WHITE PAPER

THE RELEVANCE OF NON-FINANCIAL KEY PERFORMANCE INDICATORS (KPIS)

Professional Accounting Center, University of Toronto
Bingxu Fang, Partha S. Mohanram, and Dushyantkumar Vyas

December 2019

ACKNOWLEDGMENTS

The authors gratefully acknowledge the funding received for this research through the Professional Accounting Centre of the University of Toronto from Deloitte LLP and the Chartered Professional Accountants of Ontario**.** The authors also acknowledge helpful comments from Len Brooks, Allan Donald, Steve Huddart, Linda Mezon, Stacey Nagle, Gordon Richardson, and participants in the Professional Accounting Center's board meeting of February 2019.

ABOUT THE PROFESSIONAL ACCOUNTING CENTER

The Professional Accounting Centre (PAC) (see http://www.utm.utoronto.ca/pac) at the University of Toronto Mississauga (UTM) is dedicated to exploring the challenges facing the profession and to the enhancement of the profession's relevance. The creation of the Professional Accounting Centre comes at an opportune moment as pressures mount for the development of defensible, globalized standards, and for greater integrity, accuracy, clarity, and judgement in their application.

Tomorrow's professional accountants will require a new set of knowledge and skills to function in highly competitive, globalized business environments. To succeed, they must understand the challenges facing businesses and the solutions available, and they must be able to provide effective leadership to arrive at the optimal resolutions expected.

The Professional Accounting Centre is uniquely positioned, in company with the Institute for Management & Innovation at UTM, to deliver positively on these developments. Our successful Master of Management & Professional Accounting (MMPA) program has an internationally respected reputation, built on a foundation of highly collaborative faculty with global reach, proven research ability, and significant contributions to the accounting profession. Combined with the education of Master of Forensic Accounting (MFAcc) students and B.Com. (Accounting Specialist Stream) students, PAC is providing an exceptional pool of accounting professionals and setting a worldwide standard for others to match.

CONTENTS

EXECUTIVE SUMMARY

Overview: The limitations of financials statements in assessing firm performance have long been known to the academic and practitioner accounting communities. Recent years have witnessed a sharp increase in the frequency and scope of non-financial Key Performance Indicators (KPIs) disclosed by companies and used by market participants. In this study, we investigate the capital market relevance of various voluntarily reported non-financial KPIs. In particular, we examine whether a fundamental analysis strategy involving non-financial KPIs can help investors screen firms across various industries. We find that KPIs are positively associated with future profitability, sales growth, and current stock returns; however, the stock market underreacts to the information embedded in KPIs for firms operating in opaque information environments. We conclude with a regulatory recommendation on standardization of KPIs. Salient aspects of our study are summarized below.

- **KPIs are leading indicators of future financial performance:** Market participants increasingly rely on KPIs outside the scope of traditional financial statements. Traditional financial statement metrics (GAAP and non-GAAP) may not reflect underlying business developments on a timely basis.
- **KPIs are contextual:** Value drivers vary not only across, but within industries. For example, same-store sales growth for retailers; passenger load factor and cost per seat mile for airlines; value of new orders and value of order backlog for homebuilders; number of restaurants opened/closed for restaurants.
- **Our Objectives:**
    - To examine the ***value relevance*** of a large set of industry specific non-financial KPIs.

- To study the efficacy of a ***fundamental analysis strategy*** using KPIs to screen firms in multiple industries such as airlines, retail, homebuilding, hotel, internet, oil and gas, restaurant, semiconductor, telecom, and pharmaceutical industries.
- To study ***cross-sectional and inter-temporal variation*** based on firm- and KPI characteristics.

- **Empirical Approach:** We assemble a novel dataset on industry specific KPIs from S&P Capital IQ, covering U.S. firms from 2011 to 2016 and spanning over ten industries. We allocate all KPIs into two broad categories: ***Efficiency***, considering association with cost or asset deployment efficiency; and ***Growth,*** indicating growth in sales and/or assets. We construct KPI scores for each firm and each category, denoted as ***K-Efficiency*** and ***K-Growth.***
- **Primary Measurement Challenge and Tradeoffs:** A key challenge is the lack of standardization in measurement and disclosure of KPIs even within the same industry. We confront this challenge by selecting up to five KPIs with maximum available observations for each KPI category and industry, and creating a binary variable for each KPI that equals one (zero) based on year-on-year KPI increase(decrease). Thus, KPI score = average of binary variables for each firm-year. Collapsing each KPI into a 0/1 binary variable forces standardization, but leads to loss of relevant continuous information.
- **What do we find?** We find evidence that KPIs related to efficiency (cost and asset deployment efficiency) are positively associated with future profitability, sales growth, and current stock returns. *Importantly, we find that the stock market underreacts to the information embedded in KPIs for firms operating in opaque information environments.* A long-short trading strategy based on KPIs (subject to portfolio size limitations) yields significantly positive returns over the 2011 to 2016 period.

- **Academic Contribution:** Our findings contribute to the academic literature on KPIs and indicate the extent to which the markets react to the information content of KPIs. Our study also contributes to the valuation literature by demonstrating the efficacy of a trading strategy using publicly disclosed non-financial information.
- **Policy Recommendation:** The evidence presented in this study suggests that standardization of KPI reporting may be beneficial for firms operating in opaque information environments.

1: INTRODUCTION

Information reported in financial statements only tells part of the business story for many industries. For example, in its most recent earnings announcement on August 24, 2018, Foot Locker Retail Inc (NYSE:FL) reported strong premarket earnings and sales performance that beat analysts' forecasts. However, its stock price fell as much as 12% on the trading day.[1] The sharp drop in stock price was likely due to the fact that same-store sales growth, a key non-financial performance indicator (KPI) for retail companies, rose by only 0.5%, falling short of the consensus street estimate of a 0.7% increase. The popular press is replete with such instances of KPI relevance almost on a daily basis. As another example, the stock market seems to be fixated on, among other things, the production numbers forecasted and reported by Tesla. This anecdotal evidence suggests the information contained in non-financial KPIs, which are usually voluntarily disclosed and outside the scope of traditional financial statement metrics, are value relevant and hence used by investors to assess the performance of firms.

Firms disclose various KPIs to inform analysts and investors about business developments that are not captured by traditional GAAP measures of financial performance. As expected, the use of KPIs is highly contextual. For example, while same-store sales growth is an important KPI for retailers, other commonly observed KPIs include passenger load factor and cost per seat mile for airline companies, the value of new orders and value of order backlog for homebuilding firms, and the number of restaurants opened/closed for restaurant chains.

In this study, we examine the value relevance of a large set of industry specific non-financial KPIs and the efficacy of a fundamental analysis strategy using KPIs to screen firms in

[1] https://www.nasdaq.com/article/foot-locker-stock-falls-hard-despite-q2-earnings-beat-cm1013001

multiple industries. We build on prior studies in accounting and finance that demonstrate the usefulness of combining multiple financial statement information signals in predicting future accounting performance and stock returns (e.g., Piostroski 2000; Mohanram 2005; Mohanram, Saiy, and Vyas 2018). We assemble a dataset of industry-specific KPIs from Capital IQ, which has a broad coverage over the following ten industries: airlines, retail, homebuilding, hotel, internet, oil and gas, restaurant, semiconductor, telecom, and pharmaceuticals. The resultant sample is at the firm-year level and covers the period from 2011 to 2016.

We ex ante allocate the KPIs into two broad categories, *Efficiency* and *Growth,* considering whether they are associated with asset deployment efficiency or growth in sales and/or assets. We then construct KPI indices for each category, denoted as *K-Efficiency* and *K-Growth*, respectively. A key measurement challenge encountered by external analysts is the lack of standardization in measurement and disclosure of KPIs even within firms in the same industry. We attempt to confront this empirical challenge by selecting up to five KPIs with maximum available observations for each KPI category and industry, and then calculating the change in each variable relative to the prior year. We next create an indicator variable for each KPI that equals one (zero) if the corresponding KPI increases (decreases or remains constant) over time, and create the KPI indices as the average value of the indicators. Individual KPI measures that are negatively correlated with corporate profitability are multiplied by -1 to ensure that the KPI scores increase with firm performance.[2] We also construct an overall index, *K-Total*, using all the individual KPI measures from both categories for each industry in a similar fashion.

We first examine the association between KPI scores and future accounting performance. Our results suggest that the KPI indices are positively associated with future ROA and sales growth.

[2] For example, fuel costs for airline companies are negatively associated with the firm's profitability. We multiply the KPI by -1 and an increase in the cost makes the corresponding indicator equal to zero.

We then examine whether the stock market impounds the information contained KPI scores for future performance into current stock returns. We employ the Easton and Harris (1991) framework and find that the information content of KPIs is reflected, at least to some extent, in current stock prices after controlling for concurrent information embedded in earnings. We further explore whether the markets underreact or overreact to KPI disclosures by examining their association with future stock returns. Although we find that the association is not significant using the full sample, KPI scores are significantly and positively associated with future stock returns for firms in opaque information environments, such as small firms, firms with low analyst coverage, and those with low institutional ownership. The return predictability of KPI scores persists after we control for common risk factors.

We also explore the feasibility of a potential trading strategy based on the KPI scores. We find that for firms with opaque information environment, a long-short hedge strategy based on *K-Total* earns annual abnormal one-year-ahead returns ranging from 12.21% to 14.84%, which is statistically significantly different from zero. A similar strategy using *K-Efficiency* (*K-Growth*) generates similar abnormal returns, ranging from 5.28% (6.13%) to 30.50% (13.19%). We note as a caveat, however, that these hedge returns are subject to significant portfolio size limitations.

Our study makes several contributions to the academic literature, and has important implications for policymakers. First, most prior valuation studies focus on the role of traditional accounting metrics, such as earnings and cash flows. There is only limited academic research on the impact of non-financial KPIs on business assessments made by investors and other stakeholders. Most extant research studies the role of KPIs within certain industries (Amir and Lev 1996; Trueman, Wong, and Zhang 2000, 2001; Rajgopal, Shevlin, and Venkatachalam 2003; Ittner and Larcker 1998). More recently, Givoly et al. (2019) focus on a narrow sample of KPIs with

analyst forecasts of KPIs available in the IBES database. Our study contributes to the literature by examining the value relevance of a much larger set of KPIs covering ten industries and therefore providing a broader examination of the relevance of KPIs. Our findings regarding stock return predictability of KPIs further demonstrate the extent to which the stock market reflects the information content of KPIs and point towards a potential trading strategy based on KPIs. Another contribution of our study is in extending the fundamental analysis research to non-financial performance measures. Prior studies show that the fundamental analysis based on financial statement information is useful in predicting future earnings and stock returns in specific contexts (Piotroski 2000; Mohanram 2005; Mohanram, Saiy, and Vyas 2018). Our study contributes to the literature by showing that the strategy of fundamental analysis can be extended to non-financial performance measures that are voluntarily disclosed and are not regulated by accounting standards.

Given the significant value relevance of KPIs for investors and the fact that they are voluntarily disclosed, KPIs have drawn much attention from securities regulators worldwide (SEC 2003, 2008, 2016; EU 2003; IASB 2010; AcSB 2018). Our paper provides timely implications for policymakers by highlighting the relevance of a large set of KPIs in the stock market. Moreover, our tests on the return predictability of KPIs suggest that the markets do not seem to fully incorporate their information into stock prices and indicate the need for better communication and standardization of KPIs.

2: ACADEMIC LITERATURE – WHAT HAVE WE LEARNT SO FAR?

Key Performance Indicators (KPIs) have drawn much attention from securities regulators worldwide. For example, in the U.S., the SEC has encouraged firms to discuss both financial and non-financial KPIs in the MD&A section of the annual report (SEC 2003). In 2008, the SEC Advisory Committee on Improvements to Financial Reporting recommended encouragement of private initiatives to develop high quality KPIs for specific business activities or industries. The SEC is currently seeking comments regarding potential principles-based requirements for KPI reporting and standardization (SEC 2016). Internationally, the EU and IASB have put forth guidelines to facilitate the reporting of both financial and non-financial performance measures (EU 2003; IASB 2010). In Canada, the AcSB has issued a Framework for Reporting Performance Measures in December 2018. The framework aims to enhance the reporting of performance measures, including KPIs, across different sectors and provide guidance to ensure disclosure of high quality information (AcSB 2019).

Despite their anecdotal relevance and interest from investors and regulators, there is limited academic research on the impact of KPIs on business assessments made by investors and other stakeholders. Most of the extant studies focus on the role of KPIs within certain industries. For instance, Amir and Lev (1996) show that market share and penetration rate are value relevant for wireless companies. Trueman, Wong, and Zhang (2000, 2001), Demers and Lev (2001), and Rajgopal, Shevlin, and Venkatachalam (2003) demonstrate the informational role of web usage for internet companies. Other studies examine KPIs such as customer satisfaction (Behn and Riley 1999; Ittner and Larcker 1998; Banker, Potter, and Srinivasan 2000; Riley, Pearson, and Trompeter 2003; Smith and Wright 2004; Dresner and Xu 1995; Banker and Mashruwala 2007), order

backlog (Lev and Thiagarajan 1993; Behn 1996; Liu, Livnat, and Ryan 1996; Chandra, Procassini, and Waymire 1999; Rajgopal, Shevlin, and Venkatachalam 2003; Steele and Trombley 2012; Chang, Chen, Hsu, and Mashruwala 2018), customer acquisition cost, average revenue per user, number of subscribers (Simpson 2010; Livne, Simpson, and Talmor 2011), growth in same-store sales, the number of existing numbers, and stores opened/closed (Curtis, Lundholm, and McVay 2014). More recently, Givoly, Li, Lourie, and Nekrasov (2019) focus on a much larger number of KPIs across multiple industries that have analyst KPI forecasts available in the IBES dataset. The authors provide evidence suggesting that KPIs are significantly associated with stock market reaction at earnings announcements.

Our study complements extant literature by examining the value relevance of a large list of KPIs disclosed by companies across multiple industries. We assemble a dataset of industry-specific KPIs from the S&P Capital IQ database covering ten industries, allowing us to obtain a broader view of the relevance of KPIs. More importantly, we group the KPIs into two categories and then construct indices using variables from each category. Our approach is consistent across different industries, which allows researchers to examine heterogeneous KPIs in a systematic manner as opposed to examining each separate KPI at a time. More importantly, we test a KPI-based trading strategy and examine its predictive power for future accounting and stock returns. Grouping various KPIs into indices provides us with distinct insights that are new to the literature.

Our study also contributes to the fundamental analysis literature that mainly focuses on investment strategies based on financial statement information. For example, Ou and Penman (1989) show that certain accounting metrics help predict future changes in earnings. Abarbanell and Bushee (1997) show that analysts underreact to accounting information and an investment strategy based on the measures examined in Lev and Thiagarajan (1993) earns abnormal returns.

Piotroski (2000) demonstrates that an investment strategy based on financial statement analysis earns excess returns for value stocks and Mohanram (2005) documents a similar effect of financial statement analysis for growth firms. Mohanram, Saiy, and Vyas (2018) apply the tools of financial statement analysis to banks and show that a composite score based on certain accounting measures predicts future stock returns. However, whether a similar technique can be applied to non-financial performance measures is ex ante unclear. We contribute by standardizing disclosed non-financial KPI information and demonstrating the return predictability of the standardized KPI metrics.

3: EMPIRICAL APPROACH

SAMPLE CONSTRUCTION

Panel A of Table 1 summarizes the sample-selection process.[3] We start with all firm-years over the 2010 to 2017 period from COMPUSTAT, resulting in 54,774 firm-years (10,010 unique firms). We choose this relatively recent sample period because most of the industry-specific KPIs are available in Capital IQ after 2010. Restricting our sample to firms with October, November, or December fiscal-year end reduces our sample size to 43,758 firm-years (8,280 unique firms). We then search Capital IQ obtain annual industry-specific KPIs and we are able to obtain at least one KPI for 3,199 firm-years (724 unique firms). Further conditioning on the availability of necessary accounting information from COMPUSTAT and stock returns from CRSP results in our final sample of 1,933 firm-years (502 firms).

Panel B of Table 1 tabulates the sample distribution by year and shows that the number of observations increases gradually over the sample period. Panel C presents the distribution by industry. The definition of industry is according to Capital IQ's categorization of industry specific KPIs. Overall, there are 10 industries in our sample: airlines, homebuilders, hotel & gaming, internet, oil & gas, restaurants, retail, semiconductors, telecom, and pharmaceutical firms. Pharmaceutical, oil & gas, and hotel & gaming firms have the largest representation in our sample, while other industries each represent less than 10 per cent of the full sample. We exclude the mining industry due to the large and empirically challenging heterogeneity in disclosure of commodity-specific KPIs.

[3] All tables containing statistical analyses are provided in Appendix B to this report.

DEVELOPMENT OF KPI INDICES

To construct the indices used in our tests, we start by allocating industry-specific KPIs into two broad categories: *Efficiency* and *Growth*. *Efficiency* includes measures that measure asset deployment and cost efficiency. Specifically, KPIs included under *Efficiency* can be related to cost management (e.g., the average production cost for oil & gas firms), sales per unit of assets (e.g., same store sales for retailers), or the level of activity generated by per unit of assets (e.g., load factor for airlines). *Growth* includes KPIs that capture the increase in total assets, production and sales (e.g., the total number of stores, the total number of aircraft, and the number of products). Within each category, we select up to five measures with the most observations available. For each firm-year, we calculate the *changes* in each KPI and create an indicator that equals one if the corresponding KPI increases relative to the prior year and zero if the KPI decreases or remains constant. We multiply KPIs that are ex ante deemed to be negatively associated with performance by -1, to ensure that the indicators increase with the intended construct (firm performance). We calculate the average value of the indicators to construct indices for each industry, which are denoted as *K-Efficiency* and *K-Growth*, respectively. If the number of observations varies across different variables, we calculate the mean value of the indicators using the union of their sample to increase the power of the empirical tests. We also create an overall index for each industry, denoted as *K-Total*, by taking the average value of indicators based on variables from both categories. By construction, the three KPI scores range from 0 to 1.

SUMMARY STATISTICS

All summary statistics and other statistical analyses are provided in Appendix B. Panel D of Table 1 presents the distribution of main variables in empirical analyses. The mean (median)

value of ROA is 3% (-2%), and the mean (median) value of sales growth rate is 6% (5%). The median value of sales ($4,786 million) is much larger than the mean value ($411.38 million), suggesting the presence of large firms in our sample. We also include descriptive statistics for KPI indices. All KPI indices are standardized to range from 0 to 1, with a mean value of 0.55 for *K-Growth*, 0.60 for *K-Efficiency*, and 0.53 for *K-Total*.

Panel E shows the distribution of KPI scores by industry. The mean value of *K-Efficiency* (*K-Growth*) ranges from 0.49 for homebuilders (0.27 for Pharmaceutical) to 0.88 for restaurants (0.85 for homebuilders). The number of variables used for calculating *K-Efficiency* (*K-Growth*) ranges from 1 to 5 (1 to 4), and in certain industries (e.g., internet, telecom, and pharmaceuticals), only one index is calculated due to the availability of measures in the two categories.

4: EMPIRICAL FINDINGS

CORRELATIONS

Appendix B provides details of the statistical analyses discussed in this chapter. Table 2 in Appendix B presents the Pearson correlations between future ROA, sales growth, KPI indices, current stock returns, and one-year-ahead future returns. By definition, *K-Total* is positively correlated with *K-Growth* and *K-Efficiency*. The correlation between *K-Growth* and *K-Efficiency* is positive and significant at the 1% level, which suggests that firms experiencing growth also tend to exhibit improvements in operational efficiency. We observe that future ROA and sales growth are both significantly associated with each of the three KPI indices, which provides univariate evidence that KPI indices help predict future accounting performance. Current stock returns are positively associated with *K-Efficiency*, but are not significantly correlated with *K-Growth* or *K-Total*. Future stock returns are not significantly correlated with any KPI index for the full sample. Overall, these univariate analyses based on the full sample provide some preliminary evidence that investors incorporate the information content of KPIs into current stock prices and that there is no significant return predictability in the full sample. However, it is likely that the level of market efficiency related to KPIs varies across different types of firms. In later sections, we will examine the differential level of market efficiency for KPIs of firms with different information environments.

REGRESSION ANALYSES: KPI INDICES AND FUTURE ACCOUNTING PERFORMANCE

In this section, we examine the association between KPIs indices and future financial performance. We first examine the relation between KPI indices and future earnings using a

multivariate regression framework. Specifically, we use a pooled regression framework with industry and year fixed effects to estimate the predictability of KPI indices for future ROA:

$$ROA_{i,t+1} = \alpha + \beta_1 KPI\ Index_{i,t} + \beta_2 ROA_{i,t} + \beta_3 ROA_{i,t} * LOSS_{i,t} + \beta_4 LOSS_{i,t} + \beta_5 SIZE_{i,t} + Industry\ FE + Year\ FE + \epsilon_{i,t} \quad (1)$$

Standard errors are clustered at the firm level following Petersen (2009). The regression results are presented in Table 3. The coefficient for *K-Efficiency* is positive and significant at the 1% level after controlling for current accounting information. The finding is consistent with the univariate analyses in the prior section, and suggests that KPI indices convey useful information for future earnings performance. Regarding control variables, the coefficient for ROA is positive and close to 1, and the coefficient on the interaction term between ROA and Loss indicator is negative. The results are in line with our expectations, since ROA tends to be persistent over time and positive ROA is more persistent than negative numbers due to conditional accounting conservatism (Basu 1997).

We next examine the association between KPI indices and future sales growth. We estimate a similar regression model as (1), except that the dependent variable is the natural logarithm of future sales over current sales:

$$Log\ (Sales_{i,t+1}/Sale_{i,t}) = \alpha + \beta_1 KPI\ Index_{i,t} + \beta_2 Sale_{i,t} + \beta_3 SIZE_{i,t} + Industry\ FE + Year\ FE + \epsilon_{i,t} \quad (2)$$

We control for the current level of sales and firm size in all specifications. The results are presented in Table 4. Our results suggest the *K-Efficiency* is positively associated with future sales growth and the coefficient is significant at the 1% level. However, contrary to the prior univariate results,

the coefficients for *K-Growth* and *K-Total* are not significant at conventional levels in these multivariate analyses.

Taken together, our findings suggest that KPI indices are associated with future financial performance measured by accounting metrics. In the next section, we will further explore the extent to which the markets incorporate the information content of KPIs into current stock prices.

REGRESSION ANALYSES: KPI INDICES AND STOCK RETURNS

Concurrent Returns

We begin by examining whether investors are aware of the predictability of KPI indices for future financial performance. We estimate the association between KPI indices and current stock returns using the framework developed by Easton and Harris (1991). We analyze buy-and-hold returns using a one-year horizon from 9 months prior, to 3 months after, the fiscal year-end.

The results are shown in Table 5. Following Easton and Harris (1991), we report results using both raw returns (Columns 1 to 4) and market-adjusted returns (Columns 5 to 8). We control for the information content of earnings using two measures: Earnings scaled by stock prices and change in earnings scaled by stock prices. We find that the coefficients for *K-Efficiency* are positive and significant at the 5% level or better in both specifications, suggesting that the markets are able to incorporate the information content of KPIs, at least to some extent, in concurrent stock returns. The coefficients for change in earnings scaled by stock price are positive and significant, which is consistent with the findings reported in Easton and Harris (1991).

Future Returns

Our findings regarding current stock returns do not address the question of whether the market reaction to KPIs is complete and whether the KPI indices have predictability for future

returns. Thus, we further examine the association between KPI indices and present the results in Table 6. The dependent variable is size-adjusted buy-and-hold return over a one-year horizon starting at the four months after the fiscal year-end. We control for ROA and several identified risk factors in the regressions, such as size, book-to-market ratio, and momentum. The detailed definition of variables is available in the appendix. The coefficients for the KPI indices are positive but not significantly different from zero. This suggests that the market reaction to the information content of KPIs is on-average complete, and therefore, the KPI indices do not predict for future returns in the full sample analyses.

Return Predictability in Sub-samples

Despite the on-average lack of return predictability for the full sample, we conjecture that the extent to which the markets react to KPIs may vary across firms. It is likely that the markets do not fully incorporate the information content of KPIs for firms with relatively opaque information environments. We test this conjecture and present the results in Table 7. In Panel A, we split the full sample into three groups based on firm size (industry-year specific cutoffs). In Panel B, we split firms into three groups based on analyst coverage: firms without coverage, firms with one or two analysts covering, and firms with more than two analysts covering. In Panel C, three groups are constructed based on the level of institutional ownership.

The results are consistent with our conjecture in all three analyses. In Panel A, the coefficients for *K-Growth*, *K-Efficiency*, and *K-Total* are positive and significant at the 10%, 5%, and 5% level, respectively. An increase in *K-Growth* from 0 to 1 is associated with an 18.3% increase in annual abnormal stock returns. Similarly, the magnitude of abnormal returns is 40.4% for *K-Efficiency* and 22.0% for *K-Total*. In Panel B, the coefficients for K-Efficiency and K-Total

are positive and significant at the 10% level for firms without analyst coverage. Economically, increase in *K-Efficiency* (*K-Total*) from 0 to 1 is associated with a 30.9% (15.5%) increase in annual abnormal returns. In Panel C, we find that for firms with low institutional ownership, the coefficients for *K-Growth* and *K-Total* are positive and significant at the 5% level and the magnitude is economically significant as well. Increasing *K-Growth* (*K-Total*) from 0 to 1 is associated with an 11.9% (13.3%) increase in annual abnormal returns.

Overall, the results demonstrate that the market does not completely incorporate the information of KPIs into current stock returns for firms with more opaque information environments, and consequently, the KPI indices have significant predictive power for future abnormal returns.

TRADING STRATEGY BASED ON KPI INDICES

In this section, we analyze the hedge returns to a trading strategy based on KPI indices. We focus on firms with more opaque environments, inferred by size, analyst coverage, and institutional ownership. For each KPI index, we construct three portfolios based on the value of the index. Portfolio 1 includes firms with KPI index equal to 0, and Portfolio 3 consists of firms with the KPI index equal to 1. Firms with an index value between 0 and 1 are included in Portfolio 2. Raw and hedge returns are reported in Table 8.

Panel A presents the returns to a trading strategy based on *K-Total*. The results suggest that the portfolio returns monotonically increase with *K-Total* for No Coverage Firms and Low IO firms. For small firms, the returns increase from Portfolio 1 to 2, but then decrease from Portfolio 2 to 3. The hedge returns for the three sets of firms range from 12.21% to 14.84% and are significant at the 10% level or better.

The patterns of portfolio returns are similar in Panels B and C, which respectively tabulate the returns to trading strategies based on *K-Efficiency* and *K-Growth*. The hedge returns to a strategy based on *K-Efficiency* (*K-Growth*) range from 5.28% to 30.50% (6.13% to 13.19%) and the returns are generally significantly different from zero at conventional levels using different samples. Taken together, our findings suggest that a trading strategy based on KPI indices could earn significant excess returns over the one-year ahead time horizon.

These trading strategy results are subject to an important caveat regarding the small number of observations in long/short portfolios — accordingly, these strong results may not hold in an out-of-sample analysis.

Hedge Returns over Time

We tabulate hedge returns for a trading strategy based on KPI indices by each year in our sample period from 2011 to 2016. Such analyses are crucial to ensure that the trading strategy is not driven by extreme return patterns in a single year. Panels A to C present the results for *K-Total*, *K-Efficiency*, and *K-Growth*, respectively. Within each panel, the results are separately examined for small firms, no-coverage firms, and low-IO firms. The long (short) portfolio consists of firms with KPI index equal to 1 (0).

In Panel A, the hedge returns for the *K-Total* strategy are positive in all but one years for small firms and firms with no analyst coverage firms and the returns are positive in all years for low institutional ownership firms. The mean hedge return ranges from 12.72% to 15.43% for different samples. The consistent performance of the trading strategy's performance across time suggests that the abnormal return is likely to be driven by mispricing instead of by risk. Moreover,

the Sharpe ratio ranges from 0.84 to 2.24 for different samples, which is comparable to those in prior studies (e.g., Sloan 1996, Mohanram et al. 2018).

Panels B and C present similar return patterns for strategies based on *K-Efficiency* and *K-Growth*. The mean hedge returns for *K-Efficiency* (*K-Growth*) based strategy ranges from 4.74% to 18.17% (from 9.26% to 12.41%) and the Sharpe ratio for *K-Efficiency* (*K-Growth*) ranges from 0.29 to 1.06 (from 0.77 to 3.23). For both strategies, hedge returns are positive in most years for different samples.

Overall, the patterns of abnormal returns over time supports the notion that the abnormal returns to KPI based trading strategies seem to be driven by the markets' under-reaction to the information content embedded in KPIs rather than an omitted risk factor.

5: CONCLUSIONS AND POLICY RECOMMENDATION

Anecdotal accounts suggest that industry-specific KPIs are considered to be highly value relevant by capital market participants. Not surprisingly, KPIs have drawn significant attention from securities regulators across the world. Despite the importance of KPIs to market participants, few studies examine the relevance of KPIs across multiple industries in a systematic way.

In this study, we examine the value relevance of a large set of industry-specific non-financial KPIs, and the efficacy of a trading strategy using KPIs to screen firms in multiple industries. We assemble a database of KPIs from Capital IQ and show that KPIs are significantly associated with future financial performance. We find that concurrent stock returns reflect the information content of KPIs, suggesting that investors are aware of the relevance of KPIs for future accounting performance. We also show that the extent to which the stock market reacts to KPIs varies across firms with different information environments. Our findings suggest that the markets underreact to KPIs for firms operating in opaque information environments. A hedge strategy based on composite KPI scores (subject to portfolio size limitations) earns excess returns over the one-year ahead horizon.

Our research has implications for policymakers who are concerned about the lack of standardization of KPI disclosures. The results on the return predictability of KPIs suggest that the markets do not fully incorporate their information into stock prices for firms with opaque information environments, and indicate the need for better communication or standardization of KPIs for such firms. Our findings on the efficacy of a trading strategy based on KPIs should also be of interest to investors. Our study also extends the literature on fundamental analysis and shows that similar techniques can be applied to non-financial industry-specific KPI measures.

Appendix A: Variable Definitions

Variable	Definition
K-Efficiency	An index that equals the average value of indicators that represent whether the corresponding KPIs in the *Efficiency* category increase or decrease over time.
K-Growth	An index that equals the average value of indicators that represent whether the corresponding KPIs in the *Growth* category increase or decrease over time.
K-Total	An index that equals the average value of indicators that represent whether the corresponding KPIs in both the *Efficiency* and *Growth* categories increase or decrease over time.
ROA	Return on Assets, which is calculated as operating income divided by total assets.
Sales Growth	Sales growth rate, which is calculated as the natural logarithm value of future sales over current sales.
Loss	An indicator variable that equals one if *ROA* is less than 0.
Size	The natural logarithm of total assets.
Sales	The raw value of total sales revenue.
BTM	Book value of equity, scaled by the market value of equity.
Momentum	The buy-and-hold return over the previous twelve months.
Earnings/Lag Stock Price	Raw value of earnings in the current fiscal year scaled by the stock price at the end of last fiscal year.
Delta Earnings/Lag Stock Price	Change in earnings in the current fiscal year relative to the last year scaled by the stock price at the end of last fiscal year.
One-Year-Ahead Return	Buy-and-hold size-adjusted returns using a one-year horizon starting four months after the fiscal year end. The returns are adjusted for delisting.
Concurrent Returns	Buy-and-hold returns using a one-year horizon beginning from nine months before to four months after the fiscal year-end. The returns are adjusted for delisting. The returns are either raw returns or market-adjusted returns, following Easton and Harris (1991).

Appendix B: Statistical Analyses

Table 1: Sample Selection and Summary Statistics

Panel A: Sample Selection

Criterion	Firm-Years	Unique Firms	Unique SIC2 Industries
Obtain all firm-year observations between 2010 and 2017 from COMPUSTAT	54,774	10,010	66
Keep firm-years with October, November, or December fiscal year ends	43,758	8,280	64
Obtain industry-specific performance measures from Capital IQ	3,199	724	38
Require availability of information to COMPUSTAT current and future accounting variables from COMPUSTAT and returns from CRSP	1,933	502	35

Panel B: Distribution by Year

Year	Freq.	Percent	Cum.
2011	274	14.17	14.17
2012	281	14.54	28.71
2013	306	15.83	44.54
2014	342	17.69	62.23
2015	360	18.62	80.86
2016	370	19.14	100
Total	1,933	100	

Panel C: Distribution by Industry

Industry	Freq.	Percent	Cum.
Airlines	82	4.24	4.24
Homebuilding	114	5.9	10.14
Hotel & Gaming	194	10.04	20.18
Internet	8	0.41	20.59
Oil & Gas	487	25.19	45.78
Restaurant	139	7.19	52.97
Retail	189	9.78	62.75
Semiconductor	41	2.12	64.87
Telecom	81	4.19	69.06
Pharmaceutical	598	30.94	100
Total	1,933	100	

Panel D: Descriptive Statistics

Variables	Mean	p25	Median	p75
Size	6.78	5.11	6.73	8.29
Loss	0.42	0.00	0.00	1.00
ROA	-0.02	-0.09	0.03	0.06
Sales	4786.63	47.31	411.38	2283.39
Future ROA	-0.03	-0.11	0.03	0.06
Sales Growth	0.05	-0.07	0.06	0.21
Current Return	0.09	-0.23	0.02	0.30
Future Return	-0.02	-0.31	-0.07	0.18
Institutional Ownership	0.57	0.22	0.68	0.90
Analyst Coverage	9.59	3.00	7.00	14.00
K-Growth	0.55	0.00	0.50	1.00
K-Efficiency	0.60	0.00	1.00	1.00
K-Total	0.53	0.00	0.50	1.00

Panel E: Descriptive Statistics by Industry

	Mean	p25	Median	p75
Airlines				
K-Efficiency	0.57	0.33	0.50	0.83
Fuel Expense	2769.72	327.44	602.89	4470.00
Fuel Consumed	1268.16	147.08	410.00	1901.00
Load Factor	83.69	82.30	83.75	84.80
Revenue Passenger Miles	79914.40	14159.86	32698.87	192767.00
Total Operating Revenue per ASM	13.25	12.14	13.35	14.74
K-Growth	0.74	0.67	1.00	1.00
Total Number of Aircraft	395.24	60.00	196.50	698.00
Passenger Revenue	11971.32	1854.93	4408.50	24425.50
Available Seat Miles	96136.94	17073.63	39560.96	232740.00
Retail				
K-Efficiency	0.66	0.00	1.00	1.00
Merchandise Margin	24.42	14.20	21.25	38.45
Avg Value per Transaction	371.85	44.87	99.00	169.00
Sales/Sq.Ft.	265.27	158.00	185.00	212.00
Same Store Sales	1460.02	151.51	415.29	2498.80
K-Growth	0.77	0.67	1.00	1.00
Total Number of Owned Stores	1287.32	200.00	469.00	1330.50
Total Number of Stores	3054.89	179.00	508.00	1904.50
Total Number of Franchise Stores	1073.39	78.00	185.50	741.50
Restaurants				
K-Efficiency	0.88	1.00	1.00	1.00
Avg Value per Transaction	15.99	13.46	13.97	14.48
Avg.Weekly Sales per Restaurant	40010.33	11651.00	46676.00	47655.00
K-Growth	0.80	0.67	1.00	1.00
Total Number of Restaurants	4808.30	189.00	742.50	3615.00
Total Number of Owned Restaurants	876.29	54.00	309.00	705.00
Total Number of Franchise Restaurants	4834.18	82.00	462.00	3595.00
Pharmaceutical				
K-Growth	0.27	0.00	0.00	0.50
Number of Products in Phase III	3.53	1.00	1.00	3.00
Number of Products in Phase II	3.32	1.00	2.00	4.00
Number of Products in Phase I	3.60	1.00	3.00	4.00
Number of Products in Pre-clinical Trials	2.72	1.00	2.00	3.00
Internet				
K-Efficiency	0.50	0.00	0.50	1.00

Traffic Acquisition Costs	4312.10	386.67	740.44	9883.50
Telecom				
K-Growth	0.84	1.00	1.00	1.00
Subscribers - Broadband	6.05	0.13	0.50	5.85
Oil & Gas				
K-Efficiency	0.51	0.00	1.00	1.00
Avg. Production Cost	13.75	9.29	12.88	16.92
K-Growth	0.61	0.50	0.50	1.00
Total Oil Production	34.58	0.59	3.40	16.60
Total Gas Production	211.92	3.59	19.57	168.74
Homebuilders				
K-Efficiency	0.49	0.00	0.50	0.50
Delivered Homes/ New Orders	0.94	0.91	0.95	0.99
Cancellation Rate	16.69	13.90	15.00	19.40
K-Growth	0.85	1.00	1.00	1.00
Average Homebuilding Inventories	3146.12	309.64	922.95	2758.48
Hotel & Gaming				
K-Efficiency	0.63	0.00	1.00	1.00
Total Rooms Occupancy	76.94	72.60	77.10	82.94
Total Owned Rooms Occupancy	78.69	73.70	77.90	84.00
K-Growth	0.58	0.00	1.00	1.00
Total Rooms	63683.41	3481.00	10702.50	22868.50
Total Hotel Properties	646.10	26.00	64.00	179.00
Semiconductor				
K-Efficiency	0.50	0.00	0.50	1.00
Book to Bill Ratio	0.97	0.80	0.92	1.10
K-Growth	0.37	0.00	0.00	1.00
Backlog Value	198.08	4.00	17.20	36.70

Table 2: Pearson Correlations

	Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)	K-Efficiency													
(2)	K-Growth	0.12***												
(3)	K-Total	0.76***	0.67***											
(4)	Future ROA	0.13***	0.11**	0.15***										
(5)	ROA	-0.02	0.17***	0.09*	0.62***									
(6)	Sales Growth	0.10**	0.17***	0.17***	0.37***	0.10**								
(7)	Sales	-0.07	-0.08*	-0.09*	0.05	0.07*	-0.09*							
(8)	Size	-0.06	0.03	-0.02	-0.05	-0.00	-0.08*	0.56***						
(9)	Loss	0.08*	-0.16***	-0.03	-0.36***	-0.53***	0.02	-0.11**	-0.04					
(10)	BTM	-0.15***	-0.17***	-0.20***	-0.35***	-0.23***	-0.27***	-0.05	0.07	0.21***				
(11)	Analyst Coverage	0.06	0.15***	0.14***	0.01	-0.01	0.01	0.25***	0.63***	0.06	-0.11**			
(12)	Institutional Ownership	0.05	0.17***	0.13***	0.08*	0.07*	0.02	0.10**	0.26***	-0.09*	-0.09*	0.39***		
(13)	Current Return	0.09*	-0.01	0.05	0.28***	0.15***	0.34***	0.01	-0.02	-0.10**	-0.29***	-0.03	0.04	
(14)	Future Return	0.05	0.02	0.02	0.15***	-0.06	0.14***	-0.00	-0.04	0.01	0.03	-0.05	0.03	0.06

Table 3: One-Year-Ahead ROA and KPI Indices

VARIABLES	(1)	(2)	(3)	(4)
	One-Year-Ahead ROA			
Size	0.007***	0.007***	0.004	0.007***
	(4.24)	(4.34)	(1.47)	(4.15)
Loss	0.007	0.007	0.008	0.007
	(0.81)	(0.79)	(0.76)	(0.81)
ROA	1.025***	1.027***	1.005***	1.024***
	(25.48)	(25.45)	(12.25)	(25.36)
ROA*Loss	-0.456***	-0.458***	-0.739***	-0.455***
	(-6.45)	(-6.46)	(-6.39)	(-6.44)
K-Growth		-0.007		
		(-0.93)		
K-Efficiency			0.026***	
			(3.64)	
K-Total				0.006
				(0.71)
Constant	-0.094***	-0.092***	-0.074***	-0.096***
	(-6.00)	(-5.63)	(-2.87)	(-5.91)
Observations	1,933	1,908	823	1,933
Fixed Effects	Industry	Industry	Industry	Industry
Clustering	Firm	Firm	Firm	Firm
Adj. R-squared	0.705	0.705	0.493	0.705

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Future Sales Growth and KPI Indices

VARIABLES	(1) Sales Growth	(2) Sales Growth	(3) Sales Growth	(4) Sales Growth
Size	0.007	0.003	-0.009	0.003
	(0.92)	(0.40)	(-0.88)	(0.42)
Sales	-0.000***	-0.000**	-0.000	-0.000**
	(-2.63)	(-1.99)	(-0.78)	(-2.06)
K-Growth		0.089		
		(1.63)		
K-Efficiency			0.067***	
			(2.86)	
K-Total				0.091
				(1.42)
Constant	0.016	-0.012	0.084	-0.010
	(0.27)	(-0.21)	(1.08)	(-0.19)
Observations	1,933	1,908	823	1,933
Fixed Effects	Industry	Industry	Industry	Industry
Clustering	Firm	Firm	Firm	Firm
Adj. R-squared	-0.00143	0.000209	0.0383	-0.000426

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Relation between Concurrent Returns and K Scores

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Earnings/Lag Stock Price	0.000	0.000	0.001	0.000	0.000	0.000	0.001	0.000
	(0.43)	(0.41)	(1.29)	(0.43)	(0.38)	(0.36)	(1.36)	(0.37)
ΔEarnings/Lag Stock Price	0.001***	0.001***	0.001***	0.001***	0.001**	0.001**	0.001***	0.001**
	(2.71)	(2.63)	(3.58)	(2.71)	(2.06)	(2.00)	(2.81)	(2.06)
K-Growth		-0.025				-0.021		
		(-0.88)				(-0.76)		
K-Efficiency			0.087**				0.098***	
			(2.50)				(2.96)	
K-Total				-0.003				0.003
				(-0.11)				(0.12)
Constant	0.091***	0.103***	0.030	0.093***	-0.014	-0.004	-0.083***	-0.016
	(7.56)	(5.25)	(1.15)	(4.64)	(-1.22)	(-0.24)	(-3.30)	(-0.83)
Observations	1,933	1,907	822	1,933	1,933	1,907	822	1,933
Fixed Effects	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry
Clustering	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
Adj. R-squared	0.00381	0.00342	0.0276	0.00330	0.00186	0.00145	0.0231	0.00135

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 6: One-Year-Ahead Returns and KPI Indices

VARIABLES	(1)	(4)	(5)
	One-Year-Ahead Return		
Size	-0.008*	-0.010	-0.008*
	(-1.70)	(-1.19)	(-1.76)
ROA	0.114	-0.351*	0.114
	(1.44)	(-1.93)	(1.45)
BTM	0.044**	0.029	0.045*
	(1.97)	(0.85)	(1.96)
Momentum	0.046	0.032	0.043
	(1.56)	(0.89)	(1.48)
K-Growth	0.043		
	(1.43)		
K-Efficiency		0.021	
		(0.60)	
K-Total			0.043
			(1.26)
Constant	-0.017	0.008	-0.013
	(-0.44)	(0.10)	(-0.34)
Observations	1,908	823	1,933
Fixed Effects	Industry	Industry	Industry
Clustering	Firm	Firm	Firm
Adj. R-squared	0.0251	0.0563	0.0248

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 7 Return Predictability in Subsamples

Panel A: Return Predictability by Size

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Small Firms			Medium Firms			Large Firms		
Size	0.043	-0.095**	0.041	-0.000	0.032	0.011	0.014*	0.029**	0.013
	(1.17)	(-2.23)	(1.15)	(-0.01)	(0.69)	(0.37)	(1.71)	(2.41)	(1.60)
ROA	0.139	-0.359*	0.136	0.026	-0.785***	0.002	-0.369*	-0.351	-0.346*
	(1.07)	(-1.94)	(1.05)	(0.14)	(-3.16)	(0.01)	(-1.73)	(-1.27)	(-1.67)
BTM	0.048	0.071	0.048	0.100**	0.048	0.097**	-0.005	0.006	-0.005
	(1.04)	(0.95)	(1.06)	(2.15)	(0.76)	(2.08)	(-0.21)	(0.18)	(-0.20)
Momentum	0.054	0.053	0.051	0.011	0.018	0.012	0.080*	0.066	0.077*
	(1.02)	(0.49)	(0.99)	(0.27)	(0.35)	(0.30)	(1.96)	(1.24)	(1.93)
K-Growth	0.183*			0.002			0.028		
	(1.80)			(0.04)			(0.98)		
K-Efficiency		0.404**			-0.136**			0.062	
		(2.45)			(-2.12)			(1.65)	
K-Total			0.220**			-0.080			0.045
			(2.20)			(-1.36)			(1.40)
Constant	-0.225	0.102	-0.232*	-0.054	-0.132	-0.077	-0.192**	-0.353***	-0.192**
	(-1.64)	(0.57)	(-1.71)	(-0.28)	(-0.43)	(-0.39)	(-2.22)	(-2.83)	(-2.22)
Observations	468	73	475	660	297	669	780	453	789
Fixed Effects	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry
Clustering	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
Adj. R-squared	0.0137	0.0691	0.0168	0.00584	0.0456	0.0101	0.119	0.146	0.121

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Panel B: Return Predictability by Analyst Coverage

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	No Coverage			Low Coverage			High Coverage		
Size	-0.013	-0.044	-0.018	-0.020	0.014	-0.017	-0.004	-0.002	-0.005
	(-0.51)	(-1.41)	(-0.71)	(-0.72)	(0.29)	(-0.62)	(-0.61)	(-0.21)	(-0.70)
ROA	-0.019	-0.292	-0.040	0.098	-0.697	0.110	0.108	-0.527**	0.109
	(-0.12)	(-1.43)	(-0.27)	(0.39)	(-1.28)	(0.45)	(0.89)	(-2.36)	(0.92)
BTM	0.078*	0.085	0.089**	0.055	0.021	0.058	0.056*	0.039	0.054*
	(1.91)	(1.12)	(2.10)	(1.03)	(0.28)	(1.04)	(1.80)	(0.92)	(1.74)
Momentum	0.015	-0.049	-0.001	0.004	-0.003	0.007	0.052	0.061	0.048
	(0.20)	(-0.44)	(-0.01)	(0.07)	(-0.03)	(0.12)	(1.47)	(1.41)	(1.36)
K-Growth	0.059			0.152**			0.023		
	(0.86)			(2.10)			(0.60)		
K-Efficiency		0.309*			0.047			-0.023	
		(1.92)			(0.36)			(-0.60)	
K-Total			0.155*			0.134			0.010
			(1.75)			(1.52)			(0.25)
Constant	-0.043	0.014	-0.067	-0.021	-0.149	-0.025	-0.035	-0.035	-0.021
	(-0.32)	(0.09)	(-0.51)	(-0.13)	(-0.48)	(-0.17)	(-0.52)	(-0.35)	(-0.31)
Observations	162	54	162	267	104	276	1,479	665	1,495
Fixed Effects	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry
Clustering	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
Adj. R-squared	0.0244	0.0400	0.0417	-0.00959	-0.0184	-0.0107	0.0331	0.0739	0.0319

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Panel C: Return Predictability by Institutional Ownership

VARIABLES	(1)	(2) Low IO	(3)	(4)	(5) Medium IO	(6)	(7)	(8) High IO	(9)
Size	-0.035**	-0.057***	-0.035**	-0.016*	-0.001	-0.016*	0.019*	0.006	0.018
	(-2.28)	(-2.75)	(-2.36)	(-1.81)	(-0.09)	(-1.82)	(1.66)	(0.47)	(1.63)
ROA	0.159	-0.258	0.162	-0.080	-0.639**	-0.077	-0.181	-0.487*	-0.174
	(1.12)	(-1.28)	(1.15)	(-0.48)	(-2.25)	(-0.47)	(-1.04)	(-1.78)	(-1.04)
BTM	0.073**	0.025	0.079***	0.067	0.017	0.065	0.020	0.050	0.016
	(2.51)	(0.60)	(2.68)	(1.36)	(0.25)	(1.32)	(0.40)	(0.77)	(0.33)
Momentum	0.034	-0.032	0.031	0.041	0.088	0.038	0.020	0.029	0.018
	(0.83)	(-0.45)	(0.78)	(0.77)	(1.13)	(0.72)	(0.53)	(0.76)	(0.46)
K-Growth	0.119**			0.016			0.043		
	(2.17)			(0.29)			(0.85)		
K-Efficiency		0.055			-0.085			0.055	
		(0.84)			(-1.31)			(1.12)	
K-Total			0.133**			-0.000			0.027
			(2.09)			(-0.00)			(0.51)
Constant	-0.002	0.279	-0.004	0.095	0.047	0.105	-0.211**	-0.148	-0.192*
	(-0.02)	(1.65)	(-0.05)	(1.14)	(0.35)	(1.27)	(-2.07)	(-1.19)	(-1.94)
Observations	519	229	533	632	193	641	757	401	759
Fixed Effects	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry
Clustering	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
Adj. R-squared	0.0415	0.0970	0.0452	0.00929	0.0140	0.00914	0.0449	0.0718	0.0439

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 8: Returns to Trading Strategies based on KPI Indices

Panel A: Returns to Hedge Strategy based on K-Total

	Small Firms		No Coverage Firms		Low IO Firms	
	Mean	Obs	Mean	Obs	Mean	Obs
1	-7.69%	253	-6.37%	69	-13.96%	172
2	13.00%	140	-5.46%	44	-9.55%	185
3	6.87%	82	8.47%	49	-1.75%	176
3-1	14.56%		14.84%		12.21%	
t-stat	1.77		1.72		2.34	
p-value	0.0768		0.0874		0.0195	

Panel B: Returns to Trading Strategy based on K-Efficiency

	Small Firms		No Coverage Firms		Low IO Firms	
	Mean	Obs	Mean	Obs	Mean	Obs
1	-18.30%	34	-12.11%	26	-9.99%	96
2		0	-10.33%	4	-13.69%	2
3	12.19%	39	16.23%	24	-4.71%	131
3-1	30.50%		28.34%		5.28%	
t-stat	2.07		1.94		0.87	
p-value	0.0412		0.0577		0.03832	

Panel C: Returns to Trading Strategy based on K-Growth

	Small Firms		No Coverage Firms		Low IO Firms	
	Mean	Obs	Mean	Obs	Mean	Obs
1	-6.76%	258	-2.28%	79	-13.79%	195
2	12.78%	125	-13.04%	24	-11.04%	113
3	6.42%	85	3.86%	59	-3.32%	211
3-1	13.19%		6.13%		10.47%	
t-stat	1.65		0.78		2.24	
p-value	0.0993		0.4335		0.0254	

Table 9: Hedge Returns Across Time

Panel A: Hedge Return Based on K-Total across Time

Small Firms

Year	#Long	#Short	Long Return	Short Return	Hedge Return
2011	15	39	12.12%	-5.72%	17.84%
2012	13	32	8.31%	16.54%	-8.23%
2013	11	38	-1.76%	-2.29%	0.53%
2014	15	48	-5.17%	-23.07%	17.90%
2015	14	49	19.17%	-15.96%	35.13%
2016	14	47	7.29%	-5.84%	13.13%
Mean Hedge Returns				12.72%	
SD of Hedge Returns				15.12%	
Sharpe Ratio				0.84	

No Coverage Firms

Year	#Long	#Short	Long Return	Short Return	Hedge Return
2011	25	12	6.38%	-7.80%	14.18%
2012	23	6	18.79%	-14.15%	32.94%
2013	28	12	-24.01%	-22.20%	-1.81%
2014	27	8	4.75%	-22.04%	26.79%
2015	27	15	10.77%	3.29%	7.48%
2016	32	16	21.27%	8.26%	13.01%
Mean Hedge Returns				15.43%	
SD of Hedge Returns				12.68%	
Sharpe Ratio				1.22	

Low IO Firms

Year	#Long	#Short	Long Return	Short Return	Hedge Return
2011	79	24	4.57%	1.11%	3.46%
2012	80	16	1.96%	-15.44%	17.40%
2013	77	23	-5.76%	-19.65%	13.89%
2014	93	28	-14.23%	-24.38%	10.15%
2015	103	37	-4.88%	-25.38%	20.50%
2016	101	44	14.36%	-2.44%	16.80%
Mean Hedge Returns				13.70%	
SD of Hedge Returns				6.12%	
Sharpe Ratio				2.24	

Panel B: Hedge Return Based on K-Efficiency Across Time

Small Firms

Year	#Long	#Short	Long Return	Short Return	Hedge Return
2011	18	9	4.90%	-28.70%	33.60%
2012	17	5	53.16%	27.82%	25.34%
2013	10	7	-21.99%	-37.89%	15.90%
2014	9	4	6.94%	-27.03%	33.97%
2015	12	5	-19.13%	-13.09%	-6.04%
2016	3	4	-13.77%	-16.08%	2.30%
Mean Hedge Returns				17.51%	
SD of Hedge Returns				16.61%	
Sharpe Ratio				1.05	

No Coverage Firms

Year	#Long	#Short	Long Return	Short Return	Hedge Return
2011	3	4	45.11%	-12.52%	57.62%
2012	7	2	42.09%	-6.90%	48.99%
2013	3	8	-39.00%	-19.16%	-19.85%
2014	2	5	1.22%	-42.38%	43.60%
2015	4	2	27.04%	31.29%	-4.24%
2016	5	26	-6.80%	10.34%	-17.14%
Mean Hedge Returns				18.17%	
SD of Hedge Returns				35.63%	
Sharpe Ratio				0.51	

Low IO Firms

Year	#Long	#Short	Long Return	Short Return	Hedge Return
2011	17	21	5.08%	3.30%	1.78%
2012	28	11	10.36%	-18.82%	29.18%
2013	20	18	-14.58%	-33.27%	18.69%
2014	23	18	-15.53%	-18.19%	2.66%
2015	23	14	-5.69%	4.68%	-10.37%
2016	20	14	-10.66%	2.85%	-13.51%
Mean Hedge Returns				4.74%	
SD of Hedge Returns				16.53%	
Sharpe Ratio				0.29	

Panel C: Hedge Return Based on K-Growth Across Time

Small Firms

Year	#Long	#Short	Long Return	Short Return	Hedge Return
2011	15	44	15.90%	-2.54%	18.44%
2012	12	34	6.37%	15.10%	-8.73%
2013	13	37	-2.73%	-1.71%	-1.02%
2014	16	47	-5.35%	-24.21%	18.86%
2015	14	49	19.17%	-15.40%	34.57%
2016	15	47	5.60%	-4.04%	9.64%

Mean Hedge Returns	11.96%
SD of Hedge Returns	15.51%
Sharpe Ratio	0.77

No Coverage Firms

Year	#Long	#Short	Long Return	Short Return	Hedge Return
2011	7	14	-0.49%	0.16%	-0.65%
2012	11	9	18.79%	-6.29%	25.08%
2013	9	12	-19.02%	-22.20%	3.18%
2014	14	8	-6.83%	-22.04%	15.21%
2015	7	18	10.77%	8.72%	2.05%
2016	11	18	19.63%	8.91%	10.72%

Mean Hedge Returns	9.26%
SD of Hedge Returns	9.75%
Sharpe Ratio	0.95

Low IO Firms

Year	#Long	#Short	Long Return	Short Return	Hedge Return
2011	31	25	9.93%	0.02%	9.91%
2012	35	21	-3.79%	-13.29%	9.50%
2013	30	24	-9.72%	-19.33%	9.61%
2014	44	29	-19.06%	-29.85%	10.79%
2015	43	42	-2.20%	-19.88%	17.68%
2016	28	54	12.44%	-4.56%	17.00%

Mean Hedge Returns	12.41%
SD of Hedge Returns	3.85%
Sharpe Ratio	3.23

References

Abarbanell, J., and Bushee, B. 1997. Fundamental Analysis, Future Earnings, and Stock Prices. Journal of Accounting Research, 35(1), 1-24.

AcSB. 2019. Reporting Performance Measures. Available at: https://www.frascanada.ca/en/acsb/news-listings/framework-for-performance-measures

Amir, E., and B. Lev. 1996. Value-Relevance of Nonfinancial Information: The Wireless Communications Industry. *Journal of Accounting and Economics* 22 (1): 3–30.

Banker, R., G. Potter, and D. Srinivasan. 2000. An Empirical Investigation of an Incentive Plan That Includes Nonfinancial Performance Measures. *The Accounting Review* 75 (1): 65–92.

Barth, M. E., Landsman, W. R., Lang, M., and Williams, C. 2012. Are IFRS-based and US GAAP-based accounting amounts comparable? *Journal of Accounting and Economics*, *54*(1), 68–93.

Behn, B. 1996. Value Implications of Unfilled Order Backlogs. *Advances in Accounting* 14: 61-84.

Behn, B, and R. A. Riley. 1999. Using Nonfinancial Information to Predict Financial Performance: The Case of the U.S. Airline Industry. *Journal of Accounting, Auditing & Finance* 14 (1): 29–56.

Bonacchi, M. , Kolev, K. and Lev, B. (2015), Customer Franchise—A Hidden, Yet Crucial, Asset. *Contemporary Accounting Research* 32: 1024-1049.

Riley, R. A., T. A. Pearson, and G. Trompeter. 2003. The Value Relevance of Non-Financial Performance Variables and Accounting Information: The Case of the Airline Industry. *Journal of Accounting and Public Policy* 22 (3): 231–54.

Chandra, U., A. Procassini, and G. Waymire. 1999. The Use of Trade Association Disclosures by Investors and Analysts: Evidence from the Semiconductor Industry. *Contemporary Accounting Research* 16: 643-670.

Chang, H., Chen, J., Hsu, S., and Mashruwala, R. 2018. The Impact of the Bullwhip Effect on Sales and Earnings Prediction Using Order Backlog. *Contemporary Accounting Research*, 35: 1140-1165.

Curtis, A., R. Lundholm, and S. Mcvay. 2013. Forecasting Sales: A Model and Some Evidence from the Retail Industry. *Contemporary Accounting Research* 31 (2): 581–608.

Davila, A., and M. Venkatachalam. 2004. The Relevance of Non-Financial Performance Measures for CEO Compensation: Evidence from the Airline Industry. *Review of Accounting Studies* 9 (4): 443–64.

De Franco, G., Kothari, S., and Verdi, R.S. 2011. The Benefits of Financial Statement Comparability. *Journal of Accounting Research*, 49: 895-931.

Demers, E., and B. Lev. 2001. A Rude Awakening: Internet Shakeout in 2000. *Review of Accounting Studies* 6 (2): 331–59.

Dresner, M., and K. Xu. 1995. Customer Service, Customer Satisfaction, and Corporate Performance in the Service Sector. *Journal of Business Logistics*, 16(1), 23.

Easton, P., and Harris, T. 1991. Earnings As An Explanatory Variable For Returns. *Journal of Accounting Research*, *29*(1), 19–36.

Ely, K., P. J. Simko, and L. G. Thomas. 2003. The Usefulness of Biotechnology Firms' Drug Development Status in the Evaluation of Research and Development Costs. *Journal of Accounting, Auditing & Finance* 18 (1): 163–96.

European Union (EU) Accounting and Modernisation Directive. 2003. Directive 2003/51/EC of the European Parliament and of the Council.

Francis, J., K. Schipper, and L. Vincent. 2010. The Relative and Incremental Explanatory Power of Earnings and Alternative (to Earnings) Performance Measures for Returns. *Contemporary Accounting Research* 20 (1): 121–64.

Givoly, D and Y. Li, B. Lourie, and A. Nekrasov. 2018. Key Performance Indicators: The Incremental News in Their Disclosures and the Properties of Their Analyst Forecasts. Working Paper.

Guo, R.J., B. Lev, and N. Zhou. 2005. The Valuation of Biotech IPOs. *Journal of Accounting, Auditing & Finance* 20 (4): 423–59.

Hand, J. 2000. Profits, Losses and the Non-Linear Pricing of Internet Stocks. Working Paper.

Hand, J. 2001. The Role of Economic Fundamentals, Web Traffic, and Supply and Demand in the Pricing of U.S. Internet Stocks. *European Finance Review* 5: 295–317

Hand, J. 2005. The Value Relevance of Financial Statements in the Venture Capital Market. *The Accounting Review* 80(2), 613-648.

Hand, J. and H. Laurion, and A. Lawrence, and N. Martin. 2018. Analyst Forecast Data Feeds Are Not What They Used to Be. *Working Paper*.

Harris, T., and Ohlson, J. 1987. Accounting Disclosures and the Market's Valuation of Oil and Gas Properties. *The Accounting Review*, 62(4), 651-670.

Hughes, K. 2000. The Value Relevance of Nonfinancial Measures of Air Pollution in the Electric Utility Industry. *The Accounting Review*, 75(2), 209-228.

International Accounting Standards Board (IASB). 2010. IFRS Practice Statement 1 Management Commentary: A framework for presentation.

Ittner, C., and D. Larcker. 1998. Are Nonfinancial Measures Leading Indicators of Financial Performance? An Analysis of Customer Satisfaction. *Journal of Accounting Research* 36: 1–35.

Ittner, C., D. Larcker, and M. Rajan. 1997. The Choice of Performance Measures in Annual Bonus Contracts. *The Accounting Review* 72 (2): 231–55.

Kaplan, R., and D. Norton. 1992. The Balanced Scorecard: Measures that Drive Performance. *Harvard Business Review* 70: 71–79.

Kaplan, R., and D. Norton. 2001. Transforming the Balanced Scorecard from Performance Measurement to Strategic Management: Part I. *Accounting Horizons* 15 (1): 87–104.

Keating, E. K., T. Z. Lys, and R.P. Magee. 2003. Internet Downturn: Finding Valuation Factors in Spring 2000. *Journal of Accounting and Economics* 34 (1): 189–236.

Lev, B., and S. R. Thiagarajan. 1993. Fundamental Information Analysis. *Journal of Accounting Research*, *31*(2), 190–215.

Li, K. and P. Mohanram. 2018. Fundamental Analysis: Combining the Search for Quality with the Search for Value. *Contemporary Accounting Research forthcoming*

Liu, C., J. Livnat, and S. G. Ryan. 1996. Forward-looking Financial Information: The Order Backlog as a Predictor of Future Sales. *The Journal of Financial Statement Analysis (Fall),* 89-99.

Livne, G., Simpson, A., and Talmor, E. 2011. Do Customer Acquisition Cost, Retention and Usage Matter to Firm Performance and Valuation? *Journal of Business Finance & Accounting*, 38: 334-363.

Magliolo, J. 1986. Capital Market Analysis of Reserve Recognition Accounting. Journal of Accounting Research, 24, 69-108.

Mohanram, P. S. 2005. Separating Winners from Losers among Low Book-to-Market Stocks Using Financial Statement Analysis. *Review of Accounting Studies* 10 (2): 133–70.

Mohanram, P, S. Saiy, and D. Vyas. 2018. Fundamental Analysis of Banks: The Use of Financial Statement Information to Screen Winners from Losers. *Review of Accounting Studies* 23 (1): 200–233.

Myers, J.N. 1999. "Implementing Residual Income Valuation with Linear Information Dynamics." *The Accounting Review* 74 (1): 1–28.

Ou, J.A., and S. H. Penman. 1989. Financial Statement Analysis and the Prediction of Stock Returns. *Journal of Accounting and Economics* 11 (4): 295–329.

Petersen, M. A. 2008. Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches. *The Review of Financial Studies*, *22*(1), 435–480.

Piotroski, J. 2000. Value Investing: The Use of Historical Financial Statement Information to Separate Winners from Losers. *Journal of Accounting Research*, 38, 1-41.

Rajgopal, S., T. Shevlin, and M. Venkatachalam. 2003. Does the Stock Market Fully Appreciate the Implications of Leading Indicators for Future Earnings? Evidence from Order Backlog. *Review of Accounting Studies* 8 (4): 461–92.

Rajgopal, S., M. Venkatachalam, and S. Kotha. 2003. The Value Relevance of Network Advantages: The Case of E–Commerce Firms. *Journal of Accounting Research* 41 (1): 135–62.

Schefczyk, M. 1993. Operational performance of airlines: An extension of traditional measurement paradigms. *Strategic Management Journal* 14: 301-317.

Securities and Exchange Commission (SEC). 2003. Interpretation: Commission Guidance Regarding Management's Discussion and Analysis of Financial Condition and Results of Operations.

Securities and Exchange Commission (SEC). 2008. Final report of the advisory committee on improvements to financial reporting to the United States Securities and Exchange Commission.

Securities and Exchange Commission (SEC). 2016. Concept Release: Business and Financial Disclosure Required By Regulation S-K.

Simpson, A. 2010. Analysts' Use of Nonfinancial Information Disclosures. *Contemporary Accounting Research* 27 (1): 249–88.

Smith, R.E. and W. F. Wright (2004) Determinants of Customer Loyalty and Financial Performance. *Journal of Management Accounting Research*: December 2004, Vol. 16, No. 1, pp. 183-205.

Smith, R.E. and W. F. Wright. 2004. "Determinants of Customer Loyalty and Financial Performance." *Journal of Management Accounting Research* 16 (1): 183–205.

Spear, N. A. 1994, The Stock Market Reaction to the Reserve Quantity Disclosures of U.S. Oil and Gas Producers. *Contemporary Accounting Research*, 11: 381-404.

Steele, L.B. and M.A. Trombley. 2012. The Information Content of Accounting Disclosures for Forecasting Sales of Manufacturing Firms. Working Paper, University of Wisconsin and University of Arizona.

Trueman, B., M. H. Franco Wong, & Zhang, X. 2000. The Eyeballs Have It: Searching for the Value in Internet Stocks. Journal of Accounting Research, 38, 137-162.

Trueman, B, F. Wong, and X.J. Zhang. 2001. Back to Basics: Forecasting the Revenues of Internet Firms. *Review of Accounting Studies* 6 (2): 305–29.

Xu, B., Magnan, M. L. and André, P. E. 2007. The Stock Market Valuation of R&D Information in Biotech Firms. *Contemporary Accounting Research*, 24: 1291-1318.