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USING XBRL DATA TO PREDICT EARNINGS MOVEMENTS

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ABSTRACT

The SEC requires that all publicly traded companies submit financial reports in a standardized structure using XBRL. This provides a new database to examine the usefulness of accounting information as a basis for a profitable investment strategy.

The objective of this study is to replicate previous models in attempting to predict the direction of movement of earnings, by using XBRL data. The study does not attempt to examine the validity of the models, only the ability to use XBRL filings in financial statement analysis.

The study analyzes NYSE companies XBRL quarterly data, from 2011 to 2015, using a two-step Logit regression model. The results classified companies as ones that would realize an increase or a decrease in earnings. The final model indicated a significant ability to predict subsequent earnings changes. The predictions appear to be correct on average about 70.7% of the time (higher than those of previous studies).

An attempt to create a profitable investment strategy, was successful and provided high abnormal returns.

These results suggest that there is merit using XBRL accounting information as a means for forecasting movements in earnings, and creating a profitable investment strategy.

Key Words: accounting information, earnings prediction, investment strategy, XBRL

1. INTRODUCTION

XBRL (eXtensible Business Reporting Language) is a freely available and global standard for exchanging business information. XBRL allows the expression of semantic meaning commonly required in business reporting. One use of XBRL is to define and exchange financial information, such as a financial statement.

The SEC has created the XBRL U.S. GAAP Financial Reporting Taxonomy. This taxonomy is a collection of accounting data concepts and rules that enables companies to present their financial reports electronically. The SEC's deployment was launched in 2008 in phases, and all public U.S. GAAP companies were required to file their financial reports using the XBRL reporting technology starting from June 15, 2011.

Despite the fact that COMPUSTAT has been a popular source of financial information for both academics and practitioners, it is costly while XBRL filings are freely available. XBRL filings also have a time advantage, they are published concurrently with the related PDF versions and can be used immediately (COMPUSTAT takes an average of 14 weekdays to be published).

In addition, the reliability of COMPUSTAT has also been questioned. Prior studies have shown that COMPUSTAT data may differ from the original corporate financial data (Miguel 1977; Kinney and Swanson 1993; Tallapally, Luehlfing, and Motha 2011) and data found in other accounting databases (Rosenberg and Houglet 1974; Yang, Vasarhelyi, and Liu 2003).

On the other hand, while there is still not enough research regarding the reliability of XBRL data, studies up to date seems positive: one study (Boritz and No 2013)finds that when examining the quality of interactive data XBRL tagged information it is the most complete and most accurate source of company data compared with COMPUSTAT, Yahoo Finance and Google Finance; another (Chychyla and Kogan 2015) finds that, although there was no attempt to compare COMPUSTAT and XBRL 10-K reports, COPUSTAT significantly alters numbers reported on the 10-K filings; a third study(Henselmann, Ditter, and Scherr 2015)suggests that XBRL analysis is a useful tool in assessing irregularities in accounting data. The important advantages of the XBRL data, is that it allows easy and quick access, and provides up to date information to users.

The evolving XBRL technology and data provide new research opportunities (Vasarhelyi, Chan, and Krahel 2012). The suggestion is to examine whether findings from prior research that relied on private vendor databases (such as COMPUSTAT), if replicated, will still hold using XBRL database. This paper is an attempt to follow this suggestion, and examine the ability of earnings to indicate future earnings.

The ability to predict earnings based on past performance has been recognized as a measure of earnings quality(Penman and Zhang 2002) and while others (Ball and Shivakumar 2008) conclude that earnings announcements provide only a modest amount of new information to the share market, it is shown (Bloomfield, Libby, and Nelson 2003) that investors over rely on old earnings performance when predicting future earnings performance.

These studies highlight the necessity to develop a tool to better predict future earnings and help develop various investment strategies.

Many research papers have concentrated on the importance of earnings announcements and forecasts in the determination of investment decisions. While earlier research has only been able to show relatively low informativeness of earnings (Ball, Ray; Brown 1968; Beaver 1968; Foster, Olsen, and Shevlin 1984; V. L. Bernard and Thomas 1990)later studies were able to show the incremental information content of specific components of the financial statements. One study (Finger 1994) shows that earnings provide information for future earnings and cash flows; other studies (Ou & Penman, 1989; Ou, 1990) predict sign changes in earnings per share using forecasting models developed from various income statement and balance sheet components; A "composite" model(Shroff 1999), which forecasts the predictive ability as a function of current earnings and current security prices, obtained significantly lower forecast errors relative to benchmark models; bad news periods were found to have higher earnings informativeness than good-new periods(Roychowdhury and Sletten 2012) ; and disaggregated earnings data were better able to predict next period's earnings in the banking industry(Alam and Brown 2006).

Ou & Penman (1989)were the first researchers to focus on the usefulness of accounting information to predict the direction of movement of earnings relative to trend adjusted current earnings. The study is important because it evaluates whether accounting information can consequently be used as the basis for profitable investment strategy. Given investors' reliance on earnings this could be a valuable tool for a profitable investment strategy. The authors found that financial statement analysis can provide a measure that is an indicator of future earnings which in turn is used as a successful investment strategy. However, the evidence from subsequent studies(Holthausen and Larcker 1992; V. Bernard, Thomas, and Wahlen 1997; Stober 1992; Setiono and Strong 1998; Bird, Gerlach, and Hall 2001) has been mixed.

Recently there have been studies attempting to assess the usefulness of XBRL filing data in predicting future earnings(Williams 2015; Baranes and Palas 2017), however, their database was limited as were the results. The main objective of this study is to utilize the XBRL database in financial analysis, prediction of future earnings, on a much larger scale which is more representative of the market. The XBRL data, filed by all NYSE traded companies, is used to replicate the same methodology uses by Ou & Penman (1989).

The paper is organized as follows, Section II reviews academic literature examining research conducted on the validity of XBRL as a means for data and evaluating Ou & Penman (1989)and subsequent studies. Section III outlines the method employed and the data used. Section IV presents and discusses the results for the model developed to forecast future movements in earnings, in terms of accuracy and as a basis for profitable investment strategy. The last section concludes the paper.

ACADEMIC RESEARCH

In this section will be presented a review of relevant literature on three issues: an examination of the validity of XBRL as a means for data comparison, anevaluation of the Ou & Penman (1989)study and evaluation subsequent studies, and the current literature on earnings prediction using XBRL data. The three issues will be examined separately.

Validity of XBRL

Extensible Business Reporting Language (XBRL) is a business and financial reporting technology that is being implemented to enhance internal and external reporting, electronic filing, and sharing of information.

Beginning in 2009 the SEC requires that all publicly traded companies must submit financial reports in a standardized structure using XBRL to the Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system under a three-year phase-in schedule. In the first phase, as of June 15, 2009 large accelerated filers that have a worldwide public common equity float above $5 billion as of the end of the second fiscal quarter of the most recently completed fiscal year, and who prepare their financial statements according to U.S. GAAP (Generally Accepted Accounting Principles), are subject to XBRL quarterly filings. In the second phase, as of June 15, 2010 all other large accelerated filers are required to comply. In the last phase, which started on June 15, 2011, all remaining filers, including smaller reporting companies, are required to file XBRL quarterly reports as an exhibit to the traditional filings (SEC 2009).

The novelty of the XBRL structured financial reports is that the reporting content is marked up with standardized elements (XBRL tags) from a publicized list of pre-defined items (XBRL taxonomy). For example, the 2013 U.S. GAAP taxonomy contain approximately 19,000 XBRL tags that allow the user to easily extract the desired information for analysis purposes.

Literature suggests that there are several advantages of using SEC XBRL filings both for the adopting companies as well as the capital markets and research:

1. The XBRL structure enables unique identification and reliable extraction of accounting numbers from the financial reports – additional information comes tagged and there are no distortions due to the use of different display formats (Henselmann, Ditter, and Scherr 2015).
2. There is no deviation from the expected digit distribution due to differences between varying database providers (Henselmann, Ditter, and Scherr 2015).
3. XBRL has the potential to streamline internal accounting practices leading to cost savings and improved efficiency and effectiveness in the accounting and finance function as well as enhanced internal control leading to cost savings and improved efficiency(Amrhein, Farewell, and Pinsker 2009).

The aim of the SEC XBRL mandate is to decrease information asymmetry by improving the information processing capability of regulatory filings(SEC 2009). XBRL-structured SEC filings are expected to improve data gathering and analyses by reducing manual data entries, and bringing all filings to a "common ground". The most prominent advantage seems to be for smaller investors, XBRL filings are freely available, while private databases are too costly to be used by small investors. Also, XBRL filings have a time advantage, although they are published concurrently with the related PDF versions, it takes an average of 14 weekdays from the time a company files with the SEC for that data to appear in COMPUSTAT (D’Souza, Ramesh, and Shen 2010), XBRL data is immediately available.

Although early research has found inconsistencies, errors, or unnecessary extensions in the XBRL filingsmore recent studies found XBRL data to be not only with less errors than other forms of data, but to also provide higher quality information.

A comparison of XBRL data filed with the SEC with the data provided by three data aggregators: COMPUSTAT, Google Finance, and Yahoo Finance(Boritz and No 2013), founda significant rate of omission of more than 50% in the financial statement items provided by the aggregators compared with the interactive SEC XBRL data. For items that were not omitted between 5-8% mismatches were found, with approximately 56% differences being greater than conventional materiality. The implications of the study are that XBRL information is a more complete and more accurate source of company data.

Chychyla & Kogan (2015)found that the values reported in COMPUSTAT significantly differ from the values reported in XBRL SEC filings. Although they do not attempt to compare COMPUSTAT and XBRL SEC filings they find that COMPUSTAT significantly alters numbers reported, specifically 17 (out of 30) variables reported by COMPUSTAT are differ from values reported by XBRL SEC filings. They were able to demonstrate how XBRL data can be utilized in an automated large-scale fashion to extract and process commonly used accounting numbers.

Liu & O'Farrell (2013)examine the ability of XBRL data in terms of improving transparency and quality of financial accounting information as proxied by forecast accuracy. Their results found a significant improvement in analyst forecast accuracy since XBRL mandates.

Henselmann et al. (2015)state that the XBRL data may provide the SEC and investors a simple measure to flag financial reports carrying higher probability of human interaction. Their study, which was based on XBRL 10-K filings submitted to the SEC between July 2009 and March 2013, measured a firm-year-level of abnormal digit frequency and explored its association with earnings quality. Their findings are consistent with the underlying assumption that higher manipulation of earnings is reflected in higher irregularities in the frequency of digits in accounting numbers reported in the financial reports, which may indicate lower earnings quality.

Although XBRL data and its study is still at the early stage these studies suggest that XBRL data is a useful and accurate tool for financial statement analysis and may be used to predict the direction of future movement in earnings.

Evaluation of the Ou & Penman (1989)and Consequent Studies

Ou & Penman (1989)

Ou & Penman (1989)is considered a foundation paper in accounting research literature (cited 124 times according to PROQUEST) because they were the first to focus on the usefulness of accounting information to predict the direction of the movement of earnings relative to trend adjusted current earnings.

Using an extensive financial statement analysis (68 accounting variables) the study modeled the direction of movements (increase/ decrease) in earnings per share (EPS) one year out. The sample was obtained from the 1984 COMPUSTAT annual report files and the study was conducted in several stages. In the first stage a chi-squared test was applied to a univariate LOGIT estimation and conducted for 68 accounting variables using annual report data over the period 1965-1972 and then again over the period 1973-1977. In both periods 34 (50%) of the coefficients estimated had p-values less than 0.10. In the second stage a multivariate model was used, on the variables found in the first stage, using a step-wise procedure, deleting descriptors not significant at the 0.10 level with all other descriptors included. In this stage, stage two, additional descriptors were dropped resulting in a model with 16 explanatory variables (for the 1965-1972 period) and 18 variables (for the 1973-1977 period). The results of both time periods were then used to forecast the probability of a company's EPS lying above its trend-adjusted EPS in each of the years from 1973-1983. The companies were classified with a probability above 0.5 (the test was then repeated with $p>0.6$) as one that would realize an increase in EPS or a company with a probability below 0.5 (the test was then repeated with $p<0.4$) as one that would realize a decrease in EPS.

Although the two models only had 6 descriptors which appear in both time periods, many of the descriptors captured similar operating characteristics. For example, inventories, sales and deflated earnings appear in more than one descriptor. An estimation of the correlation of the prediction ability for both time periods, provided a mean for the 11 years of 0.62, the two models classified the firms consistently 78.7% of the time (for a classification of above or below 0.5).

The results of the final models' indicated a significant ability of the descriptors to jointly describe subsequent earnings changes. The χ_1^2 values from the 2X2 contingency table are highly significant and the predictions appear to be correct about 60% of the time for a probability cutoff of (0.5, 0.5) and 66% of the time for a (0.6,0.4) cutoff.

Ou & Penman (1989)continued to develop a trading strategy based on these predictions. Stocks were assigned long and short investment positions based on their probability. They purchased an equally weighted portfolio of all stocks whose estimated probability was in access of 0.6 (long position), and sold an equally weighted portfolio of all stocks whose probability was below 0.4 (short position). This strategy realized a return of 8.3% over a one year holding period, an incremental 5.7% in the second year, and 5.5% in the third year.

Replication of Ou & Penman (1989)

There have been many replications of the Ou & Penman (1989)study over different time periods, different countries, different industries, in comparison with analysts' predictions, and with additional methodologies, with mixed results.

Holthausen & Larcker (1992)re-examined Ou & Penman (1989)using a different time period (1978-1988), including Over-the-Counter firms, and using only 60 of the original 68 ratios. The study estimated four different logit model (two exchanges: NYSE/AMEX and OTC, and two time periods: 1973-1977 and 1978-1982) which retained 15 ratios (the original Ou and Penman 1989 study had 18 ratios). The correlation in the probability scores between the 1973-1977 model and the 1978-1982 model for NYSE/AMEX (OTC) firms was 0.70 (0.58). The predictive ability of their models were qualitatively similar (to Ou & Penman, 1989), using a cut-off of 0.5

the overall accuracy is 60.1% (compared to 60%) and using cut-offs of 0.4 and 0.6 had an overall predictive accuracy of 65.0% (compared to 67%). However, the profitability of the trading strategy realized little value added over the period of their study; that is the Ou & Penman (1989)strategy worked well in the 1978-1982 period (a common period for both studies) regardless of exchange with an excess return varying from 6.9% to 10.3% (8.0% to 11.4% on OTC firms). However, the strategy performed poorly in the 1983-1988 period, where returns were negative (ranging from -4% to -5%) regardless of the exchange.

Bernard et al. (1997)replicated the Ou & Penman (1989) study using the same logit model to make predictions for the same years (1973-1977 and 1978-1983) and re-estimate logit model (using their approach over a previous estimation period) to produce probabilities for earnings increase for the 1984-1988 and 1989-1992 periods. The mean profitability of their investment strategies produced excess return of 4.74% in the first year and 1.24% in the second year.

Stober (1992)compared the Ou & Penman (1989)model prediction ability to that of analysts' forecasts of earnings. Using the same time period as Ou & Penman (1989)they found that the model accurately predicts the signs of one-year-ahead EPS 46% of the time, analysts' forecasts are correct about 54% of the time but a combined model correctly predicted the sign 78% of the time.

Setiono & Strong (1998)examined the Ou & Penman (1989) model using a UK sample over a period from 1980 to 1988 and found that a portfolio based on the forecasted probabilities realized abnormal returns.

Bird et al. (2001)extended the Ou & Penman (1989)model by covering a later time period (the years 1983-1997) and by encompassing the UK and Australian markets in addition to the US market. Their results found 12 variables (compared toOu & Penman, 1989, 18) and using a cut-off of 0.5 showed an accuracy of 57.5%- 62% (compared to 60%) and using cut-offs of 0.4 and 0.6 had an average predictive accuracy of 60.5%-66.5% (compared to 67%) depending on the country examined. Their investment strategy, based on the Ou & Penman (1989)model yielded negative returns.

In examining specific industries Jordan applied simple regression analysis to each of 25 of the variables used by Ou & Penman (1989)in order to explain variations in the E/P ratios of publicly traded oil and gas firms during the years 2005-2006. Their results showed that three independent variables were significant in relation to the E/P ratio when examined individually and remain statistically significant when combined in a multiple regression model. The model was able to explain almost 62% of the variation in firms' E/P ratios.

Alam & Brown (2006)examined the ability of disaggregated earnings to predict ROE in the banking industry. The results show that the mean adjusted R-square significantly increased from 0.576 to 0.623 with the progressive disaggregation of earnings during the years 1979-1996. The results also demonstrate that disaggregated components are better able to predict next period earnings than aggregated earnings.

All of these studies suggest that while there might be validity to using financial information to predicting earnings a more finely tuned and timely tool is necessary.

Replication of the Ou & Penman (1989)study using XBRL

As stated, the study of XBRL is still in the early stages, however, there have been a couple of attempts to use XBRL data in replicating Ou & Penman (1989) and predict changes in earnings.

Williams (2015)investigated whether XBRL company filings, filed in the years 2007-2009 are useful in the prediction of future earnings. The study examined whether 70 accounting concepts, extracted from S&P 500 companies XBRL filings, provided adequate data needed to create earnings prediction models(J. A. Ou and Penman 1989; Abarbanell and Bushee 1998)and what modifications would make XBRL much more useful.The findings of the study were that XBRL filings, during the investigated period, could not be used to create earnings prediction models; however, adjusting the data, by populating any missing accounting concepts, was shown to be more useful.

The usefulness of XBRL filings by S&P 500 companies in the prediction of future earnings, in the years 2011-2015 has been reexamines (Baranes and Palas 2017). The results show that these filings, without any modifications, were not only useful in predicting future earnings changes, based on the Ou & Penman (1989) model, but provided better predictions than previous models using COMPUSTAT data.

These recent studies suggest that XBRL filings may be used in order to predict future earnings changes.

The current study attempts to expand the above mentioned research by widening the data size and using a large scale data base of XBRL filings to examine its usefulness in predicting future earnings changes.

DATA AND METHOD

XBRL

XBRL uses meta information to describe data items and link them together through various relationships. In order for the data to be compared across companies the same taxonomy must be used by all filers. Therefore, the SEC has created the XBRL U.S. GAAP Financial Reporting Taxonomy. This taxonomy defines common rules on how to present standard accounting information in XBRL filings. For companies that wish to file information that is not standard (company specific filings) may do so through extensions. Extensions are an important part of XBRL filings that provide additional reporting flexibility, however research has found (Debreceny et al. 2011)that 40 percent of all extensions were unnecessary because the corresponding elements exist in the U.S. GAAP Financial Reporting Taxonomy.

The quarterly financial data was obtained using XBRL Analyst; an Excel plugin that allows users to access the company's XBRL tagged data from its XBRL SEC filing via the XBRL US database. Using this software not only allows for easy access and analysis of the data but also for the calculation of any missing balances. For example, the balance reported in each XBRL filing for total liabilities is not available on the original XBRL filing but is extracted and calculated on the XBRL Analyst. An accounting element may not be available due several reasons: the preparer erroneously marked the information, the SEC's taxonomy did not permit or require this balance.

Data

The sample is of all companies traded on the NYSE on Q1, 2016 who filed with the SEC financial statements in XBRL format. Since all of these firms were required to report using XBRL by June 15, 2011 (see validity of XBRL), this ensured that the longest time frame could be used for the analysis. The data is from quarterly filings from 1st quarter of 2011 to 3rd quarter of 2016 (23 quarters).

Of the 2,785 tickerslisted on the NYSE394 tickers were for companies that had more than one security and were therefore eliminated from the sample. 538 companies did not have complete financial information in XBRL format.197 companies were financial institutions (SIC codes 6000-6500, excluding SIC code 6324), because their disclosure and presentations standards differ from other types of companies, and similar to other studies(Williams 2015), they were eliminated from the sample.

The final sample included 1,656companies (59.5% of all tickers listed) that were traded on the NYSE on Q1, 2016. The final sample is compatible with previous research using XBRL, Williams (2015)sample included 296 companies (59.2%), and Baranes & Palas (2017)sample included 343 companies (68.6%) of the total population of S&P 500 companies. Table 1 lists descriptive data for these companies.

Table 1 - descriptive data for the study sample

		N	Frequency	Percent
Size (Revenues)	< $100,000,000	1,656	435	26.25
	$100,000,000-$500,000,000	1,656	492	29.69
	$500,000,000-$1,000,000,000	1,656	258	15.57
	$1,000,000,000-$10,000,000,000	1,656	411	24.80
	$10,000,000,000-$100,000,000,000	1,656	59	3.56
	>$100,000,000,000	1,656	1	0.06
Industry (SIC Code)	Agriculture, Forestry and Fishing (01-09)	1,656	3	0.18
	Mining (10-14)	1,656	142	8.57
	Construction (15-17)	1,656	38	2.29
	Manufacturing (20-39)	1,656	609	36.75
	Transportation, Communications, Electric, Gas and Sanitary Services (40-49)	1,656	207	12.49
	Wholesale Trade (50-51)	1,656	54	3.28

	Retail Trade (52-59)	1,656	113	6.82
	Finance, Insurance and Real Estate (60-67)	1,656	231	13.94
	Services (70-89)	1,656	259	15.63
	Public Administration (91-99)	1,656	0	0/00

In the attempt to duplicate the Ou & Penman (1989)study as closely as possible 58 variables (Appendix 1) were at first used from the original 68 variables. The only variables not included in the first run were those who were not available for a large number of companies (200 or more).

Method

Similar to the Ou & Penman (1989) method, a two-step approach was used to develop the model. In the first step a logistic regression univariate model was used to evaluate the significance of each explanatory variable. Only variables which were found to be associated significantly (at a 10% level) with the direction of earnings per share, above the drift, were maintained. The drift term was estimated as the mean earnings per share change over the four prior quarters to the estimated quarter(Ou & Penman, 1989).

In the second step, a stepwise logistic regression model was then used to determine the variables to be included in the final model. A two-ways (backward and forward) process of adding and removing variables to minimize the Akaike Information Criterion (AIC) measure of goodness of fit was used and implemented with the R software version 3.2.2. As discussed in (Burnham and Anderson 2004)the AIC measure has several advantages over the Bayesian Information Criterion (BIC). The first part of the process (backwards) involved a cycle of including all the remaining variables in a single regression, and then progressively removing those that did not prove significant based on the AIC measure of goodness. The same process was repeated (forward) by starting with one variable, measuring the AIC and then adding another variable. A variable was considered insignificant if the total AIC score of the model increased by adding another variable.

A different model was developed for each of the quarters for which a forecast was made, using quarterly data from the previous three years of observations – for example, the forecast period for Q3, 2015, is Q2, 2013 to Q2, 2015. This approach deviates from the method used by Ou & Penman (1989), who used the same model to arrive at a probability of the directional movement in EPS for all subsequent periods.

The method adopted wasthe one used by later modesl (Bird, Gerlach, and Hall 2001), who developed a different model for each of the periods the forecasts were made.

The logistic models, were then used to provide a forecast of the probability that the company of it EPS for the next quarter being above its current EPS. Based on these probabilities the stock can be classified. A company stock is assigned to a 'long' position (EPS are expected to increase) if the probability is greater than 0.6, and to a 'short' position (EPS are expected to decrease) if the probability is less 0.4.

MODELS

On the first run all 58 variables were used, a list of the variables found significant in each model is presented in Table 2. The number of variables found significant in the different models range from3to 5 for each model, the total number of variables found significant for all models is 8.Ou & Penman (1989)found between 16-18 variables and Bird et al. (2001)found 12 to 18 variables, and Baranes & Palas (2017)found 3-9 variables. Only one of the variables (Change in Net Profit Margin) was common for all the models, two variables (Change in Working Capital to Total assets and Change in Long Term Debt to Equity) was common to three of the four models, two variables (Change in Pretax Income to Sales and Change in EBITDA to Sales) was common to two of the models, and the other three variables were specific to only one model.

While the variable common to all models, Change in Net Profit Margin, does not appear in other models (J. A. Ou and Penman 1989; Bird, Gerlach, and Hall 2001), the other prominent variables (variables which appear in more than one model), appear in some of the models described.

The Model Forecasts

The accuracy of the forecasts are judged on the basis of the percentage of companies classified as 'long' that actually experienced an increase in EPS and those classified as 'short' that actually experience a decrease in EPS. The accuracy of the models (presented in Table 2) ranges between 53% - 87%, with an average of70.7%. These results are better than those presented by other models which averaged 67% (Ou & Penman, 1989) or ranged between 60-67%(Bird, Gerlach, and Hall 2001).

Table 2: Results of the logistic regressions for predicting Q2 2015 through Q1 2016

Variables	Q3/2015	Q4/2015	Q1/2016	Q2/2016
Change in Net Profit Margin	-0.00542	-0.00545	-0.00345	-0.02269
Change in Working Capital to Total Assets	-0.00301	-0.00309	-0.00265	
Change in Long Term Debt to Equity		-0.00013	-0.00013	-0.00015
Change in Pretax Income to Sales			-0.00776	-0.00110
Change in EBITDA to Sales			-0.00035	-0.00343
Net Profit Margin	-0.00104			
Sales to Total Accounts Receivables		0.00022		
Change in Capital Expenditure to Total Assets				-0.00006

Accuracy %	0.867	0.667	0.526	0.769
Portfolio Size	15	18	19	38
Number of companies used in model	1,507	1,367	1,149	1,429
Percentage of Portfolio size	1.00%	1.32%	1.65%	2.66%

Although the models present an impressive accuracy rate, not achieved by previous studies, the use of XBRL company filings data as forecasting tool should still be approached cautiously. The first issue has to do with the portfolio size, that is the number of companies that were assigned a probability position (long, short). The number of companies used in each model is different, based on the availability of their information for each period. The percentage of companies which were assigned a probability position ranges between 1.00% and 2.66%. This means that more than 97% of the companies could not be classified based on the prediction models.Ou & Penman (1989), using COMPUSTAT data, were able to classify approximately 50% of the companies within the same probability range (between 0.6 and 0.4).

An attempt was made to reduce the number of original variables by discarding those variables with less than 10,000 observations (maximum observations = 22*1,656= 36,432). This attempt did not yield larger portfolios or better accuracy.

5.INVESTMENT STRATEGY

An additional question addressed by this study is whether the earnings forecasts can be used as an investment strategy which will provide better returns than a price based strategy. The investment strategy was implemented as follows:

i. For each of the four models Q3 2015-Q2 2016, stocks are assigned to investment positions 45 days after the end of the quarter for which the accounting ratios were reported (Table 2). It is assumed that quarterly report information from XBRL is available at this time.
ii. Stocks are purchased (long position) if the probability is greater than 0.6 and sold (short position) if the probability is less than or equal to 0.4. For each model the same amount of money is invested in the long and short positions for zero net investment, ignoring transaction costs.
iii. Stocks are held for a period of 1 quarter and mean return differences to the long and short positions are observed at the end of the period. The return were then adjusted to annual returns.

The investment strategy defines the return for each firm as the firm's observed return for the quarter(Ball & Brown, 1968). The results of the investment strategy are presented in Table 3.

Table 3: Returns from investment based on prediction models.

Time Period	N	Return on all shares	Portfolio size	Return on Portfolio without strategy	N Long strategy	Return on Long Strategy	N Short strategy	Return on Short Strategy	Return on investment strategy
0.4 < Probability < 0.6									
Q3 2015	1507	-0.22562	15	-0.32259	9	-0.31329	6	0.43330	0.12001
Q4 2015	1367	-0.38407	18	-0.66068	9	-0.74343	9	1.10660	0.36317
Q1 2016	1149	0.74548	19	1.46176	12	2.14900	7	-0.53781	1.61119
Q2 2016	1429	0.39514	38	0.17902	17	0.41269	21	-0.07638	0.33631
Average		0.13273		0.16438		0.37624		0.23143	0.60767
Perfect Foresight Strategy									
Q3 2015						-0.05896		0.06307	0.00410
Q4 2015						6.19575		0.14590	6.34165
Q1 2016						0.31118		-0.23039	0.08079
Q2 2016						0.20199		-0.11155	0.09045
Average						1.66249		-0.03324	1.62925

The investment portfolios yielded annual returns between 12% and 161% for all periods, with an average of 60.1%. The long strategy provided higher returns (average of 36.6%) than the short strategy (average of 23.1%). These annual return results are very high, and while it should be noted that the volatility of the market at the time was higher than usual (see Appendix 2), the validity of these results should be examined further.

In order to examine the validity of the results three different benchmark investment strategies were used. The first strategy examined the average return on all companies used in the development of the different models (Table 3 – Return on all shares). The second strategy examines the average return for investing long on all companies in the portfolio, all companies with a probability below 0.4 and above 0.6 (Table 3 – Return on Portfolio without strategy). These two strategies reflect an investment without any indication for future changes. These two benchmark investment strategies yielded an average annual return between 13 and 16%.

The third investment strategy reflects the result of an investment strategy that could have been executed at the time, Perfect Foresight strategy (Ou & Penman, 1989).

In the Perfect Foresight strategy firms are separated into long positions and short positions based on actual change in EPS in the next quarter. Long positions are taken on stocks whose actual EPS for the next quarter are above trend and short positions in all stocks whose actual EPS are below trend. Positions are taken based on the portfolios used by each model. This strategy attempts to examine whether earning predictions are relevant for determining firms' values and therefore may be used to determine a profitable investment strategy. The results of this investment strategy are presented in Table 3.

The Perfect Foresight investment strategy examines whether predictive power in forecasting the movement in a company's earnings for the next period would be sufficient to identify mispriced stock. Over the four quarters investment period the long strategy yielded an average annual return of 166%, however the short strategy yielded a negative return of 3.3%. This indicates that the value of information about the directional movement of a company's earnings for the next quarter is mainly relevant for the long investment.

In conclusion, earnings prediction, based on XBRL filings data, provide a basis for a much closer profitable investment strategy to having perfect foresight, then other portfolios.

6. CONCLUSIONS

The focus of this study has been on to utilize the newly mandated accounting data format of XBRL in developing models to forecast the direction of movement in EPS (replicating the Ou & Penman, 1989study and the Bird et al., 2001study). The use of XBRL allows not only easier access to the data but also the ability to adjust the models almost immediately as current information is posted, thus providing a much more relevant tool for investors.

This study is a first attempt to utilize large scale data from XBRL filings to predict future direction of earnings and provide an investment strategy.

The findings of the study suggest that XBRL data can be used in a large scale financial statement analysis and in research as viable data source. The models developed provided a higher accuracy rate than that of previous studies(Bird et al., 2001; Ou & Penman, 1989, and others).

The investment portfolio created, based on the prediction models, and Ou & Penman (1989)strategy, created a much larger abnormal return than that of previous studies. The high abnormal returns might suggest that the study was only able to capture those companies which are extreme in their changes and therefore their returns. However, as a benchmark, other investment strategies were employed. Two investment strategies, not based on any prediction model, provided lower abnormal returns, and the perfect foresight investment strategy, provided higher returns. The abnormal returns of the prediction based investment strategy may therefore be related to the high market fluctuations during the period examined.

This study contributes to previous research by expanding the use of XBRL findings to predict future earnings and create a profitable investment strategy. However, there are still limitations which need to be further explored.

One limitation is the relatively short time period data (from 2011) of the SEC XBRL mandate. The short time period not only limits the amount of data available but may also cause other problems such as inconsistencies, errors, or unnecessary extensions in the XBRL filings (Debreceny et al. 2011; Du, Vasarhelyi, and Zheng 2013). However, given that there are indications that XBRL quality increases over time(Du, Vasarhelyi, and Zheng 2013), the methodology may be tested again in the future.

Another limitation is the portfolio size of the final prediction model. The investment portfolio contains less than 3% of companies examined, which suggests that the ability of XBRL data to predict future earnings may be limited. This might be due to the inherent deficiencies in the current XBRL filings, where much of the data is not explicitly tagged. However, Williams (2015)found that by populating missing components better prediction models can be created. Fully populating the data, with functionality built directly into the XBRL taxonomy, would not create any excess time, effort, or cost for preparers or users.

There are several possible extensions of this study among them increasing the data size, developing methods of populating missing components and implementing more advance methodologies for the ratio analysis.

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No.	Accounting Descriptor	Q3/ 2015				Q4/ 2015				Q1/ 2016				Q2/ 2016			
		Coeff	Chi	p-val	Nobs	Coeff	Chi	p-val	Nobs	Coeff	Chi	p-val	Nobs	Coeff	Chi	p-val	Nobs
1	Current Ratio	0	0.04	0.851	15,439	0	0.1	0.755	15,652	0	0.09	0.759	15,815	0	0.07	0.796	16,016
2	Quick Ratio	0	0.85	0.356	15,495	0	0.82	0.366	15,708	0	0.79	0.375	15,865	0	0.85	0.355	16,067
3	Days Sales Accounts Recv.	0	0.77	0.379	16,197	0	0.31	0.579	16,425	0	0.18	0.673	16,580	0	0	0.945	16,797
4	Inventory Turnover	0	1.03	0.309	16,116	0	1.03	0.31	16,341	0	1.02	0.313	16,477	0	1.02	0.313	16,695
5	Inventory to Total Assets	0	1.33	0.248	16,931	0	1.33	0.248	17,170	0	1.33	0.249	17,328	0	1.36	0.244	17,554
6	Depreciation to PP&E	0	1.32	0.251	14,774	0	1.31	0.252	14,998	0	1.32	0.251	15,192	0	1.33	0.25	15,416
7	ROCE	0	1.32	0.251	16,346	0	1.32	0.251	16,597	0	1.31	0.251	16,739	0	1.32	0.25	16,982
8	Total Debt to Equity	0	0.48	0.49	16,300	0	1.81	0.178	16,522	0	2.82	0.093	16,658	0	2.97	0.085	16,878
9	Long Term Debt to Equity	0	2.56	0.11	14,056	0	2.51	0.113	14,264	0	2.77	0.096	14,332	0	2.65	0.103	14,495
10	Equity to Fixed Assets	0	0.95	0.33	16,900	0	0.85	0.358	17,140	0	0.85	0.358	17,245	0	0.86	0.354	17,471
11	Times Interest Earned	0.001	2.63	0.105	16,984	0.001	2.58	0.108	17,223	0.001	2.61	0.106	17,388	0.001	2.57	0.109	17,614
12	Sales to Total Assets	0	1.24	0.266	16,991	0	1.35	0.245	17,229	0	0.97	0.324	17,396	0	0.79	0.373	17,620

13	ROA	0	0.02	0.881	15,544	0	0.01	0.912	15,756	-0.001	0.39	0.534	15,897	-0.001	0.34	0.561	16,082
14	ROCE	0	0.06	0.806	16,802	0	0.07	0.791	17,049	0	0.08	0.782	17,135	0	0.09	0.769	17,360
15	Gross Profit Margin	0	0.26	0.612	16,972	0	0.96	0.328	17,213	0	0.74	0.389	17,327	0	1.49	0.222	17,552
16	EBITDA to Sales	-0.002	9.6	0.002	16,969	-0.002	9.92	0.002	17,209	-0.001	6.23	0.013	17,324	-0.001	4.98	0.026	17,549
17	Pretax Income to Sales	0	0	0.994	16,931	0	0.06	0.801	17,173	0	0.03	0.855	17,310	0	0.7	0.403	17,534
18	Net Profit Margin	0	2.22	0.136	16,197	0	3.75	0.053	16,425	0	2.27	0.132	16,580	0	1.1	0.294	16,797
19	Sales to Total Cash	0	3.18	0.075	16,880	0	3.82	0.051	17,120	0	3.78	0.052	17,177	0	2.1	0.147	17,404
20	Sales to Total Accounts Recv.	0	1.3	0.253	16,281	0	0	0.99	16,504	0	0.05	0.816	16,596	0	0.07	0.786	16,816
21	Sales to Total Inventory	0	1.83	0.176	16,813	0	1.7	0.192	17,052	0	1.7	0.193	17,133	0	1.69	0.193	17,360
22	Sales to Total Working Capital	0	0.3	0.585	16,876	0	0.74	0.39	17,115	0	0.74	0.389	17,214	0	0.74	0.391	17,439
23	Sales to Fixed Assets	0	1.31	0.252	16,691	0	1.31	0.252	16,930	0	0.47	0.492	17,144	0	0.48	0.49	17,296
24	Working Capital to Total Assets	0.005	1.44	0.231	15,274	0.006	1.86	0.173	15,488	0.001	0.72	0.396	15,694	0.001	0.63	0.428	15,869
25	Operating Income to Total Assets	0.001	0.87	0.35	15,332	0.001	0.77	0.38	15,544	0.001	0.92	0.338	15,750	0	0.06	0.812	15,921
26	Repurchase of Equity to Equity	0	1.03	0.31	16,014	0	1.01	0.314	16,239	0	1	0.316	16,452	0	0.6	0.439	16,618

27	Δ Working Capital	0	0.27	0.604	16,901	0	0.33	0.564	17,142	0	0.38	0.537	17,337	0	0.75	0.388	17,487
28	Δ Current Ratio	0	0	0.982	15,571	0	0	0.983	15,768	0	0.01	0.916	15,952	0	0.01	0.944	16,134
29	Δ Quick Ratio	0	1.13	0.289	15,910	0	1.14	0.286	16,134	0	1.52	0.218	16,352	0	0.91	0.339	16,497
30	Δ Days sales to Accounts Recv.	0	0.24	0.624	16,734	0	0.24	0.624	16,972	0	0.24	0.624	17,175	0	0.24	0.623	17,351
31	Δ Inventory Turnover	0	2.06	0.151	16,454	0	2.21	0.137	16,685	0	1.92	0.166	16,902	0	2.8	0.094	17,010
32	Δ Inventory to Total Sales	0	1.38	0.239	14,588	0	1.38	0.24	14,811	-0.001	4.41	0.036	15,011	-0.001	3.56	0.059	15,226
33	Δ Inventory	0	1.39	0.238	16,164	0	6.04	0.014	16,413	0	6.02	0.014	16,639	0	4.77	0.029	16,807
34	Δ Total Revenue	0	1.28	0.257	16,123	0	1.48	0.224	16,345	0	1.61	0.205	16,557	0	1.6	0.206	16,714
35	Δ Total Depreciation	0	1.3	0.255	13,999	0	1.29	0.255	14,207	0	1.81	0.178	14,384	0	1.15	0.284	14,463
36	Δ Dividend per share	0	0.84	0.358	16,711	0	0.83	0.361	16,951	0	0.81	0.37	17,161	0	1.22	0.269	17,271
37	Δ Depreciation to PP&E	0.001	1.66	0.197	15,484	0.001	1.38	0.24	15,698	0	0.35	0.554	15,878	0	0.31	0.577	16,019
38	Δ ROCE	-0.001	3.29	0.07	16,735	-0.001	3.39	0.065	16,983	-0.001	3.82	0.051	17,186	-0.006	20.45	0	17,277
39	Δ Capital Expenditures to Total Assets	0	0	0.984	16,920	0	0	0.976	17,164	-0.011	68.14	0	17,362	-0.009	57.1	0	17,485
40	Δ Total Debt to Equity	-0.006	41.93	0	16,920	-0.008	53.47	0	17,164	-0.008	57.76	0	17,359	-0.028	200.97	0	17,483

41	∆ Long Term Debt to Equity	0	1.47	0.225	16,696	0	1.58	0.209	16,936	0	1.58	0.209	17,147	0	0.99	0.319	17,211
42	∆ Equity to Fixed Assets	-0.001	0.65	0.421	16,558	0	0.52	0.472	16,796	-0.001	1.61	0.205	16,996	-0.001	0.75	0.386	17,141
43	∆ Times terest Earned	0	1.31	0.252	16,761	0	1.3	0.254	17,000	0	0.85	0.356	17,213	0	0.86	0.355	17,388
44	∆ Sales to Total Assets	-0.003	8.29	0.004	16,644	-0.003	9.3	0.002	16,883	-0.003	7.79	0.005	17,096	-0.002	5.39	0.02	17,196
45	∆ Gross Profit Margin	0	4.12	0.042	16,711	0	4.09	0.043	16,950	0	4.5	0.034	17,162	0	5.57	0.018	17,270
46	∆ EBITDA to Sales	0	0.24	0.622	13,954	0	0.03	0.862	14,159	-0.001	1.58	0.209	14,362	-0.001	2.3	0.129	14,603
47	∆ Pretax Income to Sales	0	0.85	0.356	16,276	0	0.84	0.36	16,516	0	0.83	0.363	16,722	0	0.81	0.368	16,956
48	∆ Net Profit Margin	0	0.04	0.851	15,439	0	0.1	0.755	15,652	0	0.09	0.759	15,815	0	0.07	0.796	16,016
49	∆ Sales to Total Inventory	0	0.85	0.356	15,495	0	0.82	0.366	15,708	0	0.79	0.375	15,865	0	0.85	0.355	16,067
50	∆ Sales to Working Capital	0	0.77	0.379	16,197	0	0.31	0.579	16,425	0	0.18	0.673	16,580	0	0	0.945	16,797
51	∆ Production	0	1.03	0.309	16,116	0	1.03	0.31	16,341	0	1.02	0.313	16,477	0	1.02	0.313	16,695
52	∆ Total Assets	0	1.33	0.248	16,931	0	1.33	0.248	17,170	0	1.33	0.249	17,328	0	1.36	0.244	17,554
53	∆ Working Capital to Total Assets	0	1.32	0.251	14,774	0	1.31	0.252	14,998	0	1.32	0.251	15,192	0	1.33	0.25	15,416
54	∆ Operating Income to Total Assets	0	1.32	0.251	16,346	0	1.32	0.251	16,597	0	1.31	0.251	16,739	0	1.32	0.25	16,982

55	Δ Total Debt	0	0.48	0.49	16,300	0	1.81	0.178	16,522	0	2.82	0.093	16,658	0	2.97	0.085	16,878
56	Δ Capital Expenditures to Total Assets	0	2.56	0.11	14,056	0	2.51	0.113	14,264	0	2.77	0.096	14,332	0	2.65	0.103	14,495
57	Δ R & D Expense	0	0.95	0.33	16,900	0	0.85	0.358	17,140	0	0.85	0.358	17,245	0	0.86	0.354	17,471
58	Δ R & D to Sales	0.001	2.63	0.105	16,984	0.001	2.58	0.108	17,223	0.001	2.61	0.106	17,388	0.001	2.57	0.109	17,614

Appendix 2 – Fluctuations of leading market indexes over time (Yahoo Finance)