

Zeppelin Universität

Chair of Empirical Finance and Econometrics

**Measuring the information content of VIX
volatility in comparison to historic
volatility**

Humboldt Project

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Term:	Fall Semester 2018
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Due date:	31.01.2019

Contents

1	Introduction: The Importance of Volatility Measurement	2
1.1	Why Volatility matters: Volatility as Key Input to Option Pricing Models and Risk Measures	2
1.2	Weaknesses of Existing Models: VIX Introduced by CBOE	3
2	Selected models of volatility measurement	4
2.1	Stylized Facts of Financial Data	4
2.2	Models Using Historic Volatility	5
2.3	Implied volatility	5
2.3.1	Black-and-Scholes Implied Volatility	5
2.3.2	VIX and Model-Free Implied Volatility	5
3	Methodology and Data	6
3.1	Methodology: Linear Regression and HAR-RV model	6
3.2	Data and Calculation of Input Factors	6
4	Results	8
5	Discussion	8

List of Tables

List of Figures

1	Level-level regression	8
2	log-log regression	I

Glossary

BS Black-and-Scholes-Merton Model. 3, 4

Abstract

Abstract text

1 Introduction: The Importance of Volatility Measurement

1.1 Why Volatility matters: Volatility as Key Input to Option Pricing Models and Risk Measures

Distributional characteristics of asset returns are of high interest for the financial sector. They are for example key input to the pricing of financial instruments like derivatives, or to risk measures, such as the Value-at-Risk. Moreover they give information on the risk-return trade-off, which is a central question in portfolio allocation and managerial decision making. Of particular interest is the asset's return volatility, being the most dominant time-varying distribution characteristic. (Torben G Andersen et al. 2018).

Risk is important because.. . The concept of risk is closely linked to that of volatility, as the second moment characteristic of asset return distributions. Many pricing models measure risk through volatility, which thus influences the expected return (**harvey1992**). Moreover many risk-measure, such as the Value-at-Risk are very closely related to volatility. (Alternative)

Volatility “seeks to capture the strength of the (unexpected) return variation over a given period of time” (Torben G. Andersen, Bollerslev and Diebold 2001, p.7)

As volatility is not directly observable, it has to be estimated. During the last years, considerable research has been devoted to the question, how volatility can be measured or estimated. Two prominent categories of approaches are on the one hand time series models using historic volatility, and on the other hand implied models using option price data¹. In the recent years, Black-and-Scholes implied volatility measurement gained popularity, this approach uses the forward-looking nature of option prices. Options are contracts, giving the holder the right to either buy (call option), or sell (put option), an underlying asset, at a specified date in the future for a certain price (John et al. 2006). Assuming rational agents/expectation, the market uses all available information to form

¹There are, of course, various other methods, such as nonparametric methods or neural networks based models (Jiang, George J & Tian 2003), however they shall not be discussed here

it's expectation about future price movements and thus about volatility. Assuming furthermore that the market is efficient (meaning as Eugene Fama defined it, that prices reflect all available information), the market's estimate of future volatility is the best possible forecast possible, given the current information (Bent Jesper Christensen and Hansen 2002). Due to this forward looking component of option contracts, option prices indirectly contain the market participants' expectations of the underlying asset's future movements. A widely used model to price this option contracts is the Black-and-Scholes-Merton model, which uses the option's volatility as an input factor. By using observed option prices as the input and solving for volatility, it is possible to obtain a volatility measure that is widely believed to be "informationally superior to the historic volatility of the underlying asset" (Jiang, George J & Tian 2003, p.1305).

Early studies found implied volatility to be a biased forecast of realized volatility, not containing significantly more information than historic volatility. More recent studies however presented evidence that there is important information contained in option prices, that adds to the efficiency of volatility forecasting when implied volatility is included (ibid.). A reason for this discrepancy in results could be that early studies did not consider several data and methodological problems, such as long enough time series, a possible regime shift around the crash in 1987 and the use of non-overlapping samples (ibid.). Bent J Christensen and Prabhala for example took this into account and found that implied volatility outperforms historic volatility. All in all Jiang, George J & Tian summarize, that collectively "these studies present evidence that implied volatility a more efficient forecast for future volatility than historic volatility" (p.1306).

1.2 Weaknesses of Existing Models: VIX Introduced by CBOE

Even though BS implied volatility is found to be the overall more efficient forecast of realized volatility compared to historic volatility (ibid.), the BS implied volatility has some specification problems. Firstly, BS implied volatility focuses on at-the-money options. The advantage is, that at-the-money options are the once most actively traded and thus the most liquid ones. However this focus fails to include information contained

in other options. Moreover, volatility estimation with the BS model, includes the same assumptions as are made in the BS model itself. Thus tests based on the BS equation are actually joined tests of market efficiency (as market efficiency is assumed to use option prices for volatility estimation, as mentioned above) and the BS model, and therefore suffer from a model misspecification error (Jiang, George J & Tian 2003). That is why during the last years, implied volatility indexes which are not based on a pricing assumption gained popularity. One of these model-free implied volatility indexes is the VIX from CBOE.

- power of volatility models lies in out-of-sample forecasting power
- so far BS implied volatility models had the best out of sampling forecasting power, but they have several problems (most importantly joint hypothesis problem)

Volatility is for example both a key input factor to risk measures (such as Value-at-risk), or pricing of derivative securities, which both again are crucial for financial decision making. As volatility can not be observed as directly as price can, it has to be both estimated and forecasted. There are multiple ways to forecast volatility. The strenght of a volatility model however lies in it's out-of-sample forecasting power (Poon and Granger 2003).

Volatility measures play an important role for financial market stability.

Stylized facts of financial market data suggests that return distributions are not i.i.d., meaning that the variance of returns over a long horizon can not be derived from a single observed period (ibid.).

2 Selected models of volatility measurement

2.1 Stylized Facts of Financial Data

- strong persistence of the autocorrelation of square and absolute returns (Jiang, George J & Tian 2003)
- return distributions exhibits both fat tails and tail crossover (ibid.)

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2.2 Models Using Historic Volatility

- historic volatility: just lagged realized volatility
- econometric models: GARCH (as an example for a frequently used one)

2.3 Implied volatility

2.3.1 Black-and-Scholes Implied Volatility

- explain basic idea of BS implied volatility
- advantages of BS implied volatility: forward-looking nature of option prices
- disadvantages of BS implied volatility: joint hypothesis problem due to underlying pricing assumption (is a joint test of market efficiency and underlying pricing assumption), use only at-the-money options and fail to incorporate information,...

Disadvantages of Black and Scholes: Black and Scholes uses only at-the-money option and thus fails to incorporate information (Jiang, George J & Tian 2003). Black and Scholes are joint tests of market efficiency and the B-S model, thus studies are subject to model misspecification errors (ibid.).

2.3.2 VIX and Model-Free Implied Volatility

- explain basic idea of model-free implied volatility
- advantages of model-free implied volatility: solved joint hypothesis problem (direct test of market efficiency), can incorporate not only at-the-money options,...
- the VIX as the model-free implied volatility estimate from the Cboe

Primarily described and derived by Britten-Jones and Neuberger. Instead of being based on a specific option pricing model, it is derived entirely from no-arbitrage conditions. After that some papers did various corrections, such as Jiang, George J & Tian extended the model so that it is not derived under diffusion assumptions and

generalized it to processes including random jumps. Two advantage of the model-free option implied volatility, are firstly that it has no pricing assumption and thus constitutes a direct test of the option market's informational efficiency, and not a joined test of market efficiency and an assumed option pricing model. Secondly it incorporates information from options across different strike prices.

3 Methodology and Data

3.1 Methodology: Linear Regression and HAR-RV model

- Reg1: without VIX
 - Reg1a: regress realized volatility on historic volatility using simple linear regression
 - Reg1b: regress realized volatility on historic volatility using HAR-RV model
- Reg2: with VIX
 - Reg2b: regress realized volatility on historic volatility using simple linear regression
 - Reg2b: regress realized volatility on historic volatility using HAR-RV model

$$\sigma_{t,x}^{RV} = \alpha_{x,t} + \beta_{x,t}^{HV} \sigma_{x,t}^{HV} \quad (1)$$

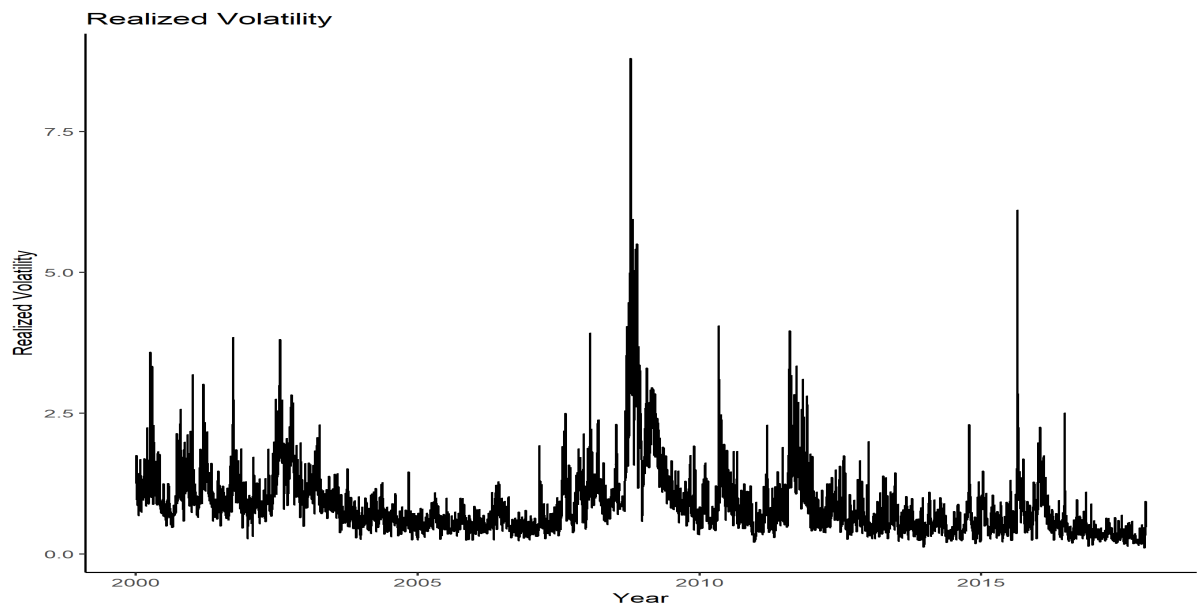
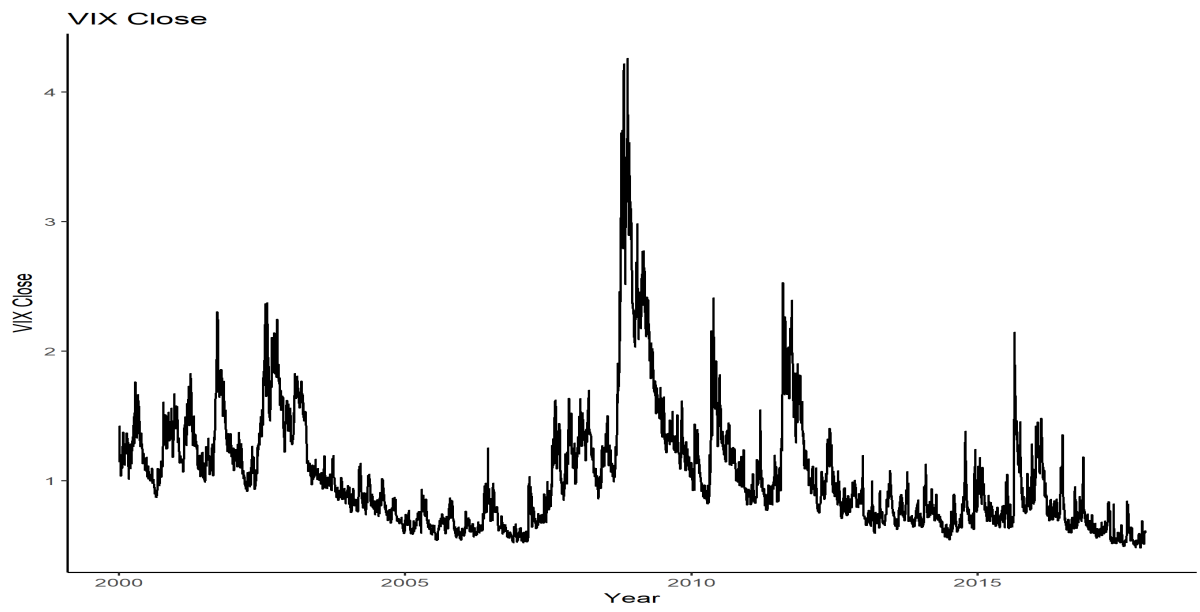
$$\sigma_{x,t}^{RV} = \alpha_{x,t} + \beta_{x,t}^{HV,d} \sigma_{x,t}^{HV,d} + \beta_{x,t}^{HV,w} \sigma_{x,t}^{HV,w} + \beta_{x,t}^{HV,m} \sigma_{x,t}^{HV,m} \quad (2)$$

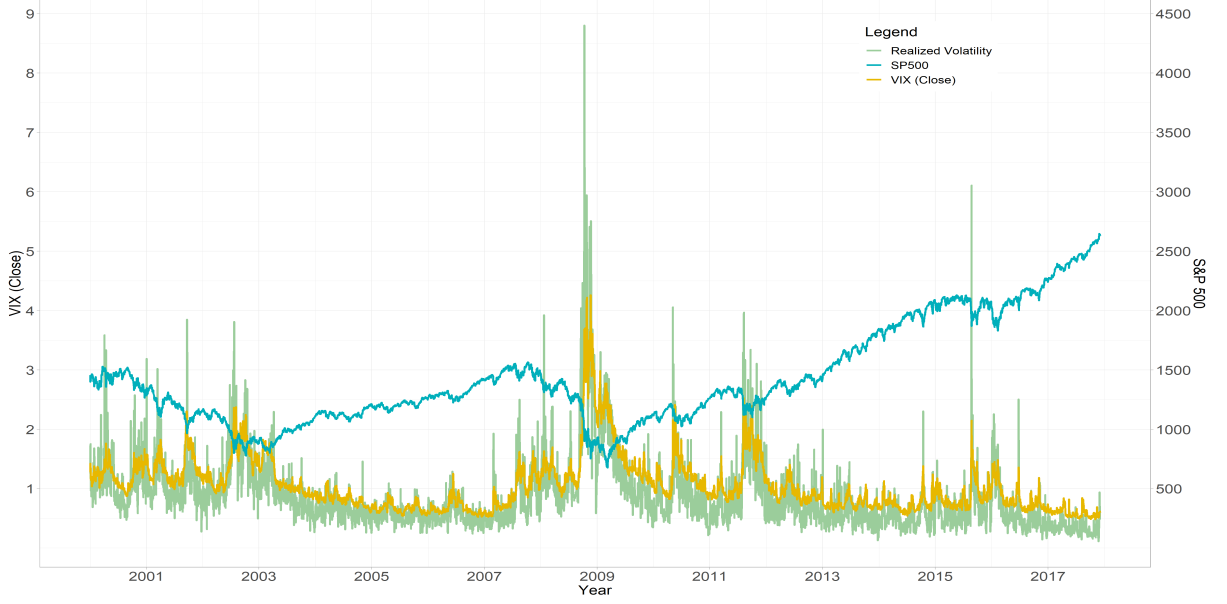
$$\sigma_{x,t}^{RV} = \alpha_{x,t} + \beta_{x,t}^{HV} \sigma_{x,t}^{HV} + \beta_{x,t}^{VIX} + \sigma_{x,t}^{VIX} \quad (3)$$

$$\sigma_{x,t}^{RV} = \alpha_{x,t} + \beta_{x,t}^{HV,d} \sigma_{x,t}^{HV,d} + \beta_{x,t}^{HV,w} \sigma_{x,t}^{HV,w} + \beta_{x,t}^{HV,m} \sigma_{x,t}^{HV,m} + \beta_{x,t}^{VIX} + \sigma_{x,t}^{VIX} \quad (4)$$

3.2 Data and Calculation of Input Factors

- S&P 500 index data on daily basis
- sampling period: 2000 - 2018





- realized volatility: daily realized volatility of S&P 500, calculated using 5 minute returns, retrieved from
- model-free implied volatility: VIX index data
- historic volatility: lagged realized volatility, for HAR-RV model use the average over the time period used to forecast

4 Results

Figure 1: Level-level regression

	Historic	Historic and VIX
Intercept	0.05*** (0.01)	-0.23*** (0.01)
RV_t^d	0.36*** (0.02)	0.23*** (0.02)
RV_t^w	0.38*** (0.03)	0.27*** (0.03)
RV_t^m	0.21*** (0.02)	-0.28*** (0.03)
VIX		0.87*** (0.03)
R^2	0.71	0.76
Adj. R^2	0.71	0.76
Num. obs.	4436	4436
RMSE	0.33	0.30

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Figure 2: log-log regression

	Historic	Historic and VIX
Intercept	-0.02** (0.01)	-0.16*** (0.01)
RV_t^d	0.34*** (0.02)	0.24*** (0.02)
RV_t^w	0.40*** (0.03)	0.28*** (0.03)
RV_t^m	0.21*** (0.02)	-0.13*** (0.03)
VIX		0.80*** (0.03)
R^2	0.73	0.77
Adj. R^2	0.73	0.77
Num. obs.	4437	4437
RMSE	0.30	0.28

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

5 Discussion

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