The Search for Peer Firms: When Do Crowds Provide Wisdom?

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Abstract

In knowledge-based economies, many businesses enterprises defy traditional industry boundaries. In this study, we evaluate six "big data" approaches to peer firm identifications and show that some, but not all, "wisdom-of-crowd" techniques perform exceptionally well. We propose an analytical framework for understanding when crowds can be expected to provide wisdom and show, theoretically and empirically, that their efficacy is related to crowd sophistication and task complexity. Consistent with this framework, we find that a "crowd-of-crowds" approach, which combines EDGAR user co-searches and analyst co-coverage, dominates other state-of-the-art methods for identifying investment benchmarks.

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1. Introduction

Academic researchers and corporate managers often need to identify peer firms for economic benchmarking purposes. For example, peer firms' market-based pricing multiples are frequently applied to a base firm's fundamental variables to derive an estimate of the latter's value to investors. These multiple-based valuations are ubiquitous in investment bankers' fairness opinions and in sell-side analysts' reports. They are also commonly used in pricing initial public offerings (IPOs), leveraged buyouts, mergers and acquisitions, and other business investments.[1] In academic research, peer firms frequently serve as counterfactuals to help evaluate some aspect of a base firm's operating performance and/or valuation. For examples, in executive compensation analysis, peer firms are helpful in inferring whether an outcome is more attributable to luck or skill.[2] Likewise, in asset pricing, peer firms are used to control for returns earned by economically-similar companies over a given time period.[3] In these and many other settings, the central challenge is to objectively and judiciously select a group of economically comparable peer firms. Despite the widespread usage of peer firms, very little academic research is available to guide their selection. Some financial practitioners even suggest that the choice of comparable firms is "an art form" that should be left to valuation/investment professionals.[4] Nevertheless the aura of mystique that surrounds the peer selection process is discomforting from a scientific perspective. In fact, the degree of subjectivity often involved in peer selection can ultimately serve to undermine the credibility of peer-based pricing as a serious alternative in equity valuation. In this study, we conduct a systematic evaluation of a number of novel peer identification solutions that are currently available to

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[1]See, for example, DeAngelo (1990); Alford (1992); Kaplan and Ruback (1995); Kim and Ritter (1999); Liu, Nissim, and Thomas (2002); Bhojraj and Lee (2002); Damodaran (2012).

[2]For example, Antle and Smith (1986); Albuquerque (2009); Gong, Li, and Shin (2011); Dikolli, Hofmann, and Pfeiffer (2013); Jenter and Kanaan (2015); Lewellen (2015); Ma, Shin, and Wang (2016).

[3]Key studies that popularized characteristic-based benchmarking in asset pricing include Daniel, Grinblatt, Titman, and Wermers (1997) and Barber and Lyon (1997).

[4]For example, Golz.Jr (1986) and Woodcock (1993).

researchers and corporate managers. Unlike traditional benchmarking techniques that rely primarily on industry groupings, many of these new approaches bring "big data" methodologies to bear on this age-old problem. We summarize these new approaches and evaluate their efficacy in explaining out-of-sample variations in base firms': (a) stock returns, (b) valuation multiples, (c) growth rates, (d) leverage, and (e) profitability ratios. We consider six peer identification schemes. Three of these approaches, which we collectively refer to as **Product-Market Schemes**, are based on similarities in firms' products markets or business operations; three other approaches, which we collectively refer to as **Wisdom-of-Crowd Schemes**, feature algorithms that extract latent intelligence from the actions of multiple investors or market participants. As a point of reference, we compare the performance of these six candidate schemes to the performance of the peers identified using six-digit industry codes from the Global Industry Classification Scheme (GICS6).[5] The three Product Market Schemes we consider are: Capital IQ ("**CIQ**"), Google Finance ("**GOOG**"), and Text Network Industry Classification ("**TNIC**"). CIQ and GOOG are commercially available peer groupings. Capital IQ constructs its peer firm list (CIQ) by culling the self-reported set of competitors from base firms' regulatory filings.[6] Google identifies its list of "related companies" using a proprietary algorithm that includes input from a detailed product-market database.[7] Finally, TNIC is a scheme for identifying product market competitors, developed by Hoberg and Phillips (2010, 2014) based on analyzing textual similarities in companies' 10-K business descriptions. The three Wisdom-of-Crowd Schemes we examine are: Analyst Co-Coverage Peers ("**ACP**"), Search-based Peers ("**SBP**"), and Yahoo Finance Peers ("**YHOO**"). Lee, Ma, and Wang

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[5]Bhojraj, Lee, and Oler (2003) show GICS is the best performing Industry Classification Scheme for peer identification. Specifically, they show that GICS outperforms SICS codes, NAICS codes, and Fama and French (1997) industry classification codes. We therefore use GICS as a point of reference in our tests.

[6]Studies that use versions of Capital IQ peers include Rauh and Sufi (2012) and Lewellen (2015).

[7]Google Finance provides this list of "related companies" on the web page for each base company. These peer firms are not identical to co-search-based peers identified by Google Knowledge Graph. Our understanding is this list is at least partially based on input from Fact Set Research (previously Revere Data), a supplier of detailed product-by-product data on market competitors.

(2015) (heretofore LMW) identified the SBP firms using investors' information co-search patterns on the Securities and Exchange Commission's EDGAR website.[8] ACP identifies economically-related peers on the basis of shared co-coverage (or being co-covered) by the same sell-side analysts (Ramnath, 2002; Israelsen, 2016, Forthcoming; Kaustia and Rantala, 2015; Muslu, Rebello, and Xu, 2014). Finally, YHOO consists of peers identified using co-searched ticker symbols on Yahoo Finance (Leung, Agarwal, Konana, and Kumar, 2013). All six candidate schemes are described in detail in the Appendix. Our study proceeds in two stages. In the first stage, we run a "horse race" between these six peer identification schemes and present large-sample empirical evidence on their performance. Our results show the two top-performing peer identification algorithms, in rank order, are SBPs and ACPs. In particular, among S&P1500 base firms, SBPs registered a median improvement of 56.6% over GICS6 peers, in explaining cross-sectional variations in base firm's next year stock returns and financial ratios. In similar comparisons, ACPs registered a median improvement of 35.5% over GICS6. In contrast, the Product Market Peers (**CIQ**, **GOOG**, and **TNIC**) generally performed on par with, or worse than, the GICS6 peers. Interestingly, YHOO peers - those whose information are most commonly co-searched with the base firms' on Yahoo Finance - perform quite poorly. In sum, two of the wisdom-of-crowd approaches (SBP and ACP) strongly outperform while one sharply underperforms. The stark difference in the performance of the three crowd-based algorithms (SBP, ACP, and YHOO) motivates the second stage of this study. In this second stage, we use the peer identification setting to address a common question from the "wisdom of crowds" literature: when does information aggregation across a heterogeneous population of agents lead to better decisions? To provide intuition, we develop a simple model of aggregated co-search (co-coverage) decisions. The model features a population of agents, each of whom receives a private signal on the similarity between the base firm

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[8]Specifically, LMW computed a "co-search fraction", which captures the share of co-searches of the base firm owned by each peer firm. Their results show peer firms with the highest co-search fraction are most similar to the base firms on multiple dimensions.

and the candidate peer firm. In the context of this model, we show that the usefulness of information aggregation will depend on the precision of investors' signals about the firm, due to either (a) the inherent sophistication/skill of the set of individuals involved (e.g., retail vs. professional investors) or (b) the complexity of the task at hand (e.g., information environment of the firm). The model makes two primary predictions. First, the degree of crowd agreement about a base firm's best peers will be higher (i.e., higher co-search or co-coverage fractions) when investors receive more precise signals about the firm, either because the investors are more sophisticated or because the firms are relatively easy to analyze. Second, the performance of peers firms identified from wisdom-of-crowd approaches will improve when the crowd is more sophisticated in relation to the task at hand. We find empirical support for these theoretical predictions. Using three base firm characteristics as proxies for the average signal precision of investors' beliefs, we find that the degree of intra-crowd agreement, as measured by the co-search or co-coverage fractions, (a) increases with the size of the base firm, (b) decreases with its number of operating segments, and (c) increases with the base firm's investor and analyst attention. Moreover, we show that the peers identified by aggregating the wisdom of investment crowds are more effective when the crowd is more sophisticated and when the information environment of the firm is better. The fact that ACPs and SBPs perform so well and YHOO peers do not, is also consistent with the model's prediction that the noisier the agents' signal (or the lower their sophistication) the less informative are co-search (or co-coverage) fractions. Prior research suggests YHOO are likely generated by searches of retail investors (Lawrence, Sun, Ryans, and Laptev, 2016, Forthcoming), while analyst co-coverage and EDGAR co-search patterns reflect the revealed decisions of relatively more sophisticated agents (sell-side stock analysts and EDGAR users). The model also provides a framework for understanding information aggregation across disparate crowds (i.e. the factors that affect "inter-crowd" agreement). We use this framework to analyze how the degree of agreement between EDGAR users (SBPs) and analysts (ACPs)

varies as a function of base firm characteristics. Findings from prior studies suggest the information contained in ACPs is unlikely to be fully subsumed by SBPs.[9] Broadly speaking, SBPs reflect the choices of buy-side participants (investors) while ACPs reflect the choices of sell-side analysts. Consistent with model predictions, we show that the level of inter-crowd agreement between EDGAR users and sell-side analysts, as reflected in the similarities between ACPs an SBPs: (a) increases with the size of the base firm, (b) decreases with its number of operating segments, and (c) increases with the base firm's investor and analyst attention. Finally, we create a composite solution for identifying economically related firms by combining the two best performing algorithms (SBP and ACP). The model suggests this "crowd-of-crowds" approach could further improve the identification of investment peers, particularly when agents have relatively noisy signals about firms. Indeed, we find that the combination of top peer firms from both SBP and ACP outperforms SBPs significantly. For example, their combination explains 22.1% of the out-of-sample cross-sectional variation in returns for the S&P500 base firms, which compares quite favorably to the GICS6 peers, who are only able to explain 14.2% of the return variation. The composite peer performance is also significantly better than each of the two individual schemes (SBP or ACP) operating on a standalone basis. Notably, the improvement in performance from composite peers is concentrated among smaller firms, where the information environment is relatively poor and investors have less precise signals. Taken together, our results provide a compelling case for the broader use of "wisdom of crowd" techniques in identifying economically-similar firms for investment purposes. Our analyses show that the efficacy of this approach will depend on the intrinsic sophistication of the individuals in the population (i.e., the inherent level of collective wisdom attainable through sampling), and the quality and complexity of the information

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[9]In particular, prior studies show sell-side analysts' stock recommendations tend to favor larger growth firms with glamor characteristics (Jegadeesh, Kim, Krische, and Lee, 2004). At the same time, due to resource constraints (Peng and Xiong, 2006; Van Nieuwerburgh and Veldkamp, 2010), sell-side analysts tend to specialize by industries or sectors, and are less likely to cover stocks with widely-diverging business economics (Liang, Riedl, and Venkataraman, 2008; Groysberg and Healy, 2013; Brown, Call, Clement, and Sharp, 2015).

environment surrounding the firm. For the moment, it would appear that the state-of-the-art benchmarking methodology is one that combines firms identified as SBPs and ACPs. To assist future researchers, we have created a complete database of these top-performing peers (combining SBP and ACP) for each base firm in the S&P1500. This database is available upon request. Our work is directly related to a growing literature in financial economics that uses "big data" methodologies to improve economic benchmarking (Hoberg and Phillips, 2014; Lewellen, 2015; Rauh and Sufi, 2012; Leung, Agarwal, Konana, and Kumar, 2013; Kaustia and Rantala, 2015; Lee, Ma, and Wang, 2015). A glaring gap in this literature is the absence of a direct comparison of these state-of-the-art peer identification schemes. We provide this benchmarking exercise by bringing together a number of disparate approaches and testing them on a comprehensive set of performance metrics.

Our work is also related to two prior studies Bhojraj, Lee, and Oler (2003) and Lee, Ma, and Wang (2015) that used the same performance tests to evaluate peer identification schemes. In Bhojraj, Lee, and Oler (2003), these tests were used to compare the performance of alternative Industry Classification Algorithms. In Lee, Ma, and Wang (2015), these tests were used to evaluate the performance of SBP peers. We extend these two studies by: (a) examining a comprehensive set of "big data" peer identification schemes, (b) developing a model of efficient information aggregation across crowds, (c) providing empirical evidence on crowd/task attributes that impact information aggregation, and (d) designing a "crowd-of-crowds" solution to the peer identification problem and showing that it significantly outperforms other methods. Our paper helps explain seemingly disparate findings in Antweiler and Frank (2004)and Chen, De, Hu, and Hwang (2014). Both papers aggregate user-generated content on Internet websites to predict future stock returns - with varying success. Chen, De, Hu, and Hwang (2014) find that aggregated user-generated articles on Seeking Alpha predict both future stock returns and earnings surprises. Antweiler and Frank (2004) find a statistically significant but

economically insignificant result by aggregating user-content from Yahoo and Raging Bull's message boards. Consistent with our results and model, aggregated content from Seeking Alpha, an arguably more sophisticated user base, were more informative of future outcomes than aggregated content from Yahoo and Raging Bull. More broadly, our paper also contributes to an interdisciplinary literature on the wisdom of the crowds. Across many diverse scientific fields, researchers have been attempting to harness the wisdom of crowds with varying success (Simmons, Nelson, Galak, and Frederick, 2011; Lorenz, Rauhut, Schweitzer, and Helbing, 2011; Muchnik, Aral, and Taylor, 2013; Mollick and Nanda, 2015). More recently in accounting and finance, researchers have crowd-sourced earnings estimates (Jame, Johnston, Markov, and Wolfe, 2016) and even forecasted stock returns from Twitter feeds (Azar and Lo, 2016). In most of these settings, it is difficult to objectively measure the value added by crowd-based solutions. However, in the peer identification setting, we are able to deploy a set of performance metrics that quantify the improvement from crowd-based results. We are also able to provide some preliminary insights on which crowd/task attributes have a significant impact on the efficacy of crowd-based solution. The question of crowd efficacy has been of open interest in a wide range of fields including the study of fantasy baseball selection (Goldstein, McAfee, and Suri, 2014), identification of early stage cancer from medical imagery (Kurvers, Herzog, Hertwig, Krause, Carney, Bogart, Argenziano, Zalaudek, and Wolf, 2016), and the quality of general knowledge (Wikipedia) vs expert journalists (Greenstein and Zhu, 2014). Like us, these papers also find that crowd sophistication and task complexity are critical to its efficacy. To our knowledge, we are the first study to explore financial economic data and provide such insights into this growing field. We caveat that the wisdom-of-crowd approach examined in this paper may not be appropriate in certain peer-selection contexts. For example, for purposes of identifying product market competitors, alternative approaches, such as TNIC, may be more suitable. Nevertheless, our work provides a practical solution to the peer identification problem faced by a broad set of financial

professionals. In particular, the union set of SBP and ACP firms represents an objectively selected and highly effective peer group for investment and performance evaluation decisions. In addition, these wisdom-of-crowd peers can also help in research settings that involve performance benchmarking. Recently, for example, Ma, Shin, and Wang (2016) examined the efficacy of the benchmark peers chosen by firms that practice explicit relative performance evaluation (RPE), by comparing the extent to which RPE benchmarks explains the common component of firm returns relative to SBPs (i.e., a normative benchmark).[10] The remainder of the paper is organized as follows. We begin in Section 2 with an analysis of the performance of the various classification schemes relative to six-digit GICS. In Section 3, we provide an analytical framework to understand conditions under which wisdom of the crowds will lead to better peer identification and testable implications. Section 4 investigates the empirical implications of the model with respect to both the degree of intra-crowd agreement (within ACPs and SBPs) and also inter-crowd agreement (SBP vs ACPs) and provides evidence on the performance of a composite revealed-choice-based benchmarking solution. Section 5 concludes.

2. Comparing Alternative Benchmarking Schemes: Product Market vs. Wisdom of Investment Crowds

We begin by assessing the relative performance of two broad classes of benchmarking schemes: product-market-based and wisdom-of-the-crowd-based. All six candidate schemes employ some form of "big data" methodology. Together, they represent the frontier of peer identification schemes proposed by both industry and academia.

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[10] A central prediction of performance-based contracting models is that the principal should design contracts that filter out common shocks to performance i.e. that are outside the CEO's control. (Hölmstrom, 1979).

2.1. Benchmarking Candidates

We consider three state-of-the-art product-market-based approaches to identifying peers. The first candidate comes from Capital IQ (CIQ), who identifies firms' product market competitors named in SEC disclosures. In particular, CIQ collects the set of companies that a given firm i considers to be its competitors (coded as "Named by Company"), as self-disclosed in the company's SEC filings, the set of companies that considers firm i a competitor (coded as "Named by Competitor"), as disclosed in their SEC filings, and finally the set of firms considered to be firm i's competitors as disclosed in third party firms' SEC filings (coded as "Named by Third Party"). We define a firm's "CIQ" peers to be those competitors who are "Named by Company" or "Named by Competitor," similar to Rauh and Sufi (2012) and Lewellen (2015). The second candidate comes from Google Finance, who generates a list of each firm's "Related Companies" (GOOG peers) through a proprietary algorithm with FactSet Research's own proprietary product-market-based industry classification as one of its inputs. Finally, we consider the "Text Network Industry Classification" (TNIC), developed by Hoberg and Phillips (2010) and Hoberg and Phillips (2014). This scheme infers product market peers by analyzing and quantifying textual similarities in firms' self-reported business descriptions in their 10-K filings. We also consider three wisdom-of-the-crowd approaches for identifying peers. The first is "Search-Based Peers" (SBPs), developed by Lee, Ma, and Wang (2015), which identifies economically related firms based on EDGAR users' co-search patterns. The fundamental premise of SBPs is that more frequently co-searched peer firms tend to be more relevant investment benchmarks. This premise seems reasonable given that EDGAR users are collectively searching for firm fundamentals to aid their investment decisions, and that an important part of this process involves the comparison of these fundamentals to economically related benchmarks. We also consider the set of peers commonly co-searched by the users of Yahoo! Finance ("YHOO peers"). For example, when search-

ing for Google's information Yahoo Finance reports "People viewing GOOG also viewed PCLN AMZN BIDU AAPL MA NFLX." These peers are similar in concept to SBPs, but are derived from a different population. Prior evidence shows Yahoo! Finance users are predominately retail investors, who are likely to be less professional and sophisticated than EDGAR users.[11] Finally, we extend the idea of aggregating revealed preferences of crowds by examining the collective wisdom of sell-side analysts. Like SBPs, Analyst Co-Coverage Peers (ACPs) are based on the premise that the collective decisions of the crowd—in this case, coverage of firms—are at least in part driven by, and thus informative of, underlying economic comparability between firms.[12] Our thesis is that like patterns of co-search for firm fundamentals, aggregate patterns of analysts' co-coverage decisions can be informative of fundamental similarities between firms.[13] The details of the data construction for each peer identification scheme can be found in the appendix.

We compare the performance of these six "big data" schemes to that of the six-digit Global Industry Classification System (GICS6). GICS is a product of a collaboration between Standard & Poor's (S&P) and Morgan Stanley Capital International. It is based on the judgment of a team of financial analysts who group firms on the basis of their

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[11]According to Lawrence, Sun, Ryans, and Laptev (2016, Forthcoming), "Yahoo Finance is the most popular web site for financial information in the U.S. with over 30 million unique daily users, the vast majority of which are retail investors rather than professional investors."

[12]In theory, analysts have an incentive to cover economically similar firms because of the reduced cost of information acquisition (e.g., Peng and Xiong, 2006); empirically, research has shown that sell-side analysts tend to specialize in industries and cover multiple firms belonging to her primary industry of expertise (e.g., Liang, Riedl, and Venkataraman, 2008), and that a firm's fundamental similarity to the analyst's existing coverage portfolio is an important aspect of his decision to cover a particular firm Brown, Call, Clement, and Sharp (2015). On the other hand, there can be various other factors — for example, relating to the analysts' incentives or brokerage house characteristics — that drive analysts' coverage decisions. Liang, Riedl, and Venkataraman (2008) documents that analysts are more likely to cover a firm based on reasons idiosyncratic to the brokerage house: when the brokerage house has had a recent investment banking relationship with the firm or when the firm was previously followed by another analyst employed in but who is no longer forecasting for the same brokerage house. The evidence documented in Liang, Riedl, and Venkataraman (2008) and Brown, Call, Clement, and Sharp (2015) is also consistent with the possibility that there are systematic biases in analysts' coverage decisions: for example, analysts are more likely to cover high growth firms or firms that have investment banking relationships with the analysts' employers.

[13]The idea of identifying related firms based on analysts' coverage choices have been explored in the works of Ramnath (2002), Israelsen (2016, Forthcoming), Kaustia and Rantala (2015), and Muslu, Rebello, and Xu (2014).

principal business activity. A number of empirical research papers have provided evidence that GICS6 outperforms alternative industry classification schemes, such as the traditional SIC or NAICS codes (Bhojraj, Lee, and Oler, 2003; Chan, Lakonishok, and Swaminathan, 2007). Table 1 reports summary statistics of the peer sets that we collected. Product-market-based peers are grouped in columns 1 to 4 while the wisdom of investment crowd peers are grouped in columns 5 to 7. For each peer set, we report the number of base firms in either the S&P500, S&P1000, or S&P1500 for which we have available peer data. This number varies from peer set to peer set e.g. there are 1075 base firms with CIQ peers, but 1,465 base firms with TNIC peers. We also report the average number of peer firms for each set. For example, there are on average 5.1 CIQ peers, 7.7 GOOGLE peers, 79.2 TNIC peers, and 5 YHOO peers. Finally, we report the fraction of a scheme's peer firms which share the same six-digit GICS code as the base firm. For example, 59% of CIQ peer firms have the same six-digit GICS code as the base firm, 69% of GOOGLE peers, 48% of TNIC peers, 69% of ACPs, 61% of SBPs, and 28% of YHOO. It is perhaps not surprising to learn that the product-market-based peer (CIQ, GOOGLE, NIC) schemes appear to have greater overlap with GICS than the investment crowd peers (ACPs, SBP, YHOO).

2.2. Return and Accounting Co-Movement Performance Tests

We begin by comparing the six peer identification schemes in terms of their usefulness in explaining the cross-sectional variations in base firms' stock and accounting performance. These tests are common in the literature for assessing the fundamental similarity and comparability between firms (Bhojraj, Lee, and Oler, 2003; Lewellen and Metrick, 2010; Lee, Ma, and Wang, 2015), and provides a useful framework for assessing the usefulness of alternative peer classification schemes for either investment purposes or performance benchmarking. Our tests estimate contemporaneous cross-sectional regressions

of the following form:

$$Var_{i,t} = \alpha_t + \beta_t Var_{p_{i,t}} + \epsilon_{i,t}, \tag{1}$$

where $Var_{i,t}$ and $Var_{p,t}$ refer to the fundamental performance variable of interest over period t for the base firm (i) and its portfolio of peers (p). We then assess the relative performance across alternative peer schemes based on the average R^2s produced from these regressions. As noted in Lewellen and Metrick (2010) and Lee, Ma, and Wang (2015), higher R^2s reflect greater similarity and comparability between base firms and their peer firms. Specifically, using GICS6 as the benchmark for evaluation, we assess the relative performance of the alternative peer-identification schemes by comparing the average R^2 produced by cross-sectional regressions using benchmark portfolios of all firms (excluding the base firm) selected from the base firms' GICS6 industries versus the average R^2 produced by portfolios of the base firms' peers. In conducting these tests, we form portfolios using the peer firms identified by the respective schemes. Our product market peer candidates, GICS6, CIQ, GOOG, and TNIC, are formed based on an equal-weighted portfolio of all of the peers that are identified by the respective schemes.[14] We obtained June 2014 snapshots of CIQ, GOOG, and YHOO peers, and conservatively applied these peers to the years 2012 and 2013 in our tests. By contrast, GICS6, TNIC, ACP, and SBP have data from 2003 to 2013. Following Lee, Ma, and Wang (2015), for ACP and SBP we form a value-weighted portfolio of a base firm's top 10 peers, weighting by the relative magnitudes of the co-coverage and co-search fractions, respectively. We form equal-weighted portfolios for YHOO peers since there are no natural weights to apply as we do not observe the co-search fractions that underly Yahoo! Finance's algorithms. Table 2 reports the results of these tests across an array of fundamental performance

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[14]We also considered value-weighted GOOGLE peer portfolios. Google Finance reports a rank ordering of peers based on some proprietary algorithm; our value-weighted portfolio weights each peer firm based on the order in which it appears in Google Finance's listing of "Related Firms." For example, the firm that is reported first out of ten will receive the weight of $\frac{10}{\sum_{i=1}^{10} i} = \frac{2}{11}$. We find qualitatively similar results using this value-weighted approach. We only consider equal-weighted portfolios for CIQ peers since there is no meaningful ranking that we can observe.

variables for the set of base firms belonging to the S&P1500 index. The first row considers returns regressions, where we run cross-sectional monthly regressions using CRSP monthly cum-dividend return for each base firm i, taken from the CRSP monthly files, and $R_{p_{i,t}}$ is the average monthly returns for a portfolio of benchmark firms specific to base firm i. The odd-numbered columns report the average R^2 where the portfolio p consists of peer firms identified by each of the six candidate peer identification schemes. The even-numbered columns report the difference between the R^2 produced by the various alternative schemes named in the column header and GICS6 peers. Positive (negative) values represent distances when the candidate scheme achieved higher (lower) R^2 than the GICS6 peers. We report in this fashion because the underlying set of common firms to GICS6 and each scheme is different for each alternative scheme.[15] The results indicate that none of the alternative product market peer identification schemes outperform GICS6 in explaining the cross-sectional variation in base firms' returns. In fact, CIQ and TNIC produce R^2 values that are statistically significantly lower than those by GICS6. Both ACP and SBP significantly outperform GICS6, producing R^2s that are 0.131 and 0.141 higher than those of GICS6 peers, both statistically significant at the 1% level. Interestingly, the remaining wisdom-of-crowd candidate, YHOO, significantly underperforms GICS6. Rows 2-9, Table 2, complement the above results by comparing the performance of the alternative peer identification schemes in explaining the cross-sectional variation in valuation multiples and financial performance ratios. To perform these additional tests, we gather quarterly data from Compustat to compute each firm's price-to-book multiples (pb), enterprise value-to-sales multiples (evs), price-to-earnings multiples (pe), returns on net operating assets ($rnoa$), returns on equity (roe), asset turnover (at), profit

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[15]Lee, Ma, and Wang (2015) formed GICS6 portfolios using 10 randomly chosen GICS6 peers. In this study, we use all available GICS6 firms outside of the base firm. We made this choice for the following reasons 1) the benchmark maps more closely to GICS6 fixed effects, 2) empirically using all peers improves GICS performance vs 10 random peers, and 3) the traffic weighted SBPs' performance is stable with respect to the number of peers due to weighting and hence differences in performance are unlikely to stem from the number of peers chosen relative to GICS (see Figure 5 in Lee, Ma, and Wang (2015)).

margins (pm), leverage (lev), and one-year-ahead realized sales growth ($salesgrowth$). The exact computation of these variables (as well as all others used in this paper) is detailed in Table 2. These additional test results suggest that, overall, none of the alternative product market peer identification schemes systematically outperform GICS6 in explaining the cross-sectional variation of base firms' fundamentals. While CIQ peers nearly always significantly underperform, the performances of GOOG and TNIC are more mixed, significantly outperforming GICS6 in certain variables (e.g., evs, at, pm) but significantly underperforming in others (e.g., pb and $salesgrowth$). Both ACP and SBP outperform GICS6 systematically; in fact, both significantly outperform GICS6 in all eight fundamental variables considered. Unlike the other two wisdom-of-crowd schemes, the performance of YHOO is mixed, significantly outperforming GICS6 in three of the eight fundamental variables (pb,roe,lev) but significantly underperforming in four (evs, at, pm, $salesgrowth$). Table 3 summarizes the overall performance of the six alternative peer identification schemes. The odd-numbered columns report the median rank for each scheme in terms of the % change in R^2 relative to that produced by GICS6, across the nine fundamental variables examined. The even-numbered columns report the median % improvement in R^2 over GICS6. Among the set of S&P1500 base firms, reported in columns 1 and 2, we find that the overall best-performing peer identification schemes are SBP and ACP, with median % improvement in R^2 of 56.6% and 35.5%. The worst-performing peer identification schemes are CIQ and YHOO, with median % improvement in R^2 of -37.8% and -14.4%. Columns 3–4 and columns 5–6 report comparable summary of test results among the subset of S&P500 and S&P1000 base firms. These sub-sample tests provide similar conclusions: SBP and ACP are consistently the best-performing schemes while CIQ and YHOO are consistently the worst-performing schemes. These results pose an interesting empirical puzzle. Wisdom-of-crowd candidates, formed by aggregating the revealed choices of economic agents, simultaneously produced both the best and the worst performing peers. In the remainder of the paper, we explore and an-

alyze the conditions under which information aggregated across crowds provide wisdom in identifying appropriate investment peers.

3.   A Framework for Analyzing the Wisdom from Aggregating Crowd Decisions

In this section, we propose a stylized model to provide a framework to understand why, and under what circumstances, aggregating the collective choices (e.g., co-search) by investors can be expected to uncover the underlying fundamental similarities between firms as well as testable comparative statics. This model is anchored on the assumptions that investors, who intend to make an investment decision for some base firm, are performing benchmarking analyses to put the base firm's fundamentals into context. While the premise of the model is anchored on co-search, the intuition and predictions can be extended to the analyst co-coverage context without loss of generality.

3.1.   Model framework

There is a population of N homogeneous investors each interested in searching for comparative firms to benchmark against base firm 0's performance. For simplicity, assume there are two potential candidate firms, 1 and 2, whose fundamental similarities to firm 0 are characterized by distances $d_1 \geq 0$ and $d_2 \geq 0$. Without loss of generality, assume that firm 1 has greater similarity to the base firm 0, hence implying that $d_1 < d_2$. While the true values of d_1 and d_2 are unobserved, each individual investor i receives a noisy private signal of d_1 and d_2:

$$\hat{d}_1 = d_1 + \epsilon_{i,1}$$

$$\hat{d}_2 = d_2 + \epsilon_{i,2} \tag{2}$$

where $(\epsilon_{i,1}, \epsilon_{i,2})' \sim_{iid} N(\mu, \Sigma)$. Here, $\mu = (c_1, c_2)$ capture the collective biases that investors may have about d, and $\Sigma = (\sigma_1^2, \sigma_2^2, \sigma_{12})$ captures the covariance structure of the investor's signals, whose elements are assumed to be finite. After receiving the private signals, each investor i makes a singular choice of a benchmarking firm (1 or 2) to co-search along with base firm 0.[16]

3.2. Co-search fraction and comparative statics

Under this framework, investor i will pick firm 1 if and only if $\hat{d}_1 < \hat{d}_2$, or equivalently when

$$\epsilon_{i,1} - \epsilon_{i,2} < d_2 - d_1. \tag{3}$$

Thus for any given investor, the probability of selecting firm 1 is $\Phi\left(\frac{(d_2-d_1)-(c_1-c_2)}{\sqrt{\sigma_1^2+\sigma_2^2-2\sigma_{12}}}\right)$, where Φ is the CDF of a standard normal distribution, and $(\sigma_1^2, \sigma_2^2, \sigma_{12})$ represent the variances of the errors and their covariance, respectively. As the sample of investors $N \to \infty$, the population of investors that co-search fundamentals for base firm 0 and peer firms 1 and 2 will be equal to the following co-search fractions $f_{i,j}$:

$$
\begin{aligned}
f_{0,1} &= \Phi\left(\frac{(d_2 - d_1) - (c_1 - c_2)}{\sqrt{\sigma_1^2 + \sigma_2^2 - 2\sigma_{12}}}\right), \text{ and} \\
f_{0,2} &= 1 - \Phi\left(\frac{(d_2 - d_1) - (c_1 - c_2)}{\sqrt{\sigma_1^2 + \sigma_2^2 - 2\sigma_{12}}}\right)
\end{aligned}
\tag{4}
$$

where the co-search fraction can be interpreted as the degree of agreement between investors about which candidate peer firm is most similar to the base firm.

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[16]We limit this choice to simplify the model but the implications are without loss of generality if the choice set expanded to N firms.

3.2.1. Implication 1

This basic model generates a number of insights. First, the collective wisdom of investors reflected in the aggregated co-search fractions will capture the correct rank ordering of the most fundamentally similar benchmarks $d_1 < d_2$ if and only if

$$\frac{(d_2 - d_1) - (c_1 - c_2)}{\sqrt{\sigma_1^2 + \sigma_2^2 - 2\sigma_{12}}} > 0 \text{ or } d_1 + c_1 < d_2 + c_2 \tag{5}$$

In other words, as long as investors' biases in co-searching (e.g., from non-benchmarking motives, informational errors, or behavioral biases), $\mu = (c_1, c_2)$, are order preserving, then in large sample, investors' aggregated search fractions reveal the correct rank ordering of fundamental similarities between firms. Although this assumption is not directly testable, the next two implications, which are empirically testable, rely on this implication being true.

3.2.2. Implication 2

A second set of implications is that, under the assumption that investors' biases are order preserving, the model generates a number of testable comparative statics relating the level of the co-search fraction Φ, or the level of agreement among the crowd, to the precision of investors' signals about the candidate peer firms (σ_1^2 and σ_2^2). In particular, the co-search fraction ($f_{0,1}$) will be higher (i.e., more crowd agreement) when i) the degree of fundamental dissimilarity between the two candidate peer firm ($d_2 - d_1$) is higher, and ii) investors possess greater precision of information about the base firm (i.e., a lower σ_1^2). In other words, there will be greater agreement among the crowd when i) one peer firm is much more obvious of a candidate than the other peer firm (the gap between d_1 and d_2 is large), and ii) when investors have better information (low σ_1^2) about the degree of similarity between the candidate peer firm and the base firm.[17]

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[17]These results follow directly from the observation that the function in Eq. 4 is monotonic in ϕ.

3.2.3.   Implication 3

The last implication is that, under the assumption that investors' biases are order preserving, the noisier the investors' signals, e.g., due to either greater task complexity (firms with poorer information environments) or lower user sophistication (retail vs non-retail investors), the less wisdom that can be gleaned from aggregating the crowd's revealed choices. This follows from the observation that the maximum sampling variation of the co-search fraction is obtained for $\Phi(0) = \frac{1}{2}$.[18] Thus increasing the noisiness in investors' signals—increasing σ_1^2 or σ_2^2 and pushing $\Phi\left(\frac{(d_2-d_1)-(c_1-c_2)}{\sqrt{\sigma_1^2+\sigma_2^2-2\sigma_{12}}}\right)$ towards $\Phi(0)$—tends to increase the sampling variation in the sample co-search fraction $\hat{\Phi}$, making the aggregation less informative for identifying the best peers.

4.   Empirical Evidence of Model Implications

This simple model provides a framework for understanding the relative performance of SBP, ACP, and YHOO reported in Table 3. The fact that ACPs and SBPs perform so well and YHOO peers do not, is consistent with the model's prediction that the noisier the investors' signal (or the lower their sophistication) the less informative are co-search (or co-coverage) fractions. Whereas YHOO peers are likely generated by a disproportionate number of retail investors (Lawrence, Sun, Ryans, and Laptev, 2016, Forthcoming), analyst co-coverage and EDGAR co-search patterns reflect the revealed decisions of relatively more sophisticated sell-side stock analysts and EDGAR users. The on-average poorer performance of SBPs, ACPs, and YHOO among small firms (S&P1000), relative to large firms (S&P500), is also consistent with this prediction. Since investors tend to have less precise information about smaller firms, either due to their relatively poorer

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[18]In finite samples with N investors, the number of investors that choose firm 1, the correct benchmark, is distributed Binomial(N,Φ), and the observed finite sample search fraction $f_{0,1}$ has a sampling distribution with a mean of Φ and variance of $\frac{\Phi(1-\Phi)}{N}$.

information environment or due to a relatively low attention to such firms,[19] the aggregating investors' revealed choices would be less informative. Below we consider the model's predictions more rigorously, by first testing the implication that co-search and co-coverage fractions (i.e., the level of agreement in the crowd) are increasing in the precision of investors' signals about fundamental similarity. We then use the model's predictions to examine the circumstances under which the collective decisions of the crowd are most likely to provide useful information about investment peers. Finally, having validated the intuition provided by this model, we illustrate the efficacy of combining the wisdom across different crowds.

4.1. Intra-Crowd Agreement and Signal Precision

In this section, we investigate Implication 2, the relationship between the degree of intra-crowd agreement, Φ, about candidate peer firms and the precision of investors' signals about fundamental similarity (σ^2). We focus our analysis on SBPs and ACPs because we do not empirically observe Yahoo co-search fractions and because we believe the order preserving bias assumption is more likely to hold for these two groupings given the results in Table 3.[20] Borrowing from the information uncertainty literature (Jiang, Lee, and Zhang, 2005), we capture a firm's information environment through the following proxies: market capitalization, the number of 2-digit SIC-based operating segments, and finally the amount of revealed investor or analyst attention. We conjecture that larger firms who command investor and or analyst attention have richer information environments and therefore should result in greater crowd agreement with respect to peer firms. In contrast, Cohen and Lou (2012) show that information concerning operationally complicated firms are harder to process, and we, therefore, expect more disagreement with

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[19]For example, Da, Engelberg, and Gao (2011) finds a positive association between abnormal Google Trends searches (a measure of retail investor interest) and firm size.

[20]In particular, if the order preserving bias did not hold, then the greater precision in investors' signals about firms (i.e., large firms) the less informative would be the search fractions.

respect to peer firms. These conjectures motivate the following regression specification:

$$\Phi_{i,t} = \beta_0 + \beta_1 SizeDeciles_{i,t-1} + \beta_2 NOperatingSegments_{i,t-1} + \beta_3 Sparsity_{i,t-1}$$
$$+ GICS2_{i,t} + Year_t + \epsilon_{i,t} \quad (6)$$

where $SizeDeciles_{i,t-1}$ refers to the within-sample decile of market cap measured at the end of the year prior to the formation of the co-search or co-coverage fractions $\Phi_{i,t}$ for firm i. To be consistent with the model, we only include the closest peer's Φ in the regression above.[21] $NOperatingSegments_{i,t-1}$ refers to the number of distinct SIC2 operating segments as reported in the Compustat Historical Segment files, and $Sparsity_{i,t-1}$ is a dummy variable which equals 1 if the base firm in year $t-1$ ranks below the 25th percentile in the distribution of firms, as sorted by their total number of co-searches (or total number of analyst co-coverages). Finally, all specifications include GICS2 and year fixed effects. Standard errors are double clustered at the firm and year level. Table 4 reports results of the empirical specification in Eq. 6. Recall that the model predicts that co-search (co-coverage) will be increasing in the quality of the information environment— i.e. larger firms operating a single segment. with a lower sparsity of co-search (co-coverage). Panel A examines the determinants of the co-search fraction of the highest ranked SBP for each base firm in the sample period. In column 1, $SizeDeciles$ is positively and significantly associated with co-search fraction at the 1% level. In column 2, $NOperatingSegments$ is negatively and significantly associated with co-search fraction at the 1% level. In column 3, $SparseSBP$ is also negatively and significantly associated with the co-search fraction. Finally, in column 4, all of the information uncertainty proxies are included, and again all of the coefficients remain significant with signs consistent in the direction of the model's predictions. Panel B of the same table reports analogous tests explaining the co-coverage fraction. We find similar results to Panel A in columns 1 to 3 with the exception that

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[21]Results are qualitatively similar if we expand to the entire list of top 10 SBPs or ACPs.

NOperatingSegements is not significant, but with the expected sign. However, when we combine all of the determinants in column 4, each determinant is significant and signed in the expected direction. Overall, the co-search and co-coverage fractions behave in a way consistent with the comparative statics of the model. That is, there is more agreement about benchmark firms when investors' signals are more precise, due to either the information environment of the firm or the inherent complexity of the firm.

4.2. Efficacy of Performance Benchmarking and Signal Precision

Implication 3 of the model states that we should find variation in the efficacy of performance benchmarking based on the signal precision of the crowd. In particular, co-search (co-coverage) fractions are more informative of appropriate investment peers when the underlying precision of signals from the crowd is greater. We test this implication by re-performing the R^2 comparison in Table 2 for alternative sets of SBPs and ACPs generated from stratifications of the crowd based on measures of signal precision. The first dimension of signal precision we focus on is the selectiveness of co-search decisions. We operationalize selectiveness by examining the intensity of co-search of EDGAR users. In particular, EDGAR users whose daily number of unique pair-wise co-searches ranks below the 95th percentile in the distribution of users, are classified as "selective", while those above the 99th percentile are classified as "unselective" users.[22] Intuitively, unselective users co-search a larger number of firms, thus each individual co-search decision is less likely to be informative of fundamental similarity.[23] Panel A of Table 5 tests for this difference in the efficacy of SBPs across the dimension of selective vs unselective users. Rows 1 and 2 construct SBPs conditioning on the underlying set of selective and unselective users within the crowd. Relative to GICS6, SBPs formed from the selective

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[22]The 95th and 99th percentile cutoffs are based on our observation that any user in the 99th percentile or above is almost certainly robotic, and any below the 95th percentile is highly likely to be human. None of our main results are sensitive to reasonable perturbations in these cutoff rules.

[23]Peng and Xiong (2006) and Van Nieuwerburgh and Veldkamp (2010) provide a model of information acquisition behavior under search costs in a manner consistent with this line of argument.

crowd perform 39.2% better in R^2 whereas SBPs formed from the unselective crowd perform 49% worse. Consistent with the model, these differences are economically large and statistically significant at the 1% level. We also examine the second dimension of signal precision which we label as sparsity and is a measure of the degree of investors' attention to the base firm. For each base firm-year, we calculate the number of unique co-searches for base firm i and any other firm j. We classify base firms as sparse annually when their annual co-search levels are in the bottom 25% of the sample distribution and non-sparse otherwise. We interpret sparse firms as those operating in poor information environments and hence lower signal precision in the context of the model. We find that the performance of SBPs is 49.5% greater in R^2 relative to GICS6 in the set of non-sparse base firms. Among our sparse co-search base firm group, there is a small but statistically insignificant difference between SBPs and GICS6 in R^2. In Panel B of the same table, we perform analog tests for analyst co-coverage. We define co-coverage selectiveness in the same intuitive manner by classifying it based on analysts whose number of followed firms falls below the 90% in the distribution of followed firms in a given calendar year.[24] Analysts who follow more firms than the cutoff are classified as unselective. Rows 1 and 2 of Panel B indicate that selective ACPs outperform GICS by 24% whereas unselective ACPs underperform GICS6 by 14%, with both differences statistically significant. When we examine co-coverage sparsity, which is defined in the same manner as co-search sparsity using the 25% cut-off rule, we find that non-sparse base firm ACPs outperform GICS6 by 42.8% whereas sparse base firms ACPs' performance is statistically and economically indistinguishable from GICS6. Again, these results are broadly consistent with the predictions of the model and the findings in Panel A for SBPs. We note that these findings are not an immediate implication of the results of Table 4. That is, the fact that there is greater agreement among investors when their signals about firms are more precise does not imply that the resultant search fractions are necessarily more informative.

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[24]The annual 90% cutoff ranges from 17-22 firms in our sample period. Results are qualitatively similar when we use alternative cutoffs such as 95%.

If investors have (non-order-preserving) biases about firms, in particular, having more precise signals could, in fact, lead to less informative search fractions. Thus, our results in Table 5 suggest that, on average, the order-preserving bias assumption is met among sell-side analysts and EDGAR users.

4.3.   Inter-Crowd Agreement and Signal Precision

Having established that intra-crowd agreement within SBPs and ACPs and their efficacy for performance benchmarking is broadly consistent with the model's predictions, we now use the intuition gleaned from this analytical framework to analyze the usefulness of combining different crowds: EDGAR users and sell-side analysts. The model can be easily extended for an inter-crowd analysis, since, without loss of generality, we only need to re-interpret the individual investor in the model as a crowd of investors. We begin by exploring the extent to which agreements between SBPs and ACPs are associated with the characteristics of the underlying base firm. Implication 2 of our model predicts that agreement between the two crowds in identifying similar firms should increase in the precision of the crowds' signals about firm similarity. To test this prediction, we estimate the following analog specification of Eq. 6 below:

$$Agree(SBP, ACP)_{i,t} = \pi'\Psi_{i,t-1} + GICS2_{i,t-1} + Year_t + \epsilon_{i,t} \qquad (7)$$

where the new outcome variable is the degree of agreement between the top ten SBPs and ACPs firms of a given base firm i in year t. $Agree(SBP, ACP)$ ranges from 0 to 1, where 0 denotes no overlap between a firm's top 10 SBPs and top 10 ACPs and 1 denotes 100% overlap.[25] $\Psi_{i,t}$ is vector of identical base firm characteristics used in Table 4 such as $SizeDeciles$, $NOperatingSegments$, $SparseACP$, and $SparseSBP$. Table 6 reports estimates of Eq. 7. In column 1, $SizeDeciles_{i,t-1}$ is positively and signifi-

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[25]However, the rank ordering of the peers need not be identical across the two peer identification schemes.

cantly associated with agreement between ACPs and SBPs at the 1% level. In column 2, $NOperatingSegments_{i,t-1}$ is negatively and significantly associated with agreement. In column 3, both $SparseSBP_{i,t-1}$ and $SparseACP_{i,t-1}$ are negatively and significantly associated with agreement. Finally, when we include all proxies of information uncertainty and task complexity in column 4, the coefficients each remain significant with signs in the expected directions. These results are broadly consistent with the results in Table 4 and provide further evidence about the behavior of investors and analysts in their information acquisition in a manner consistent with the toy model.

4.4. Performance of Crowd-of-Crowds

Finally, we investigate the usefulness of combining the wisdom of different crowds. In other words, we seek to know whether there is incremental information captured by the disagreements between SBPs and ACPs. For example, despite the generally superior performance of SBPs and ACPs, there may still be incremental information in ACPs missing in SBPs and vice versa. In Table 7, we investigate whether a hybrid approach that combines both sets of revealed-choice-based benchmarks is incremental to the standalone performance of either ACPs or SBPs. This exercise is informative to researchers and practitioners who are interested in the practical question of peer selection for the purpose of performance benchmark. We focus here on the price co-movement test from Eq (1). Columns 1 to 3 of Table 7 reports the R^2 of the regressions for GICS6, standalone SBPs, and standalone ACPs, respectively to establish the baseline performances of each group. Column 4 reports results using the union of the set of top 10 SBPs and ACPs ("SBP∪ACP"). Across both the S&P1500 base firm sample (row 1), the S&P500 subsample of larger base firms (row 2), and the S&P1000 subsample of smaller base firms (row 3), we find that the union of the peer sets modestly outperform the standalone SBP and ACP grouping. These improvements range from a 2.8% to 9.2% relative to standalone SBPs in column 5 and 12.2% to 13% relative to standalone ACPs in column 6. In par-

ticular, the incremental improvement is greater among the smaller base firms, suggesting that there is a greater value in aggregating and combining the collective wisdom gleaned from the behavior of different types of sophisticated market participants. The findings in this section provide a best-performing set of revealed-choice-based benchmarks that combines the collective wisdom of EDGAR users and sell-side analysts. Moreover, our analysis here illustrates how the analytical framework proposed in this paper can be used to understand the circumstances under which aggregating economic agents' revealed decisions, or combining the wisdom produced between disparate crowds, are likely to be fruitful in producing investment benchmarks.

5. Conclusion

In today's knowledge-based economy, sharp distinctions between services and goods are becoming more difficult to draw. Top business enterprises are combining human and organizational capital in new ways that defy traditional industrial boundaries. For example, it is no longer unusual to see an online retailer (i.e., Amazon) compete with a web engine (i.e., Google) and an electronic hardware manufacturer (i.e. Apple) to supply cloud-based enterprise software and storage solutions. In this brave new world, financial researchers often need to reach beyond traditional industry groupings to find suitable peer firms for economic benchmarking purposes. In this paper, we consider six state-of-the-art peer firm identification schemes currently available to researchers and managers. While all six schemes deploy some sort of "big data" methodology, they fall into two distinct categories: 1) algorithms that identify peers through similarities in firms' product-market or business description, and 2) algorithms that identify peers by distilling the wisdom in investment crowds. We compute a wide set of performance metrics that help quantify the performance of these different schemes relative to a set of industry-based peers. Specifically, we evaluate each scheme's efficacy in explaining out-of-sample variations in base firms': (a) stock returns, (b) valuation multiples, (c)

growth rates, (d) financial leverage, and (e) profitability ratios. Our results show that two wisdom-of-crowd approaches perform particularly well. Specifically, we find that SBPs, which aggregate EDGAR users' perceptions of fundamentally related benchmarks, and ACPs, which are gleaned from aggregate patterns of analysts' co-coverage decisions, substantially outperformed GIC6 peers across all our test metrics. In stark contrast, peers identified by investors co-searching on Yahoo Finance, perform poorly. The product-market based schemes performed on par with or somewhat worse than the GIC6 peers. To contextualize these findings, we develop an analytical framework that provides guidance on the conditions under which a crowd is more likely to deliver wisdom. This framework delivers two key implications which we test and verify in the data. The first implication is that the degree of intra-crowd and inter-crowd agreement about a base firm's best matched peers will vary as a function of the precision of the information available about that base firm. The second implication is that the efficacy of the crowd-based solution will also depend on the precision of the information signal received by each agent, which varies with agent sophistication and task complexity. Collectively, our work provides a practical and straightforward solution to the peer identification problem faced by many finance professionals. We show that a combination of the peers identified by EDGAR users (SBP) and sell-side analysts (ACP) dominates the other peer identification schemes in our tests. Thus, the union set of SBP and ACP firms represents an objectively selected and highly effective peer group for investment and performance evaluation decisions. To assist future researchers, we make available our dataset of these top-matching peers for each firm in the S&P1500 and for each year in our sample. More broadly, our work also contributes to an interdisciplinary literature on the wisdom of crowds. In this literature, it is often difficult to objectively measure the value added by crowd-based solutions. We use the peer identification setting to quantify the improvement from crowd-based results. To our knowledge, this is the first study using financial economic data to provide such insights to a growing field. We are also able to provide some preliminary insights on which

crowd/task attributions have a significant impact on the efficacy of crowd-based solutions. It is our hope and expectation that these findings will stimulate further research on the usefulness and limitations of information aggregation across crowds.

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Appendix
Construction of Alternative Identification Schemes

A Product Market Peer Schemes

A.1 Global Industry Classification Scheme (GICS)

As described in Lee, Ma, and Wang (2015), the GICS scheme is provided through a collaborative between Standard &Poor's and Morgan Stanley Capital International. It is based on the judgment of a team of financial analysts who group firms on the basis of their principal business activity, determined either by observable sources of revenues and earnings or by market perceptions. We obtain each firm's global industry classification code from Compustat. We define a base firm's GICS peers as those firms (excluding the base firm) sharing the same six-digit GICS as the base firm.

A.2 Capital IQ

We download a June 2014 snapshot of product market competitors from Capital IQ. Capital IQ collects the set of companies that a given firm i considers to be its competitors (coded as "Named by Company"), as self-disclosed in the company's SEC filings, the set of companies that considers firm i a competitor (coded as "Named by Competitor"), as disclosed by their SEC filings, and finally the set of firms considered to be firm i's competitors as disclosed in third party firms' SEC filings (coded as "Named by Third Party"). We define a firm's "CIQ" peers to be those competitors who are "Named by Company" or "Named by Competitor," similar to Rauh and Sufi (2012) and Lewellen (2015).

A.3 Google Finance

We assemble "GOOGLE" peers by downloading the "Related Firms" listed on each firm's Google Finance page as of June 2014. Our understanding is that Google generates the list through a proprietary algorithm, with FactSet Research's (previously Revere Data) own proprietary product-market based industry classification as one of the inputs.[26]

A.1.4 Text Network Industry Classification (TNIC)

This classification scheme, developed by Hoberg and Phillips (2010) and Hoberg and Phillips (2014), infer product market peers and group firms into different "industry" groupings by analyzing and quantifying textual similarities in firms' self-reported business descriptions in their 10-K filings. Data on TNIC peers are obtained from the Hoberg and

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[26]This understanding is based on prior conversations with staff at Revere Data.

Phillips Data Library online.[27] Because TNIC is based on 10-K data, we assume that TNIC peers from fiscal year t are usable for out-of-sample tests from July of $t+1$ to June of $t+2$.

B Wisdom-of-Crowd Schemes

B.1 Analyst Co-Coverage Peers (ACPs)

To construct analyst co-coverage of firms, we obtain the detailed IBES forecast file covering the universe of analyst EPS forecasts for the calendar period 2003-2013 and remove anonymous analysts (id code=000000) similar to Brown and Hugon (2009).[28] To qualify as an analyst covering firm i, the analyst must have made at least one forecast for the firm in the calendar year. We define as analyst co-coverage fraction between firms i and j in year t:

$$Analyst\ co\text{-}coverage\ fraction_{ijt} = \frac{\#\ of\ analysts\ who\ co\text{-}cover\ i\ and\ j}{\#\ of\ analysts\ who\ cover\ i} \tag{8}$$

Intuitively, this fraction answers the question: what fraction of analysts who cover i also cover j. We define a given base firm's ACPs in calendar year t as those firms with the ten highest *analyst co-coverage fraction* in calendar year $t-1$.

B.2 Search-based Peers (SBPs)

Our data comes from the traffic log on the Securities and Exchange Commission's (SEC) Electronic Data-Gathering, Analysis, and Retrieval (EDGAR) website, and is an updated version of the data used in Lee, Ma, and Wang (2015).[29] The main advantage of the update is its greater time coverage; whereas the prior version of the data spans calendar years 2008 to 2011, this updated vintage contains data on visits to the EDGAR website from calendar years 2003 to 2011.[30] The format of the updated data is largely identical to the prior vintage: each observation in the raw data contains information on the visitor's IP address, timestamp, CIK, and accession numbers which uniquely matches to a particular company's specific SEC filing. An important difference in this update is that the data extraction process the SEC used differs from the one employed for the prior vintage of the data; the process was changed in order to accommodate the longer time series. As a result, the new and the prior vintages of data are not identical in the overlapping period from 2008 to 2011. To ensure the integrity of the updated data, we verify

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[27]We downloaded the May, 2013 version from http://alex2.umd.edu/industrydata/industryclass.htm

[28]Note that an analyst is defined as the unique combination of the broker and analyst ID from IBES such that an analyst who moves from one broker to another would be treated as a different analyst in our sample.

[29]More details about the data can also be found in Drake, Roulstone, and Thornock (2015) who uses the EDGAR search data to study investors' search patterns.

[30]The new data sample extends to March 2012, but we do not use the partial data in 2012 in this paper.

that the daily-user level search characteristics—for example, filing types accessed, unique CIKs (firms) accessed, total clicks made, and average time spent by a daily user—between these two datasets are not systematically and economically different in the overlapping period. These results are available from the author upon request. One of the empirical challenges in using the data is filtering out search traffic generated by automated scripts ("robots"), written to download massive numbers of filings. To filter out these uninformative searches, we classify any daily user downloading more than the 95th percentile in the distribution of unique CIK's within the corresponding calendar year as a robot.[31] Using this filtered search traffic data, we infer investors' perceptions of relevant economic benchmarks by aggregating information from their fundamental information acquisition behavior. Under the assumption that the population of EDGAR users is collectively searching for firm fundamentals to aid their investment decisions, and that an important part of this process involves the comparison of these fundamentals to economically related benchmarks, we expect EDGAR users search sequences to be informative of their perceptions of the most relevant set of benchmark firms. Following this observation, we restrict our analysis to searches for 10-Ks and 10-Qs — including their amendments or small business variants — to focus on investors' patterns of acquiring fundamental information that most likely captures benchmarking behavior. Using this filtered data, we extract the set of most relevant economic benchmarks to any particular firm i by defining *Annual search fraction*, f_{ij}^t, between the base firm i and a peer firm j in calendar year t:

$$f_{ij}^t = \frac{\Sigma_{d=1}^{365}(\text{Unique daily-user searches for } i \text{ and } j)_d}{\Sigma_{d=1}^{365}(\text{Unique daily-user searches for } i \text{ and any firm } j \neq i)_d}. \qquad (9)$$

In words, f_{ij}^t is the fraction of unique *daily-users* searching for firm i who also searched for firm j's information, summed across all the days in a given calendar year. This is a more generalized version of the co-search algorithm employed in Lee, Ma, and Wang (2015), which defined co-searches based on chronologically sequential clicks in a given day.[32] Our *Annual search fraction* measure sums to one for each firm in a given year, and is easy to interpret. For example, $f_{GOOGLE,YHOO}^{2008}$=0.0602 means that 6.02% of daily-users searching for Google's fundamental information and at least one other firm in calendar year 2008, also searched for Yahoo's information. By construction, we do not use any information from users who only search for a singular firm's filings before leaving the EDGAR website. Based on this measure, we define a given base firm's top 10 SBPs in a given calendar year t as those peer firms with the ten highest values of *Annual search fraction* in the preceding calendar year $t-1$, similar to how we define a firm's ACPs. The analyses of this paper focus on the set of base firms that belong to the S&P1500 index

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[31]This is a generalization of the method used by Lee, Ma, and Wang (2015), which used an absolute cutoff that classifies all daily IPs downloading more than 50 unique CIKs as a robot, a cutoff that corresponded to the 95th percentile of user search activity in the 2008 to 2011 sample. Given the longer time series in our updated search data, we employ an annual percentile rather than an absolute cutoff.

[32]In Lee, Ma, and Wang (2015), if a user clicks on Google and then Yahoo, Yahoo is considered a peer of Google, but not vice versa. The co-search algorithm used in this study relaxes these chronological ordering restrictions, and consider firms i and j to be benchmarks for each other, so long as they are co-searched together by the same user within the same calendar day EDGAR session. In other words, we are building a network of firms with "weighted undirected edges" defined through co-searches.

as of January 1 of each calendar year; however, no such restrictions are placed on the set of benchmark firms.[33]

B.3 Yahoo! Finance Peers (YHOO)

Yahoo! Finance makes available to users the set of firms which also viewed the base firm: for example, when searching for Google's information Yahoo Finance reports "People viewing GOOG also viewed PCLN AMZN BIDU AAPL MA NFLX." We download a snapshot of YHOO peers in June 2014 for a total of 922 unique base firms.[34] Note that unlike SBPs and ACPs, Yahoo Peers are defined exclusively by Yahoo's own proprietary co-search algorithms.

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[33]Previously in LMW, peer firms were restricted to be within the same S&P1500 universe as base firms.

[34]Note that Yahoo displays the co-searched tickers on a randomized basis per page refresh, consistent with the issue highlighted in Kremer, Mansour, and Perry (2014) that full transparency is inefficient due to reduced incentives to provide novel information. To fully capture the Yahoo co-searched tickers, our algorithm refreshes the page until Yahoo displays the results. In contrast, EDGAR co-searches and search-based peers are not observable by investors, who receive no "recommendations."

Table 1.

Summary Statistics of Product Market and Wisdom of Crowd Solutions to Investment Peer Identification

This table reports characteristics of the S&P1500 base firms available for each identification scheme as of December 2012. Rows 1 ∼ 3 provide counts of the number of base firms falling under the S&P500 index, the converse S&P1000 index, and finally the entire S&P1500 index. Row 4 reports the average number of available benchmark firms for each specific scheme and row 5 provides the average fraction of peers from each identification scheme which share the same GICS6 grouping as the base firm. For example, 69% of a base firm's Google search peers are also in the same GICS6 grouping. Finally, row 6 describes the relevant time period for which we conduct tests under each identification scheme.

The first four set of schemes aims to capture the notion of peers in the same product market space. The first scheme represents peers based on the GICS6 grouping. The second scheme represents the set of self-reported product market competitors disclosed in SEC filings and collected by CapitalIQ (CIQ). Specifically, the CIQ peer set represents the union of the set of firms j that firm i report as its competitors and also the set of firms j that report i as a competitor. The third scheme represents the list of firms that Google Finance (GOOGLE) reports as a base firm's "Related Firms" as of June 2014. The fourth scheme is the "Text Based Network Industry Classification" (TNIC) of Hoberg and Phillips (2010, 2014), and is derived from the set of peer firms with the most similar self-reported business descriptions in their 10-K filings to the base firm's.

The next set of schemes capture peers derived from the wisdom of investment crowds. The fifth scheme represents analyst co-coverage peers (ACP), similar to that of Israelsen (2016, Forthcoming), Kaustia and Rantala (2015), and Muslu, Rebello, and Xu (2014), defined by applying the *Analyst co-coverage fraction* of Eq 8 to the entire IBES sample and retaining the ten peer firms with the highest co-coverage fractions. The sixth scheme represents the search-based peers (SBP) of Lee, Ma, and Wang (2015), defined by applying the *Annual search fraction* of Eq 9 to the SEC EDGAR search traffic data. The last scheme represents the list of common co-searched firms as reported by Yahoo Finance (YHOO) as of June 2014.

	Product Market Peers				*Wisdom of Investment Crowds Peers*		
	GICS6	CIQ	GOOGLE	TNIC	ACP	SBP	YHOO
N SP500 Base Firms	498	398	413	484	428	487	414
N SP1000 Base Firms	998	677	675	981	862	995	508
N SP1500 Base Firms	1496	1075	1088	1465	1290	1482	922
Avg. N Peers	36.7	5.13	7.69	79.18	10	10	5.04
Correspondence with GICS6	–	0.59	0.69	0.48	0.69	0.61	0.28
Sample Test Years	2003-2013	2012-2013	2012-2013	2003-2013	2003-2013	2003-2013	2012-2013

<div align="center">

Table 2.

Co-Movement Tests of Product Market and Wisdom of Crowds Approaches to Investment Peer Identification

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This table presents a comparison between GICS6 and alternative benchmark identification schemes that rely on either product market and wisdom of investment crowds approaches. Table values in the odd-numbered columns represent the baseline average R^2 from cross-sectional regressions of the form

$$Var_{i,t} = \alpha_t + \beta_t Var_{p_{i,t}} + \epsilon_{i,t}$$

where the portfolio p consists of peer firms identified by each of the six candidate peer identification schemes. Specifically, $Var_{p_{i,t}}$ is the average of each variable computed across all the peer firms identified by a particular scheme. These regressions take the form of either monthly cross-sectional returns regressions (row 1) or quarterly cross-sectional regressions using the most recently observable quarterly financial statement data from Compustat and market capitalization data from CRSP on March, June, September, and December of each year (remaining rows).

The table values in the even-numbered columns report the difference between the R^2 produced by the various alternative schemes named in the column header and GICS6 peers. Positive (negative) values represent distances when the candidate scheme achieved higher (lower) R^2 than the GICS6 peers. We report in this fashion because the underlying set of common firms to GICS6 and each scheme is different for each alternative scheme.

Each row in the table considers a different performance metric ($Var_{p_{i,t}}$). Specifically, *Returns* refers to monthly cum-dividend stock returns. *pb* refers to the price-to-book ratio and is defined as market cap scaled by total common equity [ceqq]. *evs* refers to enterprise value to sale ratio and is defined as the sum of market cap and long-term debt [dlttq] scaled by net sales [saleq]. *pe* refers to the price-to-earnings ratio and is defined as market cap scaled by net income before extraordinary items[ibq]. *roe* refers to return on equity and is defined as net income before extraordinary items [ibq] scaled by total common equity [ceqq]. *at* refers to the inverse of asset turnover and is defined as total assets[atq] scaled by net sales [saleq]. *pm* refers to profit margin and is defined as net operating income after depreciation [oiadp] scaled by net sales [saleq]. *lev* refers to leverage and is defined as long-term debt [dlttq] scaled by total stockholders' equity [seqq]. Finally, *salesgrowth* refers to one-year-ahead realized sales growth and is defined as the difference between the net sale one year ahead in the future and the current year's net sales all together scaled by the current year's net sales [saleq].

The various alternative benchmark schemes considered are Capital IQ (CIQ) peer firms (columns 1), Google Finance peer firms (column 3), Text Network Industry Classification (TNIC) peer firms (column 5), co-coverage-fraction-weighted portfolio of analyst co-coverage (ACPs) peer firms (column 7), EDGAR co-search-fraction-weighted portfolio of search-based peers (column 9), and finally Yahoo Finance co-searched peer firms (column 11).

The results are reported for the sample of base firms that belonged to the S&P1500, at the beginning of a given calendar year. Significance levels are indicated by *, **, *** for 10%, 5%, and 1%, respectively.

Table 2 [Continued]

	Product Market Peers						Wisdom of Investment Crowds Peers					
	CIQ		GOOG		TNIC		ACP		SBP		YHOO	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Returns	0.030***	-0.041***	0.084***	0.002	0.077***	-0.028***	0.131***	0.027***	0.141***	0.040***	0.055***	-0.036***
	[0.004]	[0.008]	[0.007]	[0.005]	[0.005]	[0.002]	[0.006]	[0.002]	[0.006]	[0.003]	[0.012]	[0.011]
No. Months	24	24	24	24	114	114	120	120	120	120	24	24

Valuation Multiples

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
pb	0.011**	-0.064***	0.034***	-0.034***	0.039***	-0.007**	0.083***	0.032***	0.111***	0.064***	0.138***	0.059***
	[0.003]	[0.005]	[0.003]	[0.005]	[0.002]	[0.003]	[0.003]	[0.002]	[0.004]	[0.004]	[0.011]	[0.015]
evs	0.178***	-0.108***	0.313***	0.038***	0.328***	0.023***	0.375***	0.077***	0.465***	0.168***	0.122***	-0.160***
	[0.007]	[0.004]	[0.004]	[0.008]	[0.006]	[0.004]	[0.004]	[0.002]	[0.005]	[0.004]	[0.029]	[0.027]
pe	0.013***	-0.006	0.020**	-0.003	0.027***	-0.005*	0.042***	0.011***	0.045***	0.014***	0.018**	-0.005
	[0.003]	[0.007]	[0.006]	[0.007]	[0.003]	[0.003]	[0.004]	[0.002]	[0.004]	[0.003]	[0.007]	[0.010]

Financial Statement Ratios

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
roe	0.010***	-0.011**	0.025***	0.002	0.025***	-0.007**	0.047***	0.015***	0.072***	0.041***	0.051***	0.027***
	[0.002]	[0.003]	[0.004]	[0.005]	[0.002]	[0.003]	[0.004]	[0.002]	[0.004]	[0.003]	[0.008]	[0.007]
at	0.305***	-0.043	0.583***	0.084***	0.484***	0.078***	0.543***	0.127***	0.598***	0.192***	0.355***	-0.154***
	[0.018]	[0.025]	[0.007]	[0.007]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.004]	[0.031]	[0.030]
pm	0.106***	-0.034***	0.257***	0.084***	0.246***	0.038***	0.306***	0.103***	0.385***	0.186***	0.026***	-0.149***
	[0.006]	[0.006]	[0.011]	[0.004]	[0.006]	[0.005]	[0.006]	[0.004]	[0.008]	[0.005]	[0.005]	[0.009]
lev	0.011***	-0.011*	0.033***	0.007	0.068***	-0.002	0.101***	0.039***	0.110***	0.048***	0.052***	0.029***
	[0.001]	[0.005]	[0.003]	[0.004]	[0.006]	[0.004]	[0.006]	[0.005]	[0.006]	[0.004]	[0.007]	[0.005]
salesgrowth	0.016***	-0.078***	0.138***	-0.034**	0.212***	-0.042***	0.317***	0.068***	0.312***	0.070***	0.161***	-0.027***
	[0.002]	[0.015]	[0.011]	[0.012]	[0.017]	[0.005]	[0.020]	[0.005]	[0.018]	[0.005]	[0.018]	[0.008]
No. Quarters	8	8	8	8	38	38	40	40	40	40	8	8

Table 3.
Summary of Relative Performance

This table provides a summary of the main results in Table 2. For each peer group identification scheme, we report the median percentage improvement in R^2 relative to GICS6. These R^2s are based on the cross-sectional regressions reported in Table 2, including the regression related to stock returns, valuation multiples, and financial statement ratios. For each peer identification scheme, we also report the median of its ranked performance improvement relative to GICS6 across all the performance metrics. Columns (1)-(2) report the results of the S&P1500 base firms; columns (3)-(4) report results for the S&P500 base firms; and columns (5)-(6) report results for the S&P1000 base firms.

	S&P1500		S&P500		S&P1000	
	Median Rank	Median % Improvement	Median Rank	Median % Improvement	Median Rank	Median % Improvement
	(1)	(2)	(3)	(4)	(5)	(6)
Product Market Peers						
CIQ	6	-37.8%	6	-20.9%	5	-40.0%
GOOG	3.5	8.7%	4	23.0%	4	-13.0%
TNIC	4	-2.9%	4	11.7%	4	12.2%
Wisdom of Investment Crowds Peers						
ACP	2	35.5%	2	72.7%	2	38.3%
SBP	1	56.6%	1	100.0%	1	64.6%
YHOO	5	-14.4%	4.5	7.7%	5.5	-22.2%

Table 4.
The Relation Between Signal Precision (σ^2) and Intra-Crowd Agreement (Φ)

This table tests the model's comparative statics of the relationship between the signal precision of a candidate peer firm (σ^2) and agreement within a crowd about the candidate peer firm (Φ). Panels A and B of this table report regression results of the co-search and co-coverage fraction of a base firm on firm characteristics associated with σ^2. Co-search and co-coverage fractions are defined using the nearest SBP (ACP) to be consistent with the model with observations at the base firm-year level.

We nominate the following base firm characteristics as proxies for the average signal precision of investors' beliefs. *"SizeDeciles"* are annual within-sample deciles of a firm's market capitalization. *"NOperatingSegments"* is the number of reported segments with distinct SIC2 classifications. *"SparseSBP"* and *"SparseACP"* are dummy variables which equals 1 for base firms i located in the bottom quartile in the annual distribution of total co-search or co-coverage respectively for firm i and $j \neq i$. All of the covariates described are measured in the year prior to the formation of the co-search and co-coverage fraction dependent variables.

GICS2 and year dummies are included in every specification. Standard errors reported in square brackets are two-way clustered at the base firm and year level. Significance levels are indicated by *, **, *** for 10%, 5%, and 1%, respectively.

Panel A: Determinants of Φ (Co-search Fraction)

	Expected Sign	Co-Search Fraction			
		(1)	(2)	(3)	(4)
SizeDeciles	(+)	0.002*** [0.000]			0.002*** [0.000]
NOperatingSegments	(−)		-0.003*** [0.001]		-0.004*** [0.001]
SparseSBP	(−)			-0.010*** [0.001]	-0.005*** [0.002]
Observations		14,368	14,368	14,368	14,368
Adj R^2		0.1626	0.1559	0.1580	0.1827
GICS2 Fixed Effects		Y	Y	Y	Y
Year Fixed Effects		Y	Y	Y	Y

Panel B: Determinants of Φ (Co-coverage Fraction)

	Expected Sign	Co-Coverage Fraction			
		(1)	(2)	(3)	(4)
SizeDeciles	(+)	0.017*** [0.001]			0.016*** [0.001]
NOperatingSegments	(−)		-0.000 [0.003]		-0.009*** [0.003]
SparseACP	(−)			-0.072*** [0.007]	-0.019** [0.008]
Observations		14,470	14,470	14,470	14,470
Adj R^2		0.1024	0.0428	0.0687	0.1066
GICS2 Fixed Effects		Y	Y	Y	Y
Year Fixed Effects		Y	Y	Y	Y

Table 5.
Signal Precision (σ^2) and Crowd Efficacy

This table compares the average R^2 values from monthly cross-sectional regressions of the form

$$R_{i,t} = \alpha_t + \beta_t R_{p_{i,t}} + \epsilon_{i,t}$$

using CRSP returns data from January 2004 to December 2013 generated from two dimensions of crowd sophistication: 1) selectiveness and 2) sparsity.

In both Panels, columns 1~3 report average R^2s from monthly cross-sectional regressions, regressing base firm i's' returns in a given month t on the concurrent returns of a portfolio p_i of peers. Column 1 considers an equal-weighted portfolio of all peer firms from the base firm's GICS6 industry drawn from the $S\&P1500$ index; column 2 in Panel A (B) considers a co-search-weighted (co-coverage-weighted) portfolio of the firm's 10 SBP (ACPs) firms. Column 3 test for the significance of the differences in average R^2s between the SBP or ACP portfolios and the GICS6 peer portfolio. To facilitate comparisons, all the regressions are conducted using the same underlying set of firms. The variable N in parentheses represents the average cross-sectional sample size for each monthly regression and standard errors are reported in square brackets. Significance levels are indicated by *, **, *** for 10%, 5%, and 1%, respectively.

The first dimension of crowd sophistication is co-search (co-coverage) selectiveness. We define selectiveness based on the number of concurrent firms co-searched (co-covered)by the same EDGAR user (analyst). Selective co-search refers to the set of SBPs derived from users whose number of unique daily co-searched firms is less than the 95% in the user distribution of unique daily co-searched firms and is identical to our baseline results in Table 2. Unselective co-search refers to the set of SBPs derived from users in the 99% to 99.5% percentile in the co-search distribution. For co-coverage, we define selective as the set of ACPs derived from analysts whose number of firms followed in a given year is less than the 90% in the distribution of firms followed in a given year. Unselective co-coverage refers to the set of ACPs derived from analysts in the 90% to 95% in the co-coverage distribution.

The second dimension of crowd sophistication is co-search (co-coverage) sparsity. Sparsity is defined at the base firm level and refers to whether firm i in a given calendar year is in the bottom 25% in the total amount of co-searches for i and $j \neq i$. Finally, non-sparse refers to the set of base firms who experienced total co-searches above the annual 25% level.

Table 5 [Continued]

Panel A: EDGAR Crowd Sophistication

	GICS6 (1)	SBP (2)	(2)-(1) (3)
Co-search Selectiveness			
Selective (N= 1,461)	0.102***	0.141***	0.040***
	[0.005]	[0.006]	[0.003]
Unselective (N= 1,461)	0.102***	0.052***	-0.050***
	[0.005]	[0.004]	[0.003]
Co-search Sparsity			
Non-Sparse (N= 1,095)	0.111***	0.165***	0.055***
	[0.005]	[0.006]	[0.003]
Sparse (N= 366)	0.080***	0.085***	0.005
	[0.006]	[0.006]	[0.003]
Number of Months	120	120	120

Panel B: Analyst Crowd Sophistication

	GICS6 (1)	ACP (2)	(2)-(1) (3)
Co-coverage Selectiveness			
Selective (N= 1,292)	0.104***	0.129***	0.025***
	[0.005]	[0.005]	[0.002]
Unselective (N= 892)	0.129***	0.110***	-0.018***
	[0.006]	[0.006]	[0.002]
Co-coverage Sparsity			
Non-Sparse (N= 979)	0.126***	0.180***	0.054***
	[0.006]	[0.007]	[0.004]
Sparse (N= 326)	0.056***	0.055***	-0.001
	[0.004]	[0.004]	[0.003]
Number of Months	120	120	120

Table 6.
The Relation Between Signal Precision (σ^2) and Inter-Crowd Agreement (Φ)

This table tests the model's comparative statics of the relationship between the signal precision of a candidate peer firm (σ^2) and agreement across crowds (EDGAR users and analysts) about the candidate peer firm (Φ). The outcome variable is the observed % agreement in a base firm's set of top 10 SBPS and ACPs with observations at the firm-year level. The explanatory variables are firm characteristics associated with σ^2.

We nominate the following base firm characteristics as proxies for the average signal precision of investors' beliefs about the firm's candidate peer firms. *"SizeDeciles"* are annual within-sample deciles of a firm's market capitalization. *"NOperatingSegments"* is the number of reported segments with distinct SIC2 classifications. *"SparseSBP"* and *"SparseACP"* are dummy variables which equals 1 for base firms i located in the bottom quartile in the annual distribution of total co-search or co-coverage respectively for firm i and $j \neq i$. All of the covariates described are measured in the year prior to the formation of the co-search and co-coverage fraction dependent variables.

	Expected Sign	Agreement Between SBPs and ACPs			
		(1)	(2)	(3)	(4)
SizeDeciles	(+)	0.028*** [0.002]			0.012*** [0.002]
NOperatingSegments	(−)		-0.006* [0.004]		-0.017*** [0.003]
SparseSBP	(−)			-0.102*** [0.010]	-0.078*** [0.009]
SparseACP	(−)			-0.181*** [0.008]	-0.152*** [0.009]
Observations		14,187	14,187	14,187	14,187
Adj R^2		0.1632	0.0478	0.2410	0.2567
GICS2 Fixed Effects		Y	Y	Y	Y
Year Fixed Effects		Y	Y	Y	Y

Table 7.
Performance of Crowd-of-Crowds Peers

This table compares the average R^2 values from monthly cross-sectional regressions of the form

$$R_{i,t} = \alpha_t + \beta_t R_{p_{i,t}} + \epsilon_{i,t}$$

using CRSP returns data from January 2004 to December 2013. Columns 1∼4 report average R^2s from monthly cross-sectional regressions, regressing base firm i's returns in a given month t on the concurrent returns of the relevant peer portfolio p_i. Column 1 considers an equal-weighted portfolio of GICS6 peers in the relevant base firm universe; Column 2 considers an equal-weighted portfolio of top 10 SBP firms, ranked by the prior calendar year's *Annual Search Fraction* f_{ij}, defined as the fraction of daily-users searching for both firm i and j's' information on the same day conditional on searching for firm i and any other firm $\neq i$, aggregated over the course of a calendar year; Column 3 considers an equal-weighted portfolio of top 10 ACP firms, ranked by the prior calendar year's *Annual Co-coverage Fraction* f_{ij}, defined as the fraction of analysts who issue a forecast for firm i who also issue a forecast for firm j in a given calendar year; Column 4 considers an equal-weighted portfolio of peer firms that belong to both the top 10 SBP and ACP portfolios.

The results are reported for the sample of base firms that belonged to the S&P1500, S&P500, or S&P1000 index at the beginning of each calendar year. To facilitate comparisons, all the regressions are conducted using the same underlying set of base firms. As a sampling requirement, all base firms reported here have at least one overlapping peer firm between ACPs and SBPs. The variable N in parentheses represents the average cross-sectional sample size for each monthly regression and standard errors are reported in square brackets. Significance levels are indicated by *, **, *** for 10%, 5%, and 1%, respectively.

	GICS6 (1)	SBP (2)	ACP (3)	SBP∪ACP (4)	(4)-(2) (5)	(4)-(3) (6)
SP1500 Base Firms	0.107***	0.141***	0.132***	0.150***	0.009***	0.018***
(N= 1,195)	[0.006]	[0.006]	[0.006]	[0.006]	[0.001]	[0.001]
SP500 Base Firms	0.142***	0.214***	0.197***	0.221***	0.006***	0.024***
(N= 410)	[0.008]	[0.008]	[0.008]	[0.008]	[0.002]	[0.002]
SP1000 Base Firms	0.083***	0.120***	0.115***	0.130***	0.011***	0.015***
(N= 777)	[0.005]	[0.006]	[0.006]	[0.006]	[0.001]	[0.001]
Number of Months	120	120	120	120	120	120