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Comovement as an Investment Tool

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ABSTRACT

This paper develops a new tool for discovering mispriced securities based on an analysis of comovement in asses prices. Recent research in finance has demonstrated that comovement can be due to the trading patterns of noise traders as well as underlying economic fundamentals. Because comovement can be measured much more accurately than expected returns, it can be used to identify securities for which the influence of noise traders is high. Those are situations in which mispricing is most likely to exist. Therefore, analysis of comovement can provide important information about potential mispricing.

1. Introduction

One of the more active areas of research in behavioral finance has been the study of comovement between asset prices. The traditional view, based on analysis of economies without impediments to arbitrage and with rational investors, is that comovement in prices reflects comovement in fundamental values. The alternative view, associated most prominently by the work of Vijh (1994), Barberis and Shleifer (2003) and Barberis, Shleifer and Wurgler (2003), is that in economies with limits to arbitrage and irrational investors, comovement in prices can also result from the trading patterns of specific groups of investors.

The interest in the trading based causes of comovement arises from a variety of anomalous empirical findings that potentially can be explained by trading based models. Most prominently, Fama and French (1993) find highly significant evidence of common factors in the returns on small stocks and value (high book-to-market) stocks. However, in subsequence research, Fama and French (1995) were unable to tie the common factors in returns to common cash-flow factors. Second, Hardouvelis, LaPorta and Wizman (1994) and Bodurtha, Kim and Lee (1995) report that the returns on closed-end country funds are as highly correlated with the market index of the country in which the fund shares trade as the market index of the country where the underlying assets are traded. Third, Lee, Shleifer and Thaler (1991) find that domestic closed-end funds that hold primarily large cap stocks often comove more closely with small stock indexes. Finally, Froot and Dabora (1999) study twin stocks like Royal Dutch and Shell which have claims to the same underlying cash flows. Nonetheless, Royal Dutch which is traded in the United States

commoves more closely with U.S. stock indexes than Shell which trades more heavily in the United Kingdom. The reverse is true for Shell.

What Barberis and Shleifer (2003) and Barberis, Shleifer and Wurgler (2003) demonstrate is that all these anomalies can be explained by a model that combines limitations are arbitrage with noise traders who channel funds into and out of various classes of assets. For instance, a small firm factor can be induced by noise traders who actively move funds into and out of small stocks as a group.

This paper uses the framework developed by Barberis and Shleifer to design a new tool for investment analysis. One problem that confounds investment analysis is that expected returns cannot be measured with sufficient precision. For instance, more than 30 years of data are to reject the simple hypothesis that the expected return on the S&P 500 index is equal to expected return on Treasury bills. Comovement, however, can be measured with much greater precision. Unlike expected returns, covariances and variances can be estimated with increasing accuracy by dividing the total sample into successively smaller intervals. Whereas using daily data in place of monthly data does not change the accuracy with which expected returns can be measured, it decreases the standard error of estimates of the correlation by the square root of the number of trading days in a month.

The idea suggested here is that by studying the comovement of particular securities, information can be gained about whether mispricing is more likely to exist. To be specific, suppose that at particular points in time certain groups of securities become "infected" by noise trader interest. This noise trader interest causes comovement in the manner described by Barberis and Shleifer and it also *may* cause mispricing. However, whereas mispricing is very difficult to assess, comovement can be measured easily and accurately.

Therefore, rather than attempting to identify mispriced stocks directly, a three-step procedure can be employed. At the first step, a large sample of possibly mispriced stocks is selected. In the second step, comovement is analyzed to isolate the stocks for which mispricing is most likely to exist. In step three, traditional fundamental analysis can be applied to the smaller sample of stocks identified in step two. In effect, analysis of comovement becomes a screening device that highlights situations that deserve further study.

To develop this idea, the remainder of the paper is organized as follows. The next section briefly reviews the framework employed by Barberis and Shleifer to show how trading patterns can lead to comovement when arbitrage is limited. The following section offers examples of how comovement can be used as a investment tool. The conclusions are summarized in the final section.

2. Noise trading and comovement

The framework developed by Barberis and Shleifer for analyzing trading based comovement is straightforward. There is a riskless asset which for convenience is assumed to have a zero rate of return. There are n risky assets in fixed supply each of which pays a single liquidating dividend at some later time T. This eventual dividend is determined by the equation,

$$D_{i,T} = D_{i,0} + e_{i,1} + e_{i,2} + \ldots + e_{i,T} , \tag{1}$$

where $D_{i,0}$ is revealed at 0 and $e_{i,t}$ is announced at time t. From equation (1) the change in the price of an asset from period t-1 to t, which Barberis and Shleifer define as the return, is given by

$$\Delta P_{i,t} = P_{i,t} - P_{i,t-1} = e_{i,t} . \tag{2}$$

Equation (2) implies immediately that the correlation matrix of returns in period t is identical to the correlation matrix of the "cash flow" innovations $e_{i,t}$.

The innovation introduced by Barberis and Shleifer is to assume that noise traders are attracted to certain groups of assets and that they allocate their funds across those groups rather than at the level of individual assets. For instance, value stocks, small cap stocks and technology stocks could be examples of such groups. If arbitrage is limited, change in noise trader sentiment regarding any one group will lead to price movements that push prices for that group of assets away from their fundamental value. However, this movement, and the subsequent return to fundamental value, are common across all assets in the group. As a result, the returns of assets within the group are more highly correlated than the correlation of underlying cash flow innovations.

Adding more structure to the basic framework, Barberis and Shleifer (2003) prove that if noise traders allocate their funds across groups of securities, the correlation of returns for two stocks in the same group, net of the market return, is greater than the correlation attributable to underlying fundamentals. More specifically, they prove that if two securities, i and j, are in the same group then,

$$\text{corr}(\Delta P_{i,t} - \Delta P_{M,t}, \Delta P_{j,t} - \Delta P_{M,t}) > \text{corr}(\Delta e_{i,t} - \Delta e_{M,t}, \Delta e_{j,t} - \Delta e_{M,t}), \tag{3}$$

where $\Delta P_{M,t} = (1/n) \sum_n \Delta P_{i,t}$, and $\Delta e_{M,t} = (1/n) \sum_n \Delta e_{i,t}$.

Whereas Barberis and Shleifer use this framework to explain some of the empirical anomalies described at the outset, the goal here is to use it to develop an investment tool. That tool rests on the added assumption that individual securities can become infected by investment sentiment in a fashion that leads noise traders to treat them as a group. One possible example is internet stocks. Two companies that both make widespread use of the

internet might very well have markedly different fundamental businesses. Nonetheless, if

during a period of time irrational sentiment induces noise traders to treat them as a group,

the Barberis and Shleifer model implies that the comovement in their net of market returns

will rise. Furthermore, that same sentiment may lead to significant mispricing of the

stocks. Whereas attempting to measure mispricing directly is very time consuming and

costly, and thus is not efficient to use as a screening tool, comovement can be tracked

easily and accurately. Consequently, sharp changes, particularly increases, in comovement

can serve as a an indicator of underlying mispricing. Just as a rise in fever, suggests to a

physician that further diagnosis is required, an increase in comovement should suggest to

the investment manager that further valuation analysis could prove profitable.

　　　　To illustrate the idea, consider the case of Yahoo and Amazon. Yahoo began

trading on April 12, 1996 and Amazon started trading on May 15, 1997. Starting soon

after Amazon's IPO, the two firms began to be widely referred to in the financial press as

"premier internet companies".[1] Despite their reliance on the internet, Yahoo and Amazon

are hardly in the same business. Amazon was, and is, almost exclusively a retailer. As

some have said, it is attempting to become the Walmart of the internet. Yahoo, on the

other hand, is a media company, perhaps more akin to a television network that, at least to

date, makes most of its money from advertising. From the standpoint of business

fundamentals, therefore, it is not clear why stock returns for the two companies should be

highly correlated. From a trading standpoint, however, the Barberis-Shleifer argument

may hold. Throughout most all of the internet boom, the financial media almost invariably

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[1] Following its IPO in 1998, eBay was typically added to the list.

linked the companies together. If noise traders did the same, the correlation of stock returns should be affected as predicted by Barberis and Shleifer.

To examine what actually happened, returns for both companies, net of the CRSP value weighted index, were collected for the period from June 2, 1997 through August 26, 2003. These net returns were then used to compute a sixty trading-day rolling correlation. They were also cumulated to calculate a "net of market" path of wealth for an equal weighted index of the two companies.[2] The path of wealth starts at 1.0 on August 26, 1997, the first day for which the rolling correlation can be calculated. The two series are plotted in Figure 1.

The figure is striking. At the start, the rolling correlation is low – less than 0.10. This is not surprising. Given the immense idiosyncratic variance in daily returns, due in part to the variability of order flow, one would not expect to find the net return on one stock to be highly correlated with the net return on another.[3] What is surprising is that the correlation then begins a steep run-up that does not end until the rolling correlation passes 80 percent in late 1998. It then remains above 70 percent for most of the period through the third quarter of 1999, before plunging to less than 30 percent by the first quarter of 2000. It is interesting to note that the correlation plunges just before the path of wealth begins its sharp drop. It is tempting to conclude that this demonstrates that once investors started viewing the two firms as independent business, rather than as "the premier internet companies", it was a precursor to more rational valuation. Of course, with only one observation that conclusion is little more than speculation.

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[2] The value weighted path of wealth looks largely the same.

[3] See, for example, Roll (1988).

In the period following the drop, the rolling correlation fluctuates in a range around a mean of approximately 45 percent through the end of the sample period in August 2003. This is still a very high correlation for net of market daily returns. For example, the average daily correlation in 2002 between IBM and Microsoft was 17 percent. That number is typical for companies in the same industry. The average "low" correlation between Yahoo and Amazon is almost three times that high. It is quite possible, therefore, that the correlation between Yahoo and Amazon has continued to reflect, to a lesser extent, the impact of noise traders who trade the two companies as a group. It is also interesting to note that toward the end of the sample period the rolling correlation and the path of wealth were both rising sharply. Furthermore, this rise has been accompanied by stories in the financial press about renewed investor interest in technology companies.

The Amazon-Yahoo example is based on only two companies. In situations in which the analyst believes that more than two companies have been infected, multivariate techniques are required. One approach, employed by Barberis, Shleifer and Wurgler (2003) is to use regression analysis. However, this requires explicit determination of the group of stocks that is being traded together. While this is useful for study of specific groups of stocks, like the S&P 500, it is not well suited for situations in which the set of possibly affected securities is nebulous.

A more general approach is to apply factor analysis to the net of market returns for a group of potentially affected stocks. If trading based comovement is prevalent, then the percentage of the variance explained by one or two factors should rise compared to periods of time when the covariance matrix is determined by underlying fundamentals. For instance, if factor analysis is applied to the covariance matrix of net of market returns for

Yahoo, Amazon and Ebay, one factor explains 67 percent of the variance in 1999. In 2002 that figure is down to the (still high) 59 percent.

Factor analysis also has the benefit that it allows the analyst to engage in raw empiricism. To this point, it has been assumed that the analyst has independently identified stocks that have potentially become infected by noise trader sentiment and, therefore, could exhibit excess comovement and may be mispriced. In many circumstances, however, the analyst may not have any strong prior about which stocks have potentially been affected. In that case, factor analysis can be used to telescope the first two steps of the evaluation process. In the first step a large group of stocks, some of which may possibly be infected, is selected and factor analysis is applied to the net of market returns. At step two, the factor loadings are analyzed for all of the stocks. To the extent that a particular subset of the stocks comove closely, they should all have similar loadings on the primary factors.[4] A second factor analysis can then be applied to the smaller sample to determine whether the fraction of the variance explained by one or two factors changes over time.

As an example, consider the case of telecommunications. In addition, to the run-up in internet stocks, the financial press also referred to 1999 as the year of the telecommunications boom. Does this mean that noise trader sentiment created a high level of comovement among companies in different sectors of the telecommunications industry? To examine this possibility factor analysis was applied to eight major companies with large

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[4] Factor analysis is used here only as an empirical tool. Because the loadings are presumably affected by noise trading, they cannot be interpreted as reflecting underlying fundamentals in the sense of Ross (1976).

operations in telecommunications: Cisco, AT&T, Sprint, Verizon, Qwest, Deutsche Telekom, Alacatel and JDS Uniphase. The companies were specifically picked to have diverse operations in different industry sectors and different countries to test the proposition that comovement was induced by a general telecommunications infection.

The factor analysis does not support the notion of a general infection. The first factor explains only 19 percent of the variance, the first two only 35 percent. With eight companies in the sample, this is indicative of very little comovement. The largely unrelated nature of the net returns is also evident in the factor loadings. Aside from the fact that Cisco and JDS Uniphase have relatively similar loadings, as one might expect based on their business fundamentals, there is no consistency to the loadings across companies. In fact, the overall impression conveyed by the loadings is that the investors treated the companies as basically distinct. To be sure, there was no excessive comovement.

3. Discussion and Conclusion

The investment tool presented here is limited in that it does not offer an explanation as to why a group of stocks would suddenly become infected by noise trader sentiment, nor does it predict which stocks are more likely to become infected. One possibility is that noise traders extrapolate past returns as a means of grouping stocks. Barberis and Shleifer (2003) explore this possibility. The current paper is agnostic on this point. At a deeper level, this is a flaw in any model that relies on irrationality. Whereas rationality is unambiguous (usually), irrationality can take any form. To paraphrase Tolstoy, all rational models are alike, every irrational model is irrational in its own way. As Fama (1999) notes, depending on the type of irrationality that is assumed behavioral models can explain

virtually any anomaly. Unfortunately, Fama also observes that when viewed in the aggregate these behavioral theories are often contradictory. Furthermore, Schwert (2002) finds that they often fail to be consistent with stock price behavior outside the specific sample that they were constructed to explain. Nonetheless, the objective of active investment management is to find mispriced securities. Mispricing requires some type of irrationality. Consequently, one element of successful active management is developing a mechanism for identifying the impact of irrationality. This process is further complicated by the fact that the identification mechanism depends on the nature of the irrationality. Here the assumed irrationality is the tendency of noise traders to allocate funds at the level of groups of stocks, sometimes irrationally chosen groups, instead of at the level of individual securities. Using comovement as a tool is a way of identifying that type of irrationality efficiently. Of course, if the mispricing arises from another source, say the tendency of investors to overreact, the comovement tool is unlikely to be helpful in identifying any resulting mispricing.

To summarize, the comovement investment tool developed here is based on one statistical property and one assumption. The statistical property is that the second moments of the distribution of returns, including correlation, can be measured much more accurately than the first moment by subdividing the sample period. The assumption is that the tendency of noise traders to allocate funds across groups of stocks leads to both mispricing and excessive comovement in stock prices. Taken together, these two properties imply that comovement can be used as a screening tool to identify potentially undervalued securities.

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Figure 1

Rolling Correlation and Net of Market Path of Wealth for Yahoo and Amazon: August 26, 1997 to August 26, 2003