 index) and the different strategies - either aggressive or conservative. ARS and CRS denote aggressive and conservative risk strategies, respectively. The superscript (1) represents the changes in systematic (market) risk constraint, given the same level of firm-specific risk constraint. The superscript (2) represents the changes in firm-specific risk constraint, given the same level of systematic (market) risk constraint. Relying on this specification, we set the parameter values for the two aggressive (conservative) strategies as 2.5-1.25 and 1.25-2.5 (0.25−1.25 and 1.25−0.25), respectively. The independent variables (given in the first column) are the European Business Climate Sentiment Index (BUSC), U.S. National Financial Condition Index (NFCI) and CBOE's Volatility Index (VIX). For each strategy (from ARS to CRS), the sentiment regression model admits the following form

$$R_t^p = a + bBUSC_t + cNFCI_t + dVIX_t + eVIX_{t-1} + \epsilon_t,$$

where R_t^p denotes the monthly portfolio return, a is the constant term and (b, c, d, e) are the coefficients of the baseline sentiment indicators. Unlike BUSC and NFCI, VIX index is implied (i.e., forward-looking) and hence we also control for its one-period lagged effect (i.e., VIX_{t-1}). To ease the comparison, each variable is standardized. The table reports the coefficients estimated by Ordinary Least Squares and heteroskedasticity and autocorrelation-consistent standard errors (in parenthesis). The R^2 and p-values of F-tests are provided in the last two rows of the table. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample covers the period from January 1, 2004 to December 31, 2015.

	Benchmark	$ARS^{(1)}$	$ARS^{(2)}$	$CRS^{(1)}$	$CRS^{(2)}$
Constant	0.004	0.030***	0.026***	0.020***	0.022***
	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)
$BUSC_t$	-0.0078**	-0.015***	-0.014***	-0.010***	-0.011***
	(0.003)	(0.004)	(0.005)	(0.004)	(0.004)
$NFCI_t$	-0.011***	-0.034***	-0.035***	-0.029***	-0.030***
	(0.004)	(0.011)	(0.012)	(0.009)	(0.011)
VIX_t	-0.047***	0.000	0.002	0.004	0.005
	(0.006)	(0.010)	(0.010)	(0.007)	(0.008)
VIX_{t-1}	0.041***	0.027**	0.026*	0.020*	0.020*
	(0.007)	(0.013)	(0.014)	(0.011)	(0.012)
R^2	0.55	0.18	0.16	0.15	0.14
Prob(F)	0.000	0.000	0.000	0.000	0.000

Table 3: Realized portfolio returns, market sentiment, economic and political factors

The table reports the regression results of portfolio returns on baseline sentiment measures and other factors linked to macroeconomy (Panel A), prices (Panel B) and political uncertainty (Panel C). The dependent variables (given in the first row) are realized monthly returns obtained from different risk strategies as described in Table 1. The market sentiment factors are the European Business Climate Sentiment Index (BUSC), U.S. National Financial Condition Index (NFCI) and CBOE's Volatility Index (VIX). The economic (decomposed as macro and price) factors are (aggregated) Unemployment (UEMP), Total Industrial Production (TIP), Core Consumer Price Index (CCPI) and the euro-dollar exchange rate (EURUSD). The political risk proxies are European and U.S. political uncertainty indices (EUPUX and USPUX, respectively). The table reports the coefficients estimated by Ordinary Least Squares and heteroskedasticity and autocorrelation-consistent standard errors (in parenthesis). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample covers the period from January 1, 2004 to December 31, 2015.

	Panel A. Macro factors				**Panel B. Price factors**				**Panel C. Political factors**			
	$ARS^{(1)}$	$ARS^{(2)}$	$CRS^{(1)}$	$CRS^{(2)}$	$ARS^{(1)}$	$ARS^{(2)}$	$CRS^{(1)}$	$CRS^{(2)}$	$ARS^{(1)}$	$ARS^{(2)}$	$CRS^{(1)}$	$CRS^{(2)}$
Constant	0.035***	0.032***	0.025***	0.028***	0.041***	0.037***	0.029***	0.033***	0.033***	0.030***	0.023***	0.025***
	(0.005)	(0.005)	(0.004)	(0.005)	(0.007)	(0.007)	(0.005)	(0.006)	(0.005)	(0.005)	(0.004)	(0.004)
$BUSC_t$	-0.023***	-0.022***	-0.017***	-0.019***	-0.015***	-0.015***	-0.012***	-0.013***	-0.017***	-0.016***	-0.012***	-0.013***
	(0.005)	(0.006)	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)
$NFCI_t$	-0.052***	-0.053***	-0.045***	-0.048***	-0.035***	-0.038***	-0.034***	-0.035***	-0.043***	-0.044***	-0.037***	-0.039***
	(0.014)	(0.014)	(0.011)	(0.013)	(0.014)	(0.014)	(0.011)	(0.013)	(0.013)	(0.013)	(0.010)	(0.012)
VIX_t	0.006	0.008	0.010	0.011	0.001	0.004	0.007	0.008	0.007	0.010	0.012	0.014
	(0.009)	(0.009)	(0.007)	(0.008)	(0.010)	(0.010)	(0.008)	(0.008)	(0.010)	(0.010)	(0.008)	(0.009)
VIX_{t-1}	0.032**	0.030**	0.024**	0.025**	0.029**	0.028**	0.023**	0.023*	0.032**	0.030**	0.024**	0.024**
	(0.013)	(0.014)	(0.010)	(0.012)	(0.014)	(0.014)	(0.011)	(0.012)	(0.013)	(0.013)	(0.010)	(0.011)
$UEMP_t$	-0.014**	-0.014***	-0.013***	-0.014***	.	.	.	.	.	.	.	.
	(0.006)	(0.006)	(0.005)	(0.005)	.	.	.	.	.	.	.	.
TIP_t	0.000	-0.001	0.001	0.000	.	.	.	.	.	.	.	.
	(0.004)	(0.005)	(0.004)	(0.004)	.	.	.	.	.	.	.	.
$CCPI_t$	.	.	.	.	-0.011*	-0.013*	-0.014**	-0.014**	.	.	.	.
	.	.	.	.	(0.007)	(0.007)	(0.006)	(0.006)	.	.	.	.
$EURUSD_t$	.	.	.	.	-0.012*	-0.009	-0.005	-0.007	.	.	.	.
	.	.	.	.	(0.006)	(0.007)	(0.007)	(0.007)	.	.	.	.
$EUPUX_t$	.	.	.	.	.	.	.	.	-0.010	-0.010	-0.008	-0.009
	.	.	.	.	.	.	.	.	(0.007)	(0.007)	(0.006)	(0.006)
$USPUX_t$	.	.	.	.	.	.	.	.	-0.001	-0.002	-0.003	-0.003
	.	.	.	.	.	.	.	.	(0.009)	(0.009)	(0.008)	(0.008)
R^2	0.21	0.19	0.19	0.18	0.21	0.19	0.19	0.18	0.20	0.19	0.18	0.18
Prob(F)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 4: Market sentiment and realized portfolio returns with passive and aggressive risk strategy, 2012-2015

The table reports the regression results of portfolio returns on various indicators including only sentiment measures (model (1)), sentiment measures and macro factors (model (2)), sentiment measures and price factors (model (3)) and finally sentiment measures and political risk indicators (model (4)). The dependent variable in all models is the realized monthly returns generated from the passive (STOXX Europe 600 index) and the *aggressive risk strategy* ($ARS^{(1)}$). The table reports the coefficients estimated by Ordinary Least Squares and heteroskedasticity and autocorrelation-consistent standard errors (in parenthesis). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample covers the (post-crisis) period from January 1, 2012 to December 31, 2015.

	(1)	(2)	(3)	(4)
Constant	0.041***	0.041***	0.040***	0.041***
	(0.008)	(0.007)	(0.007)	(0.008)
$BUSC_t$	-0.027***	-0.028***	-0.022***	-0.024***
	(0.007)	(0.007)	(0.008)	(0.009)
$NFCI_t$	-0.035***	-0.033***	-0.078*	-0.040***
	(0.011)	(0.011)	(0.040)	(0.014)
VIX_t	0.038**	0.037***	0.042***	0.039**
	(0.017)	(0.014)	(0.012)	(0.017)
VIX_{t-1}	0.010*	0.011	0.018	0.010
	(0.006)	(0.007)	(0.012)	(0.006)
$UEMP_t$	.	0.003	.	.
	.	(0.008)	.	.
TIP_t	.	0.019**	.	.
	.	(0.009)	.	.
$CCPI_t$	.	.	-0.050	.
	.	.	(0.047)	.
$EURUSD_t$	.	.	-0.034	.
	.	.	(0.024)	.
$EUPUX_t$	.	.	.	0.015
	.	.	.	(0.014)
$USPUX_t$	.	.	.	-0.007
	.	.	.	(0.016)
R^2	0.29	0.37	0.31	0.31
Prob(F)	0.007	0.004	0.019	0.021

Table 5: Summary statistics for excess portfolio returns and tracking errors

The table reports the summary statistics for the monthly excess (portfolio) returns over the benchmark (STOXX Europe 600 index). We consider four strategies and each strategy has different risk tolerance from aggressive to conservative, that is, $s = ARS^{(1)}, ARS^{(2)}, CRS^{(1)}, CRS^{(2)}$. We define the excess portfolio return (EPR) at time t as

$$EPR_t = R_t^p - B_t,$$

which is the difference between realized portfolio returns (R_t^p) and the benchmark index returns denoted by B_t. The table shows the minimum, maximum and mean values of excess returns. The last column displays the standard deviation of the excess portfolio returns, which indicates the tracking error of our portfolios relative to the benchmark index. Panels A and B report the statistics for the full and post-crisis samples, respectively.

	Min	Max	$Mean$	$Tracking\ Error$
Panel A. Full sample, 2000−2015				
ARS$^{(1)}$	-0.084	0.466	0.024	0.047
ARS$^{(2)}$	-0.101	0.459	0.021	0.045
CRS$^{(1)}$	-0.063	0.264	0.014	0.029
CRS$^{(2)}$	-0.071	0.309	0.017	0.033
Panel B. Post-crisis sample, 2012−2015				
ARS$^{(1)}$	-0.168	0.322	0.034	0.079
ARS$^{(2)}$	-0.155	0.325	0.024	0.076
CRS$^{(1)}$	-0.124	0.239	0.013	0.065
CRS$^{(2)}$	-0.142	0.271	0.017	0.069

Table 6: The impact of market sentiment on sector and country-specific excess returns

The table reports the regression results of excess portfolio returns (ERP) on several baseline sentiment proxies. We construct country-specific and sector-specific optimal portfolios. For the country-specific portfolios, we consider the stocks of Europe (aggregated), the UK, France and Germany (first four columns). Sector-specific portfolios include Financial stocks, Cyclical stocks and Non-cyclical stocks (last three columns). The excess portfolio returns are the difference between optimal portfolio returns (computed for each portfolio classification) and that of the benchmark index. For each category, the dependent variable is the monthly excess returns generated from the *aggressive risk strategy* ($ARS^{(1)}$). The sentiment regression model is given by

$$EPR_t = a + bBUSC_t + cNFCI_t + dVIX_t + eVIX_{t-1} + \epsilon_t,$$

where EPR_t denotes the monthly excess return, a is the constant term and (b, c, d, e) are the coefficients of the baseline sentiment indicators: the European Business Climate Sentiment Index (BUSC), U.S. National Financial Condition Index (NFCI) and CBOE's Volatility Index (VIX). The table reports the coefficients estimated by Ordinary Least Squares and heteroskedasticity and autocorrelation-consistent standard errors (in parenthesis). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample covers the (post-crisis) period from January 1, 2012 to December 31, 2015.

	Europe	UK	France	Germany	Financials	Cyclicals	Non-Cyclicals
Constant	0.031***	0.016***	0.014*	0.011**	0.012*	0.031***	0.018***
	(0.006)	(0.005)	(0.007)	(0.005)	(0.007)	(0.007)	(0.005)
$BUSC_t$	-0.027***	-0.019***	-0.029***	-0.014**	-0.025***	-0.028***	-0.008
	(0.007)	(0.006)	(0.009)	(0.007)	(0.007)	(0.009)	(0.005)
$NFCI_t$	-0.039***	-0.026***	-0.052***	-0.025***	-0.042***	-0.039***	-0.022***
	(0.007)	(0.006)	(0.006)	(0.008)	(0.009)	(0.008)	(0.006)
VIX_t	0.059***	0.050***	0.057***	0.044***	0.058***	0.054***	0.050***
	(0.013)	(0.010)	(0.012)	(0.005)	(0.014)	(0.015)	(0.010)
VIX_{t-1}	-0.005	-0.011	0.008	0.005	-0.004	-0.001	-0.009
	(0.009)	(0.007)	(0.009)	(0.006)	(0.006)	(0.010)	(0.008)
R^2	0.45	0.41	0.43	0.42	0.40	0.34	0.35
Prob(F)	0.000	0.000	0.000	0.000	0.000	0.002	0.001

Table 7: Constant and marginal effects of sentiment indicators on excess returns

The table reports the probit regression results of excess returns on baseline sentiment proxies. The (binary) dependent variable is the excess return dummy, which takes the value 1 if the realized portfolio return in month t exceeds the benchmark return in month t, and 0 otherwise. That is,

$$y_t = \begin{cases} 1 & \text{if } R_t^p > B_t, \\ 0 & \text{otherwise.} \end{cases}$$

In the table, Panels A reports the estimated coefficients of the probit model (constant effects). In Panel B, we present the marginal effects calculated as the derivatives of probabilities based on the time-series mean of each regressor. The market sentiment indicators are the European Business Climate Sentiment Index (BUSC), U.S. National Financial Condition Index (NFCI) and CBOE's Volatility Index (VIX). The effects are denoted by β'_{BUSC}, β'_{NFCI} and β'_{VIX} in Panel B. We construct country-specific and sector-specific optimal portfolios. For the country-specific portfolios, we consider the stocks of Europe (aggregated), the UK, France and Germany (first four columns). Sector-specific portfolios include Financial stocks, Cyclical stocks and Non-cyclical stocks (last three columns). The bottom row of the table reports the p-value of the χ^2 test. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample covers the (post-crisis) period from January 1, 2012 to December 31, 2015.

Panel A. Constant effects							
	Europe	UK	France	Germany	Financials	Cyclicals	Non-Cyclicals
Constant	0.685**	0.643**	0.266	0.281	0.362	1.465**	0.200
	(0.304)	(0.311)	(0.246)	(0.215)	(0.250)	(0.682)	(0.207)
$BUSC_t$	-0.721**	-0.811***	-0.702***	-0.411	-0.446*	-1.430***	-0.299
	(0.291)	(0.300)	(0.275)	(0.251)	(0.257)	(0.508)	(0.238)
$NFCI_t$	-0.979***	-1.036**	-0.800**	-0.198	-0.758**	-1.923***	-0.203
	(0.367)	(0.379)	(0.321)	(0.279)	(0.320)	(0.752)	(0.272)
VIX_t	1.733***	1.872***	1.498***	0.885**	1.526***	3.365**	0.810**
	(0.588)	(0.617)	(0.468)	(0.359)	(0.485)	(1.366)	(0.338)
Panel B. Marginal effects							
β'_{BUSC}	-0.227	-0.263	-0.270	-0.158	-0.167	-0.195	-0.117
β'_{NFCI}	-0.309	-0.336	-0.308	-0.076	-0.283	-0.262	-0.079
β'_{VIX}	0.547	0.607	0.577	0.340	0.570	0.458	0.317
Prob(χ^2)	0.000	0.000	0.000	0.003	0.000	0.000	0.018

Table 8: Flight to safety regimes and portfolio returns

The table reports the estimated coefficients of the flight-to-safety (FTS) dummy (β_{FTS}) together with that of Business Climate Sentiment Index ($BUSC_t$) and three standard risk factors. We identify the FTS events by considering two stock indices representing *risky* securities (S&P500 and STOXX600). The "safe haven" assets are gold and 10-year U.S. Treasury government bonds. Following Baele et al. (2014), we detect the flight-to-safety episode in the data when an (extreme) negative stock return and an (extreme) positive bond (or gold) return occur within the exact same day. That is,

$$FTS_t = I\left\{r_t^s < -z_s\right\} \times I\left\{r_t^b > z_b\right\},$$

where I is the indicator function, r_t^s and r_t^b are the daily returns at time t for the stock index and government bonds, respectively. To identify flights from stocks to gold, we replace bond returns r_t^b with gold returns r_t^g. The flights thresholds z_s and z_b (z_g for gold) are proportional to volatility of the returns given by $z_{s,b} = \alpha \times \sigma_{s,b}$ where α is the flight magnitude parameter indicating the number of standard deviations from the mean of returns (e.g., $\alpha = 1, 2, 3$). Panels A and B report the results for the full sample (2004-2015) and crisis sample (2007-2011), respectively. For each sample, we construct optimal portfolios and hence the weights for returns, separately. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, based on the heteroskedasticity and autocorrelation-consistent standard errors.

Panel A. Full sample						
	S&P500			STOXX600		
	(1)	(2)	(3)	(1)	(2)	(3)
Constant	0.028***	0.027***	0.027***	0.027***	0.026***	0.026***
β_{FTS}	-0.039	-0.027	-0.023	-0.039	-0.025	-0.023
$BUSC_t$	-0.014***	-0.013***	-0.013***	-0.014***	-0.013***	-0.012***
$Rm - Rf_t$	·	0.008	0.008	·	0.009	0.008
SMB_t	·	·	0.004	·	·	0.005
HML_t	·	·	0.002	·	·	0.003
R^2	0.08	0.10	0.11	0.07	0.10	0.10
Prob(F)	0.002	0.002	0.009	0.005	0.003	0.010
Panel B. Crisis sample						
Constant	0.041***	0.036***	0.035***	0.033***	0.026***	0.026***
β_{FTS}	-0.156***	-0.090***	-0.083***	-0.049	0.029	0.028
$BUSC_t$	-0.016***	-0.010**	-0.008*	-0.007	-0.002	0.000
$Rm - Rf_t$	·	0.032***	0.036**	·	0.049***	0.052***
SMB_t	·	·	0.009*	·	·	0.012*
HML_t	·	·	-0.004	·	·	-0.005
R^2	0.32	0.44	0.46	0.04	0.38	0.41
Prob(F)	0.000	0.000	0.000	0.342	0.000	0.000

Table 9: Flight to safety regimes and sector-specific portfolio returns

The table reports the estimated coefficients of the flight-to-safety (FTS) dummy (β_{FTS}) together with that of Business Climate Sentiment Index ($BUSC_t$) and three standard risk factors. We identify the FTS events by considering two stock indices representing *risky* securities (S&P500 and STOXX600). The "safe haven" assets are gold and 10-year U.S. Treasury government bonds. Following Baele et al. (2014), we detect the flight-to-safety episode in the data when an (extreme) negative stock return and an (extreme) positive bond (or gold) return occur within the exact same day. That is,

$$FTS_t = I\left\{r_t^s < -z_s\right\} \times I\left\{r_t^b > z_b\right\},$$

where I is the indicator function, r_t^s and r_t^b are the daily returns at time t for the stock index and government bonds, respectively. To identify flights from stocks to gold, we replace bond returns r_t^b with gold returns r_t^g. The flights thresholds z_s and z_b (z_g for gold) are proportional to volatility of the returns given by $z_{s,b} = \alpha \times \sigma_{s,b}$ where α is the flight magnitude parameter indicating the number of standard deviations from the mean of returns (e.g., $\alpha = 1, 2, 3$). Panels A and B report the results for the full sample (2004-2015) and crisis sample (2007-2011), respectively. For each sample and sector, we construct optimal portfolios and hence the weights for returns, separately. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, based on the heteroskedasticity and autocorrelation-consistent standard errors.

Panel A. Full sample						
	S&P500			STOXX600		
	(Financials)	(Cyclicals)	(Non-Cyclicals)	(Financials)	(Cyclicals)	(Non-Cyclicals)
Constant	0.018***	0.027***	0.020***	0.015***	0.026***	0.020***
β_{FTS}	-0.052*	-0.037	-0.018	-0.025	-0.030	-0.021
$BUSC_t$	-0.011***	-0.017***	-0.007***	-0.008**	-0.016***	-0.006**
$Rm - Rf_t$	-0.001	0.007	0.005	0.002	0.008	0.005
SMB_t	0.000	0.004	0.002	0.003	0.005	0.003
HML_t	0.002	0.001	0.003	0.003	0.002	0.004
R^2	0.08	0.10	0.07	0.04	0.09	0.07
Prob(F)	0.051	0.012	0.074	0.392	0.021	0.07
Panel B. Crisis sample						
Constant	0.009**	0.033***	0.023***	0.007*	0.022***	0.020***
β_{FTS}	-0.025*	-0.065**	-0.067***	-0.003	0.067	-0.027
$BUSC_t$	-0.010*	-0.007	-0.005	-0.008	0.002	-0.001
$Rm - Rf_t$	0.047***	0.050***	0.020***	0.051***	0.069***	0.027***
SMB_t	0.005	0.012*	0.003	0.006	0.014*	0.005
HML_t	0.004	-0.005	-0.005	0.004	-0.007	-0.005
R^2	0.74	0.45	0.51	0.74	0.45	0.42
Prob(F)	0.000	0.000	0.000	0.000	0.000	0.000

Table 10: Excess return regressions with other sentiment proxies

The table reports regression results of excess returns on various market sentiment proxies for Europe and the U.S. For all models (Model (1) to (10) as labeled in the first column), the dependent variable is the monthly active returns (i.e., difference between portfolio and benchmark index returns) generated from the *aggressive risk strategy* ($ARS^{(1)}$). The columns provide the independent variables, including the Business Climate Sentiment Index ($BUSC$), Consumer Confidence Index ($CONC$), Economic Sentiment Indicator ($ECOS$), National Financial Condition Index ($NFCI$) and Consumer Sentiment Index (CSI). We include the VIX in all specifications. $BWI^{(ort)}$ and $BWI^{(nort)}$ further denote the orthogonalized and non-orthogonalized U.S. sentiment measures developed by Baker and Wurgler (2006, 2007), respectively. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, based on the heteroskedasticity and autocorrelation-consistent standard errors. The sample covers the (post-crisis) period from January 1, 2012 to December 31, 2015 (but to October 31, 2015, due to data availability, when BWIs are included).

	EU proxies			US Proxies						
Regression	$BUSC_t$	$CONC_t$	$ECOS_t$	$NFCI_t$	CSI_t	$BWI_t^{(ort)}$	$BWI_t^{(nort)}$	VIX_t	Prob(F)	R^2
Model (1)	-0.023***	·	·	-0.032***	·	·	·	0.058***	<1%	0.42
Model (2)	·	-0.022***	·	-0.034***	·	·	·	0.060***	<1%	0.41
Model (3)	·	·	-0.024***	-0.035***	·	·	·	0.061***	<1%	0.42
Model (4)	-0.014	·	·	·	0.012	·	·	0.043***	<1%	0.34
Model (5)	-0.005	·	·	·	·	0.074	·	0.046***	<1%	0.33
Model (6)	-0.013	·	·	·	·	·	0.096	0.046***	<1%	0.34
Model (7)	-0.021***	·	·	-0.032***	·	0.041	·	0.058***	<1%	0.41
Model (8)	-0.023***	·	·	-0.031***	·	·	0.024	0.058***	<1%	0.41
Model (9)	·	-0.020**	·	-0.033***	·	0.078	·	0.061***	<1%	0.41
Model (10)	·	·	-0.026***	-0.033***	·	·	0.045	0.061***	<1%	0.42

Table 11: Excess return regressions and controlling for the Fama-French factors

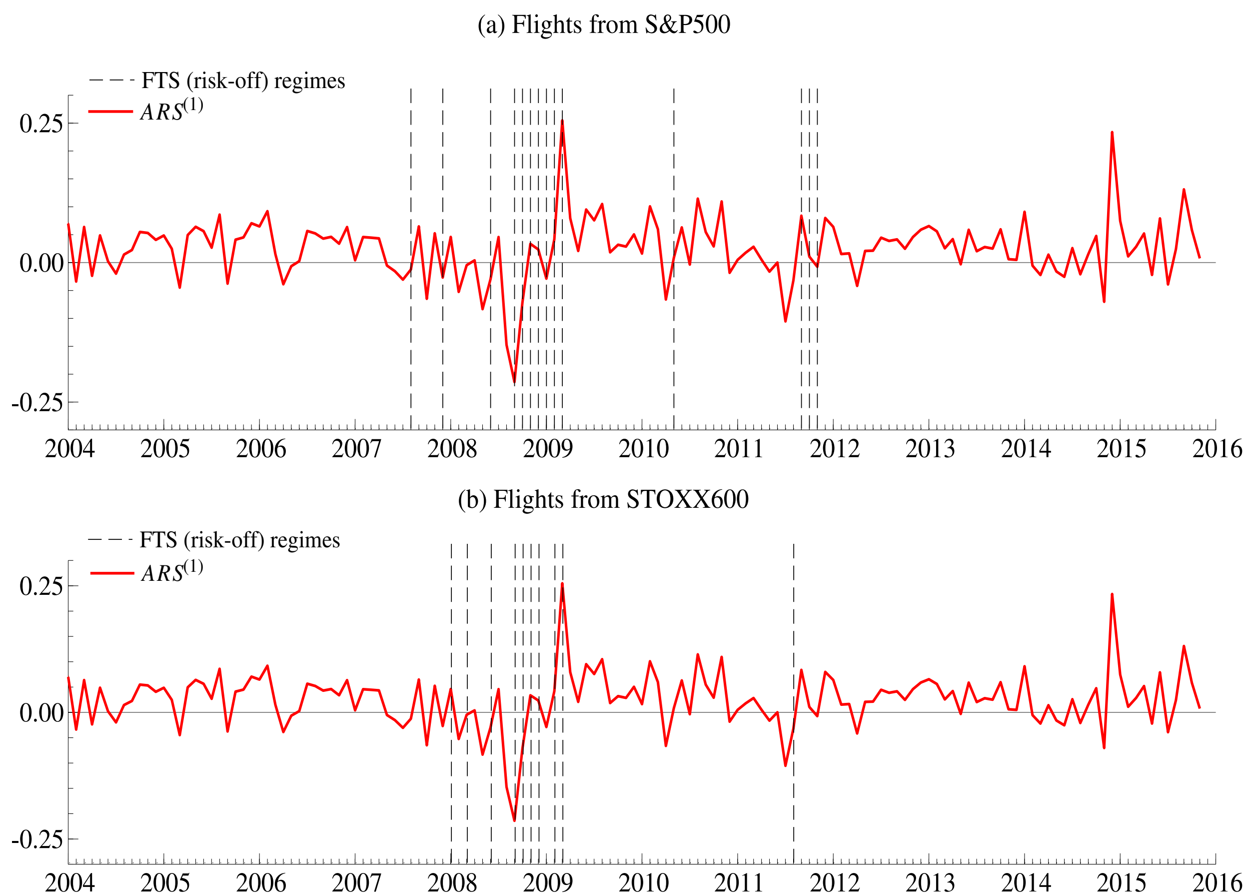
The table reports the regression results of excess (portfolio) returns on baseline sentiment proxies and Fama-French factors. The excess returns are obtained from the optimal portfolio of all European stocks. For each category, the dependent variable is the monthly excess returns generated from the *aggressive risk strategy* ($ARS^{(1)}$). See Table 3 for the description of the independent variables. Each regression model (labeled in the first row) contains different risk factors. Model (1): only benchmark sentiment indicators, Model (2): benchmark sentiment indicators and market risk premium ($Rm - Rf$), Model (3): benchmark sentiment indicators and three factors including market risk premium ($Rm - Rf$), Small-minus-Big (SMB), and High-minus-Low (HML). Model (4) has two additional factors—capturing profitability and investment—that are Robust-minus-Weak (RMW) and Conservative-minus-Aggressive (CMA), respectively, as in Fama and French (2015). In Model (5), Winners-minus-losers (WML) is the momentum factor of Carhart (1997) and Fama and French (2012). The table reports the coefficients estimated by Ordinary Least Squares and heteroskedasticity and autocorrelation-consistent standard errors (in parenthesis). The R^2 and p-values of F-tests are provided in the last two rows of the table. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample covers the (post-crisis) period from January 1, 2012 to December 31, 2015.

	(1)	(2)	(3)	(4)	(5)
	SENT only	SENT + 1F	SENT + 3F	SENT + 5F	SENT + 5F + M
Constant	0.034***	0.034***	0.034***	0.034***	0.034***
	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)
$BUSC_t$	-0.023***	-0.023***	-0.024***	-0.023***	-0.028***
	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)
$NFCI_t$	-0.032***	-0.025**	-0.021**	-0.018*	-0.022**
	(0.011)	(0.012)	(0.010)	(0.010)	(0.010)
VIX_t	0.058***	0.046***	0.036***	0.033**	0.035***
	(0.014)	(0.013)	(0.013)	(0.013)	(0.014)
$Rm - Rf_t$	·	-0.017**	-0.019**	-0.023*	-0.023*
	·	(0.008)	(0.009)	(0.013)	(0.014)
SMB_t	·	·	0.022***	0.023***	0.023***
	·	·	(0.008)	(0.009)	(0.009)
HML_t	·	·	0.004	0.016	0.008
	·	·	(0.009)	(0.023)	(0.026)
RMW_t	·	·	·	0.006	0.008
	·	·	·	(0.014)	(0.014)
CMA_t	·	·	·	-0.009	-0.004
	·	·	·	(0.016)	(0.018)
WML_t	·	·	·	·	-0.013
					(0.012)
R^2	0.42	0.45	0.51	0.52	0.53
Prob(F)	0.000	0.000	0.000	0.000	0.000

Figure 1: Post-crisis realized portfolio returns against the benchmark index returns

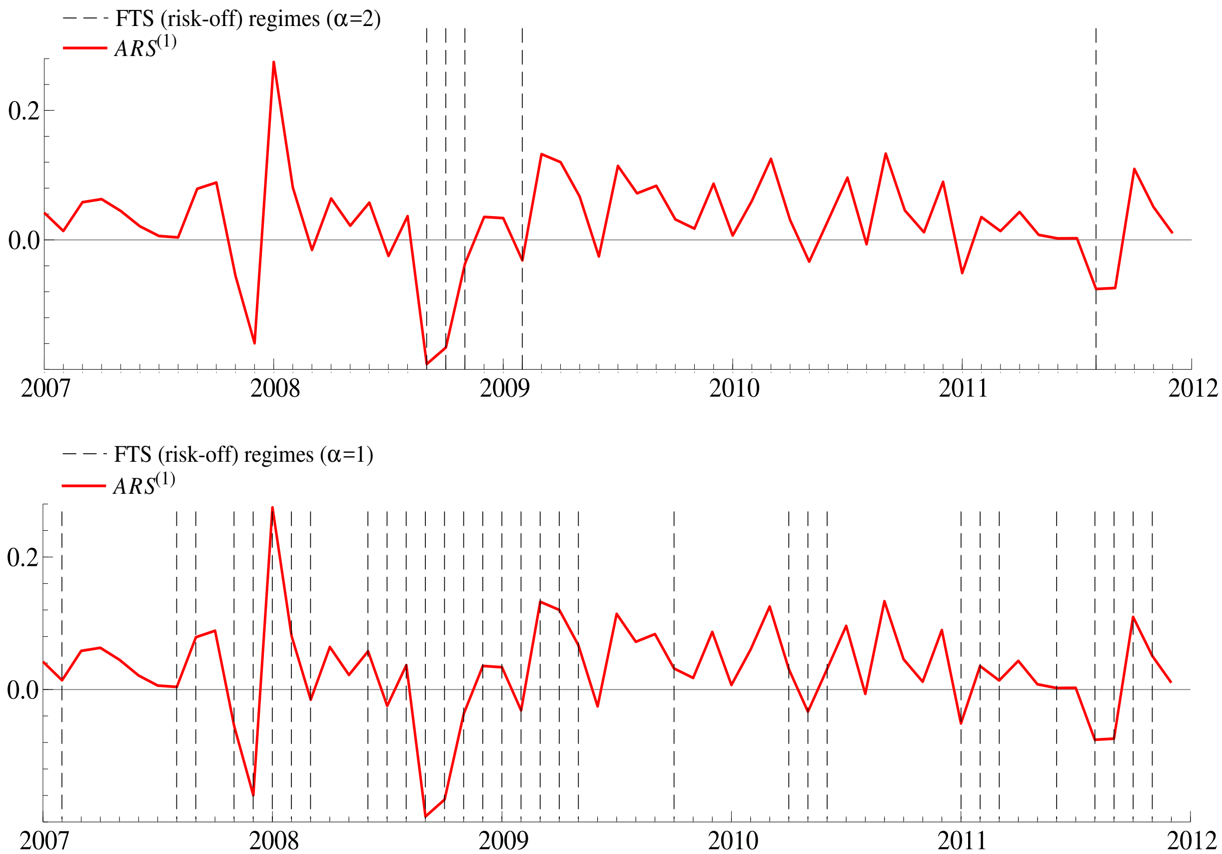
The figure plots the realized active portfolio returns over the post-crisis period (January 2012 − December 2015) together with the benchmark STOXX Europe 600 index returns. ARS and CRS denote aggressive and conservative risk exposure, respectively. The superscript (1) represents the changes in systematic (market) risk constraint, given the same level of firm-specific risk constraint. The superscript (2) represents the changes in firm-specific risk constraint, given the same level of systematic (market) risk constraint. The sample covers the period from January 1, 2012 to December 31, 2015.

Figure 2: Flight-to-safety regimes and portfolio returns



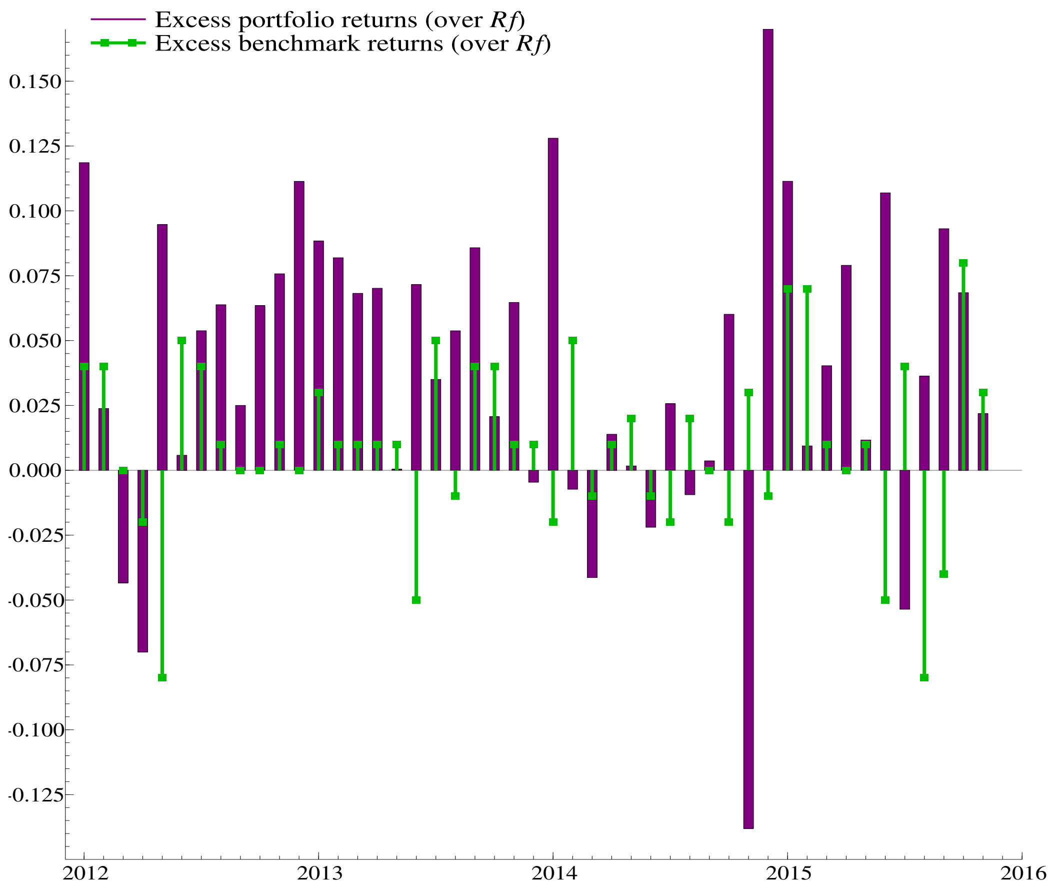
The figure plots the flight-to-safety (FTS) episodes and realized portfolio returns generated from the $ARS^{(1)}$ strategy. We identify the FTS events by considering two stock indices (S&P500 and STOXX600) representing *risky* securities. The "safe haven" assets are gold and 10-year U.S. Treasury government bonds. Following Baele et al. (2014), we detect the flight-to-safety episode in the data when an (extreme) negative stock return and an (extreme) positive bond (or gold) return occur within the exact same day. The flight threshold is set to $\alpha > 2$ (see Table 8 for the details of FTS estimation). On the figure, the dashed lines represent the months in which FTS spells are detected in the data. We aggregate the flights from gold and bond to stocks. The benchmark flight indices are S&P500 and STOXX600 in the upper and lower panels, respectively. The sample covers the period from January 1, 2004 to December 31, 2015.

Figure 3: Flight-to-safety regimes in portfolio returns in periods of crisis



The figure plots the flight-to-safety (FTS) episodes and realized portfolio returns generated from the $ARS^{(1)}$ strategy. We identify the FTS events by considering the stock index S&P500 representing *risky* securities. The "safe haven" assets are gold and 10-year U.S. Treasury government bonds. Following Baele et al. (2014), we detect the flight-to-safety episode in the data when an (extreme) negative stock return and an (extreme) positive bond (or gold) return occur within the exact same day. The flight threshold is set to $\alpha > 2$ and $\alpha > 1$ in the upper and lower panels, respectively (see Table 8 for the details of FTS estimation). On the figure, the dashed lines represent the months in which FTS spells are detected in the data. We aggregate the flights from gold and bond to stocks. The benchmark flight index is S&P500. The sample covers the periods of both subprime mortgage crisis and European sovereign debt crisis (i.e., from January 1, 2007 to December 31, 2011).

Figure 4: Comparison of excess portfolio and excess benchmark index returns over the risk-free rate



The figure displays portfolio and benchmark returns excess over the risk-free rate (U.S. one month T-bill rate). The realized European portfolio returns are generated from the *aggressive risk strategy* ($ARS^{(1)}$). The benchmark index is the STOXX Europe 600 index. On the figure, index lines and square-marked lines indicate monthly excess returns (over the risk-free rate) and benchmark excess returns (over the risk-free rate), respectively. While each index line is constructed as (R_t^p - Rf_t), each square-marked is given by (B_t - Rf_t), where Rf_t is the risk-free rate of Fama and French (2015) for the European equity data. The sample covers the period from January 1, 2012 to December 31, 2015.