

1 Key takeaways

2 Strategy

3 Backtest

4 Comparison

5 Appendix

Pairs Trading on VIX and V2X

Ada Lau ada.lau@jpmorgan.com (<mailto:ada.lau@jpmorgan.com>)

1 Key takeaways

- Using a dynamic linear regression to describe the spread can give a better estimate than simple difference between VIX and V2X
- In the regression, we allow the coefficients β_0 and β_1 to vary over time, which can be estimated efficiently with the Kalman Filter
- The modified spread from Kalman Filter identifies fewer triggers (slightly more zero positions), and less extreme positions (where we cap at 0.5)
- However, if we smooth the positions and control turnover, we lose the edge using the Kalman Filter: It is probably because the Kalman Filter makes timely calls that may occasionally lead to larger turnover
- Using the raw Kalman Filter positions with $k = 1$ and $N = 20$ (1 month) gives the highest IR = 0.84, compared with the JPOSVVM2 (IR = 0.78)

2 Strategy

The strategy relies on the mean-reversion of the spread between VIX and V2X at a daily horizon. We consider 2 versions:

2.1 Simple model:

$$spread_t = VIX_t - V2X_t$$

Calculate the moving average μ and standard deviation σ of $spread$ in the past N days ($N = 10, 20$ or 40), so as to obtain lower and upper bounds:

$$\begin{aligned} low &= \mu - k\sigma \\ high &= \mu + k\sigma \end{aligned}$$

where k is a threshold parameter.

- If $spread < low$: Our exposure is $w = (low - spread)$ \ Long w on VIX, short w on V2X
- If $spread > high$: Our exposure is $w = (spread - high)$ \ Short w on VIX, long w on V2X

2.2 Kalman Filter

The simple strategy assumes that the cointegration relationship between VIX and V2X is constant. In terms of linear regression, we assume

$$VIX = 1 \times V2X + \epsilon$$

and we are taking $spread = \epsilon$.

To capture the spread in a more dynamic way, we can use a State Space model. Consider the following dynamics for the system:

$$VIX_t = \beta_{0,t} + \beta_{1,t}V2X_t + \epsilon_t$$

Writing it in matrix form,

$$\begin{aligned} VIX_t &= (\beta_{0,t}, \beta_{1,t}) \begin{pmatrix} 1 \\ V2X_t \end{pmatrix} + \epsilon_t \\ &= \beta_t \mathbf{X}_t + \epsilon_t \end{aligned}$$

We call β_t the state of the system, and assume that it follows a random walk:

$$\beta_{t+1} = \beta_t + \mathbf{w}_t$$

We can estimate the state β_t with a Kalman Filter. Essentially, we have a prior measure of β_t , and whenever we observe new values of VIX_t and $V2X_t$, we update our estimate for β_t . Hence this is also called a Dynamic Linear Model (DLM), or Bayesian regression.

The above model depends on an important parameter: Signal-to-Noise (SNR) ratio. For smaller values of SNR , we assume that the VIX and V2X observations are more noisy, and hence we put more weight on our prior β_t . As such, β_t will be smoother over time.



The strategy using Kalman Filter is similar to the simple one above, except that we consider a dynamic relationship between VIX and V2X:

$$spread_t = VIX_t - (\beta_{0,t} - \beta_{1,t}V2X_t)$$

Calculate the moving average μ and standard deviation σ of $spread$ in the past 20 days, so as to obtain lower and upper bounds:

$$\begin{aligned} low &= \mu - k\sigma \\ high &= \mu + k\sigma \end{aligned}$$

where k is a threshold parameter.

- If $spread < low$: Our exposure is $w = (low - spread)$ \ Long w on VIX, short w on V2X
- If $spread > high$: Our exposure is $w = (spread - high)$ \ Short w on VIX, long w on V2X

3 Backtest

The backtests below rebalance every day, and have considered transaction costs in rolling the 1st and 2nd contracts in the VIX futures (0.02) and V2X futures (0.03).

Two tuning parameters:

1. Different lookback windows (10 days for 2 weeks, 20 days for 1 month, 40 days for 2 months) for estimating the mean and standard deviation of the spread.
2. Different thresholds $k = 0.5, 0.75, 1$ for determining the lower and upper bounds that trigger our positions.

3.1 Controlling turnover by smoothing the positions

We also consider smoothing the daily positions w so that

1. Minimum threshold to make a change in position = 0.05:

If the absolute difference between w at t and our final position at $t - 1$ is smaller than 0.05, we simply keep our positions yesterday

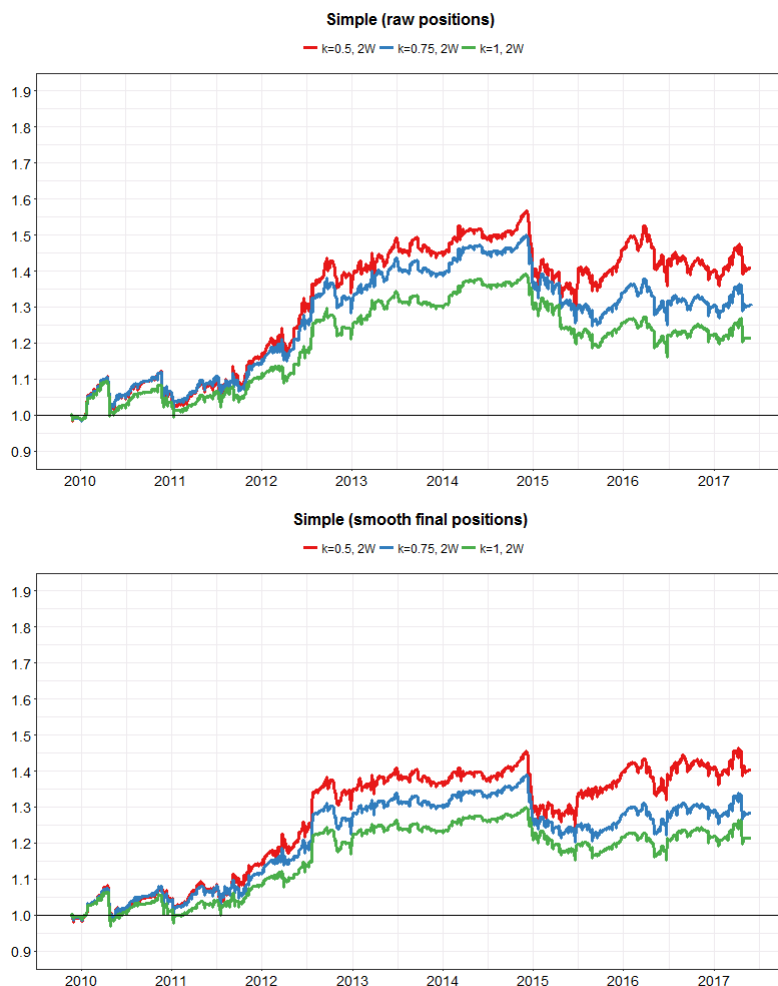
2. Maximum change in position = 0.2:

If the change between w at t and our final position at $t - 1$ is over 0.05, we allow the change in position, but cap it at a maximum change of 0.2

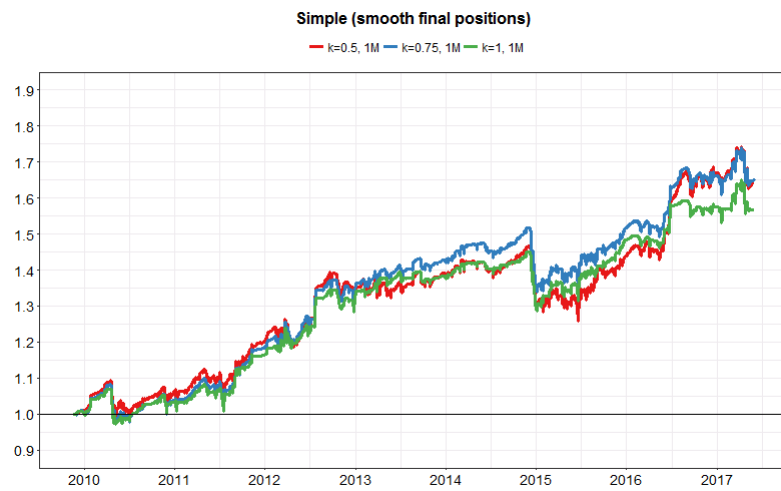
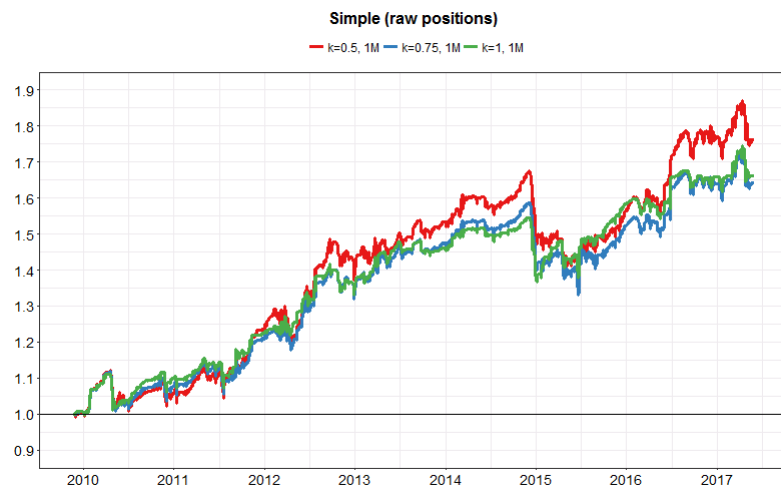
3. Maximum absolute position = 0.5

3.2 Simple model

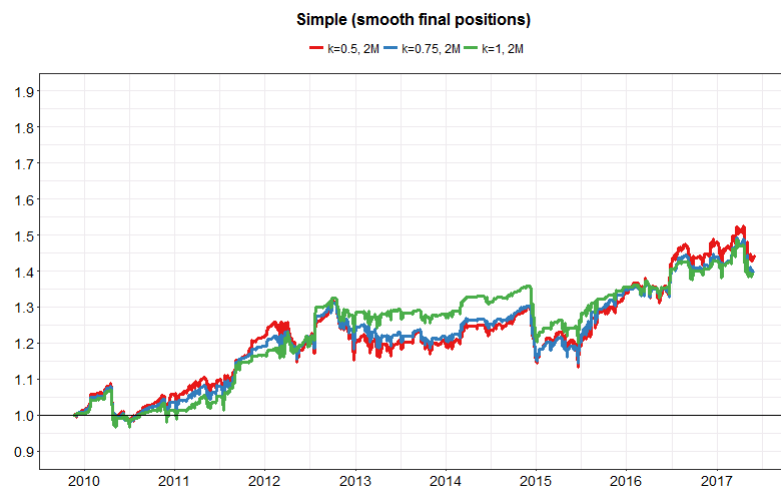
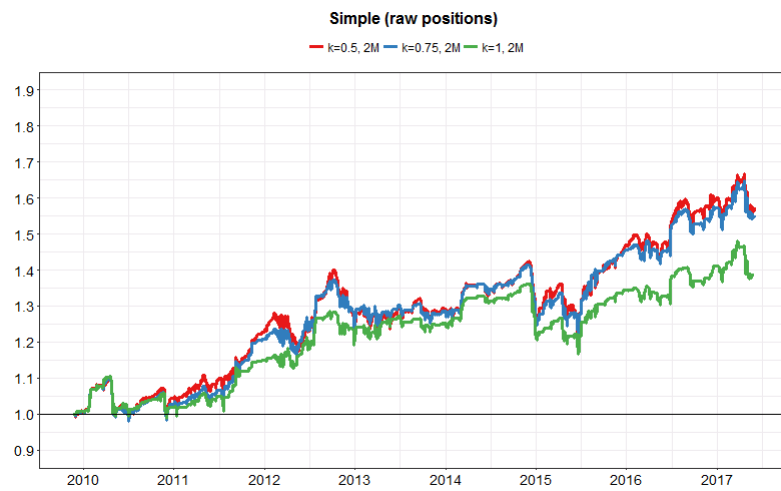
$N = 10$, 2 weeks:



$N = 20$, 1 month:



$N = 40, 2 \text{ months:}$



Simple model, raw positions

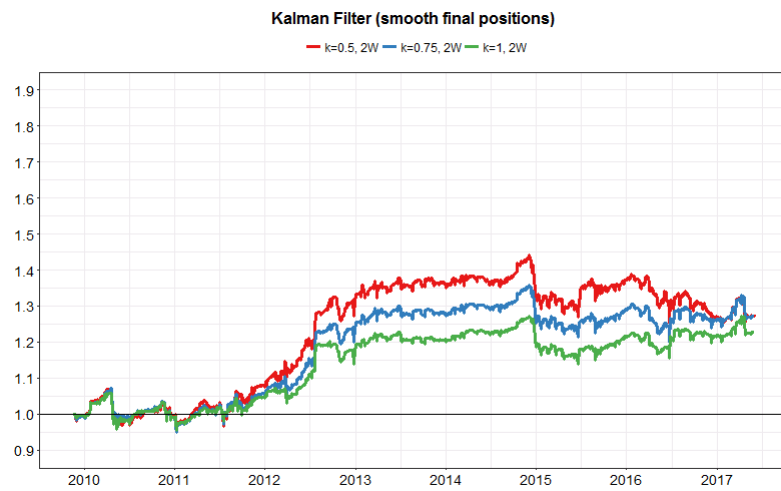
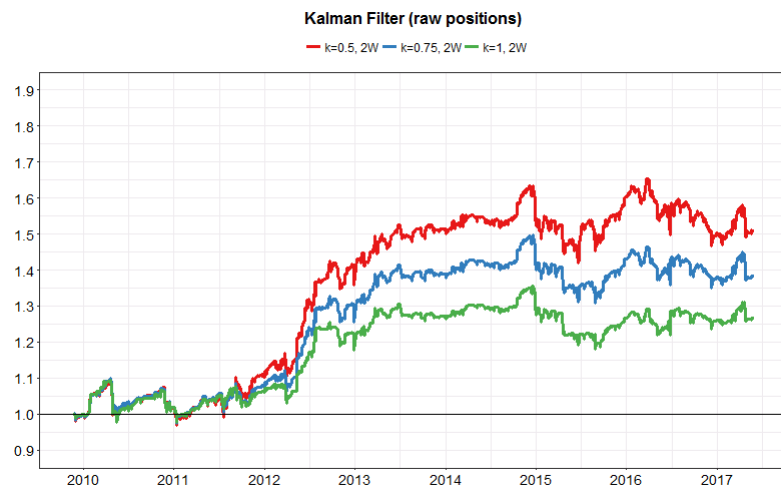
	start	end	CAGR	Vol	IR	maxDD
k=0.5, 2W	2009-11-24	2017-05-31	4.7	10.4	0.45	18
k=0.75, 2W	2009-11-24	2017-05-31	3.7	9.4	0.39	16.8
k=1, 2W	2009-11-24	2017-05-31	2.7	8.3	0.32	16.6
k=0.5, 1M	2009-11-24	2017-05-31	8	10.9	0.73	19.4
k=0.75, 1M	2009-11-24	2017-05-31	6.9	9.9	0.7	16.1
k=1, 1M	2009-11-24	2017-05-31	7.1	8.9	0.8	11.5
k=0.5, 2M	2009-11-24	2017-05-31	6.3	11.2	0.57	15.2
k=0.75, 2M	2009-11-24	2017-05-31	6.1	10.3	0.6	14
k=1, 2M	2009-11-24	2017-05-31	4.5	9.2	0.49	14.4

Simple model, smooth final positions

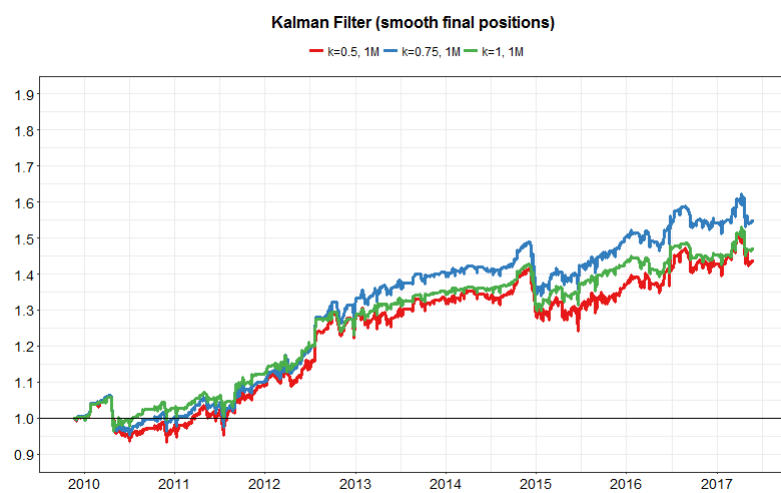
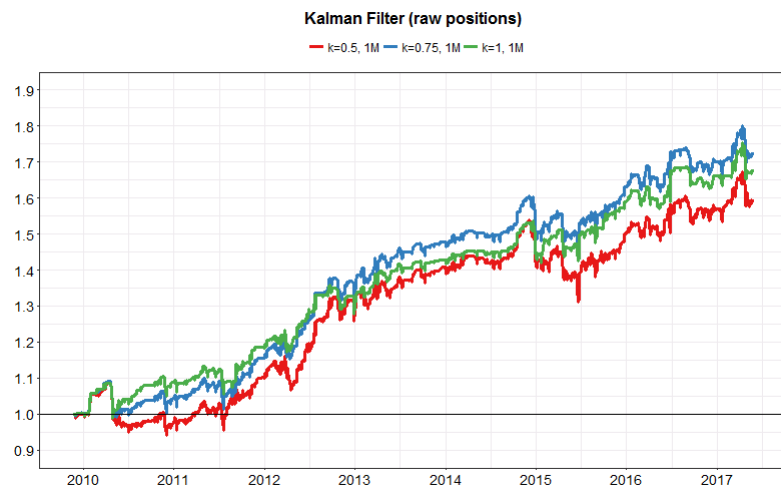
	start	end	CAGR	Vol	IR	maxDD
k=0.5, 2W	2009-11-23	2017-05-31	4.7	9.4	0.5	14.5
k=0.75, 2W	2009-11-23	2017-05-31	3.4	8.4	0.41	13.6
k=1, 2W	2009-11-23	2017-05-31	2.6	7.3	0.36	11.3
k=0.5, 1M	2009-11-23	2017-05-31	6.9	10	0.69	14.3
k=0.75, 1M	2009-11-23	2017-05-31	7	9	0.78	11.8
k=1, 1M	2009-11-23	2017-05-31	6.3	8.1	0.77	11.3
k=0.5, 2M	2009-11-23	2017-05-31	5	10.5	0.48	13.9
k=0.75, 2M	2009-11-23	2017-05-31	4.6	9.6	0.49	12.8
k=1, 2M	2009-11-23	2017-05-31	4.6	8.7	0.53	11.8

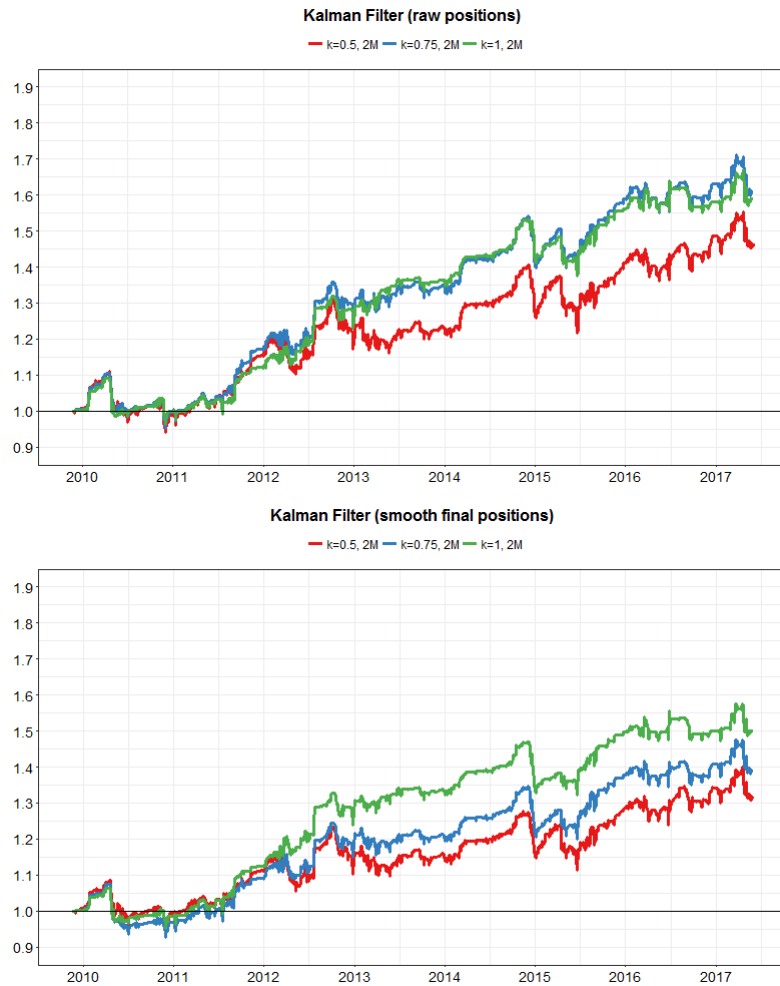
3.3 Kalman Filter

 $N = 10$, 2 weeks:



$N = 20, 1 \text{ month:}$



$N = 40$, 2 months:


Kalman Filter, raw positions

	start	end	CAGR	Vol	IR	maxDD
k=0.5, 2W	2009-11-24	2017-05-31	5.7	10.1	0.57	13.2
k=0.75, 2W	2009-11-24	2017-05-31	4.5	9.1	0.49	12.5
k=1, 2W	2009-11-24	2017-05-31	3.2	8.1	0.4	12.9
k=0.5, 1M	2009-11-24	2017-05-31	6.5	10.6	0.61	14.8
k=0.75, 1M	2009-11-24	2017-05-31	7.6	9.6	0.8	10.4
k=1, 1M	2009-11-24	2017-05-31	7.2	8.5	0.84	8.9
k=0.5, 2M	2009-11-24	2017-05-31	5.3	11.1	0.48	15.1
k=0.75, 2M	2009-11-24	2017-05-31	6.6	10	0.66	13.7
k=1, 2M	2009-11-24	2017-05-31	6.5	8.9	0.73	11.6

Kalman Filter, smooth final positions

	start	end	CAGR	Vol	IR	maxDD
k=0.5, 2W	2009-11-23	2017-05-31	3.3	9.1	0.37	13.8
k=0.75, 2W	2009-11-23	2017-05-31	3.3	8.1	0.41	11.5

	start	end	CAGR	Vol	IR	maxDD
k=1, 2W	2009-11-23	2017-05-31	2.8	7.2	0.39	10.5
k=0.5, 1M	2009-11-23	2017-05-31	5	10	0.5	12.4
k=0.75, 1M	2009-11-23	2017-05-31	6.1	8.8	0.69	10.4
k=1, 1M	2009-11-23	2017-05-31	5.3	7.8	0.69	9.2
k=0.5, 2M	2009-11-23	2017-05-31	3.8	10.6	0.36	13.3
k=0.75, 2M	2009-11-23	2017-05-31	4.5	9.4	0.48	13.8
k=1, 2M	2009-11-23	2017-05-31	5.6	8.3	0.68	10.5

4 Comparison

- In both models, smoothing with 1 month lookback window gives the highest risk-adjusted returns.
- JPOSVVM2 Index is the simple model with threshold $k = 0.75$ and lookback $N = 20$, with smoothing to control position turnover.



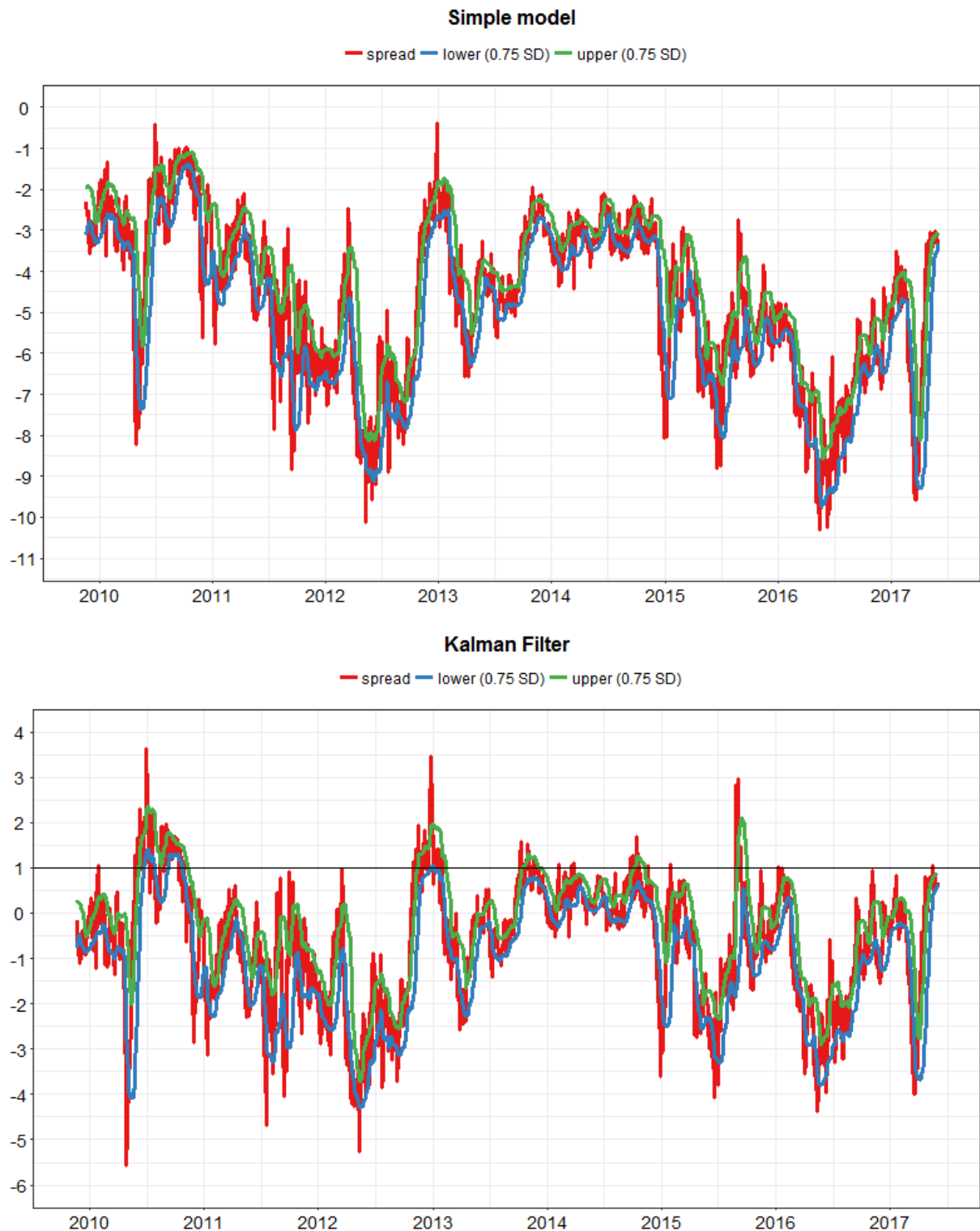
Compare with JPOSVVM2

	start	end	CAGR	Vol	IR	maxDD
KF, raw, k=0.75, 1M	2009-11-24	2017-05-31	7.6	9.6	0.8	10.4
KF, raw, k=1, 1M	2009-11-24	2017-05-31	7.2	8.5	0.84	8.9
JPOSVVM2 (Simple, smooth, k=0.75, 1M)	2009-11-24	2017-05-31	7	9	0.78	11.8

5 Appendix

5.1 Spreads

Comparing the spreads of the models, estimated with 1 month (20 days) lookback period:



5.2 Extreme positions

Below gives an idea of the positions from 2009-11-23 to 2017-05-31 (1864 days in total). We find that the Kalman Filter takes more zero positions, and hits the maximum less frequent than the simple model:

Different raw positions (no. of days)

	Simple, raw, k=0.75, 1M	Kalman Filter, raw, k=0.75, 1M
zero	697	724
0.5	237	212
-0.5	224	203

Smoothing reduces the large positions, and increase the number of days with non-zero positions.

Different smoothed positions (no. of days)

	Simple, smooth, k=0.75, 1M	Kalman Filter, smooth, k=0.75, 1M
zero	568	591
0.5	145	115
-0.5	151	140