The Dispersion Effect in International Stock Returns*

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ABSTRACT

We find that stocks exhibiting high dispersion in analysts' earnings forecasts do not only underperform in the U.S. but also in some European countries. However, testing for the dispersion effect in many countries calls for adequate multiple testing controls. Under this paradigm it turns out that none of the naïvely derived dispersion effects proves to be a sustainable phenomenon—not even the U.S. dispersion effect. Rationalizing this finding, we document that the dispersion effect's abnormal returns amass in a very narrow time frame and mainly derive from a bet against the technology bubble that would have been rather difficult to implement. We further establish the dispersion effect to be most pronounced among more opaque information environments. Since the dispersion effect is especially pronounced when limited to high idiosyncratic risk or highly illiquid stocks, we further corroborate that high arbitrage costs additionally deter investors from its exploitation.

Keywords: International Dispersion Effect, Multiple Hypotheses Testing, Information Uncertainty, Liquidity

JEL Classification: G12; G14; G15

Earnings estimates of financial analysts serve as a timely measure for assessing a company's current value. Comprising the expertise of different analysts the Institutional Brokers' Estimate System (I/B/E/S) provides a consensus estimate, which basically is a mean value of all available earnings forecasts for a given company. To judge the credibility of the earnings signal, one can resort to additional information embedded in the distribution of analysts' earnings forecasts. Especially, the latter's second moment is a natural candidate to capture the dispersion of analysts' earnings forecasts. Intuitively, one may well expect companies with higher dispersion in analysts' earnings forecast to earn higher returns, thus compensating investors for bearing uncertain earnings prospects. However, empirical evidence for the U.S. is at odds with dispersion being a priced risk factor. Even more so, Diether, Malloy, and Scherbina (2002) document that low dispersion stocks are significantly outperforming high dispersion stocks.

In rationalizing this striking result Diether, Malloy, and Scherbina (2002) contend that dispersion may thus not be viewed as a risk factor, but rather as a metric for differences of opinion. Invoking an argument of Miller (1977), they suggest that prices tend to reflect the view of the optimistic investors whenever there is disagreement about a stock's value since the pessimistic investors' views are often not revealed due to short-sale constraints. In fact, Boehme, Danielsen, and Sorescu (2006) show that the dispersion effect is most prominent among short-sale constrained firms. Of course, the high dispersion stocks' prices are bound to fall once the uncertainty is resolved.

We wonder whether this dispersion effect is common to various markets or whether it is unique to the U.S.. In that regard, we provide original evidence of a dispersion effect in some European markets. However, our finding may suffer from data snooping biases since some of the detected dispersion effects may arise by chance alone—given the multitude of tests involved. To account for these biases, we complement the traditional analysis with most recent multiple testing methods. Under this paradigm, it turns out that the dispersion effect is not a robust phenomenon across countries.

At first glance, this result is highly unexpected and we feel the need for an economic argument rationalizing the deficiencies inherent in the dispersion effects. A simple analysis of the time series nature of the dispersion effect reveals that the positive European return differentials amass in a very narrow time frame of three years, given a total sample period of twenty years. On the other hand, the U.S. dispersion effect provides a more favorable return pattern providing consistent abnormal returns most of the time. Still, the U.S. and the European dispersion strategy have a common characteristic in that they both have been very effective in hedging against the burst of the technology bubble. However, we question the practicability of the respective hedge strategy, because capturing the abnormal returns would have required short-selling of technology firms way before their stock price peaks. Hence, most investors following the dispersion strategy would have been squeezed out of the market by margin calls just before the strategy would have become profitable. Our observation that the latter bet appears to be the single driver of the naïvely derived return differentials therefore substantiates the doubts raised by our data snooping controls.

In further shaping intuition as to the dispersion effect's nature, we find it to be particularly pronounced among high and low dispersion stocks characterized by high information uncertainty as measured by analyst coverage or total stock volatility. In a related vein, Avramov, Chordia, Jostova, and Philipov (2008) find the U.S. dispersion effect to be only profitable among the worst-rated firms while it is non-existent for higher-rated firms. Likewise, Sadka and Scherbina (2007) show that analyst disagreement is closely related to trading costs in the U.S.. In particular, the mispricing is most severe for less liquid stocks. We corroborate this argument by documenting the highest mispricing when limiting the sample to stocks with high idiosyncratic volatility or to stocks subject to high illiquidity. This observation suggests that high arbitrage costs additionally deter investors from exploiting the dispersion effect.

The paper's structure is as follows. Section I presents the data we use for our study. In Section II, we screen for the dispersion effect in various developed equity markets. Section III investigates the role of data snooping biases when testing for the dispersion effect across many markets. Section IV seeks to foster the economic rationale governing the dispersion effect. First, we consider the dispersion effects' evolution over time. Second, we examine the interaction of the dispersion effect and distinct information uncertainty environments. Finally, we establish a link between the dispersion effect and liquidity. Section V concludes.

I. Data

A. Sample Selection

We use a comprehensive sample of companies domiciled in 16 equity markets, 15 European markets and the U.S., covering the period from 1987 to 2007. All data has been gathered from Datastream including I/B/E/S earnings revisions data.

Table I contains descriptive characteristics on the sample countries classified by region. We collect companies for each country by merging the live and dead research lists provided by Datastream on July 2nd, 2007 and thereby obtain a total number of 65,738 companies. To arrive at our final sample, we have pruned the initial country research lists as follows. First, we adjust each country list for secondary issues and cross-country listings to prevent us from double-counting. In particular, we extract 30,454 companies. Hence, one half of the initial list does refer to major listings. Second, we screen for non-equity issues, i.e., we exclude investment trusts, ADRs, and the like. Third, we also exclude OTC stocks and stocks that are only listed on regional exchanges. After these two screens 16,568 companies remain. We further exclude those companies having market capitalization below 10 million USD, which leaves us with a final sample of 12,998 companies. Almost one half are U.S. companies and the biggest five markets comprise around 80%. To avoid survivorship bias, the sample includes 4,524 "dead" companies, i.e., one third of the whole sample, ranging from 16.9% for Greece to 52.2% for Portugal. The label "dead" applies to companies in extreme distress and to those being merged, delisted, or converted.

Since we aim to investigate the dispersion effect, we additionally check the coverage of return and earnings revisions data. Unsurprisingly, the coverage for return data is close to 100% in each country, on average 98.4% of the companies do exhibit at least one return observation over the course of the sample period. On the other hand, the earnings estimate figures are more fragmentary. However, the average coverage still amounts to 75.5% spanning a range from 62.6% (Belgium) to 94.1% (Spain). Note that our sample contains a certain amount of penny stocks that will not be included in the investment strategies. We do not discard them right away, since being a penny stock is not a static firm characteristic. In particular, we do not invest in companies with stock price below $5 at the beginning of a given month. To give an idea of the investment universe's size over time, we provide the absolute number of companies to be considered for the dispersion strategies across countries in Table II. All in all, we have 58,510 firm-years of which one half is concentrated in the U.S. (32,787 firm-years), followed by the U.K. (4,514 firm-years) and France (4,182 firm-years). Note that the number of available companies usually increases over the years, with a peak in 1999 followed by a slight setback.

B. Return Data

We consider monthly stock returns in local currency inclusive of dividends by employing total return figures. To represent the respective markets, we choose broad market indices as compiled by Datastream and 3-month-T-bills serve as a proxy for the risk-free rate.

Ince and Porter (2006) show that the well-known price momentum effect cannot be detected in the U.S. when naïvely using raw Datastream data, an observation that appears to extend to other international markets as well, see Leippold and Lohre (2008). For curing these data issues, Ince and Porter (2006) propose two major adjustments. One is to remove non-common equity from the respective country research lists and the other is to screen for irregular return patterns. Since the former has already been dealt with when deleting secondary issues, we merely have to address the quality of return data. We follow Ince and Porter (2006) in adjusting the return data to allow for reasonable statistical and economic inferences.

Interestingly, we find our comprehensive sample to be hardly confounded by erroneous return data. For instance, the U.S. only requires to change 99 return observations, which represents 0.01% of all observations. This fraction is even smaller for Europe, for which we adjust 54 observations across all 16 countries. We assume that Datastream has significantly corrected the database in response to the objections of Ince and Porter (2006).[1] Still, the remaining issues might severely affect statistical inferences and weeding them out renders us even more comfortable with the quality of data.

[1] In fact, according to an employee of Thomson Financial Services the return time series is constantly screened for possible glitches in the price, dividend, and adjustment factor history. In particular, the history of several U.S. OTC stocks has been fixed recently, which presumably accounted for a lot of issues detected by Ince and Porter (2006).

II. Testing for the Dispersion Effect

A. Risk and Return

We implement the dispersion strategy as in Diether, Malloy, and Scherbina (2002), defining dispersion as the standard deviation of earnings forecasts over the absolute value of its mean. Based on the previous month's dispersion, we assign stocks monthly into five quintiles for larger countries or terciles for smaller countries, depending on the number of available companies. Adopting a holding period of one month the dispersion strategy is to long stocks with low dispersion and to short stocks with high dispersion in analysts' earnings forecasts.

Table III gives average monthly buy-and-hold return and volatility figures of dispersion-based portfolios by country. First, we assess the profitability of the dispersion hedge strategy by considering the return differential—low dispersion minus high dispersion stocks—along with its t-statistic. For the U.S., we confirm prior evidence of Diether, Malloy, and Scherbina (2002) or Avramov, Chordia, Jostova, and Philipov (2008). We obtain a monthly hedge return of 49 basis points at a monthly volatility of 3.85%, which give rise to a t-statistic of 1.98. Note that the returns of the dispersion-based portfolios decrease monotonically with increasing dispersion, while their volatility is positively related to dispersion. The aggregate European hedge strategy provides a somewhat smaller return of 38 basis points per month, but at a considerably lower volatility of 2.87%. Further, using the t-statistic metric, we identify the Netherlands to have an anomalous returns on a 5% level. If we relax the significance level to 10%, Germany, Italy and Sweden appear to be anomalous as well. With the exception of Norway, all of the remaining countries exhibit positive return differentials. While the low dispersion portfolio is sometimes contributing significantly to the return spread, we note that the lion's share is typically due to the high dispersion portfolio.

Given this persuasive evidence of international dispersion effects, we seek to further characterize the involved dispersion portfolios by examining some descriptive statistics in Table IV. First of all, inspecting the average dispersion of the available dispersion-based portfolios suggests that the dispersion in analysts' earnings forecasts follows a heavily right-skewed distribution. Especially, the average dispersion of the high dispersion is rather large. For instance, while the fourth U.S.

quintile portfolio has an average dispersion of 7.52%, the high dispersion portfolio figure amounts to 55.32%. Note that this pattern is even more pronounced for the European countries. Just consider the high dispersion portfolio of the European strategy, which is characterized by a mean dispersion in excess of 100% indicating considerable disagreement among the analysts. On the other hand, the low dispersion portfolio has mean dispersion of 2.39%, which is indicative of a strong consensus among the analysts.

Moreover, across all countries the dispersion-based portfolios' volatility is increasing with dispersion, which calls for controlling of a systematic risk bias possibly inherent in these portfolios. Thus, we compute betas according to the classical regression

$$R_{it} - R_{Ft} = \alpha_i + \beta_i(R_{Mt} - R_{Ft}) + \varepsilon_{it}, \tag{1}$$

where R_{it} denotes the gross return of quintile i, R_{Ft} is the risk-free rate and R_{Mt} is the country's market return. Unsurprisingly, the beta of the dispersion-based portfolios is also increasing with dispersion. Moreover, in all countries the highest betas obtain for the high dispersion quintile. Also, while the remaining portfolios with lower dispersion have rather homogenous size characteristics, we observe a severe size bias on behalf of the high dispersion portfolio. In particular, measuring size in terms of the logarithm of market value, we find that the high dispersion portfolio is mostly populated by small caps, which may in turn explain its conspicuous market exposure. Finally, turning to the hedge strategy we almost always observe considerable negative exposure to the market portfolio, suggesting distinct hedge potential with respect to market risk.

B. Time-Series Regressions

Some of the examined dispersion strategies are highly volatile and we thus wonder whether their high returns are solely compensating for risk. To check if the long-short portfolio returns can be attributed to common risk factors one usually adopts the standard approach of Fama and French (1993) and estimates a regression model of the form

$$R_{Lt} - R_{St} = \alpha + \beta(R_{Mt} - R_{Ft}) + \gamma R_{SMBt} + \delta R_{HMLt} + \varepsilon_t, \tag{2}$$

where $R_{Lt} - R_{St}$ is the return difference of the respective hedge strategy, i.e., the long leg minus the short leg. Regarding the country-specific common risk factor portfolios, the market return R_{Mt} is represented by some broad market index, the size factor R_{SMBt} is mimicked by a small cap index minus the risk-free rate, $R_{SCt} - R_{Ft}$, and the value factor R_{HMLt} is the difference between a value index and the corresponding growth index, $R_{Vt} - R_{Gt}$. Given the factor structure in (2), we can identify the hedge strategy's alpha net of common risk factors.

In addition to the Fama-French factors, one commonly considers momentum as a further factor to control for. We conjecture earnings momentum to be closely related to the dispersion effect. Indeed, in untabulated results, we find earnings momentum and the dispersion effect to be highly correlated in terms of returns and Fama-French alphas. While a high return correlation may simply be picking up systematic risk factor tilts shared by both anomalies, the high correlation in Fama-French alphas suggests that there is a common unsystematic component at work as well. Therefore, when testing for the dispersion effect, we extend the Fama-French setting of equation (2) to a four-factor model by adding an earnings momentum factor:

$$R_{Lt} - R_{St} = \alpha + \beta(R_{Mt} - R_{Ft}) + \gamma R_{SMBt} + \delta R_{HMLt} + \zeta R_{PMNt} + \varepsilon_t, \qquad (3)$$

where R_{PMNt} refers to the returns of the earnings momentum strategy (positive minus negative earnings revisions). In computing the earnings momentum factor, we follow the standard methodology of Chan, Jegadeesh, and Lakonishok (1996).

Table V displays the results of the four-factor regression for dispersion-based portfolios according to equation (3) that uses 240 monthly returns spanning the period from July 1987 to June 2007. First, we examine the results for the U.S.. We observe that the risk factors explain most of the variation in the excess returns of both legs of the dispersion strategy. In particular, the low dispersion portfolio heavily loads to the market and earnings momentum factor and exhibits a minor size bias, rendering the remaining alpha of -1 basis points insignificant. On the other hand, the high dispersion portfolio generally behaves like small-sized growth stocks with a significant negative earnings momentum loading. Still, an unexplained alpha of -57 basis points remains; thus, the long-short strategy earns a highly significant monthly alpha of 56 basis points. Interestingly, while this alpha is large, the statistical fit of the regression is fairly good considering the fact that one is analyzing a long-short strategy. More than one half of the variation in the dispersion strategy's excess returns is captured by the four-factor model. In particular, we confirm the considerate negative market exposure together with a negative loading on size. Finally, we identify a close relation between earnings momentum and the dispersion effect. However, the dispersion effect is not subsumed by earnings momentum suggesting that both represent distinct phenomena.

By and large, these observations extend to other countries as well. Of the 15 European countries, we document four alphas that are significant on the 5%-level and relaxing the latter to 10%, we obtain six significant alphas—ranging from 43 basis points for the German and Spanish strategy to 69 basis points for the Swedish strategy. Also, it appears to be a stylized fact that the alpha of the dispersion effect is governed by the underperformance of the high dispersion portfolio. While the adjusted R^2 for European strategies usually do not reach the level of the U.S. strategy we still observe remarkably high values. Half of the regressions for the long-short strategies are characterized by adjusted R^2s in excess of 30%. These figures are quite sizeable given that typical values for long-short strategies are single-digited. Note that the returns for the aggregate European strategy are fully captured by the common factor controls.

To further examine the evolution of both hedge strategies over time, we compute the related country alphas via trailing four-factor regressions according to equation (3). We use a 36-month window and plot the resulting alphas in Figure 1 for the six strategies exhibiting significant hedge returns. To also visualize the importance of adjusting for the earnings momentum factor, we additionally plot the alphas arising from a Fama-French regression according to equation (2).

[Figure 1 about here.]

First of all, we note that the inclusion of the earnings momentum factor is relevant, since the Fama-French alpha is significantly reduced in many countries. Also, while this reduction typically is present throughout the whole sample period, it appears to be weakest at the turn of the century. Second, the U.S. strategy exhibits the most sizeable alpha, which is significantly positive for the the whole sample period. Third, across the remaining countries the evolution of alpha appears downward shifted when compared to the U.S..

III. Data Snooping Biases and the Dispersion Effect

From the previous section, we learn that seven out of 16 countries exhibit positive and significant alphas. However, these alphas may be spurious, since they arise from single hypothesis tests performed for each country. Therefore, we will subject the dispersion hedge strategies to recent econometric methods that additionally account for multiple testing. These testing procedures either control the *familywise error rate* (FWE) or the *false discovery proportion* (FDP). Below, we will briefly introduce the concept behind these methods.

A. Accounting for Multiple Testing

When simultaneously testing several, say S, trading strategies against a common benchmark, some strategies may outperform others by chance alone. For instance, extensive re-use of a given database or testing one investment idea on various markets of similar nature are prime examples. The latter case applies to our setting since we wish to detect the dispersion effect in several equity markets simultaneously. Therefore, we must combine the individual hypotheses into multiple testing procedures that control for the possibility of data-snooping biases.[2]

A.1. Methods Based on the FWE

The traditional way to account for multiple testing is to control the familywise error rate, defined as the probability of rejecting at least one of the true null hypothesis. If this objective is achieved, one can be confident that all hypotheses that have been rejected are indeed false (instead of some true ones having been rejected by chance alone). Many methods that control the FWE exist and the simplest one is the well-known Bonferroni (1936) method. It consists of a plain p-value adjustment, in particular, the initial significance level α is divided by the number of hypotheses under test. Evidently, this method is strict and would result in an outright rejection of any dispersion effect in all countries. However, it is also important to use a method that provides as much power as possible, so that false hypotheses have a chance of being detected.

Romano and Wolf (2005) note that the conservativeness of classical procedures like the one of Bonferroni (1936) is due to the fact that these methods assume a worst-case dependence structure

[2]For an overview, see Lehmann and Romano (2005, Chapter 9).

of the test statistics. For instance, if we consider the extreme case of all hedge strategies yielding the very same alpha, then individual tests should be carried out at the level α, which obviously is more powerful than the Bonferroni (1936) method. Hence, accounting for the true dependence structure is important. In our set-up, we would like to detect as many countries as possible where the dispersion effect actually exists. In this respect, the recent proposal of Romano and Wolf (2005) appears to be the state of the art. On the one hand, it improves upon Bonferroni-type methods based on the individual p-values by incorporating the dependence structure across test statistics. On the other hand, it improves upon the bootstrap reality check of White (2000) by incorporating a stepwise approach and by employing studentized test statistics. We briefly describe this k-StepM method in Appendix A, which ultimately returns a confidence region for the return or the alpha of the hedge strategies.

A.2. Method Based on the False Discovery Proportion (FDP)

When the number of hypotheses under test is very large, the error control may be based on the false discovery proportion rather than on the familywise error rate. Let F be the number of false rejections arising from a multiple testing method and let R be the total number of rejections. We define the FDP as the fraction F/R, given that $R > 0$. Otherwise, the FDP is zero. A multiple testing method controls the FDP at level α if $P(\text{FDP} > \gamma) \leq \alpha$ for any P, at least asymptotically. Typical values of γ are 0.05 and 0.1.

Romano, Shaikh, and Wolf (2008) present a generalized version of the StepM method that allows for controlling the FDP, the FDP-StepM$_\gamma$ method. The method is somewhat complex and the reader is referred to the paper for the details. However, the first step of the method is easy to understand and works as follows. Consider controlling the FDP with $\gamma = 0.1$. The method starts with applying the StepM method. If less than nine hypotheses are rejected, the method stops. If nine or more hypotheses are rejected, the method continues and some further hypotheses might be rejected subsequently.

Romano, Shaikh, and Wolf (2008) compare the k-StepM method to competing methods by means of a simulation study and two empirical applications. They find that all of the methods provide control of the respective error rates. However, the FWE control is rather strict, but generalized error rates such as the k-FWE or the FDP allow for more power. Also, the StepM methods turn out to be more powerful than those methods that do not account for the dependence structure of test statistics. Therefore, the methods related to StepM are most suitable for our purpose. This assessment is substantiated by the empirical study of Leippold and Lohre (2008), who use similar multiple testing controls to conclude that the global accrual anomaly is more apparent than real—at least in most of the countries. Since this result may simply be driven by the methods' conservativeness, the authors additionally show the international price momentum effect to be robust with respect to the very same battery of tests. Hence, we feel comfortable that this framework enables us to separate the wheat from the chaff.

B. Is the Dispersion Effect Due to Data Snooping Biases?

Recapitulating the results of the traditional analysis, we are left with six positive and significant dispersion effect return differentials as well as seven positive and significant dispersion effect alphas. Since this result could have occurred by chance alone, we need to account for multiple testing issues using the methods presented above.

To control the FWE, we consider the k-StepM method for $k = 1$, which is the appropriate choice given the number of strategies under study. To control the FDP, we pursue the FDP-StepM$_\gamma$ using $\gamma = 0.1$. We keep the significance level constant at 5% across all multiple testing procedures and we present results for the return of the hedge strategies as well as their alphas arising from the four-factor time series regressions. To account for potential serial correlation in the return series, we use a kernel variance estimator based on the Parzen kernel to studentize the test statistics, see Andrews (1991). The bootstrap method is the stationary bootstrap with an average block size of 12 months.

The left panel of Table VI reports the multiple testing results for the countries' return statistics. We provide the lower confidence band c_l for the returns using studentized test statistics according to the StepM and FDP-StepM$_\gamma$ method, respectively. Since we are in a one-sided test setting, we give the lower limits of the confidence interval as computed in the last step of the respective method. The value in the column labeled rej equals 1 if $0 \notin [c_l, \infty)$, which indicates the rejection of capital market efficiency and suggests the presence of a dispersion effect in the respective country.

Concerning the results for the returns, we do not observe any rejection of capital market efficiency by the StepM method. In this case the FDP-StepM$_\gamma$ coincides with the StepM, since the number of rejections does not exceed nine. The right panel of Table VI displays the multiple testing results using the four-factor alphas as test statistics. With this metric the dispersion effect is again found to be vulnerable to data snooping biases. The StepM method yields no rejection of capital market efficiency, which implies equivalent results of the FDP-StepM$_\gamma$. Therefore, regardless of controlling the FWE or the FDP, none of the naïvely derived dispersion effects is really refuting capital market efficiency. This surprising result raises the need for sound economic inference.

IV. Explaining the Dispersion Effect

Taking the results of the previous section at face value, one may be tempted to reject the notion of international dispersion effects right away. However, we hesitate to do so given the intriguing fact of almost always positive return differentials together with positive alphas. In reconciling these results with intuition, we further delve into the economic nature of the dispersion effect. First, we consider the evolution of the related strategies over time. Second, we will analyze the interaction of the dispersion effect with measures of information uncertainty. Third, we examine the profitability of dispersion strategies among varying levels of liquidity.

A. The Dispersion Effect over Time

In the following, we seek to sharpen our intuition about the time series nature of the dispersion effect. Therefore, Figure 2 depicts the cumulative return for the six strategies exhibiting significant hedge returns, i.e., the U.S., Europe, Germany, Italy, the Netherlands, and Sweden. Across countries a striking common pattern emerges: Following a steady build-up of wealth until the end of 1998 we observe a severe drawdown. For example, the U.S. strategy erodes half of its accumulated wealth within the subsequent year. The decline in performance is reversed for almost all countries in March 2000. Even more so, the dispersion strategy is soaring to a new height within the following three years. The most recent history is characterized by rather flat return paths across all countries.

Note that the general evolution of the European dispersion effects only resembles the one of the U.S. for the second half of the sample period. While the U.S. dispersion effect amasses significant wealth in the first half of the sample period, we state that the positive European return differentials mainly derive from a narrow time frame, namely March 2000 to March 2003. Comparing the dispersion strategy performance to the evolution of a broad market index, it appears that the dispersion strategy would have been a quite effective hedge against the burst of the tech bubble at the beginning of the century.

[Figure 2 about here.]

To further disentangle the performance drivers of the dispersion effect, we investigate the performance of the low dispersion and the high dispersion portfolio in Figure 3. Focussing on the time frame March 2000 to March 2003, we find the U.S. low dispersion portfolio significantly accumulating wealth, while the high dispersion portfolio is eroding wealth. On the other hand, the European low dispersion portfolios move sideways in the respective period. Hence, the resulting dispersion effects are solely driven by a severe underperformance of the short legs. This observation is quantified by the subperiod analysis conducted in Table VII capturing the years 1998 to 2003. The choice of breakpoints is motivated as follows: At the starting point April 1998 all of the dispersion strategies exhibit a total return level close or equal to their peak prior the subsequent decline in performance. This pattern of declining performance ends for almost all countries in April 2000 defining the second breakpoint. The following three years are marked by significant outperformance of the dispersion strategy reaching a global peak in April 2003, the end of the subperiod. Interestingly, the last breakpoint coincides with the dawn of the Iraq War in 2003.

Considering the subperiod 1998-2003 in Table VII, we find results that are quite similar to the ones documented for the whole sample period in Table III. These results have been expected from our visual inspection of the cumulative return patterns. Of course, the resulting return differentials are more sizeable than those of the whole sample period, given that the European countries are characterized by rather flat return patterns outside the 5 year sub-period. Confirming our earlier assessment, the declining performance of the dispersion hedge strategy from 1998-2000 is almost always due to the extraordinary performance of the short leg. With the technology bubble bursting in March 2000, these high dispersion stocks then suffered extremely negative returns that have more than outweighed the dispersion strategies' previous losses. Of course, being short these companies would have been a favorable thing to do. However, we conjecture that the respective real-world implementation would have been rather unfeasible—just think of the up-tick rule. Of course, one may argue that most of the involved shorts would have already been in place at the beginning of 1999. However, with stock prices subsequently reaching unwarranted levels, one would have had trouble filling the according margin calls. Thus, many investors would have not been able to follow the dispersion strategy when it had really been profitable.

[Figure 3 about here.]

These findings corroborate the doubts raised by the data snooping controls. Prior to 1999, only the U.S. dispersion effect has consistently provided abnormal returns. On the other hand the most sizeable part of the effects derive from a narrow time frame of 3 years. Hence, for really capturing the respective excess returns, it would have required a rather patient investor, equipped with 13 years waiting time, who is not wiped out of the strategy following the violent swing in 1999.

B. The Dispersion Effect and Information Uncertainty

In this section, we will analyze the interaction of the dispersion effect and information uncertainty. Presumably, the respective price drift should be higher in more opaque information environments for which information diffusion is slowest. In fact, dispersion of analysts' earnings forecasts itself is a common proxy for information uncertainty. Besides this metric, Zhang (2006) recently provides evidence that the U.S. price momentum strategy is more effective when limited to highly uncertainty stocks as measured by size, firm age, analyst coverage, stock volatility, or cash flow volatility. If the dispersion effect is confined to highly uncertain information environments investors would certainly be less prone to follow such a strategy. Hence, we will examine dispersion effect profits for different degrees of information uncertainty. We consider four measures to monthly proxy for information uncertainty: Analyst coverage, size, total stock volatility, and idiosyncratic volatility. Total stock volatility is estimated using the last three year's monthly stock returns, and idiosyncratic volatility arises from a standard Fama-French regression that also uses the last three year's monthly stock returns.

Table VIII gives the according results using a similar sorting procedure as in the previous section. In particular, we first sort stocks into five quintiles based on dispersion. For each quintile the stocks are further sorted into three terciles based on one of the three information uncertainty proxies. Obviously, this double-sorting procedure requires a sufficient amount of companies in a given country to deliver meaningful results. Hence, we exclude the six smallest countries, which are Austria, Belgium, Finland, Greece, Norway, and Portugal.

Our findings are as follows. First, the dispersion effect is hardly present when limited to high and low dispersion stocks with high analyst coverage. Nevertheless, the effect is not confined to low coverage stocks. Second, using size as the metric of information uncertainty provides the most poignant results: The dispersion effect cannot be detected when focussing on large cap companies. Also, the dispersion effect is most pronounced when restricted to high volatility stocks. This relates to our finding that the dispersion effect is crucially driven by the short leg, which is mostly populated by high volatility stocks. Third, inspecting the results for idiosyncratic volatility reveals a more diverse pattern, in particular, the dispersion effect works either good when limited to low or high idiosyncratic volatility stocks. The latter result is especially telling as to why the dispersion effect has been difficult to arbitrage. In fact, a stock's idiosyncratic volatility is a common proxy for arbitrage costs and we find the dispersion effects to be most pronounced in stocks exhibiting high idiosyncratic volatility. Therefore, we contend that high arbitrage costs have prevented rational investors from exploiting the dispersion effect.

C. The Dispersion Effect and Liquidity

In further elaborating on the above argument we next examine the role of liquidity when implementing dispersion strategies. In fact, Sadka and Scherbina (2007) evidence that high dispersion companies happen to entail high trading cost. Also, the authors observe the highest mispricing for the less liquid stocks suggesting that trading costs erode all of the potential profits rendering the arbitrage opportunity an illusion. Hence, we expect liquidity to also play a crucial role in inhibiting profitable execution of European dispersion strategies.

To operationalize this conjecture we will analyze the profitability of the dispersion strategies when restricting to high and low dispersion stocks characterized by different degrees of liquidity.

Liu (2006) aptly describes liquidity "as the ability to trade large quantities *quickly* at low cost with little price impact". To account for the according distinct dimensions of liquidity we compute different metrics. A stock's dollar volume or its turnover allow to capture the trading quantity dimension. As for the price impact dimension we resort to the *ILLIQ* measure of **?** which is the absolute daily return over the associated dollar volume. To obtain an aggregate monthly value of *ILLIQ* we simply compute its mean over the corresponding daily values. The fourth measure is the one introduced by Liu (2006) which has been designed to capture multiple dimensions of liquidity, such as trading speed and trading quantity. Its definition is as follows:

$$\text{Liu Measure} = \text{Number of No-Trading Days over the prior 12 months} + \frac{1/\text{Turnover}}{1,000,000} \tag{4}$$

where turnover is the average daily turnover over the prior 12 months. This measure addresses the trading speed dimension of liquidity since it very well captures lock-in-risk, i.e., the danger of being locked in a certain position that cannot be sold.[3]

Table IX displays the profitability of dispersion strategies restricted to high and low dispersion stocks characterized by different degrees of liquidity. In particular, we first sort stocks into five quintiles based on dispersion in analysts' earnings forecasts. For each quintile the stocks are further sorted into three terciles based on one of the four liquidity measures. Again, we exclude the six smallest countries from the analysis, i.e., Austria, Belgium, Finland, Greece, Norway, and Portugal. Panel A of Table IX gives the results for the price momentum strategy. Across most countries and liquidity metrics the general pattern is that the largest dispersion effects occur for the least liquid stocks and that profitability is increasing with illiquidty. For instance, the U.S. dispersion effect is only significant for the least liquid stocks—measuring liquidity by dollar volume or *ILLIQ*. Using share turnover or the measure of Liu (2006) the dispersion strategy's profitability behaves differently.

The pattern of profitability decreasing with liquidity can also be observed for the aggregate European strategy. Judging by dollar volume, share turnover and *ILLIQ* the strategy is only useless among the most illiquid stocks while the other buckets do show similar returns. While most of the country-level results comply with this liquidity-profitability relationship Italy is the odd

[3]Note that while the first three measures only take into account the stocks' liquidity over the precedent month the Liu measure hinges on data of the preceding year.

one out since the dispersion strategy is only profitable among the most liquid stocks—regardless of the liquidity measure. Nevertheless, among the six naïvely derived significant dispersion effects we find five to be significantly affected by liquidity issues. Given that illiquidity is a common proxy for financial distress our results complement the finding of Avramov, Chordia, Jostova, and Philipov (2008) that the U.S. dispersion effect is confined to the worst rated companies. All in all, this evidence questions the successful implementation of any examined dispersion effect.

V. Conclusion

The investigation of a given security mispricing typically addresses two questions: Is the anomaly simply a compensation for risk or is the anomaly real and, if yes, what behavioral bias is driving it? Of course, these questions are only meaningful, if the security mispricing is not spurious in the first place. Hence, one needs to safeguard against data snooping biases. We find that the dispersion effect does not prevail when subjected to multiple testing controls. This startling finding is resolved by examining the time series evolution of the international dispersion effects. Most of the associated returns amass in a rather narrow time frame of 3 years. Moreover, we find the dispersion effect to be most pronounced among high and low dispersion portfolios characterized by high information uncertainty. Likewise, the highest hedge returns obtain for less liquid stocks, hence, high arbitrage costs will most likely deter investors from exploiting a given dispersion mispricing.

Appendix A: Multiple Testing based on the StepM Method

We describe the k-StepM that allows for controlling the k-FWE. Consider S individual decision problems of the form

$$H_s : \theta_s \leq 0 \text{ versus } H_s^{'} : \theta_s > 0, \quad 1 \leq s \leq S, \tag{5}$$

each referring to the hedge strategy in country s. We define the parameter θ_s in such a way that under the null hypothesis H_s, strategy s does not beat the zero benchmark. Given the time series of the hedge strategies, we can compute the test statistic $w_{T,s}$ with an estimate of its standard deviation $\sigma_{T,s}$ based on the returns and the strategies' alphas according to the Fama-French momentum regressions. In particular, using monthly hedge returns $x_{t,s}$, we compute average monthly buy-and-hold returns as in Section II. Thus, we have

$$w_{T,s} = \bar{x}_{T,s} = \frac{1}{T} \sum_{t=1}^{T} x_{t,s}, \tag{6}$$

which we studentize by $\sigma_{T,s}$ that we estimate using the Parzen kernel. Likewise, the test statistic for the alpha is the intercept from estimating equation (2)

$$w_{T,s} = \hat{\alpha}_{T,s}, \tag{7}$$

studentized by the estimated standard deviation of $\hat{\alpha}_{T,s}$.

Within the k-StepM method, we first re-label strategies such that r_1 corresponds to the largest test statistic and r_S to the smallest one. Then, we need to determine a confidence region of the form

$$[w_{T,r_1} - \sigma_{T,r_1} d_1, \infty) \times \cdots \times [w_{T,r_S} - \sigma_{T,r_S} d_1, \infty). \tag{8}$$

Whenever $0 \notin [w_{T,r_s} - \sigma_{T,r_s} d_1, \infty)$, we reject H_s for $s = 1, ..., S$. To control the FWE, d_1 ideally is given by the $(1-\alpha)$-quantile of the distribution of the largest 'centered' studentized[4] statistic

$$\frac{w_{T,s} - \theta_s}{\sigma_{T,s}}$$

among all true hypotheses. However, we do not know which hypotheses are true and we do not know the true probability mechanism P. Therefore, we take the largest difference among all hypotheses and we replace P by a bootstrap estimate $\hat{P}$, which implies that the StepM method will only allow for asymptotic control of the FWE. This feature is shared by all other commonly used multiple testing procedures.

If we suppose that we have rejected $R_1 < k$ hypotheses, we can construct a new confidence region to reexamine the remaining $(S - R_1)$ smallest test statistics

$$[w_{T,R_1+1} - \sigma_{T,R_1+1} d_2, \infty) \times \cdots \times [w_{T,r_S} - \sigma_{T,r_S} d_2, \infty), \tag{9}$$

which is a smaller confidence region, because it typically holds that $d_1 > d_2 > \cdots > d_S$. Hence, we can reject more false hypotheses. Therefore, such a stepwise procedure is more powerful than the single-step method. For the computation of d_2, we again lack both P and the set of true hypotheses. For P, we use the bootstrap estimate $\hat{P}$. However, we now only maximize over the set of hypotheses that have not been rejected yet. Since this is a smaller set, $S - R_1$ verus S elements, d_2 will typically be smaller than d_1 (and at most equally large). If no additional rejection occurs, we stop. Otherwise, we proceed in the same fashion until there are no further rejections.

[4]Studentization requires that the average return be divided by its standard error. To obtain valid confidence intervals for the expected return, we must multiply these quantiles with the country's return standard error. Romano and Wolf (2005) advocate the use of studentization, since it is more powerful and gives more appropriate coverage probabilities for individual θ_{r_s}, especially, when test statistics show different standard deviations. Clearly, the latter applies to our case.

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Table I
Country Overview

The table contains descriptive information on the companies that have been domestically traded in the sample period (1987-2007). For further reference we may use abbreviated country codes (Abbr.). The screening of country lists depicts the evolution of the countries' samples. First, we give the *total* size of the country lists followed by the number of companies surviving the first screen for *Major* listings. The column headed *Region* contains the number of companies surviving the screen eliminating regional listings and the like. The *Final* screen excludes companies which exhibit free-floating market value below 10 million USD. We further describe this final sample giving the number of a country's dead companies (#Dead) and the number of companies with at least one I/B/E/S estimate in the sample period (#I/B/E/S), along with respective percentage values (%-Dead and %-I/B/E/S). The last column gives the earliest month with sufficient Fama-French data. The table provides information for the U.S. in Panel A, while Panel B covers European countries.

Country	Abbr.	Region	Screening of Country Lists				Sample: FMV> 10						Date
			Total	*Major*	*Region*	FMV> 10	#Dead	%Dead	#Return	%Return	#I/B/E/S	%I/B/E/S	FF
Panel A: USA													
USA	USA	America	36659	20030	7279	6272	2554	40.7%	6180	98.5%	4860	77.5%	Jul 92
Panel B: Europe													
Europe		Europe	29266	10522	9383	7019	1996	28.4%	6901	98.3%	5169	73.6%	
United Kingdom	UK	Europe	7677	3444	3232	2268	732	32.3%	2232	98.4%	1652	72.8%	Jul 87
Germany	GER	Europe	10740	1833	1525	1017	228	22.4%	991	97.4%	646	63.5%	Jan 88
Austria	A	Europe	360	177	161	119	31	26.1%	115	96.6%	80	67.2%	Jan 90
Switzerland	CH	Europe	1130	387	316	277	49	17.7%	274	98.9%	217	78.3%	Jan 90
France	FR	Europe	2643	1458	1368	945	258	27.3%	917	97.0%	631	66.8%	Jan 90
Italy	IL	Europe	794	390	365	345	95	27.5%	345	100 %	305	88.4%	Jan 90
Greece	GR	Europe	523	393	360	338	57	16.9%	338	100 %	234	69.2%	Jun 98
Spain	ES	Europe	311	204	180	170	51	30.0%	168	98.8%	160	94.1%	Feb 92
Portugal	POR	Europe	296	146	134	92	48	52.2%	91	98.9%	66	71.7%	Jun 97
Netherlands	NL	Europe	791	272	250	201	77	38.3%	199	99.0%	182	90.5%	Jan 90
Belgium	BEL	Europe	1000	288	263	206	40	19.4%	200	97.1%	129	62.6%	Jan 90
Sweden	SWE	Europe	1203	549	441	346	109	31.5%	344	99.4%	280	80.9%	Jan 90
Norway	NOR	Europe	585	328	284	254	98	38.6%	252	99.2%	219	86.2%	Jan 90
Denmark	DK	Europe	685	365	230	197	55	27.9%	197	100 %	167	84.8%	Jan 90
Finland	FN	Europe	341	190	180	159	42	26.4%	155	97.5%	138	86.8%	Mar 91
		All	65738	30454	16568	13206	4524	34.3%	12998	98.4%	9966	75.5%	
		Top 5	58922	27314	13845	10848	3881	35.8%	10664	98.3%	8094	74.6%	

Table II
Country Universes by Year

The table gives the average number of companies to be considered for the dispersion strategy. Panel A covers the U.S. and Panel B covers European countries.

Year	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	Σ #
Panel A: USA																					
USA	803	867	937	936	1006	1131	1288	1409	1612	1861	2070	2151	2339	2197	1926	1772	2000	2095	2190	2197	32787
Panel B: European Countries																					
Europe	605	714	823	886	966	1024	1075	1187	1368	1466	1628	1742	1924	1804	1466	1215	1355	1419	1614	1776	26057
UK	152	146	127	141	159	161	191	189	220	264	291	279	328	268	207	171	247	291	319	363	4514
Germany	103	99	108	115	135	156	165	177	180	179	204	207	264	268	199	151	160	163	195	230	3458
Austria	14	19	22	27	31	33	33	38	41	40	36	36	37	31	24	18	20	19	28	34	581
Switzerland	70	83	95	95	93	96	97	95	100	105	112	119	127	133	129	109	108	105	129	132	2132
France	86	100	136	131	146	151	159	179	204	233	254	272	300	307	272	242	242	237	257	274	4182
Italy	17	29	37	37	39	34	30	35	41	41	55	65	68	75	68	61	66	75	99	114	1086
Greece	0	0	0	0	0	10	29	58	86	70	72	94	86	63	55	39	50	40	44	56	852
Spain	17	40	73	76	71	65	65	67	69	68	79	90	96	91	83	74	77	74	79	84	1438
Portugal	0	0	0	0	6	23	26	30	34	33	38	42	42	27	12	8	5	10	14	16	366
Netherlands	56	72	84	91	94	94	95	99	109	113	118	130	137	124	101	87	88	85	85	86	1948
Belgium	24	25	25	29	31	31	35	41	46	48	58	70	72	73	72	55	60	57	62	65	979
Sweden	10	12	13	34	36	37	38	46	63	78	101	119	132	116	77	61	76	82	92	96	1319
Norway	9	11	13	15	19	19	20	22	38	47	54	53	59	62	45	28	36	45	66	76	737
Denmark	33	62	75	77	89	93	56	59	67	72	80	80	79	77	52	39	45	61	61	58	1315
Finland	7	9	8	12	9	11	24	40	52	56	52	63	75	66	52	52	53	52	60	63	816
Σ	1401	1574	1753	1816	1964	2145	2351	2584	2962	3308	3674	3870	4241	3978	3374	2967	3333	3491	3780	3944	58510

Table III
Return and Volatility of Dispersion Portfolios

The table gives average monthly buy-and-hold returns and volatility of quintile or tercile portfolios that are built monthly dependent on the level of dispersion. All figures refer to the period from July 1987 to June 2007. We give the return differential of the respective hedge strategies along with the according t-statistic.

		Portfolio Dispersion Ranking						
Country		Low	2	Mid	4	High	$Low - High$	t-statistic
USA	Return	1.56	1.16	1.11	1.23	1.07	0.49	1.98
	Volatility	4.32	4.32	4.91	5.66	6.71	3.85	
Europe	Return	1.24	1.14	1.13	1.10	0.87	0.38	2.04
	Volatility	3.96	4.27	4.71	4.86	5.68	2.87	
UK	Return	1.15	1.13	1.00	1.05	0.99	0.16	0.72
	Volatility	4.09	4.51	4.42	4.88	5.71	3.44	
Germany	Return	0.94	0.87	0.75	0.92	0.45	0.49	1.95
	Volatility	5.11	5.46	5.56	5.77	7.28	3.88	
Austria	Return	1.56		1.25		1.26	0.30	0.93
	Volatility	5.63		5.70		6.38	4.58	
Switzerland	Return	0.93	1.08	0.95	0.80	0.87	0.05	0.24
	Volatility	4.69	5.14	5.82	5.85	6.32	3.56	
France	Return	1.35	1.32	1.25	1.00	1.05	0.30	1.20
	Volatility	5.15	5.46	6.03	6.27	7.05	3.92	
Italy	Return	0.94	0.94	0.91	0.93	0.39	0.52	1.92
	Volatility	6.22	6.85	6.43	6.39	7.52	4.16	
Greece	Return	2.15		1.75		1.99	0.16	1.17
	Volatility	9.50		9.37		10.72	3.55	
Spain	Return	1.47	1.48	0.99	1.28	1.12	0.38	1.29
	Volatility	5.06	6.10	6.46	6.84	7.68	4.62	
Portugal	Return	1.67		1.22		1.20	0.31	0.66
	Volatility	5.96		5.59		6.58	5.50	
Netherlands	Return	1.51	1.30	1.38	1.21	0.86	0.63	2.22
	Volatility	4.39	5.02	5.11	5.82	6.67	4.38	
Belgium	Return	1.12		1.19		0.85	0.26	0.62
	Volatility	4.56		5.19		5.48	2.91	
Sweden	Return	1.75	1.73	1.57	1.61	1.11	0.65	1.83
	Volatility	5.92	6.47	6.54	6.89	8.09	5.47	
Norway	Return	1.42		1.49		1.43	-0.01	-0.19
	Volatility	6.62		6.92		8.45	5.87	
Denmark	Return	1.35	1.33	1.24	1.27	1.02	0.33	1.21
	Volatility	4.68	4.88	4.73	4.70	5.61	4.21	
Finland	Return	1.57		1.56		1.45	0.12	0.72
	Volatility	6.57		7.29		8.04	5.18	

Table IV
Descriptive Statistics of Dispersion Portfolios

The table gives mean values of dispersion as well as two risk proxies, beta and log-size, over the whole period. Quintile and tercile portfolios are built monthly dependent on the level of dispersion. As for risk proxies we consider the quintile portfolios' betas (arising from a standard CAPM) and size being measured as the average of log(marketvalue).

		Portfolio Dispersion Ranking					
Country		Low	2	Mid	4	High	$High - Low$
	Dispersion	0.66	2.14	3.83	7.52	55.32	
USA	Beta	0.77	0.79	0.94	1.09	1.30	-0.53
	Size	20.53	20.74	20.45	20.14	19.78	
	Dispersion	2.39	5.68	9.51	16.70	101.82	
Europe	Beta	0.87	0.95	1.05	1.10	1.28	-0.41
	Size	21.92	21.65	21.15	20.65	20.08	
	Dispersion	1.59	3.11	4.70	7.37	38.24	
UK	Beta	0.71	0.76	0.76	0.85	0.99	-0.29
	Size	24.57	25.00	25.08	25.19	24.87	
	Dispersion	3.34	7.24	11.73	21.02	122.71	
Germany	Beta	1.06	1.12	1.17	1.23	1.52	-0.45
	Size	20.25	20.56	20.51	20.26	19.71	
	Dispersion	3.71		9.89		59.95	
Austria	Beta	1.09		1.10		1.27	-0.18
	Size	19.68		19.88		19.31	
	Dispersion	3.61	7.76	12.55	21.05	113.53	
Switzerland	Beta	0.97	1.07	1.21	1.22	1.29	-0.32
	Size	20.60	20.76	20.59	20.41	20.00	
	Dispersion	3.02	6.26	9.80	16.30	114.66	
France	Beta	0.96	1.03	1.18	1.22	1.38	-0.38
	Size	20.13	20.61	20.40	20.18	19.63	
	Dispersion	4.16	8.88	13.00	19.39	61.32	
Italy	Beta	0.91	1.00	0.94	0.98	1.17	-0.27
	Size	20.63	20.81	20.71	20.40	20.17	
	Dispersion	6.05		14.36		42.74	
Greece	Beta	0.76		0.73		0.88	-0.11
	Size	19.59		19.57		19.14	
	Dispersion	3.54	7.18	11.05	17.08	70.31	
Spain	Beta	0.77	0.90	0.93	1.01	1.13	-0.40
	Size	20.69	20.79	20.46	20.21	19.50	
	Dispersion	6.90		15.89		60.98	
Portugal	Beta	0.74		0.77		0.88	-0.14
	Size	20.35		20.07		19.46	
	Dispersion	2.12	4.51	7.29	12.61	97.50	
Netherlands	Beta	0.79	0.94	0.95	1.13	1.25	-0.46
	Size	19.93	20.01	19.87	19.61	18.83	
	Dispersion	4.48		11.41		73.16	
Belgium	Beta	1.07		1.25		1.30	-0.23
	Size	20.44		20.33		19.70	
	Dispersion	3.78	7.84	12.62	21.59	116.86	
Sweden	Beta	0.61	0.71	0.72	0.73	1.01	-0.40
	Size	22.22	22.62	22.47	22.31	22.03	
	Dispersion	6.21		14.81		140.81	
Norway	Beta	0.81		0.88		1.07	-0.26
	Size	21.71		22.02		21.62	
	Dispersion	3.66	8.06	13.81	24.21	147.75	
Denmark	Beta	1.10	1.00	1.07	1.10	1.29	-0.18
	Size	21.22	21.49	21.31	21.26	20.83	
	Dispersion	6.45		17.48		76.61	
Finland	Beta	0.87		0.95		1.12	-0.25
	Size	19.62		19.81		19.59	

Table V
Time-Series-Regressions of Dispersion Portfolios

The Table gives the results of a regression according to Equation (3) using 240 monthly returns ranging from July 1987 to June 2007 along with the according t-statistics.

		Fama-French Model										
		α	β	γ	δ	ζ	$t(\alpha)$	$t(\beta)$	$t(\gamma)$	$t(\delta)$	$t(\zeta)$	Adj. R^2
USA	Low	-0.01	0.70	0.17	0.03	0.44	-0.05	14.88	3.33	0.62	7.45	79.4
	High	-0.57	0.91	0.48	-0.17	-0.27	-4.47	20.64	10.10	-4.14	-4.78	92.8
	Low-High	0.56	-0.22	-0.31	0.19	0.71	3.24	-3.61	-4.82	3.52	9.26	62.9
Europe	Low	0.45	0.37	0.45	0.00	0.23	4.88	7.81	12.64	-0.04	4.83	91.2
	High	0.26	0.86	0.34	-0.21	-0.43	1.97	12.73	6.54	-4.12	-6.30	92.2
	Low-High	0.19	-0.49	0.12	0.21	0.65	1.15	-5.86	1.81	3.29	7.76	55.7
UK	Low	0.39	-0.12	0.80	-0.13	0.18	3.58	-1.58	11.06	-3.23	3.51	82.2
	High	0.53	0.46	0.47	-0.01	-0.40	2.84	3.48	3.77	-0.16	-4.63	75.4
	Low-High	-0.14	-0.59	0.34	-0.12	0.57	-0.68	-4.07	2.51	-1.60	6.18	29.9
Germany	Low	-0.13	0.79	0.29	-0.03	0.19	-0.83	11.96	5.07	-0.71	3.01	79.6
	High	-0.56	1.43	0.11	-0.15	-0.31	-2.56	15.55	1.38	-2.75	-3.50	82.2
	Low-High	0.43	-0.64	0.18	0.12	0.51	2.06	-7.29	2.39	2.35	5.97	44.2
Austria	Low	0.49	0.82	0.35	-0.02	0.04	2.37	10.58	5.47	-0.65	0.88	71.2
	High	0.03	0.88	0.37	0.03	-0.05	0.15	10.59	5.42	0.63	-0.95	72.4
	Low-High	0.46	-0.06	-0.02	-0.05	0.09	1.53	-0.58	-0.26	-0.92	1.32	1.0
Switzerland	Low	-0.09	0.86	0.11	0.01	0.14	-0.79	14.84	2.21	0.39	3.66	86.0
	High	-0.06	1.06	0.20	0.07	-0.41	-0.43	14.99	3.27	2.09	-9.10	90.4
	Low-High	-0.03	-0.20	-0.09	-0.06	0.55	-0.16	-2.08	-1.08	-1.31	9.01	46.8
France	Low	-0.03	0.87	0.13	-0.03	0.11	-0.17	15.29	2.56	-0.82	1.79	79.4
	High	-0.25	0.95	0.38	0.00	-0.35	-1.51	16.56	7.45	-0.01	-5.89	89.1
	Low-High	0.22	-0.08	-0.25	-0.03	0.47	0.99	-1.07	-3.84	-0.59	5.95	40.2
Italy	Low	-0.04	0.84	0.08	-0.14	0.14	-0.21	9.79	0.92	-3.28	2.23	76.4
	High	-0.51	1.10	0.04	-0.09	-0.34	-2.90	14.38	0.45	-2.23	-6.05	87.2
	Low-High	0.47	-0.26	0.04	-0.06	0.48	2.02	-2.58	0.41	-1.07	6.44	27.5
Greece	Low	0.12	0.51	0.36	-0.41	0.03	0.45	11.69	7.17	-3.81	0.51	88.0
	High	-0.15	0.60	0.38	-0.35	-0.09	-0.51	12.58	6.86	-2.97	-1.39	89.0
	Low-High	0.27	-0.09	-0.02	-0.06	0.13	1.00	-2.05	-0.32	-0.56	2.01	14.2
Spain	Low	0.04	0.64	0.21	-0.06	0.14	0.23	10.71	3.29	-1.43	3.95	79.5
	High	-0.40	0.93	0.23	-0.04	-0.19	-2.11	13.08	3.04	-0.93	-4.53	85.8
	Low-High	0.43	-0.29	-0.02	-0.01	0.34	1.76	-3.12	-0.21	-0.21	5.98	33.8
Portugal	Low	-0.33	0.37	0.52	-0.01	0.33	-1.06	4.87	9.13	-0.10	6.00	59.0
	High	-0.33	0.44	0.54	-0.16	-0.12	-1.02	5.50	9.12	-2.02	-2.14	62.6
	Low-High	0.00	-0.07	-0.03	0.15	0.45	0.01	-0.70	-0.35	1.56	6.36	19.3
Netherlands	Low	0.48	0.78	0.04	-0.03	0.17	3.37	12.67	0.62	-1.11	4.23	75.1
	High	-0.06	1.07	0.08	0.04	-0.37	-0.33	14.27	1.15	1.06	-7.48	84.8
	Low-High	0.53	-0.29	-0.05	-0.08	0.54	2.33	-3.01	-0.51	-1.51	8.43	45.7
Belgium	Low	0.07	0.67	0.35	0.04	0.08	0.56	10.57	7.35	1.08	1.99	80.9
	High	-0.14	0.97	0.27	0.02	-0.20	-0.86	12.71	4.73	0.50	-4.23	81.2
	Low-High	0.21	-0.30	0.08	0.02	0.28	1.10	-3.25	1.17	0.33	4.91	16.1
Sweden	Low	0.35	0.44	0.29	0.06	0.20	1.44	7.36	4.08	1.70	3.28	58.8
	High	-0.34	0.79	0.27	-0.06	-0.17	-1.48	14.35	4.15	-1.92	-3.04	81.9
	Low-High	0.69	-0.35	0.02	0.12	0.37	2.34	-4.98	0.18	2.90	5.08	36.9
Norway	Low	0.08	0.53	0.32	-0.01	0.17	0.34	7.41	4.80	-0.15	3.45	66.4
	High	-0.04	0.55	0.50	0.09	-0.06	-0.15	6.43	6.38	1.55	-1.00	71.0
	Low-High	0.13	-0.01	-0.18	-0.10	0.23	0.36	-0.13	-1.96	-1.42	3.32	13.1
Denmark	Low	0.03	0.73	0.33	-0.02	0.02	0.14	8.85	5.37	-0.44	0.52	68.6
	High	-0.50	0.93	0.39	-0.07	-0.07	-2.34	9.46	5.42	-1.78	-1.38	71.3
	Low-High	0.53	-0.20	-0.06	0.06	0.09	1.87	-1.52	-0.68	1.08	1.38	5.4
Finland	Low	0.28	0.57	0.32	-0.03	-0.01	1.10	6.55	3.93	-1.13	-0.15	72.2
	High	0.09	0.61	0.50	-0.02	-0.20	0.36	7.11	6.22	-0.78	-3.91	81.9
	Low-High	0.19	-0.04	-0.18	-0.01	0.19	0.53	-0.33	-1.58	-0.26	2.65	11.4

Table VI
Accounting for Multiple Testing in the Dispersion Effect

The table gives the lower confidence band c_l for the returns as obtained by the StepM method and the FDP-StepM$_{0.1}$using studentized test statistics as illustrated in Appendix A. The rej-columns contain the resulting decision where 1 indicates rejection of $\theta_s = 0$ (capital market efficiency). The left panel provides results for returns as test statistics and the right panel provides results for 4-factor alphas as test statistics.

	Return					4-Factor Alpha				
Country	θ_s	*StepM*		*FDP-StepM*$_{0.1}$		θ_s	*StepM*		*FDP-StepM*$_{0.1}$	
		c_l	rej	c_l	rej		c_l	rej	c_l	rej
USA	0.0049	-0.0032	0	-0.0032	0	0.0056	-0.0015	0	-0.0015	0
Europe	0.0038	-0.0037	0	-0.0037	0	0.0019	-0.0028	0	-0.0028	0
UK	0.0016	-0.0074	0	-0.0074	0	-0.0014	-0.0092	0	-0.0092	0
Germany	0.0049	-0.0043	0	-0.0043	0	0.0043	-0.0021	0	-0.0021	0
Austria	0.0030	-0.0060	0	-0.0060	0	0.0046	-0.0050	0	-0.0050	0
Switzerland	0.0005	-0.0072	0	-0.0072	0	-0.0003	-0.0056	0	-0.0056	0
France	0.0030	-0.0050	0	-0.0050	0	0.0022	-0.0057	0	-0.0057	0
Italy	0.0052	-0.0031	0	-0.0031	0	0.0047	-0.0030	0	-0.0030	0
Greece	0.0016	-0.0061	0	-0.0061	0	0.0027	-0.0048	0	-0.0048	0
Spain	0.0038	-0.0064	0	-0.0064	0	0.0043	-0.0040	0	-0.0040	0
Portugal	0.0031	-0.0091	0	-0.0091	0	0.0000	-0.0115	0	-0.0115	0
Netherlands	0.0063	-0.0033	0	-0.0033	0	0.0053	-0.0005	0	-0.0005	0
Belgium	0.0026	-0.0028	0	-0.0028	0	0.0021	-0.0024	0	-0.0024	0
Sweden	0.0065	-0.0065	0	-0.0065	0	0.0069	-0.0020	0	-0.0020	0
Norway	-0.0001	-0.0120	0	-0.0120	0	0.0013	-0.0076	0	-0.0076	0
Denmark	0.0033	-0.0061	0	-0.0061	0	0.0053	-0.0027	0	-0.0027	0
Finland	0.0012	-0.0097	0	-0.0097	0	0.0019	-0.0085	0	-0.0085	0
Σ			0		0			0		0

Table VII
Dispersion Effect: Sub-Period Analysis

The table gives average monthly buy-and-hold returns and volatility of quintile or tercile portfolios that are built monthly dependent on the level of dispersion. The figures refer to the period from April 1998 to April 2003, the sub-period is further split in two at April 1st, 2000. We give the return differential of the respective hedge strategies, *Lo-Hi*, along with the according t-statistic.

Country	*1998-2003*				*1998-2000*				*2000-2003*			
	Low	High	Lo-Hi	t-stat	Low	High	Lo-Hi	t-stat	Low	High	Lo-Hi	t-stat
USA	0.71	0.12	0.58		0.51	2.52	-2.01		0.83	-1.37	2.19	
	4.93	9.80	6.55	0.69	5.60	8.79	5.18	-1.86	4.54	10.21	6.85	1.95
Europe	0.13	-0.93	1.06		1.25	2.89	-1.64		-0.57	-3.31	2.75	
	4.40	7.44	4.03	2.04	4.64	6.62	2.69	-2.93	4.16	6.99	3.83	4.36
UK	0.17	-0.27	0.44		0.63	3.55	-2.92		-0.12	-2.65	2.53	
	4.33	7.97	5.69	0.60	4.59	8.45	6.36	-2.20	4.19	6.74	4.09	3.76
Germany	-0.54	-2.65	2.12		1.90	2.41	-0.50		-2.05	-5.80	3.74	
	6.96	10.60	5.84	2.81	6.62	8.02	4.03	-0.60	6.81	10.88	6.23	3.66
Austria	0.03	-0.60	0.63		-0.55	0.55	-1.09		0.39	-1.31	1.70	
	4.94	4.72	4.71	-0.16	5.67	4.59	4.28	-1.11	4.47	4.72	4.70	0.58
Switzerland	-0.26	-0.99	0.73		0.87	2.49	-1.62		-0.96	-3.15	2.19	
	5.09	8.12	4.65	1.22	5.63	8.30	3.28	-2.37	4.66	7.31	4.81	2.77
France	0.26	-0.48	0.74		1.70	2.81	-1.11		-0.63	-2.52	1.89	
	5.44	9.10	5.35	1.07	6.01	7.77	3.91	-1.36	4.92	9.36	5.84	1.97
Italy	-0.25	-1.14	0.88		1.78	2.15	-0.37		-1.51	-3.18	1.66	
	7.02	8.87	4.75	1.44	8.24	8.43	4.16	-0.43	5.93	8.62	4.98	2.03
Greece	1.77	1.93	-0.16		10.07	11.52	-1.44		-3.39	-4.02	0.64	
	13.67	15.56	4.18	-0.62	16.45	18.71	5.26	-1.36	8.35	9.35	3.17	0.78
Spain	0.35	-0.17	0.52		-0.34	0.88	-1.22		0.78	-0.82	1.60	
	5.02	6.97	3.90	1.03	6.82	8.55	3.31	-1.77	3.51	5.82	3.89	2.50
Portugal	0.75	-0.70	1.45		2.68	0.32	2.36		-0.45	-1.34	0.89	
	7.91	6.98	6.85	1.62	11.24	6.73	8.12	1.13	4.64	7.14	5.98	1.16
Netherlands	-0.48	-1.77	1.30		-0.12	0.41	-0.53		-0.70	-3.13	2.43	
	4.62	8.40	5.76	1.74	5.14	7.31	5.11	-0.50	4.33	8.83	5.92	2.50
Belgium	-0.51	-1.09	0.58		0.31	0.05	0.27		-1.02	-1.80	0.78	
	4.51	5.38	3.19	0.63	5.10	5.29	3.60	0.74	4.10	5.38	2.94	0.12
Sweden	0.63	-0.33	0.95		1.28	3.53	-2.25		0.22	-2.72	2.95	
	4.97	10.53	7.41	1.00	4.98	11.73	8.04	-1.34	4.98	9.08	6.30	2.84
Norway	-0.13	-0.98	0.85		0.53	0.40	0.13		-0.54	-1.84	1.30	
	6.57	7.39	4.81	0.85	8.17	9.06	4.61	-0.64	5.42	6.10	4.93	1.33
Denmark	-0.18	-0.40	0.22		0.34	-0.24	0.58		-0.50	-0.50	-0.01	
	4.88	6.40	4.97	0.34	3.81	4.96	3.62	0.76	5.47	7.21	5.70	-0.01
Finland	0.21	-0.42	0.63		1.78	1.00	0.78		-0.77	-1.30	0.53	
	5.97	7.15	3.13	0.90	8.10	8.78	2.75	0.77	3.98	5.87	3.39	0.56

Table VIII
Dispersion Effect and Information Uncertainty

The table gives return differentials of the dispersion hedge strategy by terciles of different information uncertainty metrics. We first sort stocks into five quintiles based on the prior month's dispersion in analysts' earnings forecasts. For each quintile the stocks are further sorted into three terciles based on analyst coverage, size, total stock volatility, and idiosyncratic volatility (arising from a rolling 36-months Fama-French regression). Below the return differentials we give t-statistics. The two last rows collect the number of countries that exhibit the highest return differential among the respective terciles and the terciles mean ranking in terms of returns.

Country	*Analyst Coverage*			*Size*			*Volatility*			*Idiosyncratic Volatility*		
	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High
USA	0.74	0.58	0.26	0.76	0.60	0.32	0.32	0.78	1.49	0.92	1.05	1.42
	3.41	2.43	0.79	3.17	2.33	1.09	1.62	4.05	6.36	3.04	4.52	6.17
Europe	0.44	0.49	0.32	0.76	0.41	0.24	0.41	0.33	0.69	0.83	0.66	0.68
	2.59	2.51	1.31	3.69	2.47	1.01	3.21	2.28	3.64	4.08	3.38	3.49
UK	0.48	0.06	-0.13	1.19	0.03	-0.09	0.18	0.36	0.43	0.07	0.38	0.50
	1.48	0.19	-0.58	2.92	0.09	-0.35	0.92	1.60	1.26	0.25	1.48	1.66
Germany	-0.10	0.83	0.31	1.09	0.54	0.09	0.11	0.81	0.83	0.60	0.72	0.95
	-0.23	2.72	0.91	2.35	1.56	0.27	0.33	2.85	2.54	1.81	2.21	3.03
Switzerland	-0.66	0.29	0.18	0.56	-0.33	0.06	-0.09	0.12	0.49	0.46	0.24	0.32
	-1.87	0.95	0.55	1.17	-1.15	0.19	-0.35	0.43	1.44	1.71	0.80	0.94
France	0.79	0.55	-0.32	0.43	0.25	0.18	0.30	-0.03	1.30	0.94	0.92	1.02
	2.22	1.71	-0.87	0.89	0.73	0.58	1.07	-0.09	3.99	3.48	2.89	2.99
Italy	-0.81	1.23	0.60	-0.93	0.43	0.58	0.28	0.10	1.21	0.98	0.61	0.77
	-1.66	2.33	1.55	-1.81	0.98	1.48	0.76	0.26	2.28	2.20	1.33	1.68
Spain	0.03	0.54	0.41	-0.09	0.41	0.68	0.57	1.22	0.29	0.73	0.66	0.22
	0.07	1.26	0.81	-0.18	1.06	1.08	1.00	2.73	0.55	1.66	1.98	0.55
Netherlands	1.30	0.44	0.16	1.35	0.59	-0.33	0.35	0.48	0.96	0.93	0.92	1.18
	3.73	1.06	0.35	3.22	1.52	-0.69	0.96	1.28	1.89	2.62	2.69	2.87
Sweden	0.04	1.05	0.26	-0.25	0.85	0.19	0.27	0.80	1.26	0.56	1.47	1.10
	0.07	2.32	0.56	-0.34	1.56	0.45	0.56	1.77	2.02	1.03	2.86	2.08
Denmark	0.61	0.45	-0.08	-0.01	0.46	-0.17	1.95	0.42	-0.28	1.31	0.89	-0.27
	1.25	1.16	-0.18	-0.02	1.08	-0.47	2.98	1.10	-0.59	2.00	2.18	-0.60
# max	5	6	0	7	2	2	1	1	9	5	1	5
ranking	2.00	1.45	2.55	1.64	1.91	2.45	2.45	2.18	1.36	1.91	2.36	1.73

Table IX
Dispersion Effect and Liquidity

The table gives return differentials of the dispersion hedge strategy by terciles of different liquidity metrics. We first sort stocks into five quintiles based on the prior month's dispersion in analysts' earnings forecasts. For each quintile the stocks are further sorted into three terciles based on dollar volume, share turnover, the ILLIQ measure of Amihud (2002), and Liu's measure. Below the return differentials we give t-statistics. The two last rows collect the number of countries that exhibit the highest return differential among the respective terciles and the terciles mean ranking in terms of returns.

Country	*Dollar Volume*			*Share Turnover*			*ILLIQ*			*Liu Measure*		
	High	Mid	Low	High	Mid	Low	Low	Mid	High	Low	Mid	High
USA	0.34	0.41	0.48	0.59	0.42	0.46	0.28	0.42	0.61	0.74	0.29	0.35
	1.08	1.65	2.25	2.09	1.66	2.26	0.97	1.57	2.70	2.64	1.19	1.74
Europe	0.07	0.39	0.59	0.13	0.46	0.40	0.12	0.33	0.49	0.43	0.19	0.48
	0.31	2.09	3.55	0.55	2.31	2.51	0.56	1.73	2.79	1.77	1.06	3.36
UK	0.04	0.35	0.57	0.27	0.17	0.55	0.05	0.12	0.66	0.27	0.19	0.41
	0.17	1.39	2.04	1.00	0.74	2.15	0.21	0.45	2.51	1.07	0.73	1.56
Germany	0.33	0.64	0.56	0.69	0.27	0.65	0.31	0.36	0.90	0.43	0.60	0.67
	0.98	2.28	1.54	2.08	1.02	1.80	1.06	1.29	2.33	1.43	2.17	1.82
Switzerland	-0.22	-0.19	0.49	0.04	-0.19	0.14	-0.28	-0.29	0.29	0.05	0.22	0.10
	-0.68	-0.62	1.43	0.14	-0.63	0.49	-0.96	-0.91	0.89	0.16	0.70	0.27
France	-0.24	0.77	0.09	-0.01	0.59	-0.07	-0.05	0.46	0.22	0.03	0.40	0.31
	-0.78	2.64	0.23	-0.03	1.97	-0.23	-0.16	1.41	0.64	0.09	1.43	0.85
Italy	0.80	0.52	0.13	0.53	0.59	0.66	0.80	0.46	-0.11	0.83	0.75	0.02
	2.31	1.25	0.26	1.36	1.72	1.51	2.42	1.23	-0.23	2.12	2.09	0.04
Spain	0.05	0.69	-0.03	0.39	0.27	0.49	-0.23	0.43	0.06	0.79	-0.37	0.20
	0.11	1.65	-0.08	0.95	0.66	1.28	-0.51	0.98	0.16	1.98	-0.89	0.50
Netherlands	0.30	0.31	1.39	0.19	0.79	1.10	0.33	0.77	0.92	0.93	0.54	0.64
	0.64	0.67	3.74	0.39	2.07	2.96	0.71	1.85	2.54	1.98	1.42	1.48
Sweden	0.27	1.02	1.14	0.36	0.58	1.12	0.47	0.74	1.57	0.37	0.67	0.73
	0.59	1.94	1.80	0.71	1.09	2.19	1.08	1.30	2.52	0.83	1.28	1.25
Denmark	0.46	0.15	0.14	0.66	-0.17	0.69	0.40	0.19	-0.38	0.35	0.38	-0.30
	1.38	0.31	0.29	1.74	-0.41	1.21	1.13	0.43	-0.67	1.03	0.97	-0.59
# max	2	3	6	2	2	7	2	2	7	4	3	4
ranking	2.55	1.73	1.73	2.18	2.36	1.45	2.55	1.91	1.55	2.00	2.18	1.82

Figure 1. Trailing Alpha of the Dispersion Effect

We plot trailing dispersion strategy alphas arising from equations (2) and (3) using 36-months windows, thus results cover July 1990 to June 2007. The dashed line gives the Fama-French alpha and the solid line is the respective four-factor alpha.

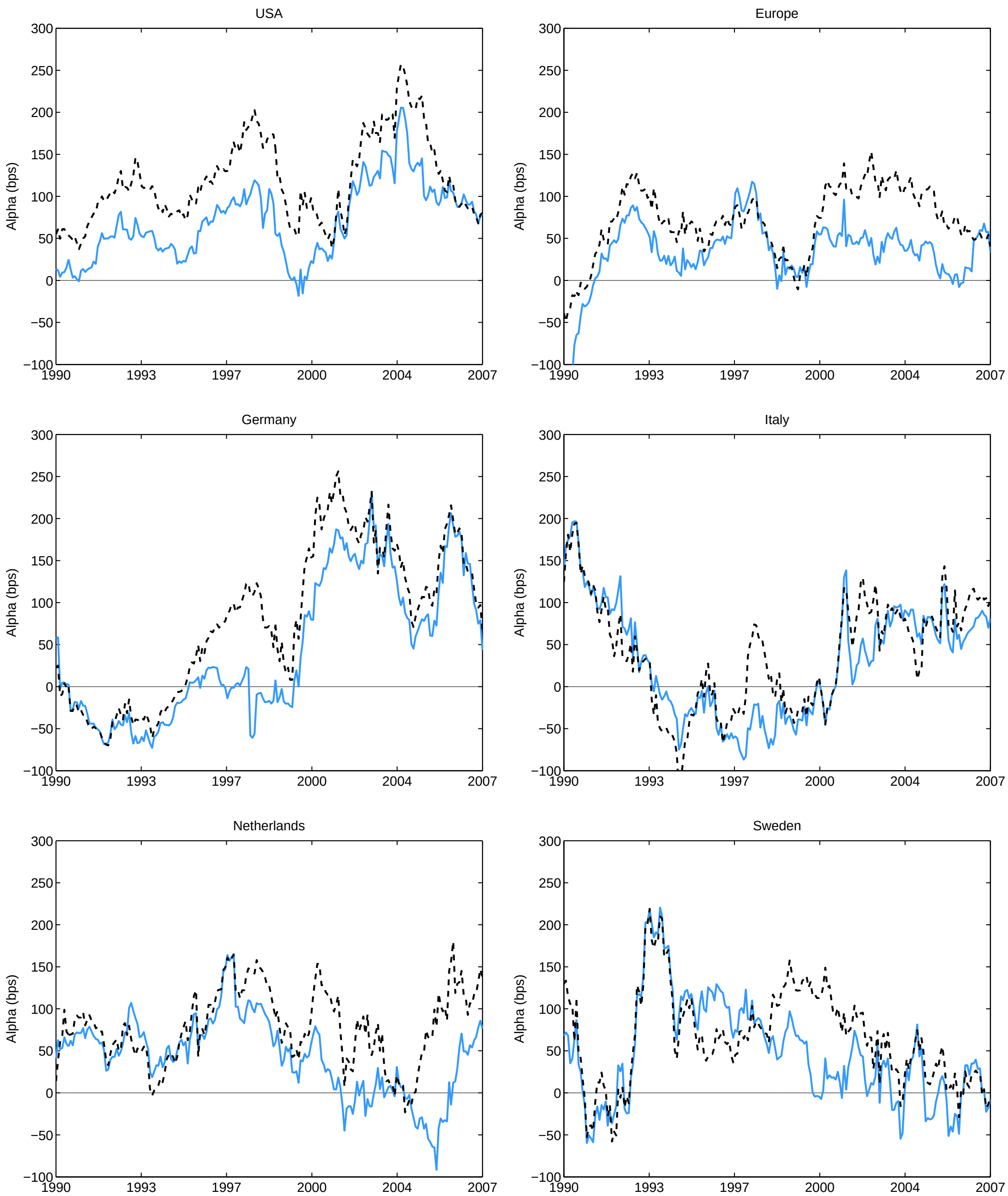

Figure 2. Cumulative Returns: Dispersion versus Market Portfolio
The figures give cumulative total returns the dispersion hedge portfolios (solid line) and to a broad market index (dashed line). Results are for the period from July 1987 to June 2007.

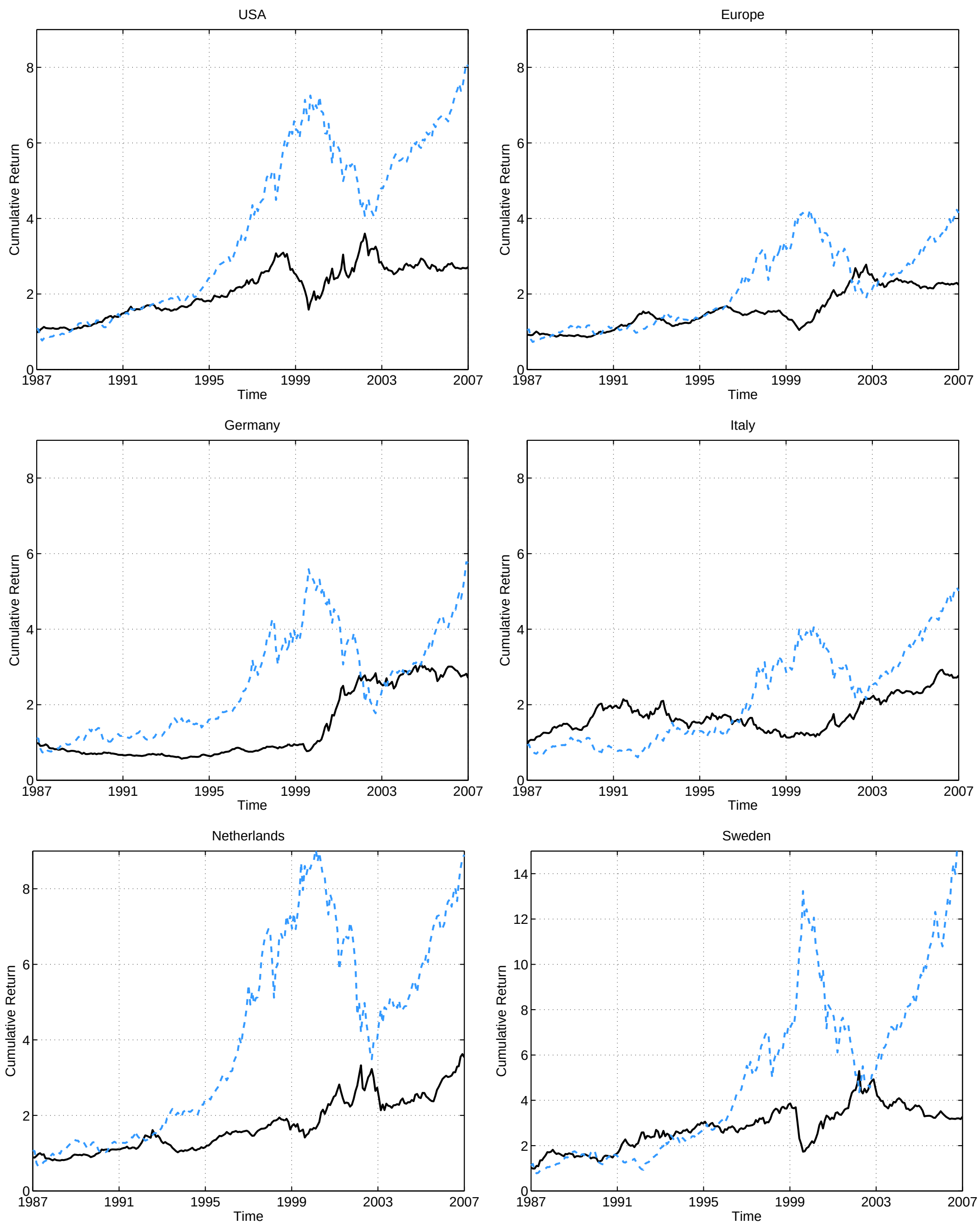

Figure 3. Cumulative Returns: Dispersion Legs versus Market Portfolio

The figures give cumulative total returns to the long and short leg of the dispersion hedge strategy. Results are for the period from July 1987 to June 2007. The solid line is for the market portfolio, the dotted line represents the low dispersion portfolio, and the dashed line represents the high dispersion portfolio.