

# System Identification Approach applied to Jitter Estimation.

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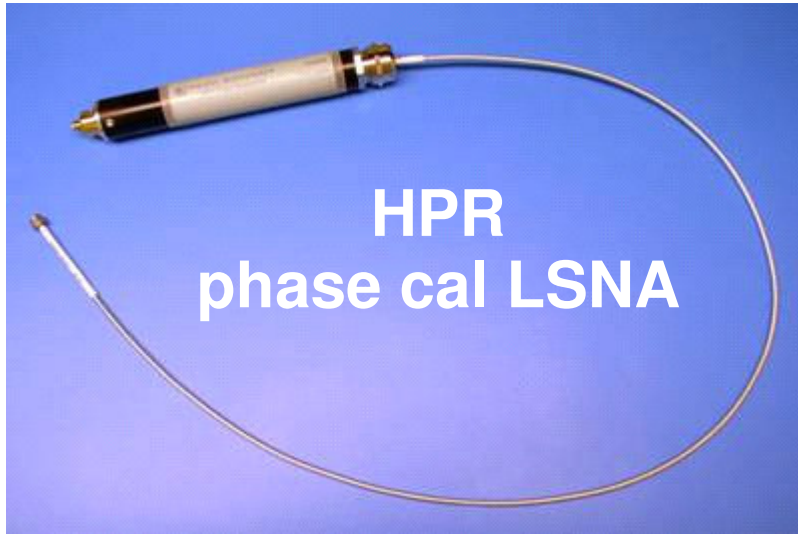


# Outline

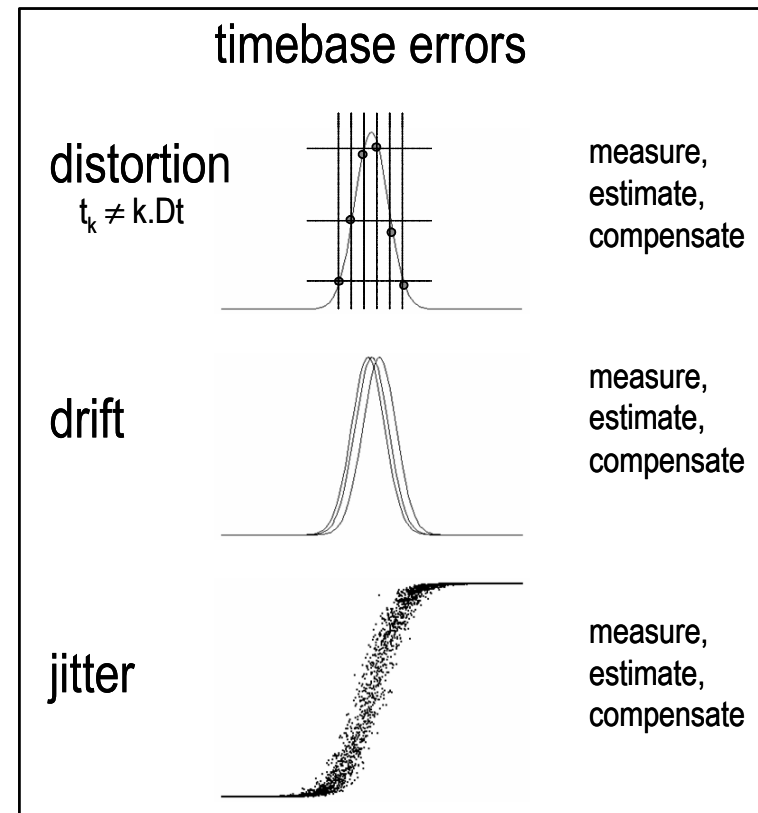
- **Motivation**
- **Introduction**
  - **Model**
  - **Estimators**
- **Simulations**
- **Measurements**
  - **Challenges**
  - **Results**
- **Conclusions**



# Motivation



calibrated  
sampling oscilloscope



# Model

$$y(t_i) = y_0(t_i + n_t(t_i)) + n_y(t_i)$$

$$n_t \sim N(0, \sigma_{n_t}) \quad n_y \sim N(0, \sigma_{n_y})$$

**1<sup>st</sup> order  
model**

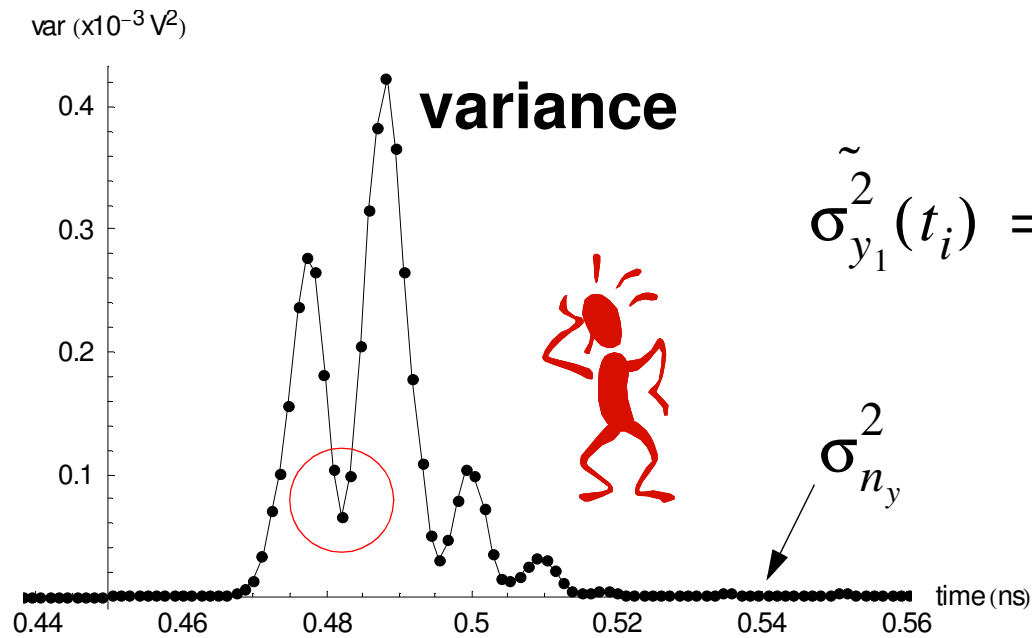
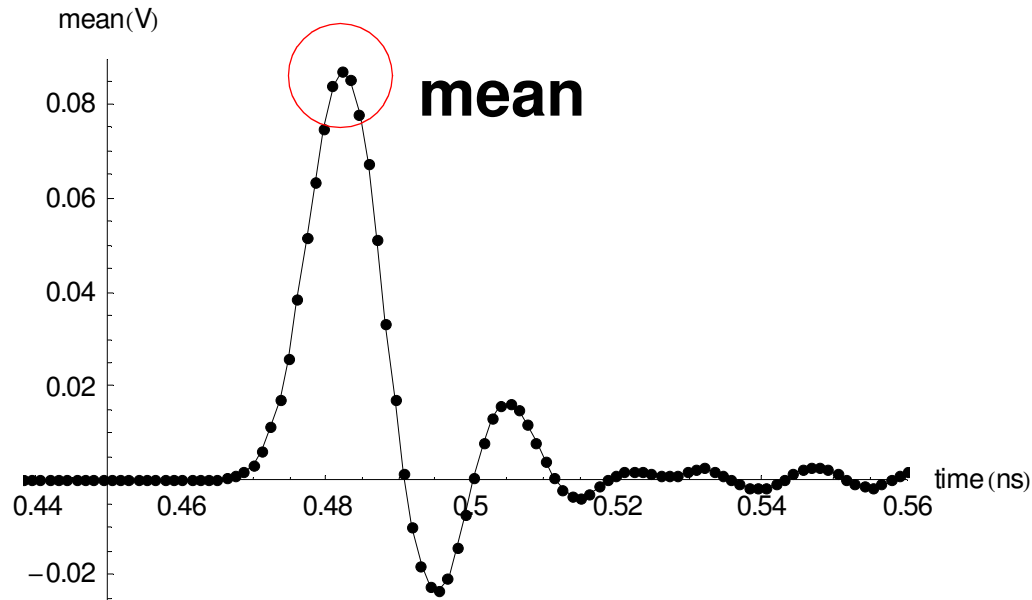
$$\tilde{y}_1(t_i) = y_0(t_i) + \left. \frac{dy_0}{dt} \right|_{t=t_i} \cdot n_t(t_i) + n_y(t_i)$$

$$E[\tilde{y}_1(t_i)] = y_0(t_i)$$



$$\sigma_{\tilde{y}_1}^2(t_i) = \sigma_{n_y}^2 + \left. \left( \frac{dy_0}{dt} \right)^2 \right|_{t=t_i} \cdot \sigma_{n_t}^2$$





$$\tilde{\sigma}_{y_1}^2(t_i) = \sigma_{n_y}^2 + \left( \frac{dy_0}{dt} \right)^2 \Big|_{t=t_i} \cdot \sigma_{n_t}^2$$



# Extended model

$$\tilde{y}_3(t_i) = y_0(t_i) + \sum_{k=1}^3 \frac{1}{k!} \cdot \left. \frac{d^k y_0}{dt^k} \right|_{t=t_i} \cdot n_t^k(t_i) + n_y(t_i)$$

3<sup>rd</sup> order  
model

$$E[\tilde{y}_3(t_i)] = y_0(t_i) + \frac{1}{2} \cdot \left. \left( \frac{d^2 y_0}{dt^2} \right) \right|_{t=t_i} \cdot \sigma_{n_t}^2$$

$$y_0(t) = A \sin \omega t \quad \Rightarrow \quad \text{img} \quad E[\tilde{y}_3(t_i)] = A(1 - \omega^2 \sigma_{n_t}^2 / 2) \cdot \sin \omega t$$

$$\begin{aligned} \sigma_{y_3}^2(t_i) = & \sigma_{n_y}^2 + \left. \left( \frac{dy_0}{dt} \right)^2 \right|_{t=t_i} \cdot \sigma_{n_t}^2 \quad \text{img} \\ & + \left[ \frac{1}{2} \cdot \left. \left( \frac{d^2 y_0}{dt^2} \right)^2 + \left( \frac{dy_0}{dt} \right) \cdot \left( \frac{d^3 y_0}{dt^3} \right) \right] \Big|_{t=t_i} \cdot \sigma_{n_t}^4 \\ & + \frac{5}{12} \cdot \left. \left( \frac{d^3 y_0}{dt^3} \right)^2 \right|_{t=t_i} \cdot \sigma_{n_t}^6 \end{aligned}$$

# Estimators

$$V_{(W)LS} = \sum_{i=1}^N e^2(t_i) \quad e(t_i) = \left[ \sigma_{t_i}^2 - \underbrace{\tilde{\sigma}_y^2(t_i, \theta)}_{\text{model}} \right] / W_i$$

$$\theta = [\sigma_{n_y}^2, \sigma_{n_t}^2]^T$$

**estimates**

$$X_i \sim N(0, 1) \quad \Rightarrow \quad \sum_{i=1}^r X_i^2 \sim \chi_r^2$$

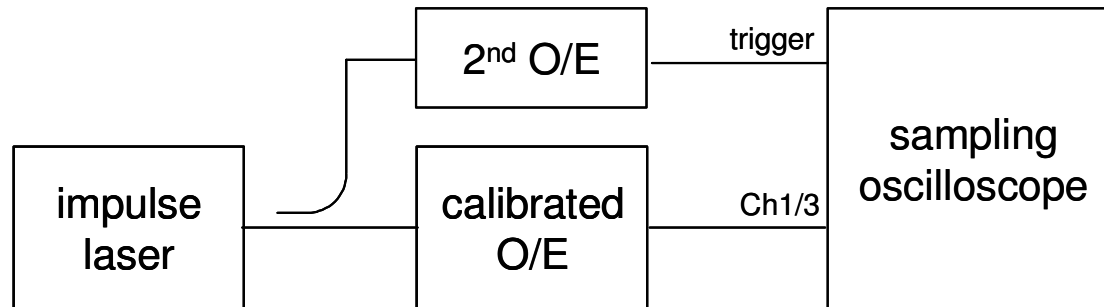
$$V_{ML} = n/2 \cdot \sum_{i=1}^N \left[ \ln \tilde{\sigma}_y^2(t_i, \theta) + \sigma_{t_i}^2 / \tilde{\sigma}_y^2(t_i, \theta) \right]$$

**solve nonlinear problem**

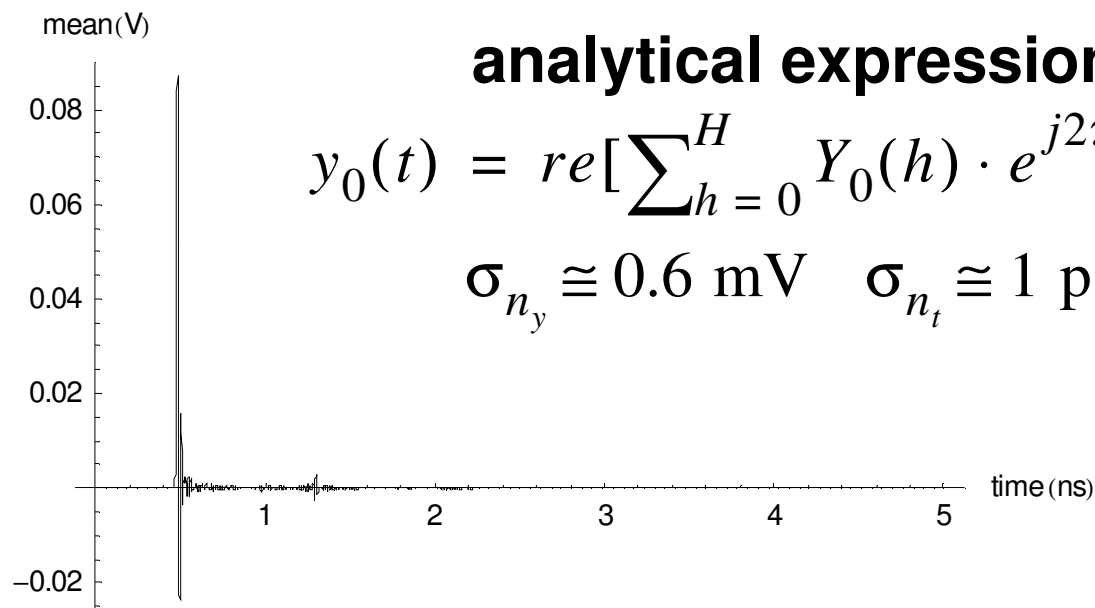


# Simulations

“as realistic as possible”



**Tracy Clement  
@ NIST**





# Simulations

$$\sigma_{n_y} = 0.6 \text{ mV} \quad \sigma_{n_t} = 0 \dots 2 \text{ ps} \quad (\Delta = 0.2 \text{ ps})$$

$$y_0(t) = \text{re} \left[ \sum_{h=0}^H Y_0(h) \cdot e^{j2\pi h \cdot \Delta f \cdot t} \right]$$

**step 1: use 3rd order model to generate data (variance)**

$$\begin{aligned} \tilde{\sigma}_{y_3}^2(t_i) &= \sigma_{n_y}^2 + \left( \frac{dy_0}{dt} \right)^2 \Big|_{t=t_i} \cdot \sigma_{n_t}^2 \\ &+ \left[ \frac{1}{2} \cdot \left( \frac{d^2 y_0}{dt^2} \right)^2 + \left( \frac{dy_0}{dt} \right) \cdot \left( \frac{d^3 y_0}{dt^3} \right) \right] \Big|_{t=t_i} \cdot \sigma_{n_t}^4 \\ &+ \frac{5}{12} \cdot \left( \frac{d^3 y_0}{dt^3} \right)^2 \Big|_{t=t_i} \cdot \sigma_{n_t}^6 \end{aligned}$$

**step 2 & 3: use realistic variance**

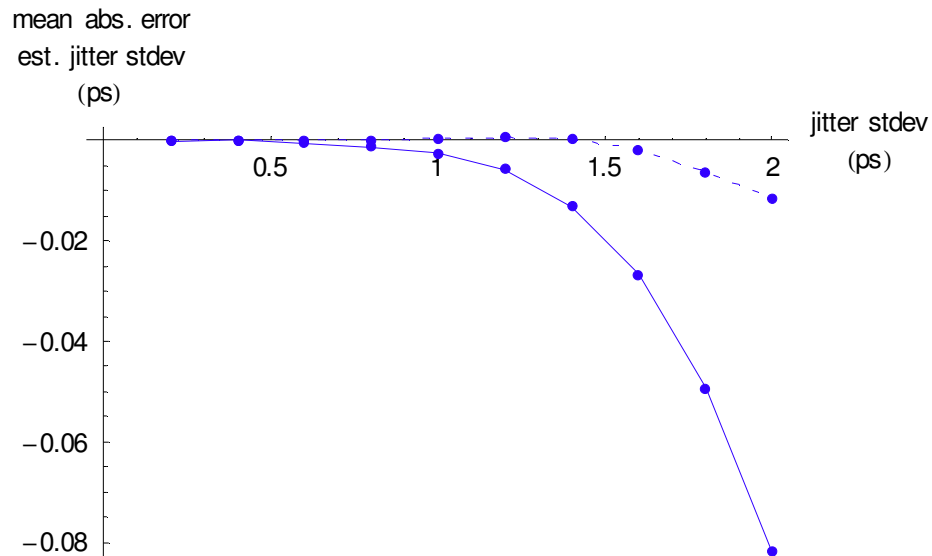
$$y(t_i) = y_0(t_i + n_t(t_i)) + n_y(t_i)$$



# Simulation results

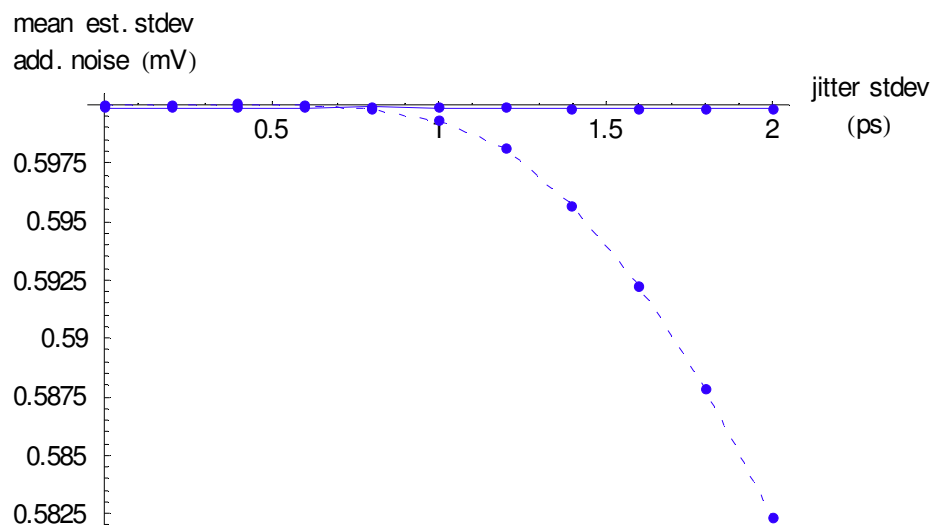
step 3: use realistic variance

**jitter**

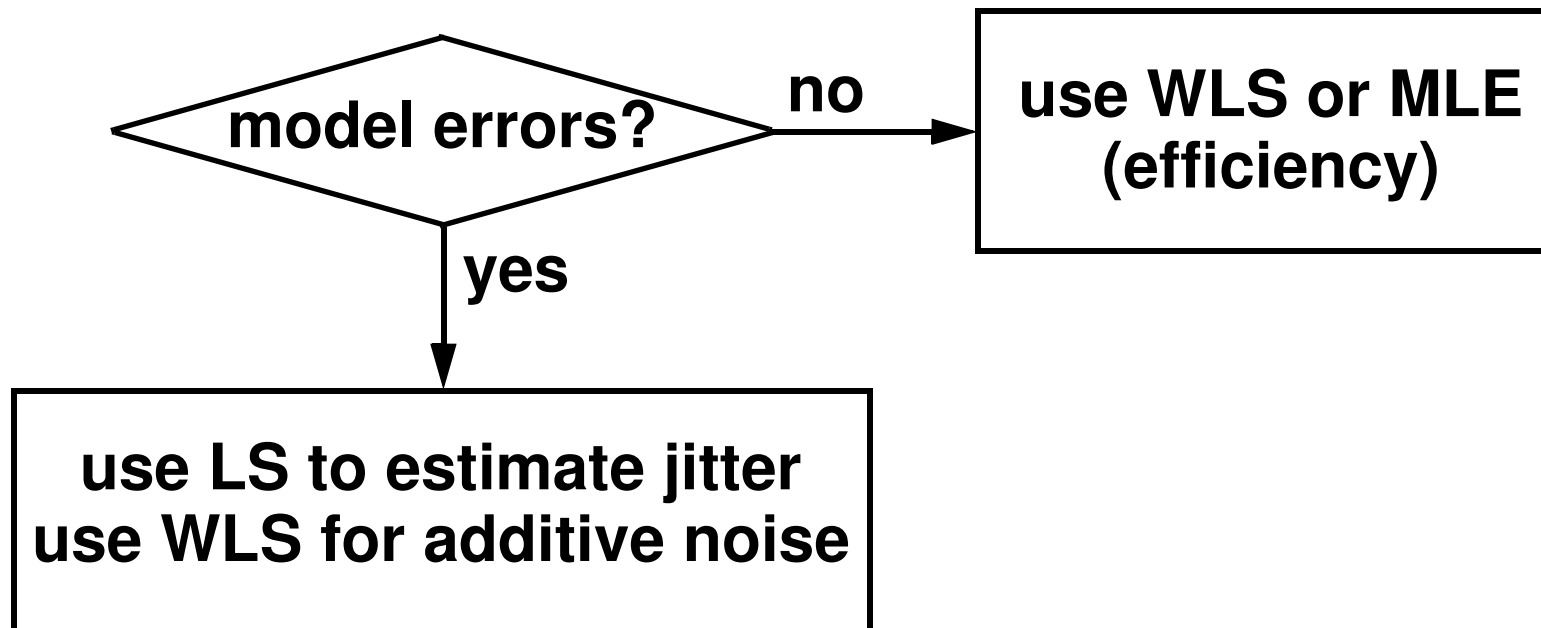
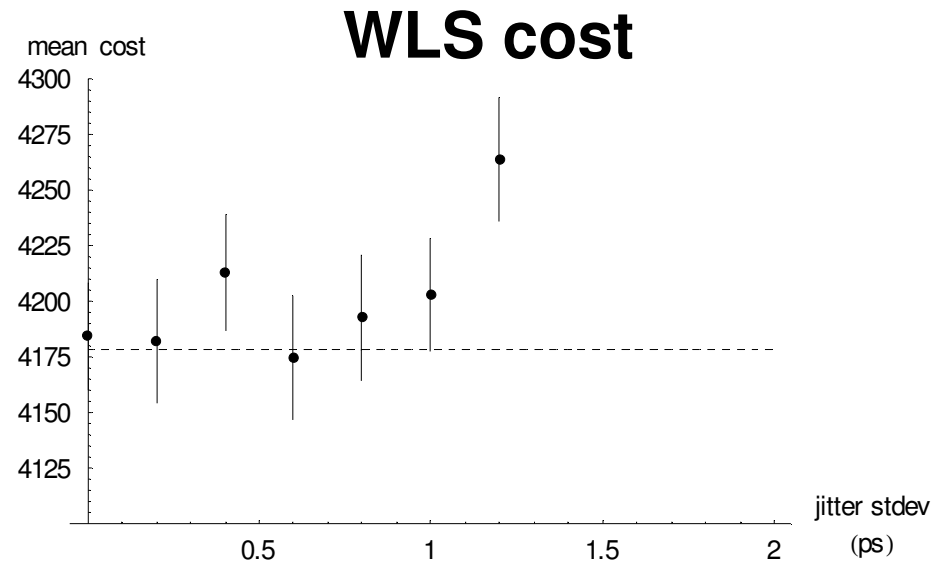


--- 3<sup>rd</sup> order LS  
— 3<sup>rd</sup> order WLS

**additive**

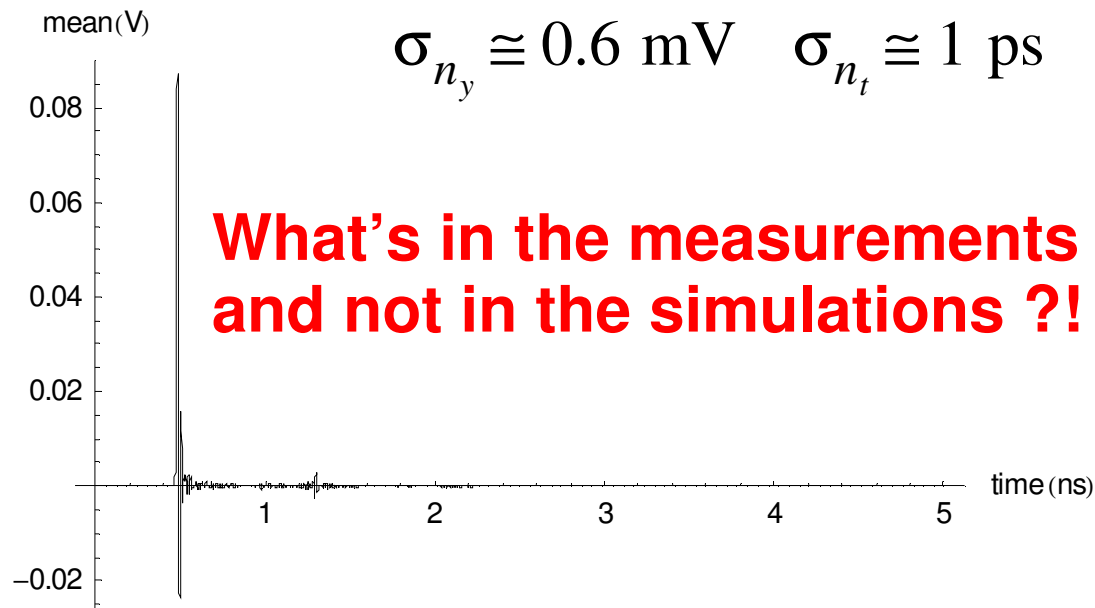
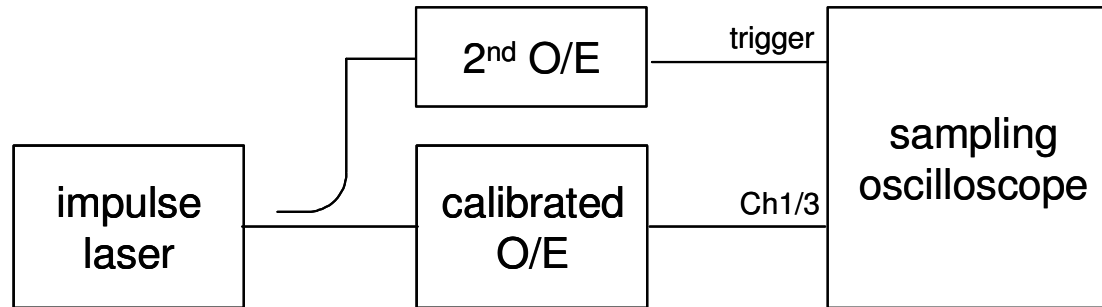


# Guidelines



# Measurements

poor fit of variance



# Time base drift

given arbitrary  $\tau$

**variance of delayed signal  $\neq$  delayed variance of signal**

**except for  $\tau = m\Delta t$  ( $m \in Z$ )**



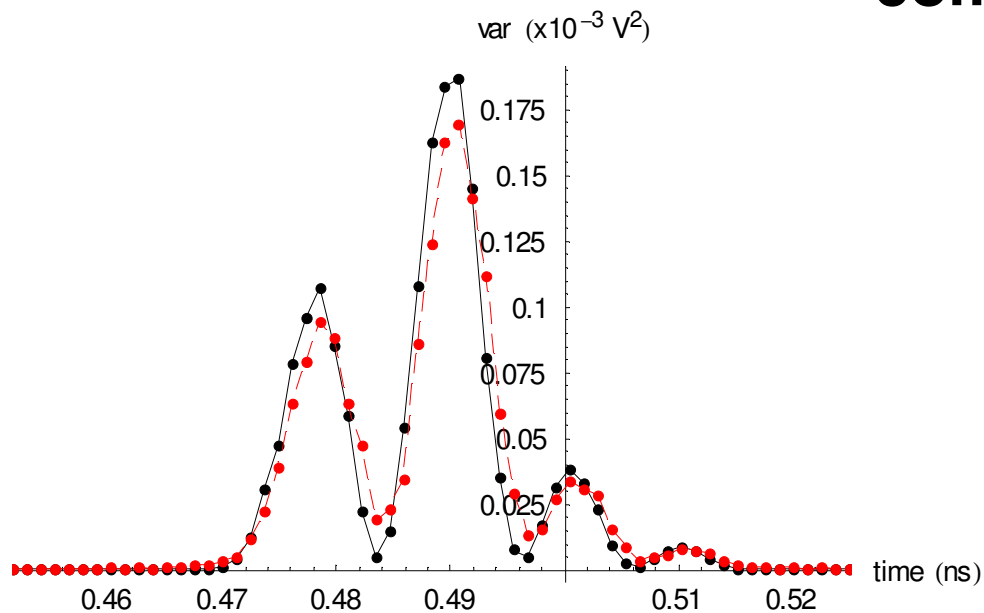
# Shaping of variance by TBDt

1000 realizations of pulse  
sample variance

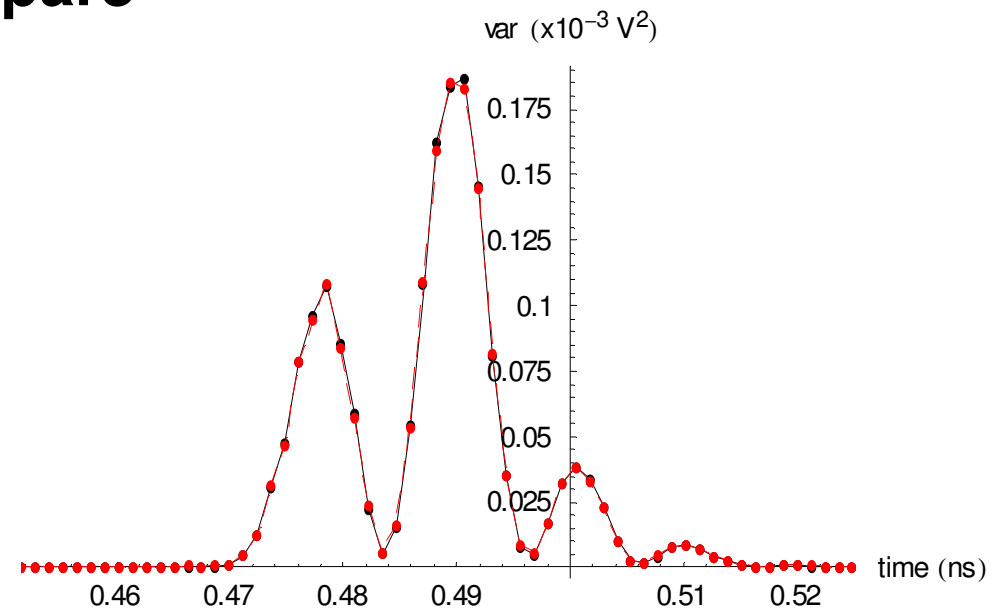


apply delay  $\tau$   
sample variance  
apply delay  $-\tau$

compare



$$\tau = \Delta t / 2$$



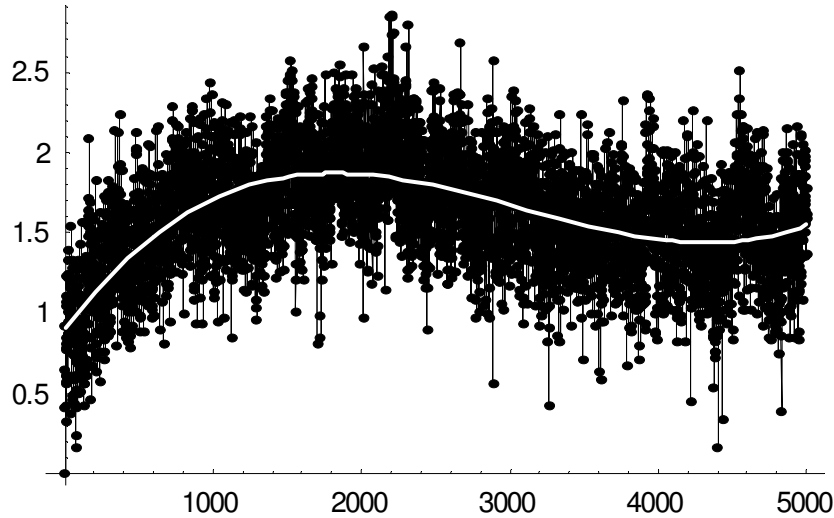
$$\tau = \Delta t / 10$$



# 2-step solution

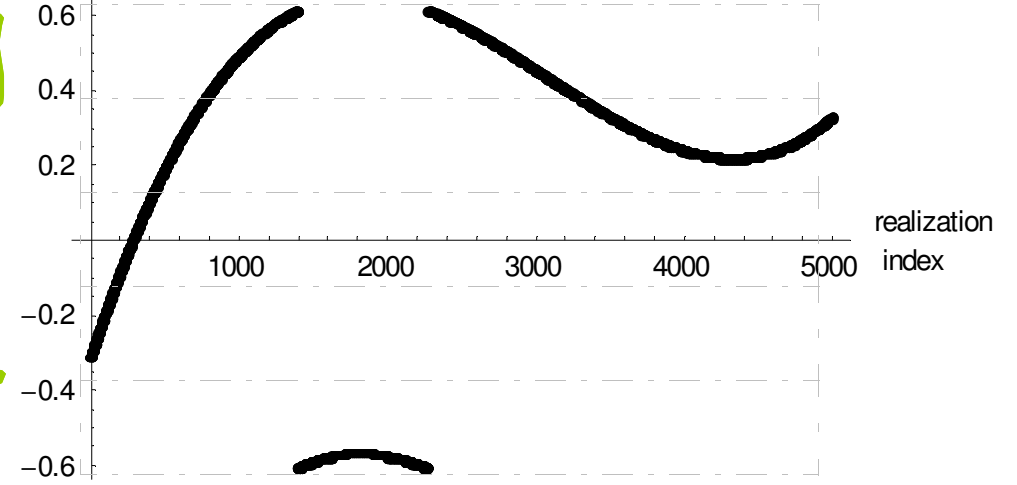
apply delay of  $k \cdot \Delta t$   
align in buckets of  $\Delta t/5$  wide

estimated  
drift (ps)



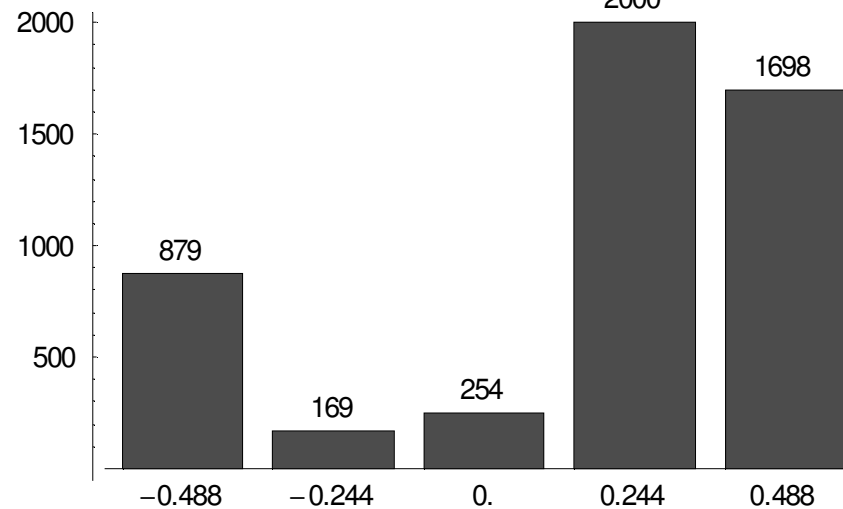
realization  
index

drift (ps)



**varying  
variance  
of  
sample  
variance**

# realizations  
per bucket

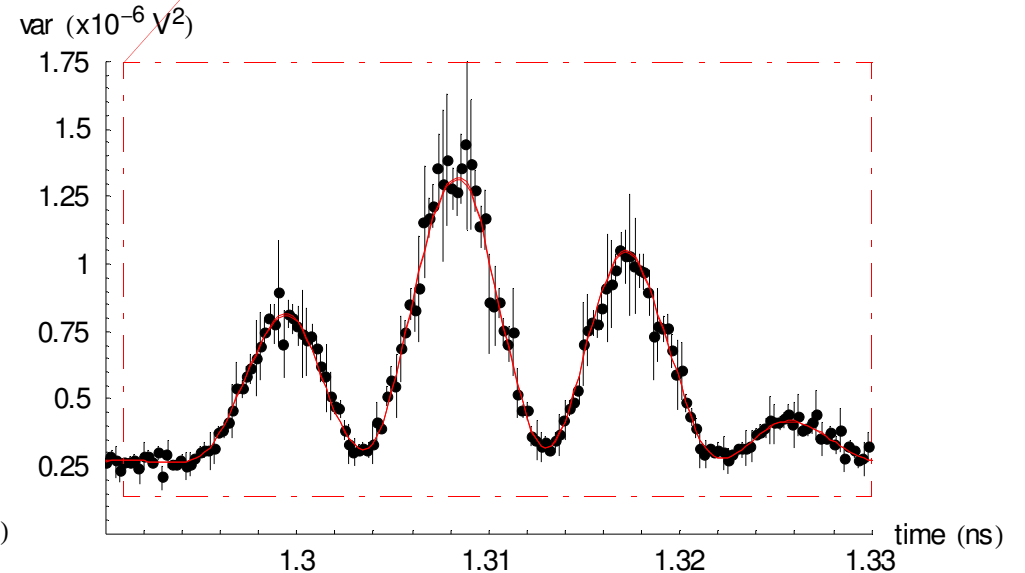
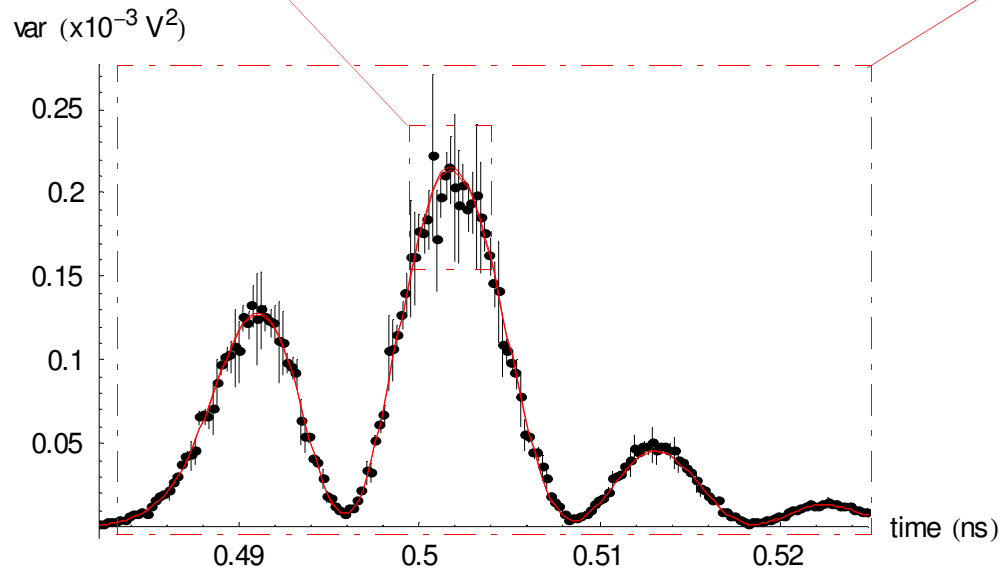
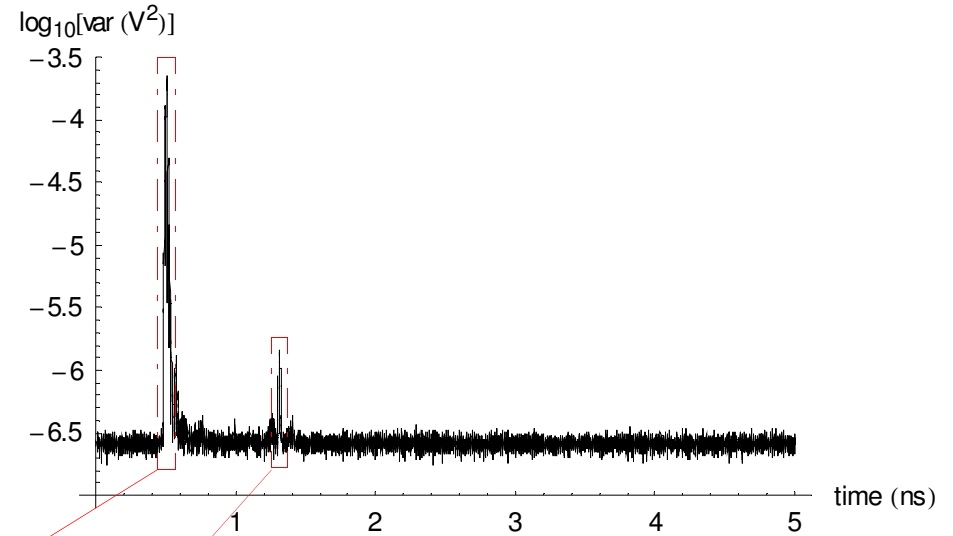
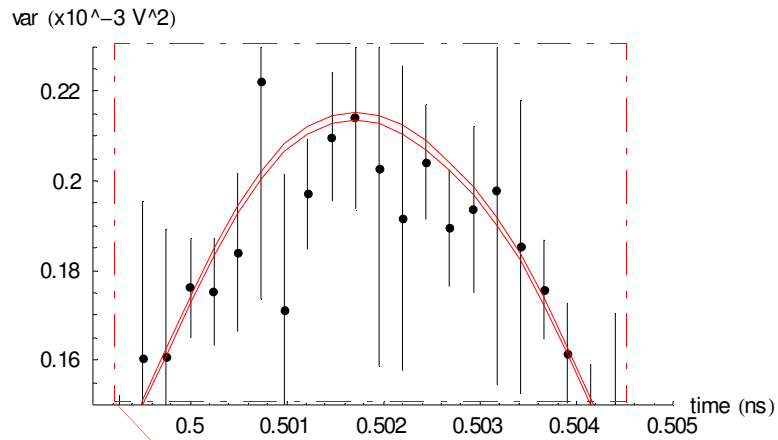


time (ps)

**max. drift  
compensation  
=  $\Delta t/10$**



# WLS results



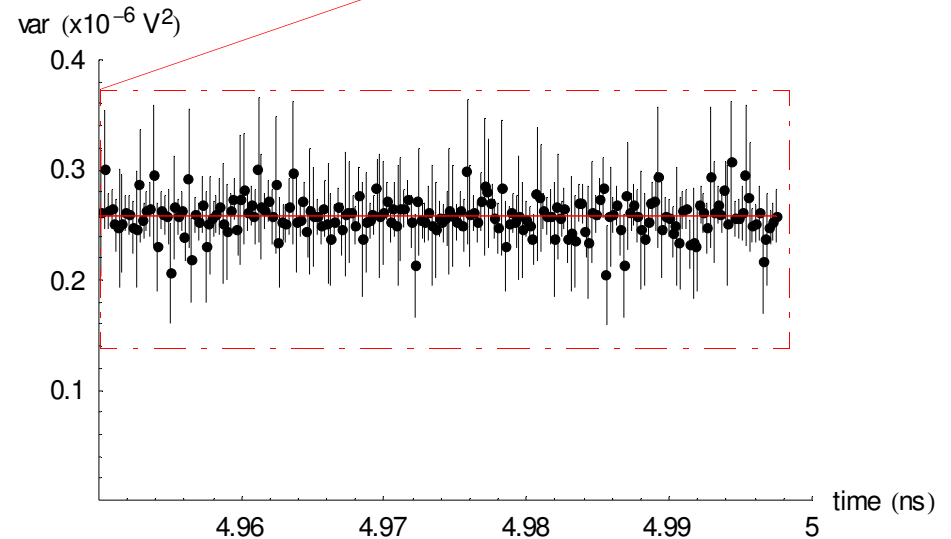
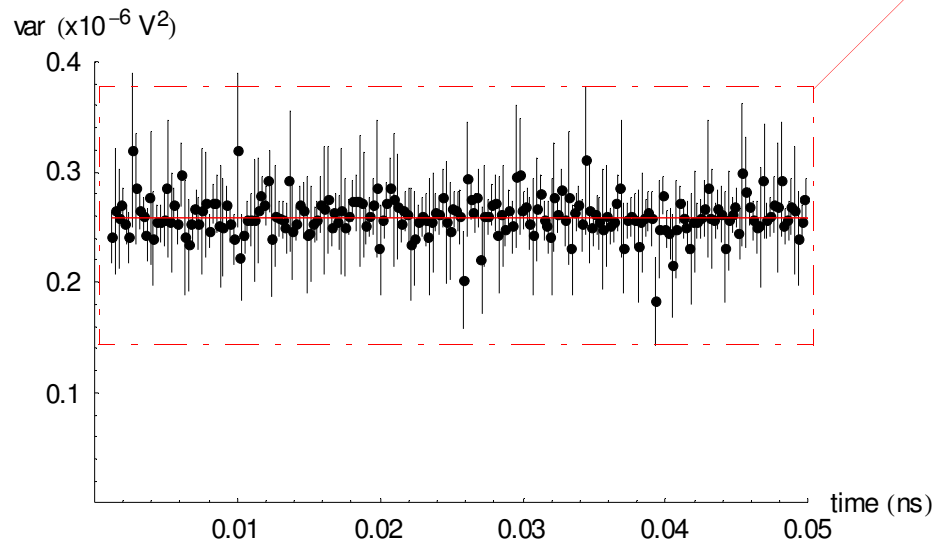
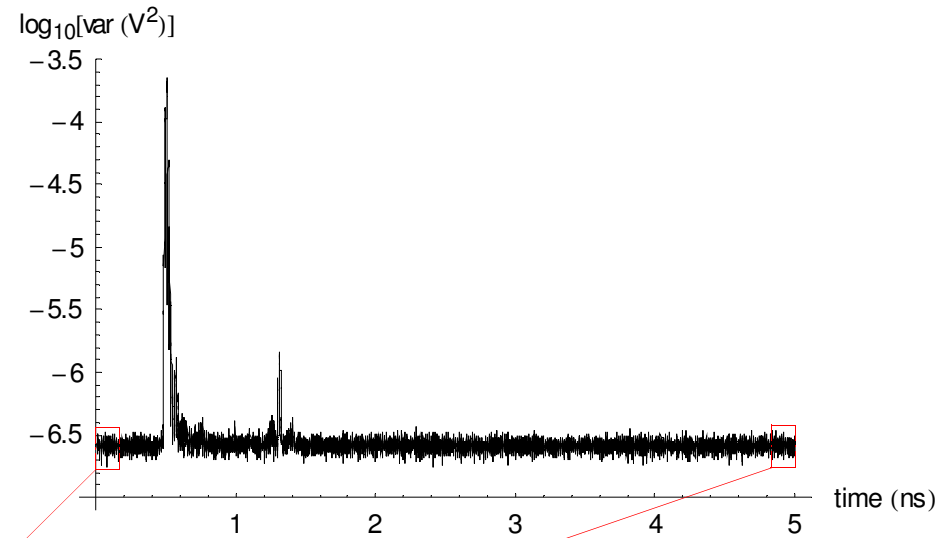
$$\sigma_{n_t} = 0.965 \pm 0.0023 \text{ ps}$$





# WLS results

expected value cost:  
**20464 ± 397**  
realized value cost:  
**21830 = +7%**



$$\sigma_{n_y} = 0.508 \pm 0.00016 \text{ mV}$$

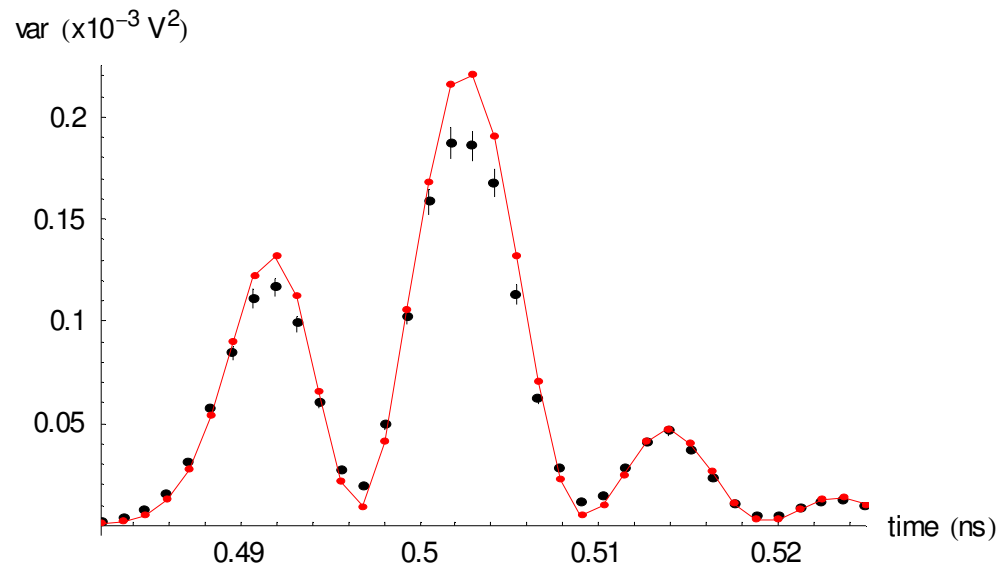


# The power of ...

What if we don't limit drift compensation to  $\Delta t/10$  ?

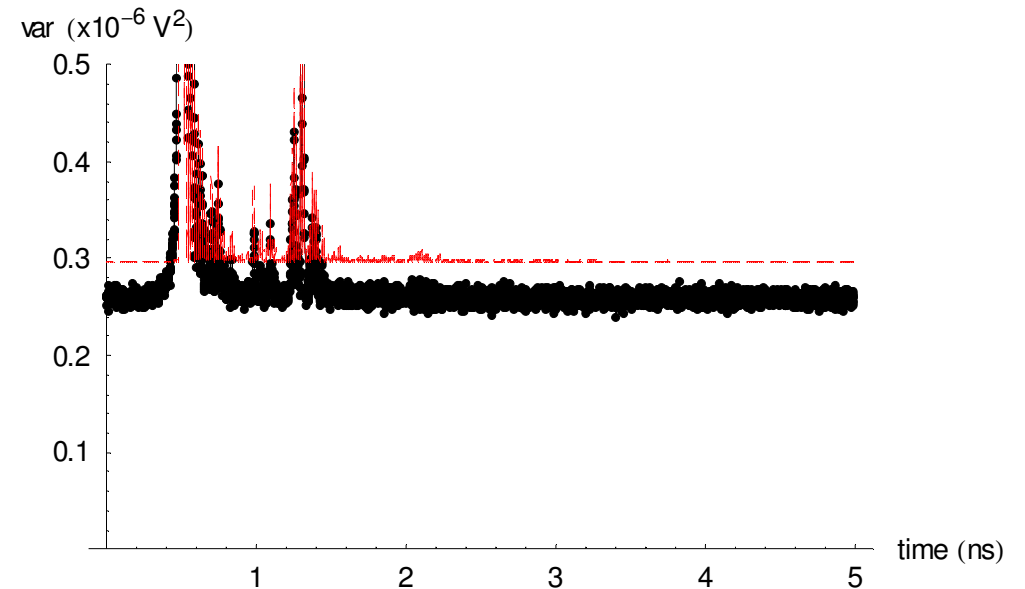
## 3rd order WLS

expected value cost:  $4212 \pm 188$   
realized value cost: 14764 (x 3.5)



## 1st order LS

bias of more than 10% on the estimate of the variance of the additive noise



# Conclusions

- extension and/or enhancement of existing methods
- able to detect model errors and anomalies
- error bounds on estimates and modeled variance
- simultaneous estimation of variance of additive noise and jitter noise
  
- **system identification works !**
- **also at microwaves !**
- **and it's not that difficult !**

