Code

binary.com Interview Question I - Interday Betting Strategy Models Comparison (Financial Betting and Stock Market)

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1 Introduction

1.1 Abstract

In order to test the timeline of daily highest and lowest price, here I created this file to read the high volume tick-data-history to test the efficiency of Kelly Criterion betting models. Kindly refer to Reference for further information.

binary.com Interview Question I - Tick-Data-HiLo For Daily Trading (Blooper) descript that the VaR figure required in order to place orders. What is the difference between Sharpe ratio and value at risk? states the difference between VaR and shape ratio where the shape ratio will be use in the future research.

ARIMA+GARCH Trading Strategy on the S&P500 Stock Market Index Using R compares the ROI of buy and hold and application of ARIMA + GARCH model.

Systematic Investor Blog : Trading Strategies introduce various trading strategies.

> The Sharpe ratio can also help explain whether a portfolio's excess returns are due to smart investment decisions or a result of too much risk. Although one portfolio or fund can enjoy higher returns than its peers, it is only a good investment if those higher returns do not come with an excess of additional risk. The greater a portfolio's Sharpe ratio, the better its risk-adjusted performance. A negative Sharpe ratio indicates that a risk-less asset would perform better than the security being analyzed.

source : Investopedia : Sharpe Ratio

1.2 Intro Reference

Currency Hedging Strategies Using Dynamic Multivariate GARCH compares DCC, BEKK, CCC and VARMA-AGARCH models to examine the conditional volatilities among the spot and two distint futures maturities, namely near-month and next-to-near-month contracts. The estimated conditionl covariances matrices from these models were used to calculate the optimal portfolios weights and optimal hedge ratios. The empirical results in the paper reveal that there are not big differences either the near-month or next-to-near-month contract is used for hedge spot position on currencies. They also reveal that hedging ratios are lower for near-month contract when the USD/EUR and USD/JPY exchange rates are anlyzed. This result is explained in terms of the higher correlation between spot prices and the next-to-near-month future prices than that with near-month contract and additionally because of the lower volatility of the long maturity futures. Finally across all currencies and error densities, the CCC and VARMA-AGARCH models provide similar results in terms of hedging ratios, portfolio variance reduction and hedging effectiveness. Some difference might appear when the DCC and BEKK models are used. Below is the table summary of the paper.

Table 8A. Alternative hedging strategies (USD/EUR)

	MODEL	OHR	Var. PF	HE	Var. UnHed	OPT. W
	Student-t error distribution					
FUT1	CCC	0.805	0.158	62.5%	0.420	0.536
FUT1	VARMA-AGARCH	0.805	0.157	62.7%	0.420	0.536
FUT1	DCC	0.794	0.157	62.7%	0.420	0.542
FUT1	BEKK	0.802	0.157	62.6%	0.420	0.542

	BEKK	0.802	0.157	62.6%	0.420	0.542
FUT2	CCC	0.808	0.157	62.7%	0.420	0.532
	VARMA-AGARCH	0.808	0.156	62.9%	0.420	0.532
	DCC	0.797	0.156	62.9%	0.420	0.535
	BEKK	0.804	0.156	62.8%	0.420	0.537
	Normal Gaussian error Distribution					
FUT1	CCC	0.792	0.158	62.5%	0.420	0.544
	VARMA-AGARCH	0.792	0.157	62.7%	0.420	0.545
	DCC	0.784	0.157	62.7%	0.420	0.554
	BEKK	0.792	0.157	62.6%	0.420	0.550
FUT2	CCC	0.799	0.157	62.7%	0.420	0.532
	VARMA-AGARCH	0.799	0.156	62.9%	0.420	0.533
	DCC	0.791	0.156	62.9%	0.420	0.538
	BEKK	0.798	0.156	62.8%	0.420	0.537

Notes: Optimal Hedging Ratio (**OHR**), Variance of Portfolios (**Var. PF**), Hedging Effective Index (**HE**), Variance of ungedged portfolio (**Var. UnHed**) and Optimal Portfolio Weights (**OPT. W**). FUT1 is when the near-month delivery contract is used for hedging and FUT2 implies that is the next-to-near-month delivery contract the one used for hedging. For each error distribution and future contract, results for the four multivariate variance models, CCC, VARMA-AGARCH, DCC and BEKK are shown.

Figure 3.1.1A : comparison of hedge strategy.

Table 8B. Alternative hedging strategies (USD/GBP)

	MODEL	OHR	Var. PF	HE	Var. UnHed	OPT. W
	Student-t error distribution					
FUT1	CCC	0.829	0.126	66.2%	0.372	0.496
	VARMA-AGARCH	0.830	0.125	66.3%	0.372	0.498
	DCC	0.822	0.126	66.2%	0.372	0.497
	BEKK	0.826	0.126	66.2%	0.372	0.490
FUT2	CCC	0.826	0.127	65.9%	0.372	0.510
	VARMA-AGARCH	0.826	0.126	66.1%	0.372	0.512
	DCC	0.817	0.127	65.9%	0.372	0.511
	BEKK	0.821	0.127	65.9%	0.372	0.505
	Normal Gaussian error Distribution					
FUT1	CCC	0.816	0.126	66.2%	0.372	0.499
	VARMA-AGARCH	0.815	0.125	66.3%	0.372	0.503
	DCC	0.818	0.126	66.1%	0.372	0.500
	BEKK	0.822	0.127	66.0%	0.372	0.495
FUT2	CCC	0.812	0.127	65.9%	0.372	0.510
	VARMA-AGARCH	0.812	0.126	66.1%	0.372	0.513
	DCC	0.813	0.127	65.8%	0.372	0.513
	BEKK	0.817	0.128	65.7%	0.372	0.508

Notes: Optimal Hedging Ratio (**OHR**), Variance of Portfolios (**Var. PF**), Hedging Effective Index (**HE**), Variance of ungedged portfolio (**Var. UnHed**) and Optimal Portfolio Weights (**OPT. W**). FUT1 is when the near-month delivery contract is used for hedging and FUT2 implies that is the next-to-near-month delivery contract the one used for hedging. For each error distribution and future contract, results for the four multivariate variance models, CCC, VARMA-AGARCH, DCC and BEKK are shown.

Figure 3.1.1B : comparison of hedge strategy.

Table 8C. Alternative hedging strategies (USD/JPY)

	MODEL	OHR	Var. PF	HE	Var. UnHed	OPT. W
	Student-t error distribution					
FUT1	CCC	0.849	0.153	64.8%	0.435	0.463
	VARMA-AGARCH	0.849	0.153	64.8%	0.435	0.464
	DCC	0.845	0.153	64.8%	0.435	0.475
	BEKK	0.849	0.154	64.7%	0.435	0.474
FUT2	CCC	0.853	0.154	64.6%	0.435	0.450
	VARMA-AGARCH	0.853	0.154	64.6%	0.435	0.450
	DCC	0.850	0.154	64.7%	0.435	0.464
	BEKK	0.854	0.154	64.6%	0.435	0.468
	Normal Gaussian error Distribution					
FUT1	CCC	0.803	0.152	65.0%	0.435	0.535
	VARMA-AGARCH	0.802	0.152	65.0%	0.435	0.537
	DCC	0.812	0.153	64.8%	0.435	0.566
	BEKK	0.817	0.153	64.7%	0.435	0.570
FUT2	CCC	0.810	0.153	64.8%	0.435	0.514
	VARMA-AGARCH	0.809	0.153	64.8%	0.435	0.515
	DCC	0.818	0.154	64.6%	0.435	0.549
	BEKK	0.823	0.154	64.5%	0.435	0.555

Notes: Optimal Hedging Ratio (**OHR**), Variance of Portfolios (**Var. PF**), Hedging Effective Index (**HE**), Variance of ungedged portfolio (**Var. UnHed**) and Optimal Portfolio Weights (**OPT. W**). FUT1 is when the near-month delivery contract is used for hedging and FUT2 implies that is the next-to-near-month delivery contract the one used for hedging. For each error distribution and future contract, results for the four multivariate variance models, CCC, VARMA-AGARCH

DCC and BEKK are shown.

Figure 3.1.1C : comparison of hedge strategy.

Tables 8A-8C report the average OHR values, the hedge effectiveness, the variance of the portfolio, the hedging effectiveness along with the average value of the optimal portfolio weights for the three currencies using FUT1 and FUT2 contracts when both the Student t and normal error distributions are assumed. We show the results for the four multivariate volatility models.

Tables 8A-8C show that hedging is effective in reducing the risks for every model, currency and maturity. In particular, we find that the average OHR using FUT2 contracts are slightly higher than when FUT1 contracts are used, except for GBP. The highest average OHR value is 0.854 for USD/JPY when FUT2 contracts are used, meaning that, in order to minimize risk, a long (buy) position of one dollar in such a currency should be hedged by a short (sell) position of $0.854 in JPYFUT2 contracts.

Additionally, when using the Gaussian error distribution, Tables 8A-8C report lower average OHR values for the three currencies analyzed. The average OHRs from each model are not particularly different, slightly smaller for the DCC and BEKK models when the Student t is used, but larger for GBP and JPY when using the Gaussian distribution. The average OHR values are higher for the USD/JPY exchange rate. On the contrary, hedging effectiveness is higher for the DCC and BEKK models.

Table 9A. Correlations between OHRs (USD/EUR)

	CCC	VARMA-AGARCH	DCC	BEKK
Student-t error distribution				
CCC	1.00			
VARMA-AGARCH	0.99	1.00		
DCC	0.66	0.65	1.00	
BEKK	0.65	0.65	0.96	1.00
Normal Gaussian error Distribution				
CCC	1.00			
VARMA-AGARCH	0.99	1.00		
DCC	0.66	0.65	1.00	
BEKK	0.67	0.67	0.96	1.00

Table 9B. Correlations between OHRs (USD/GBP)

	CCC	VARMA-AGARCH	DCC	BEKK
Student-t error distribution				
CCC	1.00	0.97	0.59	0.64
VARMA-AGARCH	0.97	1.00	0.59	0.63
DCC	0.59	0.59	1.00	0.97
BEKK	0.64	0.63	0.97	1.00
Normal Gaussian error Distribution				
CCC	1.00			
VARMA-AGARCH	0.97	1.00		
DCC	0.59	0.59	1.00	
BEKK	0.64	0.62	0.97	1.00

Table 9C. Correlations between OHRs (JPY/USD)

	CCC	VARMA-AGARCH	DCC	BEKK
Student-t error distribution				
CCC	1.00			
VARMA-AGARCH	0.99	1.00		
DCC	0.55	0.55	1.00	
BEKK	0.55	0.55	0.96	1.00
Normal Gaussian error Distribution				
CCC	1.00			
VARMA-AGARCH	0.99	1.00		
DCC	0.59	0.59	1.00	
BEKK	0.54	0.54	0.93	1.00

Figure 3.1.2 : comparison of hedge strategy.

The correlations of the dynamic patterns in Tables 8A-8C are given in Tables 9A-9C. It is clear that, across all currencies and both error densities, the OHRs are most similar between CCC and VARMA-AGARCH, which suggests that dynamic asymmetry may not be crucial empirically, and also between DCC and BEKK.

In summary, the estimates based on both OHR and optimal weight values recommend holding more FUT2 than FUT1 contracts for USD/EUR and USD/JPY spot/futures portfolios, meaning that we should increase the percentage of futures contracts for longer term portfolios when these currencies are used.

Dynamic Portfolio Optimization using Generalized Dynamic Conditional Heteroskedastic Factor Models studies the portfolio selection problem based on a generalized dynamic factor model (GDFM) with conditional heteroskedasticity in the idiosyncratic components. We propose a Generalized Smooth Transition Conditional Correlation (GSTCC) model for the idiosyncratic components combined with the GDFM. Among all the multivariate GARCH models that the authors propose, the generalized smooth transition conditional correlation provides the best result.

Table 5. Optimal portfolio results for 5% VaR.

Model	n	t	st
CCC-GJR	0.0824(0.7450)	0.0797(0.7447)	0.0834(0.7466)
CCC-APARCH	0.0823(0.7450)	0.0798(0.7447)	0.0835(0.7467)
DCC-GJR	0.0808(0.7465)	0.0793(0.7451)	0.0815(0.7471)
DCC-APARCH	0.0808(0.7464)	0.0795(0.7454)	0.0812(0.7476)
STCC-GJR	0.0805(0.7459)	0.0786(0.7436)	0.0792(0.7465)
STCC-APARCH	0.0805(0.7453)	0.0788(0.7434)	0.0795(0.7467)
GSTCC-GJR	0.0780(0.7405)	0.0792(0.7426)	0.0791(0.7404)
GSTCC-APARCH	0.0713(0.7426)	0.0772(0.7423)	0.0841(0.7377)

Note: The mean-variance model gives mean return 0.0646 and standard deviation 0.7811. The number in the parenthesis is the standard deviation. CCC-GJR- means the method of using CCC model for conditional correlation matrix and GJR model for univariate GARCH specification. Abbreviations for univariate GARCH models are in the notes of Table 3. Model abbreviations for multivariate GARCH are as follows:

1. CCC- Constant Conditional Correlation;
2. DCC- Dynamic Conditional Correlation;
3. STCC- Smooth Transition Conditional Correlation;
4. GSTCCC- Generarized Smooth Transition Conditional Correlation.

Table 6. Optimal portfolio results for 1% VaR.

Model	n	t	st
CCC-GJR	0.0817(0.7465)	0.0788(0.7461)	0.0816(0.7485)
CCC-APARCH	0.0816(0.7464)	0.0789(0.7462)	0.0817(0.7485)
DCC-GJR	0.0808(0.7459)	0.0780(0.7465)	0.0810(0.7496)
DCC-APARCH	0.0809(0.7458)	0.0778(0.7464)	0.0809(0.7498)
STCC-GJR	0.0808(0.7459)	0.0764(0.7460)	0.0772(0.7495)
STCC-APARCH	0.0809(0.7450)	0.0769(0.7456)	0.0795(0.7467)
GSTCC-GJR	0.0769(0.7440)	0.0749(0.7425)	0.0721(0.7437)
GSTCC-APARCH	0.0789(0.7447)	0.0727(0.7431)	0.0798(0.7429)

Note:The mean-variance model gives mean return 0.0646 and standard deviation 0.7811.

Table 3. In-sample period 5% VaR results.

Sector	GARCH-n	GJR-n	APARCH-n	GARCH-t	GJR-t	APARCH-t	GARCH-st	GJR-st	APARCH-st
Fishery, Agriculture & Forestry	0.0429	0.0438	0.0447	0.0447	0.0474	0.0493	0.0447	0.0474	0.0493
Mining	0.0356	0.0365	0.0356	0.0411	0.0420	0.0420	0.0474	0.0474	0.0474
Construction	0.0547	0.0493	0.0465	0.0584	0.0575	0.0547	0.0538	0.0502	0.0511
Foods	0.0566	0.0493	0.05657	0.0566	0.0529	0.0502	0.0547	0.0502	0.0465
Textiles and Apparels	0.0538	0.0529	0.0520	0.0538	0.0547	0.0557	0.0502	0.0493	0.0484
Pulp and Paper	0.0511	0.0529	0.0493	0.0538	0.0538	0.0511	0.0474	0.0511	0.0493
Chemicals	0.0557	0.0511	0.0520	0.0575	0.0557	0.0566	0.0511	0.0465	0.0493
Pharmaceutical	0.0438	0.0438	0.0374	0.0456	0.0465	0.0465	0.0456	0.0456	0.0447
Oil and Coal Products	0.0429	0.0420	0.0420	0.0438	0.0429	0.0438	0.0447	0.0447	0.0447
Rubber Products	0.0493	0.0511	0.0502	0.0502	0.0511	0.0538	0.0502	0.0511	0.0529
Glass and Ceremics Products	0.0566	0.0547	0.0547	0.0575	0.0575	0.0566	0.0511	0.0547	0.0538
Iron and Steel	0.0484	0.0474	0.0456	0.0502	0.0465	0.0484	0.0538	0.0511	0.0511
Nonferrous Metals	0.0575	0.0557	0.0557	0.0593	0.0593	0.0593	0.0575	0.0566	0.0557
Metal Products	0.0365	0.0365	0.0383	0.0401	0.0401	0.0374	0.0420	0.0420	0.0383
Machinery	0.0575	0.0602	0.0566	0.0620	0.0620	0.0611	0.0520	0.0502	0.0465
Electric Appliances	0.0502	0.0511	0.0502	0.0493	0.0511	0.0502	0.0557	0.0547	0.0538
Transportation Equipment	0.0456	0.0465	0.0456	0.0511	0.0493	0.0502	0.0511	0.0493	0.0493
Precision Instruments	0.0520	0.0484	0.0484	0.0520	0.0484	0.0502	0.0520	0.0484	0.0502
Other Products	0.0511	0.0511	0.0520	0.0547	0.0529	0.0538	0.0484	0.0502	0.0511
Electric Power and Gas	0.0420	0.0411	0.0411	0.0420	0.0420	0.0392	0.0429	0.0429	0.0411
Land Transportation	0.0420	0.0429	0.0429	0.0420	0.0420	0.0420	0.0456	0.0447	0.0456
Marine Transportation	0.0429	0.0456	0.0447	0.0465	0.0465	0.0447	0.0456	0.0456	0.0438
Air Transportation	0.0383	0.0383	0.0383	0.0429	0.0429	0.0438	0.0447	0.0456	0.0465
Warehousing	0.0474	0.0465	0.0484	0.0484	0.0493	0.0493	0.0511	0.0511	0.0511
Information & Communication	0.0420	0.0356	0.0347	0.0429	0.0401	0.0401	0.0465	0.0456	0.0420
Wholesale Trade	0.0566	0.0511	0.0511	0.0557	0.0520	0.0520	0.0557	0.0493	0.0502
Retail Trade	0.0465	0.0456	0.0456	0.0456	0.0465	0.0456	0.0465	0.0484	0.0465
Banks	0.0511	0.0511	0.0465	0.0502	.0511	0.0474	0.0557	0.0566	0.0511
Securities and Commodities Futures	0.0429	0.0429	0.0429	0.0429	0.0429	0.0429	0.0456	0.0484	0.0484
Insurance	0.0493	0.0474	0.0465	0.0529	0.0511	0.0502	0.0538	0.0511	0.0529
Other Financing Business	0.0493	0.0502	0.0511	0.0529	0.0511	0.0520	0.0529	0.0520	0.0520
Real Estate	0.0538	0.0529	0.0538	0.0520	0.0502	0.0529	0.0538	0.0520	0.0566
Services	0.0538	0.0557	0.0575	0.0566	0.0557	0.0575	0.0520	0.0538	0.0557

Note: GARCH-n—means the method of GARCH(1, 1) models with normal distribution. Respectively other abbreviation are constructed. Model abbreviations are as follows:

1. GARCH- Generalized Autoregressive Conditional Heteroskedasticity;
2. GJR- Glosten, Jagannathan and Runkle;
3. APARCH- Asymmetric Power Autoregressive Conditional Heteroskedasticity.

Table 4. In-sample period 1% VaR results.

Sector	GARCH-n	GJR-n	APARCH-n	GARCH-t	GJR-t	APARCH-t	GARCH-st	GJR-st	APARCH-st
Fishery, Agriculture & Forestry	0.0128	0.0128	0.0128	0.0109	0.0109	0.0100	0.0109	0.0109	0.0100
Mining	0.0119	0.0119	0.0128	0.0082	0.0082	0.0082	0.0109	0.0109	0.0109
Construction	0.0155	0.0146	0.0146	0.0100	0.0100	0.0109	0.0073	0.0091	0.0109
Foods	0.0173	0.0192	0.01734	0.0128	0.0146	0.0155	0.0128	0.0137	0.0137
Textiles and Apparels	0.0164	0.0155	0.0173	0.0137	0.0128	0.0155	0.0119	0.0109	0.0091
Pulp and Paper	0.0182	0.0164	0.0155	0.0146	0.0137	0.0137	0.0128	0.0119	0.0119
Chemicals	0.0155	0.0164	0.0173	0.0146	0.0128	0.0128	0.0128	0.0128	0.0100
Pharmaceutical	0.0146	0.0146	0.0109	0.0119	0.0109	0.0128	0.0119	0.0100	0.0109
Oil and Coal Products	0.0155	0.0155	0.0155	0.0137	0.0128	0.0128	0.0155	0.0146	0.0146
Rubber Products	0.0128	0.0128	0.0119	0.0109	0.0109	0.0119	0.0109	0.0109	0.0109
Glass and Ceremics Products	0.0137	0.0100	0.0109	0.0119	0.0100	0.0082	0.0100	0.0082	0.0082
Iron and Steel	0.0109	0.0091	0.0082	0.0073	0.0064	0.0064	0.0091	0.0082	0.0082
Nonferrous Metals	0.0146	0.0155	0.0146	0.0137	0.0119	0.0128	0.0119	0.0119	0.0119
Metal Products	0.0128	0.0128	0.0128	0.0119	0.0119	0.0119	0.0128	0.0119	0.0119
Machinery	0.0091	0.0100	0.0091	0.0091	0.0082	0.0091	0.0082	0.0064	0.0064
Electric Appliances	0.0091	0.0073	0.0073	0.0064	0.0064	0.0064	0.0082	0.0082	0.0082
Transportation Equipment	0.0164	0.0137	0.0146	0.0100	0.0109	0.0091	0.0109	0.0109	0.0091
Precision Instruments	0.0164	0.0164	0.0164	0.0155	0.0155	0.0155	0.0155	0.0155	0.0155
Other Products	0.0192	0.0182	0.0173	0.0146	0.0146	0.0128	0.0119	0.0128	0.0109
Electric Power and Gas	0.0146	0.0146	0.0128	0.0128	0.0119	0.0119	0.0128	0.0119	0.0119
Land Transportation	0.0128	0.0137	0.0137	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100
Marine Transportation	0.0164	0.0164	0.0164	0.0119	0.0119	0.0128	0.0119	0.0119	0.0128
Air Transportation	0.0100	0.0100	0.0109	0.0073	0.0073	0.0073	0.0073	0.0073	0.0073
Warehousing	0.0100	0.0109	0.0109	0.0082	0.0082	0.0082	0.0091	0.0082	0.0082
Information & Communication	0.0091	0.0091	0.0100	0.0055	0.0055	0.0073	0.0064	0.0073	0.0082
Wholesale Trade	0.0173	0.0155	0.0137	0.0119	0.0128	0.0137	0.0091	0.0128	0.0137
Retail Trade	0.0137	0.0137	0.0137	0.0091	0.0100	0.0100	0.0109	0.0100	0.0109
Banks	0.0091	0.0091	0.0109	0.0064	0.0064	0.0073	0.0073	0.0073	0.0100
Securities and Commodities Futures	0.0119	0.0091	0.0091	0.0100	0.0064	0.0064	0.0119	0.0100	0.0100
Insurance	0.0109	0.0082	0.0082	0.0064	0.0064	0.0064	0.0064	0.0064	0.0064
Other Financing Business	0.0155	0.0137	0.0137	0.0100	0.0100	0.0100	0.0109	0.0100	0.0100
Real Estate	0.0100	0.0100	0.0119	0.0055	0.0055	0.0082	0.0073	0.0064	0.0109
Services	0.0128	0.0100	0.0100	0.0091	0.0091	0.0100	0.0073	0.0082	0.0091

Table 5. Optimal portfolio results for 5% VaR.

Model	n	t	st
CCC-GJR	0.0824(0.7450)	0.0797(0.7447)	0.0834(0.7466)
CCC-APARCH	0.0823(0.7450)	0.0798(0.7447)	0.0835(0.7467)
DCC-GJR	0.0808(0.7465)	0.0793(0.7451)	0.0815(0.7471)
DCC-APARCH	0.0808(0.7464)	0.0795(0.7454)	0.0812(0.7476)
STCC-GJR	0.0805(0.7459)	0.0786(0.7436)	0.0792(0.7465)
STCC-APARCH	0.0805(0.7453)	0.0788(0.7434)	0.0795(0.7467)
GSTCC-GJR	0.0780(0.7405)	0.0792(0.7426)	0.0791(0.7404)
GSTCC-APARCH	0.0713(0.7426)	0.0772(0.7423)	0.0841(0.7377)

Note: The mean-variance model gives mean return 0.0646 and standard deviation 0.7811. The number in the parenthesis is the standard deviation. CCC-GJR- means the method of using CCC model for conditional correlation matrix and GJR model for univariate GARCH specification. Abbreviations for univariate GARCH models are in the notes of Table 3. Model abbreviations for multivariate GARCH are as follows:

1. CCC- Constant Conditional Correlation;
2. DCC- Dynamic Conditional Correlation;
3. STCC- Smooth Transition Conditional Correlation;
4. GSTCCC- Generarized Smooth Transition Conditional Correlation.

Table 6. Optimal portfolio results for 1% VaR.

Model	n	t	st
CCC-GJR	0.0817(0.7465)	0.0788(0.7461)	0.0816(0.7485)
CCC-APARCH	0.0816(0.7464)	0.0789(0.7462)	0.0817(0.7485)
DCC-GJR	0.0808(0.7459)	0.0780(0.7465)	0.0810(0.7496)
DCC-APARCH	0.0809(0.7458)	0.0778(0.7464)	0.0809(0.7498)
STCC-GJR	0.0808(0.7459)	0.0764(0.7460)	0.0772(0.7495)
STCC-APARCH	0.0809(0.7450)	0.0769(0.7456)	0.0795(0.7467)
GSTCC-GJR	0.0769(0.7440)	0.0749(0.7425)	0.0721(0.7437)
GSTCC-APARCH	0.0789(0.7447)	0.0727(0.7431)	0.0798(0.7429)

Note:The mean-variance model gives mean return 0.0646 and standard deviation 0.7811.

st	APARCH-st
4	0.0493
4	0.0474
2	0.0511
2	0.0465
3	0.0484
1	0.0493
5	0.0493
5	0.0447
7	0.0447
1	0.0529
7	0.0538
1	0.0511
6	0.0557
0	0.0383
2	0.0465
7	0.0538
3	0.0493
4	0.0502
2	0.0511
9	0.0411
7	0.0456
6	0.0438
6	0.0465
1	0.0511
6	0.0420
3	0.0502
4	0.0465
6	0.0511
4	0.0484
1	0.0529
0	0.0520
0	0.0566
8	0.0557

d. Model abbreviations

Table 4. In-sample period 1% VaR results.

Sector	GARCH-n	GJR-n	APARCH-n	GARCH-t	GJR-t	APARCH-t	GARCH-st	GJR-st	APARCH-st
Fishery, Agriculture & Forestry	0.0128	0.0128	0.0128	0.0109	0.0109	0.0100	0.0109	0.0109	0.0100
Mining	0.0119	0.0119	0.0128	0.0082	0.0082	0.0082	0.0109	0.0109	0.0109
Construction	0.0155	0.0146	0.0146	0.0100	0.0100	0.0109	0.0073	0.0091	0.0109
Foods	0.0173	0.0192	0.01734	0.0128	0.0146	0.0155	0.0128	0.0137	0.0137
Textiles and Apparels	0.0164	0.0155	0.0173	0.0137	0.0128	0.0155	0.0119	0.0109	0.0091
Pulp and Paper	0.0182	0.0164	0.0155	0.0146	0.0137	0.0137	0.0128	0.0119	0.0119
Chemicals	0.0155	0.0164	0.0173	0.0146	0.0128	0.0128	0.0128	0.0128	0.0100
Pharmaceutical	0.0146	0.0146	0.0109	0.0119	0.0109	0.0128	0.0119	0.0100	0.0109
Oil and Coal Products	0.0155	0.0155	0.0155	0.0137	0.0128	0.0128	0.0155	0.0146	0.0146
Rubber Products	0.0128	0.0128	0.0119	0.0109	0.0109	0.0119	0.0109	0.0109	0.0109
Glass and Ceremics Products	0.0137	0.0100	0.0109	0.0119	0.0100	0.0082	0.0100	0.0082	0.0082
Iron and Steel	0.0109	0.0091	0.0082	0.0073	0.0064	0.0064	0.0091	0.0082	0.0082
Nonferrous Metals	0.0146	0.0155	0.0146	0.0137	0.0119	0.0128	0.0119	0.0119	0.0119
Metal Products	0.0128	0.0128	0.0128	0.0119	0.0119	0.0119	0.0128	0.0119	0.0119
Machinery	0.0091	0.0100	0.0091	0.0091	0.0082	0.0091	0.0082	0.0064	0.0064
Electric Appliances	0.0091	0.0073	0.0073	0.0064	0.0064	0.0064	0.0082	0.0082	0.0082
Transportation Equipment	0.0164	0.0137	0.0146	0.0100	0.0109	0.0091	0.0109	0.0109	0.0091
Precision Instruments	0.0164	0.0164	0.0164	0.0155	0.0155	0.0155	0.0155	0.0155	0.0155
Other Products	0.0192	0.0182	0.0173	0.0146	0.0146	0.0128	0.0119	0.0128	0.0109
Electric Power and Gas	0.0146	0.0146	0.0128	0.0128	0.0119	0.0119	0.0128	0.0119	0.0119
Land Transportation	0.0128	0.0137	0.0137	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100
Marine Transportation	0.0164	0.0164	0.0164	0.0119	0.0119	0.0128	0.0119	0.0119	0.0128
Air Transportation	0.0100	0.0100	0.0109	0.0073	0.0073	0.0073	0.0073	0.0073	0.0073
Warehousing	0.0100	0.0109	0.0109	0.0082	0.0082	0.0082	0.0091	0.0082	0.0082
Information & Communication	0.0091	0.0091	0.0100	0.0055	0.0055	0.0073	0.0064	0.0073	0.0082
Wholesale Trade	0.0173	0.0155	0.0137	0.0119	0.0128	0.0137	0.0091	0.0128	0.0137
Retail Trade	0.0137	0.0137	0.0137	0.0091	0.0100	0.0100	0.0109	0.0100	0.0109
Banks	0.0091	0.0091	0.0109	0.0064	0.0064	0.0073	0.0073	0.0073	0.0100
Securities and Commodities Futures	0.0119	0.0091	0.0091	0.0100	0.0064	0.0064	0.0119	0.0100	0.0100
Insurance	0.0109	0.0082	0.0082	0.0064	0.0064	0.0064	0.0064	0.0064	0.0064
Other Financing Business	0.0155	0.0137	0.0137	0.0100	0.0100	0.0100	0.0109	0.0100	0.0100
Real Estate	0.0100	0.0100	0.0119	0.0055	0.0055	0.0082	0.0073	0.0064	0.0109
Services	0.0128	0.0100	0.0100	0.0091	0.0091	0.0100	0.0073	0.0082	0.0091

Table 3. In-sample period 5% VaR results.

Sector	GARCH-n	GJR-n	APARCH-n	GARCH-t	GJR-t	APARCH-t	GARCH-st	GJR-
Fishery, Agriculture & Forestry	0.0429	0.0438	0.0447	0.0447	0.0474	0.0493	0.0447	0.047
Mining	0.0356	0.0365	0.0356	0.0411	0.0420	0.0420	0.0474	0.047
Construction	0.0547	0.0493	0.0465	0.0584	0.0575	0.0547	0.0538	0.050
Foods	0.0566	0.0493	0.05657	0.0566	0.0529	0.0502	0.0547	0.050
Textiles and Apparels	0.0538	0.0529	0.0520	0.0538	0.0547	0.0557	0.0502	0.049
Pulp and Paper	0.0511	0.0529	0.0493	0.0538	0.0538	0.0511	0.0474	0.051
Chemicals	0.0557	0.0511	0.0520	0.0575	0.0557	0.0566	0.0511	0.046
Pharmaceutical	0.0438	0.0438	0.0374	0.0456	0.0465	0.0465	0.0456	0.045
Oil and Coal Products	0.0429	0.0420	0.0420	0.0438	0.0429	0.0438	0.0447	0.044
Rubber Products	0.0493	0.0511	0.0502	0.0502	0.0511	0.0538	0.0502	0.051
Glass and Ceremics Products	0.0566	0.0547	0.0547	0.0575	0.0575	0.0566	0.0511	0.054
Iron and Steel	0.0484	0.0474	0.0456	0.0502	0.0465	0.0484	0.0538	0.051
Nonferrous Metals	0.0575	0.0557	0.0557	0.0593	0.0593	0.0593	0.0575	0.056
Metal Products	0.0365	0.0365	0.0383	0.0401	0.0401	0.0374	0.0420	0.042
Machinery	0.0575	0.0602	0.0566	0.0620	0.0620	0.0611	0.0520	0.050
Electric Appliances	0.0502	0.0511	0.0502	0.0493	0.0511	0.0502	0.0557	0.054
Transportation Equipment	0.0456	0.0465	0.0456	0.0511	0.0493	0.0502	0.0511	0.049
Precision Instruments	0.0520	0.0484	0.0484	0.0520	0.0484	0.0502	0.0520	0.048
Other Products	0.0511	0.0511	0.0520	0.0547	0.0529	0.0538	0.0484	0.050
Electric Power and Gas	0.0420	0.0411	0.0411	0.0420	0.0420	0.0392	0.0429	0.042
Land Transportation	0.0420	0.0429	0.0429	0.0420	0.0420	0.0420	0.0456	0.044
Marine Transportation	0.0429	0.0456	0.0447	0.0465	0.0465	0.0447	0.0456	0.045
Air Transportation	0.0383	0.0383	0.0383	0.0429	0.0429	0.0438	0.0447	0.045
Warehousing	0.0474	0.0465	0.0484	0.0484	0.0493	0.0493	0.0511	0.051
Information & Communication	0.0420	0.0356	0.0347	0.0429	0.0401	0.0401	0.0465	0.045
Wholesale Trade	0.0566	0.0511	0.0511	0.0557	0.0520	0.0520	0.0557	0.049
Retail Trade	0.0465	0.0456	0.0456	0.0456	0.0465	0.0456	0.0465	0.048
Banks	0.0511	0.0511	0.0465	0.0502	.0511	0.0474	0.0557	0.056
Securities and Commodities Futures	0.0429	0.0429	0.0429	0.0429	0.0429	0.0429	0.0456	0.048
Insurance	0.0493	0.0474	0.0465	0.0529	0.0511	0.0502	0.0538	0.051
Other Financing Business	0.0493	0.0502	0.0511	0.0529	0.0511	0.0520	0.0529	0.052
Real Estate	0.0538	0.0529	0.0538	0.0520	0.0502	0.0529	0.0538	0.052
Services	0.0538	0.0557	0.0575	0.0566	0.0557	0.0575	0.0520	0.053

Note: GARCH-n—means the method of GARCH(1, 1) models with normal distribution. Respectively other abbreviation are constructe
are as follows:

1. GARCH- Generalized Autoregressive Conditional Heteroskedasticity;
2. GJR- Glosten, Jagannathan and Runkle;
3. APARCH- Asymmetric Power Autoregressive Conditional Heteroskedasticity.

Table 5. Optimal portfolio results for 5% VaR.

Model	n	t	st
CCC-GJR	0.0824(0.7450)	0.0797(0.7447)	0.0834(0.7466)
CCC-APARCH	0.0823(0.7450)	0.0798(0.7447)	0.0835(0.7467)
DCC-GJR	0.0808(0.7465)	0.0793(0.7451)	0.0815(0.7471)
DCC-APARCH	0.0808(0.7464)	0.0795(0.7454)	0.0812(0.7476)
STCC-GJR	0.0805(0.7459)	0.0786(0.7436)	0.0792(0.7465)
STCC-APARCH	0.0805(0.7453)	0.0788(0.7434)	0.0795(0.7467)
GSTCC-GJR	0.0780(0.7405)	0.0792(0.7426)	0.0791(0.7404)
GSTCC-APARCH	0.0713(0.7426)	0.0772(0.7423)	0.0841(0.7377)

Note: The mean-variance model gives mean return 0.0646 and standard deviation 0.7811. The number in the parenthesis is the standard deviation. CCC-GJR- means the method of using CCC model for conditional correlation matrix and GJR model for univariate GARCH specification. Abbreviations for univariate GARCH models are in the notes of Table 3. Model abbreviations for multivariate GARCH are as follows:

1. CCC- Constant Conditional Correlation;
2. DCC- Dynamic Conditional Correlation;
3. STCC- Smooth Transition Conditional Correlation;
4. GSTCCC- Generarized Smooth Transition Conditional Correlation.

Table 6. Optimal portfolio results for 1% VaR.

Model	n	t	st
CCC-GJR	0.0817(0.7465)	0.0788(0.7461)	0.0816(0.7485)
CCC-APARCH	0.0816(0.7464)	0.0789(0.7462)	0.0817(0.7485)
DCC-GJR	0.0808(0.7459)	0.0780(0.7465)	0.0810(0.7496)
DCC-APARCH	0.0809(0.7458)	0.0778(0.7464)	0.0809(0.7498)
STCC-GJR	0.0808(0.7459)	0.0764(0.7460)	0.0772(0.7495)
STCC-APARCH	0.0809(0.7450)	0.0769(0.7456)	0.0795(0.7467)
GSTCC-GJR	0.0769(0.7440)	0.0749(0.7425)	0.0721(0.7437)
GSTCC-APARCH	0.0789(0.7447)	0.0727(0.7431)	0.0798(0.7429)

Note:The mean-variance model gives mean return 0.0646 and standard deviation 0.7811.

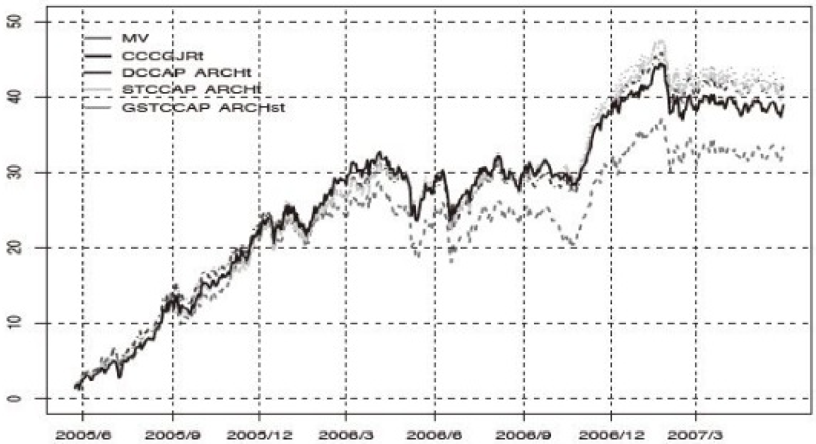

Figure 5. Wealth evolution for 500 out-of-sample 5% VaR forecast with mean-variance portfolio.

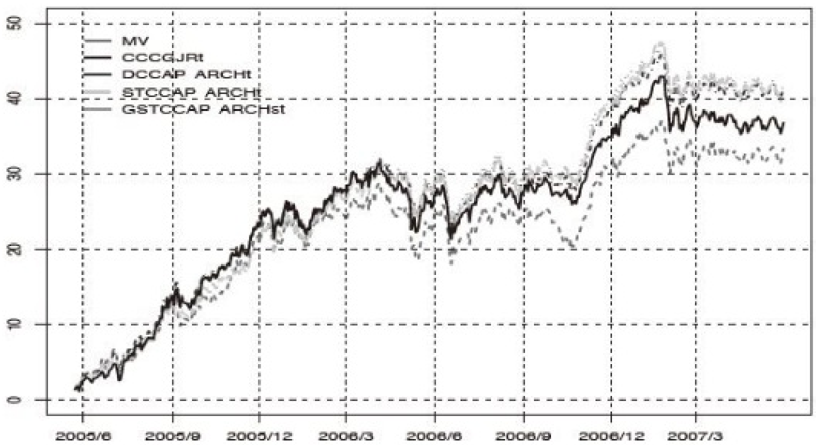

Figure 6. Wealth evolution for 500 out-of-sample 1% VaR forecast with mean-variance portfolio.

I try to surf over internet and the model has no yet widely use. Here I can only use the CCC, DCC models but the best performance GSTCC is not yet available in r packages. The `cccgarch` has STCC model but there has no examples to use it.

1.3 VaR

I stored the forecast VaR value as well, kindly refer to *How Good Are Your VaR Estimates?* for more information.

- *ARMA(1,1)-GARCH(1,1) Estimation and forecast using rugarch 1.2-2*
- An Introduction to Value at Risk (VAR)
- Multivariate GARCH with respect to Value at Risk is the another article about VaR in multivariate models.
- Difference between uGarchRoll Value at Risk and manual calculations
- ARMA(1,1)-GARCH(1,1) Estimation and forecast using rugarch 1.2-2
- Issues in estimating VaR with GARCH
- Value-At-Risk (VaR) curve with Copula-GARCH model (R)
- Calculation of VaR of a time series using a GARCH(1,1) ARMA(1,1) model
- Fitting and Predicting VaR based on an ARMA-GARCH Process

```
# conditional mean
cmu = as.numeric(as.data.frame(forecast, which = "series",
rollframe="all", aligned = FALSE))
# conditional sigma
csigma = as.numeric(as.data.frame(forecast, which = "sigma",
rollframe="all", aligned = FALSE))

I can calculate the VaR by using the property, that the normal distribution
is part of the location-scale distribution families

# use location+scaling transformation property of normal distribution:
VaR = qnorm(0.01)*csigma + cmu
```

source : rugarch VaR calculation "manually"

> For your purpose, you need a random variable with zero mean and unit variance. However, the variance of the Student-t distribution is νν−2 for ν>2 and not one, where ν are the degrees of freedom.
>
> You get the correct VaR by multiplying the quantile of the Student-t distribution with ν−2ν−−−√:
>
> 0.1262 + 1.059 * qt(0.05, 4.68) * sqrt((4.68-2) / 4.68) [1] -1.51334 Alternatively, using the rugarch package which defaults to standardized distributions:
>
> rugarch::qdist("std", 0.05, mu=0.1262, sigma=1.059, shape=4.68) [1] -1.51334

source : Difference between uGarchRoll Value at Risk and manual calculations

1.4 VaR for Long and Short

- Value-at-Risk for long and short trading positions - Evidence from developed and emerging equity markets
- Value-at-Risk for Long and Short Trading Positions
- Value at Risk for Long-Short Positions

2 Data

2.1 Read Data

I use more than 3 years data (from week 1 2015 until week 27 2018)[1] for the question as experiment, 1st year data is burn-in data for statistical modelling and prediction purpose while following 2 years data for forecasting and staking. There have 52 trading weeks within a year.

Hide

```
## get currency dataset online.
## http://stackoverflow.com/questions/24219694/get-symbols-quantmod-ohlc-currency-data
#'@ getFX('USD/JPY', from = '2014-01-01', to = '2017-01-20')

## getFX() doesn't shows Op, Hi, Lo, Cl price but only price. Therefore no idea to
```

```r
 place bets.
#'@ USDJPY <- getSymbols('JPY=X', src = 'yahoo', from = '2014-01-01',
#'@                       to = '2017-01-20', auto.assign = FALSE)
#'@ names(USDJPY) <- str_replace_all(names(USDJPY), 'JPY=X', 'USDJPY')
#'@ USDJPY <- xts(USDJPY[, -1], order.by = USDJPY$Date)

cr_code <- c('AUDUSD=X', 'EURUSD=X', 'GBPUSD=X', 'CHF=X', 'CAD=X', 'CNY=X', 'JPY=
X')

names(cr_code) <- c('AUDUSD', 'EURUSD', 'GBPUSD', 'USDCHF', 'USDCAD', 'USDCNY', 'U
SDJPY')
#'@ names(cr_code) <- c('USDAUD', 'USDEUR', 'USDGBP', 'USDCHF', 'USDCAD', 'USDCN
Y', 'USDJPY')

#'@ saveRDS(USDJPY, './data/USDJPY.rds')
USDJPY <- read_rds(path = './data/USDJPY.rds')
mbase <- USDJPY

## dateID
dateID <- index(mbase)
dateID0 <- ymd('2015-01-01')
dateID <- dateID[dateID > dateID0]
```

Hide

```r
dim(mbase)
```

```
## [1] 1476    6
```

Hide

```r
summary(mbase) %>%
  tidy %>%
  .[,-1] %>%
  kable(caption = 'MSE of daily Opened and Closed Transaction Orders') %>%
  kable_styling(bootstrap_options = c('striped', 'hover', 'condensed', 'responsiv
e')) %>%
  scroll_box(width = '100%', height = '400px')
```

MSE of daily Opened and Closed Transaction Orders

Var2	n
Index	Min. :2012-01-02
Index	1st Qu.:2013-05-29
Index	Median :2014-10-30
Index	Mean :2014-10-30
Index	3rd Qu.:2016-03-30
Index	Max. :2017-08-30
USDJPY.Open	Min. : 76.18
USDJPY.Open	1st Qu.: 97.86
USDJPY.Open	Median :103.91
USDJPY.Open	Mean :103.71
USDJPY.Open	3rd Qu.:114.27
USDJPY.Open	Max. :125.60
USDJPY.High	Min. : 76.20
USDJPY.High	1st Qu.: 98.29
USDJPY.High	Median :104.19
USDJPY.High	Mean :104.07
USDJPY.High	3rd Qu.:114.72
USDJPY.High	Max. :125.82
USDJPY.Low	Min. : 76.05
USDJPY.Low	1st Qu.: 97.46
USDJPY.Low	Median :103.54

USDJPY.Low	Median :[illegible]
USDJPY.Low	Mean :103.32
USDJPY.Low	3rd Qu.:113.74
USDJPY.Low	Max. :124.97
USDJPY.Close	Min. : 76.18
USDJPY.Close	1st Qu.: 97.85
USDJPY.Close	Median :103.93
USDJPY.Close	Mean :103.71
USDJPY.Close	3rd Qu.:114.24
USDJPY.Close	Max. :125.63
USDJPY.Volume	Min. :0
USDJPY.Volume	1st Qu.:0
USDJPY.Volume	Median :0
USDJPY.Volume	Mean :0
USDJPY.Volume	3rd Qu.:0
USDJPY.Volume	Max. :0
USDJPY.Adjusted	Min. : 76.18
USDJPY.Adjusted	1st Qu.: 97.85
USDJPY.Adjusted	Median :103.93
USDJPY.Adjusted	Mean :103.71
USDJPY.Adjusted	3rd Qu.:114.24
USDJPY.Adjusted	Max. :125.63

3 Betting Strategy

3.1 Betting Model

4 Conclusion

5 Appendix

5.1 Documenting File Creation

It's useful to record some information about how your file was created.

- File creation date: 2018-09-04
- File latest updated date: 2018-10-31
- R version 3.5.1 (2018-07-02)
- R version (short form): 3.5.1
- **rmarkdown** package version: 1.10.14
- File version: 1.0.1
- Author Profile: ®γσ, Eng Lian Hu
- GitHub: Source Code
- Additional session information:

Additional session information:

Category	session_info	Category	Sys.info
version	R version 3.5.1 (2018-07-02)	sysname	Windows
os	Windows 10 x64	release	10 x64
system	x86_64, mingw32	version	build 17134
ui	RTerm	nodename	RSTUDIO-SCIBROK
language	en	machine	x86-64

collate	Japanese_Japan.932	login	scibr
ctype	Japanese_Japan.932	user	scibr
tz	Asia/Tokyo	effective_user	scibr
date	2018-10-31	Current time	2018-10-31 20:18:53 JST

5.2 Reference

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7. Valuation of Soccer Spread Bets
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9. How Does the Fortune's Formula-Kelly Capital Growth Model Perform
10. Information Theory and Gambling or Economics
11. Investment Portfolio Optimization with GARCH Models
12. Kelly Criterion Revisited - Optimal Bets
13. Markov-Switching Autoregressive Models for Wind Times Series (ppt)
14. Markov-Switching Autoregressive Models for Wind Times Series
15. Medium Term Simulations of the Full Kelly and Fractional
16. Modelling Exchange Rates using Regime Switching Models
17. Money Management (V1)
18. Money Management (V2)
19. Optimal Betting under Parameter Uncertainty - Improving the Kelly Criterion
20. Enhancing Trading Strategies with Order Book Signals
21. Creating Optimal Portfolios of Stocks with Time-Varying Risk
22. Dynamic Portfolio Optimization using Generalized Dynamic Conditoinal Heteroskedastic Factor Models
23. Comparison of BEKK GARCH and DCC GARCH Models - An Empirical Study
24. Do We Really Need Both BEKK and DCC - A Tale of Two Multivariate GARCH Models
25. Forecasting Conditional Correlation for Exchange Rates using Multivariate GARCH Models with Historical Value-at-Risk Application
26. Volatility Spillover and Time-Varying Conditional Correlation between the European and US Stock Markets
27. Applying MGARCH Models in Finance
28. Comparison of Multivariate GARCH Models with Application to Zero-Coupon Bond Volatility
29. Forecasting the Daily Dynamic Hedge Ratios by GARCH Models - Evidence from the Agricultural Futures Markets
30. Currency Hedging Strategies Using Dynamic Multivariate GARCH
31. Which GARCH model is best for Value-at-Risk
32. Comparison of Value-at-Risk Estimates from GARCH Models
33. Comparison of Value at Risk Models and Forecasting Realized Volatility by using Intraday Data
34. binary.com Interview Question I - Tick-Data-HiLo For Daily Trading (Blooper)
35. How Good Are Your VaR Estimates?
36. Kelly's Criterion in Portfolio Optimization - A Decoupled Problem

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1. You are feel feel to get the data via FXCMTickData↩