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## Differential Impact of Investor Sentiment on the Capital Asset Pricing Model and Discounted Cash Flows Model Estimates of the Rate of Return on Equity

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Differential Impact of Investor Sentiment on the Capital Asset Pricing  
Model and Discounted Cash Flows Model Estimates of the Rate of  
Return on Equity

An Honors Thesis

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of the University of New Orleans

In Partial Fulfillment

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by

Vinh Tran

Thesis Advisor:

Dr. Sudha Krishnaswami

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## **Abstract**

Traditional asset pricing models such as Capital Asset Pricing Model (CAPM) and Discounted Cash Flow (DCF) have been used widely in academics and practice due to their simplicity and popularity. The CAPM is a prescriptive model that describes the relationship between a stock's required return and risk relative to the movements in the market, while the DCF is a descriptive model that measures the realized rate of return on a stock based on the market price of the stock, which in turn incorporates investor perceptions about the stock and the market. In an ideal, efficient market where investors behave rationally, we should not see much of a difference between stock returns estimated from these two models. However, because investor perceptions affect the DCF estimate of returns, changes in investor confidence without accompanying changes in firm risk can affect the DCF estimate without changing the CAPM estimate. High growth firm returns are more likely to incorporate changes in investor perception because more of their value is generated from realization of future growth opportunities. In this research, I study whether investor sentiment affects the DCF estimate of stock return more than the CAPM estimate, and whether this impact is more pronounced for high growth firms. I find results consistent with this hypothesis. I find that investor sentiment causes a divergence between the CAPM and DCF estimates of stock returns, and this divergence is higher for high growth firms compared to low growth firms. My findings suggest that high growth firm stock prices are more prone to distortions due to hype or investor pessimism.

Keywords: CAPM, DCF, Investor sentiment, high growth

## I. Introduction and hypothesis

Traditional asset pricing models such as Capital Asset Pricing Model (CAPM) and Discounted Cash Flow (DCF) have been used widely in academics and practice due to their simplicity and popularity. CAPM was first developed and published by Sharpe (1964). The CAPM describes the relationship between a stock's return and risk relative to the movements in the market. Under CAPM framework, a stock's required rate of return should be linearly correlated with its systematic risk. A stock's systematic risk, or its beta, is calculated by dividing the covariance between that stock and a market portfolio by the variance of that stock. An asset's total risk is comprised of two components: systematic (or market) risk and unsystematic (idiosyncratic risk).

According to modern portfolio theory developed by Markowitz (1952), idiosyncratic risks of individual companies can be diversified away if investors hold a portfolio of stocks. In contrast, systematic risk cannot be diversified, and as a result, a stock's required rate of return should compensate for its systematic risk (assuming the stock is held as part of a well-diversified portfolio).

Here is a quick look at CAPM:

$$R_S = R_f + \beta_S(R_M - R_f)$$

$R_S$  is the expected return on the stock.  $R_f$  is the risk-free rate.  $R_M$  is the expected return on the market portfolio, that is, a portfolio that includes all the assets in the market. The rationale is that a stock's required return should, at the minimum, be equal to the risk-free rate. In real life, US Treasury bonds rates are used as a proxy for this risk-free rate. While there is no such thing as risk-free, US Treasury bonds are



considered the safest investment and closest to being risk-free among all assets, so for convenience purposes, Treasury bonds rates have been used as risk-free rate in all calculations for different models. Next,  $R_M - R_f$  is called market risk premium, which is the additional return that investors demand for bearing the risks of holding a portfolio of stocks. In terms of seniority, if a company goes bankrupt, debt holders will always be given precedence over stockholders and therefore will receive their capital before the stockholders. Stockholders are residual claimants, meaning that they only receive whatever is left after the bondholders have taken their share of the asset liquidation process. Therefore, stockholders have a much higher chance of losing the capital that they have invested in the company. As a result, stockholders will demand a higher level of return relative to bondholders. That is why a stock's return will be equal to risk-free rate plus the market risk premium adjusted with a beta term. This beta term accounts for how risky, or how sensitive, this individual stock is relative to the movements in the whole market. According to Sharpe (1964), prices of stocks will adjust until there is a linear relationship between magnitude of this sensitiveness and expected return.

Extant literature has expanded the CAPM model to include more factors that try to explain the expected return on the stock, such as Nobel Laureate Fama and French's 3-factor and 5-factor models. However, original CAPM model is still widely used in academics and practice due to its simplicity. Therefore, this thesis will investigate the effects of investor sentiment on the returns given from CAPM and implied in DCF model.

The Discounted Cash Flow Model (DCF) has been around for a long time. It tries to estimate a company's intrinsic value based on its ability to generate cash flow in the

future. The value of the firm will be the net present value of all future cash flows that the firm is expected to generate. Just like CAPM, there are different variations among DCF models, however, the most popular one is discounted dividend model:

$$R_s = (D/P_0) + g$$

where  $R_s$  is the return on the stock;  $D$  is dividend;  $P_0$  is the security price, and  $g$  is the expected growth rate. For companies that do not pay dividend, especially those that are in their early development stage, free cash flow to equity can be used to substitute for dividend. In an ideal market where investors behave rationally, we should not see a significant difference among stock returns estimated from DCF and CAPM. However, we know that this is not the case because the confidence of investors will affect their investment decisions in some way, thereby affecting investor demand for the stock, and consequently the stock price. For instance, Baker and Wurgler (2006) conclude that when sentiment is low, stock returns are relatively high for small, young stocks and high volatility stocks. In the period of high sentiment, these stocks earn subsequently low returns. Moreover, Greenwood and Shleifer (2014) find that investor expectations, which are measured from 6 different surveys, are strongly negatively correlated with model-based expected returns. In addition, Stambaugh, Yu, and Yuan (2012) find that in a broad set of anomalies in cross-sectional stock returns, when sentiment is high, these anomalies are stronger (long-short strategy is more profitable). The question of whether investor sentiment really affects stock prices has been around for a long time (Cornell, Landsman, and Stubben, 2017; Baker, Wang, and Wurgler, 2008; Baker and Wurgler, 2006; Brown and Cliff, 2001), and therefore, this research tries to explore how investor sentiment will affect stock returns calculated using CAPM and DCF models.

The CAPM only incorporates the average market-wide impact of investor sentiment through its impact on the risk-free rate and the market risk premium. The DCF model captures the impact of firm-specific investor sentiment through the movement of stock price. So, I expect a differential impact of investor sentiment on the required returns derived from CAPM and the implied returns derived from the DCF model. Specifically, the analysis shows that the higher the investor confidence, the higher the absolute difference between the estimates of CAPM and DCF, hence, the more deviated the stocks are from the market-wide model (CAPM). Moreover, investor perception will have a larger impact on high growth companies because a substantial portion of their value relies on the realization of future growth opportunities (Lee and Song, 2003). Therefore, I expect investor sentiment to have a larger impact on the returns of high growth companies than on mature companies. Our findings are consistent with these hypotheses.

## **II. Data**

### *1. Estimating CAPM and DCF returns*

For this thesis, data for all stocks was from the Center for Research in Security Prices (CRSP). The period of the analysis is from January 31, 1997 till December 29, 2017. There are 12,097 unique stocks that belong to 11,815 different companies in the data. Each observation in this data set is monthly data. The first thing that I did with the data was removing all stocks whose Standard Industrial Classification (SIC) equals to 4000 -4999 and from 6000 – 6799. The reason for this is that companies with these SIC codes are in utility, finance, insurance, and real estate industries. These industries are heavily regulated by the government, so I suspect that investor sentiment would not

cause the stock returns estimated by DCF to deviate from those estimated by CAPM significantly. In other words, companies within these industries are relatively stable and not subject to a lot of change in response to changes in the economy. Therefore, removing these companies will help us detect the differential effect of investor sentiment in the market more easily and accurately.

Next, to get the stock return estimates for CAPM model, I run a rolling regression procedure on the returns on each stock with the returns on a market portfolio. In this analysis, I use value-weighted market index. Both of these returns are available in CRSP, and they both include dividends (if there is any) as part of the returns. This is the regression model:

$$R_{s,t} = \alpha + \beta_{s,t} * R_{Mkt,t} + \varepsilon$$

I regress the stock returns with the market returns because beta of each stock is the measure of how sensitive the stock is with regards to movements in the market. Therefore, each beta that is estimated from the regression is an appropriate measure of how much systematic risk the stock has. Moreover, the window for each rolling beta is 36 months, a period long enough to capture the co-movements of each stock with the market.

After getting the estimates for beta of each stock for each month, I still need the estimates for market risk premiums. For convenience, I use the data from Fama-French 3-factor model. This dataset includes both estimates for market risk premiums and risk-free rates. Market risk premiums were calculated using all the firms listed on NYSE, AMEX, and NASDAQ exchanges. Since market risk premiums should be higher than

risk-free rates, and therefore, should be positive, I use the average of a 12-month period to be the estimate for market risk premium for each month. Because the data is monthly, it is possible that in some months, market risk premiums will be negative (such as months during recessions). Therefore, I believe that a 12-month average is a more appropriate measure for risk premiums.

After estimating these estimates for market risk premiums, I merge this dataset with CRSP data. Every component that goes into estimating stock returns using CAPM is available: risk-free rate which is the 1-month Treasury bill rate from Ibbotson Associates, market risk premiums from Fama-French, and beta of each stock for each month calculated using rolling regression. CAPM estimates can be derived using its model:

$$R_{S,t} = R_{f,t} + \beta_{s,t} (R_{M,t} - R_{f,t})$$

Next, for DCF estimates of stock returns, I will use the actual returns included in CRSP data as proxy for these estimates. The reason for this is whereas CAPM estimates capture the stock' risk relative to the risks of the whole market, DCF estimates only capture the expectation of investors on the performance and profitability of each individual firm and therefore, we would expect the actual returns on the stock to be approximately equal to DCF estimates of returns in equilibrium. Hence, it is justifiable to use actual returns as proxy for DCF estimates.

## *2. Descriptive and Univariate Analysis*

I begin the univariate analysis by looking at the mean and median of the returns estimated by CAPM and DCF model. Table 1 provides these estimates and their

significance levels. The analysis shows that the monthly average return for all stocks over a period of 20 years is 0.8911% for CAPM and 1.0963% for DCF. If I annualize these returns, the average comes out to be 10-13%, which is in line with the general notion of what percentage rate of return we should get if we invest in the stock market over a long period of time. It is worth noting that the median of the returns in the table is essentially 0%. However, Wilcoxon test shows that this number is significantly different from 0 at 1% significance level. The explanation for this is that this median will have some non-zero digits towards the end, but Stata, the program that I have used for all analysis, does not show these many digits. Furthermore, the raw difference in mean estimates between CAPM and DCF is -0.1973%, indicating that on average, DCF model will give a higher estimate for stock returns than CAPM model. This implies that DCF model incorporates not only the market-wide, but also the unsystematic risk of each individual company. More risk will demand higher return. Therefore, DCF estimates should be a little bit higher than CAPM ones. The average absolute difference for monthly returns between these two models is fairly high, 12.6272%, indicating that there is a wide gap in the monthly returns estimated by these two models. All estimates are significant at 1% level.

Finally, it should be noted that the difference between the mean and the median is much higher for the DCF estimate than for the more stable CAPM estimate of returns. This reveals the much higher volatility and the inclusion of a larger number of extreme observations in the DCF estimates than in the CAPM estimates. This pattern then extends to the  $(CAPM - DCF)$  as well as the  $|CAPM - DCF|$ . Indirectly, this result is

consistent with DCF estimates reflecting changes in investor perception about the stock more than the CAPM estimates do.

Next, Table 2 provides the estimates for mean and median of returns from CAPM and DCF models, grouped into small and large market capitalization. CRSP database does not have market capitalization, so I multiplied the stock price with number of shares outstanding to get the market capitalization for each company at each month in time. After that, stocks whose market capitalization is below the median of all stocks are categorized as small. The big stocks are the ones that have market capitalization above the median.

Similar to table 1, this analysis shows that the raw difference between CAPM and DCF estimates is -0.9454% for big firms, indicating that DCF model gives out a higher estimate for the returns than CAPM does. However, this is not the case for small firms, as the difference is 0.5582%. In addition, all estimates for small market capitalization firms are smaller than those of big firms, which is contrary to the popular belief that small firms outperform big firms. This can be explained by the fact that we have taken out a lot of companies from utilities and finance industries, which might skew the results in favor on big firms than small firms. It could also be the case that small firms, due to information asymmetry, suffer more from adverse selection than big firms do, a problem that can lead to small firms having a smaller average return than big firms, especially in the DCF estimates. Specifically, the mean difference between large and small firms is 0.3927% for CAPM estimates, but that number goes up to 1.9167% for DCF estimates. In addition, the median difference between large and small firms is only 0.3177% for CAPM estimates, but it is 2.6266% for DCF estimates. Moreover, the median for small

firms using DCF model is -1.4795%, indicating that the monthly returns of all small firms skew more towards the left tail (negative returns) of the distribution.

In addition, it is worth noting that the mean raw difference between estimates of CAPM and DCF for small firms is 1.5036% more than that of big firms. This implies that the deviation from market-wide model (CAPM) of small firm returns is bigger than that of big firms. All estimates, similar to the ones in table 1, are significant at 1% level.

I continue the analysis by categorizing all firms into high growth and lower growth companies. Typically, companies in high-tech industries will invest a lot of their capital into research and development, generating a very high level of growth opportunities. Therefore, we can use high-tech industries as a proxy for high-growth. Kile and Phillips (2009) published a study on how to use the SIC to classify high-tech industries. Therefore, I have used the table provided in their study to classify the industries in my analysis as either high-tech, hence, high-growth or lower-growth. Table 3 provides all the estimates for mean and medians of the returns from CAPM and DCF with companies categorized as high-growth or lower-growth.

The analysis shows that the mean monthly return calculated using CAPM is higher for lower-growth stocks than higher-growth stocks. However, the median return using CAPM goes in the opposite direction: high-growth firms have a higher return, a result that should be expected. Since the data is skewed, using median is the more reliable method. Additionally, the mean estimate using DCF is indeed 0.42% more for high-growth stocks than lower-growth stocks. But the median return for high growth stock using DCF is -0.2433%, indicating that the returns for high-growth stock skew more towards the left tail. In addition, for high-growth stocks, the difference between



CAPM and DCF estimates is  $-0.5557\%$ , and this number is significant at 1% level. On the other hand, the difference between two models for lower-growth stocks is  $-0.00361\%$ , but this number is not significant even at 10% level. This implies that the level of growth of a stock does make a difference in how deviated that stock is from the market-wide model, that is, the difference between CAPM and DCF estimates for high-growth stock is statistically significant.

Finally, I compare the means and medians of the estimates from two models for all stocks in two categories: either in the period of high investor confidence or low investor sentiment. First, I merged the sentiment index data provided by Baker and Wurgler with CRSP data. According to the authors of the index, there are two versions of investor sentiment index. I choose the one which is based on first principle component of five standardized sentiment proxies where each proxy has been orthogonalized with six macroeconomic indicators. This will help eliminate the problem of collinearity when I perform regression analysis where investor sentiment index is used as a predictor for the estimates of the market-wide model, CAPM. In other words, later on in regression analysis, I want to see if investor sentiment truly has a significant effect on the estimates of the returns. For example, it could be the case that the significant effect is explained by some macroeconomic indicators that are built into the investor sentiment index, but not the sentiment itself.

Table 4 presents the means and medians of the returns estimated using CAPM and DCF of all firms in 2 periods: high and low investor sentiment. The result found in this table is that the estimated mean and median returns using either CAPM or DCF models are higher following periods of low confidence than following periods of high

confidence, exactly consistent with the arguments in Baker and Wurgler (2006). Moreover, in the period following high confidence, the raw difference between CAPM and DCF estimates is 0.1836%, whereas in the period following low confidence, this number is -0.6474%. This implies that average CAPM estimate of monthly return is higher than DCF one in the period following high investor confidence, and the reverse is in the period following low sentiment. All estimates are significant at 1% level.

### **III. Multivariate Regression Analysis**

#### *1. Regression Analysis on CAPM estimates of the returns*

I start the multivariate regression analysis by studying the impact of three factors: Market Capitalization, Level of Growth, and Investor Sentiment on the estimates calculated using CAPM, DCF, as well as on the absolute differences between these two models. Level of Growth is a dummy variable with high-growth stocks as the ones with hi-tech SIC codes. Market Capitalization and Investor Sentiment are used as either dummy or continuous variable. In dummy variable case, stocks whose market capitalization below the median will be categorized as small and above the median would be big. Small market capitalization companies are coded as 0 and big ones are coded as 1. Similarly, periods where investor sentiment index is below median are categorized as low sentiment (coded as 0), and above median as high sentiment (coded as 1). The result of this analysis is shown in Table 5.

The first regressions are on CAPM estimates of the returns with dummy and continuous cases. No matter what type of variable was used, the results are similar: the coefficients for Market Capitalization are positive, indicating that the bigger the market

cap a stock has, the higher the CAPM estimate for the return on that stock. This result is consistent with the phenomenon that smaller market cap companies suffer more from adverse selection, causing them to have a smaller return than bigger cap companies. Moreover, the coefficients for High-growth are negative, implying that the higher the growth prospect, the smaller the CAPM estimated return. Similarly, coefficients for investor sentiment are also negative, illustrating that as investor sentiment gets higher, the expected return on a stock using CAPM will get smaller.

## *2. Regression Analysis on DCF estimates of the returns*

Next, the regression model with the same predictors is run on the returns estimated using DCF model. Similar to CAPM case above, using dummy or continuous variables for Market Cap and Investor Sentiment would give the same results. In this case, we still have positive coefficients for Market Cap and negative coefficients for Investor Sentiment, indicating that the DCF estimated returns would get bigger for larger market cap companies and lower investor sentiment. However, the coefficients for High-growth factor have turned positive, implying that DCF would give a higher estimate for the return on a high-growth than on a lower-growth stock. This is the opposite of the result found in previous regression on CAPM returns. Possible explanation for this is that high-growth stocks might not necessarily be more sensitive to movements in the market, and as a result, might not have a higher CAPM estimate than lower-growth stocks. That is why the regression (1) and (2) give negative coefficients for High-growth factor. However, high growth stocks have more potential to generate more profits in the future, and a big portion of their value is dependent of realization of these future growth opportunities, hence, DCF model can capture this growth prospect of individual

companies, incorporates it into the model, and gives out a higher estimated return for higher-growth companies.

### *3. Regression Analysis on absolute difference of the two models' estimates*

The next thing I did was to regress the three factors on the absolute difference between CAPM and DCF estimated returns. Again, using dummy or continuous variables makes no difference. This time, the coefficient for Market Cap is negative, indicating that the bigger the market cap of a stock, the less deviation between the CAPM and DCF estimates. This is possible because larger companies are more established. There is not a lot of uncertainty that goes into estimating the value of these companies using DCF model. Therefore, estimated returns on these bigger-cap stocks using DCF model would be relatively close to those using CAPM model.

Next, the coefficient for High-growth factor is positive and significant. This implies that as a company has a higher level of growth (higher level of capital invested in research and development), the absolute difference between the estimates from 2 models will get larger. Moreover, the analysis shows that coefficient for investor sentiment is positive, indicating that as investor confidence increases, so does the gap between CAPM and DCF model estimates. This is consistent with my hypothesis that variations in investor sentiment will cause larger changes in the DCF estimates relative to the CAPM estimates, leading to higher absolute deviations between the two estimates.

*4. Regression Analysis on absolute difference of the two models' estimates with interaction effect between growth and investor confidence*

Finally, I want to investigate how investor confidence can affect CAPM and DCF estimates differently for high-growth and lower-growth stocks. In order to accomplish this, I added an interaction term between High-growth indicator and investor sentiment (a continuous variable) into the regression model. The result of this analysis is presented in Table 6.

The analysis shows that whether dummy or continuous variable was used for Market Capitalization variable, the results are the same. That is, as the market cap of a company gets larger, the absolute difference between CAPM and DCF estimates for that company gets smaller. Next, a positive coefficient for High-growth indicator shows that a higher level of growth (higher level of research and development) is associated with a bigger deviation between CAPM and DCF estimates of the return for a company. The analysis also shows a positive correlation between investor confidence and the absolute difference of the two models' estimates. All of the signs of the coefficients for these three variables are the same as in the previous regression analysis.

More importantly, in this analysis, the coefficient for the interaction term between High-growth indicator and investor sentiment is positive, which confirms the hypothesis that the effect of investor sentiment is more pronounced for high-growth firms than lower-growth firms. This implies that the deviation from the market-wide model is larger for higher growth firms. This is because of the fact that a big portion of higher growth firms depends on the realization of future growth opportunities, so when the market is in period of high-confidence, DCF model will incorporate these firm-specific growth

opportunities into its estimated returns, whereas CAPM will not. With lower-growth firms, the majority of its value is already realized in the present. There is not a lot of uncertainty or growth opportunities information that go into estimating the return, so DCF model will give a relatively equivalent return as what a market-wide model, such as CAPM, would give. Consequently, the returns of lower-growth firms will have a smaller deviation from this market-wide model's estimate.

#### **IV. Conclusions**

To sum up, this paper investigates the differential impact that investor sentiment has on the estimated returns of all publicly-traded companies in the US using two widely popular models: CAPM and DCF. If market is efficient, there would not be any significant difference between the estimates of these two models. However, that is not the case, as investor confidence plays a role in their investment decisions. I find that investor sentiment significantly affects the divergence between CAPM and DCF estimates. Specifically, as investor sentiment increases, so does the deviation of the returns estimated from these models. I also find that investor confidence effect is more pronounced for high-growth firms than lower-growth firms. This is because more of the value of high-growth firms is dependent upon the realization of their future growth and profitability opportunities, so DCF model would incorporate this firm-specific information into estimating the value of the companies, whereas a market-wide model, such as CAPM, would not. Therefore, investors, when making their investment decisions, should be more careful with these high-growth companies, as they are more prone to fluctuations caused by investor optimism or pessimism.

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TABLE 1

**Univariate statistics for CAPM and DCF estimates of returns and their raw and absolute differences**

t-test was used to perform significant test for the means. Exact Wilcoxon signed-rank test was used to test if median is significantly different than 0. Significance at 10%, 5%, and 1% levels are denoted by \*, \*\*, and \*\*\*, respectively. All estimates are already in percentage terms.

	Mean	Median
CAPM	0.89110***	0.96920***
DCF	1.09631***	0.00000***
CAPM - DCF	-0.19732***	0.99220***
CAPM - DCF	12.62724***	8.19643***

TABLE 2

**Univariate statistics for CAPM and DCF estimates for stocks categorized based on market capitalization**

t-test was used to perform significant test for the means. Exact Wilcoxon signed-rank test was used to test if median is significantly different than 0 for column (1) and (2). Significance at 10%, 5%, and 1% levels are denoted by \*, \*\*, and \*\*\*, respectively. Each combination of column and row has two estimates: mean and median. Mean is the upper number, while the lower one (the number in parentheses) is the median. Column (3) estimates are column (1) estimates subtracted from column (2) ones. Wilcoxon Mann-Whitney rank sum test was used to test significance for column (3). All estimates are already in percentage terms.

	Big Market Cap.	Small Market Cap.	Small - Big Cap.
CAPM	1.08649*** (1.11283)***	0.69375*** (0.79506)***	-0.39274*** (-0.31777)***
DCF	2.05464*** (1.14710)***	0.13798*** (-1.47950)***	-1.91666*** (-2.62660)***
CAPM - DCF	-0.94536*** (0.00428)***	0.55822*** (2.35598)***	1.50358*** (2.35170)***
CAPM - DCF	10.01405*** (6.82562)***	15.26662*** (10.07988)***	5.25257*** (3.25426)***

TABLE 3

**Univariate statistics for CAPM and DCF estimates for stocks categorized based on level of growth prospects**

t-test was used to perform significant test for the means. Exact Wilcoxon signed-rank test was used to test if median is significantly different than 0 for column (1) and (2). Significance at 10%, 5%, and 1% levels are denoted by \*, \*\*, and \*\*\*, respectively. Each combination of column and row has two estimates: mean and median. Mean is the upper number, while the lower one (the number in parentheses) is the median. Column (3) estimates are column (1) estimates subtracted from column (2) ones. Wilcoxon Mann-Whitney rank sum test was used to test significance for column (3). All estimates are already in percentage terms.

	High Growth	Low Growth	Low - High Growth
CAPM	0.80410***	0.93812***	0.13402***
	(1.06352)***	(0.92995)***	(-0.13357)***
DCF	1.36972***	0.94892***	-0.42080***
	(-0.24330)***	0.00000***	(0.24330)***
CAPM - DCF	-0.55571***	-0.00361	0.55210***
	(1.37032)***	0.83012***	(-0.54020)***
CAPM - DCF	14.71335***	11.49974***	-3.21361***
	(9.638539)***	(7.531269)***	(-2.10727)***

TABLE 4

**Univariate statistics for CAPM and DCF estimates for stock returns in the period of high and low investor confidence**

t-test was used to perform significant test for the means. Exact Wilcoxon signed-rank test was used to test if median is significantly different than 0 for column (1) and (2). Significance at 10%, 5%, and 1% levels are denoted by \*, \*\*, and \*\*\*, respectively. Each combination of column and row has two estimates: mean and median. Mean is the upper number, while the lower one (the number in parentheses) is the median. Column (3) estimates are column (1) estimates subtracted from column (2) ones. Wilcoxon Mann-Whitney rank sum test was used to test significance for column (3). All estimates are already in percentage terms.

	High Confidence	Low Confidence	Low - High Confidence
CAPM	0.87341*** (0.86992)***	0.91200*** (1.12694)***	0.03859*** (0.25702)***
DCF	0.71492*** (0.0000)***	1.55763*** (0.16000)***	0.84271*** (0.16000)***
CAPM - DCF	0.18357*** (1.11904)***	-0.64737*** (0.84655)***	-0.83094*** (-0.27249)***
CAPM - DCF	12.78351*** (8.25410)***	12.44260*** (8.12894)***	-0.34091*** (-0.12516)***

TABLE 5

## Multivariate regression analysis

Ordinary least square multiple regression was used in this analysis. The coefficients and t-stats for each predictor are presented in the table. Each row and column combination has two numbers. The upper number is the coefficient, while the one in parentheses is the t-stat. Significance at 10%, 5%, and 1% levels are denoted by \*, \*\*, and \*\*\*, respectively. Each regression uses either dummy (based on median) or continuous variable for market capitalization and investor sentiment, and high growth predictor is a dummy variable.

		Reg1	Reg2	Reg3	Reg4	Reg5	Reg6
		rCAPM	rCAPM	rDCF	rDCF	rCAPm - rDCF	rCAPm - rDCF
Intercept		1.05829 (274.27)***	0.75001 (65.35)***	1.180373 (41.78)***	0.36191 (8.98)***	0.11457 (508.11)***	14.06155 (419.79)***
Market Cap.	Dummy		0.38470 (32.97)***		1.93572 (47.41)***		-5.04720 (-148.22)***
	Continuous	7.11E-10 (3.56)***		6.56E-09 (4.45)***		-7.13E-10 (-61.14)***	
High growth		-0.11171 (-18.17)***	-0.10376 (-8.49)***	0.505776 (11.25)***	0.57500 (13.44)***	0.03373 (93.87)***	2.81781 (79.00)***
Sentiment	Dummy		-0.029193 (-2.5)**		-0.79438 (-19.42)***		.20906 (6.14)***
	Continuous	-0.60163 (-145.06)***		-1.190795 (-39.15)***		0.01380 (56.94)***	
Number of Obs.		937,921	1,031,882	961,425	1,056,457	937,921	1,031,882
Adjusted R2		0.0225	0.0012	0.0017	0.0026	0.0169	0.0285

TABLE 6

**Multivariate regression analysis with interaction between  
High-growth and Investor Sentiment**

Ordinary least square multiple regression was used in this analysis. The coefficients and t-stats for each predictor are presented in the table. Each row and column combination has two numbers. The upper number is the coefficient, while the one in parentheses is the t-stat. Significance at 10%, 5%, and 1% levels are denoted by \*, \*\*, and \*\*\*, respectively. Firms that have market cap above median are coded as 1, while below that are coded as 0.

		Reg1  rCAPM - rDCF	Reg2  rCAPM - rDCF
Intercept		14.01161 (482.21)***	11.62415 (505.26)***
Market Cap.	Dummy	-4.86066 (-141.40)***	
	Continuous		-7.15e-08 (-61.32)***
High growth		2.49787 (65.84)***	2.90847 (76.22)***
Sentiment (Continuous)		.39445 (12.78)***	.68266 (21.99)***
Interaction (Growth x Sentiment)		1.93558 (39.33)***	1.78319 (35.93)***
Number of Obs.		937,921	937,921
Adjusted R2		0.0349	.0182