FX Interventions Rules for Central Banks
A Risk-Based Framework

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Contributions

- Design a rule to **address tail-risks** related to direct and indirect FX exposures in the economy
- Provides guidance on **when** to intervene ("triggers")
- Appropriate for **floating exchange rate regimes** with FX macrofinancial risks (e.g. dollarization)
- Consistently target **FX risk** in the economy
- A **risk management framework** for central banks' financial stability mandate: aligned with **industry's practices** in risk management

Desirable Properties of FXI Rules

Foreign Exchange intervention rules should be:

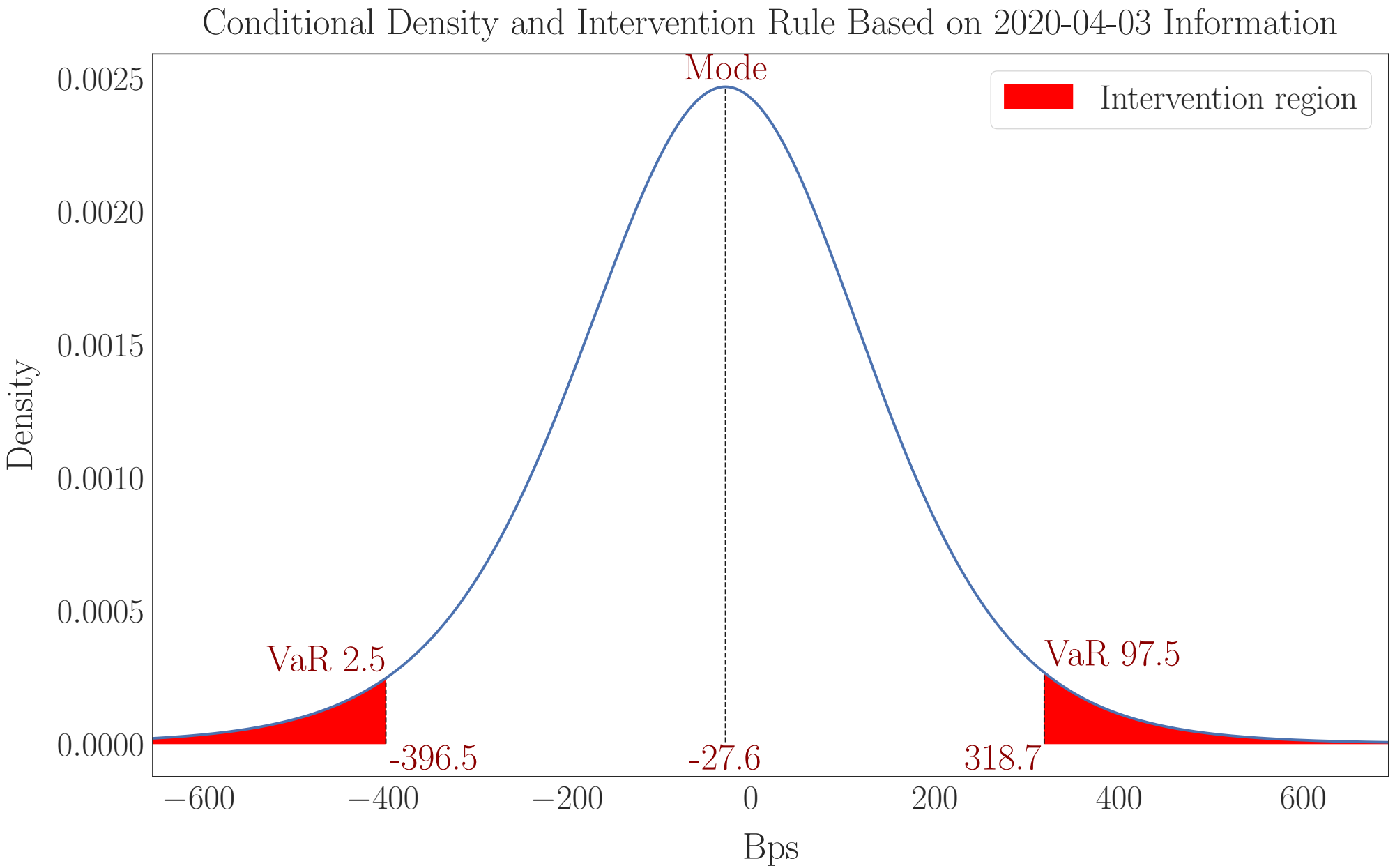
- **Adaptative**, depend on market conditions
- **Objective**, anchored to a risk tolerance level rather than an aribtrary FX level threshold
- Capture FX **non-linearities and asymmetries** between appreciation and depreciation
- Be easily **operationalizable**, and **financially viable**

We propose an FX intervention rule based on **Conditional Value-at-Risk**

Concept: Value-at-Risk FXI Rule

- Rather than using a fixed volatility rule (e.g. intervene if daily exchange rate varies by more than 2% compared to previous day)
- Use a **risk-based rule**: intervene when the daily exchange rate log-returns fall within the tails of the conditional distribution
- Measure the tail-risk via the concept of **Value-at-Risk** (the conditional quantile of the log returns distribution)
- The conditional distribution is estimated daily with a standard financial GARCH model and **varies with market conditions**
- The central bank decides on the **risk tolerance**: e.g. intervene in the tail at 1%, 5%, 10%, etc.

VaR FXI Rule


Conditional Density and Intervention Rule Based on 2020-04-03 Information
Mode
Intervention region
VaR 2.5
VaR 97.5
-396.5
-27.6
318.7
Density
0.0025
0.0020
0.0015
0.0010
0.0005
0.0000
−600
−400
−200
0
200
400
600
Bps

A Risk-Management Approach to FX Interventions

- Tail-risks hedge not always available: **incomplete markets**
- **The central bank is transferring FX risk from the market to its balance sheet**. It buys a risky asset (FX) and issues a risk-free asset (local currency)
- Provide a **public good** to address market failure. Leave a fix share of risk for the market to hedge
- Risk tolerance should depend on the **macrofinancial risk**
- The financial stability mandate of the central bank is properly formalized and quantified via VaR metric

Main Features

1. Allows flexible exchange rate to act as a **shock absorber**: more flexibility in crisis time => **avoid overshooting**

2. **No excessive interventions** in crisis time, often ineffective and costly (exhaust FX reserves)

3. No free insurance to the market: avoid **moral hazard**, foster the **development of hedging market**

4. Prevent **market speculation and windfall effects**

5. Guarantees **fixed-frequency** interventions:
   - **Certainty** about interventions: the central bank can intervene with **larger amounts**, more efficient
   - **Budget neutrality** with symmetric risk preference

6. **Financially optimized**: buy/sell at the best expected price

Operational Implementation

- **Standard data requirements**, easily accessible for a central bank, can be customized
- Parsimonious GARCH model featuring **embedded heteroskedasticity**, **asymmetries** (appreciation/depreciation), **non-linearities** (exponential volatility) and parametric **density forecasting**
- We created a Python package, **free and open-source** (available on Github): estimation, forecasting, out-of-sample evaluation, optimization, benchmarking, etc. Results are **fully replicable**
- Can be readily used by central banks and deployed during Technical Assistance (TA) missions

Challenges

- Some central banks might be reluctant to use a VaR-rule: **more difficult to communicate** to the public
  - However, FXI occur on the wholesale FX market, where market participants are fully aware of the VaR concept
- Some policymakers might **prefer to keep discretion** over FXI
  - Trade-off: a transparent rule anchors better market expectations, maximize efficiency and strengthen central bank's independence

The Framework Extends Beyond FXI triggers

1. Determine FX Intervention triggers
2. Conduct market monitoring and provide policy guidance
3. Benchmark FX interventions, including discretionary interventions

- We present below an application of the toolkit to the Mexican Peso, based on publicly available data
- More than 4500 daily observations, from 2009 to 2018, with Bank of Mexico (public) FX interventions, mostly concentrated in 2009 and 2016

Specification

- Non-linear, Exponential GARCH (EGARCH) model
- The dependent variable is the FX log-returns, $r_t = \log(\frac{e_t}{e_{t-1}})$, where e_t is the bilateral market exchange rate against the major currency (e.g. USD)
- **Drift AR-X(1):** $r_{t+1} = \alpha_d + \rho r_t + \beta X_{t+1} + \epsilon_{t-1}$
- **Exponential volatility:** $\log \sigma^2_{t+1} = \omega + \beta g(r_t)$ where $g(r_t) = \alpha_v r_t + \gamma(|r_t| - \mathbb{E}|r_t|)$
- **Error term distribution** $\epsilon_t = \sigma_t \varepsilon_t$, $\varepsilon_t \sim \text{TSK}(0, 1, \nu)$
- The forecasted conditional probability distribution function is defined as:

$$\hat{f}(r_{t+1}|r_t, X_{t+1}) = \text{TSK}(\hat{r}_{t+1}, \hat{\sigma}^2_{t+1}, \hat{\nu})$$

Estimation

- The GARCH estimation is standard and done with maximimum likelihood
- Selection of parameters is done via AIC/BIC criteria.
- Our Python package allows to flexibly select:
  - The set of exogeneous regressors
  - The number of lags
  - The volatility specification (exponential, RiskMetric, standard GARCH, etc.)
  - The distribution family of the error-terms (Gaussian, Student, Tskew, Generalized Gaussian, etc.)
- More complex models (e.g. copulas, non-parametric kernels, etc.) can be used within the same VaR framework. However, more difficult to understand and to implement

Exogeneous Regressors

1. **FX microstructure**: FX bid-ask spread (averaged over the day)
2. **CIP**: daily interest rate differential with the US Libor
3. **Hedging costs**: one-month forward exchange rate
4. **Past policy interventions**: lagged amount of central bank FX intervention
5. **Global risk sentiment**: The VIX, implied volatility on the S&P 500
6. **Global FX factor**: The EURUSD exchange rate

Regression Table

	Microstructure	CIP	Dollar move	Risk Appetite	Baseline
Intercept	-2.34	-2.29	-1.74	-2.55	-1.63
Lag FX log returns	-0.07***	-0.08***	-0.08***	-0.08***	-0.08***
Bid ask abs	5.67	24.45	-33.58	-2.68	3.22
Min max abs	35.62	34.68	33.32	34.45*	26.2
Forward points first difference	23.29***	17.79***	26.33***	19.82***	19.44***
Interbank rate vs Libor		33.61***	39.43***	34.75***	33.86***
EURUSD log returns			-0.14***	-0.17***	-0.16***
VIX first diff				15.67***	15.37***
FX intervention dummy lag					2.23
Oil prices log returns					-0.02***
Omega	0.13***	0.13***	0.12***	0.11***	0.12***
Alpha	0.17***	0.17***	0.16***	0.16***	0.15***
Gamma	0.07***	0.06***	0.06***	0.05***	0.05***
Beta	0.98***	0.99***	0.99***	0.99***	0.99***
Nu	8.33***	8.67***	8.92***	8.71***	8.54***
Lambda	0.08*	0.07	0.09*	0.07*	0.08***
R2	5.8 %	6.7 %	10.4 %	27.3 %	27.6 %
R2 adjusted	5.8 %	6.6 %	10.3 %	27.2 %	27.5 %
Number of observations	5986	5986	5682	5682	5680
Significance *10%, **5%, ***1%					

Formalization of the Intervention Rule

- Consider the estimated conditional distribution of the exchange rate log returns r_t defined as

$$\mathbb{P}[r_t \leqslant x] = \int_{-\infty}^{x} \hat{f}(r_t | r_{t-1}, X_t) dr_t$$

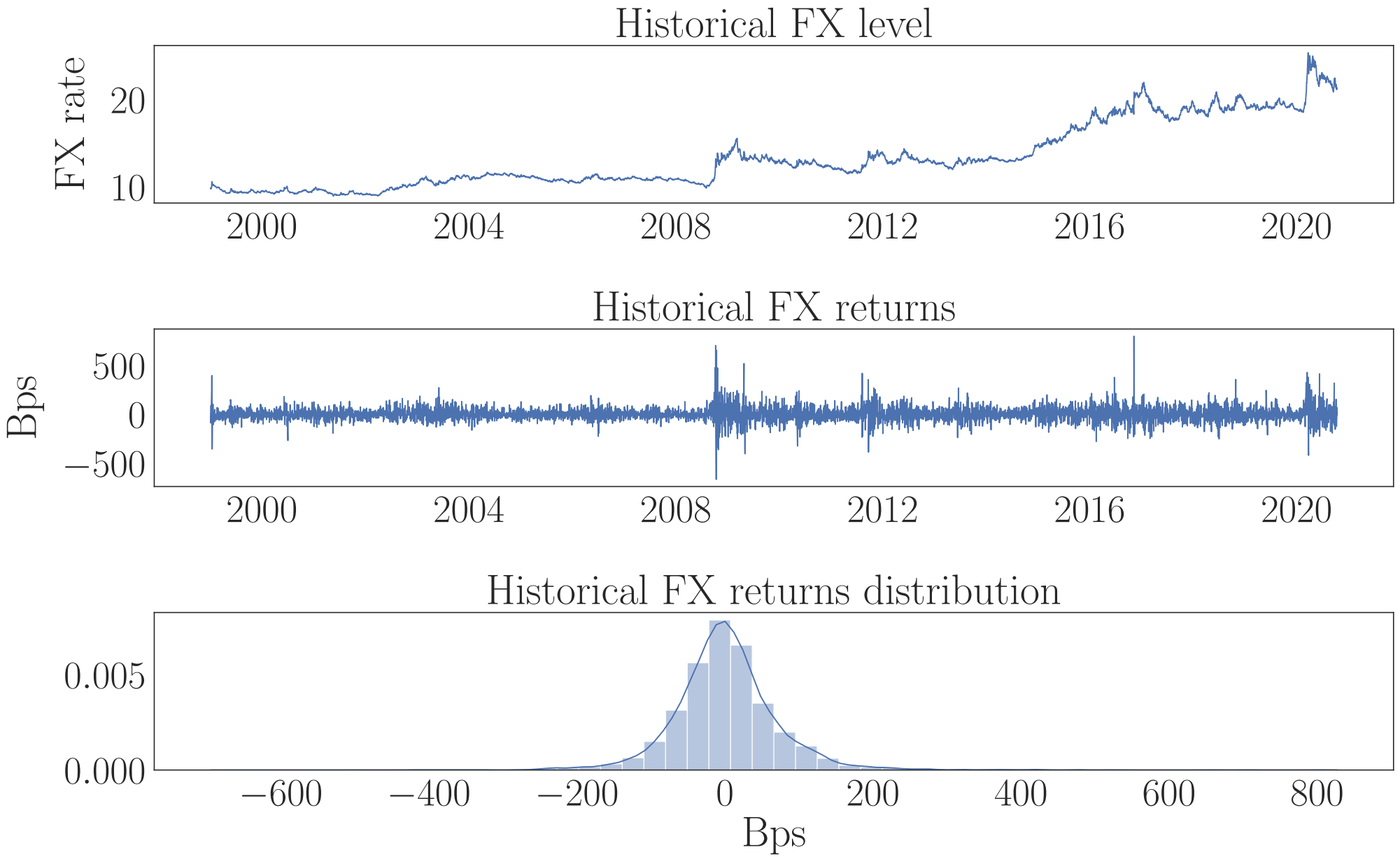
- The Conditional Value-at-Risk at threshold τ is simply defined as the conditional τ-quantile

$$Q(r_t, \tau) \equiv \mathbb{P}[r_t \leqslant Q(r_t, \tau)] = \tau, \text{ for } \tau \in (0, 1)$$

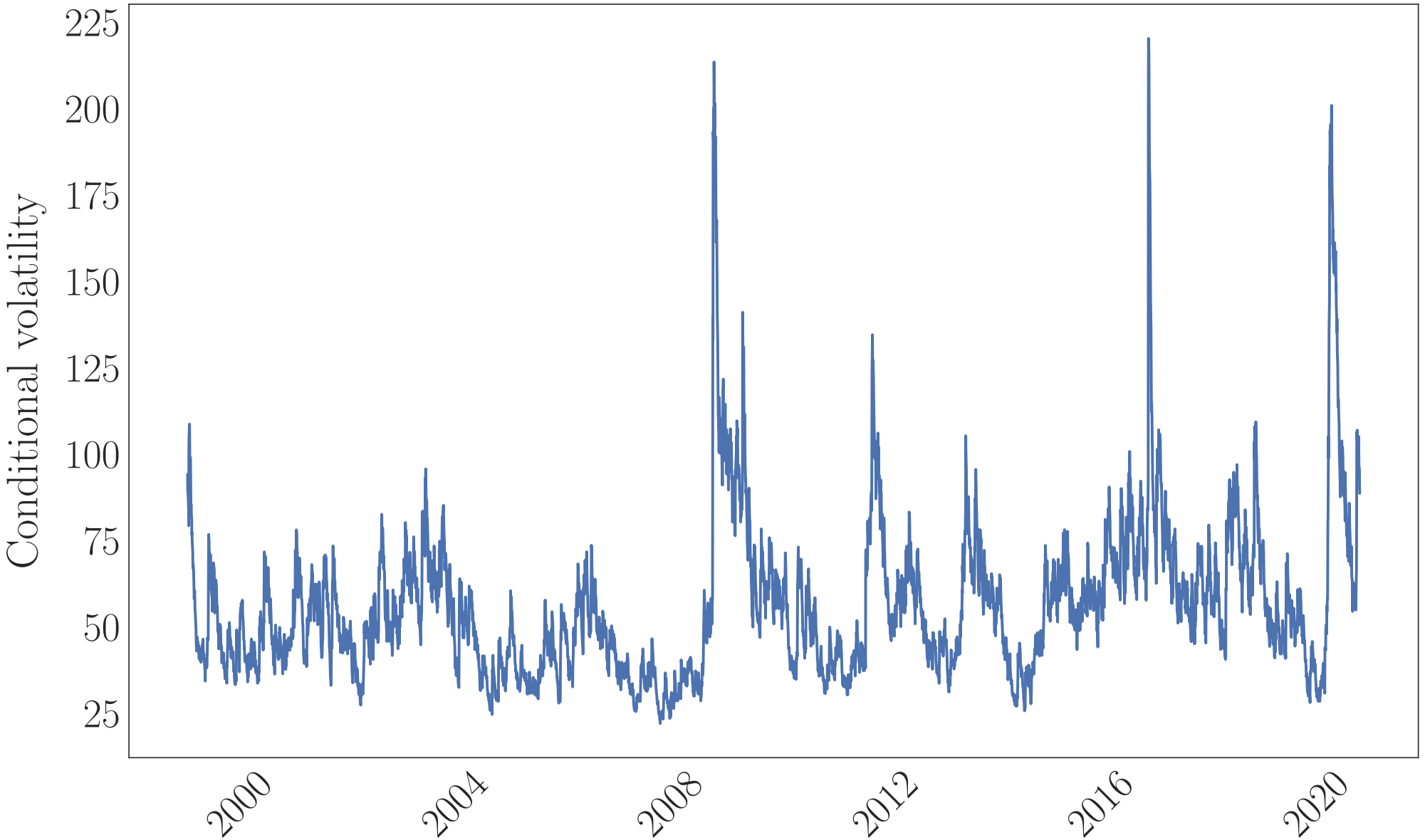
- The FXI intervention rule is a simple boolean rule, based on two risk-thresholds $(\underline{\tau}, \overline{\tau})$, for depreciation and appreciation, potentially risk-symmetric $(\overline{\tau} = 1 - \underline{\tau})$

$$\mathbb{1}\left[\{r_t \leqslant Q(r_t, \underline{\tau})\} \cup \{r_t > Q(r_t, \overline{\tau})\}\right]$$

Dynamics of the Mexican Peso against USD

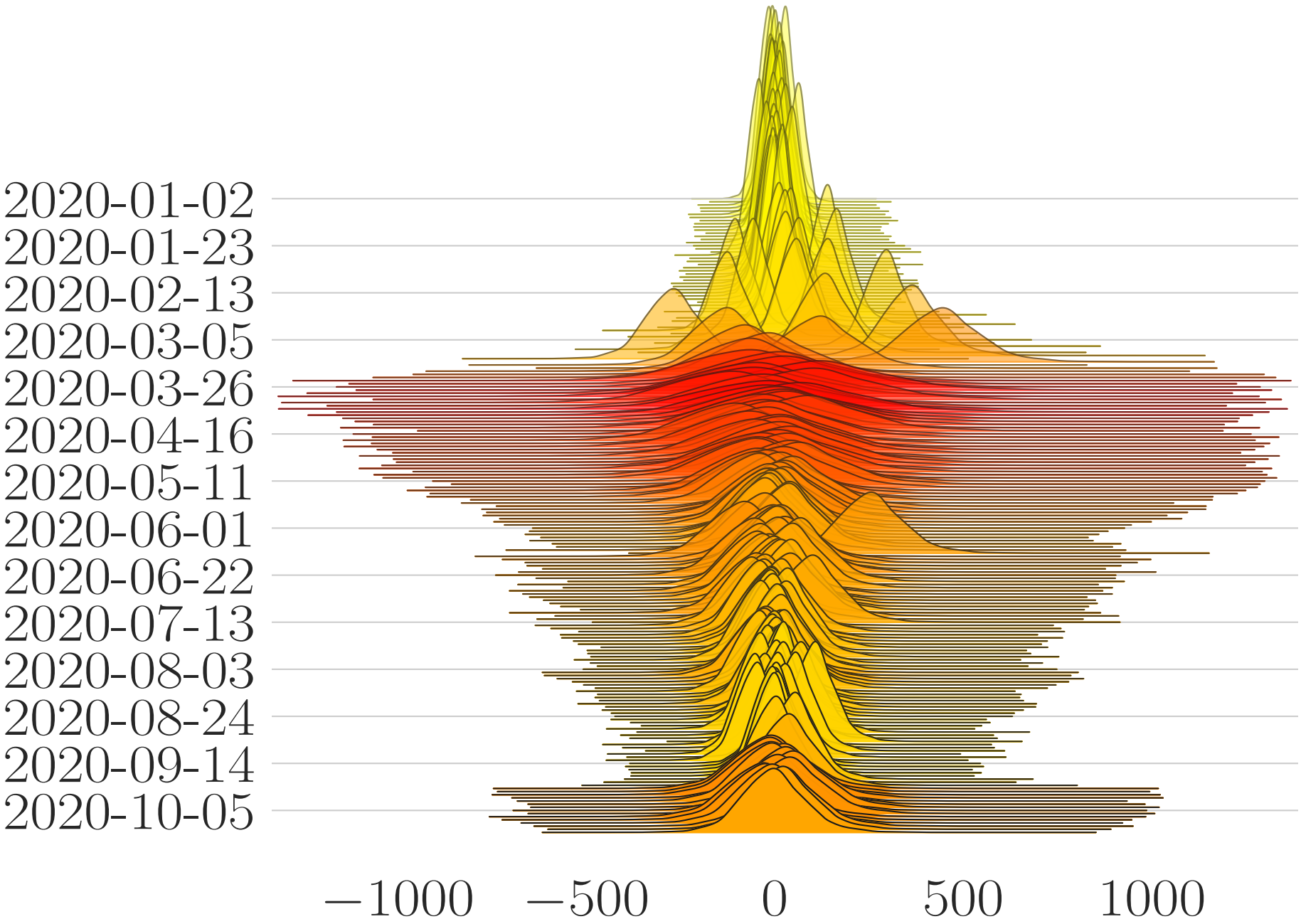


Conditional In-Sample Volatility of the Mexican Peso

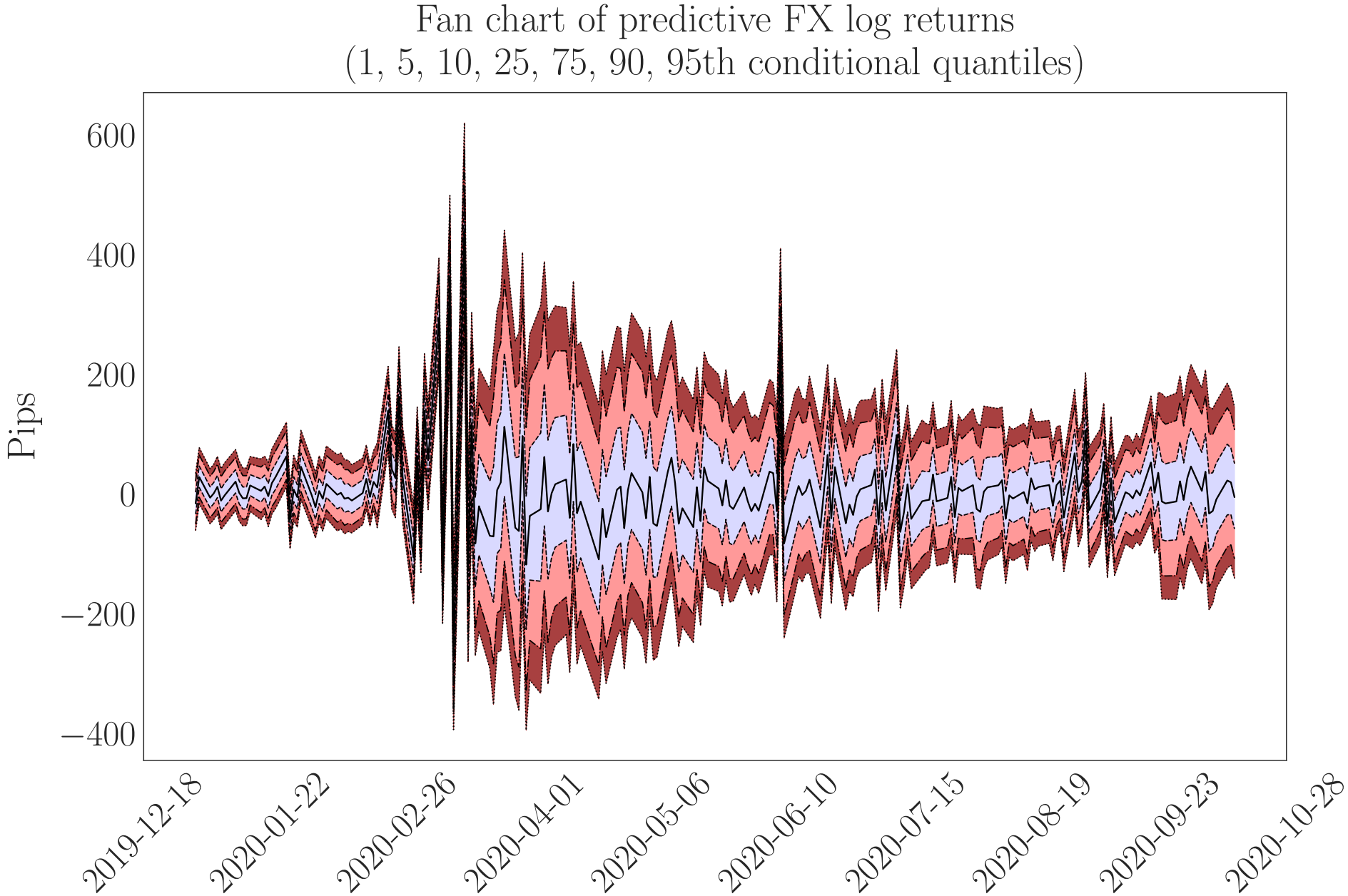


Forecasting

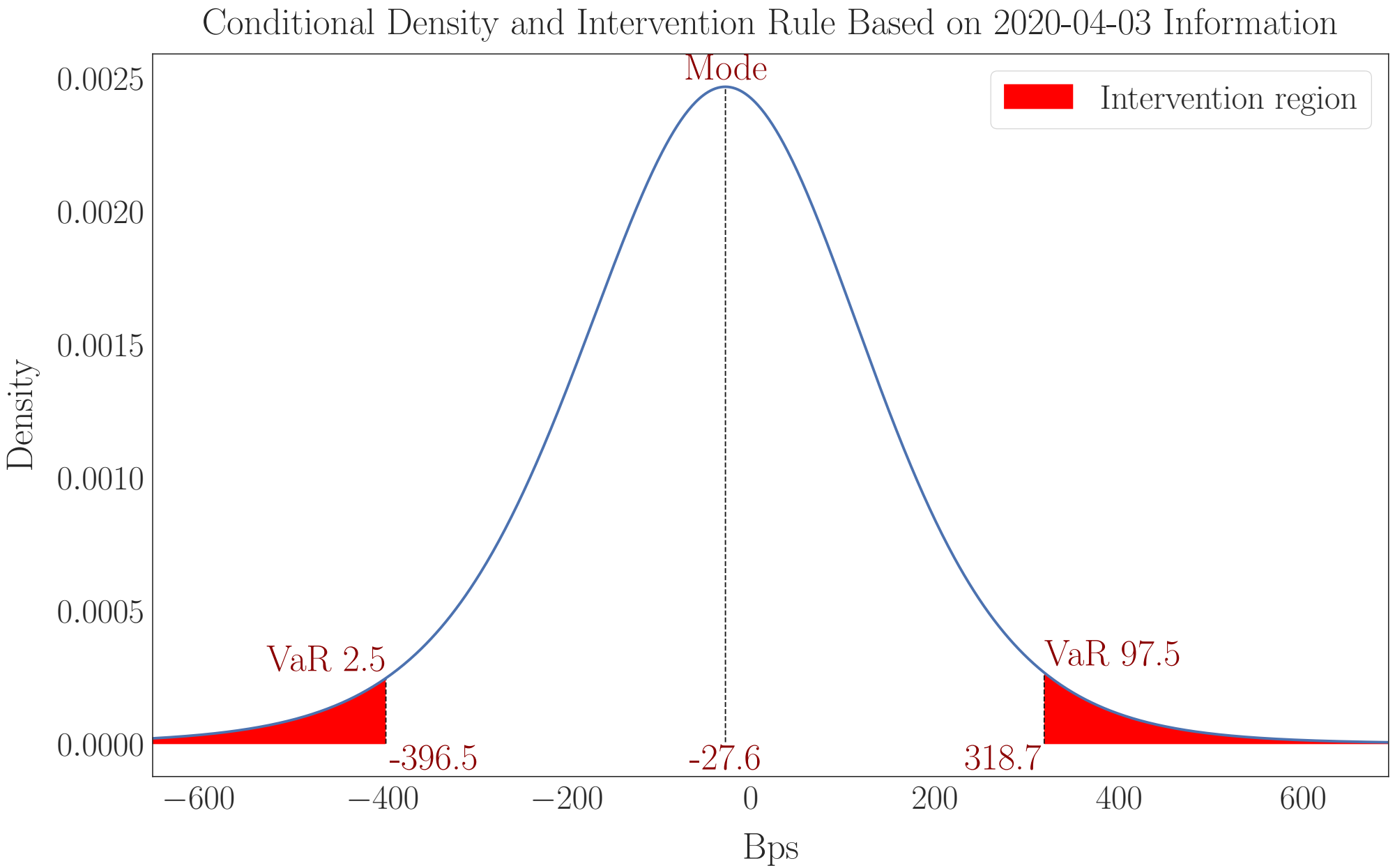
- Real-time forecasting based on market conditions
- Estimate the GARCH and derive the forecasted drift and volatility
- Infer the **full-fledged conditional distribution** of FX log returns for any point in time
- Optimize the choice of the mean (drift) and density models, specifically:
  - The model on the mean/drift
  - The model for the conditional variance
  - The distribution of the perturbations, that determines the whole distribution


2020-01-02
2020-01-23
2020-02-13
2020-03-05
2020-03-26
2020-04-16
2020-05-11
2020-06-01
2020-06-22
2020-07-13
2020-08-03
2020-08-24
2020-09-14
2020-10-05
−1000
−500
0
500
1000

Fan Chart


Fan chart of predictive FX log returns
(1, 5, 10, 25, 75, 90, 95th conditional quantiles)
Pips
600
400
200
0
−200
−400
2019-12-18
2020-01-22
2020-02-26
2020-04-01
2020-05-06
2020-06-10
2020-07-15
2020-08-19
2020-09-23
2020-10-28

VaR FXI Rule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200
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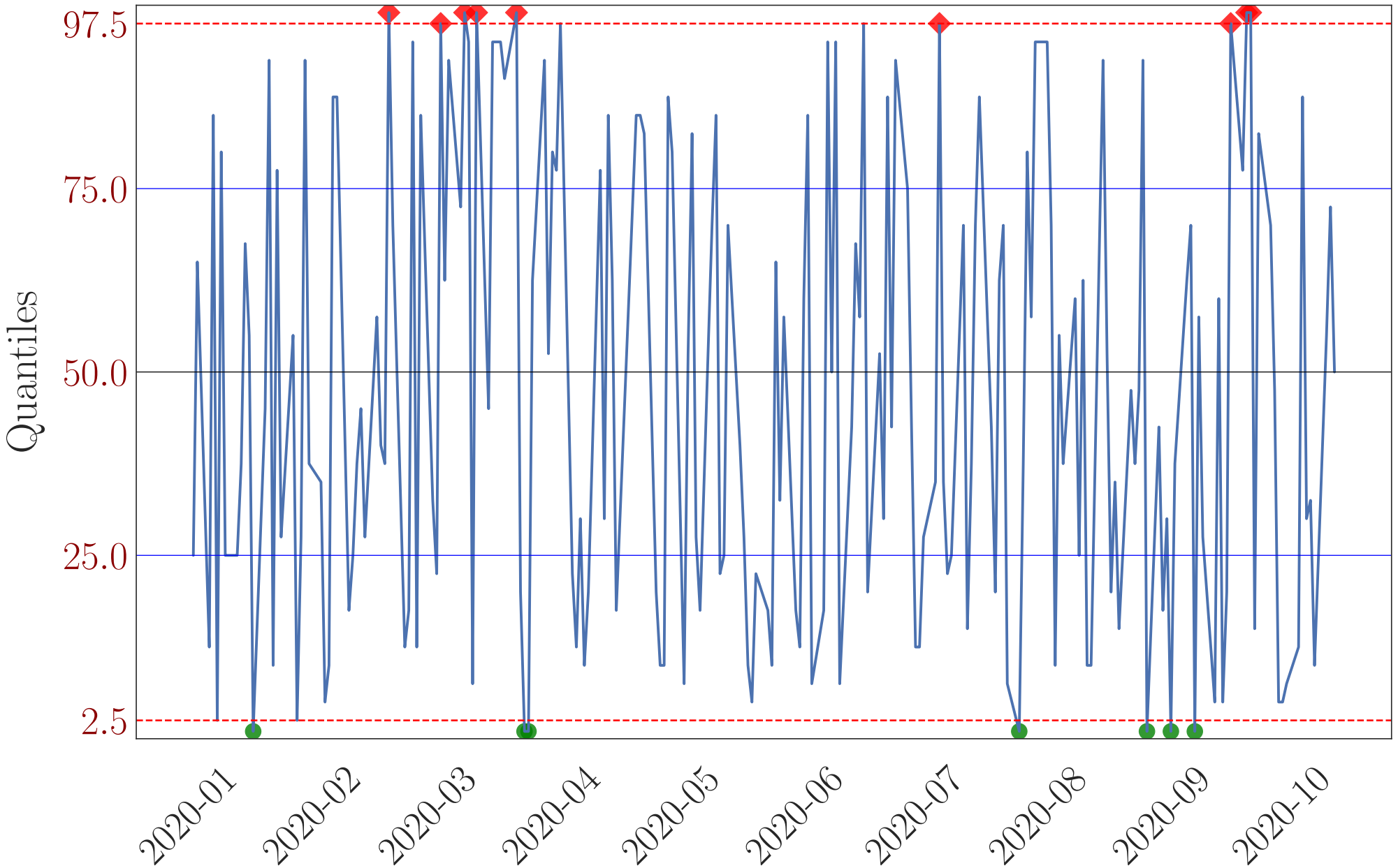
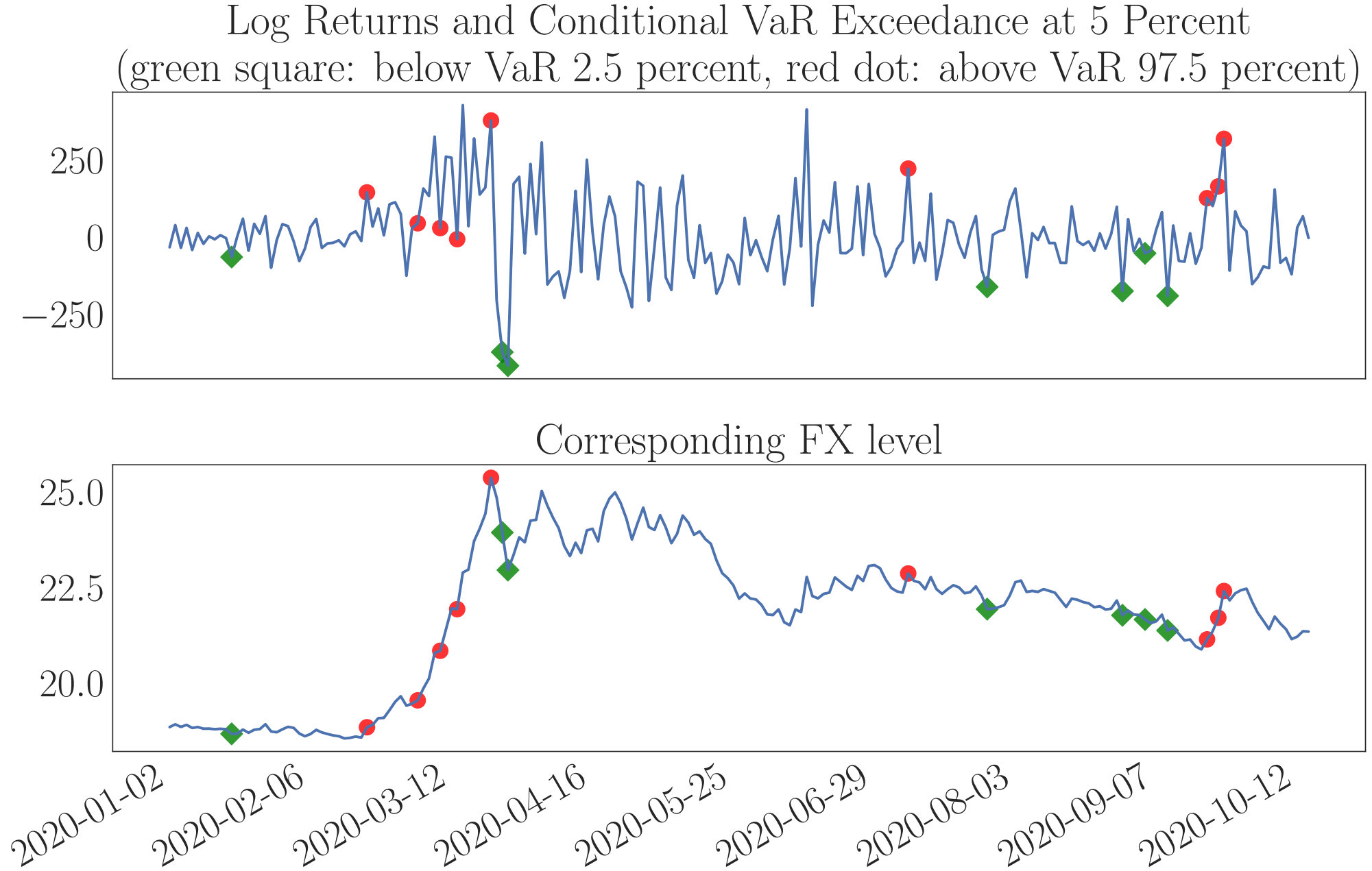
600
Bps

Conditional Cumulative Distribution Function



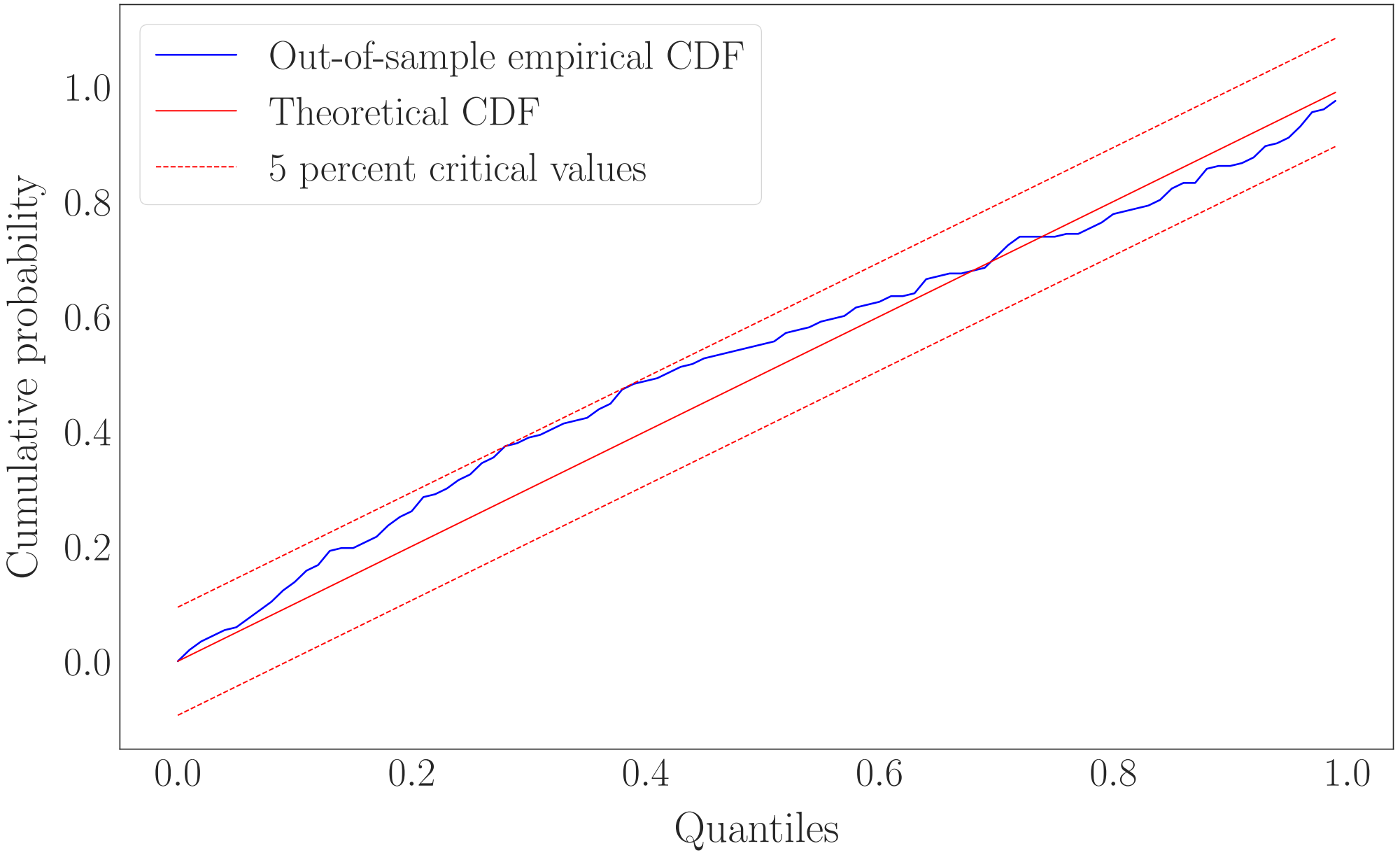
Conditional Exceedance



Optimization via Cross-Validation using the Zig-Zag Algorithm

- There are many possible choices for the models on the mean/drift, the conditional variance or the distribution of the perturbations
- We would like to choose the most appropriate ones, using performance metrics
- Problem: the GARCH estimates separately the drift and the volatility (where it imposes assumptions on the distribution), hence a direct approach is not feasible
- Idea: use the zig-zag algorithm to optimize the entire model
  1. Optimize the choice of the drift model with RMSE out-of-sample validation
  2. Optimize the choice of the distribution
  3. Estimate the parameters based on the optimal functional forms of the models (the hyperparameters) via a recursive approach

Density Evaluation



Bank of Mexico FX Interventions Setup

- The Banco Mexico (BM) implemented both ex-ante, transparent FX auctions and discretionary-rate auctions

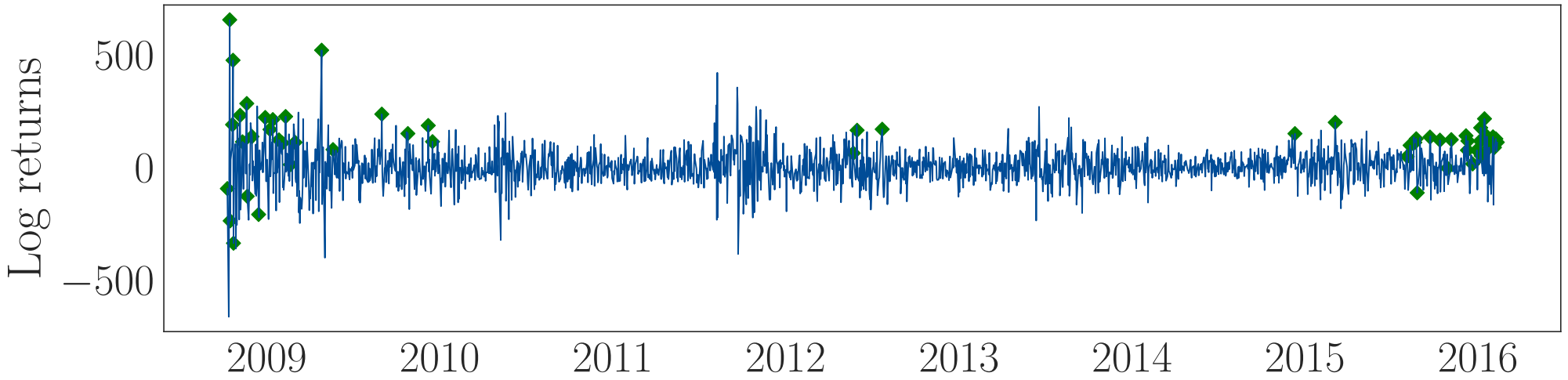
- Different reservation rates:
  - **Rule-based setting**: BM operated an auction every day with a pre-announced **a minimum rate** for eligible bids
  - **Discretionary setting**: the auction was organized at the BM's discretion without reservation rate

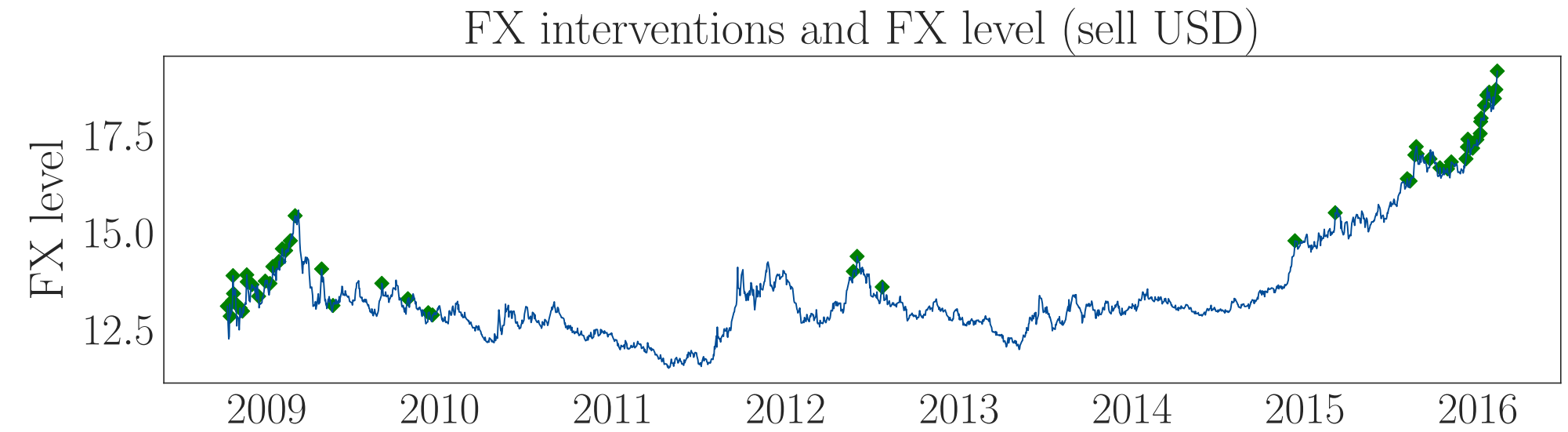
- Often, no demand for the ruled-based auction as the market rate was below the reservation rate

- No-minimum price auctions could be motivated by other considerations than the exchange rate level

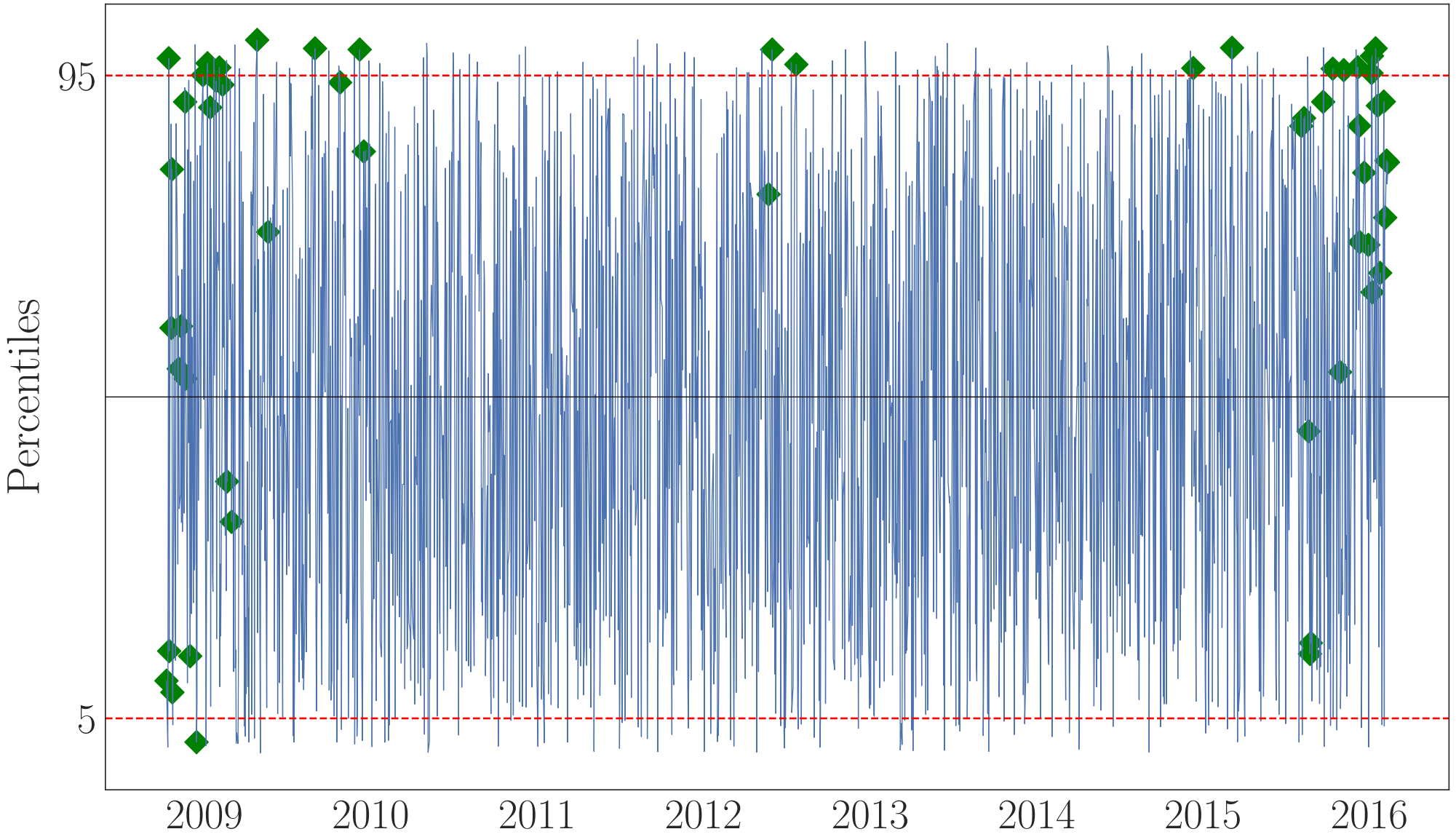
- What was the risk level when the FXI occurred?

Rule-Based Benchmarking

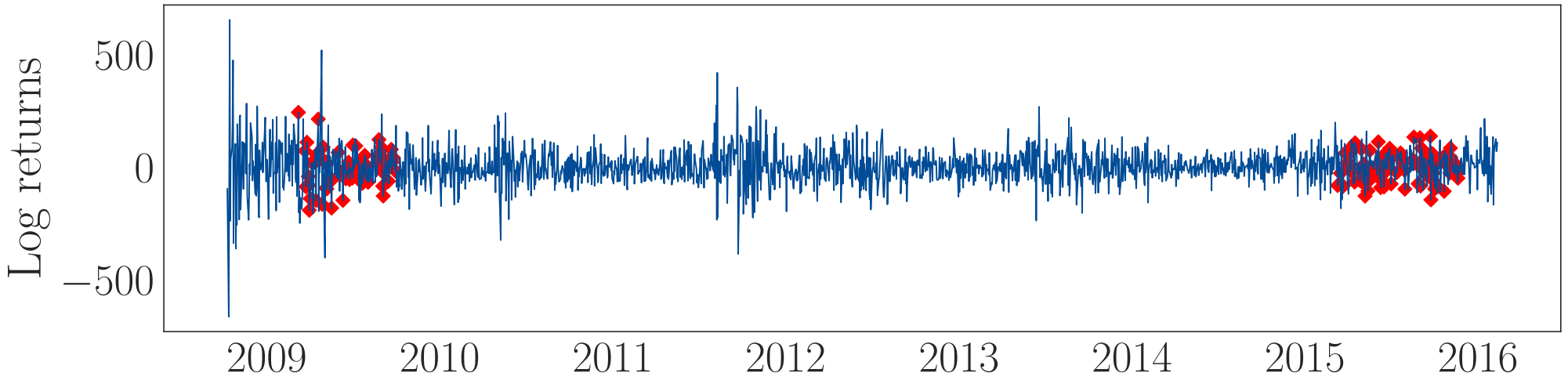


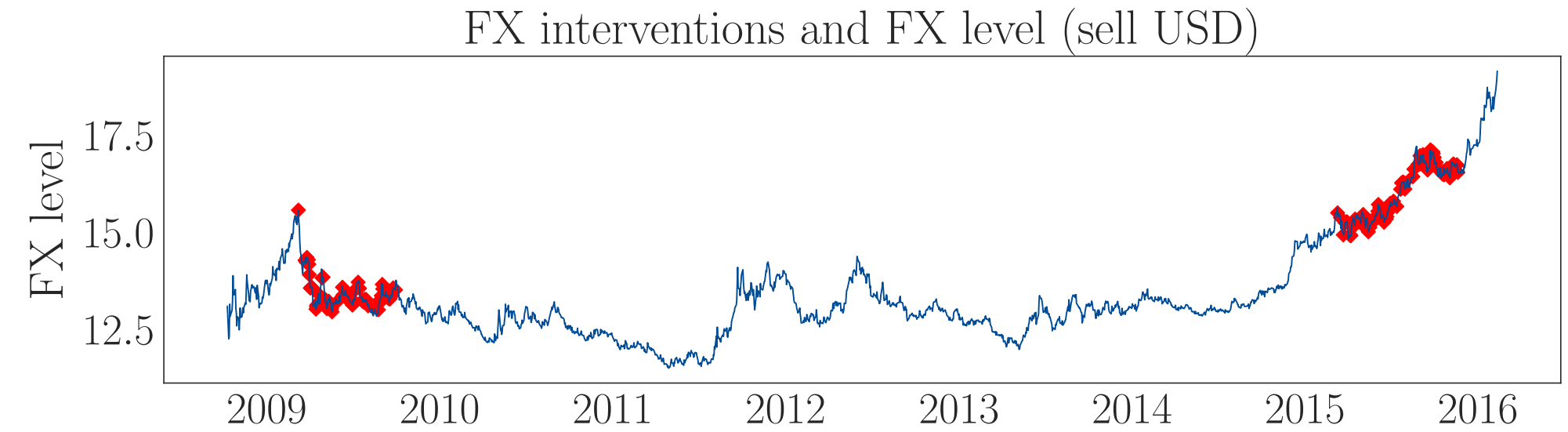


Rule-Based Benchmarking: Risk-Level

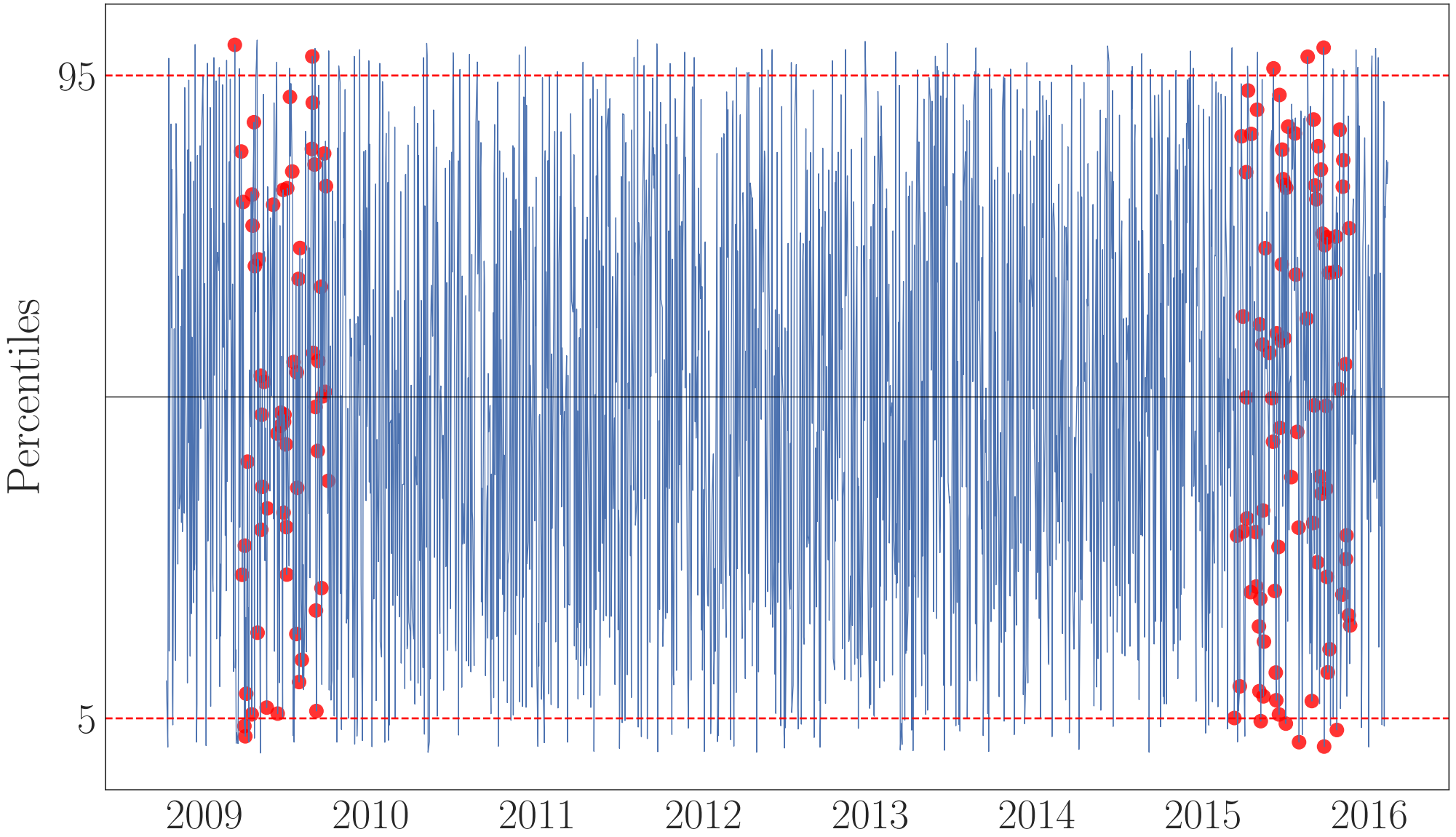


Discretion-Based Benchmarking





Discretion-Based Benchmarking: Risk-Level



Benchmarking Results

1. **FX auctions with ex-ante minimum price ("rule-based")**
   - The minimum price auctions did not fully prevented BM to intervene outside of the tails of the conditional distribution
   - In that respect, VaR-based intervention would have been better to mitigate tail-risks
2. **FX auctions with no ex-ante minimum price ("discretion-based")**
   - No minimum prices interventions occurred at almost any risk level
   - **Discretion triggers are not identifiable based on risk**

Policy Uses

- Useful for floating rate regimes to **operationalize their financial stability mandate** with a risk-management framework
- The VaR-based rule could be considered **as one option** to improve the rules that central banks currently use
- Let the nominal exchange rate acts as a **shock absorber**
- Could be used to accompany the **transition to exchange rate flexibility**, with gradually less and less interventions
- More generally, could be used by central banks for **market and risk monitoring**

Alternative Models: Benchmarking

	PIT	Logscore diff against Baseline	Diff pvalue
Baseline	Pass		
Unconditional Quantile Reg			
Gaussian EGARCH	Fail	1.54	0.938
TSkew GARCH	Fail	1.768	0.961
Gaussian GARCH	Fail	1.755	0.96