Multiples Valuation and Abnormal Returns

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Abstract

I investigate whether three commonly used valuation multiples—the Price-to-Earnings Ratio, the EV-to-EBITDA multiple, and the EV-to-Sales multiple—can be used to identify mispriced securities. I find that multiples are successful in identifying mispricing in both the equal and value weighted portfolios relative to the One-Factor CAPM. I further find, after controlling for size and value effects, that the bulk of the abnormal returns are concentrated in smaller firms. Moreover, the Sales multiple seems to outperform the other two multiples in the equal weighted design. In the value weighted design, however, the P/E ratio outperforms the others.

JEL: G12, G14, M4

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1. Introduction

Multiples valuation, otherwise known as valuation using comparables, is used extensively in practice. The academic literature to date has evaluated valuation multiples on the basis of their ability to explain cross-sectional variations in stock prices and on other metrics that are based on how close the valuations come to stock price (e.g. Alford 1992, Kaplan and Ruback 1995, and Liu, Nissim, and Thomas 2002). Practitioners such as sell-side analysts and trading professionals, however, argue that multiples can be, and should be, used to identify situations where stocks, at least to some extent, are mispriced. Implicitly, this argument implies that multiples should be useful in predicting abnormal returns in situation where the multiple is non-trivially different from stock prices. In this study, I evaluate three commonly used valuation multiples based on their ability to predict abnormal returns. Essentially, I compare the null hypothesis of market efficiency with the alternative hypothesis that valuation multiples can be used to identify deviations, for some stocks, from efficient pricing.

In multiples valuation, a ratio of value to a performance metric is calculated for a set of comparable firms:

$$Multiple_{j,i,t} = \frac{Value_{j,i,t}}{Performance\ metric_{j,i,t}}.$$

where *j* denotes the individual firm, *i* denotes the industry the firm is in, and *t* denotes the fiscal year. There are two basic types of multiples: i) Equity multiples and ii) Enterprise multiples. Equity multiples express the value of shareholders' claims on the asset and cash flow of the business. Therefore an equity multiple is an expression of that claim relative to a performance metric which applies to the shareholders only e.g. the Price-to-Earnings ratio. Enterprise multiples, on the other hand, express the value of an enterprise—the value of all claims on the firm—to a statistic that relates to the entire enterprise e.g. the EV-to-EBIDTA multiple. In calculating multiples, a variety of performance metrics, which include, but are not limited to, earnings before interest, tax, depreciation, and amortization (EBITDA), earnings before interest and taxes (EBIT), net income, and revenue may be used. The value of the firm is estimated by multiplying the ratio by the performance metric of the respective firm. Kaplan and Ruback (1995) state that multiples valuation relies on two key assumptions: i) the comparable companies have expected future cash flows proportional to and risks similar to those of the firm being valued and ii) the performance metric e.g. EBITDA is actually proportional to value. If these assumptions are met, multiples valuation will provide an accurate estimate of firm value.

Opponents of multiples valuation, however, argue that multiples tend to be: i) simplistic; ii) static; iii) biased; and iv) difficult to compare. First of all, multiples consolidate a great deal of information into a single ratio. This compression of information makes it difficult for one to analyze the effect of key value drivers such as growth on value. Second, since valuation multiples represent the value of the firm at a specific point in time, this can potentially be problematic as multiples fail to capture the dynamic and constantly evolving nature of the firm and the market. Third, as in any valuation method, multiples valuation is not free of bias. A biased analyst may choose specific multiples and the corresponding comparable firms to ensure that almost any flawed decision is justified. Lastly, comparing multiples is a complicated process as Kaplan and Ruback (1995) point out "comparable companies are not perfect matches in the sense that cash flows are not proportional and risks are not similar." From a holistic point of view, however, when properly utilized, multiples valuation can become powerful tools which provide insightful information about relative value.

Although valuing firms as a multiple of a financial or operating performance measure is a simple, popular, and theoretically sound approach to corporate valuation, there is little published research on the absolute and relative performance of different multiples. In this study, I plan to examine empirically whether or not three commonly used multiples—the Price-to-earnings ratio, the EV-to-EBITDA multiple, and the EV-to-Sales multiple[2]—can be used to identify and predict potentially mispriced securities.

The paper is organized as follows. In section 2, I examine the prior researches conducted on multiples valuation and related areas. In Section 3, I describe the theoretic framework of the research. In section 4, I present the methodologies used. In section 5, I analyze the sample data and in section 6, I present the regression results. In section 7, I describe the directions for future research and the conclusion.

2. **Background and Previous Studies**

In this section, I explore some of the prior literature on multiples valuation and long-term abnormal returns. Among the past studies on multiples I specifically focus on two themes: i) studies that assume market efficiency to assess the accuracy of valuation multiples and ii) studies that address the statistical and econometric issues that arise with different methodologies of estimating the multiples. Among the various empirical researches on long-term returns, I examine studies that relax the market efficiency assumption to identify the abnormal returns i.e. studies that analyze whether there exist mispricing, to a

[2] Kaplan and Ruback (1995) p.1066. Price-to-Earnings ratio will be denoted as P/E ratio, EV-to-EBITDA will be denoted as the EBITDA multiple, and the EV-to-Sales multiple will be denoted as the Sales multiple for the duration of this paper.

certain extent, in security prices. My research can be seen as a synthesis of multiples valuation and long term return studies; that is, I use multiples to investigate whether security prices are "correct" vis-à-vis one another.

2.1 *Multiples Valuation and Long-Term Abnormal Returns*

Alford (1992) studies the accuracy of the Price-to-Earnings (P/E) valuation method when comparable firms are selected on the basis of industry, risk, and earnings growth by comparing each firm's predicted stock price with the actual price. He finds that industry membership is an effective criterion for selecting firms. The pricing errors of the multiples decline when industry definition is narrowed from a single-digit SIC code to two and three digit codes. However, no additional improvement is made when industry is narrowed even more from three to four digit SIC codes. He also reports that controlling for size and earnings growth over and above industry levels does not improve the accuracy of the P/E multiple. Kim and Ritter (1999) find that forward P/E multiples based on forecasted earnings dominate all other multiples in valuation accuracy. Liu, Nissim, and Thomas (2002) examine the valuation performance of a comprehensive list of multiples and find that multiples derived from forward earnings explain stock prices remarkably well. They rank the multiples in the following order: forward-earnings measures are most accurate, followed by historical measures. Cash flow measures and book value of equity tie for third, and sales multiples are the worst. They also show that contrary to the view that different industries have different "best" multiples, the observed rankings are consistent for different industries examined.

Among previous researches that examine issues that arise with different methodologies in estimation, Beatty, Riffe, and Thompson (1999) derive and document the benefits of using the harmonic mean approach when calculating multiples. Baker and Ruback (1999) study the econometric issues that arise with different ways of computing industry multiples and compare the relative performance of multiples based on earnings before interest, tax, depreciation, and amortization (EBITDA), earnings before interest (EBIT), and sales. They report that multiples computed using the harmonic mean dominate alternative estimators such as simple mean, median, and value-weighted mean. They also show that industry multiples computed using the harmonic mean are close to minimum-variance estimates based on Monte Carlo simulations.

On the other hand, some studies relax the market efficiency assumption and analyze long term performance of stock returns. Frankel and Lee (1998) examine the usefulness of an analyst-based valuation model in predicting cross-sectional stock returns. They estimate the fundamental value of the firm, V, using analyst forecasts and a residual income model and find that the Value-to-Price (V/P) ratio is a good predictor of long-term cross-sectional returns when controlling for market beta, the B/P (book value-to-price) ratio and size. They report that while on a 12-month basis, the predictive power of V/P is comparable to that of B/P, on a 36-month basis, the predictive power of V/P is much stronger than that of B/P. Loughran and Ritter (1995) study initial public offerings (IPOs) and seasoned equity offerings (SEOs) and show that companies that issue stock during the 1970-1990 period, whether an IPO or a SEO, significantly underperform (for five years after the offering date) compared to firms that do not issue stock. Studies such as Basu (1977) and Stattman (1980) also examine the market efficiency hypothesis and long term abnormal returns but they use multiples in place of comprehensive valuation models. They show that portfolios derived from earnings and book value multiples earn abnormal returns.

This raises the question of whether commonly used multiples can be utilized to identify and predict potentially mispriced securities. In order to examine this issue, I briefly revisit the efficient market hypothesis in the next section.

2.2 *Efficient Market Hypothesis*

The debate surrounding market efficiency has been prevalent in the academia. Fama (1970) concludes that the efficient market hypothesis holds up well, while Grossman and Stiglitz (1980) argue that perfectly efficient markets are impossible. Fama (1970) states that an efficient market is "a market in which prices always "fully reflect" available information." He defines market efficiency in three different forms—*weak*, *semi-strong*, and *strong*. *Weak form* market efficiency, he argues, is where past information on rates of return has no effect on future rates of return. *Semi-strong form* market efficiency is when stocks reflect all publicly available information. Individual traders cannot earn additional profit from trading on any public information. Lastly, in *strong form* market efficiency stock prices reflect all information, both public and private.

Fama concludes that the evidence in support of the efficient market hypothesis is extensive while contradictory evidence is sparse. He thereby argues that the efficient market model stands up well. Grossman and Stiglitz (1980), however, suggest that perfectly efficient markets are an *impossibility*. They argue that if markets are perfectly efficient, the return to gathering the information would be zero. In such a case, there would be little reason to trade and markets will eventually collapse. In other words, since information is costly, prices cannot perfectly reflect available information. If it did, those who spent resources to obtain the new information would receive no compensation.

Examples of studies that argue markets are inefficient include Basu (1977), Stattman (1980), Loughran and Ritter (1995) and Frankel and Lee (1998). Others, however, such as Fama (1998), Mitchell and Stafford (2000), and Brav and Gompers (1997), argue otherwise. Proponents of market efficiency show that long-term abnormal returns tend to disappear under different methods of estimation. Fama (1998) shows that abnormal returns often disappear with changes in measurement. He argues that over-reactions of stock prices to information are as common as under-reactions and thus suggests that markets, on average, are efficient. Mitchell and Stafford (2000) examine the reliability of long-term stock price performance estimates using mergers, SEOs, and share repurchases. They also find little evidence of long-term abnormal returns after controlling for size and book-to-market attributes. This is also consistent with the finding of Brav and Gompers (1997) for initial public offerings.

The extant evidence suggests that the answer to the market efficiency hypothesis is much more complex than a simple yes or no. The market efficiency hypothesis, as emphasized by Fama (1970), must be tested jointly with a model for expected returns. In this study, I use two models of expected returns: the Sharpe (1964)-Lintner (1965) One-Factor CAPM and the Fama-French Three-Factor Model[3]. It is unique in that I incorporate asset pricing models such as the CAPM and the Fama-French three factor model with corporate valuation to identify potentially mispriced securities using the three commonly used valuation multiples: the P/E ratio, the EBITDA multiple, and the Sales multiple. I analyze the monthly security returns and the annual fundamentals data for all firms from the period 1962-2013 in the CRSP/COMPUSTAT merged file universe. I build time varying portfolios—one year, two year, and three year holding period portfolios—based on the three respective multiples. I perform calendar-time portfolio regressions on the portfolios and compare the intercepts, i.e. the ‘alphas’ or the abnormal returns from the three regressions. My null hypothesis is market efficiency—the intercepts are not statistically different from zero and hence the asset pricing model holds. If the null is rejected, then the asset pricing model fails to hold and this indicates inefficiency with respect to one or more multiple

[3] Fama-French Three-Factor model, in addition to being a good model for explaining returns on portfolios formed on size and BE/ME, also explains the strong patterns in returns observed when portfolios are formed on E/P, CF/P, and sales growth (Fama and French 1996). But one deficiency of this model is that it does not explain the short-term momentum in stock prices.

valuation methods. The theoretical framework and the methodologies used are discussed in more detail in the next section.

3. **Theoretical Framework**

I examine the abnormal returns i.e. the alphas in a calendar-time portfolio regression design, as strongly advocated by Fama (1998). The literature on long-term return performance uses various approaches in estimating the returns. Two examples are: i) the average/cumulative abnormal returns (AARs/CARs) and ii) the buy-and-hold abnormal returns (BHARs) [4]. There exists a methodological debate regarding which is the most appropriate way to estimate long term abnormal returns. Barber and Lyon (1997) and Kothari and Warner (1997) show that the BHAR methodology is mis-specified. Fama (1998) argues against the BHAR methodology and prefers the calendar time portfolio approach on three reasons: i) by forming monthly portfolios, the portfolio variance automatically accounts for cross-correlations of abnormal returns; ii) relative to the BHAR methodology, averaging the monthly abnormal returns are less susceptible to the bad model problem; and iii) the distribution of monthly returns is better approximated by a normal distribution, allowing for a classical statistical inference. Loughran and Ritter (2000), on the other hand, argue that calendar-time abnormal returns have low power. Mitchell and Stafford (2000), however, show that monthly calendar-time portfolio regressions have sufficient power to detect economically interesting abnormal returns and have more power than statistically-corrected buy-and-hold returns. Based on these reasons and its robustness to methodological concerns, I use the calendar-time portfolio approach to assess the magnitudes and the statistical significances of the monthly abnormal returns.

I measure abnormal returns relative to two models of expected return: the Sharpe (1964)-Lintner (1965) one factor CAPM and the Fama-French three-factor model (Fama and French 1993). The Sharpe-Lintner CAPM, as expressed by the formula

$$E(R_i) = R_f + \beta_i\left[E(R_M) - R_f\right], \qquad (1)$$

defines the expected returns on securities as a positive linear function of their market betas. Fama and French (1996) show that the three-factor model,

$$E(R_i) = R_f + \beta_i\left[E(R_M) - R_f\right] + s_i E(SMB) + h_i E(HML), \qquad (2)$$

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[4] $BHAR_i = \prod_{t=1}^{T}(1 + R_{i,t}) - \prod_{t=1}^{T}(1 + R_{benchmark,t})$, Mitchell and Stafford (2000)

can explain most of the anomalies from the CAPM discussed in the earlier empirical literature. The motivation for extending the One-Factor CAPM to the Fama-French Three-Factor model is to capture size[5] and value[6] effects that are systematically associated with returns. Within the one factor regression in (1), the average abnormal return equals the intercept from regressing the monthly portfolio excess returns from the *p'*th portfolio on the monthly excess market return for month *m*:

$$R_{p,m} - R_{f,m} = a_p + b_p(R_{M,m} - R_{f,m}) + e_{p,m} \tag{3}$$

where $R_{p,m}$ is the return to the portfolio p in the month m, $R_{f,m}$ is the monthly risk-free rate, and $R_{M,m} - R_{f,m}$ is the monthly excess market return. The three-factor abnormal return to portfolio p equals the intercept from regressing the monthly portfolio excess returns for the *p'*th portfolio $(R_{p,m} - R_{f,m})$ on the monthly excess market return $\left(R_{M,m} - R_{f,m}\right)$, the monthly return of a factor-mimicking portfolio for size SMB_m and the monthly return of a factor-mimicking portfolio for book-to-market equity HML_m:

$$R_{p,m} - R_{f,m} = a_p + b_p\left(R_{M,m} - R_{f,m}\right) + s_p SMB_m + h_p HML_m + u_{p,m}. \tag{4}$$

In the next section, I will describe the step-by-step process of creating multiples and building portfolios to estimate the monthly abnormal returns.

4. **Methodology**

The multiples employed in this study are: the P/E ratio, the EBITDA multiple, and the Sales multiple. The respective multiples are calculated as in equations (5), (6), and (7):

$$P/E\ ratio_{j,i,t} = \frac{Price_{j,i,t}}{Earning\ Per\ Share_{j,i,t}} \tag{5}$$

$$EBITDA\ Multiple_{j,i,t} = \frac{Enterprise\ Value_{j,i,t}}{EBITDA_{j,i,t}} \tag{6}$$

$$Sales\ Multiple_{j,i,t} = \frac{Enterprise\ Value_{j,i,t}}{Sales_{j,i,t}} \tag{7}$$

where *j* denotes the individual firm, *i* the industry[7] the firm is in, and *t* is the year. $Price_{j,i,t}$ denotes the fiscal year end price for a particular firm in a particular industry. The value drivers are also reported at fiscal year end. For example, the P/E ratio of Apple in the year 2012 is calculated by dividing Apple's

[5] Banz (1981) show that stocks with low market capitalizations have higher returns, on average, than large cap stocks. Basu (1983) shows that smaller firms have, on average, higher returns even after controlling for E/P ratio. Fama and French (1992) report that along with book-to-market equity, size has strongest association with returns.

[6] Stocks with high book-to-market equity have higher returns, on average, than stocks with low book-to-market equity (FF 1992).

[7] The industry codes in my data sample are four digit SIC codes. Following Alford (1992) I narrow down the industry definition from single digit SIC code to two digit codes. That is, I match firms on the first two digit SIC codes.

stock price on 12/31/2012 by Apple's reported earnings per share for 2012 on its income statement (issued at 12/31/2012, assuming Apple has a December fiscal year end). The enterprise values in equations (6) and (7) are calculated as follows:

$$Enterprise\ Value_{j,i,t} = Market\ Value\ of\ Equity_{j,i,t} + Book\ Value\ of\ Debt_{j,i,t} \qquad (8)$$

where $Market\ Value\ of\ Equity_{j,i,t} = Price_{j,i,t} * Shares\ Outstanding_{j,i,t}$ (9)

where $Book\ Value\ of\ Debt_{j,i,t} = Short\ Term\ Debt_{j,i,t} + Long\ Term\ Debt_{j,i,t}$. (10)

In calculating equation (10), if short term debt or long term debt is missing at fiscal year end, the missing value is substituted with zero. To estimate the fundamental value of firm V, I employ the harmonic mean approach used by Liu, Nissim, and Thomas (2002) and strongly advocated by others[8]. The harmonic mean approach puts less weight on extreme outliers that may arise with a standard mean. Liu, Nissim, Thomas (2002) show that the harmonic mean approach lowers proportional pricing error relative to a standard mean approach.

I first calculate the reciprocals of each respective multiple:

$$\frac{E}{P} ratio_{j,i,t} = \frac{Earning\ Per\ Share_{j,i,t}}{Price_{j,i,t}} \qquad (11)$$

$$\frac{1}{EBITDA\ Multiple_{j,i,t}} = \frac{EBITDA_{j,i,t}}{Enterprise\ Value_{j,i,t}} \qquad (12)$$

$$\frac{1}{Sales\ Multiple_{j,i,t}} = \frac{Sales_{j,i,t}}{Enterprise\ Value_{j,i,t}}. \qquad (13)$$

The harmonic mean of the each multiple is calculated as follows:

$$Harm\frac{E}{P}_{j,i,t} = \frac{1}{Avg\left(\frac{E}{P}\right)_{j,i,t}} \qquad (14)$$

$$HarmEBITDA_{j,i,t} = \frac{1}{Avg\left(\frac{1}{EBITDA\ Multiple}\right)_{j,i,t}} \qquad (15)$$

$$HarmSales_{j,i,t} = \frac{1}{Avg\left(\frac{1}{Sales\ Multiple}\right)_{j,i,t}} \qquad (16)$$

Notice for group of firms $j_{n,i,t}$ where n $\in \{1,2, \ldots \mathrm{N}\}$, the harmonic multiple is identical[9]. That is, firms $j_1, j_2, \ldots, j_N$ in industry *i* in year *t* have the same harmonic multiples. Calculating the fundamental

[8] For a more close reading on the benefits of the harmonic mean approach, see Baker and Ruback (1999) and Beatty, Riffe, and Thompson (1999).

[9] This is because while the monthly returns data—such as monthly closing stock prices and monthly returns—vary month-to-month, annual data—income statement items such as earnings per share, EBITDA, and sales—vary year-to-year. Hence, when the monthly data and the yearly data are merged, the same yearly data is recorded for months January through December in the same year. That is in for firm *i* in year 1962, I assume that firm *i*'s EPS/EBITDA/Sales will be identical for

firm value *V* differs depending on whether the multiple is an equity multiple or an enterprise multiple. First, *V* of the P/E ratio for each firm *j*, denoted V_{EPS_j}[10], is calculated by multiplying the harmonic mean of the P/E ratio with the value driver for the respective firm:

$$V_{EPS_j} = Harm(\frac{E}{P})_{j,i,t} * EPS_{j,i,t}. \tag{17}$$

For enterprise multiples, however, one needs to re-calculate the enterprise value for each firm using the harmonic mean. The new enterprise value is calculated by multiplying the harmonic mean multiple by the respective value driver for the firm. Then from the enterprise value, the book value of debt is subtracted to calculate the book value of equity. Book value of equity is divided by the number of common shares outstanding to calculate *V*:

$$\text{Enterprise Value}_{\text{new}} = HarmEBITDA_{j,i,t} * EBITDA_{j,i,t} \tag{18}$$

$$\text{Enterprise Value}_{\text{new}} - \left(Book\ Value\ of\ Debt_{j,i,t}\right) = Book\ Value\ of\ Equity_{j,i,t} \tag{19}$$

$$\frac{Book\ Value\ of Equity_{j,i,t}}{CommonSharesOutstanding_{j,i,t}} = V_{EBITDA_j}. \tag{20}$$

The same process is applied to calculate *V* of the sales multiple V_{Sales_j}. With the three *V* figures calculated, I take the ratio of *V* to December 31st closing stock price for each firm in the data. This results in a *V/P* ratio for all the firm-year combinations, where *j* denotes the specific firm and *t* is the year:

$$\frac{V_{EPS_{j,t}}}{P_{j,t}} \tag{21}$$

$$\frac{V_{EBITDA_{j,t}}}{P_{j,t}} \tag{22}$$

$$\frac{V_{Sales_{j,t}}}{P_{j,t}} \tag{23}$$

For each December 31st, I rank firms into quintiles based on the *V/P* ratios and take long (short) positions in the 20% of stocks with the highest (lowest) *V/P* ratios. From these rankings, I form equal-weighted and value-weighted portfolios with different holding periods: one year, two years, and three years. In total, there will be 18 portfolios, nine in each equal weighted and value weighted portfolios: $V_{EPS}^{1\,year}, V_{EPS}^{2\,year}, V_{EPS}^{3\,year}, V_{EBITDA}^{1\,year}, V_{EBITDA}^{2\,year}, V_{EBITDA}^{3\,year}, V_{Sales}^{1\,year}, V_{Sales}^{2\,year}, V_{Sales}^{3\,year}$[11]. The motivation behind

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the months January 1962 – December 1962. This is one of the criticisms of the multiples valuation approach: the multiple represents firm characteristics as a snapshot in time.

[10] Subscript denotes the value driver used to calculate the fundamental value *V*.

[11] Superscript denotes the holding period. For subscripts look at footnote [12].

constructing value weighted portfolios is that the abnormal returns in the equal weighted portfolios might be driven by small firms[12].

In constructing portfolios, this paper allows for a one-month gap between fiscal-year end and portfolio formation date. For the one year portfolio, the stocks of the firms that are in the top and bottom quintiles as of December 31st of year *t* are bought on January 31st of year *t*+1 and held until December 31st year *t*+1. The two and three year portfolios hold the stocks until December 31st of year *t*+2 and year *t*+3, respectively. The above procedure is repeated annually/biennially/triennially, depending on the portfolio type. Each of these portfolios may be viewed as a mutual fund with a policy of acquiring securities in a given *V/P* class on January 31st, holding them for a year, two years, or three years, and then reinvesting the proceeds from the disposition in the top and bottom *V/P* class on the following January 31st. The return to the *p'*th portfolio in month *m*, $R_{p,m}$, is the mean of the equal weighted returns or the sum of the value weighted returns across securities *s*=1, …, S in portfolio $p \in \{Long, Short, Long - Short\}$.

For each month, the portfolio excess returns are calculated by subtracting the risk-free rate from the portfolio returns. The excess returns are then regressed on the market excess returns as in equation (3). The model is then extended to the Fama-French three factor model as in equation (4). The one factor and the three-factor regressions for the long-short (LS) positions are estimated as in equations (24) and (25):

$$(R_L - R_S)_m = a_{LS} + b_{LS}(R_{M,m} - R_{f,m}) + e_{LS,m} \tag{24}$$

$$(R_L - R_S)_m = a_{LS} + b_{LS}\left(R_{M,m} - R_{f,m}\right) + s_{LS}SMB_m + h_{LS}HML_m + u_{LS,m}. \tag{25}$$

Within this framework, the intercepts a_{LS} measure the average monthly abnormal returns to the portfolio.

5. **Data**

The original data of firms consists of all domestic nonfinancial companies in the monthly security returns and the annual fundamentals data in the CRSP/COMPUSTAT merged file universe from January 1962 to December 2013. I follow Fama and French (1992) and exclude all financial firms[13] as they have high leverage which cannot be said to have the same meaning for non-financial firms. I require firms to

[12] Fama and French (1993) argue that firms with high book-to-market equity have low earnings, on average, compared to firms associated with low book-to-market equity. They construct six portfolios (S/L, S/M, S/H, B/L, B/M, B/H) and value weight within each of the six cells. Fama (1998) argues that for a test of abnormal return to have universal validity, the abnormal returns need to persist in a value weighted portfolio, Loughran and Ritter (2000) disagree.

[13] Firms with SIC codes between 6000 and 6999.

have non-missing data for earnings per share (EPS), earnings before interest, tax, depreciation, and amortization (EBITDA), revenue, monthly closing stock prices, and common shares outstanding. If the firm does not report their short term or long term debt, it is substituted with zero. Furthermore, I constrain the sample to firms with fiscal year-ends in December due to the one month gap between fiscal year end and portfolio formation date. I also require firms to have full availability of monthly returns. In addition, I use the Fama French factors—monthly risk free rate (Rf), excess return on the market (Rm-Rf), SMB (small minus big: size factor), and HML (high minus low: value factor)—in the Wharton Research Data Services (WRDS) over the same time period. In estimating (5), I remove firms with negative book values of equity as P/E ratios are only interpretable for profit firms. In estimating equations (6) firms with negative EBITDA are also eliminated. Lastly, firms with stock prices under $1 as of December 31st are removed as these firms have unstable *V/P* ratios and poor market liquidity[14]. These filters ensure that the regression results are not driven by outliers.

6. Empirical Results

Table 1 reports the annual summary statistics for the total sample. The average stock price for the entire period is $22.78. The lowest average return is in 2008 with -2.57% and the highest average return is 4.66% in 1975. The average return over the period is 1.63%. The average harmonic P/E ratio, the average harmonic EBITDA multiple, the average harmonic sales multiple are 12.94, 8.54, and 0.98, respectively. The summary statistics illustrate that the model is not driven by outliers and the parameters used are reasonably stable over time.

Table 1: Summary statistics by year

Table values represent annual, equally weighted average statistics for firm data. MVE is market value of equity as of December 31st of year *t* in millions of US dollars. EV is enterprise value as of December 31st of year *t* in millions of US dollars. MVE is calculated as in equation (9). EV is calculated as in equation (8). Price and Return are the monthly closing security prices and the monthly return as listed on the monthly security returns data in the CRSP/COMPUSTAT merged file. Harmonic P/E is the harmonic price-to-earnings ratio computed as in equation (14). Harmonic EBITDA is the harmonic EV-to-EBITDA multiple calculated as in equation (15). Harmonic Sales is the harmonic EV-to-Sales multiple calculated as in equation (16). Summary statistics for the individual multiples were calculated after dropping negative values with respect to each multiple. All years reported in the bottom row represent the time-series mean of the statistics

Year *t*	Avg MVE	Avg EV	Avg Price	Avg Return	Avg Harmonic P/E	Avg Harmonic EBITDA	Avg Harmonic Sales

[14] Frankel and Lee (1998) argue that firms with stock prices under $1 incur disproportionally large trading costs and therefore cannot be included in the equal weighted portfolio.

1962	772.37	912.05	42.89	-0.76	16.02	7.37	1.45
1963	872.92	1009.13	44.49	1.65	17.13	13.14	1.49
1964	854.29	994.68	45.41	1.45	15.86	7.78	1.49
1965	868.19	1015.07	45.08	2.2	16.03	8.99	1.54
1966	478.35	587.44	33.20	-0.72	11.82	6.93	1.09
1967	559.59	684.43	36.65	4.34	18.35	10.04	1.39
1968	589.20	730.18	37.87	2.58	22.2	10.88	1.54
1969	500.45	656.17	32.64	-1.89	15.86	8.47	1.13
1970	483.89	658.73	23.18	0.06	15.74	8.65	1.05
1971	527.73	711.10	26.75	1.84	16.83	9.34	1.07
1972	585.54	767.33	27.19	0.87	14.3	7.52	1
1973	365.77	514.48	19.91	-2.41	7.44	5.16	0.7
1974	254.15	426.18	14.43	-1.86	4.51	3.78	0.51
1975	349.04	530.79	15.44	4.66	6.81	4.92	0.6
1976	425.52	614.61	17.71	3.8	7.77	5.28	0.67
1977	404.61	614.16	17.76	1.64	7.79	4.97	0.65
1978	417.82	648.42	18.05	1.97	7	4.87	0.62
1979	461.43	708.10	17.94	3.18	7.55	5.52	0.71
1980	576.67	850.62	19.73	3.43	9.32	6.8	0.81
1981	496.07	795.41	18.62	0.52	8.85	7.41	0.75
1982	563.50	871.59	15.43	2.62	11.76	11.65	0.82
1983	654.92	943.27	20.19	3.02	13.46	10.83	1.01
1984	590.02	875.07	16.40	0.09	10.78	10.48	0.86
1985	742.68	1049.85	17.41	2.87	13	13.27	0.93
1986	879.10	1232.44	19.47	1.7	14.94	8.96	0.96
1987	960.97	1355.40	19.90	1.11	12.01	12.09	0.87
1988	1132.25	1800.89	17.98	2.21	12.34	7.38	0.94
1989	1464.40	2248.65	19.79	2.19	13.3	-1.51	0.96
1990	1454.37	2348.62	18.50	0.01	11.88	10.09	0.84
1991	1850.59	2813.82	20.15	3.45	16.58	10.86	0.98
1992	1964.92	2981.48	20.73	2.82	17.69	11.2	1
1993	2238.29	3290.20	22.19	2.12	18.25	11.35	1.05
1994	2312.70	3356.81	21.44	0.49	15.36	-27.79	1
1995	3055.31	4226.80	21.93	2.6	15.48	10.4	1.09
1996	3869.39	5138.48	24.19	2.14	14.6	12.72	1.11
1997	5171.93	6635.16	26.75	2.58	18.26	12.13	1.26
1998	6783.47	8522.03	26.86	0.79	15.75	10.66	1.18
1999	8231.54	10355.98	25.10	1.12	14.76	16.61	1.19
2000	8617.20	11135.46	24.61	1.58	13.09	20.55	1.06
2001	8467.35	11412.63	24.32	1.87	17.43	13.25	1.05
2002	6705.93	9834.61	23.61	0.19	15.35	23.13	1.05
2003	8787.96	12336.08	24.08	3.35	19.34	-0.89	1.33

2004	9888.41	13683.33	27.41	2.31	18.8	12.75	1.35
2005	10368.22	14092.22	30.03	1.44	17.16	12.18	1.34
2006	11896.59	15426.37	32.23	1.88	17.67	13.46	1.4
2007	13688.00	17875.06	35.48	1.12	17.46	22.85	1.47
2008	9252.32	13795.01	30.09	-2.57	11.13	7.33	0.94
2009	11013.06	15567.79	24.18	3.46	17.44	15.29	1.34
2010	12716.86	17340.93	29.35	2.34	16.43	14.09	1.42
2011	13424.18	18406.78	33.95	0.34	14.61	7.84	1.29
2012	14683.67	20057.52	34.48	1.59	16.53	15.71	1.38
2013	18688.79	24782.61	41.91	3.06	18.24	8.27	1.7
All years	2655.13	3648.49	22.78	1.63	12.94	8.54	0.98

6.1 Correlation with Stock Prices

Table 2 reports the annual cross-sectional Spearman rank correlation coefficients between V and stock prices. Over the sample period, V_{EPS} had an average correlation with price of 0.80, which suggests that firm V calculated using EPS as the value driver explains around 64% of the cross-sectional variation in prices. Compared to V_{EPS}, V_{EBITDA} has a similar level of correlation with price of 0.76 . V_{Sales}, however, produced considerably weaker correlations of 0.58. Thus the correlations suggest that the P/E ratio and the EBITDA multiple are more associated, on average, with stock prices compared to the Sales multiple. This is consistent with Liu, Nissim, and Thomas (2002).

Table 2: Annual cross-sectional correlation of fundamental *V*s to stock prices

Table values represent cross-sectional Spearman rank correlation coefficients between the fundamental firm value V--calculated using EPS, EBITDA, and Sales--and monthly closing stock prices. Fundamental Vs are calculated as in equations (17) and (20). All years reported at the bottom of the table are time-series mean of annual cross-sectional correlations.

Year t	V_{EPS}	V_{EBITDA}	V_{Sales}
1962	0.79	0.76	0.42
1963	0.85	0.81	0.47
1964	0.80	0.76	0.40
1965	0.75	0.70	0.41
1966	0.81	0.76	0.54
1967	0.76	0.71	0.49
1968	0.73	0.69	0.47
1969	0.72	0.66	0.42
1970	0.77	0.69	0.47
1971	0.78	0.70	0.46
1972	0.75	0.65	0.42

1973	0.75	0.65	0.42
1974	0.78	0.65	0.47
1975	0.80	0.72	0.51
1976	0.83	0.76	0.55
1977	0.86	0.79	0.56
1978	0.85	0.76	0.55
1979	0.84	0.80	0.61
1980	0.81	0.76	0.59
1981	0.77	0.71	0.58
1982	0.79	0.73	0.62
1983	0.77	0.73	0.64
1984	0.84	0.81	0.72
1985	0.82	0.82	0.72
1986	0.81	0.82	0.70
1987	0.80	0.80	0.69
1988	0.86	0.85	0.72
1989	0.84	0.85	0.73
1990	0.85	0.82	0.71
1991	0.80	0.81	0.70
1992	0.83	0.83	0.64
1993	0.80	0.85	0.64
1994	0.86	0.85	0.65
1995	0.80	0.82	0.64
1996	0.78	0.80	0.62
1997	0.74	0.78	0.62
1998	0.71	0.77	0.60
1999	0.71	0.74	0.55
2000	0.67	0.66	0.47
2001	0.63	0.68	0.52
2002	0.77	0.77	0.59
2003	0.80	0.76	0.59
2004	0.82	0.81	0.59
2005	0.83	0.84	0.62
2006	0.86	0.85	0.65
2007	0.87	0.84	0.65
2008	0.77	0.82	0.64
2009	0.80	0.84	0.69
2010	0.84	0.85	0.66
2011	0.82	0.82	0.59
2012	0.81	0.85	0.62
2013	0.82	0.86	0.64
All years	0.80	0.77	0.58

6.2 Portfolio Characteristics

Table 3 reports the characteristics of the quintiles that are formed on each December 31st. Within the quintiles, Q1 (lowest quintile) and Q5 (highest quintile) are used in the portfolio. Specifically, I take a long (short) position in Q5 (Q1) and maintain those positions according to the holding period of each portfolio.

Table 3: Characteristics of quintiles formed on *V/P*

This table reports the characteristics of the one-year, two-year, and three-year portfolios formed at the end of December 31st each year by the *V/P* ratios. *V/P* represents the value-to-price rankings calculated using the three multiples as of each December 31st as in equations (21), (22), and (23). Each panel reports the mean values for the respective quintile, where Q1 is the bottom quintile and Q5 is the top quintile. Panels A through C report the characteristics calculated from the V_{EPS} portfolio. Panels D through F report the statistics from the V_{EBITDA} portfolio. Panels G through I report the quintile characteristics from the V_{Sales} portfolio. *P/E Ratio*, *EBITDA Multiple* and *Sales Multiple* represent the mean of the Price-to-Earnings ratio, EBITDA multiple and Sales Multiple for each quintile for the sample. *Avg Ret* represent the average monthly return of the firms in each quintile. All firms represent the unconditional mean.

Panel A- $V_{EPS}^{1\,yr}$ portfolio

	Q1 (Low V/P)	Q2	Q3	Q4	Q5 (High V/P)	All firms
Avg Ret	1.246	1.196	1.354	1.503	2.039	1.468
P/E Ratio	56.073	27.493	17.802	16.929	14.361	26.531
V/P	0.677	0.841	0.962	1.098	1.387	0.993

Panel B- $V_{EPS}^{2\,yr}$ portfolio

	Q1 (Low V/P)	Q2	Q3	Q4	Q5 (High V/P)	All firms
Avg Ret	1.329	1.238	1.338	1.508	2.024	1.487
P/E Ratio	58.828	22.302	17.692	18.395	15.498	26.543
V/P	0.719	0.852	0.970	1.081	1.335	0.991

Panel C- $V_{EPS}^{3\,yr}$ portfolio

	Q1 (Low V/P)	Q2	Q3	Q4	Q5 (High V/P)	All firms
Avg Ret	1.377	1.261	1.397	1.454	1.907	1.479
P/E Ratio	51.249	25.572	22.213	17.737	15.663	26.487
V/P	0.755	0.870	0.968	1.073	1.297	0.993

Panel D- $V_{EBITDA}^{1\,yr}$ portfolio						
	Q1 (Low V/P)	Q2	Q3	Q4	Q5 (High V/P)	All firms
Avg Ret	1.141	1.186	1.264	1.506	1.878	1.395
EBITDA Multiple	18.969	8.852	9.493	7.336	6.343	10.199
V/P	1.140	1.111	1.473	1.998	3.188	1.782

Panel E- $V_{EBITDA}^{2\,yr}$ portfolio						
	Q1 (Low V/P)	Q2	Q3	Q4	Q5 (High V/P)	All firms
Avg Ret	1.169	1.227	1.291	1.443	1.848	1.396
EBITDA Multiple	20.593	8.782	7.949	7.339	6.601	10.253
V/P	1.209	1.138	1.612	2.020	3.349	1.866

Panel F- $V_{EBITDA}^{3\,yr}$ portfolio						
	Q1 (Low V/P)	Q2	Q3	Q4	Q5 (High V/P)	All firms
Avg Ret	1.245	1.184	1.317	1.431	1.762	1.388
EBITDA Multiple	18.501	8.819	9.821	7.680	6.606	10.285
V/P	1.292	1.211	1.588	2.083	3.638	1.963

Panel G- $V_{Sales}^{1\,yr}$ portfolio						
	Q1 (Low V/P)	Q2	Q3	Q4	Q5 (High V/P)	All firms
Avg Ret	0.986	1.036	1.220	1.355	1.751	1.269
Sales Multiple	13.850	1.673	1.214	0.876	0.954	3.714
V/P	0.313	0.608	0.919	1.367	3.099	1.261

Panel H- $V_{Sales}^{2\,yr}$ portfolio						
	Q1 (Low V/P)	Q2	Q3	Q4	Q5 (High V/P)	All firms

Avg Ret	0.997	1.125	1.227	1.357	1.746	1.290
Sales Multiple	13.042	1.688	1.218	1.225	0.656	3.566
V/P	0.353	0.637	0.949	1.410	3.076	1.285

Panel I- $V_{Sales}^{3\ yr}$ portfolio

	Q1 (Low V/P)	Q2	Q3	Q4	Q5 (High V/P)	All firms
Avg Ret	1.067	1.172	1.231	1.357	1.604	1.286
Sales Multiple	13.005	1.756	1.212	0.936	1.050	3.592
V/P	0.372	0.666	0.959	1.398	2.998	1.279

I require the firms to have full return availability according to the holding period of each portfolio. For example, in the 1 year holding period portfolios, I require the firms to report their monthly total returns for the duration of the period examined—January 31st year *t* to December 31st year *t*. It can be observed that for all portfolios, the top quintile (Q5) of firms generate the highest returns. Moreover, it seems that *Avg Ret* increases as we move to a higher quintile. Although for the V_{EPS} portfolios, the returns slightly decrease when moving from the bottom quintile to the second quintile, returns monotonically increase after the second quintile. It is interesting to note that when the holding period is lengthened, the returns in the bottom quintile increases, on average, and the returns in the top quintile decrease, on average. Specifically, in the V_{EPS} portfolios, it can be seen that returns in the bottom quintile steadily increase, from 1.246% to 1.377% as the holding period increases from one year to three years. The returns in the top quintile drop from 1.503% to 1.454% for the same period. This is consistent with bulk of prior literature on long-term abnormal return which suggests that abnormal returns are concentrated in the first year after portfolio formation.

Also, the benefits of using the harmonic approach can be noticed. The average of the standard mean multiple in the bottom quintile (Q1) is considerably higher compared to the averages of the standard mean multiples in other quintiles. For example, in Panel A-Q1, the Price-to-Earnings ratio is 56.073 while the same statistic is 15.498 for the highest *V/P* quintile (Q5). For the nine portfolios, using the harmonic mean based *V/P* ratios seem to smooth the distribution of the standard means.

In the next section, I analyze the intercepts from the calendar-time portfolio regression for the one-factor CAPM and the three-factor model.

6.3 Regression Results

6.3.1 Sharpe-Lintner One-Factor CAPM Regression Results

Table 4 reports the coefficients from the one factor CAPM regressions of the equally weighted and value weighted V_{EPS}, V_{EBITDA}, and V_{Sales} portfolios for the one year, two year and three year holding periods from January1962 to December 2013. As an additional test I also construct value weighted portfolios.

Table 4: Equally weighted and value weighted long minus short position calendar-time portfolio regression results on the Sharpe-Lintner One-Factor CAPM

This table reports the calendar-time portfolio regression results of the equally weighted and value weighted portfolio for the long minus short position. $V_{EPS}^{1\,year}$, $V_{EPS}^{2\,year}$, and $V_{EPS}^{3\,year}$ denote the one, two, and three year portfolios formed by taking the long (short) position on the top (bottom) quintiles of the *V/P* (using eq. (21)) ranking formed at December 31st . $V_{EBITDA}^{1\,year}$, $V_{EBITDA}^{2\,year}$, and $V_{EBITDA}^{3\,year}$ denotes the portfolios formed using *V/P* ranking from equation (22). $V_{Sales}^{1\,year}$, $V_{Sales}^{2\,year}$, and $V_{Sales}^{3\,year}$ ranks the *V/P* obtained from equation (23). In the regression, dependent variables are monthly portfolio excess returns, Rp-Rf. The *t*-statistic is in parentheses. R^2 reported is for the long minus the short position. The R^2 is low as the betas in the long and the short positions are similar. Hence from an econometric point of view, a variable that is close to zero (the independent variable) is attempting to explain the variation in the excess portfolio returns in the long-short portfolio (the dependent variable). Therefore, the low R^2 is only natural. The full regression equation is $R_p - R_f = a + b(R_m - R_f) + e$. *** denotes p<0.01, ** denotes p<0.05, * denotes p<0.1.

	Equal Weight			Value Weight		
	Intercept (*t*-statistic)	MKTRF (*t*-statistic)	R2	Intercept (*t*-statistic)	MKTRF (*t*-statistic)	R2
$V_{EPS}^{1\,year}$	0.0068***	-0.089***	0.02	0.0034**	0.0298	0.0014
	(6.37)	(-3.76)		(2.32)	(0.92)	
$V_{EPS}^{2\,year}$	0.0061***	-0.076***	0.019	0.0042**	0.0734**	0.009
	(6.24)	(-3.48)		(2.93)	(2.29)	
$V_{EPS}^{3\,year}$	0.0046***	-0.1***	0.038	0.0042***	-0.0138	0.003
	(4.82)	(-4.93)		(3.04)	(-0.44)	
$V_{EBITDA}^{1\,year}$	0.0067***	-0.004	0.0001	0.004***	0.023	0.001
	(6.65)	(-0.19)		(3.35)	(0.81)	
$V_{EBITDA}^{2\,year}$	0.0065***	0.008	0.0002	0.003**	0.079	0.013
	(6.67)	(0.38)		(2.67)	(2.79)	
$V_{EBITDA}^{3\,year}$	0.0046***	-0.016	0.001	0.0027**	-0.024	0.001
	(4.94)	(-0.8)		(2.07)	(-0.82)	
$V_{Sales}^{1\,year}$	0.0083***	-0.044	0.0044	0.0029*	0.177***	0.043
	(6.89)	(-1.64)		(1.9)	(5.21)	
$V_{Sales}^{2\,year}$	0.008***	-0.02	0.0009	0.0031**	0.197***	0.052
	(6.81)	(-0.76)		(2.01)	(5.81)	
$V_{Sales}^{3\,year}$	0.006***	-0.03	0.0026	0.002	0.144***	0.033
	(5.67)	(-1.26)		(1.31)	(4.6)	

In all nine equal weighted portfolios, the average monthly abnormal and the holding period is negatively correlated. That is, when the holding period increases, the abnormal returns decrease, on average. For example, in the $V_{EPS}^{1\,year}$ portfolio, the abnormal returns decrease from .68% to .61% and to .46%, going from the one year to the three year holding period. This phenomenon is consistent with the results from table 3. It seems to be the case that abnormal returns are concentrated in the first year of portfolio formation and tend to decrease as the holding period increases. Comparing the alphas in the equal weighted portfolio, it can be seen that all abnormal returns are statistically and economically significant. Moreover, it is interesting to note that the portfolios based on the harmonic sales multiple generate a higher monthly abnormal return, on average, compared to the other two portfolios.

In the value weighted portfolios, the abnormal returns are economically and statistically significant in all but one (3 year sales portfolio) of the portfolios. In the V_{EPS} portfolio, average abnormal returns range from 0.34% per month in the one year portfolio to a 0.42% return in the two and three year portfolios. In the V_{EBITDA} portfolio, the average monthly abnormal returns range from 0.4% in the one year to 0.27% in the three year portfolio. This is an interesting point as Fama (1998) and Mitchell and Stafford (2000) argue that most abnormal returns tend to disappear with changes to estimation techniques. It can be observed, however, that abnormal returns estimated using the one-factor CAPM tend to persist even in the value weighted portfolios. This suggests that the abnormal returns in the equal weight portfolios are not driven by smaller firms. Hence, the one factor CAPM regression suggests that widely used multiples can be used to identify potentially mispriced securities.

6.3.2 Fama-French Three Factor Regression Results

I also examine whether the results are robust when the model is extended to the Fama and French Three-Factor model. When the model is extended to capture value and size effects, which is systematically related with the price-to-earnings ratio, the explanatory power of the model also increases. Table 5 reports the coefficients from the equal weighted portfolio regression and table 6 reports the value weighted portfolio regression results. In the three-factor equal weighted V_{EPS} portfolios, the R^2 increases from 0.02 to 0.29 in the one year, 0.019 to 0.23 in the two year, and 0.038 to 0.21 in the three year portfolio. This increase in explanatory power is attributable to highly significant coefficients on the size (SMB) and value (HML) factors. It can be seen that the positive coefficient estimates on SMB and HML stem from the fact that smaller firms had, on average, higher returns than bigger firms and that high book-to-market equity firms had, on average, higher returns than firms associated with low book-to-market equity over the sample period. These are expected given the results of Fama and French (1992) which indicate that both size and value help explain cross-sectional variations in stock returns. The high loading on size and value seems to exist regardless of the multiple used or the difference in holding periods.

More importantly, it can be observed that even after controlling for size and value, all of the equal weighted and value weighted alphas are economically and statistically significant. Specifically, in the V_{EPS} portfolios, the monthly abnormal returns range from 0.04% in the one year portfolio to 0.02% in the three year portfolio. Comparing the alphas from the three portfolios, it seems that again, portfolios based on the Sales multiple, on average, outperform the two other portfolios in a given period. In particular, for the one year portfolio, Sales generates the highest abnormal return, EPS and EBITDA are tied at 0.04% per month.

In order to analyze whether these abnormal returns are driven by small firms, a value weighted portfolio is constructed. Table 6 reports the coefficient estimates from the value weighted portfolio regression for the three factor model.

Table 5: Equal weighted long minus short position calendar-time portfolio regression results from the Fama-French Three-Factor Model

This table reports the calendar-time portfolio regression results of the equal weighted portfolio for the long minus short position from the Fama-French Three-Factor model. In the regression, dependent variables are monthly portfolio excess returns, Rp-Rf. The *t*-statistic is in parentheses. R^2 reported is for the long minus the short position. The full regression equation is $R_p - R_f = a + b(R_m - R_f) + s\text{SML} + h\text{HML} + u$. *** denotes p<0.01, ** denotes p<0.05, * denotes p<0.1.

	Equal Weight				
	Intercept (*t*-stat)	MKTRF (*t*-stat)	SMB (*t*-stat)	HML (*t*-stat)	R^2
$V_{EPS}^{1\,year}$	0.0004***	-0.016	0.113***	0.51***	0.29
	(4.5)	(-0.75)	(3.64)	(15.2)	
$V_{EPS}^{2\,year}$	0.004***	-0.029	0.142***	0.408***	0.23
	(4.46)	(-1.39)	(4.76)	(12.64)	
$V_{EPS}^{3\,year}$	0.002***	-0.056**	0.088***	0.362***	0.21
	(3.08)	(-2.62)	(2.95)	(11.22)	
$V_{EBITDA}^{1\,year}$	0.004***	0.022	0.244***	0.413***	0.25
	(4.89)	(1.05)	(8.11)	(12.75)	
$V_{EBITDA}^{2\,year}$	0.004***	0.017	0.247***	0.324***	0.19
	(5.12)	(0.82)	(8.28)	(10.1)	
$V_{EBITDA}^{3\,year}$	0.003***	-0.003	0.195***	0.287***	0.16
	(3.34)	(-0.17)	(6.71)	(9.16)	
$V_{Sales}^{1\,year}$	0.0045***	-0.016	0.450***	0.636***	0.47
	(5.08)	(-0.88)	(15.08)	(19.79)	
$V_{Sales}^{2\,year}$	0.005***	-0.005	0.455***	0.587***	0.44

	(5.03)	(-0.25)	(14.86)	(17.78)	
$V_{Sales}^{3\,year}$	0.003***	-0.003	0.36***	0.548***	0.42
	(3.47)	(-0.16)	(12.85)	(18.02)	

Table 6: Value weighted long minus short position calendar-time portfolio regression results from the Fama-French Three-Factor Model

This table reports the calendar-time portfolio regression results of the value weighted portfolio for the long minus short position from the Fama-French Three-Factor model. For full description of variables see tables 4 and 5.

	Value Weight				
	Intercept (*t*-stat)	MKTRF (*t*-stat)	SMB (*t*-stat)	HML (*t*-stat)	R^2
$V_{EPS}^{1\,year}$	0.0004	0.125***	0.0768*	0.587***	0.19
	(0.32)	(3.95)	(1.71)	(12.14)	
$V_{EPS}^{2\,year}$	0.0009	0.177***	0.087**	0.642***	0.14
	(0.76)	(5.85)	(2.02)	(13.89)	
$V_{EPS}^{3\,year}$	0.001	0.098***	-0.017	0.571	0.20
	(1.19)	(3.25)	(-.039)	(12.37)	
$V_{EBITDA}^{1\,year}$	0.003**	0.051*	0.065	0.219***	0.04
	(2.45)	(1.66)	(1.5)	(4.67)	
$V_{EBITDA}^{2\,year}$	0.002*	0.09**	0.104**	0.192***	0.05
	(1.81)	(3.08)	(2.42)	(4.15)	
$V_{EBITDA}^{3\,year}$	0.002	-0.008	0.064	0.1557***	0.02
	(1.41)	(-0.26)	(1.44)	(3.23)	
$V_{Sales}^{1\,year}$	-0.0005	0.216***	0.365***	0.61***	0.27
	(-0.42)	(6.69)	(7.97)	(12.37)	
$V_{Sales}^{2\,year}$	-0.0002	0.207***	0.458***	0.558***	0.29
	(-0.21)	(6.44)	(1.03)	(11.35)	
$V_{Sales}^{3\,year}$	-0.0009	0.155***	0.363***	0.463***	0.22
	(-0.71)	(5.06)	(8.32)	(9.86)	

Table 6 displays the coefficient estimates from the value weighted portfolio. Similar to the table 5, the R^2 is higher for all nine portfolios as explained by the highly significant coefficients on the value (HML) factor. The positive coefficient estimates on SMB and HML suggest that, on average, small firms had higher returns than large firms and firms with high book-to-market equity had higher returns than firms with low book-to-market equity. One interesting characteristic is the coefficient estimate on SMB in the $V_{EPS}^{3\,year}$ portfolio is -0.017. The negative loading suggests small firms, on average, had lower returns than big firms during for the three year holding period portfolios. Comparing the equal weighted and value weighted alphas indicate that potential mispricing is concentrated in smaller companies which receive equal weights in the equally weighted portfolio but low weights in the value weighted portfolios. This is consistent with Loughran and Ritter (2000) and Fama (1998).

6.4 Discussion of Results

In this study, I test whether or not the three commonly used valuation multiples can be used to identify potentially mispriced securities. For the One-Factor CAPM, I find that the equal weighted and value weighted alphas are both economically and statistically significant. Also, when I control for size and value factors by incorporating the Fama-French Three-Factor model, the equal weighted alphas remain both economically and statistically significant. Hence, this suggests that in the equal weighted design, valuation multiples can indeed detect (some) mispricing in security prices. In a value weighted design, multiples are successful in detecting mispricing when size and value are not controlled for. After controlling for size and value, however, the value weighted alphas are insignificant at the conservative scientific levels. This indicates that the mispricing in security prices is concentrated mainly in smaller sized firms. From a market efficiency perspective, this result is consistent with the debate in the literature, in particular, with Fama (1998) and Loughran and Ritter (2000), who suggest that the mispricing is concentrated in smaller firms so that it is detectable in the equal weighted design. In terms of performance, when not controlling for size and value, the Sales multiple, on average, seems to generate higher abnormal returns than the P/E ratio and the EBITDA multiple in the equal weighted design. When the returns are value weighted without controlling for size, the P/E ratio and the EBITDA multiple perform equally well, generating a similar range of abnormal returns. Sales rank last, but the magnitudes of the alphas are still economically significant.

In sum, the evidence reported in this study suggest that commonly used multiples—the P/E ratio, the EBITDA multiple, and the Sales multiple—can be used to identify and predict potentially mispriced securities. It seems to be the case that the results point to both price efficiencies and inefficiencies as well, depending on research design choices.

7. Conclusion

In this paper, I conduct empirical analysis on whether or not three widely used valuation multiples—the Price-to-Earnings ratio, the EV-to-EBITDA multiple, and the EV-to-Sales multiple—can be utilized to identify and predict potentially mispriced securities. In assessing abnormal returns I use a calendar-time portfolio regression design, strongly advocated by Fama (1998). I draw my conclusions by comparing the intercepts, i.e. alphas, in the Sharpe (1964)-Lintner (1965) One-Factor CAPM and the Fama-French Three-Factor model.

Specifically, I find that in the one-factor CAPM, the alphas from both equal weighted and value weighted regressions for all portfolios are economically and statistically significant, which suggest that multiples can be used to identify and predict potentially mispriced securities. I also find that the equal weighted returns stay both economically and statistically significant after controlling for size and value in the three-factor regression. I find, however, after controlling for size and value, the value weighted returns, that is, when the small firms are given less weight, lose their significance. This result indicates that the mispricing in securities is concentrated in smaller size firms and is thereby detectable in an equal weighted design and/or when size is controlled for in a multi-factor model. This result is consistent with Fama (1998) and Loughran and Ritter (2000) who point out the fact that abnormal returns in equal weighted portfolios are driven by smaller firms. Moreover, from a performance perspective, the Sales multiple seem to generate, on average, higher equal weighted alphas compared to the P/E ratio and the EBITDA multiple. In a value weighted one factor CAPM design, the P/E ratio outperforms the other two multiples.

Going forward, I have several directions in which I would like to further develop the current study. First, I plan to add the I/B/E/S consensus forecasts in the model to observe how future earnings forecasts can add value in addition to using multiples to identify and predict potentially mispriced securities. By incorporating the earnings forecasts to historic figures, I will be able to gauge how much the analyst earnings forecasts add value. Second, I plan to conduct further analysis by controlling for size as in Bernard and Thomas (1990) [15]. By further sorting on size, for example, double sorting between the *V/P* quintiles and size quantiles, a more in-depth analysis of the relationship between size and returns may be conducted.

[15] Bernard and Thomas (1990), who examine another trading strategy, post-earnings-announcement-drift, divide size into deciles and further split the deciles into small, medium, and large terciles. Small consists of the bottom four deciles, large is the top three deciles and medium is the rest.

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