Investor sentiment, herd-like behavior and stock returns: Empirical evidence from 18 industrialized countries

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Abstract:

We examine whether consumer confidence – as a proxy for individual investor sentiment – affects expected stock returns internationally in 18 industrialized countries. In line with recent evidence for the U.S., we find for about half of the countries in a bias-adjusted bootstrap regression analysis that individual sentiment negatively forecasts aggregate stock market returns and thus in a way that is consistent with behavioral models of overly optimistic and pessimistic investors. When sentiment is high, future stock returns tend to be lower and vice versa. This relation also holds for returns of value stocks and growth stocks, and for different forecasting periods. Finally, we employ a cross-sectional perspective and provide evidence that the impact of sentiment on stock returns is higher for countries that are culturally more prone to herd-like behavior and overreaction, have lower levels of education and less market integrity.

Keywords: consumer confidence; growth stocks; investor sentiment; noise trader; predictive regressions; value stocks

JEL: G12, G14, G15

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1. Introduction

The recent literature has seen a rise of studies investigating the effect of individual investor sentiment on stock returns. Several papers document a strong link between the two variables both in the time series and cross-sectionally. These paper estimate predictive regressions of the form

$$r_{t+1} = \alpha + \beta \cdot \text{sentiment}_t + \eta_t \qquad (1)$$

where r_{t+1} is the return of the aggregate stock market or a (zero-cost) portfolio at time t and $sentiment_t$ is a proxy for (lagged) investor sentiment. A common finding for the US stock market is a statistically and economically significant negative coefficient estimate for β. Therefore, periods of higher investor optimism tend to be followed by significantly lower returns for the aggregate market (e.g. Brown and Cliff, 2005) and even more pronouncedly for firms that are hard to price and thus difficult to arbitrage (e.g. Baker and Wurgler, 2006, Lemmon and Portniaguina, 2006).

In order to assess the relation of sentiment and returns out-of-sample, we investigate whether consumer confidence – as a proxy for individual investor sentiment – affects stock returns along the lines of (1) in 18 countries internationally. We find, first, that for about half of the markets considered, there is a significant impact of investor sentiment on aggregate stock returns even after controlling for commonly employed macro risk factors as in Brown and Cliff (2005). Second, in cross-sectional regressions we provide some first evidence that the impact of sentiment on stock returns is stronger in countries in that are culturally more prone to herd-like behavior as predicted by Chui, Titman and Wei (2005). The effect also seems to be stronger in countries with less efficient markets.

The general finding of a sentiment-return relation is at odds with standard finance theory which predicts that stock prices reflect the discounted value of expected cash-flows and that irrationalities among market participants will be erased by arbitrageurs. Sentiment does not play any role in this classic framework. The behavioral approach instead suggests that waves of irrational sentiment, i.e. times of overly optimistic or pessimistic expectations, can persist and affect asset prices for significant time spans. DeLong, Shleifer, Summers and Waldmann (1990) show in their seminal paper, that correlated sentiment of irrational investors is a priced risk factor. Assets with higher levels of noise trader risk have higher expected returns. Thus, there is both empirical evidence for a link between sentiment and stock returns and a sound theoretical underpinning of this relationship.

On the available empirical evidence for the US, overlooked rational factors that drive the relation between sentiment and stock returns are a possible but less and less unlikely explanation. Several authors (Baker and Wurgler, 2006, Brown and Cliff, 2005, Kumar and Lee, 2006, Lemmon and Portniaguina, 2006, Hvidkjaer, 2006 to name just a few) document empirically that the link between sentiment and future returns is most likely due to overly optimistic (pessimistic) investors who drive prices above (below) intrinsic values, a misevaluation that is corrected eventually and leads to the observed negative influence of sentiment on stock returns. Data mining is a somewhat more likely possibility. There is little evidence for this relationship outside the US so that the effects of sentiment on returns might well be a statistical artefact.[1] Out-of-sample tests of an anomaly are one means to investigate this possibility.

Therefore, we investigate the link between asset prices and investor sentiment for 18 industrialized countries around the world. "Geographical" out-of-sample tests are a common way to amass or to weaken earlier evidence (e.g. Ang et al., 2006, Griffin, Ji, Martin, 2003). This is the first major contribution of the paper. Furthermore, to assess the behavioral explanation from a different viewpoint, we also examine whether cross-sectional variation in demographic, cultural and market efficiency related factors systematically affects the magnitude of the link between sentiment and stock returns. To the best of our knowledge, we are the first to investigate this issue and this makes up the second major contribution of the paper.

The investigation whether cultural factors play a role is motivated by the paper of Chui, Titman and Wei (2005) who investigate whether individualism as measured by Hofstede (2001) is a cross-country determinant of momentum profits. The authors argue that countries with a more individualistic culture are more prone to certain behavioral biases that benefit the existence of momentum profits. Their findings support this hypothesis. As for the case considered here, if the impact of investor sentiment on stock returns is truly due to correlated behavior of irrational traders, one should expect this effect to be higher in countries that are collectivistic since collectivism boosts “herd like overreaction” (see Chui, Titman and Wei, 2005, p.28). Therefore, an alternative test of the implicit assumption that the effect of sentiment on stock returns is due to overreaction on the part of noise traders and not due to

[1] Jackson (2003) finds no evidence for short-run reversals after waves of optimism and pessimism for Australia for the period 1991 - 2002. Schmeling (2006) finds evidence of such reversals for Germany for a period spanning 2001 to 2006.

time-varying fundamental risk factors can be conducted by investigating whether the sentiment-return relationship varies according to this cultural dimension cross-sectionally between different countries.

As noted above, we also check whether institutional quality or informational efficiency of a country explains the cross-section of the sentiment-return relation. We find some evidence for this hypothesis although less pronounced than for the cultural factors. Therefore, our paper also contributes to a growing literature that cross-sectionally relates market outcomes to market institutions (cf. La Porta, Lopez-de-Silanes, Shleifer, and Vishny, 1998).

The plan of action is as follows. The next section selectively reviews the existing literature. Section 3 describes the data and provides some descriptive statistics. Section 4 provides estimates of predictive regressions of returns on sentiment similar to equation (1). Section 5 investigates cross-country results and section 6 concludes.

2. Literature Review

As Baker and Wurgler (2006, p. 1648) point out, "a mispricing is the result of both an *uninformed demand* shock and a *limit to arbitrage*" (emphasis added). Regarding the first ingredient, uninformed demand shocks, Brown and Cliff (2005) argue that sentiment is most likely a very persistent effect so that demand shocks of uninformed noise traders may be correlated over time to give rise to strong and persistent mispricings. However, the second ingredient, limits of arbitrage, deter informed traders from eliminating this situation (cf. Black, 1986, or more formally, Shleifer and Vishny, 1997) since it is a priori unclear how long buying or selling pressure from overly optimistic or pessimistic noise traders will persist. However, every mispricing must eventually be corrected so that one should observe that high levels of investor optimism are on average followed by low returns and vice versa.

As discussed in the introduction, there is now substantial empirical evidence for the U.S that (proxies for) investor sentiment indeed forecast stock returns negatively in the time series (cf. Brown and Cliff, 2005, Lemmon and Portniaguina, 2006).

An influence of sentiment is also found in the cross-section of U.S. stock returns. Baker and Wurgler (2006) document that those stocks are more affected by shifts in sentiment that are (a) hard to value because valuations are highly subjective and (b) for those stocks that are hard to arbitrage. Indeed they find that sentiment effects are stronger among stocks that can reasonably be assumed to fulfill at least one of these criteria, e.g. young, small, unprofitable, distressed, extreme growth or dividend-nonpaying firms. For the U.S. this finding for distressed stocks is underscored by the finding of Kumar and Lee (2006) who show that retail investors, which are commonly thought of being noise traders (Kaniel, Saar and Titman, 2005), tend to overweight value stocks relative to growth stocks and that shifts in the buy-sell imbalance of these retail investors are positively correlated with returns of value stocks. This clearly is a prime example of noise trader risk.

Also in this spirit, Barber, Odean and Zhu (2005) investigate returns of stocks that are heavily bought and sold by U.S. individual retail traders and provide somewhat even more direct evidence on the story that individuals are noise traders. They show that stocks heavily sold by individuals outperform stocks heavily bought by a hefty 13.5% the following year. They also document strong herding among individual investors so that the notion of correlated trading by irrational investors seems to be a likely cause for these return differentials. Hvidkjaer (2006) sorts stocks from NYSE, AMEX and NASDAQ based on past difference between sell and buy volume from small trades, i.e. trades that most likely come from individual traders. He finds that stocks with large individual selling pressure outperform stocks with large individual buying pressure over horizons of up to three years. Depending on the sorting procedure, Hvidkjaer (2006) tends to find large return differences of up to 0.94% per month for a portfolio long in stocks that have been sold most heavily by individuals over the last 6 months and short in stocks that have most heavily been bought by individuals over the last 6 months. As with the results from Barber, Odean and Zhu (2005), these numbers suggest that irrational trading of noise traders is an important determinant of expected stock returns.[2]

A natural question that arises when attempting to quantify the influence of sentiment on stock returns is how to measure (unobserved) sentiment? Existing studies have used different proxies, of which closed-end fund discounts are one major vehicle (c.f. Lee, Shleifer and Thaler, 1991, Swaminathan, 1996, or Neal and Wheatley, 1998). Baker and Wurgler (2006) construct a sentiment proxy from several market price based variables such as closed-end fund discounts, number of IPO's, turnover etc. Recent studies have started to use micro trading data, such as Kumar and Lee (2006) who use broker data or Barber, Odean and Zhu (2005) who use the TAQ/ISSM data. Finally, some studies use data from investor surveys (cf. Brown and Cliff, 2005). Charoenrook (2003) and Lemmon and Portniaguina (2006) use consumer confidence indexes to proxy for sentiment, based on the observation that Brown

[2] Frijns, Koellen and Lehnert (2006) provide experimental evidence that, among others, market sentiment can be a determining factor of portfolio choice. Lux (1998) provides simulation evidence on how waves of optimism and pessimism may arise in a model with heterogenous agents.

and Cliff (2004) find no evidence that closed-end fund discounts reflect sentiment and that Qiu and Welch (2005) report only weak correlation of these fund discounts with UBS/Gallup surveys of investor sentiment. The consumer confidence indexes do better in this respect. Furthermore, Fisher and Statman (2003) provide evidence that consumer confidence correlates well with other sentiment proxies such as the sentiment measure from the American Association of Individual Investors (AAII) whereas Doms and Morin (2004) find that consumer confidence contains an irrational element since it responds to the tone and volume of economics news reports while being hardly affected by the content of news. All these findings make consumer confidence seem to be a reasonable proxy for individual sentiment and we follow these findings by using measures of consumer confidence as a sentiment proxy throughout the paper.

Finally, given the accumulated evidence of the influence of sentiment on returns the question remains whether one should expect this relation to hold outside the U.S. as well. Evidence from a different market anomaly based most probably on behavioral biases by market participants, namely the abnormal size of momentum profits documented by Jegadeesh and Titman (1992), suggests that this does not necessarily need to be the case. Momentum profits, though large and significant in the U.S. and most of Europe (Rouwenhorst, 1998), are completely absent in Japan and almost non-existent in the rest of Asia.

Recently, Chui, Titman and Wei (2005) propose that cultural differences might play a role for the relative strength of behavioral biases between countries.[3] Specifically, they argue that individualism as measured by Hofstede (2001) drives certain behavioral biases that are assumed to generate the apparent momentum profits. The authors also argue that a lack of individualism, i.e. collectivism, might drive certain biases "that generate even more important market inefficiencies" (p. 28) than the momentum premium. Collectivistic countries have societies in which people are integrated into strong groups and, as such, "may place too much weight on consensus opinions, and may thus exhibit *herd-like overreaction* …" (emphasis added). Herd-like overreaction, i.e. correlated actions of noise traders based on overly optimistic or pessimistic expectations, is precisely what is assumed to drive the sentiment-return relation in financial markets. Therefore, one may expect that collectivistic countries show a stronger impact of sentiment waves on returns whereas individualistic countries, in

[3] Guiso, Sapienza and Zingales (2006) and Chuah et al. (2006) document that culture may significantly affect economic outcome although yet little attention has been paid to these factors in economics. However, there seems to be even less empirical evidence for the role of culture in finance than in economics.

which people tend to put more weight on their own information and opinion, should be less affected by these behavioral biases.

3. Data and Descriptive Statistics

As noted above, we are interested in measuring the effect of noise trader demand shocks on stock markets. Doing this in a consistent way is exacerbated by the fact that there is no consensus on what kind of proxies to employ when measuring individual sentiment for a single country. This problem naturally aggravates when attempting to find a proxy that is available for different countries.

However, given the recent detailed analysis of consumer confidence as measure for investor sentiment by Lemmon and Portniaguina (2006) it seems natural to use this metric for an international analysis. First of all, consumer confidence is available for several industrialized countries and, second, it is available for reasonable time spans. Third, consumer confidence, albeit measured slightly different in various countries, seems to be the only consistent way to obtain a sentiment proxy that is largely comparable across countries.

Therefore, we use data on stock returns and consumer confidence for 18 industrialized countries around the globe to investigate the sentiment-return relation internationally. Our sample of countries is largely dictated by data availability but consumer confidence is available for several countries on horizons of up to 20 years. We include the U.S., Japan, Australia, New Zealand and 14 European countries (see Table 1 for a complete list of countries). These markets cover the lion's share of international stock market capitalization, cover the most liquid markets in the world - namely the U.S., Europe and Japan - and thus provide a representative sample. Consumer sentiment for the European countries is available from a single source so the comparability of sentiment data is especially attractive for this large sub-sample of countries.

For each of the 18 countries we collect a monthly measure of consumer confidence, monthly returns for (a) the aggregate stock market, (b) a portfolio of value stocks and (c) a portfolio of growth stocks.[4] We investigate aggregate market returns as well as value and growth stocks for the following reasons. First, there is evidence (Baker and Wurgler, 2006) that sentiment affects the cross-section of returns differently for different investment styles, e.g. value and growth. Second, Shiller (2001, p.243) quotes Paul Samuelson with the following claim: "I

[4] Stock market returns are from value-weighted portfolios in local currency. The value portfolio consists of the top three deciles of stocks sorted by B/M whereas the growth portfolio comprises the bottom 30% of stocks sorted by B/M.

[hypothesize] considerable *macro* inefficiency, in the sense of long waves in the time series of aggregate indexes of security prices below and above various definitions of fundamental values." Therefore, it seems to make sense to look for this macro inefficiencies in aggregate market returns, too.

Stock market data come from Prof. Kenneth French's web site and are employed because they are collected in a consistent manner across countries, are relatively free of survivorship bias (Fama and French, 1998) and were used in other studies before (e.g. Chui, Titman and Wei, 2005, motivate their herding and collectivism result with this data).

Furthermore, for each country we collect data on consumer confidence. For all 14 European countries the data comes from the "Directorate Generale for Economic and Financial Affairs" (DG ECFIN)[5] which, among other things, conducts research for the European Union. Confidence indices for the remaining countries are obtained from Datastream. There are several possible high-quality consumer confidence indices for the U.S. We employ the Michigan Survey (see Lemmon and Portniaguina, 2006). Finally, the consumer confidence index for Japan is available on a quarterly frequency only. We convert it to a monthly frequency by using the last available values for months without data as in Baker and Wurgler (2006).

Table 1 provides descriptive statistics for returns and consumer confidence indices. Column three shows the time spans available for each country. We include the time from January 1985 to December 2005 wherever possible. Data limitations enforce somewhat shorter periods for several countries. However, we have a minimum of 120 monthly observations even for the most data-constrained country Austria.

As can be seen, value stocks have higher mean returns than growth stocks for most countries, a fact documented before in a voluminous literature on the so-called value premium (Fama and French, 1998). The descriptive statistics for the consumer confidence indices show a high degree of serial correlation in the time-series. First order autocorrelations (ρ_{-1}) are extremely high and uniformly above 90%. We will take special care of this high serial correlation in our empirical analyses.

Table 2 shows correlation coefficients of the consumer confidence above the main diagonal and correlations for monthly changes in consumer confidence below the main diagonal. As can be seen from both the correlation coefficients computed in levels and in changes, the comovement across countries is not prohibitively strong, i.e. we are not using

[5] These consumer confidence indices have also been used by Jansen and Nahuis (2003). Data can be downloaded from: *http://ec.europa.eu/economy_finance/indicators_en.htm*.

essentially one sentiment series. There are several countries that show a large correlation (e.g. Austria and Germany), essentially no correlation (e.g. Australia and Switzerland) or a negative correlation (e.g. Sweden and Japan).

4. Predictive Regressions of Stock Returns on Consumer Confidence

4.1. Methodology

Brown and Cliff (2005) argue that the building up of overly optimistic or pessimistic views is a persistent process which might not be detectable over short horizons. Information about the degree of optimism or pessimism is contained in sentiment levels rather than changes. Therefore, it is necessary to measure the impact of past sentiment levels on returns. Furthermore, both Brown and Cliff (2005) as well as Hvidkjaer (2006) document that the effect of individual sentiment can have long lasting effects of several months up to two or three years. To accommodate these prior findings we estimate long-horizon return regressions of the form

$$\frac{1}{\kappa}\sum_{\kappa=1}^{k} r^{i}_{t+\kappa} = \delta_0^{i,(k)} + \delta_1^{i,(k)}\text{sent}^{i}_{t} + \Psi^{i}_{t}\gamma^{i,(k)\prime} + \xi^{i,(k)}_{t+1\mapsto t+k} \quad (2)$$

with the average k-period return[6] for country i as dependent variable and several predictors on the right-hand side. These predictors include consumer confidence as a proxy for individual sentiment (*sent*) and additional macro variables which are collected in matrix Ψ. Specifically, we include annual CPI inflation, the annual percentage change in industrial production, the annual change in employment and the term spread in Ψ to net out effects of macro risk factors on returns. The component of consumer confidence that is not attributable to these macro factors yields our proxy for individual sentiment.[7] As usual, we employ known up-to-week t information to forecast mean excess returns beginning in month $t+1$ only. Furthermore, to facilitate comparisons of the sentiment-return relation between countries we standardize all variables used in (2).

A well known problem with regressions of the form in (2) is, that standard econometric inference, even when accounting for the serial correlation in the standard errors induced by overlapping horizons, most probably yields biased estimates of the slope coefficients. Several authors (see Stambaugh, 1999, Valkanov, 2003, or Ferson et al., 2003) have documented this problem, which is caused by highly persistent regressors. In this case

[6] As in Hong et al. (2007) we use raw returns since reliable data on risk-free rates is hard to obtain outside the U.S.

[7] Baker and Wurgler (2006) and Lemmon and Portniaguina (2006) also net out macro risk factors from their sentiment proxy to obtain an explanatory variable that is unrelated to fundamental risk factors.

OLS estimation results are still consistent but suffer more than likely from severe biases in finite samples although all regressors are predetermined. For simple regressions with only one predictor it can be shown analytically that the bias in coefficient point estimates increases in the degree of persistence of the regressor (see Stambaugh, 1999). As we show in Table 1 the consumer confidence indexes employed are highly persistent.[8] As noted above, a further complication arises from the overlapping of the means of returns, which induces a moving average structure of order (k-1) to the error terms.

There are several, necessarily imperfect ways to handle this problem. Several authors (e.g. Brown and Cliff, 2005) rely on some form of simulation procedure. Another way is to use auxiliary regressions (Amihud and Hurvich, 2004).[9] In order to establish comparability with the results of Brown and Cliff (2005) which is closest to our approach of detecting an influence of past sentiment on aggregate market returns, we exactly follow their method which consists of simulating small sample p-values and test statistics for the coefficient estimates of each country's return regression separately.

A detailed description of the method employed can be found in Appendix 1 of Brown and Cliff (2005). Here we only note the main steps for completeness. First, we estimate a VAR(1) that consists of all variables used, i.e. returns, consumer confidence and all macro factors for country i. The residuals are stored. Next we simulate artificial time series for all endogenous variables by bootstrapping from the residuals obtained in the first step. Importantly, to simulate time series under the null of no influence of sentiment in returns, we turn off this influence by setting the coefficient of lagged sentiment on returns in the VAR coefficient matrix to zero. In this fashion, we simulate 10,000 artificial time series for all variables *without* return predictability. With these series in hand, we estimate equation (2) 10,000 times on the new time series to obtain the bootstrapped distribution of slope coefficients. This distribution can then be used to measure the bias in coefficient estimates $\hat{\delta}_1$ introduced by the persistence in regressors and to obtain bootstrap p-values for the significance of the estimated coefficients. We report bias-adjusted coefficient estimates and bootstrap p-values throughout the rest of this section.

[8] Brown and Cliff (2005) also find individual sentiment from direct investor surveys in the U.S. to be highly correlated over time. Therefore, the high degree of persistence is not special to the consumer confidence indices employed here.
[9] Campbell and Yogo (2006) provide a method for efficient tests of stock return predictability in the presence of near unit-root regressors. However, their method does not extend directly to multiple regressors and multi-period forecasts.

4.2. Results

Results of this estimation procedure are shown in Table 3 for aggregate stock market returns. We provide coefficient estimates for forecasting horizons of one, three, six, twelve and 24 months to document the time pattern of the sentiment-return relation. As is evident, the estimated coefficients for the impact of sentiment on expected returns are negative for the majority of markets and horizons. This is in line with earlier findings for the U.S.

The estimated coefficients are directly comparable across countries since we have standardized both dependent and independent variables for each country. As can be inferred from the magnitude of coefficients, the impact of sentiment on returns varies quite a lot across markets. For example, for the U.S. a two standard deviation shock of sentiment leads to a decline in returns in the following month of only 0.12%.[10] The same calculations for e.g. Austria, Italy and Japan give numbers of about 0.25%, 0.50% and 1.20%, respectively. Therefore, the effect of sentiment waves on returns is not overly strong for the U.S. but much stronger for several countries in Europe and, surprisingly, for Japan.

Looking at another dimension of predictability, the incremental adj. R^2s, i.e. the differences between the adj. R^2 when including macro factors and consumer sentiment jointly and the adj. R^2 when including macro factors only, are of economic significance for the same set of the markets. For example, the adj. R^2 for Italy rises from 0% to 3% on a monthly horizon and from 5% to 18% on a 6 months horizon when adding lagged sentiment to the predictive regression. It seems that sentiment has quite some explanatory power in these markets.

Overall, statistical significance is only obtained for 10 of 18 countries, indicating that the negative effect of sentiment on stock returns does not seem to be a universal phenomenon across countries. We will investigate the nature of this cross-sectional pattern in section 5.

Looking at the forecasting performance at different horizons more closely one can see that statistical significance of the sentiment predictor does not seem to uniformly increase with horizon. It is often argued that long-horizon regressions with nearly integrated regressors spuriously generate significant results at increasing horizons (cf. Hong et al. (2007), p. 17 for a discussion). If there was a bias in our results not eliminated by the bootstrapping procedure that mechanically generated significant results over longer horizons, one would expect to see exactly such a result. Yet, this is not the case here. In fact, there are several countries, e.g.

[10] This effect is smaller than the effect reported in Brown and Cliff (2005) where a two standard deviation shock leads to a monthly decline of roughly 0.29% over three years (calculated from Table 5 of their paper). However, the paper uses a different sentiment proxy and different sample period so that direct comparisons may be misleading.

Japan, Spain or Switzerland, where sentiment predicts aggregate market returns only at short horizons but not at longer horizons. Furthermore, the estimated coefficients tend to decrease in horizons and do not increase. Both findings are comforting and suggest that our regressions are informative and not just due to estimation biases.

Table 4 (Table 5) show estimated coefficients for the relation between sentiment and value (growth) stocks internationally. Baker and Wurgler (2006) argue that the sentiment-return relation should be notably strong for firms that are hard to value and hard to arbitrage and find that both value and glamour stocks are prone to the influence of sentiment whereas Lemmon and Portniaguina (2006) find slightly weaker evidence for sentiment effects on these groups of stocks and document an effect mainly for value stocks. Our results for value and glamour stocks are by and large consistent with Baker and Wurgler's findings. Almost all stock markets that are statistically significantly affected by lagged sentiment also show a statistically significant effect of sentiment on value and growth stocks. However, these effects are on average only marginally larger than for the aggregate market. Continuing with the countries mentioned above, we find an impact of a two standard deviation sentiment movement on value (growth) stocks for the U.S. of 0.11% (0.13%), for Austria of about 0.40% (0.30%), for Japan of 1.37% (1.25%) and for of Italy of roughly 0.7% (0.45%).

Finally, we note that our results are also in line with the scant earlier evidence for other countries. As in our results, Jackson (2003) finds no significant evidence for return reversals in Australia while Schmeling (2006) finds evidence for a significant impact of individual sentiment on aggregate market returns in Germany.

4.3. Some Perspective on Robustness

A natural objection might be that consumer confidence indices are not collected in a consistent way across countries which leads to spurious findings for some countries but to no significant results for others. This argument clearly overlooks, that we obtain sentiment measures for the 11 European countries from a single source, so that sentiment in these countries is collected in exactly the same way and at the same time. However, the results on the sentiment-return relation vary markedly among the 11 European countries. This cannot be attributed to differences in the survey design.

A second objection might be that econometric results based on predictors with such a hefty autocorrelation as documented in Table 1 are very unreliable so that results seem to be spurious. However, several confidence indexes compiled from the same data collector (DG ECFIN) are available for the European countries. These other confidence indices share almost the same degree of serial correlation and describe measures of economic expectations too, such as the "DG ECFIN economic confidence index" that analyzes economic expectations for several groups including consumers, manufacturers etc.. Employing these sentiment indices as predictors in regression (2) produces hardly any significant results.[11] The estimated coefficient is actually positive for most countries. Therefore, the high degree of persistence in the confidence indices does not seem to drive the results. These are obtained by consumer sentiment only, as it is predicted by the notion that irrational individuals drive markets above or below fundamentally warranted levels.

As a third test, we estimate the specification (2) on sub samples and with a varying number of macro factors included. We do not report the results for brevity but note that our conclusions are qualitatively unchanged.

Finally, we look at the correlation of unexpected returns and sentiment innovations as suggested by Pastor and Stambaugh (2006). The idea in the sentiment-return context here is that in a predictive regression of the form

$$r^i_{t+1} = \delta^i_0 + \delta^i_1 sent^i_t + \Upsilon^i_t \gamma^{i\prime} + \xi^i_{t+1} \tag{3}$$

$$sent^i_{t+1} = \alpha^i_0 + \alpha^i_1 sent^i_t + \eta^i_{t+1} \tag{4}$$

a plausible result would be that the innovations ξ^i_t, i.e. the unexpected return, and η^i_t, i.e. the innovation in noise trader optimism, are positively correlated since it is presumably a wave of unexpected optimism that boosts prices. Therefore, under a behavioral story one would expect to see a positive correlation of ξ^i_t and η^i_t whereas one would most probably expect to see a negative correlation under a rational story (see the discussion in Pastor and Stambaugh, 2006) where consumer confidence is informative about discount factors.

We report the correlation of ξ^i_t with η^i_t for all countries *i* in Table 6. It is obvious that the typical correlation of unexpected returns with sentiment shocks is positive. Furthermore, countries that show a significant relation between returns and sentiment tend to have higher correlation coefficients of the two shocks. This is in line with the story that irrational noise trader sentiment drives price away from fundamentally warranted levels.

5. Cross-Sectional Analyses

5.1. Possible Determinants of Cross-Sectional Variation in the Sentiment-Return Relationship

[11] Results are not reported to conserve space but are available from the authors upon request.

In this section we discuss possible explanatory variables for the cross-sectional analysis of the sentiment-return relation for our 18 countries. We start by identifying behavioral factors based on the analysis by Chui, Titman and Wei (2005) and then move on to some often used proxies for market efficiency that might drive cross-country results.

Behavioral factors

The behavioral explanation of the sentiment-return relation says that individuals herd and overreact. Therefore, our findings could be explained by systematic cross-country differences in herd-like overreaction. As noted in the introduction, Chui, Titman and Wei (2005) suggest that differences in collectivistic behavior might be a driver of the tendency of investors to herd. Therefore, we employ a measure of collectivism constructed by Hofstede (2001) which serves to quantify the degree to which people in different countries are programmed to act in groups and not as individuals.[12]

However, herd-like behavior, or correlated behavior across individuals, is not the only ingredient to this behavioral story. Individuals also have to overreact to create the negative relation between sentiment and returns. This point is crucial and is suggested by the findings of Jackson (2003). Jackson (2003) shows with broker level trading data for individual investors in Australia, that there is considerable systematic trading by individuals, i.e. trading decision are correlated and do not wash out on an aggregate level. However, he does not find evidence for short-run return reversals after waves of correlated behavior. Therefore, any empirical test of the behavioral story must take into account both dimensions, herding and overreaction.

We employ a second index by Hofstede to capture the likely degree of overreaction across countries. The uncertainty avoidance index (UAI) measures the degree to which a culture programs its members to react to unusual and novel situations. While this is not directly addressed in our analysis here, Hofstede documents that people in more uncertainty avoiding countries act and react more emotional compared to countries with low levels of uncertainty avoidance. People in the latter countries act more contemplative and thoughtful. Therefore, we employ the uncertainty avoidance index as a rough proxy for the tendency of individuals to overreact. Furthermore, it is known that UAI is correlated with the collectivism index since the UAI also captures cross-country differences in the tendency of people to follow the same sets of rules and thus behave in the same manner. This is correlated with

[12] Chui, Titman and Wei (2005) use the same index to measure individualism which is the original index by Hofstede (2001) where higher values mean higher individualism. We just pre-multiply index values by -1 to obtain our measure for collectivism.

collectivism and in our sample the correlation between collectivism and uncertainty avoidance indeed is about 0.50. Therefore, higher levels of the uncertainty avoidance index (UAI) should indicate both a tendency towards more overreaction-like behavior and herd behavior.

We are well aware of the data-mining problem involved here. While the index on collectivism has proved powerful in the paper by Chui, Titman and Wei (2005) and is thus less affected from this problem, we are not aware of a finance paper that uses the UAI of Hofstede. Therefore, we will carefully investigate whether this measure has its predicted effect on the sentiment-return relationship individually and in combination with other factors.

Market integrity

As a second set of explanatory variables we use proxies for what Chui, Titman and Wei (2005) call "stock market integrity". The idea behind these variables is that markets with higher institutional quality should have a more developed flow of information and are consequently more efficient. In order to allow for a direct comparison with CTW (2005) we include the same variables as in their study. However, we collect additional variables related to the informational efficiency of a country which are detailed and grouped into “other factors” below.

The market integrity variables include a dummy for the legal origin of a country (DL, the dummy equals one when a country is common law and zero for civil law), the index of anti-director rights (a higher index means better investor protection), the corruption perception index (Cpix, higher levels mean less corruption) and accounting standards (acct, a higher index means better accounting standards). These variables are taken from La Porta, Lopez-de-Silanes, Shleifer, and Vishny (1998). Additionaly, we follow Chui, Titman and Wei (2005) and include the risk of earnings managements index (emgt., a higher value means a higher risk of earnings management in that country).

Other factors

As highlighted above, superior institutional characteristics should alleviate the impact of noise traders on markets. The market integrity factors are not the only proxies which might intuitively be related to the sentiment-return relation. We consider additional factors, most of which have been employed in earlier studies, and document these below.

As proxies for the information environment we employ the following variables from Chang, Khanna and Palepu (2000): (average) number of analysts, the average forecast error, and the forecast dispersion per stock. These variables are included since it might be expected that a higher number and forecast quality of analysts leaves less room for systematic misevaluations and reduces limits to arbitrage, respectively. Griffin, Nardari and Stulz (2006) also use these variables as explanatory variables to single out rational vs. behavioral factors.

As another potentially important determinant we include in the analysis is the share of institutional investors in a country. A larger market share of institutions should benefit market efficiency since it is implicitly assumed that institutions fulfill the role of informed investors or rational arbitrageurs due to their size and relative sophistication (compared to irrational individual investors). We would therefore expect to see a lower impact of sentiment on returns in countries with a large market share of institutions. Data come from the OECD.

Also, we collect data on turnover and data on market capitalization in relation to GDP as two proxies for the activity and size (maturity) of a country, respectively. These variables capture the conjecture that more liquid and larger markets leave less room for misevaluation due to overreaction of individual traders. The turnover data is the average turnover in relation to market capitalization from Griffin, Nardari and Stulz (2006) whereas the ratio of market capitalization to GDP is from the World Bank data base.

We furthermore employ a dummy variable that equals one if short-selling is practiced in a respective country and zero otherwise. Short-selling might allow rational investors to better arbitrage overvaluations and could therefore lower the impact of sentiment on returns. The short-selling dummy (SSD) is constructed from the paper by Bris, Goetzmann and Zhu (2006) who show that short-selling benefits market efficiency and price discovery.

Finally, we employ World Bank data on education since it may be reasonably assumed that countries with a superior level of education accommodate fewer irrational noise traders. We take the percentage of a country's population that enjoyed enrolment in tertiary education as our proxy for education.

5.2. Results

To investigate the potential determinants of the cross-sectional variation in sentiment-return relation we start by running regressions of the following form

$$\hat{\delta}_1^{i,(k)} = \beta_0 + \beta_1{}' x_i + \vartheta_i \tag{5}$$

where $\hat{\delta}_1^{i,(k)}$ is the estimated impact of individual sentiment on average returns over *k* months and x_i is a scalar or column vector of characteristics (detailed in the previous subsection) for country i and ϑ_i is an error term. We will generally work with the direct impact of this month's sentiment on next month's return, i.e. k=1, but note, that results reported in the following are very similar for other horizons k>1. For future interpretation of results we note, that lower values of the dependent variable $\hat{\delta}_1^i$ imply a stronger effect of sentiment on returns.

Table 7 shows results for simple OLS regressions with White standard errors. As for the behavioral factors, both higher levels of collectivism and higher levels of the UAI (recall that higher levels of this index mean more emotional and blindfolded actions by people in that country) are significantly related to a stronger sentiment-return relation, i.e. the coefficients are negative. This is well in line with the predictions of Chui, Titman and Wei (2005) that collectivism boosts herd like overreaction and our discussion in the preceding subsection about the influence of UAI on the link between noise trader sentiment and returns. The adj. R^2s of roughly 23% (collectivism) and 36% (UAI) are quite large and suggest that cultural factors might play a key role for the occurrence of market anomalies across countries as suggested by Chui, Titman and Wei (2005).

From the group of variables belonging to the market efficiency proxies, only the Cpix and the index on earnings management play a significant role with similarly high adj. R^2s of 30% for the Cpix and 17% for the earnings management index.

Additional variables often have the expected sign, e.g. larger forecast errors, larger forecast dispersion, less institutional investors as well as higher turnover and a larger size of the market as measured by market cap. to GDP that are associated with larger effects of return on sentiment. However, all of these additional variables fail to be significant or to provide an acceptable explanatory power in terms of their adj. R^2 except for the education variable. Better education significantly reduces the effect of sentiment on returns as one would intuitively expect with an adjusted R^2 of roughly 16% which comes close to the explanatory power of the behavioral factors.

A natural question to ask is whether the cultural factors are more powerful in explaining the cross-section compared to the market efficiency proxies. Since our sample of 18 countries is too small to allow for a large set of regressors we proceed in the following way. We use the first principal component of the collectivism index and the UAI of all 18 countries as a culture proxy

$$\text{PC culture} = 0.71 \cdot \text{collectivism} + 0.71 \cdot \text{UAI} \tag{6}$$

which captures 76% of the covariance of the two series. Both loadings are positive, so we would expect to see a larger impact of past sentiment on returns in countries with a high value of this first principal component. For the market efficiency proxy we obtain the first principal component of the market integrity factors[13] for all 18 countries

$$\text{PC market efficiency} = \text{-}0.58 \cdot \text{Acct-}0.47 \cdot \text{Anti-}0.32 \cdot \text{Cpix+}0.58 \cdot \text{Emgt} \tag{7}$$

which captures about 65% of the total covariation between the four series. Due to the scaling of the involved indices, a higher value of the principal component indicates worse institutions. Running regression (5) with both principal components as explanatory variables yields the following result:

$$\underset{}{\hat{\delta}_1^i} = \underset{(0.02)}{-0.014} + \underset{(0.04)}{0.013}\,\text{PC culture}_i - \underset{(0.99)}{0.00}\,\text{PC market efficiency}_i \;\;, \;\; \bar{R}^2 = 0.41 \tag{8}$$

with p-values in parentheses. Evidently, as in Chui, Titman and Wei (2005), the cultural factors heavily dominate the market integrity variables in terms of cross-country explanatory power.

As a next step we follow Chui, Titman and Wei (2005) and conduct a bootstrap analysis which is build on randomly assigning values of an explanatory variable to the dependent variable of country *i*. We use 10,000 simulations for each country and explanatory variable and compute the slope coefficient each time. As before, we denote the estimated slope coefficient from equation (5) as $\hat{\beta}$, the average of the 10,000 bootstrap estimates of the slope coefficient as $\bar{\hat{\beta}}$ and the standard deviation of these slope coefficients by $\sigma\left(\hat{\beta}\right)$. The bootstrap t-values of a slope coefficient can then be computed via

$$t_{\text{boot}} = \left(\hat{\beta} - \bar{\hat{\beta}}\right)^2 / \sigma\left(\hat{\beta}\right). \tag{9}$$

The results of this procedure are shown in <u>Table 8</u> and are confirmative of the conclusions drawn from Table 7. The behavioral factors, i.e. collectivism and the overreaction proxy (UAI) are statistically significant and so is the first principal component of the two cultural dimensions shown in equation (7). Likewise, the only other significant variables are the Cpix and Emgt and education as before.

[13] We only use the 4 non-dummy variables used by CWT since they seem to have most explanatory power as documented in Table 7. Other combinations yield qualitatively identical results.

As a final robustness check, we employ a binary logit model where the dependent variable equals one if the coefficient of sentiment in regression equation (2) is significant, i.e. when there is a statistically significant effect of sentiment on returns, and zero otherwise. We employ the same explanatory variables on the right hand side. Results are presented in Table 9 and show that the cultural and market integrity factors also do a reasonable job in explaining whether a certain country has a significant sentiment-return relationship or not. Note that education is not significant in this setting.

6. Conclusions

We investigate the relation between investor sentiment and future stock returns for 18 industrialized countries in the world and find, that sentiment plays a role in only one half of the countries in our sample. As a pure out of sample test of the sentiment-return relation uncovered for the U.S., this is not very compelling evidence that noise traders move stock prices above or below fundamentally warranted levels. This is true for aggregate market returns as well as for value and growth stocks. The story seems to be more complex than this.

In order to investigate this issue, we look at possible determinants of the strength of the relation between sentiment and returns and find that the influence of noise traders on markets varies cross-sectional in a way that is economically intuitive. The impact of sentiment on returns is higher for countries that are culturally more prone to herd-like investment behavior as hypothesized by Chui, Titman and Wei (2005) and for countries that have less efficient regulatory institutions or less market integrity.

All in all, the findings do not support the notion that irrational noise traders move markets uniformly across countries. Rather than that, institutional quality and more trading culture are strong determinants of the sentiment-return relation.

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Table 1. Descriptive Statistics

This table shows descriptive statistics for all countries used in the analysis. In particular, the table shows the start month of the sample (all series end in December 2005) and the source of the data. Furthermore, it shows means (μ) and standard deviations (σ) for the market return (Market), returns of value stocks (High B/M) and growth stocks (Low B/M). Finally, the last three columns show the mean, standard deviation and first order autocorrelation for the consumer confidence indices employed.

Country	Label	Start	Source	Market		High B/M		Low B/M		Consumer Confidence		
				μ	σ	μ	σ	μ	σ	μ	σ	ρ_{-1}
Australia	ATRL	1985 M1	Datastream	1.24	4.86	1.55	5.11	1.06	5.55	100.59	12.66	0.92
Austria	ATR	1996 M1	DG ECFIN	1.40	4.67	1.91	6.45	0.80	4.54	-1.36	6.41	0.91
Belgium	BEL	1985 M1	DG ECFIN	1.29	5.09	1.83	6.69	1.13	5.30	-7.00	9.53	0.95
Denmark	DEN	1989 M1	DG ECFIN	1.06	5.13	1.24	5.93	1.03	6.10	5.38	8.36	0.95
Finland	FIN	1995 M11	DG ECFIN	1.46	8.97	1.54	7.16	1.69	10.90	14.90	3.84	0.89
France	FRA	1985 M1	DG ECFIN	1.23	5.89	1.54	6.99	1.10	5.83	-18.60	8.49	0.94
Germany	GER	1986 M1	DG ECFIN	0.79	6.16	1.42	6.65	0.69	6.93	-8.98	8.79	0.97
Ireland	IRE	1991 M1	DG ECFIN	1.33	5.26	1.87	7.66	1.05	6.33	-3.87	13.52	0.97
Italy	ITA	1985 M1	DG ECFIN	1.29	7.09	1.25	8.14	1.26	7.20	-12.78	7.06	0.93
Japan	JAP	1985 M1	Datastream	0.49	5.80	1.11	6.70	0.20	6.40	43.26	4.62	0.97
Netherlands	NET	1985 M1	DG ECFIN	1.11	5.07	1.62	7.15	1.04	4.90	4.02	11.68	0.97
New Zealand	NEWZ	1989 M1	Datastream	0.64	5.30	-0.35	8.51	0.80	5.95	112.95	12.00	0.99
Norway	NOR	1992 M9	Datastream	1.44	5.86	2.05	9.57	1.27	5.97	20.06	13.38	0.97
Spain	SPA	1988 M1	DG ECFIN	1.20	5.75	1.74	5.69	0.77	6.28	-10.34	8.96	0.95
Sweden	SWE	1995 M9	DG ECFIN	1.29	6.69	1.65	6.53	1.10	8.35	7.39	7.21	0.94
Switzerland	SWI	1985 M1	Datastream	1.08	4.97	1.31	6.82	0.97	4.84	-10.83	21.66	0.99
United Kingdom	UK	1985 M1	DG ECFIN	1.07	4.64	1.25	5.48	0.99	4.75	-8.25	7.81	0.93
United States	US	1985 M1	Datastream	1.08	4.43	1.23	4.10	1.09	4.88	95.29	12.90	0.84

Table 2. Correlations of international consumer confidence indices

This table shows correlation coefficients of consumer confidence indices across countries. The upper right triangular corresponds to consumer confidence levels whereas the lower left triangular shows correlations for changes in consumer confidence.

	ATRL	ATR	BEL	DEN	FIN	FRA	GER	IRE	ITA	JAP	NET	NEWZ	NOR	ESP	SWE	SWI	UK	US
ATRL		-0.04	-0.02	0.66	-0.26	0.15	-0.30	0.43	0.03	-0.41	-0.02	0.76	0.33	0.20	-0.11	-0.05	0.48	0.31
ATR	0.22		0.75	-0.07	0.27	0.77	0.71	0.17	0.42	-0.29	0.17	-0.14	-0.41	0.33	0.76	0.72	-0.07	0.13
BEL	0.02	0.14		0.09	0.52	0.83	0.65	0.58	0.61	-0.02	0.55	-0.23	0.06	0.73	0.80	0.50	0.35	0.35
DEN	-0.01	-0.07	0.08		0.32	0.27	-0.10	0.66	0.27	-0.37	0.26	0.55	0.73	0.34	0.13	0.07	0.62	0.24
FIN	0.06	0.12	0.18	0.00		0.52	0.43	0.77	0.07	0.15	0.75	-0.47	0.26	0.63	0.61	0.37	0.54	0.61
FRA	0.04	0.11	0.30	0.12	0.05		0.63	0.67	0.54	-0.10	0.55	0.08	0.06	0.66	0.83	0.59	0.34	0.36
GER	-0.02	0.19	0.11	-0.09	0.11	0.03		0.48	0.67	0.25	0.55	-0.31	-0.01	0.62	0.70	0.83	-0.01	0.26
IRE	0.03	0.17	0.15	0.12	0.10	0.16	0.07		0.50	-0.17	0.82	0.18	0.44	0.82	0.47	0.71	0.74	0.66
ITA	0.06	0.22	0.17	0.24	0.08	0.03	-0.01	0.09		-0.03	0.56	-0.05	0.27	0.73	0.24	0.60	0.34	0.34
JAP	0.08	-0.05	0.20	0.01	0.08	0.12	0.00	0.05	0.06		0.01	-0.38	0.50	-0.06	-0.10	0.22	-0.29	0.02
NET	0.03	0.16	0.24	0.25	0.13	0.17	0.11	0.24	0.19	0.04		-0.17	0.33	0.76	0.44	0.52	0.35	0.60
NEWZ	0.11	-0.05	0.01	-0.06	0.05	0.12	0.02	0.00	-0.03	-0.03	-0.05		0.32	-0.08	-0.38	-0.07	0.33	0.05
NOR	-0.01	0.16	0.07	0.04	0.19	-0.01	0.01	0.09	0.02	0.11	0.17	0.13		0.33	-0.19	0.11	0.49	0.28
SPA	-0.02	-0.02	0.13	0.11	0.07	0.26	0.15	0.03	0.25	0.02	0.16	-0.05	0.05		0.55	0.70	0.60	0.57
SWE	0.16	0.27	0.13	0.13	0.25	0.19	0.18	0.04	0.17	0.14	0.14	-0.06	0.13	0.02		0.69	0.18	0.45
SWI	-0.02	0.00	0.14	-0.03	0.10	0.12	0.23	0.11	0.12	0.03	0.14	-0.04	0.16	0.09	0.06		0.22	0.44
UK	0.12	0.08	0.19	0.21	0.09	0.00	0.00	0.24	0.21	0.00	0.08	0.09	0.14	0.22	0.18	-0.07		0.46
US	0.20	0.14	0.14	0.16	0.05	0.09	-0.05	0.11	0.09	0.00	0.17	-0.01	-0.10	0.05	0.17	0.02	0.13	

Table 3. Predictive regression results: aggregate stock market
This table shows predictive regression results for the model specified in (2) with aggregate market returns as dependent variables. $\Delta\overline{R}^2$ denotes the incremental adj. R^2 when sentiment is included in the regression specification. Reported coefficient estimates are bias adjusted and bootstrap p-values are shown. Stars refer to the level of significance: *** 1%, ** 5%, * 10%.

	1 month		3 months		6 months		12 months		24 months	
	coef./ p-val	$\overline{R}^2$/ $\Delta\overline{R}^2$	coef./ p-val	$\overline{R}^2$/ $\Delta\overline{R}^2$	coef./ p-val	$\overline{R}^2$/ $\Delta\overline{R}^2$	coef./ p-val	$\overline{R}^2$/ $\Delta\overline{R}^2$	coef./ p-val	$\overline{R}^2$/ $\Delta\overline{R}^2$
ATRL	0.001	-0.01	0.000	0.00	0.000	0.01	0.001	0.00	0.002	-0.01
	(0.96)	0.00	(0.74)	0.00	(0.80)	0.00	(0.95)	0.00	(0.79)	0.00
ATR	-0.028	0.00	-0.031	0.08	-0.038	0.28	-0.023	0.22	-0.005	0.36
	**(0.03)	0.02	**(0.03)	0.07	**(0.01)	0.22	**(0.02)	0.17	(0.54)	0.01
BEL	-0.021	0.07	-0.021	0.12	-0.021	0.23	-0.020	0.42	-0.018	0.54
	***(0.00)	0.04	***(0.00)	0.10	***(0.00)	0.21	***(0.00)	0.38	***(0.01)	0.54
DEN	0.008	0.03	0.005	0.00	0.003	0.00	0.002	0.03	0.005	0.04
	(0.56)	0.00	(0.76)	0.00	(0.94)	0.00	(1.00)	-0.01	(0.75)	0.01
FIN	0.020	0.01	0.032	0.10	0.039	0.24	0.015	0.42	0.007	0.50
	(0.65)	-0.01	(0.42)	0.01	(0.20)	0.04	(0.37)	0.01	(0.76)	0.00
FRA	-0.018	0.00	-0.012	0.01	-0.007	0.02	-0.007	0.06	-0.015	0.23
	*(0.09)	0.01	(0.21)	0.01	(0.37)	0.01	(0.35)	0.02	**(0.01)	0.16
GER	-0.015	0.03	-0.018	0.04	-0.019	0.10	-0.017	0.17	-0.015	0.30
	**(0.05)	0.01	**(0.02)	0.05	**(0.02)	0.11	*(0.05)	0.18	*(0.06)	0.27
IRE	0.003	0.04	0.002	0.07	0.001	0.14	0.000	0.20	-0.004	0.41
	(0.78)	0.00	(0.97)	-0.01	(0.99)	-0.01	(0.82)	0.00	(0.22)	0.08
ITA	-0.035	0.03	-0.033	0.10	-0.033	0.18	-0.028	0.24	-0.009	0.09
	***(0.00)	0.03	***(0.00)	0.08	***(0.00)	0.13	***(0.01)	0.17	(0.38)	0.03
JAP	-0.102	0.06	-0.075	0.11	-0.057	0.16	-0.029	0.09	-0.019	0.06
	***(0.00)	0.05	***(0.00)	0.07	**(0.02)	0.07	(0.21)	0.04	(0.22)	0.03
NET	0.002	0.03	0.002	0.03	0.001	0.05	0.000	0.08	-0.003	0.12
	(0.96)	0.00	(0.95)	0.00	(0.86)	0.00	(0.75)	0.00	(0.48)	0.05
NEWZ	0.009	0.06	0.006	0.13	0.004	0.09	0.002	0.21	-0.001	0.19
	(0.44)	0.00	(0.66)	0.00	(0.86)	0.00	(0.89)	0.00	(0.68)	0.02
NOR	-0.005	-0.01	-0.003	0.00	-0.003	0.04	-0.005	0.14	-0.003	0.28
	*(0.09)	0.01	(0.24)	0.02	(0.25)	0.04	(0.14)	0.11	*(0.09)	0.14
SPA	-0.017	0.09	-0.015	0.13	-0.015	0.15	-0.013	0.20	-0.012	0.18
	*(0.06)	0.01	**(0.05)	0.04	*(0.07)	0.08	(0.21)	0.12	(0.30)	0.16
SWE	-0.002	0.04	-0.008	0.10	-0.009	0.21	-0.016	0.40	-0.011	0.45
	(0.77)	-0.01	(0.53)	0.00	(0.52)	0.01	*(0.09)	0.06	(0.32)	0.05
SWI	-0.020	0.04	-0.019	0.14	-0.013	0.21	-0.009	0.37	-0.010	0.48
	***(0.01)	0.03	**(0.03)	0.07	(0.11)	0.06	(0.17)	0.07	(0.15)	0.16
UK	-0.006	0.00	-0.007	0.02	-0.003	0.08	-0.004	0.15	-0.004	0.20
	(0.31)	0.00	(0.28)	0.01	(0.50)	0.01	(0.40)	0.03	(0.36)	0.04
US	-0.013	0.02	-0.014	0.10	-0.009	0.13	-0.005	0.17	-0.004	0.12
	**(0.02)	0.03	***(0.01)	0.09	*(0.07)	0.09	(0.20)	0.07	(0.29)	0.08

Table 4. Predictive regression results: value stocks
This table shows predictive regression results for the model specified in (2) with returns of value stocks as dependent variables. $\Delta\overline{R}^2$ denotes the incremental adj. R^2 when sentiment is included in the regression specification. Reported coefficient estimates are bias adjusted and bootstrap p-values are shown. Stars refer to the level of significance: *** 1%, ** 5%, * 10%.

	1 month		3 months		6 months		12 months		24 months	
	coef./ p-val	$\overline{R}^2$/ $\Delta\overline{R}^2$	coef./ p-val	$\overline{R}^2$/ $\Delta\overline{R}^2$	coef./ p-val	$\overline{R}^2$/ $\Delta\overline{R}^2$	coef./ p-val	$\overline{R}^2$/ $\Delta\overline{R}^2$	coef./ p-val	$\overline{R}^2$/ $\Delta\overline{R}^2$
ATRL	-0.001	-0.01	-0.003	0.00	-0.003	0.03	-0.002	0.14	-0.002	0.14
	(0.65)	0.00	(0.45)	0.00	(0.50)	0.01	(0.49)	0.02	(0.46)	0.03
ATR	-0.030	0.00	-0.030	0.04	-0.031	0.14	-0.022	0.24	-0.010	0.33
	**(0.04)	0.02	*(0.06)	0.06	**(0.02)	0.16	**(0.01)	0.23	**(0.04)	0.10
BEL	-0.013	0.04	-0.013	0.05	-0.011	0.08	-0.009	0.13	-0.007	0.18
	**(0.04)	0.01	**(0.02)	0.04	**(0.03)	0.08	*(0.06)	0.14	(0.16)	0.19
DEN	0.011	0.01	0.011	0.00	0.008	-0.01	0.008	0.01	0.007	0.08
	(0.37)	0.00	(0.35)	0.01	(0.61)	0.01	(0.59)	0.02	(0.54)	0.04
FIN	-0.023	0.00	-0.014	0.03	-0.031	0.10	-0.033	0.21	-0.020	0.50
	(0.49)	0.00	(0.64)	0.00	(0.21)	0.04	**(0.03)	0.11	**(0.04)	0.24
FRA	-0.018	0.00	-0.013	0.02	-0.008	0.04	-0.008	0.10	-0.015	0.24
	*(0.10)	0.01	(0.17)	0.01	(0.26)	0.01	(0.33)	0.02	**(0.03)	0.18
GER	-0.015	0.04	-0.017	0.05	-0.018	0.09	-0.017	0.17	-0.015	0.30
	*(0.09)	0.01	**(0.05)	0.04	**(0.04)	0.09	*(0.06)	0.18	(0.11)	0.26
IRE	0.002	-0.02	0.004	-0.02	0.003	-0.02	0.004	0.06	0.004	0.18
	(0.92)	-0.01	(0.79)	0.00	(0.84)	0.00	(0.70)	0.01	(0.26)	0.06
ITA	-0.041	0.04	-0.041	0.12	-0.041	0.22	-0.038	0.33	-0.012	0.12
	***(0.00)	0.04	***(0.00)	0.11	***(0.00)	0.19	***(0.00)	0.29	(0.21)	0.05
JAP	-0.102	0.06	-0.071	0.10	-0.064	0.20	-0.049	0.24	-0.027	0.19
	***(0.00)	0.05	***(0.01)	0.07	**(0.04)	0.11	*(0.06)	0.12	*(0.10)	0.08
NET	-0.007	0.05	-0.006	0.04	-0.006	0.06	-0.005	0.12	-0.005	0.25
	(0.19)	0.01	(0.22)	0.02	(0.16)	0.04	(0.19)	0.07	(0.14)	0.18
NEWZ	0.007	0.04	0.006	0.06	0.006	0.08	0.006	0.21	0.007	0.48
	(0.34)	0.00	(0.42)	0.01	(0.46)	0.02	(0.35)	0.06	*(0.10)	0.21
NOR	-0.010	0.03	-0.009	0.10	-0.010	0.15	-0.010	0.18	-0.005	0.31
	**(0.03)	0.03	**(0.03)	0.06	*(0.07)	0.12	*(0.08)	0.19	(0.14)	0.17
SPA	-0.006	0.04	-0.006	0.09	-0.005	0.06	-0.003	0.06	-0.003	0.02
	(0.45)	0.00	(0.29)	0.00	(0.34)	0.01	(0.65)	0.01	(0.65)	0.01
SWE	-0.040	0.04	-0.037	0.14	-0.033	0.22	-0.015	0.17	-0.004	0.52
	**(0.02)	0.04	***(0.00)	0.11	***(0.00)	0.17	*(0.10)	0.08	(0.45)	0.02
SWI	-0.013	0.04	-0.014	0.14	-0.009	0.24	-0.007	0.36	-0.011	0.46
	*(0.09)	0.01	*(0.08)	0.03	(0.24)	0.03	(0.34)	0.02	(0.14)	0.14
UK	-0.009	0.01	-0.010	0.03	-0.006	0.09	-0.007	0.14	-0.006	0.11
	(0.17)	0.00	(0.19)	0.02	(0.39)	0.02	(0.27)	0.05	(0.23)	0.07
US	-0.014	0.02	-0.015	0.09	-0.009	0.13	-0.003	0.23	-0.002	0.15
	**(0.02)	0.03	***(0.01)	0.09	*(0.09)	0.08	(0.34)	0.03	(0.18)	0.06

Table 5. Predictive regression results: growth stocks
This table shows predictive regression results for the model specified in (2) with returns of growth stocks as dependent variables. $\Delta\overline{R}^2$ denotes the incremental adj. R^2 when sentiment is included in the regression specification. Reported coefficient estimates are bias adjusted and bootstrap p-values are shown. Stars refer to the level of significance: *** 1%, ** 5%, * 10%.

	1 month		3 months		6 months		12 months		24 months	
	coef./p-val	$\overline{R}^2$/ $\Delta\overline{R}^2$	coef./ p-val	$\overline{R}^2$/ $\Delta\overline{R}^2$	coef./ p-val	$\overline{R}^2$/ $\Delta\overline{R}^2$	coef./ p-val	$\overline{R}^2$/ $\Delta\overline{R}^2$	coef./ p-val	$\overline{R}^2$/ $\Delta\overline{R}^2$
ATRL	0.003	0.00	0.001	0.03	0.000	0.04	0.001	0.01	0.001	0.00
	(0.72)	0.00	(0.91)	0.00	(0.81)	0.00	(0.97)	0.00	(0.95)	0.00
ATR	-0.033	0.01	-0.036	0.11	-0.039	0.27	-0.025	0.19	-0.006	0.39
	**(0.02)	0.03	***(0.01)	0.10	***(0.01)	0.21	*(0.09)	0.13	(0.68)	0.00
BEL	-0.020	0.06	-0.022	0.14	-0.021	0.24	-0.021	0.44	-0.018	0.53
	***(0.00)	0.03	***(0.00)	0.11	***(0.00)	0.23	***(0.00)	0.41	**(0.02)	0.52
DEN	-0.001	0.03	-0.003	0.02	-0.005	0.04	-0.006	0.06	0.000	0.00
	(0.75)	0.00	(0.59)	0.00	(0.55)	0.01	(0.44)	0.02	(0.96)	-0.01
FIN	0.033	0.00	0.034	0.09	0.044	0.23	0.019	0.39	0.011	0.49
	(0.42)	0.00	(0.35)	0.01	(0.12)	0.06	(0.27)	0.01	(0.64)	0.00
FRA	-0.019	0.00	-0.011	0.00	-0.006	0.01	-0.005	0.03	-0.012	0.19
	*(0.10)	0.01	(0.27)	0.01	(0.48)	0.00	(0.50)	0.01	*(0.10)	0.09
GER	-0.014	0.04	-0.018	0.04	-0.018	0.09	-0.016	0.16	-0.016	0.33
	*(0.08)	0.01	**(0.02)	0.05	**(0.02)	0.10	*(0.07)	0.17	**(0.04)	0.31
IRE	-0.001	0.04	-0.003	0.11	-0.004	0.22	-0.004	0.25	-0.007	0.52
	(0.73)	0.00	(0.51)	0.00	(0.46)	0.01	(0.41)	0.03	(0.14)	0.15
ITA	-0.031	0.02	-0.029	0.09	-0.029	0.16	-0.024	0.21	-0.008	0.11
	***(0.00)	0.02	***(0.00)	0.06	***(0.00)	0.10	**(0.02)	0.12	(0.45)	0.02
JAP	-0.098	0.06	-0.070	0.10	-0.051	0.14	-0.020	0.07	-0.012	0.05
	***(0.00)	0.04	***(0.00)	0.06	**(0.01)	0.06	(0.32)	0.02	(0.36)	0.01
NET	-0.002	0.02	-0.001	0.02	-0.002	0.04	-0.004	0.10	-0.007	0.24
	(0.51)	0.00	(0.53)	0.00	(0.43)	0.01	(0.30)	0.04	(0.16)	0.17
NEWZ	0.008	0.06	0.005	0.18	0.003	0.20	0.001	0.38	-0.001	0.32
	(0.58)	0.00	(0.81)	0.00	(0.96)	0.00	(0.66)	0.00	(0.66)	0.03
NOR	0.000	-0.02	0.002	-0.02	0.002	-0.01	-0.002	0.07	-0.003	0.26
	(0.47)	0.00	(0.78)	-0.01	(0.79)	0.00	(0.36)	0.04	(0.19)	0.12
SPA	-0.022	0.14	-0.020	0.20	-0.020	0.27	-0.018	0.37	-0.014	0.30
	**(0.02)	0.02	**(0.01)	0.06	**(0.02)	0.14	*(0.06)	0.22	*(0.10)	0.21
SWE	0.004	0.06	-0.001	0.11	-0.002	0.21	-0.017	0.39	-0.011	0.43
	(0.99)	-0.01	(0.79)	-0.01	(0.79)	0.00	(0.19)	0.05	(0.41)	0.04
SWI	-0.023	0.05	-0.022	0.16	-0.016	0.22	-0.012	0.41	-0.012	0.59
	***(0.00)	0.04	***(0.01)	0.11	**(0.03)	0.10	*(0.06)	0.11	**(0.04)	0.20
UK	-0.002	0.00	-0.001	0.02	0.002	0.08	0.000	0.14	-0.001	0.21
	(0.59)	0.00	(0.64)	0.00	(0.96)	0.00	(0.77)	0.00	(0.65)	0.01
US	-0.013	0.02	-0.013	0.09	-0.007	0.11	-0.004	0.16	-0.004	0.16
	**(0.02)	0.03	**(0.01)	0.08	(0.13)	0.06	(0.28)	0.05	(0.38)	0.05

Table 6. Correlation of consumer confidence innovations and unexpected returns

This table shows correlation coefficients for unexpected returns and sentiment innovations from the predictive system in equations (3) and (4) for market returns and returns of value and growth stocks.

	market	value	growth
ATRL	0.03	0.05	0.04
ATR	0.13	0.03	0.11
BEL	0.08	0.02	0.12
DEN	0.02	0.06	0.02
FIN	0.03	-0.03	0.04
FRA	0.14	0.16	0.12
GER	0.02	0.02	0.01
IRE	0.03	0.09	0.07
ITA	0.09	0.10	0.07
JAP	0.10	0.16	0.07
NET	0.13	0.14	0.12
NEWZ	0.20	-0.02	0.22
NOR	0.15	0.10	0.13
SPA	0.16	0.07	0.17
SWE	0.15	0.15	0.11
SWI	0.02	0.05	0.02
UK	0.12	0.12	0.12
US	0.12	0.17	0.10

Table 7. Cross-sectional analysis of the sentiment-return relation

The table shows univariate regression results for the cross-section of countries. Each row represents a regression with the impact of consumer confidence on next month's stock return as dependent variable and the row's variable as the explanatory variable. The second column (+ / −) shows the theoretically expected effect of a respective regressor on the dependent variable. Statistically significant results (at least at the 10%-level) are in bold numbers.

		slope coef.	t-stat	$\overline{R}^2$
Behavioral factors				
Collectivism	–	-0.109	**-2.442**	0.23
Uncertainty avoidance	–	-0.077	**-3.267**	0.36
PC culture	–	-1.371	**-3.533**	0.40
Market integrity				
Legal origin		1.672	1.229	0.03
Anti-director rights	+	0.111	0.243	-0.06
Corruption perception	+	1.524	**2.907**	0.30
Accounting standards	+	0.137	1.606	0.09
Earnings management	–	-0.157	**-2.083**	0.17
Other factors				
No. of Analysts	+	-0.024	-0.282	-0.06
Forecast dispersion	–	0.675	0.068	-0.06
Forecast error	–	-4.559	-0.712	-0.03
Share inst. investors	+	2.823	0.825	-0.02
Marketcap. / GDP	+	0.006	0.473	-0.05
Turnover	+	0.189	0.180	-0.06
Short selling	+	-2.073	-1.271	0.03
Education	+	0.096	**2.071**	0.16

Table 8. Bootstrap analysis

This table shows results from a bootstrap analysis where values of explanatory variables are randomly permuted across countries. Specifically, each country is assigned its own value of the regressand, the impact of sentiment on returns, and the explanatory variable for each country is drawn randomly from the pool of all countries. For the first univariaten regression for example, Australia is assigned the education level of Belgium, Belgium is assigned the education level of Austria and so. This procedure is repeated 10,000 times and the empirical distribution of slope coefficients is used to construct bias adjusted test statistics as indicated in the text. The second column (+ / −) shows the theoretically expected effect of a respective regressor on the dependent variable. Statistically significant results (at least at the 10%-level) are in bold numbers.

		slope coefficient	mean slope coefficient from bootstrap	stand. dev. from bootstrap	bootstrap t-statistic
		$\hat{\beta}$	$\bar{\beta}$	$\sigma(\bar{\beta})$	$(\hat{\beta}-\bar{\beta})/\sigma(\hat{\beta})$
Behavioral factors					
Collectivism	–	-0.109	0.000	0.051	**-2.137**
Uncertainty avoidance	–	-0.077	0.001	0.029	**-2.635**
PC culture	–	-1.371	0.002	0.499	**-2.745**
Market integrity					
Legal origin		1.672	0.006	1.383	1.209
Anti-director rights	+	0.111	-0.008	0.449	0.247
Corruption perception	+	1.524	-0.004	0.618	**2.469**
Accounting standards	+	0.137	0.001	0.090	1.517
Earnings management	–	-0.157	0.000	0.084	**-1.872**
Other factors					
No. of Analysts	+	-0.024	0.000	0.082	-0.293
Forecast dispersion	–	0.675	0.143	9.506	0.071
Forecast error	–	-4.559	0.021	6.276	-0.727
Share inst. investors	+	2.823	0.001	3.369	0.838
Marketcap. / GDP	+	0.006	0.000	0.012	0.482
Turnover	+	0.189	-0.022	1.016	0.186
Short selling	+	-2.073	0.023	1.673	-1.239
Education	+	0.096	0.000	0.050	**1.925**

Table 9. Probit regressions

This table shows results from univariate probit regressions where the dependent variable equals one if there is a significant sentiment-return relation for country *i* and zero otherwise. The second column (+ / −) shows the theoretically expected effect of a respective regressor on the dependent variable. Statistically significant results (at least at the 10%-level) are in bold numbers.

		slope coefficient	t-stat	Mc-Fadden's R^2
Behavioral factors				
Collectivism	+	0.051	**1.707**	0.14
Uncertainty avoidance	+	0.090	**2.026**	0.52
PC culture	+	1.023	**2.325**	0.39
Market integrity				
Legal origin		-1.344	**-1.828**	0.15
Anti-director rights	−	-0.273	-1.172	0.06
Corruption perception	−	-1.550	**-2.473**	0.45
Accounting standards	−	-0.114	**-2.019**	0.23
Earnings management	+	0.096	**2.023**	0.21
Other factors				
No. of Analysts	−	0.055	1.285	0.07
Forecast dispersion	+	6.213	1.251	0.07
Forecast error	+	5.317	1.585	0.11
Share inst. investors	−	-2.349	-1.015	0.06
Marketcap. / GDP	−	-0.002	-0.351	0.00
Turnover	−	0.495	0.928	0.04
Short selling dummy	−	0.684	0.837	0.03
Education	−	-0.023	-0.938	0.04