Volatility of Dynamic Pricing: An Empirical Study of the Low Cost Airline Industry in Thailand

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Abstract

The purposes of the study were to find and compare volatility in ticket prices of low cost airline companies for domestic and international flights departing Bangkok to various destinations such as Chiang Mai, Phuket, Tokyo and Melbourne as well as to compare relative volatility between domestic and international ticket prices in a particular time frame. Econometric model is used in this research to find any dynamic pricing volatility in airlines ticketing system during the study period of 6 months. Daily ticket prices were obtained via official airline. Microsoft Excel NumXL (addins) was used to construct and examining volatility model to calculate the GARCH (1,1) results.

By observing ticket price changes in various flight routes including domestic and international routes to analyze and identify volatility level of the change in ticket prices over the study period of 6 months, we found that level of volatility increases as time to departure approaches. Empirical analyses reveal that distributions of the change in ticket prices deviate from normality with volatility varying over time. The results of the volatility tests show that the ticket prices were quite volatile when purchasing tickets close to departure date.

Keywords: volatility, dynamic pricing, price optimization, airline industry in Thailand, GARCH model

Introduction

In recent years, there was a rapid growth in airline industry especially in Asian countries. An increase in numbers of new entrants stimulated competitive environment in the industry. International Air Transport Association (IATA) (2019) made some prediction that number of passengers would grow from 3.5 billion to 7 billion within 2037 and could create 100 million jobs globally. Thailand is expected to enter the top 10 markets in 2030, according to the forecast.

Airlines update their airfares frequently utilizing advanced dynamic pricing and revenue management systems, in which they often adjusted ticket prices over time as time to departure approaches. Due to demand fluctuation, airlines generate booking curves for each flight, which demonstrates the predicted progression of their ticket prices and booking for individual flight. When demand falls short of the booking curve, airlines usually reduce ticket

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prices. On the other hands, during excess demand may result in an upward change in ticket prices. The sensitivity level of dynamic pricing system illustrates how rapidly prices are adjusted to reflect changes in the forecasted demand.

Therefore, the sensitivity of these systems could very well describe the level of uncertainty about demand in airline business. Alternatively, price volatility could be determined by the sensitivity of these systems. Ticket price volatility could be the outcome employed by airliners.

Research Questions

1. How significance is the change in ticket prices for domestic flights during normal day?
2. How significance is the change in ticket prices for domestic flights during public holiday/long weekend?
3. How significance is the change in ticket prices for international flights during normal day?
4. How significance is the change in ticket prices for international flights during public holiday/long weekend?

Research Objectives

1. To find and compare volatility in ticket prices for domestic flights departing Bangkok to Chiang Mai and Phuket during normal working day.
2. To find and compare volatility in ticket prices for domestic flights departing Bangkok to Chiang Mai and Phuket during public holiday/long weekend.
3. To find and compare volatility in ticket prices for international flights departing Bangkok to Tokyo and Melbourne during normal working day.
4. To find and compare volatility in ticket prices for international flights departing Bangkok to Tokyo and Melbourne during public holiday/long weekend.

Literature Review

Dynamic Pricing Model

It is assumed that the airline sells only one type of service/product, in this case, flight ticket. In each time period $t \in \mathbb{N}$, airliner sets on a selling price $p_t \in [p_l, p_h]$, where $0 \leq p_l < p_h < \infty$ denote the lowest and highest acceptable price. After selecting the acceptable price, the airline notices demand d_t, which is a apprehension of the random variable $D_t(p_t)$. Conditional on the selling prices, the demand in different time frame is independent. According to Broder and Rusmevichientong (2012), the expected demand in period *t*, against a price *p*, can be formulated as:

$$E[D_t(p)] = M(t) + g_t(p).$$

where $(M(t))_{t\in N}$ is a stochastic process, and this could be unobservable for the airline, and taking values in an interval $M \subset R$.

The function g_g model the dependence of expected demand on selling price. These variable are assumed to be known by airliners. Later, by observing demand, the airline collects revenue $p_t d_t$, and proceeds to the next period. Hence, this process maximizes airline's revenue (Besbes and Saure 2012).

$\mathcal{F}_t$ can be generated by $d_1, p_1, M(1), \ldots, d_t, p_t, M(t), \mathcal{F}_o$ the trivial σ-algebra, and write $\epsilon_t = d_t - g_t(pt) - M(t)$; then we assume that $M(t)$ and ϵ_t are $\mathcal{F}_{t-1}$ measurable, for all $t \in N$. Furthermore, it is possible to impose the following mild conditions on the moments of $M(t)$ and ϵ_t: there are positive constants σ_M and σ, such that

$$\sup_{t\in N} E[M(t)^2|\mathcal{F}_{t-1}] \leq \sigma_M^2 \ a.s. \quad \text{and} \quad \sup_{t\in N} E[\epsilon_t^2|\mathcal{F}_{t-1}] \leq \sigma^2 \ a.s.$$

In addition, $r_t(p, M) = p(M + g_t(p))$ denote the expected income in period $t \in N$, when the market procedure equals M and the selling price is set at p. The price that generates the highest value of expected revenue, given that the current market equals M, is denoted by $p_t^*(M) = p \in [p_t, p_h] r_t(p, M)$.

Hence, it is possible to assume that for all $M \in \mathcal{M}$ and all $t \in N$ the revenue function $r_t(p, M)$ is identified as unique optimum $p_t^\#(M) \in R$ which satisfying function $r'_t\left(p_t^\#(M), M\right) = 0$.

According to Cope (2007), the value of the market process and the corresponding optimal price are unknown to airliners. The goal of the airline is to determine a pricing policy that minimizes this loss of revenue. In order to assess the quality of a dynamic pricing policy, Φ, Cope (2007) models this pricing policy into the following two functions.

$$\text{AR}(\Phi, T) = \frac{1}{T-1}\sum_{t=2}^{T} E\left[r_t\left(p_t^*\big(M(t)\big), M(t)\right) - r_t\big(p_t, M(t)\big)\right]$$

$$\text{LRAR}(\Phi) = \limsup_{T \to \infty} \text{AR}(\Phi, T).$$

Demand Function in Airline Industry

By applying demand function in Dolan and Jeuland's (1981) models, the heterogeneity of demand for a ticket of the flight can be explained as follows.

$$N(t,\mathcal{H}_t) = (N_1(t,\mathcal{H}_t), \dots, N_d(t,\mathcal{H}_t))$$

where $N_j(t,\mathcal{H}_t)$ is the cumulative potential demand up to time t from factor j given the available information $\mathcal{H}_t$.

In dynamic pricing condition, it is possible for the airlines with the ability to partially serve demand when the airlines produce profit. Given the sale, demand and price processes, the dynamics of the available capacity are functioned by the following conditions.

$$C_t = C_0 - AS(t) \text{ and } S(t) \leq D(t, P, \mathcal{H}_t) \text{ for all } t \in [0, T]$$

Therefore, the ticket price is the only functioned that the airline can implement to reach maximum profit in dynamic pricing strategy (Raman and Chatterjee 1995).

According to Gallego and Ryzin (1994), to forecast and predict the demand for an appropriate flight schedule, the model take deterministic demand into a set of different factors, which each function addressing a specific aspect of the problem in the dynamic pricing process, where:

$$D^{det}(t,p,\mathcal{H}_t) = \mathcal{D}(t)\,\mathcal{G}(p)\,\mathcal{F}(\mathcal{H}_t)$$

Denoted that $\mathcal{D}(t)$ is an estimate of the market size as a function of schedule/time, $\mathcal{G}(p)$ captures price elasticity and $\mathcal{F}(\mathcal{H}_t)$ shows the influence of the available information on customers buying behavior.

Diffusion models are widely used to model fluctuation of demands (Raman and Chatterjee, 1995). In this case, a population of customers of size N gradually purchases the flight ticket. In diffusion model, the rate of purchase/booking a flight at time t is given by:

$$\frac{d\mathcal{D}(t)}{dt} = pN + (q-p)\mathcal{D}(t) - \frac{q}{N}\mathcal{D}^2(t)$$

Volatility in Stochastic Process

According to Bertsimas and Perakis (2006), volatility can be measured by the fluctuation between the demands and ticket prices, so called volatility in dynamic pricing, given the demand rate at time t and price level p is $\lambda(t,p)$. We assume that a company sets the ticket at price $p(t,n,r)$ in the state (n,r) at time t. Thus, according to the continuous-time Markov chain, it is possible to make transitions from the state (n,r) to the state $(n-1, r+p)$ with a rate $\lambda(t, p(t,n,r))$. Let $P_{(n,r)}(t)$ be the probability that the function is in the state (n,r) at time t. Then, $P_{(n,r)}(t)$ is governed by the continuous time Markov chain for ordinary differential functions as follow:

$$\frac{dP_{(n,r)}}{dt} = -\lambda\big(t, p(t,n,r)\big)P_{(n,r)}(t) + \sum_{r':r'=r-p(t,n+1,r')} \lambda\big(t, p(t,n+1,r')\big)P_{(n+1,r')}(t)$$

for $0 < n < Y_t,\ 0 \le r \le (Y_T - n)P_{max'}$

$$\frac{dP_{(0,r)}}{dt} = \sum_{r':r'=r-p(t,1,r')} \lambda\big(t, p(t,1,r')\big)P_{(1,r')}(t)$$

for $0 \le r \le Y_{tPmax'}$

$$\frac{dP_{(Y_T,o)}}{dt} = -\lambda\big(t, p(t,Y_T,0)\big)P_{(Y_T,0)}(t),$$

with the initial conditions $P_{(n,r)}(T) = 0$ for $(n,r) \in \bar{\mathcal{P}} \setminus (Y_T,0)$ and $P_{(Y_T,0)}(T) = 1.$

Methodology

We use Excel as a method of volatility estimation and forecasting. Based on the daily airline ticket prices. Generalized Autoregressive Conditionally Heteroscedastic (GARCH) model is used in estimating and forecasting the volatility. The Excel program on which the estimation and forecasting is constructed by using appropriate calculation and functions to ensure its reliability in volatility estimation. Moreover, the most commonly used method for comparing the evaluation of econometric models is presented.

The general process for a GARCH model involves three steps. The first is to estimate a best-fitting autoregressive model. The second is to compute autocorrelations of the error term. The third step is to test for significance.

Data Collection

Data of ticket prices in term of time series for both domestic and international flights departing from Bangkok had been observed.

For domestic routes, the most popular routes were selected, i.e. Bangkok to Chiang Mai, and Bangkok to Phuket.

For international routes, Bangkok to Tokyo, and Bangkok to Melbourne were selected. Airlines ticket prices are collected from Nok Air, Thai AirAsia, NokScoot and Jetstar webpages. We compared ticket prices and volatility between normal day and long weekends (including public holidays) in this study.

All prices with each departing schedule within a day are recorded up to six months in advance during the study period during January 2019 to August 2019. We also recorded price changes of the same flight when booking at a different day compared to the base day (t) up to 180 days ahead (t_{+180}).

Research Model and Tool

GARCH model allows the conditional change in variance over time as well as changes in the time-dependent variance, which includes conditional increases and decreases in variance. As such, the model introduces a new parameter "*p*" that describes the number of lag variance terms:

- *p*: The number of lag variances to include in the model.
- *q*: The number of lag residual errors to include in the model.

$$x_t = \mu + a_t$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \, \alpha_{t-i}^2 + \sum_{j=1}^{q} \beta_j \, \sigma_{t-j}^2$$

$$\alpha = \sigma_t \times \epsilon_t$$
$$\epsilon_t = P_v(0,1)$$

Results and Discussion

In GARCH(1,1) model estimates, we used data of ticket prices with each departing schedule within a day up to 6 months in advance. M_6 represents the volatility of ticket price for a period of six months (or 180 days, D_{t+180}) in advance, where $M_6 = D_{t+180}$, $M_5 = D_{t+150}$, $M_4 = D_{t+120}$, … , $M_1 = D_{t+30}$. M_2 and M_3 represent the fluctuation of ticket price changes for a period of two and three months in advance respectively. $D_{t+1}...D_{t+7}$ are price changes of the same flight when booking at a different day compared to the base day up to 7 days ahead.

A. Domestic Flights (Normal Day)

i. Bangkok to Chiang Mai (operated by Nok Air) departure on Tuesday, 23rd July 2019, 16.00-17.40

ii. Bangkok to Phuket (operated by Thai Air Asia) departure on Tuesday, 23rd July 2019, 19.35-21.00

The ticket price volatility of domestic flights between Bangkok and Chiang Mai indicates low volatility during M_2 to M_4, where p=0.173 and q=0.1567. During this period, Nok Air had launched the promotion campaign "flying everyday low price at 750 Baht including taxes (Nok Air's promotional campaign during May-July 2019)". However, the volatility was significant higher when the departure time was less than one month, which the ticket prices started to increase with promotional exclusive, especially a week before departure where p=0.324 and q=0.176.

The result of GARCH (1,1) for Bangkok to Phuket route indicates low volatility of ticket prices from m_4 to m_6 (February – April 2019), where p=0.1339 and q=0.0855. The volatility of ticket prices was increased during 3 months before departure, where p=0. 185 and q=0.1555.

In conclusions, for domestic flights during normal day, volatility of the ticket prices in dynamic pricing strategy in low-cost domestic airlines such as Nok Air and Thai Air Asia, measured by p and q, is considerably low throughout the study period.

B. Domestic Flights (Long Weekend / Mother day)

i. Bangkok to Chiang Mai (operated by Nok Air) departure on Friday, 9th August 2019, 16.00-17.40

ii. Bangkok to Phuket (operated by Thai Air Asia) departure on Friday, 9th August 2019, 19.35-21.00

The results of volatility test for domestic flight during long weekends between Bangkok and Chiang Mai route indicate high volatility between M_1 to M_3 (up to three months before departure), where (M_3) p=0.273 and q=0.1664; (M_1) p=0.357 and q=0.2348. This explains that travelers were planning advance during 30-60 days before departure date. During two weeks before departure, d_{t+14} to d_{t+14}, moderate volatility was but not very significant.

For Bangkok to Phuket route, we found that on-line ticket prices between Bangkok to Phuket during m_2 to m_6 (February–June 2019) were rather stable with slight increase in ticket prices because of Airline's promotional campaign, which were evident by low volatility of ticket prices during the study period. On the other hand, higher volatility of ticket prices was increased just a month before departure, we found a sharp increase in ticket prices during a month before departure. High volatility is identified during a week before departure. Especially during a week before departure where d_{t+1} to d_{t+5} where p were 0.3458, 0.3912, 0.3421, 0.3466, 0.3251 and q were 0.1833, 0.1587, 0.1888, 0.0987, 0.1234 respectively.

C. International Flights (Normal Day)

i. Bangkok to Tokyo (operated by Nok Scoot) departure on Tuesday, 23rd July 2019, 00.45-09.05

ii. Bangkok to Melbourne (operated by Jetstar) departure on Tuesday, 23rd July 2019, 21.25-10.30(D+1)

Bangkok to Tokyo route is considered one of the most popular for Thai people. According to Bangkok Post (2018), Japan is the top travel destination for Thai travelers, followed by China, Singapore and South Korea. The results show some fluctuation of volatility in ticket prices over the study period. We noticed low volatility during M_6. In addition, the ticket prices steadily rose overtime during the study period. Medium volatility in ticket prices occurred three months before the departure. High volatility was evident during three days before departure, where p was above 0.4. It was interesting to see that volatility of Nok Scoot ticket was moderate to high over 5 months before travel (flight from Bangkok to Tokyo). This could be explained that the ticket price was initially set a low price and the price was increase over time. Comparing to volatility of ticket prices by Jetstar, flight from Bangkok to Melbourne that the initial price was set rather high. Therefore, Jetstar's ticket price changes were less volatile when we compared to those by Nok Scoot. However, the ticket price volatility was significant during the last two weeks before departure on normal day.

On the other hand, Melbourne is not considered as a popular destination for Thai travelers. Jetstar operates flight between Bangkok and Melbourne every two days. The result of GARCH (1,1) for this route indicates low volatility of ticket prices from m_1 to m_6 (February – July 2019) for international departure on 23th July 2019 by Jetstar and arrives on the following day. In addition, during a week before departure, d_{t+1} to d_{t+7}, we observed the constant volatility during this period. This means that the flight was fully booked and no ticket was available.

D. International Flights (Long Weekend / Mother day)

i. Bangkok to Tokyo (operated by Nok Scoot) departure on Saturday, 10th August 2019, 00.45-09.05

ii. Bangkok to Melbourne (operated by Jetstar) departure on Friday, 9th August 2019, 21.25-10.30(D+1)

We found that the flight between Bangkok and Tokyo during long weekends/ holiday was highly demanded. Travelers anticipated in advance booking, which resulted in a sharp increase up in ticket prices overtime. According to the results, we noticed low volatility during M_5 to M_6 and moderate volatility during M_3. However, during up to two months before departure M_2, there was an evidence of highest volatility, which measured by coefficient in p

of 0.4230 and q of 0.2936. This explains that travelers were planning their holidays two months before departure date. In addition, during a week before departure, d_{t+1} to d_{t+7}, we observed the constant volatility during this period. This means that the flight was fully booked and no ticket was available.

Even though, the flight between Bangkok and Melbourne are not popular comparing to Tokyo, however, the flight on 9th August was almost fully booked. GARCH (1,1) shows the coefficients on both the lagged squatted residual and lagged conditional variance in the Variance Equation are highly statistically significant. The results of GARCH (1,1), indicate that the on-line ticket prices between Bangkok to Melbourne during m_1 to m_6 (February – July 2019) were gradual increase in ticket prices, which were evident by low volatility of ticket prices where the coefficient is less than 0.3. We found high volatility of ticket prices was increased just about 14 days before departure. We found a sharp increase in ticket prices during two weeks before departure. Low volatility was found during five to six months before departure and then rose steadily. The ticket prices' volatility of Jetstar airline had risen just a month before the departure especially a week before travel. However, we cannot compare volatility of ticket prices during the last two weeks between Nok Scoot and Jetstar, because flight tickets to Tokyo were already sold out just a week before travel. This could be explained that flight during holiday/long weekend are more demanded than during normal working day. As the result, international flights operated by Nok Scoot and Jetstar, volatility of the tickets prices is arguably moderate to high. The results of this study, the ticket price volatility is more significant at M_1, while M_2 and M_3 were less volatile as time to departure is further away up to M_6. Moreover, the results of volatility of D_{t+1} prove to be highest followed by D_{t+3} and D_{t+7} respectively.

Conclusions

Airline industry has experience explosive growth over the last decade especially in a low cost airline. They are getting more market share by stimulating passenger demand with attractive fares and new routes using their dynamic pricing strategies. Thailand is expected to enter the top ten markets in the near future as the top tourist destination. For dynamic pricing strategy, low cost airliners frequently update their ticket prices to their prospects in order to maximize their profit. They use revenue-generating system to forecast future demand corresponding to departure/arrival rates of different customers' types and remaining capacity, and offer a large pool of ticket classes to price-discriminate. In theory, as time progresses, the ticket prices would increase substantially.

The main purposes of the study are to find and compare volatility in ticket prices for domestic and international flights departing Bangkok to various destinations such as Chiang Mai, Phuket, Tokyo and Melbourne as well as to compare relative volatility between domestic and international ticket prices in a particular time frame. Finally, this research is conducted to find any dynamic pricing behaviors in airlines ticketing system during the study period of 6 months.

We construct and test volatility model by using GARCH(1,1) by observing ticket price changes in various flight routes including domestic and international routes. We test volatility by examining the determinants of movements for the volatility of ticket prices in time series with seasonal factors such as normal day and long weekend/holiday effect. Ticket prices have been obtained by four Airline companies' websites such as Nok Air, Thai Air Asia, Nok Scoot and Jetstar.

We collect data of ticket prices in term of time series for both domestic and international flights departing from Bangkok via Nok Air, Thai AirAsia, NokScoot and Jetstar websites. Domestic routes, i.e. Bangkok to Chiang Mai, and Bangkok to Phuket ticket prices has been gathered; and international routes, i.e. Bangkok to Tokyo, and Bangkok to Melbourne, ticket prices are collected from their respective websites. This research compared ticket prices and volatility between normal day and long weekends/holiday.

All prices with each departing schedule within a day are recorded up to six months in advance during the study period between January 2019 to August 2019 from four airline companies' websites. We also recorded price changes of the same flight when booking at a different day compared to the base day (t) up to 180 days ahead (t_{+180}).

To construct a volatility model, GARCH(1,1), we uses a model developed by Islam and Watanapalachaikul (2004) to detect the sensitivity and volatility level of dynamic pricing. The GARCH type model has led to the development of other related formulations in order to identify and explain the variance of time series. We hypothesize that given the variance of time closer to the departure date; significant volatility in dynamic pricing would be detected.

We use Microsoft Excel NumXL (addins) to calculate the GARCH results. The general process for GARCH model involves three steps. The first is to estimate a best-fitting autoregressive model. The second is to compute autocorrelations of the error term. The third step is to test for significance. Two other widely used approaches to estimating and predicting financial volatility are the classic historical volatility method and the exponentially weighted moving average volatility method.

Empirical analyses reveal that distributions of the change in ticket prices deviate from normality with volatility varying over time and being highly correlated. The results of the volatility tests show that the ticket prices were quite volatile when purchasing tickets close to departure date.

Domestic Flights

The results show that volatility was significant higher when the departure time was less than one month, which the ticket prices started to increase with promotional exclusive, especially a week before departure. The ticket prices gradually increased everyday for the last 7 days prior to departure on normal days.

On normal working day, low volatility was found during *m2 to m6* before departure. In addition, the ticket prices' volatility of Nok Air airline had risen just a month before the departure especially a week before travel. Thai Air Asia ticket prices rose significantly during last two weeks before departure but not as frequent as Nok Air's. Therefore, Thai Air Asia ticket prices were less volatile than Nok Air during the last two weeks before departure. However, low volatility of ticket prices was evident during 4-6 months prior to departure and it was gradually increased during 3 months before departure. This explains that travelers were not really anticipated in planning to travel during long weekend. We also found a sharp increase in ticket prices during a month just before departure.

On the other hand, during holiday/long weekend, high volatility was detected during two to three months before departure, especially flight to Chiang Mai operated by Nok Air. It could be seen that passengers are planning their trip to Chiang Mai early for their holiday/long weekend. We also notice the ticket prices had increased significantly during last week before departure resulting in higher volatility.

International Flights

The results show some fluctuation of volatility in ticket prices over the study period. In addition, low volatility is evident further the departure date. The ticket prices steadily rose overtime and medium volatility in ticket prices was found during three months before the departure. In fact, the volatility of ticket prices was increased noticeably around three months before departure. On normal day, the ticket price volatility was significant during the last two weeks before departure, which resulted from an increase in ticket prices during this period.

For long weekends/ holiday, traveler anticipated in advance booking, which resulted in a sharp increase up in ticket prices overtime just around three to four months before travel date. We also found that the flight between Bangkok and Tokyo during long was highly demanded. On the other hand, the flight between Bangkok and Melbourne are not popular comparing to Tokyo but the result has the same direction where higher volatility is evident when closer to departure date.

Recommendations

In this research, we study the volatility of the dynamic pricing in the low-cost airline industry in Thailand. The modified GARCH model is used to analyze and identify volatility level of the change in ticket prices over the 6 months time. The results clearly show that level of volatility increases as time to departure approaches.

Implications of the research are as follows: 1) Airlines could update their ticket prices constantly to maximize their potential profits; 2) Customers could book flight tickets in advance to avoid confusion and hence save some money.

Instead of running a model on historical data, this research has attempted to use future (pre-booking) ticket prices data. This innovative way of using the modified GARCH model on the future data may cause some doubt regarding to reliability and accuracy of the results. Therefore, similar tests with longer time duration could be conducted to verify the model's validity and reliability. Furthermore, we suggest a usage of historical data when information is available and applicable in comparison to this modified GARCH method. Forecasting ticket prices in a dynamic pricing policy by the use of volatility models could be attempted to provide more accurate prediction of ticket prices to maximize airline's profit at different time horizon.

For future research, we suggest some issues need an in-depth investigation such as the techniques used to study volatility. Different order levels and lag times could be employed to compare these results with current findings. Future studies may also focus on a stochastic process for ticket pricing with economic variables. The use of GARCH models with macroeconomic variables could also be an interesting area to investigate.

The usefulness of assuming a normal distribution and finding alternatives could also be tested. In addition, other Thai and international important holidays such as Songkran Festival, Christmas and New Year could be included in the further study to find the volatility of the ticket prices.

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