PORTFOLIO SELECTION, PEAD ANOMALY AND VALUE RELEVANCE OF EARNINGS

By

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ABSTRACT OF THE DISSERTATION

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Finance and accounting research has recently focused on extracting the tone or sentiment of a document by using positive or negative words/phrases in the document. The first essay of this dissertation exploits the information content of qualitative data in addition to quantitative signals in selecting optimal portfolios. Using optimization techniques developed by Brandt, Santa-Clara, and Valkonov[2009], this essay shows that significantly higher returns can be obtained combining quantitative and qualitative data obtained from firms' Management Discussion and Analysis sections of their Form 10-Q (10-K) SEC filings than just using quantitative signals.

The second essay uses option market characteristics to examine the two leading explanations for the Post-Earnings-Announcement Drift (PEAD) anomaly. PEAD points towards an inexplicable inefficiency in the equity markets where traders seem to ignore the autocorrelations in extreme earnings surprises across adjacent quarters. By contrast, there is mounting evidence that option markets are very efficient. If so, there should be no PEAD like anomaly in the pricing of equity options. This essay tests this using a straddle strategy around earnings announcements and its empirical results indicate that option traders already incorporate the autocorrelation in extreme earnings surprises in option prices. It also uses the change in implied volatilities obtained from options prices

immediately before and after the earnings announcements as risk metric to examine the risk premium hypothesis of PEAD. However, its findings favor the competing under-reaction hypothesis, which assumes equity traders do not completely utilize the auto-correlations of earnings surprises.

The third essay examines the potential explanations for the observed decline in the value relevance of earnings over the years by exploring the time-series change of information transfer. Specifically, it examines how the importance of information transfer itself changes over time and the time-series change in value relevance of earnings by industry. It shows that the decline in usefulness of earnings is not significant in all industries, although the decline is significant on average. It also indicates that the time-series change in the magnitude of information transfer is insignificant on average and for most industries, after controlling for the decline in the value relevance of earnings over time.

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CHAPTER 1

OPTIMAL PORTFOLIO SELECTION BASED ON QUALITATIVE AND QUANTITATIVE SIGNALS

1.1 INTRODUCTION

The objective of this study is to construct an optimal portfolio of stocks using timely quantitative financial signals as well as firm-specific signals capturing changes in managerial optimism and pessimism from the Management Discussion and Analysis (MD&A) sections that accompany periodic (annual and quarterly) filings with the SEC.

The metric of MD&A tone change is first developed by Feldman et al. [2010], and is based on analyzing text to construct a signal derived from qualitative data. This study uses a statistical methodology for portfolio optimization first proposed by Brandt, Santa-Clara, and Valkanov (BSCV) [2009], and later modified by Hand and Green (HG) [2011] to include accounting-based signals.

Specifically, this study uses firm size, book-to-market ratio, momentum, earnings change, accruals, and operating cash flow (rather than the asset growth variable used by HG [2011]), in addition to the aforementioned qualitative MD&A signal to construct the optimal portfolio.

The two main innovations in this study are: (1) An additional qualitative-based measure is used as an input in the optimization procedure; and (2) Point-In-Time (PIT) monthly data, unlike the coarser annual data used by earlier papers, is used. The former innovation is, to the best of my knowledge, a first in the literature, while the later innovation mimics portfolio optimization used in practice.

Results indicate that using more timely data (i.e. monthly rather than annual quantitative data) in the portfolio construction yields higher portfolio returns. Furthermore, consistent with Feldman et al [2010], when the MD&A tone change signal is added to the quantitative financial and accounting signals, the optimal portfolio yields significantly higher returns than only using quantitative signals to construct the optimal portfolio.

This study contributes to the literature in two ways. It shows that portfolio optimization can be improved by using signals based on qualitative data to supplement the traditional finance or accounting-based quantitative signals. Further, it shows that using timely data in a manner that mimics portfolio rebalancing in quantitative asset management practice can yield higher returns than rebalancing based upon stale annual data.

Section 1.2 reviews the literature. Section 1.3 describes the methodology. Section 1.4 reviews the sample selection criteria and presents the main results. Section 1.5 summarizes this study and its conclusions.

1.2 LITERATURE REVIEW

The literature on portfolio optimization goes back to Markowitz [1952], and there have been many variations of the model since then. However, a vexing problem that has plagued the Markowitz method (the so-called mean variance approach) for optimally constructing a portfolio of stocks has been the computational complexity involving large variance-covariance matrices.

This problem becomes particularly acute when one tries to incorporate firm-specific characteristics that have been shown in recent years to be associated with the expected returns, variance, and covariance of the firm's stock returns. A complete implementation of the Markowitz approach for portfolio optimization would demand that the moments of every individual stock and its covariance with other stocks be modeled as a function of all these firm-specific characteristics.

Given that the dimensionality of the variance-covariance matrix increases nonlinearly in the number of stocks being considered, solving the Markowitz model would be a daunting task theoretically, and its implementation would prove to be impractical for most portfolio managers. In fact, if the Markowitz model has to be implemented with anything other than for investors with quadratic preferences, then an unmanageable number of higher moments have to be considered in optimizing the portfolio. While some simplifications and approximations have been proposed in the literature, most have proven to be less than satisfactory.

Recently, a promising and practical approach to portfolio optimization called the Parametric Portfolio Policy (PPP) has been proposed by BSCV [2009]. In their model, irrespective of investor preferences and the joint distribution of stock returns, the dimensionality of the portfolio optimization problem for a group of N characteristics is only of the order N. This sidesteps the curse of dimensionality that plagues the Markowitz approach. In addition, the optimal portfolio weights for each stock can be estimated by using well known statistical techniques.

The idea behind the BSCV model is to begin by holding the value weighted market (VWM) portfolio of equities, and then optimally tilt (by adding and subtracting from the market portfolio) the weight given to each stock in the market portfolio using a vector of firm specific characteristics. The tilting process involves finding the optimal weight that has to be given to each firm characteristic. The weights are computed using well known data-intensive statistical estimation procedures.

For a representative investor with constant relative risk aversion (CRRA) utility, and using annual data, BSCV show that the optimal incorporation of a few characteristics such as firm size, book-to-market ratio, and momentum, all price-based characteristics (PBC) that have previously been shown to explain returns (the so called Fama-French-Carhart factors), produces 5.4% higher Certainty Equivalent returns out-of-sample than simply investing in a VWM portfolio.

Many authors have extended the BSCV model by using a larger set of quantitative characteristics. As one example, DeMiguel, Garlappi, and Uppal [2009] use asset-specific characteristics similar to the ones used by BSCV [2009] but only allow investment in a fraction of the assets that are available for investment. In another variation, Plyakha and Vilkov [2008] apply this method to select optimal option portfolios using option characteristics (such as implied volatility and smile-skew). Castro [2009] extends this method by incorporating region and industry factors. He also includes bond portfolios and related characteristics such as maturity and ratings. Chavez-Bedoya and Birge [2009] extend this approach to handle non-linear and non-convex objectives functions, and show that certain parametric characteristics, such as correlations of the stock return with the index return, maximum deviations of the stock return with respect to the index return and beta deviations, can predict the ability of a stock to track or beat the returns on chosen indexes.

However, the most relevant extension for this study is by Hand and Green (HG) [2011]. Using annual data, and incorporating three additional accounting characteristics, namely, accruals, change in earnings, and asset growth, they show that their optimal portfolio earns significantly higher returns than the BSCV portfolio. Note that both BSCV and HG use annual financial disclosures while rebalancing their monthly portfolios, rather than the more timely quarterly disclosures, or even monthly disclosures for some variables (for example, the momentum metric). In practice, investors and portfolio managers have ready access to quarterly and monthly disclosures and use these to update their portfolios.

To the best of my knowledge, there is no prior work in the financial literature that attempts to optimize over signals derived from qualitative characteristics. The above cited papers, as well as the majority of prior research in financial economics and accounting, have primarily focused on quantitative financial data. However, given recent developments of specific methods and tools that are able to quantify the information content of verbal communications in a relatively objective way, more and more researchers are beginning to rigorously analyze the impact of qualitative communications.

Tetlock [2007] was perhaps the earliest to use qualitative data and show that the depth of pessimism expressed in a daily news column from The Wall Street Journal exerts a significant downward (temporary) pressure on prices of the stock indices. In a follow up study, Tetlock, Saar-Tsechansky and Macskassy [2008] show that increases in the negative words used in The Wall Street Journal and the Dow Jones News Service columns about S&P 500 firms relative to prior stories predict larger negative shocks to future earnings. Moreover, they also provide evidence that potential profits could be made by trading on signals based on negative words from Dow Jones News Service. Since then, there have been a number of others who have incorporated qualitative data in their studies on asset pricing. In particular, the research field of qualitative factors advanced significantly after the SEC's 1989 guideline on MD&A disclosures and after the availability of Securities and Exchange Commission (SEC) filings on the Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system. Feldman et al. [2010] provides a good summary of research in this area.

1.3 METHODOLOGY

1.3.1 The BSCV Procedure[1]

The basic assumption of the PPP method proposed in BSCV [2009] is that at every date t, the investor chooses a set of portfolio weights $\{w_{i,t}\}$, $i=1,2\ldots\ldots N_t$ of a set of stocks N_t so as to maximize the conditional expected utility of that portfolio's one-period ahead return $r_{p,t+1}$. For each date t, the return of stock i from date t to t+1 is given by $r_{i,t+1}$. The problem then is to find the optimal weight for each stock in the optimized portfolio to maximize the investor's expected utility of the portfolio's return $r_{p,t+1}$. If the weight of each stock in the optimized portfolio at date t is assumed to be $w_{i,t}$, then the conditional optimization problem is described as:

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[1] Only a brief introduction to the BSCV [2009] procedure is provided here. The interested reader can refer to the original article for details.

$$\max_{\{w_{i,t}\}_{i=1}^{N_t}} E_t\left[u(r_{p,t+1})\right] = E_t\left[u(\sum_{i=1}^{N_t} w_{i,t} r_{i,t+1})\right]$$

EQUATION 1: Optimization of the conditional expected utility function

A linear form for the weights $w_{i,t}$ is specified, following BSCV [2009], in the vector of cross-sectionally standardized characteristics $\hat{x}_{i,t}$ of stock i, weighted by a coefficient vector $\vec{\theta}$, that is,

$$w_{i,t} = f(x_{i,t};\vec{\theta}) = \overline{w}_{i,t} + \frac{1}{N_t}\vec{\theta}^{\mathrm{T}}\hat{x}_{i,t}$$

EQUATION 2: Linear form for the weights of stocks in the portfolio following BSCV [2009]

Here $\overline{w}_{i,t}$ is the weight of stock i at time t in a benchmark portfolio, such as the value-weighted market portfolio. $\vec{\theta}$ is a vector of coefficients that has to be estimated. The second term $\frac{1}{N_t}\vec{\theta}^{\mathrm{T}}\hat{x}_{i,t}$ is the tilting of weight of stock i away from its weight in the benchmark portfolio based on its characteristics.

$\hat{x}_{i,t}$ has been standardized cross-sectionally to have zero mean and unit standard deviation across all stocks at time t to ensure stationarity over time. Additionally, the standardization ensures that the average cross-sectional of $\vec{\theta}^{\mathrm{T}}\hat{x}_{i,t}$ will be zero; and the deviations of the optimal portfolio weights from the weights in the benchmark portfolio will always sum to zero, ensuring that the optimal portfolio weights will sum to unity[2]. Scaling by N_t corrects for the possibility that the number of stocks may be varying over time. Because the estimated weights are generated by a single function of the characteristics that applies to all stocks over time – rather than estimating one weight for each stock at each point in time – BSCV refer to this as selecting a “portfolio policy".

Given the assumption that coefficients $\vec{\theta}$ are constant across assets, the estimated weight of each stock in the optimized portfolio only depends on the stock's characteristics instead of its historical returns. In other words, two stocks that are similar in the characteristics that determine risk and expected returns will be assigned similar weights in the portfolio even if their historical returns are very different. As a result of the “constant coefficients through time” assumption, the coefficients that maximize the investor’s conditional expected utility at a given date are the same for all dates, or time independent. Therefore, the conditional optimization problem can be rewritten as an unconditional optimization problem and θ can be estimated by maximizing the corresponding sample analog of the unconditional expectation,

$$\max_{\theta} E_t\left[u(r_{p,t+1})\right] = E\left[u(\sum_{i=1}^{N_t}(\overline{w}_{i,t} + \frac{1}{N_t}\vec{\theta}^{\mathrm{T}}\hat{x}_{i,t})r_{i,t+1})\right]$$

$$= \max_{\theta}\frac{1}{T}\sum_{t=0}^{T-1}u(\sum_{i=1}^{N_t}(\overline{w}_{i,t} + \frac{1}{N_t}\vec{\theta}^{\mathrm{T}}\hat{x}_{i,t})r_{i,t+1})$$

EQUATION 3: Maximization of the corresponding sample analog of the unconditional expected utility function

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[2] This also ensures that portfolio rebalancing would not require any additional cash flows.

Since the above is a well-defined optimization problem, BSCV estimate the parameter $\vec{\theta}$ by maximizing the expected utility using the usual first order condition (FOC) approach with respect to this parameter, that is,

$$\frac{1}{T}\sum_{t=0}^{T-1} h(r_{t+1}, x_t; \vec{\theta}) \equiv \frac{1}{T}\sum_{t=0}^{T-1} u'(r_{p,t+1})(\frac{1}{N_t}\hat{x}_t^{\mathrm{T}} r_{t+1}) = 0$$

EQUATION 4: First order condition (FOC) approach

Given equation (4) is the sample moments of a moment condition and it equals to zero, the generalized method of moments (GMM) formalized by Hansen [1982] can be applied to estimate the parameter $\vec{\theta}$ here, where $\vec{\theta} = \arg\max_{\theta} \frac{1}{T}\sum_{t=0}^{T-1} u(\sum_{i=1}^{N_t}(\overline{w}_{i,t} + \frac{1}{N_t}\vec{\theta}^{\mathrm{T}}\hat{x}_{i,t})r_{i,t+1})$.

BSCV [2009] empirical results demonstrate the importance of the firm's market capitalization, book-to-market ratio, and one-year lagged return (the PBC characteristics) to explain deviations of the optimal portfolio for a constant relative risk aversion (CRRA) investor from the value-weighted market portfolio. Following the work of HG [2011], who find that inclusion of three accounting-based characteristics, namely, accruals, change in earnings, and asset growth, generates a higher out-of-sample, pre-transactions-costs annual information ratio compared to that for the standard price-based (PBC) Fama-French-Carhart characteristics of firm size, book-to-market ratio, and momentum, this study follows a similar procedure in the analysis described below.

1.3.2 Research Design

There are 4 parts to the empirical work of this study. First, as a benchmark, it reproduces the results of HG [2011] using annual data as they did, and for the same time horizon studied by them, that is, from 1964 to 2008. It uses the same variables as used by HG [2011], namely firm size, book-to-market ratio, momentum, accruals, change in earnings and asset growth.

Next, as an improvement on the BSCV [2009] and HG [2011], it repeats the above study using PIT monthly data and compares the results with results obtained from annual data. This is particularly important because, in practice, portfolios are rebalanced frequently using the most current information. The time period for this monthly portion of this study ranges from 1987 to 2008 for data reasons discussed in the next section.

In the third part, one change in the choice of accounting variables used by HG is made. Instead of asset growth, operating cash flows is used because this variable is consistent with prior accounting literature on asset pricing (see Penman, 2009), while asset growth is at best an ad hoc choice. These 6 characteristics with operating cash flows are referred to as HG Modified (HGM) characteristics.

Lastly, the qualitative tone change metric is incorporated as in Feldman et al. [2010] in the portfolio optimization (in addition to the HG and HGM characteristics) to test whether the combination of quantitative and qualitative factors produces superior performance to that using quantitative factors alone. The time horizon for this portion of the study is dictated by the availability of MD&A data, and ranges from November 1994 till July 2008. This is further discussed below.

1.4 SAMPLE AND RESULTS

1.4.1 Data

This section first describes the data and sampling approach, and then presents results. As mentioned above, the availability of data on qualitative MD&A, and monthly PIT data dictates the choice of the sample time periods of this study. To demonstrate that this study achieves results that are comparable to those of prior research with my own optimization program, annual data from fiscal year 1964 (lagged variables from 1963) through fiscal year 2008 (collected from the COMPUSTAT annual industrial file and CRSP monthly files) is first used.

To test the change in portfolio performance by using PIT monthly data rather than the annual data used by HG (and BSCV), PIT monthly data from the earliest available date of 1987 and ending in 2008[3] is used. Since the GMM procedure requires that the first seven years (1987 to 1993) of data be used to estimate the initial parameter choice of the optimized portfolio policy, the out-of-sample portfolio performance for the PIT portfolio is shown for the period 1994 to 2008.

Then, to test the impact of adding qualitative factors, financial and accounting data from November 1994 to July 2008 is used because the qualitative MD&A factor is derived from the SEC EDGAR data, and due to the construction of this qualitative signal, it is first available in November 1994. The out-of-sample portfolio performance shown is from 2000 to 2008 because the 1994-1999 data are used to estimate the initial coefficients

[3] The Charter Oak PIT data, which is available from February 1987, is used. The Charter Oak PIT data is a compilation of Compustat quarterly data that are available as of each month-end.

of the portfolio policy. Apart from the addition of the MD&A factor, all other factors are selected in the same fashion as the preceding case, i.e., using monthly PIT data from the Compustat quarterly files.

1.4.2 Implementation Procedure

1.4.2.1 Utility function and "tone" change metric

Unless otherwise stated, an investor with CRRA preference and a relative risk aversion of five is assumed throughout this study. Specifically, the utility function is given by:

$$u(r_{p,t+1}) = \frac{(1 + r_{p,t+1})^{1-\gamma}}{1-\gamma}$$

EQUATION 5: Utility function

with γ =5. This is consistent with prior studies. In addition, following BSCV, the investor is restricted to invest only in U.S. stocks. Risk-free asset is not included in the investment opportunity set because "a first-order approximation including the risk-free asset affects only the leverage of the optimized portfolio" (see HG [2011]).

This study follows Feldman et al. [2010] in choosing the metric for measuring managerial optimism and pessimism tones from the MD&A. To be precise, tone change rather than level is used for reasons given by Feldman et al. [2010] to capture managerial pessimism and optimism. That is, if the proportion of positive (negative) words out of total words in the MD&A reports increases from the average of the past four periodic filings, it is deemed that managers are turning more optimistic (pessimistic) in their outlook for the future.

To obtain signals about the "tone" change of the MD&A section in the 10-Q or 10-K, the MD&A sections are extracted and the number of words in the MD&A sections are counted. The cases where the total number of words in the MD&A is less than 30 are eliminated. The number of "positive" and "negative" words is counted as classified by the Harvard's General Inquirer (GI), after prefixes and suffixes[4] properly handled.

Two main variables are defined as the signals: (1) the number of "negative" words divided by the total number of words in the MD&A section; and (2) the difference between the number of positive and negative words divided by the total number of words. Then the corresponding average measures using the four periodic SEC filings during the prior 12 months are subtracted from these measures to get a sense for change in managerial outlook.[5] The former is a signal of pessimism (NEGSIG), while the latter is a measure of the differential or net optimism/pessimism (SIG).

1.4.2.2 HG [2011] Replication

The HG Characteristics

To show that results comparable to those obtained by HG [2011] are obtained with my own optimization program, the 1963 to 2008 annual dataset are collected as described by them (and by BSCV [2009] as well). The financial statement data, price-per-share and the number of shares outstanding which are used to calculate the accounting-based characteristics, book value of equity, and market value of equity are collected from the

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[4] See description and categories in wjh.harvard.edu/~inquirer/homecat.htm.
[5] The change in each measure from prior filings is standardized by the standard deviation of the measure over the previous filings to make comparisons across firms more meaningful, depending on management's prior tone changes.

COMPUSTAT annual industrial file; while monthly stock returns are collected from the CRSP monthly files. The one-month Treasury bill rates (risk-free rate) are collected from the Fama-French factor dataset from Wharton Research Data Services (WRDS). All COMPUSTAT variables from fiscal year 1963 through fiscal year 2008 are collected together with CRSP data from January 1963 through December 2008.

To replicate HG [2011] study, their six firm-specific characteristics are used for portfolio optimization. Firm size or market capitalization (MVE) is defined as the market value of common equity at the firm's fiscal year end, or the product of market price per share times the number of shares outstanding. Book-to-market (BTM) ratio is the fiscal year end book value scaled by MVE (Stattman, 1980; Rosenberg, Reid and Lanstein, 1985). Book value of equity is computed as total assets net of liabilities, plus deferred taxes and investment tax credits, minus preferred stock value. Momentum (MOM) at month t is the compounded monthly returns for months t-12 through t–1. When the operating cash flow is available, annual accruals, ACC is the net income less operating cash flow scaled by average total assets; otherwise following Sloan [1996], ACC = Δcurrent assets – Δcash – Δcurrent liabilities – Δdebt in current liabilities – Δtaxes payable – Δdepreciation all scaled by average total assets (where Δ refers to change over the relevant period). If any of the above components is missing, the missing component is set to zero. The change in annual earnings, UE, is net income in the most recent fiscal year less net income of the prior year, scaled by average total assets (Ball and Brown, 1968; Foster, Olsen and Shevlin, 1984). Lastly, asset growth AGR is defined as the natural log of one plus total assets at the end of the most recent fiscal year less the natural log of one plus total assets one year earlier (Cooper, Gulen and Schill, 2008, 2009).

Data Collection and Matching

This study uses CUSIP and calendar year to match the CRSP and COMPUSTAT data for the entire universe of U.S. stocks. If both the CUSIP and calendar year match, they are considered to be the same firm and the data are merged.

After the two databases are matched, the availability of monthly stock returns, the availability of all the market data items (price, number of shares outstanding), and lastly the availability of sufficient data to compute a firm's accruals, change in earnings, and asset growth for each firm, are checked.

Specifically, for the purpose of calculating momentum, this study also checks the availability of the firm's monthly return for the months between t−12 and t–1. If any of the monthly returns during this period is not available, the firm is removed from the dataset for month t. Following BSCV, the smallest 20% of firms as measured by MVE are also deleted since such small firms tend to have low liquidity, high bid-ask spreads and disproportionately high transactions costs.

The final number of firms varies greatly by year, rising from a low of only 359 in 1965 to a peak of 4,773 in 1998. The average number of firm observations per year is 2917.

Following the methodology used by BSCV [2009], and HG [2011], for each month over the period January 1965-December 2008, this study assumes that investors have price-based information up to the end of the month, and that accounting-based information is available with a six-month lag past a firm's fiscal year-end. For instance, at the end of September 1998, it assumes that investors only have access to annual accounting information published by firms with fiscal years ending on or before March 31, 1998. For those firms with fiscal years ending April 1st through September 30th, it assumes that the most recently available annual accounting information available to investors is from the prior fiscal year end. This study imposes this constraint in order to avoid look-ahead bias, and to make the methods consistent with those of HG [2011]. The six-month delay rule to MVE in addition to all other accounting variables from annual report is also applied.

To make the comparison of cross-sectional characteristics meaningful, and to reduce the impact of outliers on parameter estimation, all raw firm characteristics are transformed by a ranking method. For every month t, each characteristic are ranked into 100 groups (0-99) and then divided by 99. Then the ranked characteristics are subtracted by 0.5 to guarantee that the characteristics have a mean of zero and a range of -0.5 to 0.5. It should be noted that the same standardization method is applied throughout this study.

Following HG [2011], this study uses the 408 monthly returns between January 1975 and December 2008, to calculate the in-sample results. Therefore, the full period January 1975 to December 2008 is used to estimate one single parameter set.

Following BSCV, this study calculates out-of-sample returns based on a "partially-rolling parameter estimation period" method or "quasi-fixed time period". For each month in the first year of the out-of-sample period, it uses data from January 1965 to December 1974 to estimate the coefficients.

Then this study combines the initial parameter set with the standardized and monthly varying firm characteristics to generate out-of-sample returns of the optimized portfolio for January to December 1975. Next, for each month in the following year (1976) of the out-of-sample period, January to December 1976, the ending point, but not the beginning point, of the parameter estimation period is rolled forward one year through December 1975 to estimate the parameter set.

The same method is repeated every year from 1976 to 2008 to obtain a specific θ for that given year. This "partially-rolling parameter estimation period" method also applies to all the out-of-sample results that are shown throughout this study.

1.4.2.3 Quarterly Data and the PIT Database

The PIT data sample from 1987-2008 is obtained from Charter Oak PIT data, which compiles quarterly Compustat data as of each month-end. At each month-end, market value, the market to book ratio using the most recently reported quarterly book value of equity, and the 12-month return momentum for the months t-12 through t-1, are calculated. This study also calculates the earnings surprise as earnings for the most recently reported quarter minus earnings for the same quarter in the prior year, scaled by average total assets for the most recently reported quarter (i.e., the average total assets in the most recently reported quarter and the immediately preceding quarter). It calculates accruals as net income minus net operating cash flow for the most recently reported quarter, scaled by average total assets. Asset growth is measured as before, except that it uses total assets at the beginning and end of the most recently reported quarter.

Firms that had market value and average total assets value below $10 million are eliminated, since such companies are not of interest to most professional investors. This study also eliminates firms with missing book value of equity or 12-month momentum.

Finally, of the remaining firms, it eliminates the bottom quintile in terms of market value of equity.

Every month-end, each of the characteristics are ranked into 100 groups, assigned to each observation its group rank (a number between 0 and 99), divided by 99 and subtracted by 0.5. If an observation is missing for a particular characteristic, it is assigned the value of zero. Thus, each observation has a score between -0.5 to 0.5.

1.4.2.4 The HGM Variation

An additional change in the analysis as compared to HG is that this study replaces the asset growth variable with net operating cash flow for the most recently reported quarter, scaled by average total assets.

1.4.2.5 The Tone Change Signals

To obtain the management tone change signal, the same procedures are followed as in Feldman et al (2010). This study first extracts the MD&A sections of all 10-Q and 10-K forms that are filed with the SEC.[6] In each extract, the number of positive words and the number of negative words are counted as provided by the GI dictionary, as well as the total number of words.

This study then constructs the two measures, namely, of the ratio of negative words to total words, and the ratio of positive minus negative words to total words. Then the signal is constructed by subtracting from each measure the average measure from the periodic filings for the same firm in the prior year, scaled by the standard deviation of the measure

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[6] Only the first filed form is used and not any subsequent amendments.

over that time period. The ratio with negative words is referred to as NEGSIG, and the differential ratio with positive minus negative words is referred to as SIG.

Thus, this study derives signals of a tone change, i.e., whether management became more pessimistic or optimistic than in the prior SEC filings. Feldman et al. [2010] show that the tone change signals can be useful for investors beyond the quantitative earnings surprises and accruals. Therefore, these signals can potentially be useful for portfolio optimization to obtain superior returns.

At each month-end, the two tone change signals in the most recent periodic SEC filing are identified, as long as the filing is not more than 12 months old. Then the two tone change signals are ranked each month into 100 groups, each observation is assigned its rank between 0 and 99, divided by 99, and subtracted by 0.5. If an observation does not have a tone change signal, it is assigned the value of zero.

1.4.3 Empirical Results

1.4.3.1 Replicating the HG Results

Since the Matlab coding for the HG [2011] is proprietary, this section demonstrates that my own portfolio optimization program yields results that are similar to theirs. This study, like HG [2011], follows the BSCV PPP methodology described earlier. On average, there are 2,829 firm observations per month. No short-sale constraints are imposed in the optimization, and no transactions costs are accounted for. The number of firms by year in the annual dataset of this section is shown in Figure 1. The overall shape of the curve is highly similar to the dataset curve presented in Table 1 of HG [2011].

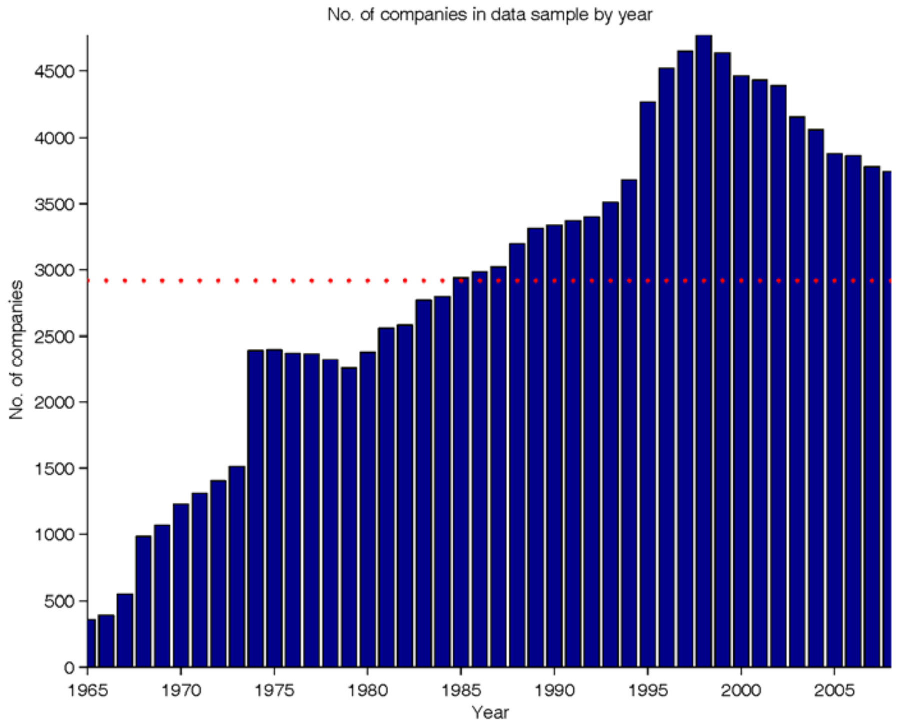

Figure 1: Number of firms by year in the annual dataset

To provide a comparison, the statistics on the returns generated by the optimal portfolios in this section are reported, and the returns reported by HG [2011] are also displayed in Table 1. Following BSCV, the annualized return is defined as the simple sum of the calendar year's monthly returns. Specifically, Table 1 provides the Certainty Equivalent (CE) of the optimal portfolio's mean annualized return, the mean and standard deviation of the annualized return, together with the portfolio's annualized Sharpe ratio and Information ratio (IR).[7]

[7] Information ratio (IR) is defined in the literature as the difference between the return of the optimal portfolio and the benchmark value weighted market portfolio, scaled by the standard deviation of the difference between returns of the optimal portfolio and the benchmark portfolio

Table 1: Descriptive statistics on the returns generated by optimal portfolio of this study compared to those of Hand and Green [2011]

Statistics for annual returns	VW market	PPP Results of this study		Hand&Green's PPP Results	
		in-sample	out-of-sample	in-sample	out-of-sample
Certainty equivalent(CE)	6.2%	66.3%	72.0%	48.4%	43.6%
Mean	12.7%	105.0%	115.0%	74.7%	75.5%
Std. dev. (σ)	15.4%	54.7%	68.6%	31.7%	37.0%
Sharpe ratio	0.45	1.83	1.60	2.18	1.89
Information ratio(IR)		1.68	1.51	2.31	2.02

Table 1 shows that the returns of this study as well as those of HG beat the VWM portfolio returns. However, compared to HG, mean returns from all the PPP optimized portfolios (both in- and out-of-sample) of this study are higher, and correspondingly, the standard deviations of returns from the PPP optimized portfolios are also higher.

It is believed that this difference is attributable to details of the empirical implementation. As a case in point, there is difference in the definition of the firm characteristics of this study vis-a vis HG [2011]. For example, MOM is defined as cumulative raw return for the twelve months ending one month before the portfolio construction date in this study, while HG [2011] define MOM as cumulative raw return for the twelve months ending four months after the most recent fiscal year end.

A second cause of difference could be the methodology that is used in filtering the unrestricted CRSP universe and matching the CRSP database with the COMPUSTAT database (the dataset here is 10-15% smaller), leading to different efficiency of the GMM estimator.

Table 1 also shows a higher Certainty Equivalent than HG [2011] for both in-and out-of-samples are achieved. In other words, the procedure of this study would better serve a risk-averse utility maximizing investor, at least for the sample period under consideration. While the annualized Sharpe ratios and information ratios for all optimal portfolios in this section are lower than those reported by HG, they are still higher than those of the VWM portfolio.

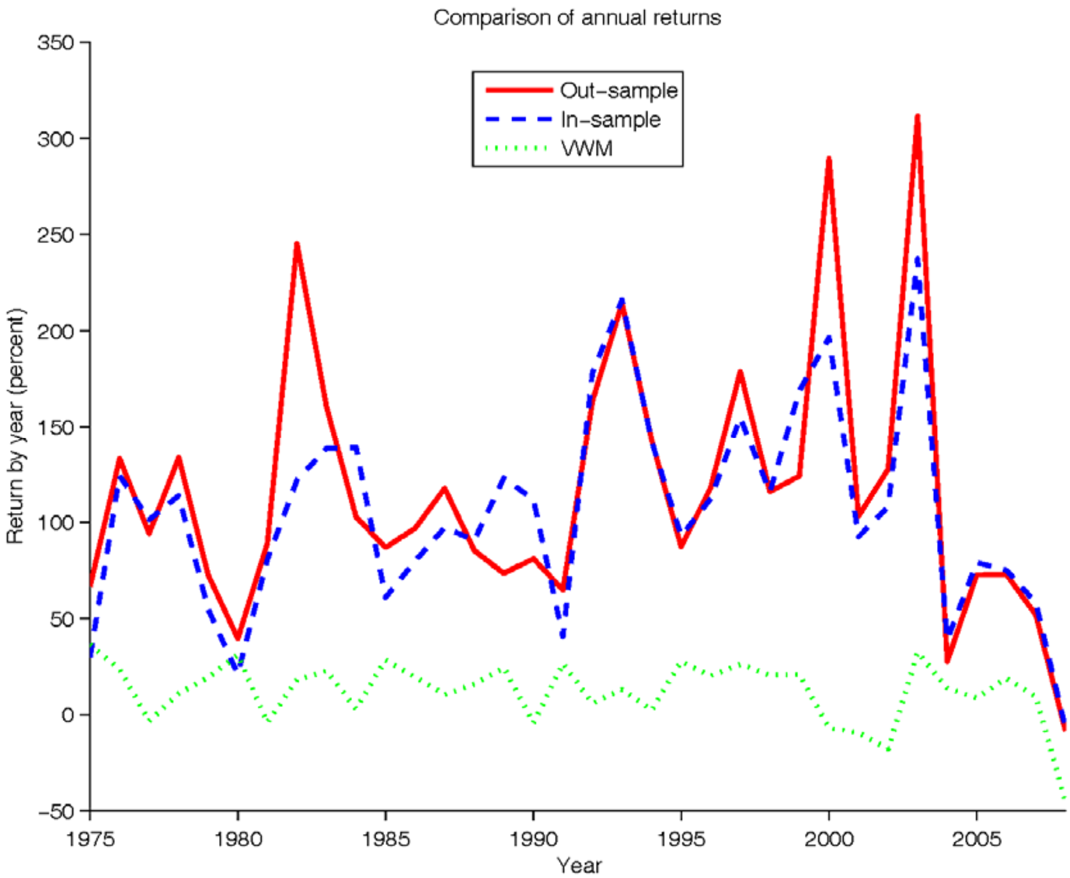

Figure 2: Comparison of annual returns for the PPP out-of-sample optimal portfolio, the in-sample optimal portfolio and the value-weighted market portfolio

Figure 2 shows the comparison of annual returns for the in-sample optimal portfolio, out-of-sample optimal portfolio of this section, and the value-weighted market portfolio which serves as a benchmark, for the time horizon of 1975 to 2008.

As in HG [2011], six accounting-based and price-based firm characteristics are included to optimize investor's average utility as described in equation (3). Table 2 presents the average out-of-sample and in-sample parameter estimates, descriptive statistics on portfolio weights, and the average monthly weighted firm characteristics. VWM portfolio is defined by all observations included in this dataset, not the unrestricted CRSP universe.

Specifically, for the PPP in-sample scenarios, a single PPP parameter θ is estimated over the full sample period January 1975-December 2008. Unlike for the in-sample scenarios, PPP out-of-sample scenarios show the average of 34 different $\vec{\theta}$s for the period 1975 to 2008. The sample period for out-of-sample scenarios is defined by the "quasi-fixed time period" method explained in Sub-section 1.4.2.2. The standard errors for in-sample scenarios are taken from the sample asymptotic covariance matrix of the GMM optimization.

Following HG [2011], an alternative method is used to calculate the standard errors for the out-of-sample scenarios. The standard errors of the parameter estimates are the average of the standard errors of the 34 out-of-sample coefficients estimated by "partially-rolling parameter estimation periods" method described earlier.

Table 2 also provides the parameter estimates, average portfolio weights, and average firm characteristics. Table 2 indicates that the deviations of the optimal weights from the value-weighted market portfolio weights decrease with the firm's market capitalization (firm size), accruals, and asset growth. On the other hand, the deviations increase with the firm's book-to-market ratio, change in earnings and its momentum (lagged one-year return).

The signs of these estimates are consistent with those demonstrated by HG [2011]. These findings are also consistent with the findings of BSCV [2009], that is, to overweight small firms (low market capitalization), value firms (high book-to-market ratio), and past winners (high lagged one-year return), and underweight large firms, growth firms, and past losers. Given that these characteristics are standardized cross-sectionally, the magnitudes of the estimated parameters can be compared with one another.

Table 2: Parameter estimates, average portfolio weights, and average firm characteristics in the optimal portfolio

	PPP in-sample	PPP out-of-sample
θ_{me}	-5.06	-7.18
$se[\theta_{me}]$	[3.03]	[4.26]
θ_{btm}	21.10	13.04
$se[\theta_{btm}]$	[4.36]	[8.05]
θ_{mom}	7.33	3.78
$se[\theta_{mom}]$	[3.15]	[3.94]
θ_{acc}	-46.05	-3.27
$se[\theta_{acc}]$	[10.14]	[14.76]
θ_{ue}	51.24	66.51
$se[\theta_{ue}]$	[11.67]	[11.53]
θ_{agr}	-32.17	-53.84
$se[\theta_{agr}]$	[10.50]	[13.21]
$Avg.\|w_i\|\times 100$	0.50	0.57
$Avg.\max w_i \times 100$	3.24	3.28
$Avg.\min w_i \times 100$	-2.25	-2.29
$Avg.\sum w_i I(w_i < 0)$	-7.48	-8.63
$Avg.\sum I(w_i \leq 0)/N_t$	0.48	0.49
$Avg.$ weighted MVE	-0.11	-0.40
$Avg.$ weighted BTM	1.46	1.01
$Avg.$ weighted MOM	1.12	1.15
$Avg.$ weighted ACC	-3.27	0.43
$Avg.$ weighted UE	2.58	4.15
$Avg.$ weighted AGR	-2.45	-3.54

Among all six firm characteristics, a high change in earnings leads to the quantitatively largest overweighting of a stock compared to the value-weighted market portfolio. If only the three PBCs, namely, MVE, MOM and BTM are considered, a high book-to-market ratio leads to the quantitatively largest overweighting of a stock. This is consistent with the finding of BSCV [2009].

Table 2 also reports the PPP in-sample and out-of-sample monthly absolute weight of the optimal portfolio, the monthly maximum and minimum weights, the total short weights, and the proportion of negative weights. The lower half of Table 2 reports the time-series average of the monthly weighted averages of the firms' standardized characteristics in the optimal portfolio. Positive values indicate an overall preference for firms with relatively higher normalized characteristic. For example, a positive value for the characteristic BTM indicates that for the sample period of the empirical test, the optimal portfolio is on average weighted toward value firms.

A few observations from Table 2 are particularly worth noting. First, for the in-sample PPP parameter estimates, five out of six firm characteristics parameter estimates go beyond two standard errors from zero (BTM, MOM, UE, ACC and AGR). For out-of-sample PPP parameter estimates, only the parameter estimates for UE and AGR go beyond two standard errors from zero.

Second, the PPP method generates an average maximum (around 3.2%) and minimum (around –2%) portfolio weights (in-sample and out-of-sample). Lastly, across estimated optimal portfolios from 1975 to 2008, the average proportion of short position is close to 50% for PPP in-and out-of-sample. This is consistent with prior literature which shows that, in the absence of constraints on short selling, the proportion of risky assets held short in both the mean-variance tangency portfolio and the minimum variance portfolio tends in the limit to reach 50% [Levy, 1983; Green and Hollifield, 1992; Levy and Ritov, 2001].

In general, the results of this section are very consistent with those of HG [2011]. This validation provides a benchmark to compare the results obtained by using monthly PIT data and the qualitative MD&A tone change variable.

1.4.3.2 PPP Methodology using Monthly PIT data in the BSCV and HG study

To test the impact of using up-to-date monthly data, the 1987-2008 dataset is used as described earlier.

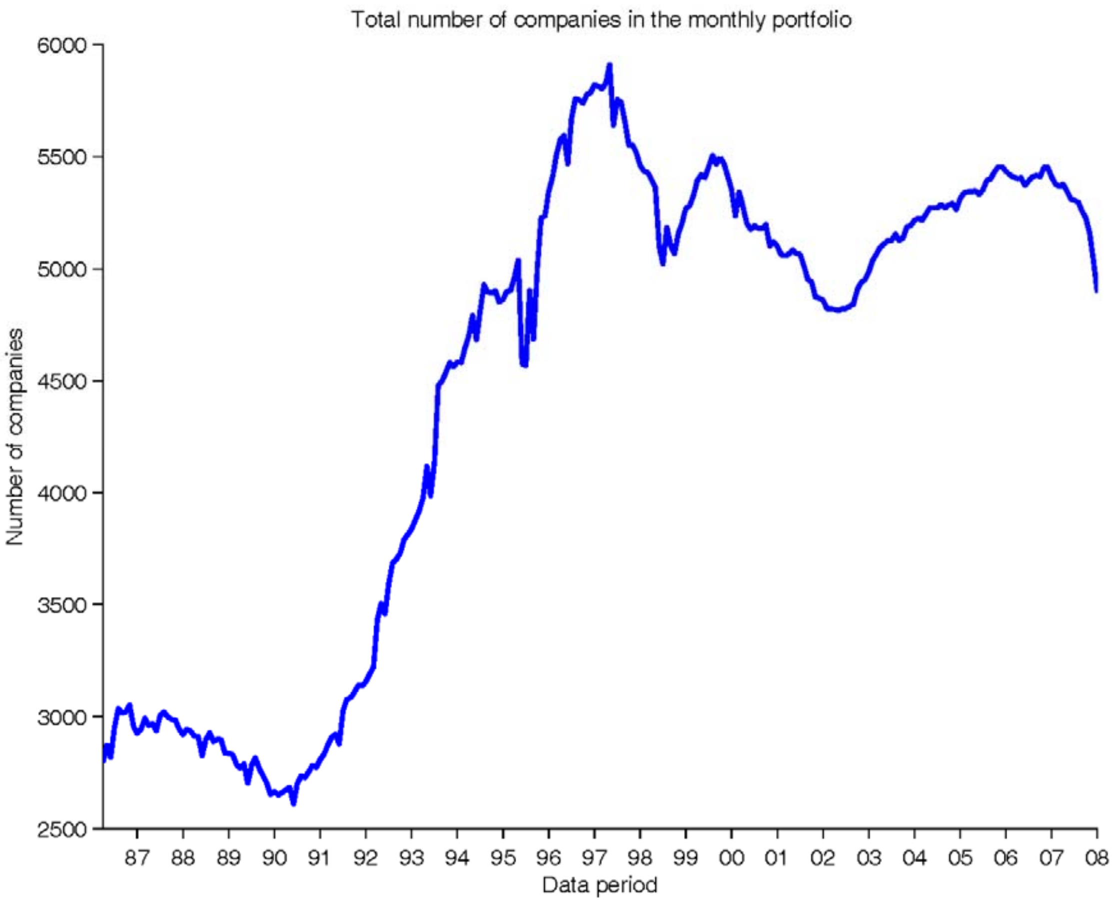

Figure 3: The number of companies in the monthly portfolio from 1987-2008

Figure 3 provides a graphical representation of the number of companies in the monthly portfolio from 1987-2008 of the underlying monthly data. The average number of companies in the monthly portfolio in this time period is 4,482, the maximum number of companies in the monthly portfolio in this time period is 5,912 and the minimum number of companies in the monthly portfolio in this time period is 2,609.

Table 3 presents the summary statistics of the underlying monthly data. For the full sample period (February 1987 to December 2008), the median market value is $329 million and the mean is $2.627 billion. The minimum firm size is $24 million while the maximum firm size is $602.433 billion. For the range from the 10th percentile ($64 million) and the 90th percentile ($4.245 billion), it can be seen that the market values of 80% of the sample of this study fall between $64 million and $4.245 billion. Therefore, this data sample includes a wide distribution of firm size without any specific bias.

Table 3: Summary of statistics of underlying PIT monthly data

Period	N	Mean	Std. dev. (σ)	Min	10th Pctl	Median	90th Pctl	Max
Feb, 1987-Dec, 2008	1174399	2627.337	12400.63	23.848	64.1711	328.692	4244.73	602432.6
Nov, 1994-July, 2008	862943	3091.377	14069.16	34.5569	74.0919	379.7809	5001.875	602432.6

For the sub-sample from November 1994 to July 2008, median market value is $380 million and the mean is $3.091 billion. The minimum firm size is $35 million while the maximum firm size is still $602.433 billion. From the 10th percentile $74 million and the 90th percentile $5.002 billion, it can be seen that the market values of 80% of this sub-sample fall between $74 million and $5.002 billion. Compared to the full sample period, this sub-sample firm sizes are slightly larger but still include a wide distribution. Note that the market value distribution is also similar for the sub-sample (from November 1994 to July 2008) for which qualitative MD&A data are available.

Table 4.1 Summary of descriptive statistics of monthly returns for portfolios using monthly data or annual data

1994-2008	Mean	Std. dev. (σ)	Sharpe ratio	CE	IR
VWM annual	0.0067	0.0470	0.1233	0.0390	0.0000
VWM monthly	0.0067	0.0452	0.1293	0.0011	0.0000
PBC annual	0.0459	0.1618	0.2782	-0.0812	0.2169
PBC monthly	0.0945	0.2488	0.3760	-0.9541	0.3287
HG annual	0.2165	0.3923	0.5496	-0.6770	0.5337
HG monthly	0.8257	1.4134	0.5836	-0.7833	0.5774

Table 4.1 shows that using up-to-date monthly data rather than annual data with the BSCV three price-based (PBC) characteristics portfolio, or HG's six-characteristics portfolio, can yield a much higher average monthly return as well as a higher Sharpe ratio. For BSCV's three price-based characteristics portfolio, when using annual data, the average monthly return of the optimized portfolio over the time horizon of 1994 to 2008 is 4.6%. When PIT monthly data are used, it jumps to 9.5%. In other words, the returns double when PIT monthly data is used instead of annual data.

The improvement over HG's six-characteristics-based optimal portfolios is even more pronounced. Table 4.1 shows that the average monthly return of the optimized portfolio over the time horizon from 1994 to 2008 is 21.65% when using annual data with the HG six-characteristics portfolio, while the average monthly return of the optimized portfolio over the same period is 82.57% with PIT monthly data. This a four-fold increase in returns.

It should also be noted from Table 4.1 that these results are consistent with those of HG who show that introducing accounting variables in addition to the BSCV market-based variables significantly improve the optimized monthly portfolio performance.

All the above results and comparisons indicate that using more updated monthly data for portfolio optimization significantly improves the PPP performance.

To ascertain that these improvements are statistically significant, the Fama-Macbeth tests are conducted. Table 4.2 shows the results of the Fama-Macbeth test for portfolio performance improvement. The t-statistics are 5.35 for the performance improvement of PBC portfolio with monthly data over PBC portfolio with annual data as in BSCV, and 6.00 for the performance improvement of HG portfolio with monthly data over HG portfolio with annual data, respectively. Furthermore, the t-statistics are 7.06 for the performance improvement of HG portfolio with annual data over PBC portfolio of BSCV with annual data, and 7.28 for the performance improvement of HG portfolio with monthly data over PBC portfolio of BSCV with monthly data, respectively.

Thus, all t-statistics are well above the critical value at 5% level of significance. In other words, portfolio performance improves significantly by using more updated monthly data rather than annual data for both BSCV three price-based characteristics portfolio and HG six-characteristics portfolio.

Table 4.2 The results of the Fama-Macbeth test for improvement in portfolio performance

1994-2008	Mean	Std. dev. (σ)	t Statistic
PBC monthly over PBC annual	0.05	0.12	5.35
HG annual over PBC annual	0.17	0.32	7.06
HG monthly over HG annual	0.61	1.36	6.00
HG monthly over PBC monthly	0.73	1.35	7.28

1.4.3.3 PPP Methodology using Monthly Financial data and HGM Characteristics

Table 5.1 shows that for the sample time period, 2000 to 2008, when the asset growth variable used by HG is replaced with operating cash flow (the HGM variable), the average return of the portfolio is marginally higher, but the Sharpe ratio is a little lower. The average monthly return of HG's six-characteristics portfolio is 71.5% for the time horizon of 2000-2008 while the average monthly return of HGM six-characteristics portfolio is 75.1% for the same time period.

Table 5.1 Summary of descriptive statistics of monthly returns for the HG six-characteristics portfolio using monthly data and for portfolio with three accounting variables replaced by accruals, earning surprise and operating cash flow (HGM formulation)

2000-2008	Mean	Std. dev. (σ)	Sharpe ratio	CE	IR
HG	0.715	1.147	0.623	-0.927	0.617
HGM	0.751	1.217	0.616	-0.997	0.612

The corresponding Sharpe ratio for the HG six-characteristics portfolio in this time period is 0.623, while it is 0.616 for HGM six-characteristics portfolio. Therefore, the average portfolio return improves slightly when replacing the asset growth with the operating cash flow in HG six-characteristics portfolio, but the Sharpe ratio is lower because the volatility of the HGM portfolio is higher than that of the HG portfolio.

Table 5.2 The results of the Fama-Macbeth test for improvement in portfolio performance

2000-2008	Mean	Std. dev. (σ)	t Statistic
HGM over HG	0.036	0.225	1.611

Table 5.2 shows the Fama-Macbeth test for the return improvement. From Table 5.2, it can be seen the return improvement when replacing the asset growth with the operating cash flow in HG six-characteristics portfolio is not statistically significant.

1.4.3.4 PPP Methodology using Monthly Financial data and HGM Characteristics with qualitative signals added

Table 6.1 shows the summary of descriptive statistics of monthly returns for portfolios using monthly data for the HG six-characteristics portfolio and for the HGM six-characteristics with the qualitative signals added. As described previously, a subset of the sample from 1994 to 2008 of the above dataset are used to test the impact of including qualitative optimism and pessimism signals.

The qualitative HG’s portfolio with NEGSIG (negative tone change) produces an average monthly return of 74.4% for the time horizon of 2000-2008 and the HG portfolio with SIG (differential tone change) delivers an even higher average monthly return of 99.6% for the same time period. This is a significant increase over the original HG portfolio (without the qualitative signal) that generates an average monthly return of just 71.5% for this time period.

Table 6.1 Summary of descriptive statistics of Monthly Returns for the HG's six-characteristics portfolio plus the GI tone signals using monthly data and for the portfolio with three accounting variables replaced by accruals, earning surprise and operating cash flow (HGM formulation) plus the qualitative signals

2000-2008	Mean	Std. dev. (σ)	Sharpe ratio	CE	IR
HG	0.715	1.147	0.623	-0.927	0.617
HG+SIG	0.996	1.668	0.597	-0.653	0.594
HG+NEGSIG	0.744	1.173	0.633	-0.979	0.629
HGM	0.751	1.217	0.616	-0.997	0.612
HGM+SIG	1.177	2.069	0.568	-0.748	0.566
HGM+NEGSIG	0.780	1.247	0.625	-0.936	0.621

For the modified qualitative HGM portfolio with the NEGSIG, an average monthly return of 78% is obtained for the time horizon of 2000-2008, while the HGM portfolio with SIG produces an even higher average monthly return of 117.7% for the same time period. Note that without the qualitative signal, the HGM portfolio generates an average monthly return of 75.1% for this time period. Note that compared to NEGSIG, the improvement with SIG is higher.

Table 6.2 shows the results of Fama-Macbeth test. As expected, the t-statistics are 3.62 for the performance improvement of the HG portfolio with SIG over the original HG portfolio without the qualitative signal; and 2.53 for the performance improvement of the HG portfolio with NEGSIG over the original HG portfolio without the qualitative signal. In addition, the t-statistic is 4.01 for the performance improvement of the HGM portfolio with SIG over HGM portfolio without the qualitative signal. The t-statistic is 2.46 for the performance improvement of the HGM portfolio with NEGSIG compare to the returns generated by the HGM portfolio without the qualitative signal. Thus, all t-statistics are above the critical value at the 5% level of significance.

Table 6.2 The results of Fama-Macbeth test for improvement in portfolio performance using qualitative tone signals

2000-2008	Mean	Std. dev. (σ)	t Statistic
HG+SIG over HG	0.281	0.791	3.623
HG+NEGSIG over HG	0.029	0.117	2.525
HGM+SIG over HGM	0.426	1.082	4.014
HGM+NEGSIG over HGM	0.029	0.121	2.458

In sum, portfolio performance improvements resulted from adding qualitative signals obtained using the GI classifications in addition to the traditional quantitative accounting variables are significant. The results are statistically significant for both the original HG six-characteristics portfolio and for the HGM six-characteristics portfolio. Although the absolute magnitudes of improvements may not be very high, this does represent additional improvements above and beyond using PIT monthly data alone.

1.5 SUMMARY AND CONCLUSIONS

This study has made two main contributions to the existing literature on portfolio construction and optimization. First, it shows that incorporating and optimizing over qualitative MD&A signals in addition to the quantitative financial signals proposed by HG [2011] within a BSCV [2009] setting, yields significantly higher returns. To the best of my knowledge, this is the first time qualitative data have been used for optimal portfolio construction. This opens up the possibility that other qualitative information such as news items in newspapers or other media, could be profitably mined for enhancing portfolio returns.

Second, Point-In-Time (PIT) monthly data are used instead of the coarser annual data used by earlier papers as input for the portfolio optimization, and this study shows that using PIT monthly data leads to substantial increase in portfolio returns. Using such timely informational inputs is also consistent with practice.

This study shows that using timely information and incorporating qualitative data in constructing portfolios could produce significant payoffs. The BSCV [2009] optimization that is used offers a flexible method for practical implementation. However, it still remains to be shown that this strategy will remain profitable with high frequency trading and the associated transaction costs.

CHAPTER 2

THE POST EARNINGS ANNOUNCEMENT DRIFT AND OPTION TRADERS

2.1 INTRODUCTION

The well-known Post-earnings announcement drift (PEAD) anomaly traces its origins to Ball and Brown [1968], and refers to the continued upward (downward) drift for weeks following the announcement of positive (negative) earnings surprises. Since such price behavior would be inconsistent with the predictions of efficient markets, this phenomenon is viewed as an anomaly. Despite years of research and study, the PEAD phenomenon continues to robustly persist as an anomaly (see for example, Bernard and Thomas [1989, 1990], for a survey).

Currently there are two prominent explanations for the PEAD anomaly. The first proposes that risk is not properly measured by existing equity valuation models; and, asserts that a better metric of the risk would "explain" this anomaly (Sadka [2006], and Ball, Sadka, and Sadka [2009]). This is the risk premium hypothesis (RPH).

The competing theory is rooted in behavioral economics. It proposes that investors under-react to information in earnings announcements (Bernard and Thomas, [1990]). This is referred to as the under-reaction (behavioral) hypothesis (URH). The implications of the URH hypothesis is that equity market prices fail to completely incorporate the information in current earnings about future earnings surprises, i.e., equity traders seem to ignore the autocorrelations in extreme earnings surprises across adjacent quarters (see, for example, Bernard and Thomas [1990]). It has been repeatedly shown that it is possible to construct equity based trading strategies to profit from the PEAD anomaly.

This study investigates whether trading strategies using options can be constructed to exploit the PEAD phenomenon and earn abnormal returns in the option markets; that is, to examine if option markets suffer from the same inefficiency and under-reaction bias as equity markets. This issue is particularly interesting because it has been argued in the literature that the option market attracts more sophisticated traders compared to the equity market, and therefore is more efficient (Black [1975]).

To examine if option prices suffer from the URH bias as equity prices, this study exploits the fact that earnings surprises are positively correlated across quarters. Earnings surprises are ranked into ten groups from the most negative to the most positive. Noting that prior research has found that the implied volatilities of at-the-money (ATM) call options increase around earnings announcements (Patell and Wolfson [1981], Rogers et al. [2009], Billing and Jennings [2011]), due to increased uncertainty, this study implements a trading strategy of buying straddle contracts prior to the next quarterly earnings announcement date, and selling the straddles after the quarterly earnings announcement has been made. The straddle strategy is a common strategy to exploit the increased volatility observed around earnings announcements.

Given that extreme earnings surprises are associated with greater uncertainty, and given that they are more likely to be followed by extreme earnings surprises in the next quarter, straddle strategies for extreme earnings surprises should be more profitable than straddle strategies for non-extreme earnings surprises if option traders ignore the positive autocorrelations in earnings surprises as equity traders do.

This study finds that there are no significant differences in the returns of these straddles between the two extreme, (top and bottom deciles/quintiles), earnings surprises groups, and the remaining intermediate groups. In contrast to findings in the equity markets, where it has been shown that simple and profitable strategies exploit the fact that equity investors do not fully incorporate the autocorrelations of earnings surprises across quarters (URH) into equity prices, the attempt to take advantage of these autocorrelations in the option markets does not yield significant returns. This suggests that option prices efficiently price risk, and that option market does not exhibit the under-reaction bias (URH) that is prevalent in the equity market.

If the options market seems to process and price risk appropriately, it seems natural to examine whether the implied volatility could be the risk metric that could explain (partly or wholly) the PEAD anomaly in the equity markets and provide support for the RPH theory alluded to earlier. To the best of my knowledge, this risk metric has not been used in the prior literature to examine the PEAD anomaly. However, there are prior studies that indicate that implied volatility derived from the options market may serve as a better metric for equity risk than risk metrics derived from equity prices (Xing et al. [2010] and Cremers and Weinbaum [2010]).

As mentioned above, the implied volatilities of at-the-money (ATM) call options increase around earnings announcements due to increased uncertainty. An increased uncertainty implies higher risk in the underlying stock. Implied volatility measure is known to proxy for expected total future volatility of equity returns, that is, it captures both systematic and unsystematic equity risk. Although in perfect frictionless markets investors can diversify away the unsystematic component by holding a well-diversified portfolio, there are prior studies suggesting that markets are neither perfect (Shleifer and Vishny [1997], and Wurgler and Zhuravskaya [2002]), nor frictionless (Garman and Ohlson [1981]), and there exists a positive relation between unsystematic risk and stock returns (Levy [1978], Merton [1987], Malkiel and Xu [2001]), and indicate that conditioning on total volatility can bring significant economic benefits to investors (Goyal and Santa-Clara [2003]).

Most significantly for this study, in his study of the PEAD anomaly, Mendenhall [2004] shows that unsystematic risk (or arbitrage risk) may provide an explanation for this phenomenon. His results present the most persuasive evidence that in the real world unsystematic risk cannot be diversified away, and it does matter for equity returns. Since option volatility subsumes both systematic and unsystematic risk, it is a natural candidate for a risk metric in the equity markets.

From the point of view of estimation, there are two advantages of using implied volatility as a risk measure compared to using the traditional beta estimates: (1) There is no need to use long time horizon historical data normally required to estimate beta, and, therefore, the implied volatility risk measure will likely better reflect current changes in risk; and (2) given that the option implied volatility data is available on a daily basis, this risk measure is more timely, and can be used to examine changes in risk in short windows around earnings announcements.

Results using the implied volatility risk measure, however, do not support RPH as an explanation for PEAD. Note that to explain why extreme positive earnings surprises are followed by excess drift returns, the RPH assumes that risk levels have increased, and the drift returns are adequate compensation for the increased risk. The converse should be true for extreme negative earnings surprises, where risk levels will have to decrease to explain negative excess drift returns. However, (1) this study does not find a positive correlation between the implied volatility changes and earnings surprises as suggested by RPH; and (2) contrary to RPH, this study finds that that implied volatilities actually decline the most after earnings announcements for firms with the most positive earnings surprises. To the extent that option implied volatility is a more accurate and timely metric of equity risk, the findings seem to rule out RPH as an explanation for PEAD.[1]

I believe this study is the first to use option market characteristics to examine the two leading explanations (RPH and URH) for the PEAD anomaly. Others, using more traditional and well known measures of risk, have also concluded that the RPH does not explain PEAD (Bernard and Thomas, [1990]). However, it cannot be ruled out that there may be other yet to be developed measures of risk that may completely "explain" the PEAD anomaly. Given that this study finds the option prices to be efficient, the scales of the empirical results seemed to be tilted in favor of under-reaction to earning announcements by equity investors as a behavioral explanation for this PEAD phenomenon.

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[1]This study also confirms prior research findings that uncertainties regarding equity prices (implied volatilities) increase during the days leading to the earnings announcement.

The rest of this chapter proceeds as follows. The next section reviews related literatures. Section 2.3 describes the sample and research design. Section 2.4 presents and discusses the main results. Section 2.5 concludes this chapter.

2.2 A BRIEF REVIEW OF THE PRIOR LITERATURE

The post-earnings announcement drift (PEAD) anomaly refers to the observed positive correlation between measures of earnings surprise and subsequent abnormal returns that persist for weeks after the earnings are announced. This finding, first pictorially laid out in Ball and Brown [1968], runs contrary to the efficient market hypothesis. Not surprisingly, it remains a subject of considerable research in the finance and accounting literature (for example, Jones and Litzenberger [1970], Litzenberger et al [1971], Joy et al [1977], Latané and Jones [1977, 1979]).

A comprehensive review of the early literature of PEAD can be found in Ball [1978, 1992] and Bernard and Thomas [1989]. While there is a substantial body of work studying the PEAD anomaly with respect to the equity markets, there is no study of the PEAD anomaly in the options market. This study fills in this gap and contributes to the literature of the efficiency of options market.

Option Market and Equity Prices

Regarding the use of options prices based metrics to estimate the risk (and expected returns) of equities, this study is guided by findings and arguments in the prior literature. The key point of these arguments is that implied volatility (that subsumes both the systematic and the unsystematic risk) imbedded in option prices predicts the volatility of equity returns better than risk metrics computed from equity returns (Hull [2008]).

In a perfect market, options are redundant securities in the sense that they can be replicated by investments in stocks and bonds (Black and Scholes [1973]). However, in the real world, due to many imperfections and frictions, options cannot be simply replicated by other more simple securities (Ross [1976]; Back [1993]), and there are marked differences across the equities and option markets.

Relative to the equities markets, the option markets offer unique features that attract more informed traders (Black [1975], Grossman [1977], Diamond and Verrecchia [1987]). These features include (but are not limited to): (1) Traders can get more leverage for each investment dollar, and this is particularly true when they face wealth constraints; (2) Given that options have a truncated payoff structure, traders have limited downside risk; (3) The transaction costs of trading in options are usually lower than equivalent trades in the underlying stocks, especially for taking short positions (Black [1975]; Cox and Rubinstein [1985]; Amin and Lee [1997]).

As a consequence of its relative advantages, the option market trader may be better informed compared to equity trader; and there is prior literature supporting this argument (Amin and Lee [1997], Easley et al. [1998], Cao et al. [2005]). Skinner [1990] shows that price efficiency in the equity market can be enhanced by allowing options to be traded on the stock.

Recent findings on the information content of the implied volatility of an option by Xing et al. [2010] and Cremers and Weinbaum [2010] show that two implied volatility based measures, namely, the volatility skew and the volatility spread, are good predictors of returns in the equity market. Perhaps the work that is closest to this study is by Jin et al. [2012]. They find that both the volatility skews and the volatility spreads computed immediately prior to earnings announcement dates tend to have better predictive ability for short-term event returns during and after the earnings announcements. Their findings support the argument that the option market rather than the equity market attracts traders with superior information. The Jin et al. [2012] paper itself is motivated by prior research showing that the implied volatilities of at-the-money (ATM) call options increase around earnings announcements (Patell and Wolfson [1981], Rogers et al. [2009], Billing and Jennings [2011]) due to increased uncertainty. Skinner [1997] argues that an informed trader's information advantage is most probably largest immediately before significant information releases such as earnings announcement.

Theories on the PEAD anomaly and Equity Prices

As stated earlier, prior research has provided two predominant explanations for the PEAD anomaly. One is the risk-premium hypothesis (RPH), which argues the subsequent abnormal returns are simply a fair compensation for risk. The competing hypothesis is the under-reaction hypothesis (URH), which argues the abnormal returns are due to investors' under-reacting to information in extreme earnings announcements.

Bernard and Thomas [1990], among others, suggest that market prices fail to impound the complete implication of the past and current earnings information. Some researchers (Bernard and Thomas [1990]; Bartov [1992]; Ball and Bartov [1996]) argue that PEAD may be partly a result of investors' mis-estimating the time series properties of earnings.

However, Jacob et al [1999] disagree with this argument, and claim that the results are driven by methodological shortcomings in prior work. Following a different approach, Livnat and Mendenhall [2006] use analysts' forecasts data and show that for the firms with analyst coverage, the under-reaction to earnings surprises is even more pronounced when using analyst forecasts to measure the earnings surprise. In addition, it has also been found that PEAD, (like most anomalies), is generally larger for smaller, lower-priced, less-liquid firms with a smaller set of analysts following (e.g., Ng, Rusticus, and Verdi [2008]; Chordia et al [2009]; Latané and Jones [1979]; Bernard and Thomas [1989]; Bhushan [1994]; Bartov et al [2000]).

Of the two explanations for PEAD discussed above, the under-reaction hypothesis that relies on behavioral theories seems to be the more popular one. Nevertheless, there are a number of recent studies providing support for a risk-premium explanation for the PEAD anomaly. For example, Sadka [2006] and Ball, Sadka,and Sadka [2009], argue that a large portion of abnormal returns due to the PEAD anomaly is fair compensation for the liquidity risk, or information-asymmetry risk. Refining the approach by Livnat and Mendenhall [2006], Konchitchki et al. [2012] claim that by using an improved measure of earnings surprises, the abnormal returns due to the PEAD anomaly can be reduced by up to 43 percent. They argue that their results are consistent with the risk-premium explanation and do not support the under-reaction explanation. Still, the literature does not have one single risk factor or story that can fully explain the drift returns after earnings announcements.

Despite the voluminous prior literature focusing on examining the PEAD anomaly, and given the vast literature suggesting that the option market traders may have an information advantage compared to equity traders, it is a bit surprising that risk metrics from option prices have not been used to study the PEAD anomaly. This study also fills in this gap, and adds to the literature on the RPH or the URH explanation for the PEAD anomaly.

2.3 SAMPLE AND RESEARCH DESIGN

2.3.1 Sample, Variables and Databases

The 15-year study period ranges from the first quarter of 1996 to the fourth quarter of 2010.

All option market characteristics are obtained from the OptionMetrics historical option prices database. This database provides implied volatilities, open/close prices, strike price, open interest, expiration date, and option Greeks (e.g., delta, gamma, theta, et cetera) for all put and call options listed in the U.S. option market. Particularly, OptionMetrics calculates the underlying implied volatilities of individual options based on binomial trees considering early exercise of individual stock options and the dividends expected during the life span of the options.

Compustat Fundamentals Quarterly are used to collect earnings surprise related information, and the information required for constructing matched portfolios required to calculate the excess return in the time horizon examined.

All stock return information are obtained from CRSP. Analyst forecasts and actual earnings per share information are obtained from I/B/E/S, to calculate earnings surprises for firms with I/B/E/S data.

This study uses three measures of standardized earnings surprises (SUE) to improve robustness. The first SUE measure (sueaf1) is calculated as the actual earnings per share from I/B/E/S minus the mean analyst EPS forecast in the 90-day period prior to the earnings announcement, scaled by the standard deviation of analyst EPS forecasts in the 90-day period prior to the earnings announcement.[2] The second SUE measure (sueaf2) is calculated as the actual earnings per share from I/B/E/S minus the mean analyst EPS forecast in the 90-day period prior to the earnings announcement, scaled by the adjusted stock price at the end of the fiscal quarter that generated the announced earnings. The third SUE measure (sue3) is calculated following the seasonal random walk (SRW) model. Specifically, this study uses “Income Before Extraordinary Items” from Compustat of this quarter, t, minus “Income Before Extraordinary Items” of the quarter t-4, scaled by market value of equity at the end of the month immediately prior to earnings announcement month.

This study measures excess returns as the buy-and-hold return over the designated window minus the average buy-and-hold return on a portfolio of stocks of similar size (2 groups), book-to-market ratio (3 groups), and momentum (12-month compounded return, 3 groups) similar to Daniel et al. [1997]. In the Fama-Macbeth regression analyses, earnings surprise (SUE) are ranked within each quarter into deciles (0 to 9, where 0 is the most negative earnings surprise, and 9 is the most positive earnings surprise), divide by 9, and subtract +0.5. Thus, each standardized SUE has a value between -0.5 and +0.5. A dummy variable is used for option measure in the regression (1 is for firms with

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[2] Only the most recent forecast by an analyst in the 90-day period is included in the mean and standard deviation.

increased implied volatility immediately prior to the earnings announcement date, 0 otherwise).

For the time window of calculating PEAD returns, this study uses the excess returns from day +2 after an earnings announcement to one day after the subsequent quarter's earnings announcement, if available; and to day +90 after the current earnings announcements otherwise. If a security is de-listed from an exchange before the end of the above stated holding period of drift returns, the delisting return from CRSP, if available, is used, or 100% otherwise.

2.3.2 Re-examining Option Prices for Under-Reactions

Given the substantial evidence from prior empirical research that equity investors are not completely incorporating the autocorrelations of earnings surprises, this study designs a trading strategy in the option market to examine if option traders suffer from a similar URH bias as equity traders.

Specifically, for every quarterly earnings announcement of a firm, a straddle contract (i.e., purchasing an at-the-money (ATM) call option and a put option with the same strike price and expiration date) is bought on either day -7 or day -14 relative to the earnings announcement date. To reduce the impact of any other concurrent event rather than the quarterly earnings announcement, the straddle contract is sold on day +5 relative to earnings announcement date. If day -7 or day -14 is not a trading day, the straddle contract is bought on the last trading day before day -7 or day -14 then. If day +5 is not a trading day, the straddle contract is sold on the next trading day after day +5.

As known in the option literature and practice, a straddle strategy is likely to generate positive returns if the implied volatility increases, because both the option call and put will become more valuable with an increased implied volatility.

At the time the straddle contracts are bought (prior to quarter t's earnings announcement day), information on earnings surprises is only available up to the preceding quarter t-1. Therefore, quarter t-1's earnings surprise information is used to classify the full sample to ten groups (deciles), and calculate the mean straddle return for each decile. Straddle return is defined as the sum of the call and put option prices of the straddle contract on the selling day (day +5) divided by the sum of their option prices on the buying day (day -7 or day -14) minus 1.

This study examines if option traders suffer from the same URH bias as equity traders by taking a long position in the highest unexpected earnings (SUE) decile/quintile and the lowest unexpected earnings (SUE) decile/quintile of the immediately previous quarter (quarter t-1), and a short position in the middle (the groups sandwiched between the two extremes) unexpected earnings deciles/quintiles. If option traders suffer from the same URH bias as equity traders do, the difference in straddle returns between the extreme and middle deciles/quintiles should be significantly different from zero. That is to say, if option traders ignore the positive autocorrelations in earnings surprises between quarters t-1 and t, the greater will be the implied volatilities around quarter t's earnings announcement for firms with extreme earnings surprises in quarter t-1 relative to firms with less extreme earnings surprises in quarter t-1.

For any given day on which a straddle contract is bought, options of a firm whose expiration date is between 10 and 60 days away, and with an expiration date after day +5, are selected. This study includes only those options that have positive open interests, and for which implied volatilities are available in this sample. In setting up the straddles, calls and puts with the same expiration date and strike price for a given day are selected. Then all call options that have a delta between 0.4 and 0.7 are chosen, and the one closest to 0.5 is kept as the ATM options.

2.3.3 Re-examining the Risk Premium Hypothesis as an explanation for PEAD

This study examines the RPH using implied volatilities as the risk measure for equity. Given prior findings (Patell and Wolfson [1979]) suggest that implied volatilities of at-the-money (ATM) call options systematically increase in the weeks before an earnings announcement as a function of the anticipated spike in volatility upon the announcement, this study first defines three intervals relative to the earnings announcement after identifying the earnings announcement date (day 0): (1) the Base-Window interval which is the period from 50 to 15 days prior to the earnings announcement day; (2) Different Pre-Window intervals ranging from 14 to 1 day before the earnings announcement; and (3) Post-Window intervals ranging from 1 day to 90 days after the earnings announcement day.

For any given day, all call options of a firm with an expiration date between 10 and 60 days after the day 0 are selected, because implied volatility very close to the expiration date may be impacted by many other factors. This study only includes call options with positive open interest in its sample. Like Jin et al (2012), this study then selects all call options that have a delta between 0.4 and 0.7, and keep the one closest to 0.5, as the implied volatility of the ATM option.

This study measures the average implied volatility change between two time windows, namely, days [–14, –1] (Pre-Window) and days [–50, –15] (Base-Window). For robustness check, average implied volatility of a later Pre-Window compared to an earlier Pre-Window is also used. For example, this study measures the average implied volatility for days [–7, –1] relative to days [-14, -8], and for days [–3, –1] compared to days [-14, -4]. In addition to the average implied volatility change over a time window, it also checks the implied volatilities change between two specific days. Specifically, this study computes the change between the daily implied volatility of day -1 and the daily implied volatility of day -14, and the change between the daily implied volatility of day -1 and the daily implied volatility of day -7.

This study uses the average (daily) implied volatility change of a Pre-Window (Pre-day) relative to that of Base-Window to identify the firms with increased implied volatility immediately prior to the earnings announcement date. If the RPH is true, systematically higher drift returns and greater increases in implied volatility immediately prior to the earnings announcement date for firms with the most extreme positive earnings surprises, compared to firms with small earnings surprises, should be observed, or those with the most extreme negative earnings surprises, should actually have declined implied volatilities to justify their negative drift returns. The rationale behind this expectation is that increased implied volatility of an option immediately prior to the earnings announcement date relative to its normal level (Base-Window) implies a higher risk of the underlying stock. Stocks with higher risks should generate higher drift returns as a compensation for the increased risk.

To confirm the findings in prior literature (Patell and Wolfson [1979, 1981]) that implied volatilities tend to decline after earnings announcement, this study also shows the average implied volatility of a Post-Window relative to that of Pre-Window declines across all segments of SUE deciles.

This study then uses Fama-Macbeth regressions to examine whether implied volatilities changes immediately prior to the earnings announcements have incremental explanatory power for subsequent drift returns after these announcements, after controlling for the magnitude and sign of the earnings surprise. If the RPH is true, for a given SUE level, stocks with higher risk (increased implied volatility) should generate higher drift return as a compensation for risk. In other words, the estimated coefficient of the interaction term between SUE and the dummy variable (1 for firms with increased implied volatility immediately prior to the earnings announcement date, 0 otherwise) should be significantly positive if the RPH holds.

A number of tests are also performed to check the relationship between the changes in implied volatility after the earnings announcement and drift returns. It is expected that firms with higher risks should revert back to their normal implied volatility level slower after earnings announcement because investors are still highly uncertain about their future performance even after the earnings announcement. Under the RPH, such risky firms should have higher drift returns compared to firms with lower risk.

2.4 EMPIRICAL RESULTS

2.4.1 Descriptive statistics

Table 7.1 describes four subsamples of the data divided along two dimensions: availability on OptionMetrics and I/B/E/S.

Table 7.1: Descriptive Statistics of four subsamples based on availability on I/B/E/S and OptionMetrics

subgroup	N Obs	Variable	Mean	Median
IBES with options[1]	70694	Book to market	0.638	0.452
		Market value(in million)	6,882	1,533
		Daily return w/o dividend	0.001	0.001
		Std of daily return w/o dividend	0.030	0.025
		Turnover[5]	0.011	0.008
IBES w/o options[2]	44577	Book to market	0.949	0.615
		Market value(in million)	515	210
		Daily return w/o dividend	0.001	0.001
		Std of daily return w/o dividend	0.033	0.027
		Turnover	0.005	0.003
non-IBES with options[3]	22821	Book to market	1.871	0.502
		Market value(in million)	5,466	1,000
		Daily return w/o dividend	0.000	0.001
		Std of daily return w/o dividend	0.032	0.028
		Turnover	0.010	0.006
non-IBES w/o options[4]	80295	Book to market	2.505	0.710
		Market value(in million)	303	75
		Daily return w/o dividend	0.001	0.001
		Std of daily return w/o dividend	0.042	0.034
		Turnover	0.005	0.002

1. IBES with options is the subsample that is available on both OptionMetrics and I/B/E/S.
2. IBES w/o options is the subsample that is available on I/B/E/S but not available on OptionMetrics.
3. non-IBES with options is the subsample that is available on OptionMetrics but not have quarterly earnings forecasts on I/B/E/S.

4. non-IBES w/o options is the subsample that is unavailable on neither OptionMetrics nor I/B/E/S.
5. std of daily return is calculated as the standard deviation of daily return between [-45, +45] relative to an earnings announcement date of a specific firm, and then averaged across all earnings announcement events in that subsample, where the daily return information is obtained from the daily stock file of CRSP.
6. Turnover is defined as share volume (i.e. the total number of shares of a stock sold on that day) scaled by the number of shares outstanding.

Consistent with prior research, the observations from Table 7.1 show that both, the mean and median market value of firms with options, are significantly higher than those of firms without options. This suggests that firms without options are generally smaller. As can be expected, firms without options generally have higher book-to-market ratio, indicating that options are more likely to be written on glamour, growth stocks. Further, both the mean and median turnover (volume scaled by number of shares outstanding) of firms with options are significantly higher than those of firms without options, suggesting that firms without options are in general less liquid than firms with options. Firms without options on average have higher standard deviation of daily returns than firms with options.[3]

Also consistent with the fact that analysts tend to follow large firms, the firms on I/B/E/S generally have higher market value, lower book-to-market ratio, and are more liquid. Based on the higher average daily volatility, firms not on I/B/E/S usually have more variation in terms of daily price than firms followed by analysts likely due to their lower liquidity. Furthermore, the subsample for the "non-IBES firms without options" has the lowest turnover, smallest market value, and largest variation of daily return among the four subsamples.

[3] Returns without dividends are used from CRSP daily file to minimize the impact of dividend distribution, and to focus on the price change effect. The results for returns with dividends are very similar.

Table 7.2 presents the mean drift return in each sue3 (seasonal random walk model for earnings prediction) decile for the four subsamples and the return of a hedge portfolio that is long in the top decile of SUE and is short in the bottom decile of SUE.

Table 7.2: Mean drift returns for each SUE3 decile of four subsamples based on availability on I/B/E/S and OptionMetrics

	Drift return[2]			
Rank for SUE3[1]	**IBES with options**	**IBES w/o options**	**non-IBES with options**	**non-IBES w/o options**
0	-0.001	-0.012	0.010	-0.006
1	-0.002	-0.019	-0.019	-0.038
2	-0.003	-0.018	-0.017	-0.025
3	0.001	-0.015	-0.006	-0.022
4	-0.005	-0.008	-0.003	-0.010
5	0.002	-0.002	-0.005	-0.006
6	0.003	0.000	-0.002	-0.002
7	0.001	0.005	-0.007	0.006
8	0.002	0.014	-0.002	0.014
9	0.010	0.027	-0.003	0.036
hedge portfolio[3]	0.011	0.039	-0.013	0.042

1. SUE3 is calculated following the seasonal random walk (SRW) model. Specifically, this study uses “Income Before Extraordinary Items” from Compustat of this quarter(t) minus “Income Before Extraordinary Items” of the quarter t-4, scaled by market value of equity prior to earnings announcement date. 0 is the most negative earnings surprise, and 9 is the most positive earnings surprise.
2. Drift return is the excess returns from day +2 to one day after the subsequent quarter’s earnings announcement, if available; and to day +90 after the current earnings announcements otherwise. This study measures excess returns as the buy-and-hold return over the designated window minus the buy-and-hold return from a portfolio of stocks of similar size, book-to-market ratio, and momentum (12-month compounded return) similar to Daniel et al. [1997].
3. The return of a hedge portfolio that is long in the top decile of SUE and is short in the bottom decile of SUE.

As expected, sue3 is positively correlated with drift return regardless of the subsample. However, the correlation is much stronger for firms without options. For example, a trading strategy of taking a long position in the highest unexpected earnings (SUE) decile, and a short position in the lowest unexpected earnings decile, yields an abnormal drift return of approximately 4.2% for the “non-IBES without options” subsample, and merely 1.1% for the “IBES with options” subsample. This is consistent with Livnat and Mendenhall (2006).

2.4.2 Tests of the Under-reaction Hypothesis (URH) in the Options Market

As mentioned previously, this study exploits the well-known straddle strategy to examine whether the options market traders efficiently price the autocorrelations in extreme earnings surprises. The findings are discussed next.

2.4.2.1 The relation between the mean straddle returns and SUE of the immediately previous quarter

Table 8.1 and Table 8.2 present the mean straddle return and the percentage with positive straddle return for each SUE decile of quarter t-1.

As shown in Table 8.1, although the straddle returns are significantly positive for straddle contract bought on day -7 relative to earnings announcement date and sold on day +5, the percentage with positive straddle return are all below 50% across all segments of SUE deciles. These results, in addition to the fact that this study does not account for transaction costs in the straddle returns, suggest the high efficiency of the options market. These results are consistent with prior literature that shows that more informed traders tend to operate in the options market.

Table 8.1: Mean straddle return for SUE deciles(straddle contract bought on day -7 relative to earnings announcement date and sold on day +5)

Straddle Return [-7,+5][1]				
Rank for sueaf1[2]	**Mean**	**t Value**	**Pr > |t|**	**Positive return %**
0	0.049	5.63	<.0001	38.4
1	0.045	6.67	<.0001	38.6
2	0.039	6.20	<.0001	38.4
3	0.045	7.10	<.0001	38.1
4	0.037	6.45	<.0001	37.5
5	0.040	6.83	<.0001	38.4
6	0.040	6.76	<.0001	38.2
7	0.038	6.46	<.0001	38.9
8	0.040	6.67	<.0001	38.1
9	0.043	6.67	<.0001	38.3

Straddle Return [-7,+5][1]				
Rank for sueaf2[3]	**Mean**	**t Value**	**Pr > |t|**	**Positive return %**
0	0.052	5.85	<.0001	38.2
1	0.048	6.62	<.0001	38.5
2	0.042	6.96	<.0001	39.1
3	0.041	6.92	<.0001	38.0
4	0.027	5.24	<.0001	36.9
5	0.041	7.46	<.0001	38.6
6	0.041	7.04	<.0001	38.9
7	0.046	7.30	<.0001	38.4
8	0.043	6.71	<.0001	38.2
9	0.038	5.10	<.0001	38.1

Straddle Return [-7,+5][1]				
Rank for sue3[4]	**Mean**	**t Value**	**Pr > |t|**	**Positive return %**
0	0.047	6.23	<.0001	38.3
1	0.051	7.10	<.0001	38.2
2	0.052	7.72	<.0001	39.4
3	0.037	5.75	<.0001	37.6
4	0.042	6.72	<.0001	38.6
5	0.036	5.88	<.0001	38.2
6	0.033	5.47	<.0001	37.9
7	0.026	4.27	<.0001	36.6
8	0.036	5.42	<.0001	38.0
9	0.039	5.51	<.0001	38.7

1. For every quarterly earnings announcement of a firm, a straddle contract (i.e., purchasing an at-the-money (ATM) call option and a put option with the same strike price and expiration date) is bought on day -7 relative to earnings announcement date. To reduce the impact of any other concurrent event rather than the quarterly earnings announcement, the straddle contract is sold on day +5 relative to earnings announcement date. If day -7 is not a trading day, the straddle contract is bought on the last trading day before day -7 then. If day +5 is not a trading day, the straddle contract is sold on the next trading day after day +5 then. Straddle return is defined as the sum of the call and put option prices of the straddle contract on the selling day (day +5) divided by the sum of their option prices on the buying day (day -7) and then minus 1.
2. sueaf1 is calculated as the actual earnings per share from I/B/E/S minus the mean analyst EPS forecast in the 90-day period prior to the earnings announcement, scaled by the standard deviation of analyst EPS forecasts in the 90-day period prior to the earnings announcement. The rank (decile) of sueaf1 is based on quarter t-1's earnings surprise information. 0 is the most negative earnings surprise, and 9 is the most positive earnings surprise.
3. sueaf2 is calculated as the actual earnings per share from I/B/E/S minus the mean analyst EPS forecast in the 90-day period prior to the earnings announcement,

scaled by adjusted stock price at the end of the fiscal quarter. The rank (decile) of sueaf2 is based on quarter t-1's earnings surprise information. 0 is the most negative earnings surprise, and 9 is the most positive earnings surprise.

4. sue3 is calculated following the seasonal random walk (SRW) model. Specifically, this study uses "Income Before Extraordinary Items" from Compustat of this quarter t minus "Income Before Extraordinary Items" of the quarter t-4, scaled by market value of equity prior to earnings announcement date. The rank (decile) of sue3 is based on quarter t-1's earnings surprise information. 0 is the most negative earnings surprise, and 9 is the most positive earnings surprise.

From Table 8.2, it seems that the straddle returns are even smaller in magnitude for straddle contract bought on day -14 relative to earnings announcement date and sold on day +5, and the percentage with positive straddle return are also consistently below 50% across all segments of SUE deciles.

Table 8.2: Mean straddle return for SUE deciles(straddle contract bought on day -14 relative to earnings announcement date and sold on day +5)

Straddle Return [-14,+5][1]				
Rank for sueaf1[2]	**Mean**	**t Value**	**Pr > |t|**	**Positive return %**
0	0.038	3.77	0.0002	39.0
1	0.040	4.72	<.0001	37.3
2	0.017	2.26	0.0239	35.7
3	0.035	4.85	<.0001	37.9
4	0.018	2.77	0.0056	37.0
5	0.017	2.56	0.0105	36.7
6	0.031	4.55	<.0001	38.1
7	0.025	3.78	0.0002	38.1
8	0.022	3.07	0.0021	37.2
9	0.035	4.29	<.0001	37.5

Straddle Return [-14,+5][1]				
Rank for sueaf2[3]	**Mean**	**t Value**	**Pr > |t|**	**Positive return %**
0	0.040	3.85	0.0001	37.5
1	0.039	4.45	<.0001	37.3
2	0.026	3.52	0.0004	37.4
3	0.027	3.90	<.0001	37.4
4	0.014	2.31	0.021	36.4
5	0.027	4.24	<.0001	37.8
6	0.019	2.88	0.0039	37.5
7	0.026	3.63	0.0003	37.7
8	0.042	5.38	<.0001	38.3
9	0.021	2.41	0.0162	36.7

Straddle Return [-14,+5][1]				
Rank for sue3[4]	**Mean**	**t Value**	**Pr > |t|**	**Positive return %**
0	0.043	4.64	<.0001	37.3
1	0.034	4.19	<.0001	37.9
2	0.043	5.30	<.0001	38.0
3	0.022	2.96	0.003	36.5
4	0.035	4.79	<.0001	38.6
5	0.016	2.26	0.0236	36.9
6	0.017	2.53	0.0113	37.4
7	0.009	1.29	0.1971	36.0
8	0.026	3.32	0.0009	37.3
9	0.024	2.85	0.0043	37.6

1. For every quarterly earnings announcement of a firm, a straddle contract (i.e., purchasing a at-the-money(ATM) call option and a put option with the same strike price and expiration date) is bought on day -14 relative to earnings announcement date. To reduce the impact of any other concurrent event rather than the quarterly earnings announcement, the straddle contract is sold on day +5 relative to earnings announcement date. If day -14 is not a trading day, the straddle contract is bought on the last trading day before day -14 then. If day +5 is not a trading day, the straddle contract is sold on the next trading day after day +5 then. Straddle return is defined as the sum of the call and put option prices of the straddle contract on the selling day (day +5) divided by the sum of their option prices on the buying day (day -14)and then minus 1.
2. sueaf1 is calculated as the actual earnings per share from I/B/E/S minus the mean analyst EPS forecast in the 90-day period prior to the earnings announcement, scaled by the standard deviation of analyst EPS forecasts in the 90-day period prior to the earnings announcement. The rank (decile) of sueaf1 is based on quarter t-1's earnings surprise information. 0 is the most negative earnings surprise, and 9 is the most positive earnings surprise.
3. sueaf2 is calculated as the actual earnings per share from I/B/E/S minus the mean analyst EPS forecast in the 90-day period prior to the earnings announcement, scaled by adjusted stock price at the end of the fiscal quarter. The rank (decile) of sueaf2 is based on quarter t-1's earnings surprise information. 0 is the most negative earnings surprise, and 9 is the most positive earnings surprise.
4. sue3 is calculated following the seasonal random walk (SRW) model. Specifically, this study uses "Income Before Extraordinary Items" from Compustat of this quarter t minus "Income Before Extraordinary Items" of the quarter t-4, scaled by market value of equity prior to earnings announcement date. The rank (decile) of sue3 is based on quarter t-1's earnings surprise information. 0 is the most negative earnings surprise, and 9 is the most positive earnings surprise.

2.4.2.2 The difference in straddle returns between extreme and middle deciles/quintiles SUE of the immediately previous quarter

Table 9 shows the Fama-Macbeth tests results which examine if the difference in straddle returns between extreme and middle deciles/quintiles is significantly different from zero. As shown in Table 9, the difference in straddle returns between extreme and middle deciles/quintiles is insignificantly different from zero although mostly positive. In other words, option traders will be unable to consistently achieve significant abnormal returns by taking long straddle positions in the highest unexpected earnings (SUE) decile/quintile and lowest unexpected earnings (SUE) decile/quintile of previous quarter (quarter t-1), and short straddle positions in the middle unexpected earnings deciles/quintiles.

Table 9: Fama-Macbeth tests for the difference in straddle returns between extreme and middle SUE deciles (quintiles)

Fama-Macbeth Tests[8]					
SUE	Holding period	Extreme decile/quintile	Mean[9]	t Value	Pr > |t|
sueaf1[1]	[-7,+5][4]	decile[6]	0.003	0.43	0.6683
	[-7,+5]	quintile[7]	0.003	0.65	0.5152
	[-14,+5][5]	decile[6]	0.006	0.86	0.3954
	[-14,+5]	quintile[7]	0.007	1.31	0.1950
sueaf2[2]	[-7,+5]	decile	-0.007	-0.87	0.3897
	[-7,+5]	quintile	0.002	0.29	0.7758
	[-14,+5]	decile	-0.002	-0.20	0.8412
	[-14,+5]	quintile	0.010	1.53	0.1308
sue3[3]	[-7,+5]	decile	0.000	-0.08	0.9403
	[-7,+5]	quintile	0.002	0.34	0.7377
	[-14,+5]	decile	0.006	0.70	0.4848
	[-14,+5]	quintile	0.004	0.57	0.5700

1. sueaf1 is calculated as the actual earnings per share from I/B/E/S minus the mean analyst EPS forecast in the 90-day period prior to the earnings announcement, scaled by the standard deviation of analyst EPS forecasts in the 90-day period prior to the earnings announcement.
2. sueaf2 is calculated as the actual earnings per share from I/B/E/S minus the mean analyst EPS forecast in the 90-day period prior to the earnings announcement, scaled by adjusted stock price at the end of the fiscal quarter.
3. sue3 is calculated following the seasonal random walk (SRW) model. Specifically, this study uses “Income Before Extraordinary Items” from Compustat of this quarter(t) minus “Income Before Extraordinary Items” of the quarter t-4, scaled by market value of equity prior to earnings announcement date.

4. For every quarterly earnings announcement of a firm, a straddle contract (i.e., purchasing a at-the-money (ATM) call option and a put option with the same strike price and expiration date) is bought on day -7 relative to earnings announcement date. To reduce the impact of any other concurrent event rather than the quarterly earnings announcement, the straddle contract is sold on day +5 relative to earnings announcement date. If day -7 is not a trading day, the straddle contract is bought on the last trading day before day -7 then. If day +5 is not a trading day, the straddle contract is sold on the next trading day after day +5 then. Straddle return is defined as the sum of the call and put option prices of the straddle contract on the selling day (day +5) divided by the sum of their option prices on the buying day (day -7) and then minus 1. (This applies to sueaf2 and sue3 as well).
5. For every quarterly earnings announcement of a firm, a straddle contract (i.e., purchasing a at-the-money (ATM) call option and a put option with the same strike price and expiration date) is bought on day -14 relative to earnings announcement date. To reduce the impact of any other concurrent event rather than the quarterly earnings announcement, the straddle contract is sold on day +5 relative to earnings announcement date. If day -14 is not a trading day, the straddle contract is bought on the last trading day before day -14 then. If day +5 is not a trading day, the straddle contract is sold on the next trading day after day +5 then. Straddle return is defined as the sum of the call and put option prices of the straddle contract on the selling day (day +5) divided by the sum of their option prices on the buying day (day -14)and then minus 1. (This applies to sueaf2 and sue3 as well).
6. This study examines if option traders are able to achieve abnormal returns by taking a long position in the highest unexpected earnings (SUE) decile (decile 9) and lowest unexpected earnings (SUE) decile (decile 0) of the immediately previous quarter (quarter t-1), and a short position in middle unexpected earnings deciles (1 to 8). (This applies to sueaf2 and sue3 as well).
7. This study examines if option traders are able to achieve abnormal returns by taking a long position in the highest unexpected earnings (SUE) quintile (quintile 4 obtained from merging deciles 8 and 9) and lowest unexpected earnings (SUE) quintile (quintile 0 obtained from merging deciles 0 and 1) of the immediately previous quarter (quarter t-1), and a short position in middle unexpected earnings quintiles (constructed from deciles 2 to 7). (This applies to sueaf2 and sue3 as well).
8. Fama-Macbeth tests examine if the difference in straddle returns between extreme and middle deciles/quintiles is significantly different from zero, by constructing a portfolio of taking a long position in the highest unexpected earnings (SUE) decile/quintile and lowest unexpected earnings (SUE) decile/quintile of the

immediately previous quarter (quarter t-1), and a short position in middle unexpected earnings deciles/quintiles.

9. This is the mean return of the portfolio constructed as described in note 8.

Therefore, in contrast to prior empirical results about equity investors who do not completely incorporate the autocorrelations of earnings surprises, the Fama-Macbeth tests results show that straddle strategies in options that attempt to take advantage of the autocorrelations in earnings surprise do not yield significant returns, implying that option prices (and traders) are less susceptible to the under-reaction bias observed in the equity market.

Given that the option market is more efficient than the equity market, and given that risk measures are available almost immediately from option market data, using option market characteristics to re-examine the Post-Earnings Announcement Drift sheds light on the key possible explanations for the PEAD anomaly.

2.4.2.3 Robustness Checks

1. This study runs the tests of Table 8 for two sub-periods. One is from 1996 to 2003 and the other is from 2004 to 2010. There are no significant differences observed between the two sub-periods in both percentage of firms with positive straddle return and mean straddle returns for each SUE decile.

2. This study also runs the tests of Table 8 for the financial crisis period 2008-2010 compared to the remaining periods. Results indicate that straddle returns are in general much less significant positive for 2008-2010 sub-period compared to the remaining

periods across all segments of the SUE deciles. This may suggest that option traders become even smarter during the financial crisis or more sophisticated traders flood into the option market during the recession.

3. Instead of selecting all call option with a delta between 0.4 and 0.7 and keep the one closest to 0.5 as the ATM option, this study also uses moneyness criteria for ATM option following Goyal and Saretto [2009] and Goodman et al. [2011], and the results are similar.

2.4.3 Tests of the Risk Premium Hypothesis (RPH)

Given prior findings that implied volatilities of at-the-money (ATM) call options increase around earnings announcements due to increased uncertainty, this study uses the implied volatilities change prior to earnings announcements as the main risk measure.

2.4.3.1 The relation between the implied volatility changes prior to earnings announcement and earnings surprises

Table 10.1 present the mean ratios of average implied volatility of Pre-Window over average implied volatility of Base-Window, and the percentage of firms with increased implied volatility prior to earnings announcement for each sue2 and sue3 decile.

Table 10.1: Ratio of average implied volatilities for different combinations of Pre- or Base-Windows (the earnings announcement date is day 0)

Rank for sueaf2[1]	[-14,-1] vs [-50,-15][2]	% of firms with increased IV[3] for [-14,-1] vs [-50,-15]	day -1 vs day -14[4]	% of firms with increased IV for day -1 vs day -14
0	1.048	56.5	1.058	55.0
1	1.048	58.0	1.053	56.6
2	1.049	59.6	1.055	57.5
3	1.050	60.3	1.052	57.3
4	1.057	62.6	1.051	58.4
5	1.057	62.4	1.051	57.6
6	1.050	60.3	1.047	56.6
7	1.053	60.7	1.053	57.7
8	1.051	59.0	1.051	56.9
9	1.043	57.4	1.052	55.9

Rank for sue3[5]	[-14,-1] vs [-50,-15]	% of firms with increased IV for [-14,-1] vs [-50,-15]	day -1 vs day -14	% of firms with increased IV for day -1 vs day -14
0	1.046	57.8	1.049	55.0
1	1.049	58.8	1.061	57.2
2	1.050	59.7	1.050	57.5
3	1.055	61.7	1.052	57.3
4	1.056	61.9	1.051	58.0
5	1.056	62.1	1.052	58.3
6	1.052	60.8	1.051	57.9
7	1.054	60.3	1.048	56.0
8	1.050	59.9	1.048	56.4
9	1.046	58.3	1.046	55.7

1. sueaf2 is calculated as the actual earnings per share from I/B/E/S minus the mean analyst EPS forecast in the 90-day period prior to the earnings announcement, scaled by adjusted stock price at the end of the fiscal quarter. 0 is the most negative earnings surprise, and 9 is the most positive earnings surprise.
2. [-14,-1] vs. [-50,-15] is the mean ratios of average implied volatility of Pre-Window ([-14,-1]) over average implied volatility of Base-Window ([-50,-15]) for each SUE decile.
3. IV stands for "implied volatility"
4. day -1 vs day -14 is the mean ratios of the implied volatility of day -1 over the implied volatility of day -14.
5. sue3 is calculated following the seasonal random walk (SRW) model. Specifically, this study uses "Income Before Extraordinary Items" from Compustat of this quarter (t), minus "Income Before Extraordinary Items" of the quarter t-4, scaled by market value of equity prior to earnings announcement date. 0 is the most negative earnings surprise, and 9 is the most positive earnings surprise.

Consistent with prior research that the implied volatilities of at-the-money (ATM) call options increase around earnings announcements (Patell and Wolfson [1981], Rogers et al. [2009], Billing and Jennings [2011]), results show that all mean ratios of average implied volatility of the Pre-window over average implied volatility of the Base-window are greater than 1.

However, from Table 10.1, for both sue2 and sue3 measures, there is no consistent relationship observed between the implied volatility increase prior to earnings announcement and the rank of SUE. There is also no consistent relationship between the percentage of firms with increased implied volatility prior to earnings announcement and the rank of SUE.

Table 10.2 shows Spearman rank correlations between SUE and ratios of changes in average implied volatility prior to earnings announcement. As expected, using Spearman rank correlations between SUE and ratios of changes in average implied volatility (risk measure), results indicate that for both sue2 and sue3 measures of SUE, the rank correlation between SUE and the risk measure are not statistically significantly different from zero. In sum, results show no positive correlation between SUE rank and risk as measured by implied volatilities.

Table 10.2: Spearman Rank Correlation between SUE and implied volatility change *before* earnings announcement

Spearman Rank Correlation	IV change between[2] [-14, -1] and [-50,-15]	IV change between[3] day -1 and day -14
sueaf2[1]	0.0001	0.0008
P-Value	0.9735	0.8738
sue3[4]	0.0005	0.0016
P-Value	0.9062	0.7749

1. sueaf2 is calculated as the actual earnings per share from I/B/E/S minus the mean analyst EPS forecast in the 90-day period prior to the earnings announcement, scaled by adjusted stock price at the end of the fiscal quarter.

2. IV stands for "implied volatility". IV change between [-14,-1] and [-50,-15] is the mean ratios of average implied volatility of Pre-Window ([-14,-1]) over average implied volatility of Base-Window ([-50,-15]) for each SUE decile.
3. IV change between day -1 and day -14 is the mean ratios of the implied volatility of day -1 over the implied volatility of day -14.
4. sue3 is calculated following the seasonal random walk (SRW) model. Specifically, this study uses "Income Before Extraordinary Items" from Compustat of this quarter (t), minus "Income Before Extraordinary Items" of the quarter t-4, scaled by market value of equity prior to earnings announcement date.

Table 10.3 presents the ratios of average implied volatilities for a post window over a pre window and the percentage of firms with implied volatilities that decline after earnings announcement.

Table 10.3 verifies prior findings (Patell and Wolfson [1979, 1981]) that implied volatilities tend to decline across all segments of the SUE deciles after earnings announcement as the ratios of average implied volatilities for a post window over a pre window all fall below 1.

In addition, the monotonically increasing relationship between the percentage of firms with declined implied volatilities after earnings announcement, and SUE rank contradicts the prediction under RPH. If, in fact, RPH were to hold, it would be expected that firms with higher drift return or positive earnings surprise have higher risk associated with them, and therefore, their implied volatilities should be less likely to decline after earnings announcement.

Table 10.3: Ratio of average implied volatilities for different combinations of Post and Pre-Windows (the earnings announcement date is day 0)

Rank for sueaf1[1]	[+1,+30] vs[2] [-7,-1]	% of firms with decreased IV[3] for [+1, +30] vs [-7,-1]	[+1,+5] vs [-5,-1]	% of firms with decreased IV for [+1, +5] vs [-5,-1]
0	0.990	59.9	0.983	61.9
1	0.977	64.4	0.971	64.9
2	0.967	66.2	0.964	66.8
3	0.961	67.5	0.957	69.2
4	0.951	70.0	0.946	71.5
5	0.947	70.8	0.942	72.7
6	0.945	71.9	0.937	73.1
7	0.938	73.0	0.931	75.5
8	0.941	71.9	0.931	75.2
9	0.941	71.4	0.930	74.7

Rank for sueaf1	[+1,+5] vs [-3,-1]	% of firms with decreased IV for [+1, +5] vs [-3,-1]	[+1,+5] vs[4] day -1	% of firms with decreased IV for [+1, +5] vs day -1
0	0.976	63.7	0.969	64.4
1	0.965	65.5	0.961	66.0
2	0.959	67.5	0.957	67.8
3	0.952	69.6	0.951	69.0
4	0.940	72.6	0.937	72.9
5	0.936	73.6	0.932	74.5
6	0.931	74.3	0.928	74.6
7	0.927	76.3	0.924	76.3
8	0.923	75.8	0.921	76.1
9	0.923	75.6	0.918	76.1

1. sueaf1 is calculated as the actual earnings per share from I/B/E/S minus the mean analyst EPS forecast in the 90-day period prior to the earnings announcement, scaled by the standard deviation of analyst EPS forecasts in the 90-day period prior to the earnings announcement. 0 is the most negative earnings surprise, and 9 is the most positive earnings surprise.
2. [+1,+30] vs. [-7,-1] is the mean ratios of average implied volatility of Post-Window ([+1,+30]) over average implied volatility of Pre-Window ([-7,-1]) for each SUE decile.
3. IV stands for "implied volatility"
4. [+1,+5] vs. day -1 is the mean ratios of average implied volatility of Post-Window ([+1,+5]) over the implied volatility of day -1.

2.4.3.2 The predictive ability of implied volatility change prior to earnings announcement for subsequent drift returns

The main regression analyses of the predictive ability of implied volatility change prior to earnings announcement for subsequent drift returns are presented in Table 11.

Table 11: Predictive ability of implied volatility change prior to earnings announcement for subsequent drift returns: Regression Analysis[1]

Variable	Coefficient	t value
Intercept	-0.001	-0.450
sueaf2[2]	0.026	3.39***
[-14,-1] vs [-50,-15][3]	-0.014	-1.93*
Intercept	-0.001	-0.370
sueaf2	0.021	3.44***
[-7,-1] vs [-14,-8][4]	-0.005	-0.730
Intercept	-0.001	-0.440
sueaf2	0.015	1.99*
[-14,-4] vs [-3,-1][5]	0.005	0.750
Intercept	-0.003	-0.720
sueaf2	0.019	2.72***
day -1 vs day -14[6]	-0.007	-0.560
Intercept	-0.003	-0.810
sueaf2	0.010	1.140
day -1 vs day -7[7]	0.010	1.010

1. The dependent variable is the drift return, which measures the excess returns from day +2 to one day after the subsequent quarter's earnings announcement if available; and until day +90 after the current earnings announcements otherwise.
2. sueaf2 is calculated as the actual earnings per share from I/B/E/S minus the mean analyst EPS forecast in the 90-day period prior to the earnings announcement, scaled by adjusted stock price at the end of the fiscal quarter. ***,** and * indicate significance levels at 0.01, 0.05 and 0.10 levels respectively based on two-sided p-values. The earnings announcement date is day 0.
3. This is the interaction term between standardized sueaf2 and the dummy variable indicating if the firm's average implied volatility over [-14,-1] is higher than its average implied volatility over [-50,-15] (1 for yes, 0 otherwise). The earnings announcement date is day 0.
4. This is the interaction term between standardized sueaf2 and the dummy variable indicating if the firm's average implied volatility over [-7,-1] is higher than its

average implied volatility over [-14,-8] (1 for yes, 0 otherwise). The earnings announcement date is day 0.

5. This is the interaction term between standardized sueaf2 and the dummy variable indicating if the firm's average implied volatility over [-3,-1] is higher than its average implied volatility over [-14,-4] (1 for yes, 0 otherwise). The earnings announcement date is day 0.
6. This is the interaction term between standardized sueaf2 and the dummy variable indicating if the firm's implied volatility of day -1 is higher than its implied volatility of day -14 (1 for yes, 0 otherwise). The earnings announcement date is day 0.
7. This is the interaction term between standardized sueaf2 and the dummy variable indicating if the firm's implied volatility of day -1 is higher than its implied volatility of day -7 (1 for yes, 0 otherwise). The earnings announcement date is day 0.

Since the results for sueaf1 and sue3 are very similar to sueaf2, only the regression results with sueaf2 are shown. In this regression model, the dependent variable is the drift return, which measures the excess returns from day +2 to one day after the subsequent quarter's earnings announcement if available; and until day +90 after the current earnings announcements otherwise.

This study ranks earnings surprises (SUE) within each quarter into deciles (0-9, where 0 is the most negative earnings surprise, and 9 is the most positive earnings surprise), divide by 9 and subtract 0.5. Thus, each standardized SUE has a value between -0.5 to +0.5.

A dummy variable is used for option volatility measure in the regression (1 for firms with increased implied volatility immediately prior to the earnings announcement date, 0 otherwise).

The regression includes both standardized SUE and the interaction term between standardized SUE and the option volatility dummy variable as the independent variables.

Consistent with previous research, SUE has strong associations with subsequent drift returns and the direction is positive as expected. However, based on the regression statistics, the coefficient of interaction terms between SUE and the dummy variable that indicate if firms have increased implied volatility prior to earnings announcement for different Pre-and-Base-Windows is generally insignificant. The only significant coefficient for the interaction term (Pre-Window [-14, -1] and Base-Window [-50, -15]) is of negative sign (-0.014). Under the RPH, for any given SUE level, stocks with higher risk (increased implied volatility) should generate higher drift return as a compensation for risk. Therefore, the estimated parameter of the interaction term between SUE and the dummy variable should be significantly positive if the RPH for PEAD holds.

Contrary to expectation under RPH, the regression results show that the parameter of the interaction term between SUE and the dummy, indicating if firms have increased implied volatility prior to earnings announcement, is generally insignificant; and, if significant, is of the opposite sign. These results are not supportive of the RPH for PEAD.

2.4.3.3 The relation between the implied volatility change after earnings announcement and drift returns

A number of tests are also performed to check the relation between changes in implied volatility after earnings announcement and drift returns.

Table 12.1 presents the mean 3-day-return [-1, +1] and mean drift return within each decile of implied volatility change ratio after earnings announcement (average implied volatilities within Post-window ([+2, +90]) over average implied volatilities within Base-Window [-50, -15] or Pre-Window [-14, -1]. Surprisingly, there is a clear monotonically decreasing relation between the mean drift return and implied volatility change ratio after earnings announcement. In other words, those firms with their implied volatilities decreasing to their normal level (Base-Window) faster after the earnings announcement date generally have higher drift returns.

These results again, contradict the risk-premium hypothesis (RPH) which predicts that firms with higher risks should revert back to normal implied volatility levels at a slower rate after earnings announcement, because investors are still uncertain about their future performance even after the earnings announcement. Under this hypothesis, such risky firms should have higher drift returns compared to firms with lower risk that revert back to their normal implied volatility levels faster. However, given that the monotonic relation shown in Table 12.1 is exactly the opposite, it can be concluded that the empirical finding is again inconsistent with the risk-premium explanation for the PEAD anomaly.

The three-day event period return also has a monotonically decreasing relation with the implied volatility change ratio after earnings announcement. This is consistent with prior literature (Bernard and Thomas [1989], Foster, Olsen and Shevlin [1984]) suggesting that firms with higher immediate returns ([-1,+1] three-day return) also have higher drift returns.

Table 12.1: Mean 3-day-return between [-1, +1] and mean drift return for each decile of implied volatility change ratio(earnings announcement date is day 0)

Rank for ratio of avg IV of [+2, +90] over [-50,-15][1]	3-day-return[2] [-1,+1]	drift return[3]
0	0.013	0.038
1	0.012	0.027
2	0.009	0.021
3	0.007	0.017
4	0.006	0.006
5	0.004	0.001
6	0.000	-0.008
7	-0.001	-0.017
8	-0.007	-0.026
9	-0.017	-0.048

Rank for ratio of avg IV of [+2, +90] over [-14,-1]	3-day-return [-1,+1]	drift return
0	0.020	0.045
1	0.013	0.030
2	0.009	0.020
3	0.007	0.018
4	0.004	0.006
5	0.003	0.001
6	0.000	-0.014
7	-0.005	-0.023
8	-0.007	-0.033
9	-0.019	-0.053

1. This is the rank (decile) of the mean ratios of average implied volatility of Post-Window ([+2,+90]) over average implied volatility of Base-Window([-50,-15]). The same notation applies to Rank for ratio of [+2, +90] over [-14,-1].
2. This is the mean 3-day-return between [-1, +1].
3. This is the mean drift return within each decile of implied volatility change ratio. Drift return is the excess returns from day +2 to one day after the subsequent quarter's earnings announcement, if available; and to day +90 after the current earnings announcements otherwise. This study measures excess returns as the buy-and-hold return over the designated window minus the buy-and-hold return from a portfolio of stocks of similar size, book-to-market ratio, and momentum (12-month compounded return) similar to Daniel et al. [1997].

Table 12.2: Spearman Rank Correlation between SUE and the ratio of average implied volatilities within Post-Window over average implied volatilities within Base/Pre-Window

Spearman Rank Correlation	sueaf1[1]	sueaf2[2]	sue3[3]
IV change between [+2, +90] and [-50,-15][4]	-0.0343	-0.0455	-0.0094
P-Value	<.0001	<.0001	0.0142
IV change between [+2, +90] and [-14,-1]	-0.0487	-0.0465	-0.0104
P-Value	<.0001	<.0001	0.0087

1. sueaf1 is calculated as the actual earnings per share from I/B/E/S minus the mean analyst EPS forecast in the 90-day period prior to the earnings announcement, scaled by the standard deviation of analyst EPS forecasts in the 90-day period prior to the earnings announcement.
2. sueaf2 is calculated as the actual earnings per share from I/B/E/S minus the mean analyst EPS forecast in the 90-day period prior to the earnings announcement, scaled by adjusted stock price at the end of the fiscal quarter.
3. sue3 is calculated following the seasonal random walk (SRW) model. Specifically, this study uses "Income Before Extraordinary Items" from Compustat of this quarter(t) minus "Income Before Extraordinary Items" of the quarter t-4, scaled by market value of equity prior to earnings announcement date.
4. This is the rank (decile) of the mean ratios of average implied volatility of Post-Window ([+2,+90]) over average implied volatility of Base-Window ([-50,-15]). The same notation applies to Rank for ratio of [+2, +90] over [-14,-1].

Table 12.2 shows the Spearman Rank correlation matrix. Consistent with the above results in Table 12.1, all correlation coefficients between SUE (all three measures), and the implied volatility change ratio after earnings announcement are significantly negative at the 0.01 level of significance. Given SUE has been proven to be strictly positively correlated with the three-day returns and the subsequent drift returns, this again supports the finding in Table 12.1 and is inconsistent with the RPH explanation for the PEAD.

2.4.3.4 Robustness Checks

1. This study uses three different measures of standardized earnings surprises (SUE). The empirical results using different measure of SUE are very similar. This study also uses a sample based on the seasonal random walk (SRW) model of SUE only. Therefore, firms on Compustat but without analyst following are not excluded from this sample simply because of their unavailability on I/B/E/S. Results are similar to those for I/B/E/S samples.

2. The tests in Table 10.1 are run for a variety of pre-announcement time windows. For example, the tests are run for [-7,-1] vs. [-14,-8], [-3,-1] vs. [-14,-4], and day -1 vs. day -7 and the results are similar.

3. The tests in Table 10.3 are also run for various combinations of Post and Pre-Windows. For example, the tests are run for [+1,+5] vs. [-7,-1], [+1,+30] vs. [-5,-1], [+1,+30] vs. [-3,-1], and [+1,+30] vs. day -1 and similar results are obtained.

4. Given the implied volatilities from the option prices of small firms may not accurately reflect their risk, the tests in Table 10 are run for large, medium and small firms. The results hold across different firm sizes.

2.5 CONCLUSIONS

This study has (1) examined if the option traders suffer from the PEAD malaise afflicting the equity markets; and (2) re-examined the two major competing explanations for the PEAD anomaly using option market data. To the best of my knowledge, this study is the first to use option market characteristics to examine the two leading explanations (RPH and URH) for the PEAD anomaly.

Although it cannot be ruled out that there may be other measures of risk (yet to be developed) that may completely "explain" the PEAD anomaly, or that there may be other (more complex) trading strategies that may achieve abnormal returns in a possibly "inefficient" option market, the empirical results (1) indicate that option traders are less susceptible to the under-reaction bias than equity traders; and (2) do not support the risk premium explanation for the PEAD anomaly, and the scales seem to be tilted in favor of under-reaction to earning announcements by equity investors as a behavioral explanation for this phenomenon.

From the point of view of future research, the findings of this study leave some of the existing interesting questions still intact. One such question is why equity traders do not learn over time to not under-react to earnings announcements just like their counterparts trading options? Why should equity traders be less rational than the option traders? If, as suggested by many authors, the inherent institutional structure of the equity market vis-a-vis the option market is the reason, then, perhaps, the metric of risk in the equity market should be re-calibrated before concluding that the behavioral explanation is the right one for equity investors. In addition, it would be interesting to study if and how the implied volatility metric from the option market itself has to be suitably modified to measure risk in the equity market to explain the PEAD anomaly.

CHAPTER 3

INFORMATION TRANSFER AND VALUE RELEVANCE OF EARNINGS

3.1 INTRODUCTION

Prior literature shows that the importance of earnings declines over time. One explanation for the decreasing importance of earning over the years is that there are substantially more non-earning accounting data (e.g., inventories, R&D, capital expenditures) and non-financial information released around the time of earnings announcement and therefore the relative importance of earnings themselves declines. The other explanation is that firms become more intangible assets oriented but the earnings do not correctly measure some expense such as R&D expense. In other words, the value relevance of earnings diminishes as a result of earnings' ineffectiveness in reflecting and measuring some expenses(e.g., R&D).

Another line of literature study the association between quarterly earnings surprise and the contemporaneous stock price reaction of announcing and non-announcing firms in the same industry, also known as "Information Transfer". One possible source of an information transfer is that the earnings releases of firms in the same industry convey information about the impact of the industry-wide trends for any other firm in that industry. Another possible source of an information transfer could be the earnings releases of firms in the same industry reveal information about the competitiveness shifts within that industry.

Therefore, a natural question to ask is how the magnitude of information transfer itself changes over the past few decades. If the levels of information transfer keep constant over time, then the latter explanation that argues the diminishing value relevance of earnings over time is a result of earnings' ineffectiveness in reflecting and measuring some expenses would be supported. Furthermore, given the obvious differences in business environment and operation among different industries, it would make sense to examine the time-series change in earnings' usefulness and information transfer level by industry.

My empirical results indicate that the change in the magnitude of information transfer itself over time is not significantly different from zero on average as well as for most industries when controlled for the decline in the value relevance of earnings over time. In other words, this study suggests that the earnings' ineffectiveness in reflecting and measuring some expenses(e.g., research and development expenses) may be responsible for the observed decline in the usefulness of earnings over the years. I also show that the decline in value relevance of earnings is not significant in all industries, although the decline is significant on average.

This study contributes to the literature in several ways. First, it sheds light on the potential explanations for the observed decreasing usefulness of earnings over the past few decades. Second, it adds to the existing information transfer literature as a time-series study compared to the traditional cross-sectional information transfer research. Third, it adds to the existing value relevance of earnings literature as an industry-specific study.

The rest of this chapter proceeds as follows. The next section reviews related literature. Section 3.3 describes my sample and research design. Section 3.4 presents and discusses the main results. Section 3.5 concludes this chapter.

3.2 A BRIEF REVIEW OF THE PRIOR LITERATURE

Lev and Zarowin [1999] find a decline in the usefulness of reported earnings along with other financial information. Lev [1989] documents earnings surprise account for only 5% to 10% of the variation in stock returns. He shows that the consistency between the information embedded in reported earnings and the information relevant to investors' valuation has decreased over time, regardless of the quality of analysts' forecasts.

Similarly, Hail [2013] finds that the loss in relevance of earnings continues over the last 30 years and exists in a large international sample, especially in countries that have strong institutions. However, Core, Guay, and Van Buskirk [2003] find only mixed evidence of such a decrease in value relevance during the dotcom boom period.

In terms of the possible explanations for the phenomenon, Lev and Zarowin [1999] argue that the increasing rate of business environment change (e.g., innovation, new technologies, etc.) together with the ineffectiveness of earnings in reflecting and measuring the effects/consequences of these change is the main reason for the decline in the value relevance of earnings over time. Along the same line, Lev and Thiagarajan [1993] and Livnat and Zarowin [1990] find that non-earnings accounting data (e.g., inventories, R&D, capital expenditures) increase the explanatory power of financial information in terms of stock returns to 15-25%. Similarly, Hail [2013] suggest that changes in the overall economy, the institutional environment, and in how firms are operated all impact the importance of accounting information(e.g., earnings) in firm valuation by external investors.

Another line of explanation for declining usefulness of earnings over time argue that: 1) Analysts' forecasts reflect the entire information set available to them (e.g., managerial voluntary disclosures) that are not limited to earnings; 2) There are substantially more non-earnings or even non-financial information released around the time of earnings announcement in recent years, and consequently, the relative informativeness and importance of earnings decline (Liu and Thomas [2000]).

There are also mounting literatures for information transfer in the past few decades. Information transfer refers to the phenomenon that the stock market's reaction to the first reporting firm in an industry exceeds that for the subsequent reporting firms. Foster [1981] suggests two potential source of information transfer. One possible source of an information transfer is that the earnings releases of early-announcing firms in an industry convey information about the impact of industry-wide commonalities for later-announcing firms in the same industry, and therefore the information content of the earnings releases of these subsequent reporters is reduced. Another possible source of an information transfer, as indicated by Foster [1981], is that the earnings releases of early-announcing firms reveal information about the impact of competitiveness shifts within that industry for later-announcing firms. He also points out that one determinant of the magnitude of information transfers is the effect of early-announcing firms' earnings releases on their own security prices.

Han and Wild [1990] also find a significantly positive association between the contemporaneous stock returns of announcing and non-announcing firms around earnings announcement dates and between earnings surprise of announcing firms and stock returns of non-announcing firms. Besides, they find that there is a difference in the magnitude of the association depending on the choice of earnings surprise. Generally speaking, they find that this association is stronger if earnings surprises are measured with analysts' forecasts than if based on seasonal random walk models of earnings.

Freeman and Tse [1989] and Bernard and Thomas [1990] also show that later-announcing firms' earnings-announcement-period stock price reactions may already include components inferred from early-announcing firms' earnings. Olsen and Dietrich [1985] examine retailers and their suppliers and arrive at similar conclusion. Schipper [1991] indicates that non-earnings announcements may also provide important information transfer mechanisms.

3.3 SAMPLE AND RESEARCH DESIGN

My 25-year study period ranges from the second quarter of 1986 to the first quarter of 2011.

For industry classification, I use Fama-French 48 Industry Portfolio definitions. I also run the same empirical tests for Fama-French 38 and 30 Industry Portfolio respectively as a robustness check.

To increase the overall sample size, I use standardized earnings surprises (SUE) measure calculated following the seasonal random walk (SRW) model rather than based on mean analyst EPS forecast. Therefore, I was allowed to use all firms in the Compustat universe for the study period. Specifically, I use "Income Before Extraordinary Items" from Compustat of this quarter, t, minus "Income Before Extraordinary Items" of the quarter t-4, scaled by market value of equity at the end of the month immediately prior to earnings announcement month.

I measure excess returns as the buy-and-hold return over the designated window minus the average buy-and-hold return on a portfolio of stocks of similar size (2 groups), book-to-market ratio (3 groups), and momentum (12-month compounded return, 3 groups) similar to Daniel et al. [1997]. In the regression analyses, I rank earnings surprise (SUE) within each quarter into deciles (0-9), divide by 9, and subtract 0.5. Thus, each standardized SUE has a value between -0.5 to 0.5.

The regression models I use to test the change in the magnitude of information transfer over time are described as follows,

$$R_j = \alpha_j + \beta_j \cdot SUE_j \text{ ....Model 1}$$

$$R_{j \neq f} = \alpha_j + \beta_j \cdot SUE_j + \beta_{pj} \cdot SUE_{pj} \text{ ....Model 2}$$

R_j is the immediate stock returns after earnings announcement([-1,+1] three-day return relative to earnings announcement date) of firm j. $R_{j \neq f}$ is the immediate stock returns after earnings announcement of firm j which is not the first reporting firm in the industry for that quarter. SUE_j is the standardized earnings surprise of firm j, while SUE_{pj} is the average standardized earnings surprise of all firms announcing at an earlier date in the same quarter and same industry.

To eliminate potential look-ahead bias, I use quarter t-1's ranking/deciles to determine the rank of SUE of quarter t for all analyses throughout this study.

For regression purpose, I also require at least 20 non-first-reporting firms in a certain industry for a certain quarter for non-first-reporters subsample.

Given prior literature indicate that the usefulness of earnings declines over the years, I first use my sample and study period to verify their finding. Second, I control for the decline in the value relevance of earnings over time to see if the magnitude of information transfer change over time in addition to the decline in the value relevance of earnings. Specifically, I use the following two regression models:

$$RSQ(Model2) = \alpha + \beta \cdot RSQ(Model1) + residual \text{ ....Model 3}$$

$$residual = \alpha + \beta \cdot Time \text{ ....Model 4}$$

where RSQ(Model2) and RSQ(Model1) stand for the regression R^2 from Model 2 and Model 1 respectively, while Time is a ranked quarter variable for the full study period 1986Q2-2011Q1.

If the parameter β of Model 4 is significantly different from zero, then the magnitude of information transfer does change over time in addition to the decline in the value relevance of earnings. Otherwise, the levels of information transfer keep constant over time.

Given the differences in business environment and operation among different industries, I also examine the time-series change in earnings' usefulness and information transfer level by industry, per Fama-French 48 Industry Portfolio classification.

3.4 Results of the overall time-series trend for non-first-reporters subsample

3.4.1 Tests of the change in the value relevance of earnings over time

Table 13 describes the regression analyses for all non-first-reporter firms, with R^2 from Model 1 as the dependent variable and ranked Time variable as the independent variable, for Fama-French 48 Industry Portfolio, Fama-French 38 Industry Portfolio and Fama-French 30 Industry Portfolio, respectively.

Table 13: Tests of the change in the value relevance of earnings over time

Industry Classification	Time Variable Coefficient[1]	t value
Fama-French 48 Industry Portfolio	-0.00021***	-5.76
Fama-French 38 Industry Portfolio	-0.00019***	-4.22
Fama-French 30 Industry Portfolio	-0.00028***	-6.65

1. This table presents the regression analyses of R^2 of Model 1 regressed on ranked Time variable(1986Q2-2011Q1). Model 1 is $R_{j\neq f} = \alpha_j + \beta_j \cdot SUE_j$ where $R_{j\neq f}$ is the immediate stock returns after earnings announcement([-1,+1] three-day return, while the earnings announcement date is day 0) of firm j which is not the first-announcing firm in the industry for that quarter, and SUE_j is the standardized earnings surprise of firm j.
2. *** indicate significance levels at 0.01 levels based on two-sided p-values.

Consistent with prior research(e.g., Lev and Zarowin[1999]), the observations from Table 13 show that the estimated Time coefficients in the regression are consistently significantly negative across different industry classifications, which suggests the decline in the informativeness of earnings over the 25-year study period is statistically significant. In other words, Table 13 indicates that the association between stock returns around earnings announcement and earnings surprise, as measured by R^2, has been declining throughout the study period (i.e. 1986Q2 – 2011Q1).

3.4.2 Tests of the time series change in the combined value relevance of firm's earnings surprises(SUE) AND average SUE of all firms announcing at an earlier date in the same quarter and same industry

Table 14 presents the regression analyses, with R^2 from Model 2 as the dependent variable and ranked Time variable as the independent variable, for Fama-French 48 Industry Portfolio, Fama-French 38 Industry Portfolio and Fama-French 30 Industry Portfolio, respectively.

Table 14: Tests of the time series change in the combined value relevance of firm's earnings surprises(SUE) AND average SUE of all firms announcing at an earlier date in the same quarter and same industry

Industry Classification	Time Variable Coefficient[1]	t value
Fama-French 48 Industry Portfolio	-0.00025***	-5.61
Fama-French 38 Industry Portfolio	-0.00023***	-4.38
Fama-French 30 Industry Portfolio	-0.00031***	-6.28

1. This table presents the regression analyses of R^2 of Model 2 regressed on ranked Time variable(1986Q2-2011Q1). Model 2 is $R_{j \neq f} = \alpha_j + \beta_j \cdot SUE_j + \beta_{pj} \cdot SUE_{pj}$, where $R_{j \neq f}$ is the immediate stock returns after earnings announcement([-1,+1] three-day return, while the earnings announcement date is day 0) of firm j which is not the first-announcing firm in the industry for that quarter, SUE_j is the standardized earnings surprise of firm j, and SUE_{pj} is the average standardized earnings surprise of all firms announcing at an earlier date in the same quarter and same industry. The difference in the regression R^2 of Model 2 and Model 1 is used as the measure of the information transfer magnitude of each industry for every quarter in Table 15.
2. *** indicate significance levels at 0.01 levels based on two-sided p-values.

After controlling for information transfer by adding early-announcing firms' average earnings surprise to the independent variables in Model 2, similar to the results in Table

13, the estimated Time coefficients in the regression are consistently significantly negative across different industry classifications, which suggests the decline in the combined value relevance of earnings of announcing firms and earnings of earlier-announcing firms is also statistically significant over the 25-year study period.

3.4.3 Descriptive statistics of Magnitude of Information Transfer

Table 15 describes the magnitude of information transfer, as measured by R^2 of Model 2 minus R^2 of Model 1, for Fama-French 48 Industry Portfolio, Fama-French 38 Industry Portfolio and Fama-French 30 Industry Portfolio, respectively.

Table 15: Descriptive statistics of Magnitude of Information Transfer[1]

Industry Classification	Mean	Median	t value
Fama-French 48 Industry Portfolio	0.0212***	0.0075	33.33
Fama-French 38 Industry Portfolio	0.0198***	0.0060	26.39
Fama-French 30 Industry Portfolio	0.0192***	0.0058	28.22

1. The difference in the regression R^2 of Model 2 and Model 1 is used as the measure of the information transfer magnitude of each industry for every quarter.
2. *** indicate significance levels at 0.01 levels based on two-sided p-values.

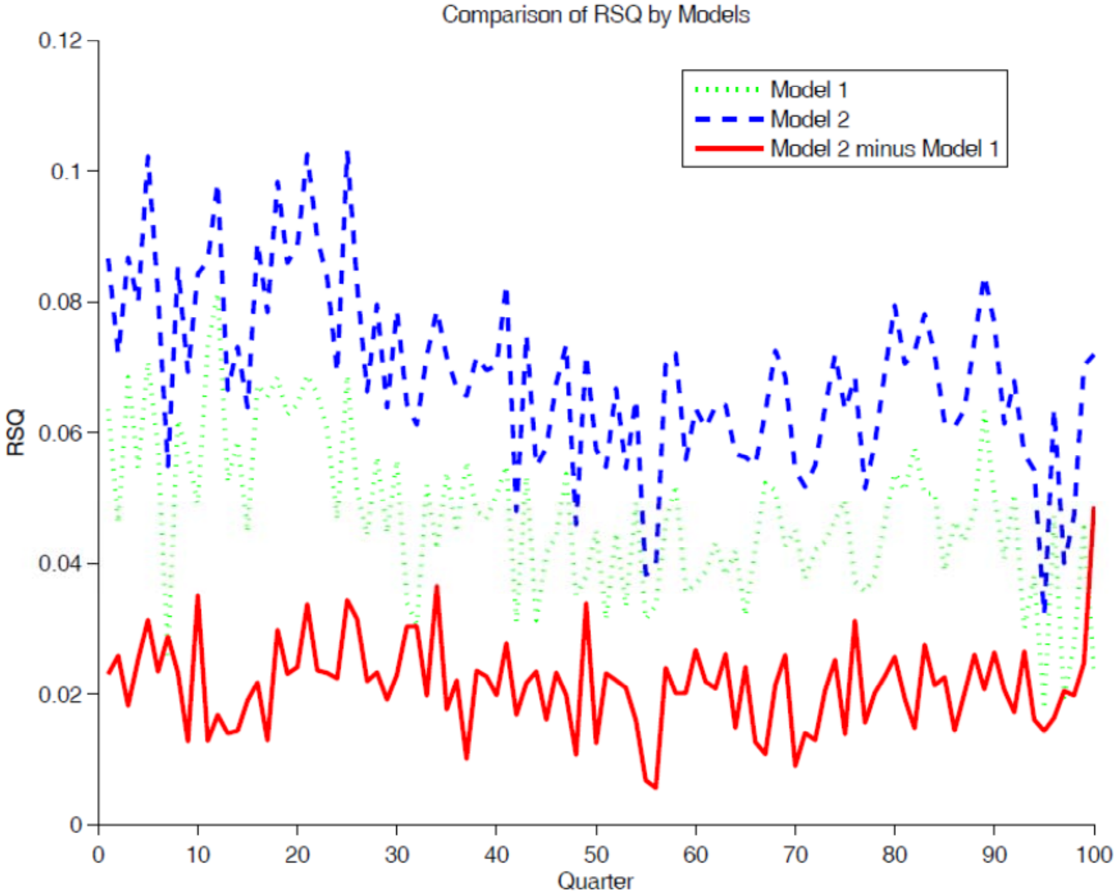
Without controlling for the decline in the value relevance of earnings over time, the average magnitude of information transfer for the time horizon of 1986-2011 and Fama-French 48 industries is 0.0212, which is statistically significant, while the median magnitude of information transfer is 0.0075 for the same time period.

When using Fama-French 38 Industry Portfolio and 30 Industry Portfolio classifications, the statistics are very similar.

3.4.4 Graphic Illustration of the Magnitude of Information Transfer over time

Figure 4 shows the comparison among regression R^2 of Model 1, regression R^2 of Model 2, and the difference in R^2 between Model 2 and Model 1 over the time period from the second quarter of 1986 to the first quarter of 2011(a total of 100 quarters).

Figure 4: Graphic Illustration of the Magnitude of Information Transfer over time



1. Model 1: $R_{j \neq f} = \alpha_j + \beta_j \cdot SUE_j$

   Model 2: $R_{j \neq f} = \alpha_j + \beta_j \cdot SUE_j + \beta_{pj} \cdot SUE_{pj}$
2. RSQ stands for regression R^2 of Model 2 and Model 1
3. The difference in the regression R^2 of Model 2 and Model 1 is used as the measure of the information transfer magnitude of each industry for every quarter.

The green dotted line represents the R^2 of Model 1 over time, while the blue dashed line represents the R^2 of Model 2 over time. As shown on the graph, the R^2 of Model 2 is almost consistently higher than the R^2 of Model 1 throughout the 100-quarter time period. However, the overall trend of both lines is decreasing over time. In other words, both the usefulness of earnings and the combined value relevance of earnings of announcing firms and earnings of earlier-announcing firms in the same quarter and same industry, are declining over time.

On the other hand, the red solid line represents the difference in R^2 between Model 2 and Model 1, which is a measure of the level of information transfer. Apparently, the time series decreasing trend for the red solid line is much weaker compared to the green dotted line and blue dashed line.

3.4.5 Tests of Change in Magnitude of Information Transfer over time after controlling for time series decline in the usefulness of earnings

Table 16 shows the regression analyses of Model 4, with residuals from Model 3 as the dependent variable and ranked Time variable as the independent variable, for Fama-French 48 Industry Portfolio, Fama-French 38 Industry Portfolio and Fama-French 30 Industry Portfolio, respectively.

Table 16: Tests of Change in Magnitude of Information Transfer over time after controlling for time series decline in the usefulness of earnings[1]

Industry Classification	Time Variable Coefficient	t value	Pr > |t|
Fama-French 48 Industry Portfolio	-0.00003	-1.30	0.20
Fama-French 38 Industry Portfolio	-0.00004	-1.44	0.15
Fama-French 30 Industry Portfolio	-0.00002	-0.98	0.33

1. This table presents the regression analyses of residuals of Model 3 regressed on ranked *Time* variable(1986Q2-2011Q1). Model 3 is $RSQ(Model2) = \alpha + \beta \cdot RSQ(Model1) + residual$, where RSQ(Model2) and RSQ(Model1) stand for the regression R^2 of Model 2 and of Model 1, respectively.

As Model 3 represents a regression of R^2 of Model 2 on R^2 of Model 1, I take the residuals of Model 3 as the dependent variable in Model 4($residual = \alpha + \beta \cdot Time$) to control for the observed decline in the value relevance of earnings over time. Therefore, the estimated coefficient of Time variable in Model 4 indicates the time series change in magnitude of information transfer in addition to the decline in the usefulness of earnings over time. Table 16 shows the estimated coefficient of Time variable in Model 4 for Fama-French 48 Industry Portfolio has a t value of -1.30. In other words, the coefficient of Time variable in Model 4 is not significantly different from zero although the estimated coefficient has a negative sign. Similarly, the absolute t values of the estimated coefficient of Time variable when using Fama-French 38 and 30 Industry Portfolio are both below 1.50. Thus, all t-statistics are well below the critical value at 5% level of significance.

Therefore, the observations from Table 16 suggest that the level of information transfer does not change over time in addition to the decline in the usefulness of earnings over time. In other words, it indicates that the earnings' ineffectiveness in reflecting and measuring some expenditure (e.g., research and development expenditures) may be the main reason for the observed decline in the usefulness of earnings over the years.

3.5 Results by industry

The results in Section 3.4 describe the average trend of the Compustat universe firms (excluding first reporters) across all industries. Given the obvious differences in business environment and operation among different industries, it makes perfect sense to examine the time-series change in earnings usefulness and information transfer level by industry, per Fama-French 48 Industry Portfolio classification.

3.5.1 Change in the value relevance of earnings over time by industry for Compustat Universe

Panel A of Table 17 presents the regression results for the Compustat universe including all first reporters, with R^2 (β_j) from Model 1 as the dependent variable and ranked Time variable as the independent variable, irrespective of industry.

Panel B of Table 17 shows the industry-specific (Fama-French 48 Industry Portfolio classification) regression results for the Compustat universe including all first reporters, with R^2 from Model 1 as the dependent variable and ranked Time variable as the independent variable, ordered by the t statistics of the estimated Time coefficients (most negative to most positive).

Panel C of Table 17 shows the industry-specific regression results for the Compustat universe including all first reporters, with the estimated earnings surprise(SUE) coefficient β_j from Model 1 as the dependent variable and ranked Time variable as the independent variable, ordered by the t statistics of the estimated Time coefficients (most negative to most positive).

Table 17: Change in the value relevance of earnings over time for Compustat Universe

Panel A: Change in the value relevance of earnings over time for the Compustat Universe including all first reporters

Dependent variable	Time Est.	t-Stat	Pr > |t|
R-squared	-0.00060	-6.79***	<.0001
β_j	0.00018	3.92***	<.0001

Panel B: Change in the value relevance of earnings as measured by R^2 over time by industry[1]

Industry[2]	Industry Ref[3].	Time Est.	t-Stat	Pr > |t|
Candy & Soda	3	-0.00809	-8.02***	<.0001
Precious Metals	27	-0.00147	-5.06***	<.0001
Business Services	34	-0.00044	-4.09***	<.0001
Tobacco Products	5	-0.00475	-3.93***	0.0002
Shipbuilding, Railroad Equipment	25	-0.00343	-3.84***	0.0002
Personal Services	33	-0.00129	-3.28***	0.0014
Beer & Liquor	4	-0.00214	-3.12***	0.0023
Food Products	2	-0.00105	-2.88***	0.0048
Wholesale	41	-0.00047	-2.67***	0.0088
Machinery	21	-0.00039	-2.66***	0.0090
Chemicals	14	-0.00041	-2.65***	0.0093
Real Estate	46	-0.00120	-2.65***	0.0094
Coal	29	-0.00290	-2.58***	0.0118
Restaraunts, Hotels, Motels	43	-0.00060	-2.46**	0.0156
Transportation	40	-0.00031	-2.36**	0.0203
Pharmaceutical Products	13	-0.00022	-2.25**	0.0266
Healthcare	11	-0.00068	-2.21**	0.0298
Non-Metallic and Industrial Metal Mining	28	-0.00101	-1.93*	0.0560
Insurance	45	-0.00027	-1.70*	0.0924
Agriculture	1	-0.00194	-1.67*	0.0983
Electronic Equipment	36	-0.00016	-1.60	0.1125
Trading	47	-0.00016	-1.56	0.1224
Electrical Equipment	22	-0.00031	-1.49	0.1399
Automobiles and Trucks	23	-0.00041	-1.42	0.1584
Entertainment	7	-0.00046	-1.29	0.2004
Defense	26	-0.00117	-1.28	0.2034
Construction Materials	17	-0.00030	-1.26	0.2111
Banking	44	-0.00012	-1.17	0.2446
Almost Nothing	48	-0.00045	-1.14	0.2576

Industry[2]	Industry Ref[3].	Time Est.	t-Stat	Pr > |t|
Steel Works Etc	19	-0.00022	-1.09	0.2781
Computers	35	-0.00011	-1.01	0.3165
Shipping Containers	39	-0.00048	-0.78	0.4344
Aircraft	24	-0.00033	-0.73	0.4679
Measuring and Control Equipment	37	-0.00012	-0.66	0.5136
Business Supplies	38	-0.00006	-0.28	0.7786
Apparel	10	-0.00012	-0.25	0.8015
Retail	42	-0.00001	-0.05	0.9604
Communication	32	0.00002	0.11	0.9101
Construction	18	0.00013	0.48	0.6329
Medical Equipment	12	0.00012	0.65	0.5156
Recreation	6	0.00032	0.73	0.4673
Rubber and Plastic Products	15	0.00026	0.92	0.3607
Petroleum and Natural Gas	30	0.00011	0.93	0.3554
Consumer Goods	9	0.00024	0.95	0.3432
Utilities	31	0.00020	1.57	0.1207
Printing and Publishing	8	0.00075	1.68*	0.0953
Fabricated Products	20	0.00228	3.00***	0.0035
Textiles	16	0.00305	4.86***	<.0001

1. This table presents the regression analyses of R^2 of Model 1 regress on ranked Time variable(1986Q2-2011Q1). Model 1 is $R_j = \alpha_j + \beta_j \cdot SUE_j$ where R_j is the immediate stock returns after earnings announcement([-1,+1] three-day excess return, while the earnings announcement date is day 0) of firm j for all firms in Compustat universe in the industry for that quarter, and SUE_j is the standardized earnings surprise of firm j.
2. Industry names are cited from Fama-French 48 Industry Portfolios. Their definitions can be found at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_48_ind_port.html
3. Industry reference number refers to the reference number of each industry in the original Fama-French 48 Industry Portfolios.
4. ***, **, and * indicate significance levels at 0.01, 0.05, and 0.10, respectively, based on two-sided p-values.

Panel A indicates that, consistent with the finding in Section 3.4.1, the time-series decline in the value relevance of earnings, as measured by R^2 following Lev and Zarowin[1999], is significant on average for Compustat universe including all first reporters, regardless of industry. However, regardless of industry, the slope coefficient β_j actually increases, on average, over time.

Also, there are a few observations from Panel B. First, the value relevance of earnings for firms with high R&D spending tend to decline over time(e.g., Pharmaceutical Products). Second, the decline is very significant for social media companies(e.g. Facebook) and other Internet-related services companies(e.g. Google), which both belong to the Business Services industry. The Business Services industry includes but is not limited to information retrieval services(e.g., Facebook), computer programming and data processing(e.g. Google, Linkedin). Third, the time-series decline in the usefulness of earnings is also highly significant for the Candy & Soda, Beer & Liquor and Tobacco Products industry. These industries feature some dominant players (e.g. Coca-Cola) and have a small number of firms in Compustat universe. Fourth, the Precious Metals industry (e.g. Gold mining companies such as Barrick Gold Corp) also has a significant decline in value relevance of earnings over the years, which probably results from the huge price volatility of gold and its sensitivity to the macroeconomics factors.

On the contrary, the earnings' usefulness as measured by R^2 even increases significantly over time for 3 out of 48 industries (i.e. Textiles, Fabricated Products, Printing and Publishing). These are more traditional and relatively stable industries which are less susceptible to stock market bubble or crash (e.g. dot-com boom, Housing Bubble, financial crisis, etc.).

Panel C indicates that, unlike R-squared as shown in Panel B, the estimated earnings surprise(SUE) coefficient β_j keeps constant or increase significantly for most industries.

β_j is the slope coefficient for the regression of the three-day([-1,+1]) contemporaneous returns of firm j centered on its earnings announcement date(day 0), on its standardized earnings surprise(SUE_j).

Panel C: Change in the slope coefficient β_j over time by industry[1]

Industry[2]	Industry Ref[3].	Time Est.	t-Stat	Pr > |t|
Textiles	16	-0.00071	-1.65*	0.1029
Apparel	10	-0.00056	-1.37	0.1737
Chemicals	14	-0.00013	-1.07	0.2873
Shipping Containers	39	-0.00030	-0.97	0.3353
Defense	26	-0.00058	-0.70	0.4846
Non-Metallic and Industrial Metal Mining	28	-0.00012	-0.61	0.5423
Transportation	40	-0.00007	-0.61	0.5455
Business Services	34	-0.00005	-0.51	0.6138
Machinery	21	-0.00006	-0.48	0.6331
Construction	18	-0.00009	-0.40	0.6866
Entertainment	7	-0.00011	-0.36	0.7164
Computers	35	-0.00004	-0.31	0.7593
Insurance	45	-0.00002	-0.19	0.8483
Coal	29	-0.00005	-0.11	0.9135
Shipbuilding, Railroad Equipment	25	0.00000	0.00	0.9972
Personal Services	33	0.00002	0.07	0.9463
Automobiles and Trucks	23	0.00003	0.17	0.8615
Construction Materials	17	0.00006	0.41	0.6806
Printing and Publishing	8	0.00017	0.51	0.6095
Real Estate	46	0.00014	0.68	0.4991
Tobacco Products	5	0.00040	0.69	0.4915
Restaraunts, Hotels, Motels	43	0.00014	0.70	0.4864
Steel Works Etc	19	0.00012	0.75	0.4567
Candy & Soda	3	0.00050	0.88	0.3821
Wholesale	41	0.00011	0.88	0.3793
Pharmaceutical Products	13	0.00011	0.96	0.3407
Almost Nothing	48	0.00030	1.17	0.2440
Rubber and Plastic Products	15	0.00026	1.19	0.2375
Healthcare	11	0.00028	1.21	0.2297
Beer & Liquor	4	0.00071	1.26	0.2094
Business Supplies	38	0.00021	1.26	0.2098
Precious Metals	27	0.00028	1.38	0.1709
Trading	47	0.00014	1.43	0.1570

Industry[2]	Industry Ref[3].	Time Est.	t-Stat	Pr > |t|
Food Products	2	0.00031	1.47	0.1452
Agriculture	1	0.00100	1.59	0.1144
Electronic Equipment	36	0.00016	1.61	0.1098
Utilities	31	0.00015	1.80*	0.0743
Electrical Equipment	22	0.00032	1.92*	0.0578
Retail	42	0.00033	1.97**	0.0514
Communication	32	0.00022	1.99**	0.0489
Measuring and Control Equipment	37	0.00031	2.03**	0.0453
Medical Equipment	12	0.00034	2.08**	0.0403
Aircraft	24	0.00092	2.55***	0.0124
Consumer Goods	9	0.00053	2.76***	0.0070
Fabricated Products	20	0.00170	2.78***	0.0066
Petroleum and Natural Gas	30	0.00025	2.81***	0.0059
Recreation	6	0.00068	2.88***	0.0049
Banking	44	0.00031	3.97***	0.0001

1. This table presents the regression analyses of β_j of Model 1 regress on ranked Time variable(1986Q2-2011Q1). Model 1 is $R_j = \alpha_j + \beta_j \cdot SUE_j$ where R_j is the immediate stock returns after earnings announcement([-1,+1] three-day excess return, while the earnings announcement date is day 0) of firm j for all firms in Compustat universe in the industry for that quarter, and SUE_j is the standardized earnings surprise of firm j.
2. Industry names are cited from Fama-French 48 Industry Portfolios. Their definitions can be found at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_48_ind_port.html
3. Industry reference number refers to the reference number of each industry in the original Fama-French 48 Industry Portfolios.
4. $***$, $**$, and $*$ indicate significance levels at 0.01, 0.05, and 0.10, respectively, based on two-sided p-values.

The slope coefficient of this regression can be interpreted as either the predictive ability of earnings for the short-term announcement returns([-1,+1]), or a return on a hedge portfolio that is long in the top decile of SUE (most positive) and is short in the bottom decile (most negative) of SUE. β_j also indicates the association of earnings surprise with short-window returns around earnings announcement date. Countless prior literature have already shown that earnings surprise is positively correlated with contemporaneous returns around earnings announcement day. Therefore, observations from Panel C suggest that, for majority of industries, this predictive ability of earnings for the short-term announcement returns, or the association between earnings surprise and three-day event returns, either keeps constant over time or has increased over the years. Alternatively, the results in Panel C can be interpreted as the return on the hedge portfolio constructed by taking a long position in the top decile of SUE (most positive) and a short position in the bottom decile (most negative) of SUE, either keeps constant or increases significantly for most industries.

From a statistical perspective, the R-squared value shows how reliable the beta number is and a higher R-squared value indicates a more useful beta figure. Therefore, the different time-series trend of R^2 and the slope coefficient β_j observed from Table 18 is not surprising, and the average increasing trend of β_j over time as observed in Panel A does not necessarily contradict the findings of Lev and Zarowin[1999].

Overall, Table 17 indicates that when examining the time-series change in the value relevance of earnings by industry, the results are mixed.

3.5.2 Change in the value relevance of earnings over time by industry for non-first-reporters subsample

Table 18 is the counterpart of Table 18 for the non-first-reporters subsample. Panel A of Table 18 presents the regression results for the Compustat universe excluding all first reporters, with R^2 (β_j) from Model 1 as the dependent variable and ranked Time variable as the independent variable, irrespective of industry.

Panel B of Table 18 shows the industry-specific (Fama-French 48 Industry Portfolio classification) regression results for the Compustat universe excluding all first reporters, with R^2 from Model 1 as the dependent variable and ranked Time variable as the independent variable, ordered by the t statistics of the estimated Time coefficients (most negative to most positive).

Panel C of Table 18 shows the industry-specific regression results for the Compustat universe excluding all first reporters, with the estimated earnings surprise(SUE) coefficient β_j from Model 1 as the dependent variable and ranked Time variable as the independent variable, ordered by the t statistics of the estimated Time coefficients (most negative to most positive).

Table 18: Change in the value relevance of earnings over time for non-first-reporters subsample

Panel A: Change in the value relevance of earnings over time for non-first-reporters subsample

Dependent variable	Time Est.	t-Stat	Pr > |t|
R-squared	-0.00021	-5.76***	<.0001
β_j	0.00014	4.61***	<.0001

Panel A indicates that the conclusion drawn from Table 17 still holds for the non-first-reporters subsample. That is, the time-series decline in the value relevance of earnings, as measured by R^2 following Lev and Zarowin [1999], is significant on average for Compustat universe excluding all first reporters, regardless of industry, while the slope coefficient β_j actually increases, on average, over time.

Panel B: Change in the value relevance of earnings as measured by R^2 over time by industry for non-first-reporters subsample[1]

Industry[2]	Industry Ref[3].	Time Est.	t-Stat	Pr > |t|
Business Services	34	-0.00044	-4.17***	<.0001
Restaraunts, Hotels, Motels	43	-0.00090	-3.87***	0.0002
Automobiles and Trucks	23	-0.00073	-3.21***	0.0018
Wholesale	41	-0.00054	-2.90***	0.0047
Chemicals	14	-0.00044	-2.81***	0.0061
Textiles	16	-0.00710	-2.32**	0.0339
Machinery	21	-0.00034	-2.30**	0.0236
Transportation	40	-0.00030	-2.29**	0.0245
Pharmaceutical Products	13	-0.00021	-2.24**	0.0275
Communication	32	-0.00020	-1.88*	0.0634
Insurance	45	-0.00030	-1.88*	0.0632
Electronic Equipment	36	-0.00020	-1.85*	0.0675
Electrical Equipment	22	-0.00035	-1.69*	0.0952
Construction	18	-0.00038	-1.58	0.1174
Entertainment	7	-0.00039	-1.37	0.1753
Banking	44	-0.00015	-1.37	0.1749
Trading	47	-0.00014	-1.33	0.1879
Retail	42	-0.00025	-1.30	0.1968
Computers	35	-0.00013	-1.17	0.2468
Medical Equipment	12	-0.00013	-1.14	0.2553
Steel Works Etc	19	-0.00023	-1.06	0.2929
Almost Nothing	48	-0.00096	-1.05	0.2979
Precious Metals	27	-0.00029	-1.01	0.3193
Food Products	2	-0.00032	-0.99	0.3247
Construction Materials	17	-0.00021	-0.85	0.3975
Apparel	10	-0.00037	-0.78	0.4391
Personal Services	33	-0.00027	-0.66	0.5133
Printing and Publishing	8	-0.00049	-0.61	0.5461
Measuring and Control Equipment	37	-0.00009	-0.44	0.6586
Business Supplies	38	-0.00009	-0.41	0.6863
Real Estate	46	-0.00027	-0.25	0.8009
Consumer Goods	9	-0.00005	-0.23	0.8221
Healthcare	11	-0.00001	-0.07	0.9477
Rubber and Plastic Products	15	0.00037	0.73	0.4700
Recreation	6	0.00069	0.92	0.3617
Petroleum and Natural Gas	30	0.00012	0.94	0.3489
Utilities	31	0.00017	1.32	0.1904
Non-Metallic and Industrial Metal Mining	28	0.00207	1.41	0.1803

1. This table presents the regression analyses of R^2 of Model 1 regress on ranked Time variable(1986Q2-2011Q1). Model 1 is $R_{j \neq f} = \alpha_j + \beta_j \cdot SUE_j$ where $R_{j \neq f}$ is the immediate stock returns after earnings announcement([-1,+1] three-day excess return, while the earnings announcement date is day 0) of firm j which is not the first reporting firm in the industry for that quarter, and SUE_j is the standardized earnings surprise of firm j.
2. Industry names are cited from Fama-French 48 Industry Portfolios. Their definitions can be found at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_48_ind_port.html
3. Industry reference number refers to the reference number of each industry in the original Fama-French 48 Industry Portfolios.
4. ∗∗∗, ∗∗, and ∗ indicate significance levels at 0.01, 0.05, and 0.10, respectively, based on two-sided p-values.

Compared to Panel B of Table 17, Panel B of Table 18 has fewer industries as a result of the restriction that there should be at least 20 non-first-reporting firms in a certain industry for a certain quarter for non-first-reporter subsample as mentioned earlier. A closer look at Panel B indicates that some industries with very negative t statistics of the estimated Time coefficients in Panel B of Table 17 are not present here. In other words, those industries have so small sample size or such limited number of public firms that they have been excluded from the current non-first-reporter subsample. Such industries include but are not limited to Candy&Soda, Tobacco Products, Beer&Liquor, Shipbuilding, Railroad Equipment and Coal, which generally have relatively few but very dominant players.

There are another two interesting findings from Panel B of Table 18. First, Textiles industry now has a significant negative Time variable coefficient for the non-first-reporter subsample, while it has a significant positive Time variable coefficient for the full sample including the first reporters. In other words, the first-day-reporter(s) of the Textiles industry tend to have a very different pattern than non-first-reporters in terms of

Panel C: Change in the slope coefficient β_j over time by industry for non-first-reporters subsample[1]

Industry[2]	Industry Ref[3].	Time Est.	t-Stat	Pr > |t|
Non-Metallic and Industrial Metal	28	-0.00308	-1.66	0.1189
Textiles	16	-0.00148	-1.27	0.2238
Chemicals	14	-0.00014	-1.15	0.2535
Construction	18	-0.00017	-0.79	0.4334
Transportation	40	-0.00007	-0.60	0.5510
Business Services	34	-0.00005	-0.54	0.5914
Insurance	45	-0.00003	-0.37	0.7103
Printing and Publishing	8	-0.00022	-0.30	0.7638
Automobiles and Trucks	23	-0.00005	-0.29	0.7702
Computers	35	-0.00003	-0.29	0.7747
Personal Services	33	-0.00008	-0.17	0.8638
Apparel	10	-0.00005	-0.11	0.9163
Machinery	21	-0.00001	-0.05	0.9571
Restaraunts, Hotels, Motels	43	0.00002	0.09	0.9270
Almost Nothing	48	0.00015	0.26	0.7984
Real Estate	46	0.00014	0.28	0.7779
Entertainment	7	0.00008	0.33	0.7422
Rubber and Plastic Products	15	0.00018	0.44	0.6608
Steel Works Etc	19	0.00012	0.71	0.4799
Wholesale	41	0.00009	0.71	0.4818
Business Supplies	38	0.00015	0.85	0.3959
Medical Equipment	12	0.00012	0.94	0.3511
Precious Metals	27	0.00022	0.94	0.3522
Pharmaceutical Products	13	0.00011	0.98	0.3304
Recreation	6	0.00058	1.11	0.2716
Construction Materials	17	0.00017	1.13	0.2631
Retail	42	0.00024	1.45	0.1490
Trading	47	0.00014	1.47	0.1448
Electronic Equipment	36	0.00015	1.48	0.1414
Utilities	31	0.00013	1.61	0.1113
Communication	32	0.00019	1.76*	0.0808
Healthcare	11	0.00052	2.04**	0.0443
Consumer Goods	9	0.00042	2.33**	0.0221
Measuring and Control Equipmen	37	0.00036	2.35**	0.0205
Food Products	2	0.00062	2.70***	0.0082
Electrical Equipment	22	0.00048	2.87***	0.0050
Petroleum and Natural Gas	30	0.00026	2.90***	0.0047
Banking	44	0.00030	3.85***	0.0002

1. This table presents the regression analyses of β_j of Model 1 regress on ranked Time variable(1986Q2-2011Q1). Model 1 is $R_{j\neq f} = \alpha_j + \beta_j \cdot SUE_j$ where $R_{j\neq f}$ is the immediate stock returns after earnings announcement([-1,+1] three-day excess return, while the earnings announcement date is day 0) of firm j which is not the first reporting firm in the industry for that quarter, and SUE_j is the standardized earnings surprise of firm j.
2. Industry names are cited from Fama-French 48 Industry Portfolios. Their definitions can be found at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_48_ind_port.html
3. Industry reference number refers to the reference number of each industry in the original Fama-French 48 Industry Portfolios.
4. ∗∗∗, ∗∗, and ∗ indicate significance levels at 0.01, 0.05, and 0.10, respectively, based on two-sided p-values.

the earnings' usefulness change over time. Second, similar to Panel B of Table 17, the value relevance of earnings for Pharmaceutical industry which tends to have high R&D spending still declines over time for the non-first-reporter subsample.

Relative to Panel C of Table 17, Panel C of Table 18 has fewer industries as a result of the restriction that there should be at least 20 non-first-reporting firms in a certain industry for a certain quarter for non-first-reporter subsample for regression purpose as mentioned earlier. Specifically, Panel C indicates that some industries with significant positive estimated Time coefficients in Panel C of Table 17 are not present here (e.g., Aircraft, Fabricated Products). A few industries that have a significant estimated Time coefficients in the full sample, regardless of the sign, now have an insignificant estimated Time coefficients in the non-first-reporters subsample (e.g., Retail, Textiles, Utilities, Medical Equipment, Recreation). On the other hand, some industries(e.g., Food Products, Healthcare) that have an insignificant estimated Time coefficients in the full sample, now have a significant positive estimated Time coefficients in the non-first-reporters subsample. However, consistent with the full sample results in Panel C of Table 17, majority of industries have an insignificant estimated Time coefficients, and therefore generate constant return on hedge portfolio constructed by extreme earnings surprise deciles over the years, or their earnings surprises have constant predictive ability for the short-term excess returns around their earnings announcements.

3.5.3 Change in the estimated earnings surprise (SUE) coefficient over time by industry after controlling for information transfer (for non-first-reporters subsample)

Panel A of Table 19 presents the regression results for the Compustat universe excluding all first reporters, with β_j from Model 2 as the dependent variable and ranked Time variable as the independent variable, irrespective of industry.

Panel B of Table 19 shows the industry-specific (Fama-French 48 Industry Portfolio classification) regression results for the Compustat universe excluding all first reporters, with β_j from Model 2 as the dependent variable and ranked Time variable as the independent variable, ordered by the t statistics of the estimated Time coefficients (most negative to most positive).

Table 19: Change in the estimated earnings surprise (SUE) coefficient over time after controlling for information transfer

Panel A: Change in the estimated earnings surprise (SUE) coefficient over time after controlling for information transfer

Dependent variable	Time Est.	t-Stat	Pr > |t|
β_j	0.00013	4.34***	<.0001

Panel B: Change in the estimated earnings surprise (SUE) coefficient over time by industry after controlling for information transfer[1]

Industry[2]	Industry Ref[3].	Time Est.	t-Stat	Pr > |t|
Non-Metallic and Industrial Metal Mining	28	-0.00311	-1.79*	0.0945
Textiles	16	-0.00215	-1.59	0.1312
Chemicals	14	-0.00017	-1.32	0.1893
Business Services	34	-0.00005	-0.60	0.5517
Construction	18	-0.00011	-0.48	0.6289
Automobiles and Trucks	23	-0.00007	-0.46	0.6452
Transportation	40	-0.00005	-0.45	0.6543
Insurance	45	-0.00004	-0.41	0.6841
Computers	35	-0.00003	-0.22	0.8263
Apparel	10	-0.00007	-0.16	0.8767
Personal Services	33	-0.00008	-0.16	0.8709
Machinery	21	-0.00002	-0.12	0.9012
Printing and Publishing	8	-0.00003	-0.04	0.9696
Restaraunts, Hotels, Motels	43	0.00000	0.02	0.9821
Rubber and Plastic Products	15	0.00002	0.04	0.9661
Real Estate	46	0.00002	0.04	0.9681
Almost Nothing	48	0.00009	0.14	0.8906
Entertainment	7	0.00009	0.38	0.7058
Wholesale	41	0.00007	0.51	0.6107
Business Supplies	38	0.00012	0.68	0.4993
Precious Metals	27	0.00017	0.71	0.4826
Steel Works Etc	19	0.00013	0.78	0.4372
Medical Equipment	12	0.00011	0.86	0.3904
Recreation	6	0.00055	1.06	0.2936
Construction Materials	17	0.00019	1.25	0.2147
Pharmaceutical Products	13	0.00014	1.29	0.2004
Retail	42	0.00022	1.35	0.1815
Trading	47	0.00014	1.48	0.1417
Electronic Equipment	36	0.00015	1.50	0.1368
Utilities	31	0.00013	1.59	0.1141
Communication	32	0.00019	1.74*	0.0843
Healthcare	11	0.00051	2.01**	0.0476
Measuring and Control Equipment	37	0.00036	2.23**	0.0284
Consumer Goods	9	0.00043	2.37**	0.0199
Food Products	2	0.00060	2.54***	0.0127
Petroleum and Natural Gas	30	0.00026	2.79***	0.0063
Electrical Equipment	22	0.00048	2.83***	0.0056
Banking	44	0.00031	3.92***	0.0002

1. This table presents the regression analyses of β_j of Model 2 regress on ranked Time variable(1986Q2-2011Q1). Model 2 is $R_{j\neq f} = \alpha_j + \beta_j \cdot SUE_{j\neq f} + \beta_{pj} \cdot SUE_{pj}$ where $R_{j\neq f}$ is the immediate stock returns after earnings announcement([-1,+1] three-day excess return, while the earnings announcement date is day 0) of firm j which is not the first reporting firm in the industry for that quarter. $SUE_{j\neq f}$ is the standardized earnings surprise of firm j. SUE_{pj} is the average standardized earnings surprise of all firms announcing at an earlier date in the same quarter and same industry.
2. Industry names are cited from Fama-French 48 Industry Portfolios. Their definitions can be found at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_48_ind_port.html
3. Industry reference number refers to the reference number of each industry in the original Fama-French 48 Industry Portfolios.
4. $***$, $**$, and $*$ indicate significance levels at 0.01, 0.05, and 0.10, respectively, based on two-sided p-values.

Similar to Panel A of Table 18, Panel A of Table 19 indicates that the estimated coefficient of the earnings surprise of the announcing firm j (β_j) on average increases over time, even after controlling for information transfer.

Panel B shows that, after controlling for the information transfer by adding average earnings surprise of earlier reporters in the same industry as additional independent variable, the predictive ability of earnings surprise as measured by β_j show very similar time-series trend as Panel C of Table 18. Specifically, industries that have significant positive estimated Time coefficients in Panel C of Table 18 (without controlling for information transfer) still have similar trend of β_j after controlling for information transfer. In other words, the subsample of 48 industries that have significant positive estimated Time coefficients is exactly the same with or without controlling for information transfer.

In general, the time-series trend of β_j for each industry is very similar with or without controlling for information transfer.

3.5.4 Change in information transfer over time by industry (for non-first-reporters subsample)

Panel A of Table 20 presents the regression results for the Compustat universe excluding all first reporters, with the estimated coefficient β_{pj} of average earlier-announcing-firms' earnings surprise (SUE_{pj}) from Model 2 as the dependent variable and ranked Time variable as the independent variable, irrespective of industry.

Panel B of Table 20 shows the industry-specific (Fama-French 48 Industry Portfolio classification) regression results for the Compustat universe excluding all first reporters, with β_{pj} from Model 2 as the dependent variable and ranked Time variable as the independent variable, ordered by the t statistics of the estimated Time coefficients (most negative to most positive).

Table 20: Change in information transfer over time

Panel A: Change in information transfer over time

Dependent variable	Time Est.	t-Stat	Pr > |t|
β_{pj}	-0.00019	-1.26	0.2085

Consistent with Section 3.4.5, Panel A of Table 20 shows that information transfer level as measured by β_{pj} in Model 2 does not change over time on average, after controlling for earnings surprise of the announcing firm. This is exactly the same conclusion as drawn from Table 16 where the information transfer level is measured by the difference in R^2 between Model 1 and Model 2.

Panel B: Change in information transfer over time by industry[1]

Industry[2]	Industry Ref[3].	Time Est.	t-Stat	Pr > |t|
Real Estate	46	-0.00559	-2.17**	0.0387
Wholesale	41	-0.00121	-1.91*	0.0589
Rubber and Plastic Products	15	-0.00302	-1.77*	0.0813
Textiles	16	-0.01050	-1.66	0.1161
Automobiles and Trucks	23	-0.00098	-1.24	0.2169
Apparel	10	-0.00258	-1.20	0.2353
Measuring and Control Equipment	37	-0.00137	-1.20	0.2324
Precious Metals	27	-0.00153	-1.14	0.2590
Construction Materials	17	-0.00081	-1.13	0.2624
Machinery	21	-0.00071	-1.05	0.2944
Business Supplies	38	-0.00056	-0.82	0.4154
Insurance	45	-0.00042	-0.72	0.4724
Food Products	2	-0.00051	-0.58	0.5642
Chemicals	14	-0.00037	-0.53	0.5951
Business Services	34	-0.00040	-0.52	0.6021
Utilities	31	-0.00022	-0.51	0.6099
Communication	32	-0.00035	-0.40	0.6913
Trading	47	-0.00025	-0.38	0.7045
Medical Equipment	12	-0.00013	-0.18	0.8561
Consumer Goods	9	-0.00011	-0.12	0.9024
Petroleum and Natural Gas	30	-0.00006	-0.08	0.9353
Construction	18	0.00000	0.00	0.9978
Steel Works Etc	19	0.00006	0.08	0.9345
Transportation	40	0.00006	0.10	0.9235
Banking	44	0.00008	0.11	0.9124
Healthcare	11	0.00015	0.13	0.8960
Non-Metallic and Industrial Metal Mining	28	0.00172	0.14	0.8894
Personal Services	33	0.00067	0.19	0.8520
Retail	42	0.00023	0.28	0.7830
Electrical Equipment	22	0.00028	0.41	0.6809
Electronic Equipment	36	0.00053	0.71	0.4767
Entertainment	7	0.00106	0.78	0.4364
Almost Nothing	48	0.00224	0.96	0.3425
Restaraunts, Hotels, Motels	43	0.00095	1.01	0.3140
Recreation	6	0.00286	1.10	0.2781
Computers	35	0.00093	1.15	0.2512
Printing and Publishing	8	0.00408	1.26	0.2163
Pharmaceutical Products	13	0.00177	2.05**	0.0434

1. This table presents the regression analyses of β_{pj} of Model 2 regress on ranked Time variable(1986Q2-2011Q1). Model 2 is $R_{j\neq f} = \alpha_j + \beta_j \cdot SUE_{j\neq f} + \beta_{pj} \cdot SUE_{pj}$ where $R_{j\neq f}$ is the immediate stock returns after earnings announcement([-1,+1] three-day excess return, while the earnings announcement date is day 0) of firm j which is not the first reporting firm in the industry for that quarter. $SUE_{j\neq f}$ is the standardized earnings surprise of firm j. SUE_{pj} is the average standardized earnings surprise of all firms announcing at an earlier date in the same quarter and same industry.
2. Industry names are cited from Fama-French 48 Industry Portfolios. Their definitions can be found at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_48_ind_port.html
3. Industry reference number refers to the reference number of each industry in the original Fama-French 48 Industry Portfolios.
4. $***$, $**$, and $*$ indicate significance levels at 0.01, 0.05, and 0.10, respectively, based on two-sided p-values.

Panel B of Table 20 suggests that, to predict or explain the three-day announcement returns of firm j, the contribution by information transfer (from earlier reporters) as measured by β_{pj} does not change over the years for most industries. A few exceptions: 1) it increases over time for Pharmaceutical Products; 2) it decreases over time for Real Estate, Wholesale and Rubber and Plastic Products. As pharmaceutical industry tends to have higher R&D intensity, this may partially explain the finding of Lev and Zarowin [1999] that “an increase in R&D intensity is associated with an abnormally steep decrease in earnings informativeness”.

To account for the effect of some firms’ delayed earnings announcement, I also run the same tests but add the constraint that the first-reporter of an industry in a certain quarter should report its earnings no later than 45 days from the end of the fiscal quarter that generated the announced earnings. The results are very similar.

Thus, in sum, the information transfer level, as measured by β_{pj}, keeps constant over the years for most industries.

3.6 CONCLUSIONS

In this chapter, I have re-examined the two major competing explanations for the decline in the usefulness of earnings over the past few decades, as documented in most prior literature, using a time-series study of the magnitude of information transfer. Given the obvious differences in business environment and operation among different industries, I also examine the time-series change in earnings' usefulness and information transfer level by industry.

My empirical results indicate that the change in the magnitude of information transfer itself over time is not significantly different from zero on average as well as for most industries when controlled for the decline in the value relevance of earnings over time. In other words, this study suggests that the earnings' ineffectiveness in reflecting and measuring some expenses(e.g., research and development expenses) may be responsible for the observed decline in the usefulness of earnings over the years. I also show that the decline in value relevance of earnings is not significant in all industries, although the decline is significant on average.

This study contributes to the literature in several ways. First, it sheds light on the potential explanations for the observed decreasing usefulness of earnings over the past few decades. Second, it adds to the existing information transfer literature as a time-series study compared to the traditional cross-sectional information transfer research. Third, it adds to the existing value relevance of earnings literature as an industry-specific study.

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