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How Visualization and Computer Science (AI) Could Support Pension Funds

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- Many Publications for International Actuarial Conferences/ Journals and Research project for Federal Social Insurance Office (FSIO)
- Risk Management for Swiss Pension Funds
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Agenda

Summary

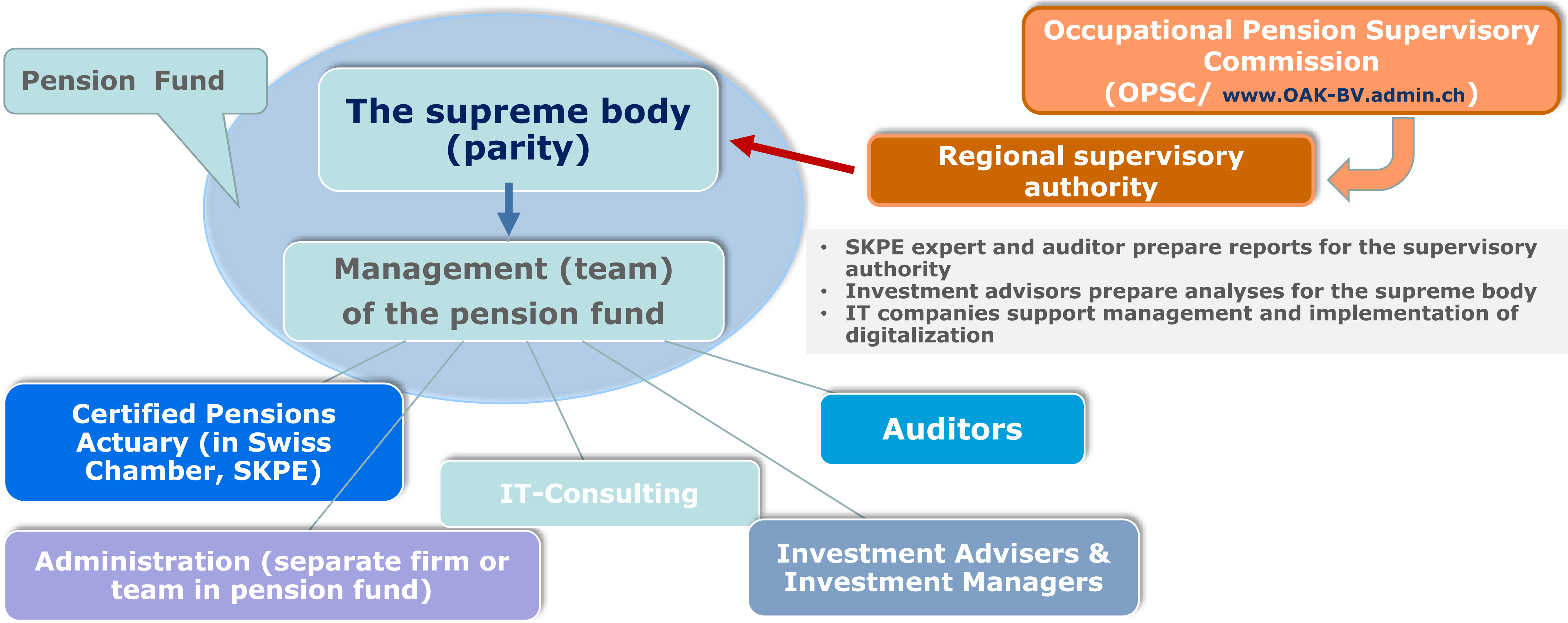
Our main topics in this on-line workshop

- Forecasting inflation, government bond yields and AA corporate bond yields is useful for making forecasts of local benefit obligations and liability positions in international accounting.
- In order to explain the projected results to the Board of Trustees and to obtain their confirmation, it is worthwhile to visualize these results and to forecast tests and approaches:
  - Visualization would be very useful on the home page
    - ✓ With our examples would be shown
- Sometimes it would be important to present as a "second opinion" a comparison of the results produced by other consultancies
- Even though the prediction approach and the "second opinion" analysis are very complicated, it would be useful to find a simple, well-understood approach to confirm your results.
  - The Threshold Portfolio Return calculated based on the annual accounts report for pension fund helps to produce exacter forecasting

Governance Budget of the supreme body

Environment of Swiss pension fund

Business partners of the supreme body (board of trustees)



- SKPE expert and auditor prepare reports for the supervisory authority
- Investment advisors prepare analyses for the supreme body
- IT companies support management and implementation of digitalization

The supreme body is responsible for choosing the business partners and is supported by consulting firms in all relevant issues.

Pension Fund Risks (for Liability Return)

- Many pension funds (Swiss as well) are **cash balance plans** for active membership:
  - **Only high interest credits (IC) help active members to reach high level of saving capital at retirement**;
- Interest credit level depends on the funding ratio and portfolio performance:
  - If the funding ratio < 100% the interest credit on the lowest level (could be even zero)
  - In Switzerland for registered pension funds (with mandatory benefits) it is prohibited to use “negative” interest credits like in “Defined Contribution” plans (based on negative portfolio return).
- Inflation level impacts practically all parameters (Portfolio return, Liability Return, Assumptions Parameters for International Accounting
  - ***Inflation as a Liability Risk has a strong impact on the benefit level of active membership and pensioners***

Pension Fund Risks (for Liability Return)

- Many pension funds (Swiss as well) are **cash balance plans** for active membership:
  - **Only high interest credits (IC) help active members to reach high level of saving capital at retirement**;
- Interest credit level depends on the funding ratio and portfolio performance:
  - If the funding ratio < 100% the interest credit on the lowest level (could be even zero)
  - In Switzerland for registered pension funds (with mandatory benefits) it is prohibited to use "negative" interest credits like in "Defined Contribution" plans (based on negative portfolio return).
- The BVG/LPP guaranteed Interest Credit over the last years is 1% (2017-2023) on the mandatory saving capital (ca. 40%-55% of the individual total saving capital)
  - Now for year 2024 the mandatory level could be 1.25%
- ***Inflation as a Liability Risk has a strong impact on the benefit level of active membership and pensioners***
- Inflation impacts **Liability Return**

Tasks of the supreme body of the pension scheme

Legal Requirements

- The supreme body of the pension fund is responsible for the overall management of the pension fund (**Art. 51a para. 1 BVG/LPP**)
- The supreme body of the pension fund is responsible for the overall management of the pension fund (**Art. 51a para. 1 BVG/LPP**)
  - *Two of these tasks*:
    - Setting of the financing system and
    - Determination of the ***objectives*** and ***principles of asset management*** as well as the ***implementation and monitoring of the investment process***

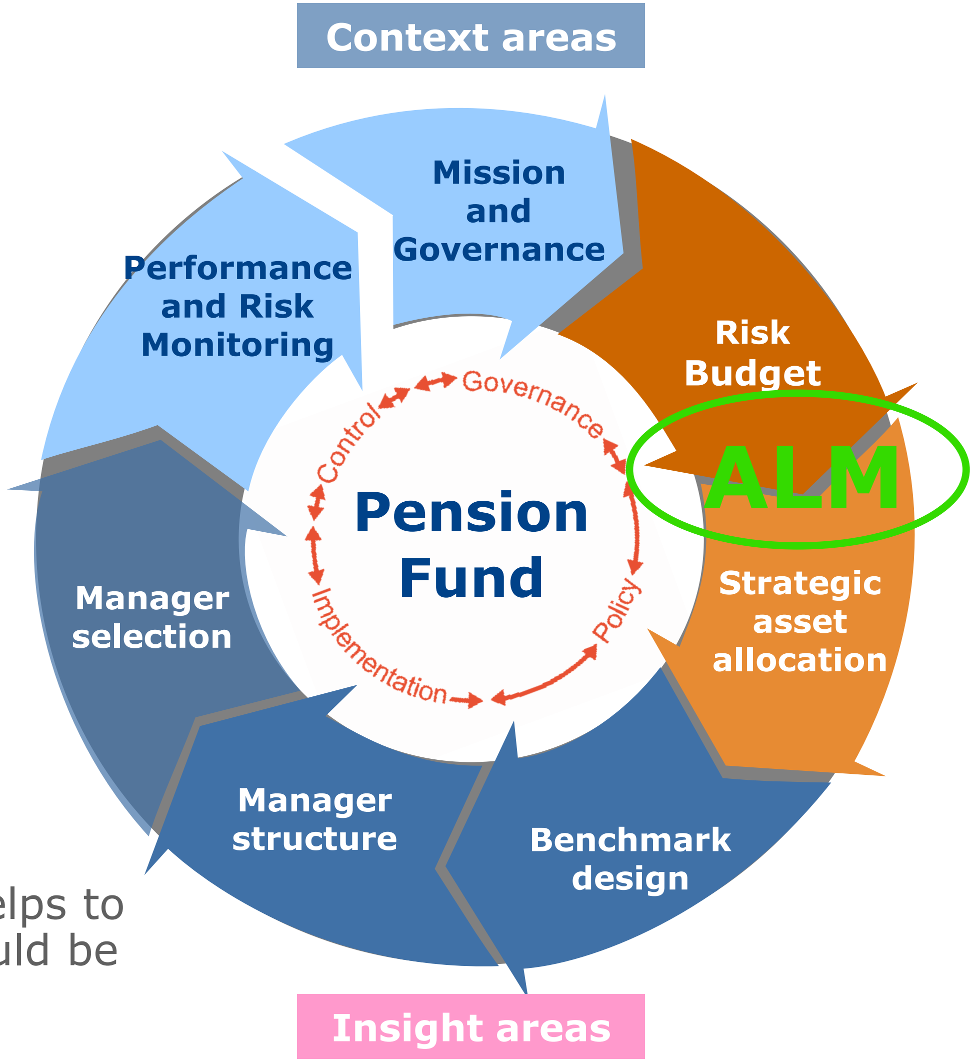
- The management responsibility of the supreme body with regards to the investment of assets
  - The supreme body comprehensibly ***designs***, ***monitors*** and ***controls*** the management of assets in a manner that is appropriate to earnings and risks

Asset Management Process

- **Manager monitoring and evaluation**
- Compliance and style monitoring
- Performance reporting
- Asset-liability risk monitoring

- Custodian selection
- **Manager searches**
- Transition management

Asset management process helps to understand if plan benefits could be financed or should be reduced

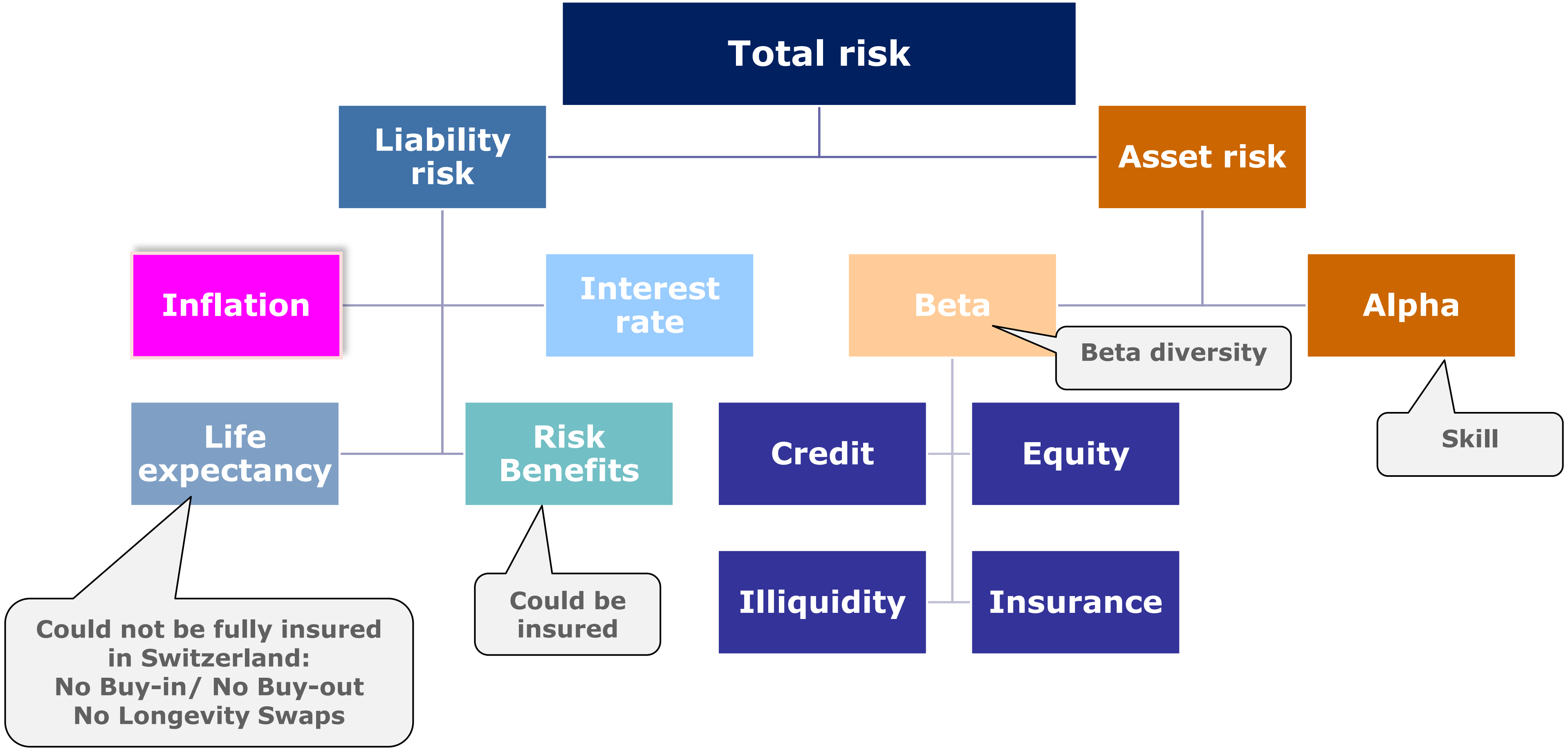


- Internal governance
- Investment objectives
- Investment policy
- **Risk budgeting**

- Design and analysis of (overlay-) strategies
- Implementation of hedge strategies
- Monitoring and evaluation of (overlay-) hedges
- **Asset/liability modeling**
- Custom benchmarks
- Manager structure
- Asset allocation funds

Overview of typical Pension Fund Risks

Risk budgeting looks only at investment risks



Governance Budget of the supreme body

- The ***governance budget*** *) is the ***capacity*** of the decision-making supreme bodies to ***manage all issues related to risk management***
- Membership in the supreme body is ***not a full-time job***
  - However, the scope of duties is enormous: the fulfilment of the legal requirement (Art. 51a BVG/LPP) requires a lot of time and expertise.
- Evaluation of the governance budget based on 3 parameters:
  - Time, Expertise and Organizational Structure
  - Training & Further Education for supreme body members legally requested

Training & Further Education for supreme body

- Visualize risk figures defined and declared by the supervision authorities (OPSC/ OAK BV) as minimum standard -> ***FRP4 Guidelines and FRP5 Guidelines***
  - ***FRP4 Guidelines*** annually defines the Upper Limit for the technical interest rate based on monthly historical data of the 10-year government bond yield per September 30, 20XX over last 12 months
  - ***FRP5 Guidelines*** request that the pension fund expert gives a feedback to the pension fund ***Threshold Portfolio Return (TPR)*** *that* should be lower compared to the expected portfolio return
- *Threshold Portfolio Return depends on the* ***Liability Return*** *(liability growth rate) and* ***pension fund cash flows*** *(all kind of payments, administration costs and contributions)*

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Definition of Threshold Portfolio Return, TPR (R^{TPR})

What does it mean «Threshold Portfolio Return»?

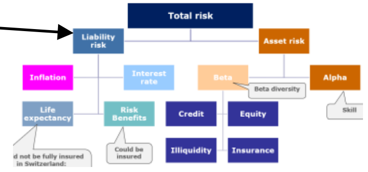
The formular to valuate R^{TPR}

$$R^{TPR} \approx R^{Liab} - CF^{\%(A)} + \ldots$$

- **R^{Liab}** **Liability Return**
  - It means liability growth rate
- **$CF^{\%(A)}$** Cash Flows in % of pension fund assets to begin of the financial year
- If **$CF^{\%(A)}$** ≈ 0 -> **$R^{TPR} \approx R^{Liab}$**
  - It means that all aggregated out-payments are equal to the contributions & in-payments
  - In this case the threshold portfolio return equals to the liability increase or liability decrease over year

Threshold Portfolio Return Definition

- According to SKPE guidelines (FRP 5), the threshold portfolio return corresponds to the portfolio return that the pension fund must achieve to maintain a constant funding ratio compared to the last year
- Analysis & Forecast of Liability Return are very important and depend on the ***Liability Risk***



Definition of Threshold Portfolio Return (TPR) based on annual financial statements for the pension fund

31.12.2018

Financial statement 2018

A_1 – Assets
V_1 – Total Liability
per 31.12.2018

$FR_1 = A_1 / V_1$

Cash Flow (CF)
Middle of the year

Assumption: all payments are in the middle of the year

31.12.2019

Financial statement 2019

A_2 – Assets
V_2 – Total Liability
per 31.12.2019

$FR_2 = A_2 / V_2$

To ensure that the funding ratio (FR) over one year stay constant **(i.e. $FR_1 = FR_2$)** it is necessary that the asset value at the year end (**A_2**) amounts to **$A_2 = A_1 * (V_2 / V_1)$**

$$A_2 = A_1 * (V_2 / V_1) \quad = A_1 * (1 + R^{Liab})$$
$$= A_1 * (1 + R^{TPR}) + CF * (1 + R^{TPR} / 2)$$

CF = Cash-In – Cash-out; $CF^{\%(A1)} = CF / A_1$ (i.e. Cash flow divided by the asset value at the former year)
R^{TPR} -> Threshold Portfolio Return; R^{Liab} -> Total liability change rate $= V_2 / V_1 - 1$

$$\boxed{R^{TPR} \approx R^{Liab} - CF^{\%(A1)} + \ldots}$$

- **TPR** is a portfolio return necessary to keep the funding ratio on the same level like at the last Measurement Date (MD): ***here Dec 31, 2019, vs. Dec 31, 2018.***
  - Funding ratio = Assets/ Total Liability
- Based on cash flow and liability positions in the annual accounts it is possible to analyse TPR components

Threshold Portfolio Return Role in Risk Management:

$R^{TPR} \approx R^{Liab} - CF^{\%(A1)} + \ldots$

Increase (or decrease) of the funding ratio between two measurement dates (EoY and BoY)

Portfolio return - $R^{TPR} \approx$ FR (EoY)/FR (BoY) -1

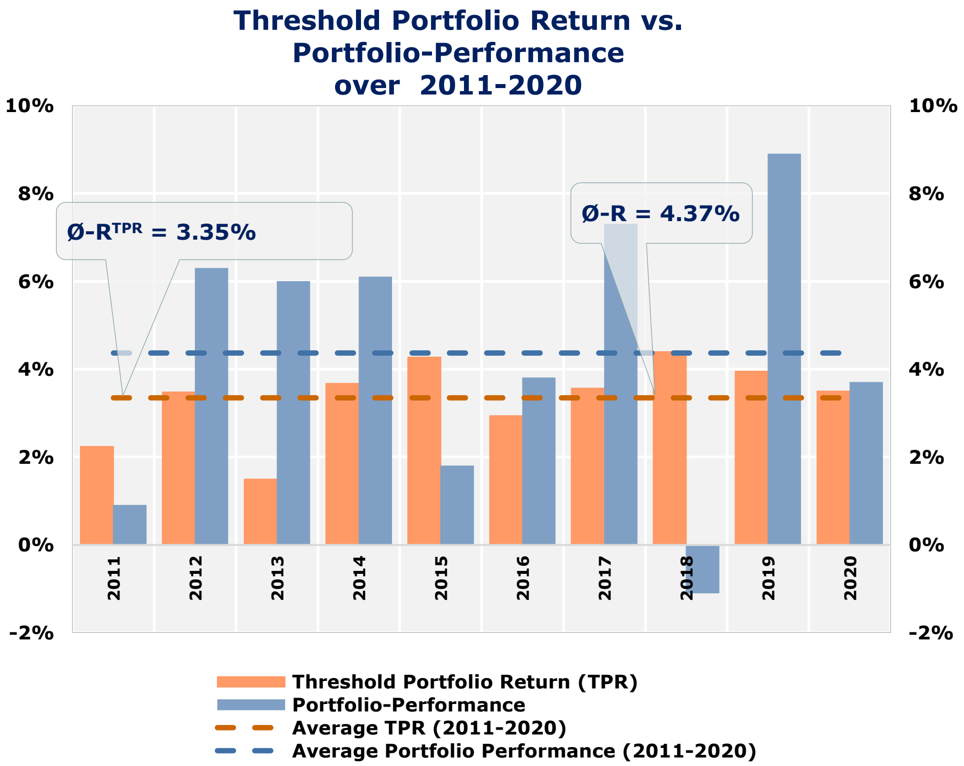
(Portfolio return - R^{TPR}) * FR(BoY) $\approx$ FR (EoY) - FR (BoY)

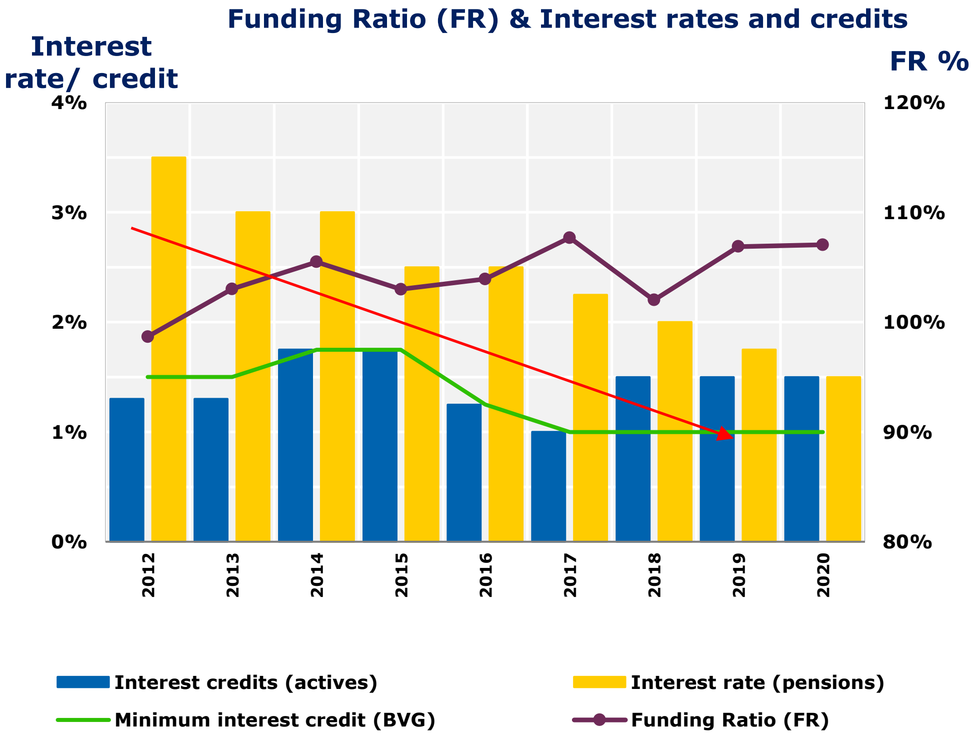
- **If the funding ratio at the beginning of the year FR(BoY) is ca. 100% then the change of the funding ratio over the year is ca. the difference between the portfolio performance and the TPR for this year**
- **If the FR(BoY) < 100% (>100%) then the funding ratio change is smaller (bigger) than the difference between the portfolio return and TPR**

- The difference between the portfolio return and the Threshold Portfolio Return explains the increase (or decrease) of the funding ratio over the year
- The dynamic funding ratio forecasting could be implemented with the future TPR

Comments/ Explanations:
BoY – Begin of the Year, **EoY** – End of the Year, **R^{Liab}** – Liability Return (Increase or reduction rate of the total liability between two measurement dates), **$CF^{\%(A1)}$** –total cash flow over the year (between **EoY** and **BoY**) % of the asset value of the first measurement date (**BoY**).

Example: fully autonomous pension fund (PF Pattern)



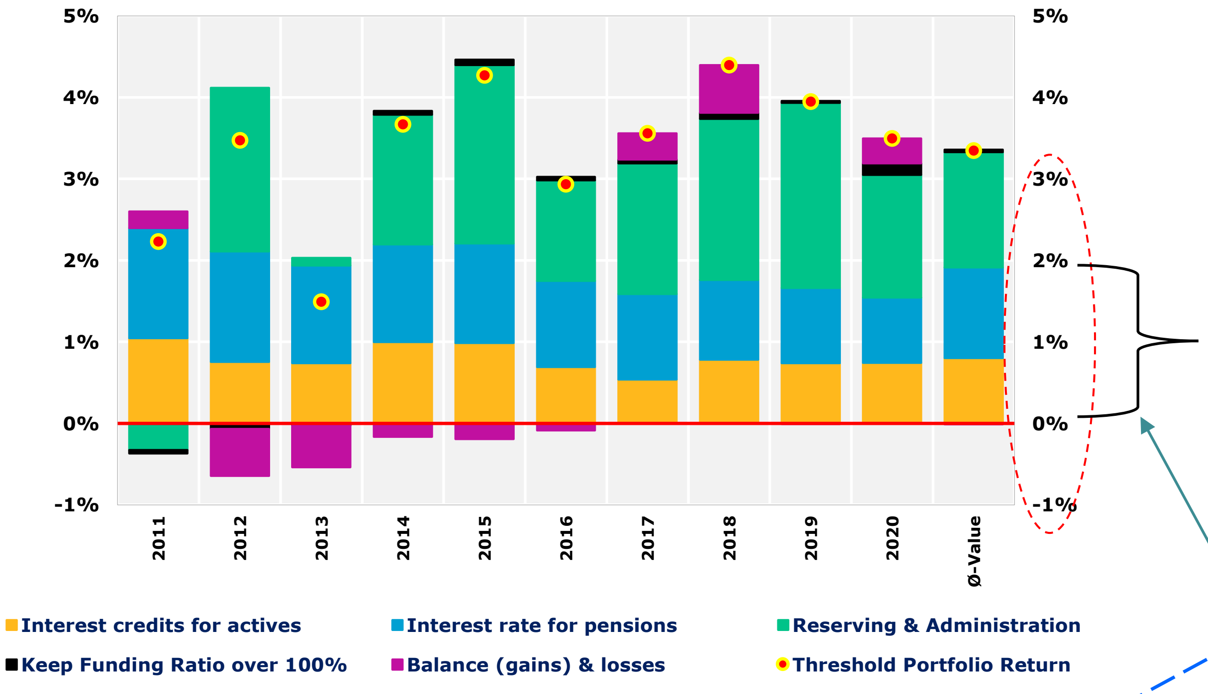


The analysis is based on financial statements (of existing pension fund) over the period 2011-2020

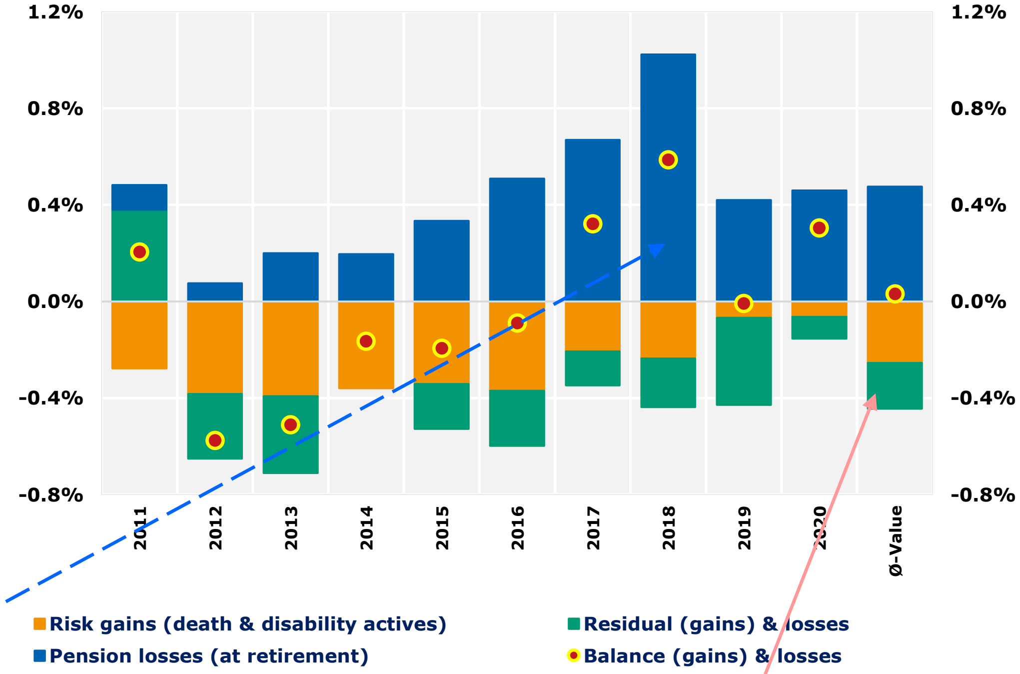
- The average Threshold Portfolio Return: **$Ø\text{-}R^{TPR}$ = 3.35%** // The average portfolio-performance: **Ø-R = 4.37%**
- **Funding ratio (FR) increased from 97% to 107% over 10 years (i.e. $Ø\text{-}(R\text{-}R^{TPR})$ ≈ 1% multiplied by 10 years)**
- Portfolio-Volatility, **σ(R) = 3.12%**; **$TE(R\text{-}R^{TPR})$ = 3.35%** // **LSR = 32.7%** // **LIR = 30.5%**
- The **interest credits for actives** were relatively low, i.e., **1.47%** on average per annum over period 2011-2020
- Supreme body decision on interest credit depends as a rule on the FR-level and the portfolio-performance

Analysis: Attribution empirical Threshold Portfolio Return

Attribution Threshold Portfolio Return (% assets)



Attribution Balance (gains) & losses (% assets)



- On average (Ø) total costs of interest rates and interest credits = **1.9% per annum** over period 2011-2020
- Reserving (decrease interest rate from 3.5% to 1.5% & change to generational tables since 2014) = **1.4% per annum**
- Pension liability ratio compared to the total liability was growing from 39% to 46% over this period due to interest rate decreasing step-by-step
- **Pension losses** were substantial (**1%** of assets in 2018) because of decreasing interest rates; due to definitive reduction of the conversion rate in 2019 these losses got smaller (and were fully "financed" by the **risk benefit gains** and **residual gains:** it means that, generational mortality tables more conservative compared to the pension fund life expectancy development)

Useful key figures based on threshold portfolio return

They fit into "ex-post" and "ex-ante" risk management

Liability Sharpe Ratio, LSR

$$LSR = \frac{R - R^{TPR}}{\sigma}$$

Liability Sharpe Ratio (LSR)

- corresponds to the difference between the portfolio return and the threshold portfolio return (TPR) divided by the portfolio volatility
- shows the increase (or decrease if $R^{TPR} > R$) of the funding ratio normalised by portfolio volatility
- The larger the ***LSR*** is, the faster the funding ratio can increase.
- **For the same difference (R-R^{TPR}), the pension fund's ability to implement the re-development measures in case of underfunding will be lower with greater volatility, σ**

Liability Information Ratio, LIR, over Threshold Portfolio Return (TPR)

$$LIR\left(R - R^{TPR}\right) = \frac{R-R^{TPR}}{TE\left(R-R^{TPR}\right)} = \frac{R-R^{TPR}}{\sigma\left(R-R^{TPR}\right)}$$

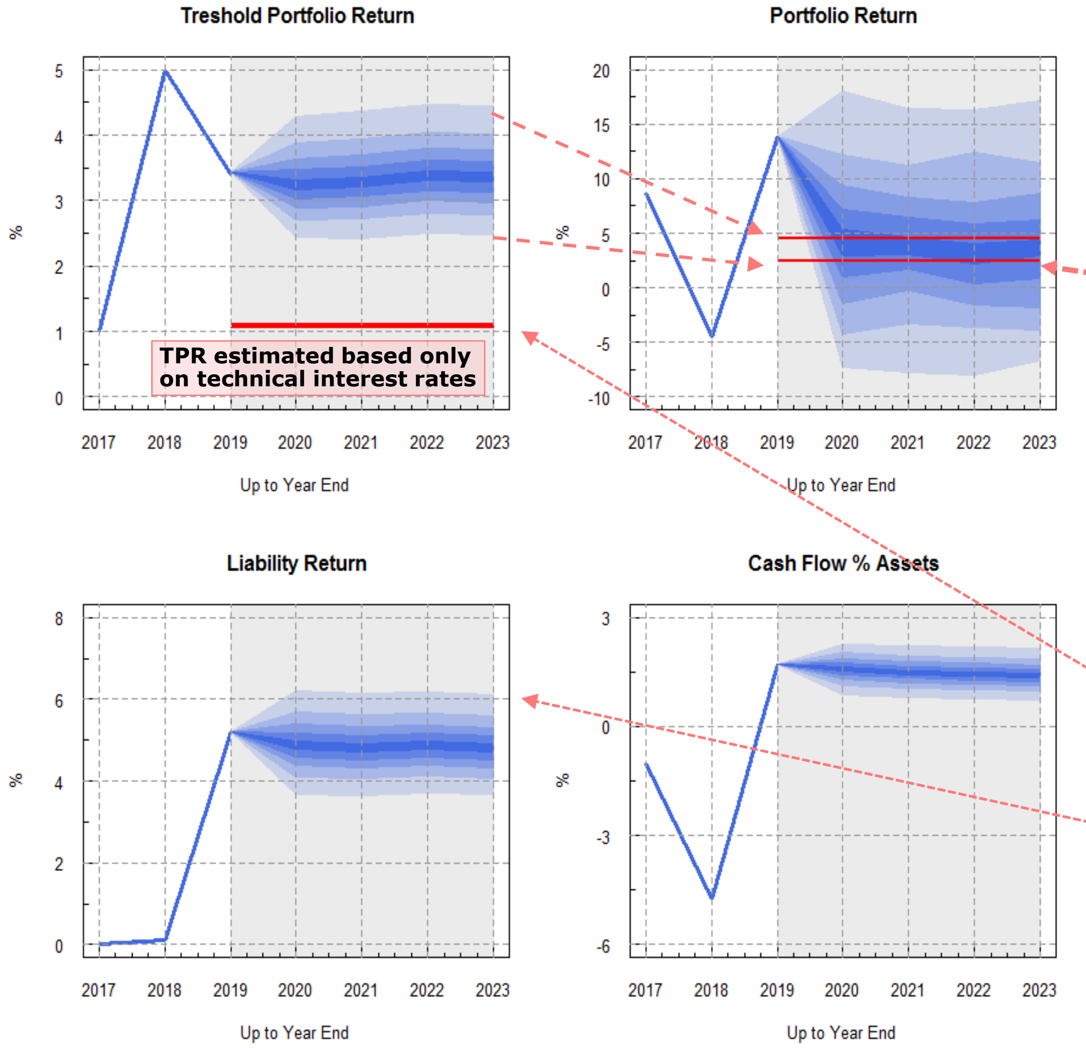
- **Liability Information Ratio (LIR)** equals the difference between the portfolio return and the threshold portfolio return divided by the volatility of the difference between the portfolio return and threshold portfolio return (i.e. TE, tracking error)

- If the difference between the portfolio return and the target return is relatively stable, then their volatility is smaller compared to pension funds with more volatile differences
- **The larger this ratio is, the faster the funding ratio (FR) can increase**

TE – Tracking Error, i.e., the volatility of the difference between portfolio return and threshold portfolio return

Example: Threshold Portfolio Return - 1

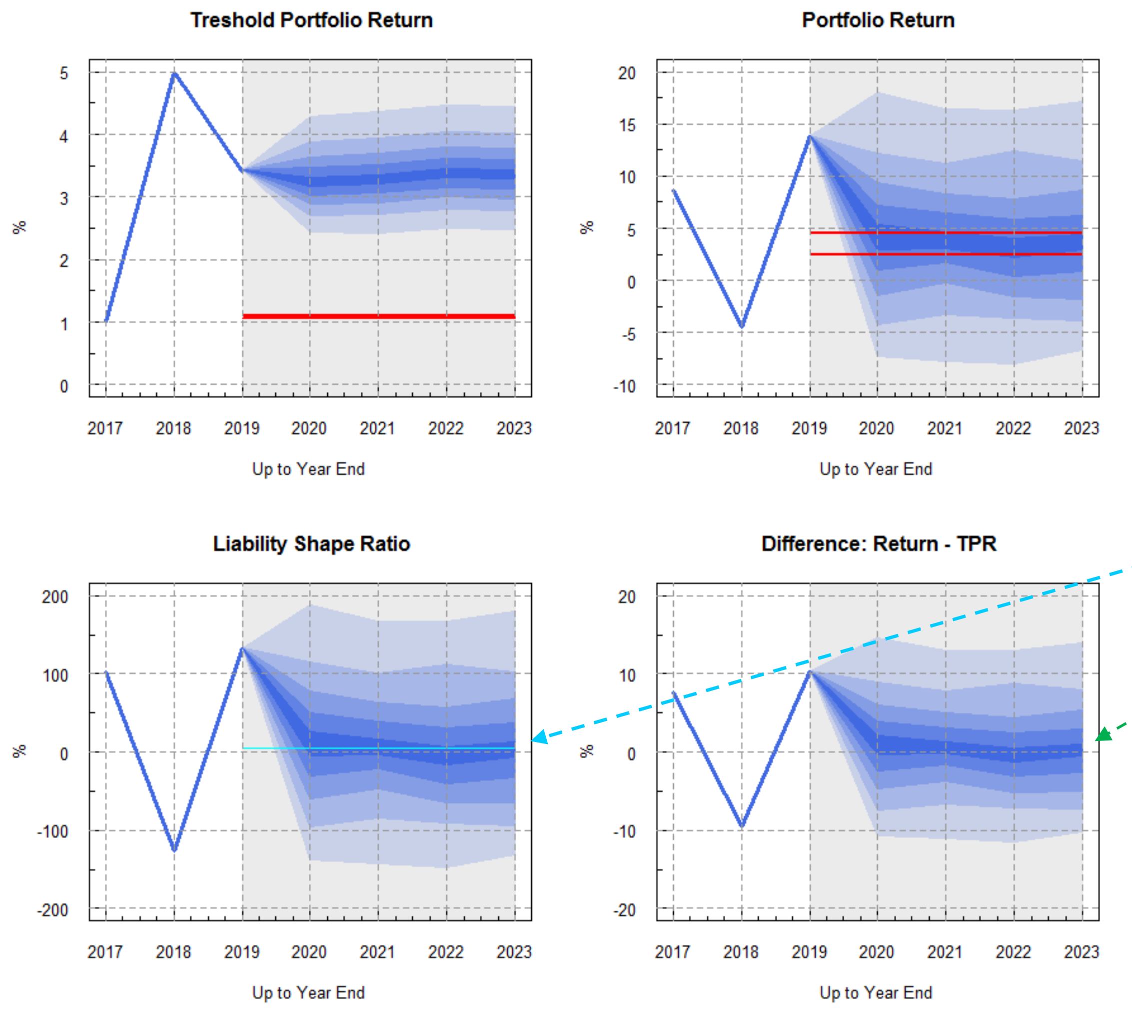
For forecast TPR it is necessary to forecast 10-year bond yield (upper level for technical interest rate)



- **Example: Results over period 2020-2023**:
  - The median of the TPR is 3.31% and the expected value 3.35%, StDev = 0.60%
    - ➢ **≈ Liability Return – CF % Assets + … (slide 5)**
  - TPR's bandwidth (5%÷95%) is ca. (**2.5%÷4.5%**)
  - ---
  - The median of portfolio return 3.68% and its expected value 4.0%, StDev = 7.52%
  - Portfolio return bandwidth (5%÷95%) is ca. (-7.5%÷16.5%)
  - ---
  - As a rule, the estimate of the TPR by pension fund board of trustees is done based on the technical interest rate (here 1.5%) and the expected interest credits (here 1.0%) plus administration costs
    - ➢ here it would be ca. 1.05%-1.1% (red line on TPR figure)
- The highest level (95%) of liability development (Liability Return) of ca. 6.0%

Example: Threshold Portfolio Return - 2

Liability Shape Ratio – this parameter helps to estimate financing



- **Liability Shape Ratio (LSR)**
  - = **(Portfolio Return – TPR)/σ**
  - **σ** - Portfolio volatility
- The higher the LSR value, the faster the funding ratio grows
  - The median of the difference (Portfolio Return – TPR) over 2020-2023 is **0.33%**
    - ➢ i.e. it is positive but small that is why the funding ratio could only slowly grow
  - The portfolio volatility **σ** over 2020-2023 is **7.52%**
  - The median LSR = **4.4%** (i.e. very low)
  - The volatility of the difference (Portfolio Return – TPR) is **7.55%**
    - ✓ i.e., slightly higher than **σ**

- **It is useful to reduce the volatility of this difference (Portfolio return – TPR) vs. portfolio volatility**
  - It means the benefits should be improved and additional actuarial provisions increased if the portfolio return would be enough high

Investment Driven Liabilities

- Swiss pension funds over last 8 years adjusted their liability structure based on the FRP4 & FRP5 Guidelines:
  - Due to the very low level (even negative) of the 10-year government bond yield the Upper Limit of technical interest rate was ca. 2.0% with generational and 1.7% with periodical mortality tables
  - Based on technical interest rates below 2.0% the conversion rate (to define the retirement pension) was reduced from 6%-7% to ca. 4%-5% by many pension funds
- The interest credit for saving accounts has a guaranteed BVG-minimum interest credit value annually confirmed by the LPP/BVG-Commission
  - It is to be guaranteed only for the mandatory saving account, ca. 30%-60%
  - 1% in the period 2017 – 2023; but it was 4% over 1985-2002 and reduced over 2003-2016
  - In 2008 the BVG-minimum interest credit value was 2.75% (vs. Inflation ca. 2.8%-3.0%)
- The board of trustees annually decides the interest credit level for saving accounts based on the funding ratio level and the actual portfolio return
- **The forecasting of government bond yields and inflation is very important**

Investment Driven Liabilities

The supreme body determines, based on legal requirements the strategic objectives and principles of the pension fund

Correct forecasting of liability development to verify the expected threshold portfolio return (neither to low and nor to high)

- Gives a chance to improve benefits for actives and pensioners
- Finances them better via the third contribution payer (portfolio strategie and its performance)

If the expected threshold portfolio return is estimated to be too high, then it is usually suggested reducing benefits to decrease the future threshold portfolio return as well

- Active membership is very affected in this case

Analysis & Visualisation Inflation Development

Analysis Inflation Development and its Visualization

Important to provide some clarity of thought on the issue of inflation

- Inflation relates to assets and liabilities as well as affects the benefits (esp. for pensions in payment without *COLA*, *cost of living adjustment*).
- Impact on assets:
  - In general, when **inflation falls relative to the prior period, assets perform well**
  - Should inflation start to rise, it is necessary to expect
    - Asset returns to be adversely affected
  - Historical experience/analysis of asset returns vs. inflation development helps to prepare expectations concerning asset returns based on forecasted inflation
  - The direction of inflation determines the direction of interest rates
    - In turn, the direction of interest rates has a big influence on the pricing of assets that are sold on the basis of their projected cash flows (bonds, equities and real estate)
    - The interest rates used to discount the cash flows change faster that the cash flows can adjust (if at all) thereby changing the net present value of those flows.

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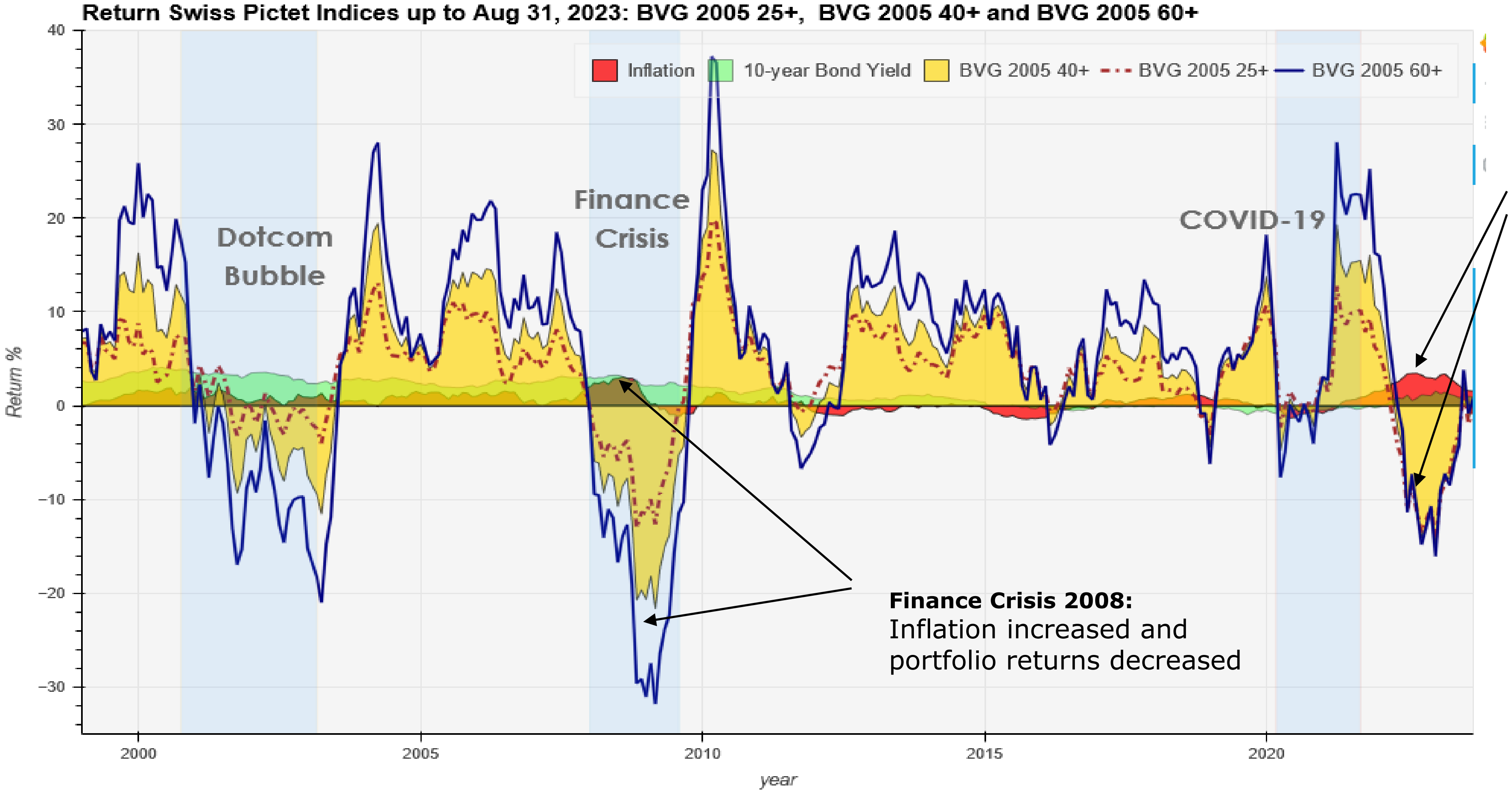
Impact Inflation Rate on Portfolio Returns

Pictet LPP/ BVG Indices 2005 25+, 2005 40+ and 2005 60+



Finance Crisis 2008:
Inflation increased and portfolio returns decreased

The current situation:
Inflation increased and portfolio returns decreased
But the 10-year Bond Yield increased as well

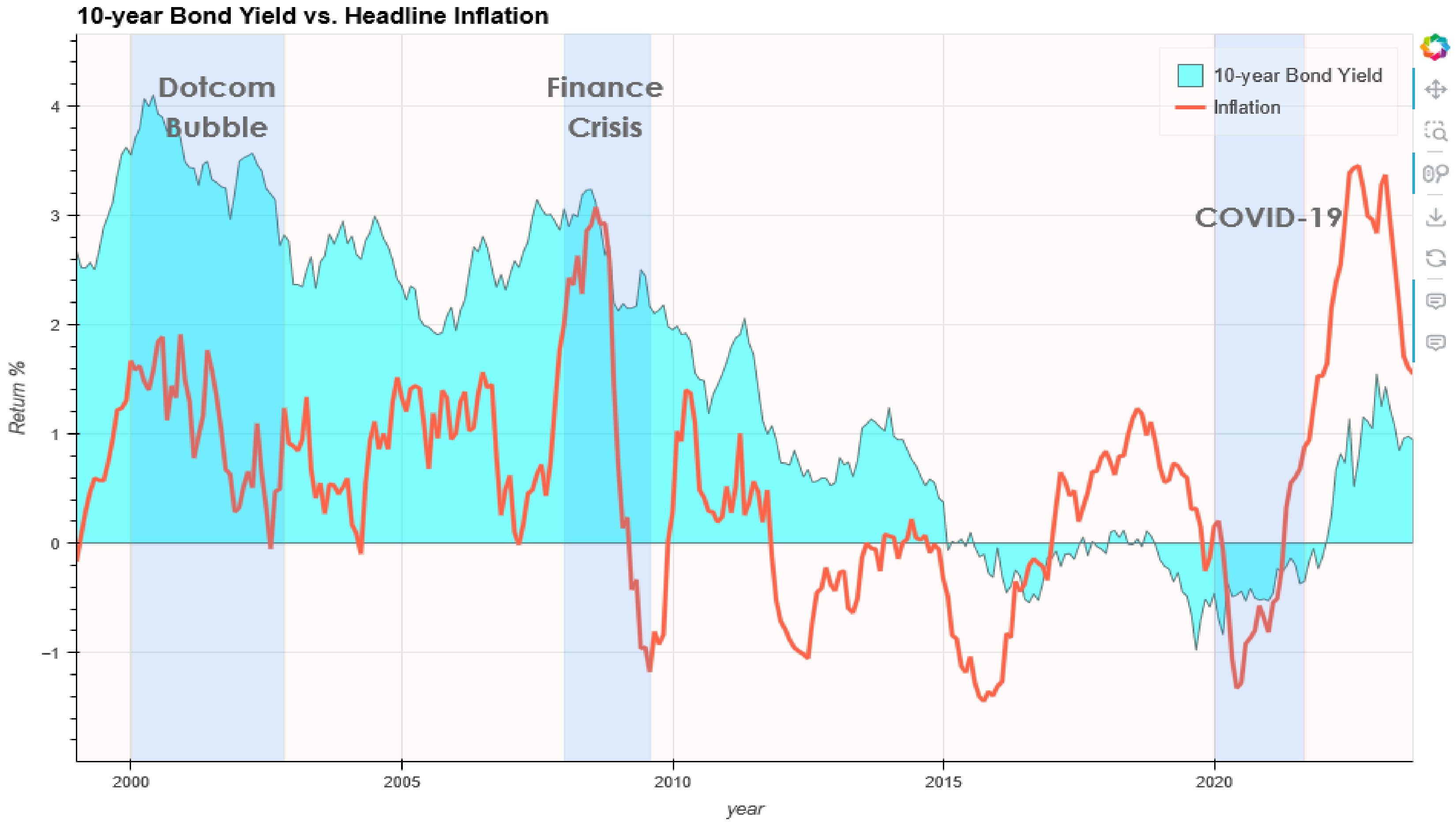
Inflation values:
Monthly values valuated over last 12 months (via inflation index)

Portfolio return values:
Monthly values valuated over last 12 months (via portfolio return index)

10-year Bond Yield:
Monthly values

Impact Inflation Rate on Government Bond Yields

Inflation rates vs. 10-year Government Bond Yields (over last 25 years)



Analysis Correlation based on historical monthly data

- Correlation Portfolio Return vs. Inflation and vs. 10-year Bond Yield

```
# Correlation
pictet_plus_corr = read_Pictet_data[param_list].corr().round(2)
pictet_plus_corr
```

	Headline CPI	10-year Bond Yield	R 2005 25+	R 2005 40+	R 2005 60+
Headline CPI	1.00	0.41	-0.36	-0.22	-0.13
10-year Bond Yield	0.41	1.00	-0.07	-0.09	-0.10
R 2005 25+	-0.36	-0.07	1.00	0.96	0.90
R 2005 40+	-0.22	-0.09	0.96	1.00	0.99
R 2005 60+	-0.13	-0.10	0.90	0.99	1.00

```
read_Pictet_data[param_list].head().round(2)
```

Datum	Headline CPI	10-year Bond Yield	R 2005 25+	R 2005 40+	R 2005 60+
1998-12-30	-0.17	2.67	6.75	7.17	7.93
1999-01-30	0.07	2.52	6.64	7.24	8.20
1999-02-28	0.29	2.52	4.19	3.96	3.68
1999-03-30	0.47	2.57	4.10	3.54	2.75
1999-04-30	0.59	2.50	7.43	8.05	8.68

```
print(pictet_plus_corr.to_markdown(tablefmt = "grid"))
```

```
+--------------------+----------------+----------------------+--------------+--------------+--------------+
|                    |   Headline CPI |   10-year Bond Yield |   R 2005 25+ |   R 2005 40+ |   R 2005 60+ |
+====================+================+======================+==============+==============+==============+
| Headline CPI       |           1    |                 0.41 |        -0.36 |        -0.22 |        -0.13 |
+--------------------+----------------+----------------------+--------------+--------------+--------------+
| 10-year Bond Yield |           0.41 |                 1    |        -0.07 |        -0.09 |        -0.1  |
+--------------------+----------------+----------------------+--------------+--------------+--------------+
| R 2005 25+         |          -0.36 |                -0.07 |         1    |         0.96 |         0.9  |
+--------------------+----------------+----------------------+--------------+--------------+--------------+
| R 2005 40+         |          -0.22 |                -0.09 |         0.96 |         1    |         0.99 |
+--------------------+----------------+----------------------+--------------+--------------+--------------+
| R 2005 60+         |          -0.13 |                -0.1  |         0.9  |         0.99 |         1    |
+--------------------+----------------+----------------------+--------------+--------------+--------------+
```

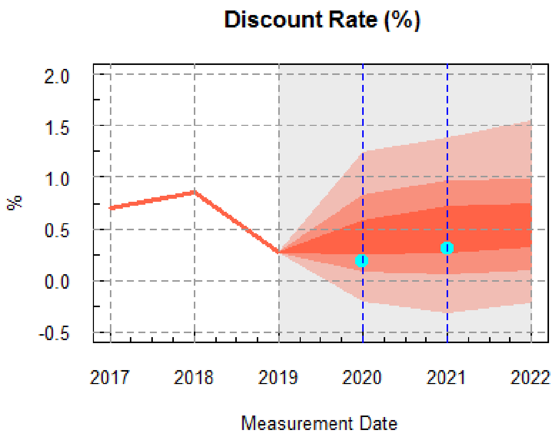
- Positive correlation between inflation rate and 10-year bond yield
  - Inflation and bond yields are increasing together
- Negative correlation between portfolio return and inflation rate
  - The lower the equity allocation and higher the bond allocation the impact on negative return is stronger (**R 2005 25+**)

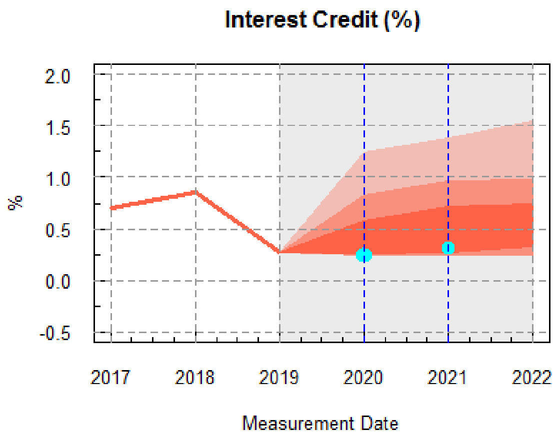
Important to provide some clarity of thought on the issue of inflation

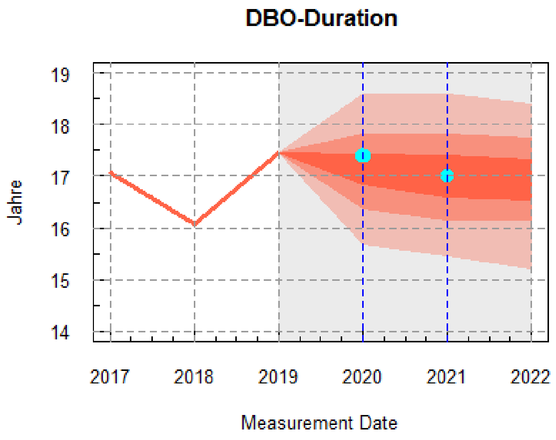
- Impact on liabilities:
  - Should inflation start to rise, it is expected that liability values would fall as well
    - ✓ **For local liabilities**: it depends on plan rules and guidelines in each country
    - ✓ **In International Accounting**: the liability would fall if the discount rate increases (i.e., AA-Yield increasing together with inflation).
  - In Switzerland:
    - ✓ the discount rate/ technical interest rate depends on the average value of 10-year government bond yield over the last year (for example per Sept 30, 2022, for the period October 1, 2022 – Sept 30, 2023) plus 2.5% (but never higher than 4.5%) – **As a rule**: it is not suggested to increase the technical interest rate, but it is possible always to decrease the technical interest rate
    - ✓ The interest credit for savings accounts depends on the funding ratio and the portfolio return (the higher the funding ratio and the higher the portfolio return – the higher the interest credit)
      - The mandatory interest credit is 1.0% (for 2024 suggested now 1.25%)

Inflation and Government Bond Yield affect the AA-Yield curve

IAS19 Discount rate is a AA-Yield based on Liability duration (DBO-Duration)







Interest Credit as assumption

for International Pension Accounting

= max(Discount Rate, mandatory Interest Credit)

Mandatory Interest Credit = 1% * Mandatory saving capital

(here 1% * 25% = 0.25%)

Discount Rates and DBO-Durations are determined based on the forecasted AA Yield Curve per measurement date (MD):

- Examples (●) from IAS19 Disclosures
  - Per Dec 31, 2020, and per Dec 31, 2021
- The forecast of Discount rates, DBO-Durations and Interest Credits depends on the Model used for AA Yield Curve Forecasting
  - Earlier we used an affine model, and the bandwidths of forecasted assumptions were wider:
    - ✓ For example, per 2021 the bandwidth was [-1.0%,2.0%] between 5% and 95% percentiles (i.e., 3% vs. 1.75% based on NNAR)
  - The forecast approach used now is NNAR (Neural Network Autoregression)

Analysis of Historical Inflation data is very useful to understand its forecasting

Important to provide some clarity of thought on the issue of inflation

- Pension funds should be run in a holistic manner:
  - Considering both assets and liabilities together – and verify if benefits could be reduced
- That is why that risk budgeting framework is particularly useful in this regard
- The analysis of inflation historical data is very important:
  - To prepare the forecasting and
  - Understand its impact on pension fund liabilities and
  - The impact on the benefit level
- Inflation historical data could be found on home page international banks as well as World Bank and International Monetary Fund (IMF)

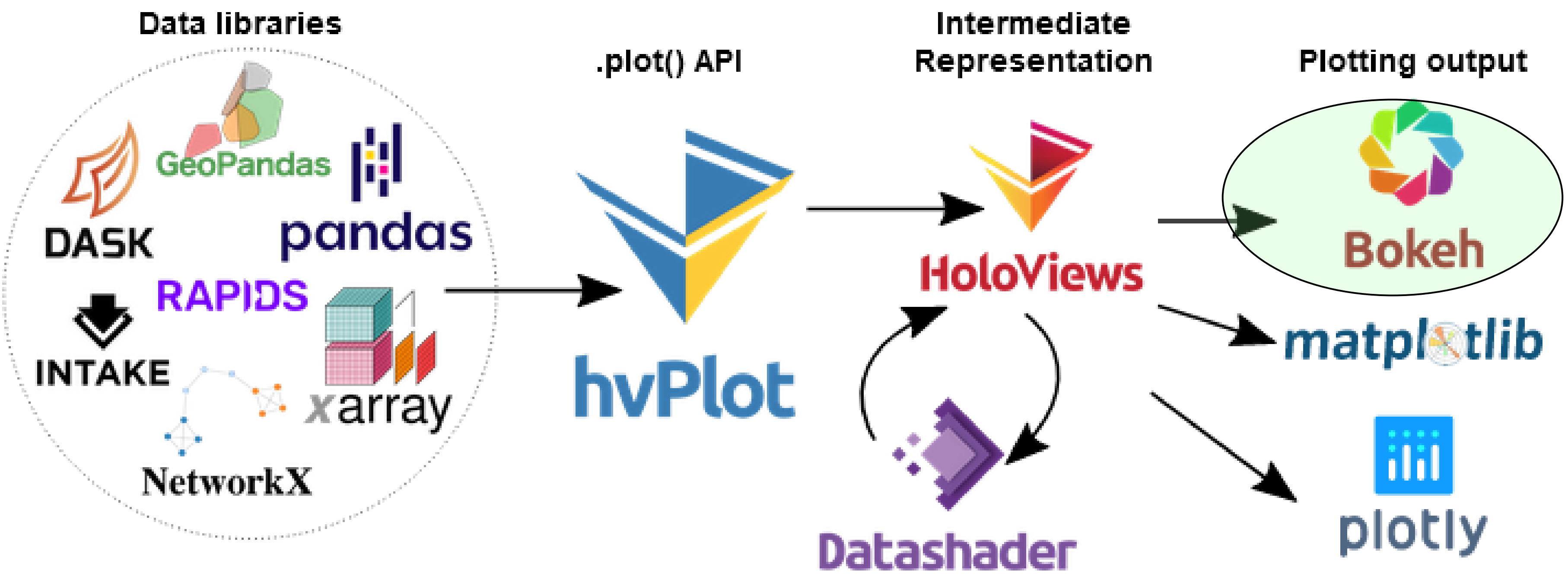
Why it is useful to program with Python (Anaconda)

Why to use Python for Data Visualisation?

- Python has a lot of libraries for data visualization – free of charge and with a lot of examples
- Anaconda with Jupiter and Spyder helps to prepare any kind of Visualizations fast
- Visualizations Libraries “Matplotlib”, “Bokeh” and “Plotly” are constantly developed and updated
  - They have different arts of visualization
- Esp. “Bokeh” helps to produce graphs as a HTML-file that can be uploaded to your firm’s home page without problems

hvPlot

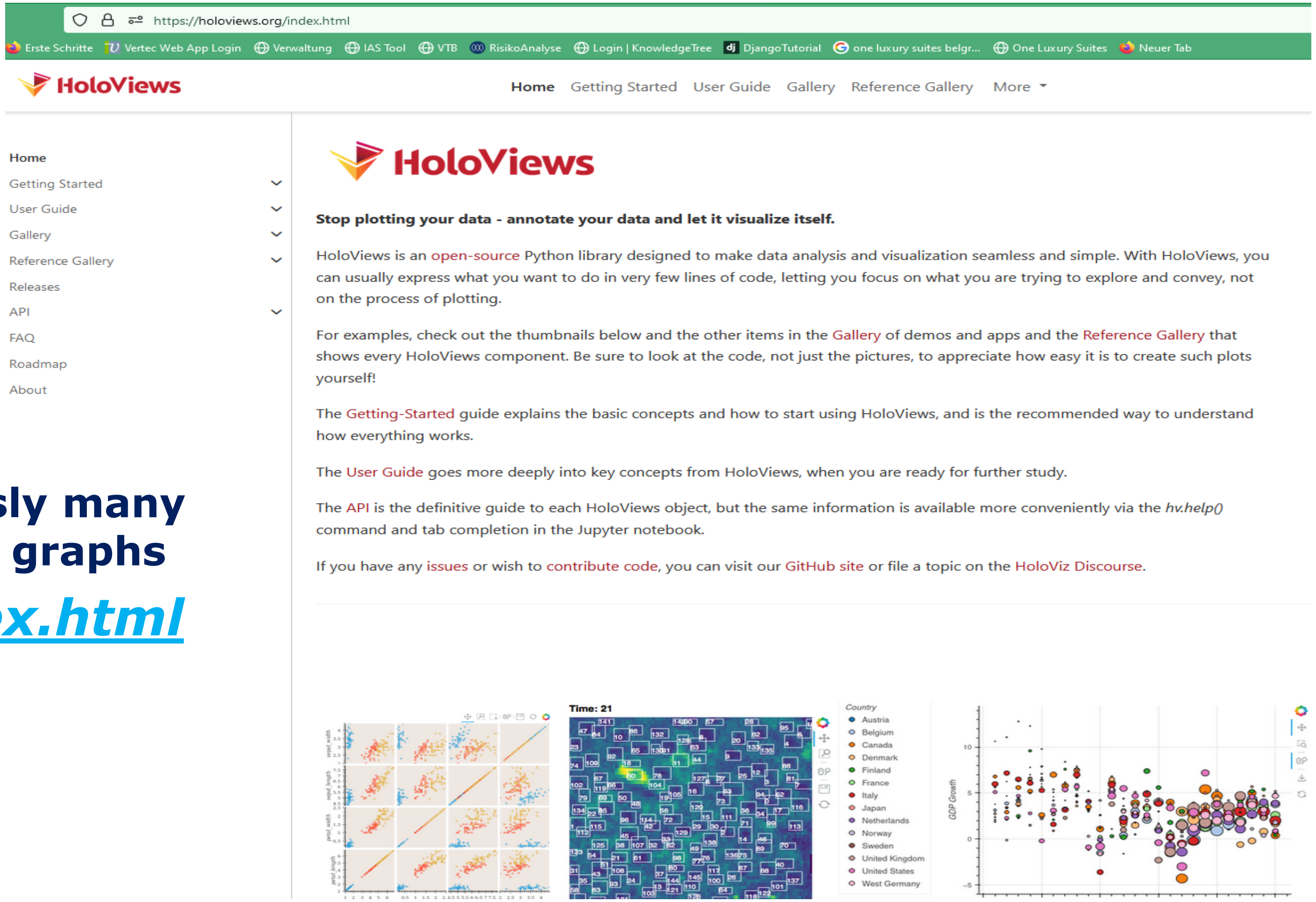
A familiar and high-level API for data exploration and visualization



`.hvplot()` **is a powerful and interactive Pandas-like** `.plot()` **API**

Link to HoloViews Library (Python)

Introduction in Software Library HoloViews (Python)



HoloViews Library offers enormously many examples to prepare visualisation graphs

https://holoviews.org/index.html

Examples with World Bank data for CPI and others

BI4 | 2016

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	Data Source	World Development Indicators													
2	Last Updated Date	25.07.2023													
3															
4	Country Name	Country Code	Indicator Name	Indicator Code	1960	1961	1962	1963	1964	1965	1966	1967	1968	1969	1970
5	Aruba	ABW	Inflation, consumer prices (annual %)	FP.CPI.TOTL.ZG											
6	Africa Eastern and Southern	AFE	Inflation, consumer prices (annual %)	FP.CPI.TOTL.ZG											
7	Afghanistan	AFG	Inflation, consumer prices (annual %)	FP.CPI.TOTL.ZG											
8	Africa Western and Central	AFW	Inflation, consumer prices (annual %)	FP.CPI.TOTL.ZG											
9	Angola	AGO	Inflation, consumer prices (annual %)	FP.CPI.TOTL.ZG											
10	Albania	ALB	Inflation, consume												
11	Andorra	AND	Inflation, consume												
12	Arab World	ARB	Inflation, consume												
13	United Arab Emirates	ARE	Inflation, consume												
14	Argentina	ARG	Inflation, consume												
15	Armenia	ARM	Inflation, consume												
16	American Samoa	ASM	Inflation, consume												
17	Antigua and Barbuda	ATG	Inflation, consume												
18	Australia	AUS	Inflation, consume												
19	Austria	AUT	Inflation, consume												
20	Azerbaijan	AZE	Inflation, consume												
21	Burundi	BDI	Inflation, consume												-0.199
22	Belgium	BEL	Inflation, consume												
23	Benin	BEN	Inflation, consume												
24	Burkina Faso	BFA	Inflation, consume												1.7726
25	Bangladesh	BGD	Inflation, consume												
26	Bulgaria	BGR	Inflation, consume												
27	Bahrain	BHR	Inflation, consume												1.6289
28	Bahamas, The	BHS	Inflation, consume												6.1520

Worksheet Order	Variable Name	Indicator Type	Series
1	HCPI_M	Index	Headline consumer price index, monthly
2	HCPI_Q	Index	Headline consumer price index, quarterly
3	HCPI_A	inflation rates	Headline consumer price inflation, annual
4	FCPI_M	Index	Food price index, monthly
5	FCPI_Q	Index	Food price index, quarterly
6	FCPI_A	inflation rates	Food price inflation, annual
7	ECPI_M	Index	Energy price index, monthly
8	ECPI_Q	Index	Energy price index, quarterly
9	ECPI_A	inflation rates	Energy price inflation, annual
10	CCPI_M	Index	Official core consumer price index, monthly
11	CCPI_Q	Index	Official core consumer price index, quarterly
12	CCPI_A	inflation rates	Official core consumer price inflation, annual
13	PPI_M	Index	Producer price index, monthly
14	PPI_Q	Index	Producer price index, quarterly
15	PPI_A	inflation rates	Producer price inflation, annual
16	DEF_Q	Index	GDP deflator index, quarterly
17	DEF_A	inflation rates	GDP deflator growth rate, annual
18	CCPI_Q_E	inflation rates	Estimated core consumer price inflation, quarterly
19	CCPI_A_E	inflation rates	Estimated core consumer price inflation, annual
20	HCPI_Q_T	inflation rates	Estimated trend component of headline CPI inflation, quarterly
21	HCPI_Q_C	inflation rates	Estimated transitory (cyclical) component of headline CPI inflation, quarterly
22	AGGREGATE	inflation rates	Aggregate annual average inflation, by inflation measures, country groups and EMDE regions, based on median, average, and GDP-weighted average.

* all the inflation rates are based on changes in annual averages unless specified otherwise

- World Bank data could be downloaded from home page World Bank as Excel-file (or *.CSV)

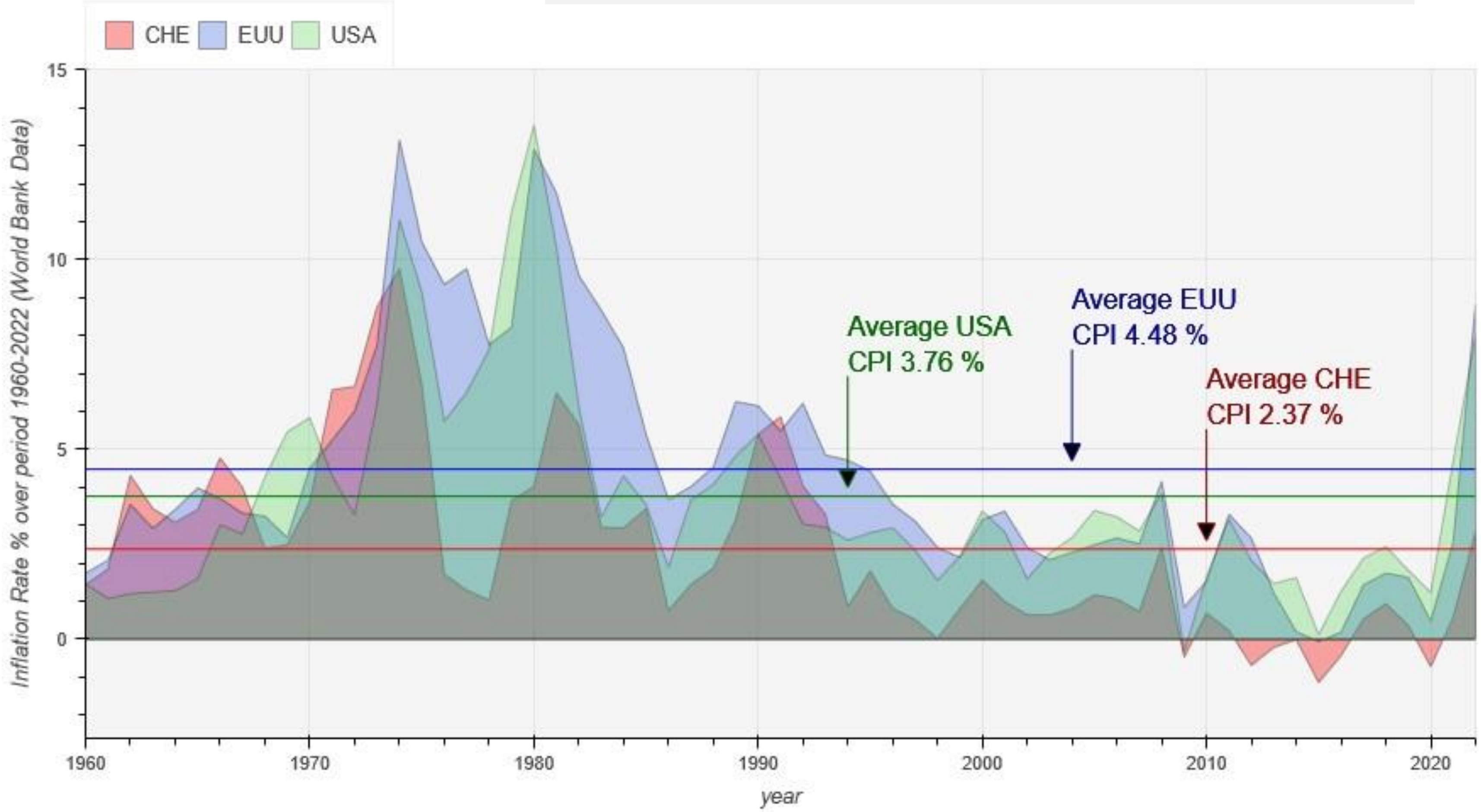
https://www.worldbank.org/en/research/brief/inflation-database

- HoloViews has many examples with such data

World Bank Data: CPI Worldwide – Visualisation with Bokeh

- CPI Development in USA, European countries (EUU) & Switzerland (CHE)
  - Graphs prepared with «bokeh» can be scrolled, increased or decreased (*saved as *.html*)

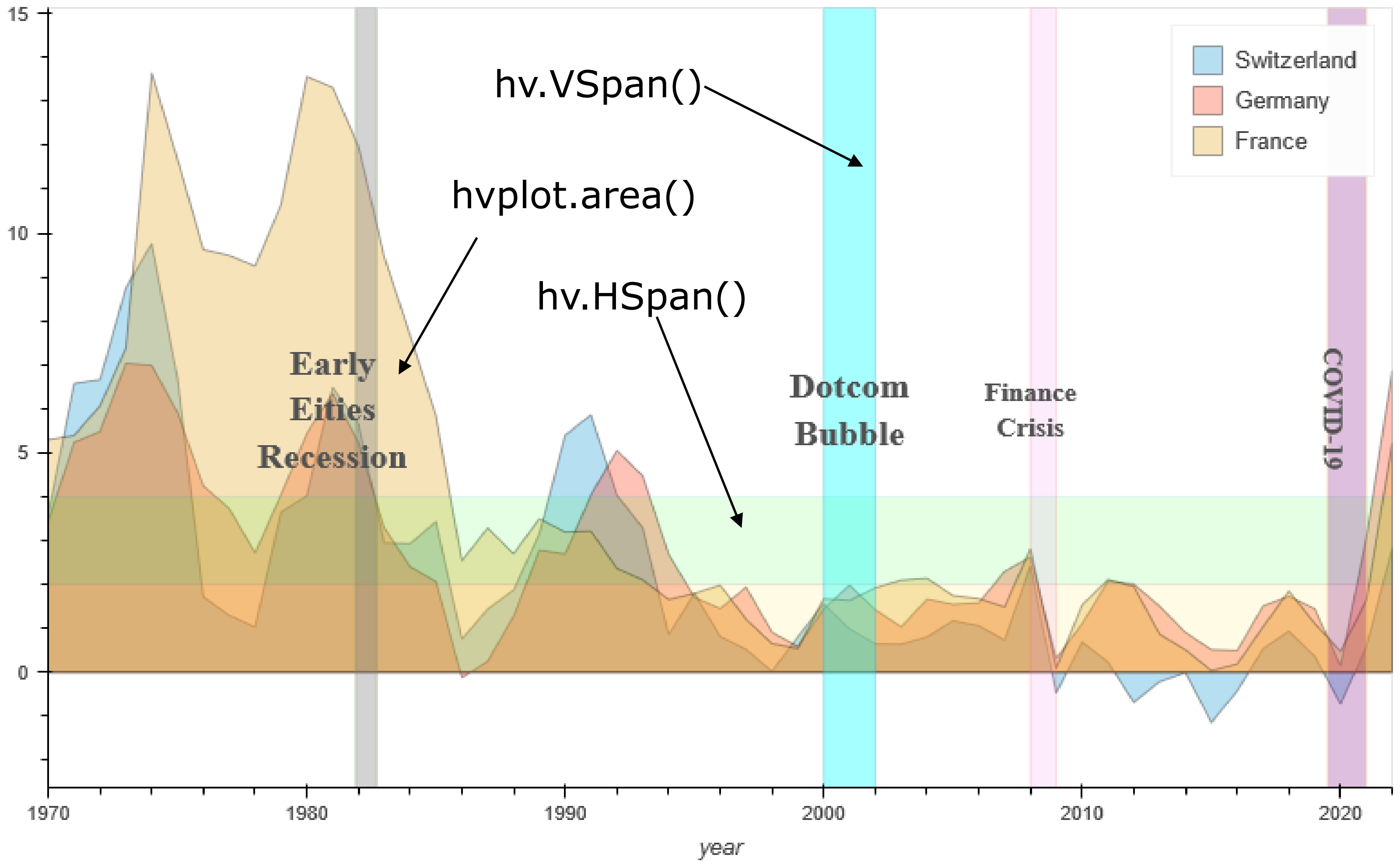
df_var.hvplot.**area**().opts(…, bgcolor = «snow», …)



- Example to compare headline inflation (CPI) for 2-3 countries
  - i.e., to compare only one variable (here CPI)
- CPI World Bank data:
  - Annual inflation rates (CPI) over the period 1960-2022
  - For all countries
  - as well as for different regions (like OECD, World, Europe, etc.)

World Bank Data: CPI Worldwide – Visualisation with Bokeh

Example to produce such graph with «bokeh» Python



Bokeh Python programming on the next slide

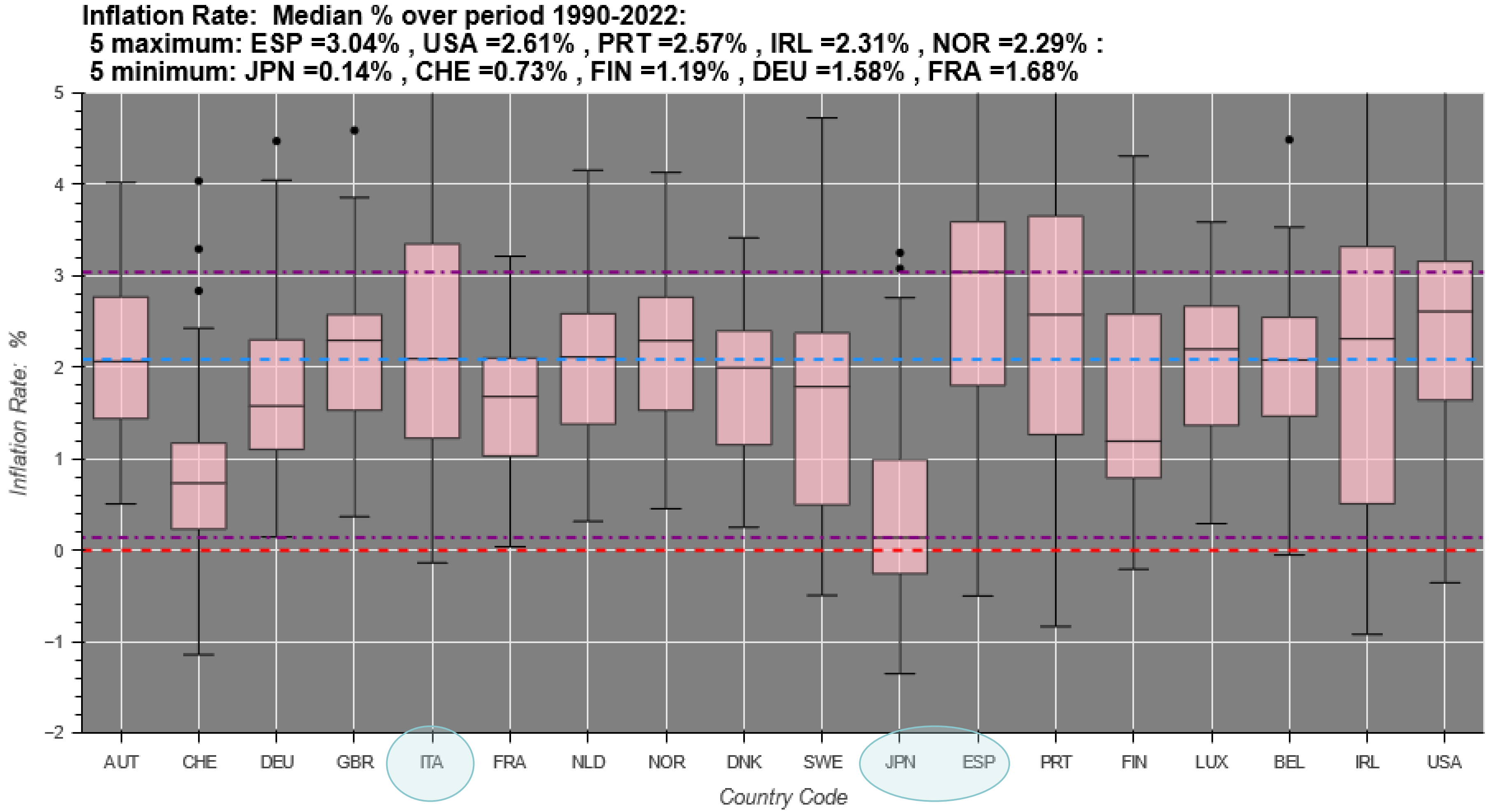
World Bank Data: CPI Worldwide – Visualisation with Bokeh

```
key_dimensions   = [('year', 'Year'), ('Country Name', 'Country')]
value_dimensions = [('GDP', 'GDP Growth'), ('CPI', 'Inflation Rate'),
                    ('CPI_GDPdef', 'GDP Deflator'),
                    ('real GDP', 'Real GDP Growth'),
                    ('Unempl', 'Unemployment')]

macro = hv.Table(macro_df, key_dimensions, value_dimensions)
```

```
macro.to.curve('Year', 'Inflation Rate')
con_name = 'Switzerland'; con_name2 = 'Germany'; con_name3 = 'France'

year = macro.select(Country = con_name)['Year']

test_1 = macro.select(Country = con_name)['Inflation Rate']
test_2 = macro.select(Country = con_name2)['Inflation Rate']
test_3 = macro.select(Country = con_name3)['Inflation Rate']
#test_2 = macro.select(Country = 'Switzerland')['Real GDP Growth'].mean().round(2)
test_df = pd.DataFrame({'year': year , con_name : test_1, con_name2 : test_2, con_name3 : test_3},
                        columns =['year', con_name, con_name2, con_name3])
test_df.index = test_df['year']
test_df[con_name].hvplot.area(alpha = 0.8)

hspan_1  = hv.HSpan(2, 4).opts(fill_color = 'lime', alpha = 0.10)
hspan_2  = hv.HSpan(0, 2).opts(fill_color = 'gold', alpha = 0.10)

#hspan_vert_1  = hv.VSpan(2000, 2002).opts(fill_color = 'red', alpha = 0.15); text_1 = hv.Text(2001,6,"Dotcom\nbubble");
test_grey1 = '#030303' ; test_grey3 = '#080808' ; test_grey4 = '#282828'; test_grey2 = '#515151'

hspan_vert_4 = hv.VSpan(1981.9,1982.7).opts(fill_color = 'grey', alpha = 0.35)
text_4       = __function_produce_text(x = 1981, y = 6, name_text = "Early\nEities\nRecession", text_col = test_grey2, \
                         font_style = 'bold', font_size = '15pt', font_typ = 'Tenorite', my_angle = 0)

hspan_vert_1 = hv.VSpan(2000,2002).opts(fill_color = 'cyan', alpha = 0.35)
text_1       = __function_produce_text(x = 2001, y = 6, name_text = "Dotcom\nBubble", text_col = test_grey2, \
                         font_style = 'bold', font_size = '15pt', font_typ = 'Century Gothic', my_angle = 0)

hspan_vert_2  = hv.VSpan(2008, 2009).opts(fill_color = 'violet', alpha = 0.15); #text_2 = hv.Text(2008,6,"Finance\nCrisis")
text_2        = __function_produce_text(x = 2008, y = 6, name_text = "Finance\nCrisis", text_col = test_grey2, \
                         font_style = 'bold', font_size = '15px', font_typ = 'Century Gothic', my_angle = 0)


hspan_vert_3  = hv.VSpan(2019.5, 2021).opts(fill_color = 'purple', alpha = 0.25); #text_3 = hv.Text(2019,6,"COVID-19")
text_3        = __function_produce_text(x = 2019.75, y = 6, name_text = "COVID-19", text_col = test_grey2, \
                         font_style = 'bold', font_size = '15px', font_typ = 'Century Gothic', my_angle = -90)

extra_Text = hspan_1*hspan_2*hspan_vert_1*text_1*hspan_vert_2*text_2*hspan_vert_3*text_3*hspan_vert_4*text_4


((test_df[con_name].hvplot.area(alpha = 0.8) * test_df[con_name2].hvplot.area(alpha = 0.35)* \
                   test_df[con_name3].hvplot.area(alpha = 0.35)).opts(opts.Area(alpha = 0.35)) * \
                       (extra_Text)).opts(width = 800, height = 500)
```

Analysis bandwidth of historical inflation data for 18 countries as well as their median()

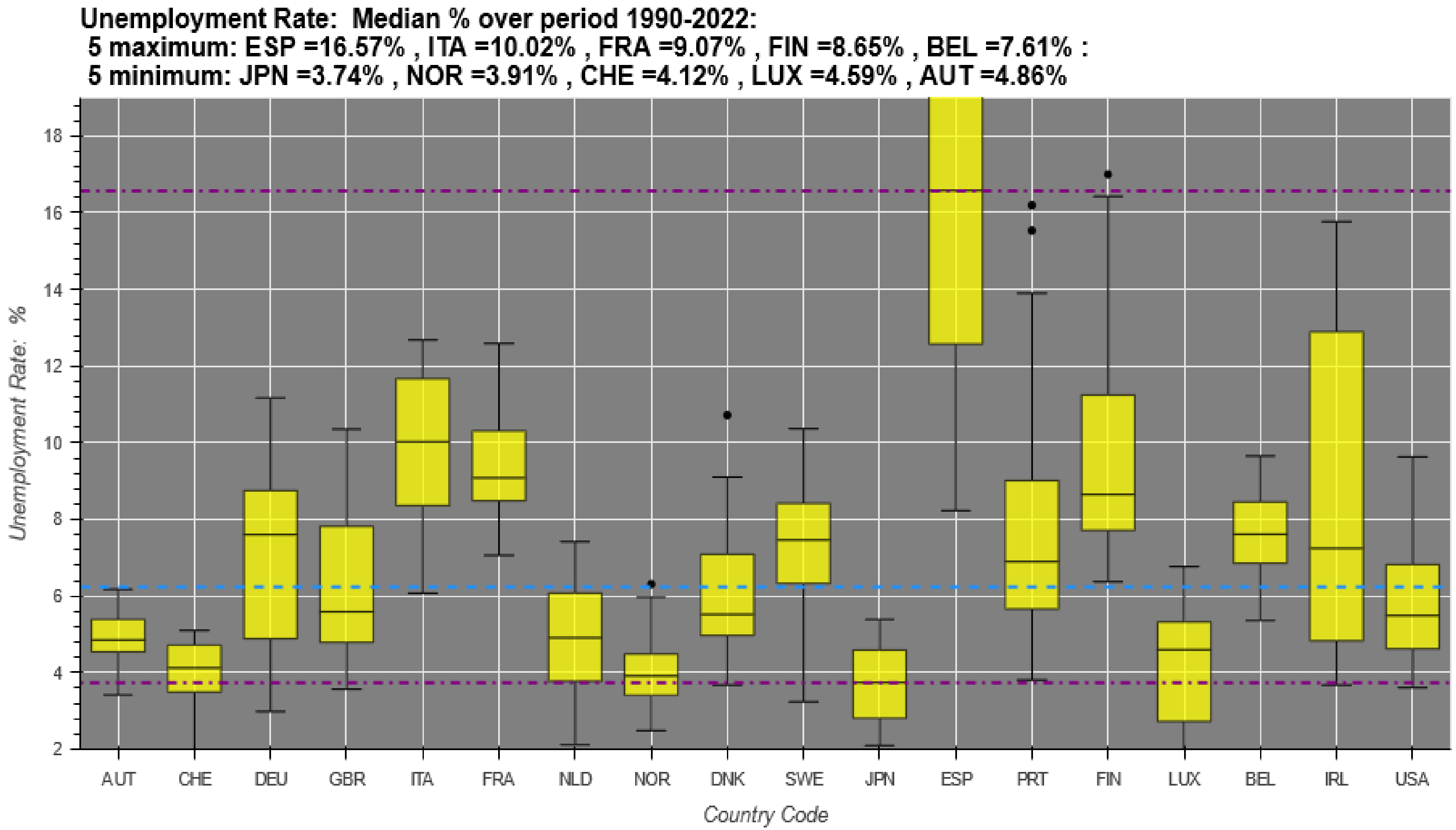
Historical Inflation data (World Bank data) over 1990-2022 (Box() graph)



- «Rose» bandwidth corresponds to 50% (i.e., between percentiles 25 to 75)
- The line in «rose» bandwidth is a median
- On this graph the lowest median level is in Japan (JPN)
- The median level of all medians is in Italy (ITA) – **blue line level**
- The highest level of median is in Spain (ESP) _._._

Analysis bandwidth of historical Unemployment data for 18 countries as well as their median()

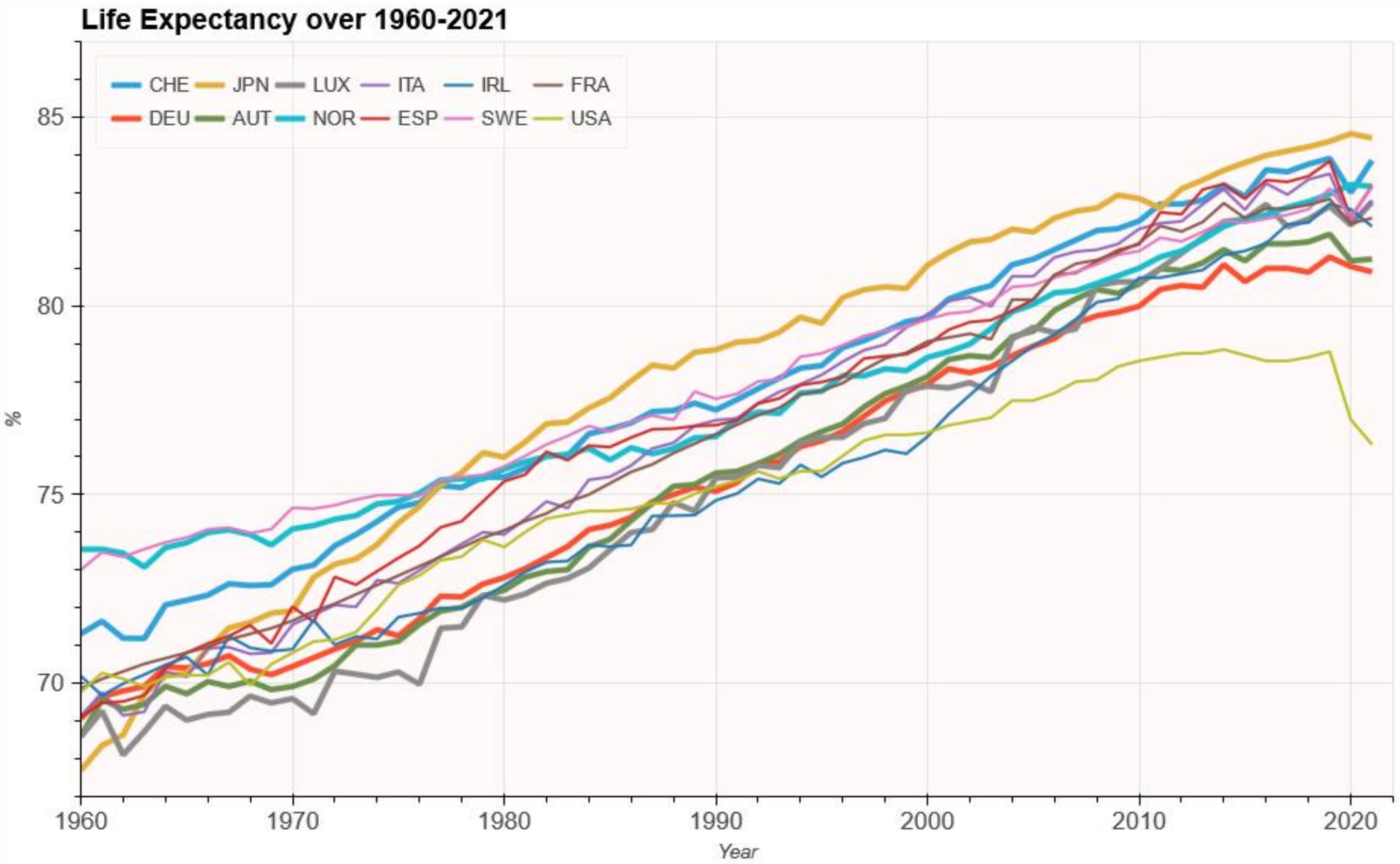
Unemployment Rate (World Bank data) over 1990-2022 (Box() graph)



- As a rule: the Unemployment rate is lower for countries with lower and less volatile inflation rate
- The highest level of inflation median over period 1990-2022 was in Spain (ESP)
- The heist median level of Unemployment Rate over the same period was in Spain as well
- The lowest inflation and unemployment rate medians are in Japan (JPN)

Life Expectancy World Bank data

The highest Life Expectancy is in Japan (JPN) and Switzerland (CHE)



Life Expectancy in Norwegian (NOR), Sweden (SWE), France (FRA), Italy (ITA), Ireland (IRL), Spain (ESP) is nearly on the same level and high

The Life Expectancy in Japan developed based on its inflation

After COVID-19 the Life Expectancy again increased

Many of these countries have low level of inflation over this period 1960-2021

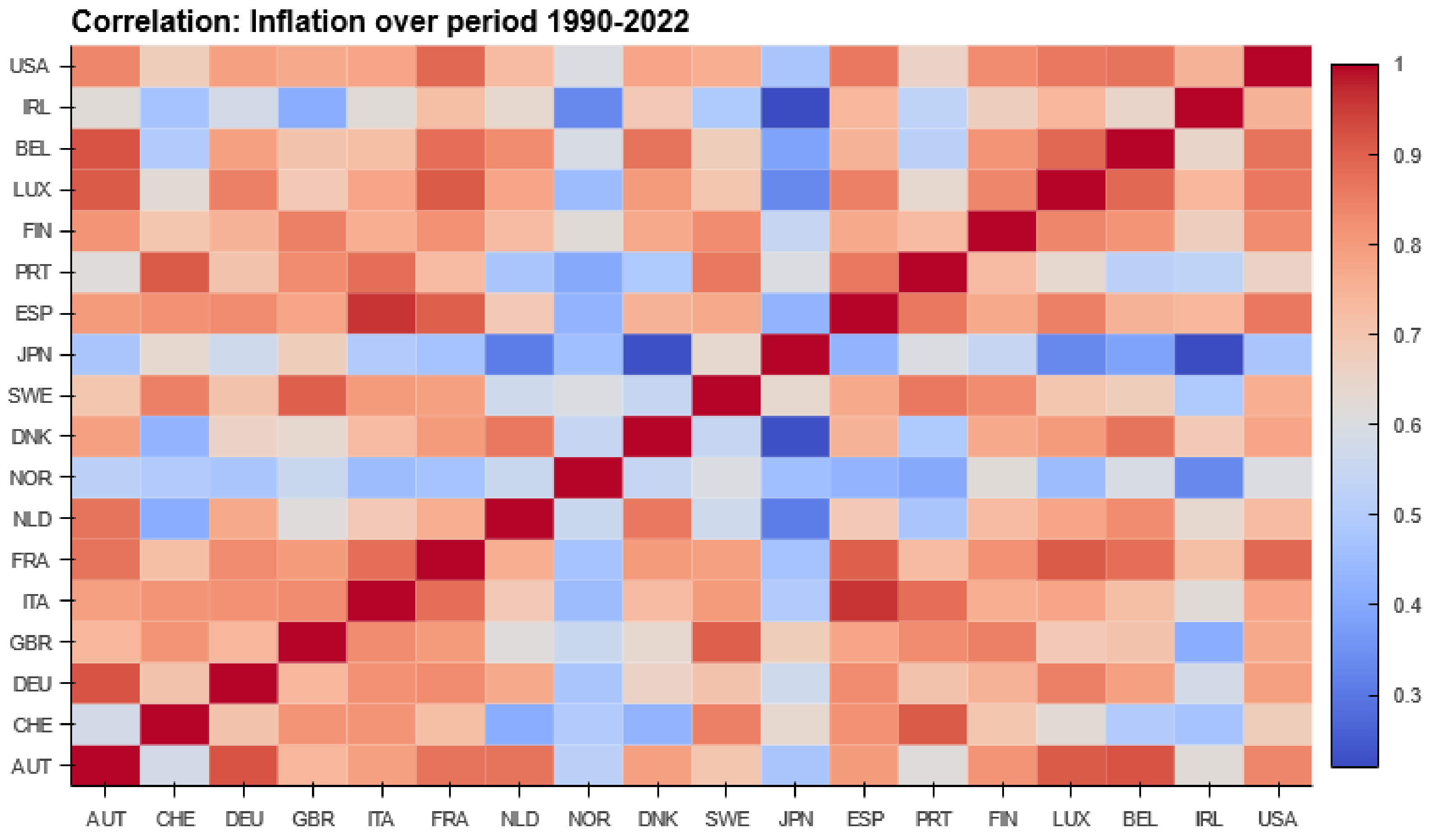
Correlation: Inflation historical data 1990-2022 (annually average)

Correlation: Inflation over period 1990-2022

#	Country	AUT	CHE	DEU	GBR	ITA	FRA	NLD	NOR	DNK	SWE	JPN	ESP	PRT	FIN	LUX	BEL	IRL	USA
0	AUT	1.0	0.69	0.96	0.92	0.91	0.89	0.92	0.57	0.91	0.9	0.48	0.85	0.8	0.9	0.9	0.96	0.66	0.89
1	CHE	0.69	1.0	0.72	0.63	0.75	0.82	0.62	0.55	0.75	0.72	0.28	0.85	0.7	0.7	0.8	0.75	0.74	0.82
2	DEU	0.96	0.72	1.0	0.9	0.9	0.89	0.89	0.57	0.87	0.9	0.46	0.87	0.78	0.88	0.89	0.92	0.69	0.92
3	GBR	0.92	0.63	0.9	1.0	0.84	0.83	0.81	0.53	0.86	0.86	0.45	0.77	0.68	0.84	0.83	0.9	0.46	0.8
4	ITA	0.91	0.75	0.9	0.84	1.0	0.95	0.89	0.49	0.97	0.86	0.26	0.95	0.92	0.88	0.95	0.91	0.76	0.85
5	FRA	0.89	0.82	0.89	0.83	0.95	1.0	0.82	0.45	0.91	0.87	0.33	0.95	0.88	0.84	0.94	0.91	0.76	0.89
6	NLD	0.92	0.62	0.89	0.81	0.89	0.82	1.0	0.6	0.88	0.87	0.33	0.79	0.79	0.84	0.82	0.85	0.65	0.78
7	NOR	0.57	0.55	0.57	0.53	0.49	0.45	0.6	1.0	0.57	0.63	0.39	0.44	0.37	0.55	0.44	0.62	0.32	0.57
8	DNK	0.91	0.75	0.87	0.86	0.97	0.91	0.88	0.57	1.0	0.87	0.25	0.9	0.87	0.91	0.93	0.92	0.7	0.82
9	SWE	0.9	0.72	0.9	0.86	0.86	0.87	0.87	0.63	0.87	1.0	0.39	0.82	0.82	0.86	0.84	0.91	0.69	0.84
10	JPN	0.48	0.28	0.46	0.45	0.26	0.33	0.33	0.39	0.25	0.39								
11	ESP	0.85	0.85	0.87	0.77	0.95	0.95	0.79	0.44	0.9	0.82								
12	PRT	0.8	0.7	0.78	0.68	0.92	0.88	0.79	0.37	0.87	0.82								
13	FIN	0.9	0.7	0.88	0.84	0.88	0.84	0.84	0.55	0.91	0.86								
14	LUX	0.9	0.8	0.89	0.83	0.95	0.94	0.82	0.44	0.93	0.84								
15	BEL	0.96	0.75	0.92	0.9	0.91	0.91	0.85	0.62	0.92	0.91								
16	IRL	0.66	0.74	0.69	0.46	0.76	0.76	0.65	0.32	0.7	0.69								
17	USA	0.89	0.82	0.92	0.8	0.85	0.89	0.78	0.57	0.82	0.84	0.4	0.91	0.79	0.84	0.91	0.89	0.78	1.0

```
corr_matrix_1990 = help_CPI_1990.corr().round(2)
table_title = "Correlation: Inflation over period 1990-2022"
corr_matrix_Table = \
    hv.Table(corr_matrix_1990.reset_index()).\
            opts(width = 900, height = 550, title = table_title)

heatmap_1990_2022 = corr_matrix_1990.hvplot.heatmap(cmap = 'coolwarm').\
            opts(width = 800, height = 450, title = table_title)
```

Correlation: Inflation historical data 1960-2022 (annually average)



- Sometimes it is difficult to analyse data in a big matrix (here: correlation values in matrix for 18 countries)
- Such visualisation with the function **hvplot.heatmap()** helps like here to understand that
  - Japan (JPN) and Norwegian (NOR) have lower correlations with other countries
- The level of correlation visualised with the color variable

  "cmap" = "**coolwarm**"

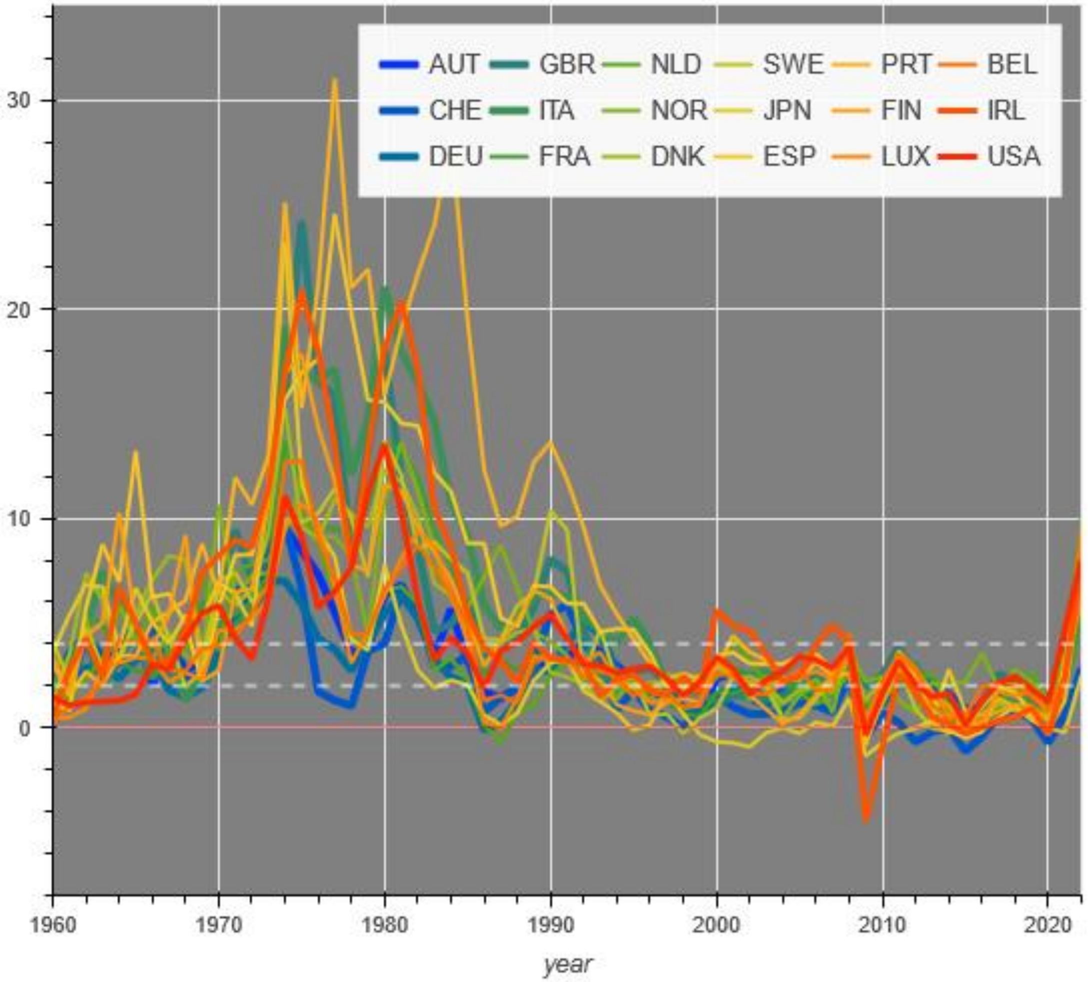
european actuarial academy

Curves Visualisation for many countries together

CPI, annual Inflation rate, % in 18 countries over 1960-2022

```
countries_table = hv.Table(country_names_CPI.reset_index()).\
    opts(width = width_table, height = height_table)
```

#	Country Code	Country Name	mean CPI	median CPI	std CPI
0	AUT	Austria	3.3	2.8	2.1
1	CHE	Switzerland	2.4	1.7	2.4
2	DEU	Germany	2.6	2.1	1.8
3	GBR	United Kingdo	5.1	3.4	4.8
4	ITA	Italy	5.7	4.0	5.5
5	FRA	France	4.1	2.6	3.7
6	NLD	Netherlands	3.4	2.5	2.6
7	NOR	Norway	4.4	3.3	3.2
8	DNK	Denmark	4.4	2.9	3.5
9	SWE	Sweden	4.3	3.0	3.7
10	JPN	Japan	2.9	1.8	4.1
11	ESP	Spain	6.3	4.7	5.6
12	PRT	Portugal	7.9	4.2	8.0
13	FIN	Finland	4.5	3.0	4.2
14	LUX	Luxembourg	3.3	2.7	2.6
15	BEL	Belgium	3.5	2.5	2.8
16	IRL	Ireland	5.3	3.3	5.5
17	USA	United States	3.8	3.0	2.8



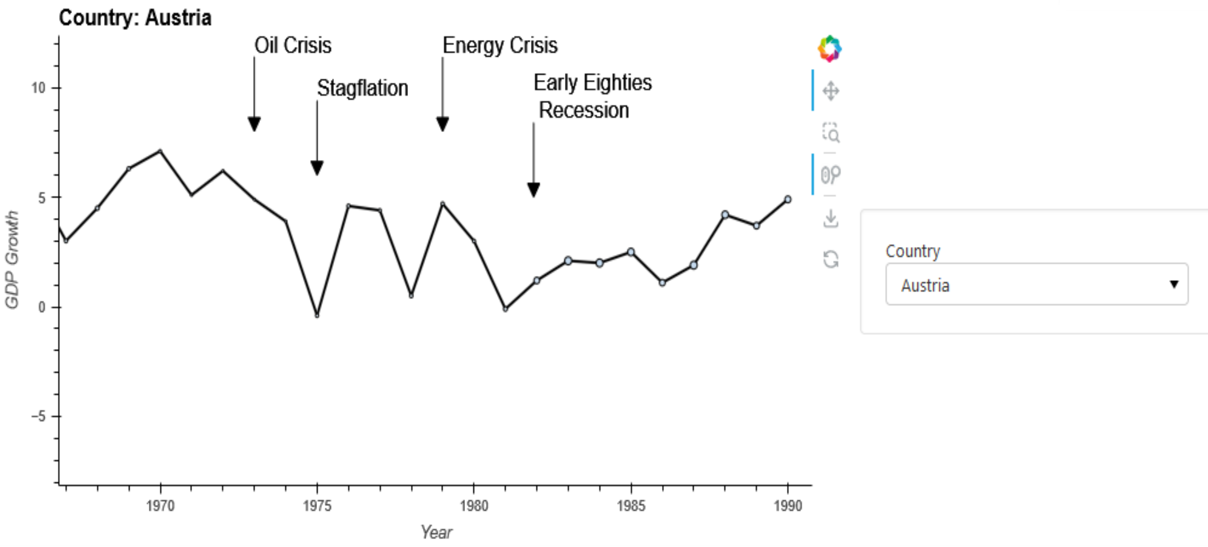
Country_names_CPI is the «variable» (a table) with 18 countries that are analysed for their historical inflation rates over the period 1960-2022, i.e., over 63 years.

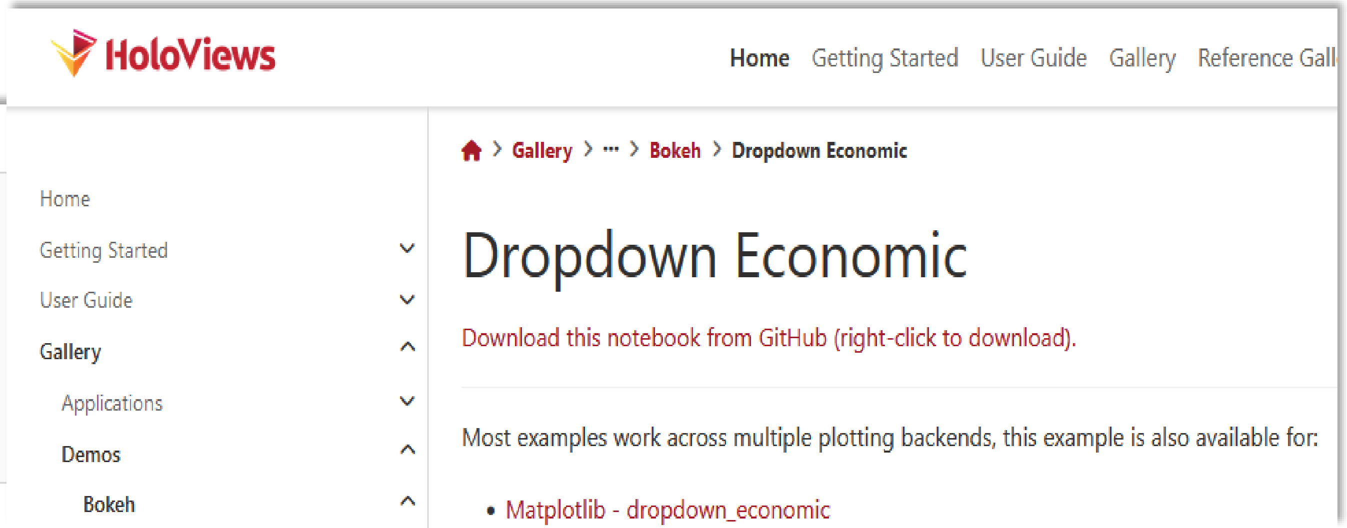
Based on inflation correlation analysis for these countries, their inflation development very similar.
To understand better the individual development per country compared to other countries as well with other variables it would be useful to implement **"Dropdown Economic" HoloViews** example -> next slide

Dynamic Visualisation based on examples in HoloViews (Python)

Plot

```
gdp_curves = macro.to.curve('Year', 'GDP Growth')
gdp_unem_scatter = macro.to.scatter('Year', ['GDP Growth', 'Unemployment'])
annotations = hv.Arrow(1973, 8, 'Oil Crisis', 'v') * hv.Arrow(1975, 6, 'Stagflation', 'v') *\
hv.Arrow(1979, 8, 'Energy Crisis', 'v') * hv.Arrow(1981.9, 5, 'Early Eighties\n Recession', 'v')

(gdp_curves * gdp_unem_scatter* annotations).opts(
    opts.Curve(color='k'),
    opts.Scatter(cmap='Blues', color='Unemployment',
                 line_color='k', size=dim('Unemployment')*1.5),
    opts.Text(text_font_size='13px'),
    opts.Overlay(height=400, show_frame=False, width=700))
```

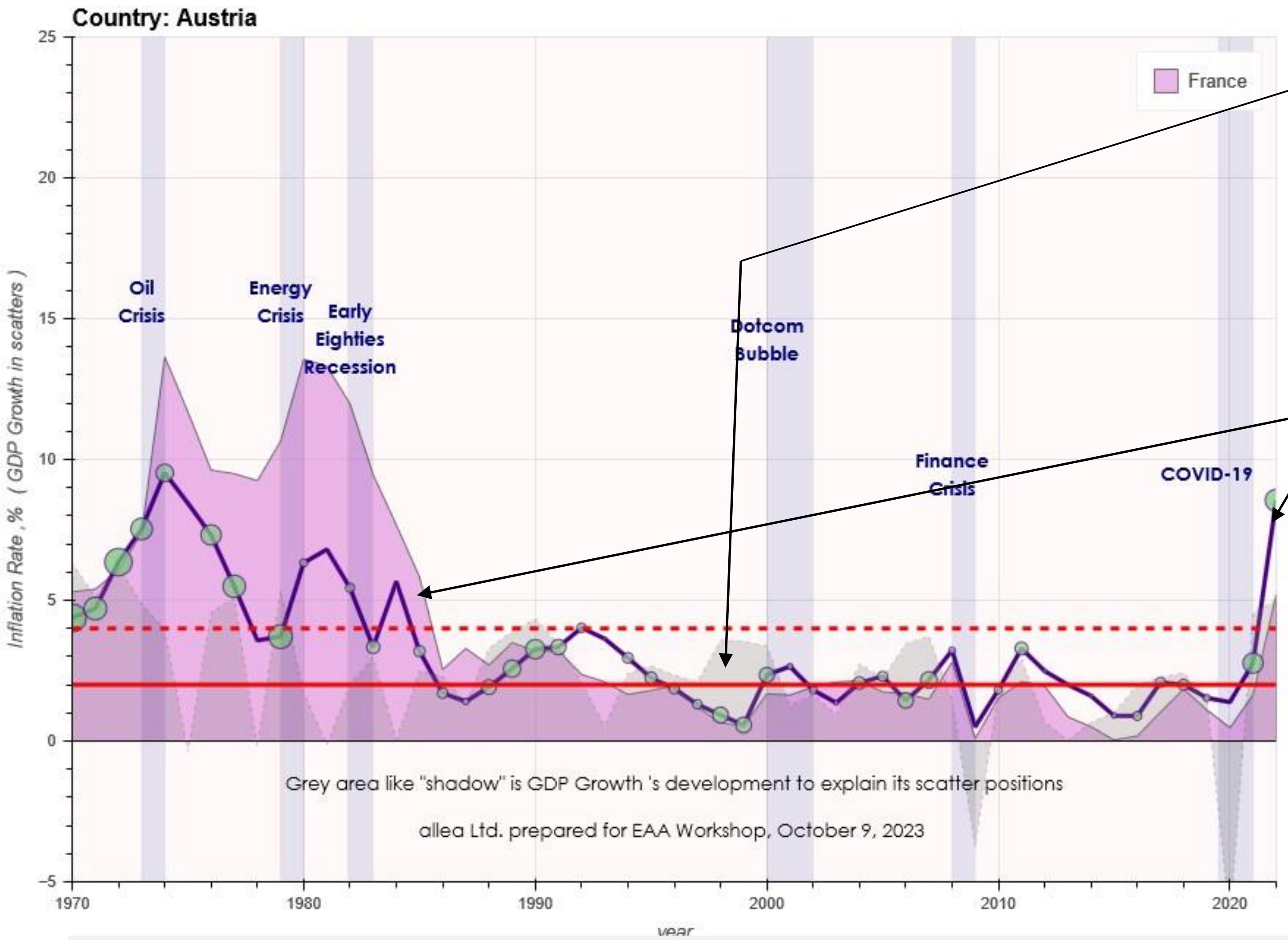




- Our Visualisation Inflation World Bank data based on:
  - Dropdown Economic

https://holoviews.org/gallery/demos/bokeh/dropdown_economic.html

Visualization based on World Bank data (to compare with France)



GDP Growth Austria

Inflation rate Austria:
The country could be changed

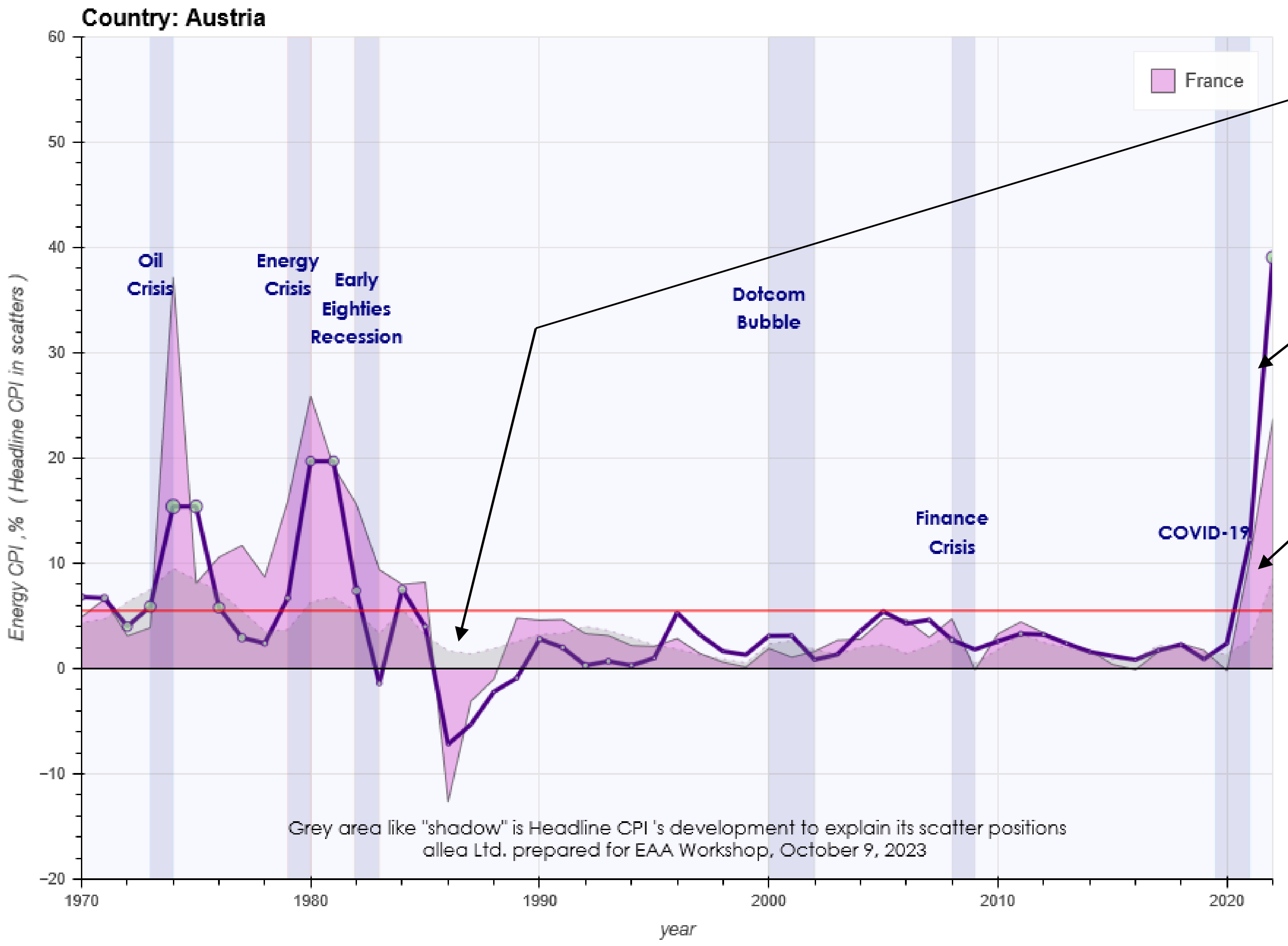
Headline Inflation France
(before 1986 already below 4%)

This graph is HTML-File prepared with «bokeh» library and all curves can be moved on home page (increased or decreases to understand results)

Such graphs could be verified in the allea home page: https://allea.ch/inflation/

Examples to find: https://allea.ch/de/inflation_de/ **Publications:** https://allea.ch/blog/

Visualization based on World Bank data (to compare with France)



Headline CPI (Inflation) Austria

Energy CPI (Inflation) Austria
The country could be changed

Energy Inflation France

This graph is HTML-File prepared with «bokeh» liability and all curves can be moved (increased or decreases to understand results)

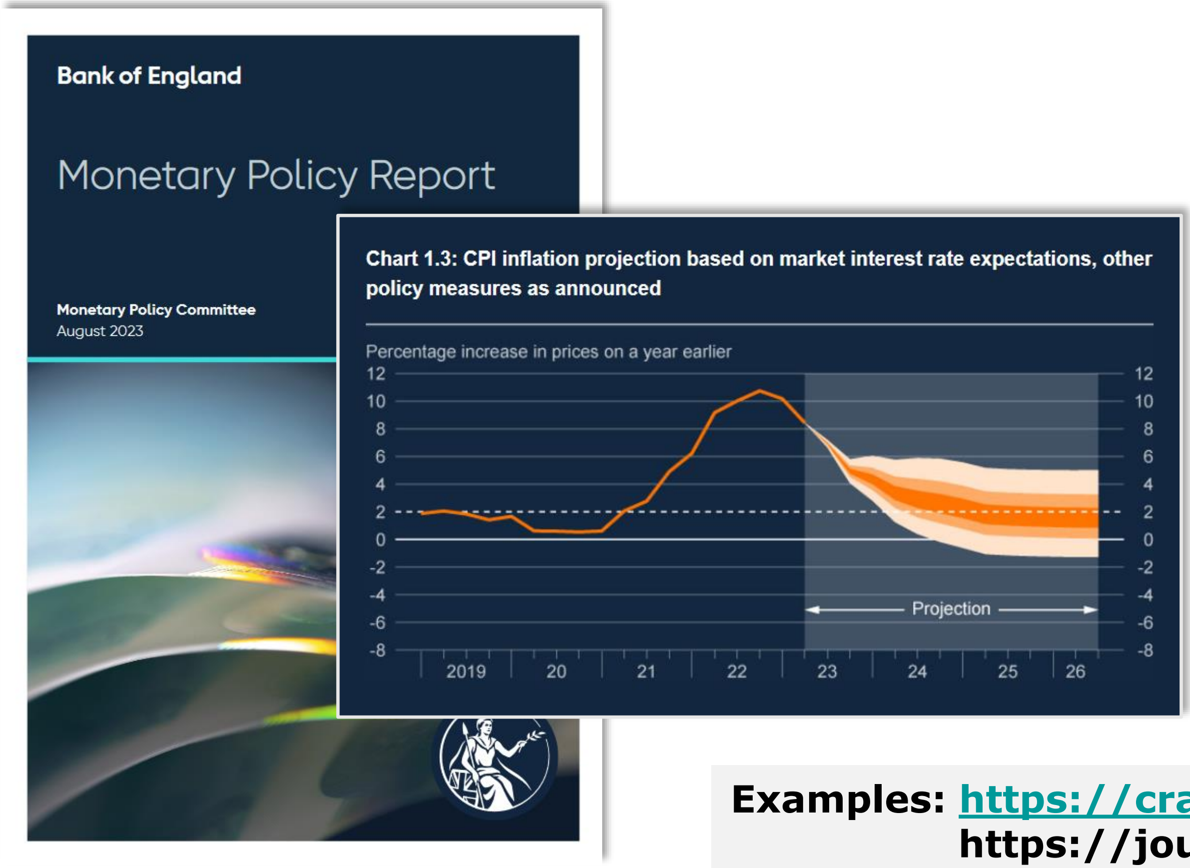
Such graphs could be verified in the allea home page: https://allea.ch/inflation/

Introduction: NNAR Forecasting Approach (AI)

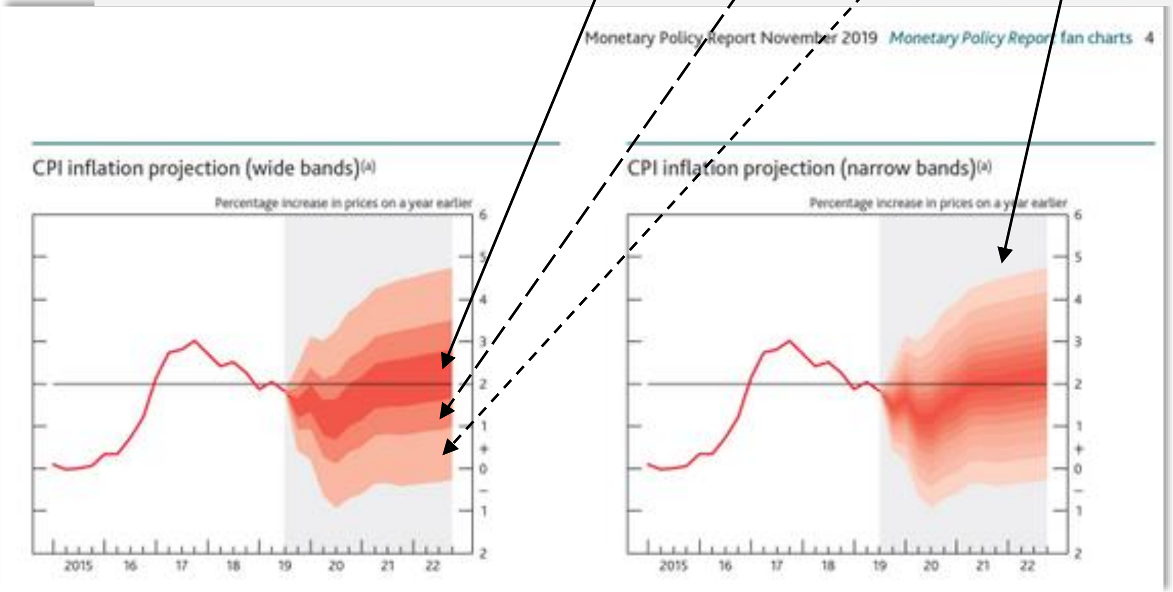
Visualisation Inflation Forecasting with R-project „fanplot"

Bank of England (BoE): CPI Inflation Forecast (August, 2023)

- **This graph on Page 20 of this report:**
- **https://www.bankofengland.co.uk/-/media/boe/files/monetary-policy-report/2023/august/monetary-policy-report-august-2023.pdf**



Initially: it was used 5% as a percentile step (scientific)
Now: the band widths are 30% - 60% and 90%
It is much easier to understand



Examples: https://cran.r-project.org/web/packages/fanplot/fanplot.pdf
https://journal.r-project.org/archive/2015-1/abel.pdf

Examples Visualisation with «fanplot» R-project

R-project: https://journal.r-project.org/archive/2015-1/abel.pdf

Now will Python as well: https://pypi.org/project/fanchart/

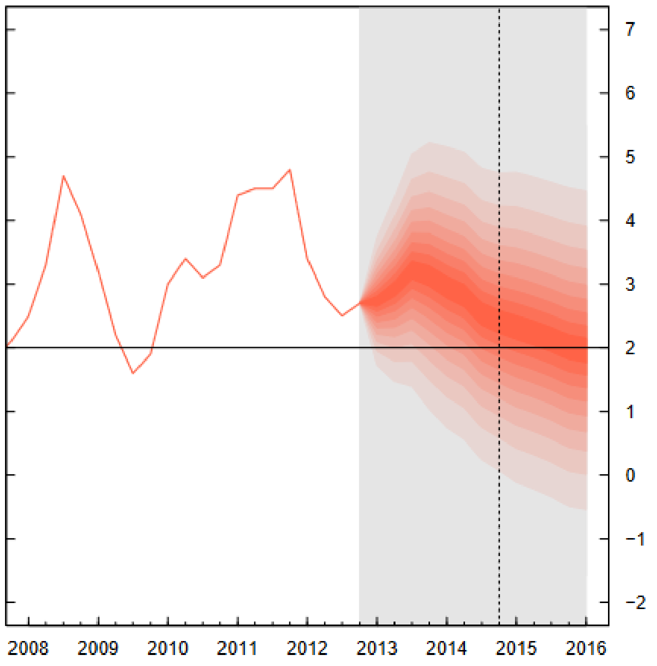


Figure 4: Fan chart, in the Bank of England style, for the MPC Q1 2013 forecast of the percentage increase in prices on year earlier.

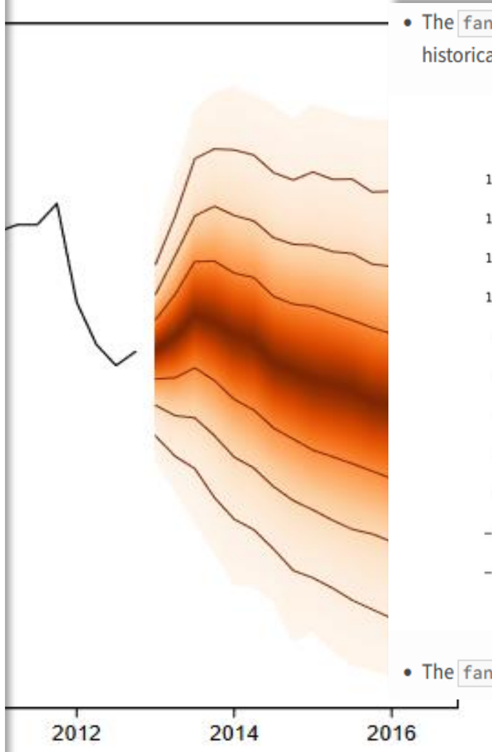
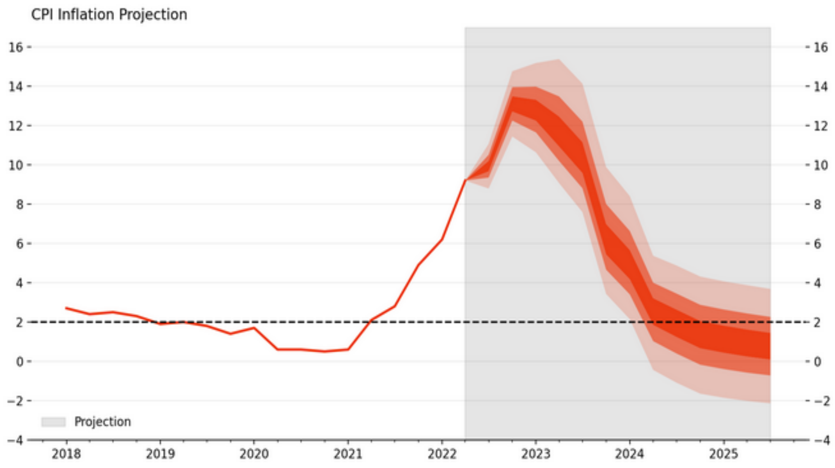


Figure 5: Alternative fan chart for the MPC Q1 2013 CPI forecast.

- The `fan` function illustrates the distribution of all the forecasts available; and it has the option to display the historical values for reference.

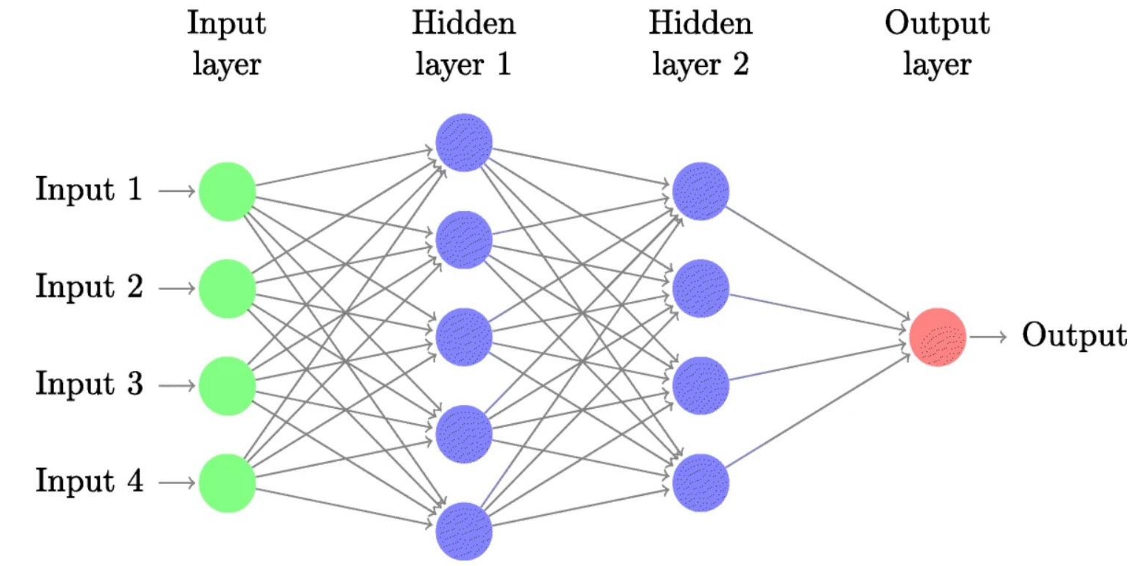


- The `fan_single` function illustrates the pdf/cdf of one forecast distribution

- Approach and Programms with R-project to find in the link above (Produced by Guy J. Abel)

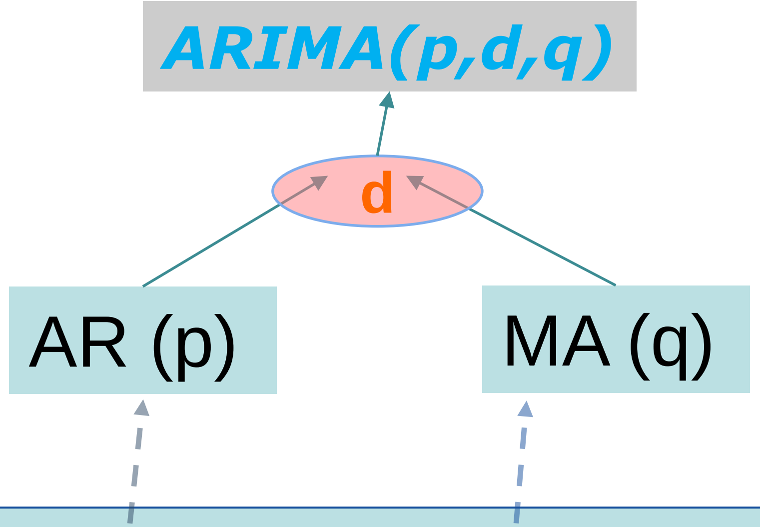
european actuarial academy

Forecasting Approach NNAR vs. ARIMA



ANN. A schematic artificial neural network (ANN) with two hidden layers and a single neuron output

- The forecast based on the **affine** model (like ARIMA) produces higher bandwidth of inflation rates and 10-year government bond yields
- That is why much wider bandwidths for other parameters forecasted based on inflation and/ or 10-year bond yields.
  - *Our analysis of the forecasting was made based on the affine model and presented in AFIR Paris 2020 Colloquium and published initially in EXPERT FOCUS (Dec 2020) for International Accounting Forecasting.*

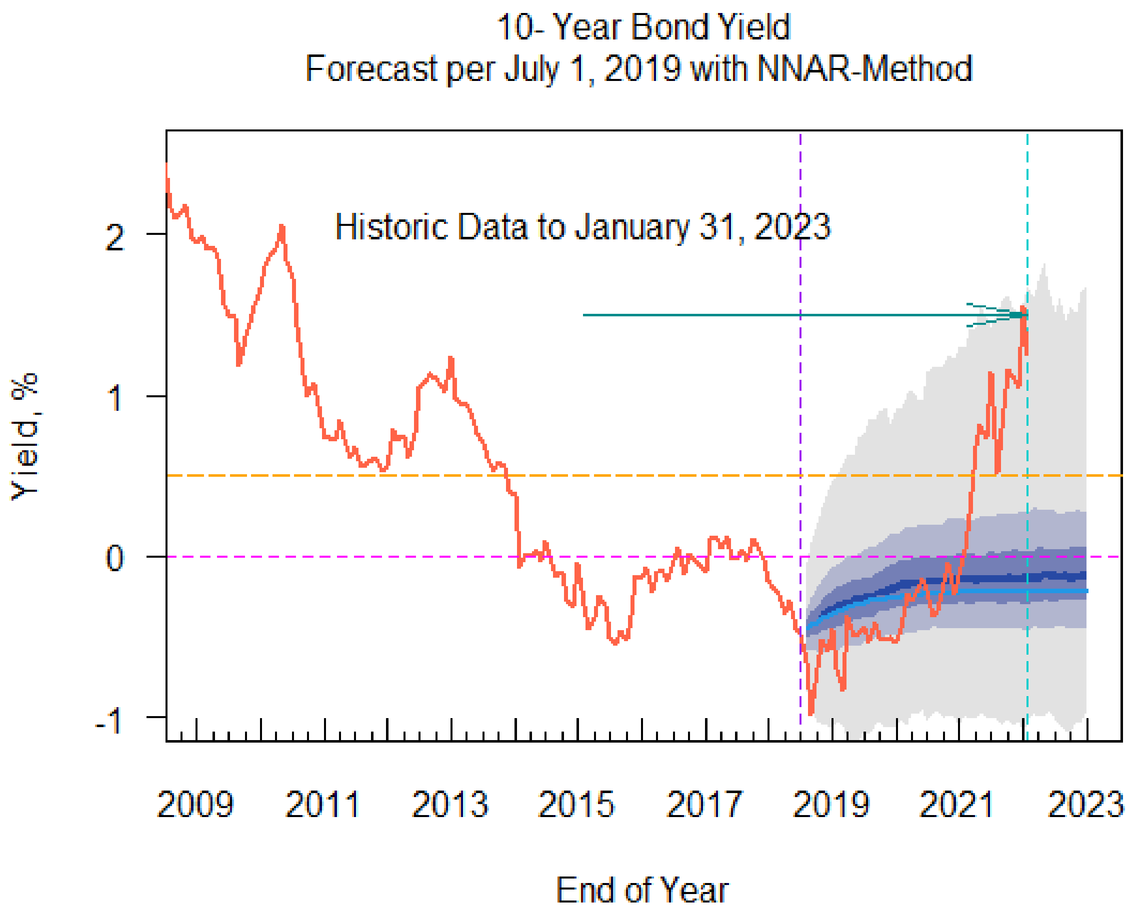


Box & Jenkins (1976) introduced the concept of **AutoRegressive** **Integrated** **Moving** **A**verage (ARIMA) time series models.
This **is a linear (affine), stationary** AR(p) and MA(q) model. The ARIMA-Variance and -Mean increase linearly (NNAR is not linearly).

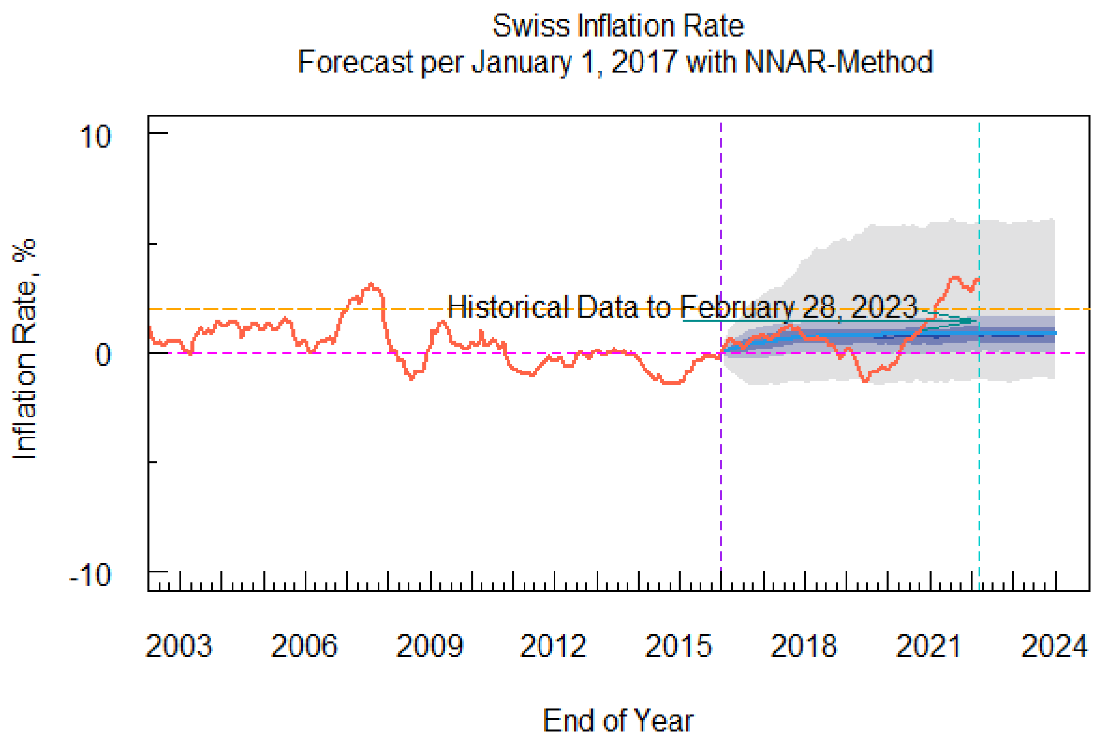
- NNAR-Approach without „Hidden layers“ formally corresponds to the ARIMA(p,0,0)-Approach (i.e., AR(p))

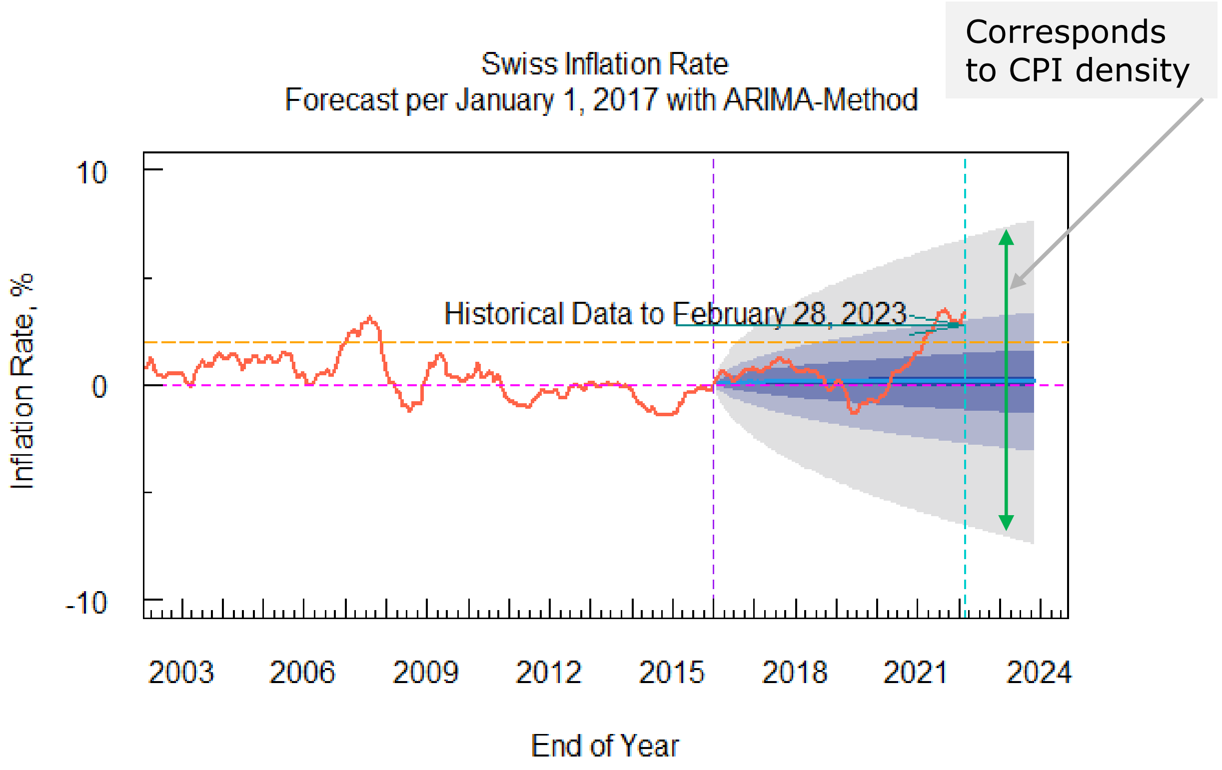
NNAR Forecasting Approach (prepared with R-project)

- Neural Network Auto-Regressive (NNAR) Approach (AI) used for forecasting.
- Scientific publications showed that forecasts for inflation, exchange rates, spot interest rates and other yields using this (AI) method produce very good predictions
- **Example:**
  - Comparison of the historical development (red line on the figure) shows that the forecasted 10-year government bond yield per July 1, 2019, complies with the historical development between July 2019, and January 2023.
  - Very strong increase of 10-year bond yield in 2022 is within the forecasted bandwidth.



NNAR Forecasting Approach vs. ARIMA (R-project)





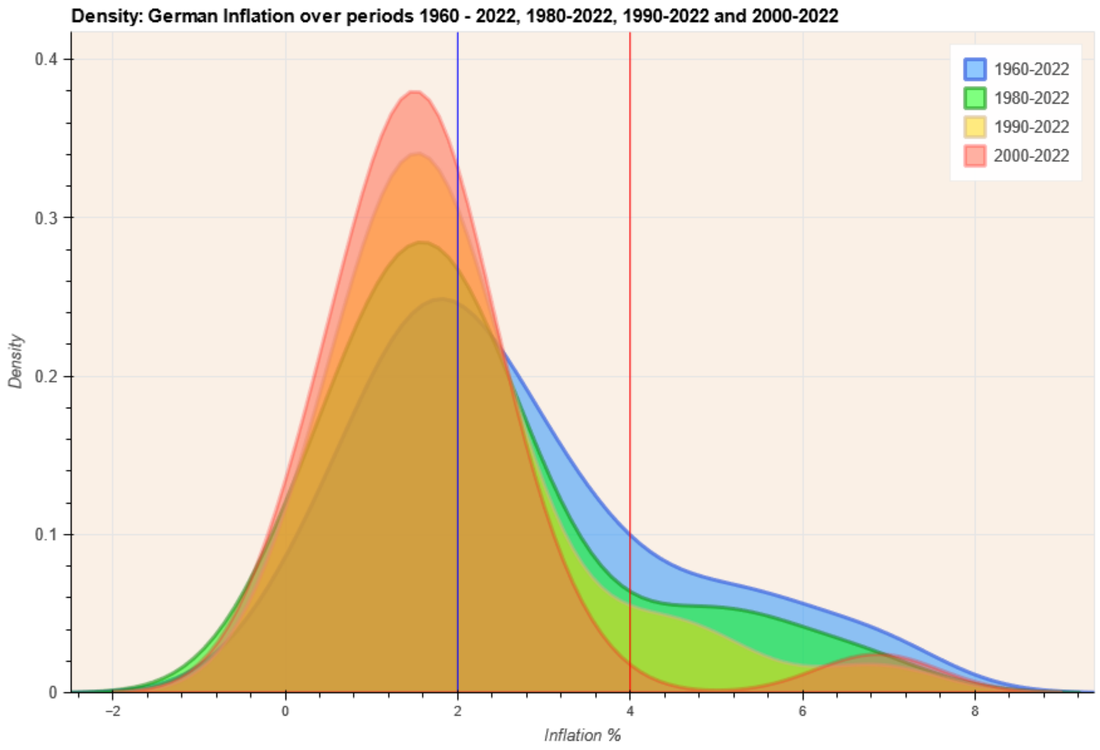
- Inflation rate forecast produced with NNAR (left) vs. ARIMA (right) per January 1, 2017, shows that the volatility (bandwidth of forecasted values) with ARIMA is much higher compared to the NNAR approach.
  - Especially the forecasted negative inflation rates were not observed (next two slides).
- The forecasted inflation rate with the NNAR approach per January 1, 2017, corresponds better to its historical values.

Inflation density is not symmetric (NNAR reflects such layout)

Example: Inflation Densities based on World Bank historical data since 1960

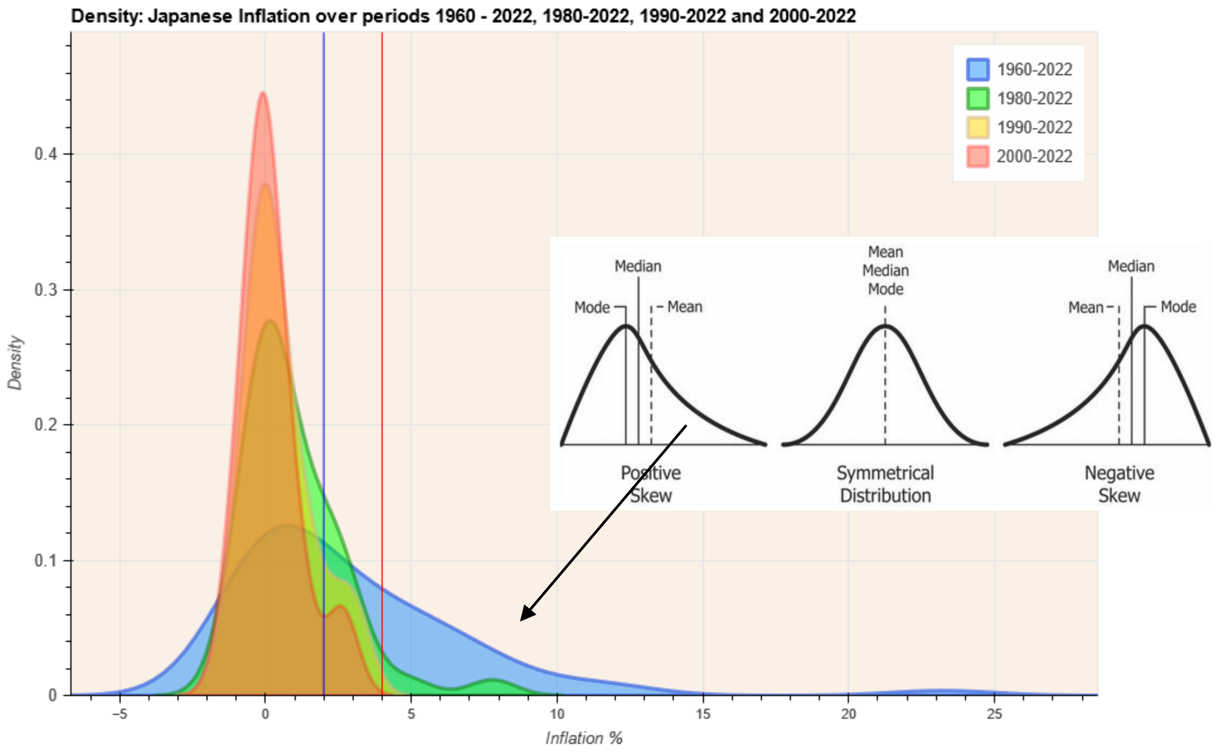
Density: Inflation in Germany (kde() graph)

- **Over 63 years,**
- **Over 43, 33 and 23 years.**



Density: Inflation in Japan

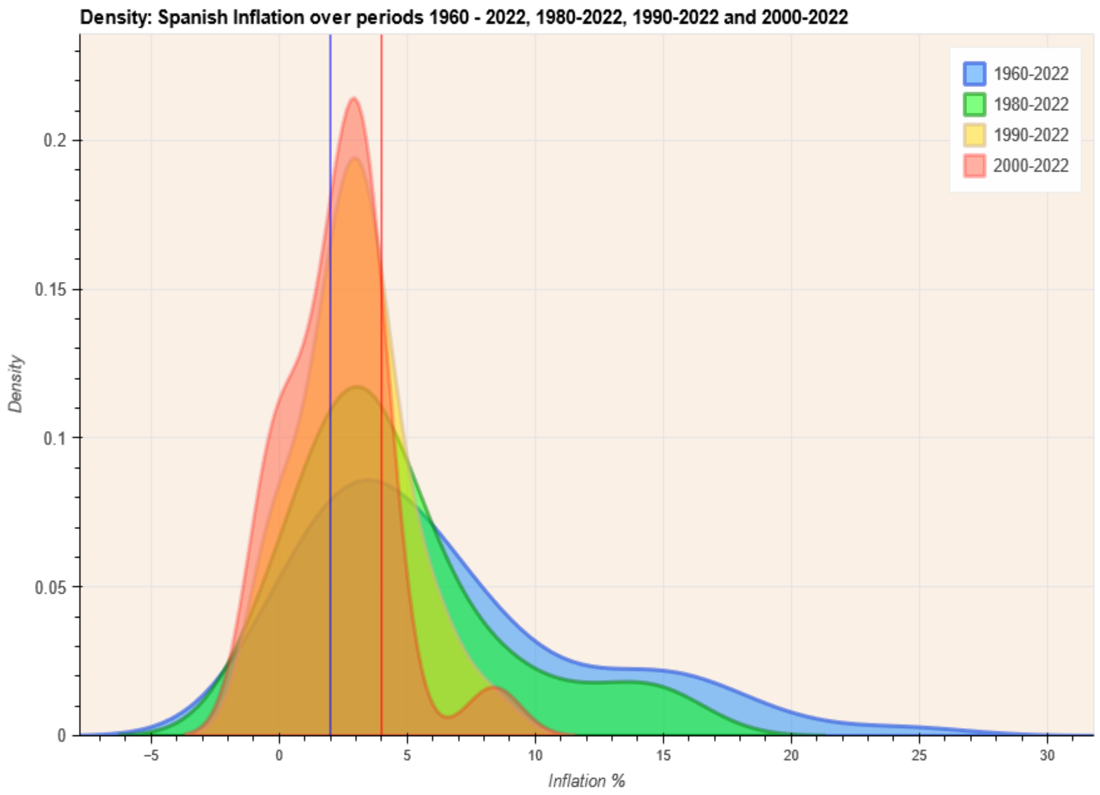
- **Over 63 years,**
- **Over 43, 33 and 23 years.**



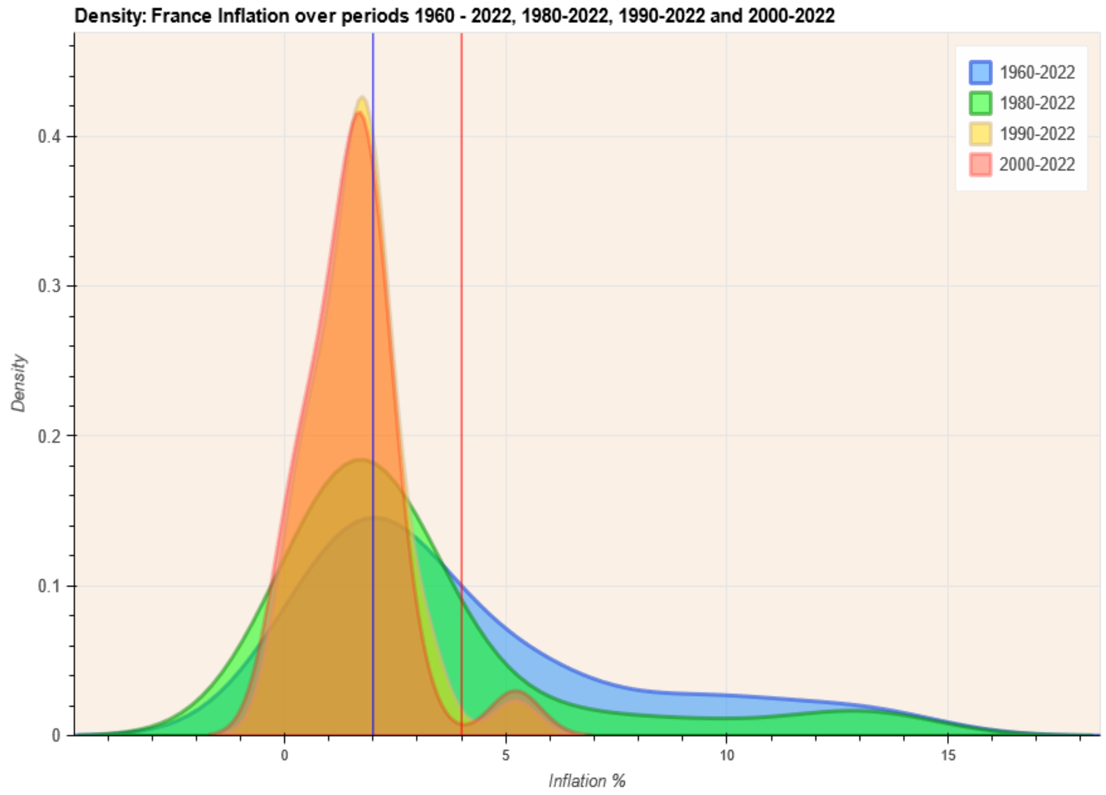
Inflation density is not symmetric (NNAR reflects such layout)

Example: Inflation Densities based on World Bank historical data since 1960

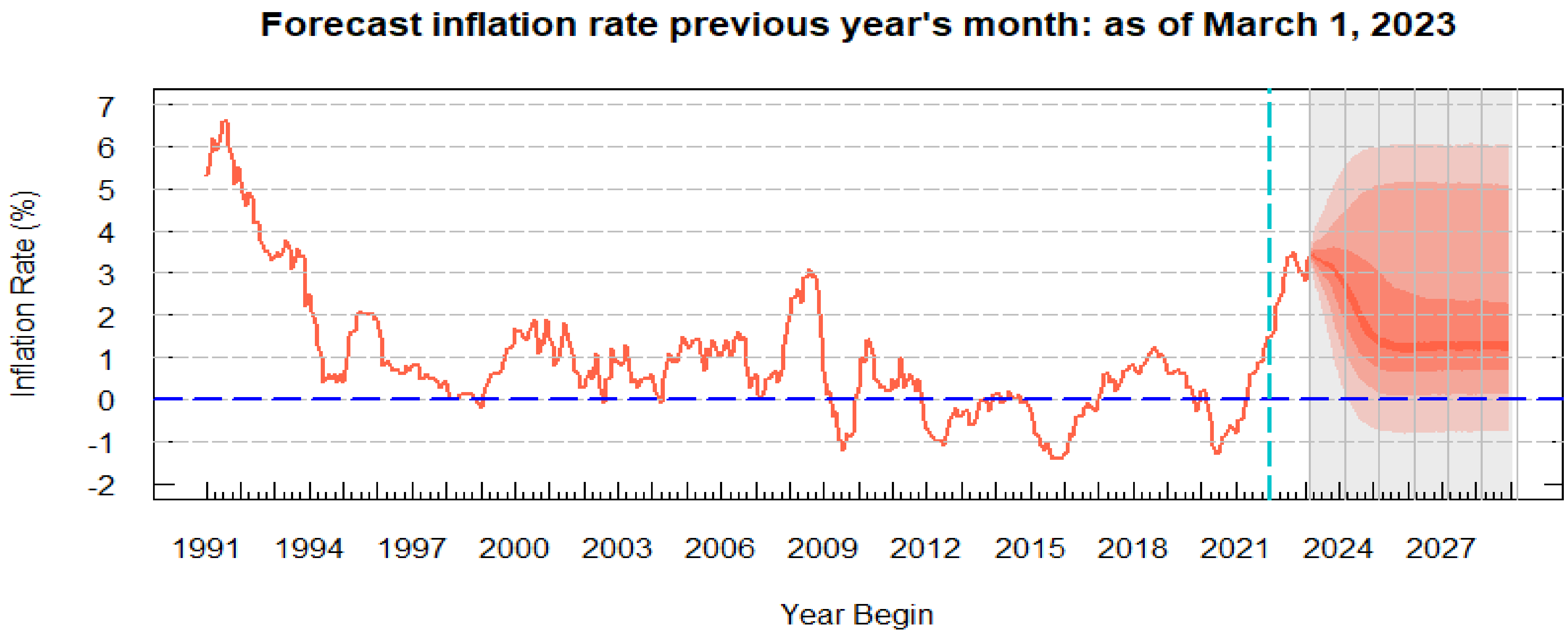
Density: Inflation in Spain
- **Over 63 years,**
- **Over 43, 33 and 23 years.**



Density: Inflation in France
- **Over 63 years,**
- **Over 43, 33 and 23 years.**



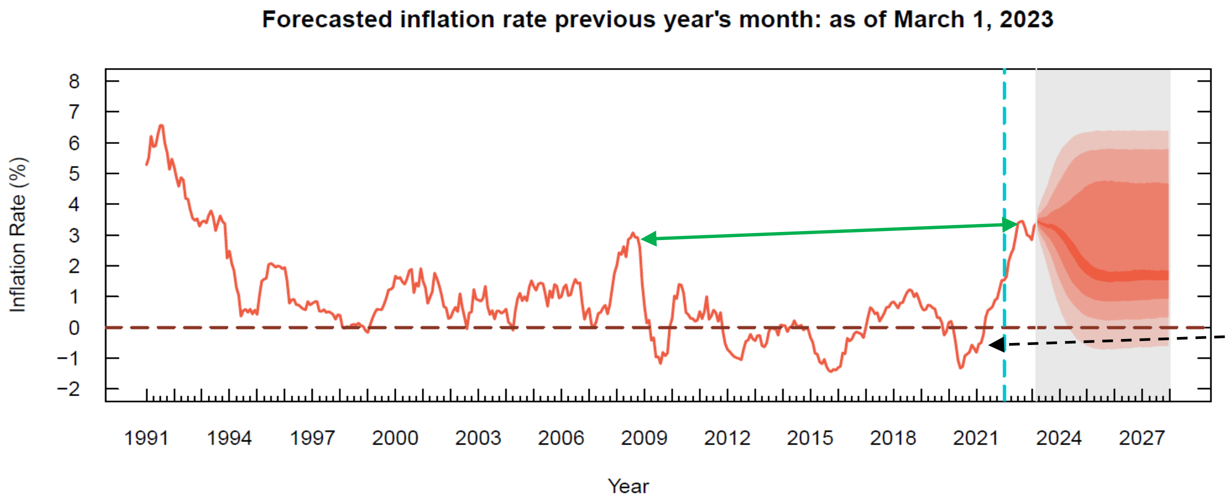
NNAR Forecasting Approach for monthly Swiss Inflation Rate Presented at ICA 2023

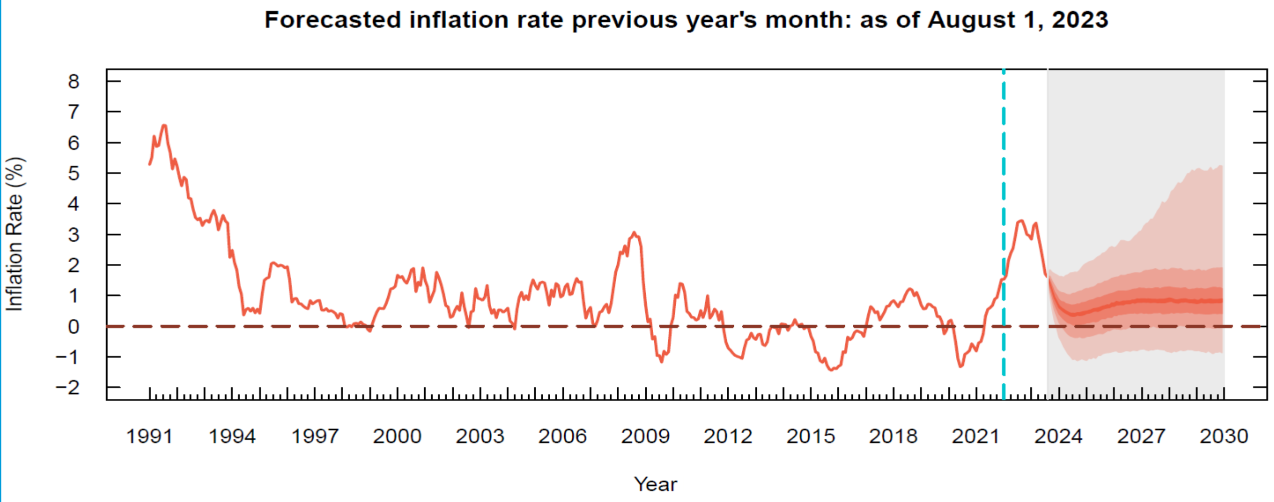


- It is useful to compared results as a "second opinion" with the forecasts prepared by the IMF (International Monetary Fund)

IMF: Switzerland	2023: 2.4%	2024: 1.6%	2025: 1.3%	2026: 1%	**2027: 1%**	**2028: 1%**

R-project: Visualisation with the «fanplot» library



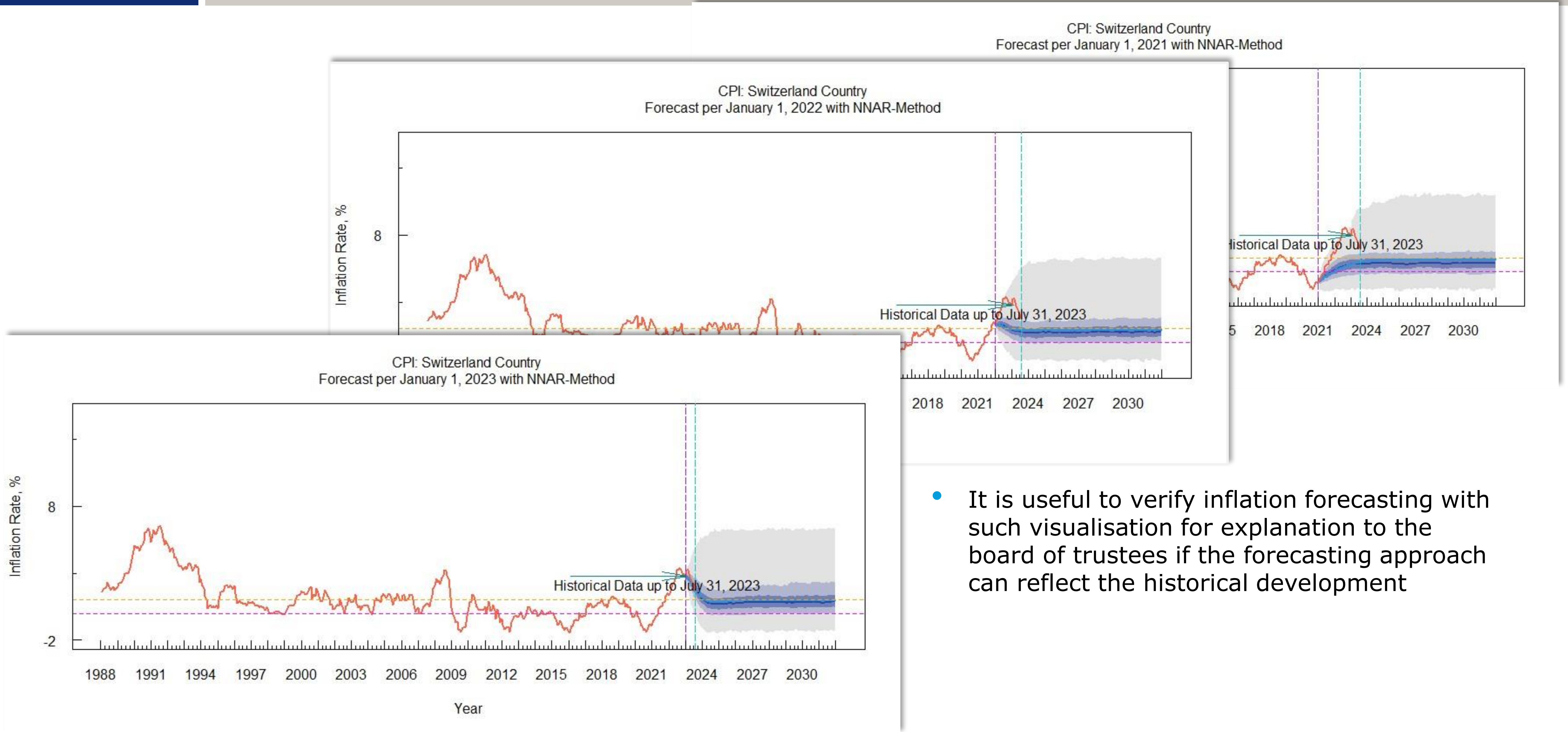


- The «fanplot» library was initially developed for the Bank of England to show the forecasted inflation rate.
- In Switzerland strong increase inflation started in 2020 (COVID-19).
- In August 2022 up to Feb 2023 the inflation rate had even slightly higher level compared to year 2008.

Our Presentation at ICA 2023 (Australia):

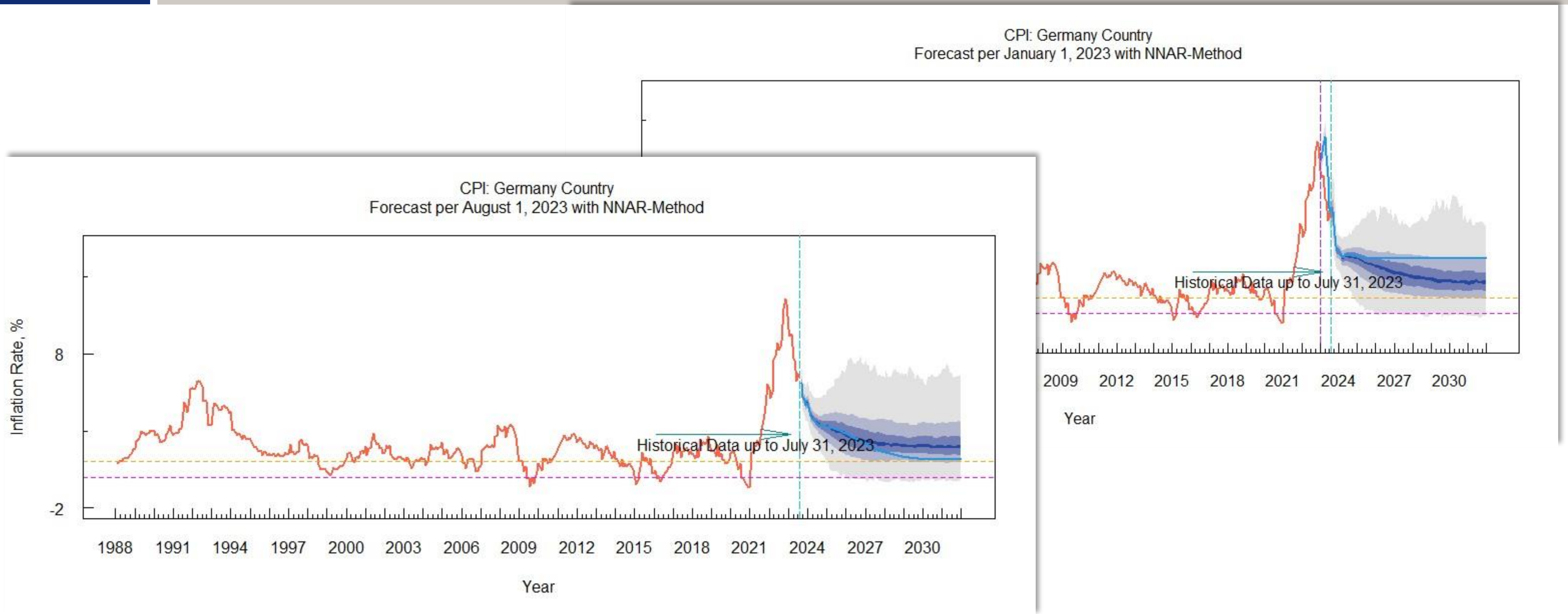
- The median of the forecasted inflation rate per March 1, 2023, showed that it is to expect that the inflation rate would soon decrease:
  - **Per July 31, 2023, the inflation rate is 1.6%,**
  - **Compared to the inflation rate 3.37% per February 28, 2023.**

NNAR Forecasting Approach for monthly Swiss Inflation Rate



- It is useful to verify inflation forecasting with such visualisation for explanation to the board of trustees if the forecasting approach can reflect the historical development

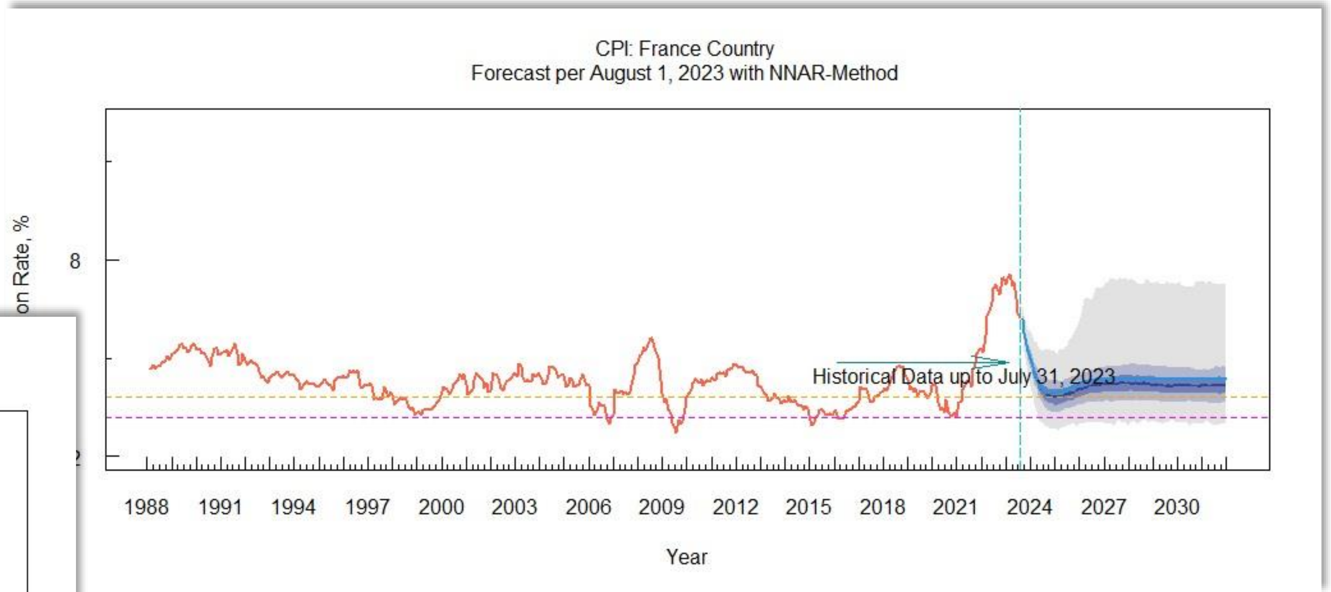
NNAR Forecasting Approach for monthly Inflation Rate

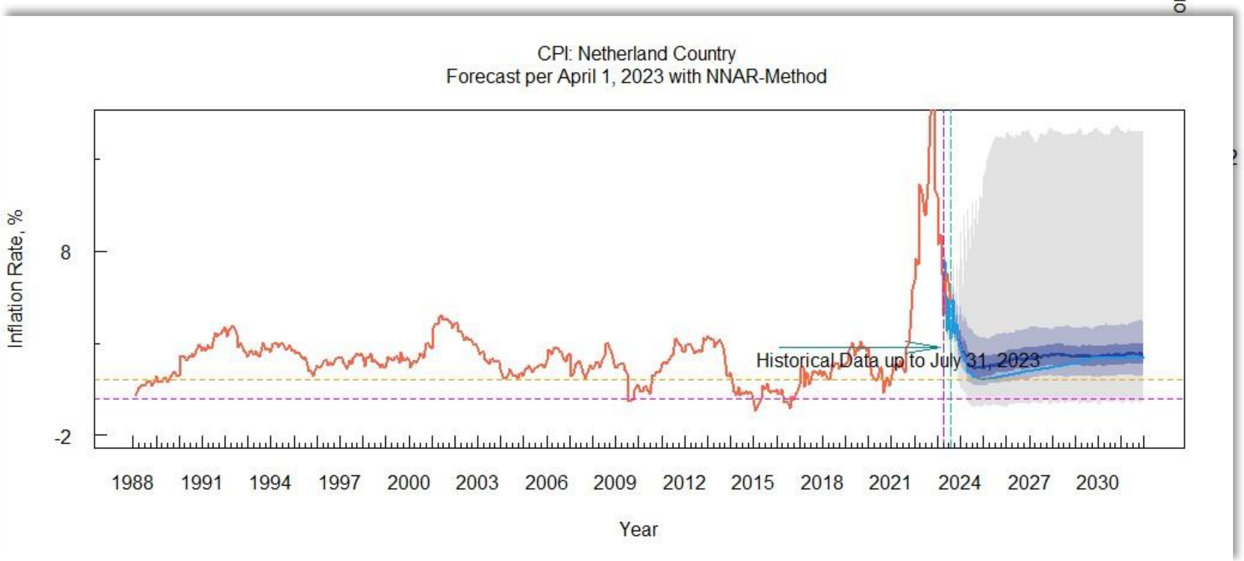


- Forecast Inflation for Germany per January 1, 2023, and per August 1, 2023, based on NNAR-Approach.

IMF: Germany	2023: 6.2%	2024: 3.1%	2025: 2.3%	2026: 2.1%	**2027: 2%**	**2028: 2%**

NNAR Forecasting Approach for monthly Inflation Rate





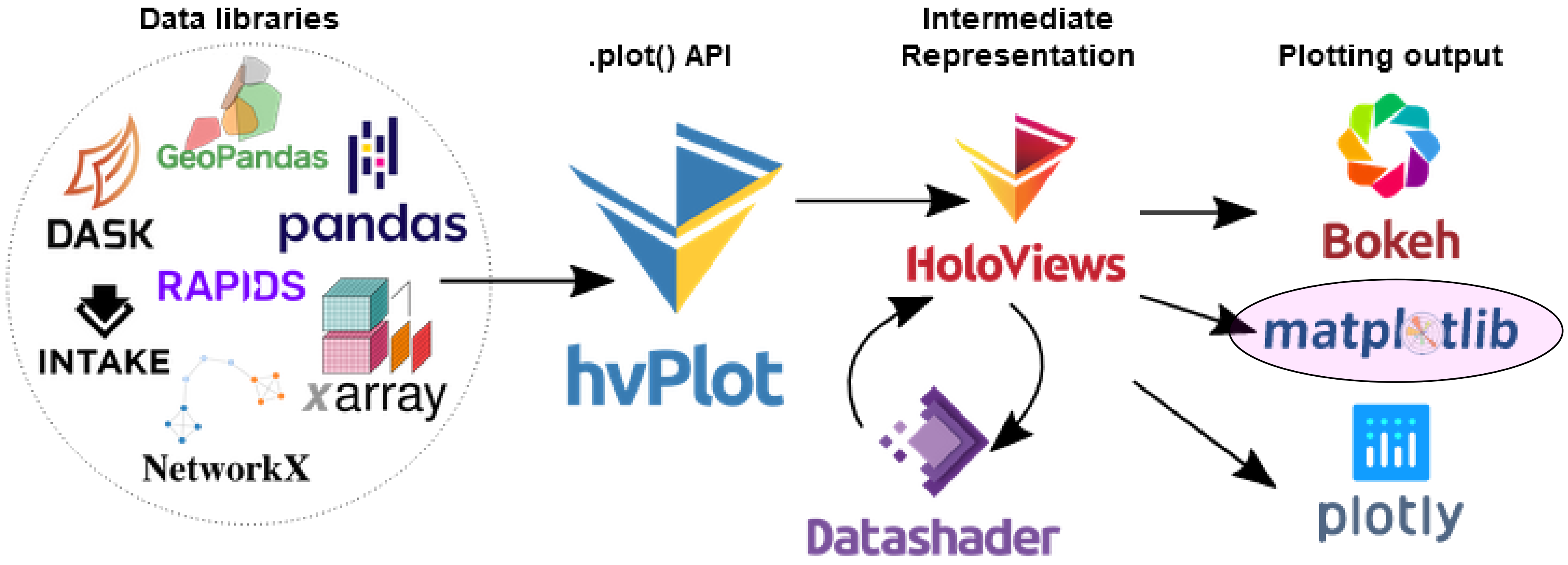
- Forecast Inflation for Netherland & France per August 1, 2023, based on NNAR-Approach.

IMF: Netherland	2022: 11.6%	2023: 3.9%	2024: 4.2%	2025: 2.1%	2026: 2.0%	**2027: 2.0%**	**2028: 2.0%**
IMF: France	2022: 5.9%	2023: 5.0%	2024: 2.5%	2025: 2.1%	2026: 1.7%	**2027: 1.6%**	**2028: 1.6%**

Yield Curve Visualisation

hvPlot

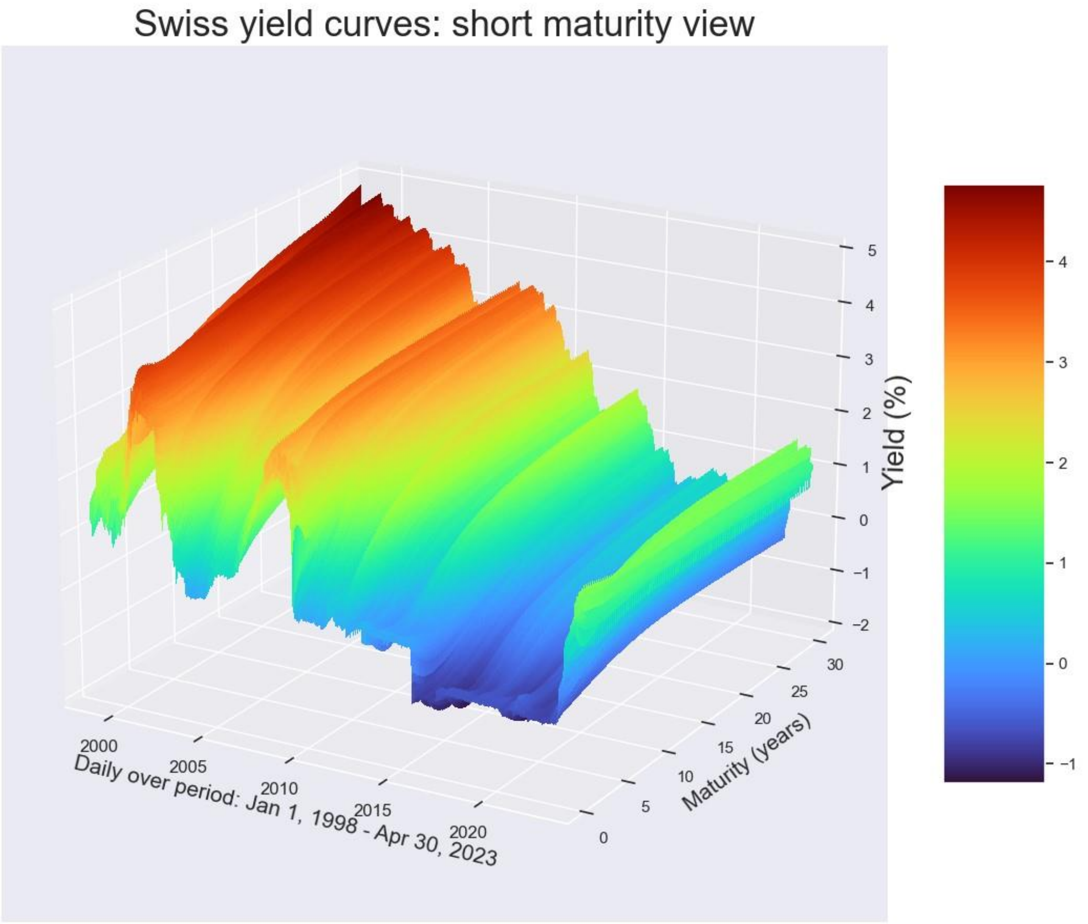
A familiar and high-level API for data exploration and visualization

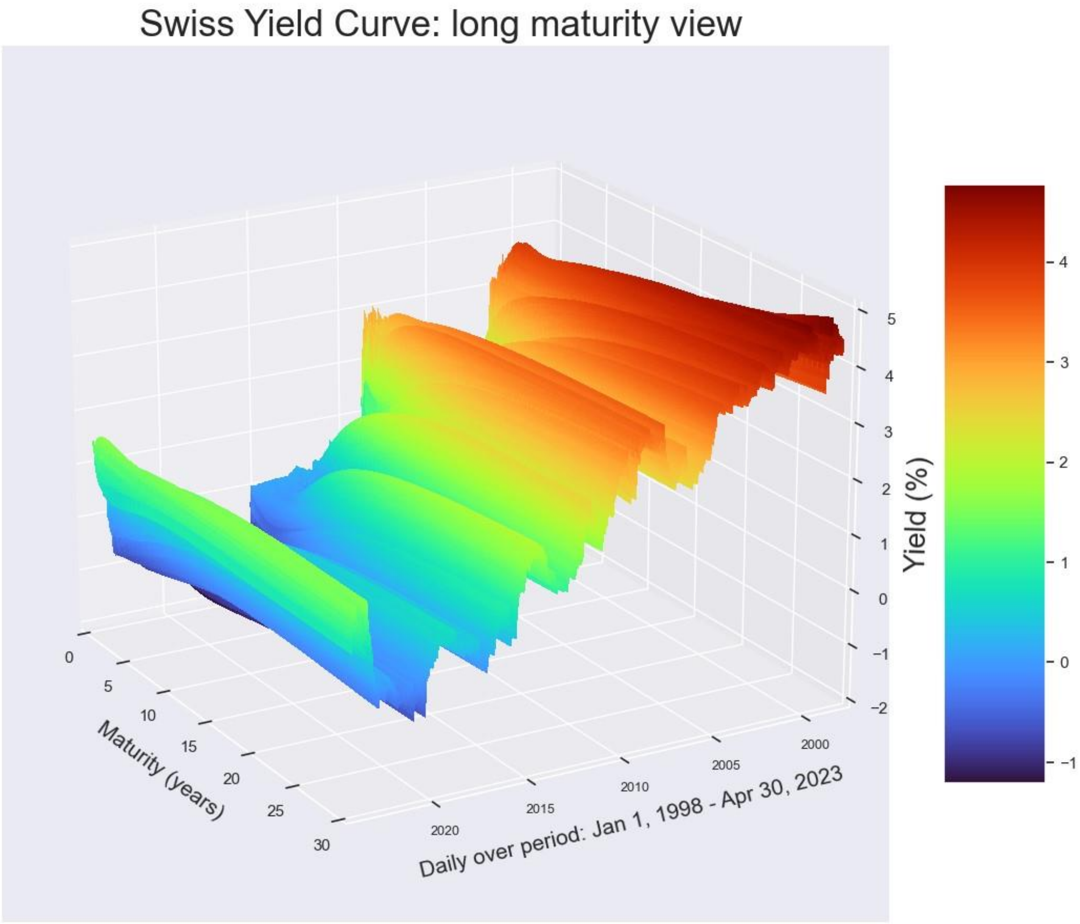


`.hvplot()` **is a powerful and interactive Pandas-like** `.plot()` **API**

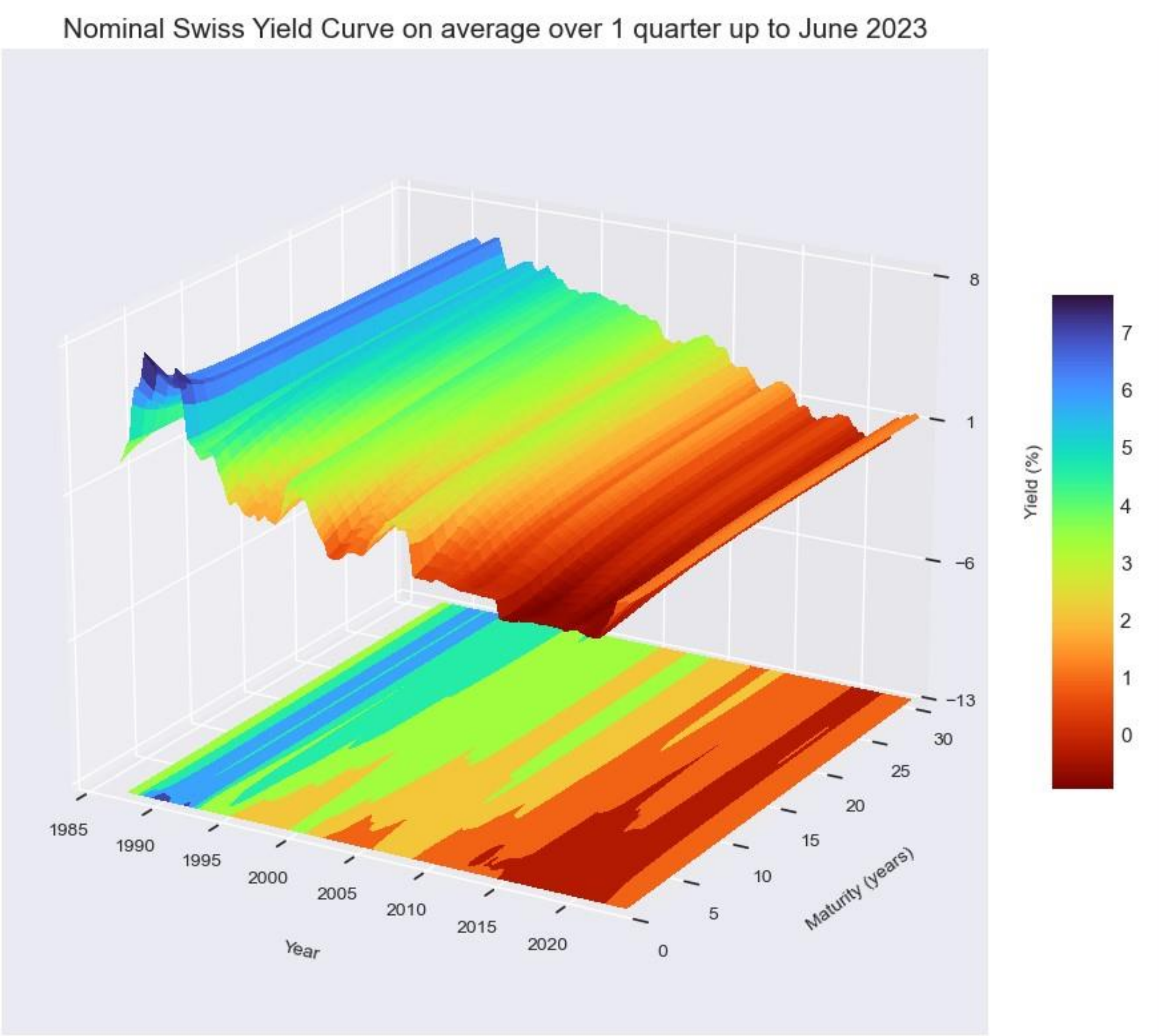
Nominal daily Swiss Yield Curves (over Jan 1998-Apr 2023)

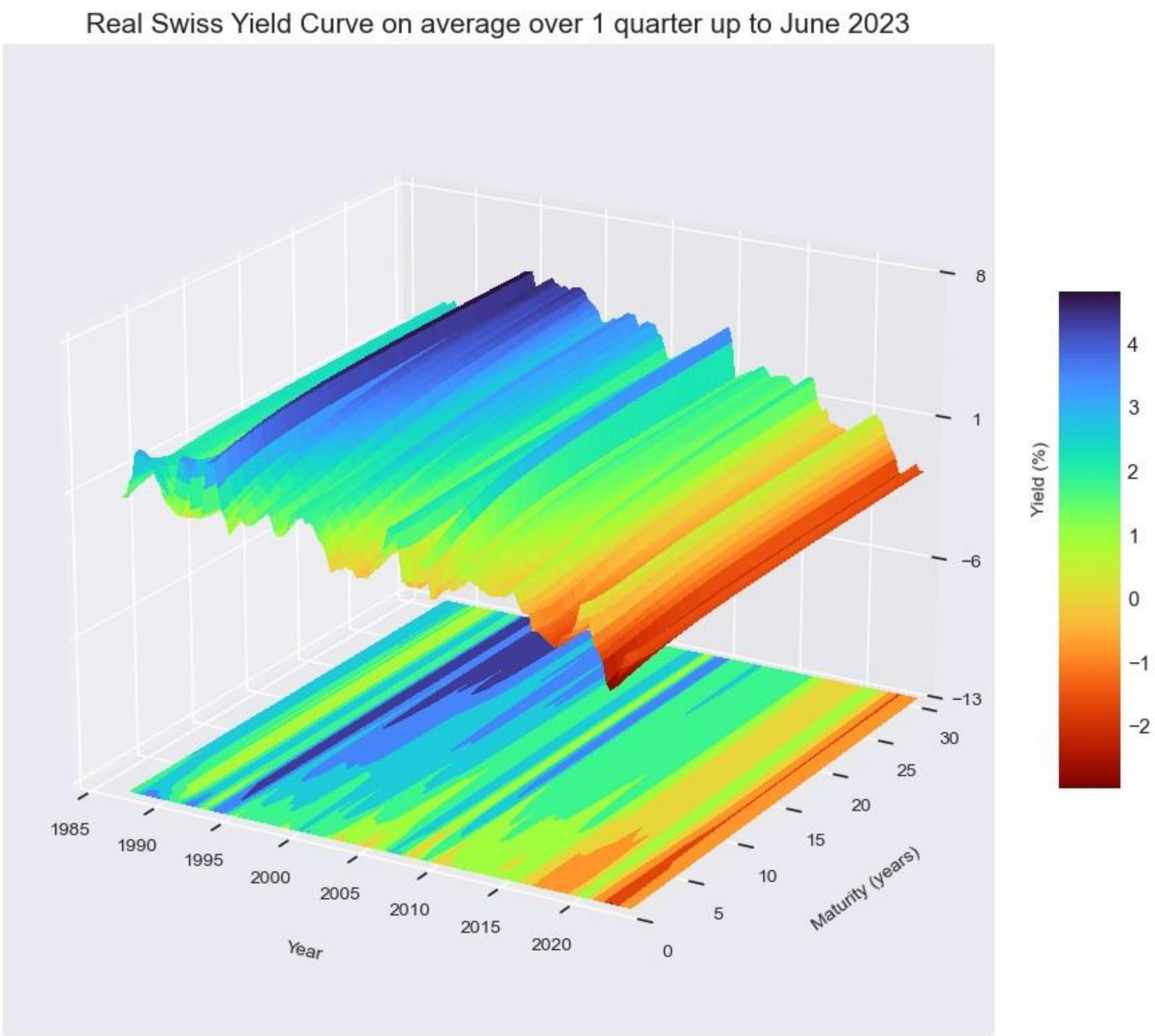
- Daily bond yields with maturity lower than 5 years are more volatile compared to bond yields with maturity higher than 10 years. (Prepared with «Matplotlib» Python Anaconda Jupiter)





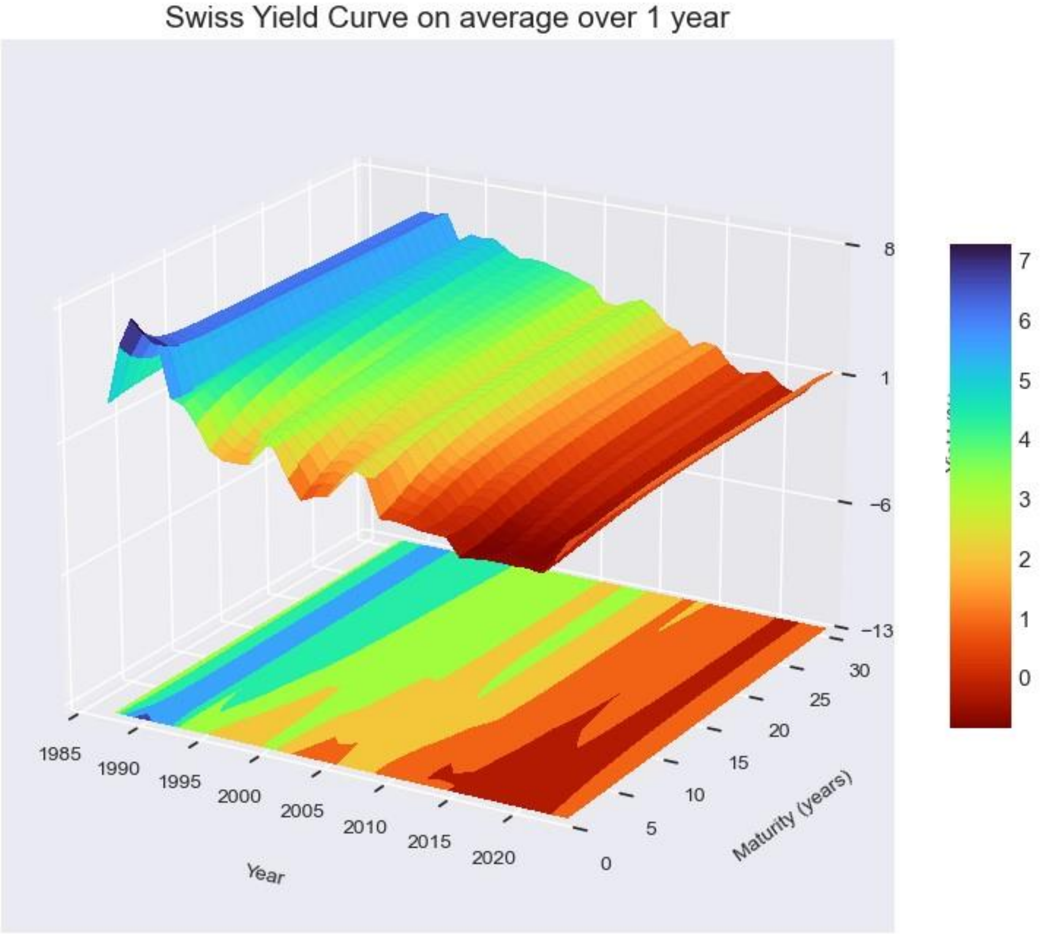
Nominal and real yield curves over Jan 1988 – June 2023 on average per quarter

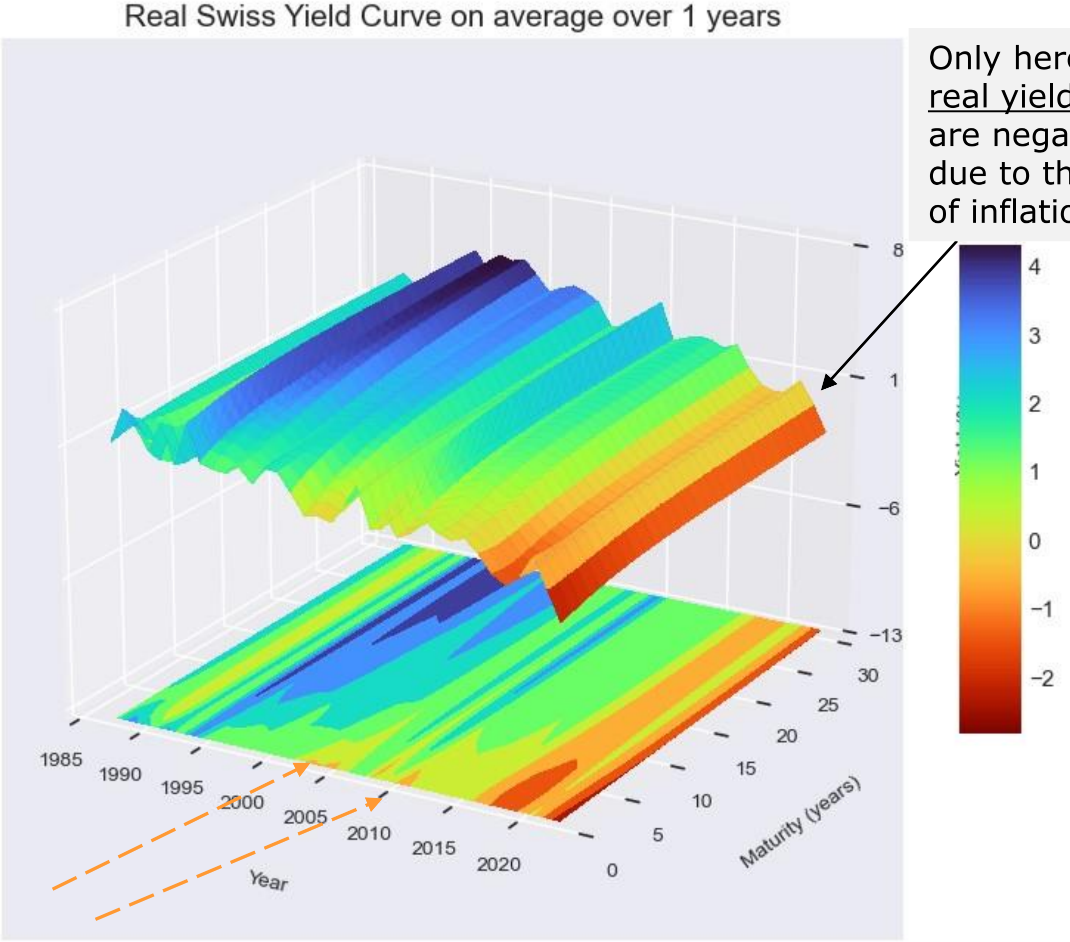




Nominal and real yield curves over Jan 1988 – June 2023

- Inflation impact on nominal yield curves is strong (esp. with maturity lower than 5 years)
- Real yield curves (graph rights) are flatter compared to nominal ones (graph lefts)

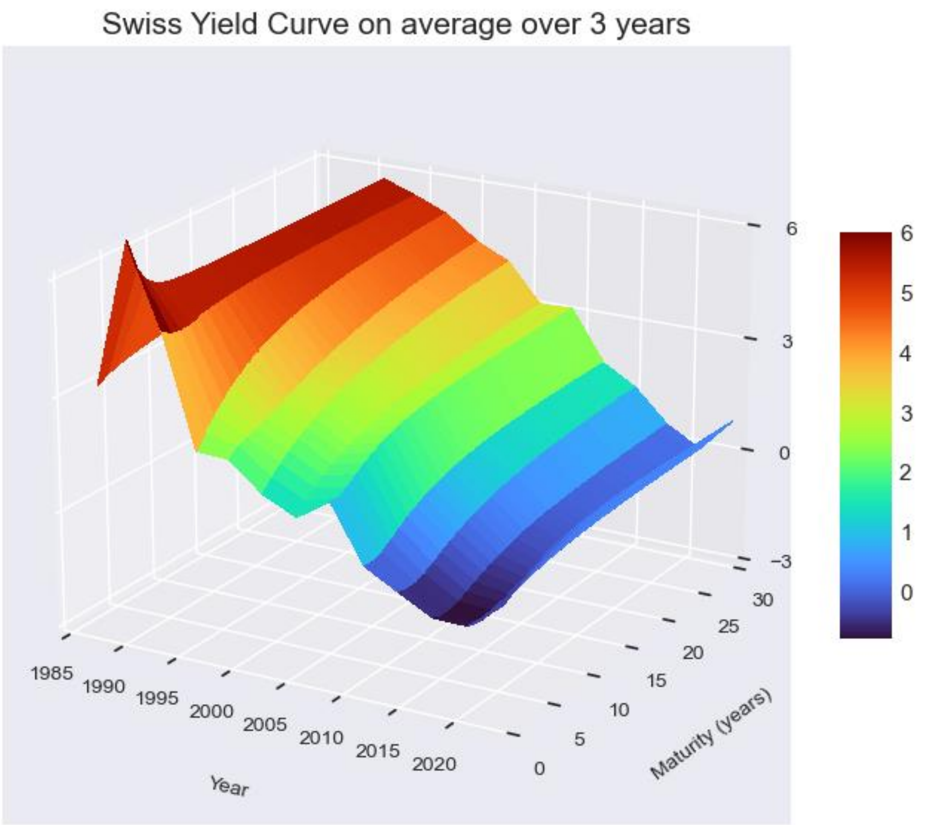


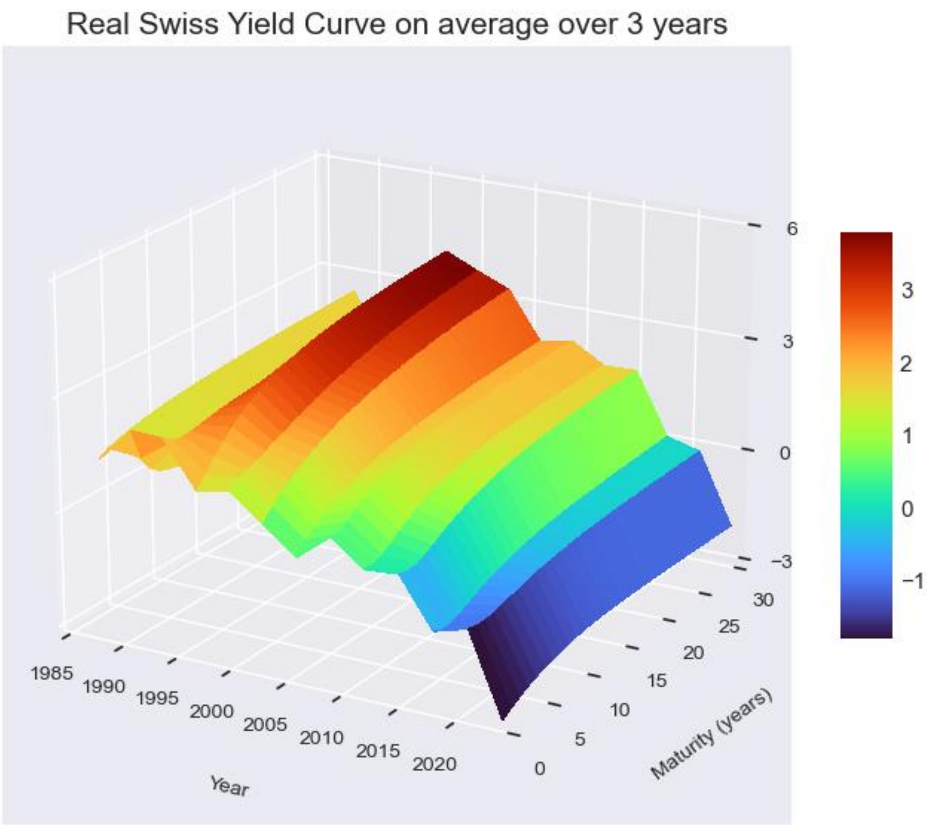


Only here the <u>real yield curves</u> are negative due to the level of inflation

Nominal and real yield curves over Jan 1988 – Dec 2022

- Inflation impact on nominal yield curves is strong (esp. with maturity lower than 5 years)
- Real yield curves (graph rights) are flatter compared to nominal ones (graph lefts)





- Analysis Inflation rate on average over 3-5 years is used for bonus annuity or Cost-of-Living Adjustment

Based on Pictet Bank Portfolio Indices for Pension Funds

PICTET
1805
Asset Management

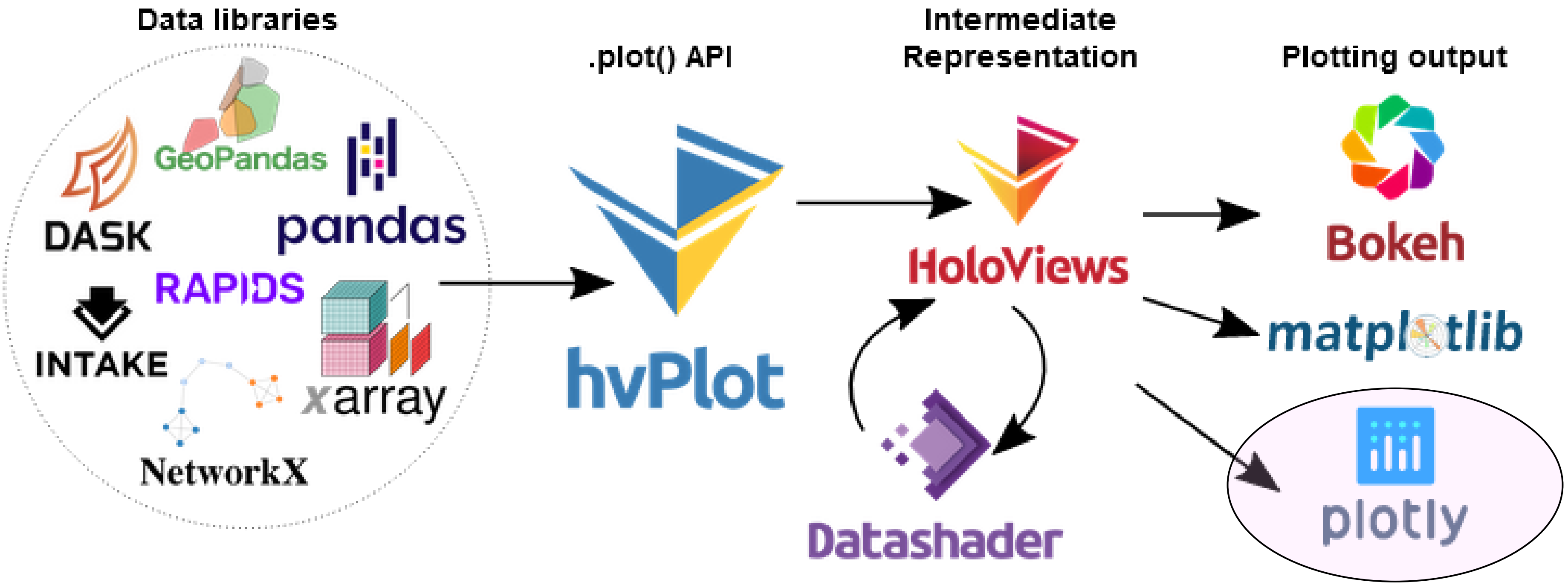
Pictet Swiss Pension Fund Indices: LPP/BVG 2000, 2005 and 2015

https://am.pictet/en/switzerland/articles/lpp-indices#overview

BVG - Bundesgesetz über die berufliche Alters-, Hinterlassenen- und Invalidenvorsorge
LPP - 2ème pilier: caisse de pension

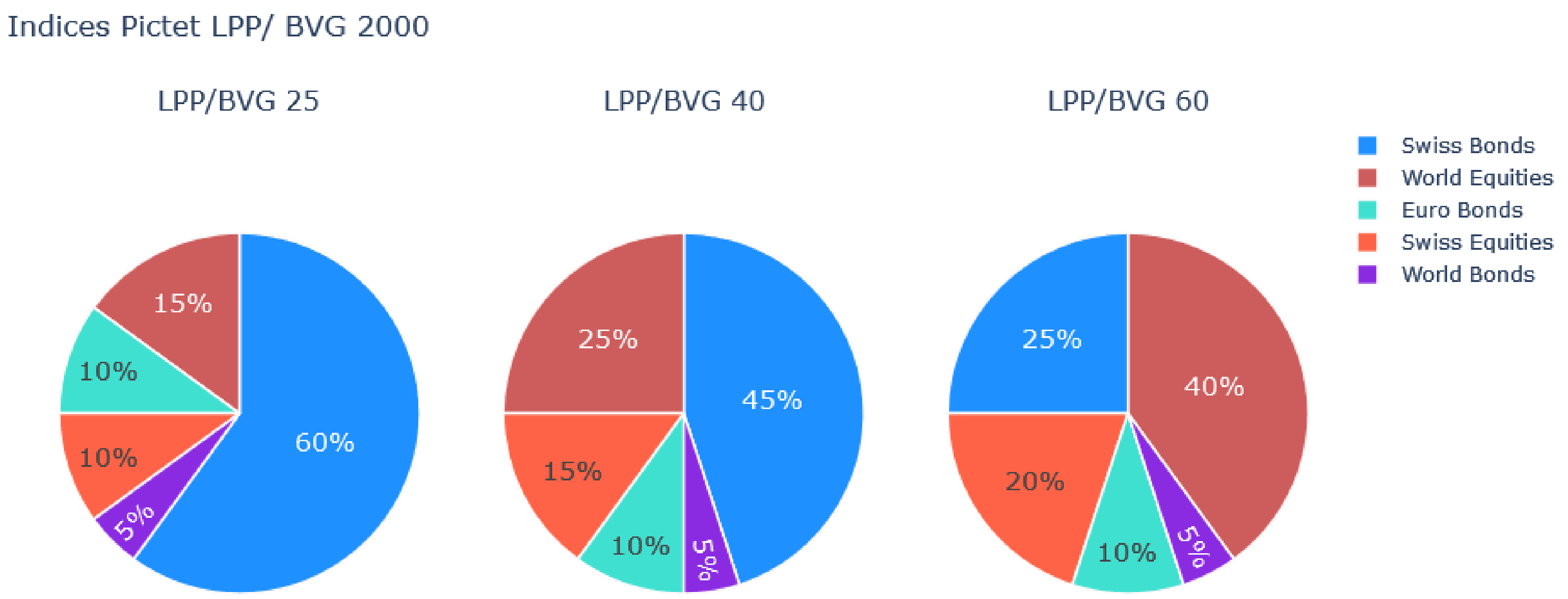
hvPlot

A familiar and high-level API for data exploration and visualization



`.hvplot()` **is a powerful and interactive Pandas-like** `.plot()` **API**

Pictet LPP/ BVG 2000 – only Bonds & Equities: daily and monthly



Python text next slide

Asset Allocation Pictet LPP/ BVG 2000 25, 40 and 60 (with Plotly Python)

```
import plotly.graph_objects as go
from plotly.subplots import make_subplots

colors = ['dodgerblue', 'turquoise', 'blueviolet', 'tomato', 'indianred']

labels = ['Swiss Bonds', 'Euro Bonds', 'World Bonds','Swiss Equities', 'World Equities']

fig = make_subplots(rows=1, cols=3, specs=[[{'type':'domain'}, {'type':'domain'}, {'type':'domain'}]],
                         subplot_titles=['LPP/BVG 25', 'LPP/BVG 40', 'LPP/BVG 60'])

fig.add_trace(go.Pie(labels=labels, values=[60,10,5,10,15], name="Pictet BVG 2000 25" , pull=[0, 0.0]), 1, 1)
fig.add_trace(go.Pie(labels=labels, values=[45,10,5,15,25], name="Pictet BVG 2000 40", pull=[0, 0.0]), 1, 2)
fig.add_trace(go.Pie(labels=labels, values=[25,10,5,20,40], name="Pictet BVG 2000 60", pull=[0, 0.0]), 1, 3)


fig.update_traces(hoverinfo='label+percent', textinfo='percent', textfont_size=15, textposition = 'inside',
                  marker=dict(colors=colors, line=dict(color='snow', width=1.5) ))

fig.update_layout(title_text = "Indices Pictet LPP/ BVG 2000" )

fig.show()
```

Asset Allocation Pictet LPP/ BVG 2000 25, 40 and 60 (with Plotly Python)

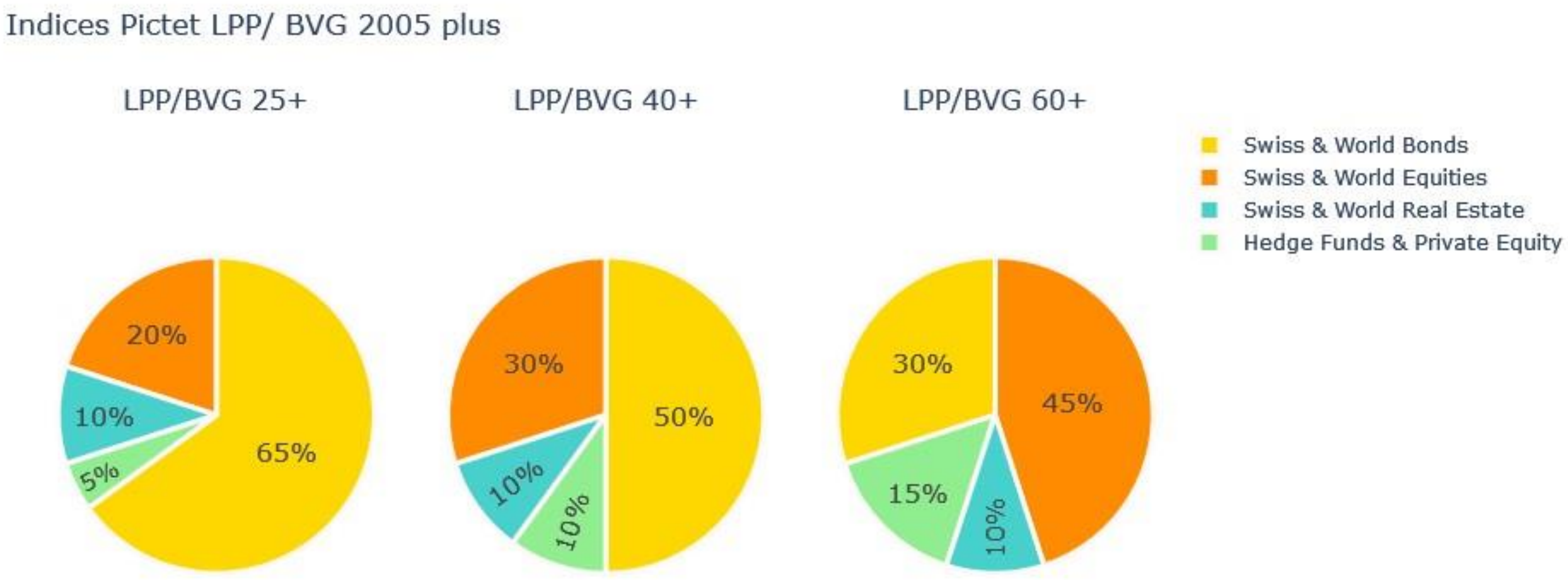
Composition of the Pictet LPP 2000 Indices

The table below shows the weightings of the three indices

INVESTMENT CATEGORIES	INDICES	LPP-25 2000	LPP-40 2000	LPP-60 2000
BONDS		75	60	40
Swiss	Swiss Bond Index AAA-BBB	60	45	25
EUR	Bloomberg Euro Aggregate	10	10	10
World	Bloomberg Global Aggregate	5	5	5
EQUITIES		25	40	60
Switzerland	Swiss Performance Index	10	15	20
World	MSCI AC World	15	25	40
Currency exposure		30	40	55

Source: Pictet Asset Management

Asset Allocation Pictet LPP/ BVG 2005 plus Indices



Python text next slide

Asset Allocation Pictet LPP/ BVG 2000 25, 40 and 60 (with Plotly Python)

```
import plotly.graph_objects as go
from plotly.subplots import make_subplots

colors = ['gold', 'mediumturquoise', 'darkorange', 'lightgreen']

labels = ['Swiss & World Bonds','Swiss & World Real Estate','Swiss & World Equities','Hedge Funds & Private Equity']

fig = make_subplots(rows=1, cols=3, specs=[[{'type':'domain'}, {'type':'domain'}, {'type':'domain'}]],
                         subplot_titles=['LPP/BVG 25+', 'LPP/BVG 40+', 'LPP/BVG 60+'])

fig.add_trace(go.Pie(labels=labels, values=[65,10,20,5], name="Pictet BVG 2005 25+" ), 1, 1)
fig.add_trace(go.Pie(labels=labels, values=[50,10,30,10], name="Pictet BVG 2005 40+"), 1, 2)
fig.add_trace(go.Pie(labels=labels, values=[30,10,45,15], name="Pictet BVG 2005 60+"), 1, 3)


fig.update_traces(hoverinfo='label+percent', textinfo='percent', textfont_size=15, textposition = 'inside',
                  marker=dict(colors=colors, line=dict(color='snow', width=3) ))

fig.update_layout(title_text = "Indices Pictet LPP/ BVG 2005 plus" )

fig.show()
```

Asset Allocation Pictet LPP/ BVG 2000 25+, 40+ and 60+

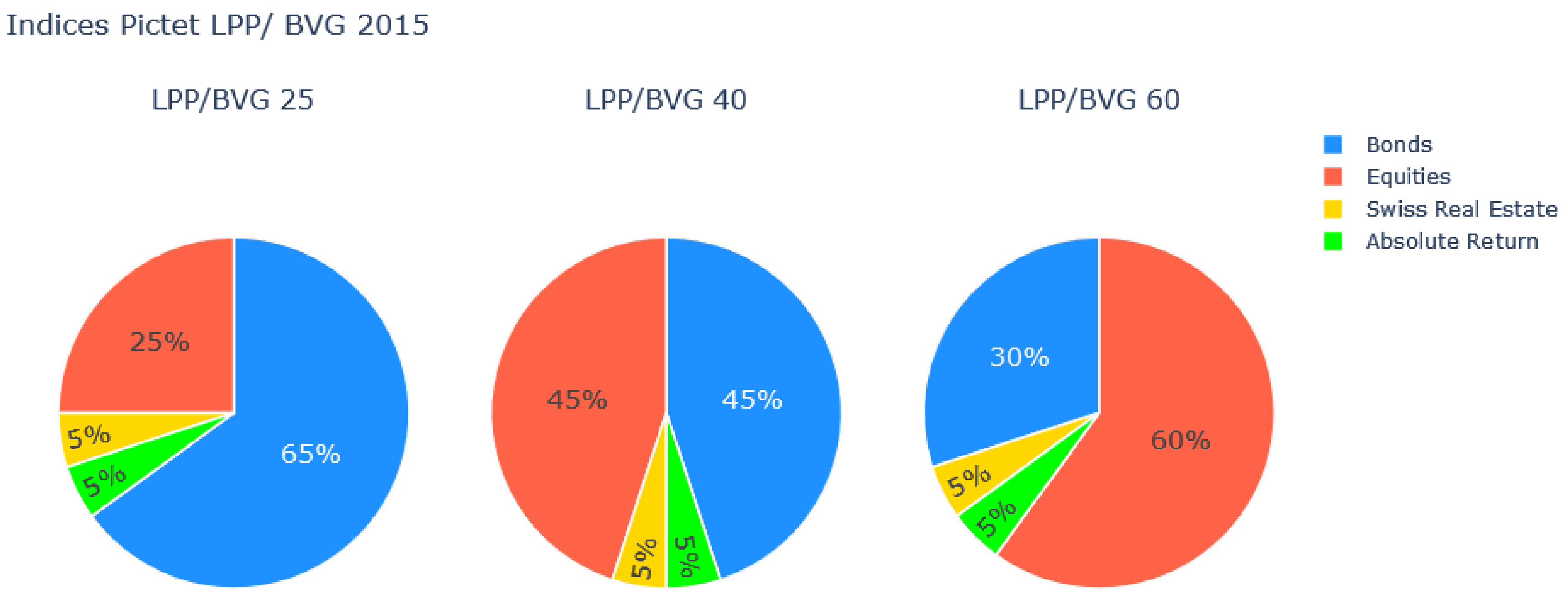
Composition of the Pictet LPP 2005 Indices

The table below shows the weightings of the three indices

INVESTMENT CATEGORIES	INDICES	LPP-25 PLUS 2005	LPP-40 PLUS 2005	LPP-60 PLUS 2005
BONDS		**65**	**50**	**30**
Swiss	Swiss Bond Index AAA-BBB	40	30	15
World	Bloomberg Multiverse (*)	25	20	15
EQUITIES		**20**	**30**	**45**
Swiss	Swiss Performance Index	7.5	10	15
World	MSCI AC World IMI	12.5	20	30
REAL ESTATE		**10**	**10**	**10**
Swiss	SXI Real Estate Funds	7.5	5	2.5
World	Dow Jones Global Select RESI	2.5	5	7.5
HEDGE FUNDS	HFRX Global Hedge Fund (*)	**2.5**	**5**	**7.5**
PRIVATE EQUITY	LPX50	**2.5**	**5**	**7.5**
Currency exposure		17.5	30	45

(*) hedged in CHF

Asset Allocation Pictet LPP/ BVG 2015 Indices



Indices: Pictet LPP 2015 25, 40 and 60

Composition of the Pictet LPP 2015 Indices

The table below shows the weightings of the three indices

INVESTMENT CATEGORIES	INDICES	LPP-25 2015	LPP-40 2015	LPP-60 2015
BONDS		**65**	**50**	**30**
Swiss	Swiss Bond Index AAA-BBB	45	30	10
Developed countries	FTSE World Government Bond Index (*)	10	10	10
Emerging countries	Bloomberg EM LC Government Capped	5	5	5
Corporates	Bloomberg Euro Aggregate Corporate (*)	5	5	5
EQUITIES		**25**	**40**	**60**
Swiss	Swiss Performance Index	10	15	20
World	MSCI AC World	15	20	30
World Small Cap	MSCI World Small Cap	0	5	10
SWISS REAL ESTATE	SXI Real Estate Funds	5	5	5
ABSOLUTE RETURN	HFRX Global Hedge Fund (*)	5	5	5
Currency exposure		20	30	45

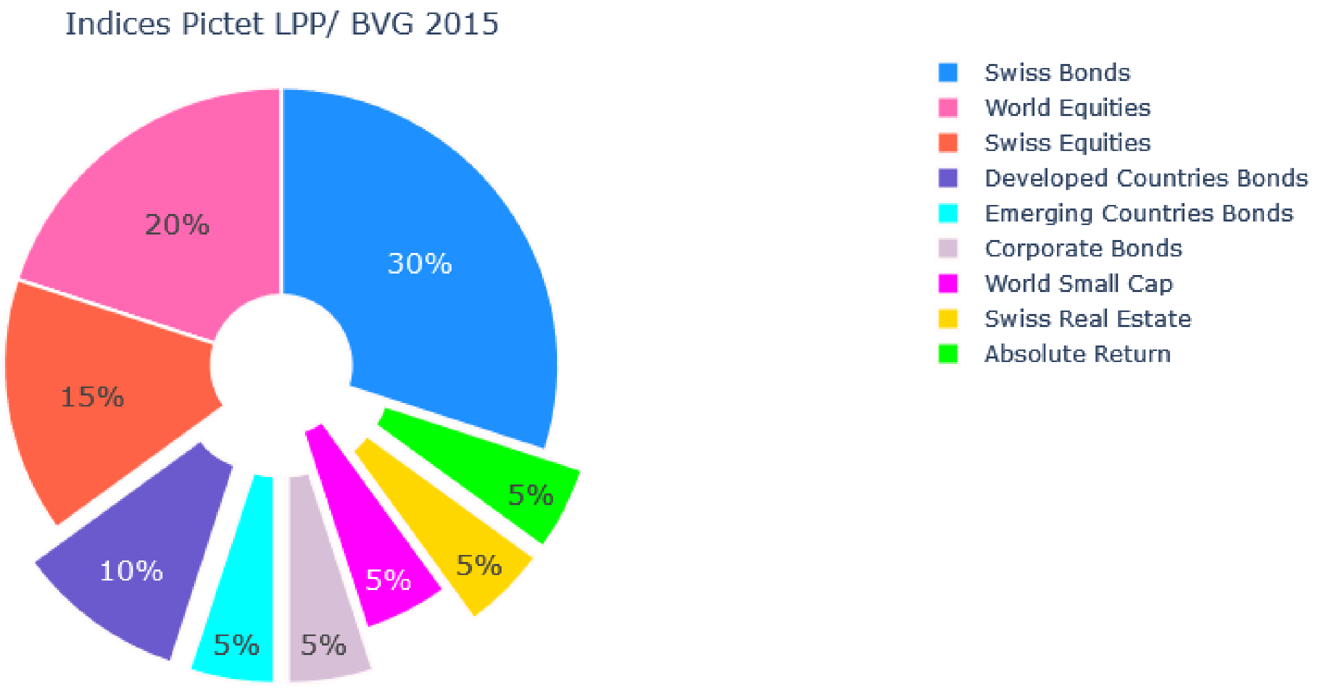
(*) hedged in CHF

Source: Pictet Asset Management

Pictet 2015 LPP/BVG-40: exact asset allocation

- Bonds positions
  - “**Emerging countries**” and “**Corporate Bonds**” in all three indices (LPP-25, LPP-40, LPP-60) are 5%
  - “**Developed Countries Bonds**” is 10% in all indices
- Each position “**Swiss Real Estate**” and “**Absolute Return**” are 5% in all three indices Pictet 2015 (LPP-25, LPP-40, LPP-60)
- “**World Small Cap**” is 0%, 5% and 10% in LPP-25, LPP-40, LPP-60.

Python text next slide

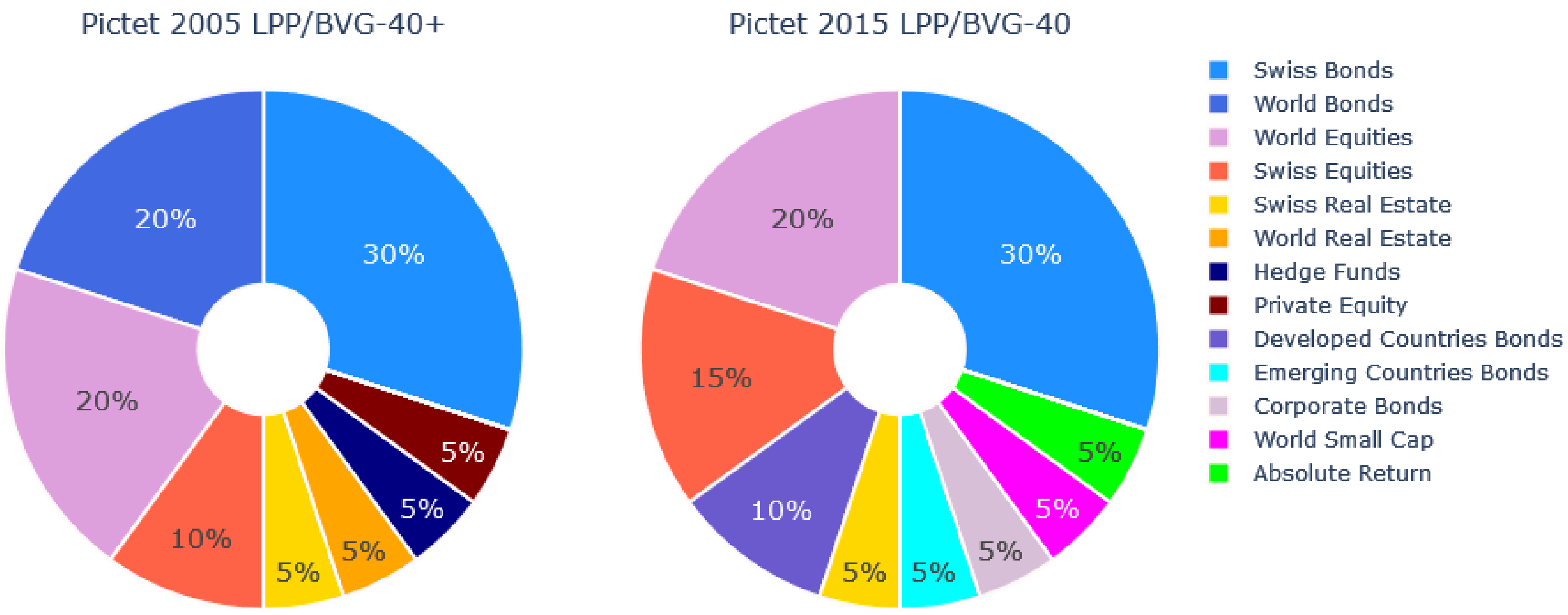


Asset Allocation Pictet LPP/ BVG 2015 40 Index (with Plotly Python)

```
# -------------------Index  Pictet LPP/BVG 2015 40 -------------
import plotly.graph_objects as go
from plotly.subplots import make_subplots

colors = ['dodgerblue', 'slateblue', 'aqua', 'thistle', 'tomato', 'hotpink', 'fuchsia','gold', 'lime']

labels = ['Swiss Bonds', 'Developed Countries Bonds', 'Emerging Countries Bonds','Corporate Bonds',
         'Swiss Equities', 'World Equities','World Small Cap','Swiss Real Estate','Absolute Return']

fig = make_subplots(rows=1, cols=1, specs=[[{'type':'domain'}]],
                         subplot_titles=['Indices Pictet LPP/ BVG 2015'])


fig.add_trace(go.Pie(labels=labels, values=[30,10, 5, 5, 15,20, 5,5,5], name="Pictet 2015 LPP-40",
                     hole = 0.25, pull=[0, 0.15,0.15,0.15,0,0,0,0.15,0.15]), 1, 1)

fig.update_traces(hoverinfo='label+percent', textinfo='percent', textfont_size=15, textposition = 'inside',
                  marker=dict(colors=colors, line=dict(color='snow', width=2) ))

fig.show()
```

The most typical asset allocations for Swiss pension funds

- Based on daily and monthly return and index data it helps to analyse pension fund portfolio returns



Python text next slide

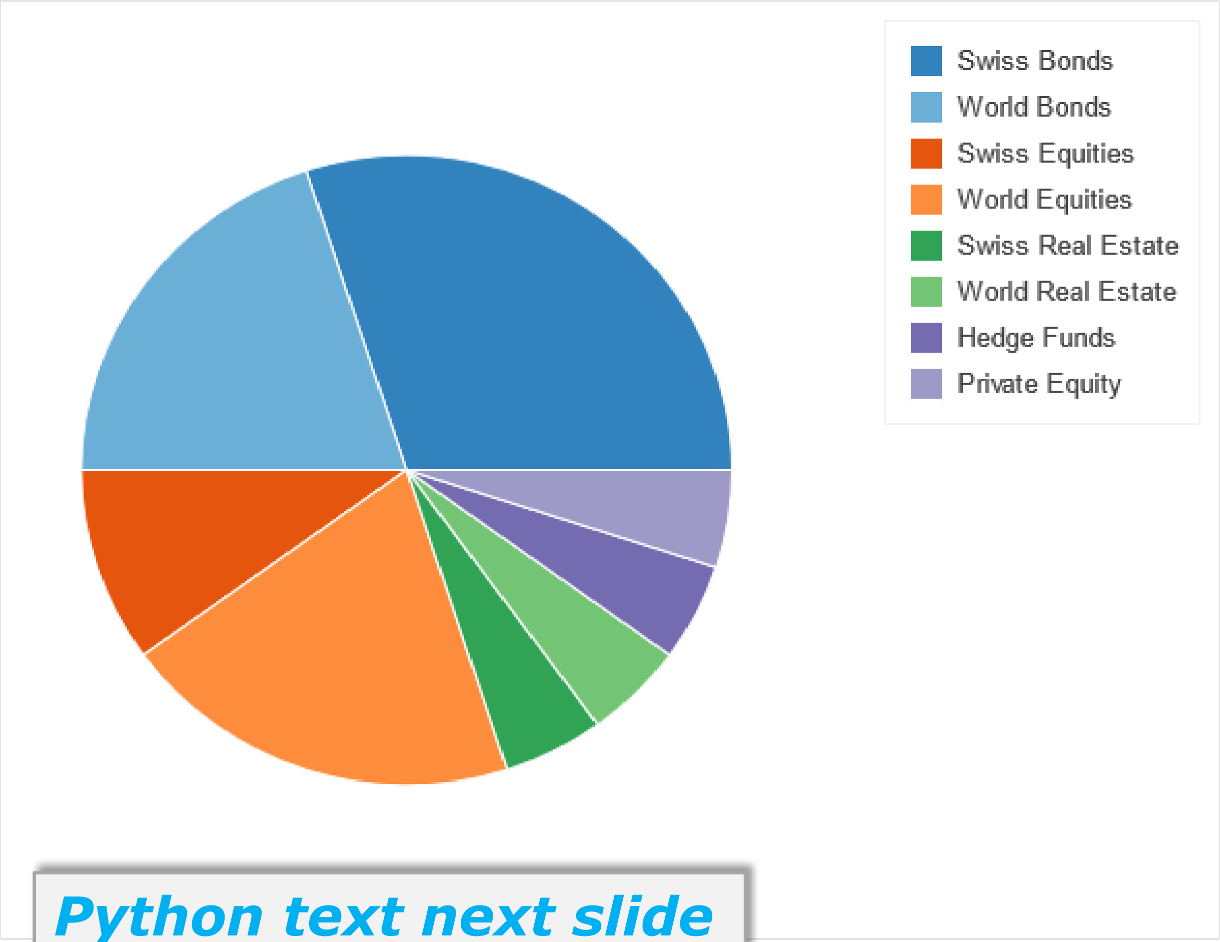
Asset Allocation Pictet LPP/ BVG 2005 40+ and LPP/ BVG 2015 40

```
# ------------------ Pictet LPP/BVG 2005 40+ & 2015-40    -------------
import plotly.graph_objects as go
from plotly.subplots import make_subplots

colors = ['dodgerblue', 'royalblue', 'tomato', 'plum', 'gold', 'orange', 'navy', 'maroon',
           'dodgerblue', 'slateblue', 'aqua', 'thistle', 'tomato', 'hotpink', 'fuchsia','gold', 'lime']

labels = ['Swiss Bonds', 'World Bonds', 'Swiss Equities', 'World Equities',
                'Swiss Real Estate','World Real Estate','Hedge Funds', 'Private Equity',
              'Swiss Bonds', 'Developed Countries Bonds', 'Emerging Countries Bonds','Corporate Bonds',
          'Swiss Equities', 'World Equities','World Small Cap','Swiss Real Estate','Absolute Return']

fig = make_subplots(rows=1, cols=2, specs=[[{'type':'domain'}, {'type':'domain'}]],
                         subplot_titles=['Pictet 2005 LPP/BVG-40+','Pictet 2015 LPP/BVG-40'])


fig.add_trace(go.Pie(labels=labels, values=[30,20, 10, 20, 5,5, 5,5,0,0,0,0,0,0,0,0,0], name="Pictet 2005 LPP-40+",
                      hole = 0.25, ), 1, 1)

fig.add_trace(go.Pie(labels=labels, values=[0,0,0,0,0,0,0,0,30,10, 5, 5, 15,20, 5,5,5], name="Pictet 2015 LPP-40",
                      hole = 0.25, ), 1, 2)

fig.update_traces(hoverinfo='label+percent', textinfo='percent', textfont_size=15, textposition = 'inside',
                  marker=dict(colors=colors, line=dict(color='snow', width=2) ))

fig.show()
```

Pie Graph with Bokeh (Python) HTML-file

This file type (*.html) is easy to upload to the home page

Pictet LPP 2005 40 plus



Python text next slide

- HoloViews uses “bokeh” as its underlying engine but reduces the verbosity by having the user declare attributes about their data and allowing the visualizations to infer themselves from the dependent and independent variables, referred to as value dimensions (vdims) and key dimensions (kdims).

Asset Allocation Pictet LPP/ BVG 2005 40+ with Bokeh Library (*.html)

```
# https://docs.bokeh.org/en/3.0.1/docs/user_guide/topics/pie.html
# https://docs.bokeh.org/en/2.4.3/docs/reference/models/glyphs/annular_wedge.html
from math import pi
import pandas as pd
from bokeh.palettes import Category20c
from bokeh.plotting import figure, show
from bokeh.transform import cumsum

test_Dir = "C:/EAA_9Oct2023/Graphs/Jupiter"; day_today = "26Sept2023"

my_dir_file_name = test_Dir +"/"+ day_today +"/" + "Pictet_2005_40_plus_Pie.html"
output_file(my_dir_file_name)

x = {   'Swiss Bonds': 30, 'World Bonds': 20, 'Swiss Equities': 10, 'World Equities': 20,
     'Swiss Real Estate': 5, 'World Real Estate': 5, 'Hedge Funds': 5, 'Private Equity': 5  }

data = pd.Series(x).reset_index(name='value').rename(columns={'index': 'assets'})
data['angle'] = data['value']/data['value'].sum() * 2*pi

my_colors = [Category20c[16][0], Category20c[16][1], Category20c[16][4],  Category20c[16][5],
                 Category20c[16][8], Category20c[16][9], Category20c[16][12], Category20c[16][13] ]
data['color'] =  my_colors

p = figure(height=500, width = 600, title="Pictet LPP 2005 40 plus", toolbar_location=None,
           tools="hover", tooltips="@assets: @value", x_range=(-0.5, 1.0) )

p.wedge(x=0, y=1, radius=0.4,
        start_angle=cumsum('angle', include_zero=True), end_angle=cumsum('angle'),
        line_color="white", fill_color='color', legend_field='assets', source=data)

p.axis.axis_label = None
p.axis.visible = False
p.grid.grid_line_color = None

show(p)
```

Based on Pictet Bank Portfolio Indices for Pension Funds

PICTET 1805 Asset Management

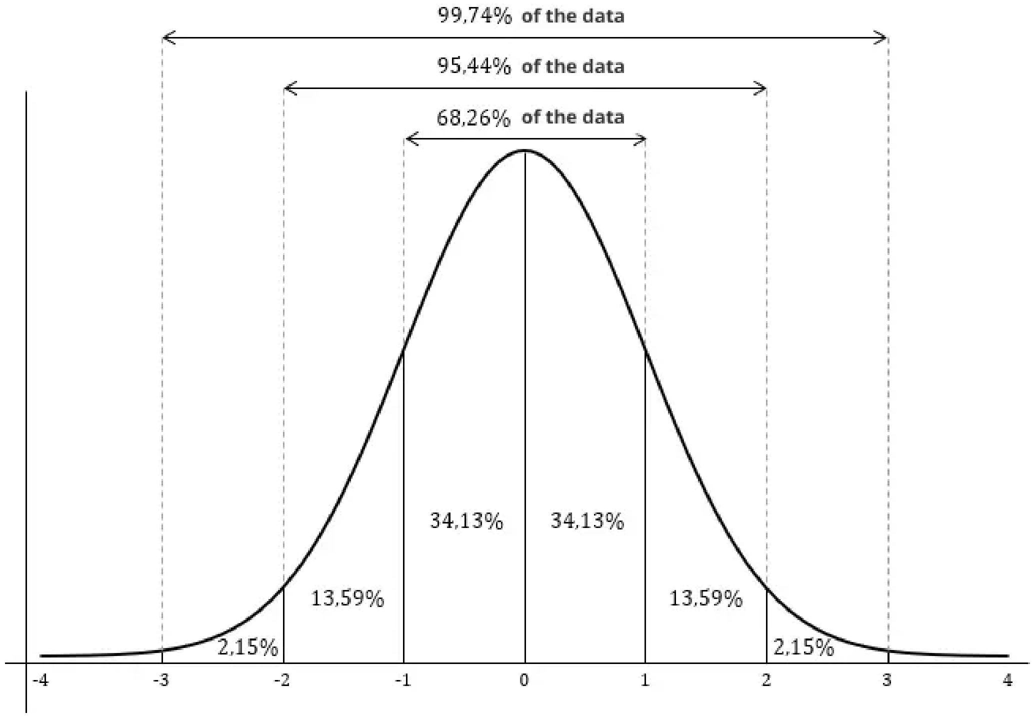
Analysis Portfolio Return based on Pictet Indices LPP/BVG 2000, 2005 and 2015

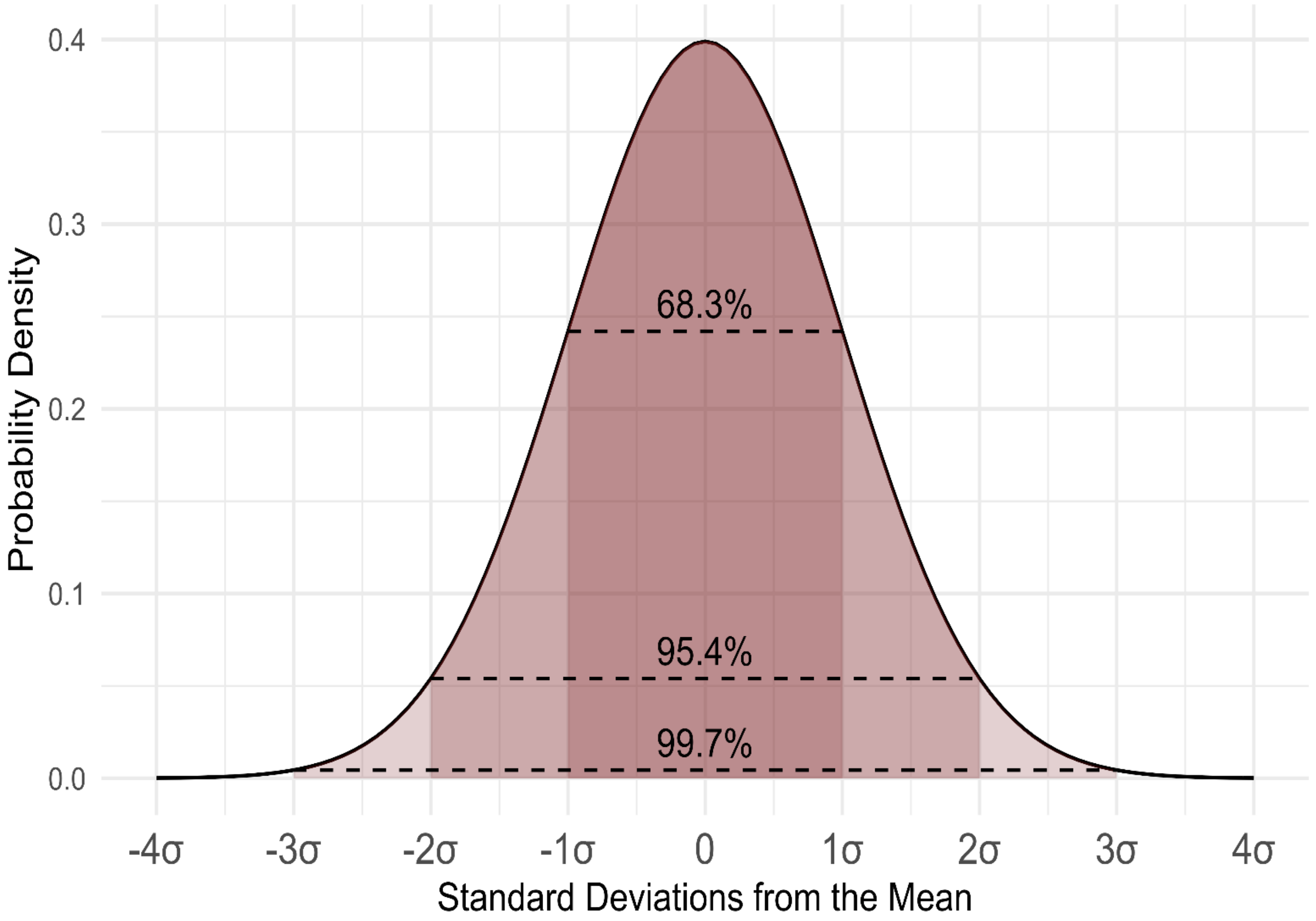
https://am.pictet/en/switzerland/articles/lpp-indices#overview

Density Normal Distribution to compare with skewness and kurtosis of historical data

Bandwidths

https://en.wikipedia.org/wiki/Statistics



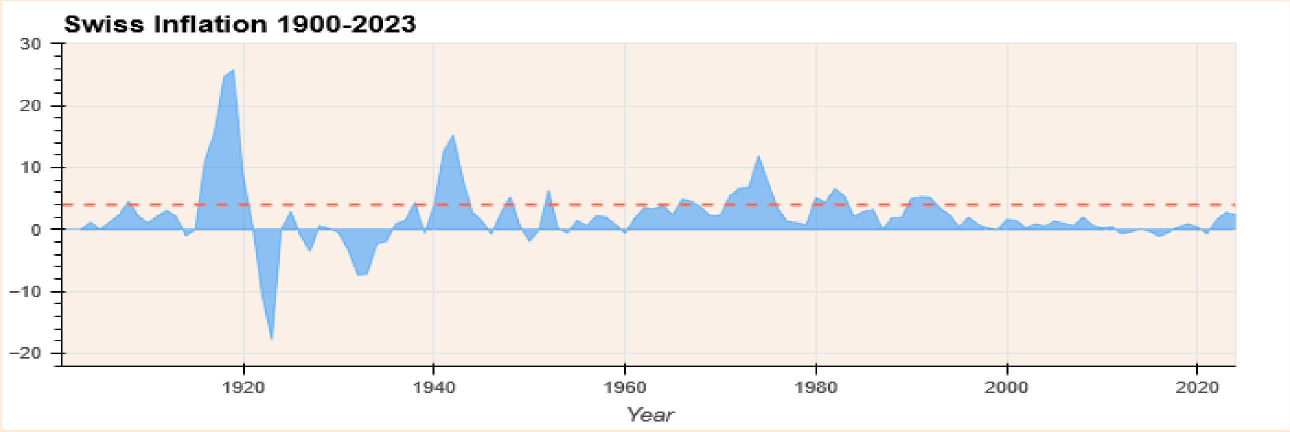


Example: read data, save as pd.DataFrame, rename() & plot()

Excel-File with historical data Inflation (CPI) over 1900-2023

```python
read_Pictet_data_1900 = pd.read_excel(file_excel_Pictet_1900,  \
                         sheet_name = "Return", header = 0, index_col = 0)

read_Pictet_data_1900 = read_Pictet_data_1900.rename(\
                    columns = {'Year' : "year", 'LPP 25' : "R 2000 25", \
                                'LPP 40': 'R 2000 40', \
                                'LPP 60': 'R 2000 60'})
```

```python
read_Pictet_data_1900['Inflation'].hvplot.area().\
       opts(fill_color = 'dodgerblue', alpha = 0.5, ylabel = "%",\
            line_color = 'blue', bgcolor = 'linen', \
            show_grid = True, title = 'Swiss Inflation 1900-2023') * \
    hv.HLine(4).opts(color='tomato', line_width = 2, line_dash = 'dashed')
```

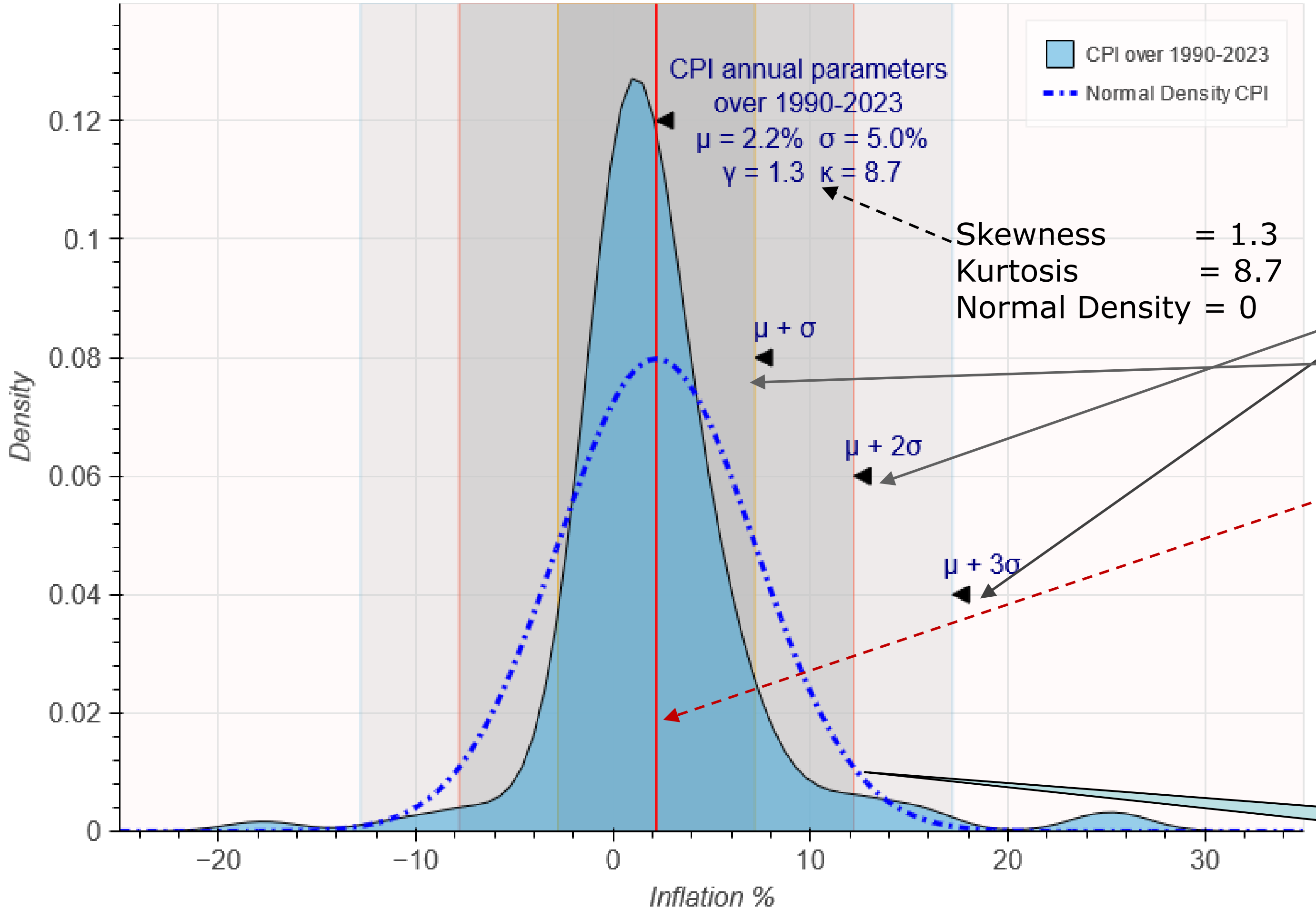


	A	B	C	D	E
1	Year	LPP 25	LPP 40	LPP 60	Inflation
2	1900	7.68%	7.00%	6.25%	0.000
3	1901	7.30%	6.55%	5.63%	0.000
4	1902	4.22%	4.81%	5.53%	0.000
5	1903	4.10%	3.55%	2.61%	0.012

LPP 60	Inflation
11.72%	0.000
9.03%	0.012
6.12%	0.024
-5.80%	0.046
12.06%	0.022
9.50%	0.011
2.54%	0.021
4.95%	0.031
2.76%	0.020
2.14%	-0.010
-0.52%	0.000
5.91%	0.111
4.56%	0.157
-4.82%	0.247
10.75%	0.257
0.20%	0.087

Year	R 2000 25	R 2000 40	R 2000 60	Inflation
1900-12-31	7.68	7.00	6.25	0.00
1901-12-31	7.30	6.55	5.63	0.00
1902-12-31	4.22	4.81	5.53	0.00
1903-12-31	4.10	3.55	2.61	1.20
1904-12-31	7.78	9.46	11.72	0.00
...	...	...	...	...
2019-12-31	8.84	12.36	17.05	0.40
2020-12-31	2.57	3.39	4.45	-0.70
2021-12-31	3.89	7.30	12.05	1.59
2022-12-31	-14.16	-14.80	-15.69	2.80
2023-12-31	3.62	4.47	5.49	2.40

Density Parameters for Swiss Inflation over period 1900-2023 with kde()




```
mean_CPI     = read_Pictet_data_1900['Inflation'].mean().round(1)
std_CPI      = round(read_Pictet_data_1900['Inflation'].std(),0)
skew_CPI     = round(read_Pictet_data_1900['Inflation'].skew(),1)
kurt_CPI     = round(read_Pictet_data_1900['Inflation'].kurt(),1)
```

```
kde_CPI = ((hv.VSpan(mean_CPI-3*std_CPI,mean_CPI+3*std_CPI).\
        opts(fill_color = 'silver', alpha = 0.25) * \
    hv.VSpan(mean_CPI-2*std_CPI,mean_CPI+2*std_CPI).\
        opts(fill_color = 'silver', alpha = 0.5) * \
    hv.VSpan(mean_CPI-1*std_CPI,mean_CPI+1*std_CPI).\
        opts(fill_color = 'silver', alpha = 0.75)) * \
    read_Pictet_data_1900['Inflation'].hvplot.kde(label = 'CPI over 1990-2023') * \
    v.VLine(mean_CPI).\
        opts(line_color = 'red', line_width = 1.5) * \
            help_ND_CPI  * help_arrow) .\
        opts(\
        opts.Overlay(width = my_width, height = my_height, \
                    xlim = my_xlim, show_grid = True, \
          bgcolor = 'snow', xlabel = "Inflation %", ylabel = "Density" , \
                    legend_position = 'top_right', \
           legend_cols = 1, legend_opts={'background_fill_alpha': 0.5}, \
           fontsize = {'title':14, 'xlabel': 12, 'ylabel' :12 , \
                      'legend':9 , 'xticks':12, 'yticks':12}))
```

Density of Normal Distribution (ND) with mean value 2.2% and standard deviation 5.0%. Kurtosis and skewness for ND are zeros.

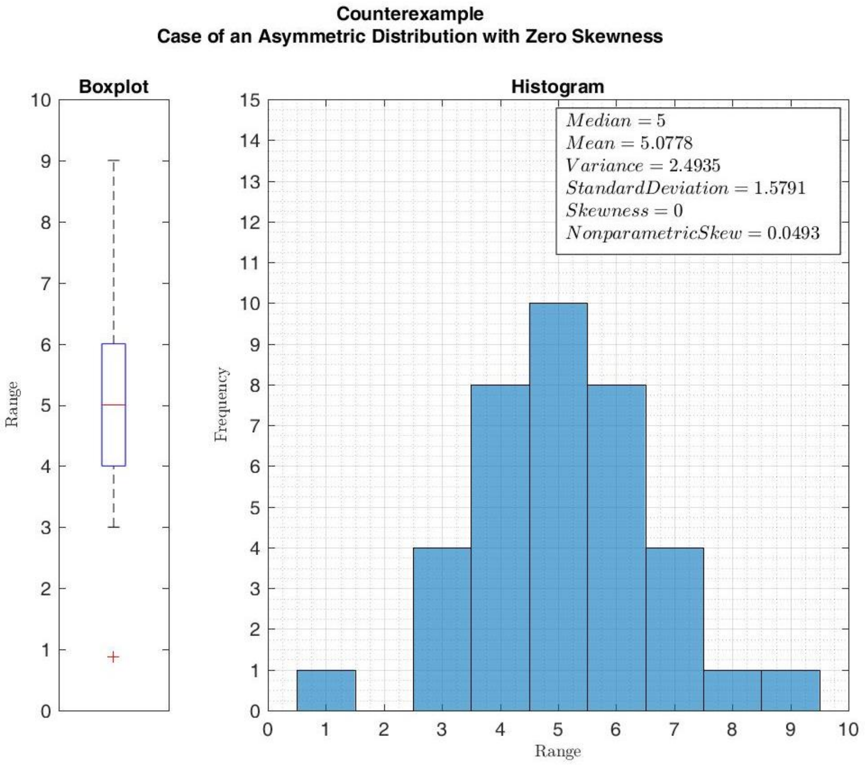
Density Struckture based on Skewness value

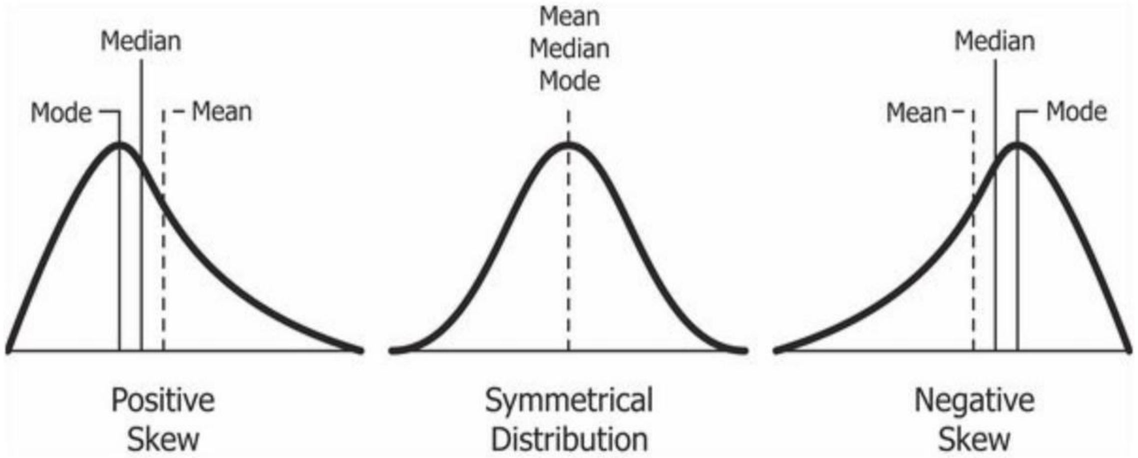
https://en.wikipedia.org/wiki/Skewness#/media/File:Asymmetric_Distribution_with_Zero_Skewness.jpg

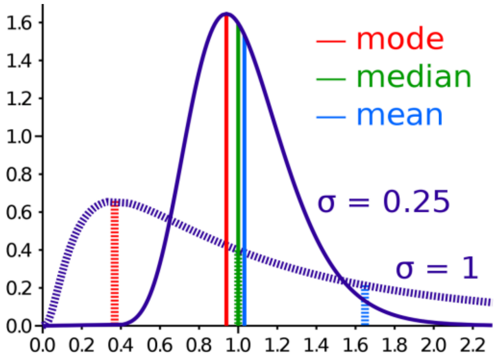
Fisher's moment coefficient of skewness [edit]

The skewness γ_1 of a random variable X is the third standardized moment $\tilde{\mu}_3$, defined as:

$$\gamma_1 := \tilde{\mu}_3 = \mathrm{E}\left[\left(\frac{X-\mu}{\sigma}\right)^3\right] = \frac{\mu_3}{\sigma^3} = \frac{\mathrm{E}\left[(X-\mu)^3\right]}{\left(\mathrm{E}\left[(X-\mu)^2\right]\right)^{3/2}} = \frac{\kappa_3}{\kappa_2^{3/2}}$$



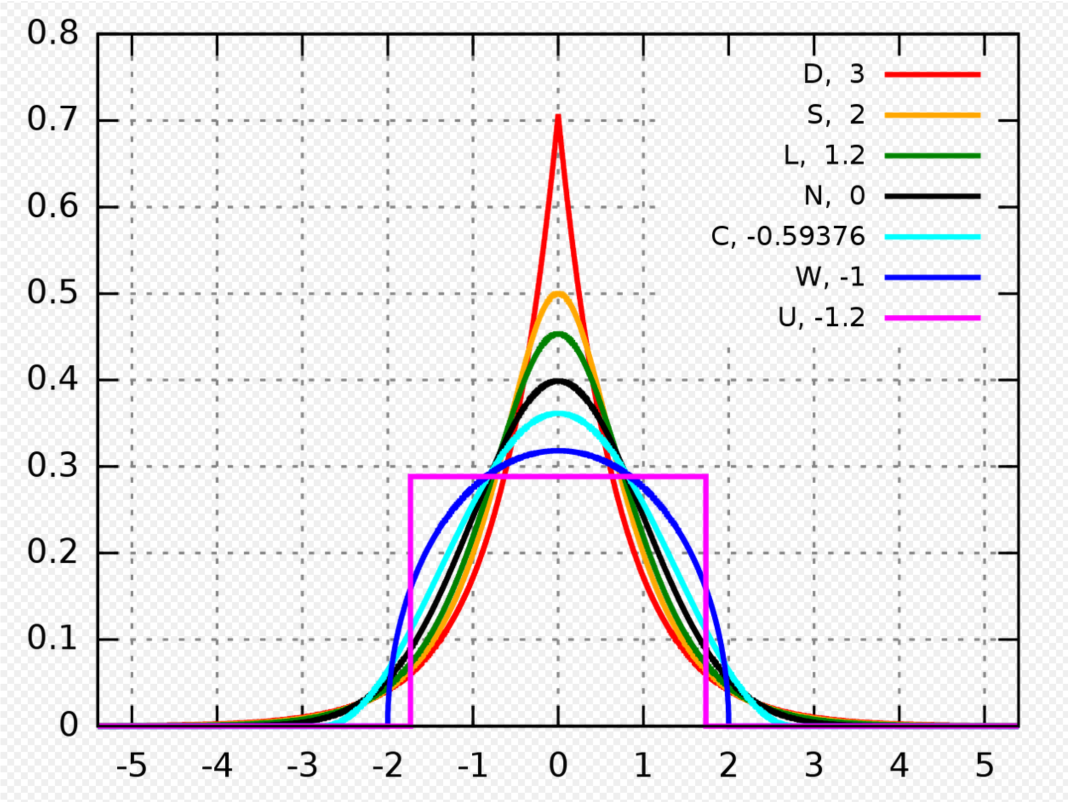




The **mode** is the value that appears most often in a set of data values

Example Kurtosis of different Distributions ([excess kurtosis – 3])

https://en.wikipedia.org/wiki/Kurtosis



$$f(x \mid \mu, b) = \frac{1}{2b} \exp\left(-\frac{|x-\mu|}{b}\right)$$

$$f(x) = \frac{1}{2} \operatorname{sech}\left(\frac{\pi}{2} x\right),$$

where "sech" denotes the hyperbolic secant function.

$$f(x; \mu, s) = \frac{e^{-(x-\mu)/s}}{s\left(1+e^{-(x-\mu)/s}\right)^2} = \frac{1}{s\left(e^{(x-\mu)/(2s)} + e^{-(x-\mu)/(2s)}\right)^2} = \frac{1}{4s} \operatorname{sech}^2\left(\frac{x-\mu}{2s}\right).$$

$$f(x; \mu, s) = \frac{1}{2s}\left[1 + \cos\left(\frac{x-\mu}{s}\pi\right)\right] = \frac{1}{s} \operatorname{hvc}\left(\frac{x-\mu}{s}\pi\right)$$

$$f(x) = \frac{2}{\pi R^2}\sqrt{R^2 - x^2}$$

$$f(x) = \begin{cases} \frac{1}{b-a} & \text{for } a \le x \le b, \\ 0 & \text{for } x < a \text{ or } x > b. \end{cases}$$

- D: Laplace distribution, also known as the double exponential distribution, red curve (two straight lines in the log-scale plot), excess kurtosis = 3
- S: hyperbolic secant distribution, orange curve, excess kurtosis = 2
- L: logistic distribution, green curve, excess kurtosis = 1.2
- N: normal distribution, black curve (inverted parabola in the log-scale plot), excess kurtosis = 0
- C: raised cosine distribution, cyan curve, excess kurtosis = −0.593762...
- W: Wigner semicircle distribution, blue curve, excess kurtosis = −1
- U: uniform distribution, magenta curve (shown for clarity as a rectangle in both images), excess kurtosis = −1.2.

The kurtosis is the fourth standardized moment, defined as

$$\operatorname{Kurt}[X] = \operatorname{E}\left[\left(\frac{X-\mu}{\sigma}\right)^4\right] = \frac{\operatorname{E}[(X-\mu)^4]}{\left(\operatorname{E}[(X-\mu)^2]\right)^2} = \frac{\mu_4}{\sigma^4},$$

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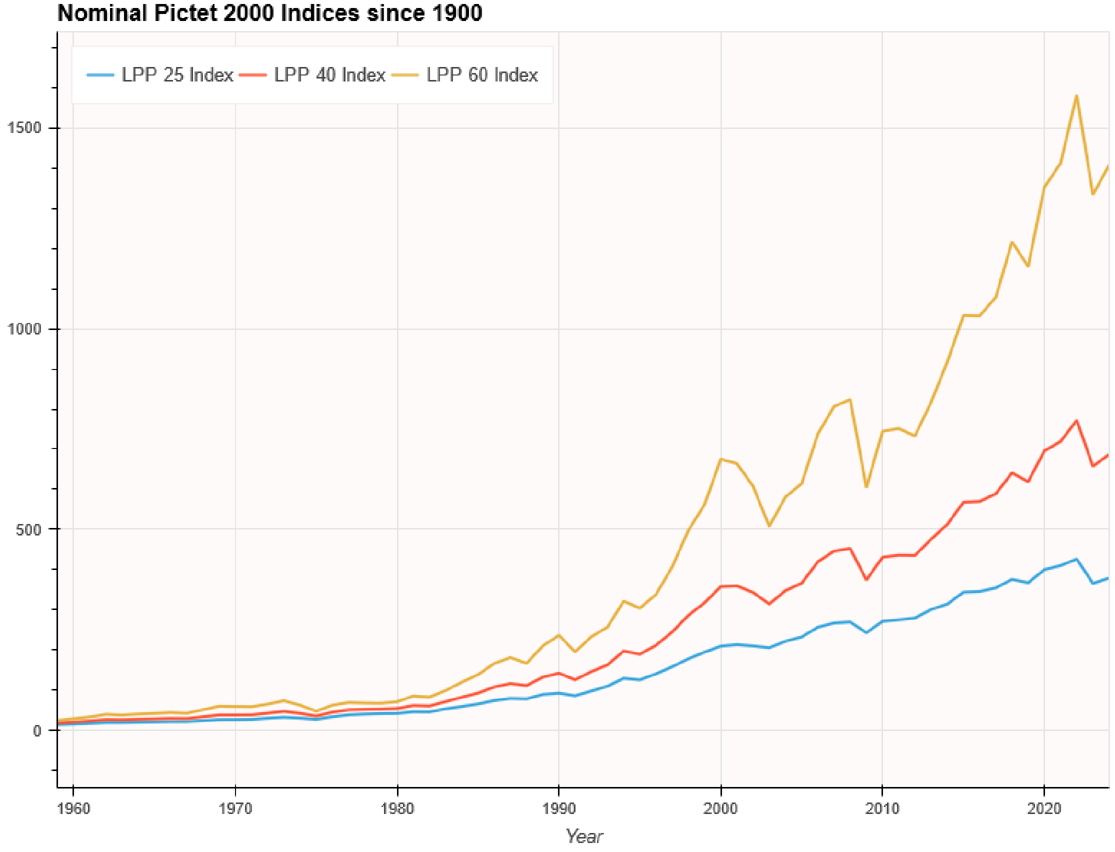
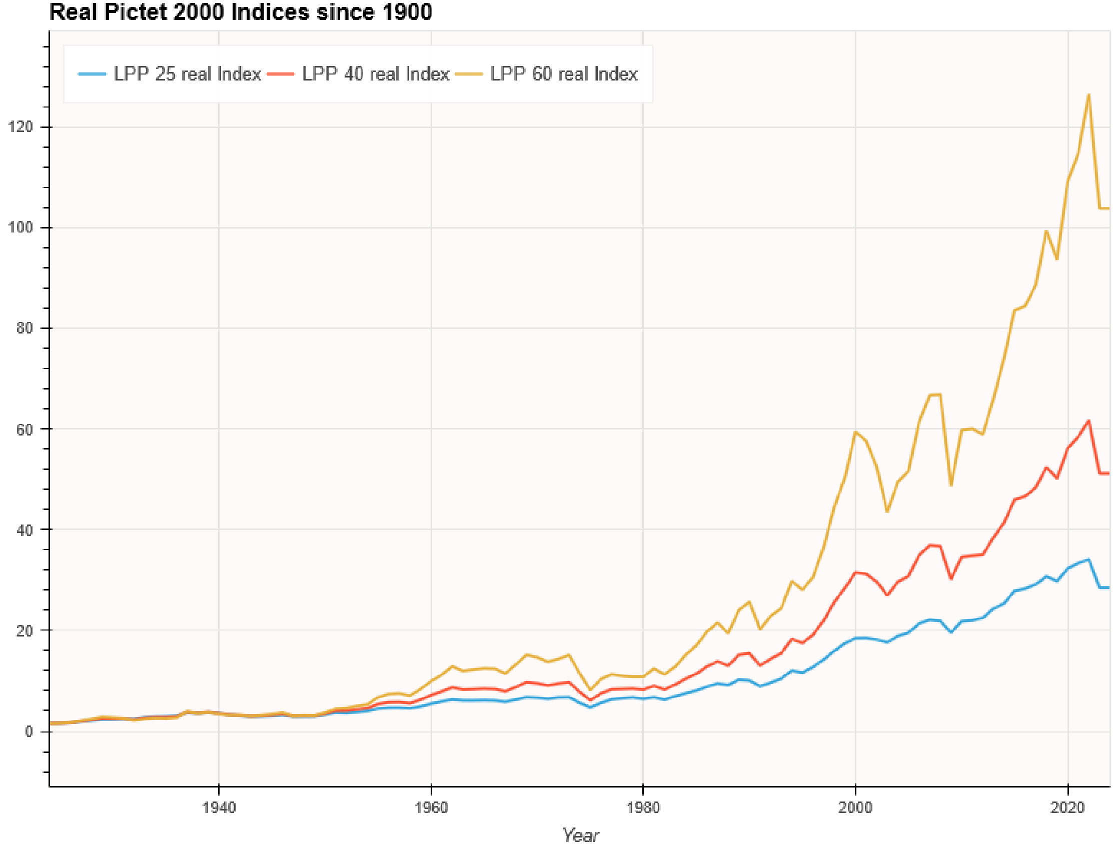
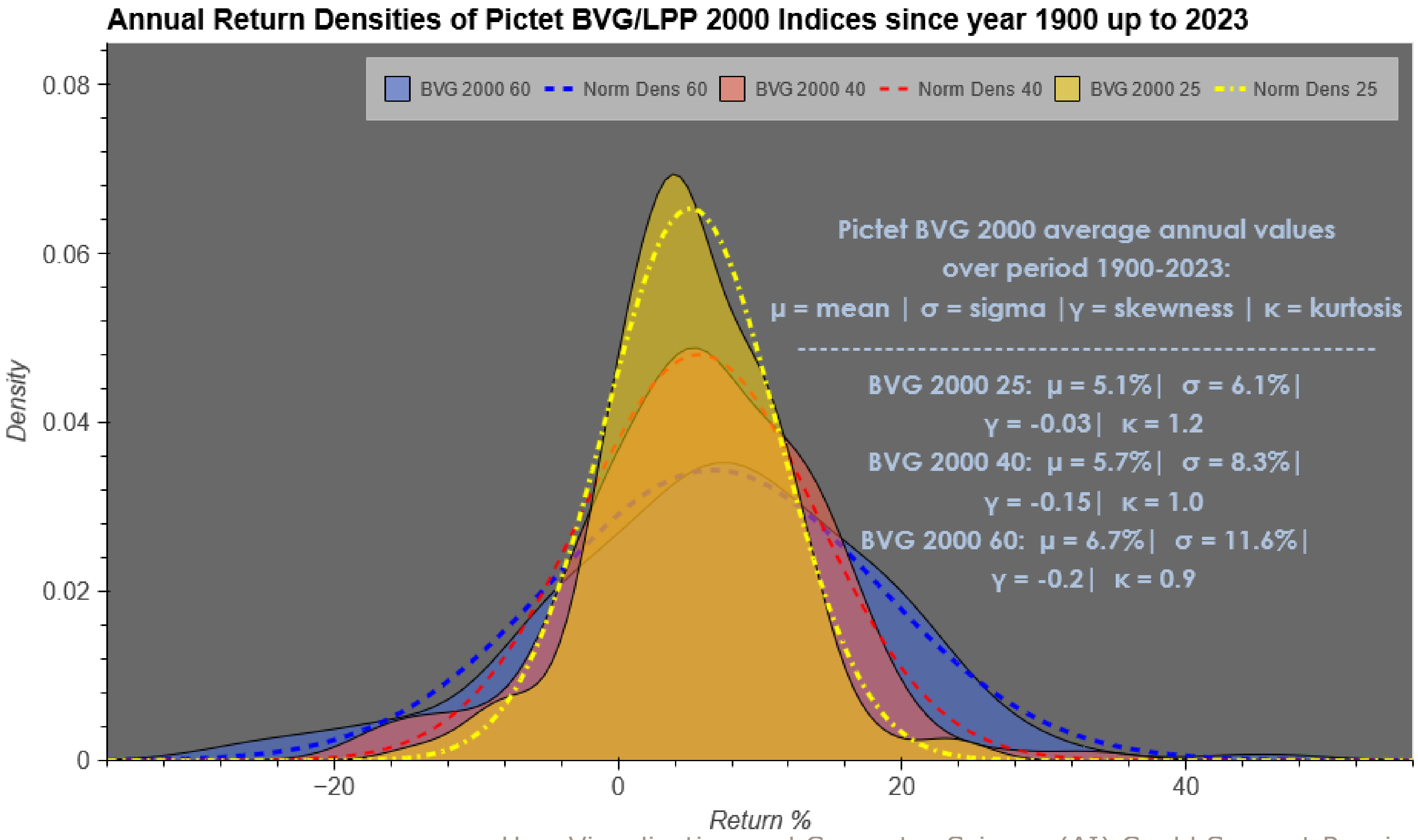
Pictet BVG 2000 Indices over 1900-2023 (nominal vs. real)





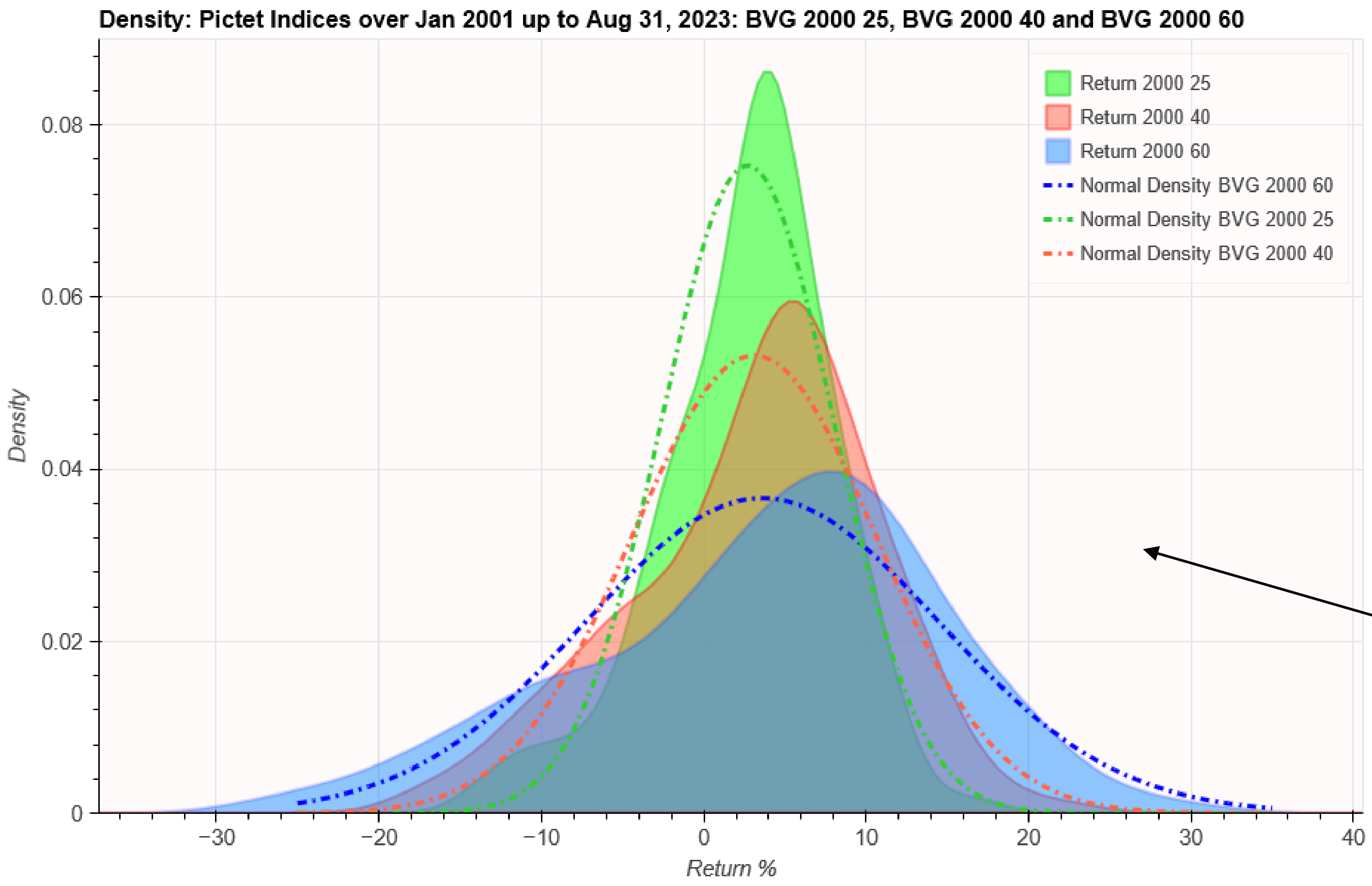
Skewness and Kurtosis for average annual historical data

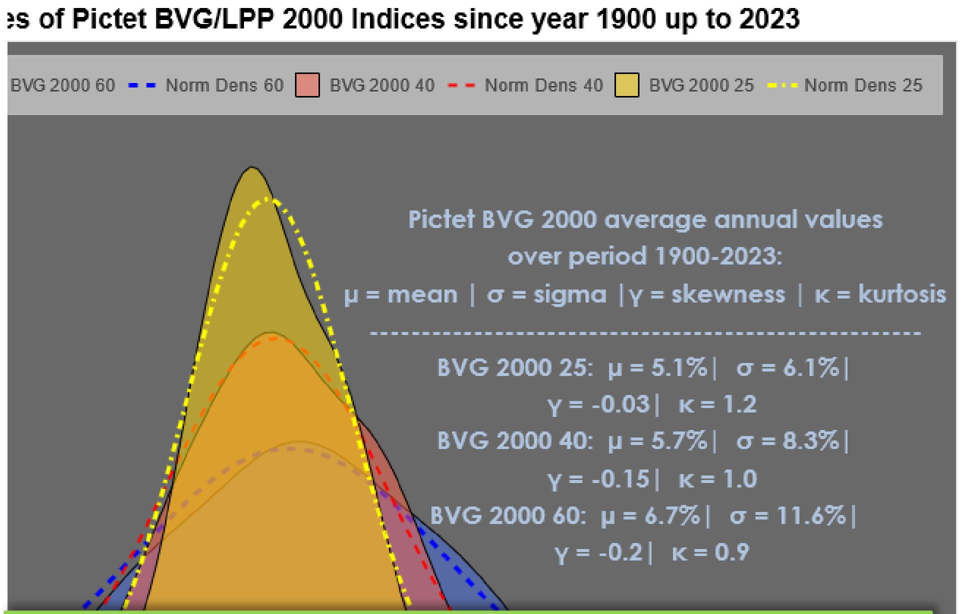
Pictet BVG 2000 Indices over 1900-2023 (average annual return values)



Skewness and Kurtosis for average monthly historical data

Pictet LPP/BVG 2000 Indices over 2000-2023 (monthly values)

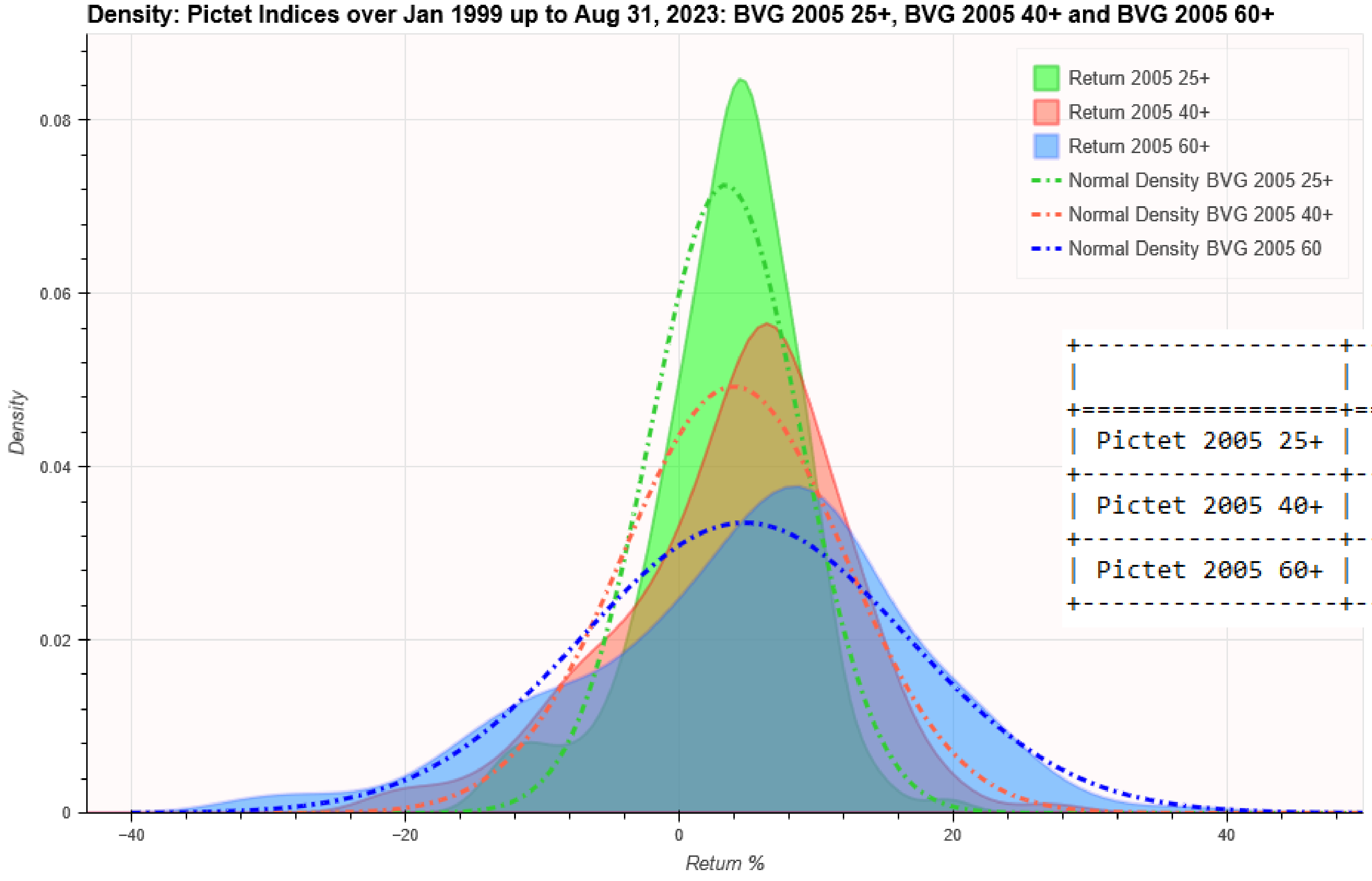


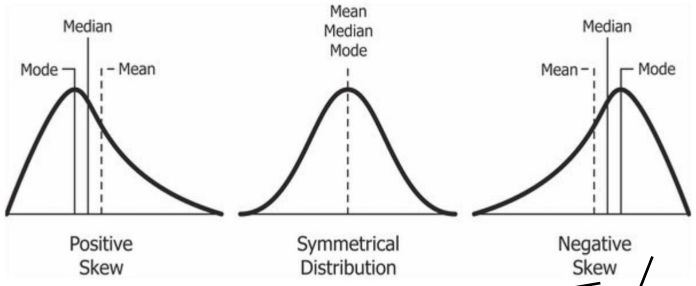


	mean	stDev	skew	kurt
Pictet 2000 25	2.7	5.3	-0.61	0.75
Pictet 2000 40	3.1	7.5	-0.47	-0.01
Pictet 2000 60	3.6	10.9	-0.48	-0.07

Skewness and Kurtosis for average monthly historical data

Pictet BVG 2005 Indices over 2000-2023 (monthly values)





	mean	stDev	skew	kurt
Pictet 2005 25+	3.4	5.5	-0.69	1.22
Pictet 2005 40+	4	8.1	-0.57	0.64
Pictet 2005 60+	4.8	11.9	-0.5	0.41

	mean	stDev	skew	kurt
Pictet 2000 25	2.7	5.3	-0.61	0.75
Pictet 2000 40	3.1	7.5	-0.47	-0.01
Pictet 2000 60	3.6	10.9	-0.48	-0.07

Why the density analysis for portfolio return is important?

- The density analysis of monthly portfolio return values is necessary for the valuation of Cornish Fisher Value-at-Risk (CF VaR)

VaR	CF VaR
$VaR_\alpha = \mu + Z^{normal}_\alpha * \sigma$	$CF\ VaR_\alpha = \mu + X^{empirish}_\alpha * \sigma$
μ and σ are valuated based on monthly portfolio returns Z^{normal}_α is Quantile σ of standard normal distribution $X^{empirish}_\alpha$ add additionally the skewness and kurtosis of hisotrical return values	
$CF\ VaR_\alpha = VaR_\alpha - \Delta^{Skewness,\ Kurtosis*}\sigma$	
If historical portfolio return normal distributed: CF VaR = VaR	

- Cornish Fisher Value-at-Risk (CF VaR) could be used
  - for setting up the target value of investment fluctuation reserves for autonomous pension funds
  - and determine a desirable level for them to better ensure benefits payments during times of volatile financial markets
    - ✓ To ensure that the funding ratio will be not lower 100%

Inflation Impact on Portfolio Return, Equities and Bond Yields

- Correlation Portfolio Return vs. Inflation and vs. 10-year Bond Yield

```
# Correlation
pictet_plus_corr = read_Pictet_data[param_list].corr().round(2)
pictet_plus_corr
```

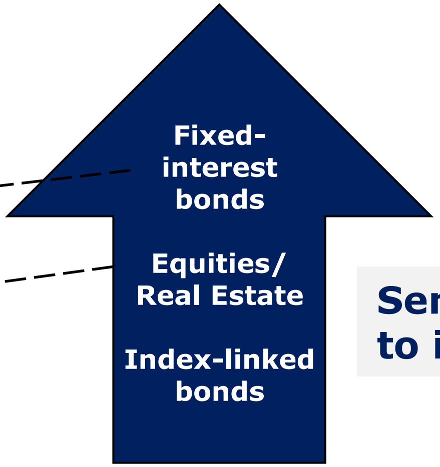
	Headline CPI	10-year Bond Yield	R 2005 25+	R 2005 40+	R 2005 60+
Headline CPI	1.00	0.41	-0.36	-0.22	-0.13
10-year Bond Yield	0.41	1.00	-0.07	-0.09	-0.10
R 2005 25+	-0.36	-0.07	1.00	0.96	0.90
R 2005 40+	-0.22	-0.09	0.96	1.00	0.99
R 2005 60+	-0.13	-0.10	0.90	0.99	1.00

```
read_Pictet_data[param_list].head().round(2)
```

Datum	Headline CPI	10-year Bond Yield	R 2005 25+	R 2005 40+	R 2005 60+
1998-12-30	-0.17	2.67	6.75	7.17	7.93
1999-01-30	0.07	2.52	6.64	7.24	8.20
1999-02-28	0.29	2.52	4.19	3.96	3.68
1999-03-30	0.47	2.57	4.10	3.54	2.75
1999-04-30	0.59	2.50	7.43	8.05	8.68

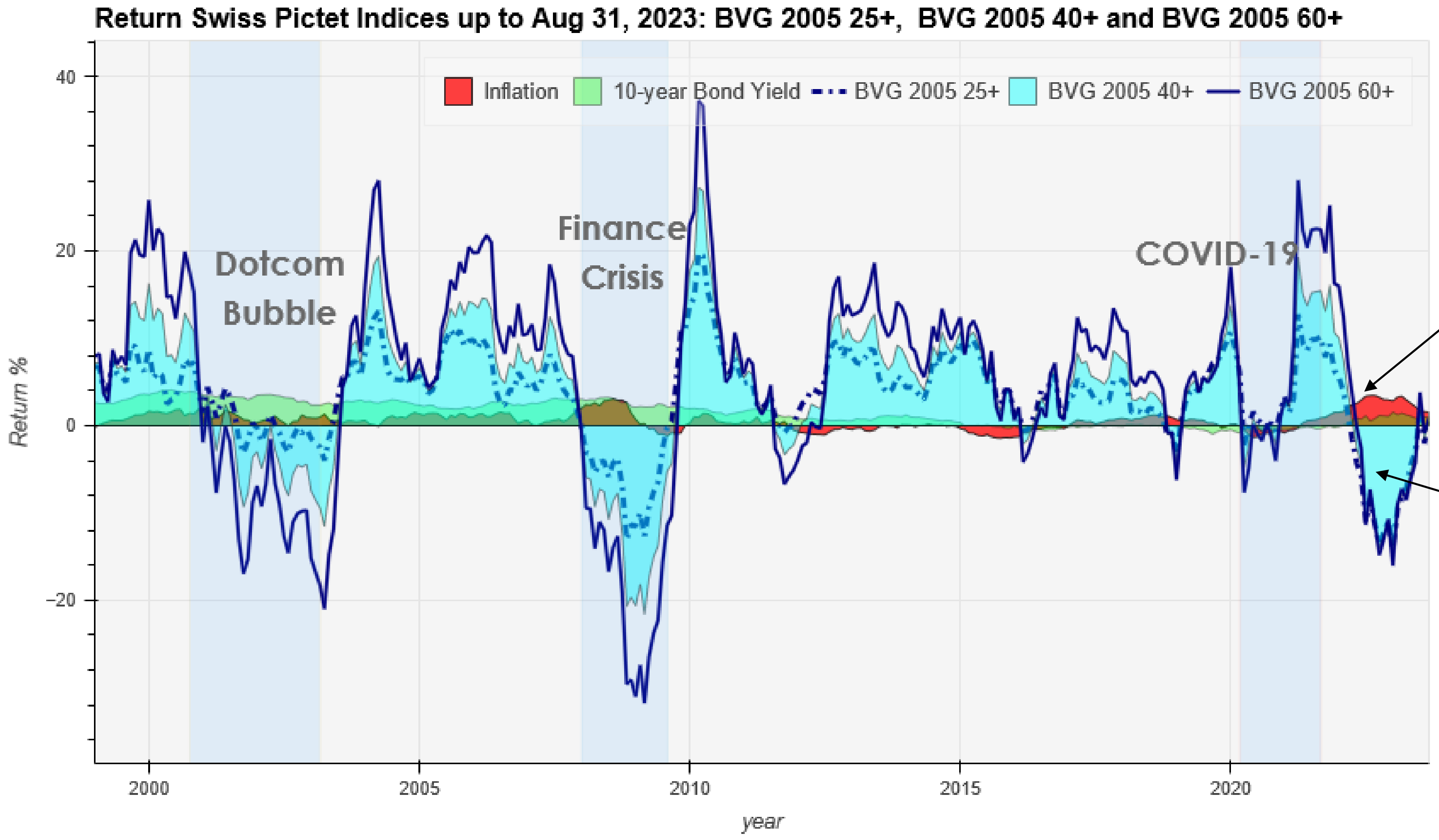
```
print(pictet_plus_corr.to_markdown(tablefmt = "grid"))
```

```
+--------------------+----------------+----------------------+--------------+--------------+--------------+
|                    |   Headline CPI |   10-year Bond Yield |   R 2005 25+ |   R 2005 40+ |   R 2005 60+ |
+====================+================+======================+==============+==============+==============+
| Headline CPI       |              1 |                 0.41 |        -0.36 |        -0.22 |        -0.13 |
+--------------------+----------------+----------------------+--------------+--------------+--------------+
| 10-year Bond Yield |           0.41 |                    1 |        -0.07 |        -0.09 |         -0.1 |
+--------------------+----------------+----------------------+--------------+--------------+--------------+
| R 2005 25+         |          -0.36 |                -0.07 |         1    |         0.96 |          0.9 |
+--------------------+----------------+----------------------+--------------+--------------+--------------+
| R 2005 40+         |          -0.22 |                -0.09 |         0.96 |         1    |         0.99 |
+--------------------+----------------+----------------------+--------------+--------------+--------------+
| R 2005 60+         |          -0.13 |                -0.1  |         0.9  |         0.99 |         1    |
+--------------------+----------------+----------------------+--------------+--------------+--------------+
```



Sensitivity to inflation

Portfolio Index Pictet BVG/LPP 2005 plus: 25+, 40+ and 60+



When Inflation is increasing the portfolio returns are decreasing

As soon as inflation starts decreasing portfolio returns goes up

Over the “Finance crisis” and the current period the strong increase of inflation had a strong impact on portfolio returns

Correlation of Inflation Rate with Portfolio Returns

Pictet BVG 2005 Indices over 1998-2023 (Correlation)

	Headline CPI	10-year Bond Yield	R 2005 25+	R 2005 40+	R 2005 60+
Headline CPI	1	0.41	-0.36	-0.22	-0.13
10-year Bond Yield	0.41	1	-0.07	-0.09	-0.1
R 2005 25+	-0.36	-0.07	1	0.96	0.9
R 2005 40+	-0.22	-0.09	0.96	1	0.99
R 2005 60+	-0.13	-0.1	0.9	0.99	1

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