Analysts' Choice of Peer Companies

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Abstract

This is the first large-scale study to examine the peer companies used by sell-side equity analysts in their research reports. Using a unique hand-collected data set, we investigate the manner in which analysts choose peer companies as well as the relation between peer valuation and peer choice by analysts. We first show that analysts are more likely to choose peer firms that are similar in size, leverage, asset turnover, industry classification, and trading volume, to the firm they are recommending. However, controlling for those firm characteristics, we find that analysts on average select peer companies with *high valuations*, consistent with analysts choosing peers strategically. We further find that this effect varies systematically with analysts' reputation, analysts' incentives, and expected firm growth. We also find partial support for the idea that the selection of peers with high valuations helps explain the widely documented optimistic bias in stock recommendations.

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1. Introduction

This is the first study to systematically examine sell-side equity analysts' choice of peers in a large sample. Analysts are sophisticated users of financial statement information who provide, among other things, earnings estimates, valuations (including target prices), and stock recommendations for the firms they cover. These analysts often use peers in their research to compare performance and valuations across firms as well as to estimate the valuation of the firms they cover. Moreover, analysts' within-industry comparisons comprise a large part of their value-added (Boni and Womack 2006).

Financial analysis textbooks commonly recommend the use of peers. Yet, there is little theory to guide the choice of peers in valuation and performance comparisons. While empirical researchers have studied which multiples best explain stock price as well as how to choose peers (Boatsman and Baskin 1981; Alford 1992; Bhojraj and Lee 2002; Liu, Nissim, and Thomas 2002, 2007), the extant literature has not yet examined how peers are chosen in practice.

We hand-collect analysts' reports from Thomson Investext and manually extract the information on peer firms from the reports. Using this unique data set, we are able to observe and examine the peers used by analysts in their research reports. In cross-sectional analyses, we first show that analysts are more likely to choose peers that are similar in size, leverage, asset turnover, industry classification, and trading volume, to the firm they are recommending. Documenting how analysts choose peer firms in practice is new to the literature.

Next, we consider the relation between peer valuation and peer choice by analysts. If an analyst is induced to estimate a high valuation for a firm she covers, one possible strategy would be to choose peer companies with high valuation multiples so as to make the firm in question appear relatively undervalued. We test for this effect using four valuation multiples: earnings to price, book to price, sales to enterprise value, and EBITDA to enterprise value. Controlling for the above firm characteristics, we show that analysts tend to *select peers with higher valuations*, consistent with analysts choosing peers in an optimistic manner. In addition to being a novel finding by itself, this result could potentially explain (or at least contribute to explaining the mechanisms for) findings in the extant analyst literature, such as optimistically-biased stock recommendations.

We further examine whether the relation between peer valuation and peer choice varies systematically with analyst and firm factors. Specifically, we focus on analyst reputation, analyst incentives, and expected firm growth. Previous research suggests that analysts who are ranked by *Institutional Investor Magazine* (*II*-ranked analysts) exhibit superior performance in a variety of settings. We find that the relation between peer valuation and peer choice is reduced (and in fact disappears for three of the four valuation multiples we consider) for *II*-ranked analysts, suggesting that higher analyst skill significantly reduces the optimistic bias in peer selection. Second, we investigate whether the relation between peer valuation and peer choice is increasing in analyst incentives. Indeed, we find that this is the case; our results indicate that the bias is larger for firms with greater external financing needs, suggesting analysts choose peers strategically to increase the chances of attracting investment banking business. Finally, prior research, such as Bradshaw (2004) and Barniv, Hope, Myring, and Thomas (2009, 2010), suggests that analysts tend to overemphasize firms' growth opportunities. Consistent with this idea, we find that the relation between peer valuation and peer choice increases in firms' expected growth. We further provide some evidence supporting the idea that the bias in peer choice partially explains some of the well-documented optimistic bias in stock recommendations.

While the literature normally considers analysts as sophisticated financial information intermediaries with significant firm-specific knowledge, given that our empirical evidence suggests that there is an optimistic bias in analysts' peer selection, it is an empirical question whether the manner in which peers are chosen by analysts is helpful in forecasting firm fundamentals. Thus, although our primary interest in this study is to examine how analysts choose their peers, as additional analyses we also test whether a peer prediction model based upon how sell-side analysts choose peers in practice has incremental ability to forecast future firm valuation multiples. Specifically, using the Bhojraj and Lee (2002) model of peer choice as a benchmark, we find that the peers predicted by our analyst model have additional explanatory power. In other words, using the peer prediction model in this paper improves upon the Bhojraj and Lee model, suggesting the usefulness of analysts in predicting peers for relative valuation.

Our research, which benefits from being the first to employ a comprehensive data set of the comparables actually used by sell-side analysts in their research reports, offers a unique contribution to the literature. Our study responds to Bradshaw's (2011) call for research into analysts' activities beyond their earnings forecasts and stock recommendations.[1] While the extant literature typically relies on industry- and/or size-based peers, we offer insights about the peers used in practice by sell-side financial analysts. Whereas existing research recommends how peer firms should be selected for valuation purposes, our research design describes which comparables are used by analysts, investigates whether and how peer valuation affects the selection of peers, and shows how this varies cross-sectionally.[2]

[1] In a recent survey reported in *Institutional Investor* (October 2010), investors were asked to rate the importance they place on a dozen sell-side equity analyst research attributes. The highest ranked attribute was industry knowledge (see also Kadan, Madureira, Wang, and Zach 2012). In contrast, earnings estimates ranked last out of the twelve attributes. One way that analysts impart their industry knowledge is through their written reports, which include analyses employing peer firms as benchmarks.

[2] Our study also adds to the valuation literature (e.g., Bhojraj and Lee 2002) by showing that using our peer prediction model improves the forecasting ability of existing models to forecast future valuation multiples.

In addition to contributing directly to research on financial analysts, our paper also relates to an emerging stream of research that examines peers or benchmarks. Using comparable or peer companies ("peers" hereafter) as a benchmark is common among both practitioners and researchers. Peers are used by financial analysts to support their valuation multiples, earnings forecasts, and overall stock recommendations (e.g., Bradshaw, Miller, and Serafeim 2010), by investors to judge the merits and comparability of investments (e.g., De Franco, Kothari, and Verdi 2011), by fund managers in structuring their investment portfolios (e.g., Chan, Lakonishok, and Swaminathan 2007), by compensation committees in setting executive compensation (e.g., Albuquerque 2009; Albuquerque, De Franco, and Verdi 2012), in determining valuation multiples (e.g., Bhojraj and Lee 2002), by auditors in applying analytical procedures (e.g., Hoitash, Kogan, and Vasarhelyi 2006; Minutti-Meza 2011), and by researchers in choosing estimation samples to detect earnings management (e.g., Ecker, Francis, Olsson, and Schipper 2011). To use peer-firms as benchmarks or comparables requires relying on the comparability of financial information and its mapping into valuation, compensation, or other variables of interest. Our study investigates the manner in which analysts choose peer firms.

The next section reviews the relevant literature and develops our research questions. Sections 3 and 4 present the research design and sample selection, respectively. Section 5 discusses the main empirical findings and corroborative findings. Section 6 concludes the article.

2. Background and Research Questions

2.1. Brief Background on Peer Firms in Equity Valuation

Financial analysis textbooks commonly recommend the use of peer firms in valuation (Healy and Palepu 2007; Stickney, Brown, and Wahlen 2007; Damodaran 2009). Valuing firms using multiples of their financial or operating drivers is a simple and popular approach to valuation (e.g., Baker and Ruback 1999; Imam, Barker, and Clubb 2008; Block 2010). Using multiples to estimate a firm's value assumes the firm should be valued by capitalizing earnings (or cash flows, or sales, or some other metric) at a given price-earnings (or price-cash flow, enterprise value-sales, or other) multiple, such as the mean or median multiple for a set of comparable firms. Unlike the discounted cash flow and residual income valuation approaches, the use of multiples (at least seemingly) avoids the problems of estimating the required return (i.e., the discount rate or cost of capital) and of forecasting terminal values. However, implementing a multiples approach has its challenges. As Baker and Ruback (1999) outline, these challenges include choosing the appropriate value driver (i.e., cash flow or earnings or otherwise), choosing the peers against which to compare the firm, and measuring the peer multiple associated with these peers.

There is little theory to guide the selection and use of peers in valuation and performance comparisons. Empirical researchers have considered which multiples best explain stock price, as well as how to choose peer firms. Liu, Nissim, and Thomas (2002; 2007) compare the performance of numerous value drivers (forward earnings, historical earnings, cash flows, book value, and sales) and find that multiples derived from forward earnings best explain stock price. Boatsman and Baskin (1981) test the price-to-earnings (P/E) valuation method using as a firm's peer each of a random firm from the same industry, and the firm from the same industry with the most similar earnings growth rate. They conclude that the second approach is more accurate. In a study of P/E multiples, Alford (1992) finds that comparable firms from the same industry or with similar risk and earnings growth outperform comparable firms chosen from the broader market or with similar size or analyst long-term growth forecasts. Kim and Ritter (1999) and Roosenboom (2007) investigate the use of multiples by underwriters for firms undergoing initial public offerings.[3] Bhojraj and Lee (2002) argue that the choice of comparable firms used should be a function of the variables that drive cross-sectional variation in a given valuation multiple and demonstrate the efficacy of their approach. (In additional analyses below we compare their model to our analyst-based peer choice model.)

2.2. How Are Peer Firms Selected?

The initial focus of our study is how peers are chosen in practice by sell-side equity analysts. To the best of our knowledge, no prior large-scale empirical evidence exists on this issue. As Litov, Moreton, and Zenger (2012) argue, analysts make substantial investments in understanding complementarities within groups of similar firms. Litov et al. note that, the more unusual the strategy relative to peer companies in an industry, the less coverage the firm receives by analysts. We are motivated by these observations as well as by arguments in widely used financial statement analysis texts and well-cited academic studies in picking variables to construct our set of economic factors. Thus, although we acknowledge that there is limited theory to guide the empirical analyses, our approach is grounded in extant research. Generally speaking, we consider comparable firms to be those firms in the same industry that have similar size, similar accounting return drivers, and similar share characteristics (see Section 3 for details). To the extent that the explanatory variables load as predicted, and to the extent that the model has explanatory power for analysts' actual selection of peer firms, we consider analysts to be making peer choices guided by economic factors.

[3] In a recent study, Ecker et al. (2011) examine how the criteria for choosing estimation samples (peer firms) affect the ability to detect discretionary accruals.

2.3. Potential Effect of Bias in Peer Selection

Although we expect analysts to pick peer firms based on attributes described in financial statement analysis texts and elsewhere, we know from the literature that analysts have incentives other than to merely maximize investor wealth. (Bradshaw (2011) provides an overview of the literature on biased analysts.) In other words, given the discretion in peer selection, there is a potential for analysts to choose peers in a biased manner. Specifically, if, based on her incentives the analyst wants to recommend that investors "buy" a stock, one way to justify the higher value would be to strategically pick peer firms with high valuations. However, as there are incentives for analysts to also be accurate, it is an empirical question whether analysts on average choose peers with higher valuations.

2.4. Conditional Analyses to Explore Variation in Bias (if any)

Given that the literature suggests there are both costs as well as benefits to being optimistic, we expect optimistic bias to be more prevalent in certain contexts. In the following, we explore the effects of analyst ability, analyst incentives, and expected firm growth.

2.4.1. Effects of Analyst Ability

We are interested in examining whether "high-ability" analysts, defined to include those analysts who are ranked by *Institutional Investor* (*II*) magazine, exhibit less bias than other analysts. This ranking is a first-order determinant of an analyst's compensation (Groysberg, Healy, and Maber 2011). Extant research suggests that *II*-ranked analysts exhibit higher ability as evidenced through their greater forecasting accuracy, stock recommendation profitability, and report readability (e.g., Stickel 1990, 1992; Gleason and Lee 2003; De Franco, Hope, Vyas, and

Zhang 2012).[4] We further expect that institutional investors demand less biased (or more neutral) advice.[5] Accordingly, we test whether the relation between peer choice and peer valuation is mitigated for higher-ability analysts.

2.4.2. Effects of Analyst Incentives (External Financing)

Research shows that sell-side analysts do not always act in the best interests of investors. Rather, analysts may be serving personal objectives, such as increasing their compensation, improving relations with management, garnering investment banking business for their brokerage firm, "hyping" the stock to garner brokerage trading volumes, and increasing the value of shares personally owned (e.g., Lin and McNichols 1998; Michaely and Womack 1999, 2005; Heflin, Subramanyam, and Zhang 2003; Ertimur, Sunder, and Sunder 2007; Ke and Yu 2007; Barniv et al. 2009, 2010). Prior research demonstrates that affiliated analysts (i.e., those with direct investment banking business with the firm) issue more optimistic forecasts (Dugar and Nathan 1995; Lin and McNichols 1998; Dechow, Hutton, and Sloan 2000).[6] Based on these prior findings, we predict that the relation between peer choice and peer valuation, if any, in peer selection will increase in analysts' incentives, proxied for by firms' external financing needs following Bradshaw, Richardson, and Sloan (2006).[7]

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[4] Gleason and Lee (2003) find that forecasts made by *Institutional Investor* analysts (1) elicit a stronger immediate price response and (2) are followed by a less pronounced subsequent price drift.

[5] For example, Clarke, Khorana, Patel, and Rau (2007, 728) state that, "one explanation for our results is that the reputational concerns of all-star analysts make them less likely to succumb to pressure from their investment bank to alter their earnings forecasts and recommendations to increase deal flow."

[6] Das, Levine, and Sivaramakrishnan (1998) and Lim (2001) suggest that forecast optimism is used to increase access to management, especially in cases where the information asymmetry between management and investors is high.

[7] We use firms' external financing needs rather than investment banking affiliation because it can be objectively computed for all sample firms.

2.4.3. Effects of Expected Firm Growth

Financial analysts appear to be especially focused on firms' growth opportunities. For example, Bradshaw (2004) shows that analysts give the highest recommendations to growth stocks. In particular, analysts recommend stocks with strong growth potential, even if such potential is already impounded into the stock price (Barniv et al. 2009, 2010). Consistent with these ideas, Bradshaw (2004) finds that stock recommendations are not significantly associated with buy-and-hold one-year future returns.[8] Given analysts' preoccupation with growth, we conjecture that the relation between peer selection and peer valuation is increasing in firms' expected growth opportunities.

3. Research Design

Using a unique hand-collected data set, we first observe and describe which peers are used by analysts in their research reports. Using a probit specification, we then consider how analysts choose peer firms.

$$PeerChoice_{ijk} = \alpha + \Sigma\, \beta_m\, Economic\ Factor_{m,ij} + \varepsilon_{ijk}. \tag{1}$$

In Equation 1, $PeerChoice_{ijk}$ is an indicator variable that equals one if analyst k's report on firm i contains peer j in determining valuation, and equals zero otherwise. The treatment sample (i.e., *PeerChoice* = 1) for this test includes peers actually chosen by analysts in their reports. To estimate the model, we require a sample of peers not chosen by analysts. To provide observations in which *PeerChoice* = 0, we randomly match each selected peer j with a firm from

[8] Bradshaw (2004) concludes that analysts rely on simple heuristics rather than more sophisticated residual income valuations to recommend stocks.

the universe of companies in the same GIC 2-digit industry as the firm *i*, with available data, and not chosen by the analyst in the report. Thus we have an equal number of selected and non-selected peers in the sample, for each firm *i*. We limit the sample of peers chosen and not chosen by analysts to those in the same GIC 2-digit industry because for the analysts' reports in our sample, we find that 92% of the peer firms chosen by analysts are from the same 2-digit GIC industry. Similar to Boni and Womack (2006), we note that GIC industry definitions seem to better represent analyst choices than SIC classifications as only 68% of peers are from the same 2-digit SIC industry.

Economic Factor is a set of *M* variables expected to explain the choice of peers within a similar industry.[9] This set designates factors not associated with any bias by the analyst. These factors include standard economic factors, such as similar size and industry, on which firms are often matched by academic researchers (e.g., Barber and Lyon 1996), as well as several other potential dimensions. From a practitioner perspective for example, Koller, Goedhart, and Wessels (2005) recommend choosing peers based on similarity in risk, growth, and after-tax return on capital. It is an empirical question as to which economic factors better explain peers actually used in practice.

The following are the economic factors used in our tests. Based on a review of leading financial analysis texts and prior academic research, we start with similarity in revenues (i.e., size), revenue growth, leverage, asset turnover, profit margin, stock price volatility, trading volume turnover, and stock return. *LogSales* is the natural logarithm of total revenues in year *t-1*. *SalesGrowth* is year *t-1* revenues less year *t-2* revenues scaled by year *t-2* revenues. *Leverage* is total long-term debt divided by total assets at the end of year *t-1*. *AssetTurnover* is total revenues divided by total assets in year *t-1*. *ProfitMargin* is income before extraordinary items divided by

[9] All variables used in the study are defined in Appendix A.

total revenues in year *t-1*. *Volatility* is the standard deviation in monthly stock returns during the four years ending in year *t-1*. *Turnover* is the volume of shares traded divided by shares outstanding in year *t-1*. *Return* is the stock return during year *t-1*.

To measure the "similarity" between firms and their potential peers, we take the absolute value of the difference between firm *i*'s and peer *j*'s respective variables at time *t-1* and multiply the difference by -1. We then add the prefix *Sim_* to the variable. For example, *Sim_LogSales* is our proxy for similar size and equals the absolute value of the difference between the logarithm of total revenues for firm *i* and the logarithm of total revenues for peer *j*, both measured at the end of fiscal year *t-1*. We multiply the variable by -1 so that greater values indicate more similarity.[10]

Note that we focus on the similarity in accounting return components (i.e., sales, sales growth, leverage, asset turnover, and profit margin) between firms to capture closeness in firm fundamentals. At the same time, we extend our analysis to stock-based components including volatility, turnover, volume, and returns. This allows our analysis to capture similarities in firm fundamentals as well as in a firm's information and trading environments. In addition, because stock returns reflect both realized and anticipated performance, tests that encompass stock-related components might capture similarities in longer-term economic performance. These measures can also capture similarity in risk.

Our economic factors further include comparability in earnings and returns as employed by De Franco, Kothari, and Verdi (2011) and Bhojraj, Lee, and Oler (2003). *ComparabilityEarn* is the R^2 from a regression of firm *i*'s quarterly earnings on the quarterly earnings of firm *j* during the 16 quarters ending in year *t-1*. *ComparabilityRet* is the R^2 from a regression of firm *i*'s monthly returns on the monthly returns of firm *j* during the four years ending in year *t-1*. These

[10] A value of zero for *Sim_LogSales* would apply when the firm and its (potential) peer have identical sales.

measures are defined so that greater values indicate more comparability. The intuition underlying these measures is as follows. Changes in input prices or customer demand for firms with similar business models should translate into similar changes in accounting and economic profitability, which in turn translates into stock returns and earnings performance covarying over time for similar peers.

Last, we include variables that indicate whether the peers and firms are in the same industry using more finely partitioned industry categories.[11] *SameGIC3digit* is an indicator variable that equals one if the firm is in the same 3-digit GIC code as the potential peer, and zero otherwise. *SameGIC5digit* is an indicator variable that equals one if the firm is in the same 5-digit GIC code as the potential peer, and zero otherwise.

For each of the above economic factors, a positive association between a potential peer *j*'s similarity to firm *i* and the probability that the company (*j*) is chosen as a peer is consistent with analysts using economic factors to guide peer selection, ceteris paribus.

We next consider the effect of peers' valuation multiples on analysts' choice of peers. We augment the Equation 1 specification with peers' valuation multiple.

$$PeerChoice_{ijk} = \alpha + \gamma\ Multiple\ Peer_j + \Sigma\ \beta_m\ Economic\ Factor_{m,ij} + \varepsilon_{ijk}. \qquad (2)$$

Multiple Peer is a peer's valuation multiple and is measured in the reciprocal, that is with enterprise valuation or price in its denominator so as to reduce the impact of extreme values (Liu, Nissim, and Thomas 2002; De Franco, Gavious, Jin, and Richardson 2011). We consider the following four widely used valuation multiples: earnings to price (*E/P*), book to price (*B/P*), sales to enterprise value (*S/EV*), and EBITDA to enterprise value (*EBITDA/EV*). A negative

[11] Kadan et al. (2012) conclude that industry expertise is an important aspect of sell-side research.

association between a potential peer's valuation multiple and the probability that the company is chosen as a peer, after controlling for the economic factors, is consistent with peers being chosen in an optimistically-biased manner.

Next, we test whether peer selection bias varies with the three conditioning factors using the following model:

$$PeerChoice_{ijk} = \alpha + \gamma_1\, Multiple\ Peer_j \times CondFactor + \gamma_2\, Multiple\ Peer_j + \gamma_3\, CondFactor + \Sigma\, \beta_m\, Economic\ Factor_{m,ij} + \varepsilon_{ijk}. \tag{3}$$

where *CondFactor* is either *II-Rank*, *ExtFin*, or *ExpGrowth.* A positive coefficient on the interaction between *II-Rank* and *Multiple Peer* would be consistent with *II*-ranked analysts being less optimistically biased than other analysts. Finding a negative coefficient on the interaction between *ExtFin* and *Multiple Peer* would suggest that analysts are more likely to be optimistically biased when the firm needs external financing. Finally, observing a negative coefficient on the interaction between *ExpGrowth* and *Multiple Peer* would provide support for the idea that any optimistic bias is increasing in expected firm growth.

We measure *II-Rank* as an indicator variable that takes the value of one if the analyst is *II*-ranked in a given year, and zero otherwise. *ExtFin* is a continuous measure of external financing. We follow Bradshaw et al. (2006) in defining *ExtFin* as the change in both equity and debt financing. Finally, we proxy for the firm's expected growth (*ExpGrowth*) by its market-to-book ratio. To be precise, we use the book-to-market ratio multiplied by minus one. (We use book-to-market instead of market-to-book as the latter has more extreme observations.)

4. Data, Sample Selection, and Descriptive Statistics

The peers that an analyst uses in her analysis are not available in a machine-readable form in existing databases. We use a hand-collected sample of analysts' reports from Thomson Investext and manually extract peer information from the reports. We collect a sample of analyst reports from 2005 and 2008.[12] The high cost of collecting the peer information limits our analysis to two years of data. For examples of peer valuations used in sell-side equity analysts' research reports, we direct the reader to Appendix B.

The reports are chosen as follows. We begin with all firms (i.e., firm *i*'s) in our sample with data available on Compustat and CRSP. For a randomly-selected subset of these firms, we search Investext to find up to three reports per firm *i*, each written by a different analyst and each mentioning the word "comparable" or "peer" firms (i.e., potential peer *j*'s) in the report. Peer information is manually collected from the analysts' reports. We read through the analyst report to ensure that the peer companies listed are the ones used for benchmarking purposes. This is important because peers can also be used in other contexts, such as in written discussions of firm *i*'s industry dynamics. We find that about 98% of the analyst reports that we identify explicitly use peers to benchmark valuation. We collect financial information from CRSP and Compustat for each of the peer *j* firms mentioned in the analysts' reports. As discussed below, we also collect information for a sample of non-selected peers within the same industry. The sample is further reduced by the requirement of financial variables for the peer *j* firms, plus the random matching process we employ. The final sample is 1,575 report-year observations (for 1,339 unique firms) and 8,968 peers (3,090 unique peers). To mitigate the influence of outliers, all continuous variables are winsorized at the top and bottom 1%.[13]

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[12] Inferences throughout this study are unchanged when we limit our sample to only the 2005 or the 2008 reports.
[13] Inferences are unaffected if we do not winsorize variables.

Table 1, Panel A presents descriptive statistics for the number of peers mentioned per analyst report. For the final sample of firms, the average firm has approximately 5.7 peers with available data to perform the analyses. In addition, there is considerable cross-sectional variation in the number of peers selected per analyst report. Specifically, the 5th percentile equals one peer firm per analyst report whereas the 95th percentile equals 14 peer firms.

We compare the characteristics of firms covered by analyst reports, and firms chosen by analysts as peers in their reports. Table 1, Panel B provides these descriptive statistics. We find that the firms covered in analyst reports and those chosen as peers in the analyst reports, are similar in sales growth, leverage, and asset turnover.

5. Test Results

This section describes the results of our main tests. The first subsection provides analyses of economic factors in explaining peer choice, followed by an analysis of the relation between peer selection and peer valuation multiples. We next report conditional analyses in which we consider the effects of analyst ability, analyst incentives, and expected firm growth. We further provide some preliminary evidence on the relation between optimistic biases in peer choice and stock recommendations. Finally, we report the results of whether our prediction model is useful in forecasting future valuation multiples. Reported standard errors are clustered at the firm level because the estimation of Equations 1 through 3 could suffer from time-series dependence.[14]

5.1. Regression Analyses

5.1.1. Benchmark Regressions Using Only Economic Factors

Table 2, Panel A shows the Probit estimation results of various specifications of

[14] Inferences throughout are similar when we instead cluster standard errors by analyst.

Equations 1 and 2. Model-fit statistics indicate that the number of companies correctly classified as chosen peers is 87.9%, and the pseudo-R^2 is 54.1%, suggesting that the model captures a large portion of the variation in peer firm selection.

The first column of Table 2 Panel A presents results using only the economic factors (i.e., Equation 1) and provides support for the assertion that analysts' peer selection captures similarity in firm characteristics. In particular, analysts are more likely to choose companies as peers if the company is similar in size, leverage, asset turnover, and share turnover, as well as when the potential peer is of the same industry (using both three- and five-digit GIC codes). For example, the coefficient on *Sim_LogSales* is 0.175 and significantly different than zero. In addition, the coefficients on both the earnings and returns comparability measures are positive and statistically significant. The tests provide some weaker evidence that sales growth, return volatility, and recent returns matter (i.e., the two-sided *p*-values are 0.14, 0.15, and 0.11, respectively). We do not find evidence that profit margin differences are important to peer selection. Overall, we conclude that analysts select peer firms that are similar along several important economic dimensions, addressing our first research question regarding how peers are selected in practice.

5.1.2. Tests of Peer Valuation and Peer Selection

We next test the effects of peer valuation multiples on peer selection. The second through fifth columns of Table 2, Panel A show the results of the full estimation of Equation 2. Specifically, the coefficient on *Multiple Peer* is negative and significantly different from zero (at the one percent level) in each column. In Column 2 the coefficient on *Multiple Peer - E/P* is

-2.516,[15] while in Column 3, the coefficient on *Multiple Peer - B/P* is -0.320. In Column 4, the coefficient on *Multiple Peer - S/EV* is -0.067; in Column 5, the coefficient on *Multiple Peer - EBITDA/EV* is -0.618. These results are consistent with analysts choosing peers with higher valuation multiples. These findings support the idea that analysts choose peers in an optimistically-biased manner.

To assess the economic significance of the results, in untabulated analyses, we rerun the analyses with each continuous variable standardized to mean zero and unit variance. Using this approach, in Column 3, for every one-standard deviation increase in *Multiple-B/P Peer*, there is an approximate 18% change in the probability that firm *j* is chosen as a peer. For *Multiple Peer - E/P*, *Multiple Peer - S/EV*, and *Multiple Peer - EBITDA/EV*, the equivalent economic effects are 11%, 9%, and 10%, respectively. As a comparison, for a one-standard deviation change in *SimSales*, there is an approximate 24 to 29% change in the probability that firm *j* is chosen as a peer.

5.1.3. Robustness Tests

We provide several robustness tests in Panel B of Table 2. For brevity we only tabulate the results for *Multiple Peer - E/P test* (the most widely used multiple in practice) but the inferences for the other valuation multiples are similarly unaffected in these sensitivity analyses. In Column 1, we use a different sampling approach. We re-estimate our tests using *all* firms from the same 2-digit GIC industry as peers, either analyst chosen or not chosen. This alternative approach yields a much larger sample of 714,698 observations. The inference with respect to the peer *E/P* multiple is unaltered. In this much larger sample, all the economic factors except *Sim_Volatility* and *Sim_Return* have the predicted sign and are statistically significant at the two

[15] The number of observations is lowest for *Multiple Peer - E/P* as the use of this multiple requires positive earnings.

percent level or better.

In Column 2, we consider the possibility that analyst *k* is more likely to choose company *j* as a peer for firm *i* when the analyst also formally provides research coverage of company *j*. We re-estimate the test to control for this possibility by including in our regressions a variable (*Follow*) that indicates whether the analyst also covers company *j*. We find that analyst coverage of a company increases the probability that it will be used as a peer. More importantly, the inference with respect to the peer *E/P* multiple is unaltered.

In Column 3, we examine the effect of analyst *k* potentially being more likely to choose company *j* as a peer for firm *i* when company *j* is larger and more well known. We re-estimate the test to control for this possibility by including in our regressions the size of firm *j* (*jSales*). We find that the size of a company increases the probability that it will be used as a peer. More importantly, the inference with respect to the peer *E/P* multiple is unaltered.

Finally, in Column 4, we control for the relative valuation multiple of firm *j*. We re-estimate the test by including in our regressions the negative of the absolute value of the difference between the valuation multiples of firm *i* and firm *j* (*Sim_E/P*). We find that analysts are more likely to choose firms that are similar in valuation multiple. Controlling for the relative valuation of firm *j*, we continue to find that analysts choose peers with higher *E/P* multiples.

In summary, Table 2 provides evidence that analysts choose peers that are similar in performance, size, industry, and stock return performance to the firms they are being compared with. Earnings and return comparability are also key factors explaining peer choice. However, after controlling for these factors, firms with higher valuation multiples are more likely to be chosen by analysts as peers. These are new findings in the literature.

5.1.4. Conditional Analyses: Analyst Reputation, Analyst Incentives, and Expected Firm Growth

Table 3 presents the results of the conditional analyses. Panel A shows the results of tests that examine whether relation between peer valuation and peer choice is mitigated by analyst reputation, proxied for by *II*-rank. Across all four columns, the interaction term is positive and significant. Specifically, the interaction is significant at the one percent level for *Multiple Peer - E/P*, *Multiple Peer - S/EV*, and *Multiple Peer - EBITDA/EV*, and significant at the ten percent level for *Multiple Peer - B/P* (using two-sided tests). These results support our hypothesis and are consistent with the highest-skilled and most successful analysts being less optimistically biased than other analysts. In untabulated *F*-tests, we find that *II*-ranked analysts do not exhibit any bias when using *Multiple Peer - S/EV*, *Multiple Peer - EBITDA/EV*, and *Multiple Peer - E/P* as valuation metrics.

Panel B tabulates the results relating to analyst incentives, operationalized as the firm's external financing needs. Across all four models, the interaction is negative as predicted. The interaction terms are statistically significant except for *Multiple Peer - E/P*. In other words, analysts are more likely to pick peer firms with high valuations when they or their employers are more likely to benefit through new fees for services related to the raising of external financing.

Finally, Panel C reports the expected firm growth results. For three of the four valuation metrics, the interaction with the growth variable is negative and significant at the one percent level (whereas the interaction with *Multiple Peer - EBITDA/EV* is not significant). These findings indicate that analysts are more optimistic for firms that have high expected growth prospects, consistent with Bradshaw's (2004) and Barniv et al.'s (2009) conclusions that analysts are "obsessed" with growth (even if it is impounded into the current stock price).[16]

In addition to highlighting how the bias in peer firm selection varies systematically with fundamental analyst and firm characteristics, the conditional analyses provide further support for our primary tests. That is, we find that the optimistic bias in peer selection is most pronounced in subsamples for which we have ex ante reasons to believe that such a bias is more likely to exist.[17]

5.2. Some Empirical Evidence on Bias in Peer Selection and Stock Recommendations

Although the primary purpose of this study is not to "explain" prior research findings about optimism in analysts' recommendations, it is interesting to explore whether the relation between peer valuation and peer choice is stronger for analysts with Buy recommendations. If that is the case, our findings could partially explain the mechanism through which analysts justify their recommendations. A large literature finds that equity analysts' Buy recommendations are (much) more prevalent than Hold or Sell recommendations (e.g., Barber, Lehavy, McNichols, and Trueman 2001; Malmendier and Shanthikumar 2007; Ke and Yu 2006; Barniv et al. 2009).

To provide initial evidence on this issue, we estimate Equation (2) augmented with an interaction between buy recommendations (*Buy*) and the valuation multiple (as well as the main effect of *Buy*). Specifically, we code *Buy* as one for analyst reports containing buy or strong buy recommendations, and zero otherwise.[18] Results in Table 4 show that the interaction term is

[16] In untabulated results, we simultaneously test for the effects of both external financing and expected growth. For E/P and B/P, we find that both results hold. For S/EV we find that the expected growth result holds but the external financing result does not, while for EBITDA/EV, we find that the external financing result holds but the expected growth result does not.
[17] These contextual analyses also help rule out "alternative explanations" (beyond what our control variables pick up) for why analysts choose peer firms with high valuations.
[18] In our sample, 58% of analyst reports are coded as *Buy*.

negative and statistically significant for *Multiple Peer - B/P* and *Multiple Peer - E/P*, which are the two most widely used valuation metrics in practice (e.g., Barker 1999; Block 1999, 2010). There is no significant interaction effect for the other two valuation multiples. These findings provide partial support for the notion that positively skewed stock recommendations may be justified by analysts by selecting peer firms with high valuation.

5.3. Additional Analyses: The Usefulness of Peer Selection in Forecasting Future Valuation Multiples

We know from practice and research that an important part of analysts' work is firm valuation. Given that the above findings suggest that there is an element of strategic behavior in analysts' choice of peers, it is an empirical question whether analysts' peer selections help forecast firm valuations. Thus, although our primary interest in this study is to examine how analysts choose their peers, test whether the choice is affected by relative valuation, and explore cross-sectional variations in this effect, we also test whether a peer selection model based upon how sell-side analysts choose peers in practice can add to existing models in forecasting future valuation multiples.

A widely cited study by Bhojraj and Lee (2002) develops a systematic approach to predict valuation multiples based on valuation theory. In addition to using industry valuation multiples and industry-size-matched multiples, Bhojraj and Lee produce "warranted multiples" for each firm that are based on systematic variations in the observed multiples in cross-section over large samples. They then test the efficacy of each of the selected comparable multiples in predicting future (one- to three-year ahead) valuation multiples of book to price and sales to enterprise value. Their results indicate that their warranted multiple offers clear improvements over alternative techniques, such as industry and size matches. Thus, we view the Bhojraj and Lee (2002) approach as natural benchmark to test the usefulness of our peer prediction model.

In Table 5, we first estimate regressions highly similar to the Bhojraj and Lee results for current through two-year ahead forecasts of *P/B* and *EV/S* valuation multiples (e.g., our Column 1 is highly similar to Column 5 in their Table 5 for one-year ahead forecasts).[19] For the *P/B* analysis we estimate:

$$Current\ or\ Future\ P/B_{it} = \alpha + \beta_1\ I\_P/B_{it} + \beta_2\ IS\_P/B_{it} + \beta_3\ W\_P/B_{it} + \beta_4\ ICOMP\_P/B_{it} + \varepsilon_{it}. \quad (4)$$

The explanatory variables in this regression are defined as in Bhojraj and Lee (see Appendix A for more details). We also estimate the analogous regression using *EV/S* valuation multiples. Although our sample period is different from Bhojraj and Lee, our results are largely consistent with what they tabulate. For example, firms identified using Bhojraj and Lee's "warranted" multiples (variables with the prefix *W_*) have strong ability to predict current or future multiples.

We extend the Bhojraj and Lee tests by including an *Analyst Predicted* multiple, which is defined as follows. For each firm *i* with non-missing Compustat and CRSP data, we use the coefficients in Table 2, Panel A, Column 1 to estimate a peer prediction score for all firm *j*'s in the same GIC 2-digit industry. For each firm *i*, we keep the four firm *j*'s with the highest peer prediction scores. We calculate the average multiple (*P/B* or *EV/S* in panels A and B, respectively) across these four highest-ranked firm *j*'s and refer to this average multiple as the *Analyst Predicted* multiple.

[19] Note that, for this table, we follow Bhojraj and Lee (2002) and use *P/B* and *EV/S* rather than the inverse *B/P* and *S/EV* as in previous tables. This choice is made for consistency with their study; however no inferences are affected if we use the alternative variable definitions.

More importantly, in the next column we illustrate the additional explanatory power of the *Analyst Predicted* multiple. In all six specifications, *Analyst Predicted* multiple is positive and statistically significant, consistent with the idea that the peers chosen in a manner similar to how analysts choose peers in practice help forecast future valuation multiples.[20] Overall, we conclude that our analysts' peer prediction model adds value to extant forecasting models, further validating our approach and highlighting the importance of considering how analysts choose peer firms.

In untabulated analyses, also like Bhojraj and Lee, we further examine the distribution of absolute valuation errors, defined as the absolute difference between the actual price and the price implied by the multiples used in Equation 4 as explanatory variables. These results support the above regression analysis. For example, the smallest errors are generally produced when we use the implied price from Bhojraj and Lee's "warranted" multiples and the multiple from our analyst peer prediction model.

6. Concluding Remarks

Although a considerable literature on sell-side analysts exists, a large amount of this research has focused on the earnings forecasting task, which perhaps is surprising given that earnings forecasts are either less important than other activities or just one of the inputs into analysts' other activities (Schipper 1991; Bradshaw 2011). We contribute to a better understanding of analysts' work, in particular their choice of peer firms for benchmarking purposes, beyond that of well-studied analysts' tasks such as recommendations and forecasts.

[20] Adding *Analyst Predicted* to the model increases the adjusted R^2 for the *P/B* tests (Panel A) between 9.6 (i.e. 2.2/22.8), and 12.2 percent. For *EV/S* (Panel B), the increases in explanatory power are more modest at between 4.4 and 6.7 percent.

Using a unique hand-collected data set, we observe and examine which peer companies are used by sell-side equity analysts in their research reports. We first show that analysts are more likely to choose peer firms that are similar in size, growth, leverage, asset turnover, industry classification, share price returns, volatility, and trading volume to the firm they are recommending. However, controlling for the above factors, we further find that analysts select peer companies with higher valuations than the firms they are recommending, consistent with analysts choosing peers in an optimistically biased manner.

We next investigate whether the bias in peer selection varies systematically with analyst reputation, analyst incentives, and expected firm growth. Providing further support for the above findings, we find that the bias is especially pronounced for non-II-ranked analysts, in firms with relatively greater external financing needs, and for firms with high expected growth. In addition, there is at least some indication that the previously documented positive bias in stock recommendations may be justified by analysts in selecting peer firms with high valuations. Finally, we show that our peer prediction model helps improve upon extant models for forecasting future valuation multiples.

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APPENDIX A – Variable Definitions

*Analyst Predicted_*	=	Prefix added to either *EV/S* or *P/B* ratio. It indicates the average *EV/S* or *P/B* ratio of the four highest-ranked peers, according to our peer prediction model from Table 2.
AssetTurnover	=	Total revenues divided by total assets in year *t-1*
B/P	=	Book value per share divided by price per share, at the end of year *t-1*
BUY	=	Indicator variable equal to one for analyst reports containing buy or strong buy recommendations, and zero otherwise
ComparabilityEarn	=	R^2 from a regression of firm *i*'s quarterly earnings on the quarterly earnings of firm *j* during the 16 quarters ending in year *t-1*
ComparabilityRet	=	R^2 from a regression of firm *i*'s monthly returns on the monthly returns of company *j* during the four years ending in year *t-1*
EBITDA/EV	=	Operating income before depreciation and amortization divided by *EV*, at the end of year *t-1*
EV/S	=	*EV* divided by total revenues, at the end of year *t-1*
EV	=	Sum of *Market Value* plus total long-term debt, at the end of year *t-1*
ExtFin	=	Net cash received from sale (and/or purchase) of common and preferred stock less cash dividends plus net cash received from issuance (and/or reduction) of debt, scaled by lagged total assets
ExpGrowth	=	Book value per share divided by price per share multiplied by -1
E/P	=	Earnings per share excluding extraordinary items divided by price, at the end of year *t-1*
Follow	=	Indicator variable equal to one when analyst k follows firm j in year t, and zero otherwise
*I_*	=	Prefix added to either *EV/S* or *P/B*. It indicates the harmonic mean of the industry *EV/S* or *P/B* ratios, but excluding firm *i*. Industry membership is defined in terms of the two digit GIC codes.
*ICOMP_*	=	Prefix added to either *EV/S* or *P/B*. It indicates the harmonic mean of the actual *EV/S* or *P/B* ratio of the four closest firms based on their warranted multiple in the same industry. To construct this variable, we rank all the firms each year on the basis of the *W_EV/S* or *W_P/B* in the same industry, and compute the harmonic mean of the actual *EV/S* or *P/B* for these firms.
II-Rank	=	Indicator variable that equals one if the analyst is ranked an All-American analyst in year *t* according to *Institutional Investor* magazine, and equals zero otherwise
*IS_*	=	Prefix added to either *EV/S* or *P/B*. It indicates the harmonic mean of the actual *EV/S* or *P/B* ratios for the four firms from the same industry with the closest market capitalization. Industry membership is defined in terms of the two digit GIC codes.
Leverage	=	Total long-term debt divided by total assets
Multiple Peer	=	Peer's valuation multiple and is measured in the reciprocal. It takes on one of four valuation multiples: *E/P*, *B/P*, *S/EV*, and, *EBITDA/EV*.
P/B	=	Price per share divided by book value per share, at the end of year *t-1*
PeerChoice	=	Indicator variable that equals one if the analyst's report on firm *i* contains peer *j* in determining valuation, and equals zero otherwise.
ProfitMargin	=	Income before extraordinary items divided by total revenues in year *t-1*
Return	=	Stock return during year *t-1*
S/EV	=	Total revenues divided by *EV*, at the end of year *t-1*
Sales	=	Total revenues in year *t-1*

APPENDIX A – Variable Definitions (Continued)

SalesGrowth	=	Year *t-1* revenues less year *t-2* revenues scaled by year *t-2* revenues
SameGIC3digit	=	Indicator variable that equals one if the firm is in the same 3-digit GIC code as the potential peer, and zero otherwise
SameGIC5digit	=	Indicator variable that equals one if the firm is in the same 5-digit GIC code as the potential peer, and zero otherwise
*Sim_*	=	Prefix added to variables that are measured as the absolute value of the difference between firm *i*'s and peer *j*'s respective variables, multiplied by -1
Turnover	=	Volume of shares traded divided by shares outstanding in year *t-1*
Volatility	=	Standard deviation in monthly stock return during the four years ending in year *t-1*
*W_*	=	Prefix added to either *EV/S* or *P/B* ratio. It indicates the predicted value computed using accounting or market-based variables from the current year and the estimated coefficients from a prior year's regression of *EV/S* (or *P/B*) on (1) the harmonic mean of the *EV/S* in the same industry, (2) the harmonic mean of the *P/B* ratio in the same industry, (3) the industry-adjusted profit margin, (4) the industry-adjusted profit margin when the adjusted profit is negative, (5) industry-adjusted analyst growth estimates, (6) book leverage (long-term debt scaled by book value of common equity), (7) return on net operating assets, (8) return on equity, and (9) R&D expenditures divided by sales.

APPENDIX B – Excerpts from Selected Analyst Reports

B1: PepsiCo (by Bear, Stearns)

Comparable Consumer Peers (Millions of U.S. dollars, except per share data)

	Price	P/E		EV/EBITDA		Market
	per Share	2002E	2003E	2002E	2003E	Cap.
Campbell Soup (CPB)	$27.26	19.0x	17.9x	11.2x	10.5x	$11,204
General Mills (GIS)	44.60	27.7x	17.1x	13.0x	9.9x	16,854
Heinz (HNZ)	42.48	15.7x	14.3x	10.2x	9.4x	14,985
Hershey (HSY)	68.57	21.9x	20.0x	10.8x	9.9x	9,478
Kellogg (K)	35.99	20.8x	18.9x	11.2x	10.7x	14,695
Kraft (KFT)	41.08	20.2x	18.1x	12.6x	11.9x	71,356
Sara Lee (SLE)	20.66	14.1x	13.6x	10.1x	9.8x	16,921
Average Multiples:		**19.9x**	**17.1x**	**11.1x**	**10.0x**	
PepsiCo (PEP)		27.2x	23.7x	15.5x	13.9x	$95,003
Coca-Cola Company (KO)		32.4x	27.2x	21.3x	18.6x	140,775

Source: Bear, Stearns & Co. Inc. estimates.

B2: Jackson Hewitt Tax Services (by William Blair & Co.)

Jackson Hewitt Tax Services, Inc.

RAL-Comparable Businesses: PayDay Loan and Pawn Companies

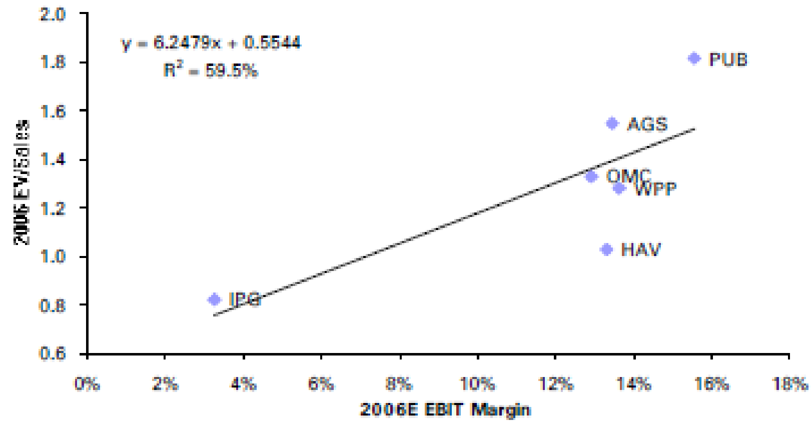
Company	Ticker	Stock Price 10/13/2005	FY1 EPS	P/E1
First Cash Financial Services	FCFS	$ 24.02	$ 1.52	15.8
EZ Corp	EZPW	$ 13.85	$ 1.05	13.2
Cash America International	CSH	$ 19.93	$ 1.48	13.5
Dollar Financial	DLLR	$ 11.10	$ 1.20	9.3
Advance America	AEA	$ 13.38	$ 0.81	16.5
QC Holdings	QCCO	$ 11.66	$ 0.40	29.2
ACE Cash Express	AACE	$ 19.63	$ 1.93	10.2
			Median:	13.5

Source: First Call

APPENDIX B – Excerpts from Selected Analyst Reports (Continued)

B3: Interpublic Group (by Deutsche Bank Securities)

Figure 4: 2006E EV/Sales vs. EBIT Margin



Source: Deutsche Bank estimates and company data

B4: Verizon Communications (by Citigroup Smith Barney)

Figure: Trading Comparables as of June 27, 2003

	P/E		PEG	P/FCF		FCF/G	FV/EBITDA		Mult/G	Current	FV/Revenue		Mult./G	FV/(Lines and Subs)	
Company	**2003E**	**2004E**	**2003E**	**2003E**	**2004E**	**2003E**	**2003E**	**2004E**	**2003E**	**Div. Yield**	**2003E**	**2004E**	**2003E**	**2003E**	**2004E**
Integrated Telcos															
BellSouth	13.6x	13.6x	17.5x	13.4x	12.8x	-4.5x	5.1x	5.2x	NM	3.3%	2.2x	2.2x	5.8x	$1,866	$1,869
SBC	15.9x	16.7x	-10.6x	11.4x	11.3x	-3.6x	5.5x	5.5x	NM	4.6%	2.0x	2.0x	NM	$1,396	$1,419
Verizon	14.4x	13.9x	4.4x	11.7x	11.1x	3.6x	6.1x	6.2x	NM	3.9%	2.7x	2.7x	4.4x	$1,896	$1,903
ALLTEL	15.3x	14.9x	5.1x	15.0x	15.4x	4.9x	6.7x	6.5x	3.0x	2.9%	2.7x	2.7x	1.1x	$1,918	$1,903
FON Group	11.0x	11.9x	-2.0x	7.0x	8.8x	-1.0x	3.5x	3.8x	NM	3.4%	1.0x	1.1x	NM	$1,850	$1,874
Sprint Corp ($Mil)	27.0x	24.1x	1.5x	9.8x	10.3x	1.2x	4.7x	4.7x	9.7x	2.3%	1.4x	1.4x	12.6x	$1,472	$1,424
IXCs															
AT&T	9.6x	13.3x	-0.5x	4.1x	8.0x	-0.1x	3.0x	3.4x	NM	3.9%	0.7x	0.8x	NM	$2,888	$2,299
RBOCs	**14.7x**	**14.7x**	**3.8x**	**12.2x**	**11.7x**	**-1.5x**	**5.6x**	**5.6x**	**NM**	**3.9%**	**2.3x**	**2.3x**	**5.1x**	**$1,719**	**$1,731**
Integrated Telcos	**14.0x**	**14.2x**	**2.9x**	**11.7x**	**11.9x**	**-0.1x**	**5.4x**	**5.4x**	**3.0x**	**3.6%**	**2.1x**	**2.1x**	**3.7x**	**$1,785**	**$1,794**
IXCs	**9.6x**	**13.3x**	**-0.5x**	**4.1x**	**8.0x**	**-0.1x**	**3.0x**	**3.4x**	**NM**	**3.9%**	**0.7x**	**0.8x**	**NM**	**$2,888**	**$2,299**
S&P500	**19.4x**	**17.6x**	**2.8x**	--	--	--	--	--	--	1.7%	--	--	--	--	--

TABLE 1 – Descriptive Statistics

This table presents means and medians of firm characteristics for firms covered by analysts, the peers actually chosen by these analysts for valuation purposes, and a randomly-matched set of peers from the same GIC 2-digit industry. ***, **, and * denote significance at the 1%, 5%, and 10% levels. Variables are defined in Appendix A.

Panel A: Number of peers per analyst report

		Percentiles						
Mean	Std. Dev.	1^{st}	5^{th}	25^{th}	Median	75^{th}	95^{th}	99^{th}
5.7	4.4	1.0	1.0	2.0	4.0	8.0	14.0	20.0

Panel B: Firm characteristics

	Firm Reports (N = 1,575)		Analyst-Chosen Peers (N = 8,968)	
	Mean (1)	Median (2)	Mean (3)	Median (4)
Sales ($mm)	7,884	2,462	5,075	771
SalesGrowth	0.175	0.140	0.179	0.127
Leverage	0.178	0.145	0.187	0.130
AssetTurnover	0.770	0.658	0.785	0.661
ProfitMargin	-0.023	0.039	0.026	0.078
Volatility	0.204	0.167	0.223	0.178
Turnover	1.387	1.336	2.009	1.746
Return	0.128	0.128	0.161	0.123

TABLE 2 – Probit Analysis of Peer Choice

This table reports the results of estimating Probit models predicting the analyst's peer choice based on financial factors (Column 1) and the potential peer's valuation (remaining columns) in Panel A. Panel B provides robustness tests using all possible peers from the same GIC 2-digit industry (Column 1); after controlling for whether the analyst follows firm *j* (Column 2); after controlling for the size (i.e., sales) of firm *j* (Column 3); and after controlling for the similarity of firm *j*'s valuation relative to firm *i*. Intercepts are included in all regressions but not tabulated for brevity. Standard errors are in parentheses and are clustered at the firm-level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Variables are defined in Appendix A.

		Multiple Peer is:			
		E/P	*B/P*	*S/EV*	*EBITDA/EV*
Panel A	(1)	(2)	(3)	(4)	(5)
Multiple Peer		-2.516***	-0.320***	-0.067***	-0.618***
		(0.353)	(0.054)	(0.013)	(0.107)
Sim_Sales	0.175***	0.149***	0.176***	0.176***	0.150***
	(0.014)	(0.016)	(0.014)	(0.014)	(0.016)
Sim_SalesGrowth	0.070	0.024	0.079*	0.085*	0.012
	(0.047)	(0.065)	(0.047)	(0.048)	(0.065)
Sim_Leverage	0.366***	0.513***	0.378***	0.388***	0.454***
	(0.092)	(0.113)	(0.093)	(0.093)	(0.106)
Sim_AssetTurnover	0.284***	0.260***	0.298***	0.225***	0.267***
	(0.037)	(0.039)	(0.038)	(0.040)	(0.038)
Sim_ProfitMargin	-0.003	-0.011	-0.002	-0.001	-0.015
	(0.009)	(0.010)	(0.009)	(0.009)	(0.013)
Sim_Volatility	-0.187	-0.312**	-0.095	-0.183	-0.286*
	(0.130)	(0.156)	(0.128)	(0.129)	(0.148)
Sim_Turnover	0.056***	0.056***	0.048***	0.052***	0.054***
	(0.009)	(0.010)	(0.009)	(0.009)	(0.010)
Sim_Return	0.037	0.043	0.058**	0.040*	0.058**
	(0.023)	(0.030)	(0.024)	(0.023)	(0.028)
ComparabilityEarn	0.177**	0.201**	0.193***	0.163***	0.133*
	(0.073)	(0.082)	(0.073)	(0.073)	(0.080)
ComparabilityRet	1.597***	1.491***	1.552***	1.572***	1.439***
	(0.133)	(0.150)	(0.136)	(0.133)	(0.147)
SameGIC3digit	0.797***	0.816***	0.789***	0.798***	0.810***
	(0.068)	(0.070)	(0.068)	(0.068)	(0.070)
SameGIC5digit	1.092***	1.112***	1.086***	1.089***	1.111***
	(0.050)	(0.055)	(0.051)	(0.050)	(0.054)
% Concordant	87.9	87.5	88.2	87.9	87.2
Pseudo-R^2 (%)	54.1	53.4	54.8	54.3	52.5
Observations	17,936	14,277	17,936	17,931	15,046

TABLE 2 (continued)

Panel B	(1)	(2)	(3)	(4)
Multiple Peer – E/P	-1.588***	-2.787***	-3.390***	-1.069**
	(0.210)	(0.468)	(0.401)	(0.489)
Follow		1.683***		
		(0.101)		
Sales			0.023***	
			(0.0002)	
Sim_E/P				2.378***
				(0.563)
Sim_Sales	0.117***	0.185***	0.206***	0.180***
	(0.009)	(0.019)	(0.015)	(0.018)
Sim_SalesGrowth	0.106**	-0.011	-0.030	0.166**
	(0.045)	(0.132)	(0.066)	(0.069)
Sim_Leverage	0.283***	0.494***	0.470***	0.587***
	(0.068)	(0.167)	(0.113)	(0.132)
Sim_AssetTurnover	0.141***	0.297***	0.322***	0.212***
	(0.022)	(0.059)	(0.044)	(0.041)
Sim_ProfitMargin	-0.013**	-0.189***	-0.018*	1.225***
	(0.005)	(0.033)	(0.011)	(0.157)
Sim_Volatility	0.020	-0.864***	-0.498***	-0.449**
	(0.090)	(0.315)	(0.160)	(0.184)
Sim_Turnover	0.027***	0.066***	0.054***	0.042***
	(0.006)	(0.016)	(0.010)	(0.011)
Sim_Return	0.026	-0.011	0.021	0.052
	(0.018)	(0.068)	(0.031)	(0.034)
ComparabilityEarn	0.240***	0.297**	0.245***	0.167*
	(0.045)	(0.143)	(0.084)	(0.086)
ComparabilityRet	1.621***	0.699***	1.315***	1.623***
	(0.074)	(0.223)	(0.149)	(0.160)
SameGIC3digit	0.577***	0.675***	0.806***	0.769***
	(0.039)	(0.098)	(0.072)	(0.078)
SameGIC5digit	0.726***	1.022***	1.141***	1.162***
	(0.032)	(0.083)	(0.056)	(0.059)
% Concordant	87.3	92.1	88.5	88.3
Pseudo-R^2 (%)	24.9	65.1	55.9	55.5
Observations	714,698	6,642	14,277	12,416

TABLE 3 – Peer Choice and Analyst Skill, Analyst Incentives, and Expected Firm Growth

This table reports the results of estimating Probit models predicting the analyst's peer choice based on financial factors, the potential peer's valuation, and either the analyst's skill level (Panel A), the analyst's incentives (Panel B), or the firm's growth prospects (Panel C). Intercepts are included but not tabulated. Standard errors are in parentheses and are clustered at the firm-level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Variables are defined in Appendix A.

Panel A: Effect of analyst skill

	Multiple Peer is:			
	E/P (1)	*B/P* (2)	*S/EV* (3)	*EBITDA/EV* (4)
Multiple Peer × II-Rank	3.164***	0.172*	0.097***	0.611***
	(0.726)	(0.099)	(0.027)	(0.209)
Multiple Peer	-3.111***	-0.343***	-0.087***	-0.784***
	(0.415)	(0.062)	(0.016)	(0.137)
II-Rank	-0.243***	-0.169**	-0.161***	-0.136**
	(0.071)	(0.083)	(0.057)	(0.060)
Sim_Sales	0.147***	0.175***	0.175***	0.148***
	(0.016)	(0.014)	(0.014)	(0.016)
Sim_SalesGrowth	0.022	0.079*	0.087*	0.012
	(0.065)	(0.047)	(0.048)	(0.064)
Sim_Leverage	0.510***	0.376***	0.383***	0.446***
	(0.112)	(0.093)	(0.093)	(0.105)
Sim_AssetTurnover	0.259***	0.295***	0.220***	0.269***
	(0.039)	(0.038)	(0.040)	(0.038)
Sim_ProfitMargin	-0.010	-0.001	-0.0003	-0.015
	(0.010)	(0.009)	(0.009)	(0.013)
Sim_Volatility	-0.276**	-0.068	-0.167	-0.271*
	(0.156)	(0.128)	(0.130)	(0.148)
Sim_Turnover	0.057***	0.049***	0.054***	0.054***
	(0.010)	(0.009)	(0.009)	(0.010)
Sim_Return	0.045	0.060**	0.042*	0.060**
	(0.030)	(0.024)	(0.023)	(0.028)
ComparabilityEarn	0.200**	0.191***	0.159**	0.136*
	(0.083)	(0.074)	(0.074)	(0.080)
ComparabilityRet	1.494***	1.560***	1.581***	1.430***
	(0.151)	(0.138)	(0.136)	(0.148)
SameGIC3digit	0.819***	0.792***	0.798***	0.811***
	(0.070)	(0.068)	(0.068)	(0.070)
SameGIC5digit	1.112***	1.082***	1.088***	1.108***
	(0.055)	(0.051)	(0.051)	(0.054)
% Concordant	87.5	88.2	87.9	87.2
Pseudo-R^2 (%)	53.1	54.8	54.3	52.5
Observations	14,213	17,862	17,857	14, 991

TABLE 3 (continued)

Panel B: Effect of analyst incentives

	Multiple Peer is:			
	E/P (1)	*B/P* (2)	*S/EV* (3)	*EBITDA/EV* (4)
Multiple Peer × *ExtFin*	-3.939	-0.475**	-0.122*	-1.708*
	(3.196)	(0.191)	(0.071)	(0.935)
Multiple Peer	-2.220***	-0.305***	-0.069***	-0.621***
	(0.381)	(0.056)	(0.015)	(0.124)
ExtFin	-0.041	0.139*	0.042	-0.004
	(0.203)	(0.076)	(0.049)	(0.165)
Sim_Sales	0.147***	0.171***	0.170***	0.146***
	(0.017)	(0.015)	(0.015)	(0.017)
Sim_SalesGrowth	0.028	0.086*	0.095*	0.038
	(0.075)	(0.051)	(0.053)	(0.074)
Sim_Leverage	0.578***	0.432**	0.444***	0.521***
	(0.131)	(0.110)	(0.108)	(0.123)
Sim_AssetTurnover	0.258***	0.293***	0.217***	0.262***
	(0.042)	(0.041)	(0.043)	(0.041)
Sim_ProfitMargin	-0.009	0.006	0.008	-0.007
	(0.013)	(0.006)	(0.006)	(0.014)
Sim_Volatility	-0.387**	-0.156	-0.242*	-0.383**
	(0.180)	(0.144)	(0.145)	(0.168)
Sim_Turnover	0.067***	0.058***	0.062***	0.065***
	(0.011)	(0.010)	(0.010)	(0.010)
Sim_Return	0.034	0.070**	0.050*	0.051
	(0.035)	(0.029)	(0.028)	(0.032)
ComparabilityEarn	0.139	0.150*	0.113	0.071
	(0.087)	(0.079)	(0.078)	(0.084)
ComparabilityRet	1.425***	1.492***	1.513***	1.395***
	(0.161)	(0.147)	(0.143)	(0.156)
SameGIC3digit	0.764***	0.735***	0.745***	0.763***
	(0.077)	(0.075)	(0.075)	(0.077)
SameGIC5digit	1.150***	1.120***	1.124***	1.144***
	(0.060)	(0.056)	(0.056)	(0.059)
% Concordant	87.5	88.1	87.9	87.3
Pseudo-R^2 (%)	53.2	54.6	54.1	52.5
Observations	11,942	14,980	14,976	12,635

TABLE 3 (continued)

Panel C: Effect of expected firm growth

	Multiple Peer is:			
	E/P (1)	*B/P* (2)	*S/EV* (3)	*EBITDA/EV* (4)
Multiple Peer × ExpGrowth	-4.697***	-0.280***	-0.037***	-0.213
	(0.675)	(0.054)	(0.006)	(0.274)
Multiple Peer	-5.283***	-0.551***	-0.085***	-0.668***
	(0.600)	(0.073)	(0.015)	(0.183)
ExpGrowth	0.392***	0.203***	0.108**	0.126**
	(0.071)	(0.065)	(0.044)	(0.057)
Sim_Sales	0.150***	0.176***	0.176***	0.151***
	(0.016)	(0.014)	(0.014)	(0.016)
Sim_SalesGrowth	0.047	0.097**	0.106**	0.035
	(0.066)	(0.046)	(0.047)	(0.065)
Sim_Leverage	0.651***	0.529***	0.532***	0.597***
	(0.122)	(0.102)	(0.101)	(0.118)
Sim_AssetTurnover	0.266***	0.308***	0.240***	0.277***
	(0.039)	(0.038)	(0.041)	(0.039)
Sim_ProfitMargin	-0.012	-0.003	-0.003	-0.017
	(0.010)	(0.009)	(0.009)	(0.013)
Sim_Volatility	-0.228	-0.036	-0.118	-0.220
	(0.156)	(0.129)	(0.131)	(0.150)
Sim_Turnover	0.055***	0.048***	0.049***	0.050***
	(0.011)	(0.009)	(0.009)	(0.010)
Sim_Return	0.043	0.062**	0.046*	0.060**
	(0.031)	(0.025)	(0.024)	(0.029)
ComparabilityEarn	0.188**	0.189**	0.166**	0.135*
	(0.083)	(0.074)	(0.074)	(0.081)
ComparabilityRet	1.488***	1.544***	1.575***	1.420***
	(0.152)	(0.138)	(0.136)	(0.150)
SameGIC3digit	0.817***	0.782***	0.796***	0.807***
	(0.071)	(0.069)	(0.069)	(0.071)
SameGIC5digit	1.109***	1.087***	1.089***	1.110***
	(0.056)	(0.051)	(0.051)	(0.054)
% Concordant	87.7	88.4	88.0	87.2
Pseudo-R^2 (%)	53.8	55.3	54.5	52.6
Observations	14,048	17,578	17,574	14,781

TABLE 4 – Peer Choice and Analyst Stock Recommendations

This table reports the results of estimating Probit models predicting the analyst's peer choice based on financial factors, the potential peer's valuation, and the analyst's stock recommendation. Intercepts are included but not tabulated. Standard errors are in parentheses and are clustered at the firm-level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Variables are defined in Appendix A.

	Multiple Peer is:			
	E/P	*B/P*	*S/EV*	*EBITDA/EV*
	(1)	(2)	(3)	(4)
Multiple Peer × BUY	-2.228***	-0.166*	0.010	0.045
	(0.711)	(0.099)	(0.026)	(0.211)
Multiple Peer	-1.182**	-0.222***	-0.071***	-0.610***
	(0.476)	(0.058)	(0.022)	(0.163)
BUY	0.200***	0.168***	0.087**	0.082*
	(0.055)	(0.063)	(0.039)	(0.045)
Sim_Sales	0.151***	0.179***	0.180***	0.153***
	(0.016)	(0.014)	(0.015)	(0.016)
Sim_SalesGrowth	0.052	0.108**	0.115**	0.043
	(0.071)	(0.048)	(0.049)	(0.070)
Sim_Leverage	0.480***	0.373***	0.380***	0.431***
	(0.115)	(0.095)	(0.094)	(0.109)
Sim_AssetTurnover	0.234***	0.273***	0.202***	0.242***
	(0.041)	(0.039)	(0.042)	(0.040)
Sim_ProfitMargin	-0.011	-0.005	-0.004	-0.016
	(0.010)	(0.009)	(0.009)	(0.013)
Sim_Volatility	-0.264*	-0.089	-0.173	-0.239*
	(0.154)	(0.129)	(0.130)	(0.144)
Sim_Turnover	0.057***	0.050***	0.054***	0.055***
	(0.010)	(0.009)	(0.009)	(0.010)
Sim_Return	0.033	0.059**	0.041*	0.050*
	(0.032)	(0.025)	(0.025)	(0.030)
ComparabilityEarn	0.192**	0.185**	0.155**	0.128
	(0.084)	(0.074)	(0.074)	(0.081)
ComparabilityRet	1.575***	1.632***	1.647***	1.518***
	(0.155)	(0.141)	(0.138)	(0.153)
SameGIC3digit	0.828***	0.803***	0.815***	0.823***
	(0.072)	(0.070)	(0.070)	(0.072)
SameGIC5digit	1.114***	1.087***	1.089***	1.108***
	(0.057)	(0.053)	(0.053)	(0.056)
% Concordant	87.6	88.3	88.1	87.3
Pseudo-R^2 (%)	53.8	55.3	54.7	52.8
Observations	13,545	16,954	16,949	14,229

TABLE 5 – Prediction regressions

This table reports the results of estimating OLS models predicting current, one-year ahead, and two-year ahead valuation multiples using current year multiples as constructed by Bhojraj and Lee (2002) and our predicted peer valuation multiple using our model in Table 2. In Panel A, the dependent variable is the price-to-book ratio (*P/B*). In Panel B, the dependent variable is the enterprise-value-to-sales ratio (*EV/S*). Standard errors are in parentheses and are clustered at the firm-level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Variables are defined in Appendix A.

Panel A: Dependent variable is P/B

	Current year *P/B*		One-year ahead *P/B*		Two-year ahead *P/B*	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.13	-0.36	0.31	-0.14	0.42	0.01
	(1.11)	(-2.32)	(1.35)	(-0.54)	(1.46)	(0.04)
I_P/B	-0.33***	-0.41***	-0.31**	-0.38**	-0.29**	-0.36**
	(-5.86)	(-6.10)	(-5.73)	(-5.66)	(-4.85)	(-5.19)
IS_P/B	0.14***	0.12***	0.16***	0.14***	0.18***	0.16***
	(8.69)	(8.08)	(9.34)	(9.44)	(6.49)	(5.99)
W_P/B	0.88***	0.86***	0.78***	0.77***	0.67***	0.65***
	(9.29)	(9.12)	(15.16)	(14.93)	(9.74)	(9.53)
ICOMP_P/B	0.22**	0.20*	0.17**	0.16**	0.16***	0.15**
	(3.50)	(2.87)	(4.65)	(3.84)	(4.16)	(3.58)
Analyst Predicted_P/B		0.32***		0.29***		0.26**
		(8.88)		(13.96)		(5.83)
Adj. R^2 (%)	22.8	25.0	17.2	19.0	13.1	14.7
Observations	5,132	5,132	4,595	4,595	4,068	4,068

TABLE 5 – Prediction regressions (Continued)

Panel B: Dependent variable is EV/S

	Current year *EV/S*		One-year ahead *EV/S*		Two-year ahead *EV/S*	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.21*	0.11	0.07	-0.03	0.07	-0.03
	(2.76)	(1.62)	(0.53)	(-0.20)	(0.74)	(-0.26)
I_EV/S	-0.35	-0.47**	-0.10	-0.23	0.04	-0.09
	(-2.21)	(-3.36)	(-0.82)	(-1.90)	(0.34)	(-0.89)
IS_EV/S	0.07	0.04	0.07	0.03	0.04	0.01
	(1.22)	(0.71)	(1.19)	(0.63)	(0.54)	(0.14)
W_EV/S	0.91***	0.80***	0.79***	0.68***	0.71***	0.61***
	(28.23)	(29.88)	(20.13)	(12.11)	(10.24)	(8.97)
ICOMP_EV/S	0.19***	0.15***	0.17**	0.13*	0.08	0.06
	(6.33)	(5.95)	(3.69)	(3.03)	(1.75)	(1.17)
Analyst Predicted_EV/S		0.32***		0.34***		0.32***
		(10.68)		(9.79)		(10.23)
Adj. R^2 (%)	54.3	56.7	48.9	51.8	46.3	49.4
Observations	5,132	5,132	4,595	4,595	4,068	4,068