Explaining Differences in Mutual Fund Performance Persistence

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In this study we use a comprehensive database of mutual funds covering a broad range of asset classes and study performance persistence within the different asset classes. First, we find strong evidence of persistence in performance within all of the asset classes. Secondly, we also find that the persistence in performance differs from one asset class to the next. Interestingly, we find that the performance persistence is unrelated to market efficiency; opposing the often heard argument that the added value of active management is more pronounced in less efficient markets. Breadth within asset classes, on the other hand, is positively related to persistence in performance. This finding holds across asset classes as well as within asset classes over time.

Keywords: mutual funds, performance persistence, breadth, market efficiency, return dispersion

JEL Classification: *G11, G14, G15, G24*

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1. Introduction

Following Sharpe's (1991) 'arithmetic of active management', the average active manager owns the market and before costs the return will be equal to the return of the average passive manager. Since active management is more costly, however, after costs the marginal dollar invested actively underperforms the marginal dollar that is passively invested. Importantly, however, while the *average* active manager does not seem to add value, this does not mean that active management per se cannot be successful.

Still, Bernstein (1998) shows it has become increasingly difficult for active equity portfolio managers to significantly beat their benchmark. His argument explaining this finding is that markets have become increasingly efficient with the passage of time. For instance, professional as well as nonprofessional investors are better educated in how to invest, making it harder for active managers to beat their competing investors. Bernstein (1998) makes the interesting analogy to baseball in which the '.400 hitters' of the early days seem to have disappeared.[1] It is unlikely, he explains, that the batters of modern times have less skill than the big hitters of yesteryear. A more probable explanation is that the average level of the defenders has increased, e.g. better pitchers and basemen (see Gould, 1996); just like that the average investor has become better skilled in investing.

A few years later, De Silva *et al.* (2001) published a related study in the same journal. The authors convincingly show that the downward trend in the mutual fund return dispersion, shown by Bernstein (1998), is not because of increasing market efficiency, but simply the result of changes in return dispersion in the underlying securities. Moreover, the authors show that the return dispersion of U.S. equity mutual funds is much higher in the years before the burst of the tech-bubble, hence following the publication of Bernstein (1998). Clearly, in periods in which assets move less in line with one another, it is more likely for a skillful manager to beat the market by a significant amount and become a .400 hitter. This finding is also in line with the fundamental law of active management of

[1] In baseball, the batting average is defined as the total number of hits divided by at bats. In modern baseball, a season's average of .300 is seen as excellent while an average of .400 or higher is seen as impossible. Since the 1870s, there have been 35 .400 hitters by 26 different baseball players. However, a season's average of .400 has not occurred since Ted Williams hit an average of .406 in 1941. See Gould (1996) for a discussion on the explanation of the disappearance of the .400 hitters.

Grinold (1989) and Grinold and Kahn (2001), which postulates that the value added of active management depends on both managerial investment skill and the investment opportunity set. If there is more breadth, defined as the number of independent investment opportunities the portfolio manager can choose from, a skilled investment manager is more likely to outperform.

Following the *law*, persistence in mutual fund performance is, 1) expected to be stronger for asset classes with more breadth, and 2) expected to be stronger in periods in which there is a relatively abundant number of independent investment opportunities available within the asset class. In this paper, we examine these two conjectures and will look more closely to the performance of top mutual fund managers and the two alternative hypotheses explaining differences in performance, i.e. asset class efficiency and breadth. More specifically, in this study, we estimate mutual fund performance persistence for a broad range of asset classes and examine differences in the persistence in performance across asset classes as well as within asset classes over time. Do the .400 hitters exist in national baseball competitions in which the sport is relatively undeveloped? Or do .400 hitters only exist in leagues in which the rules prescribe the batting team is allowed to use two batters simultaneously instead of one at a time? In other words, is market efficiency indeed an important determinant for skillful managers to persistently outperform? Or, alternatively, are differences in the breadth of the mutual fund managers' investment universes able to explain differences in performance persistence across asset classes and/or within asset classes over time? And more broadly: what is the value of active management in different asset classes and what can explain the value of active management in the first place?

Surprisingly, very little is known about potential differences of the value of active management within different markets. Thus far, studies on persistence in performance of actively managed mutual funds are mainly concentrated on the U.S. and particularly on equity funds.[2] Our paper is

[2] Hendricks *et al.* (1993), Goetzmann and Ibbotson (1994), Brown and Goetzmann (1995) and Elton *et al.* (1996) all find persistence in U.S. equity mutual fund performance. Carhart (1997) finds that, using a four-factor model, persistence can be attributed to fund expenses and momentum in the underlying securities. Bollen and Busse (2005), however, find evidence of persistence in performance beyond expenses and momentum.

the first to study differences in the persistence in performance *across* asset classes and the first to relate the differences to asset class' efficiency and to the breadth of the asset class; two asset class characteristics that are discussed in detail in the next section.

For the purpose of our study, we make use of a comprehensive database of monthly mutual fund returns that starts in January 1990 and ends in December 2010. In total, we study funds with an investment universe that can be allocated to one of 20 different asset classes, including seven bond classes, six broad equity classes covering different geographical regions, and seven sub classes within U.S. equity in which funds differ in their focus on capitalization and/or growth versus value or funds that invest in real estate equity.

The main results that follow from this study are summarized as follows. First, we find that in each of the asset classes there is evidence of strong persistence in performance that is economically as well as statistically significant. By comparing persistence in performance across the asset classes, we find that differences between asset classes can be very large. For instance, the past winners of U.S. small-cap equity funds outperform their peer losers by 84 basis points the following month, on average. U.S. large-cap equity fund winners outperform the losers by 46 basis points; hence, almost halve the magnitude. And the performance persistence within the different bond-fund classes is even lower. We conclude from these results that the (potential) value of active management in certain asset classes, i.e. asset classes for which persistence in performance is stronger, is higher then in other asset classes.

Interestingly, the results indicate that the value added of active management is not restricted to inefficient markets but can also be achieved within highly developed markets like U.S. equity. Moreover, the differences in performance persistence cannot be explained by differences in the degree of asset class efficiency. Hence, it seems not to be the case that the value of active management is higher in less developed, relatively inefficient markets like emerging markets.

Breadth, on the other hand, is able to explain a large part of the differences in performance persistence across asset classes. In line with the fundamental law of active management of Grinold (1989) and Grinold and Kahn (2001), we find that asset classes with more breadth show stronger persistence in performance. Importantly, we also find that breadth is important in driving the dynamics in persistence; in periods in which the number of independent investment opportunities is abundant, past winners outperform their peers by a greater extent compared to periods in which breadth is relatively scarce, i.e., there are more .400 hitters in times asset classes provide more breadth.

Our paper is closely related to Connor and Li (2009) who show that hedge funds have higher performance in periods when there are more different investment opportunities to produce active returns. In addition, our paper is related to a recent strand of literature that looks at the portfolio concentration of active fund managers and shows that funds that hold more concentrated portfolios outperform funds that are more diversified (see, e.g., Kacperczyk *et al.,* 2005; Cremers and Petajisto, 2009; and Amihud and Goyenko, 2010). At first, these findings seem inconsistent with the fundamental law of active management. Huij and Derwall (2011) show, however, that this observed relation is mainly driven by the breadth of the underlying fund strategies. Huij and Derwall find that funds with a broader investment universe not focusing on a certain investment style have higher returns compared to funds that are more concentrated towards certain investment segments.

Our paper differs from the aforementioned studies in three important respects. First, we do not evaluate the *overall* performance of mutual funds within a certain asset class but evaluate determinants for the *persistence* in performance across and within asset classes. Secondly, we look at a broad number of different asset classes while these existing studies are concentrated towards funds belonging to a particular asset class. And finally, we relate the performance of mutual funds to the relative efficiency of the asset classes considered, as well as (dynamics in) the breadth of the different asset classes. In summary, while these studies provide interesting insights, we try to answer a different question related to the performance of active fund management.

The rest of the paper proceeds as follows. First we describe our methodology and explain how we measure efficiency and breadth of the different asset classes. Section 3 describes the data we use for this study. In Section 4 we discuss the empirical results, beginning by an examination of the relation between asset class efficiency and performance persistence. Next we investigate the relation between breadth and persistence in performance across the asset classes. Finally, we analyze dynamics in persistence over time using breadth as explanatory variable. We conclude in Section 5.

2. Methodology

In this study we analyze if actively managed mutual funds, covering a broad range of asset classes, that have investment skills are able to persistently add value to their clients. Moreover, we are interested in potential differences of persistence in the performance of skillful managers across different asset classes and test two alternative explanations that have been put forward in the literature to explain persistence in performance, i.e., market efficiency and breadth. In this section, we shortly introduce these concepts and discuss how we measure skill, market efficiency and breadth, respectively.

2.1 Skill

First, if skill is an important determinant of mutual fund returns, we expect to find persistence in the performance of funds. To examine the persistence in fund performance within the different asset classes we follow a traditional approach that uses dynamically ranked portfolios (see, e.g., Carhart, 1997; and Bollen and Busse, 2005). That is, we rank the funds that belong to a certain asset class at the end of each month on their previous twelve-month return and sort the funds into quintile portfolios. Next, we evaluate the performance of each quintile portfolio of funds over the following month.

2.2 Market Efficiency

If markets are fully efficient and any new information is directly and also correctly incorporated in financial markets, then it would be impossible for any fund manager to persistently outperform the market. Outperformance can only be achieved by sheer luck. If, on the other hand, markets are not fully efficient, it might be possible for skillful active managers to exploit informational advantages and persistently have higher returns compared to their peers and/or compared to their benchmarks. An important question that arises is whether the degree of market efficiency determines the potential value added of active fund management. For instance, a common believe among many academics and practitioners is that active management can only add value in inefficient market segments in which information diffuses slowly.

For this study, we will estimate efficiency using five different measures. These measures include a variance ratio test, a non-parametric runs test and three serial correlation tests with different lags. The measures have in common that they test for predictability in returns by looking at autocorrelations in returns. The higher is the degree of predictability, the less efficient an asset class is considered to be. Since these five efficiency measures are very standard in the literature, we postpone the discussion on the efficiency measures to the appendix.

2.3 Breadth

The fundamental law of active management of Grinold (1989) and Grinold and Kahn (2000) asserts that the value of active management depends on the skill of the portfolio manager in selecting securities and of the breadth of the investment strategy. The breadth of an investment strategy (i.e., the investment universe for, e.g., an equity or bond fund manager) is defined as the number of independent investment bets a portfolio manager can choose to invest in. Hence, it denotes the investment opportunity set of the manager in order to achieve active returns. In this study, we use three different measures to estimate breadth within an asset class.

The first approach is the average cross-sectional return dispersion of the funds that invest in the relevant asset class. Cross-sectional volatility, or market dispersion, is an often used measure of the alpha potential in the market (see, e.g., Gorman *et al.*, 2010a, 2010b). In a related study on the performance of hedge funds, Conner and Li (2009) show that the average hedge fund performance is positively related to market return dispersion. Return dispersion, measured by the cross-sectional standard deviation of returns, is a natural candidate measure to proxy for breadth. For example, in the extreme and unrealistic case that all securities have the same return, the cross-sectional dispersion will be zero and there will be no breadth. If, on the other hand, the securities within a market have high idiosyncratic volatility there will also be high return dispersion and there will be many opportunities for a manager to produce active returns.[3]

In this study, we will proxy breadth by the average cross-sectional return dispersion of all the mutual funds belonging to the asset class instead of by using the dispersion in returns of the underlying securities themselves. Using mutual fund returns has the attractive property that the dispersion measure can be estimated using a uniform approach across the asset classes. For instance, bonds are traded much less frequently compared to equities, making it difficult to calculate the monthly bond returns and thus cross-sectional return dispersion. Moreover, De Silva *et al.* (2001) and Ankrim and Ding (2002) convincingly show that mutual fund return dispersion is highly correlated with the return dispersion of the underlying securities.[4] For asset class *i*, the cross-sectional return dispersion is given by

$$\sigma_{CS,i,t} = \sqrt{\frac{1}{N_{i,t}-1}\sum_{k=1}^{N_{i,t}}\left(R_{k,i,t} - R_{B_i,t}\right)^2}, \tag{1}$$

where $N_{i,t}$ equals the number of funds belonging to asset class i at time t, $R_{k,i,t}$ is the return on the kth fund and $R_{B_i,t}$ denotes the return on the benchmark.

Secondly, we estimate breadth within an asset class by the average tracking error funds realize within the asset class. Tracking error, defined as the time-series standard deviation of fund returns in excess of the fund's benchmark (the fund's benchmarks are discussed in the next section), denotes by how much fund portfolios deviate from the benchmark. The higher is the tracking error, the more active a fund is expected to be (see, e.g., Wermers, 2003). We conjecture that the average realized tracking error, within an asset class, proxies for breadth as it shows the opportunity for mutual fund managers to deviate from the benchmark.

A third measure for breadth within an asset class is the average diversification effect. The diversification effect measures the degree by

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[3] De Silva, *et al.* (2001) show that cross-sectional dispersion is primarily driven by the idiosyncratic volatility of the securities. In periods of extreme returns in the market there will be additional cross-sectional dispersion.

[4] In unreported results we also use the cross-sectional dispersion of the underlying securities of the broad equity markets and the conclusions are not materially changed.

how much adding another fund to the portfolio contributes to a more diversified portfolio. A higher value for the diversification effect implies that fund returns within an asset class are relatively less correlated and thus more dispersed. Hence, it seems that the diversification effect of adding another fund in a portfolio of funds is a good candidate to proxy for breadth within an asset class. To measure the diversification effect for the different asset classes, we follow Evans and Archer (1968). At the end of each month, we perform 1000 simulations for each asset class. In each of these simulations we randomly draw 1 to 10 funds from all the funds within the asset class that have twelve months of past return observations and calculate the equal weighted portfolio returns. Next, for each of the 10 thousand simulated portfolios, we calculate the standard deviations of the portfolio returns using the past twelve months. Then, for each asset class we have portfolio standard deviations of returns related to portfolios consisting of 1 to 10 funds and take the average of the 1000 simulations. These will be used to estimate the diversification effect per asset class; the speed of which average portfolio return volatility is lowered by adding another fund to the portfolio. This diversification effect is estimated by the slope coefficient in the following regression:

$$\bar{\sigma}_{i,j,t} = \alpha_{j,t} + \beta_{j,t} \frac{1}{N_{i,j,t}} + \varepsilon_{i,j,t}, \tag{2}$$

where $\bar{\sigma}_{i,j,t}$ is the average standard deviation of asset class *j* in month *t* of portfolio *i,* with *i = 1,2,..,10*; $N_{i,j,t}$ denotes the number of funds in portfolio *i* in month *t* for asset class *j*; $\alpha_{j,t}$ and $\beta_{j,t}$ are parameters to be estimated were the first corresponds to the systematic risk component that cannot be diversified away and the latter denotes the effect of diversification in which we are interested. Finally, we use the time-series averages of the slope coefficients as the relevant proxy for breadth. The higher the average slope coefficient is the higher is the diversification effect within the asset class and thus the more breadth the asset class is expected to have.

3. Data

The data we use for this study come from the Morningstar Database. The data cover monthly U.S. dollar denominated mutual fund returns from

January 1990 to December 2010; resulting in a time-series of 252 monthly observations. The database includes funds that are still active as well as defunct funds and therefore the results are unlikely to suffer from a survivorship bias as described by Brown *et al.* (1992). We are interested in the performance of actively managed mutual funds and thus exclude funds that passively invest in an index (by visually checking the names and deleting funds with, e.g., "index", or "S&P500" in the name). Moreover, we require a fund to have at least twelve consecutive return observations to be included in the analysis. Morningstar lists multiple share classes as separate funds even though they share the same underlying portfolio. In order not to double count returns, we eliminate multiple share classes by averaging the returns over the different share classes.

Each fund is allocated to a different asset class depending on the investment universe of the particular fund. The different asset classes considered in this study are reported in Table 1. The funds are grouped into a total of 20 different asset classes. Six broad equity classes: 'Global equity', 'U.S. equity', 'European equity', 'Japanese equity', 'Asia-Pacific excluding Japan equity', and 'Emerging markets equity'; seven different, more focused U.S. equity classes: small caps, mid-caps, large caps, large cap blend, large cap value, large cap growth and real-estate equity; and seven different bond classes: 'Global bonds', 'U.S. bonds', U.S. government bonds', 'U.S. high yield bonds', 'European bonds', 'European government bonds' and 'European corporate bonds'. The relevant benchmarks that are used for the different asset classes are reported in the second column of the table. The average benchmark returns and standard deviation of returns for the different benchmarks are reported in the following two columns. Over the period January 1990 to December 2010, emerging markets equity has the highest average return as well as the highest volatility of return. The U.S. government bond benchmark reports the lowest return over the same period.

[INSERT TABLE 1 ABOUT HERE]

Furthermore, Table 1 also presents the number of funds we use in our analysis at the start of the sample period as well as at the end of the sample period. Interestingly, it can be seen that the mutual fund industry, in general, has seen an explosive growth in the number of different funds. Except for the number of U.S. government bond funds, there has been a sharp increase in the number of funds within an asset class. Especially for the emerging markets equity class, the growth in the number of funds has been impressive, starting with only 10 back in January 1990 to 1,233 at the end of 2010. For the empirical analysis, we restrict the number of funds to be at least 10 in order to be able to accurately analyze performance persistence. Consequently, for U.S. REITs funds the sample period starts in November 1993 instead of January 1990.

4. Empirical Results

This section presents our empirical results. We begin by analyzing persistence in performance within the different asset classes. Then we will study if there is a relation between the strength in performance persistence on the one hand and the asset class efficiency in which these funds operate, on the other hand. Next, we investigate the relation between differences in the persistence in performance across and within asset classes and the breadth of an asset class.

4.1 Performance Persistence in Different Asset Classes

A fair amount of research is conducted on the persistence in mutual fund performance. The vast majority of these studies are performed on U.S. equity mutual funds since, presumably, historical data is and has been widely available for the U.S. Studies on the persistence in performance of U.S. equity mutual funds are, for instance, Hendricks *et al.* (1993), Goetzmann and Ibbotson (1994), Brown and Goetzmann (1995), Elton *et al.* (1996), Carhart (1997) and Bollen and Busse (2005). The literature on equity funds that invest outside of the U.S. is much less abundant. Examples are Otten and Bams (2002) who look at the performance persistence of European equity funds; Huij and Post (2011) who examine persistence in performance of emerging markets equity funds; and Lin and Yung (2004) who study the persistence of U.S. real estate equity funds. And even though actively managed bond funds constitute a sizeable part of the mutual fund industry, studies on the persistence in bond funds is also relatively scarce. A few papers that do study persistence among bond funds are, for instance, Blake *et al.* (1993) and Huij and Derwall (2008).

The data we use for our study cover many of these different asset classes. This enables us to compare the persistence in performance across the different asset classes that we analyze.

Table 2 presents the results on persistence in performance across the different asset classes. For each quintile portfolio constructed by sorting funds on their past twelve-month returns, the next month equal weighted portfolio return minus the return on the benchmark are shown together with a portfolio that is long in the recent winner funds and that shorts the recent loser funds. The first noticeable result is that the portfolio consisting of the funds with the lowest past twelve-month performance (the loser portfolio) persistently underperforms its benchmark the following month in each of the asset classes. For instance, emerging markets equity fund losers, on average underperform the benchmark by 49 basis points in the following month. And the recent loser funds investing in U.S. government bonds on average underperform the benchmark by 12 basis points the following month. The portfolios consisting of recent winner funds, on the other hand, have a much higher performance, albeit not significantly above their benchmark.[5] Moreover the performance is, in general, monotonically increasing over the quintiles, indicating that the performance of the mutual funds is indeed persistent and this persistence is present in each of the asset classes.

For almost all of the asset classes, except Asia-Pacific equities and U.S. government bonds, we find significant return spreads between the recent winner funds and the recent loser funds. Moreover, the persistence in performance differs to a great extent from one asset class to the next. For instance, U.S. small cap equity fund winners outperform their peer losers by 84 basis points, on average; almost twice the winner minus loser return spread for U.S. large cap funds (46 basis points) which itself is higher compared to the return spreads of each of the seven bond classes.

[INSERT TABLE 2 ABOUT HERE]

[5] If active managers, on average, own the 'market' (approximately), the average mutual fund performance before fees and other costs are taken into account should track benchmark. Then after fees and other costs, the average mutual fund will underperform the benchmark. Consequently, we do not expect to see a symmetric return distribution around the benchmark return (see, e.g., Sharpe, 1991).

4.2 Asset Class Efficiency

An often heard, and perhaps, conventional wisdom is that it is easier for a portfolio manager to persistently show an outperformance in less efficient markets. If this is true, the added value of active management is expected to be higher in, for instance, emerging markets which are generally perceived to be less efficient than more developed markets like the U.S. An argument in favor of this conjecture is that these markets are followed by less analysts resulting in lower confidence of the 'true' prices and information is expected to diffuse more gradually. Hence, as skillful managers are expected to be able to exploit these inefficiencies, persistence in performance is expected to be higher in inefficient markets. In this subsection, we analyze the relation between the persistence in performance and asset class efficiency using the measures discussed in detail in the appendix.

The five different efficiency test statistics (the variance ratio test statistic, the runs test statistic and three Ljung-Box portmanteau test statistics) and their relative rankings are reported for each asset class in Panel A of Table 3. Also, we report the overall ranking that is based on the average of the five individual rankings. The benchmark with the most random monthly return patter (rank equals 1) is the S&P 500. Hence, as for both the U.S. large cap equity and the U.S. large cap blend equity classes the S&P 500 is the relevant benchmark, these are the found to be the asset classes that are the most efficient. This is not surprising given that the U.S. equity market, and in particular the large cap segment, is very well developed with an enormous number of investors participating in trading every day including many institutional, professional investors, as well as many analysts that follow the securities. Other asset classes, besides U.S. equity, that are considered to be amongst the most efficient are Japanese equity and global equity (of which the U.S. and Japanese equity markets are a big part of). Asia-Pacific equity and emerging markets equity are the least efficient equity classes and are only considered to be more efficient than the U.S. corporate high yield bond class. The bond classes are considered to be less efficient compared to the equity classes with a similar geographical focus. While the U.S. government bond class is the most efficient bond class, the U.S. corporate high yield bond class is the least efficient bond class (or any other class).

Also, the U.S. bond classes seem to be more efficient than the corresponding European bond classes.

[INSERT TABLE 3 ABOUT HERE]

Using these results as input, we investigate if market efficiency is an important determinant for skillful managers to add value in a persistent manner. If market efficiency is indeed an important determinant for skillful portfolio managers to persistently outperform the benchmark and/or their peers, we expect to see that persistence is more prevalent among bond fund managers and emerging markets equity fund managers than among, for instance, U.S. equity fund managers. For this reason, we calculate rank correlations between the efficiency measures and the outperformance of recent winner funds compared to their peer losers and compared to their benchmark. These rank correlations are shown in Panel B of Table 3. Interestingly, the correlation between the overall efficiency rank (where relative efficient asset classes have a low number) and the average winner minus loser return spread rank (asset classes with high average return spreads have large numbers) equals -0.25; not a positive number what would be expected if persistence is stronger in efficient markets. Similar results hold for the outperformance of recent winners against their benchmark and also for the different efficiency measures separately.

Hence, we do not find evidence consistent with the conventional wisdom that the added value of active management is mostly prevalent within inefficient markets. This can also be seen in Figure 1 in which the asset class' ranks of the return spreads between past winners and past losers is plotted against the overall efficiency ranks. The dots are scattered around the graph without seeing a clear pattern. In fact, if persistence is higher within less efficient markets, the dots are expected to be located mostly within the lower left and upper right quadrants. Obviously, no such pattern exists, and if at all there would be a relation, it seems to be a negative one.

[INSERT FIGURE 1 ABOUT HERE]

4.3 Breadth

An alternative hypothesis, provided by Grinold (1989) and Grinold and Kahn (2001), is that the value of active management depends on both managerial investment skill and the investment opportunity set. Their 'fundamental law of active management' postulates that the expected outperformance of a skilled managers is positively related to, *ceteris paribus,* breadth, defined as the number of independent investment opportunities available in the manager's investment universe. Hence, following the *law*, persistence in mutual fund performance is, 1) stronger for asset classes with more breadth, and 2) stronger in periods in which there is a relatively abundant number of independent investment opportunities available within the asset class. In this subsection we will investigate the former conjecture and postpone the empirical investigation of the latter conjecture to the next subsection.

For each of the asset classes the three breadth measures (the average cross-sectional return dispersion, the average fund' tracking errors and the average diversification effect) are reported in Table 4, Panel A. Also, we report the corresponding ranks (a high number corresponds to relatively more breadth within the asset class) as well as the overall breadth rank which is based on the average rank of the three breadth measures. Not surprisingly, the emerging markets equity class and the global equity class are the asset classes for which the breadth is found to be the most prevalent. U.S. large cap blend equity, on the other hand, is the equity class that is considered to have the least amount of breadth, even lower than two of the bond classes. In general, the bond classes, not surprisingly, score low on breadth. This is to be expected since the returns on fixed-income securities can be explained to a large extent by just a few factors (see, e.g., Knez *et al.*, 1994), while the idiosyncratic component of equity returns is relatively higher. The bond classes in which breadth is most prevalent are global bonds and European corporate bonds. U.S. government bonds and U.S. bonds provide the least amount of breadth.

[INSERT TABLE 4 ABOUT HERE]

In Figure 2, the past winners minus losers return spread ranks are plotted against the overall breadth ranks of the asset classes. Contrary to the figure on market efficiency, a clear positive relation seems to exist between breadth and persistence in performance. Asia-Pacific equity is the big outlier as persistence in performance is relatively low while the estimated market breadth is relatively high.

[INSERT FIGURE 2 ABOUT HERE]

In Panel B of Table 4, we present results of more formal tests on the relation between performance persistence across asset classes, measured by the rank of the past winners minus past losers return spreads, and the breadth of the asset classes. First, the rank correlation is highly positive and equals 0.69 in case of the overall breadth rank. Also the rank correlations with the separate breadth measures are highly positive and are between 0.48 for the diversification effect and 0.78 for the cross-sectional return dispersion variable. The slope estimates of simple OLS regressions are all significantly positive. For instance, using the overall breadth rank as explanatory variable, the estimated slope equals 0.70 (with a *t*-statistic of 4.04) and it can explain forty-five of the variability in performance persistence across the asset classes (the estimated regression line corresponds to the solid line in the graph of Figure 2). As a final formal test, we also provide the X^2 test-statistics of the contingency tables. Again, we can conclude that there is a significant positive relation between breadth and persistence in performance. This can also be seen from Figure 2, in which the big majority of the asset classes are located in either the lower left or upper right quadrants, while only few are located in the upper left and lower right quadrants.

For the sake of robustness, we also present similar test results on the relation between breadth and persistence in performance, but this time use the rank on the return spread between past winners and their benchmark. The results, presented in Panel C of the table, are qualitatively similar. Again, we find high positive rank correlations, significantly positive slope coefficients and significant X^2 statistics. Hence, from these results, we conclude that asset class breadth is indeed an important determinant for the differences in persistence that is found across the asset classes.

4.4 Breadth and Persistence over Time

In the previous subsection, we showed there is a positive relation between breadth and performance persistence across asset classes. Clearly, breadth within an asset class can change over time; however, in the previous analysis we ignored any potential dynamics in breadth within the asset classes. Bernstein (1998), for instance, shows that the cross-sectional return dispersion of U.S. equity mutual funds has declined over the period from 1969 to 1997. In another study, De Silva *et al.* (2001) show that the return dispersion of U.S. equity mutual funds is much higher in the years before the burst of the tech-bubble, hence following the sample period of Bernstein (1998).

In Figure 3 twelve-month moving average cross-sectional return dispersions are plotted for each of the asset classes separately. In line with earlier studies (see, e.g., Bernstein, 1998; Campbell *et al.*, 2001; De Silva *et al.*, 2001; and Connor and Li, 2009), we find clear evidence of dynamics in cross-sectional mutual fund return dispersions and thus dynamics in breadth within the asset classes. In the early 1990s, the first years of our sample period, cross-sectional return dispersion is decreasing for the equity classes. In the years before the burst of the tech-bubble, there is a sharp increase and a similar decline around the time of the burst. Starting at the end of 2007, cross-sectional dispersions are again increasing with the peak occurring in 2009. Interestingly, within this period, the same pattern of increasing breadth, followed by a decrease, holds for both equity funds as well as bond funds.

[INSERT FIGURE 3 ABOUT HERE]

Now that we showed that breadth is not constant over time, the next step is to investigate if the dynamics in breadth within asset classes can explain dynamics in performance persistence. If this is the case, we expect to see stronger (weaker) persistence in performance in periods in which breadth is relatively high (low). In a first approach to analyze this conjecture we use a non-parametric method in which we sort the monthly observations on the cross-sectional return dispersion within the asset classes. That is, we divide the sample into three equal sized but different states-of-nature of low, medium and high dispersion months and calculate, per state-of-nature, the average return spreads between past winners and past losers as well as the benchmark adjusted return of past winner funds. The results of this analysis are reported in Table 5.

Comparing the winners minus losers return spread of high dispersion months with low dispersion months, we find that persistence in performance is indeed higher in times there is more breadth in the market. On average, the return spread in high dispersion months is 64 basis points while in low dispersion months the return spread is only 26 basis points, on average. Moreover, in seventeen out of the twenty asset classes, return spreads are higher in months with high dispersion compared to months with low dispersion. The results are similar for the benchmark adjusted performance of recent winners, albeit somewhat less strong. Interestingly, on average the winners do not persistently outperform their benchmarks in periods with low to mediocre breadth. However, the outperformance is persistent in periods with relatively high breadth and equals 27 basis points per month. Hence, we conclude that breadth indeed is an important determinant for persistence in performance. Not only to explain differences in persistence across asset classes, but also the dynamics in persistence within asset classes.

[INSERT TABLE 5 ABOUT HERE]

In a final analysis, we perform cross-sectional Fama and MacBeth (1973) type of regressions and pooled OLS regressions to be able to account for dynamics in breadth and its relation with mutual fund performance persistence. We estimate the following two regressions:

(3) $$R_{k,t}^{W-L} = \alpha + \beta_k^{Bench} R_{B_k,t}^2 + \beta_k^{Disp} \sigma_{k,t}^{CS} + IE_k + \varepsilon_{k,t},$$

and

(4) $$R_{k,t}^{W-B} = \alpha + \beta_k^{Bench} R_{B_k,t}^2 + \beta_k^{Disp} \sigma_{k,t}^{CS} + IE_k + \varepsilon_{k,t},$$

where $R_{B_k,t}$ is the excess benchmark return of asset class k at time t, $k = 1,2,..,20$; $\sigma_{k,t}^{CS}$ is the demeaned contemporaneous cross-sectional return dispersion for asset class k at time t; and IE_k is a dummy variable that equals one in case asset class k belongs to the ten least efficient asset classes (which follows from Table 3) and is zero otherwise. The variables to be explained are the return spreads between past winners and past losers, $R_{k,t}^{W-L}$, and the return difference between past winners and their benchmark return, $R_{k,t}^{W-B}$.

The estimated coefficients on the different regressions are reported in Table 6. Consistent with our earlier results, we again find a positive relation between persistence in performance on the one hand and breadth, measured by the cross-sectional return dispersion, on the other hand, even after controlling for extreme benchmark returns and asset class efficiency.

[INSERT TABLE 6 ABOUT HERE]

5. Conclusions

The fundamental law of Grinold (1989) and Grinold and Kahn (2000) puts forward that the value of active management depends on the skill of the manager and the breadth of the investment strategy. A competing hypothesis states that that the value added of active management is low in developed markets and that active managers are better able to produce alpha in, for instance, emerging markets as these markets are much less efficient. In this paper we analyze what the effect is of both types of market conditions on the persistence in the performance of actively managed mutual funds.

Using a comprehensive database of mutual funds from a broad range of asset classes, we find that performance persistence is positively related to the average breadth that is present within an asset class. That is, asset classes with more breadth show stronger persistence in returns compared to asset classes for which breadth is relatively scarce. Moreover, we find that breadth is also important in explaining dynamics in persistence; in periods with more breadth, past winner funds outperform to a larger extent than in periods with less breadth. Interestingly, we do not find evidence that market efficiency is an important determinant of performance persistence among mutual fund managers.

Appendix

In this appendix, we discuss the measures of market efficiency we use for this study. In total, we will consider five different measures to estimate efficiency within the different asset classes. The measures we use are a variance ratio test, a non-parametric runs test and three serial correlation tests. All these measures have in common that we use the sample period monthly returns of the relevant benchmarks, which are reported in Table 1 of the main text.

The variance ratio test, developed by Lo and MacKinlay (1988), is a widely used test for random walk behavior in financial markets. The idea behind the test is that if the natural logarithm of a monthly price index, Y_t, follows a random walk, a necessary condition for an asset to be weak-form efficient (see Fama, 1970), return variances should increase proportionally to the observation interval, q. The variance ratio, $VR(q)$, of asset class j is defined as

$$\text{(A1)} \quad VR_j(q) = \frac{VAR[q]}{qVAR[1]},$$

where $VAR[q] = \frac{1}{m_j}\sum_{t=q+1}^{T_j}\left(Y_{j,t} - Y_{j,t-q} - q\hat{\mu}_j\right)^2$, $m_j = q\left(T_j - q + 1\right)\left(1 - \frac{q}{T_j}\right)$, T_j is equal to the length of the sample period, in months, and $\hat{\mu}_j = \frac{1}{T_j}\left(Y_{j,T_j} - Y_{j,1}\right)$. A variance ratio greater (less) than one, implies positive (negative) autocorrelation in the benchmark return series. The standard normal test statistic, $Z_j(q)$, for the null hypothesis of a random walk is estimated as

$$\text{(A2)} \quad Z_j(q) = \frac{VR_j(q) - 1}{\sqrt{\phi_j(q)}},$$

where $\phi_j(q) = \frac{2(2q-1)(q-1)}{3qT_j}$. Following Chow and Denning (1993) we use the multiple variance ratio test. This test considers the maximum absolute value of the test statistics in Equation (A2) for $q = 1,2,..,12$. Hence, the multiple variance ratio test we use in this study is defined as

$$\text{(A3)} \quad Z_j^*(q) = \max_{1 \le i \le 12}\left|Z_j(q_i)\right|.$$

The second measure we use in order to test the randomness of the sequence of the monthly benchmark returns for the particular asset classes is a non-parametric runs test. If the successive change in the returns behaves randomly, this is an indication of weak-form efficiency.

However, if the behavior is not random, then the asset class return is predictable and therefore expected to be less efficient.

The monthly return series of the asset classes are divided into two different types: positive excess returns and negative excess returns. A sequence of (at least one) positive (negative) return(s) is counted as a single run. We make use of the Wald-Wolfowitz runs test which is approximately normal with an expected number of runs, $E[M_j]$, and is equal to

$$\text{(A4)} \quad E[M_j] = \frac{2N_j^{Up}N_j^{Down} + N_j^{Up} + N_j^{Down}}{N_j^{Up} + N_j^{Down}},$$

where N_j^{Up} and N_j^{Down} is the observed number of positive monthly returns and negative monthly returns of benchmark *j*, respectively. The variance equals

$$\text{(A5)} \quad \sigma_{M_j}^2 = \frac{2N_j^{Up}N_j^{Down}\left(2N_j^{Up}N_j^{Down} - N_j^{Up} - N_j^{Down}\right)}{\left(N_j^{Up} + N_j^{Down}\right)^2\left(N_j^{Up} + N_j^{Down} - 1\right)}.$$

If the actual number of runs is significantly greater or smaller than expected, it simply indicates that the sequence does not appear to be random as there is mean reversion or mean aversion, respectively.

Finally, we estimate asset class efficiency using serial correlation tests. The Ljung-Box portmanteau statistic is used to test whether the return series of the relevant benchmarks are white noise. The $Q^{LB}(s)$-statistic at lag s is a test statistic with the null hypothesis that there is no autocorrelation in the monthly returns up to order s and is given by

$$\text{(A6)} \quad Q_j^{LB}(s) = T_j\left(T_j + 2\right)\sum_{k=1}^{s}\frac{r_{j,k}^2}{T_j - k},$$

where T_j is the number of months of the sample of asset class j and $r_{j,k}$ is the sample autocorrelation coefficient of the benchmark of asset class j with lag k. We restrict the analysis to the first, sixth and twelfth-order autocorrelations.

A final note we make is that for this study we are not so much interested in testing whether markets are efficient or not, however, we are interested in the relative efficiency of the different asset classes we consider in this study. Therefore, we will use the relevant rankings of the efficiency test statistics for the empirical analyses.

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Table 1: **The Different Asset Classes and its Benchmarks**

This table presents the different asset classes included in the analysis of this study. In the second column, the relevant benchmark is shown. Columns three and four report the average benchmark return and standard deviation, respectively. The final two columns report the number of funds in our database in January 1990, the beginning of the sample period and in December 2010, the end of the sample period.

Asset Class	**Benchmark**	**Average return (%)**	**Stdev (%)**	**# of funds 01/1990**	**# of funds 12/2010**
Global Equity	MSCI World	0.61	4.50	99	1,176
U.S. Equity	MSCI U.S.	0.80	4.40	659	2,674
European Equity	MSCI Europe	0.78	5.10	38	613
Japanese Equity	MSCI Japan	0.09	6.38	135	1,070
Asia-Pacific (Ex Japan) Equity	MSCI Asia Pacific Ex Japan	0.92	6.40	27	237
Emerging Markets Equity	MSCI Emerging Markets	1.12	6.96	10	1,233
U.S. Small Caps	Russell 2000	0.90	5.69	85	567
U.S. Mid Caps	Russell MidCap	1.00	4.90	124	587
U.S. Large Caps	S&P 500	0.78	4.38	450	1,520
U.S. Large Caps Blend	S&P 500	0.78	4.38	153	486
U.S. Large Cap Value	Russell 1000 Value	0.82	4.30	116	416
U.S. Large Cap Growth	Russell 1000 Growth	0.77	5.07	181	618
U.S. REITs	NAREIT Equity	1.04	6.07	10*	77
Global Bonds	BarCap. Global Aggr. Bond	0.59	1.62	151	1,506
U.S. Bonds	BarCap. U.S. Aggr. Bond	0.57	1.10	150	438
U.S. Government Bonds	BarCap. U.S. Aggr. Government	0.55	1.26	169	147
U.S. High Yield Bonds	BarCap. U.S. Corp. High Yield	0.76	2.73	61	150
European Bonds	JP Morgan Euro Aggr.	0.62	3.25	271	2,406
European Government Bonds	JP Morgan Euro Government Bond	0.68	3.00	44	291
European Corporate Bonds	BarCap. Euro Aggr. Corporate	0.65	3.28	13	364

* Due to the low number of funds for the U.S. REITs asset class, the sample period starts in November 1993.

Table 2: **Performance Persistence per Asset Class**

This table presents average portfolio returns. At the end of each month, all funds belonging to a certain asset class are sorted into quintiles based on the previous twelve-month return. The reported returns are the equal weighted portfolio returns over the following month minus the return on the benchmark. The final column reports the returns of a portfolio that is long in the recent winner portfolio and is short the portfolio consisting of recent loser funds. The sample period is from January 1991 to December 2010. *t*-Statistics are reported within brackets.

Asset Class	Losers	2	3	4	Winners	W-L
Global Equities	-0.26	-0.08	-0.09	0.04	0.32	0.58
	[-2.36]	[-1.26]	[-1.33	[0.49]	[2.13]	[3.20]
U.S. Equities	-0.24	-0.12	-0.04	0.09	0.35	0.60
	[-1.79]	[-1.35]	[-0.57]	[0.81]	[1.73]	[2.51]
European Equities	-0.32	-0.21	-0.25	-0.22	-0.05	0.27
	[-4.00]	[-3.64]	[-4.25]	[-3.33]	[-0.48]	[2.26]
Japanese Equities	-0.25	-0.12	-0.07	0.03	0.37	0.63
	[-1.89]	[-1.46]	[-0.82]	[0.24]	[1.81]	[2.83]
Asia-Pacific Equities	-0.29	-0.13	-0.12	-0.11	-0.10	0.19
	[-2.38]	[-1.58]	[-1.48]	[-1.33]	[-0.91]	[1.27]
Emerging Markets Equities	-0.49	-0.37	-0.26	-0.17	0.06	0.55
	[-2.84]	[-2.78]	[-2.14]	[-1.41]	[0.35]	[2.80]
U.S. Small Cap Equities	-0.41	-0.17	-0.01	0.13	0.43	0.84
	[-2.90]	[-1.68]	[-0.22]	[1.54]	[3.01]	[3.43]
U.S. Mid Cap Equities	-0.44	-0.26	-0.19	0.00	0.22	0.66
	[-3.65]	[-3.54]	[-2.99]	[0.02]	[1.23]	[2.62]
U.S. Large Cap Equities	-0.28	-0.18	-0.11	-0.01	0.18	0.46
	[-2.83]	[-3.18]	[-2.56]	[-0.03]	[1.52]	[2.52]
U.S. Large Cap Blend Equities	-0.29	-0.16	-0.11	-0.02	0.11	0.39
	[-3.72]	[-3.77]	[-2.75]	[-0.29]	[1.55]	[3.56]
U.S. Large Cap Value Equities	-0.30	-0.19	-0.12	-0.11	-0.01	0.29
	[-4.26]	[-4.07]	[-2.87]	[-2.29]	[-0.14]	[3.04]
U.S. Large Cap Growth Equities	-0.17	-0.13	-0.06	0.05	0.25	0.42
	[-1.78]	[-1.81]	[-0.80]	[0.57]	[1.89]	[2.45]
U.S. REITs	-0.17	-0.08	-0.05	0.01	0.10	0.28
	[-1.85]	[-1.85]	[-1.17]	[0.14]	[1.17]	[2.18]
Global Bonds	-0.23	-0.11	-0.08	-0.07	0.04	0.27
	[-2.54]	[-2.05]	[-1.66]	[-1.23]	[0.51]	[2.14]
U.S. Bonds	-0.18	-0.11	-0.07	-0.04	0.01	0.18
	[-3.58]	[-3.58]	[-3.43]	[-2.09]	[0.24]	[3.54]
U.S. Government Bonds	-0.12	-0.10	-0.08	-0.08	-0.06	0.06
	[-2.40]	[-2.74]	[-2.71]	[-3.33]	[-1.53]	[0.71]
U.S. High Yield Bonds	-0.36	-0.14	-0.10	-0.06	0.02	0.38
	[-7.25]	[-4.12]	[-2.62]	[-1.18]	[0.34]	[5.45]
European Bonds	-0.29	-0.19	-0.15	-0.08	-0.02	0.26
	[-3.88]	[-3.59]	[-3.29]	[-1.95]	[-0.51]	[4.16]
European Government Bonds	-0.24	-0.14	-0.10	-0.09	-0.03	0.20
	[-4.11]	[-3.55]	[-2.91]	[-2.49]	[-0.79]	[2.85]
European Corporate Bonds	-0.33	-0.16	-0.12	-0.11	0.04	0.36
	[-4.68]	[-4.06]	[-3.06]	[-2.94]	[0.65]	[4.39]

Table 3: **Relative Efficiency of the Asset Classes**

Panel A of this table presents estimated test values and corresponding ranks for five different measures of asset class efficiency. Also, an overall rank is reported that is based on the average rank of the five different efficiency measures. The first measure is based on the multiple variance ratio test of Chow and Denning (1993). The second efficiency measure is based on a non-parametric runs test that counts the number of sequences with positive excess benchmark returns and negative excess benchmark returns. Positive values for the test-statistic correspond to mean aversion and negative values for the test-statistic correspond to mean reversion in the asset class returns. The final three measures are based on the Ljung-Box portmanteau test statistics for the first, sixth and twelfth-order autocorrelations, respectively. A detailed discussion on the measures can be found in the appendix of the paper. In Panel B formal rank correlations between winner minus loser return spread ranks or winner minus benchmark return ranks and the efficiency ranks are shown. The sample period is from January 1991 to December 2010. A *, **, or *** denotes the test statistic exceeds the critical value at the 10%, 5% or 1% significance level, respectively.

Panel A: Asset class efficiency

Asset Class	Benchmark	Overall Rank	Variance Ratio	Rank	Runs Test	Rank	$Q_{LB}(1)$	Rank	$Q_{LB}(6)$	Rank	$Q_{LB}(12)$	Rank
Global Equity	MSCI World	**5**	1.80*	7	-0.06	2	3.22*	9	6.88	6	11.12	4
U.S. Equity	MSCI U.S.	**3**	1.90*	8	0.03	1	1.18	3	5.13	4	11.58	6
European Equity	MSCI Europe	**9**	2.04**	11	-1.44	11	3.52*	11	8.86	10	13.14	9
Japanese Equity	MSCI Japan	**6**	1.27	1	-0.47	6	1.75	5	6.18	5	19.35*	15
Asia-Pacific Equity	MSCI Asia Pacific Ex Japan	**18**	3.46***	18	-2.15**	14	7.40***	18	14.55**	17	21.38**	16
Emerging Markets Equity	MSCI Emerging Markets	**19**	3.67***	19	-1.70*	12	10.47***	19	22.12***	18	24.41**	17
U.S. Small Caps	Russell 2000	**11**	2.08**	12	-1.14	9	4.40**	14	12.49*	15	11.74	7
U.S. Mid Caps	Russell MidCap	**14**	2.48***	15	-0.87	8	6.02**	15	12.77**	16	14.69	11
U.S. Large Caps	S&P 500	**1**	1.70*	3	0.24	3	1.05	1	4.81	2	10.87	2
U.S. Large Caps Blend	S&P 500	**1**	1.70*	3	0.24	3	1.05	1	4.81	2	10.87	2
U.S. Large Cap Value	Russell 1000 Value	**7**	1.69*	2	0.36	5	2.35	6	8.00	7	16.91	14
U.S. Large Cap Growth	Russell 1000 Growth	**4**	2.09**	13	0.55	7	1.30	4	3.45	1	8.01	1
U.S. REITs	NAREIT Equity	**16**	2.09**	14	-2.10**	13	2.87*	7	46.35***	19	72.36***	20
Global Bonds	BarCap. Global Aggr. Bond	**17**	2.49***	16	-3.25***	17	7.13***	17	10.22	11	26.79***	18
U.S. Bonds	BarCap. U.S. Aggr. Bond	**10**	2.01**	10	-3.79***	19	4.29**	13	8.05	8	11.32	5
U.S. Government Bonds	BarCap. U.S. Aggr. Government	**8**	1.74*	5	-3.87***	20	3.06*	8	8.74	9	12.81	8
U.S. High Yield Bonds	BarCap. U.S. Corp. High Yield	**20**	5.82***	20	-3.62***	18	35.46***	20	46.72***	20	47.03***	19
European Bonds	JP Morgan Euro Aggr.	**13**	1.91*	9	-2.52***	16	4.13**	12	10.28	12	14.43	10
European Government Bonds	JP Morgan Government Bond	**11**	1.78*	6	-2.29**	15	3.29*	10	10.75*	13	15.43	13
European Corporate Bonds	BarCap. Euro Aggr. Corporate	**15**	2.57***	17	-1.25	10	7.06***	16	10.99*	14	15.12	12

Panel B: Rank correlations efficiency measure and return spreads

	Overall Rank	Variance Ratio	Runs Test	$Q_{LB}(1)$	$Q_{LB}(6)$	$Q_{LB}(12)$
Winners minus Losers	-0.25	-0.04	-0.72	-0.18	-0.15	-0.19
Winners minus Benchmark	-0.39	-0.14	-0.67	-0.35	-0.32	-0.31

Table 4: **Breadth and Performance Persistence**

Panel A of this table presents estimated values and corresponding ranks for three different measures of asset class breadth. Also, an overall rank is reported that is based on the average rank of the three different breadth measures. The measures of breadth are the time-series averages of monthly cross-sectional mutual fund return dispersions, time-series averages of twelve-month tracking errors and the times-series average diversification effect. A detailed discussion on the measures can be found in Section 2 of the paper. In Panel B (Panel C) formal tests of the relation between winner minus loser return spread ranks (winner minus benchmark return ranks), based on Table 2, and the four breadth measures are shown. These tests include rank correlations; OLS regression estimates, in which the return rank is regressed on a constant and one of the four breadth ranks; and X^2 statistics corresponding to contingency tables using median ranks. The sample period is from January 1991 to December 2010. *t*-Statistics are reported within brackets.

Panel A: Asset class breadth

Asset Class	**Overall Rank**	**CS Disp.**	**Rank**	**Tracking Error (%)**	**Rank**	**Div. Effect**	**Rank**
Global Equity	**19**	2.64	19	2.17	18	0.66	17
U.S. Equity	**14**	2.41	15	2.19	19	0.49	12
European Equity	**12**	1.95	11	1.56	11	0.48	11
Japanese Equity	**16**	2.50	16	2.12	17	0.52	14
Asia-Pacific Equity	**16**	2.37	14	1.96	14	0.72	19
Emerging Markets Equity	**20**	3.08	20	2.57	20	0.83	20
U.S. Small Caps	**14**	2.58	18	2.07	15	0.51	13
U.S. Mid Caps	**18**	2.51	17	2.08	16	0.53	16
U.S. Large Caps	**10**	1.97	12	1.63	12	0.38	8
U.S. Large Caps Blend	**6**	1.55	9	1.25	8	0.30	6
U.S. Large Cap Value	**7**	1.54	8	1.38	9	0.32	7
U.S. Large Cap Growth	**13**	2.11	13	1.74	13	0.39	9
U.S. REITs	**10**	1.43	7	1.07	7	0.72	18
Global Bonds	**9**	1.57	10	1.48	10	0.43	10
U.S. Bonds	**2**	0.57	1	0.40	2	0.11	2
U.S. Government Bonds	**1**	0.73	2	0.33	1	0.10	1
U.S. High Yield Bonds	**4**	0.92	4	0.82	5	0.24	4
European Bonds	**5**	0.94	5	0.89	6	0.14	3
European Government Bonds	**3**	0.73	3	0.66	3	0.27	5
European Corporate Bonds	**8**	0.97	6	0.74	4	0.53	15

Panel B: Relation with winners minus losers returns

		Overall Rank	**CS Disp.**	**Tracking Error**	**Div. Effect**
Pearson's rank correlation		0.69	0.78	0.76	0.48
OLS Regressions	Intercept	3.25	2.27	2.51	5.42
		[1.59]	[1.30]	[1.37]	[2.19]
	Slope	0.70	0.78	0.76	0.48
		[4.04]	[5.35]	[4.98]	[2.35]
	Adjusted R-squared	0.45	0.59	0.56	0.19
Contingency Tables	X^2	5.56	7.20	7.20	0.80
	p-value	(0.02)	(0.01)	(0.01)	(0.37)

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Table 4: **Continued from previous page**

Panel C: Relation with winners minus benchmark returns

		Overall Rank	**CS Disp.**	**Tracking Error**	**Div. Effect**
Pearson's rank correlation		0.55	0.65	0.64	0.37
OLS Regressions	Intercept	4.68	3.66	3.79	6.58
		[1.99]	[1.71]	[1.74]	[2.51]
	Slope	0.56	0.65	0.64	0.37
		[2.82]	[3.64]	[3.53]	[1.71]
	Adjusted R-squared	0.27	0.39	0.38	0.09
Contingency Tables	X^2	8.10	7.20	7.20	3.20
	p-value	(0.00)	(0.01)	(0.01)	(0.07)

Table 5: **Return Spreads for Different States-of-Nature**

This table presents average return spreads between past winners and past losers as well as the return difference between past winners and its benchmarks. Reported return spreads are the average return spreads within three different states-of-nature: low, medium and high cross-sectional return dispersion month. These states-of-nature are asset class dependent, i.e., 'low' cross-sectional dispersion months in one asset class do not necessarily correspond to a low state-of-nature in another asset class. The final set of columns report the average return dispersion for the relevant state-of-nature. The sample period is from January 1991 to December 2010, resulting in a total of 240 return observations and 80 observations per state-of-nature.

	Winners minus Losers			Winners minus Benchmark			Cross-Sectional Dispersion		
Asset Class	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
Global Equity	0.42	0.50	0.82	0.17	0.29	0.49	1.78	2.43	3.72
U.S. Equity	0.27	0.36	1.17	0.14	0.15	0.77	1.47	2.07	3.70
European Equity	0.18	0.36	0.26	-0.09	-0.04	-0.03	1.23	1.80	2.83
Japanese Equity	0.15	0.43	1.29	-0.14	0.02	1.24	1.58	2.22	3.71
Asia-Pacific Equity	0.35	0.39	-0.18	-0.08	-0.17	-0.05	1.53	2.14	3.44
Emerging Markets Equity	0.59	0.44	0.62	0.10	-0.03	0.10	2.02	2.78	4.45
U.S. Small Caps	0.42	0.45	1.65	0.13	0.20	0.97	1.60	2.18	3.95
U.S. Mid Caps	0.24	0.33	1.42	-0.04	-0.09	0.78	1.50	2.08	3.93
U.S. Large Caps	0.17	0.22	1.00	0.02	0.06	0.50	1.23	1.67	3.01
U.S. Large Caps Blend	0.18	0.31	0.68	0.03	0.02	0.31	1.01	1.36	2.28
U.S. Large Cap Value	0.20	0.33	0.34	-0.03	-0.05	0.04	0.99	1.36	2.26
U.S. Large Cap Growth	0.12	0.11	1.04	0.09	0.00	0.67	1.34	1.81	3.17
U.S. REITs	0.15	0.22	0.46	0.06	0.03	0.22	0.86	1.25	2.17
Global Bonds	0.37	0.10	0.33	0.14	0.02	-0.04	1.01	1.42	2.27
U.S. Bonds	0.18	0.07	0.29	0.04	-0.02	0.00	0.29	0.45	0.98
U.S. Government Bonds	0.10	0.11	-0.05	0.00	-0.02	-0.15	0.32	0.59	1.27
U.S. High Yield Bonds	0.20	0.29	0.65	0.09	0.08	-0.11	0.45	0.75	1.56
European Bonds	0.19	0.15	0.46	0.04	0.00	-0.10	0.52	0.75	1.55
European Government Bonds	0.07	0.12	0.41	-0.08	0.00	-0.02	0.32	0.54	1.34
European Corporate Bonds	0.12	0.30	0.67	-0.06	0.03	0.14	0.47	0.85	1.60
Average	0.26	0.29	0.64	0.04	0.02	0.27	1.14	1.63	2.78

Table 6: **Regression Results: Breadth and Performance Persistence**

This table presents estimated coefficients of monthly Fama-MacBeth (1973) type of regressions (FM) and pooled OLS regressions. The dependent variable is the monthly past winners minus past losers return spread (W-L) of each asset class or the past winners return above its benchmark return (W-B). Explanatory variables are the demeaned cross-sectional return dispersion of the asset classes, the squared returns on the asset class' benchmarks and a dummy variable that equals one in case the asset class belongs to the ten most inefficient asset classes and is zero otherwise. The sample period is January 1991 to December 2010. The pooled OLS regressions include time fixed effects. *t*-Statistics are reported within brackets.

	Winners minus Losers		**Winners minus Benchmark**	
	FM	OLS	FM	OLS
Constant	0.31	-0.01	0.21	-0.83
	[4.63]	[-0.02]	[3.79]	[-2.32]
Cross-Sectional Dispersion	0.19	0.59	0.24	0.42
	[1.88]	[14.50]	[3.23]	[12.83]
(Benchmark Return)^2 * 100	0.64	-0.23	-0.57	-0.28
	[2.18]	[-3.07]	[-2.02]	[-4.67]
Inefficiency Dummy	0.00	-0.12	-0.07	-0.17
	[-0.04]	[-2.21]	[-1.60]	[-3.74]
Adjusted R-squared	0.29	0.35	0.27	0.29

Figure 1: **Return Spread vs. Market Efficiency**
This figure plots the ranks of the return spread between past winners and past losers versus the overall efficiency ranks. The solid line represents the estimated linear relation between the two. The dashed horizontal (vertical) line is equal to the median spread rank (median efficiency rank).

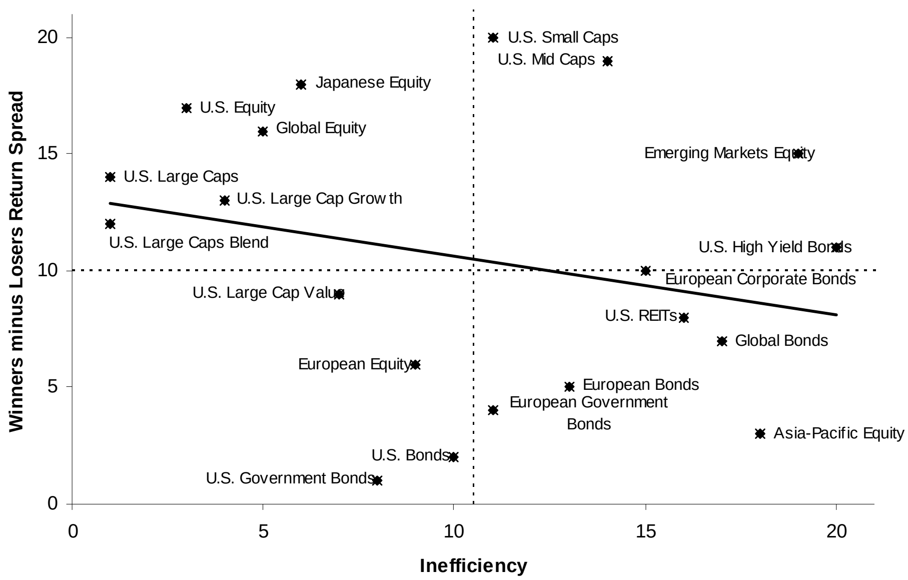


Figure 2: **Return Spread vs. Return Dispersion**
This figure plots the ranks of the return spread between past winners and past losers versus the overall breadth ranks. The solid line represents the estimated linear relation between the two. The dashed horizontal (vertical) line is equal to the median spread rank (median breadth rank).

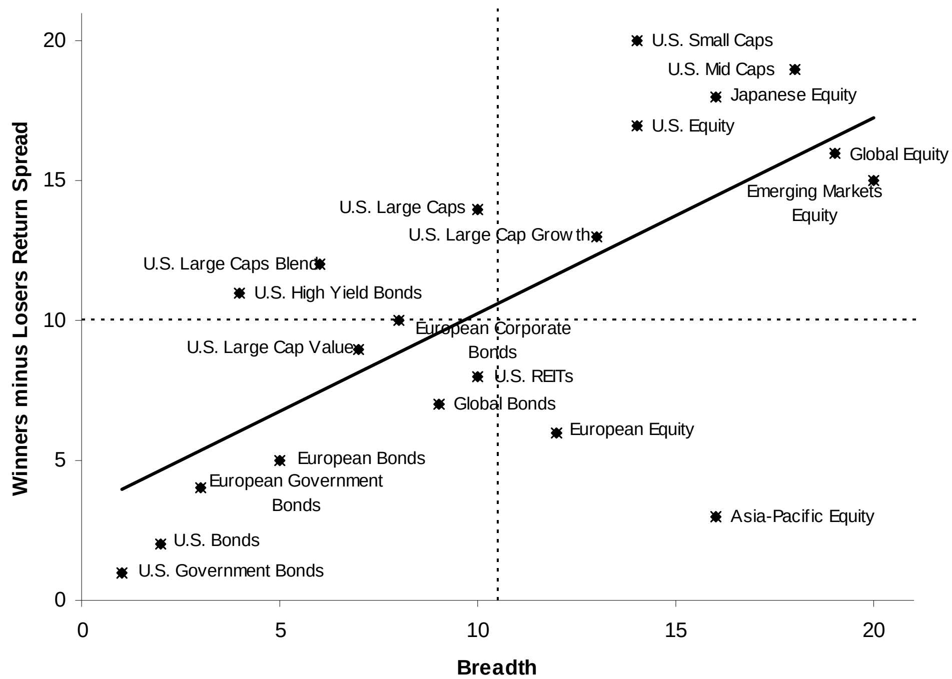
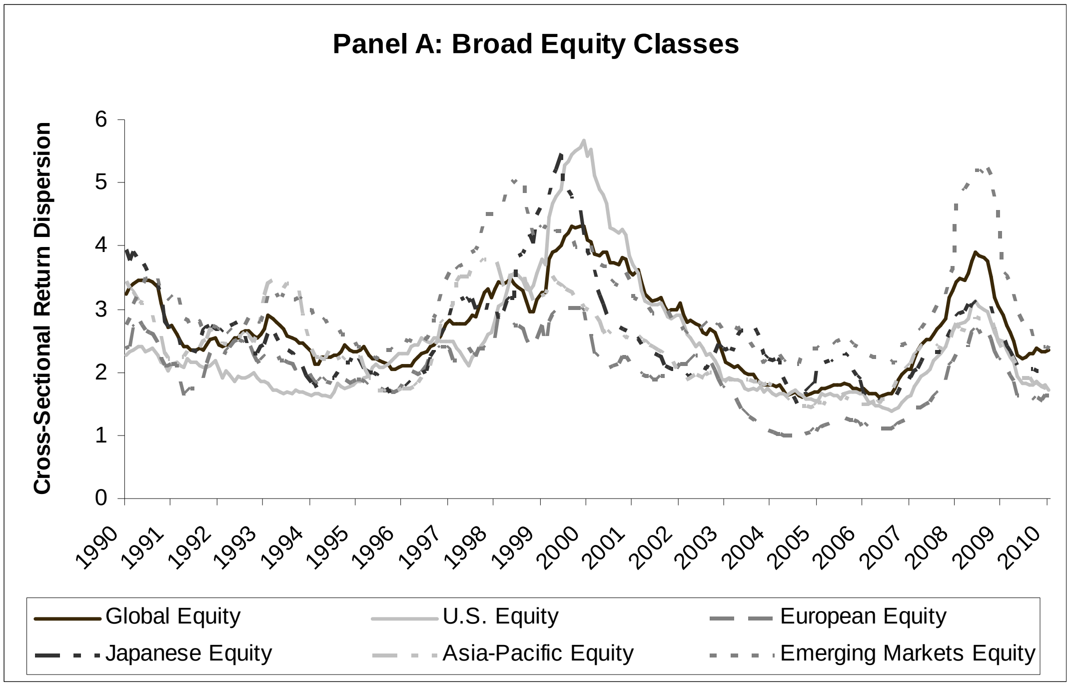
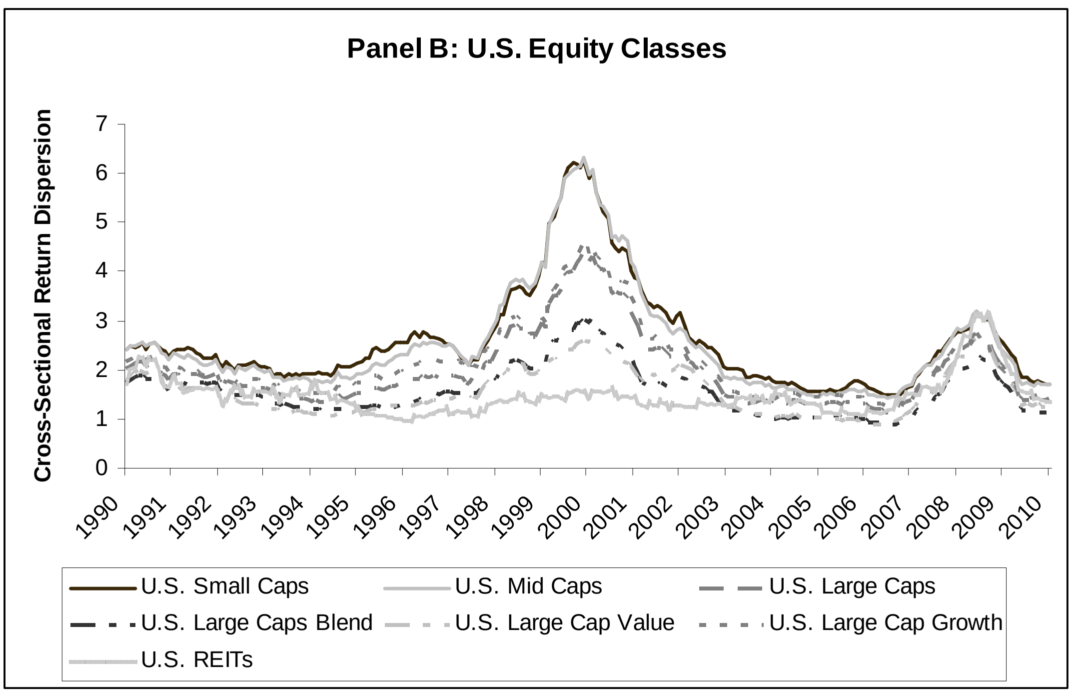
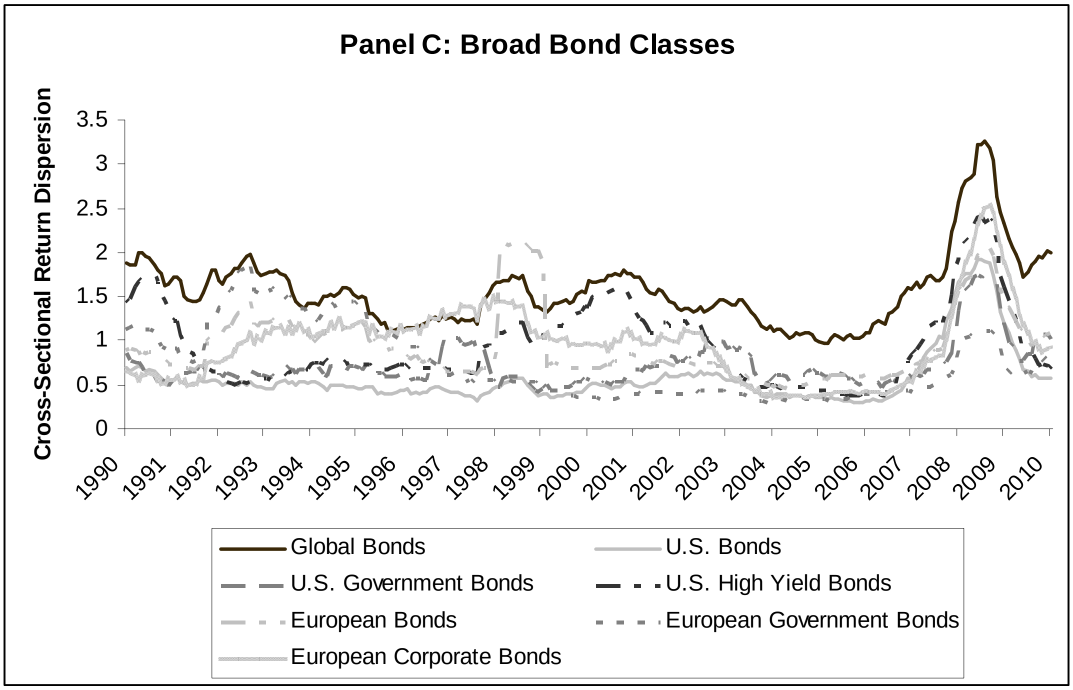


Figure 3: **Cross-Sectional Return Dispersion per Asset Class**
In the three panels below, the twelve-month moving average cross-sectional return dispersions for each of the asset classes are plotted. The return dispersion is measured using Equation (1) in the text. In Panel A, the six broad equity classes are plotted, Panel B plots the seven U.S. equity classes and Panel C plots the seven broad bond classes. The sample period is from December 1990 to December 2010.






Panel C: Broad Bond Classes
Cross-Sectional Return Dispersion
3.5
3
2.5
2
1.5
1
0.5
0
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
Global Bonds
U.S. Bonds
U.S. Government Bonds
U.S. High Yield Bonds
European Bonds
European Government Bonds
European Corporate Bonds