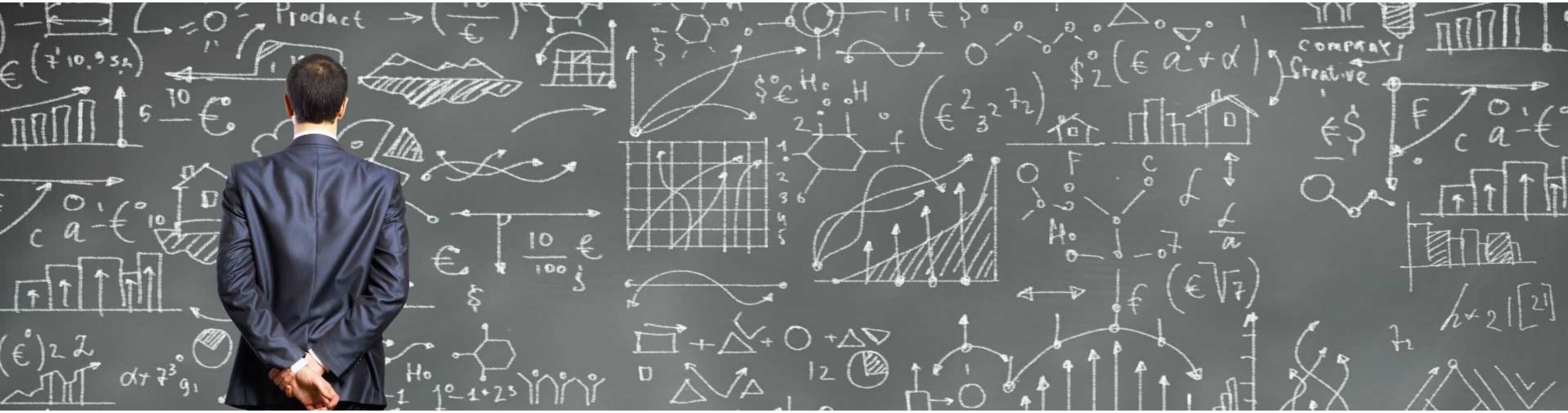
Khanh Ho



Testing Value-at-Risk models on long run Sovereign bond data

[10/04/2020]

Agenda

Testing Value-at-Risk (VaR) models on long run Sovereign Bond

Background / Business Problem

[Risk management]

Risk prediction tools for investors or organization in the debt market

Situation

- Refer to the organizations and investors in the financial market, risk management is an urgent requirement in controlling losses. In a scope of liability management, an accurate model for risk prediction is an effective investment tool for the current chaos in finance and support them in the portfolio optimization.

Complication

- To find the best models, it requires a clean dataset and clear insight or patterns of 220,000 bond returns of 91 countries. With a target of optimizing the portfolios, the bonds need to be constructed as national or global portfolio before applying the models
- Value-at-Risk model is popular and also controversial in stock application but not in debt market; therefore, it is an opportunity and also a challenge to check the efficiency of models

Executive Summary / Key Takeaways

Approach & Solution

- Based on Portfolio and Value-at-Risk (VaR) theories and with idea of portfolio selection, it considers the trade-off between expected returns and the real volatility. To optimize the portfolios, one way is to restrict the downside risk or shortfall probability by identifying the shortfall target VaR at first. Target, to find the best models estimating the accurate VaRs
- Approaching 3 methods to estimate VaR: non-parametric (Historical Simulation), parametric (GARCH) and Expected Shortfall (ES)
- To validate the efficiency of those model, use the Back testing with 3 kinds of tests (Kupiec test, Independence test and Conditional Coverage test)
- Relied on the tests to execute the results and conclusions for the problem

Target: find the best models to estimate the VaRs

Data Set Characteristics

[Data patterns]

Dataset Information

- **Size:** 152,448 bonds with 24 countries (highest frequencies)
- **Shape:** high peak, fat tail, not normality
- **Observations:** positively skewed (investors often lose little and make less extreme gains) and excess leptokurtosis (in danger to experience occasionally serious outliers)
- **Features:** weight the exponential monthly returns to construct portfolios
- **Labels:** bondId (ID), Name, Country (c), issue date (issuey), maturity date (maturityy), monthly return (rdrealy), amount of issue (amtISS), currency, year y and month m
- **Missing values:** drop the bonds without the returns and were noted as 'safe asset' (no transaction), correct the wrong spelling
- **Duplicates:**
  - The bonds with different returns (by various resources), take the returns closer to previous months
  - The bonds with different maturity or issue date: recheck and leave the incorrect one
  - The bonds with same IDs but with different names: check the differences of returns, if they are the same, drop one bonds, otherwise, recheck the IDs and names, they are probably different

Dataset Visualizations

	c	ID	tm	rmdreal	issuey	maturityy	amtISS	currency	y	m
1	Venezuela	10002	1862m1	.1302836	1859	.	1.50	GBP	1862	1
2	Venezuela	10002	1862m2	.6783779	1859	.	1.50	GBP	1862	2
3	Venezuela	10002	1862m3	-.3932821	1859	.	1.50	GBP	1862	3
4	Venezuela	10002	1862m4	.0007719	1859	.	1.50	GBP	1862	4
5	Venezuela	10002	1862m5	-.020297	1859	.	1.50	GBP	1862	5
6	Venezuela	10002	1862m6	.0442837	1859	.	1.50	GBP	1862	6
7	Venezuela	10002	1862m7	.0429097	1859	.	1.50	GBP	1862	7
8	Venezuela	10002	1862m8	.0211958	1859	.	1.50	GBP	1862	8
9	Venezuela	10002	1862m9	.1321864	1859	.	1.50	GBP	1862	9
10	Venezuela	10002	1862m10	.0728996	1859	.	1.50	GBP	1862	10

Variables

Filter variables here

Name	Label
c	country
ID	ID
tm	Month
rmdreal	Monthly Portfolio
issuey	issue year
maturityy	maturity year
amtISS	amount issued in ...
currency	
y	year
m	month
rmdreal_L1	

Variables Snapshots

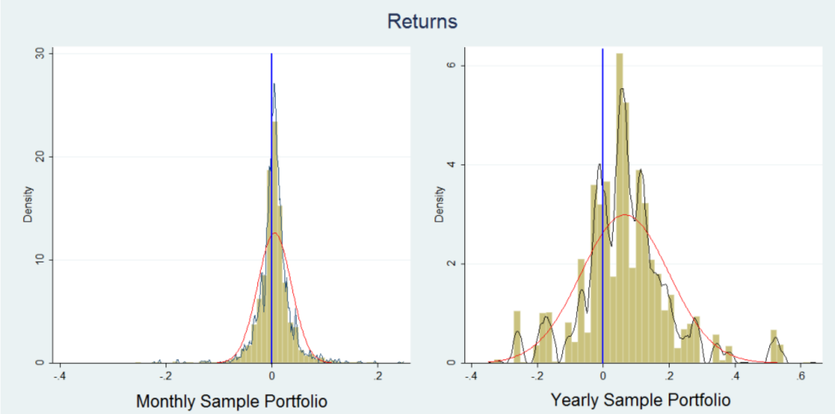
Properties

Variables	
Name	c
Label	country
Type	str53
Format	%-25s
Value label	
Notes	
Data	
Filename	25 countries.dta

EDA – Exploratory Data Analysis

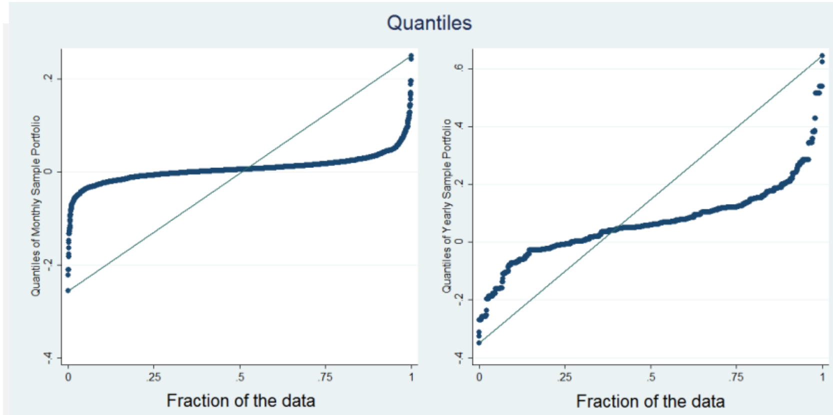
[Descriptive analysis and visualization]

Visualization EDA 1



Monthly (left) and Yearly (right) Sample Portfolio in 1815-2017

Visualization EDA 2



According quantiles in 1815-2017

Visualization EDA 3

Country	Database							Portfolio by country and sample						Degree of freedom
	N	mean**	sd	min	max	skewness	kurtosis	mean**	sd	min	max	skewness	kurtosis	v
Argentina	13824	.646	.068	-.842	.757	.311	27.393	.668	.051	-.449	.375	-.364	21.949	4.317
Australia*	11016	.379	.020	-.187	.195	.390	10.213	.378	.018	-.095	.159	.628	9.035	4.994
Belgium*	2496	.588	.043	-.630	.563	.386	71.791	.599	.037	-.484	.424	-.008	67.100	4.094
Brazil	17064	.729	.067	-.552	.918	.890	20.488	.735	.057	-.422	.495	.469	17.974	4.401
Canada*	8112	.304	.019	-.281	.163	-1.391	30.037	.299	.016	-.181	.096	-1.655	27.494	4.245
Chile	10668	.646	.078	-.627	1.617	3.886	69.497	.602	.072	-.448	1.079	4.392	73.335	4.085
China	7020	.199	.087	-.560	1.744	4.035	62.127	.252	.072	-.560	1.465	4.926	84.507	4.074
Colombia	3396	.689	.065	-.413	.709	1.406	20.725	.749	.064	-.376	.527	1.132	17.166	4.537
Egypt	3120	.534	.043	-.364	.511	.478	27.949	.586	.042	-.319	.379	.887	25.086	4.272
Germany	2544	.479	.104	-.817	1.223	1.388	29.179	.453	.090	-.817	1.060	1.278	32.867	4.201
Greece	6180	.892	.086	-.656	1.671	2.305	34.570	1.027	.071	-.359	.543	1.125	10.856	4.764
Hungary	2556	.588	.073	-.555	.824	1.770	28.293	.656	.071	-.469	.823	1.993	29.454	4.227
Indonesia	2736	.510	.039	-.260	.314	.218	13.497	.528	.036	-.202	.240	.165	11.383	4.716
Italy	2712	.610	.041	-.627	.466	-.052	47.232	.628	.040	-.627	.466	-.383	50.074	4.128
Japan	5316	.628	.069	-.702	1.800	3.913	106.166	.613	.057	-.505	.560	1.257	24.284	4.282
Mexico	9156	.803	.078	-.557	1.364	3.553	55.396	.812	.061	-.314	1.024	3.104	43.597	4.147
New Zealand*	5220	.420	.025	-.504	1.030	11.827	580.957	.457	.029	-.252	.519	8.427	180.401	4.034
Peru	3960	.611	.094	-.508	1.823	3.444	52.995	.586	.080	-.381	.623	1.496	15.082	4.497
Philippines	3360	.591	.027	-.329	.201	-.669	16.335	.624	.024	-.192	.139	-.708	11.429	4.712
Poland	3144	.667	.108	-.814	1.379	1.951	25.555	.693	.089	-.773	.791	1.173	20.960	4.334
Russia	9528	.523	.080	-.793	1.757	3.383	65.812	.489	.067	-.708	1.757	4.546	105.284	4.059
Sweden*	2712	.440	.026	-.289	.209	-.408	19.623	.450	.023	-.289	.169	-.761	25.036	4.272
Turkey	7236	.630	.069	-.441	1.286	3.585	68.783	.635	.061	-.389	.889	4.018	68.303	4.092
Uruguay	5268	.563	.053	-.403	.475	.370	17.655	.570	.045	-.358	.384	.0788	18.165	4.396
Venezuela	4104	.885	.072	-.470	.678	.289	11.927	.884	.067	-.393	.679	.209	10.192	4.834
Sample	152448	.589	.067	-.842	1.822	2.854	63.373	.546	.032	-.257	.250	.129	14.063	4.542

Summary Statistics comparison between database and monthly portfolio by country and sample from 1815 to 2017, and the degrees of freedom in t-distribution

OVERVIEW

- high peak, fat tail, not normality

- positively skewed (investors often lose little and make less extreme gains) and excess leptokurtosis (in danger to experience occasionally serious outliers)

- => Group by country can reduce the risk

Data Cleansing & Pre-processing

[Clean data and construct portfolios]

Clean and format data

- Drop the data with country noted as “safe asset”
- Format the dataset and label the variables
- Check duplicates to find the missing values and correct the wrong spelling “NewZealand” to get the full clean dataset

```
drop if c=="safe asset"
format ID %-9.0g
format c %-25s
keep c ID tm rdreal rdrealy name desc1 DebtName issuey maturityy amtISS* currency y m
label var m "month"
label var y "year"
label var c "country"
label var rdrealy "Annual Return"
replace c="NewZealand" if c=="New Zealand"
```

Separate the data

- Choose the countries that have many available bond returns and drop the less returns
- Separate returns into default (default = 0) or not default

```
bysort c: gen freq=_N
drop if freq < 2496

*Seperate default and not-defaulted
gen default=.
replace default=0 if c=="Australia"|c== "Belgium"|c=="Canada"|c=="New Zealand"| c=="Sweden"
replace default=1 if default==.

* Annual returns
tsset ID tm
sort ID tm
bys ID y: egen lrdrealy = sum( ln( rdreal + 1 ) )
replace rdrealy = exp( lrdrealy ) - 1
```

Build portfolios

- Construct weights by the amount of bond issue according to the country and date

```
* Weights
bys c y m: egen totalweight=sum(amtISSUSD)
gen weight_per_bond = amtISSUSD / totalweight

* Weighted returns
gen rmdreal_weighted_bond = rdreal * weight_per_bond
gen rydreal_weighted_bond = rdrealy * weight_per_bond

* Portfolio returns
bys c y m: egen rmdreal = total(rmdreal_weighted_bond), missing
bys c y m: egen rydreal= total(rydreal_weighted_bond), missing
```

Modelling, Tuning & Evaluation

[Time series and portfolio analysis]

Model Selection

Time series analysis, use

- **Historical Simulation (HS):**
  - no distribution assumption
  - linear regression
  - roll windows to proceed one-day prediction
- **GARCH model:** describe irregular pattern in model
  - normality and t-distribution assumption
  - non-linear regression, dynamic deviation (evolution of risk)
- **Expected Shortfall (ES):** average VaRs, expected returns when returns exceed the break of extreme threshold – VaR
  - Appy for HS and GARCH

Model Evaluation

Perform Back testing

- **Kupiec test**
  - rate of failure which loss returns exceed the VaR
  - Reject when result of log likelihood ratio (LR test) exceed the critical values
- **Independence test:** violation at time t has no correlation with fluctuation at previous time (t-1)
  - Reject the result similar to Kupiec test
- **Conditional average test :** overcome the shortcoming of 2 above test: Kupiec – no time correlation and Independence test – lack the rate of failure
  - Accept when proportion of violations equal confidence interval α and past violation has no impact on current one

Model Performance Results

- Kupiec test: Normal GARCH (23/25 portfolios), ES Normal GARCH (21) and HS (19) yield good estimates
- Independence test: Normal GARCH (16), ES Normal GARCH (16)
  - This test reduced the amount of approved portfolios, compared to Kupiec
- Conditional average test: HS (10) and ES-HS (10) are recommended

Analysis Results & Recommendations

[No persistent model for the time-series returns]

- Some results and recommendations:

Result #1

- Historical Simulation and Expected Shortfall of Historical Simulation are most effective
- Normal GARCH(1,1) and ES Normal GARCH(1,1) are also potential.
- Conditions: the length of time-series should be larger than 5 years

Result #2

- a persistent model applied throughout time should be carefully considered, especially in crisis.
- Recommendation: should separate the returns into stable time and crisis time and apply different models on that periods

Result #3

- 1% percentile is more effective than 5% percentile in most approaches. In other word, extreme quantile executes more accurate estimates

Next Steps & Improvements

[more variables in regression and new tool to collect data]

- Source other data sets: should perform the low-frequency returns to compare the results with high-frequency returns (in the project)
- Research another data science technique: can use SQL, Python or Tableau to perform the data analysis
- Try other ideas: In the next research, I can collect and analyze the stock market to see how bond reflected the stock market. Besides, I can implement more variables in regression , for examples default =0/1 or crisis = 0/1, to improve the models

Project/Approach Improvements

1. Use historical data in a certain time-series over 200 years and make one-day prediction, then compare to the reality to see how difference the forecast and the fact. This project applied the Excel and Stata, paid attention on the quantile regression and compared the fitness of linear and non-linear model in practice

2. By using the 3 types of testing (Inferential Staitistics), the results are much more objective and accurate

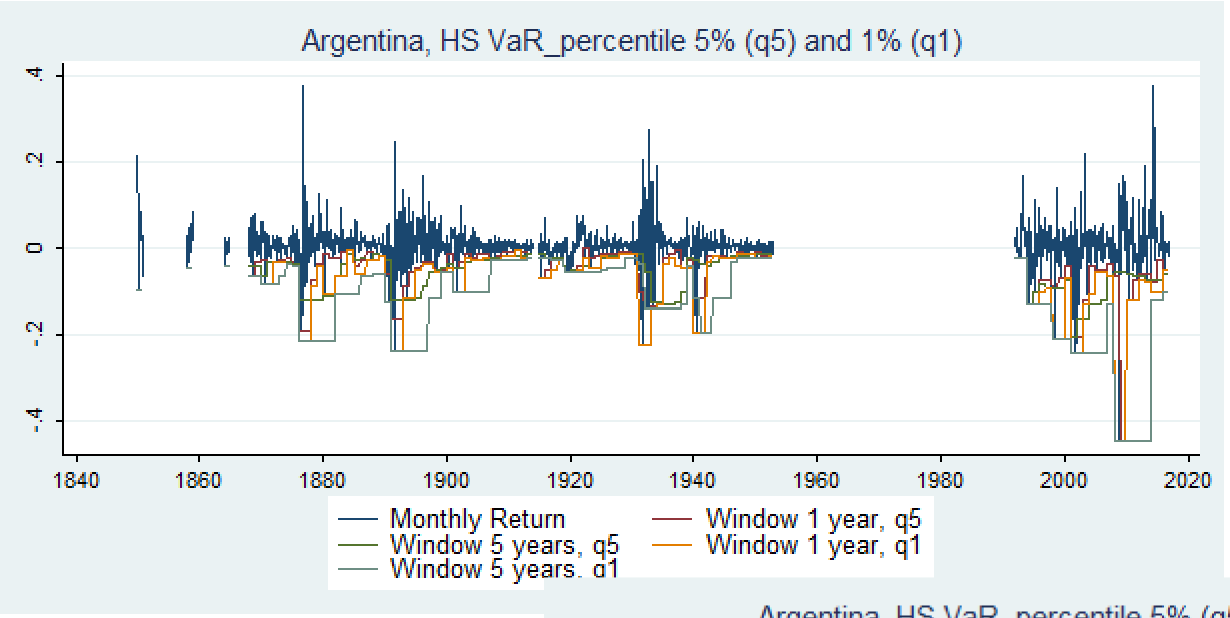
Lessons learned

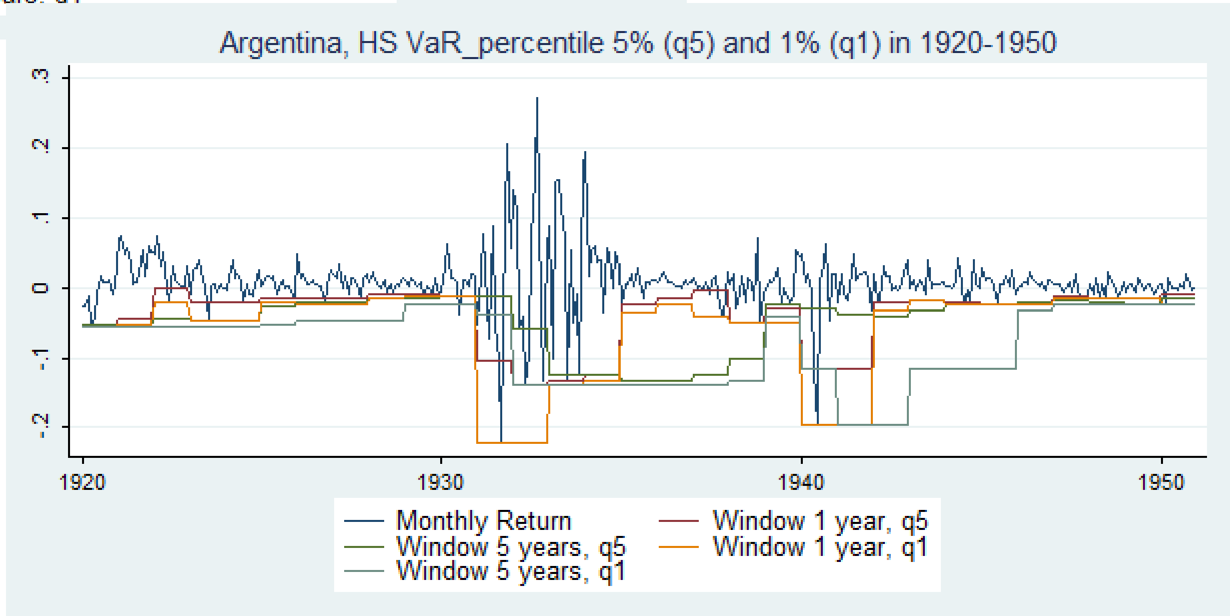
1. Even the debt market is less violated than the stock (monthly returns instead of daily ones as stock market), this market reveals insights for investors in the risk management aspect and there is also reflection between those market. That is the reason why this market needs to be considered carefully

2. The long run dataset is such a convenience for investors to build up model investigating the risk, but the dataset is actually not available and took lots of time and effort to gather and clean, especially most of the collected prices are from the pdf files. API from Python maybe a good idea to automatically collect data instead of manually

Appendix - Visualization

Portfolio returns in different models





- Historical Simulation

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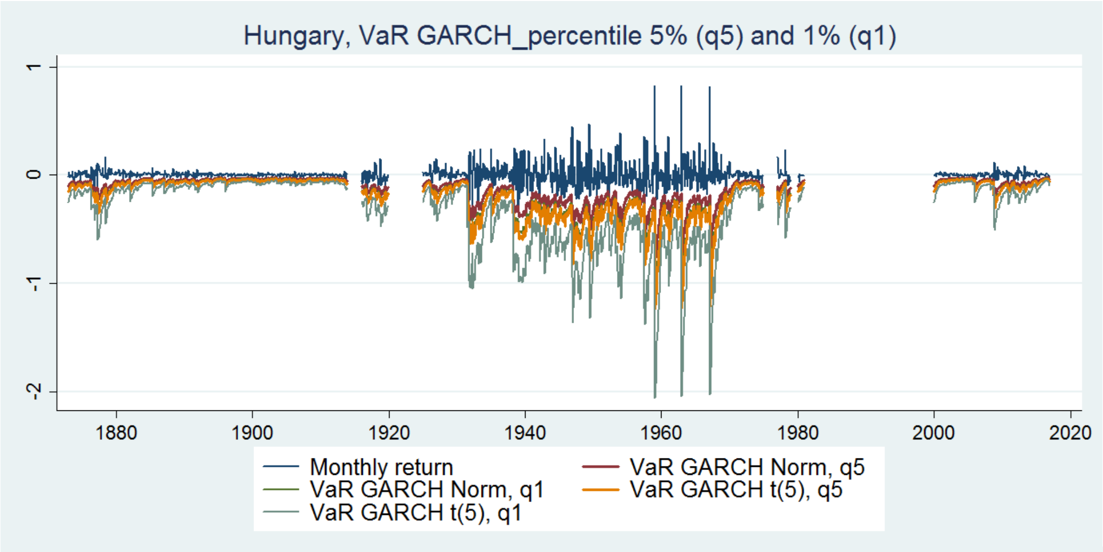
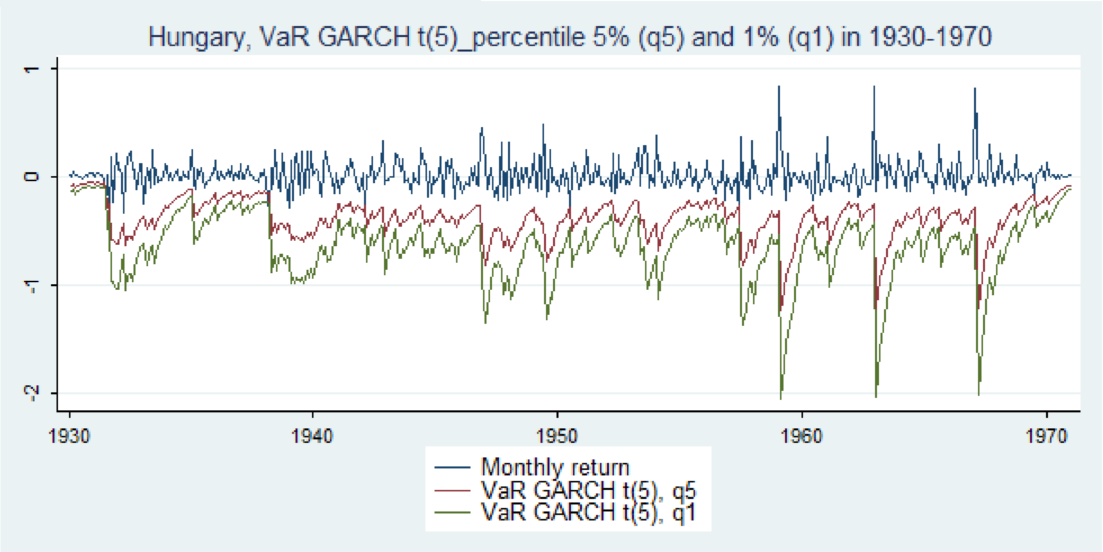


- GARCH in normal and t-distribution



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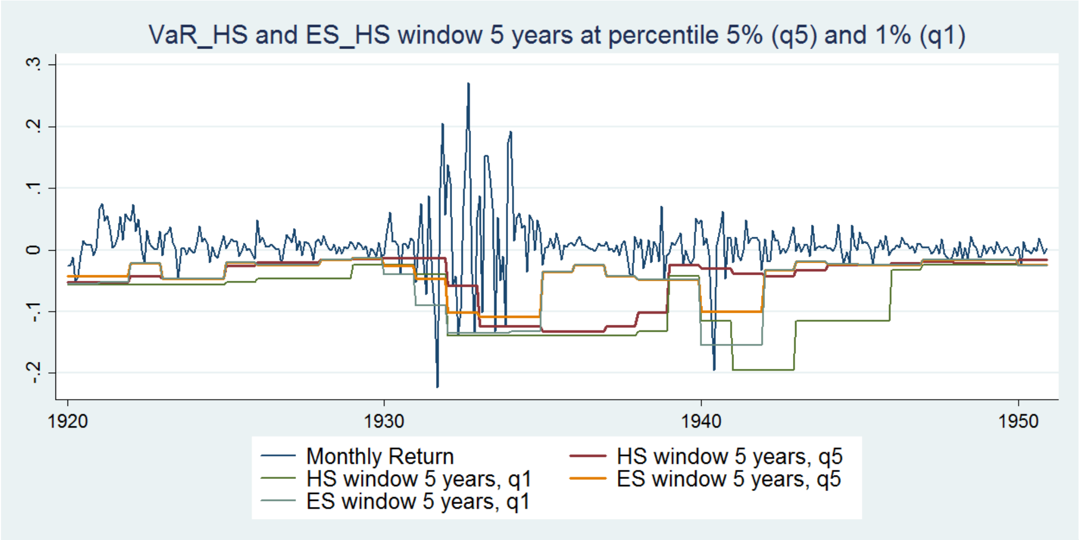
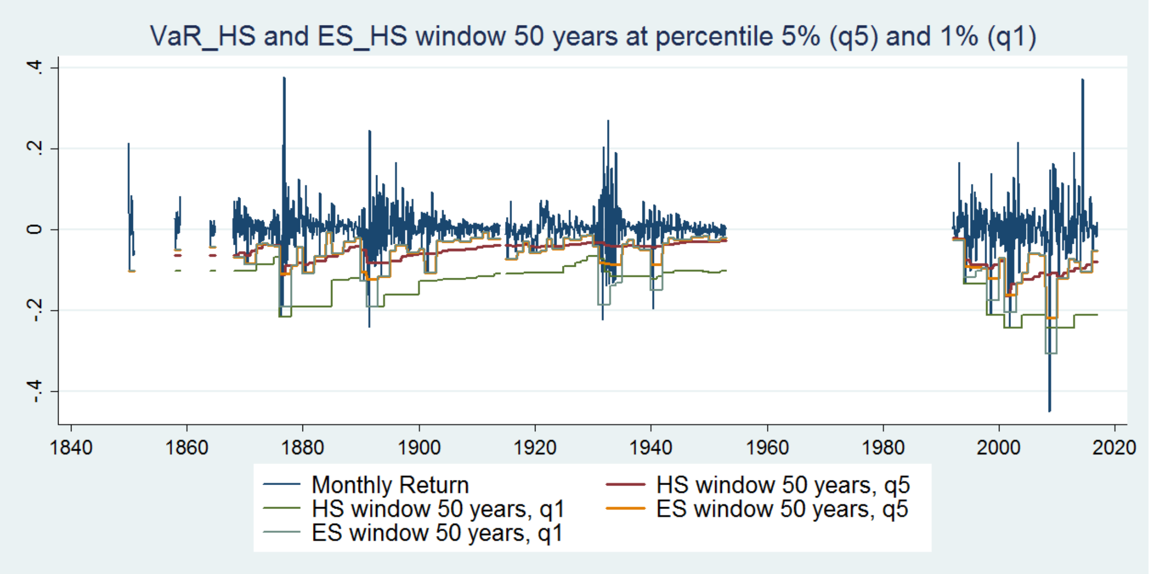


Expected Shortfall for Historical Simulation



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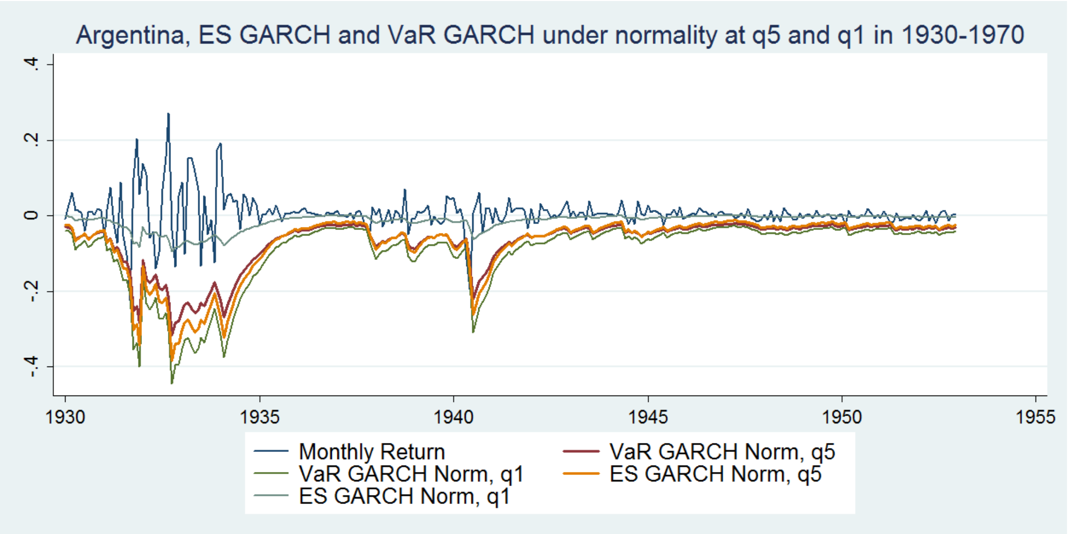

Expected Shortfall for GARCH models