WP/99/148

INTERNATIONAL MONETARY FUND

Research Department

Idiosyncratic Risk: An Empirical Analysis, with Implications for the Risk of Relative-Value Trading Strategies[1]

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IMF WORKING PAPER

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Idiosyncratic Risk: An Empirical Analysis, with Implications for the Risk of Relative-Value Trading Strategies[1]

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Abstract

This paper models the idiosyncratic or asset-specific return of an asset as the return on a portfolio that is long in that asset and short in other assets in the same class, thereby removing the common components of returns. This is the type of "hedged" position that is held by relative-value investors. Weekly returns data for seven different asset classes suggest that idiosyncratic risk is: higher at times of large return outcomes for the asset class as a whole; positively autocorrelated; and correlated across different asset classes. The implications for risk management are discussed.

JEL Classification Numbers: G1, G12, G11, G15

Keywords: Idiosyncratic Risk, Dispersion, Risk Management, Hedge Funds

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[1]I am grateful to Charles Adams, Torbjörn Becker, Bankim Chadha, and Charles Kramer for comments on an earlier draft. The views expressed in this paper are those of the author and do not necessarily reflect those of the International Monetary Fund.

Contents Page

I. Introduction

Losses by some hedge funds during periods of high market volatility in 1998 prompt the question of how reliably the "hedges" put in place by such investors perform during periods of volatility. While data on the exact positions held by "arbitrage" or "relative-value" investors are not generally available, this paper attempt to shed light on this question indirectly. Specifically, it examines some of the properties of the idiosyncratic or asset-specific component of asset returns.[2] This is proxied by the return on portfolios that are long in one asset within a class and short in other assets in the class, thereby removing the common components of returns and leaving only the idiosyncratic or asset-specific component of returns. This is the type of "hedged" position that is taken—often with substantial leverage—by relative-value investors, including many hedge funds.[3]

Based on the cross-section of idiosyncratic returns for all assets in the asset class, time-series measures of the average idiosyncratic risk of the asset class can be constructed and studied. The study of idiosyncratic risk is of interest both for understanding the nature of the risk incurred by those investors that are most exposed to it and in light of the paucity of literature studying this component of asset risk. The reason that idiosyncratic risk has traditionally been ignored is that it generally can be diversified away and therefore should not carry a risk premium. By contrast, the common components of returns, which cannot be diversified away, carry risk premia and have therefore been the focus of most empirical research. That is, almost all the empirical literature on the behavior of asset returns has implicitly been concerned about long positions, with little attention paid to the return properties of portfolios where long and short positions in different assets are combined.[4] More

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[2]The terms "idiosyncratic" and "asset-specific" are henceforth used interchangeably.

[3]A very broad classification of hedge funds would divide them into two types: (i) macro or directional funds; and (ii) relative-value or arbitrage funds (see BIS (1999)). The former take positions on expected movements in major asset prices such as interest rates, exchange rates and stock prices, typically using leverage and derivatives. The latter—which are closer to concept of the original hedge fund of A.W. Jones—attempt to gain from perceived misvaluations of related assets by "hedging out" most exposure to overall market risk and then applying leverage to magnify the returns on these hedged positions. The type of positions taken by the latter group (and other similar investors) are the focus of this paper. Further discussions of hedge funds are provided by Lederman and Klein (1995) and Eichengreen et al. (1998).

[4]There is, of course, a substantial literature about the effectiveness of hedging a physical position in an asset by a derivative on that asset, and on dynamic hedging strategies for replicating the payoff on an option. There is also a substantial literature on the effect of diversification strategies within an asset class. However, this paper appears to be the first

(continued...)

attention to the latter would, however, appear justified given that an increasing number of investors now actively seek out positions in idiosyncratic or asset-specific risk, while sometimes also incurring substantial leverage. Indeed, in one recent case the degree of leverage and size of positions were so large that the stability of parts of the financial system was reportedly threatened when positions moved unfavorably (see BIS (1999)).

Previous research on idiosyncratic or asset-specific risk is limited, but includes work by Christie and Huang (1995), Malkiel and Xu (1997, 1999), Stivers (1998), and Campbell and Lettau (1999) that examines the cross-sectional dispersion or idiosyncratic risk of U.S. equities. In the case of the latter two papers, the focus is on the predictive power of idiosyncratic risk for market risk. This paper instead focuses on the nature of idiosyncratic risk, and the implications more generally for the risk of portfolios where long and short positions are combined. The innovations of this paper with respect to some or all of these other papers are the extension into several different asset classes, the allowance (implicitly) for more than one factor driving returns, the focus on a richer class of hedging strategies than is implicit in those papers, and the construction of measures of average idiosyncratic risk that are not dominated by high-variance assets.

Using weekly returns data for seven different "asset classes", I construct three measures of the idiosyncratic component of returns, and then of the time-series of cross-sectional average idiosyncratic risk within the asset class. While there appears to be little conventional wisdom among practitioners about idiosyncratic risk, one notion that appears to be reasonably well accepted is that correlations within asset classes increase at times of market turmoil, which might suggest that idiosyncratic risk will be smaller and that "hedges" within an asset class will perform more reliably at such times. The results of this paper would, however, suggest otherwise. There is evidence that idiosyncratic risk tends to increase somewhat at times of large positive or negative outcomes for the common component in returns. That is, positions that are constructed to be invariant to market risk have greater return variance when market risk is high. Hence, it may not be surprising that some relative-value hedge funds reported large losses after the large market movements of 1998. The paper also finds that there is substantial persistence in idiosyncratic risk, implying that high volatility in the return on a hedged portfolio in one period is likely to be followed by high volatility in the next. In addition, there is evidence that the level of idiosyncratic risk in one asset class tends to be positively correlated with the level of idiosyncratic risk in other asset classes. That is, when the returns on hedged portfolios in one asset class are volatile, investors may find that there is also high volatility in the return on hedged portfolios in other asset classes. These risk properties have implications for investors that seek out idiosyncratic risk and for firms that provide financing to such investors.

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[4](...continued)
empirical paper to focus on the return on a position in one asset that is hedged using other assets in the class. Theoretical discussions of long-short or market-neutral portfolio strategies are provided by Jacobs et al. (1999) and Kwan (1998).

The rest of the paper is organized as follows. Section II introduces the different approaches used to proxy the idiosyncratic component of returns and the average level of idiosyncratic risk within each asset class. Section III outlines the data used, while Section IV presents results. Section V concludes with some implications for risk management by financial firms.

II. Methodology

Investors, including many hedge funds, that take long positions in some assets and short positions in others are generally highly secretive about their positions. By maintaining secrecy, these investors—which I refer to henceforth as relative-value investors—ensure that other traders do not try to profit from knowledge of their positions. This secrecy makes it difficult to study the risks of the actual positions taken by such investors. Furthermore, given that such investors may be continually moving between assets and asset classes in their trading, even a high frequency time-series of their portfolio returns might not be of much assistance in attempting to infer the positions taken by such investors. Indeed, in their study of the monthly returns (the highest frequency that is generally available) of hedge funds and commodity trading advisors, Fung and Hsieh (1997a) find that investment strategies are highly dynamic.[5]

In light of the difficulties involved in studying actual positions taken by such investors, any study that seeks to understand the nature of the risk in such positions must inevitably take an indirect approach. In this paper, I examine some of the properties of the returns on a class of positions that may have some features in common with the types of positions taken by relative-value investors. In particular, I use weekly returns data for assets within a number of different "asset classes" and then examine the properties of different proxies for the idiosyncratic or asset-specific component of returns. In each case, the asset-specific component is proxied by a long position in the asset in question and short positions in other assets within the class. In the case of two of the three proxies, I focus on portfolios where the offsetting positions in other assets are chosen specifically to minimize the risk of the overall position.[6]

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[5]Other research into the performance of hedge funds includes work by Ackerman and McEnally (1999) who address the risk-adjusted return performance of hedge funds and its relationship with fees and other managerial compensation, and Brown, Goetzmann and Ibbotson (1998) who examine the annual returns of hedge funds, persistence in manager performance, and the determinants of a fund's survival.

[6]I do not attempt to identify the "valuation" aspect of positions, i.e., to identify which assets might be viewed as "cheap" (and warrant long positions) and which are viewed as "expensive" (and warrant short positions). One reason for this is that different valuation models might (continued...)

Based on the week-by-week cross-section of idiosyncratic returns for all assets in the asset class, time-series measures of the average idiosyncratic risk of the asset class are constructed and studied. Three different proxies for average idiosyncratic risk are constructed, each being a variant of the cross-sectional dispersion of asset returns in the class, i.e. a measure of the extent to which there are divergences in the return performance of the different assets in the class in each week. In weeks when there are relatively large divergences in asset returns—i.e., high idiosyncratic risk—it will follow that the gains or losses on relative-value positions within the asset class will tend to be larger than usual. Further, to the extent that the statistical results are consistent across asset classes and across proxies for the asset-specific component, it would seem reasonable to conclude that these statistical results may be representative of the risk characteristics of positions where an investor takes a position in one asset and then "hedges" against price changes common to the entire asset class by taking offsetting positions in one or more other assets in the class.

It should be stressed that the analysis of the paper has relevance only for the market risk of relative-value trades, and not the credit risk or operational risk associated with these positions. Nor does the paper explicitly model the liquidity risk associated with hedging strategies, or the transactions costs or feasibility of establishing particular positions.[7] In addition, it should be stressed that the paper addresses the effectiveness of hedged portfolios (with long and short positions) rather than diversified portfolios (with only long positions). The distinction between the two types of portfolios is that the former seeks to eliminate the common component of returns within an asset class and load on the asset-specific component while the latter seeks to reduce asset-specific risk, leaving only common or undiversifiable risk.

How might one estimate the idiosyncratic or asset-specific component of returns? In the simplest case, the common component might be proxied by an equally-weighted average

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[6](...continued)
suggest different conclusions: indeed, one trader's short position in a perceived overpriced asset is another trader's long position in a perceived underpriced asset. Instead, the measure of average idiosyncratic risk that is used in this paper can be thought of as an average of the asset-specific risk of all assets in the class. However, Gatev, Goetzmann, and Rouwenhorst (1999) do model the decision to go long and short in particular assets in a study of "pairs trading" where they search all possible pairs of U.S. stocks for those which have highest correlations in levels, and then simulate the profitability of positions that put in place based on the size and sign of deviations from the relationship over the previous 12 months.

[7]See BIS (1999) for a discussion of some of these other risks in the context of the near-failure of Long-Term Capital Management.

of the returns on all the n assets in the class, denoted by $\bar{r}_t$.[8] The asset-specific component, denoted $\hat{r}_{it}^{idio1}$, could then be simply defined as the asset return less the equally-weighted average return,

$$\hat{r}_{it}^{idio1} = r_{it} - \bar{r}_t \, . \tag{1}$$

Equation 1 defines the first proxy studied in this paper for the idiosyncratic component of returns.

However, a simple measure such as is defined by Equation 1 will not be a measure of the asset-specific component if the return generating process is characterized by non-unit factor loadings or more than one common factor. A fairly general specification, along the lines of the Arbitrage Pricing Theory (APT) would be to allow for some additional factors, with each asset having different loadings on these factors. In this case, if the factors were identified, the asset-specific component could be estimated as the residual from the regression of the asset return on all the factors. In practice, however, there is little consensus among financial researchers on the economic factors that drive returns in different asset classes.[9] Rather than entering the debate over the appropriate pricing model for each of the several different asset classes studied here, the second proxy in this paper takes a data-driven approach which is to model the asset-specific component as the component of returns that is left unexplained by a regression on the returns of the other assets in its class. This approach is attractive in that it enables a direct correspondence between the risk of the asset-specific component and the risk of the more general class of hedging strategies which is long in one asset and short in others. In addition, if one makes the assumption that the n assets within the class are all determined by k factors (where $k<<n$), then regressing against the returns on the n-1 other assets in the class can be viewed as a way of extracting the loadings on the k factors without having to specify the factors (see, e.g., Ferson (1990)).[10]

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[8]The use of the market capitalization-weighted average return would also an option, but the necessary data for this were not available for all asset classes used in the study.

[9]For example, there is substantial debate—see, e.g., Fama and French (1993) and Daniel and Titman (1997)—as to the role of variables such as firm size and book-to-market ratios in determining returns on U.S. equities.

[10]This technique—like any other technique for extracting the idiosyncratic component of returns—is not without measurement error. The likely magnitude of the error and its implications for the tests conducted in this paper have been addressed in Monte Carlo simulations of plausible statistical models of asset returns. The results (available upon request) suggest that a specified time-series for the idiosyncratic risk of an asset class can be closely approximated using the regression approach used in this paper. Further, the simulations

(continued...)

Accordingly, the second proxy for the asset-specific return component is derived by first running the following OLS regression,

$$r_{it} = a_{0i} + a_{1i} r_{1t} + a_{2i} r_{2t} + \ldots + a_{n-1,i}\, r_{n-1,t} + e_{it} \tag{2}$$

for each of the n assets in the class, using the full sample of data. The asset-specific component, denoted $\hat{r}_{it}^{idio2}$, could then be simply defined as the residual from equation 2,

$$\hat{r}_{it}^{idio2} = r_{it} - \hat{a}_{0i} - \sum_{k=1}^{n-1} \hat{a}_{ki} r_{kt} \tag{3}$$

Equation 3 defines the second measure of the idiosyncratic component of returns used in this paper.[11] [12]

However, a possible criticism about the second proxy are that it fails to allow for time-variation in the regression coefficients (and implicitly in the loadings on the underlying factors). To offset this, a third proxy for the asset-specific component uses rolling regressions to produce time-varying regression coefficients. Further, since one of the purposes of the current paper is to draw conclusions about the performances of hedging strategies, the third proxy contains an out-of-sample element. **In particular, the third proxy for the idiosyncratic component is generated by: (i) estimating Equation 2 for rolling samples of 100 observations; (ii) using the regression coefficients to form notional one-period-ahead "hedging portfolios" for each asset; and (iii) defining the asset-specific return to**

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[10](...continued)
suggest that it is highly unlikely that measurement error can explain the three empirical findings about idiosyncratic risk that are highlighted in Section IVB.

[11]An alternative is to collapse the data for all n assets into its first k principal components and then to treat these principal components as factors. The asset returns can then be regressed against the principal components, with the residuals serving as proxies for the asset-specific component. This approach was tried in preliminary work (with k=3) and yielded very similar conclusions to the results presented below.

[12]It might be noted that there is no constraint that the estimated a_1-a_{n-1} coefficients should sum to unity, implying that the implied underlying hedging portfolio is not necessarily a zero-net-investment portfolio. The constraint is not imposed since both finance theory and hedging practice allow for the possibility that the hedging coefficients might not sum to unity, in particular if factor loadings differ substantially across assets. The results of Section IV do not, however, appear especially sensitive as to whether this constraint is imposed.

be the actual return for the out-of-sample observation less the return on the hedging portfolio.[13]

Based on each of the three proxies for idiosyncratic returns for each asset, some of the time-series properties of the idiosyncratic component of returns on each asset can be studied. Further, a time-series for cross-sectional average asset-specific risk (ASR_t) within the asset class can be constructed by weighting the squared individual asset-specific returns with weights w_i,

$$A\hat{S}R_t = \sqrt{\sum_{i=1}^{n} w_i \, (\hat{r}_{it}^{idio})^2)} \quad . \tag{4}$$

In averaging the individual asset-specific risk measures, $(\hat{r}_{it}^{idio})^2$, I use as weights the inverse of the full-sample asset-specific risk for each asset,

$$w_i = \frac{\dfrac{1}{V(\hat{r}_{it}^{idio})}}{\displaystyle\sum_{i}^{n} \frac{1}{V(\hat{r}_{it}^{idio})}} \quad . \tag{5}$$

This choice of weighting is based on the observation that different assets typically have distinctly different levels of asset-specific risk, implying that equally-weighted measures will effectively be dominated by those assets, typically small assets, which have the highest levels of asset-specific risk. The weighting system shown in Equation 4 and used is this paper avoids this problem and ensures that all assets have the same influence on the measure of cross-sectional average asset-specific risk.[14]

The average asset-specific risk measure defined by Equations 1 and 4 is indeed close to the variable that is described by Christie and Huang (1995), Malkiel and Xu (1997), Malkiel and Xu (1999), Campbell and Lettau (1999), and Stivers (1998) as the "cross-sectional

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[13]The use of only 100 observations raises the possibility of estimation error in cases where a large number of assets (up to 26 in the analysis that follows) are included. In practice, when hedging a position in one asset, a practitioner would no doubt substantially limit the number of assets in the hedging portfolio, and would take steps to minimize estimation error.

[14]Weighting the idiosyncratic risk measures according to market capitalization would also be an option, but data for the latter were not available for all asset classes used in the study.

dispersion" of equity returns.[15] However, a simple dispersion measure—such as is defined by Equations 1 and 4—will not be a measure of asset-specific or idiosyncratic variance if there is more than one common factor. In particular, if the true model is a multifactor one along the lines of the APT, and the variances of the omitted factors are related to the variance of the first factor, one would expect a simple dispersion measure to be larger at times when there are large movements in the common component of returns.[16] [17] The second and third idiosyncratic risk measures that are used in this paper should not, however, be subject to this potential problem.

III. DATA

In order to make the conclusions about asset-specific risk as general as possible, a study should ideally use a number of different datasets to ensure that any findings are not peculiar to one asset class. Accordingly, and while it must be admitted that the definition of an "asset class" is highly subjective, this paper uses data for 7 different asset classes for

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[15]A key difference between the measures in the first two cited papers and the current paper is that those papers use equal weights which, in the context of their samples of all U.S. stocks, will yield dispersion measures that are dominated by high-variance smaller stocks. This can be simply illustrated using the data for 26 large and 26 smaller U.S. stocks used in Section IV. When equally-weighted dispersion measures are calculated for the separate groups and for all 52 stocks combined, the combined dispersion measure is substantially more highly correlated with the small-stock dispersion measure than with the large-stock dispersion measure (correlation coefficients of 0.89 and 0.64, respectively). This effect would be magnified substantially using a database with all stocks within a market, most of which are small stocks with high idiosyncratic risk. That is, the dispersion measures used in those two papers are essentially measures for small-stock dispersion which may not be representative of the dispersion of the larger, and more economically important, stocks.

[16]Specifically, denoting the factors by f_{jt}, and the loadings by β_{ij}, and assuming that the error term (u_{it}) and factors are uncorrelated, then even adjusting for different loadings on the first factor (f_{1t}), one obtains $V(r_{it} - \beta_{i1} f_{1t}) = \sum_{j=2}^{k} \beta_{ij}^2 Var(f_{jt}) + V(u_{it})$. Indeed, Epps and Kramer (1997) rely on the relationship of the cross-sectional variance of returns to factor realizations to propose a test for the existence of priced factors in returns.

[17]The assumption that the variance of any omitted factors is independent of the variance of the first factor can be tested in a rudimentary way by extracting (say) the first three principal components from each of the asset classes and then regressing the square of the second and third factors against the square of the first factor. When this is done for the seven asset classes used in this paper, the regressions frequently yield highly significant correlations.

decomposing asset returns into common and asset-specific components, with asset classes defined to range from very wide (e.g., stock markets in different countries) to very narrow (e.g., stocks of U.S. oil producing companies). Further, a study that is attempting to make inferences about the returns on hedging strategies should use fairly high frequency data. While daily data might be ideal, most of the tests in this paper use weekly data so as to minimize any possible problems in daily data from non-trading effects or (in the case of the cross-country datasets) of asynchronous trading due to differences in time zones.

The following seven datasets of weekly asset returns—which are further described in Appendix 1—are used[18]:

(i) mature market stock returns for January 1992-October 1998, in U.S. dollars, for 20 markets, based on major benchmark indices for each country;
(ii) emerging markets returns for January 1992-October 1998, in U.S. dollars, for 16 countries based on the "investible" total return series in the Emerging Markets Data Base (EMDB) of the International Finance Corporation (IFC);
(iii) returns for 26 large U.S. stocks for January 1980-October 1998;[19]
(iv) returns for 26 smaller U.S. stocks for January 1985-October 1998;[20]

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[18]All weekly data are based on Friday observations. With the exception of the EMDB data which are obtained directly from the IFC and the fixed income data which were obtained from Merrill Lynch, all asset price/returns series are taken from Bloomberg. All series were checked for any obvious errors, with corrections made in a few cases. The starting points for each asset class were based on data availability.

[19]These include the 26 (out of 30) stocks in the Dow Jones Industrial Average as of November 1998 for which price data are available in Bloomberg from January 1980 (the missing stocks are Allied Signal, Citigroup, Chevron, and Exxon). The data from Bloomberg account for all large capitalization changes such as stock splits, but do not account for ordinary dividends. Since the latter tend to be small, their exclusion should not be material. The use of the higher-quality CRSP database would clearly have been preferable, but this was not available. The use of a constant sample of (surviving) stocks is dictated by the regression approach that is used. While the limited sample clearly introduces some sample selection bias, the tests in this paper do not appear likely to be affected in any substantial way by survivorship bias (which most affects studies of long-run returns). It is worth noting in this regard that the results for the three samples of U.S. stocks are very similar to the results for the four other asset classes where survivorship is presumably a substantially smaller issue.

[20]These include 26 stocks chosen randomly from the stocks included in the S&P MidCap 400 index as of November 1998 for which data were available since January 1985. The S&P MidCap index consists of stocks which are not included in the S&P 500 index, and thus are substantially smaller stocks than those in the Dow Jones index. The data issues discussed in

(continued...)

(v) returns on 12 U.S. oil stocks for January 1985-October 1998;[21]
(vi) government bond market returns for January 1988-October 1998, in U.S. dollars, for 15 mature markets, based on the total returns indices produced by J.P. Morgan;[22] and
(vii) returns for April 1989-October 1998 for 8 different types of U.S. fixed income instruments, calculated from the total returns indices produced by Merrill Lynch.[23]

Depending on their starting date, the weekly datasets include between 355 and 981 weekly observations. These long data series should ensure that the results are not especially affected by market movements in any particular week. However, as a robustness check of the results with weekly data, I provide estimates based on a longer, lower-frequency dataset, using data for monthly mature market stock returns for January 1970-October 1998, for 18 countries. These data are based on the standard Morgan Stanley Capital International (MSCI) indices for total returns, measured in U.S. dollars.

As a further robustness check, within the cross-country datasets, results are also presented for some country groups which might also be regarded as asset-classes. For the mature markets, results are presented for the European countries. For the emerging markets, two subgroups include Latin America (Argentina, Brazil, Chile, Colombia, Mexico, and Venezuela) and East Asia (Indonesia, Korea, Malaysia, the Philippines, Taiwan Province of China, and Thailand). Results are only presented where there are at least five countries to form a group, but preliminary work treating the Nordic countries (Denmark, Finland, Norway, and Sweden), East Asia (Hong Kong SAR, Japan, and Singapore), North America (Canada and the United States), and Australasia (Australia and New Zealand) as groups gave similar results.

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[20](...continued)
the previous footnote clearly apply even more strongly to this sample, since the requirement of a continuous sample rules out many of today's small stocks. Nonetheless, the industry coverage of the 26 stocks selected seems quite broad, and there is no immediately apparent reason why the empirical results here would not also apply to other smaller U.S. stocks.

[21]These include the 12 oil producing and oil exploring companies included in the AMEX Oil Index in November 1998 for which data were available since January 1985.

[22]While the data used here are for unhedged U.S. dollar returns, it must be acknowledged that relative-value trades in government bonds are more likely to use hedging to eliminate currency risk: good data for hedged returns were not, however, available.

[23]The series included are: US Treasury securities of 1-5, 5-10 and more than 10 years; investment-grade corporate securities of 1-5, 5-10 and more than 10 years; and the returns on mortgage-backed securities backed by current-coupon GNMA 15-year and 30-year mortgages.

Some summary data for return volatility in the different asset classes are provided in Table 1. For each asset class, the table provides an estimate of the standard deviation of: (i) the return on the equally-weighted portfolio of all assets in the class; (ii) the returns on individual assets within the class; and (iii) the idiosyncratic component of returns. For the second and third items, the standard deviation of returns is calculated for all assets in the class, and the median standard deviation is then shown. The idiosyncratic component of returns is proxied separately by each of the three measures described in Section III.[24]

The data for the standard deviation of returns in Table 1 yield some perspectives on the nature of the asset classes that are included and the proxies for idiosyncratic risk that are used. The asset classes chosen for the analysis include some (in particular, the U.S. fixed income groups, and the European bond markets) where the assets within the class are highly correlated, and the standard deviation of the common component is high relative to that of the idiosyncratic component. Other asset classes (e.g., the small U.S. stocks, and the 16 emerging equity markets) are far less correlated, and the standard deviation of the idiosyncratic component is high relative to that of the common component. From a hedging perspective, the former (high correlation) group would clearly allow a larger proportion of the risk of individual assets to hedged out using other assets than would be possible in the (low correlation) latter group. As an illustration, based on the volatility of the second and third proxies of idiosyncratic returns in the U.S. fixed-income class being only one-fourth or one-fifth of the volatility of individual assets in this class, a hedged position in this class could typically be levered up 4 or 5 times without increasing total portfolio volatility beyond the volatility of a single long position in an individual asset. That is, this asset class would allow gross (i.e., long plus short) positions that were 8-10 times larger, but no riskier in terms of standard deviation, than a single long position. By contrast, in some other asset classes, there would be relatively little risk reduction from adding short positions.

IV. Empirical Results

This section analyzes the return and risk properties of the three proxies described in Section II for the idiosyncratic component of returns, using the data described in Section III. The analysis first considers whether the asset-specific component of returns shares some of the same statistical properties (nonnormality, autocorrelation) that are typically found in the returns of individual assets and in long portfolios of these assets. To the extent that the asset-specific component of returns demonstrates different statistical properties, we can conclude that the return properties of "hedged" portfolios of long and short positions may have some fundamental differences to the return properties of pure long portfolios. The analysis then

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[24]In the case of the first proxy, the idiosyncratic return is defined as the asset return for asset i less the average return for all n assets in the class, where the latter contains an amount of $1/n$ of asset i. To make this proxy comparable with the other two proxies, the standard deviations shown in Table 1 for the first proxy are scaled up by a factor of $n/(n-1)$.

considers the nature of idiosyncratic risk in different asset classes. Some obvious questions suggest themselves. For example, does the level of asset-specific risk increase at times of large positive or negative returns for the asset class as a whole? If so, this would imply that "hedges" become less reliable at times of large market movements. In addition, is the level of asset-specific risk positively autocorrelated? If so, this would imply that unreliability of a hedge in one period will likely imply higher-than-average unreliability in the next. Finally, is the level of asset-specific risk correlated across asset classes? If so, this would imply that when the volatility of returns on a hedged portfolio in one asset class is high, it is likely to be high in other asset classes too.

A. The Properties of the Idiosyncratic Component of Returns

The analysis proceeds initially by testing for skewness and autocorrelation in the asset-specific component. Since these tests can be conducted for each asset in each class, the full results are too numerous to report. Hence, only the median result for each asset class is reported. For comparison, these tests are also run for the common component of returns in each class, which is proxied by the equally-weighted average of returns for all assets in the class.

Table 2 provides the results of tests for skewness, where the test statistics have been transformed to be asymptotically distributed as normal (0,1) variables.[25] [26] The tests confirm the usual finding for some tendency towards negative skewness in conventional returns, an indication of the existence of a greater than expected incidence of very large negative returns. For the equally-weighted portfolios, 5 out of the 13 tests suggest rejection of the hypothesis of normality, with all rejections indicating negative skewness. However, the tests using the asset-specific returns show no evidence of skewness: none of the 39 median statistics indicate rejection at conventional levels, and most test statistics indicate a tendency towards positive skewness, albeit not statistically significant skewness. With the regard to the individual asset returns, which can be thought of as the sum of the negatively-skewed common component and the slightly positively-skewed asset-specific component, all 13 median test statistics indicate negative, albeit not statistically significant, skewness.[27]

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[25]Since the return on portfolios with only long positions are bounded below at -100 percent, they cannot strictly be normally distributed, so the tests for individual asset returns and the average returns use returns defined as *log(1+r)*. Returns on hedged portfolios are not subject to this bound, so the tests for asset-specific returns use conventional percentage returns.

[26]Tests for excess kurtosis were also conducted but are not shown: these failed to suggest any consistent differences in the properties of the different components of returns.

[27]The finding that the idiosyncratic return is free of some property (e.g., negative skewness) that characterizes the common component of returns may at first seem true almost by

(continued...)

Table 3 provides results for tests for first-order autocorrelation in weekly returns since this is a property of returns that has been of some interest to researchers in finance. The test statistics are frequently not statistically significant, but a relatively clear qualitative pattern seems to emerge. In most cases (31 out of 39), the asset-specific component of weekly returns shows a tendency for negative autocorrelation, with all 19 statistically significant cases indicating negative autocorrelation. This is in contrast to the equally-weighted portfolio return which more frequently shows indications of positive (albeit not statistically significant) autocorrelation. That is, these results would suggest that the tendency towards positive autocorrelation that is frequently observed in weekly returns is a function of the common component in returns, and that once this component is removed, there is a tendency for negative autocorrelation at this horizon. This would appear consistent with the results of Lo and MacKinlay (1988) who find evidence for momentum in weekly returns of portfolios of U.S. stocks, but negative autocorrelation in the returns of individual stocks. Further, given that some of the findings of negative autocorrelation are for indices (the bond and stock indices) it seems unlikely that the findings of negative autocorrelation are purely a result of data problems such as the bid-ask bounce that might be possible for individual stocks. However, regardless of whether the finding is robust to data problems, it is likely that the observed negative autocorrelations in idiosyncratic returns would not be sufficient to allow profitable trading rules, as there would be significant transactions costs from multiple short positions and weekly rebalancing.

One should not, of course, draw too many conclusions about the properties of returns from an analysis focussing on two aspects of weekly returns. However, these results for skewness and autocorrelation suggest that there may be differences in the statistical properties of the common and asset-specific components of returns that are worthy of further study. Further, the results of this section imply that there may be some fundamental differences between the nature of the returns on long portfolios and those on hedged portfolios.

B. The Properties of Idiosyncratic Risk

The second set of tests involves the properties of idiosyncratic risk (rather than returns). For these tests, the estimates of the asset-specific component of returns for each asset are combined via Equations 4 and 5 into a time-series for the cross-sectional average asset-specific risk.

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[27](...continued)
definition. There is, however, no reason why asset returns should not show skewness due to negative skewness in both the common and idiosyncratic components of returns, with some large negative outturns being shared by all assets in the class (and therefore in the common component), and others peculiar to the asset in question (being idiosyncratic, and diversified away when combined with other assets into a portfolio of all assets).

Is idiosyncratic risk persistent?

Tests for persistence in asset-specific risk are conducted via tests for autocorrelation in the measure defined by Equation 4. The results are shown in Table 4. The results provide very strong evidence for persistence in the level of asset-specific risk in all asset classes, with first-order autocorrelation coefficients almost always above 0.30, with around half over 0.40. Further, when additional lags of the idiosyncratic risk variable are added to a regression to explain the current level of idiosyncratic risk, several additional lags are generally significant, with coefficients frequently summing to around 0.60.

Indeed, the decay of the autocorrelation structure of idiosyncratic risk is generally very slow. For weekly returns, autocorrelations for each of the three proxies for idiosyncratic risk (not shown) indicate that correlations are typically still significant after ten weeks. For the monthly equity data, significant correlations are still observed for about eight months. That is, high idiosyncratic risk in one period is likely to be followed by higher-than-average idiosyncratic risk for many subsequent periods.[28] The finding is also suggestive of the likelihood that the risk of relative-value trades might be highly persistent: that is, it is likely that there will be clustering in the reliability of the hedges that underlie relative-value trades, with high volatility in the return on the hedged portfolio in one period being followed by higher-than-average volatility in subsequent periods..

The finding that idiosyncratic risk is highly persistent for periods of months rather than weeks is noteworthy given that standard parametric (e.g., GARCH) modeling of the volatility of market risk (i.e., the volatility of the common component of returns) frequently tends to decay at horizons of around ten days (see, e.g., Christofferson, Diebold, and Schuermann (1998)). The explanation may well be that the cross-sectional estimate of idiosyncratic risk across the asset class allows a much more precise estimate of idiosyncratic risk than would be allowed by a standard GARCH-type estimate of idiosyncratic risk for any single asset. The use of cross-sectional data to avoid the use of GARCH techniques is somewhat akin to a recent study by Anderson et al. (1999) which finds extremely high persistence in exchange rate risk, by using high-frequency intraday data to build a measure of daily exchange rate volatility that avoids the need to use GARCH techniques.

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[28]In other work, Chang et al. (1998) have shown that a simple daily dispersion measure for stock returns in the U.S., Japan, Hong Kong SAR, Korea and Taiwan POC is highly autocorrelated. While such results with daily data might easily be attributable to nontrading biases in small stocks, the results shown here with weekly (and monthly) data suggest that their result might be robust to nontrading biases. Campbell and Lettau (1999) have also shown that monthly measures of market, industry and idiosyncratic volatility in the U.S. equity market are also highly autocorrelated.

Does the level of idiosyncratic risk vary in very good and bad outcomes for the asset class?

The degree to which idiosyncratic risk varies in different "states of the world" for the asset class is examined in two ways, first statistically and then graphically. The purpose of these analyses is to provide some evidence as to whether the risk of relative-value hedges might be somewhat dependent upon the outturn for the common component of returns that such hedges are supposed to eliminate.

The level of idiosyncratic risk in different outcomes for the asset class is first addressed via estimation of the following OLS regression

$$\log(A\hat{S}R_t) = a_0 + a_1 * D1 * ABS(\log(1+\bar{r}_t)) + a_2 * D2 * ABS(\log(1+\bar{r}_t)) + e_{it}\ , \qquad \textbf{(6)}$$

where $A\hat{S}R_t$, the cross-sectional asset-specific risk, is defined as in Equation 4, *ABS* denotes absolute value, and the zero-one dummy variables *D1* and *D2* take the value of unity for positive and negative outcomes, respectively, for the return on the common component.

This regression allows one to test formally if idiosyncratic risk tends to get larger or smaller for large negative or positive return outcomes for the class as a whole. If a_1 and a_2 are consistently estimated to be positive and significant, one would conclude that asset-specific risk is larger at times of large movements in the common component of returns. Further, if either of a_1 and a_2 is consistently larger than the other, one could conclude that there is an asymmetry in asset-specific risk in up- and down-markets.[29] [30]

The regression results are shown in Table 5. In almost all cases, there is very strong evidence that asset-specific risk increases at times of large return outcomes, both positive and

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[29]The estimated regression coefficients can be interpreted as the percentage increase in idiosyncratic risk that is associated with a one percentage point increase or decrease in the overall market return.

[30]This exercise can be contrasted with the work of Stivers (1998) who regresses a raw dispersion measure against the absolute value of the market return and calls the residual the relative return dispersion (RRD) measure. His procedure is motivated by a desire to remove the impact of different CAPM risk loadings on a simple dispersion measure: it is easily shown that raw dispersion measures should be a function of the product of the dispersion of betas and the absolute deviation of the market return from its expected value. His procedure will, however, also remove any non-beta-related impact of market volatility on dispersion. By contrast, the second and third measures of idiosyncratic risk used in this paper should account for the possibility of different risk loadings, allowing a pure measure of the impact of market volatility on idiosyncratic risk.

negative, for the asset class as a whole. Thus, we can conclude that hedges will tend to perform less reliably during such episodes, and that traders will tend to make larger gains or losses on so-called "hedged" positions at such times.

With regard to the possibility of asymmetry for positive or negative return outcomes, there is mixed evidence. For five of the asset classes (emerging equity markets, large U.S. stocks, small U.S. stocks, U.S. oil stocks, and the monthly returns data for mature equity markets) there is evidence that idiosyncratic risk increases more in up-markets than in down-markets. In the case of the other three classes (national bond markets, U.S. fixed income, and the weekly returns data for mature equity markets) the data suggest that idiosyncratic risk increases more in down-markets. It is not clear if these differences are due to some fundamental differences in the properties of idiosyncratic risk in different markets, or if they are due simply to statistical noise.[31]

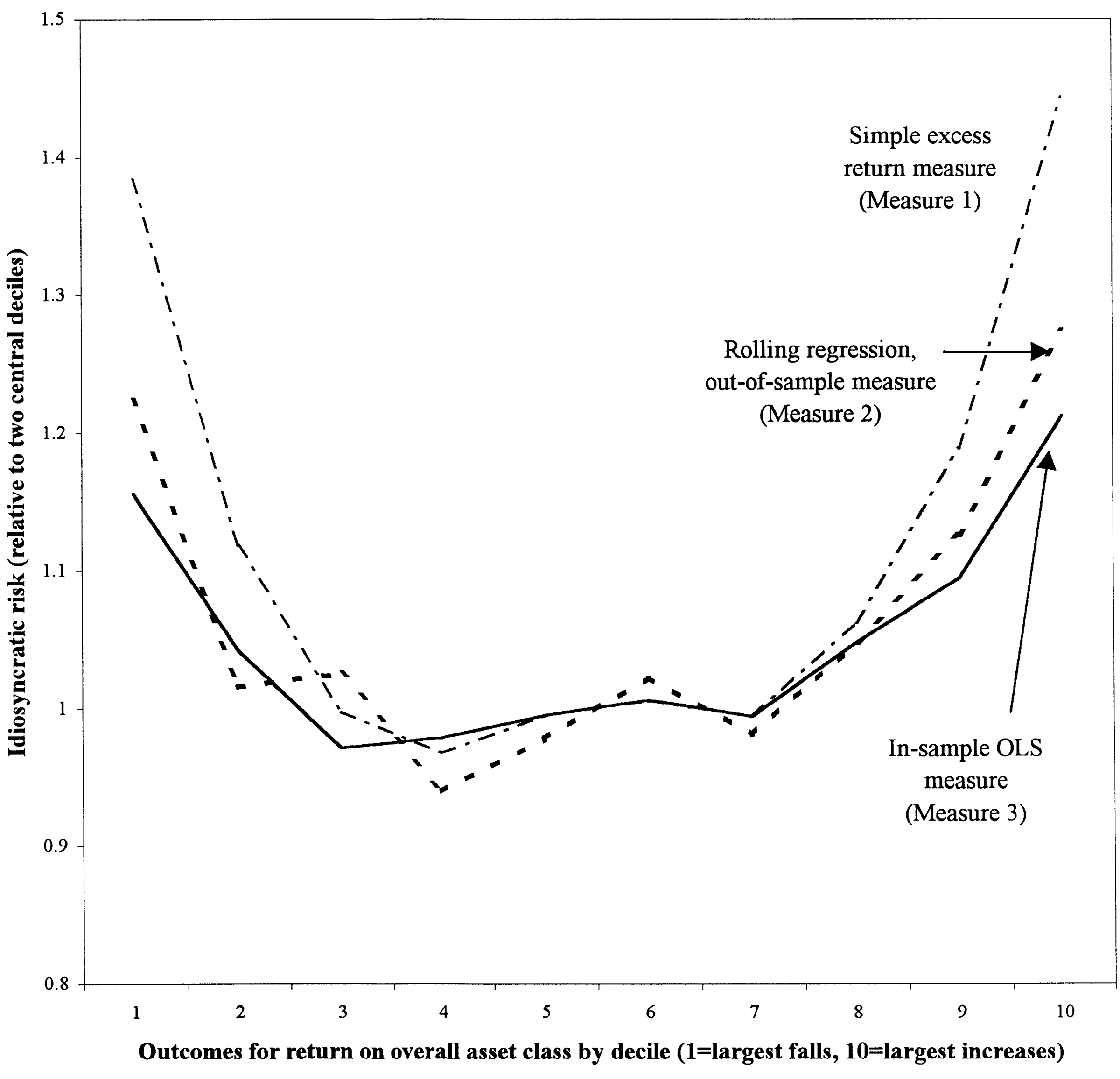
The economic significance of the differences in the level of idiosyncratic risk in different states can be assessed from the information in Figure 1. To calculate this, the time-series for the returns on each asset class (proxied by the average return on all assets in the class) is first sorted into deciles from extremely bad states (the largest negative returns) to extremely good states (the largest positive returns). Then, the average level of asset-specific risk is calculated for each decile of outcomes for each asset class. For each of the three hedging risk measures and each asset class, the level of asset-specific risk in the middle two deciles is normalized to unity. The idiosyncratic risk profiles are then averaged for the seven asset classes for which weekly data are used, and then charted in Figure 1.

The results suggest fairly strongly that there is U-shape in the level of asset-specific risk across the return outcomes for the asset class. In particular, regardless of which proxy is used for cross-sectional asset-specific risk, there is a consistent pattern for asset-specific risk to be highest in the very bad or very good outcomes for the asset class. This implies that hedged portfolios will show greater return volatility in these circumstances. A comparison of the profile for the simple dispersion measure with that for the regression-based measures (which allow implicitly for multiple factors in returns and non-unit risk loadings) suggest that the approximately 40 percent increase in dispersion in extreme states may overstate the extent to which idiosyncratic risk increases. Nonetheless, the regression-based measures would seem to indicate a quantitatively important worsening in the reliability of hedges in extreme return

[31]Some related evidence suggesting that it may not be spurious comes from Chang et al. (1998) who find that a simple daily dispersion measure increases more in up-markets than in down-markets in data for the U.S., Japan, Hong Kong SAR, Korea, and Taiwan POC.

Figure 1: Idiosyncratic Risk in Different Market Conditions

This figure illustrates the average level of idiosyncratic risk for different return outcomes for the overall asset class. The three measures of idiosyncratic risk (see Section II) are calculated for each of the seven asset classes with weekly data (see Section III). The return outcomes for each asset class are then sorted into deciles, with Decile 1 including the largest falls and Decile 10 including the largest positive return outcomes. The average level of idiosyncratic risk is then calculated for each decile of returns, and then standardized as a ratio to the central two deciles (Deciles 5 and 6). The average profile for idiosyncratic risk in different states of the world are then averaged across the seven asset classes and shown in this chart.



outcomes.[32] [33] In particular, the average level of asset-specific risk in these very good and very bad states is estimated to be about 20 percent higher than in the periods when the return on the asset class is closest to its median outcome. Further, perhaps consistent with the majority of the regression results, there appears to be some evidence for idiosyncratic risk to be slightly higher in the extreme up-markets than in extreme down-markets.

The results of this subsection would suggest that the returns-generating process differs somewhat in extremely good and bad states. These states apparently differ from other states not only because of the large changes in the common component of returns, but also because there is a tendency for the asset-specific component to be larger in these states.[34] That is, the results can be interpreted as indicating that markets distinguish more—rather than less—between different assets at times of large market movements. This is not to say, of course, that they distinguish correctly or enough between different assets, or that the results for asset returns apply also to the market's discrimination in the provision of new financing flows at times of crisis. However, this result would support Christie and Huang's (1995)

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[32]One possibility is that the larger idiosyncratic risk that is seen in extreme market outcomes might be related to the standard result that the variance of a forecast is positively related to the distance of the explanatory variables from their mean (although this clearly cannot explain the result for Method 1, which is not subject to estimation risk). If so, it would be of interest to know if hedging portfolios can be designed that are not subject to this problem. This issue was investigated by recalculating the third proxy for idiosyncratic risk using weighted OLS with the weights based on the absolute value of $\log(1+\bar{r}_{it})$. These weighted OLS parameters were then used to form the out-of-sample hedging portfolios. The results suggest a profile for idiosyncratic risk in different market outcomes that is almost exactly the same as shown for Measure 3 in Figure 1. It might also be noted that Monte Carlo simulations suggest that only a small fraction of the U-shaped profile for Measures 2 and 3 can be explained by estimation error.

[33]One possibility is that the higher level of idiosyncratic risk in the extreme market states is actually a manifestation of a tendency for relative-value trades to turn profitable in those extreme states: after all, relative-value investors do not want their hedges to remain perfect forever, merely to eliminate most of the overall market risk until the supposed misvaluation is removed. While it is impossible to test this, one problem with this possible explanation is that conventional wisdom about such trades appears to be that misvaluations are removed gradually, and not specifically in turbulent conditions. On the other hand, some evidence in Fung and Hsieh (1997b) for a few large commodity trading advisors suggests that they may perform better in the best and worst states for the world equity market.

[34]Alternatively, the result may be due to some nonlinearity in the returns-generating process that shows up most in these extreme states. Indeed, one of these asset classes—U.S. fixed-income—includes the returns on mortgage-backed securities which are known as having nonlinear payoffs.

rejection of a strong form of herding by investors. Christie and Huang use their measure of cross-sectional dispersion to test for herding in daily returns in the U.S. equity market. Their rationale is that if returns on individual stocks are more than usually clustered around the market at times of large market movements, there is evidence that markets have suppressed their assessment of individual stocks and treated all stocks similarly. They find that there is a tendency for higher rather than lower dispersion at times of large market movements, which they interpret as evidence against herding. Of course, an obvious caveat surrounding the Christie and Huang test (and a related test by Chang et al. (1998)) is that it looks only for evidence of a specific form of herding and only in the data for the asset-specific component of returns. In particular, there may be other forms of herding that show up in the common component of returns, for example when the prices of all assets within a class fall with no apparent rational explanation. That is, the Christie and Huang test should perhaps be regarded as a test for a very strong form of herding, and the absence of evidence for this form should not be regarded as evidence against the existence of other forms of herding that common sense suggests do at times exist.

Is idiosyncratic risk correlated across asset classes?

The possibility that idiosyncratic risk might be correlated across asset classes is tested by calculating correlations in the measures of cross-sectional average asset-specific risk defined by Equation 4. The results are shown in Table 6.

The results indicate that idiosyncratic risk is substantially correlated across most asset classes. Combining the three measures of hedging risk, the median correlation coefficient across asset classes is nearly 0.20. The significant correlations in idiosyncratic risk appear across all types of asset groups, including within different equity and fixed income classes and between some equity and fixed income classes. That is, risk appears to cross asset classes, even in portfolios that have been designed to remove the common risk factors within the asset class.

The only other previous finding related to this would appear to be the work of Campbell and Lettau (1999) who show that monthly measures of market, industry and idiosyncratic volatility in the U.S. stock market are correlated with each other, with correlation coefficients of over 0.5.[35] However, there does not appear to be any empirical literature showing that the level of idiosyncratic risk in one asset class is correlated with the level of idiosyncratic risk in other asset classes. Taking the case of large and small U.S. stocks, for example, it is well known that returns in these two classes are highly correlated and that the conditional variances of the average return in each class are also correlated (see, e.g., Kroner and Ng (1998)), but there appears to be no prior literature suggesting that

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[35]Interestingly, those authors also find evidence that some forms of volatility appear to Granger-cause other volatility measures. Stivers (1998) also tests for predictability among volatilities and finds that idiosyncratic risk predicts overall market volatility.

idiosyncratic risk (or dispersion) within these two asset classes is also correlated. Further, existing theory would not appear to suggest any reasons for such linkages between idiosyncratic risk in different asset classes. Accordingly, the current result would appear to remain a puzzle. Market microstructure factors arising from the market making process would be one possible expalanation, perhaps related to the factors that lie behind the commonality in liquidity recently documented in the U.S. equity market by Chordia et al. (1999) and others. Whatever the explanation, this result and the others in this suggestion suggests that idiosyncratic risk is a highly pervasive factor that warrants further study.

Implications for asset pricing models

The empirical findings of this section would appear to have some tentative implications for the nature of asset return generating functions. I begin with a fairly general (APT-like) specification for the process generating returns within an asset class, with some additional factors (f_{jt}) in addition to the first common factor (f_{1t}), and different (but fixed over time) loadings (β_{ij}) on these factors,

$$r_{it} = \alpha_i + \beta_{i1} f_{1t} + \sum_{j=2}^{k} \beta_{ij} f_{jt} + \epsilon_{it}. \tag{7}$$

It should be noted that this equation is for actual returns, and that it makes no assertions about the nature of the process for expected returns or the pricing of different risks.

There is, of course, a large amount of literature suggesting that the volatility of the overall stock market (presumably a good proxy for the first factor in equity pricing models) is not constant, but is correlated over time, i.e. $V_t(f_1)$ depends positively on $V_{t-1}(f_1)$.[36] The results of this paper would, however, suggest four other relationships that may apply across different asset classes:

(i) The variance of the idiosyncratic component of returns is also not constant but is also correlated over time, i.e. $V_t(e_i)$ depends positively on $V_{t-1}(e_i)$;

(ii) The variance of the idiosyncratic component of returns is correlated with the variance of the first common factor, i.e. $V_t(e_i)$ depends positively on $V_t(f_1)$;

(iii) The variance of the idiosyncratic component of returns is correlated across assets in the same class (otherwise the cross-sectional variance would be constant) and also across assets in different classes, i.e. $V_t(e_{ia})$ depends positively on $V_t(e_{nb})$, where assets *i and n* are different asset in asset classes *a* and *b*, respectively; and (more tentatively)

[36]The notation $V_t(\ )$ is used to denote the conditional variance in period *t* and to indicate that this is time-varying.

(iv) The variance of different common factors in returns are not independent but are correlated, i.e. $V_t(f_i)$ depends positively on other $V_t(f_j)$: this last relationship is not shown in this section but is suggested by the results discussed briefly in Footnote 17.

These proposed relationships may have implications for tests of asset pricing models. One implication would seem to be that the various aspects of time variation will reduce the efficiency of empirical tests.

V. Conclusion

In discussing the large losses suffered by some financial institutions in late 1998, *The Economist* (November 14, 1998, p.85) described the apparent prior attractiveness of relative-value trades:

> "Shareholders tend to shun institutions that take outright punts on markets. Better instead, they think, to take what appear less risky bets on the difference in price between two assets: in the jargon, "relative-value" trades. .... Traders ... took big punts on the relative value of a variety of financial instruments, including among others: yields on liquid, newly issued American Treasuries compared with older issues; yields on European government bonds in the run-up to monetary union; and the relative volatility of European interest-rates and equities. Returns on such trades were low but apparently safe, so the firms borrowed heavily to leverage their bets."

As is now well known, the extremely large and highly leveraged relative-value trades put in place by some investors turned out to be extremely reliant on the maintenance of high market liquidity and an environment where the credit of counterparties remained unquestioned. In the market turmoil of August-October 1998, market liquidity dried up and counterparty risk became a major concern, leading to large price changes and margin calls on leveraged positions.[37] Relative-value trades turned out to be far riskier in this episode than envisaged. The recent withdrawal by several large commercial and investment banks from this type of trading presumably reflects a reassessment of the risks of such trading strategies.

The findings of this paper on the nature of idiosyncratic risk would seem to provide further evidence of the risk of strategies that supposedly eliminate most market risk by going long in some assets and short in others in the asset class. The analysis provides a picture of risk as an all-pervasive factor that remains even in portfolios that are designed to minimize it. In particular, idiosyncratic risk, which is the type of risk incurred by relative-value investors, appears to have at least three undesirable characteristics: (i) it is higher within asset classes at times of extreme return outcomes for the asset class as a whole; (ii) it is strongly positively

[37]See Chapter 3 of IMF (1998).

correlated over time; and (iii) it is substantially correlated across asset classes. One cannot, of course, rule out the possibility that more complex (possibly dynamic) hedging strategies than those studied here might eliminate these undesirable risk characteristics from relative-value trades. However, the fact that three different proxies for idiosyncratic risk yield very similar conclusions would suggest that these undesirable risk properties may be fairly general.

In managing risk, the most important principle for "relative-value", "long-short" or "market neutral" investors is presumably to hold a portfolio with a reasonably large number of different relative-value trades with returns that are as uncorrelated as possible. In practice, however, it may be difficult to ensure low correlation of returns on different trades since managers may inevitably use similar valuation paradigms in coming up with their judgments about the relative valuation of different assets. In the case of Long-Term Capital Management, for example, it is widely reported that the firm's problems came not from just one or two trades that incurred large losses but from losses on many trades that turned out to be substantially correlated. But even if the returns on different relative-value or market neutral trades are uncorrelated, the results of this paper would suggest that the variances of returns on different trades will be correlated. While this does not directly impact the variance of a portfolio of different trades, it will lead to returns on a portfolio of such trades being "fat-tailed." That is, a fund taking such positions will make large gains or losses more frequently than would occur by simply assuming normally distributed returns.

The results of this paper would also suggest some other principles for risk management. First, positions that have been constructed to remove overall market risk may prove to be substantially less reliable hedges in periods of high market risk. That is, relative-value investors may tend to make larger-than-usual gains and losses on so-called hedged positions at such times. Institutions involved in such trades need to simulate the risk of such trades in turbulent market conditions as well as stable times. A second implication is based on the finding of strong persistence in asset-specific risk. This persistence implies that institutions providing financing for relative-value trades should perhaps increase margins on such financing at times of high idiosyncratic risk, even if the borrower's position has not yet moved unfavorably. A third implication comes from the correlation of idiosyncratic risk across different asset classes. In particular, financial institutions with "hedged" positions in different asset classes cannot simply assume that the risk of the positions in different asset classes is uncorrelated, but should manage risk across all asset classes.

Data: Further Details

The following countries and stocks were included in the asset classes described in the text.

(i) Mature stock market returns (weekly): Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong SAR, Italy, Japan, the Netherlands, New Zealand, Norway, Singapore, Spain, Sweden, Switzerland, the United Kingdom, and the United States. Returns are based on the Friday closing levels for stock prices, converted to U.S. dollars using exchange rates (from WEFA) as of noon in London on the same day.

(ii) Emerging stock market returns: Argentina, Brazil, Chile, Colombia, Greece, Indonesia, Jordan, Korea, Malaysia, Mexico, Pakistan, the Philippines, Taiwan Province of China, Thailand, Turkey, and Venezuela.

(iii) 26 large U.S. stocks (tickers): AA, AXP, BA, BAT, DIS, DD, EK, GE, GM, GT, HWP, IBM, IP, JPM, JNJ, KO, MCD, MMM, MO, MRK, PG, S, T, UK, UTX, and WMT.

(iv) 26 smaller U.S. stocks (tickers): AFL, ALEX, BOBE, CSN, CRS, CT, DF, FMO, FPC, FSCO, IDA, IRIC, KNE, MRBK, MOLX, NBL, NES, NFG, OG, RGO, ROL, SGO, TDS, VSH, WGO, and ZION.

(v) 12 U.S. oil stocks (tickers): AHC, ARC, BPA, CHV, KMG, MOB, OXY, P, RD, TX, UCL, and XON.

(vi) 15 mature government bond markets: Australia, Belgium, Canada, Denmark, France, Germany, Ireland, Italy, Japan, the Netherlands, New Zealand, Spain, Sweden, the United Kingdom, and the United States.

(vii) mature stock market returns (monthly): Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong SAR, Italy, Japan, the Netherlands, Norway, Singapore, Spain, Sweden, Switzerland, the United Kingdom, and the United States.

Table 1. The Volatility of Various Components of Returns

This table shows data for the standard deviation in percent per week (or month) of various components of asset returns. The first column shows the standard deviation of the return on an equally-weighted portfolio of all assets in the class. The second column shows the typical standard deviation of returns for the assets in each class, as measured by the median standard deviation. The final three columns provide various estimates of the standard deviation of the idiosyncratic component of returns, where this is proxied by the three different measures described in Section II: the median for all assets in the class is shown. Data sources are described in Section III.

	Standard Deviation of Returns				
	Common Component of Returns	Simple Asset Returns	Asset-Specific Return (Median Estimates) as Proxied by:		
			Simple Excess Return (Method 1)	In-Sample OLS Regression (Method 2)	Out-of-Sample Rolling Regression (Method 3)
20 Mature equity markets	1.68	2.55	2.03	1.87	1.98
--12 European markets	1.86	2.63	2.25	1.90	1.87
16 Emerging equity markets	2.43	4.86	4.60	3.88	4.67
--6 East Asian markets	3.97	5.51	4.79	4.29	4.96
--6 Latin American markets	3.17	4.74	4.39	3.76	3.81
26 Large U.S. stocks	2.24	3.55	3.04	2.86	3.41
26 Small U.S. stocks	1.77	3.78	3.59	3.45	3.96
12 U.S. oil stocks	2.46	3.27	2.47	2.41	2.47
15 National bond markets	1.04	1.51	1.11	0.75	0.83
--10 European markets	1.35	1.53	0.70	0.62	0.66
8 U.S. fixed income classes	0.63	0.67	0.34	0.15	0.13
Monthly returns:					
18 Mature equity markets	4.37	6.52	5.17	4.75	5.29
--12 European markets	4.45	6.27	4.95	4.63	4.65

Table 2. Testing for Skewness in Idiosyncratic Returns

This table shows tests for skewness in asset returns. The data shown are skewness coefficients multiplied by $\sqrt{n/6}$ where n is the number of observations. The test statistics are asymptotically distributed as Normal (0,1). Rejections of normality that are significant at the 0.1, 1, 5, and 10 percent (one-sided) significance levels are denoted by ***, **, *, and # respectively. Negative values indicate negative skewness, typically the existence of outcomes far below the mean value that are inconsistent with a normal distribution. The first column shows the test statistics for an equally-weighted index of all assets in the class. Columns 2-5 show the median test statistics based on the individual statistics for each asset in the class. Column 2 is based on raw asset returns and columns 3-5 are based on the asset-specific component of returns, where these are estimated via three different methods, as described in Section II. Data sources are described in Section III.

	Skewness Test Statistics				
	Common Component of Returns	Individual Asset Returns	Asset-Specific Return (Median Estimates) as Proxied by:		
			Simple Excess Return (Method 1)	In-Sample OLS Regression (Method 2)	Out-of-Sample Rolling Regression (Method 3)
20 Mature equity markets	1.09	-0.12	-0.44	-0.02	-0.06
--12 European markets	1.18	-0.10	0.55	0.24	0.08
16 Emerging equity markets	-2.31*	-0.87	0.28	0.53	0.12
--6 East Asian markets	-0.31	-1.14	0.96	1.28	0.48
--6 Latin American markets	-1.62	-0.87	0.42	0.16	0.15
26 Large U.S. stocks	-1.74#	-0.47	0.51	0.78	0.84
26 Small U.S. stocks	-7.07***	-0.59	1.40	1.33	0.68
12 U.S. oil stocks	-1.06	-0.36	0.78	0.75	0.43
15 National bond markets	-0.24	-0.77	0.00	-0.39	-0.58
--10 European markets	-0.71	-0.52	0.06	-1.01	-0.89
8 U.S. fixed income classes	-1.36	-1.37	-0.08	-0.08	1.09
Monthly returns:					
18 Mature equity markets	-3.06**	-0.07	0.92	0.87	0.40
--12 European markets	-2.22*	-0.07	1.26	1.28	0.72

Table 3. Testing for First-Order Autocorrelation in Idiosyncratic Returns

This table shows tests for one form of predictability in returns, namely first-order autocorrelation. The data shown are first-order autocorrelation coefficients, with *t*-statistics shown in parentheses. The first column shows the autocorrelation coefficient for an equally-weighted index of all assets in the class. Columns 2-5 show the median autocorrelation coefficient and median *t*-statistic based on the individual autocorrelation coefficients for each asset in the class. Column 2 is based on raw asset returns and columns 3-5 are based on the asset-specific component of returns, where these are estimated via three different methods, as described in Section II. Data sources are described in Section III. Rejections of normality that are significant at the 0.1, 1, 5, and 10 percent (one-sided) significance levels are denoted by ***, **, *, and # respectively.

	First-Order Autocorrelation Coefficients				
	Common Component of Returns	Individual Asset Returns	Asset-Specific Return (Median Estimates) as Proxied by:		
			Simple Excess Return (Method 1)	In-Sample OLS Regression (Method 2)	Out-of-Sample Rolling Regression (Method 3)
20 Mature equity markets	0.032	-0.026	-0.074	-0.101#	-0.078
	(0.6)	(-0.5)	(-1.4)	(-1.9)	(-1.2)
--12 European markets	-0.014	-0.065	-0.105*	-0.122*	-0.079
	(-0.3)	(-1.2)	(-2.0)	(-2.3)	(-1.2)
16 Emerging equity markets	0.079	0.039	0.016	-0.020	-0.018
	(1.5)	(0.7)	(0.3)	(-0.4)	(-0.3)
--6 East Asian markets	-0.016	-0.005	-0.107*	-0.071	-0.087
	(-0.3)	(-0.1)	(-2.0)	(-1.3)	(-1.1)
--6 Latin American markets	0.196***	0.087	0.023	0.037	-0.016
	(3.8)	(1.6)	(0.4)	(0.7)	(-0.2)
26 Large U.S. stocks	-0.027	-0.067*	-0.083**	-0.111***	-0.078*
	(-0.8)	(-2.1)	(-2.6)	(-3.5)	(-2.3)
26 Small U.S. stocks	0.060	-0.054	-0.069#	-0.109**	-0.100*
	(1.6)	(-1.5)	(-1.9)	(-2.9)	(-2.5)
12 U.S. oil stocks	-0.098**	-0.116**	-0.162***	-0.158***	-0.147***
	(-2.6)	(-3.1)	(-4.4)	(-4.3)	(-3.7)
15 National bond markets	-0.010	-0.035	-0.052	-0.133***	-0.080#
	(-0.2)	(-0.8)	(-1.2)	(-3.2)	(-1.7)
--10 European markets	-0.020	-0.032	-0.068	-0.137***	-0.094*
	(-0.5)	(-0.8)	(-1.6)	(-3.3)	(-2.0)
8 U.S. fixed income classes	-0.077#	-0.082#	-0.102*	-0.178***	-0.129**
	(-1.7)	(-1.8)	(-2.3)	(-4.0)	(-2.6)
Monthly returns:					
18 Mature equity markets	0.088	0.057	0.027	-0.020	0.006
	(1.6)	(1.1)	(0.5)	(0.4)	(0.1)
--12 European markets	0.072	0.057	0.041	0.014	0.017
	(1.3)	(1.1)	(0.8)	(0.3)	(0.3)

Table 4. Testing for Persistence in Idiosyncratic Risk

This table shows tests for persistence in the level of average asset-specific risk. The data shown are first-order autocorrelation coefficients, with t-statistics shown in parentheses. The three panels show the test statistics for the three different measures of asset-specific risk (see Equation 4), where the latter is estimated via three different methods, as described in Section II. Data sources are described in Section III. Autocorrelation coefficients that are significant at the 0.1, 1, 5, and 10 percent significance levels are denoted by *** and **, respectively.

	First-Order Autocorrelation for Cross-Sectional Asset-Specific Risk, with Asset-Specific Risk Proxied by:		
	Simple Excess Return (Method 1)	In-Sample OLS Regression (Method 2)	Out-of-Sample Rolling Regression (Method 3)
20 Mature equity markets	0.504***	0.415***	0.431***
--12 European markets	0.459***	0.338***	0.276***
16 Emerging equity markets	0.531***	0.437***	0.409***
--6 East Asian markets	0.584***	0.523***	0.530***
--6 Latin American markets	0.326***	0.390***	0.307***
26 Large U.S. stocks	0.334***	0.332***	0.239***
26 Small U.S. stocks	0.402***	0.363***	0.229***
12 U.S. oil stocks	0.347***	0.348***	0.329***
15 National bond markets	0.330***	0.427***	0.410***
--10 European markets	0.450***	0.473***	0.510***
8 U.S. fixed income classes	0.136**	0.435***	0.411***
Monthly returns:			
18 Mature equity markets	0.389***	0.348***	0.354***
--12 European markets	0.334***	0.304***	0.329***

Table 5. Testing for Correlation between Idiosyncratic Risk and Market Risk

This table shows tests for correlation between the level of asset-specific risk within classes of assets and market risk for the class. The data shown are regression coefficients for the regression of measures of asset-specific risk on the absolute value of the return on the class as a whole, with dummy variables used to provide separate estimates for up- and down-markets for the asset class (see Equation 6). The data shown in parentheses are heteroskedasticity-consistent *t*-statistics. The three different measures of asset-specific risk (see Equation 4) are described in Section II. Data sources are described in Section III. Regression coefficients that are significant at the 0.1, 1, 5, and 10 percent significance levels are denoted by ***, **, *, and # respectively.

	Regression Estimates for Relationship Between Asset-Specific and Market Risk, with Asset-Specific Risk Proxied by:					
	Simple Excess Return (Method 1)		In-Sample OLS Regression (Method 2)		Out-of-Sample Rolling Regression (Method 3)	
	Up-Markets	Down-Markets	Up-Markets	Down-Markets	Up-Markets	Down-Markets
20 Mature equity markets	7.6***	9.4***	3.2**	5.8***	5.2***	7.4***
--12 European markets	4.8**	8.9***	2.5#	7.3***	3.9**	8.4***
16 Emerging equity markets	13.7***	11.0***	10.0***	6.3***	12.3***	8.8***
--6 East Asian markets	10.6***	8.8***	9.5***	8.1***	9.7***	8.8***
--6 Latin American markets	9.8***	6.8***	8.5***	6.6***	11.8***	8.0***
26 Large U.S. stocks	4.9***	2.2#	3.9***	1.5#	4.0***	1.8
26 Small U.S. stocks	11.4***	7.4***	8.7***	4.1***	10.4***	5.3***
12 U.S. oil stocks	6.3***	4.5***	4.6***	3.6***	4.8***	4.2***
15 National bond markets	24.0***	31.5***	7.3**	10.7**	9.1**	11.3*
--10 European markets	8.2**	10.6**	6.6*	10.5**	8.6*	12.1**
8 U.S. fixed income classes	79.5***	104.9***	34.4***	38.3***	41.5***	51.7***
Monthly returns:						
18 Mature equity markets	3.8***	2.4***	2.9***	1.3**	2.9**	2.7***
--12 European markets	3.4***	1.8**	3.1***	1.3*	3.4***	2.0**

Table 6. Testing for Correlation in Idiosyncratic Risk Across Asset Classes

This table shows tests for correlation in idiosyncratic risk across assets classes. Panels A, B, and C show correlation coefficients for the measures of cross-sectional average asset-specific risk (defined by Equation 4) where asset-specific risk is estimated via three different methods, as described in Section II. As a memorandum item, Panel D shows correlations between the average returns in the different asset classes. The data are described in Section III. Correlation coefficients that are significant at the 0.1, 1, 5, and 10 percent significance levels are denoted by ***, **, *, and # respectively: critical values were calculated from Monte Carlo simulations of data with autocorrelations approximately matching the actual data.

	16 Emerging Equity Markets	26 Large U.S. Stocks	26 Small U.S. Stocks	12 U.S. Oil Stocks	15 National Bond Markets	8 U.S. Fixed Income Classes
A: Correlation coefficients for idiosyncratic risk proxied by simple market-adjusted return (Method 1)						
20 Mature equity markets	0.405***	0.232***	0.263***	0.234***	0.432***	0.182***
16 Emerging equity markets		0.263***	0.302***	0.240***	0.197***	0.195***
26 Large U.S. stocks			0.347***	0.255***	0.105**	0.099*
26 Small U.S. stocks				0.326***	0.041	0.286***
12 U.S. oil stocks					0.067#	0.193***
15 National bond markets						0.148***
B: Correlation coefficients for idiosyncratic risk proxied by in-sample OLS regression (Method 2)						
20 Mature equity markets	0.277***	0.203***	0.171***	0.248***	0.348***	0.154**
16 Emerging equity markets		0.212***	0.183***	0.312***	0.144**	0.281***
26 Large U.S. stocks			0.268***	0.271***	0.004	-0.025
26 Small U.S. stocks				0.324***	0.069#	0.208***
12 U.S. oil stocks					0.037	0.168***
15 National bond markets						0.163***
C: Correlation coefficients for idiosyncratic risk proxied by out-of-sample rolling regression (Method 3)						
20 Mature equity markets	0.405***	0.162**	0.238***	0.332***	0.244***	0.179**
16 Emerging equity markets		0.257***	0.235***	0.338***	0.232***	0.325***
26 Large U.S. stocks			0.186***	0.220***	-0.018	0.036
26 Small U.S. stocks				0.309***	0.014	0.257***
12 U.S. oil stocks					-0.025	0.149**
15 National bond markets						0.200***
D: Correlation coefficient for average return on asset class						
20 Mature equity markets	0.583***	0.585***	0.482***	0.406***	0.391***	0.146**
16 Emerging equity markets		0.430***	0.360***	0.314***	0.065*	-0.064
26 Large U.S. stocks			0.708***	0.503***	-0.029	0.229***
26 Small U.S. stocks				0.583***	0.054	0.305***
12 U.S. oil stocks					0.083**	0.136**
15 National bond markets						0.311***

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