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Common Analysts: Method for Defining Peer Firms

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Abstract

We develop a method for defining groups of peer firms on the basis of joint analyst coverage. Besides industry boundaries, analysts' coverage choices reflect other aspects of firm relatedness such as business model. We find that the analyst-based method produces substantially more homogeneous groups of firms compared to common industry classifications, and has a number of other desirable properties. The paper has two broader implications. First, it demonstrates the advantages of a self-organizing approach to classification, as opposed to a hierarchical system. Second, it illustrates a new positive information production externality generated by the institution of security market analysis.

I. Introduction

Forming groups of similar firms is a rudimentary component of methodology in countless academic papers as well as industry and policy analyses. Most studies rely on standard industry classifications for defining related firms. The most well-known such system is the Standard Industrial Classification (SIC) developed in the 1930s. Fama and French (1997) reorganize SIC information to form 48 industry groups. These 'Fama–French industries' are probably the most widely used classification in finance research today. In 1997 the U.S. government introduced the North American Industry Classification System (NAICS) intended to replace the SIC. The leading privately provided solution is the Global Industry Classification Standard (GICS) developed jointly by Morgan Stanley Capital International and Standard & Poor's.

Peer firm identification is not a trivial task as boundaries of industries change, entirely new fields emerge, and others vanish. Even if industry boundaries were

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static, sorting firms into pre-defined bins based on their operations is not straightforward, as illustrated by different SIC codes allocated to the same firms by different data vendors (Guenther and Rosman (1994)). A good classification system should have the following properties. First, groups should be homogeneous, also in characteristics unobservable to the econometrician. Second, firms within a group would be related via genuine economic links as opposed to merely statistical similarity. Third, it would react promptly to changes in firms and the structure of the economy. Fourth, it would be simple to understand and easy to use. Fifth, costs would be low.

In this paper we develop a new method for defining peer firms, that we believe fulfills the aforementioned criteria, on the basis of firms followed by the same sell side security analysts. It provides a natural measure of firm relatedness, reflecting well-informed professionals' views on industry boundaries and similarities between firms. Analysts' industry specialization is apparent, for example, in analyst rankings, such as the *Institutional Investor* All-America Research Team. Analysts' coverage choices also reflect other aspects of firm similarity such as customer segment (e.g., local vs. international), business model (e.g., producer vs. distributor), as well as vertical links between firms. Albuquerque, De Franco, and Verdi (2013) show that also chief executive officer (CEO) compensation reference groups reflect aspects of firm similarity in addition to industry, such as, business complexity, index membership, and governance.

The technology underlying our method involves comparing analysts' actual coverage choices to simulated random choices. The simulations account for the differences in the extent of coverage across analysts and firms. The method identifies firms that have more analysts in common than expected by chance and produces firm- and year-specific peer groups. The method is self-organizing in the sense that we do not specify the size or granularity of the peer groups ex ante. We only define the confidence level used in the simulation, and all other aspects of peer group composition are determined by analysts' coverage choices. This confidence level, which we set at 1%, can be thought of as the probability that two firms are classified as peers by chance. The choice of this parameter affects group size and closeness of peer firms. The choice of 1% is ad hoc, but chosen before running any performance tests. On an average sample year, we are able to compile an analyst-based peer group for 69% of U.S. based New York Stock Exchange (NYSE) firms.

We compare the performance of the analyst-based method to traditional industry classifications (SIC, Fama–French), the leading recent approaches (NAICS, GICS), as well as a classification utilizing textual analysis of firms' product descriptions (10-K statements) by Hoberg and Phillips (2016). As the performance metric we use peer group homogeneity in finance and accounting variables, as in Bhojraj, Lee, and Oler (2003) who compare various traditional industry classifications. We make this choice for three reasons. First, it is the only methodology for comparing firm classification systems documented in the literature. Second, it is an externally developed comparison methodology. Third, homogeneity in known variables is also useful regarding unobservable characteristics: classification that produces groups that are homogeneous in many

variables, without directly using those variables to form groups, will more likely produce homogeneity in unobservable characteristics as well.[1]

The Bhojraj et al. (2003) method involves running regressions explaining, for each firm *i*, various firm-specific characteristics with the peer group averages of those characteristics. Firm *i* is never included when computing group average. The adjusted R^2 values from these regressions are high when the distances of individual firms' figures from their respective group averages are small. For example, consider the market value-based leverage ratio among analyst-covered firms.[2] A regression explaining individual firms' leverage ratios by their peer group average produces adjusted R^2 values from 14.0% to 17.6% in the SIC system, depending on the number of SIC code digits used. The common analyst-based method achieves an adjusted R^2 of 20.0%, and so produces more homogeneous groups in this dimension. Altogether, we use 20 characteristics: variables related to the scope of the firm's operations (e.g., sales), valuation (e.g., market-to-book), basic financials (e.g., profitability), and corporate finance policies (e.g., dividend payment).

The analyst-based method comes out ahead in these tests with remarkable consistency. Out of a total of 180 separate pairwise comparisons with alternative methods, our method produces more homogeneous groups in 167 (93%) cases. It also excels in finding the closest single peer firm. To ensure that this outperformance is not driven by differences in test data across methods we report all performance results using a common set of firms.[3] Overall, the analyst-based method represents a significant improvement in firm classification. One way to see this is to establish the best result obtainable using any classification method for each test variable, then tally how close to this result each method gets on average. Our method on average gets to 93% of the best result, while other methods yield 70–84%.

We suspect that the superior performance of the analyst-based method is due to analysts' more accurate and timely information on firm similarities and boundaries. Firms also change over time. There are slower changes due to industry migration, but also sudden changes due to mergers and divestitures, or changes in corporate strategy. Analysts likely react to such changes more promptly than standard classification systems do, partly due to their direct communication with corporate managers (Francis, Hanna, and Philbrick (1997)). Consistent with this conjecture, we show that changes in the composition of analyst-based groups lead similar

[1]Using the book-to-market ratio, for example, to construct firm groups (such as deciles), is the best way to ensure homogeneity in that ratio within groups. However, it gives little assurance that the firms would be similar in other characteristics. In contrast, if one forms groups by not using the book-to-market ratio, and they still end up having similar such ratios, then this would be encouraging as to the firms' overall similarity.

[2]Our main tests concentrate on NYSE firms. In ancillary analysis we extend the sample to all Center for Research in Security Prices (CRSP) firms.

[3]The smaller group size of analyst-based peer groups may be partially responsible for the method's performance. However, the analyst-based method also outperforms 4-digit SIC codes, 5-digit NAICS codes, and 8-digit GICS codes, the most fine-grained standard classifications that produce similarly small group sizes.

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changes in all other classifications. We discuss the underlying economic forces generating an informative coverage network in Section II.

To summarize the case for the analyst-based method, and also to discuss some broader implications of the paper, let us revisit the criteria for a good classification system laid out earlier: i) The analyst-based method clearly produces more homogeneous firm groups than other methods; ii) peer firms share genuine economic links reflected by analyst coverage choices; iii) as evidenced by our results on peer group dynamics, the system likely reacts promptly to changes in firms and the structure of the economy; and iv) it is easy to understand and use based on anecdotal evidence from discussions with researchers and practitioners. We have made publicly available commented code for generating the peer groups and allowing customization, such as groups of different sizes.

The analyst-based method is likely to be especially efficient when identifying listed firms that are being compared or lumped together (explicitly or implicitly) by firm managers or capital market participants.[4] Analysts cater to their clients, and the coverage choices reflect firms that investors and finance professionals perceive as related. Another benefit is that the method makes it possible to study firms and analysts as a network, thus lending itself to the use of analysis tools of networks science. One can utilize not only the existence of a link between two firms, but also the strength of the link. In addition to firms, the method is handy in measuring distances between industries or other types of firm clusters.

A more general point is that our results can be viewed as an illustration of the advantages to a self-organizing approach to classification, as opposed to a hierarchical system. One could think of our method as a market-based solution, while some other methods are more bureaucratic. For example, the NAICS manual from 2002 is 1,400 pages, and the most recent 2012 definitions document is 508 pages. The issue of costs of firm classification is also a more general one. Whatever the total net benefit of the sell side analyst function to the society is, our paper illustrates a new potential positive information production externality generated by this institution. The marginal cost of utilizing information on the coverage choices of analysts, once they are there, is very low. In comparison, systems like SIC and the new NAICS seem expensive. For example, the development of NAICS involved 7 subcommittees representing 20 government agencies, and is scheduled to be reviewed every 5 years.[5] In public responses to government queries respondents indicated substantial concerns about costs (Federal Register (1994)). The strength of NAICS is that it covers most firms, including private firms. So while NAICS clearly has its place, our method could still help reduce the cost of NAICS to U.S. taxpayers, for example, by providing leading indicators of trends in industry structure obtained with listed firms.

The method developed and tested in this paper is used in Kaustia and Rantala (2015) to generate peer groups in a study of corporate peer effects involving stock

[4]Examples of such studies include those focusing on peer effects among firms (Leary and Roberts (2014), Foucault and Frésard (2014)), executive compensation peer groups (Faulkender and Yang (2010), Bizjak, Lemmon, and Nguyen (2011)), spillover effects of financial misreporting (Beatty, Liao, and Yu (2013), Li (2016)), as well as investment strategies involving return differences among very similar firms (Gatev, Goetzmann, and Rouwenhorst (2006)).

[5]Source: https://www.census.gov/eos/www/naics/, accessed Sept. 1, 2017.

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splits. It has also been independently evaluated in a contemporaneous paper by Lee, Ma, and Wang (2016). They find that combining two recent approaches, one based on chronologically adjacent searches by the same individual performed on SEC's Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system (Lee, Ma, and Wang (2015)) and the analyst-based method, is especially effective.

In the rest of the paper, Section II discusses the economics of analyst coverage choice. Section III presents the data and methodology, and describes peer group composition. Section IV reports the main performance tests on group homogeneity. Section V discusses peer group dynamics. Section VI provides extensions and robustness checks, and Section VII discusses research applications with an eye on the potential value added by our method. Section VIII concludes the paper.

II. The Economics of Analyst Coverage Choice

This section discusses aspects of security analysts' incentives and institutional practices contributing to the informativeness of the analyst coverage network. We also provide case examples illustrating these ideas.

A. Industry Focus

Analysts' coverage choices usually reflect some dimension of specialization or information acquisition synergies. Analysts tend to focus on following related firms that belong to the same industry (Michaely and Womack (1999), Mikhail, Walther, and Willis (2004), and Boni and Womack (2006)). Analysts also actively adapt their coverage choices reflecting changes in firms and industries, as evidenced by studies on initial public offerings (Das, Guo, and Zhang (2006)) and conglomerate breakups (Gilson, Healy, Noe, and Palepu (2001)). Large elite brokerage houses employ a large number of individual analysts who cover many industries, whereas smaller brokerage houses specialize in specific industries or types of stock (Hong and Kubik (2003), Merkley, Michaely, and Pacelli (2017)).

Besides institutional and information acquisition reasons, analysts' incentives favor industry focus. Industry knowledge is the single most important determinant of their compensation (Brown, Call, Clement, and Sharp (2015)). Public analyst rankings, such as the *Institutional Investor* All-America Research Team and the *Wall Street Journal* Best on the Street survey, are based on identifying top analysts in different industry sectors. Being selected in the All-America Research Team has a significant effect on analyst compensation (Stickel (1992), Michaely and Womack (1999), and Hong, Kubik, and Solomon (2000)). Also, industry expertise acquired outside of the security analyst industry has been shown to be valuable. It increases the probability of being selected all-star analyst (Bradley, Gokkaya, and Liu (2017)), and is positively associated with the analyst playing an effective monitoring role in issues such as detecting earnings management (Bradley, Gokkaya, Liu, and Xie (2017)).

B. Other Dimensions of Similarity and Links Between Firms

Analysts' coverage choices can also reflect other aspects of firm similarity. Brown et al. (2015) report that 48% of analysts agree to the notion that

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"The similarity of the company with other companies you follow" is very important when considering coverage choice. In general, similarity of the covered firms likely leads to synergies in the analysts' work. For example, cost of information acquisition is known to be an important determinant of coverage choice (Beyer, Cohen, Lys, and Walther (2010)).

Depending on analyst, different aspects of similarity can receive different weights in the coverage decision. Along the supply chain, analysts who follow a firm's suppliers or customers are known to have better forecast accuracy than other analysts for these firms (Guan, Wong, and Zhang (2015)). Luo and Nagarajan (2015) show that these analysts provide lower-quality forecasts for other firms in their portfolios. This suggest that analysts allocate resources strategically, optimizing their coverage choice.

Geographical proximity is another key dimension. Malloy (2005) finds that analysts who are geographically closer to a firm are more accurate than others. Geographic considerations also affect coverage choice: O'Brien and Tan (2015) report that analysts are 80% more likely to cover local IPO firms than non-local ones. Jennings, Lee, and Matsumoto (2017) argue that analysts incur additional costs when following distant firms. When the firms in an analyst's portfolio are located farther away from other firms in the same industry, the analyst's portfolio size is smaller and average forecast accuracy is lower.

There are likely trade-offs among dimensions of similarity. Consider an analyst who ideally wants to cover firms in the same industry and located very close to each other. Often this is not possible, however, and so the analyst will then need to trade off industry similarity with geographical proximity. The analyst will also want to weave in other considerations, such as whether to expand coverage along the supply chain, and how many firms to cover overall. Our key argument is that these considerations likely vary, and the analyst coverage network will do a good job in optimizing over firm similarity in general. One can think of the overall network as optimizing over many dimensions of similarity, taking into account the goals of the analysts' work while minimizing information acquisition costs.

C. Examples on Alternative Dimensions of Similarity

To get a handle on the alternative dimensions of similarity, we now discuss some examples. We start with cases in which the SIC produces unintuitive peers, while analyst-based peers seem to make sense (the detailed description of the analyst-based classification methodology is provided in Section III). We then provide some examples related to the Hoberg–Phillips text-based network industry classification (TNIC) method.

First, consider Newell Brands. It is a global consumer marketer selling various different products from pens to healthcare. It owns a large portfolio of brands, such as Rubbermaid, Parker, and Dymo. Its common analyst-based peer firms include Procter Gamble, Kimberly Clark, and Colgate Palmolive. These are also big consumer goods companies with brands ranging from garden care to cosmetics. In contrast, none of these firms are in the same SIC code with Newell Brands, not even in the same first-digit SIC.

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Second, take Black & Decker Corp, a global manufacturer and marketer of power tools and accessories. Its four-digit SIC is 3540, which stands for "Metal-working Machinery". It only includes two other firms, Kennametal Inc. and Illinois Tool Works. They are designers and producers of engineered components and tools. When we look at common analyst peer firms for Black & Decker, they include tool manufacturers, home improvement retailers, and construction companies, such as Stanley, Home Depot, and Toll Brothers. Its analysts-based peer group seems to combine key features of the product markets and the customer base.

Third, consider Dolby Laboratories, which is in the business of licensing audio, 3D and other technologies used in DVDs, Blu-Rays, and movie theaters. The SIC places it under code 6794, for "Patent owners and lessors". While this is technically correct, the only other firms in their group (4 Kids Entertainment, Choice Hotels International) are in a totally different line of business. Common analyst peer firms for Dolby are entertainment and media firms, both in production and delivery, such as DreamWorks, Time Warner, and Viacom. Dolby is vertically linked to these firms.

Which links should matter in classification? In the Dolby example, the 4-digit SIC emphasizes the business model (licensing patents), while analysts seem to emphasize the entertainment business. For Black & Decker, SIC emphasizes industrial production, while analysts seem to emphasize the broader business and customer base.

Analysts are also likely to capture aspects of firm relatedness that are not based on direct product-market links. To illustrate this, we look at some cases in which our method and the Hoberg–Phillips TNIC product-market method assign different firms as peers. One such example is Precision Castparts, a company that produces components for aircraft engines and industrial gas turbines. TNIC matches it with a number of other technology and manufacturing companies, such as United Technologies and ITT Inc., and the peers do not include aircraft manufacturers. The closest analyst-based peers, on the other hand, are Boeing and Lockheed, which are the end-users of engine components. The nature of the business model can matter as well. For example, Ryder System Inc. is known for its fleet of rental trucks but the company also specializes in supply chain management and third party logistics solutions for corporate clients. Its TNIC peers are Hertz and Penske, which are car rental firms. The closest analyst-based peers, however, are United Parcel Service (UPS) and FedEx Corporation, which offer logistics solutions. In these examples, both methods assign peers that are intuitively related, but they emphasize different aspects of firm similarity.

D. Examples on Analyst Responses to Changing Industries

Another major benefit of the analyst-based method is that it is dynamic and not based on predefined bins like conventional industry classifications. Industry boundaries change over time, sometimes new ones emerge and old ones can disappear altogether. Analysts' coverage choices can respond rapidly to such changes and they are less rigid than pre-defined codes. We provide some examples below.

New technology has changed many industries potentially affecting peer firm identification. One example is consumer credit reporting agencies which nowadays

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serve customers and update records in real time. Prior to the 2015 listing of TransUnion, Equifax was the only U.S. listed credit reporting agency. In the 1990s, Equifax's closest analyst-based peers include firms such as Dun & Bradstreet, McGraw Hill, and Dow Jones, which have market research operations. In the 2000s, there is a change and analyst-based peers start including firms such as Automatic Data Processing and First Data Corporation, which are information technology firms serving the financial industry. Equifax's SIC code since the early 1990s has been 7320 "Market Research and Public Opinion Polling" and its 8-digit GICS group has been either "Diversified Commercial & Professional Services" or "Research & Consulting Services." These codes do not reflect the current IT focus of the industry.

An example in which an old industry effectively ceases to exist is film and camera manufacturing, where digital photography forced firms to seek alternative lines of business. Two major NYSE-listed players in the industry were Eastman Kodak and Polaroid, which are each other's analyst-based peers in the 1980s and 1990s. Polaroid was declared bankrupt in 2001 and Eastman Kodak reacted to the changing market environment by shutting down film factories and investing into the printer business.[6] Eastman Kodak's SIC code has always been 3861 "Photographic Equipment and Supplies" and its 8-digit GICS code is also labeled "Photographic Products." Analyst-based peers, on the other hand, reflect the change in the company's operations and in the late 2000s they include printer manufacturers such as Hewlett Packard, Lexmark, and Xerox.

III. Methodology and Data

This section describes the simulation-based method of obtaining the analyst-based peer groups, as well as data sources involved in testing classification performance.

A. Forming Analyst-Based Peer Groups

A crucial question is what number of common analysts between two firms is a sufficient indication of their relatedness. Even when analysts generally focus on following firms in specific industries, unrelated firms may have common analysts just by chance because of analysts who cover several industries or groups of unrelated firms. Establishing how many common analysts are required to indicate a nonrandom connection between two firms is a key part of our method. Before proceeding, it is instructive to glance at Figure 1, where Graph A shows a network graph linking two firms whenever they have even a single common analyst. Graph B, on the other hand, shows a network generated after applying our method. Whereas Graph A of the figure is basically a mess, clear structure emerges in Graph B.

The key insight is that two widely-followed firms can more easily have one or more common analysts even if the firms are unrelated, while this is less likely for firms with less analyst coverage. Our method is based on deriving the minimum number, denoted C_{it}, of analysts for each firm i that it must share with any other

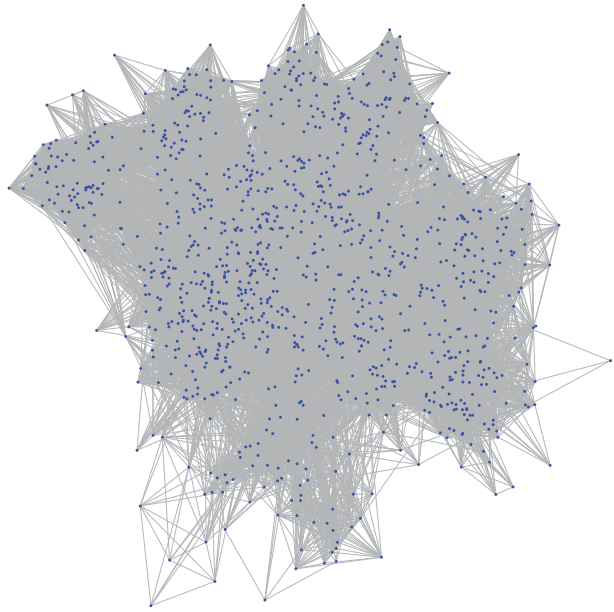
[6]See, for example, "Kodak Enters Inkjet-Printer Market," *New York Times*, Feb. 6, 2007.

FIGURE 1

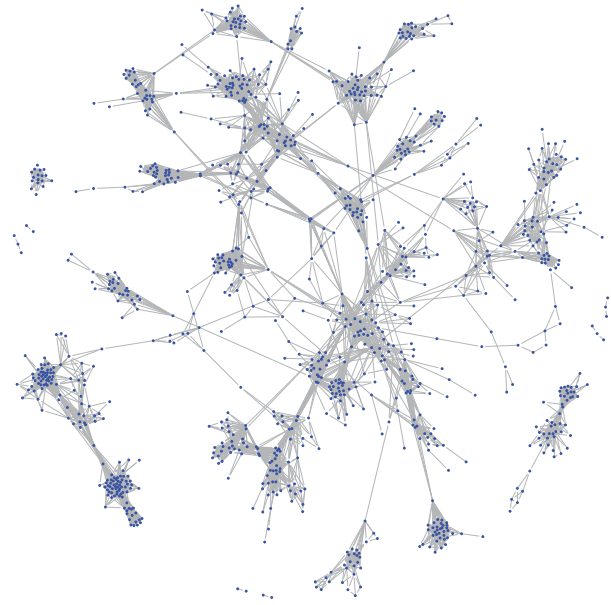
Network Graphs Illustrating the Analyst-Based Peer Method

Graphs A and B in Figure 1 are based on NYSE firms with analyst-based peers in 2013. The plots represent individual firms. Graph A shows connections between all firm pairs that share at least one common analyst. Graph B only connects firms that are analyst-based peers according to our method, that is, they share at least *C* common analysts, where *C* is the firm-year specific criterion defined in Section III.A. The graphs have been drawn using the Fruchterman-Reingold algorithm.

Graph A. Connections Between All Firm Pairs That Share At Least One Common Analyst



Graph B. Connections Between Firms That Are Analyst-Based Peers According to Our Method



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firm *j*, to include *j* in *i*'s peer group in year *t*. This criterion is an increasing function of two factors: i) The number of analysts following *i* in year *t*;[7] and ii) the number of other firms followed by each such analyst. Specifically, we run a simulation, in which the analysts following *i* counterfactually choose the other firms they follow at random among firms that have analysts in year *t*. The criterion *C* for each firm is selected so that the probability of having *C* or more common analysts by chance is less than 1%. More specifically, we set *C* sufficiently large so as not to assign unrelated firms as peers. After *C* has been derived, a firm's peer group is defined as all other firms that have at least *C* common analysts with it (4.1 on average). The simulation uses 1,000 repetitions for each firm-year, and the peer groups are updated annually. The choice of a 1% confidence interval is ad hoc. Tinkering with this parameter affects the size of the peer groups, and increasing the figure would lead to larger peer groups.

The peer relationships identified by the method are not always mutual: If firms A and B have different peer criteria, it is possible that firm A is firm B's peer, but B is not A's peer. Suppose, for example, that A's analyst criterion is 5, B's criterion is 3, and the firms have 4 common analysts. Because B has a lower criterion, A makes it to B's peer group, but B does not make it to A's. Nonmutual peer relationships can be intuitively justified in some situations.[8]

B. Data Used for Forming Peer Groups and Comparing Methods

This subsection describes the data we use when comparing different classification schemes. In addition to analyst-based peer groups, we consider conventional industry classifications, namely SIC codes, Fama–French 49 industries, and the more recently introduced NAICS and GICS classifications. We include various granularities, such as 2-, 3-, and 4-digit SIC groups. Additionally, we consider the Hoberg–Phillips TNIC. The TNIC differs methodologically from conventional classifications and is based on measuring product-market similarity by way of a textual analysis of the firms' 10-K statements. We nevertheless include it for completeness. Similar to the analyst-based groups, the TNIC groups are firm-specific and change annually.[9] Lewellen (2012) also utilizes 10-K statements to

[7]We consider an analyst following a firm in year *t* whenever she provides any estimate for the firm during year *t*. Analysts are identified based on Analyst Code in the Institutional Brokers' Estimate System (IBES) Detail History. The code is normally assigned to individual analysts, but can sometimes refer to analyst teams. We exclude analyst codes associated with more than 50 firms in a single year (0.52% of analyst-years) because they likely represent teams. Ljungqvist, Malloy, and Marston (2009) report that the IBES Recommendation database has ex post alterations of recommendations, additions and deletions of records, and the removal of analyst names. Such changes are automatically reflected in the yearly peer criteria and should not have any systematic impact on the peer groups.

[8]For example, suppose that firms A, B, and C are the only firms operating in a specific industry. Assume A and B are large firms, and C is small. A and B are likely to be each others' best comparables because of their similar size. The best comparable for firm C could also be either A or B in the same industry, or another smaller firm from a related industry. But if it is A or B, then C would have a nonmutual peer relationship with A or B.

[9]Hoberg and Phillips have another version of the classification (Fixed Industry Classification), in which industry membership is transitive (i.e., industry peers are not firm-specific). We run the comparisons with the TNIC classification as it is methodologically more similar to our analyst-based method, and should better reflect the peers of a particular firm.

build peer groups covering the time period 2002–2008, but the groups are not publicly available.

The SIC and Fama–French industry groups are available in Compustat from 1987. Some studies augment the Compustat SIC codes with the CRSP SIC codes when Compustat SIC codes are not available. We keep to Compustat codes because they are generally deemed more accurate (e.g., Guenther and Rosman (1994)). The use of Compustat SIC codes also ensures comparability with other industry classifications because their data are exclusively from Compustat.

The NAICS was introduced in 1997 and is replacing SIC codes with U.S. Federal agencies. The system was backfilled to cover historical data, and Compustat covers the years 1985–2013. The GICS classification, introduced in 1999, was jointly developed by MSCI and Standard & Poor's. The GICS codes in Compustat were originally available only from 1999, but were recently backfilled to cover the years starting from 1985. The TNIC classification groups are available in the Hoberg–Phillips data library for years 1996–2011.

Analyst data are from the IBES Detail database. The main sample consists of all NYSE firms with Share Code 10 or 11 and covers the years 1983–2013. We focus on NYSE firms in our main analyses because of their ample analyst coverage (Chang, Dasgupta, and Hilary (2006)). In an ancillary analysis, we also report results using an extended sample of all CRSP firms. The sample begins in 1983 because of limited availability of analyst data prior to 1983. The stock price and firm data are from CRSP and Compustat.

C. Statistics on Sample Firms and Characteristics of the Analyst-Based Peer Groups

Table 1 reports the descriptive statistics on sample firms and analysts. There are 1,569 firms and 2,485 analysts on an average year, and over two thirds of the firms have an analyst-based peer group. The groups are larger in the years when the average number of firms followed by an analyst is higher (e.g., on average 10.4 in 2009 vs. 19.0 in 1989). The composition of firm-specific peer groups does change over the years, but overall remains quite stable. On average, 79% of firm *i*'s peers this year were its peers also in the prior year (the median is 86%). A firm with 10 peers thus experiences a change of about 1 peer firm in a year.

The average analyst criterion C is 4.1 (median 4) and 61% of the criteria are between 3 and 5, and the maximum is 8. The smallest possible peer criterion is 2 analysts so a firm with only a single analyst cannot have peers. In general, a firm does not have a peer group if the number of common analysts with other firms is always below the firm-specific peer criterion.

Table 2 compares firms with analyst-based peers to all NYSE firms. Firms with analyst-based peers are larger, as small firms without analyst coverage drop out. In the top market capitalization quartile, 98% of NYSE firms have analyst-based peers, whereas 35% in the bottom quartile do.

Panel A of Table 3 reports group size statistics for the analyst-based peer groups and other classification schemes. The average size of an analyst-based peer group is 14.2 firms, and the median is 11. The group sizes are smaller with 4-digit and 3-digit SIC codes (median sizes 6 and 9 firms), 5-digit NAICS codes (median

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TABLE 1

Descriptive Statistics by Year

Table 1 reports annual statistics on sample firms, analysts, and analyst-based peer groups. The annual number of NYSE firms is based on firms that have a CRSP share code 10 or 11. The sample analysts are those that have provided at least one estimate for a sample firm during the year, and individual analysts are separated based on the Analyst Code item in the IBES Detail database. The analyst-based peer groups are formed using a simulated peer criterion: A firm's peer group in year *t* consists of all firms that are followed by at least the criterion number of the same analysts in year *t*. The criterion is calculated as the number of analysts a firm shares with another firm with a probability less than 1% in a simulation in which the firm's analysts choose the other firms they follow randomly among NYSE firms with analysts.

Year	Sample NYSE Firms	NYSE Firms with Peers	Analysts per Year	Average No. of Firms Followed by an Analyst	Average Peer Group Size	Median Peer Group Size
1983	1449	967	2220	10.2	17.2	15
1984	1457	921	2076	10.4	17.1	14
1985	1443	962	2269	10.3	18.2	15
1986	1436	1004	2203	10.9	18.0	14
1987	1428	944	2159	10.2	18.9	14
1988	1426	931	2064	9.8	18.1	13
1989	1384	930	2253	9.7	19.0	14
1990	1384	883	2046	8.8	17.9	13
1991	1426	891	1849	9.2	16.9	12
1992	1534	952	1761	9.9	17.4	13
1993	1632	1039	1971	10.4	18.7	14
1994	1706	1135	2114	9.9	18.1	13
1995	1793	1154	2190	9.4	16.8	12
1996	1915	1223	2307	8.9	15.5	12
1997	2020	1290	2590	8.1	14.6	11
1998	2029	1313	2749	7.6	13.5	11
1999	1975	1309	2900	7.3	12.4	10
2000	1833	1202	2799	7.0	11.8	10
2001	1689	1079	2814	6.4	10.8	9
2002	1600	1057	2939	6.0	10.5	9
2003	1545	1063	2885	6.3	10.7	10
2004	1540	1102	2809	6.3	11.0	10
2005	1540	1135	2813	6.4	11.2	10
2006	1529	1140	2791	6.4	11.1	10
2007	1512	1150	2770	6.5	10.9	10
2008	1444	1111	2689	6.3	10.6	9
2009	1389	1054	2626	6.5	10.4	9
2010	1394	1065	2801	6.6	11.2	10
2011	1390	1091	2890	6.8	11.9	11
2012	1378	1109	2892	6.8	12.0	11
2013	1405	1125	2795	7.2	12.8	12
Average	1568.5	1075.2	2485.0	8.1	14.4	11.6

7 firms), and 8-digit GICS codes (median 10 firms). The coarser versions of these classification schemes lead to larger group sizes than the analyst-based peers. In terms of average group size, the industry-classification closest to the analyst-based peer groups is 5-digit NAICS, and the closest in terms of median group size is 8-digit GICS.

Panel B of Table 3 describes the extent to which conventional classification schemes overlap with analyst-based peers. The average number of different codes within an analyst-based peer group ranges from 1.9 when using 6-digit GICS codes to 4.3 when using 4-digit SIC codes. On average, less than half of a firm's analyst-based peers share its own 4- or 3-digit SIC code, or 5-digit NAICS code.[10] With less detailed classifications, the industry classification codes of peers are more similar,

[10]Because the TNIC groups are firm-specific, we cannot directly calculate similar statistics with them. However, we can measure the overlap between a firm's analyst-based peers and TNIC peers: The average percentage of a firm's analyst-based peers that belong to its TNIC group is 49.6% when calculated for firms that have both an analyst-based peer group and a TNIC group.

TABLE 2

Size of Analyst-Based Peer Firms Compared to All NYSE Firms

Table 2 reports comparative statistics between firms with analyst-based peers and all NYSE firms in Compustat. The statistics are based on annual observations of firms between 1983–2013. The analyst-based peer groups are formed based on a simulated peer criterion. The criterion is calculated as the number of analysts a firm shares with another firm with a probability less than 1% in a simulation in which the firm's analysts choose the other firms they follow randomly among NYSE firms with analysts. A firm's peer group in year *t* consists of all firms that are followed by at least the criterion number of the same analysts in year *t*. MARKET_CAP (market capitalization) is calculated as the price times shares outstanding at the end of the year. Share prices are from CRSP and shares outstanding are from Compustat (item 25). COMMON_EQUITY is based on Compustat item 60. MARKET_CAP and COMMON_EQUITY values are in millions of dollars. The market capitalization quartile statistics are calculated using year-specific market capitalization breakpoints in the data.

Panel A. Market Capitalization and Common Equity

	MARKET_CAP		COMMON_EQUITY	
	Average	Median	Average	Median
All NYSE firms	28,766	1,018	2,162	502
Firms with analyst-based peers	38,843	1,677	2,761	810

Panel B. Firms with Analyst-Based Peers in Different Market Capitalization Quartiles (%)

Quartile 1	Quartile 2	Quartile 3	Quartile 4
35.3	71.1	89.8	98.1

for example the average number of peers in the same Fama–French group is 68%. Overall the GICS system has the highest overlap with the analyst-based peer groups, with the 6-digit version having most overlap (73%).

IV. Homogeneity of Peer Groups

In this section, we study how similar the firms within peer groups are. Having similar firm characteristics may or may not be an end in itself. For example, if a researcher wants peer firms to be as similar as possible in size, then using size alone to find the closest firms is the best way to go. However, one often wants to have peers that are similar in unobservable characteristics. While this is always challenging, it helps if peers are similar in many observable characteristics, without being explicitly matched on any of them.

We compare the analyst-based peer groups to other generally available classification schemes, that is, SIC, NAICS, GICS, as well as the TNIC groups by Hoberg and Phillips. We refer to Section III.B for a more detailed description of these schemes as well as data availability issues.

The NAICS and GICS codes were backfilled in Compustat. When developing a classification system based on measurable firm characteristics, it is rational to consider historical data to separate meaningful clusters in the firm characteristics space. However, this can introduce a bias in classification performance evaluation: future firms may not organize as neatly according to the criteria as past or current firms do. In contrast to backfilled classification systems, the analyst-based peer groups at any historical date t are based only on information available at date t. Performance results vis-à-vis backfilled systems are thus actually understated for the analyst-based groups from the perspective of predicting future performance.

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TABLE 3

Peer Group Size and Industry Overlap

Table 3 reports comparative statistics between the analyst-based peer groups, SIC Codes, Fama–French 49 industry groups, NAICS and GICS Codes, and Hoberg–Phillips TNIC classification groups. The analyst-based peer groups are formed based on a simulated peer criterion. The criterion is calculated as the number of analysts a firm shares with another firm with a probability less than 1% in a simulation in which the firm's analysts choose the other firms they follow randomly among NYSE firms with analysts. A firm's peer group in year *t* consists of all firms that are followed by at least the criterion number of the same analysts in year *t*. The composition of the industry classification groups is based on classification codes at the end of the calendar year. Panel A reports average and median group sizes and standard deviations of group size for the peer groups and the industry classifications. The industry classification statistics are calculated based on the number of other NYSE firms sharing the same classification code in year *t*. Panel B reports statistics on the industry classification codes of analyst-based peer firms. The statistics include the average and median number of different classification codes in the peer groups and the average and median number of peer firms sharing the firm's own classification code. Statistics for analyst-based peer groups are based on annual values between 1983–2013 and the statistics for the industry classifications are based on the subperiod for which they are available.

Panel A. Group Size Statistics Based on Analyst-Based Peer Groups or Other Firms with the Same Industry Code

Statistic	Analyst-Based Peer Groups	4-Digit SIC	3-Digit SIC	2-Digit SIC	Fama–French 49 Industries	5-Digit NAICS	3-Digit NAICS	8-Digit GICS	6-Digit GICS	TNIC
Average group size	14.2	9.9	13.4	45.7	46.1	14.1	43.1	13.8	23.9	23.2
Median group size	11.0	6.0	9.0	40.0	36.0	7.0	31.0	10.0	22.0	14.0
Average/median group size	1.3	1.7	1.5	1.1	1.3	2.0	1.4	1.4	1.1	1.7
Standard deviation of group size	13.6	11.2	12.2	35.9	32.2	16.8	33.8	12.4	14.4	24.6
Std. dev./ average group size	1.0	1.1	0.9	0.8	0.7	1.2	0.8	0.9	0.6	1.1

Panel B. Distribution of Industry Codes with Analyst-Based Peer Groups

Statistic	4-Digit SIC	3-Digit SIC	2-Digit SIC	Fama–French 49 Industries	5-Digit NAICS	3-Digit NAICS	8-Digit GICS	6-Digit GICS
Average number of different industry codes in analyst-based peer group	4.3	3.8	2.5	2.3	4.0	2.6	2.6	1.9
Median number of different industry codes in analyst-based peer group	4.0	3.0	2.0	2.0	3.0	2.0	2.0	2.0
Average percentage of peers sharing the firms' own industry code	34.7	42.7	63.0	68.0	40.8	61.5	53.7	72.7
Median percentage of peers sharing the firms' own industry code	25.0	40.0	72.7	83.3	33.3	70.6	50.0	85.7

A. Method

We adopt the method of Bhojraj et al. (2003) who compare conventional industry classification schemes against each other. We adopt all the test variables used by Bhojraj et al., and then also augment that list to cover even more variables of interest to finance researchers. Specifically, we compare the adjusted R^2 values from the following regression:

$$\text{VARIABLE}_{i,t} = \alpha_1 + \text{PEER_AVERAGE}_{i,t} + \varepsilon_{i,t}, \quad (1)$$

where $\text{VARIABLE}_{i,t}$ refers to any firm characteristic of interest observed for firm i in year t, and $\text{PEER_AVERAGE}_{i,t}$ refers to the average value among the peers of firm i. Importantly, the peer average does not include firm i itself. The adjusted R^2 value

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shows the explanatory power of the peer average on the variable value of the firm. It is a metric for how concentrated the values among peers are: the adjusted R^2 is higher when the squared distance of each firms' observation from its own peer group average is lower.

In pairwise comparisons of analyst-based groups with other systems, we always present results that come from the same set of firm-years (i.e., those with analyst-based peers as well as industry classification data available). In the tables these results appear under heading "Industry groups based on firms with analyst-based peers". For completeness we also show results when calculating the industry code averages among all NYSE firms. Groups are less homogeneous among all firms because this includes firms with low or no analyst coverage that are typically small. The time period for these comparisons is the subperiod of 1983–2013 for which classification data are available for each scheme. Later we study a time period common to all systems (1996–2011) and, with the benefit of hindsight, include only the best version of each method. For example, with SIC we would include the best among the 2, 3, or 4-digit versions.

The first set of test variables consists of 10 variables commonly of interest in finance research, including those related to stock return correlation, firm size, valuation, dividend policy, and capital structure. The second set consists of 10 variables related to valuation multiples, financial statement ratios, and other financial information variables from Bhojraj et al. (2003).[11] Full variable definitions are provided in the Appendix.

All test variables except monthly stock returns are based on annual values at the end of the year. Financial statement information of year t is based on the fiscal year ending in year t. To eliminate the effect of possible outliers, we exclude observations with the lowest and highest 1% for all variables except MONTHLY_RET and the binary variable DIV_PAYMENT. Also, we do not exclude the lowest 1% for SCALED_R&D_EXPENSE where many firms report zero.

In our analyst-based method, the number of shared analysts is a measure of the strength of the similarity relation between two peer firms (standard classification schemes are binary; either firms are peers, or they are not). We utilize this property for generating analyst-weighted peer averages, calculated by weighting the test variable values for each peer firm with the number of common analysts with that peer. Other applications can also benefit from using information on the degree of relatedness. We run all regressions using these analyst-weighted peer averages as well as equal-weighted averages that ignore this information on the strength of the peer relation.

[11]We use a market-to-book-ratio that follows the common definition in corporate finance literature (book value of assets less the book value of equity plus the market value of equity all divided by the book value of assets), as in, for example, Rajan and Zingales (1995) and Fama and French (2001). For completeness, we also include PRICE_TO_BOOK calculated according to the variable definition of Bhojraj et al. (2003) in the second set of variables. It is calculated as market cap divided by total common equity (Compustat item 60). Bhojraj et al. also include analysts' long-term growth forecast as a test variable but we do not. The reason is that a test based on this variable might be biased in favor of our method. With the second set of test variables, following Bhojraj et al., we require that firms must have positive common equity and total stockholders' equity and net sales above $10 million. When calculating PRICE_TO_EARNINGS we additionally require that net income before extraordinary items be positive.

B. Main Results

Tests using the common finance variables are reported in Table 4. When the classification averages are calculated based on firms having analyst-based peers, the equal-weighted analyst-based groups outperform the other classifications in 82 out of 90 pairwise comparisons: The SIC classifications, Fama–French, and 3-digit NAICS have higher R^2 values only in DIV_PAYMENT, TNIC classification has a higher R^2 in leverage variables MARKET_LEVG and BOOK_LEVG, and 6-digit GICS has a 0.1 percentage point higher R^2 in stock returns, but only when month fixed effects are not included. When we use analyst-weighted, instead of equal-weighted analyst-based peers, our method loses only to 2- and 3-digit SIC codes and Fama–French industries in DIV_PAYMENT, and to 6-digit GICS codes in stock returns without fixed effects. It outperforms all other classifications with every variable. That is, it is the best in 86 out of 90 pairwise comparisons.

Stock return co-movement is the focus of attention in numerous studies, so it is particularly interesting to note that analyst-based peers perform strongly relative to other systems in explaining monthly stock returns: Both equal-weighted and analyst-weighted peer averages outperform all other classification methods in the stock return regressions when month fixed effects are included, and only barely lose to 6-digit GICS codes without them. Ramnath (2002) studies analysts' earnings forecast revisions for later announcers after one of the firms they cover announces its earnings. It is conceivable that firms with shared analysts have more synchronous stock price movements in part due to analysts facilitating the incorporation of common information into stock prices (see also Piotroski and Roulstone (2004), Chan and Hameed (2006), Muslu, Rebello, and Xu (2014), Hameed, Morck, Shen, and Yeung (2015), Israelsen (2016), and Kumar, Rantala, and Xu (2019)).

Comparing just the performance of 2-, 3-, and 4-digit SIC codes in Table 4 gives insight regarding the possible advantage of more fine-grained industry classification. The results do not uniformly improve as one moves from 2-digit groups to more granular groups. When using all NYSE firms, 2-digit SIC codes are the best performing SIC code scheme in 5 out of 10 tests, 3-digit codes are the best performing scheme in three cases, and 4-digit codes in only two cases. When limiting the sample to firms having analyst-based peers, the 3-digit SIC codes perform the best in five cases, followed by 2-digit codes in four cases, and 4-digit codes in one case. The 3-digit codes have the highest average adjusted R^2 both among all NYSE firms and among firms with analyst-based peers. With NAICS and GICS codes, the more detailed classification levels perform relatively better on most tests, but there are exceptions with individual variables. These results support the notion that greater granularity may lead to misclassification in these systems.

Analyst-based peer groups also perform strongly with the accounting variables used in Bhojraj et al. (2003). The results of these tests are reported in Table 5. When using the set of firms having analyst-based peers, an equal-weighted analyst-based peer average outperforms other methods in 85 out of 90 cases, losing to 3-digit and 4-digit SIC codes in EV_TO_SALES, to 8-digit GICS codes in PROFIT_MARGIN and LEVG, and to TNIC classification in SALES_GROWTH. The analyst-weighted analyst-based peer average outperforms all the classifications

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TABLE 4

R^2 Values from Peer Group Homogeneity Regressions: Set of Common Finance Variables

Table 4 compares the explanatory power of analyst-based peer averages to the explanatory power of industry classification-based peer averages in a set of common finance variables. The reported figures are adjusted R^2 values from a regression where the dependent variables is a firm's variable value, and the independent variable is either the average variable value among analyst-based peers or among other firms sharing the same industry classification code. The regression includes a constant. Panel A compares the analyst-based peer groups to SIC codes and Fama–French industries, Panel B to NAICS codes, Panel C to GICS codes, and Panel D to TNIC groups. The sample includes all NYSE firms with CRSP share code 10 or 11. The results in each panel are based on the time period for which the industry groups are available. Analyst-based peer regressions are also run separately using analyst-weighted peer average values, with the number of common analysts between firms as weights. Industry classification regressions are run separately based on classification groups among all NYSE firms and among NYSE firms with analyst-based peers. The test variables are MONTHLY_RET (monthly return from CRSP), MONTHLY_RET_FE (monthly return with month fixed effects), BETA from the single index model based on monthly returns over the previous 36 months, MARKET_CAP (price times shares outstanding, prices are from CRSP and shares outstanding are from Compustat), TOTAL_ASSETS (Compustat item 6), NET_SALES (item 12), MARKET_TO_BOOK (book assets (item 6) minus book equity plus market capitalization all divided by book assets), DIV_PAYMENT (binary variable equal to 1 if a firm has non-zero dividends per share by the ex date (item 26) and 0 otherwise), BOOK_LEVG (book debt to total assets) and MARKET_LEVG (book debt divided by the result of total assets minus book equity plus market equity). BOOK_EQUITY is stockholders' equity (216) (or first available of common equity (60) plus preferred stock par value (130) or book assets (6) minus liabilities (181)) minus preferred stock liquidating value (10) (or first available of redemption value (56) or par value (130)) plus balance sheet deferred taxes and investment tax credit (35) if available and minus postretirement assets (330) if available. BOOK_DEBT is defined as total assets minus book equity. All variable values except the monthly returns are annual values at the end of the year. Financial statement items for year t are based on the fiscal year ending in year t. The highest adjusted R^2 value for each variable in each panel is boldface.

	MONTHLY_RET	MONTHLY_RET_FE	BETA	MARKET_CAP	TOTAL_ASSETS	NET_SALES	MARKET_TO_BOOK	DIV_PAYMENT	BOOK_LEVG	MARKET_LEVG
Panel A. Analyst-Based Peers Compared to SIC Codes and Fama–French Industries										
Analyst-based peers										
Analyst-weighted average	29.1	**31.5**	**45.7**	**14.2**	**27.7**	**17.8**	**24.6**	38.9	**7.8**	**20.9**
Equal-weighted average	**29.2**	31.3	45.2	9.9	23.0	13.5	23.9	38.1	7.3	20.0
Industry groups based on all firms										
2-digit SIC	22.3	23.3	28.0	8.9	20.1	8.0	13.6	35.8	3.0	11.8
3-digit SIC	19.4	23.1	30.1	7.6	19.5	9.9	17.6	32.7	4.0	13.4
4-digit SIC	18.1	22.9	29.4	6.9	18.0	9.6	17.6	30.8	4.8	13.5
Fama–French industries	22.9	23.5	29.6	8.0	17.1	6.2	17.4	37.1	2.6	12.2
Industry groups based on firms with analyst-based peers										
2-digit SIC	27.4	28.4	33.5	8.9	19.6	7.9	16.2	42.9	3.5	14.0
3-digit SIC	26.0	29.1	36.5	7.4	19.0	10.1	23.0	40.3	5.4	17.6
4-digit SIC	24.8	28.8	35.8	6.4	17.3	9.8	22.7	38.7	5.8	17.5
Fama–French industries	28.0	28.6	35.1	7.8	16.9	6.0	20.3	**43.6**	3.3	13.9
Panel B. Analyst-Based Peers Compared to 3- and 5-digit NAICS Industries										
Analyst-based peers										
Analyst-weighted average	**29.4**	**31.7**	**45.5**	**15.0**	**27.3**	**18.3**	**25.0**	**41.0**	**7.8**	**20.9**
Equal-weighted average	29.4	31.5	45.0	10.6	22.4	13.9	24.2	40.4	7.3	20.0
Industry groups based on all firms										
3-digit NAICS	22.1	23.3	30.3	8.3	16.5	7.8	13.9	34.1	3.7	12.8
5-digit NAICS	19.3	23.5	30.4	9.0	17.2	9.9	19.8	29.5	5.0	15.1

(continued on next page)

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TABLE 4 (continued)

R^2 Values from Peer Group Homogeneity Regressions: Set of Common Finance Variables

	MONTHLY_RET	MONTHLY_RET_FE	BETA	MARKET_CAP	TOTAL_ASSETS	NET_SALES	MARKET_TO_BOOK	DIV_PAYMENT	BOOK_LEVG	MARKET_LEVG
Panel B. Analyst-BasedPeers Compared to3-and5-digitNAICS Industries (continued)										
Industry groups based on firms with analyst-based peers										
3-digit NAICS	27.4	28.6	35.8	8.4	17.2	8.0	17.1	41.0	5.4	16.1
5-digit NAICS	25.6	29.2	36.8	8.6	17.8	10.0	22.2	37.3	6.6	19.1
Panel C. Analyst-Based Peers Compared to 6- and 8-digit GICS Industries										
Analyst-based peers										
Analyst-weighted average	31.3	33.7	**47.5**	**13.6**	**28.1**	**15.8**	**26.6**	**46.0**	**8.2**	**20.7**
Equal-weighted average	32.3	**34.0**	47.0	9.6	23.5	11.7	25.6	45.8	7.5	19.6
Industry groups based on all firms										
6-digit GICS	30.2	31.0	41.2	8.0	21.5	7.1	20.8	40.9	2.8	12.8
8-digit GICS	29.0	31.0	42.3	7.7	22.5	10.3	19.3	40.0	4.8	15.5
Industry groups based on firms with analyst-based peers										
6-digit GICS	**32.4**	33.1	44.6	8.3	21.7	7.5	23.2	45.0	4.3	15.1
8-digit GICS	31.2	33.2	45.6	7.7	22.9	10.0	21.6	43.9	5.4	18.0
Panel D. Analyst-Based Peers Compared to TNIC 3 Groups										
Analyst-based peers										
Analyst-weighted average	29.6	**32.1**	**44.5**	**10.9**	**23.3**	**17.5**	**24.2**	**32.1**	**9.6**	**23.2**
Equal-weighted average	**29.8**	32.0	43.9	7.2	18.7	13.0	24.0	31.1	8.9	22.4
TNIC										
Groups based on all firms	23.7	25.8	34.5	4.0	10.9	6.4	19.1	24.9	7.1	18.9
Groups based on firms with analyst-based peers	28.7	30.3	39.5	3.9	11.7	7.3	22.1	28.7	9.4	22.9

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TABLE 5

R^2 Values from Peer Group Homogeneity Regressions: Accounting-Based Financial Information Variables

Table 5 compares the explanatory power of analyst-based peer averages to the explanatory power of industry classification group-based peer averages in a set of accounting-based financial information variables. The reported figures are adjusted R^2 values from a regression where the dependent variables is a firm's variable value, and the independent variable is either the average variable value among analyst-based peers or among other firms sharing the same industry classification code. The regression includes a constant. Panel A compares the analyst-based peer groups to SIC codes and Fama–French industries, Panel B to NAICS codes, Panel C to GICS codes, and Panel D to TNIC groups. The sample includes all NYSE firms with CRSP share code 10 or 11. The results in each panel are based on the time period for which the industry groups are available. Analyst-based peer regressions are also run separately using analyst-weighted peer average values with the number of common analysts between firms as weights. Industry classification regressions are run separately based on classification groups among all NYSE firms and among NYSE firms with analyst-based peers. The test variables are PRICE_TO_BOOK (market cap divided by total common equity (Compustat Item 60), EV_TO_SALES (the sum of market cap, long-term debt (Item 9), and debt in current liabilities (item 34) all divided by net sales (item 12)), PE (market cap divided by net income before extraordinary items (item 18)), RNOA (net operating income after depreciation (item 178) divided by the sum of property, plant, and equipment (item 8), =current assets (item 4), and less current liabilities (item 5)), ROE (net income before extraordinary items divided by total common equity), AT (total assets (item 6) divided by net sales), PROFIT_MARGIN (net operating income after depreciation divided by net sales), LEVG (total liabilities (item 9) divided by total stockholders' equity (item 216), SALES_GROWTH (net sales 1 year in the future divided by current value), and SCALED_R&D_EXPENSE (research and development expense (item 46) divided by net sales). All variable values are annual values at the end of the year. Financial statement items for year *t* are based on the fiscal year ending in year *t*. The highest adjusted R^2 value for each variable in each panel is boldface.

	PRICE_ TO_BOOK	EV-TO-SALES	PE	RNOA	ROE	AT	PROFIT_ MARGIN	LEVG	SALES_ GROWTH	SCALED_ R&D_ EXPENSE
Panel A. Analyst-Based Peers Compared to SIC Codes and Fama–French Industries										
Analyst-based peers										
Analyst-weighted average	**16.8**	45.5	**4.6**	**25.1**	**7.9**	**78.8**	**35.7**	**51.0**	**16.6**	**53.2**
Equal-weighted average	15.7	43.2	4.6	24.1	7.5	77.6	34.2	49.8	16.2	51.2
Industry groups based on all firms										
2-digit SIC	10.6	35.3	2.6	12.2	3.8	65.3	22.1	40.1	11.0	18.3
3-digit SIC	11.5	40.4	2.8	10.5	3.9	72.0	24.7	43.0	10.4	32.1
4-digit SIC	11.3	40.2	2.5	9.6	2.9	72.7	24.1	43.0	10.2	37.8
Fama–French industries	12.0	35.0	3.2	12.7	3.5	62.1	22.5	38.4	10.9	32.2
Industry groups based on firms with analyst-based peers										
2-digit SIC	13.0	38.0	3.9	17.6	4.2	67.7	26.7	44.6	12.8	21.6
3-digit SIC	15.2	44.3	3.6	15.8	4.6	74.5	31.1	47.8	12.9	35.9
4-digit SIC	14.5	**45.7**	3.2	14.7	4.0	75.6	30.3	48.0	12.6	45.9
Fama–French industries	14.3	38.0	4.2	17.0	4.0	65.0	26.7	43.4	12.6	36.6
Panel B. Analyst-Based Peers Compared to 3- and 5-digit NAICS Industries										
Analyst-based peers										
Analyst-weighted average	**17.4**	**45.7**	**4.6**	**25.8**	**8.5**	**79.5**	**36.4**	**52.5**	**16.7**	**53.1**
Equal-weighted average	16.3	43.5	4.3	24.7	8.1	78.4	35.0	51.4	16.3	51.2
Industry groups based on all firms										
3-digit NAICS	10.7	34.6	2.6	13.1	4.4	62.9	24.6	37.9	11.5	24.4
5-digit NAICS	12.6	40.6	2.7	11.7	3.6	70.5	26.0	40.2	10.9	37.3

(continued on next page)

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TABLE 5 (continued)

R^2 Values from Peer Group Homogeneity Regressions: Accounting-Based Financial Information Variables

	PRICE_ TO_BOOK	EV-TO-SALES	PE	RNOA	ROE	AT	PROFIT_ MARGIN	LEVG	SALES_ GROWTH	SCALED_ R&D_ EXPENSE
Panel B. Analyst-Based Peers Compared to3-and5-digitNAICS Industries (continued)										
Industry groups based on firms with analyst-based peers										
3-digit NAICS	12.9	37.3	3.7	18.0	5.8	65.4	29.9	42.6	13.9	27.4
5-digit NAICS	14.2	43.4	3.0	15.6	4.8	72.3	30.4	44.2	13.4	42.3
Panel C. Analyst-Based Peers Compared to 6- and 8-digit GICS Industries										
Analyst-based peers										
Analyst-weighted average	**18.8**	**47.7**	**4.6**	**27.3**	**7.9**	**81.3**	**42.2**	**54.6**	**17.9**	**57.9**
Equal-weighted average	17.6	44.9	4.4	26.0	7.4	79.8	40.7	53.5	17.7	55.6
Industry groups based on all firms										
6-digit GICS	14.5	36.9	3.2	19.4	6.1	74.9	34.8	49.8	16.5	47.3
8-digit GICS	13.4	40.5	3.3	19.8	7.0	78.6	38.0	52.9	16.1	46.6
Industry groups based on firms with analyst-based peers										
6-digit GICS	16.1	39.7	3.4	24.4	6.5	75.7	38.3	50.9	17.4	55.2
8-digit GICS	14.8	44.1	3.9	23.7	7.1	79.3	41.6	53.6	16.7	54.2
Panel D. Analyst-Based Peers Compared to TNIC 3 Groups										
Analyst-based peers										
Analyst-weighted average	**15.1**	**46.8**	**4.2**	**24.7**	**8.8**	**79.5**	**37.4**	**42.4**	**20.4**	**55.2**
Equal-weighted average	14.1	44.6	4.1	23.4	8.5	78.2	36.0	41.2	20.1	53.0
TNIC										
Groups based on all firms	11.1	37.0	2.6	16.1	6.7	63.1	26.4	31.7	16.5	47.7
Groups based on firms with analyst-based peers	13.1	39.7	3.2	20.2	7.4	65.4	30.8	35.6	20.2	50.4

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in 89 out of the 90 pairwise comparisons, losing only to 4-digit SIC codes in EV_TO_SALES ratio.

Altogether, the results show that the analyst-based method outperforms in producing homogeneous firm groups. When the industry groups are formed based on firms with analyst-based peers, the equal-weighted average performs better than alternative classifications in 167 out of 180 pairwise comparisons. The analyst-weighted average performs even better, outperforming the alternatives in 175 comparisons.

C. Horse Race on a Common Time Period

The time periods over which the more recently introduced classifications are available differ from each other. The cross-sectional firm coverage of conventional industry classifications can also vary even during the years when data are available. So far we have always used all available data for each method, and compared them to our method one at a time. To facilitate comparison across all the methods, Table 6 uses a time-period common to all, 1996–2011. In this analysis we focus on the particular granularity version of each classification that performed best thus far, that is, 3-digit SIC, 5-digit NAICS, and 8-digit GICS. The Fama–French industries and TNIC come in one version only, and are also included. To make sure that all methods are classifying an identical pool of firms, we use data only for firms that have analyst-based peers, TNIC peers, and classification codes available for all the different classification schemes included.

Excluding our analyst-based method for a moment, it is interesting to see how the other methods compare against each other among the 20 test variables. All methods score at least one win. On the 10 'finance' variables, GICS scores five victories, while NAICS and TNIC both score two and Fama–French gets one. On the 'accounting' variables, SIC scores 5 victories followed by GICS with 4, and TNIC with 1. Counting these results together, the overall winner among the other methods is the (8-digit) GICS with 9 victories, followed by (3-digit) SIC with 5.

Then, bringing the analyst-based method back in the game, we see that it continues to perform strongly: the equal-weighted measure outperforms the other methods in 12 cases, while the next best measure (3-digit SIC) scores 4 victories, followed by TNIC with 2, and NAICS and GICS with 1 each. The analyst-weighted measure performs even better and outperforms other classifications in 16 cases.

D. Economic Significance

Even if the analyst-based method outperforms other classifications in group homogeneity, one can ask whether the improvement is sufficient to justify its use in empirical research. To get a sense on how significant the relative improvement from one classification to the next is, we measure how close each individual method on average gets to the highest adjusted R^2 value obtainable with any classification method for a given firm characteristic. Based on the results in Table 6, we compute the average value of (R^2/highest R^2) for each method. As illustrated in Figure 2, this value is 0.99 with the analyst-weighted analyst-based peer average, and 0.93 with the equal-weighted analyst-based peer average. The best-performing industry classification (8-digit GICS) obtains a value of 0.84, and the weakest classification in

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TABLE 6

R^2 Values from Peer Group Homogeneity Regressions: Common Time-Period 1996—2011

Table 6 compares the explanatory power of analyst-based peer averages to the explanatory power of 3-digit SIC, Fama–French 49, 5-digit NAICS, 8-digit GICS, and Hoberg–Phillips TNIC classification peer averages in two sets of firm characteristic variables during the 1996–2011 time period. The sample is based on firms that have an analyst-based peer group and classification data for all the industry classifications. The reported figures are adjusted R^2 values from a regression where the dependent variables is a firm's variable value, and the independent variable is either the average variable value among analyst-based peers or among other firms in the same industry classification group. Analyst-based peer regressions are also run separately using a weighted peer average with the number of common analysts between firms as weights. The industry classification groups are formed based on NYSE firms that have analyst-based peers. The regression includes a constant. Variable list 1 consists of the common finance variables which are defined as in Table 4 and variable list 2 consists of the financial ratios and accounting-based financial information variables defined as in Table 5. The highest adjusted R^2 value for each variable is boldface.

Variable	Analyst-Based Peers		Industry Classification Groups Based on Firms with Analyst-Based Peers				
	Analyst-Weighted Average	Equal-Weighted Average	3-Digit SIC	Fama–French	5-Digit NAICS	8-Digit GICS	TNIC
List 1							
MONTHLY_RET	30.7	**31.9**	28.7	27.9	29.4	31.2	30.0
MONTHLY_RET_FE	33.4	**33.9**	31.8	30.2	31.5	33.1	31.7
BETA	**46.1**	45.8	40.8	35.8	41.1	43.4	41.0
MARKET_CAP	**10.1**	6.9	3.7	3.5	4.6	4.1	3.4
TOTAL_ASSETS	**23.1**	18.7	12.9	12.0	13.3	15.4	11.4
NET_SALES	**16.3**	11.9	7.0	3.1	6.2	8.2	5.2
MARKET_TO_BOOK	24.1	23.8	25.0	19.9	**25.7**	20.1	22.8
DIV_PAYMENT	**37.5**	37.1	32.9	36.3	34.4	34.9	32.5
BOOK_LEVG	**10.4**	9.4	5.2	3.9	9.0	8.2	9.8
MARKET_LEVG	**22.0**	21.2	17.8	13.7	19.9	20.1	21.2
List 2							
PRICE_TO_BOOK	**16.0**	14.9	15.0	12.2	14.4	11.8	14.0
EV_TO_SALES	**48.6**	46.1	45.0	38.5	44.4	43.3	39.0
PE	**4.3**	4.2	4.2	3.9	3.5	3.7	4.1
RNOA	**25.8**	24.7	18.1	15.8	18.6	22.7	20.2
ROE	7.5	7.0	5.7	3.9	4.6	6.3	**8.3**
AT	**80.4**	78.8	79.8	69.5	76.0	77.3	66.0
PROFIT_MARGIN	**42.0**	40.5	40.6	34.3	40.4	40.7	35.2
LEVG	45.8	44.4	**46.6**	41.6	44.1	45.6	40.2
SALES_GROWTH	**20.8**	20.7	17.6	16.6	18.5	19.9	19.3
SCALED_R&D_EXPENSE	**57.9**	55.7	40.6	42.5	46.2	54.6	51.8
Average of variable R^2/highest R^2	0.99	0.93	0.80	0.70	0.81	0.84	0.82

this respect (Fama–French) a value of 0.70. When Fama–French (which has a much larger group size) is excluded, the R^2/highest R^2-ratios for all industry classifications are between 0.80 and 0.84. The difference between the analyst-weighted peer method and the next best other method is 9 percentage points, which is greater than the entire range of performance among the other systems (i.e., 4 percentage points). Based on these values, using the analyst-based peers provides a leapfrog improvement in explanatory power compared to other methods.

V. Peer Group Dynamics

A good peer identification method should respond to changes in firms and industries in a timely manner. In this section, we analyze reclassifications where a firm switches to a different peer group according to a particular classification method. To ensure comparability across different methods, we use annual observations of firms having analyst-based peers, TNIC peers, and SIC, NAICS, GICS classification codes in Compustat and we include the same classification levels as in

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FIGURE 2

Average Performance Relative to Best Results in Peer Group Homogeneity Tests

Figure 2 shows the relative explanatory power of the analyst-based peer method and other classification systems. The bars for each method show the average value for the ratio adjusted R^2/highest R^2 obtainable with any method based on the 20 test variables reported in Table 6.

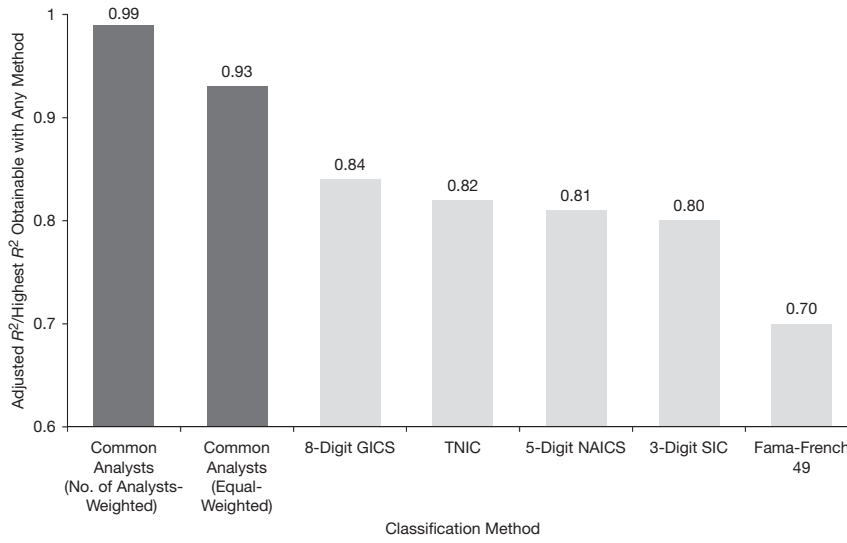


TABLE 7

Peer Group Dynamics

Table 7 reports statistics on peer group dynamics for analyst-based peers, 3-digit SIC codes, Fama–French Industry Groups, 5-digit NAICS codes, 8-digit GICS codes, and Hoberg–Phillips TNIC peers. The sample consists of NYSE firms that have all the industry classification codes in Compustat, a TNIC peer group, and an analyst-based peer group. We additionally require that each firm has these items also in year $t - 1$ to ensure that the captured changes in peer groups are exclusively due to reclassifications. The statistics are based on annual firm observations. New peers are defined as firms that are in the firm's peer group in year t, but not in year $t - 1$. Former peers are defined as firms that are in the firm's peer group in year $t - 1$, but not in year t. The reported statistics are the average percentages of new firms in the peer group each year, the average percentages of new peers that were analyst-based peers in year $t - 1$, and the average percentages of former peers that are current analyst-based peers.

Classification Method	Mean % of New Firms in the Peer Group Each Year	Mean % of New Peers That Were Already Analyst-Based Peers in Previous Year	Mean % of Former Peers That Are Current Analyst-Based Peers
3-digit SIC	8.3	25.1	2.9
Fama–French	9.2	11.6	0.6
5-digit NAICS	7.8	26.4	3.6
8-digit GICS	9.7	23.9	5.8
TNIC	31.2	13.4	8.6
Analyst-based peers	19.9		

Table 6. We require that each firm has these data items also in year $t - 1$ because here we want to exclude peer group changes related to mergers, IPOs, and delistings.

Column 1 of Table 7 reports peer group turnover based on the average percentage of new firms in the peer group each year. The statistics show that analyst-based peers and Hoberg–Phillips TNIC have more turnover compared to conventional methods. Less than 10% of peers in the SIC, NAICS, and GICS

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groups were not in the peer group the year before. In comparison, analyst-based peers have on average 20% new peers and the TNIC classification has the highest turnover with 31%. High turnover can be an advantage if it is based on a more timely reaction to changes in the nature of firms and industries.

To understand if turnover can contribute to the performance of the analyst-based method, we analyze whether analyst-based peers lead or lag other methods on peer group reclassifications. We calculate, for each method, the percentage of new peers that were already analyst-based peers in year t - 1 and the percentage of former peers (firms in the peer group in year t - 1, but not in year t) that are analyst-based peers in year t. If reclassifications in other methods lag, rather than foreshadow, analyst-based peer relationships, the new peer percentage should be higher than the former peer percentage.

This is indeed what columns 2 and 3 of Table 7 show: The percentage of new peers that were already analyst-based peers is higher than the percentage of former peers that are current analyst-based peers. This holds for all classification methods. For example, with 3-digit SIC codes, 25% of new peers were already analyst-based peers, whereas only 3% of former peers are current analyst-based peers. The relative difference between the two percentages is lowest with TNIC, but even their 14% of new peers are analyst-based peers and 8% of old peers are current analyst-based peers. The evidence from these lead-lag relations is consistent with the notion that analyst-based peers react faster to changes in firms and industries.

VI. Extensions

Next, we briefly cover some extensions of the method, while delegating some of the discussion and most of the tables we refer to here into the Supplementary Material.

A. Comparison with Statistically Matched Peers

In this section, we form groups of similar firms by matching on the 10 test variables of Table 5. We then see how such statistically matched peers compare to the analyst-based peers in homogeneity tests based on another set of 10 variables, from Table 4. We take all firms having analyst-based peers, and form purely statistically matched peer groups with the same group sizes. We take Euclidean distances between every firm pair each year for each of the 10 matching variables (normalized by standard deviation) and calculate the sum of the distances for each pair. We then assign the firms with the smallest sum of distances as peers.[12]

To ensure comparability with previous results, we run the homogeneity tests with the same sample of firms that was used in Panel A of Table 5. Table 8 reports adjusted R^2 values from regressions that are similar to the previous homogeneity tests. Analyst-based peers outperform the statistically matched peers on all except 3 variables, which are MARKET_TO_BOOK, MARKET_LEVG, and BOOK_LEVG. On these particular variables, the statistically matched peers obtain very

[12]In case some variables are missing, we match on the remaining variables.

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TABLE 8

R^2 Values from Peer Group Homogeneity Regressions: Analyst-Based Peers Compared to Statistically Matched Comparable Firms

Table 8 compares the explanatory power of analyst-based peer groups to the explanatory power of statistically matched comparable firms based on a set of finance variables. The variables are defined as in Table 4. The reported figures are adjusted R^2 values from a regression where the dependent variable is a firm's variable value, and the independent variable is either the average variable value among analyst-based peers or among statistically matched peers. Analyst-based peer regressions are also run separately using a weighted peer average with the number of common analysts between firms as weights. The statistically matched peer groups are formed based on the Euclidean distance in the firm characteristics. We form a statistically matched peer group for each firm with analyst-based peers so that the group size is equal to the number of analyst-based peers. We use the 10 accounting-based financial information variables of Table 5 as the matching variables and conduct the matching among firms that have analyst-based peers. We first calculate the Euclidean distance between each possible firm pair each year for each of the 10 matching variables and then calculate the sum of the distances for each firm pair. We define the firms with the smallest sum of distances as peers. When calculating the sum of distances, we normalize each variable with its standard deviation. The regression sample consists of NYSE firms that have a SIC code in Compustat. The highest adjusted R^2 value for each variable is boldface.

	MONTHLY_ RET	MONTHLY_ RET_FE	BETA	MARKET_ CAP	TOTAL_ ASSETS
Statistically matched peers	21.3	23.9	34.0	9.7	20.1
Analyst-based peers					
Analyst-weighted average	29.1	**31.5**	**45.7**	**14.2**	**27.7**
Equal-weighted average	**29.2**	31.3	45.2	9.9	23.0
	NET_SALES	MARKET_TO_BOOK	DIV_ PAYMENT	BOOK_ LEVG	MARKET_ LEVG
Statistically matched peers	7.0	**76.6**	22.1	**60.0**	**71.0**
Analyst-based peers					
Analyst-weighted average	**17.8**	24.6	**38.9**	7.8	20.9
Equal-weighted average	13.5	23.9	38.1	7.3	20.0

high R^2 values, but this is due to the fact that the matching variable list already included almost identical and highly correlated variables (PRICE_TO_BOOK and LEVG as defined by Bhojraj et al. (2003)). If we leave out these overlapping variables, the analyst-based peer groups outperform on all remaining 7 test variables. A comparison with Panel A of Table 4 shows that the statistically matched peers, in turn, outperform all SIC code specifications and Fama–French industries on 5 of the 10 variables.

B. Sample Covering All CRSP Firms

We run similar pairwise comparisons on an extended sample, using all CRSP firms instead of focusing only on NYSE. An analyst-based peer group is obtained for 40% of the firm-year observations in CRSP during the 1983–2013 period, so coverage outside the NYSE is significantly lower.[13] Supplementary Material Tables A.1, A.2, and A.3 report results analogous to Tables 4–6 that use NYSE firms only. The equal-weighted analyst-based peer average outperforms other classifications in 166 out of 180 cases and the analyst-weighted average in 170 out of 180 cases. If the sample is restricted to firms with analyst-based peers, the equal-weighted average outperforms in 139 cases and the analyst-weighted

[13]We have also experimented with forming the analyst-based peer groups separately among Nasdaq firms and among AMEX firms. Based on annual observations from the 1983–2013 period, peer groups are obtained for 29% of the Nasdaq firms and only 6% of the AMEX firms.

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average in 147 cases. The analyst-based peer groups continue to perform well also when they are compared to 3-digit SIC, Fama–French, 5-digit NAICS, 8-digit GICS, and TNIC classifications using the same sample of firms and the same sample period as in Table 6. The average value for variable R^2/highest R^2 is 0.98 for the analyst-weighted analyst-based peer average and 0.91 for the equal-weighted average. The best performing industry classification based on this ratio is GICS with a value of 0.87.

C. Selecting a Single Matching Firm

In this section, we study the effectiveness of common analysts in identifying single best match peer firms. One important application is the calculation of abnormal stock returns in long-run event studies (Barber and Lyon (1997), Lyon, Barber, and Tsai (2003)). It has become common practice to use characteristic-matched comparables also in studies measuring operational performance and valuation.

The common analyst best match peer for firm i in year t is the firm with the greatest number of common analysts with firm i in year t. In case of a tie, one peer firm is selected randomly. In this analysis we use the whole CRSP universe. Analyst-based matches can be found even for firms with a single analyst, so the lower analyst coverage outside of NYSE is less of an issue.

We compare the common analyst match to size (MARKET_CAP) matching, MARKET_TO_BOOK matching, and joint MARKET_CAP/MARKET_TO_BOOK matching. We run the matching procedure separately among all sample CRSP firms, and, alternatively, among firms within the same 4-SIC code. Joint MARKET_CAP/MARKET_TO_BOOK matching is conducted as in Barber and Lyon (1997): firm i's comparable is the firm with the closest MARKET_TO_BOOK ratio among the firms having market capitalization within ±30% of firm i's. We again judge performance by R^2 values from firm characteristic regressions, but now the group average is just the single value from the best match peer firm. Where peers are matched based on MARKET_CAP or MARKET_TO_BOOK, we do not report adjusted R^2 values in tests involving the same variables, as they are being used in selecting the peer.

Results are reported in Supplementary Material Table A.4. With most variables, the adjusted R^2 values among common analyst matched comparables increase monotonically with the minimum analyst criterion (the number of common analysts a firm must have with its comparable to be included in the sample). But even just requiring a single common analyst, the method produces more similar matching firms than combinations of MARKET_CAP, BOOK_TO_MARKET, and 4-digit SIC factors in all characteristics except those that are mechanically linked to the matching variables (such as firm size). For example, looking at monthly stock returns, the analyst-based match is better than any of the non-analyst-based matches even when no requirements are imposed on analyst coverage. Performance could of course be further improved by combining common analysts with other matching variables, such as MARKET_CAP or MARKET_TO_BOOK.

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D. Rules of Thumb for Defining Analyst-Based Peer Firms

Supplementary Material Section I discusses how to derive meaningful "rules of thumb" for defining peer firms based on analyst coverage without resorting to running the full simulation. The idea is to predict the simulation-generated peer groups with only basic information on analyst coverage, available from any analyst database. Simple prediction rules explain a significant part of the variation in the analyst criterion C (Table A.5). Peer groups based on these rules perform very well in homogeneity tests (Table A.6).

E. Extending the Peer Groups to Firms That Are Not Covered by Analysts

A limitation of the analyst-based method is that it cannot be used on firms with no analyst coverage. Supplementary Material Section II shows that it is possible to expand the reach of our method by placing uncovered firms into existing groups on the grounds of some other similarity metric. The general idea is to ask which firms might analysts 'assign' as peers (by their coverage choices) for an uncovered firm if it were covered. We discuss how to do this utilizing Hoberg–Phillips TNIC peer groups, and Table A.7 reports results from homogeneity regressions with the extended peer groups.

VII. Discussion

Here we discuss the relative merits of the analyst-based method compared to alternative approaches, as well as identify a set of research topics in which it is likely to generate new insight.

A. Potential Value Added with Respect to Alternative Approaches

Different peer firm identification methods suit different applications and the optimal method depends on the research question. For some questions, one may need to select peer firms by a specific algorithm, or even by hand. In many research questions, however, one is concerned of overall similarity, particularly in unobservable characteristics. The analyst-based method can be useful in such applications particularly if the benchmark firm needs to be similar on multiple dimensions. A method that is known to produce high overall homogeneity, without explicitly matching on any firm characteristic, should be more likely to minimize firm distances also in any unobservable characteristics.

The vast majority of finance studies that seek to identify close comparable firms either utilize a granular version of an existing industry classification, such as 4-digit SIC codes, or use purely statistical matching based on firm characteristics. Alternative approaches, such as executive compensation peer groups or web search-based peers, are not available through common data vendors, and have a much shorter time series. Firms' self-reported peers are also known to exhibit systematic selection bias (Faulkender and Yang (2010), Bizjak et al. (2011)). Director interlocks, which can be very useful for identifying word-of-mouth effects

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between firms, typically do not exist between competing firms, rendering them inefficient in many applications. The endogeneity of such networks can be a benefit or weakness, depending on the research question. Even in studies that successfully utilize compensation peers or shared directors, it may still be useful to employ analyst-based peers as an alternative independent benchmark.

The analyst-based method can produce small peer groups that are homogeneous and arguably similar on dimensions important for those particular firms. Other value adding aspects are the existence of a network structure, and that the strength of the relation between two firms is measurable. Furthermore, most industry classifications assign peers exclusively based on information collected from the firm's own financial reporting, whereas analysts can utilize information that cannot be found in the 10-K statements.

B. Potential Value Added in Specific Research Topics

In corporate finance, the method can be particularly useful when studying corporate peer effects. Or more generally, in settings where the idea is to identify related firms that are subject to managers' or investors' attention. Additionally, comparing the overlap between analyst-based peers and product market classifications, such as Hoberg–Phillips TNIC peers, offers a potential way to separate product-market and non-product market peers. This can be useful in many finance applications and it is also potentially interesting for industrial organization studies. For example, in mergers and acquisitions analyses, this comparison can be used to define the nature of the similarity between merging firms.

In asset pricing, previous studies have identified lead-lag structures in stock returns across various dimensions, such as firm size, industry, and the supply chain. A recent paper by Ali and Hirshleifer (2020) finds that using common analysts to trace a lead-lag structure generates particularly strong momentum strategy profits. Shared analysts offer a potential way to identify related firms for applications such as pairs trading strategies, and analyst connections can be related to information transfers that contribute to co-movement in stock returns. Analysts cater to institutional investors, so the method is also suitable for identifying firms they consider as related. Institutional investor trading data are now available through ANcerno, so it is possible to study their trading behavior at the investor level.

Analyst-based peers can be studied as a network, which opens up possibilities for many types of studies utilizing tools developed in networks science. Network applications have started to appear in finance, for example, related to corporate financial policies (Larcker, So, and Wang (2013), El-Khatib, Fogel, and Jandik (2015), and Fracassi (2017)). Analysts function as information intermediaries and the network structure can also have implications for information spillovers and the propagation of shocks. For example, Hilary and Shen (2013) explore the role of analysts in facilitating the transfer of information between firms and the associated impact on the efficiency of price formation.

Additionally, common analysts can be useful in measuring links between industries. One can, for example, identify individual firms that function as bridges

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between different industries or firm clusters. Previous papers utilizing industry linkages have relied on industry input-output tables (see Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012) for macroeconomic shocks, Ahern and Harford (2014) for mergers and acquisitions, and Herskovic (2018) for asset pricing). Building links between industries using common analysts is easy and can be done for virtually all industries because analyst coverage is required only for a subset of firms in each industry. Links uncovered by analysts are based on many notions of relatedness, and provide substantially more nimble data compared to input-output tables.

Our method can also be used in studies that focus on analysts themselves, such as analyses on forecast or recommendation accuracy and coverage choice. Previous papers have studied how analysts' forecasts are affected by the disclosures of related firms (Ramnath (2002), Hilary and Shen (2013)). Based on our method, one could measure how much the portfolio of firms an analyst covers overlaps with the analyst-based peer groups. This shows to what degree the coverage choices of the focal analyst are typical versus deviating from other analysts' coverage. Existing literature does not tell whether deviating coverage leads to better or worse analyst performance.

VIII. Conclusion

This paper develops a method for identifying peer firms on the basis of shared analyst coverage. The method is independent of conventional industry classification systems and outperforms them in producing homogeneous groups of firms. Part of the method's success likely derives from coverage choices reflecting, and adapting to, the emergence of new types of firm clusters as well as changes within individual firms.

The analyst-based method is not intended to replace the standard classifications - obviously it cannot even be used for firms with no analyst coverage, such as most privately held firms. Other methods are likely to be more suitable also when accurate measurement of product-market relationships is important, or where the ideal number of peer firms is larger, such as in industry portfolios for asset pricing tests. Standard classifications are also more convenient for filtering data, for example, excluding financial firms from the sample is simpler based on SIC codes. The ideal characteristics of a system for selecting peer firms ultimately depend on the research problem at hand.

In general, our results suggest that identifying peer firms through common analysts is a powerful yet simple tool for selecting comparable firms, and could also be used effectively as part of other firm selection schemes. The complementary nature of the analyst-based method has an interesting policy implication. It might be possible to improve the accuracy of conventional systems such as the NAICS, as well as to reduce their costs, by using information on analysts' coverage choices as a guide to changes in industry boundaries.

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Appendix. Variable Definitions

This Appendix provides definitions of the variables used in this article. All variable values except the monthly returns are annual values at the end of the year. Financial statement items for year *t* are based on the fiscal year ending in year *t*. Item numbers refer to items in Compustat. Panel A includes test variables used in Table 4 (common finance variables) and Panel B includes test variables used in Table 5 (accounting-based financial information variables). Panels C lists variables that are used elsewhere in the paper or in other variable definitions.

Variable Name	Full Name	Definition
Panel A. Common Finance Variables		
MONTHLY_RET	Monthly return	Monthly return from CRSP.
MONTHLY_RET_FE	Monthly return with month fixed effects	Indicates a regression specification that uses monthly return with month fixed effects.
BETA	Beta (36 months)	Beta from the single index model based on monthly returns over the previous 36 months.
MARKET_CAP	Market capitalization	Price times shares outstanding, prices are from CRSP and shares outstanding are from Compustat (item 25).
TOTAL_ASSETS	Total assets	Item 6.
NET_SALES	Net sales	Item 12.
MARKET_TO_BOOK	Market-to-book ratio	Book assets (item 6) minus book equity plus market capitalization all divided by book assets.
DIV_PAYMENT	Dividend payment	Binary variable which is equal to 1 if a firm has non-zero dividends per share by the ex date (item 26) and 0 otherwise.
BOOK_LEVG	Book leverage	Book debt to total assets.
MARKET_LEVG	Market leverage	Book debt divided by the result of total assets minus book equity plus market equity.
Panel B. Accounting-Based Financial Information Variables		
PRICE_TO_BOOK	Price-to-book	Market capitalization divided by total common equity (item 60).
EV_TO_SALES	Enterprise value-to-sales	The sum of market cap, long-term debt (item 9), and debt in current liabilities (item 34) all divided by net sales (item 12)).
PE	Price-to-earnings	Market capitalization divided by net income before extraordinary items (item 18).
RNOA	Return on net operating assets	Net operating income after depreciation (item 178) divided by the sum of property, plant, and equipment (item 8) and current assets (item 4), less current liabilities (item 5).
ROE	Return on equity	Net income before extraordinary items (item 18) divided by total common equity.
AT	Asset turnover	Total assets (item 6) divided by net sales.
PROFIT_MARGIN	Profit margin	Net operating income after depreciation (item 178) divided by net sales.
LEVG	Leverage	Total liabilities (item 9) divided by total stockholders' equity (item 216).
SALES_GROWTH	Sales growth	Net sales 1 year in the future divided by current value.
SCALED_R&D_EXPENSE	Scaled R&D expense	Research and development expense (item 46) divided by net sales.
Panel C. Other Variables Used in the Paper		
COMMON_EQUITY	Common equity	Item 60.
BOOK_EQUITY	Book equity	Stockholders' equity (216) (or first available of common equity (60) plus preferred stock par value (130) or book assets (6) minus liabilities (181)) minus preferred stock liquidating value (10) (or first available of redemption value (56) or par value (130)) plus balance sheet deferred taxes and investment tax credit (35) if available and minus postretirement assets (330) if available.
BOOK_DEBT	Book debt	Total assets minus book equity.

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Supplementary Material

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