FX Interventions Rules for Central Banks
A Risk-Based Framework

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1. Conceptual Framework
2. Model
3. Forecasting
4. Benchmarking
5. Policy Uses

Quant Methods for Rule-Based and Discretionary FXI

- Fundamentally, for floating regimes, **FX interventions are about mitigating risk** (volatility risk, funding risk, risk of pass-through to inflation, etc.)
- Hence, **measuring and anticipating risk is critical**... and relevant both for discretionary and rule-based interventions
- While there is no consensus about rule vs discretion, rule-based interventions are better suited to offer a **consistent macro-risk management**
  - Macro risk derives from risk-taking behavior from market participants and international factors
  - Rules are among the best tools to effectively build a strategy geared towards tilting agents' behavior
  - Via **signalling** and **moral-hazard mitigation**

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:

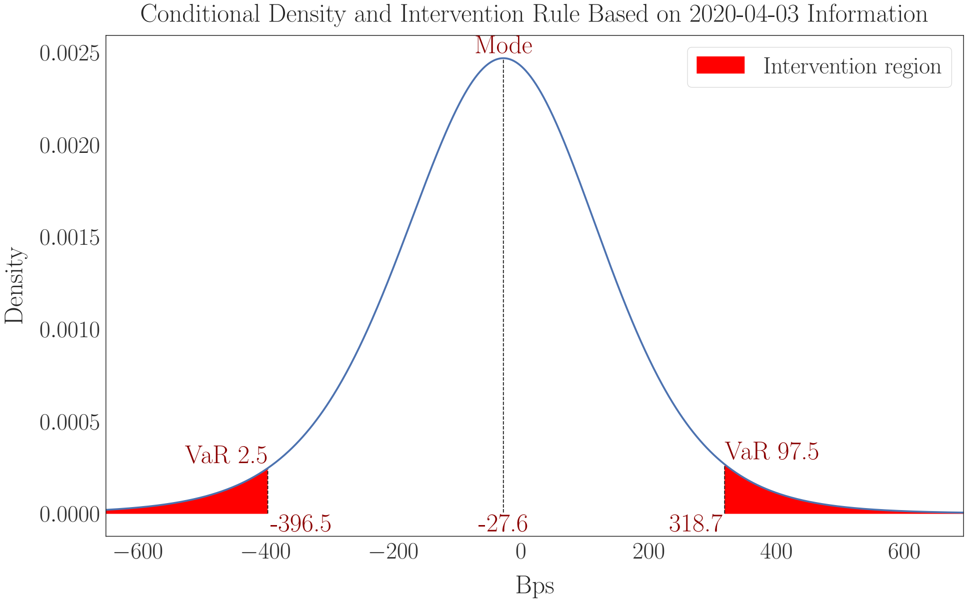
- **Adaptative**, depending on market conditions
- **Objective**, anchored to a risk tolerance level rather than an aribtrary FX level threshold
- Capture FX **non-linearities and asymmetries** between appreciation and depreciation
- Be easily **operationalizable**, and **financially viable**

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
- Especially efficient to support market development, especially on derivatives (typically FX forwards)

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 pypi and Github): estimation, forecasting, out-of-sample evaluation, optimization, benchmarking, etc. Results are **fully replicable**

- Can be used alongside other types of interventions: put auctions, NDF, etc.

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, **under certain conditions** maximize efficiency and strengthen central bank's independence

A Complementary Rule

- The VaR FXI rule is fundamentally a rule to intervene on the spot market to directly take risk out of the market
- Can easily be associated with other types of interventions, such as auctions of forwards or non-deliverables forwards (NDF).
- Auctions of NDF provides an insurance to the market without endangering the FX reserves of the central bank.
  - **But** require a relatively developped forward market and sophisticated market participants to operate
  - Supposes a relatively good arbitraging between the forward and spot market to impact the volatility on the spot
  - Doesn't help on funding issues (can be alleviated with spot interventions or swaps)
- VaR FXI interventions are done on the spot market. They have a direct impact on the market, provides funding in hard currency
  - **But** will impact the level of FX reserves of the central bank (at least, over the short-term)

The Framework Extends Beyond FXI triggers

1. Can be used for **market monitoring** by measuring conditional volatility on the market (especially when implied volatility is not available)

2. Provide policy guidance for **discretionary interventions**

3. Can be used for structural analysis on the FX markets, for instance to study the dynamic of capital flows as a function of conditional volatility

4. Benchmark ex-post FX discretionary interventions (what was the risk level when the central bank intervened ?)

- *We present below an application of the toolkit to the Mexican Peso to benchmark their interventions ex-post*

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:** $\log \sigma_{t+1}^2 = \omega + \beta g(r_t)$ where $g(r_t) = \alpha_v r_t + \gamma(|r_t| - \mathbb{E}|r_t|)$
- **Error term distribution** $\epsilon_t = \sigma_t \varepsilon_t \ , \varepsilon_t \sim \mathrm{TSK}(0, 1, \nu)$
- The forecasted conditional probability distribution function is defined as:

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

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

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

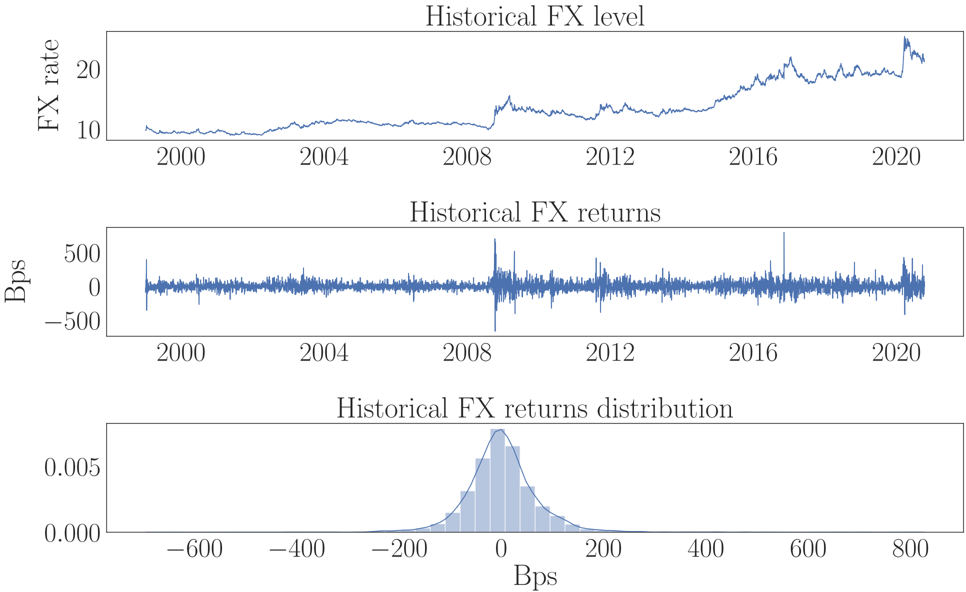
- The Conditional Value-at-Risk at threshold τ is simply defined as the conditional τ-quantile

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

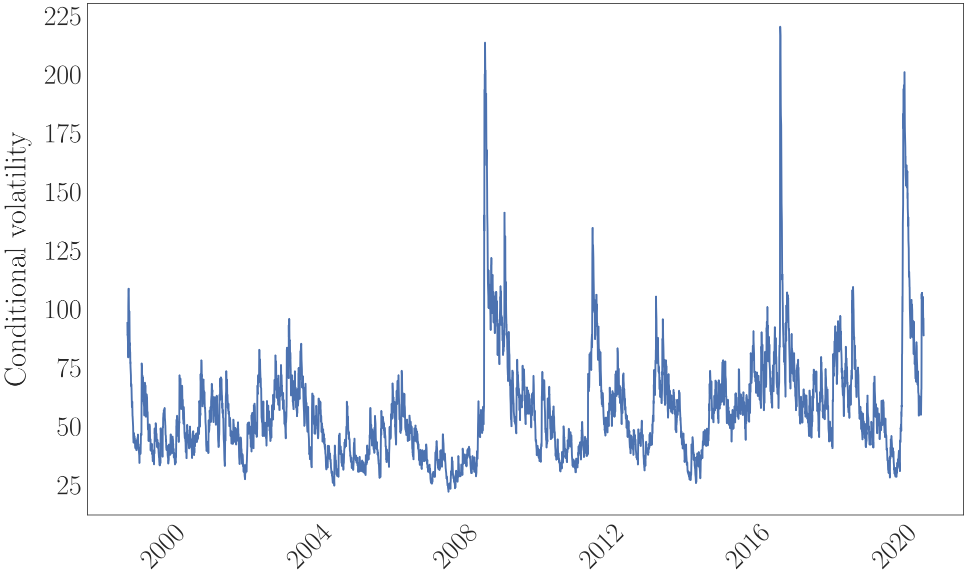
- The FXI intervention rule is a simple boolean rule, based on two risk-thresholds $(\underline{\tau}, \overline{\tau})$, for depreciation and appreciation, potentially risk-symmetric $(\overline{\tau} = 1 - \underline{\tau})$

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

Dynamics of the Mexican Peso against USD

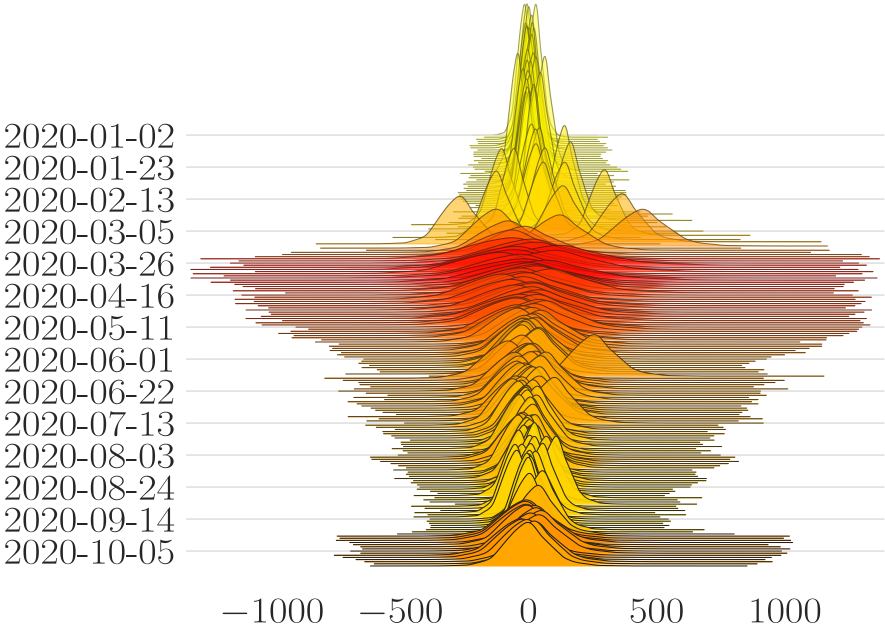


Conditional In-Sample Volatility of the Mexican Peso

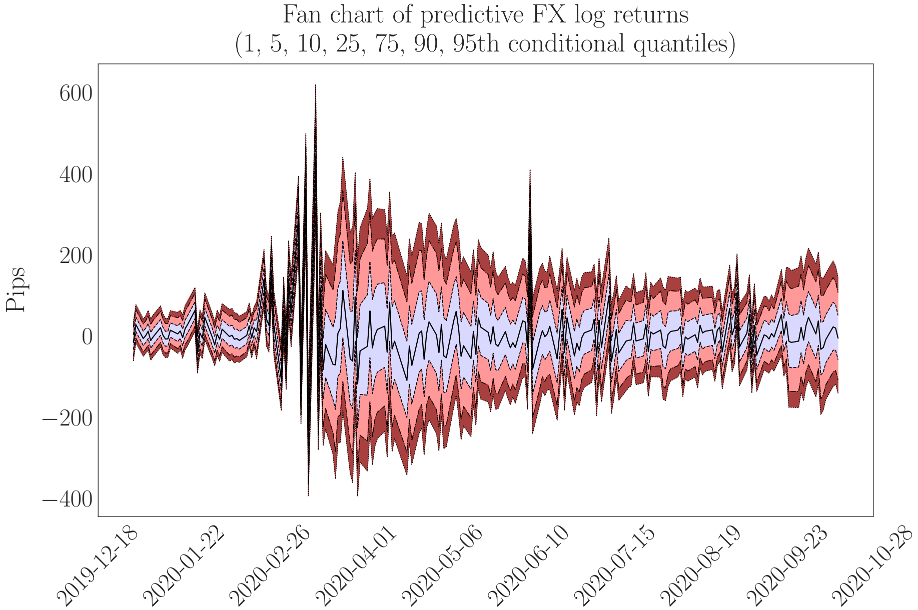


Forecasting

- 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

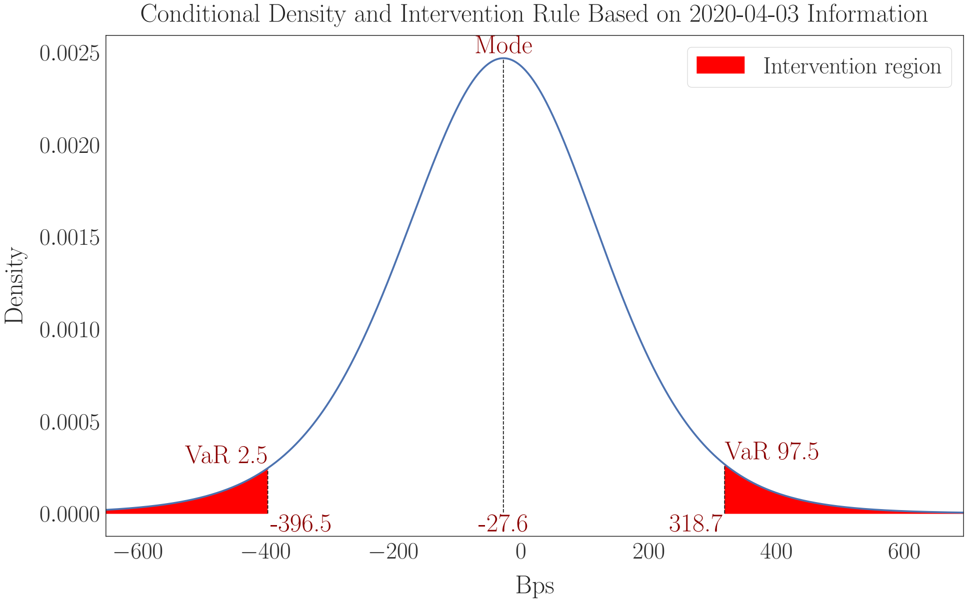

2020-01-02
2020-01-23
2020-02-13
2020-03-05
2020-03-26
2020-04-16
2020-05-11
2020-06-01
2020-06-22
2020-07-13
2020-08-03
2020-08-24
2020-09-14
2020-10-05
−1000
−500
0
500
1000

Fan Chart



Fan chart of predictive FX log returns
(1, 5, 10, 25, 75, 90, 95th conditional quantiles)
600
400
200
0
−200
−400
Pips
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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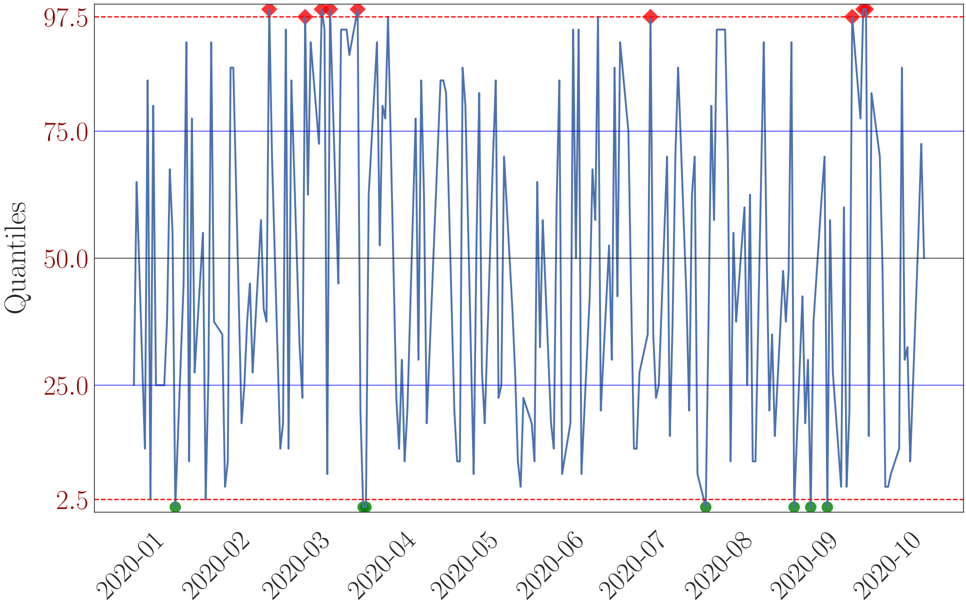
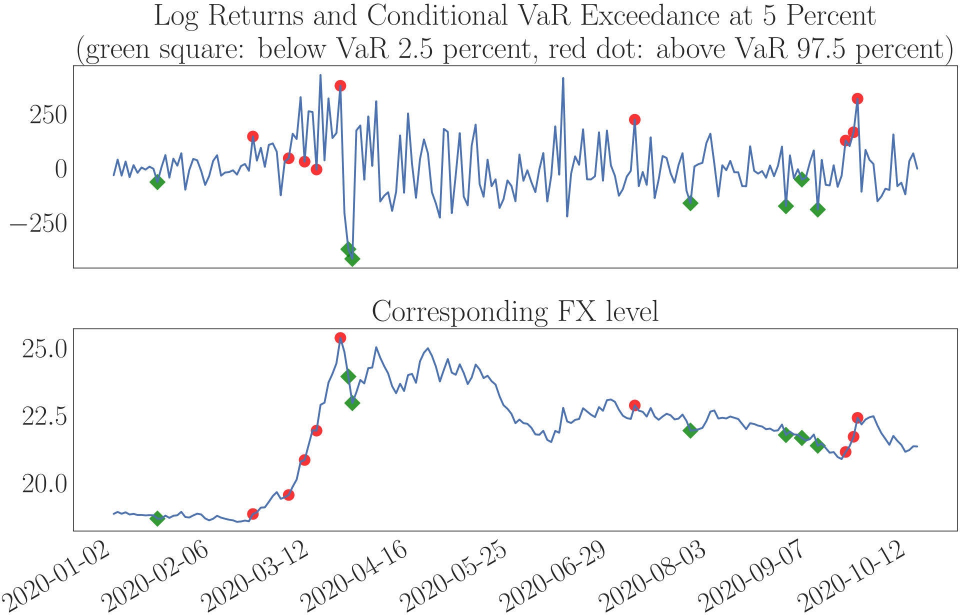
318.7
0.0025
0.0020
0.0015
0.0010
0.0005
0.0000
Density
−600
−400
−200
0
200
400
600
Bps

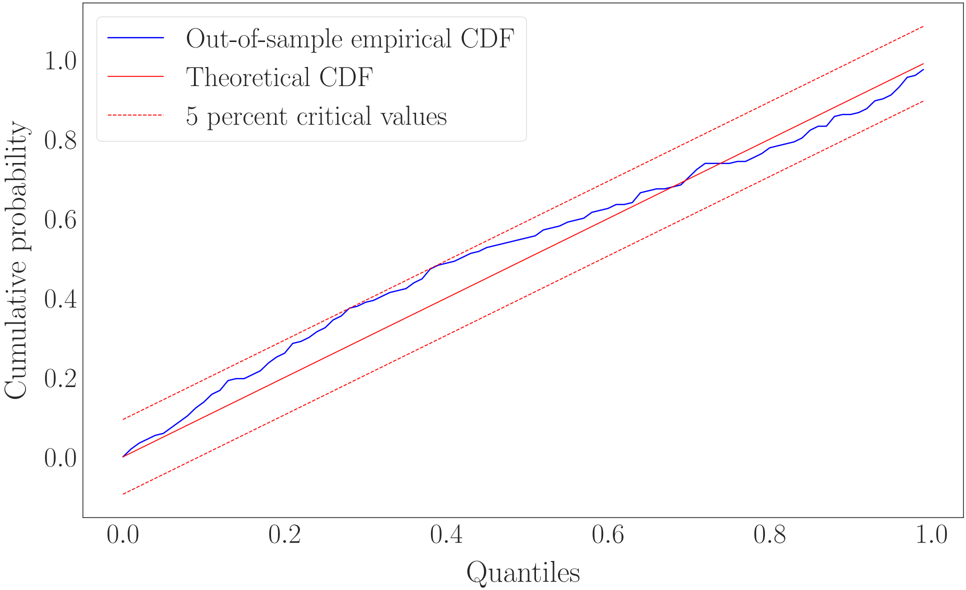
Conditional Cumulative Distribution Function



Conditional Exceedance



Density Evaluation



In Practice

- In practice, optimizing **out-of-sample** a density model is complex
- The package we designed handles the optimization seamlessly (see the Zigzag discussed previously)
- It outputs the optimal functional forms and parameters
- Offers the possibility to optimize based on the performance **on the tails**
  - Since FX Interventions will occur in the tails, it matters that the model performs well on the tails

Zig-Zag Output

	KS_PIT_test	KS_PIT_test_pvalues	Rossi_Shekopysan_PIT_test_right_tail	tails_log_score	left_tail_log_score	right_tail_log_score
volatility_model						
Constant	False	0.0	False	False	-5.04257	-1.566547
ARCH	False	0.0	False	False	-5.009953	-1.459077
RiskMetric	False	0.000547	False	False	-4.986837	-1.467944
GARCH	False	0.000742	False	False	-4.980809	-1.470709
GJR-GARCH	False	0.005783	False	False	-4.974227	-1.4876
EGARCH	False	0.000092	False	False	-4.97205	-1.485041
EWMA	False	0.024125	False	False	-4.95291	-1.506733
RiskMetric	False	0.010851	False	False	-4.879082	-1.604971
GJR-GARCH	False	0.039789	False	False	-4.875905	-1.62644
EGARCH	False	0.026603	False	False	-4.873035	-1.629643
GARCH	False	0.012535	False	False	-4.867998	-1.621192

How to Select a Model from our Package?

1. **Look for well-specified density models**: distributions that can NOT reject the PIT hypothesis (can not reject the hypothesis that the PIT is uniformly distributed). Want **high** p-values

2. Ideally, should be well-specified in the tails (PIT tails) as well as in the bell part

3. Then among the well-specified density models, choose the **best performing model: the one with the best logscore**

4. What if all models fail the PIT test? If they are all mis-specified?
   - Directly go for the best performing one

5. Deep question: why focusing on well-specified models? Why not only focusing on the best performing ones?
   - Mis-specified models indicate a consistent bias
   - They can perform well over short-periods but it is likely that they might strongly underperform in the future

Best Out-of-Sample Model from the Package

```
mean_optim = dgo.optimize_mean()
```

```
Optimizing the Mean model. step 1: exog_l
```

```
100%|██████████| 255/255 [00:21<00:00, 11.97it/s]
```

```
Best Out-Of-Sample combination of exogenous variables:
Bid ask abs,Forward points first difference,EURUSD log returns,VIX first diff,Oil prices log returns,
Optimizing the Mean model. step 2: number of lags
```

```
100%|██████████| 10/10 [00:00<00:00, 11.14it/s]
```

```
Best Out-Of-Sample number of lags: 0
```

```
vol_dist_optimization = dgo.optimize_vol_distrib()
vol_dist_optimization
```

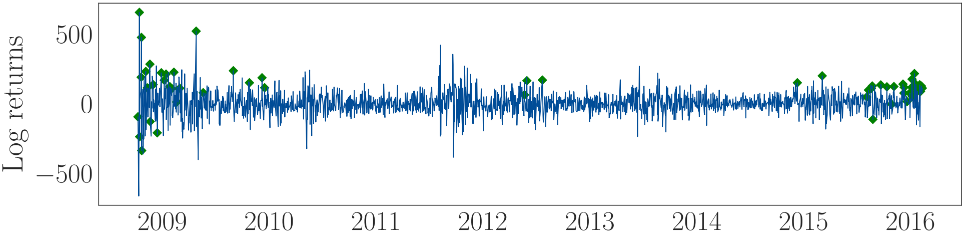
```
100%|██████████| 28/28 [03:17<00:00,  7.04s/it]
```

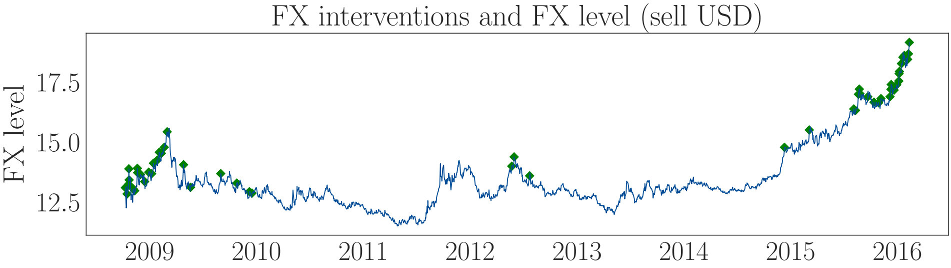
```
Best Out-Of-Sample Volatility Model: RiskMetric
Best Out-Of-Sample Distribution Family: SkewStudent
```

Bank of Mexico FX Interventions Setup

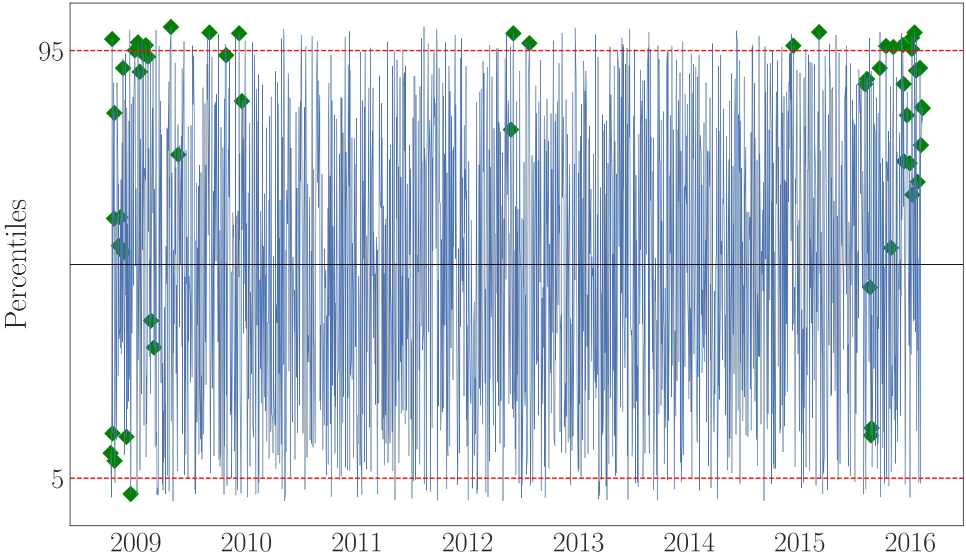
- The Banco Mexico (BM) implemented both ex-ante, transparent FX auctions and discretionary-rate auctions
- Different reservation rates:
  - **Rule-based setting**: BM operated an auction every day with a pre-announced **a minimum rate** for eligible bids
  - **Discretionary setting**: the auction was 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

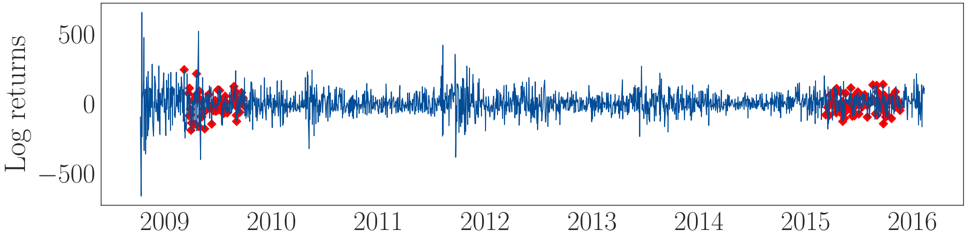


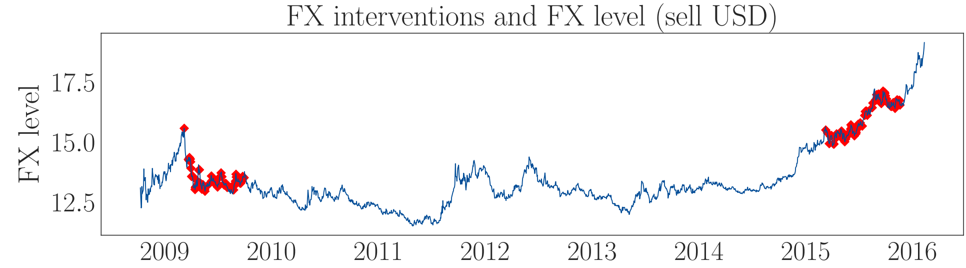


Rule-Based Benchmarking: Risk-Level

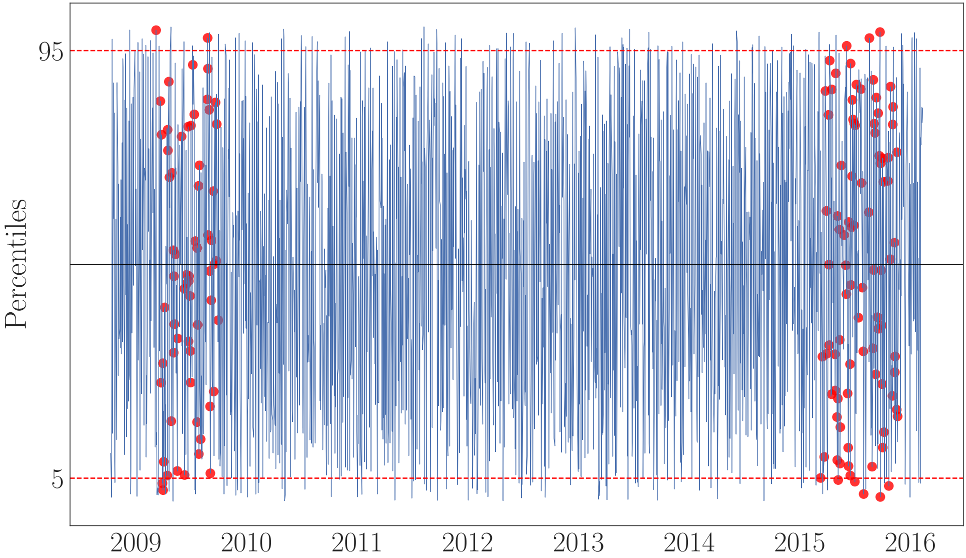


Discretion-Based Benchmarking





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