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Analysis of Contrarian Strategies on Risk Dimension

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Abstract

The concept of value strategies outperforming glamour strategies have been dominating in finance literature, but the reason is still contentious. In this thesis, we are replicating the LSV paper and in addition to that, we analyze the source of value premium in the dimension of risk. The risk characteristics we are using are Altman Z-score, Amihud illiquidity, Share turnover Liquidity and Accruals. We undertake one-way classification of stocks, forming decile portfolios of stocks on basis of the risk characteristics we construct. Followed by double sorts of the risk characteristics with the book to market ratio. We use Fama-MacBeth regression to investigate the importance of the variables in explaining returns. We find that all variables are important. Lastly, we use our model which is inspired by the Fama French three Factor model and Carhart model to investigate the abnormal return of value minus glamour strategy. The results suggest that, the risk factor from Amihud illiquidity (LIQ) and accruals (ACC) explain the value minus glamour strategy i.e. makes the abnormal return of this strategy to be zero and statistical insignificant. These results hold in different time periods, as well as when we adjust for small cap and penny stocks. From our findings, we can say that abnormal return from the value minus glamour strategy is explained by illiquidity risk and risk of stocks having low Accruals. We conclude that value strategies outperform glamour strategies because they are fundamentally riskier.

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CHAPTER 1: INTRODUCTION

Value investing is an investment strategy which selects stocks with lower price relative to some measures of their fundamental value. The concept of value strategies outperforming glamour strategies has been a dominant theme in the finance world as it continues to attract scholars and investment professionals. Graham and Dodd (1934) and Dreman (1977) argue that value strategies outperform the market. Some papers show that stocks with high earning to price ratios yield higher returns (See for instance Basu (1977), Chan, Hamao and Lakonishok (1991), Fama and French (1992), Jaffe, Keim and Westerfield (1989), Strong and Xu (1997), Levis and Liodakis (1999)).

While the value strategies continue to outperform the market, the reason is still controversial. One of the explanation why value stocks produce high returns is that the value strategies are contrarian to naive strategies followed by other investors. Naive investors extrapolate past earning growth too far into the future, overreact to good or bad news, or assume the trend in the stock prices continue, leading to an overvaluation or undervaluation of the stocks. Lakonishok, Shleifer, and Vishny (1994) examine the contrarian strategies, conclude that value strategies produce high returns and their findings have little or no evidence to support the view that the value strategies are fundamentally riskier.

On the other hand, Fama and French (1992) argue the reason why value stocks outperform the market is because they are fundamentally riskier. Stocks which have high book-to-market tend to have high returns because of the risk they bear. Under risk model, Fama and French argue that the measures of value stocks under the contrarian model such as book-to-market and earnings-to-price, are in fact proxies for sensitivity to certain risk factors associated with, for instance, financial distress.

There is also an argument that the time varying risk explains the value premium (Zhang, 2005). Further, Zhang explains that value betas tend to vary positively with excess returns while vary negatively with glamour betas, as a result, value minus glamour strategies riskiness is higher in bad times when expected excess return is high and low-risk in good time when expected excess return is low. Choi (2013) more recently argues that value strategies yield higher returns due to the risk of economic downturn. He continues by arguing that value stocks have high leverage, high asset beta and high equity beta on the downside of the economy, while glamour stocks have less sensitive asset beta, less leverage and stable equity beta. Since value firms are riskier during economic downturn, they yield high expected returns.

In our thesis, we first replicate the "Contrarian Investment, Extrapolation, and Risk" written by Lakonishok, Shleifer, and Vishy in 1994 (LSV). We form portfolios on four fundamentals namely book-to-market (B/M), cash flow-to-price (C/P), earnings-to-price (E/P), and past sales growth (GS). The tables we are replicating from the LSV are returns for portfolios based on one and two-dimensional classification by various measures of value, regression on characteristics and year by year returns of value minus Glamour.

We find that our replication results are very close to the original results. We briefly discuss our results here by choosing the B/M characteristic. For simple sort, we report the average returns for value is 18.6% while glamour is 10.9%. The LSV report 19.8% for value and 9.3% for glamour. The deviation is 1.2% for value and 1.6% for glamour. For the double sort of B/M with C/P, the deviation is 0.9% for value and 1.2% for glamour. In the regression of returns on characteristics, the magnitude of B/M characteristic in the replication is 0.031 (2.030) while in LSV report 0.039 (2.132) where the deviation is only 0.008. For Year by Year returns of Value minus Glamour table, we have the same signs and the magnitudes for each year. On average for 1-Year, 3-Year, and 5-year for B/M we deviate by 2.3%, 4.7%, and 4.9%. Based on these deviations, we conclude that our replication is very successful.

Secondly, we further investigate the risk dimension of the value stocks by including four risk characteristics as our contribution to the paper. To measure risk, we include Accruals, Altman Z-score (Z-score), Amihud illiquidity (Amihud ratio) and Share turnover liquidity (Turnover). The Z-score characteristic is measuring the credit default risk or likelihood of the firm to face bankruptcy. Amihud ratio and turnover measure the illiquidity and liquidity of the stocks respectively. Since investors tend to only focus on earnings and not cash generation, we take accruals into account (Sloan, 1996). We expect the riskiness of the above-mentioned characteristics to explain the high returns of the value stocks.

Our study is interesting because it seeks to answer the question of why value stocks earn higher returns than glamour stocks. We think that there must be a risk that leads to this effect. Otherwise, there would be a free lunch in the market and people would simply buy value stocks and sell glamour stocks to earn the premium. Yet, that is not what we see in reality. Hence, we are investigating the riskiness of value stocks using different approaches.

Following the methodology developed by LSV, undertake one and two-way classification of stocks, forming decile portfolios of stocks on basis of the variables, and regression of returns on the risk-characteristics. In one-way classification of stocks, we find that Accruals, Amihud ratio, and Turnover explain the cross-sectional returns in the way that we expect, that is the higher the risk the higher the return. On the other hand, Z-score gives an opposite outcome. It shows that when the firm faces high default risk, it yields lower return.

Next, we double sort each risk characteristic variable with the B/M to distinguish between the value and glamour stocks. The aim of doing this is to see whether value stocks continue to outperform glamour stocks regardless of risk characteristic introduced or not. We find that value stocks outperform glamour stocks, however no evidence that this is caused by risk.

We further investigate our risk characteristics to see their importance in explaining the returns. Thus, we regress the returns of stocks on the risk characteristics. First, we regress the stocks returns on each risk characteristic and B/M. We find that all characteristics were significant. Secondly, we perform a regression of returns on all characteristics and B/M. The result we get from this regression is that B/M, Accruals and Amihud ratio are significant in explaining the returns.

To check what drives the abnormal return from the value strategy, we investigate the abnormal return using the model we construct which is inspired by the Fama-French three factor model and Carhart model. The reason for having our model is that we cannot control for HML, considering that the strategy that we are investigating is buying undervalued stocks and selling overvalued stocks based on B/M. The model is describing the value minus glamour returns by controlling for different risk factors. The risk factors that we are controlling for are market risk premium (MRP), small minus big (SMB), and up minus down (UMD) from the Fama-French three Factor model and Carhart model. In addition, we include our own risk factors that we construct based on the risk characteristics.

First, we regress the value minus glamour returns on each risk factor that we construct together with MRP, SMB, and UMD. For the risk factors ZCO and LIQT, the abnormal return is positive and statistically significant. On the other hand, for the LIQ and ACC risk factors, the abnormal return of the value minus glamour strategy becomes statistically insignificant and the value is close to zero. The reason for abnormal return to disappear after adding LIQ risk factor can be that by selling "expensive" stocks and buying "cheap" using B/M characteristic, it is simply selling liquidity while taking on illiquidity. On the other hand, Accruals is another measure of value. Hence, this can be the reason for the value minus glamour strategy to be explained by it.

The main contribution of our paper is that, we investigate the reason of the higher yields of the value stocks using different dimensions of risk. In the one sort of variables, we find that higher risk leads to higher returns for Amihud ratio, Accruals, and share turnover risk characteristics while Z-score gives opposite evidence. However, by double sorting B/M and the risk characteristics, we do not find any evidence that value stocks are riskier than glamour stocks. By further investigating the value minus glamour strategy, using our model reveals that this strategy is explained by the LIQ and ACC factors. We conclude that the value stocks are fundamentally riskier than glamour stocks.

The remainder of the paper is structured as follows: Chapter 2 contains a literature review of the topics that are discussed in this paper. In Chapter 3, we describe the data and methodology we use in our paper. Chapter 4 contains the empirical analysis which is the main part of our paper, this chapter includes both replication and our contribution results. In addition, this chapter consists of robustness test and checking the validity of our risk factors. Chapter 5 and 6 marks the discussion and conclusion of our paper respectively.

CHAPTER 2: LITERATURE REVIEW

In the following chapter, we introduce papers that are closely related to our main contribution to our thesis. In the first part, we briefly refer to the foundation of value investing. In the second part, we present different papers arguing whether the value premium is driven by risk or mispricing. Finally, we describe how our thesis contributes to the literature.

2.1 Historical background

Previously, Graham and Dodd has introduced an intellectual foundation of value investing in 1934 (Security Analysis) which is generally investing in stocks that trade for less than their intrinsic values. Value investors actively seek stocks they believe the market has undervalued. Investors who use this strategy believe that the market overreacts to good and bad news, resulting in stock price movements that do not correspond with a company's long-term fundamentals giving an opportunity to profit when the price is deflated. These stocks are underpriced or undervalued relative to earnings, dividends, book assets or other fundamental measures of value. In the next section, we provide literature that argues why value investing yields high returns.

2.2 Risk or Mispricing

In this section, we introduce different literature that provide arguments for the outperformance of value stocks to glamour stocks. As later shown, our results conclude that the value stocks outperform glamour stocks because they are fundamentally riskier. In the next two sections, we decompose this dilemma into mispricing and risk, by first looking at the mispricing and then risk arguments of the value strategy.

2.2.1 Mispricing

Lakonishok, Shleifer, and Vishny (1994) examine the contrarian model whereby naive investors extrapolate past earning growth too far into the future. The contrarian model argues that the overpriced (Glamour stocks) are those which have performed well in the past and are expected by the market to perform well in the future, whereas the underpriced stocks (Value stocks) are those which have performed bad in the past and are expected to perform poorly in the future. The contrarian investors bet against naive investors by investing in stocks that are undervalued and under-invest in stocks that are overvalued. LSV find their results to be consistent with the contrarian model.

LSV further investigate whether value strategies are fundamentally riskier by examining traditional measures of risk such as beta and standard deviation of returns to compare value and glamour strategies. The results suggest that the difference in the standard deviation is quite small compared to the returns and the reward-to-risk for investing in the value stocks. Hence, using standard deviation as a risk measure cannot explain the superior returns on value stocks. The same argument is used for beta as a measure of risk. The beta of value is 0.1 higher than glamour, and that cannot be used to explain 10 to 11 percent difference in value minus glamour returns. LSV state that the evidence they find is very little to support the risk-based explanation of value strategies.

In addition to what LSV concludes, Jingzi Chen and Yongchoel Chin (2016) most recently examine whether the fundamental or the sentiment-based theories can provide appropriate explanation on the value premium anomaly. To answer this question, they predict two models. First model under fundamental-based view where arbitrageurs in value stocks tend to generate lower initial mispricing correction and noise momentum. Second model, under sentiment-based view where arbitrageurs in value stocks are more likely to generate lower mispricing correction but higher noise momentum. They conclude that the larger determinant of the value premium anomaly is sentimental based view (mispricing is due to investors sentiments). However, they do not disagree that both models can jointly explain the value premium.

2.2.2 Risk

On contrary to the mispricing arguments, Fama and French (1992) argue that the reason that value stocks outperform the market is because they are fundamentally riskier. The stocks which have high book-to-market tend to have high returns because of the risk they bear. Under risk model, Fama and French argue that the measures of value stocks under the contrarian model such as book-to-market and earnings-to-price, are in fact proxies for sensitivity to certain risk factors associated with, for instance, financial distress.

In addition, Fama and French (1993 and 1996) show that excess returns to value strategies can be explained by the three-factor model comprising market factor and mimicking portfolios for the book-to-market and size factors. After controlling for the loading that each portfolio has on these three factors, they show that there is no systematic difference between the returns to value and glamour portfolios, using a range of variables to define value. Fama and French interpret this as evidence in favor of the risk-based explanation and argue that the mimicking portfolios for book-to-market and size reflect systematic risk, rather than irrational mispricing.

Apart from Fama and French arguments above, Lu Zhang (2005) shades new light on the value strategies by studying the time varying risk patterns of value and glamour strategies. They find two significant outcomes. First, time-varying risk goes in the right direction in explaining the value premium. Value betas tend to covary positively, and glamour betas tend to covary negatively with the expected market risk premium. As a result, value-minus-glamour betas tend to covary positively with the expected market risk premium. This result holds for most sample periods and for various value and glamour strategies. Second, although time-varying risk goes in the right direction, the estimated covariation between the value-minus-glamour betas and the expected market risk premium is too small to explain the observed magnitude of the value premium in the context of the conditional capital asset pricing model (CAPM). Specifically, the estimated alphas of value-minus-glamour strategies from conditional market regressions are mostly positive and significant.

Choi (2013) follows the investigation to show what drives the value premium. He finds that during economic downturns the asset risk and leverage of the value firms increase, leading to a sharp rise in equity betas. In contrast, glamour firms' equity betas remain stable over time due to low leverage and asset betas that are less sensitive to economic conditions. Thus, value stocks become particularly risky during downturns when the risk premium is high.

In contrast to what Choi (2013) conclude, Mohammed and G. Macmillan (2014) investigate on value premium associated with the default risk. They use leverage and default risk as proxies for financial distress when applying time volatility methodology. This article reports a positive relationship between default risk and the value premium for both large and small firms together with a leverage effect. The results also show that the default premium volatility has some predictive power for the volatility of value premium. These results provide new evidence that the value premium is working as a proxy for a macroeconomic risk factor associated with financial distress. This leads to support the risk-based explanation for the source of the value premium.

In our thesis, we use different risk measures to explain the source of the value premium. We find that the risk factors associated with Amihud ratio (LIQ) and accruals (ACC) explain the value premium. According to this finding, we conclude that the source of value premium is risk and not mispricing. This finding is consistent with the literature that supports the idea of the risk-based explanation for value premium

The contribution of our finding to the literature is that contrarian strategy is risky. The strategy faces risk of buying illiquid stock and stocks which have low accruals. Since an investor faces inconvenience to hold these stocks, the market compensates him with high return.

Our results are inconsistent with Mohammed and G. Macmillan (2014), they provide results that value premium is working as a proxy for a macroeconomic risk factor associated with financial distress. In our study, we use ZCO as a risk factor associated with default risk (Z-score). We find no evidence that ZCO is explaining the value premium. However, we use different measures of financial distress from them, and this can lead to different findings.

CHAPTER 3: DATA AND METHODOLOGY

In this chapter, we have three sections. Firstly, we illustrate the data we obtain and the period we covered in our thesis. Secondly, we describe the methodology to implement different strategies. Finally, we explain how we construct the variables to implement the strategies outlined in our methodology.

3.1 Data

Our thesis covers two sample periods where the first one begins at the end of April 1963 to the end of April in 1990 and the second one starts at the end of April 1993 to the end of April 2015 which we only report on robustness test. We do not include the first five years in the formation period, but we use the past accounting data to create portfolios. Hence, we start our formation period in April 1968.

The reason we choose the first sample period is that we are replicating LSV and the only way to know whether the approach we use in replicating is correct or not is by being consistent with them. [1]In our contribution we use both periods. To be able to compare LSV with our contribution we report tables using first period (end of April 1968 to 1990) and report the second period (end of April 1993 to 2015) only in robustness test.

We use the Wharton Research Data Services (WRDS) to get all the data we need. We obtain accounting data and returns data from COMPUSTAT and The Center of Research in Security Prices (CRSP) respectively. We obtain data on MRP, HML, SMB, and UMD from the Fama-French factors (FF3) file. We also obtain data on Pastor-Stambaugh liquidity factor from WRDS. Lastly, we use a link file to merge COMPUSTAT and CRSP.

We exclude all shares that are not classified as common shares (Share code 10 or 11). Additionally, we exclude firms that have a Standard Industrial Classification code from 6000 to 6999 (Financial, insurance or real estate firms). These firms have higher leverage than other firms. However, the leverage does not have the same interpretation as for non-financial firms. For non-financial firms, high leverage is more likely an indicator of financial distress.

We use New York Stock Exchange (NYSE) and American Stock Exchange (AMEX) (Exchange code 1 and 2). The rationale to exclude NASDAQ is that we are equally weighting

[1] We have used all the time periods for all the tables. We see the same trend, however for consistency we report only LSV period. We report the second period only in robustness test.

our portfolios. Hence, having many small stocks, can make our results biased. The NASDAQ expansion in 1978 led to an increase in many small stocks where the look ahead bias is most severe. To overcome this bias and be consistent with the LSV approach, we do not include NASDAQ in our analysis. Our CRSP file has 665,586 monthly observations after the above adjustments (I,538,032 before adjustments).

3.2 Methodology

We follow the methodology of LSV to implement the strategies. To be precise, we create portfolios according to the variables in the sample period covered from the end of April 1968 to end of April 1990. We compute the returns corresponding to the size decile and substitute this to the stock that is delisted during the year. The stocks are rebalanced, and each surviving stock gets the same weight at the end of each year. Within each of our portfolios we equally weigh all the stocks and compute the returns using annual buy hold strategy for Years +1, +2, ...,+5 relative to the formation period. Furthermore, we report average returns and compounded returns over five post-formation years.

In addition to that, we also present annual size-adjusted return (SAAR). To adjust a portfolio for size, we first identify the market capitalization (MCAP) decile of every stock in the sample at the end of the previous year. Then we create SIZE portfolios based on that. Thereafter the returns are equally weighted across all stocks in its size portfolio for that year. For each stock in the original portfolio, the return is replaced by the annual buy and hold return on equally weighted portfolio of all stocks in its size decile for that year. Finally, the annual size-adjustment is the original portfolio return minus the size portfolio return.

We continue this section with three subsections. The first subsection explains the reasons for rebalancing annually. The second subsection elaborates on the rationale for choosing equally-weighted over value-weighted portfolios. The third subsection describes how we deal with delisted stocks.

3.2.1 Rebalancing

We rebalance our portfolios yearly to maintain consistency in our methodology. Some variables such as book value of equity are from COMPUSTAT which provides annual data and other variables such as Amihud ratio are from CRSP which provides monthly data. For measures that have monthly data, we calculate simple mean to obtain yearly measures.

Another reason for this is that yearly rebalancing reduces transaction costs. Costs of rebalancing can include taxes (For example tax on asset sold if it has appreciated value), transaction cost to execute and process the trade (Brokerage commission, bid ask-spread for the individuals or purchase and redemption fees for mutual fund etc.).

The third reason for our use of yearly rebalancing is that it is easy to implement and LSV use the same methodology.

3.2.2 Equally weighted & value-weighted portfolios

In our expansion, we continue to use LSV methodology by equally weighting our portfolios. Equal weighting gives each stock the same weight while the value-weighting gives greater weight to the stocks with large MCAP.

The argument for value-weighting is that bigger stocks (In terms of MCAP) are more liquid and hence have smaller bid-ask spread. If a stock is very small (In terms of MCAP), most likely has a higher bid-ask spread. The argument against value-weighting is that it puts more focus on the biggest stocks. Hence, to remove the strong bias towards larger stocks we prefer equally weighted over value-weighted portfolios. However, we report value-weighted portfolios in the robustness test.

3.2.3 Dealing with delisted stocks

From Table 1, a stock gets delisted in August, which means it does not have return from September until April (End of our fiscal year). For these missing observations we replace it with the corresponding size portfolio return.

Table 1 Adjusted Returns for Delisted Stock

Stock ID	Date	Return	Size Portfolio	Size Portfolio Return	Adjusted Return
xx	May	3 %	1	2 %	3 %
xx	June	4 %	1	10 %	4 %
xx	July	-10 %	1	5 %	-10 %
xx	**Delisted in August**	-5 %	1	-1 %	-5 %
xx	September	.	1	1 %	1 %
xx	October	.	1	3 %	3 %
xx	November	. →	1 →	7 % →	7 %
xx	December	.	1	-8 %	-8 %
xx	January	.	1	2 %	2 %
xx	February	.	1	9 %	9 %
xx	March	.	1	-4 %	-4 %
xx	April	.	1	1.5%	1.5%

LSV use the above described approach in dealing with stocks that disappear during the year. We believe that LSV assumes that when the firm gets delisted during the year, the investor does not lose money. Instead, the investor gets the return from a similar size firm for that year.

Although LSV do not provide reasons for this, we believe that for some portfolios in some years, especially for the double-sorted portfolio have very few observations. Hence this is a crude way of replacing missing returns in a year so that our result would not suffer from bias of having lower observations at the end of the year.

The second reason can be that, at the end of each year the portfolios are rebalanced, and each surviving stock gets the same weight. Here we mean that we rebalance our portfolios yearly. So, if in the middle of the year the stock is delisted, meaning that it disappears during the year, then we will have the weight of that stock, but the stock is not there. Hence the yearly rebalancing will have a lot of additional weights with fewer stocks and this will lead to errors.

3.3 Variables

This section consists of two subsections. In the first subsection, we briefly describe how to construct the variables to replicate the LSV strategies. The second subsection elaborates on how we construct the variables for our contribution. For both subsections, we create the variables using the period from the end of April 1968 to end of April 1990. We form and rebalance the portfolios at the end of April each year.

3.3.1 Replication

We use four variables to replicate LSV strategies, namely book-to-market (B/M), earnings-to-price(E/P), cash flow-to-price (C/P), and growth sales (GS).
For B/M, the book value of equity is taken from COMPUSTAT for the end of the previous fiscal year and the market value is taken from CRSP as the market value at the portfolio formation time. Market value is calculated as shares outstanding multiplied by price. Earnings are measured before extraordinary items and cash flow is defined as earnings plus depreciation.

The growth sales (GS) is more complicated to compute. First, for each company for each yea -1, -2,…,-5 prior to formation, we calculate the GS in that year. Then for each year we rank all firms by GS for that year. Thereafter we compute each firm's weighted average rank giving the weight of 5 to its growth rank in year -1, weight of 4 to its growth rank year -2 etc. LSV argue that this procedure is a crude way to pick stocks with consistently high past GS and to give greater weight to the more recent sales growth.

3.3.2 Contribution

In our contribution, we are investigating the riskiness of the value stocks using different risk characteristics. The risk characteristics that we include are accruals, Amihud ratio, turnover, and Z-score. The reason behind why value stocks have higher return than glamour stocks is controversial. We do not completely disagree with the behavioral effect that makes the value stocks yield higher returns than glamour stock. However, we believe that the biggest portion of this abnormal return comes from risk.

In the Dissecting Anomalies written by Fama and French in 2008, they argue that the accrual anomaly is a rough proxy for expected cash flow (Fama, French, 2018). Firms with more accruals tend to have lower net cash flow since they have higher investment relative to earnings (Fairfield, Whisenant, Yohn, 2003).

Further on, the “accrual anomaly” and the pricing of glamour stocks may be related since firms with high sales growth in the past, glamour stocks are more likely to have larger positive accruals than firms with low sales growth in the past, “value stocks” (Desai, Rajgopal and Vehkatachalam, 2004).

Remember that we are replicating LSV, and in the first Fama-MacBeth regression we run, the two variables that stand out are C/P and GS. Since accruals are related to past sales growth and cash flow to price, we find it a natural extension from their paper to include accruals.

We define accruals the following way (Sloan, 1996):

$$ACC= ((\Delta CA- \Delta Cash) - (\Delta CL- \Delta STD- \Delta TP)-Dep)/TA$$

Where

ΔCA = change in current assets,

$\Delta Cash$ = change in cash/cash equivalents,

ΔCL = change in current liabilities,

ΔSTD = change in debt included in current liabilities,

ΔTP = change in income taxes payable,

Dep = depreciation and amortization expense,

TA = Average of the beginning and end of year book value of total assets
All accounting variables are taken from COMPUSTAT.

We know that one of the reasons for the existence of the liquidity premium is a rational underpinning. Those who buy cheap stocks and sell expensive ones, need to earn a higher return because they must be compensated for bearing some sort of inconvenience. We think that the stocks that are liquid are very attractive and they bear less inconvenience. Hence the market provides low returns to these stocks which lead to higher prices. On the other hand, the illiquid stocks are not very attractive as they bear inconvenience. Therefore, the market compensates the investors for holding these stocks with higher returns which lead to low prices. By selling "expensive" stocks and buying "cheap" ones, is like selling liquidity while taking on illiquidity. The riskiness of value stocks may come from the fact that value stocks are illiquid, making them risky and hence leading to higher returns. To measure the liquidity of stocks we use two different measures.

The first measure of liquidity is the Amihud ratio. The daily ratio of absolute stock return to its dollar volume averaged over period. It can be interpreted as the daily price response associated with one dollar of trading volume, thus serving as a proxy measure of price impact. For this study, we replace the dollar volume with the number of shares traded (Vol) to mitigate the size effect similar to Niall O' Sullivan (2015). The higher level of the Amihud ratio measure is associated with lower level of liquidity.

$$Amihud = \frac{1}{Nr.Days} \sum_{t=1}^{Nr.Days} \frac{|r_t|}{v_t}$$

The second measure of the liquidity is turnover which is used in several studies such as Niall O' Sullivan (2015). Turnover is a measure of stock liquidity calculated by dividing the total number of shares traded over a period by the average number of shares outstanding for the period. The higher level of turnover is associated with higher level of liquidity.

$$Turnover = \frac{1}{Nr.Days} \sum_{t=1}^{Nr.Days} \frac{Volume_t}{Shares\ outstanding_t}$$

We compute both ratios using daily data from CRSP. We excluding Share code 10 or 11 and Standard Industrial Classification code from 6000 to 6999 (Financial, insurance or real estate firms). We remove firms that have price of less than 5 dollars and more than 1000 dollars. We compute the daily liquidity ratios and remove any stock that have less than 15 observations. Both surviving and non-surviving stocks are included to control for survivorship bias.

Next, we compute the simple mean of the daily ratios to obtain the monthly ratios, followed by computing the simple mean of monthly ratio to obtain yearly ratios. These yearly ratios are taken forward to the next year as we are trying to predict the returns next year. We calculate the yearly ratio for these two variables to be consistent with other variables that we construct from COMPUSTAT such as B/M. Since we are rebalancing our portfolio at the end of April each year, it would be inconsistent with our approach to rebalance monthly.

We could use the bid-ask spread (quoted or effective), but this requires a lot of market microstructure data that are not available in many stock markets. Even when available, the data does not cover very long periods of time. We believe that the liquidity measures we choose are equally accurate.

Another aspect of risk that we want to focus on is credit risk. We use different types of risk measure such as leverage ratio, market value leverage and book value leverage. [2]The variables show a nonlinear relationship with the cross-sectional returns. The credit rating can be used to determine the credit risk, but we have no access to credit ratings from WRDS and hence we cannot test the credit risk using credit ratings.

We continue by thinking of default risk as it is usually defined as the possibility that a company will not be able to meet its financial obligations in the future. Given the customary assumption that equity-holders receive nothing upon default, economic intuition would suggest that the equity of a company with a higher level of default risk should demand a higher expected return. We use Z-score to measure the risk of default. The Z-score is a combination of five weighted financial ratios used to estimate the likelihood of financial distress. We expect that the reason that the value stocks have higher return is that they have high bankruptcy risk.

The formula of the Z-score is as follows:

[2] We create one sort tables for these variables. However, due to its flat relationship with cross sectional returns we decide not to report the tables.

$$Z\text{-Score} = 1.2A + 1.4B + 3.3C + 0.6D + 1.0E$$

Where:

A = Working capital / Total assets

B = Retained earnings / Total assets

C = Earnings before interest and tax / total assets

D = Market value of equity / Total liabilities

E = Sales / Total assets

All accounting variables are taken from COMPUSTAT.

Furthermore, we divide the stocks into three groups i.e. risky, middle, and safe. The stocks that have a Z-score of less than 1.81 are defined as risky, a Z-score between 1.81 to 2.99 are defined in the middle (Grey area), and stocks that have a Z-score above 2.99 are considered safe.

The Ohlson O-score is an equivalent measure to the Z-score, which is said to be more accurate as it was derived from a pool of 2,000 companies while for the Z-score was derived using 66 companies. Due to the difficulty of the O-score formulation and unavailability of some factors to construct it, we decided to use Z-score as a proxy for bankruptcy risk.

In the table 2 below, we provide the summary statistics of the variables we use in our replication and contribution in Panel A and Panel B respectively. Since LSV do not report the summary statistics of their variables, we cannot compare our results with the original results.

Table 2 Summary Statistics of The Variables

The table shows the summary statistics of the variable in the replication (LSV 1994) and our estimates of the variables we use in the contribution. Reported in Panel A and Panel B are the number of firms, observations, mean of the whole time-series, standard deviation, minimum- and maximum values.

Summary statistics						
Panel A: Replication Variables						
Variable	Firms	Obs.	Mean	Std. Dev.	Max	Min
B/M	3314	39850	0.993	0.810	23.109	0.003
C/P	3389	40747	0.148	0.515	19.643	-74.589
E/P	3389	40747	0.047	0.584	3.038	-90.463
GS	2541	31132	870.995	316.015	1978.267	8.600

Table 2: continues

Panel B: Contribution Variables						
Variable	Firms	Obs.	Mean	Std. Dev.	Max	Min
Accruals	3178	38406	-0.019	0.092	1.425	-1.278
Amihud	3105	31097	8.652E-06	1.24E-05	0.000261	6E-09
Turnover	3105	31097	1.910	2.420	253.690	0.015
Z-score	3291	40071	4.427	20.235	3210.011	-86.864

CHAPTER 4: EMPIRICAL ANALYSIS

This chapter is structured into seven sections. The first three sections consist of one-way sorted portfolios, double-sorted portfolios and regressions of returns on characteristics for all stocks, where we present both replication and our contribution results. The fourth section contains our replication results of the year by year performance of the value strategy relative to glamour strategy. In the fifth section we present regressions results using our model which is inspired by Fama-French 3 Factor model and Carhart model. The last two sections contain robustness test and validity of our risk factors.

4.1 One-way sorted portfolios

In this section, we present one-way sorted portfolios. We group the stocks in 10 deciles using the characteristics. The first subsection shows the replication results whereas the final subsection shows our contribution.

4.1.1 Replication

In Table 3, we present the returns of the one-way sorted portfolios on four firms characteristics. Panel A, B, C and D shows the results of B/M, C/P, E/P, and GS respectively. For every panel we present returns from year 1 through 5 after the formation, the average annual 5-year return (AR), the cumulative return and at last the size-adjusted average annual 5-year return (SAAR).

In panel A of Table 3, we present the results of sorting stocks on the B/M ratio. The average annual return (AR) difference between value and glamour portfolios are 7.7% and has a cumulative return difference of 67.1%. To check whether these results are driven by size, we adjust the portfolios for size. After this adjustment, the average annual return decreases to 5% difference, but it still quite large.

For panel B and C in Table 3, we use C/P and E/P as a proxy for future expected growth. By using Gordon formula LSV argue that dividends are proportional to cash flow and earnings with different payout ratios. Holding discount rate and payout constant, the firm with high C/P has low expected growth while the firm with low C/P has a high expected growth. This applies to the E/P as well.

In panel B of Table 3, we present the results of sorting stocks on the C/P ratio. High C/P firms are defined as value firms because their expected growth rate of cash flow is expected to be low and the opposite for glamour firms. The difference in average annual returns (AR) between value and glamour firms are 11.7%. The cumulative return difference is about 100% and the size-adjusted average return SAAR is 10.3%.

Table 3 Returns for Decile Portfolios Based on One Dimensional Classification by Various Measures of Value

At the end of each April between 1968 and 1989, 10 decile portfolios are formed in ascending order based on B/M, C/P, E/P and GS. B/M is the ratio of book value of equity to market value of equity; C/P is the ratio of cash flow to the market value of equity; E/P is the ratio of earnings to market value of equity and GS refers to preformation 5-year average growth rate of sales. The returns presented in the table are averages over formation periods. R_t is the average return in year t after formation, t=1,2…,5, AR is the average annual return over 5 post-formation years. CR_5 is the compounded 5-year return assuming annual rebalancing. SAAR is the average annual size adjusted return computed over 5 post-formation years. The glamour portfolio refers to the decile containing stocks ranking lowest on B/M, C/P, or E/P or highest on GS. The value portfolio refers to the decile portfolio containing stocks ranking highest on B/M, C/P, or E/P or lowest on GS.

	Glamour 1	2	3	4	5	6	7	8	9	Value 10
					Panel A: B/M					
R1	0.103	0.117	0.128	0.130	0.130	0.144	0.158	0.172	0.182	0.180
R2	0.100	0.114	0.128	0.128	0.129	0.140	0.154	0.169	0.179	0.173
R3	0.122	0.137	0.151	0.152	0.151	0.162	0.176	0.193	0.202	0.197
R4	0.113	0.130	0.141	0.145	0.144	0.154	0.168	0.182	0.195	0.187
R5	0.105	0.131	0.146	0.152	0.150	0.159	0.175	0.189	0.203	0.193
AR	0.109	0.126	0.139	0.141	0.141	0.152	0.166	0.181	0.192	0.186
CR5	0.675	0.808	0.915	0.937	0.932	1.027	1.158	1.295	1.410	1.346
SAAR	-0.031	-0.018	-0.008	-0.008	-0.008	0.001	0.011	0.021	0.026	0.019

	Glamour 1	2	3	4	5	6	7	8	9	Value 10
					Panel B: C/P					
R1	0.082	0.124	0.140	0.145	0.155	0.144	0.164	0.171	0.183	0.199
R2	0.075	0.122	0.136	0.144	0.152	0.144	0.160	0.170	0.181	0.195
R3	0.099	0.145	0.161	0.167	0.175	0.168	0.183	0.193	0.202	0.219
R4	0.093	0.138	0.152	0.158	0.168	0.160	0.176	0.184	0.195	0.205
R5	0.094	0.138	0.156	0.160	0.172	0.167	0.182	0.191	0.205	0.213
AR	0.089	0.134	0.149	0.155	0.164	0.157	0.173	0.182	0.193	0.206
CR5	0.528	0.872	1.001	1.054	1.140	1.069	1.220	1.307	1.418	1.554
SAAR	-0.061	-0.012	-0.002	0.002	0.010	0.004	0.019	0.027	0.031	0.042

Table 3: continues

	Glamour 1	2	3	4	5	6	7	8	9	Value 10
					Panel C: E/P					
R1	0.107	0.124	0.144	0.129	0.135	0.146	0.165	0.170	0.193	0.175
R2	0.106	0.124	0.147	0.129	0.137	0.148	0.168	0.173	0.196	0.181
R3	0.116	0.133	0.156	0.137	0.144	0.155	0.176	0.181	0.206	0.190
R4	0.122	0.139	0.163	0.141	0.148	0.160	0.180	0.186	0.211	0.196
R5	0.127	0.142	0.167	0.145	0.152	0.163	0.184	0.191	0.216	0.203
AR	0.115	0.132	0.155	0.136	0.143	0.154	0.175	0.180	0.204	0.189
CR	0.726	0.861	1.057	0.894	0.954	1.050	1.236	1.289	1.533	1.375
SAAR	-0.039	-0.025	-0.012	-0.033	-0.025	-0.016	0.005	0.008	0.033	0.037

	Value 1	2	3	4	5	6	7	8	9	Glamour 10
					Panel D: GS					
R1	0.176	0.175	0.160	0.153	0.153	0.152	0.151	0.149	0.120	0.107
R2	0.181	0.181	0.163	0.158	0.156	0.156	0.154	0.157	0.123	0.111
R3	0.189	0.189	0.169	0.165	0.162	0.163	0.160	0.165	0.130	0.118
R4	0.194	0.195	0.174	0.169	0.166	0.167	0.164	0.168	0.134	0.123
R5	0.198	0.201	0.178	0.173	0.169	0.171	0.167	0.171	0.138	0.126
AR	0.188	0.188	0.169	0.163	0.161	0.162	0.159	0.162	0.129	0.117
CR	1.363	1.366	1.179	1.131	1.111	1.117	1.092	1.119	0.835	0.739
SAAR	0.025	0.026	0.023	0.019	0.001	0.005	0.007	0.006	-0.004	-0.033

Panel C of Table 3 presents the results of sorting stocks on the E/P ratio. The classification scheme of which stocks are value and glamour are the same as it is for C/P. On average, the annual return difference (AR) is 7.4% between value and glamour portfolio. The cumulative return difference is 64.9%. The size-adjusted average return (SAAR) is 7.6%.

Panel D of Table 3 presents the results of sorting stocks on GS. Value stocks are defined as stocks which have low previous growth in sales whereas glamour stocks are defined as stocks which have high previous growth in sales. The average return (AR) difference is 7.1% between value and glamour firms. The cumulative return difference is 62.4%. The size-adjusted average return (SAAR) is 5.8%.

In this paragraph we compare our results with the original LSV paper. For panel A, the replication results of the average returns for value is 18.6% while glamour is 10.9%. The LSV (AR) results are 19.8% and 9.3% for value and glamour respectively. The deviation is 1.2% for value and 1.6% for glamour. For panel B, the replication results of the average returns for value is 20.6% while glamour is 8.9%. The LSV (AR) results are 20.1% and 9.1% for value and glamour respectively. The deviation is 0.5% for value and 0.4% for glamour. For panel C, the replication results of the average returns for value is 18.9% while glamour is 11.5%. The LSV report (AR) of 19% and 11.4% for value and glamour respectively. The deviation is

0.1% both stocks. For panel D, the replication results of the average returns for value is 18.8% while glamour is 11.7%. The LSV report (AR) of 19.5% and 12.7% for value and glamour respectively. The deviation is 1% for value and 0.7% for glamour.

Our replication results are consistent and very close to LSV original results. We find that simple value strategies based on one variable produces very high return over our sample period. In the next part, we show results from our contribution and discuss them.

4.1.2 Contribution

In this subsection, we create one-way sorted portfolios into 10 deciles for the risk characteristics we describe in the methodology. The purpose of doing this is to check whether the risk characteristics explain cross sectional returns or not. The stocks that have high risk should yield higher returns. For example, if the stocks are illiquid we expect them to yield higher returns as they are riskier than the liquid stocks.

In Table 4, we present the returns for deciles based on one-dimension classification by various risk characteristics (Accruals, Amihud ratio, Turnover and Z-score). Panel A, B, C and D shows the results of Accruals, Amihud ratio, Turnover, and Z-score respectively. For every panel we present returns from year 1 through 5 after the formation, the average annual 5-year return (AR), the cumulative return and at last the size-adjusted average annual 5-year return (SAAR).

For Panel A in Table 4, we create deciles based on Accruals. Panel A shows that the stocks that have low accruals yield higher returns than high accruals firms. We see that the average return (AR) difference between low accruals firms and high accruals firms are 11.1 % and the cumulative return difference is 85.2%. The size-adjusted average return (SAAR) is 8.5%.

For Panel B in Table 4, we create deciles based on the Amihud ratio. As we explained earlier that the higher the Amihud ratio the lower the liquidity.
Panel B shows that the stocks that are liquid have low returns and the stocks that are illiquid have high returns. Its shows a very clear pattern of the returns increasing with the illiquidity. The difference in the average returns (AR) between liquid and illiquid stocks is about 11.6%. The cumulative return difference is 107.8% and for size-adjusted average return (SAAR) the difference is 8.5%.

Table 4 Returns for Decile Portfolios Based on One Dimensional Classification by Various Measures of Risk

At the end of each April between 1968 and 1989, 10 decile portfolios are formed in ascending order based on Accruals, Amihud ratio and Turnover. For the Z-score only 3 deciles are formed. The returns presented in the table are averages over formation periods. R_t is the average return in year t after formation, t=1,2…,5, AR is the average annual return over 5 post-formation years. CR_5 is the compounded 5-year return assuming annual rebalancing. SAAR is the average annual size adjusted return computed over 5 post-formation years. The risky portfolio refers to the deciles containing stocks ranking lowest on Z-score, Turnover, or accruals or highest on Amihud ratio. The less risky portfolio refers to the deciles containing stocks ranking highest on Z-score, Turnover, or accruals or lowest on Amihud ratio.

	1	2	3	4	5	6	7	8	9	10
Panel A: Accruals										
R1	0.163	0.144	0.137	0.118	0.157	0.106	0.133	0.079	0.076	0.052
R2	0.165	0.149	0.140	0.123	0.158	0.113	0.141	0.081	0.078	0.055
R3	0.172	0.158	0.148	0.131	0.165	0.122	0.151	0.088	0.086	0.063
R4	0.176	0.162	0.153	0.136	0.169	0.127	0.157	0.092	0.091	0.068
R5	0.180	0.167	0.158	0.138	0.173	0.132	0.160	0.095	0.096	0.072
AR	0.171	0.156	0.147	0.129	0.164	0.120	0.148	0.087	0.085	0.062
CR	1.202	1.066	0.989	0.836	1.141	0.763	0.995	0.519	0.506	0.350
SAAR	0.007	-0.011	-0.019	-0.037	0.003	-0.039	-0.009	-0.065	-0.060	-0.078

	1	2	3	4	5	6	7	8	9	10
Panel B: Amihud										
R1	0.098	0.120	0.119	0.142	0.139	0.144	0.159	0.154	0.185	0.218
R2	0.098	0.121	0.119	0.139	0.142	0.147	0.158	0.151	0.182	0.210
R3	0.119	0.140	0.141	0.160	0.164	0.171	0.183	0.174	0.207	0.232
R4	0.109	0.131	0.132	0.153	0.157	0.162	0.176	0.165	0.198	0.225
R5	0.113	0.134	0.137	0.155	0.164	0.170	0.180	0.172	0.201	0.229
AR	0.107	0.129	0.130	0.150	0.153	0.159	0.171	0.163	0.194	0.223
CR5	0.665	0.836	0.841	1.009	1.040	1.089	1.202	1.128	1.430	1.733
SAAR	-0.005	0.004	-0.003	0.011	0.008	0.012	0.024	0.015	0.040	0.080

	1	2	3	4	5	6	7	8	9	10
Panel C: Turnover										
R1	0.187	0.171	0.171	0.174	0.183	0.176	0.159	0.171	0.143	0.115
R2	0.188	0.173	0.170	0.172	0.181	0.169	0.156	0.166	0.138	0.114
R3	0.204	0.189	0.186	0.189	0.201	0.191	0.179	0.191	0.165	0.141
R4	0.198	0.182	0.183	0.182	0.194	0.184	0.170	0.180	0.155	0.132
R5	0.203	0.187	0.188	0.188	0.197	0.186	0.173	0.183	0.160	0.137
AR	0.196	0.181	0.180	0.181	0.191	0.181	0.167	0.178	0.152	0.128
CR5	1.447	1.293	1.284	1.299	1.399	1.301	1.167	1.272	1.032	0.825
SAAR	0.061	0.041	0.043	0.045	0.052	0.040	0.023	0.035	0.007	-0.020

	1	2	3
Panel D: Z score			
R1	0.101	0.143	0.155
R2	0.094	0.136	0.153
R3	0.112	0.162	0.177
R4	0.104	0.154	0.168
R5	0.108	0.162	0.171
AR	0.104	0.152	0.165
CR5	0.639	1.024	1.143
SAAR	-0.046	-0.003	0.010

Panel C in Table 4 shows the relationship between turnover and returns. As previously stated that stocks with higher turnover are associated with higher liquidity. Panel C shows clear trend of the returns decreasing with liquidity. The difference in average returns (AR) between liquid and illiquid stocks is about 6.8% The cumulative return difference is 62.2% and the size-adjusted average return (SAAR) difference is 8.1%.

For the Z-score, we could not divide the stocks into [3]10 deciles due to its definition of which firms are risky and safe from bankruptcy. Hence, we decided to divide them into 3 groups.

Panel D in Table 4, we create three groups based on the Z-score. The first group consists of stocks that have high risk of bankruptcy and have average return is 10.1%, the last group consists of stocks that are safe from bankruptcy and have average return of 16.5%. The difference in average return (AR) is 6.1% between safe stocks and risky stocks. The cumulative return difference is 50.4% and the size-adjusted average return (SAAR) difference is 5.6%. The trend shows that the returns are increasing from the firm the has high risk of bankruptcy to firms that are considered safe from bankruptcy. The Z-score gives us unexpected results, which shows higher return for safer stocks and low return for the stocks which have high bankruptcy risk.

The first reason behind this trend might be that 90% of publicly-listed firms filing for Chapter 11 (Bankruptcy) cease trading on the main exchanges at or before the filing date (Dawkins, Bhattacharya and Bamber, 2007). Secondly, at the Behavioral Finance Working Group (BFWG) conference in April 2011, L. Coelho, K. John, Stern, and R. Taffler presented a paper (Gambling on the market: who buys the stock of bankrupt firms?) that conclude the stock prices of the firms that remain listed in the post-bankruptcy period, observe a negative and statistically significant post-bankruptcy announcement drift of -28% over the following year. Lastly, despite the existence of the bankruptcy anomaly, the costs of arbitrage trading is severe. This limits trading such that the deviations of the prices of such stocks from those implied by the Efficient Market Hypothesis (EMH) may persist in the long-run. In the broader context, such effects have been documented by Taffler, Lu and Kausar(2004) and Lesmond, Schill and Zhou (2004).

In the two previous subsections, we have shown that by creating simple strategies of the characteristics they explain cross-sectional returns. Where the replication part shows that

[3] We tried to divide them into 10 deciles, however we got more flat returns in the deciles between.

value strategies outperform glamour strategies. Our contribution subsection shows that stocks that are riskier outperform stocks that have lower level of risk, except for the Z-score.

The difference of average return (AR) between value and glamour stocks ranges from 7.1% to 11.7% whereas the average return (AR) between risky and non-risky stocks ranges from 6.8% to 11.6%. The difference in the average return (AR) between contrarian strategies and risk strategies yields almost the same average return. However, for risky and non-risky stocks measured by Z-score, the average return difference is - 6.1%. This trend for Z score proposes that buying non-risky (safe) and selling risky stocks yields 6.1% while opposite strategy yields negative return. We see the same trend of results in the cumulative return and the size-adjusted average return (SAAR).

In the next section, we first look at a more sophisticated method of LSV strategies since some firms could be misclassified, for example low C/P stocks (Who are glamour stocks), include many stocks with temporarily low cash flow that are expected to recover. Next, we double sort the risk characteristics with B/M ratio. We do this exercise to distinguish the risk variables between value and glamour firms

4.2 Double-sorted portfolios

In this section, we present two-way sorted portfolios. The first subsection shows the replication results whereas the final subsection shows our contribution.

4.2.1 Replication

In Table 5, we present the returns of the double-sorted portfolios. We sort firms into three groups (low 30 percent, medium 40 percent, and high 30 percent) on each variable. Next, nine sets of portfolios are formed as the intersections of the sales-rank sort and the sorts on BE/ME, E/P, or C/P. Panel A, B, and C show the results of C/P, E/P and B/M with GS respectively. Panel D and E show results of E/P and B/M, and B/M and C/P respectively. For every panel we present returns from year 1 through 5 after the formation, the average annual 5-year return, the cumulative return and at last the size-adjusted average annual 5-year return.

For panel A in Table 5, the average return (AR) of the glamour portfolio has 11.7% whereas the value portfolio has 22.3%, which yields a difference of 10.6%. The cumulative difference in return is 100%. The size-adjusted average return difference is 8.3%.

Table 5 Returns for Decile Portfolios Based on Two-Dimensional Classification by Various Measures of Value

At the end of each April between 1968 and 1989, 9 groups of stocks are formed. The stocks are independently sorted in ascending order into 3 groups (1) bottom 30 percent, (2) middle 40 percent and (3) top 30 percent based on each two variables. The sorts are for 5 pairs of variables: C/P and GS, B/M and GS, E/P and GS, E/P and B/M and B/M and C/P. B/M is the ratio of book value of equity to market value of equity; C/P is the ratio of cashflow to the market value of equity; E/P is the ratio of earnings to market value of equity and GS refers to preformation 5-year average growth rate of sales. The returns presented in the table are averages over formation periods. R_t is the average return in year t after formation, t=1,2…,5, AR is the average annual return over 5 post formation years. CR_5 is the compounded 5-year return assuming annual rebalancing. SAAR is the average annual size adjusted return computed over 5 post formation years. Depending on two variables being used for classification, the value portfolio either refers to portfolio containing stocks ranked in the top group (3) on both variables from among B/M, C/P, or E/P, or else the portfolio containing stocks ranking in the top on one of those variables and in the bottom group (1) on GS. The glamour portfolio contains stocks with precisely the opposite set of ranking.

Panel A: C/P and GS									
			Glamour				Value		
C/P	1	1	1	2	2	2	3	3	3
GS	1	2	3	1	2	3	1	2	3
R1	0.139	0.130	0.107	0.174	0.149	0.130	0.212	0.195	0.157
R2	0.139	0.130	0.107	0.181	0.153	0.136	0.216	0.201	0.164
R3	0.132	0.148	0.127	0.190	0.161	0.144	0.224	0.209	0.174
R4	0.147	0.150	0.122	0.195	0.166	0.147	0.229	0.212	0.178
R5	0.169	0.153	0.121	0.201	0.169	0.151	0.233	0.216	0.182
AR	0.145	0.142	0.117	0.188	0.160	0.142	0.223	0.206	0.171
CR	0.969	0.943	0.738	1.367	1.097	0.939	1.734	1.555	1.200
SAAR	-0.009	-0.015	-0.03	0.023	0.012	0.001	0.053	0.039	0.002

Panel B: E/P and GS									
			Glamour				Value		
E/P	1	1	1	2	2	2	3	3	3
GS	1	2	3	1	2	3	1	2	3
R1	0.135	0.138	0.122	0.180	0.151	0.140	0.222	0.195	0.163
R2	0.157	0.139	0.119	0.182	0.159	0.161	0.241	0.193	0.156
R3	0.148	0.157	0.138	0.202	0.177	0.147	0.236	0.213	0.178
R4	0.155	0.145	0.121	0.196	0.167	0.151	0.246	0.199	0.165
R5	0.177	0.148	0.118	0.205	0.174	0.175	0.265	0.206	0.172
AR	0.154	0.145	0.124	0.193	0.165	0.155	0.242	0.201	0.167
CR	1.049	0.972	0.791	1.418	1.149	1.052	1.954	1.499	1.163
SAAR	-0.006	0.002	-0.016	0.036	0.022	0.008	0.076	0.045	0.018

For Panel B in Table 5, presents the return for a classification scheme using both E/P and GS. The average annual difference in the returns between value and glamour portfolios is 11.8 % and the cumulative difference is 118 %. Size-adjusted average return difference is 9.2%.

Table 5: continues

Panel C: B/M and GS									
			Glamour				Value		
B/M	1	1	1	2	2	2	3	3	3
GS	1	2	3	1	2	3	1	2	3
R1	0.138	0.133	0.128	0.164	0.150	0.140	0.188	0.201	0.170
R2	0.159	0.133	0.133	0.165	0.157	0.129	0.191	0.189	0.163
R3	0.156	0.149	0.151	0.182	0.175	0.150	0.212	0.210	0.187
R4	0.165	0.137	0.134	0.174	0.165	0.137	0.206	0.197	0.172
R5	0.188	0.139	0.131	0.182	0.171	0.140	0.213	0.205	0.179
AR	0.161	0.138	0.135	0.173	0.164	0.139	0.202	0.201	0.174
CR	1.111	0.910	0.884	1.224	1.133	0.918	1.511	1.494	1.233
SAAR	0.011	0.000	-0.002	0.016	0.018	-0.003	0.039	0.043	0.015

Panel D: E/P and B/M									
	Glamour								Value
E/P	1	1	1	2	2	2	3	3	3
B/M	1	2	3	1	2	3	1	2	3
R1	0.109	0.132	0.153	0.136	0.144	0.178	0.078	0.167	0.203
R2	0.109	0.133	0.158	0.137	0.147	0.183	0.082	0.171	0.208
R3	0.116	0.141	0.167	0.143	0.153	0.192	0.091	0.180	0.216
R4	0.120	0.146	0.172	0.145	0.156	0.198	0.096	0.184	0.222
R5	0.122	0.151	0.177	0.147	0.159	0.203	0.100	0.188	0.228
AR	0.115	0.141	0.165	0.142	0.152	0.191	0.089	0.178	0.216
CR	0.724	0.930	1.149	0.941	1.028	1.395	0.534	1.268	1.653
SAAR	-0.023	-0.001	0.014	-0.004	0.006	0.031	-0.009	0.019	0.037

Panel E: B/M and C/P									
	Glamour								Value
B/M	1	1	1	2	2	2	3	3	3
E/P	1	2	3	1	2	3	1	2	3
R1	0.110	0.141	0.129	0.124	0.146	0.166	0.131	0.175	0.200
R2	0.109	0.144	0.130	0.125	0.149	0.169	0.132	0.181	0.205
R3	0.116	0.152	0.138	0.132	0.157	0.176	0.141	0.191	0.214
R4	0.119	0.156	0.141	0.137	0.161	0.178	0.147	0.197	0.218
R5	0.121	0.159	0.143	0.144	0.165	0.181	0.152	0.202	0.223
AR	0.115	0.150	0.136	0.133	0.156	0.174	0.141	0.189	0.212
CR	0.724	1.015	0.892	0.863	1.061	1.229	0.931	1.377	1.615
SAAR	-0.029	0.003	-0.002	-0.016	0.002	0.012	-0.003	0.023	0.043

For the two panels we describe above, both C/P and GS contribute a great deal of explanatory power of this double-sorted portfolio. For example, in the high C/P portfolio the average returns range from 17.1% to 22.3%. Likewise, when we look across the lowest GS portfolios, the average returns vary from 14.5 % to 22.3%. In panel B, the in the high E/P portfolio returns ranges from 16.7% to 24.2% while in the lowest GS portfolios, the returns vary from 15.4% to 24.2%.

Panel C presents the return for a classification scheme using B/M and GS. As we see from the results, GS has a statistically explanatory power for returns. For example, for stocks in the highest B/M decile, the average return (AR) difference between the low sales growth and the high sales growth are 6.7%. However, as we notice the B/M ratios across GS groups they are not very different, so the results do not appear to be driven by the role of the GS.

For the last two panels, we notice the usefulness of double-sorting stocks. For example, among firms with the lowest B/M ratio, future returns vary very much according to B/M ratios. The last panel provides the same pattern, whereas the firms with the lowest C/P ratio whereas the average return varies from 11.5% (Glamour portfolio) to 14.1% for stock who has high B/M but low C/P ratio.

The results for this subsection can be summed up and interpreted in the following way. Firstly, double-sorted portfolios return difference is large. The difference between each value and glamour portfolios average return is around 7 % - 12%. Secondly, we notice that some strategies when combined gives higher return then each strategy alone. For instance, we see that when implementing the B/M strategy, the return ranges from 10.9% to 18.6%. But if an investor decides to implement B/M and E/P strategy together the return varies from 11.5% to 21.6%.

In this paragraph we compare our results with the original LSV paper. The deviations in all panels between value and glamour range between 0.3% to 2.1%. We have two places where the deviation is 9.4% and 4.9% for Panel D and E (3,1) respectively. We believe the deviation is caused by the procedure of two-dimensional sort between two variables which leaves some very small cells. Due to having few observations in group (3,1), we obtain very small returns compared to LSV. In addition, we do not know how LSV deal with this problem to obtain those returns.

In the next subsection, we double-sort the variables from our contribution by using only B/M ratio since it the most famous measure of value. The purpose of doing this is to see whether the high returns of value stocks are driven by the risk characteristics.

4.2.2 Contribution

In Table 6, we present the returns of the double-sorted portfolios. We sort firms into three groups (low 30 percent, medium 40 percent, and high 30 percent) on each variable expect Z-score as it has three groups already defined. Next, nine sets of portfolios are formed as the intersections of the B/M ratio and the sorts on Accruals, Amihud ratio, Turnover and Z-score. Panel A, B, C and D show the results of Accruals, Amihud ratio, Turnover and Z-score with B/M respectively. For every panel we present returns from year 1 through 5 after the formation, the average annual 5-year return, the cumulative return and at last the size-adjusted average annual 5-year return.

Panel A in Table 6 presents the return for a classification scheme using B/M and accruals. The average return (AR) difference for value and glamour stocks when the stocks have high accruals is 5.7% and when they have low accruals is 5.5%. The difference between returns for low accruals and high accruals when the stocks are value is 6.3% and when the stocks are glamour 6.5%

Panel B in Table 6 shows the double-sort of B/M and the Amihud ratio. The returns increase with the Amihud ratio for both value and glamour stocks. The difference in average returns for value and glamour stocks when the stocks are liquid is about 7.8% and when they are illiquid is 6.6%. The difference between average returns for illiquid and liquid when the stocks are value is 5.8% and when they are glamour 7%.

When the investor does not consider liquidity then the value strategy yields an average return of about 7%. When the investor implements the liquidity strategy without considering the value strategy, it yields an average return of about 7%. This may suggest that that liquidity premium have an impact on the value premium.

Panel C in Table 6, the results are very close aligned with Panel B with regards of the liquidity. The difference in average returns for value and glamour stocks when the stocks are liquid is about 6.4% and when they are illiquid is 8%. The difference between average returns for illiquid and liquid when the stocks are value is 4.7% and when they are glamour 3.1%.

For panel D in table 6, we still see that the stocks with high bankruptcy risk exhibits lower return and stocks with lower risk of bankruptcy exhibits higher return. This trend can be seen in both value firms and glamour firms. When there is high bankruptcy risk, the glamour stocks and value stock has an average return of 10.8% and 13.1% respectively.

Table 6 Returns for Decile Portfolios Based on Two-Dimensional Classification by Measure of Value and Risk

At the end of each April between 1968 and 1989, 9 groups of stocks are formed. The stocks are independently sorted in ascending order into 3 groups (1) bottom 30 percent, (2) middle 40 percent and (3) top 30 percent based on each two variables. The Sort is done between the risk characteristics and B/M. B/M is used define value and glamour stocks. The sorts are for 4 pairs of variables: B/M and Accruals, B/M and Amihud ratio, B/M and Turnover and B/M and Z-score. B/M is the ratio of book value of equity to market value of equity. The returns presented in the table are averages over formation periods. R_t is the average return in year t after formation, t=1,2…,5, AR is the average annual return over 5 post formation years. CR_5 is the compounded 5-year return assuming annual rebalancing. SAAR is the average annual size adjusted return computed over 5 post formation years. The value portfolio refers to portfolio containing stocks ranked in the group (3) on B/M while the glamour portfolio refers to portfolio containing stocks ranked in the group (1) on B/M. The risky portfolio refers to the deciles containing stocks ranked group (1) on accruals, Turnover, Z-score or group (3) on Amihud ratio. The less risky portfolio contains stocks with precisely the opposite ranking of risky.

Panel A: B/M and ACC

B/M	1	1	1	2	2	2	3	3	3
ACC	1	2	3	1	2	3	1	2	3
R1	0.149	0.118	0.083	0.161	0.133	0.114	0.196	0.164	0.135
R2	0.147	0.122	0.085	0.162	0.136	0.117	0.199	0.171	0.139
R3	0.153	0.131	0.088	0.169	0.143	0.124	0.209	0.180	0.145
R4	0.156	0.136	0.090	0.173	0.146	0.126	0.214	0.186	0.148
R5	0.158	0.138	0.089	0.177	0.150	0.129	0.219	0.193	0.151
AR	0.152	0.129	0.087	0.168	0.142	0.122	0.207	0.179	0.144
CR	1.033	0.832	0.517	1.178	0.940	0.780	1.567	1.276	0.956
SAAR	0.005	-0.001	-0.032	0.019	0.001	-0.018	0.040	0.023	-0.002

Panel C : B/M AND TO

B/M	1	1	1	2	2	2	3	3	3
TO	1	2	3	1	2	3	1	2	3
R1	0.151	0.136	0.116	0.155	0.172	0.138	0.225	0.207	0.179
R2	0.154	0.133	0.113	0.156	0.170	0.135	0.224	0.204	0.177
R3	0.166	0.153	0.140	0.172	0.191	0.163	0.244	0.226	0.204
R4	0.159	0.144	0.129	0.167	0.183	0.155	0.241	0.219	0.190
R5	0.157	0.142	0.130	0.174	0.188	0.160	0.250	0.224	0.198
AR	0.157	0.142	0.126	0.165	0.181	0.150	0.237	0.216	0.190
CR5	1.077	0.938	0.807	1.146	1.295	1.012	1.896	1.658	1.381
SAAR	0.027	0.008	-0.017	0.027	0.041	0.006	0.097	0.068	0.039

Panel D : B/M AND Z

B/M	1	1	1	2	2	2	3	3	3
Z	1	2	3	1	2	3	1	2	3
R1	0.092	0.099	0.122	0.089	0.124	0.161	0.128	0.167	0.201
R2	0.093	0.088	0.121	0.086	0.119	0.159	0.122	0.161	0.198
R3	0.119	0.114	0.144	0.100	0.145	0.184	0.142	0.187	0.223
R4	0.117	0.112	0.134	0.092	0.138	0.176	0.129	0.177	0.215
R5	0.118	0.121	0.131	0.098	0.146	0.181	0.134	0.185	0.222
AR	0.108	0.107	0.130	0.093	0.134	0.172	0.131	0.175	0.212
CR5	0.667	0.660	0.845	0.560	0.878	1.213	0.851	1.243	1.613
SAAR	-0.044	-0.040	-0.012	-0.049	-0.012	0.016	-0.029	0.014	0.046

On the other hand, when risk of bankruptcy is low the average returns are 13% and 21.2% for glamour and value stocks respectively. The difference in average return between value and glamour is 8.2% when the stocks are safe and 2.3% when the stocks face risk of bankruptcy.

Our results in panel D suggests that the value strategy works best if the stocks are safe. The investor will earn higher abnormal returns on value strategy when the stocks are safe from bankruptcy. The Z-Score does not explain the riskiness of the stocks in relation to returns.

In this table we notice that when combining the risk strategies with the B/M strategies together yield higher return then each strategy alone. For instance, we see that when implementing the Amihud ratio strategy, the average return from liquid and illiquid is 10.7% to 23.3% respectively which yields the difference of 12.6%. On the other hand, implementing the B/M strategy, the average return from glamour and value are 10.9% and 18.6% respectively, the difference is 7.7%. When an investor decides to implement B/M and Amihud strategy together the average return difference is 13.5% between value and glamour stocks. This pattern exists for accruals and turnover.

In this subsection we show that by double-sorting the risk characteristics and B/M yields higher returns. Moreover, there is a big difference in the returns within the B/M portfolios and across the B/M portfolios for all variables, except Z-score for the lowest B/M portfolio. This difference in returns is driven by the characteristic of B/M and not risk. Hence the double sort table suggests that the value stocks outperform the glamour stocks even after controlling for risk characteristics.

4.3 Regression Analysis

In the past two sections we presented replication and contribution results. Both sections show the relationship between the returns and the firm characteristics. In this section, we are performing Fama-MacBeth regressions of the characteristics included in the replication and our contribution. The purpose of this section is to investigate whether the variables are significant in explaining returns in a multiple regression.

4.3.1 Replication

In this subsection, we perform a Fama-MacBeth regression on the variables we use in our replication to check whether they are important in explaining returns. We run 22 separate cross-sectional regressions for post formation Year +1. The dependent variable for this regression is the annual return on each stock and independent variable are characteristics of each stock observed at the beginning of the year. In our analysis, [4]we have 22 portfolio formation periods. Then using Fama-MacBeth procedure, the coefficients for these 22 cross sectional regressions are averaged and t statistics are computed.

For stocks that have negative E/P or C/P ratios we deal with this problem the same way as Fama and French (1992). We define C/P+ and E/P+ which are equal to zero if one of the ratios are negative and are equal to C/P or E/P ratio if it is positive. We include dummy variables, that are named DC/P and DE/P, which take the value of 1 when C/P or E/P are negative and zero otherwise. The purpose of doing this is to treat observations with negative ratios (E/P and C/P) differently from observations with positive ratios. Since the stocks with negative ratios cannot be interpreted as future expected growth rates, dummy variables of these ratios are introduced in the regression.

We first perform separate regressions in Table 7, where we use GS, B/M, SIZE, E/P+ and C/P+. We find that all variables are statistically significant, except SIZE. We also notice that E/P+ and C/P+ are very significant compared to GS and B/M. Next, we combine the variables in a multiple regression, we notice that B/M becomes weaker, relatively to the other variables and eventually becomes insignificant. However, we do not see the same pattern for GS. In the multiple regressions C/P+ and E/P+ are significant at 1% level. The variables that stand out from the other variables in the regression are E/P+, C/P+, and GS.

In this paragraph we compare our results with the original LSV paper. Our coefficients and t-statistics are very close to what LSV obtains. The coefficients and t-statistics have approximately the same magnitude. Compared to LSV, we highly deviate two places where the dummy DC/P is highly significant (1% level) while in the original LSV the dummy is not statistical significant at 10% significance.

The reason for this deviation can be due to number of observations. We may have more or fewer observations compared to LSV. Another reason is that we winsorize the variables at 1% level to avoid giving extreme observations heavy weights in the regressions.

[4] Our period starts from the end of April 1968 to end of April1989.

LSV does not mention the point of winsorizing. So, it can be that LSV winsorize at different level and do not winsorize.

Table 7 Regression of Returns on Characteristics for all firms

At the end of each April between 1968 and 1989, we compute for every firm in the sample the 1-year holding period return starting at the end of April. We run 22 cross-sectional regressions with these returns for each formation period as dependent variables. The independent variables are (1) GS, the preformation 5-year weighted average rank of sales growth; (2) B/M the ratio of end of previous year's book value of equity to market of equity; (3) SIZE, the end of April natural logarithm of market value of equity (in millions); (4) E/P+, equal to the E/P—the ratio of previous year's earnings to end of April market value of equity- if E/P is positive and to zero if E/P is negative; (5) DE/P , equal to 1 if E/P is negative and zero if E/P is positive; (6) C/P+, equal to the C/P—the ratio of previous year's earnings to end of April market value of equity- if C/P is positive and to zero if C/P is negative; (7) DC/P , equal to 1 if C/P is negative and zero if C/P is positive. The reported coefficients are averages over 22 formation periods. The reported t-statistics are based on the time series variation of 22 coefficients.

	Int.	GS	B/M	SIZE	E/P+	DE/P	C/P+	DC/P
mean	0.190	-0.062						
t-statistics	-3.710	-1.990						
mean	0.106		0.031					
t-statistics	2.340		2.030					
mean	0.135			-0.002				
t-statistics	1.610			-0.230				
mean	0.102				0.458			
t-statistics	2.110				3.060			
mean	0.095						0.271	
t-statistics	1.990						4.690	
mean	0.150	-0.071	-0.001				0.213	-0.028
t-statistics	3.760	-2.990	-0.060				3.920	-1.320
mean	0.170		0.011	-0.006			0.130	-0.050
t-statistics	1.110		1.050	-0.560			3.220	-2.560
mean	0.175	-0.056	-0.001	-0.007			0.235	-0.059
t-statistics	2.200	-2.000	-0.110	-0.730			4.260	-4.440
mean	0.176	-0.060	0.012	-0.007	0.348	-0.043		
t-statistics	2.110	-2.070	0.980	-0.690	2.110	-1.950		

4.3.2. Contribution

In this subsection, we perform Fama-MacBeth regression on the variables we use in our contribution to check whether they are important in explaining returns. [5]We run 22 separate cross-sectional regressions for post formation Year +1. The dependent variable for this regression is the annual return on each stock and the independent variables are risk characteristics of each stock observed at the beginning of the year. Then using Fama-MacBeth procedure, the coefficients for these 22 cross sectional regressions are averaged and t statistics

[5] Our period starts from the end of April 1968 to end of April1989.

are computed. In the regression we take the natural logarithm of the Amihud ratio because of the severe skewness in its distribution (Lu, Hwang, 2007).

Table 8 Regression of Returns on Characteristics for all firms

At the end of each April between 1968 and 1989, we compute for every firm in the sample the 1-year holding period return starting at the end of April. We run 22 cross-sectional regressions with these returns for each formation period as dependent variables. The independent variables are (1) B/M the ratio of end of previous year's book value of equity to market of equity; (2) SIZE, the end of April natural logarithm of market value of equity (in millions); (3) Amihud ratio; (4) Turnover; (5) Accruals; (6) Z-score. The reported coefficients are averages over 22 formation periods. The reported t-statistics are based on the time series variation of 22 coefficients.

	Int.	B/M	SIZE	ZSCORE	AMIHUD	TURNOVER	ACC
mean	0.104	0.028		0.002			
t-statistics	2.150	2.500		1.790			
mean	0.475	0.036			0.028		
t-statistics	3.870	2.910			3.790		
mean	0.149	0.034				-0.010	
t-statistics	3.700	3.370				-1.840	
mean	0.105	0.029					-0.213
t-statistics	2.340	2.300					-4.3
mean	0.400	0.033		0.000	0.022	-0.007	-0.309
t-statistics	2.780	1.950		-0.050	2.470	-1.130	-4.170
mean	0.130	0.024	-0.030	0.002			
t-statistics	1.830	1.940	-0.250	1.690			
mean	0.496	0.033	-0.012		0.018		
t-statistics	3.580	2.210	-0.860		2.530		
mean	0.410	0.023	-0.021			-0.014	
t-statistics	3.380	1.840	-2.580			-2.910	
mean	0.115	0.023	-0.017				-0.240
t-statistics	1.230	1.800	-0.300				-5.600
mean	0.408	0.023	-0.022	0.000	0.001	-0.015	-0.312
t-statistics	2.760	1.290	-2.540	0.130	0.160	-2.880	-4.140

In table 8, we first regress annual returns of each stock on all risk characteristics individually while controlling for B/M. All the risk characteristics and B/M are statistically significant. Furthermore, the Z-score is giving an opposite result, but it is consistent with the previous results (Table 4 and 6). However, on stand-alone basis accruals and Amihud are most significant variable and followed by B/M. Secondly, we include all characteristics mentioned above in the same regression. The result suggests that Turnover and Z-score are not important as Amihud ratio and accruals. Accruals and Amihud ratio are the only characteristics which are highly significant followed by B/M.

Thirdly, we first regress annual returns of each stock on all risk characteristics individually while controlling for B/M and SIZE. B/M, Z-score and Amihud ratio coefficients drop, as well as their significance. Accruals and turnover become more significant when we additionally control for SIZE.

Finally, we perform a multiple regression which contains all variables mentioned. In this regression we notice that all the characteristics loses their significance except for SIZE, turnover and accruals.

The reason for this might be that SIZE is a confounder that influences the independent variables (B/M and turnover) and the dependent variable (Returns) which causes a spurious association. Confounding is a causal concept and cannot be described in terms of correlations or associations. This effect can be seen more when we regress the returns on B/M, SIZE and turnover. The SIZE and turnover become highly significant. Thus, the fact that adding SIZE variable make the turnover highly significant and others in significant in the multiple regression, we can define this as a confounding problem which is giving us spurious results. The interaction effect might be another reason for this. This occurs when two variables affect each other. In our case we believe that SIZE variable and Turnover variable affect each other.

Due to the arguments above, we do not consider the last regression. Hence, we conclude that the variables that stand out from other variables in the regression are Amihud ratio, Accruals and B/M from the fifth regression in Table 8.

4.4 Examining the riskiness of the contrarian strategies

In the previous sections, we replicate LSV one-way sort, two-dimensional sort, and Fama-MacBeth. We find that the Contrarian strategies produce high return. In this section, we replicate the LSV table which shows the year by year performance of value strategies relative to glamour strategies, to investigate the riskiness of these strategies. The reason behind this is that value stocks would be fundamentally riskier if they underperform in bad states of the world. The risk-averse investors would hence stray away from these stocks in bad states because they would make loss.

Table 9, in Panel 1 and 3, we show the cumulative return difference between C/P and B/M respectively. The difference is calculated as the difference between the upper 2 deciles and the bottom 2 deciles. For panel 2, we show the cumulative return difference between the value (3,1) and glamour (1,3) portfolio in the two-dimensional sort for C/P and G/S.
We present 1-, 3- and 5-year holding period in our sample. At the bottom of the table, we provide the mean and t-statistic across years for each horizon. The t-statistic are computed using Hansen-Hodrick (1980).

In Panel 1 of Table 9, we notice that value stocks outperform glamour stocks 16 out of 22 years for the 1-year horizon. In Panel 2, the value stocks outperform glamour stocks in 18 out of 22 years for the 1-year horizon. In Panel 3, the value stocks outperform glamour stocks in 17 out of the 22 years for the 1-year horizon.

When we look at the 3- and 5-year horizon for all panels, we notice that value strategy consistently outperforms glamour strategies. The returns increase for every portfolio we consider in these two horizons. This effect is very strong in the 5- year as there is no downside at all. If value strategy is risky then an investor would lose a lot in the downside. However, that is not what we notice from the Table 9. By using this table, LSV argue that any risk-based explanation is hard to prove, since the upside for the value strategy is very high compared to the downside.

Our results and LSV original results are very close. For every panel in the 1-year horizon we have the same signs as LSV. However, in panel 1 in 1980 we have negative sign, but the deviation is not big (4.9%). For every panel in the 3-year horizon, we observe that on average, we have the same signs as LSV except 1979 panel 1 and 1969 panel 2, we deviate by 28.2% and 15.1% respectively. In the 5-year horizon the magnitude of the cumulative return is not very different from LSV and we have the same signs.

Finally, by looking at the averages of the year by year returns for every panel. Our results are very close to LSV results for 5- year in every panel. Followed by the 3- year, the panel 2 and 3 are close to LSV results except for panel 1 we deviate by 7.8%. Lastly for 1-year, the panel 1, 2 and 3 are very close to LSV values. We conclude that our replication is successful.

Table 9 Year by Year Returns: Value minus Glamour

Panel 1; At the end of each April between 1968 and 1989, 10 deciles portfolios are formed based on the ratio of previous cash flow to end of April market value equity(C/P). For each portfolio, 1-, 3-, and 5- year holding period returns are computed. For each formation period, panel 1 reports the difference in the 1-, 3- and 5-year return between the 2 highest C/P (value) and 2 lowest C/P (glamour) portfolios.

Panel 2; At the end of each April between 1968 and 1989, 9 groups of stocks are formed. The stocks are independently sorted in ascending order into 3 groups (1) bottom 30 percent, (2) middle 40 percent and (3) top 30 percent by the ratio of previous year's cash flow to end of April market value equity(C/P) and by the preformation 5-year weighted average rank of sales growth (GS). The 9 portfolio intersections resulting from these two-independent classifications. For each portfolio 1-,3- and 5-year holding period returns are computed. For each formation period, panel 2 reports the difference in 1-,3- and 5-year returns between lowest GS, highest C/P(value) and highest GS, lowest C/P (glamour) portfolios.

Panel 3; At the end of each April between 1968 and 1989, 10 deciles portfolios are formed based on the ratio of previous book value equity to end of April market value equity(B/M). For each portfolio, 1-, 3-, and 5- year holding period returns are computed. For each formation period, panel 3 reports the difference in the 1-, 3- and 5-year return between the highest B/M(value) and lowest B/M (glamour) decile portfolios.

The last two rows respectively report the arithmetic mean across periods and t-statistics for the test of the hypothesis that the difference in returns between value and glamour is equal to zero. These t- statistics are based on the standard errors computed according to Hansen and Hodrick (1980).

	PANEL 1 (C/P: 9,10 - 1,2)			PANEL 2 (C/P -GS: 3,1 - 1,3)			PANEL 3 (B/M: 9,10 - 1,2)		
YEARS	1-YEAR	3-YEAR	5-YEAR	1-YEAR	3-YEAR	5-YEAR	1-YEAR	3-YEAR	5-YEAR
1968	0.018	0.401	0.525	0.164	0.226	0.367	0.109	0.302	0.346
1969	0.149	0.317	0.400	0.047	0.008	0.319	0.091	0.110	0.257
1970	0.163	0.385	0.395	-0.025	0.172	0.487	0.059	0.176	0.343
1971	-0.024	0.180	0.471	-0.040	0.264	0.940	-0.081	0.146	0.731
1972	0.183	0.192	0.782	0.156	0.366	1.251	0.136	0.242	0.997
1973	0.029	0.269	1.136	0.150	0.823	1.968	0.080	0.737	1.681
1974	-0.012	0.660	1.632	0.096	1.031	2.273	0.067	1.016	2.044
1975	0.247	1.131	1.287	0.439	1.370	1.502	0.526	1.377	1.355
1976	0.238	0.734	0.858	0.215	0.723	0.847	0.161	0.503	0.262
1977	0.190	0.112	0.804	0.212	0.076	0.906	0.184	-0.069	0.517
1978	0.061	-0.194	0.374	0.062	-0.212	0.985	-0.006	-0.465	0.735
1979	-0.143	0.181	0.716	-0.186	0.229	1.299	-0.195	0.104	1.325
1980	-0.010	0.483	1.749	0.043	1.029	2.068	-0.044	0.983	1.836
1981	0.229	0.625	1.458	0.251	0.942	1.308	0.233	1.043	1.446
1982	-0.084	0.712	1.335	0.175	0.773	1.280	0.269	0.815	1.257
1983	0.199	0.657	1.003	0.226	0.277	0.797	0.258	0.355	0.597
1984	0.256	0.547	1.052	0.067	0.149	0.555	0.020	0.054	0.298
1985	0.052	0.309	0.560	-0.124	0.252	0.520	-0.027	0.168	0.020
1986	0.080	0.419		0.146	0.426		0.042	0.217	
1987	0.109	0.270		0.138	0.306		0.099	-0.001	
1988	0.170			0.057			0.040		
1989	-0.005			0.073			-0.138		
Average	0.095	0.419	0.919	0.107	0.462	1.093	0.086	0.391	0.891
t-statistics	4.88	5.83	6.72	3.61	4.08	5.82	2.46	3.19	4.71

4.5 Investigating value minus glamour strategy

In the previous section we present the table of year by year performance of the value strategy relative to glamour strategy which concludes that the upside for the value strategy is very high compared to the downside. Hence LSV argues that any risk-based explanation is hard to prove. In this section we are investigating the riskiness of the Contrarian strategy in a different approach using our model that is inspired by Fama-French 3 Factor model and Carhart model.

The Fama and French Three Factor Model (1993) is an asset pricing model that expands on the capital asset pricing model (CAPM) by adding size risk (SMB) and value risk factors (HML) to the market risk factor to CAPM (Investopedia, 2018).

In addition to that, we extend the model by including the momentum factor (Carhart, 1997). Momentum is described as the tendency for the stock price to continue rising if it is going up and to continue declining if it is going down. The momentum factor (UMD) is a zero-cost portfolio that is long for the previous 12-month return winners and short previous 12-month loser stocks.

The strategy we are investigating is value minus glamour using B/M ratio. Therefore, we cannot add HML factor on the right-hand side of the regression as it is equivalent to this strategy. Due to this we cannot say that we are using the two models mentioned-above directly. However, the model we construct is inspired by them.

The following is the regression equation:

$$Rv - Rg = \alpha + b(Rm - Rf) + sSMB + uUMD + aACC + lLIQ + tLIQT + zZCO$$

Where, R_v is monthly returns of value stocks and R_g is monthly returns of glamour stocks. Later we call this difference VMG.

The aim of doing these regressions is to see if the abnormal return (Estimated alpha) disappears after controlling for the risk factors. If the model fully explains stock returns, the estimated alpha should be statistically indistinguishable from zero.

We create our risk factors by first sorting the stocks into 3 groups ((1) bottom 30 percent, (2) middle 40 percent, and (3) top 30 percent,) by using Accruals, Amihud ratio, turnover, and B/M. The only risk characteristic that deviates from this approach is Z-score. For Z-score has established rules of which firms that are considered risky and safe. We divide stocks into 3 groups for Z-score, (1) risky, (2) middle, and (3) safe.

The low accruals portfolio is defined as group 1 and the high accruals portfolio is defined as group 3. For Amihud ratio, the liquid portfolio is defined as group 1 and the illiquid portfolio is defined as the group 3. For B/M, the glamour portfolio is defined as group 1 and the value portfolio is defined as group 3. For turnover, the illiquid portfolio is defined as group 1 and the liquid portfolio is defined as group 3. For Z-score, the risky portfolio is defined as group 1 and the safe portfolio is defined as group 3.

Definition of risk factors:
ACC = The difference in monthly return between group 1 and group 3 (Accruals),
LIQ = The difference in monthly return between group 3 and group 1 (Amihud ratio),
LIQT = The difference in monthly return between group 1 and group 3 (Turnover),
VMG = The difference in monthly return between group 3 and group 1 (B/M),
ZCO = The difference in monthly return between group 3 and group 1 (Z-score).

As explained in the methodology chapter, we create our variables annually and rebalance our portfolios annually. The portfolios are also equally-weighted. We run monthly time-series regressions from end of April 1968 to April 1990. The t-statistics are computed using Newey-West method to overcome autocorrelation and heteroskedasticity of the error term.

We run monthly regressions with the value minus glamour (VMG) returns as dependent variable. The independent variables are accruals risk factor (ACC), Amihud liquidity risk factor (LIQ), market excess returns (CAPM BETA), small minus big (SMB), turnover risk factor (LIQT), up minus down (UMD), and Z-score risk factor (ZCO).

In Table 10, we run the first regression where we include the CAPM BETA to control for market risk. The results that emerge from this regression shows that the alpha exist, and it is statistically significant. Secondly, we run the same regression again, but we control for SMB and UMD. We notice that when we control for these two effects, the alpha remains significant.

Next, we expand the second regression by controlling for ACC, LIQ, LIQT, and ZCO separately. When we control for ACC and LIQ we notice that the alpha disappears. It is statistical insignificant with values 0.003 (1.46) and 0.002 (0.95) respectively. When we control for LIQT and ZCO we notice that the alpha exists and statistically significant with values 0.004 (2.79) and 0.008 (4.18) respectively.

Table 10 Regression of Returns on risk factors for all firms

For the period from end April 1968 to 1990, We run monthly regressions with the value minus glamour returns as dependent variable. The independent variables are (1) market excess returns; (2) small minus big (SMB; (3) Up minus down (UMD); (4) Amihud liquidity risk factor (LIQ); (5) Turnover risk factor (LIQT); (6) Z-score risk factor (ZCO); (7) Accruals risk factor (ACC).

	Value - Glamour							
	α	CAPM BETA	SMB	UMD	ACC	LIQ	LIQT	ZCO
Mean	0.006							
t-statistic	2.590							
Mean	0.006	-0.166						
t-statistic	3.000	-2.940						
Mean	0.008	-0.252	0.389	-0.249				
t-statistic	4.320	-5.660	2.780	-3.270				
Mean	0.003	-0.150	0.629	-0.299	0.615			
t-statistic	1.460	-2.790	4.870	-5.230	4.800			
Mean	0.002	-0.138	-0.412	-0.317		0.895		
t-statistic	0.950	-2.640	-2.360	-4.380		4.580		
Mean	0.004	-0.034	0.710	-0.214			0.626	
t-statistic	2.790	-0.740	4.910	-3.740			5.940	
Mean	0.008	-0.222	0.425	-0.192				0.466
t-statistic	4.180	-4.580	3.620	-2.550				3.560
Mean	0.005	-0.031	0.709	-0.169			0.563	0.392
t-statistic	3.020	-0.700	5.630	-3.430			6.140	3.840
Mean	0.003	-0.007	0.785	-0.200	0.278		0.507	0.352
t-statistic	1.630	-0.140	6.430	-4.490	2.250		4.570	3.670
Mean	0.002	0.006	0.190	-0.216		0.530	0.476	0.385
t-statistic	1.050	0.130	1.110	-3.870		3.360	5.590	3.760
Mean	0.000	0.033	0.251	-0.250	0.298	0.551	0.411	0.096
t-statistic	-0.140	0.700	1.540	-5.400	2.290	3.980	3.980	3.550

In the last regression, we control for all risk factor in one regression. The estimated alpha we get is 0.000 and it is statistically insignificant with a t-statistics of -0.14. The alpha does not exist after controlling for either ACC or LIQ in any of the regressions. Therefore, the results suggest that the value minus glamour strategy is explained by the risk factors ACC and LIQ.

Before moving to the next section, we want to describe the fifth regression in table 10. We notice that in this regression the SMB sign becomes negative while it is always positive. Table 11 shows that there is correlation between LIQ and SMB of 0.855. The correlation is high, but it is not a surprise as it is believed that, small stocks tend to be illiquid and vice versa. We suspect that there is multicollinearity problem which leads to this effect. To check for multicollinearity, we calculate variance inflation factors (VIF). We obtain a VIF of 7.14

which confirm the collinearity between the two variables. Since the VIF is not above 10 (rule of thumb), we conclude that we can use this regression (MATLAB Blog by Eric Heckman 2015).

Table 11 The correlation matrix between different factors

For the period from end April 1968 to 1990, we show the correlation matrix between market excess return, SMB, UMD, ACC, LIQ, LIQT, and ZCO. To compute the correlation between the risk factors the Spearman method is used.

	MKTRF	SMB	UMD	ACC	LIQ	LIQT	ZCO
MKTRF	1						
SMB	0.296	1					
UMD	-0.046	-0.100	1				
ACC	-0.539	-0.574	0.100	1			
LIQ	0.079	0.855	-0.029	-0.413	1		
LIQT	-0.696	-0.544	0.002	0.622	-0.292	1	
ZCO	-0.155	-0.147	-0.146	0.294	-0.110	0.188	1

4.6 Robustness Result

To summarize the previous section, it comes to our attention that when we control for either ACC or LIQ in the regression the estimated alpha becomes statistically insignificant. Hence, we conclude that the value minus glamour strategy is explained by these risk factors. In this section, we check whether our results are robust by focusing exclusively on ACC and LIQ.

The aim of doing this is to see whether our results hold for different time periods. Next, we control for small caps and penny stocks, to check whether our results are not driven by small stocks and penny stocks. Lastly, we value-weight our portfolios.

We run monthly regressions for different time periods with the value minus glamour (VMG) returns as dependent variable. The independent variables are accruals risk factor (ACC), Amihud liquidity risk factor (LIQ), market excess returns (CAPM BETA), small minus big (SMB), and up minus down (UMD).

$$Rv - Rg = \alpha + b(Rm - Rf) + sSMB + uUMD + aACC$$

$$Rv - Rg = \alpha + b(Rm - Rf) + sSMB + uUMD + lLIQ$$

There are two panels in the table 12. Panel A is reporting the equally weighted portfolio while panel B is reporting the value weighted portfolio. We perform the first and second equations for ACC and LIQ columns respectively. Both panels have first five rows which report the abnormal return and t-statistics for various sample and subsamples period.

The first row reports the abnormal return and t-statistic for our extended period (1993 May to 2015 April). Furthermore, there are four different subsamples, the first subsample (1968 May - 1979 April), the second subsample (1979 May - 1990 April), the third subsample (1993 May - 2004 April) and the fourth subsample (2004 May - 2015 April). We report the abnormal return and t-statistic after controlling for penny stocks in row six and small cap in row seven in Panel A.

Table 12 Robustness Results

For the period from end April 1968 to 1989, We run monthly regressions with the returns as dependent variables. The independent variables are (1) market excess returns; (2) small minus big (SMB; (3) Up minus down (UMD); (4) Amihud liquidity risk factor (LIQ); (5) Accruals risk factor (ACC). the regressions have different time periods. Extended period (1993 May-2015 APR). The subsample 1 and 2 is the full original period divide by 2 and the subsample 3 and 4 is the extended period divide by 2 as well.

Panel A: Equally weighted portfolio				
	LIQ		ACC	
	Alpha	t-statistic	Alpha	t-statistic
Subsamples				
Extended period (1993MAY - 2015APR)	0.002	1.320	0.005	2.920
Subsample 1 (1968MAY - 1979APR)	0.000	-0.100	0.002	0.900
Subsample 2 (1979MAY - 1990APR)	0.003	1.030	0.002	0.860
Subsample 3 (1993MAY-2004APR)	0.003	1.530	0.007	4.370
Subsample 4 (2004MAY-2015APR)	0.001	0.350	0.002	0.760
Other controls				
Exduding penny stocks (1%)	0.002	1.190	0.032	1.810
Exduding small cap (1%)	0.003	1.570	0.004	2.020

Panel B: Value weighted portfolio				
	LIQ		ACC	
	Alpha	t-statistic	Alpha	t-statistic
Subsamples				
Extended period (1993MAY - 2015APR)	0.002	1.120	0.003	1.440
Subsample 1 (1968MAY - 1979APR)	0.003	0.760	0.003	0.720
Subsample 2 (1979MAY - 1990APR)	0.007	2.810	0.003	1.050
Subsample 3 (1993MAY-2004APR)	0.004	1.310	0.004	1.880
Subsample 4 (2004MAY-2015APR)	0.001	0.720	0.001	0.570

4.6.1 Performance of the value minus glamour strategy in different sample and subsamples

From Table 12, panel A, we can see that the abnormal return of value minus glamour is insignificant for every period when controlling for LIQ. However, the alpha is insignificant in the subsample 1, 2, and 4 when controlling for ACC. In the extended period the alpha is very significant, and we can see that this significance come from the subsample 3. We conclude that our main results hold in the different samples and subsamples despite alpha being significant in the extended period for ACC.

4.6.2 Performance of removing penny stocks (1%) and small stocks (1%)

To make our strategy more realistic, our next test of robustness includes deleting the 1% percentile of stocks with the lowest price (Penny stocks) and lowest market capitalization (Small cap) calculated at the end of each month. The sample period covered here is the same as our original sample (1968 April - 1990 April).

From Table 12, panel A, the results show that the alpha of value minus glamour strategy is insignificant when control for LIQ after excluding penny and small stocks. This is different from ACC when we exclude for these two elements. The alpha is significant for ACC.

4.6.3 Performance of value-weighted portfolio

Table 12 in panel B, the stocks with greater market capitalization have greater impact whereas stocks with low market capitalization will have less impact of our results. Our results show that by altering the weight of the stocks we find that in subsample 2, the alpha of value minus glamour the strategy becomes statistically significant when control for LIQ whereas the same thing applies for ACC in subsample 3. Our results show that by altering the weight of the stocks does not have any fundamental impact of our original results of our different samples.

Given our results, we can conclude that ACC and LIQ make the abnormal return of value minus glamour strategy to be zero. Our results are strong in different time periods, when we excluded small stocks and penny stocks, and when we value-weighted the portfolios. However, LIQ appears to be the stronger than ACC. In the next section we discuss the validity of our risk-factors.

4.7 Validity of our risk factors

In this section, we check the validity of our ACC, LIQ, and VMG. To investigate this, we start by looking at the LIQ i.e. the Amihud illiquidity factor. We download Pastor-Stambaugh liquidity factor (PS) from WRDS for the period from end April 1968 to 1990. Next, we discuss ACC. Last, discuss HML versus VMG.

We are expecting the negative correlation between these two factors (LIQ and PS factors) since Acharya and Pedersen (2005) mention that, measure of correlation between innovations in market illiquidity and innovations in liquidity used by Pastor and Stambaugh (2003) are negatively correlated with the value -0.33. This negative correlation is because Pastor and Stambaugh measure liquidity while Amihud ratio is considering illiquidity.

We find that the Amihud ratio factor (LIQ) and Pastor and Stambaugh (PS) factor are negatively correlated with the value -0.1. One reason for not getting -0.33 could be that PS is value-weighted while LIQ is equally weighted. Another reason can be that the way we create our factor LIQ. The factor LIQ is constructed using three terciles (difference of Group 3 and group 1) while the PS factor is using 10 deciles (difference of decile 10 and 1).

We prefer using equally-weight than value-weight approach because liquid firms are normally overrepresented in the sample (Acharya and Pedersen ,2005). This problem is due the fact that the sample does not include corporate bonds, private equity, real estate and many small firms. Since the value-weight would heavily represent the largest firms in the sample, the problem becomes worse.

Another evidence of showing that our LIQ factor is not wrongly constructed is that, we look at the correlation between the LIQ factor and SMB and it was positively correlated with the value 0.855 (Table 11). Similarly, Hwang and Lu (2007) show that the correlation of Amihud factor and SMB is 0.75. Although the correlation is not the same due to the different period, different observations used when constructing LIQ and Amihud factor (Hwang, Lu, 2007).

The last evidence is that the Amihud factor (LIQ) is negatively correlated with the distress factor. In our paper we use ZCO as a measure of a distress factor. We find negative correlation of -0.11 between LIQ and ZCO. Viral V. Acharya et al. (2009) find that the correlation between the distress factor and Illiquid innovation is -0.18. From the arguments above, we are confident that we can rely on the LIQ factor we construct.

We are unable to find any provided data on the ACC factor. Due to time constraint, we do not have time to replicate another factor to check whether ACC is correctly created.

However, we have reason to believe it is correctly constructed. First, Accruals shows a negative relationship with cross sectional returns. This is consistent with previous research (Sloan, 1996). Furthermore, in the Fama-MacBeth regression gives evidence that Accruals has a negative relationship with returns and appears as strong characteristics in our Fama-MacBeth regression. This is consistent with Fama-French in 2008. Since we use same variable (which is consistent with previous work) to create the factor ACC, we are confident that it is correctly constructed and can rely on it.

Until now, we discuss the validity of LIQ and ACC. Another thing that is worthwhile discussing is whether it is correct to use VMG instead of HML. The main difference is that HML is adjusted for the size effect, whereas VMG is not. To check the validity of VMG we first perform the correlation between them and next to check whether our main results hold with HML instead of VMG.

The correlation between VMG and HML is 0.748. The correlation between those two factors is high. This is not surprising because both strategies are based on the same variable (B/M) and the same breakpoints, although it is not perfectly correlated with each other due to that HML is adjusted for size.

The next step we check whether our result change significantly when we use HML instead of VMG. We perform the same regressions as in empirical analysis section 4.5, but only regression four and five where the alpha becomes statistically insignificant.

For the fourth regression the estimated alpha has a mean of 0.001 and a t-statistic of 0.62, while for the fifth regression the estimated alpha has a mean of 0.003 and a t-statistic of 1.58. We conclude that the main conclusion still holds when we use HML instead of VMG.

CHAPTER 5: DISCUSSION

Before we conclude our thesis based on our findings on ACC and LIQ, we address a few topics that are worth discussing in relation to our results on contrarian investing. First, we discuss on how we answer the underlying question whether the contrarian strategy is risky. Next, we continue discussing why ACC and LIQ explain the contrarian strategy. Finally, we argue why one should use ACC and/or LIQ instead HML.

In the empirical analysis section 4.5, we find that the alpha for the value minus glamour strategy is statistical insignificant when controlling for risk factors ACC and LIQ. This finding concludes that the value strategy is fundamentally riskier than glamour strategy. This is an interesting finding in our thesis. To obtain this result we perform the monthly regression of value minus glamour returns on the risk factors ACC, CAPM BETA, LIQ, SMB, and UMD. We do not control for HML in our model because value minus glamour is equivalent to it. In addition to that we wish to use the risk factors we construct instead of HML to see the if these risk factors capture the HML unexplained risk.

For our study, we do not use Fama-French 3 factor model or Carhart model directly. The difference between our model and Fama-French 3 factor model and Carhart model is that we are using the value minus glamour monthly returns in the left-hand side of the regression and not control for HML in the right-hand side of the regression. Hence, we can say that our model is inspired by Fama and French 3 Factor and Carhart model. We believe the approach we use is correct in answering the question of whether contrarian strategy is risky or not.

The result of the empirical analysis section 4.5 contradicts with section 4.4 which concludes that it is hard to gives risk-based evidence of value minus glamour strategy. These two sections yield different results, from the fact that they use different methods in investigating the riskiness of the contrarian strategy. The empirical analysis section 4.4 uses year by year returns of value minus glamour to see the downside of the value strategies while section 4.5 uses a model inspired by Fama and French 3 factor model to investigate the risk of the value minus glamour strategy. In our model we are not checking the downside of the value strategy rather we are investigating which kind of risk drives the value premium. Hence, we believe that the model we use in section 4.5 is better in investigating which risk is associated with the value premium.

Now we elaborate why ACC and LIQ explain the value minus glamour strategy. First, we start by explaining LIQ followed by ACC.

We know that illiquid stocks are not easy to sell, and investors must be compensated for holding these stocks hence yield higher returns. From this, we draw a conclusion that the liquid stocks are expensive and illiquid stocks are cheap. The strategy of the buying cheap stocks and selling expensive using liquidity measure yields high return. Since the same strategy applies for the value and glamour stocks, we believe that the value minus glamour strategy, is simply selling liquidity while taking on illiquidity.

Buying low-accruals stocks and selling high-accruals strategy yields higher return for the accruals component since low-accruals firms are value stocks and vice versa. This is another dimension of the value minus glamour strategy. This is a strategy of buying cheap stocks and selling expensive stocks hence this may be a reason why ACC explains value minus glamour strategy.

Finally, we discuss on why we think ACC and LIQ are important in explaining the value minus glamour strategy compared to HML.

When we perform the Fama-MacBeth regression in the empirical analysis subsection 4.3.2, we find that Accruals and Amihud ratio have higher statistically significant compared to the B/M characteristic in explaining returns. Since we are using these characteristics to create the risk factors, we believe that LIQ and ACC have high statistical power in explaining the returns of the value minus glamour strategy than HML.

We know that HML is a proxy for risk in other words it is capturing the unknown risk. We agree on that however according to our findings the risk that HML is capturing is [6]ACC and/or LIQ. Therefore, we think that controlling for risk that is coming from ACC and LIQ directly is more appropriate than using their proxy which is HML.

In the next chapter we summarize our findings and conclude our thesis by answering the question whether the value premium is due to risk or mispricing.

[6] We say ACC **or/and** LIQ is capturing the HML unexplained risk because, when we run the regression without controlling for ACC the abnormal return of value minus glamour is insignificant and vise versa. Additionally, when we run a regression and control for both ACC and LIQ, the abnormal return of the strategy becomes insignificant as well. Hence the HML effect is captured by ACC and LIQ individually as well as together.

CHAPTER 6: CONCLUSION

In this thesis, we study whether value premium is due to risk or mispricing. Using the methodology of Lakonishok et al. (1994), we successfully replicate the contrarian investment strategies and in addition to that we expand our thesis by adding four different risk characteristics (Accruals, Amihud ratio, turnover and Z-score).

Our results indicate strategies that involve buying value stocks have outperformed glamour stocks and risky stocks have outperformed non-risky stocks (Except Z-score) from end of April 1968 to April 1990. We also observe that by combining two strategies yield higher return than individual strategy. In the Fama-MacBeth regression, accruals and Amihud ratio has the highest statistical power in explaining returns, followed by B/M.

We continue by investigating the riskiness of the value minus glamour strategy, by creating a model which is inspired by Fama-French 3 Factor model and Carhart model. We regress monthly returns of value minus glamour strategy on all risk factors from the models mentioned- above (Except HML) and the risk factors we construct. The abnormal return (alpha) becomes insignificant when we control for risk factors ACC or LIQ together with the risk factors from the models mentioned-above. This finding suggests that the value minus glamour strategy can be explained by ACC and/or LIQ risk factors. Our results hold when controlling for a variety of elements and tests of robustness.

Hence, when investors implement the value strategies, they are facing the risk of buying illiquid stocks and hence market compensate them by giving them higher returns. Moreover, we notice the same appears for Accruals. Given our findings, we conclude that the reason for the value strategies to produce higher returns is because they are fundamentally riskier.

References list

A. Kausar, J. Lu, and R. J. Taffler. In denial? Stock market underreaction to going-concern audit report disclosures. Journal of Accounting and Economics, 38: 263-296, December 2004

B. Graham, and D. Dodd. Security Analysis. 1934

D. A. Lesmond, M.J. Schill, and C. Zhou. The illusory nature of momentum profits. Journal of Financial Economics, 71(2): 349-380, 2003

Desai, H., S. Rajgopal, and M. Vehkatachalam. Value-glamour and accruals mispricing. One anomaly or two?, The Accounting Review 79(2), 355-385, November 2003.

D. Dreman. Psychology and the Stock Market: Investment Strategy Beyond Random Walk. American Management Association. 1977

E. F. Fama and K. R. French. The cross-section of expected stock returns. The Journal of Finance, 47(2):427–465, June 1992

E. F. Fama, and K. R. French. Multifactor Explanations of Asset Pricing Anomalies. Journal of Finance, 51 (1): 55-84, March 1996

Investopedia contributors. (2018). Fama And French Three Factor Model. Investopedia. Retrived 16:03, June 13, 2018, from https://www.investopedia.com/terms/f/famaandfrenchthreefactormodel.asp

J. Chen, and Y. Chin. Revisiting value premium anomaly: fundamental or Noise Trader Risk. March 12, 2016

J. Choi. What Drives the Value Premium?: The Role of Asset Risk and Leverage, The Review of Financial Studies, 26(11), 2845-2875, November 2013

J. Jaffe, D. B. Keim, and R. Westerfield. Earnings Yields, Market Values, and Stock Returns, Journal of Finance, 44(1): 135-148, March 1989

J. Lakonishok, A. Shleifer, and R.W. Vishny. Contrarian Investment, Extrapolation, and Risk. Journal of Finance, 49(5): 1541 – 1578, December 1994.

J. Stokes. (2013, February 13). Improving on the Altman Z-Score, part 2: The Ohlson O-Score. Stockopedia. Retrieved 14:58, June 13, 2018, from https://www.stockopedia.com/content/improving-on-the-altman-z-score-part-2-the-ohlson-o-score-70800/

K. Daniel and S. Titman. Evidence on the Characteristics of Cross Sectional Variation in Stock Returns, Journal of Finance, 52(1): 1-33, March 1997

L. K. C. Chan, Y. Hamao, and J. Lakonishok. Fundamentals and Stock Returns in Japan, Journal of Finance, 46(5): 1739-1764, December 1991

L. S. Bamber, N. Bhattacharya, and M. C. Dawkins. Systematic Share Price Fluctuations after Bankruptcy Filings and the Investors Who Drive Them. Journal of Financial and Quantitative Analysis, 42 (2): 399-419, 2007

L. Zhang. The Value Premium, Journal of Finance, 60(1):63-103, February 2005

M. Elgammel and D. G. Mcmilan. Value Premium and Default Risk. Journal of Asset Management, 15, 48-61. February 2014

M. M. Carhart. On Persistence in Mutual Fund Performance. Journal of Finance, 52(1): 57-82, March 1997

P. M. Fairfield, J.S. Whisenant, and T. L. Yohn. Accrued Earnings and Growth: Implications for Future Profitability and Market Mispricing. The Accounting Review, 78 (1): 353 – 371, January 2003.

R. G. Sloan. Do Stock Prices Fully Reflect Information in Accruals and Cash Flows about Future Earnings?, The Accounting Review, 71(3): 289-315, July 1996

S. Basu. Investment Performance of Common Stocks in Relation to Their Price-Earnings Ratios: A Test of the Efficient Market Hypothesis. Journal of Finance, 32(3): 663-682, June 1977

S. Satchell. Forecasting expected returns in the financial markets. Academic Press, July 16, 2007

V.V. Acharya, Y. Amihud, and S. Bharath. Liquidity Risk of Corporate Bond Returns: A Conditional Approach. Journal of Financial Economics, 110(2): 358-386, November 2013

Wikipedia contributors. (2017, December 9). Altman Z-score. In Wikipedia, The Free Encyclopedia. Retrieved 14:53, June 13, 2018, from https://en.wikipedia.org/w/index.php?title=Altman_Z-score&oldid=814580065

Wikipedia contributors. (2016, November 13). Ohlson o-score. In Wikipedia, The Free Encyclopedia. Retrieved 14:54, June 13, 2018, from https://en.wikipedia.org/w/index.php?title=Ohlson_o-score&oldid=749301482