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What's My Line? A Comparison of Industry Classification Schemes for Capital Market Research

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ABSTRACT

This study compares four broadly available industry classification schemes in a variety of applications common to capital market research. Standard Industrial Classification (SIC) codes have been available since 1939 but are being replaced by North American Industry Classification System (NAICS) codes. The Global Industry Classifications Standard (GICS)^{SM} system, jointly developed by Standard & Poor's and Morgan Stanley Capital International (MSCI), is popular among financial practitioners, whereas the Fama and French [1997] algorithm is used primarily by academics. Our results show that GICS classifications are significantly better at explaining stock return comovements, as well as cross-sectional variations in valuation multiples, forecasted and realized growth rates, research and development expenditures, and various key financial ratios. The GICS advantage is consistent from year to year and is most pronounced among large firms. The other three methods differ little from each other in most applications.

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1. *Introduction*

Capital market research often calls for firms to be divided into more homogenous groups, and the most common method for achieving this end is through industry classifications. In recent studies, academic researchers have used industry groupings to limit the scope of their investigation, identify control firms, secure performance benchmarks, and provide descriptive statistics on sample firms.[1] In all these applications, an industry classification scheme is used to separate firms into finer partitions, with the expectation that these partitions will then offer a better context for financial and economic analysis.

Industry classification is a long-standing problem in financial research. Although Standard Industry Classification (SIC) codes have been available since 1939, they are in the process of being replaced by North American Industry Classification System (NAICS) codes. At the same time, the Global Industry Classifications Standard (GICS)[SM] system, jointly developed by Standard & Poor's (S&P) and Morgan Stanley Capital International (MSCI), is also becoming widely accepted, particularly among financial practitioners. As a result of these changes, major data vendors, such as S&P Compustat, now carry all three sets of industry codes. In addition, financial researchers have also sought their own solution to the industry classification problem (e.g., the FF algorithm developed by Fama and French [1997]).

In this study we evaluate each of these four industry classification schemes in a variety of applications common to capital market research. Our main objective is to document the relative merits of each scheme in settings that are most commonly encountered by financial researchers. Specifically, we examine their usefulness and limitations in explaining cross-sectional variations in firm-level stock returns, as well as in market-based valuation multiples, forecasted and realized growth rates, research and development (R&D) expenditures, and other key performance ratios extracted from firms' financial statements.

Despite its well-documented problems, most past researchers have used SIC codes to form their industry partitions.[2] We suspect that the continuing popularity of SIC codes is attributable to the absence of a superior, and widely available, alternative. Although financial analysts and professional asset managers use many proprietary industry classification schemes, most of these are not available to academic researchers at a reasonable cost.[3]

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[1] In a survey of the seven major accounting and finance journals from 2000 to 2001, we identified 116 studies that used some sort of industry classification scheme in their research design, some for multiple purposes. More than half of these studies used industry classifications to identify control firms.

[2] Among the studies that used a general industry classification scheme, we found that more than 90% used SIC codes. Studies that discuss problems and limitations of SIC codes include Clarke [1989], Kahle and Walking [1996], Guenther and Rosman [1994], and Fan and Lang [2000].

[3] For example, proprietary industry classification schemes are available from analytical software providers such as BARRA[TM] and FactSet[TM].

Each of the four algorithms we examine is general enough to encompass the universe of actively traded firms and is widely available at low cost.

Our analysis shows a high degree of correspondence among SIC, NAICS, and FF classifications. However, GICS classifications are much more likely to disagree with the other three. Specifically, we find that when firms grouped by two-digit SIC codes are mapped into their primary equivalent by NAICS codes, 80% of these mappings resulted in a one-to-one correspondence.[4] Similarly, two-digit SIC groupings agree with their primary FF industry groupings for 84% of these firms. The primary GICS industry groupings, on the other hand, agreed with the SIC groupings only 56% of the time.

One measure of the economic relatedness of firms is the extent to which their stock returns are contemporaneously correlated. We form equal-weighted industry portfolios using each classification scheme and compare the ability of these industry portfolios to explain contemporary monthly firm-level stock returns. Our results show that industry portfolios formed using GICS consistently explain a significantly greater proportion of the variation in cross-sectional firm-level returns. This result is robust. GICS outperforms SIC and FF in each of the eight years in our sample (1994–2001). GICS also outperforms NAICS in seven of eight sample years.

Another measure of homogeneity across firms is the extent to which the market ascribes similar valuation multiples to their key accounting measures, such as earnings, book value of equity, and sales revenue. We evaluate the four classification schemes by forming industry portfolios using each scheme and by comparing the ability of the mean industry multiple to explain firm-level multiples. Using annual data, we show that industry means based on GICS classifications explain a much greater proportion of the variation in firm-level price-to-book (*pb*), enterprise-value-to-sales (*evs*), and price-to-earnings (*pe*) ratios than the other three methods. The margin of victory varies across time and accounting constructs. On average, we achieve a 10% to 30% increase in the adjusted R^2 when using GICS rather than one of the other three classification schemes.

Financial researchers are also often interested in identifying firms with similar operating characteristics, for comparison and control purposes. We form industry portfolios using each scheme and compare the ability of the mean industry ratio to explain key firm-level ratios. The financial ratios we consider include: (1) return on net operating assets (*rnoa*), (2) return on equity (*roe*), (3) asset-turnover ratio (*at*)[5], (4) net profit margin (*pm*), and (5) debt-to-book equity (*lev*). We find that industry means computed using GICS consistently outperform industry means computed using the other three methods in terms of their ability to explain cross-sectional variations in firm-level *rnoa, roe, at,* and *pm*. For *lev,* we find that SIC and NAICS

[4] We define an industry group in a given classification scheme as a primary equivalent if its member firms have the highest level of correspondence with the member firms in a particular two-digit SIC group.

[5] We use the inverse of the asset turnover ratio (i.e., total assets over total sales) because it contains fewer outliers.

classifications perform better than GICS, perhaps because SIC and NAICS are production-technology-based algorithms that better capture the amount of debt firms tend to assume.

A variable of increasing importance in financial research is a firm's forecasted five-year earnings growth rate as supplied by sell-side analysts (*ltgrowth*). Prior researchers use this variable in equity valuation (e.g., Frankel and Lee [1998], Lee, Myers, and Swaminathan [1999]), tests of market efficiency (e.g., La Porta [1996]), cost of capital estimations (e.g, Gebhardt, Lee, and Swaminathan [2001], Claus and Thomas [2001]), and identification of peer firms (Bhojraj and Lee [2002]). To the extent that an industry classification scheme groups firms into more homogenous units by their expected growth, the mean forecasted growth for each industry should explain a greater proportion of the firm-level variations. Our results show that GICS industry groupings produce the best results on for this variable. Specifically, mean industry forecasted growth rates under GICS explain, on average, 41.9% of the cross-sectional firm-level variation. The closest competing scheme (NAICS) explains only 33.7%.

Finally, we examine the effectiveness of the various classification schemes in grouping firms by their one-year-ahead realized sales growth (*sales growth*) and R&D expenditures scaled by sales (*R&D*). Because both *ltgrowth* and GICS classifications are affected by analyst perceptions, one concern with the forecasted growth results is that they reflect analyst bias rather than economic realities. The *sales growth* and *R&D* variables avoid this problem because they measure economic phenomena over which analysts have no control.

Our results show that GICS is again significantly better than the other three classification schemes in grouping firms based on these two measures. In the case of *sales growth,* mean industry growth rates under GICS explain, on average, 16.1% of the cross-sectional firm-level variation, whereas the nearest competing scheme (NAICS) explains only 13.2%. In the case of *R&D,* GICS industry means explain 64.2% of the firm-level variation, whereas the nearest competing scheme (FF) explains only 52.7%.

Further analysis shows that the GICS advantage has little to do with differences in the size and number of industry categories used by the four schemes. The four classification schemes do not divide firms into the same number of industry categories. For example, two-digit SIC codes result in 54 functional categories, NAICS results in 56 categories, GICS results in 51 categories, and FF results in 40 categories.[6] To ensure our results are not due to these differences, we conduct Monte Carlo simulations that neutralize the advantage a scheme derives from having a greater number of industry categories. These tests have little effect on our findings.

Finally, we show that the GICS advantage is most pronounced among the largest firms. For firms in the S&P 500 index, we find that GICS industry means dominate the industry means from the other three methods in terms

[6] We define a functional category as one that contains five or more member firms.

of their ability to explain firm-level returns and valuation multiples in each of our sample years. The GICS margin of victory, although still significant, is lower for mid-cap (S&P MidCap 400) and small-cap (S&P SmallCap 600) stocks.

In sum, we find that in most research applications encountered by financial academics, the GICS classification system provides a better technique for identifying industrial peers. Given the increased availability of GICS information at relatively low cost and its wide acceptance by financial practitioners, we believe our findings provide a strong case for its wider adoption by academic researchers in projects that involve industry classifications.

The next section discusses prior related research. Section 3 provides background information on each of the four competing classification algorithms. Section 4 describes our research method and sample. Section 5 presents the empirical results, and section 6 concludes.

2. *Related Research*

Despite the widespread use of industry classification schemes by academic researchers, few studies directly test their efficacy. Two studies that address this issue focus on differences in the SIC codes reported by Compustat and the Center for Research in Security Prices (CRSP) database. This problem arises because although the SIC categories are established by the Federal Census Bureau, the responsibility for assigning the primary industry code to a specific firm falls to the data vendor. Frequently, this assignment is not made on a consistent basis across data vendors.

For example, Guenther and Rosman [1994] compare the SIC codes across Compustat and CRSP and find that the primary two-digit SIC code from these two sources disagreed, on average, 38% of the time. Moreover, they show that Compustat SIC codes yield higher intraindustry correlations in stock returns, and lower intraindustry variances in financial ratios. Kahle and Walkling [1996] confirm the Guenther and Rosman results and further show that Compustat-matched samples are more likely to detect abnormal performance than CRSP-matched samples. Perhaps because of these findings, most recent papers that feature SIC codes obtain them from Compustat rather than from CRSP. We also use Compustat SIC codes.

Two other studies from the industrial organization literature highlight the shortcomings of SIC codes in producing homogeneous industries. Clarke [1989] examines whether firms in the same SIC category exhibit more similar sales changes, profit rates, or stock price changes. He concludes that SIC codes are not successful at identifying firms with such similar characteristic variables. Fan and Lang [2000] use commodity flow data from input-output (IO) tables to construct alternative measures of economic relatedness. They show that, at the industry level, the two IO-based measures they construct provide a richer description of firms' relatedness than traditional SIC-based measures. However, their technique involves data that are not widely available and is more suited to interindustry analysis than the firm-level applications common in capital market research.

Although the issue of industry classification is not his main focus, Ramnath [2001] discusses an analyst-based definition of industry groups. Specifically, in section 4.1 of that study, he defines an industry as a group of firms having at least five analysts in common with every other firm in the group. For example, if firms A, B, C, and Z all have at least five analysts who also follow each of the other firms, then A, B, C, and Z are deemed to be in the same industry. He finds that industrial delineations defined in this fashion differ sharply from those based on SIC codes. Although this approach to industry partitioning has appeal for financial analysis, it is applicable only to firms with five or more analysts and will leave many firms unclassified. Finally, Krishnan and Press [2003] investigate the implications of the NAICS for accounting research. Using the Guenther and Rosman [1994] methodology, they show that NAICS offers some improvement over the SIC system in defining manufacturing, transportation, and service industries.

In sum, most prior studies document problems with the SIC system without nominating a decidedly superior alternative, and none examines the efficacy of general industry classification schemes beyond SIC and NAICS.

3. Background Information

In this section we provide information on the historical development, intent, and basic philosophy behind each of the four competing classification algorithms. See Appendix A for a summary of background information on the four classification schemes.

3.1 SIC CODES

The oldest of the four, the SIC system, was established in the 1930s by the Interdepartmental Committee on Industrial Classification operating under the jurisdiction of the Central Statistical Board. The goal of this committee was "to develop a plan of classification of various types of statistical data by industries and to promote the general adoption of such classification as the standard classification of the Federal Government" (Pearce [1957], as quoted by OMB [1998, p. 11]). True to this mandate, SIC has become the primary algorithm for delineating industrial activities in the United States and is widely used not only by governmental agencies but also by marketers and financial economists. This system has been periodically revised to reflect the economy's changing industrial composition and organization, but recent revisions have been deferred in anticipation of the NAICS. The last revision of the SIC was in 1987.

3.2 NAICS CODES

In response to rapid changes in both the U.S. and world economies, governmental statistical agencies in Canada, Mexico, and the United States undertook the joint development of a uniform classification system. In 1999, the three countries announced the introduction of the NAICS. The aim of NAICS is to improve the SIC "by using a production-based framework throughout to eliminate definitional differences; identifying new industries and reorganizing industry groups to better reflect the dynamics of our economy; and allowing first-ever industry comparability across North America" (Saunders [1999, p. 37]).[7]

Eventually, the NAICS is expected to replace SIC codes in the reporting of all governmental statistics. However, during the current transition period, data vendors generally carry both codes in their databases. For example, beginning February 2000, NAICS codes have been available in the master files of the Compustat database for firms in both the current and research files. For firms in the research file, Compustat reports the NAICS code that is applicable before delisting. Because NAICS categories have been available only since 1997, the assignments are made on a retroactive basis for firms that were in existence before 1997.

SIC and NAICS share many commonalities. Both emanate from similar sources (i.e., governmental agencies interested in collecting broad industrial statistics) and have a common hierarchical lineage (i.e., they are "erected on a production-oriented or supply-based conceptual framework in that establishments are grouped into industries according to similarity in the process used to produce goods or services").[8] Neither system is designed with the specific concerns of the finance community in mind. Therefore, it is perhaps not surprising that their performances are fairly similar in most financial applications.

3.3 FF INDUSTRY CLASSIFICATIONS

In contrast, the FF industry classifications were developed by financial academics. In their study of industrial costs of capital, Fama and French [1997] devise an algorithm that reclassifies existing SIC codes into 48 industry groupings (see Fama and French [1997, Appendix] for a concordance of these industries and their corresponding SIC codes). Their aim is to address some of the more glaring problems with the SIC codes by forming industry groups that are more likely to share common risk characteristics. Although these industry groupings are used by other researchers (e.g., Gebhardt, Lee, and Swaminathan [2001], Lee, Myers, and Swaminathan [1999]), their efficacy has never been directly tested.

3.4 GICS CODES

The GICS structure was also developed with the financial community in mind. This system is the result of collaboration between MSCI and S&P.

[7] This is as quoted by Krishnan and Press [2002], who also provide an excellent summary of the differences between SIC and NAICS groupings.

[8] See OMB [1998, p. 11].

As leading providers of stock indexes and benchmark-related products and services, both companies have an interest in serving the needs of financial professionals. In fact, the GICS guide book describes the system as a product that "aim[s] to enhance the investment research and asset management process for financial professionals worldwide."[9]

According to the GICS guide book, companies are classified on the basis of their principal business activity. In making these assignments, S&P and MSCI analysts are guided by information from annual reports and financial statements, as well as investment research reports and other industry information. Specifically, a company's sources of revenue and earnings play important roles, as does market perception as revealed by investment research reports. This approach represents a sharp departure from the SIC and NAICS codes, which rely on a production-oriented, supply-based approach in delineating industry categories.

The GICS guide book offers further guidelines for companies that do not fall neatly into a single category. A company significantly diversified across three or more sectors, none of which contributes the majority of revenues or earnings, is classified under either the Industrial Conglomerates subindustry (Industrial Sector) or the Multi-Sector Holdings subindustry (Financial Sector). When a company is engaged in two or more substantially different business activities, none of which contributes 60% or more of revenues, it is classified in the subindustry that provides the majority of the company's revenues and earnings. When no subindustry provides the majority of the company's revenues and earnings, the classification is determined by more extensive analysis.

3.5 AVAILABILITY OF GICS CODES

Although widespread availability of GICS information is a recent phenomenon, the algorithm has deep historical roots. The current GICS system is a refinement of the S&P industry classification system, which has been in existence for more than 30 years. S&P introduced GICS in an August 1999 press release and officially switched its flagship index products to GICS in January 2001. Going forward, GICS is expected to be the *de facto* standard in the company's domestic as well as foreign products.

S&P supplies GICS information in two forms. The first, *current gics* (mnemonic: *spgicx*) is the most recent GICS code for a given firm. For inactive firms, this variable represents the GICS applicable for the firm immediately before delisting. The second, *historical gics* (mnemonic: *spgicm*) is a monthly history of GICS. In theory, historical GICS (*spgicm*) provides the most accurate measure of the company's industry grouping as of a given historical date. Therefore, our tests are based on historical GICS codes. Occasionally, a firm's historical GICS, NAICS, or SIC code was not

[9] See S&P and MSCI [2002, p. 3].

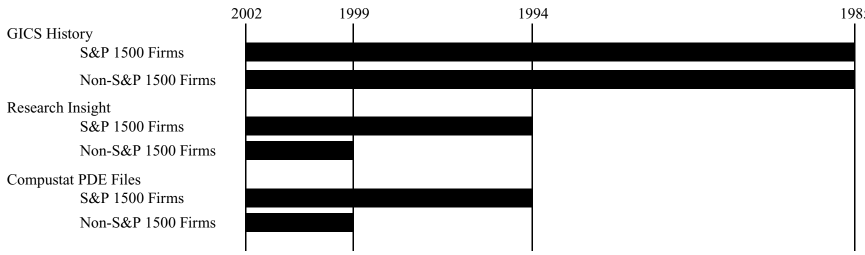

FIG. 1.—Availability of historical Global Industry Classifications Standard (GICS) codes in various Standard & Poor's data products. GICS information is provided in two forms. The first, *current gics* (mnemonic: *spgicx*) is the most recent GICS code for a given firm. For inactive firms, this variable represents the GICS applicable for the firm immediately prior to delisting. The second, *historical gics* (mnemonic: *spgicm*) is a monthly history of GICS codes for a given firm. Current GICS data (*spgicx*) are broadly available for firms in the Compustat universe, but historical GICS codes (*spgicm*) are available on a more limited basis. This figure depicts data availability for historical GICS codes (*spgicm*) in the three commercial products currently available from Standard & Poor's. GICS History is a new product that contains comprehensive GICS information on more than 20,000 active and inactive U.S. companies, Canadian companies, and American Depository Receipts. At present, GICS History must be purchased separately. Historical GICS codes are also available on a more limited basis in the Research Insight and Compustat's PDE (Price, Dividend, and Earnings) files. For firms in the S&P 1500 Super Composite Index (i.e., the S&P 500, the Midcap 400, and the Smallcap 600), historical GICS data are available from 1994. For non-S&P 1500 firms, historical GICS data are only available from 1999.

available for a given year. In these instances, we substituted the current industry classification.[10]

Beginning in 2002, researchers have been able to obtain GICS codes for U.S. firms in three S&P products: GICS History, Research Insight, and Compustat PDE (price, earnings, and dividends) files. Figure 1 summarizes the availability of historical GICS codes (*spgicm*) in each product. GICS History has the most comprehensive historical coverage, going back to 1985 and embracing more than 20,000 active and inactive firms. However, this product became available only in 2003 and at present it must be purchased separately.

For this study, we use GICS codes from Research Insight, a PC-based product developed by S&P. The February 29, 2002, release of Research Insight that we use contains historical GICS for all members of the S&P Super Composite 1500 back to 1994. As of January 2002, S&P also began providing GICS codes in its Compustat PDE files. We use Research Insight because of data problems encountered with the GICS information contained in the current Compustat release. Some of these problems had not yet been corrected as

[10] In practice, industry classifications for a given firm rarely change from year to year. Our analysis of S&P 1500 firms from 1994 to 2001 indicates that, on average, 2.8% of these firms had a change in their GICS code assignment each year. This percentage is slightly higher for SIC and NAICS (3.4% and 3.5%, respectively). Our results are not significantly different if we delete observations with missing *spgicm* rather than substituting the current industry classification. Our results are also unaffected if we replace missing historical codes with the nearest adjacent historical code (from subsequent or prior years) rather than the current code.

of this writing.[11] We expect that in the near future, researchers will be able to use GICS codes obtained directly from Compustat.

4. *Data and Sample Description*

In conducting our analyses, we focus primarily on S&P 1500 firms. We draw our information on GICS, SIC, and NAICS, from S&P Research Insight (the February 29, 2002, release), using S&P 500 (large-cap), 400 (mid-cap), and 600 (small-cap) membership lists as of the end of December of the prior year. Our decision to focus on S&P 1500 firms is driven largely by data availability. As indicated in figure 1, historical GICS information on Research Insight is available for S&P 1500 firms starting in 1994, but coverage for non-S&P 1500 firms did not begin until 1999. Our main analyses are based on a sample consisting of both active and inactive firms. The exclusion of the inactive firms does not significantly change our results.

We use two-digit SIC codes as our primary definition of industry because these groupings appear extensively in prior research. Conveniently, the FF [Fama and French, 1997] classification scheme produces a similar number of industry groupings as two-digit SIC codes. To ensure that the number of partitions using GICS and NAICS are also comparable, we use the first three digits of the NAICS code and the first six digits of the GICS code.

Table 1, panel A provides a breakdown of SIC, NAICS, FF, and GICS categories at various levels. Although the official number of categories for SIC and NAICS (especially at the four- and five-digit levels) is large, many of these categories are not used by data vendors that make firm-level assignments. Moreover, a large number of these industries have fewer than five member firms. To ensure that the industry groupings are meaningful, we define an industry category as functional if it encompasses at least five member firms in any given year. Industries with fewer than five firms are excluded from our analyses. Panel A shows that, for our purposes, SIC has 54 functional categories, NAICS has 56, FF has 40, and GICS has 51.

Panel B of table 1 provides statistics on the number of firms per industry, according to the preceding definitions. These results show that GICS codes distribute firms more evenly across its industry categories. The median number of firms per GICS industry category is 21, with a mean of 26 firms per industry. The maximum number of firms in an industry based on GICS is 87, as compared with 137, 173, and 140 based on SIC, NAICS, and FF, respectively. NAICS results in the most skewed distribution (a median of 9 firms, with a mean of 20 firms per industry). Classification schemes that produce a more uniform distribution of firms across categories are not necessarily better because the firms within each industry grouping are not

[11] Specifically, we found significant errors in the historical *gics* data (mnenmonic: *spgicm*) in Compustat's research file, which contains all inactive stocks. We confirmed these problems with S&P, which plans to release a corrected version soon.

TABLE 1

Univariate Statistics for SIC, NAICS, Fama French, and GICS

This table reports univariate statistics for each classification level for SIC (Standard Industrial Classification), NAICS (North American Industry Classification System), FF (Fama French), and GICS (Global Industry Classification Standard), using S&P 1500 firms as of December 2001. Fama French refers to the industry classification system they develop in their paper "Industry Costs of Equity" (1997). Panel A reports the number of classification levels, the official number of categories, and the functional number of categories for each classification level for each level of classification. A category is defined as functional if it has at least five members. Although some research uses the first digit as the broadest level, SIC codes are officially broken into 11 major divisions, labeled A through K. The sixth digit of the NAICS code is an additional level of detail specific to each country. For comparison purposes, the categories in the fifth and sixth digit levels are combined in this table, consistent with the 1997 NAICS manual. The level of industry we use for our analysis is boldface. Panel B reports univariate statistics for each of the preceding classification systems, using S&P 1500 firms as of December 2001, for the corresponding boldface level from panel A.

Panel A: Official and functional categories (using S&P 1500 firms as of December 31, 2001)

		Title	Official Categories	Digits	Functional Categories
SIC	Level 1 (broadest)	Division	11	first digit	9
	Level 2	**Major Group**	**81**	**first 2 digits**	**54**
	Level 3	Industry Group	416	first 3 digits	87
	Level 4 (narrowest)	Industry (b)	1004	all 4 digits	98
NAICS	Level 1 (broadest)	Sector	20	first 2 digits	17
	Level 2	**Subsector**	**96**	**first 3 digits**	**56**
	Level 3	Industry Group	311	first 4 digits	89
	Level 4 (narrowest)	Industry	1170	first 5 digits	75
FF	**Level 1 (broadest)**	–	**48**	–	**40**
GICS	Level 1 (broadest)	Sector	10	first 2 digits	10
	Level 2	Industry Group	23	first 4 digits	23
	Level 3	**Industry**	**59**	**first 6 digits**	**51**
	Level 4 (narrowest)	Sub-industry	123	all 8 digits	89

Panel B: Univariate statistics of number of firms per industry

	SIC (2 digit)	NAICS (3 digit)	FF	GICS (6 digit)
Minimum number of firms per industry	1	1	1	2
Maximum number of firms per industry	137	173	140	87
Median number of firms per industry	12	9	24	21
Mean number of firms per industry	24	20	31	26
Standard deviation	31	29	32	21
Skewness	2.2	3.1	1.6	1.0
Kurtosis	4.3	11.5	2.5	0.5

necessarily more homogenous.[12] However, *ceteris paribus,* more uniform distributions offer a statistical advantage when researchers use industry groups to identify control firms.

[12] For example, in underdeveloped countries where firms are concentrated in a few industries, an accurate classification scheme should produce a highly skewed distribution of firms across industry categories.

We obtain returns, share prices, and shares outstanding information from the 2001 CRSP monthly database. Share prices and shares outstanding are as of the last trading day of December of each year. Financial statement information is from the 2000 merged (active and research) Compustat database. For each sample year, we use the most recent median IBES consensus analyst long-term growth forecasts as of December. To evaluate the efficacy of various classification schemes, we also compute several market multiples and financial ratios. The measures used and their definitions are provided in Appendix B.

In carrying out our analyses (other than the returns regressions), we need to impose additional data-availability requirements. Specifically, we drop all firms with missing total assets (Compustat annual data item #6), total long term debt (D9), net income before extraordinary items (D18), debt in current liabilities (D34), and operating income after depreciation (D178). To reduce the effect of outliers, we also require that the share price on the last day of December be more than \$3, net sales (D12) be more than \$100 million, and both total common equity and total shareholders' equity (D60 and D216) be positive.

In addition to these general requirements, we also impose certain restrictions for specific regressions. For regressions involving *pe* multiples, we impose a constraint of positive net income before extraordinary items (D18), and in regressions involving *rnoa*, we require nonmissing values for current assets (D4), current liabilities (D5), and property, plant, and equipment (D8). Finally, to reduce further the influence of outliers, we delete the top and bottom 1% of observations, sorted by the variable of interest. These restrictions, coupled with the need to match CUSIP with PERMNO to obtain share trading information, result in fewer than 1,500 annual observations per year. The actual observations used in various tests vary depending on data availability.

5. *Empirical Results*

Table 2 provides a concordance between SIC and the other classification codes. For each two-digit SIC code, we report the number of firms within that category as of December 2001 (e.g., for SIC industry 20, we have 38 firms in the S&P 1500). We then show the corresponding NAICS, FF, and GICS industry that contains the highest number of those firms (i.e., the primary equivalent).

In some cases, we find a perfect match (e.g., SIC industry 17 has 3 firms, and all 3 firms are found within NAICS industry 235 and within FF industry "Construction"). In other cases, the match is poor (e.g., SIC industry 50 has 30 firms, only 5 of which are found in GICS industry 452030, which is the *largest* number of those 30 firms found in any single GICS industry). The bottom row of this table, labeled "Sum," shows that for a given S&P 1500 firm, if you select a NAICS classification based only on that firm's SIC industry, you will (on average) be correct 80% of the time. If you select an FF industry based on that firm's SIC industry, you will be correct 84% of the

TABLE 2

Bridging Between SIC and NAICS, Fama French, and GICS

This table reports the degree of correspondence between SIC, Fama French (FF), NAICS, and GICS for the December 2001 S&P 1500 firms by showing the level of agreement between SIC and the other three classifications. Fama French refers to the industry classification system they develop in their paper "Industry Costs of Equity" (1997). See their Appendix A for a description and definition of their industry names. We show the primary equivalent (i.e., the other system's category that has the highest level of correspondence) measured by the total number of firms for each two digit-SIC code. Only industry classifications that actually have member firms are considered. For example, the S&P 1500 has 38 firms in SIC industry 20 (Food and Kindred Products). The NAICS classification system classifies 30 of these firms in subsector 311 (Food Manufacturing) for a 79% correspondence. The FF classification system classifies 29 of these firms in their category of "Food" for a 76% correspondence. Finally, the GICS classification system classifies 25 of these firms in industry 302020 (Food Products) for a 66% correspondence. For brevity, only the category with the highest level of correspondence is shown. Note that the FF correspondence is slightly misleading because there is an explicit mapping from SIC into FF using all four SIC digits. However, for comparative purposes, we use only two-digit SIC here.

		NAICS (3 digit)			Fama French			GICS (6 digit)		
Two-Digit SIC Group	Total Firms	Primary Equivalent	Firms	Proportion of Total	Primary Equivalent	Firms	Proportion of Total	Primary Equivalent	Firms	Proportion of Total
01	2	111	2	100%	Agric	2	100%	302020	2	100%
10	6	212	6	100%	Gold	3	50%	151040	6	100%
12	2	212	2	100%	Coal	2	100%	151040	2	100%
13	43	211	26	60%	Enrgy	43	100%	101020	26	67%
14	3	212	3	100%	Mines	3	100%	151020	2	100%
15	10	233	10	100%	Cnstr	10	100%	252010	10	100%
16	6	234	6	100%	Cnstr	6	100%	201030	6	100%
17	3	235	3	100%	Cnstr	3	100%	201030	2	67%
20	38	311	30	79%	Food	29	76%	302020	25	66%
21	3	312	3	100%	Smoke	3	100%	302030	3	100%
22	5	313	2	40%	Txtls	5	100%	252010	2	40%
23	13	315	13	100%	Clths	13	100%	252030	11	85%
24	10	321	8	80%	BldMt	10	100%	151050	5	50%
25	11	337	8	73%	Hshld	6	55%	252010	5	45%
26	24	322	22	92%	Paper	21	88%	151050	10	42%

TABLE 2— *Continued*

		NAICS (3 digit)			Fama French			GICS (6 digit)		
Two-Digit SIC Group	Total Firms	Primary Equivalent	Firms	Proportion of Total	Primary Equivalent	Firms	Proportion of Total	Primary Equivalent	Firms	Proportion of Total
27	28	511	17	61%	Books	20	71%	254010	16	57%
28	98	325	98	100%	Drugs	51	52%	151010	36	37%
29	14	324	14	100%	Enrgy	13	93%	101020	12	86%
30	10	326	8	80%	Not Classified	4	40%	251010	3	30%
31	6	316	6	100%	Clths	6	100%	252030	6	100%
32	5	327	5	100%	BldMt	2	40%	151020	2	40%
33	32	331	28	88%	Steel	32	100%	151040	19	59%
34	26	332	25	96%	BldMt	17	65%	201060	8	31%
35	91	333	58	64%	Mach	59	65%	201060	29	32%
36	128	334	102	80%	Chips	100	78%	452050	44	34%
37	40	336	40	100%	Autos	24	60%	201010	12	30%
38	73	334	41	56%	LabEq	33	45%	351010	35	48%
39	12	339	12	100%	Toys	7	58%	252020	6	50%
40	5	482	5	100%	Trans	5	100%	203040	5	100%
42	9	484	9	100%	Trans	9	100%	203040	9	100%
44	6	483	5	83%	Trans	6	100%	203030	3	50%
45	15	481	12	80%	Trans	15	100%	203020	10	67%
47	5	488	5	100%	Trans	5	100%	203010	3	60%
48	27	513	27	100%	Telcm	27	100%	501010	12	44%
49	99	221	86	87%	Util	99	100%	551010	54	55%
50	30	421	29	97%	Whlsl	30	100%	452030	5	17%
51	21	422	21	100%	Whlsl	21	100%	351020	6	29%
52	5	444	4	80%	Rtail	5	100%	255040	4	80%
53	19	452	19	100%	Rtail	19	100%	255030	19	100%
54	7	445	7	100%	Rtail	7	100%	301010	7	100%

55	6	441	5	83%	Rtail	6	100%	255040	5	83%
56	25	448	25	100%	Rtail	25	100%	255040	22	88%
57	9	442	5	56%	Rtail	9	100%	255040	9	100%
58	24	722	24	100%	Meals	24	100%	253010	24	100%
59	22	451	6	27%	Rtail	22	100%	255040	11	50%
60	92	522	92	100%	Banks	92	100%	401010	87	95%
61	13	522	13	100%	Banks	13	100%	402010	11	85%
62	21	523	21	100%	Fin	21	100%	402010	19	90%
63	61	524	60	98%	Insur	61	100%	403010	47	77%
64	9	524	9	100%	Insur	9	100%	403010	4	44%
67	15	533	8	53%	Fin	15	100%	253010	2	13%
70	6	721	6	100%	Meals	6	100%	253010	6	100%
72	5	812	3	60%	PerSrv	5	100%	202010	4	80%
73	140	511	55	39%	BusSv	123	88%	451030	59	42%
75	2	532	1	50%	BusSv	1	50%	203040	1	50%
78	1	512	1	100%	Fun	1	100%	254010	1	100%
79	10	713	4	40%	Fun	10	100%	253010	9	90%
80	22	621	13	59%	Hlth	22	100%	351020	20	91%
82	6	611	6	100%	PerSrv	6	100%	202010	6	100%
87	15	541	13	87%	BusSv	15	100%	202010	7	47%
99	6	999	6	100%	Misc	6	100%	201050	6	100%
Sum	1,500		1203	80%		1267	84%		842	56%

time.[13] But if you select the firm's GICS industry based on that firm's SIC industry, you will be correct only 56% of the time.

5.1 CORRELATION IN MONTHLY RETURNS

Next, we form equal-weighted industry portfolios using each classification scheme and compare the ability of these industry portfolios to explain contemporaneous monthly firm-level stock returns. The result of this analysis is shown in table 3. Panel A provides year-by-year results of monthly return regressions using the industry mean from each of the four industry specifications. We find that industry definitions based on SIC and FF result in adjusted R^2s that are similar to each other (22.9% and 22.6%, respectively). NAICS performs better, yielding an average adjusted R^2 of 24.2%. But the best result is achieved using GICS industries (average adjusted R^2 of 26.3%).

Panel B shows that GICS explains more firm-level returns than SIC and FF in all eight years. It does better than NAICS in seven of the eight years studied. On average, GICS outperforms SIC, NAICS, and FF by 3.4%, 2.1%, and 3.7%, respectively, which are significant at the 5% level or better. Furthermore, the gap between GICS and the others is widening over time, with the best results occurring in the last three years. For example, GICS outperformed SIC, NAICS, and FF by 1.7%, 0.5%, and 1.9%, respectively, in 1994, and by 7.8%, 6.1%, and 6.7%, respectively, in 2000.

Figure 2 plots the average yearly adjusted R^2 for each classification scheme for both S&P 500 and S&P 1500 firms. As discussed earlier, GICS outperforms the other classification schemes, with the separation getting larger in recent years.[14] The results also suggest that the performance of GICS becomes stronger when the analysis is restricted to S&P 500 firms.

5.2 VALUATION MULTIPLES AND FINANCIAL RATIOS

Although return association is a telling metric of economic relatedness, other measures are also important. Table 4 reports results for various other measures. With only one exception (leverage), GICS provides a higher average R^2 than competing classifications. In most cases the difference is statistically significant. For example, panel B provides evidence on valuation multiples. We find that variations in *pe* multiples are the most difficult to explain using industry membership, and variations in *evs* multiples are the easiest. More important, GICS outperforms the other systems across all three multiples (*pb, evs,* and *pe*). Improvements in explaining *pb* range from 4.2% to 5.1%, whereas improvements for *evs* range from 3.8% to 5.9%. These represent proportional increases of 10% to 30%. Improvements relating to the *pe* multiple are about 1% (vs. SIC and NAICS) and 2.3% (vs. FF), representing proportional improvements of, once again, 8% and 18%.

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[13] FF industries are a reclassification of four-digit SIC codes. Therefore, using all four SIC digits would result in a 100% correspondence between FF and SIC.

[14] This trend is evident only for stock return comovements and is not significant for most of the other variables.

TABLE 3

Comparison of Adjusted R^2 Among SIC, NAICS, Fama French, and GICS for Returns

$$R_{i,t} = \alpha_t + \beta R_{ind,t} + \varepsilon_{i,t}$$

This table reports the firm-months and adjusted R^2 for the above monthly OLS regression. The dependent variable, R, is the monthly return for firm i within industry ind at month t, from the CRSP monthly database. The independent variable, R_{ind}, is the monthly average return for all firms in that industry classification. Industries are defined by either the first two digits of the firm's SIC code, the first three digits of the firm's NAICS code, the firm's Fama French classification (FF), or the first 6 digits of the firm's GICS code. Each industry included in these regressions must have at least five members. Because classifications differ among SIC, FF, NAICS, and GICS, there will be differences in the number of firm-months reported for each regression. We use all firms from the S&P index as at December for each year (from Research Insight) for which we are able to find a PERMNO from CRSP by matching based on CUSIP.

Panel A: Adjusted R^2 for all S&P 1500 firms

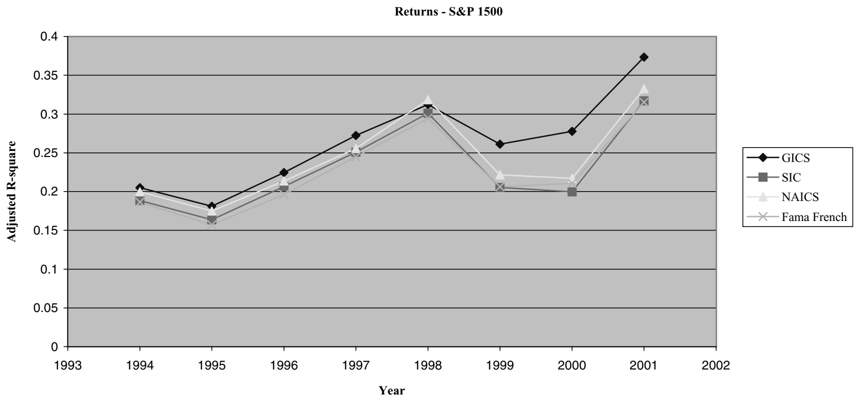
	SIC		NAICS		Fama French		GICS	
Year	Firm-Months	Adj R^2	Firm-Months	Adj R^2	Firm-Months	Adj R^2	Firm-Months	Adj R^2
1994	17,119	18.8%	17,002	20.0%	17,191	18.6%	17,191	20.5%
1995	17,091	16.4%	17,084	17.5%	17,132	15.7%	17,276	18.1%
1996	17,066	20.7%	16,838	21.4%	17,126	19.6%	17,222	22.5%
1997	17,204	25.1%	16,976	25.5%	17,307	24.5%	17,379	27.2%
1998	17,370	30.1%	16,994	31.9%	17,294	29.5%	17,462	31.2%
1999	17,185	20.5%	17,143	22.2%	17,303	20.6%	17,347	26.1%
2000	17,303	20.0%	17,075	21.7%	17,339	21.1%	17,323	27.8%
2001	17,471	31.7%	17,123	33.3%	17,351	31.5%	17,399	37.4%
Average		22.9%		24.2%		22.6%		26.3%

Panel B: Difference between other classification and GICS

Year	GICS vs. SIC	GICS vs. NAICS	GICS vs. FF
1994	1.7%	0.5%	1.9%
1995	1.7%	0.6%	2.4%
1996	1.8%	1.1%	2.9%
1997	2.1%	1.7%	2.7%
1998	1.1%	−0.7%	1.7%
1999	5.6%	3.9%	5.5%
2000	7.8%	6.1%	6.7%
2001	5.7%	4.1%	5.9%
Average	3.4%***	2.1%**	3.7%***

***Significant at the 1% level (two-tailed t-test).
**Significant at the 5% level (two-tailed t-test).

Panels C and D provide evidence on the effect of the classification schemes on financial ratios and other financial information, including realized sales growth, analyst forecasts, and R&D. The strongest results are for R&D, where GICS beats its closest competitor (FF) by an average margin of 11.5% (proportionately, an increase of 21.8%). Overall, the closest competitor to GICS is probably NAICS. GICS performs better than NAICS in most categories, but the difference is not statistically significant for *pe, rnoa, roe,* and *pm.*



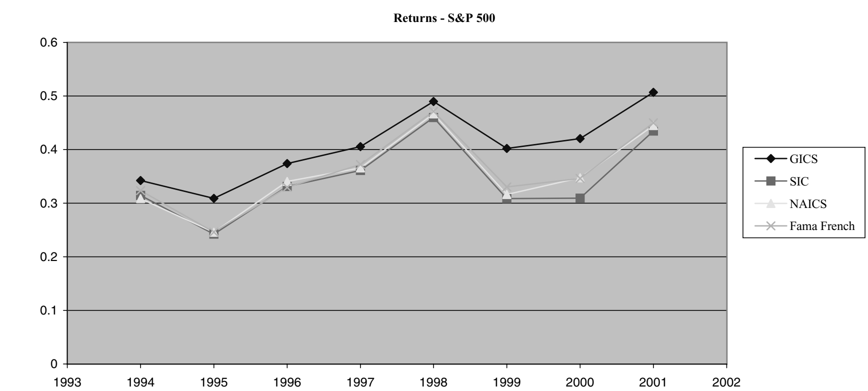


FIG. 2.—Comparison of adjusted R_2 of returns regressions for S&P 1500 and S&P 500 firms by year:

$$R_{i,t} = \alpha_t + \beta R_{ind,t} + \varepsilon_{i,t}.$$

This figure reports the average annual adjusted R_2 for the above monthly OLS regression, in which industry membership is defined using four classification schemes. A separate regression is performed for each year in our sample (1994 to 2001). The dependent variable, R, is the monthly return for firm i within industry ind at month t, from the CRSP monthly database. The independent variable, R_{ind}, is the monthly average return for all firms in that industry classification. Industries are defined by either the first two digits of the firm's SIC code (SIC), the first three digits of the firm's NAICS code (NAICS), the firm's Fama-French classification (Fama French), or the first six digits of the firm's GICS code (GICS). Each industry included in these regressions must have at least five members. We use all firms from the S&P 1500 and S&P 500 indices as at December for each year (from Research Insight) for which we are able to find a PERMNO from CRSP by matching based on CUSIP.

The only metric on which GICS underperforms the other schemes is leverage: we find significant variation in leverage across firms within the same GICS group. SIC and NAICS classifications result in more homogeneity, perhaps because they are production-based classification systems, and leverage is associated with production technology, with capital-intensive industries having higher leverage. In research settings in which capital structure is

TABLE 4

Comparison of Adjusted R^2 for S&P 1500 Firms Among SIC, NAICS, Fama French, and GICS Industries for Returns, Financial Ratios, and Other Financial Information

$$vble_{i,t} = \alpha_1 + \beta vble_{ind,t} + \varepsilon_{i,t}$$

This table reports the average adjusted R^2 for S&P 1500 firms, from Research Insight for the above OLS regression. Returns are from CRSP's monthly database. Share prices and shares outstanding are drawn from CRSP as at December 31 of each year. Financial statement information is from Compustat, for the fiscal year ended in that year. Analyst long-term growth forecasts are the most recent December consensus forecast for that year, from IBES. The dependent variable, *vble* is one of the following: returns, price-to-book (*pb*, market cap divided by total common equity), enterprise value-to-sales (*evs*, the sum of market cap and long-term debt divided by net sales), price-to-earnings (*pe*, market cap divided by net income before extraordinary items), return on net operating assets (*rnoa*, net operating income after depreciation divided by the sum of property, plant, and equipment and current assets, less current liabilities), return on equity (*roe*, net income before extraordinary items divided by total common equity), asset turnover (*at*, total assets divided by net sales), profit margin (*pm*, net operating income after depreciation divided by net sales), leverage (*lev*, total liabilities divided by total stockholders' equity), long-term analyst growth forecast (*ltgrowth*), one-year-ahead realized sales growth (*sales growth*), and scaled research and development expense (*R&D* research and development expense divided by net sales) for firm i within industry ind at year t. The independent variable, $vble_{ind}$, is the yearly average for that variable for all firms in that industry classification. Industries are defined by either the first two digits of the firm's SIC code, the firm's Fama French classification (FF), the first three of the firm's NAICS code, or the first six digits of the firm's GICS code. Each industry included in these regressions must have at least five members. For each variable, the highest adjusted R^2 is boldface. We perform a two-tailed t-test on the difference between GICS and other classification based on the time series of differences from 1994 to 2000 (2001 for returns). Panel A shows our results for returns, panel B shows our results for valuation multiples, panel C shows our results for financial ratios, and panel D shows our results for other financial information.

		SIC	NAICS	Fama French	GICS
Panel A: Returns					
Returns	1994 to 2001	22.9%	24.2%	22.6%	**26.3%**
	GICS vs. Competitor	3.4%***	2.1%**	3.7***	
Panel B: Valuation multiples					
pb	1994 to 2000	18.2%	19.1%	18.8%	**23.3%**
	GICS vs. Competior	5.1%***	4.2%***	4.5%***	
evs	1994 to 2000	31.5%	32.7%	33.6%	**37.4%**
	GICS vs. Competitor	5.9%**	4.7%**	3.8%*	
pe	1994 to 2000	13.7%	14.1%	12.7%	**15.0%**
	GICS vs. Competitor	1.3%	0.9%	2.3%**	
Panel C: Financial statement ratios					
rnoa	1994 to 2000	18.3%	19.8%	20.0%	**20.9%**
	GICS vs. Competitor	2.6%**	1.1%	0.9%	
roe	1994 to 2000	9.7%	10.8%	8.6%	**11.4%**
	GICS vs. Competitor	1.7%**	0.6%	2.8%***	
at	1994 to 2000	86.2%	81.7%	82.9%	**87.2%**
	GICS vs. Competitor	1.0%***	5.5%***	4.3%***	
pm	1994 to 2000	40.9%	41.9%	40.5%	**42.7%**
	GICS vs. Competitor	1.8%	0.8%	2.2%**	
lev	1994 to 2000	19.6%	**21.3%**	17.9%	17.8%
	GICS vs. Competitor	−1.8%**	−3.5%***	−0.1%	

TABLE 4 — *Continued*

		SIC	NAICS	Fama French	GICS
Panel D: Other financial information					
ltgrowth	1994 to 2000	32.8%	33.7%	33.5%	**41.9%**
	GICS vs. Competitor	9.1%***	8.2%***	8.4%***	
sales growth	1994 to 2000	12.4%	13.2%	12.0%	**16.1%**
	GICS vs. Competitor	3.7**	2.9%**	4.1%***	
R&D	1994 to 2000	42.5%	51.9%	52.7%	**64.2%**
	GICS vs. Competitor	21.7%***	12.3%***	11.5%***	

***Significant at the 1% level.
**Significant at the 5% level.
*Significant at the 10% level.

important, we recommend the inclusion of leverage as an additional control variable.[15]

5.3 MONTE CARLO SIMULATIONS

Although we attempt to ensure that the numbers of industry groups are similar across the classification schemes, differences remain. Because we require at least five firms per industry, one possible concern is that one industry definition might have a mechanical advantage over others. For example, a classification system with fewer industry partitions has an inherent disadvantage when the total number of firms is held constant. If one scheme has 10 functional industries consisting of 6 member firms each, and another scheme has 3 functional industries consisting of 20 members each, we can expect the first scheme to achieve a higher R^2 than the second, even if the actual allocation of firms for both schemes was random.

To ensure our results are not due to these differences, we conduct Monte Carlo simulations that neutralize the advantage a scheme derives from having a greater number of industry categories. To conduct the simulation, we randomly assign S&P 1500 firms into the same number of industry categories, with the same number of firms per industry, as a given scheme. We then conduct the regression on the simulated data, generating a simulated R^2. We then repeat the procedure 500 times, producing an average simulated R^2 for each classification scheme. Each simulated R^2 serves as a performance benchmark for the scheme in question.

For example, panel A of table 5 shows that, for the returns regressions, random assignment into the 54 two-digit SIC industries results in an average simulated R^2 of 14.5%. In other words, even if SIC codes have no ability to partition firms into more homogeneous groups, we would still observe an average R^2 of 14.5% in this regression.[16] We also compute a revised R^2 (the difference

[15] More broadly, we view an industry-based control sample as a pragmatic solution to dealing with a host of firm characteristics not easily identified through other means. To the extent that specific identifiable firm attributes, such as leverage, can be further controlled for, we think they should be added by the researcher.

[16] The Monte Carlo R^2 can also be partially attributed to global (interindustry) commonalities.

between the actual R^2 achieved by the scheme and its average simulated R^2). In the case of the returns regression, the SIC classifications produce a revised R^2 of 8.4%, compared with 11.9% for the GICS classifications.

Table 5 indicates that mechanical differences among classification standards have little effect on our results. Although the simulated R^2s differ largely in the direction we expected, the revised R^2s show that GICS continues to outperform its competitors. In fact, the GICS advantage over SIC and NAICS generally widens after this adjustment. For example, in panel A, the GICS outperforms SIC, NAICS, and FF by 3.5%, 2.2%, and 3.8%, respectively. This indicates an improvement of about 0.1% compared with panel A in table 4.

Panels B, C, and D describe the simulation adjusted performance of GICS for valuation multiples, financial ratios, and other financial information. In these panels the simulated R^2s suggest that purely mechanical differences should cause GICS to perform about the same as SIC, outperform FF by approximately 0.8% (3.9%–3.1%), and underperform NAICS by about 0.5% (3.9%–4.4%). However, as seen from the revised R^2 numbers, GICS actually significantly outperforms both SIC and NAICS. In general, GICS also continues to outperform FF, with significance levels similar to table 4 (except for minor erosion in the statistical significance of a few results). Thus, in evaluating performance relating to market multiples and financial ratios, the results in table 5 are similar to those in table 4.

5.4 EFFECT OF FIRM SIZE

Finally, we study the effect of firm size on the performance of the industry classification schemes by examining S&P 500, 400 (mid-cap), and 600 (small-cap) firms separately. Panel A of table 6 shows that for the S&P 500, GICS is superior to the other classification systems in all dimensions evaluated. The results for the S&P 500 are much stronger than the results based on the S&P 1500 (see table 4).

The results using the S&P 400 (mid-cap) firms are weaker, with GICS outperforming in 10 of the 12 metrics used (see panel B). However, in those 10 metrics, GICS outperforms the others by a larger margin than when considering the entire 1500 firms. For example, when considering returns, GICS outperforms SIC, NAICS, and FF by 7.5%, 6.4%, and 6.6%, respectively, as compared with 3.4%, 2.1%, and 3.7%, respectively (table 4). The weakest results relate to the S&P 600 (small-cap) firms (see panel C). However, even among small firms, GICS outperforms the others in 8 of the 12 categories.[17]

[17] During our interviews with S&P personnel in charge of the GICS project, two possible explanations for these findings were suggested. One explanation is that smaller firms tend to have a single line of business, and SIC and NAICS tend to do a reasonable job of classifying these firms. Another explanation is that, because of the nature of indexing, GICS industry definitions were formulated primarily on the basis of the businesses in which larger firms operate. The smaller firms with unusual business lines have to be classified into the closest existing industry group, rendering a generally poorer fit.

TABLE 5

Monte Carlo Simulated Adjusted R^2

This table compares the average adjusted R^2 from the S&P 1500 fims from table 4 to simulated adjusted R^2's created by randomly allocating fims to industry classifications. We repeated each simulation 500 times and present the average adjusted R^2. The "Revised" column is created by subtracting the actual average R^2 from the average of the simulations. Returns are from CRSP's monthly database. Share prices and shares outstanding are drawn from CRSP as at December 31 of each year. Financial statement information is from Compustat for the fiscal year ended in that year. Analyst long-term growth forecasts are the most recent December consensus forecast for that year, from IBES. The dependent variable is one of the following: returns, price-to-book (*pb*, market cap divided by total common equity), enterprise value-to-sales (*evs*, the sum of market cap and long-term debt divided by net sales), price-to-earnings (*pe*, market cap divided by net income before extraordinary items), return on net operating assets (*rnoa*, net operating income after depreciation divided by the sum of property, plant, and equipment and current assets, less current liabilities), return on equity (*roe*, net income before extraordinary items divided by total common equity), asset turnover (*at*, total assets divided by net sales), profit margin (*pm*, net operating income after depreciation divided by net sales), leverage (*lev*, total liabilities divided by total stockholders' equity), long-term analyst growth forecast (*ltgrowth*), one-year-ahead realized sales growth (*sales growth*), and scaled research and development expense (*R&D*, research and development expense divided by net sales) for firm *i* within industry *ind* at year *t*. Panel A shows our results for returns, panel B shows our results for valuation multiples, panel C shows our results for financial ratios, and panel D shows our results for other financial information. Industries are defined by either the first two digits of the firm's SIC code, the firm's Fama French classification (FF), the first three digits of the firm's NAICS code, or the first six digits of the firm's GICS code. Each industry included in these regressions must have at least five members. We perform a two-tailed *t*-test on the adjusted difference between GICS and other classifications based on the time series of differences from 1994 to 2000 (2001 for returns). We treat the average simulated adjusted R^2 as a constant for these tests.

		Actual	Simulated	Revised	GICS vs. Competitor
Panel A: Returns					
Returns	SIC	22.9%	14.5%	8.4%	3.5%***
	NAICS	24.2%	14.5%	9.7%	2.2%**
	FF	22.6%	14.5%	8.1%	3.8%***
	GICS	26.3%	14.4%	11.9%	
Panel B: Valuation multiples					
pb	SIC	18.2%	3.9%	14.3%	5.1%***
	NAICS	19.1%	4.4%	14.7%	4.7%***
	FF	18.8%	3.1%	15.7%	3.7%***
	GICS	23.3%	3.9%	19.4%	
evs	SIC	31.5%	3.9%	27.6%	5.9%**
	NAICS	32.7%	4.4%	28.3%	5.2%**
	FF	33.6%	3.1%	30.5%	3.0%
	GICS	37.4%	3.9%	33.5%	
pe	SIC	13.7%	4.2%	9.5%	1.3%
	NAICS	14.1%	4.7%	9.4%	1.4%
	FF	12.7%	3.4%	9.3%	1.5%*
	GICS	15.0%	4.2%	10.8%	

TABLE 5 — *Continued*

		Actual	Simulated	Revised	GICS vs. Competitor
Panel C: Financial statement ratios					
moa	SIC	18.3%	4.3%	14.0%	2.5%**
	NAICS	19.8%	4.8%	15.0%	1.5%
	FF	20.0%	3.5%	16.5%	0.0%
	GICS	20.9%	4.4%	16.5%	
roe	SIC	9.7%	3.9%	5.8%	1.7*
	NAICS	10.8%	4.4%	6.4%	1.1%
	FF	8.6%	3.1%	5.5%	2.0%**
	GICS	11.4%	3.9%	7.5%	
at	SIC	86.2%	3.9%	82.3%	1.0%***
	NAICS	81.7%	4.4%	77.3%	6.0%***
	FF	82.9%	3.1%	79.8%	3.5%***
	GICS	87.2%	3.9%	83.3%	
pm	SIC	40.9%	3.9%	37.0%	1.8%
	NAICS	41.9%	4.4%	37.5%	1.3%
	FF	40.5%	3.1%	37.4%	1.4%
	GICS	42.7%	3.9%	38.8%	
lev	SIC	19.6%	3.9%	15.7%	−1.8%**
	NAICS	21.3%	4.4%	16.9%	−3.0%**
	FF	17.9%	3.1%	14.8%	−0.9%
	GICS	17.8%	3.9%	13.9%	
Panel D: Other financial information					
ltgrowth	SIC	32.8%	3.9%	28.9%	9.1%***
	NAICS	33.7%	4.4%	29.3%	8.7%***
	FF	33.5%	3.1%	30.4%	7.6%***
	GICS	41.9%	3.9%	38.0%	
sales growth	SIC	12.4%	4.0%	8.4%	3.7%**
	NAICS	13.2%	4.5%	8.7%	3.4%***
	FF	12.0%	3.2%	8.8%	3.3%***
	GICS	16.1%	4.0%	12.1%	
R&D	SIC	42.5%	5.8%	36.7%	21.1%***
	NAICS	51.9%	6.1%	45.8%	12.0%***
	FF	52.7%	5.2%	47.5%	10.3%***
	GICS	64.2%	6.4%	57.8%	

***Significant at the 1% level.
**Significant at the 5% level.
*Significant at the 10% level.

5.5 ANALYST PERCEPTION VERSUS ECONOMIC REALITY

Because analyst perceptions play a role in GICS classifications, one concern with our results is that it reflects analyst bias rather than economic realities. In other words, these results may be induced by the fact that GICS classifications and analyst perceptions are endogenous, thus rendering the findings less interpretable.

Although it is impossible to rule out this concern, we believe analyst perceptions are unlikely to explain our findings for two reasons. First, we conducted detailed interviews with top-ranking S&P personnel in charge of

TABLE 6

Comparison of Adjusted R^2 Among SIC, NAICS, Fama French, and GICS Industries for Returns, Financial Ratios, and Other Financial Information

$$vble_{i,t} = \alpha_t + \beta vble_{ind,t} + \varepsilon_{i,t}$$

This table reports the average adjusted R^2 for firms from 1994 to 2000 (2001 for returns) from Research Insight for the above OLS regression. Returns are from CRSP's monthly database. Share prices and shares outstanding are drawn from CRSP as of December 31 of each year. Financial statement information is from Compustat for the fiscal year ended in that year. Analyst long-term growth forecasts are the most recent December consensus forecast for that year, from IBES. The dependent variable, *vble*, is one of the following: returns, price-to-book (*pb*, market cap divided by total common equity), enterprise value-to-sales (*evs*, the sum of market cap and long-term debt divided by net sales), price-to-earnings (*pe*, market cap divided by net income before extraordinary items, for firms with positive net income only), return on net operating assets (*rnoa*, net operating income after depreciation divided by the sum of property, plant, and equipment and current as assets, less current liabilities), return on equity (*roe*, net income before extraordinary items divided by total common equity), asset turnover (*at*, total assets divided by net sales), profit margin (*pm*, net operating income after depreciation divided by net sales), leverage (*lev*, total liabilities divided by total stockholders' equity), long-term analyst growth forecast (*ltgrowth*), one-year-ahead realized sales growth (*sales growth*), and scaled research and development expense (*R&D*, research and development expense devided by net sales) for firm *i* within industry *ind* at year *t*. The indepedent variable, $vble_{ind}$, is the yearly average (monthly average for returns) for that variable for all firms in that industries classification. Industries are defined by either the first two digits of the firm's SIC code, the firm's Fama French classification (FF), the first three digits of the firm's NAICS code, or the first six digits of the firm's GICS code. Each industry included in these regressions must have at least five members. For each variable, the highest average adjusted R^2 is boldface. We perform a two-tailed t-test on the difference between GICS and other classifications based on the time series of differences. Panel A shows our results for S&P 500 firms, panel B shows our results for S&P 400 (midcap) firms, and panel C shows our results for S&P 600 (smallcap) firms.

		SIC	NAICS	Fama French	GICS
Panel A: S&P 500 firms					
Returns	1994 to 2001	34.5%	35.4%	35.9%	**40.6%**
	GICS vs. competitor	6.1%***	5.2%***	4.7%***	
pb	1994 to 2000	24.1%	27.9%	30.1%	**37.0%**
	GICS vs. competitor	12.9%***	9.1%***	6.9%***	
evs	1994 to 2000	31.5%	32.0%	40.6%	**44.6%**
	GICS vs. competitor	13.1%***	12.6%***	4.0%***	
pe	1994 to 2000	14.0%	15.2%	14.8%	**19.6%**
	GICS vs. competitor	5.6%***	4.4%**	4.8%**	
rnoa	1994 to 2000	30.2%	30.3%	34.5%	**36.4%**
	GICS vs. competitor	6.2%**	6.1%**	1.9%*	
roe	1994 to 2000	20.2%	22.2%	23.8%	**28.6%**
	GICS vs. competitor	8.4%***	6.4%***	4.8%***	
at	1994 to 2000	83.5%	80.5%	80.1%	**85.3%**
	GICS vs. competitor	1.8%***	4.8%***	5.2%***	
pm	1994 to 2000	45.3%	45.1%	48.8%	**56.8%**
	GICS vs. competitor	11.5%***	11.7%***	8.0%***	
lev	1994 to 2000	24.4%	27.7%	25.8%	**29.4%**
	GICS vs. competitor	5.0%***	1.7%	3.6%**	
ltgrowth	1994 to 2000	27.9%	32.8%	31.1%	**47.8%**
	GICS vs. competitor	19.9%***	15.0%***	16.7%***	
sales growth	1994 to 2000	17.4%	18.8%	17.8%	**23.1%**
	GICS vs. competitor	5.7%***	4.3%***	5.3%***	
R&D	1994 to 2000	37.0%	44.9%	60.3%	**72.5%**
	GICS vs. competitor	32.5%***	27.6%***	12.2%***	

TABLE 6 — *Continued*

		SIC	NAICS	Fama French	GICS
Panel B: S&P 400 firms (midcap)					
Returns	1994 to 2001	28.8%	29.9%	29.7%	**36.3%**
	GICS vs. competitor	7.5%***	6.4%***	6.6%***	
pb	1994 to 2000	21.8%	20.6%	23.0%	**29.6%**
	GICS vs. competitor	7.8%***	9.0%***	6.6%***	
evs	1994 to 2000	27.5%	24.9%	34.5%	**40.6%**
	GICS vs. competitor	13.1%	15.7%***	6.1%*	
pe	1994 to 2000	18.6%	15.8%	18.8%	**21.8%**
	GICS vs. competitor	3.2%	6.0%**	3.0%**	
moa	1994 to 2000	22.5%	**22.7%**	20.6%	21.0%
	GICS vs. competitor	−1.5%	−1.7%	0.4%	
roe	1994 to 2000	12.0%	9.8%	11.5%	**15.7%**
	GICS vs. competitor	3.7%**	5.9%***	4.2%**	
at	1994 to 2000	89.9%	87.6%	87.4%	**90.5%**
	GICS vs. competitor	0.6%	2.9%	3.1%**	
pm	1994 to 2000	43.9%	46.6%	42.7%	**48.9%**
	GICS vs. competitor	5.0%**	2.3%	6.2%**	
lev	1994 to 2000	19.7%	22.2%	**24.8%**	21.7%
	GICS vs. competitor	2.0%**	−0.5%	−3.1%**	
ltgrowth	1994 to 2000	43.4%	41.3%	47.9%	**51.8%**
	GICS vs. competitor	8.4%***	10.5%***	3.9%*	
sales growth	1994 to 2000	13.2%	12.8%	14.0%	**23.2%**
	GICS vs. competitor	10.0%***	10.3%***	8.2%**	
R&D	1994 to 2000	43.7%	54.3%	53.2%	**59.7%**
	GICS vs. competitor	16.0***	5.4%***	6.5%***	
Panel C: S&P 600 firms (smallcap)					
Returns	1994 to 2001	22.5%	23.8%	22.0%	**25.1%**
	GICS vs. competitor	2.6%**	1.3%	3.1%***	
pb	1994 to 2000	20.6%	20.6%	17.9%	**21.8%**
	GICS vs. competitor	1.2%	1.2%	3.9%**	
evs	1994 to 2000	38.0%	**41.6%**	36.9%	37.6%
	GICS vs. competitor	−0.4%	−4.0%**	0.7%	
pe	1994 to 2000	15.0%	15.1%	13.7%	**16.0%**
	GICS vs. competitor	1.0%	0.9%	2.3%**	
moa	1994 to 2000	12.8%	13.5%	15.1%	**18.1%**
	GICS vs. competitor	5.3%**	4.6%**	3.0%**	
roe	1994 to 2000	9.8%	11.2%	9.3%	**15.2%**
	GICS vs. competitor	5.4%**	4.0%*	5.9%**	
at	1994 to 2000	**89.9%**	82.9%	87.2%	89.7%
	GICS vs. competitor	−0.2%	6.8%***	2.5%***	
pm	1994 to 2000	41.8%	**42.7%**	41.6%	**42.7%**
	GICS vs. competitor	0.9%	0.0%	1.1%	
lev	1994 to 2000	22.4%	**24.5%**	19.5%	20.5%
	GICS vs. competitor	−1.9%	−4.0%**	1.0%	
Itgrowth	1994 to 2000	36.4%	38.5%	36.9%	**40.4%**
	GICS vs. competitor	4.0%***	1.9%	3.5%***	
sales growth	1994 to 2000	14.3%	15.4%	14.1%	**19.3%**
	GICS vs. competitor	5.0%**	3.9%***	5.2%***	
R&D	1994 to 2000	29.2%	36.1%	45.9%	**74.0%**
	GICS vs. competitor	44.8%***	37.9%***	28.1%***	

***Significant at the 1% level.
**Significant at the 5% level.
*Significant at the 10% level.

GICS classifications to determine the extent to which analyst perceptions play a role in GICS assignments. The clear impression from these interviews is that, although analyst perceptions influence the original formulation of industry categories, analysts play no role in the assignment of individual firms to the specific categories. Second, although analyst perception might affect some of our test variables (e.g., *ltgrowth* and possibly the valuation multiples), most of the variables we test are beyond analyst control (e.g., *sales growth, R&D,* the fundamental ratios, and stock returns). The fact that GICS outperforms the other classification schemes using variables such as R&D, realized sales growth, and stock returns suggests that analysts' perceptions are unlikely to account for most of our results.

6. *Conclusion*

This study evaluates alternative industry classification schemes in various applications common to capital market research. Specifically, we compare: (1) the SIC, (2) the NAICS, (3) FF (Fama and French [1997]) industry groupings, and (4) the GICS.

We find that GICS classifications are significantly better at explaining stock return comovements, as well as cross-sectional variations in valuation multiples, forecasted growth rates, and key financial ratios. The GICS advantage is consistent from year to year and is most pronounced among large firms. For most of these applications, the performances of the other three methods differ little from each other.

We believe that the superior performance of GICS is attributable to two main factors: (1) the financial-oriented nature of the industry categories themselves, and (2) the consistency of the firm-assignment process. Unlike SIC and NAICS, GICS industry groupings are established to meet the needs of investment professionals and are not primarily shaped by firms' production technology.[18] In addition, the assignment of GICS codes to individual firms is done by a team of specialists at S&P and MSCI, and is not left to the discretion of the data vendor. This centralized assignment process also appears to improve the consistency and usefulness of the industry groupings.

As we mention in the introduction, industry classification is important to financial academics and practitioners. Indeed, the usefulness of industry groupings affects, to varying degrees, virtually every significant area of empirical research. The relative importance of the improvements we document varies across specific research settings. However, the fact that GICS performs as well as, or better than, each of the other methods in virtually all our tests suggests that it should be the preferred method to group firms by industry in most research settings.

[18] Even though FF classifications are also intended for a financial audience, these industry groupings are based on a reclassification of SIC codes and do not reflect a fundamental shift away from the production orientation of SIC and NAICS.

For example, studies of earnings management often use a cross-sectional approach to compute abnormal or discretionary accruals (e.g., Subramanyam [1996], Hribar and Collins [2002], Kothari, Leone, and Wasley [2003]). These studies generally feature industry-based control samples with the expectation that the relation between operating accruals and changes in sales or property, plant, and equipment are constant within an industry. The power of these tests, in turn, depends on our ability to effectively group firms with similar operating characteristics. We expect GICS codes to provide more powerful tests than SIC codes in these settings. More broadly, the GICS algorithm offers an advantage whenever the research objective involves identifying (or quantifying) unusual or abnormal operating activities.

Industry classification is also critical in fundamental analysis and valuation studies. For example, valuation models that compute terminal values by reverting firm returns on equity or returns on assets to industry means or medians (e.g., Frankel and Lee [1998], Lee, Myers, and Swaminathan [1999]) should benefit from improved industry classifications. Industry membership is crucial in determining a firm's cost of capital (e.g., Fama and French [1997], Gebhardt, Lee, and Swaminathan [2001]), estimating valuation multiples (Alford [1992], Liu, Nissim, and Thomas [2002]), and identifying better comparable firms (Bhojraj and Lee [2002]). More generally, we expect GICS codes to provide superior industry classifications for most fundamental analysis and valuation studies that call for industry-based control samples.

Finally, we expect GICS industry classifications to be particularly useful in studies of analyst behavior. In these studies, grouping firms by analyst perception is generally an advantage rather than a drawback, thus accentuating the GICS advantage. For example, a recent study by Boni and Womack [2003] uses the GICS classification scheme to develop an industry-based strategy of buying stocks net upgraded in each industry and shorting stocks net downgraded in each industry. The authors argue that the contribution of analysts is most evident only after properly controlling for industry membership. In this context, they argue for the superiority of the GICS approach.

In summary, our evidence suggests that in most research applications encountered by financial academics, the GICS classification system provides a better technique for identifying industrial peers. Historical GICS codes are already available at relatively low cost for most active, as well as inactive, U.S. firms. When historical GICS codes are not available, our results suggest that the current GICS code is a close substitute. When neither a current nor historical GICS code is available, the NAICS code appears to be the next-best solution.

In any event, the case for wider adoption of GICS industry classification codes by financial academics is compelling. Given the increased availability of this information at low costs, its wide acceptance by practitioners, and the uniformity of its industry definition across different countries, we believe financial researchers should seriously consider using the GICS system in future projects that involve industry classifications.

APPENDIX A

Background Information on Four Industry Classification Schemes

	SIC	NAICS	FF	GICS
Official name	Standard Industrial Classification	North American Industry Classification System	Fama-French Industry Classification Codes	Global Industry Classification Standard
Developer of categories and definitions	U.S. Census Bureau[a]	U. S. Census Bureau[a]	Fama and French [1997]	S&P and MSCI[b]
Stated basis for categories and definitions	Production and technology oriented	Production and technology oriented	Not specified	Principal business activity
Assigner of category code to each firm	Vendor-specific	Vendor-specific	Fama and French	S&P and MSCI
Stated criteria for assignment of firms to each category	Not specified	Not specified	Not specified	Revenue, earnings, and market perception
Current availability	From both Compustat and CRSP	From Compustat (since 2001)	See Fama and French [1997, Appendix]	GICS History and other S&P and MSCI products and services (including Research Insight and Compustat)[c]

[a]The NAICS is jointly developed with Canada and Mexico, with the goal of establishing comparable statistics among the three countries.
[b]S&P = Standard & Poor's; MSCI = Morgan Stanley Capital International.
[c]See figure 1.

APPENDIX B

Variable Descriptions

All share price and shares outstanding data used to calculate market capitalization (market cap) are taken from the CRSP monthly data set. Where annual information is used, CRSP data are taken as at the end of December of each year. All financial statement information is from the combined Compustat Active and Research files. Compustat data item number is reported in parentheses. Analyst forecast long-term growth is the latest median IBES consensus forecast available in December for each sample year.

Variable	Description	Calculation
Returns	Monthly share price returns	
pb	Price to book	Market cap/total common equity (D60)
evs	Enterprise value to sales	(Market cap + long-term debt (D9) + debt in current liabilities (D34))/net sales (D12)
pe	Price to earnings	Market cap/net income before extraordinary items (D18)
rnoa	Return on net operating assets	Net operating income after depreciation (D178)/(property, plant, and equipment (D8) + current assets (D4) – current liabilities (D5))
roe	Return on equity	Net income before extraordinary items (D18)/total common equity (D60)
at	Asset turnover	Total assets (D6)/net sales (D12)[a]
pm	Profit margin	Net operating income after depreciation (D178)/net sales (D12)
lev	Leverage	Total liabilities (D9)/total stockholders' equity (D216)
ltgrowth	Median analyst long-term growth forecast	
sales growth	One-year-ahead realized sales growth	(Net sales one year in the future – current year net sales)/current year net sales (D12)
R&D	Scaled research and development expense	R&D expense (D46)/net sales (D12)

[a]This is the inverse of the standard asset turnover ratio. We find that the inverse ratio has fewer outliers.

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