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Market Regimes, Investor Sentiment And Stock Classification=Excess Return

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Abstract
There are a number of papers studying on factors that affect stock returns. For forty years, the researchers have tested all of macroeconomic and firm specific factors theoretically and empirically in developed and developing markets. But the results are inconsistent with theories and models based on these theories. For this reason, there have been new concepts to explain stock returns as investor sentiment. Previously, these concepts are used explaining anomalies of efficient market hypothesis. But it has seemed that these concepts explain not only anomalies but also market regimes.
In this paper, I investigate whether three factors (market regimes, stock classification and investor sentiment) explain stock's excess return or not. I classify stocks via market based indicators; Book to Market (B/M) ratio and Return on Equity (ROE), and I suggest that market has two regimes and determine these regimes using Markov Process. Finally, I test my hypothesis that different stock classification and being in different market regimes effect on investor sentiment which is thought to determine stock excess return? I find that all of factors in this paper determine sock excess return strongly.

1. Introduction

The traditional models of financial instrument valuation assume that all of investor in the market is rational while they decide to buy or sell any securities. So, the market price must equal fair price and thus, there isn't any arbitrage opportunity. In 1990's, some of authors Delong, Shleifer, Summers, and Waldmann (1990) and Shleifer and Vishny (1997)) find that investors are not objective, so some securities are overvalued or undervalued. In the following years, a lot of authors examined whether investor sentiment, with a generally accepted name, affects stock price or not. Schmeling (2007), Ding, Charoenwong, and Seetoh (2004), and Semmler and Zhang (2009) are examples of these studies.

Today, the studies focus on two main questions about investor sentiment. The first question is which stocks are affected by investor sentiment heavily or softly. The other question is what the best proxy for investment sentiment is. Moller, Norholm and Rangvid (2004), Schmeling (2009), Yu and Yuan (2011), and Baker and

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Wurgler(2006) are examples of these questions. Specially Baker and Wurgler(2006), measure the effect of investor sentiment on stock returns. They figure out that this affect is higher for "value" stocks which are highly subjective and have growth potential in the future. Also they find that these stocks have low returns after the high sentiment period. On the other hand, Tsai (2017), Canbas and Kandir (2009), Brzeszczyński, Gajdka and Kutan (2015) are examples of the investor sentiment in the emerging markets.

I add the third question in the investor sentiment literature with this study. Third question is "Does the effect of investor sentiment on stock prices vary depending on market timing?" According to behavioral finance theory the investors buy or sell stocks with same motivation, so they act like a herd. Lee and Swaminathan (2000), Dorn et al. (2008), Barber et al. 2009), Smith et al. (1988), Lakonishok et al. (1991), Wermers (1999) and Ben-Rephael et al. (2012) are examples of systematic investor behavior. According to these studies, investors buy or sell similar type stocks at the same time and this movement creates a wave in the market. In this study, I set up a model which has three dimensions; investor sentiment, stock classification and market timing. I use the consumer confidence index as the proxy of investor sentiment. I use six factors, three of them are market-related and others are business-related, to classify stocks. To determine market timing, I use MS-GARCH model which is actually used to determine the time varying volatility at two regimes.

Unlike the efficient market hypothesis (EMH), there are two types of investors in the investor sentiment literature; individual investors who tend to act be a member of herd and arbitrageurs who make money over herd. Many of literature about investor sentiment turned to predict the securities prices using sentiment proxies. Although there is a large body of literature on this issue, current research focuses on the.

The main assumption of efficient market hypothesis is that stock prices include all of the information what investors can access. In this case, there is not any arbitrage opportunity in the capital market because investors are rational, and all of investors use the same risk measure for any securities, so finding an overvalued or undervalued asset is impossible. Also, investors trade randomly and they can't influence prices in order to their transaction volume. In summary, there are no factors affecting the market as investor sentiment.

The empirical studies which test to EMH tried to explain the deviations in theory by anomalies. But, in the 1990's, some studies, i.e. Jegadeesh and Titman (1993), Bernhard (1993), Barberis et al. (1998), and Hong and Stein (1999), proved that stocks have different return in the different periods. Investors show different reaction to information about stock prices, so this creates anomalies in the market. The behavioral finance calls it bias (i.e. anchoring, conservatism, overconfidence, representativeness and herding behavior). DeLong et al. (1990), Bikhchandani et al. (1992), Barberis et al. (1998), Odean (1998), Hong and Stein (1999), Frazzini (2006), and Barberis and Xiong 2009 are examples for heuristics in the behavioral finance.

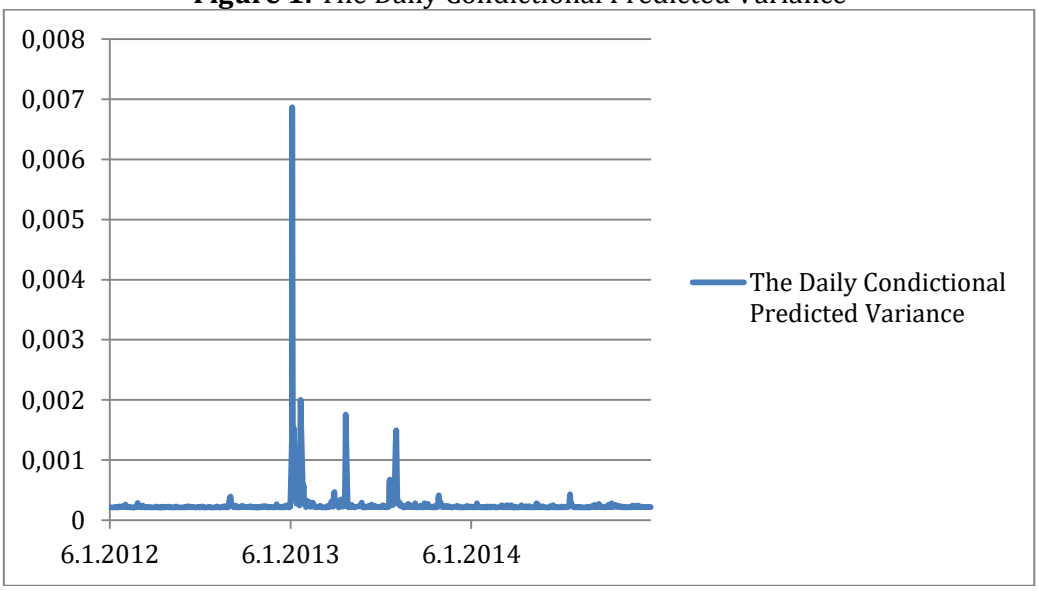
The anomalies in the efficient market hypothesis and the biases in the behavioral finance are combined using investor sentiment proxies. The biases just explain investor's individual characteristics when he or she is trading. The anomalies just explain the deviations from investors in the market. Because these factors create a wave which arises from investor behaviors, the sentiment explains stock returns with both of them. Wurgler (2006), and Brown and Cliff (2004) are examples that sentiment is a systematic movement in the market, thus not random.

I show that there are three factors which determine the stock price variability as systematically by retail or institutional investors. These factors combine investor sentiment or in other words "investor inducement".

2. Model

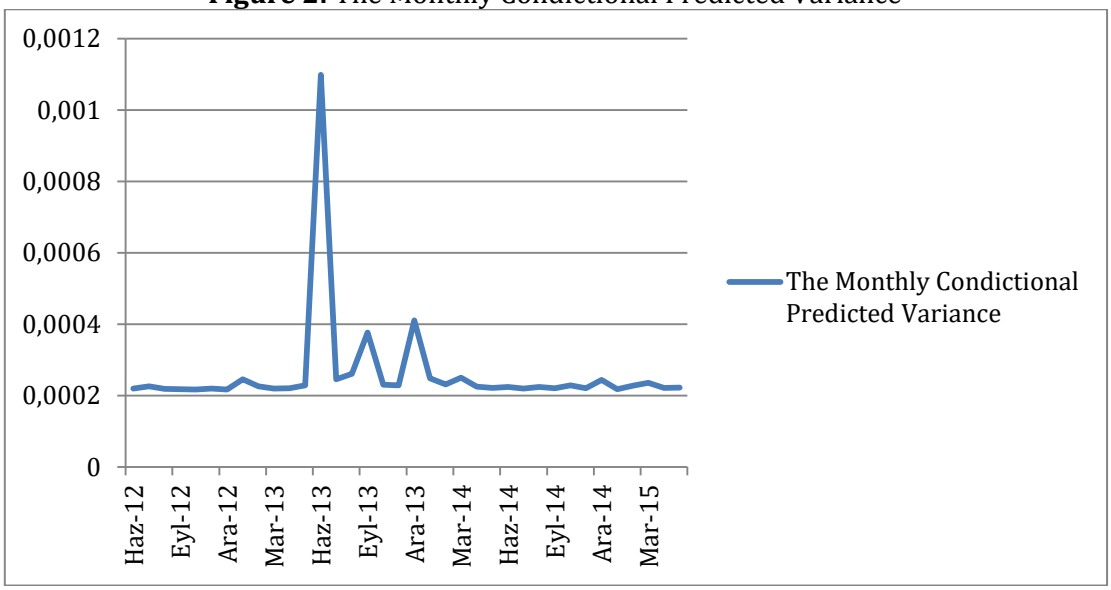
It is assumed that there are two regimes in sock markets as Bull and Bear. Also, some authors accept three regimes as Bull, Bear and Flat. But volatility constantly changes over time. For this reason, stock prices change in whichever direction they change, volatility will increase or decrease. The first factor which affect stock price is the market regime of volatility. I determine market regime timing by using two methods. The main method is Markov Switching GARCH Model (MS-GARCH). This method uses GARCH specification to find time varying variance. Also it assumed that there are two regimes in market for volatility; stable regime and non-stable regime (Bauwens, Preminger & Rombouts, 2016). After finding MS-GARCH parameters (persistence parameter, constant parameter, and mean reversion parameter), I predict daily and monthly conditional variances for June 2012 – May 2015.

Figure 1: The Daily Condictional Predicted Variance



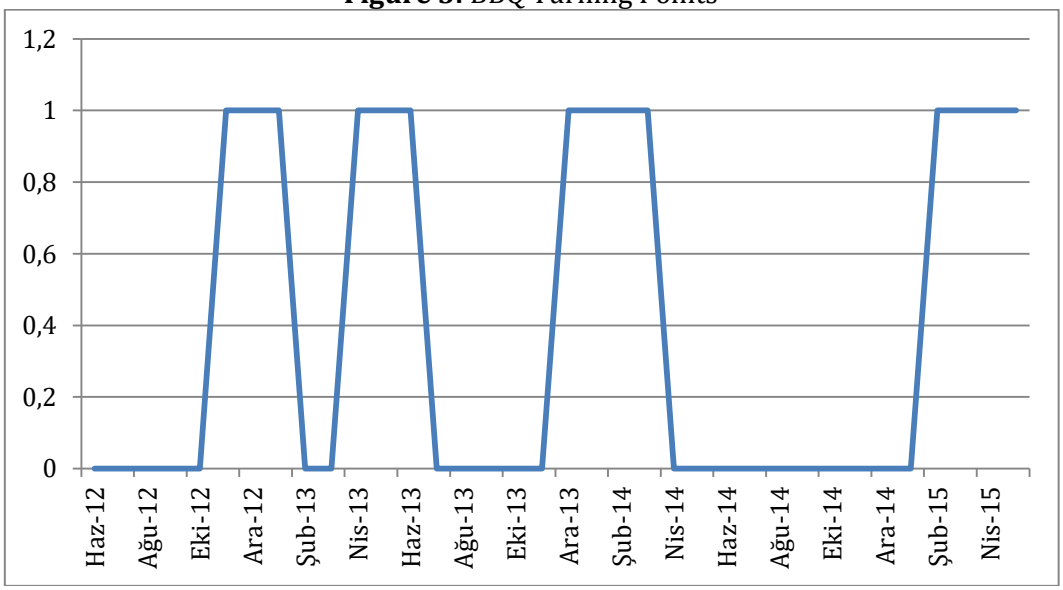
As Figure 1, the variance peaks occurred on 30th January 2013, 4th and 21th June 2013, 28th August 2013, 20th September 2013, 18th December 2013, 27th March 2014, and 17th December 2014. This shows that the second half of 2013 was an abnormal period for volatility. Also this regime had continued with gradually declining until 17th September 2014.

Figure 2: The Monthly Condictional Predicted Variance



If we look at it monthly, we can see an abnormal volatility period between March 2013 and January or March 2014. This shows that there is a high volatility period between March 2013 and March 2014. To confirm this result, I use BBQ algorithm. The BBQ algorithm is used for dating any economic time series. Bry and Boschan (1971) formed a cyclical turning points algorithm to dating for a selection problem. I use the Harding and Pagan Matlab Codes to form Bry-Boschan Quarterly (BBQ) algorithm.

Figure 3: BBQ Turning Points



At Figure 3, we can see just turning points in volatility. But if we want to time volatility regimes, we would determine the periods between peaks and troughs. In this way, I find the periods as follow:

Table 1: BBQ Turning Points

Peak	Trough	Period
November 2012	February 2013	High: November 2012-January 2013 Low: February 2013-March 2013
April 2013	July 2013	High: April 2013-June 2013 Low: July 2013-November 2013
December 2013	April 2014	High: December 2013-March 2014 Low: April 2014-January 2015

Because BBQ algorithm catches all turning points in volatility, it doesn't give the market volatility periods as ready. But we can see that there is an abnormal movement in volatility between April 2013 and March 2014. Volatility changed two times in this period and high volatility took a long time at each part of this periods. Finally, because two models give same results, I can say that the MS-GARCH model determine the volatility regimes periods correctly.

The second factor is investor sentiment to explain excess returns. In the efficient markets, it is assumed that all of stocks in market are fairly priced, so investors cannot obtain excess return. But, last studies have revealed that investors act as a group and they choose same stocks systematically. Finance world calls it "investor sentiment".

The models based on investor sentiment are separated two groups. The first is a model that attempts to explain the behavior of the market by way of the investor using inductive method. These use biases (overconfidence, representativeness, herd behavior, etc.) in behavioral finance (Shefrin; 2005). But, it is impossible to reach a single truth with these models reaching the conclusion that there are differences of opinion among investors. The psychology that dominates the market is trying to be explained with similar forms. The second group of models is trying to explain the behavior of the investor by coming from the macroeconomic variables using deductive method (Baker & Wurgler; 2007).

Models based on the investor sentiment have been the subject of literature since 1980's. However, the first researchers who test the wrong pricing on the market do not have a theoretical base. DeLong, Shliefer, Summers and Waldmann (1990) have divided investors into two groups; 1) the rational arbitrageurs without sentimental biases 2) Non-rational traders with external direction. In the light of this classification, I can do a new classification about investors and markets; Investors have two groups as directed (sentimental) investors and leading (inducer) investors and markets have two groups as volatile market (directed or induced) and stable market (without sentiment or inducement)

I use the consumer confident index to measure investor sentiment. In literature, many different proxies are used to measure it. The close-end fund discount, stock turnover, the average first-day returns on IPOs, and the dividend premium are examples for investor sentiment proxies. Also Baker–Wurgler (2006) constructed a sentiment index using six proxies. But, there is not any evidence which is best. The consumer confidence index has been used widely at the literature. For this reason, I use consumer confidence index as investor sentiment proxy.

Table 2: Portfolios' Statistics and Performance Measures

The Portfolios Constructed According to ROE					
Min.		**2012**	**2013**	**2014**	**2015**
1	Mean	-0,8625	0,015433	0,003556	0,013975
	St.Dev.	0,086499	0,032065	0,080056	0,044961
	Sharpe	-0,17687	0,304458	-0,04612	0,149608
	Beta	1,145773	0,353462	0,805881	0,619972
	Treynor	-0,01335	0,02762	-0,00458	0,01085
2	Mean	-0,82345	0,024245	-0,00157	-0,00084
	St.Dev.	0,078994	0,032755	0,091902	0,044438
	Sharpe	-0,18813	0,567075	-0,09592	-0,18211
	Beta	1,02003	-0,00963	0,897213	0,583821
	Treynor	-0,01457	-1,92917	-0,00982	-0,01386
3	Mean	-0,6455	0,040229	0,005288	0,028015
	St.Dev.	0,079136	0,04433	0,086673	0,044537
	Sharpe	-0,17072	0,779568	-0,02263	0,466265
	Beta	0,865193	0,238029	0,863622	0,491924
	Treynor	-0,01562	0,145186	-0,00227	0,042214
4	Mean	0,59245	0,04597	0,002828	0,008771
	St.Dev.	0,063252	0,045468	0,070428	0,040257
	Sharpe	-0,01285	0,886309	-0,06277	0,037817
	Beta	0,629385	0,077368	0,58205	0,486587
Max.	Treynor	-0,00129	0,520873	-0,00759	0,003129
The Portfolios Constructed According to B/M Ratio					
Max		**2012**	**2013**	**2014**	**2015**
1	Mean	-1,95534	0,022434	-0,00961	0,004326
	St. Dev.	0,082922	0,034734	0,089693	0,04631
	Sharpe	-0,30038	0,482621	-0,1805	-0,06312
	Beta	1,066178	0,180772	0,893854	0,661907
	Treynor	-0,02134	0,092731	-0,01811	-0,00442
2	Mean	-0,80323	0,043896	-0,00375	0,003151
	St. Dev.	0,082209	0,048925	0,093106	0,059925
	Sharpe	-0,1637	0,781294	-0,11096	-0,06838
	Beta	0,890353	0,241233	-0,10675	0,911075
	Treynor	-0,01376	0,158455	0,096773	-0,0045
3	Mean	-0,3734	0,042943	0,005596	0,012548
	St. Dev.	0,080632	0,04879	0,078346	0,046924
	Sharpe	-0,11263	0,763936	-0,01253	0,112943
	Beta	0,882551	0,091812	0,770965	0,573843
	Treynor	-0,00928	0,405967	-0,00127	0,009236
4	Mean	1,49856	0,040833	0,007457	0,025466
	St. Dev.	0,060866	0,03524	0,073651	15,85302
	Sharpe	0,156203	0,997799	0,011944	0,001149
	Beta	0,595922	0,112387	0,656555	0,54261
Min.	Treynor	0,01488	0,312869	0,00134	0,033573

Third factor is stock classification to explain excess return. Stocks can be classified in different ways. But I look for what should we classify to understand investor's point of view. For this reason, I use two indexes, which are investors can easily reach, related company and market. These are Return on Equity (ROE) and Book to Market (B/M) Ratio. First, I set up four portfolios according to B/M ratio from highest to lowest. The portfolio which has highest B/M ratio is "value" stock's portfolio, so stocks in this portfolio have low capitalization, high growth potential

and high risk. The portfolio which has lowest B/M ratio is "growth" stock's portfolio, so stocks in this portfolio have high capitalization, low growth potential and low risk. Second, I use ROE to construct four portfolios to classify stocks according to company performance. The first portfolio consists of stocks that have negative ROE and it represents "value" stocks. The fourth portfolio contains "growth" stocks with highest ROE.

I use Istanbul Stock Exchange monthly and daily data of June 2012-June 2015 to apply my model. Firstly, I find stock returns and form portfolios using two indexes. There are descriptive statistics and performance measures in following table.

While the ROE portfolios are ranked from lowest to highest, the B/M portfolios are ranked from highest to lowest. Because the lowest ROE and the highest B/M indicate "value portfolio" and the highest ROE and the lowest B/M indicate "growth" portfolio. B/M portfolios show stable performance all the years. The fourth portfolio which has lowest B/M has highest mean and Sharpe ratio all the year. The B/M portfolios show stable performance. But the ROE portfolios are not so successful. These are ranked different in terms of all indicators. In the period of March 2012 – March 2013 (the table above is seen as the year 2013), all of portfolios have the highest Sharpe ratio. The high volatility regime dominate in market and investors can get excess returns form all portfolios. Also, the highlight result is that if investors follow the investment strategy in terms of B/M or ROE, they can get highest excess return using the growth stocks in the volatile market.

Table 3: Regression Results. Dependent variables; Stock returns for six portfolios. Independent variable; Consumer Price Index

	1th Portfolio (Value Stocks)						2th Portfolio (Mild Value Stocks)					
B/Mt	39,869						29,389					
	(4,522)						(7,210)					
B/Mt-1		-20,935						-1,324				
		(-0,776)						(-0,053)				
B/Mt-2			-32,575						-27,659			
			(-1,214)						(-1,116)			
ROEt				23,937						31,683		
				(0,962)						(1,170)		
ROEt-1					-19,723						-8,890	
					(-0,780)						(-0,320)	
ROEt-2						-32,236						-30,041
						(-3,289)						(-2,090)
Adj-R2	0,027	-0,008	0,010	-0,001	-0,008	0,014	0,010	-0,022	0,005	0,008	-0,0209	0,012
	3th Portfolio (Mild Growth Stocks)						4th Portfolio (Growth Stocks)					
B/Mt	24,915						13,510					
	(0,947)						(0,534)					
B/Mt-1		8,438						-24,250				
		(0,314)						(-0,953)				
B/Mt-2			-45,252						-20,673			
			(-1,729)						(-0,812)			
ROEt				30,583						26,837		
				(1,202)						(0,998)		
ROEt-1					-6,822						3,141	
					(-0,261)						(0,114)	
ROEt-2						-31,597						-33,998
						(-0,220)						(-0,253)
Adj-R2	-0,002	-0,020	0,042	0,009	-0,020	0,010	-0,015	-0,002	-0,007	-0,0001	-0,021	0,012

As you see in the table, I didn't find powerful relation variables. But there are several important finding from the results. First and second B/M portfolios have positive Adjusted R2 and significant t values. These are the value and the mild value portfolios. They are more influenced by investor sentiment. You can see same results in the ROE portfolios. The first two portfolios, value and mild value stocks portfolio, have positive adjusted R2 and significant t-values. But the important difference from the B/M is that these results can be seen in 2th lagged portfolios. Investors can get this information after two months. The highlight result

is the ROE coefficients in all models are negative. According to this, investors believe that if the ROE is high, dividend will be high, so price will down.

3. Conclusion

The variables used to explain the returns of equities are not stable in terms of markets and periods. Empirical studies made for a very long time prove this judgment completely. Macroeconomic variables (CAPM, Arbitrage Pricing Theory etc.) testing theoretical assumptions and financial information of the business (the Fama-French two factors, three factors model etc.) are the most frequently used variables. However, the variables used were not limited to this, even the variables such as the weather (Lu and Chou; 2012) and the region in which investors lived were also used (Huang et all., 2016).

The assumptions about stochastic processes for explaining stock returns are not always valid for even the most advanced markets. It is not possible to ignore these assumptions because all the models working on the assumption that the returns have normal distributions use stochastic processes. A solution is found by using multiple distributions together for processes that cannot be explained by a single distribution. However, at this point, the application of the theoretical model has become either very difficult or impossible.

Efforts to explain the stock return with econometric models stem from the unpredictability of investor behavior. The fact that investor behavior and the investment strategy that can be used accordingly will be as numerous as fingerprints, which has led to the unpredictability of stock price and return processes. But that is not the case. It is not difficult to understand this but it can be hard to accept. The fact that investors are making the same investment decisions unaware of each other shows that a systematic process dominates the market. First, this systematic behavior is interpreted as the fact that the process has an autoregressive process. GARCH, Asymmetric GARCH, Exponential GARCH models etc. tried to explain the returns by setting off from this hypothesis. However, it was concluded that the fluctuations in the currencies must be explained by different regimes and these models are made to disclose two or more market regimes. For this, the Markov Switching Model (MS-GARCH) is widely used today.

The main feature that differentiates this study from other studies is that it tries to explain the excessive return of the shares with three factors that guide investors' behavior. Using the MS-GARCH model with two market regimes (high volatility and low volatility), the investor is informed about the periods when the market is more risky and where there are more opportunities for excessive returns. In order to classify the shares, B/M ratio is used as the most frequently used market-based stock selection criterion and ROE is used as the company-specific benchmark. Thus, shares were classified based on the investor's point of view. As a third factor, the relationship between the investor sentiment and returns has been analyzed. Thus, the relationship between the average returns of portfolios constructed based on the selection methods used by investors in different market regimes and the consumer confidence index, which is the indicator of investor orientation, was investigated by the regression method.

With this model, investors may have the chance to obtain an excessive return in from the market against the risk they experience in periods of high volatility. If they invest in Growth shares during these periods, they will get the highest chance of meeting the lowest risk. This result provided parallel findings with other empirical studies and disproved the judgment which was widespread but wrong that a higher return would be obtained from value equity shares.

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