

# Test-Driving Industry Classifications

Correlation coefficients in market-based industry classifications

By Geoffrey Horrell and Richard Meraz



Industry classifications drive many aspects of modern investment management. For an industry grouping to be useful, its constituents should have a tighter correlation to each other than each has to the overall market. Indeed, analyses based on industry classifications assume that the personality of each industry group differs from that of the market in general, and that each industry responds to economic factors in a consistent but unique way. This paper examines these assumptions; shows that industry groupings in Thomson Reuters Business Classification (TRBC) are effective; and contrasts pairs of industries commonly selected during the five stages of the economic cycle, based on a simple sector rotation strategy.

## Introduction

Most portfolio managers, index builders and exchange-traded fund developers implicitly assume that market-based industry classification schemes are sound tools, that companies within industries are more tightly correlated than a random sample of companies. From retail investors reviewing mutual fund reports to institutional custodians allocating assets, the ability to make investment choices based on industry categories has never been greater. Clearly, market participants endorse industry groupings constructed by third parties as a meaningful way to analyze the market, balance risk and create benchmarks. But is this a reliable way to segment the market—and is every industry grouping equally robust?

Over 1 billion pairs of time series data for the U.S. market were used to test the correlation between constituents within industry groups, between the groups themselves and between groups and the market. The results demonstrate that correlations are higher within industry groups, on average, and that the effectiveness of an industry group to perform distinctly from the market varies across time and between industries.

## Usage Of Industry Data Within The Investment Community

Industry-based investment strategies are often centered on a belief that sector rotation will allow investment managers to select groups of equities that will behave in accordance with the economic cycle. For example, if a manager believes the economy is heading for a downturn, he may overweight defensive industries, such as consumer noncyclicals or utilities, because consumers continue to purchase tobacco, beer and electricity, irrespective of economic cycles. If the manager believes the economy is entering a growth phase, he may overweight consumer cyclicals or technology, anticipating a rise in these sectors as consumers increase discretionary spending and businesses accelerate capital investment. Such a top-down approach allows managers to focus on understanding and predicting broader economic trends, versus a bottom-up approach involving more time-consuming stock-by-stock analyses.

A standard interpretation of a five-phase economic cycle, coupled with some commonly used sector group-

ings, is shown in Figures 1A and 1B. It was originally published in Stovall and further explored in Stangl, Jacobsen and Visaltanachoti.

The proliferation of index vehicles has made it easier than ever to build cost-effective strategies to adjust industry weightings throughout the cycle. For example, Thomson Reuters sector indexes will provide approximately 7,000 industry indexes across 42 countries and seven regions.

Stovall's analysis uses a grouping of standard industrial classification codes. In 1996, there were no widely used market-based classification systems available. But today there are many market-based systems, prompting the question, why are these favored by the investment community? Analysis by Bhojraj, Lee and Oler shows that market-based schemes, such as the Global Industry Classification Standard (GICS),<sup>1</sup> offer several advantages over production-based codes.

## Market-Based Classification: What Is It?

The defining feature of a market-based classification system is that companies are categorized based on the market they serve rather than on the products they produce—the idea being that the share price performance of companies that, for example, produce ball bearings for planes will differ from companies that provide ball bearings for wind turbines. The airline industry is driven by business travel and is hindered by high energy prices, whereas the wind turbine industry is driven by tax incentives and is helped by high energy prices. Intuitively, businesses that serve the same end markets are more likely to have similar reactions to headwinds and tailwinds, as opposed to peers that produce the same materials for different market segments. This is why providers of market-based classification systems assign companies to industries after researching various revenue streams, examining each business unit within larger organizations to determine which markets are being served.

## Market-Based Classification: The Providers

The major index providers offer a number of market-based tools. S&P and MSCI publish GICS. FTSE and Dow Jones publish the Industry Classification Benchmark (ICB). And Thomson Reuters has recently announced the release of a new market-based system, the Thomson Reuters Business Classification (TRBC), which will serve as the basis for approximately 7,000 sector indexes and become a global standard across Thomson Reuters content and product offerings.

These three industry classifications share many characteristics (see Figure 2). Each has four levels of detail, with companies classified at the lowest level within a strict hierarchy, rolling up into higher levels that provide larger baskets of stocks used to create indexes, compile aggregates or conduct other analyses.

While each provider has written extensive marketing literature on the benefits of a market-based approach, there is little publicly available academic research that tests the underlying assumptions or gauges the effectiveness of each industry grouping.<sup>2</sup>

The next section describes the testing conducted by Thomson Reuters in evaluating the rigor of the TRBC market-based scheme.

## Methodology

The study selected a universe of U.S. stocks, which varied in number between approximately 7,400 and 9,400 during the period considered. Within this universe, 10 years of stock price return data were examined to determine whether stocks within the top three levels of the classification were more closely correlated to one another than to stocks outside the industry group. This method used a correlation coefficient as a simple and measurable metric to evaluate the strength of each group. Additional aspects that could have been considered are discussed in the conclusion.

Figure 1A

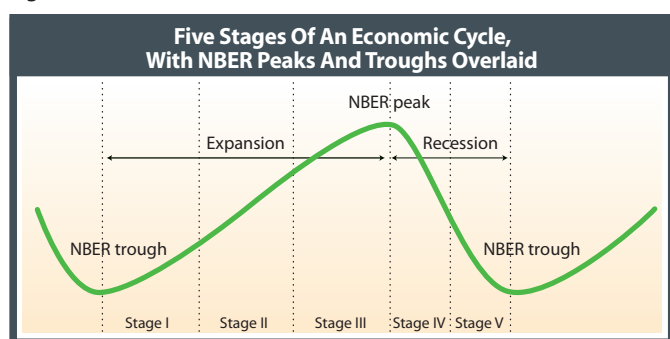


Figure 1B

Suggested Industries To Overweight At Each Of The Five Stages				
Three Stages Of Expansion			Two Stages Of Recession	
Stage One	Stage Two	Stage Three	Stage Four	Stage Five
<b>Technology</b> <ul style="list-style-type: none"> <li>• Computer software</li> <li>• Measuring and control equipment</li> <li>• Computers and electronic equipment</li> </ul> <b>Transportation</b> <ul style="list-style-type: none"> <li>• General transportation</li> </ul>	<b>Basic Materials</b> <ul style="list-style-type: none"> <li>• Precious metals</li> <li>• Chemicals</li> <li>• Steel</li> <li>• Non-metallic and metal mining</li> </ul> <b>Capital Goods</b> <ul style="list-style-type: none"> <li>• Fabricated products</li> <li>• Defense and aircraft</li> <li>• Machinery</li> <li>• Ships and railroad equipment</li> <li>• Electrical equipment</li> <li>• Services</li> <li>• Business services</li> </ul>	<b>Consumer Staples</b> <ul style="list-style-type: none"> <li>• Agriculture</li> <li>• Beer and liquor</li> <li>• Candy and soda</li> <li>• Food products</li> <li>• Health care</li> <li>• Medical equipment</li> <li>• Pharmaceutical products</li> <li>• Tobacco products</li> </ul> <b>Energy</b> <ul style="list-style-type: none"> <li>• Coal</li> <li>• Petroleum and natural gas</li> </ul>	<b>Utilities</b> <ul style="list-style-type: none"> <li>• Gas and electrical utilities</li> <li>• Telecom</li> </ul>	<b>Consumer Cyclical</b> <ul style="list-style-type: none"> <li>• Apparel</li> <li>• Automobiles and trucks</li> <li>• Business supplies</li> <li>• Construction</li> <li>• Construction materials</li> <li>• Consumer goods</li> <li>• Entertainment</li> <li>• Printing and publishing</li> <li>• Recreation</li> <li>• Restaurants, hotels and motels</li> <li>• Retail</li> <li>• Rubber and plastic products</li> <li>• Textiles</li> <li>• Wholesale</li> </ul> <b>Financial</b> <ul style="list-style-type: none"> <li>• Banking</li> <li>• Insurance</li> <li>• Real estate</li> <li>• Trading</li> </ul>

Sources: Stovall; Stangl et al. The National Bureau of Economic Research (NBER) provides an official view of key stages in the economic cycle, as presented above. The industries to overweight are Standard Industrial Classification (SIC) groups suggested within Stovall.

## Price Correlation Coefficient

Two stocks show similar price movement if they tend to show the same direction of returns over time. Standard time series correlation can be used to quantify the strength of the comovement. The Pearson product-moment correlation coefficient ( $\rho$ ) is a number between -1 and 1, where a value of -1 indicates perfect anti-correlation (an exact opposite movement), and a value of 1 indicates perfect positive correlation. Zero values would indicate that no linear relationship exists between the time series of the two stocks. To illustrate, Figure 3 shows that monthly returns of Halliburton and Microsoft are slightly anti-correlated in the years 1998 and 1999 ( $\rho = -0.04$ ). The lower graphic shows the same return series as a scatter plot to further illustrate that the relationship between the stock returns is very weakly anti-correlated. The correlation coefficient is the square root of the familiar  $R^2$ , or goodness of fit, obtained from fitting the linear regression of the two return time series (shown as the trend line in this plot); though, in practice, the correlation is computed using a more efficient method.

This correlation coefficient was computed for all pairs of stocks, tradable on a given date in history, using a trailing time series of monthly returns. Let the indexes  $i$  and  $j$  indicate two securities, and  $\rho_{ij}$  indicate the correlation coefficient of the return time series for the securities terminating at a given date.

Given all the pairwise correlations for a single security, they are segregated into two subsets: 1) correlations between the security and other securities within the same TRBC group (W: within-group), and 2) correlations between the security and other securities not within the

Figure 2

Comparison Of Three Available Market-Based Classification Schemes			
	TRBC	GICS	ICB
Top Level	10 Economic Sectors	10 Sectors	10 Industries
Second Level	25 Business Sectors	24 Industry Groups	19 Supersectors
Third Level	52 Industry Groups	64 Industries	41 Sectors
Fourth Level	124 Industries	139 Sub-Industries	114 Subsectors

Source: Thomson Reuters, S&P/MSCI, FTSE/Dow Jones

same TRBC group (O: outside-group). For each security  $i$ , the average was computed of the within-group correlations ( $W_{iG}$ ), and the outside-group correlations ( $O_{iG}$ ), where G designates TRBC group:

$$W_{iG} = \frac{1}{N-1} \sum_{j \in G, j \neq i} \rho_{ij}$$

$$O_{iG} = \frac{1}{K-N} \sum_{j \notin G} \rho_{ij}$$

Above,  $N$  is the number of securities in the TRBC group and  $K$  represents the total number of securities passing our data requirements. By TRBC group (G), we mean the economic sector, industry group and business sector, represented by two-, four- and six-digit codes, respectively. The analysis of the lowest level, industry or eight-digit code is omitted from the results to concentrate on the levels most commonly used by top-down investment practitioners.

Finally, the ability of the TRBC taxonomy as a whole to explain return comovement was measured. The average within-group correlation and outside-group correlation of all securities was computed, treating each level of the TRBC taxonomy (two-, four- and six-digit codes) separately:

$$W = \frac{\sum_{i=1}^K W_{iG}}{K}$$

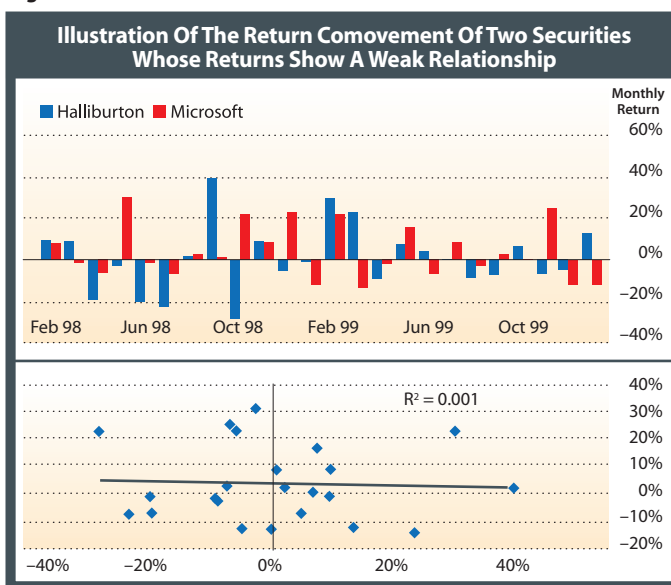
$$O = \frac{\sum_{i=1}^K O_{iG}}{K}$$

It is expected that  $W > O$  for a given level of TRBC, as discussed below. Subsets of the universe can also be analyzed by computing  $W$  and  $O$ ; for example, by dividing the universe into tertiles of market capitalization (small-, mid- and large-cap). The expectation is that TRBC will show a more robust grouping of larger, more stable companies, compared with smaller, more volatile ones.

**Data**

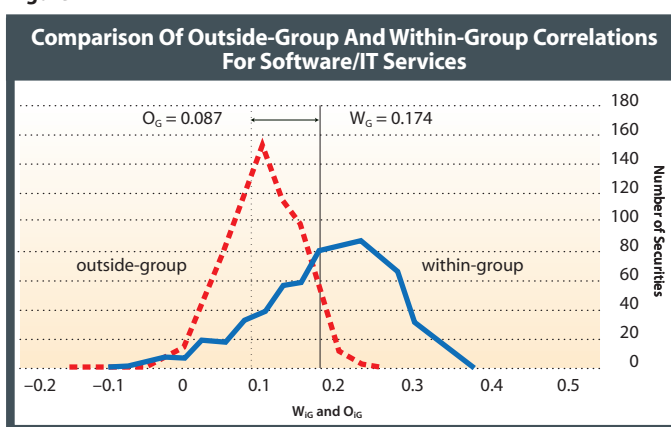
All tradable North American securities with an assigned Thomson Reuters Business Classification in 1999-2009 were included only if the stock never closed at \$2.00 or below. Securities pricing under \$2.00 are likely to be poorly traded and show unrealistic biases in their return distributions.

Figure 3



Source: Thomson Reuters

Figure 4



Source: Thomson Reuters

Mergers, acquisitions and historical TRBC assignments were taken into account to approximate point-in-time reference information. Stock price returns were computed on a monthly basis, using fully adjusted prices. Monthly returns are defined as the difference between last closing prices on the first trading day of adjacent months. Prices were fully adjusted for splits and stock dividends. Securities were divided into small-, mid- and large-cap classes using Thomson Reuters share and price data to compute histori-

Figure 5

Average Of  $W_G$  And  $O_G$  Correlations For The Top Three Levels Of TRBC

Market Cap	Within-Group (W)			Outside-Group (O)			Difference (W-O)		
	Economic Sector	Business Sector	Industry Group	Economic Sector	Business Sector	Industry Group	Economic Sector	Business Sector	Industry Group
Large	0.180	0.199	0.208	0.127	0.130	0.131	0.053	0.069	0.078
Mid	0.144	0.153	0.156	0.107	0.109	0.109	0.037	0.044	0.047
Small	0.095	0.099	0.100	0.069	0.070	0.070	0.026	0.029	0.030

Source: Thomson Reuters. Measurements are averaged from five nonoverlapping two-year blocks in 1999-2009. The differences between the within-group and outside-group averages are statistically significant  $P > 0.95$  (t-statistic not shown). Averages are taken within market-cap tertiles, measured at the end of each two-year interval.

Figure 6

Suggested Industry Groupings From Figure 1B Matched To TRBC Industry Groups And Ranked By Correlation

Three Stages Of Expansion						Two Stages Of Recession			
Stage One		Stage Two		Stage Three		Stage Four		Stage Five	
Industry Group	W-O	Industry Group	W-O	Industry Group	W-O	Industry Group	W-O	Industry Group	W-O
<b>Technology</b>		<b>Basic Materials</b>		<b>Consumer Staples</b>		<b>Utilities</b>		<b>Consumer Cyclical</b>	
• Software/IT services	0.039	• Chemicals	0.030	• Personal/household products/services	0.001	• Telecommunications services	0.039	• Textiles/apparel	0.010
• Computers/office equipment	0.050	• Containers/packaging	0.037	• Food/tobacco	0.006	• Utilities - water/others	0.060	• Hotels/entertainment services	0.023
• Communications equipment	0.085	• Construction materials	0.047	• Beverages	0.008	• Electric utilities	0.091	• Household goods	0.022
• Semiconductors/semiconductor equipment	0.159	• Metal/mining	0.082	• Health care providers and services	0.009	• Gas utilities	0.115	• Media/publishing	0.029
		• Paper/forest products	0.099	• Health care equipment/supplies	0.011	• Utilities - multiline	0.289	• Automobiles/auto parts	0.041
<b>Transport</b>		<b>Capital Goods</b>		• Food/drug retailing	0.030			• Retailers - diversified	0.051
• Air freight/courier services	0.034	• Commercial services/supplies	-0.004	• Pharmaceuticals	0.056			• Retailers - specialty	0.051
• Airline services	0.078	• Industrial conglomerates	0.120					<b>Financials</b>	
• Marine services	0.094	• Construction/engineering	0.021	<b>Energy</b>				• Investment trusts	0.010
• Rails/roads transportation	0.100	• Aerospace/defense	0.022	• Oil/gas	0.083			• Banking services	0.042
		• Machinery/equipment/components	0.025	• Coal	0.097			• Insurance	0.076
				• Oil/gas-related equipment/services	0.139			• Financial services - diversified	0.096
								• Real estate operations	0.100
								• REIT - residential/commercial	0.100

Source: Thomson Reuters

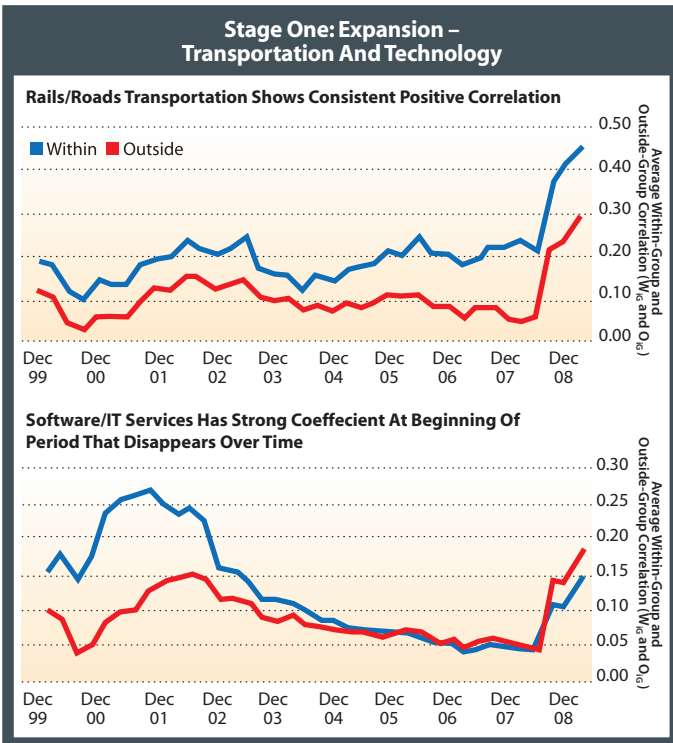
cal, company-level market capitalizations.

Correlation coefficients were calculated using time series composed of 24 months of returns. Twenty-four months was chosen as a balance between having enough data for a statistically meaningful correlation coefficient, and being able to have sufficient independent, nonoverlapping intervals from within a 10-year period. The 10-year period, 1999-2009, was sampled at three-month intervals beginning on 1/31/2000. For pooled analysis over the whole period (Figure 5), we averaged results from five nonoverlapping two-year intervals ending on April 30 in each of 2001, 2003, 2005, 2007 and 2009.

Correlation coefficients were calculated for all stocks, using monthly total returns. Average coefficients were calculated for each industry group, as well as for each industry group compared with the overall market.

This type of research requires a high degree of computational intensity. For example, on April 30, 2009, there were approximately 8,900 securities that met our data requirements for this analysis. This results in 8,900 separate time series of monthly returns to compare, and 39.6 million separate correlation coefficients to compute (note that  $p_{ij} = p_{ji}$ , and a securities correlation coefficient to itself is not calculated). The remaining steps involve

Figure 7



Source: Thomson Reuters

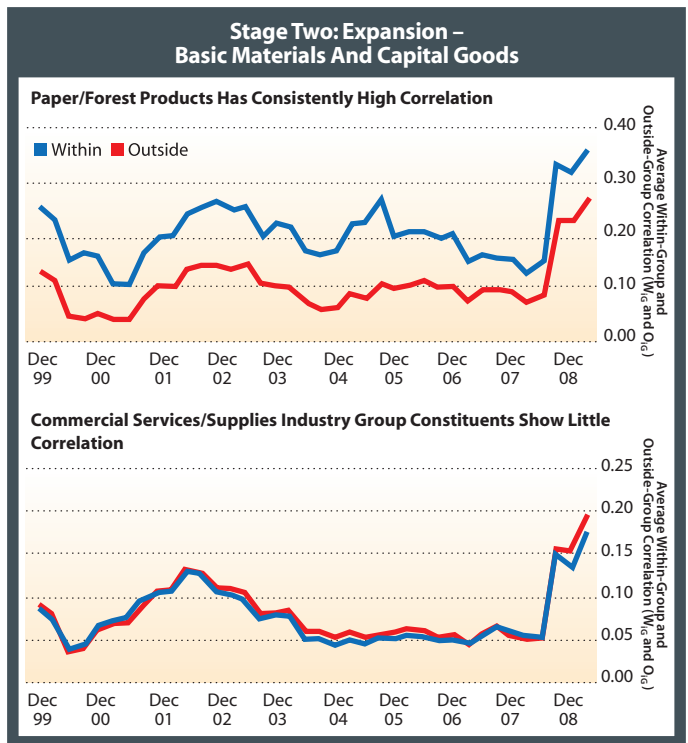
grouping these correlation coefficients in various ways and computing averages. This is repeated for approximately 40 month-end dates in the history. The resulting matrices require a nontrivial amount of storage. The computations used algorithms for distributed computation on a 24-core Linux cluster, where each node had a minimum of 16 GB of RAM. All codes were implemented in the Python programming language, making heavy use of the numerical Python library (NumPy).

If the companies within an industry shared no performance characteristics, the average coefficient for stocks paired to stocks within an industry group would be very close to the average for those same industry group stocks paired to stocks not inside the industry group.

The results emphatically show that this is not the case and that there is a tighter correlation of stocks within industry groups. Figure 4 illustrates this for the software/IT services sector.

Figure 4 reveals that comparisons within group ( $W_G$ ) versus outside group ( $O_G$ ) illustrate how well TRBC market-based classifications explain price comovements. Compiled with trailing two years of monthly returns, terminating on May 31, 2000, for the software/IT services sector, the vertical lines indicate the mean of each distribution,  $W_G$  &  $O_G$ . If the TRBC group explains some significant part of the return comovement of its securities, the  $W_G$  distribution should be shifted right relative to the  $O_G$ , and  $W_G$  should be greater than  $O_G$ . Indeed, this fits with the observation for the example in Figure 4, which shows the distribution of  $W_G$  and  $O_G$  for all securities in software/IT services on May 31, 2000. The separation of the two distributions demonstrates the ability of the TRBC group to capture comovements of returns of its constituent securities.

Figure 8



Source: Thomson Reuters

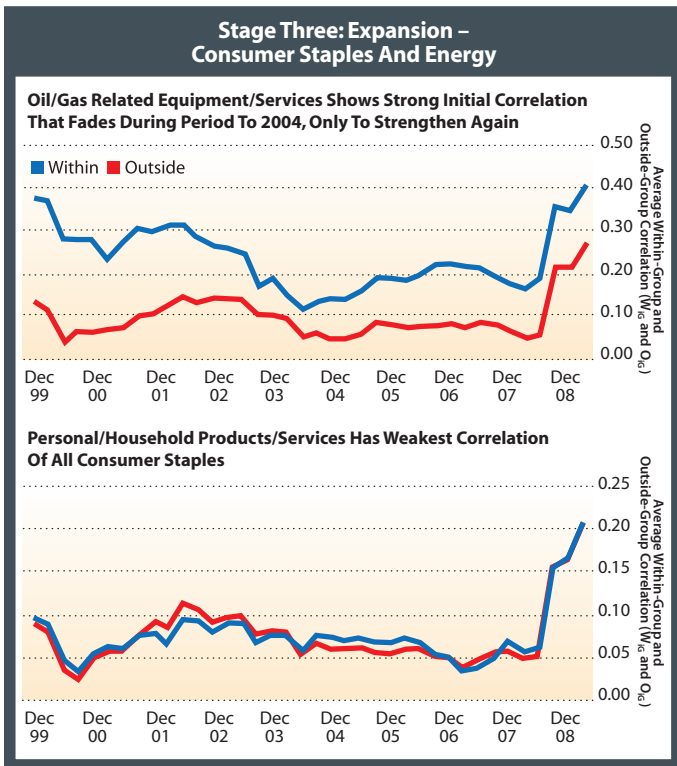
It is also useful to measure the ability of the TRBC taxonomy, as a whole, to explain return comovement and compare the various levels. To do this, the average within-group correlation and outside-group correlation of all securities is computed, treating each level of the TRBC taxonomy (economic sector, business sector and industry group) separately. Again, the insight revealed in Figure 4 applies for each level of the taxonomy:  $W$  should be greater than  $O$  for a given level of TRBC. Taking the analysis one step further,  $W$  and  $O$  were computed for market-cap tertiles (small-, mid- and large-cap). The expectation is that TRBC will show a more robust grouping of larger, more stable companies, compared with smaller, more volatile ones.

## Results

The main result of the study quantitatively demonstrates that two stocks within a TRBC group are more likely to show coordinated share price movements than are two stocks in different TRBC groups. Figure 5 demonstrates the average  $W$  and  $O$  correlations, for each level of the TRBC hierarchy, averaging the results of five nonoverlapping, two-year intervals of history with market-cap tertiles.

There are four major observations. First, the  $W$  correlation increases as the industry groupings go from coarser to finer. Industry groups are more tightly correlated than economic sectors, and this trend holds within the three market-cap groups. This indicates that, overall, the TRBC taxonomy is robustly constructed, since progressively finer categorizations are grouping securities with a stronger relationship in return movements. It also provides helpful guidance for builders of indexes and ETFs who seek to isolate tightly correlated baskets of securities;

Figure 9



Source: Thomson Reuters

where possible, they should employ the lower levels of the classification.

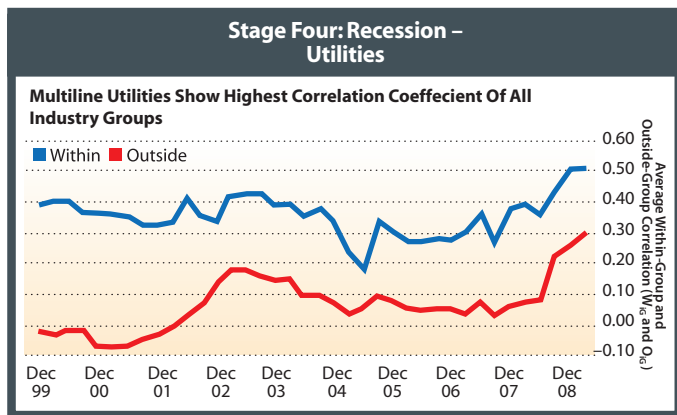
The second set of findings is that the W correlation is higher for large-cap than for small-cap stocks within any given TRBC level. This relationship is consistent for economic sectors, business sectors and industry groups. This is slightly counterintuitive, as larger companies are generally more operationally diverse and can serve multiple markets. However, this is another strong result demonstrating the consistency of the TRBC taxonomy and market-based classifications overall.

Critically, the difference between the W and O correlations is statistically significant for all levels of the TRBC hierarchy, across market capitalizations, and over the 10-year period measured. This means that, regardless of the underlying correlation structure of the market, TRBC is grouping securities that are more likely to behave similarly.

There are substantial differences between each industry, and these are highlighted in Figure 6, in which the suggested industry groupings from Figure 1B are matched to TRBC industry groups, and ranked by strength of correlation. By examining these differences in the context of a five-stage sector rotation strategy, as discussed above, some worthwhile observations emerge. For example, a consistent and high-correlation coefficient may be interesting to investors who seek to maximize the chances of selecting stocks or industries that provide a predictable response during a particular stage of the cycle. In each case, the industry group or third level is used.

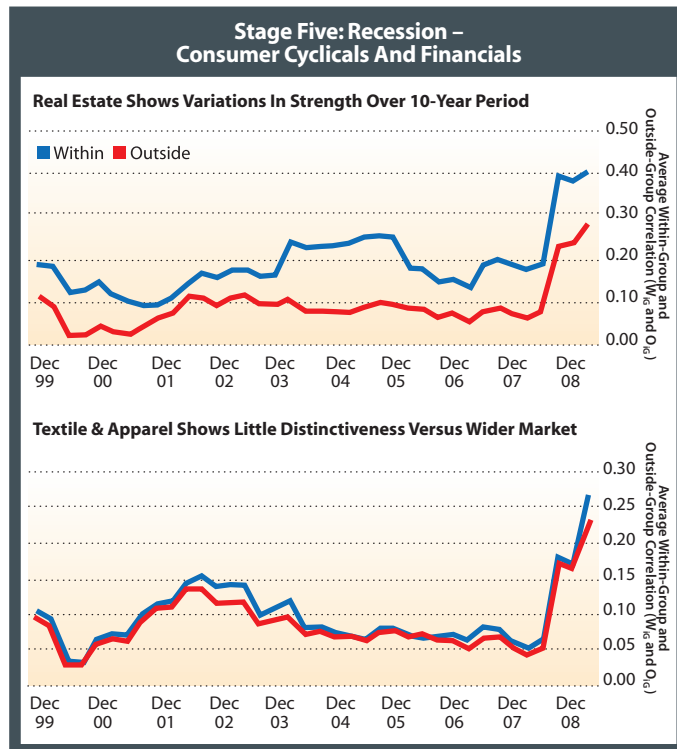
Note that in each case there is a marked spike in the data around the exceptional market events of the credit crisis.

Figure 10



Source: Thomson Reuters

Figure 11



Source: Thomson Reuters

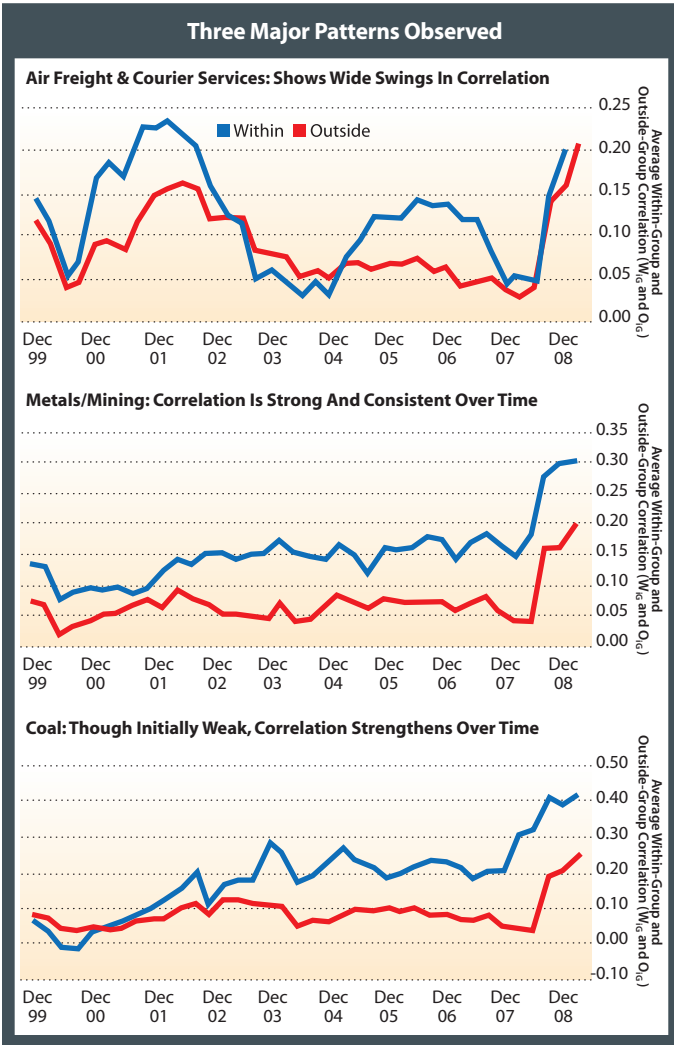
*Stage 1: Expansion – Transportation & Technology*

Transportation has higher coefficients, overall, in stage one. The most consistent industry group is rails/roads transportation, while the least consistent is air freight/courier services. Within technology, communication equipment has the highest correlation, and software/IT services has the lowest. (See Figure 7.)

*Stage 2: Expansion – Basic Materials & Capital Goods*

Basic materials show higher correlations overall, with the paper/forest products being the strongest. Commercial services/supplies has weak and sometimes negative correlations. (See Figure 8.) This is not altogether unexpected, as the companies serve a wide variety of markets. In the most recent TRBC review, this group was extensively revised to provide more granular industries.

Figure 12



Source: Thomson Reuters

### Stage 3: Expansion – Consumer Staples & Energy

Energy is the stronger of the two areas, with oil and gas equipment manufacturers and suppliers being more consistent over time than any other group. Personal/household products/services has the lowest correlation of the coefficients. (See Figure 9.)

### Stage 4: Recession – Utilities

The small set of around 20 companies within utilities multiline shows very high correlations, higher than any other group within the selected universe. (See Figure 10.)

### Stage 5: Recession – Consumer Cyclical & Financials

Real estate is the strongest; however, the correlations in both financials and consumer cyclicals are weak. (See Figure 11.) Further study is required to examine why this is the case.

## Analysis

Overall, three major patterns are observed (see Figure 12):

- Wide swings from high to low degrees of correlation.
- Consistently strong or weak correlations.
- Trending from strong to weak, or vice versa.

## Conclusion

Investors are correct to rely on market-based classifications, and many of the underlying assumptions withstand empirical testing. TRBC, specifically, is shown in this data to be a robust system that indeed does show statistically significant correlation of price movements of securities within the same group and at all hierarchical levels. The relationship holds, overall, across history and market cap. Investment practitioners must be careful, however, to note that not all the industry groups are robust in this way. Not all industry groupings show equally strong correlation coefficients, and investors should take this into account when devising sector rotation or other industry-based investment strategies. Additional studies are planned to examine the lowest level of the taxonomy, as well as performance of TRBC groupings to economic indicators and fundamental factors. Time series data of sectors in which correlations are weak or erratic will be used in the forthcoming TRBC annual review.

As mentioned in the methodology section, there are a number of assumptions that were made that could be relaxed to further test the robustness of the study. Additional efforts to remove any survivorship bias in the study might help to explain certain industry-specific movements, particularly around the 1991-2001 technology bubble. Studies using deeper history with variable lengths of price-return time series would also be helpful to further compare the relative strength of industries, especially those coefficients that vary over time.

## References

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- "Standard & Poor's Guide to Sector Investing," Sam Stovall, McGraw-Hill, 1996.
- "Sector Rotation Over Business Cycle," Jeffrey Stangl, Ben Jacobsen, Nuttawat Visaltanachoti, New Zealand Financial Colloquium, 2008.
- "What's My Line? A Comparison of Industry Classification Schemes for Capital Market Research," Bhojraj (Cornell University), Lee (Barclays Global Investors) and Oler (Texas Tech University), May 2003.

## Endnotes

- 1 The Global Industry Classification Standard (GICS) was developed by and is the exclusive property of Morgan Stanley Capital International Inc. and Standard & Poor's. GICS is a service mark of MSCI and S&P and has been licensed for use by Thomson Reuters.
- 2 For an accessible review of production versus market-based schemes, see: Bhojraj, Lee and Oler, "What's My Line? A Comparison of Industry Classification Schemes for Capital Market Research," May 2003.