**Discussion of:**

# 'Rare Shocks, Great Recessions' by Vasco Curdia, Marco Del Negro, Daniel Greenwald

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ESSIM, Tarragona, 22 May 2012

**The question that this paper studies:**

Suppose we use a linear model of the macroeconomy.

**Which is the best way to model shocks?**

- Gaussian
- Occasionally large i.i.d. shocks (**t**), or
- Gradually time-varying volatility of shocks (**SV**)

**The empirical evidence in this paper:**

This paper estimates a linear model of the macroeconomy with shocks that are either gaussian, or **t**, or **SV**, or both **t** and **SV**.

Findings:

- Models with **t** and/or **SV** fit the data much better than the commonly used model with gaussian shocks.

- **t** is important even in presence of **SV** (they complement each other)

**My main comment**

Missing a natural third alternative to gaussian shocks:

(1) Occasionally large i.i.d. shocks (**t**)

(2) Gradually time-varying volatility of shocks (**SV**)

**(3) Abruptly time-varying volatility of shocks (RS)**

$\rightarrow$ **R**egime **S**witches, like Sims and Zha (2006) and others

**My main comment**

Missing a natural third alternative to gaussian shocks:

(1) Occasionally large i.i.d. shocks (**t**)
$\hookrightarrow$ a large shock can occur suddenly, expect nothing

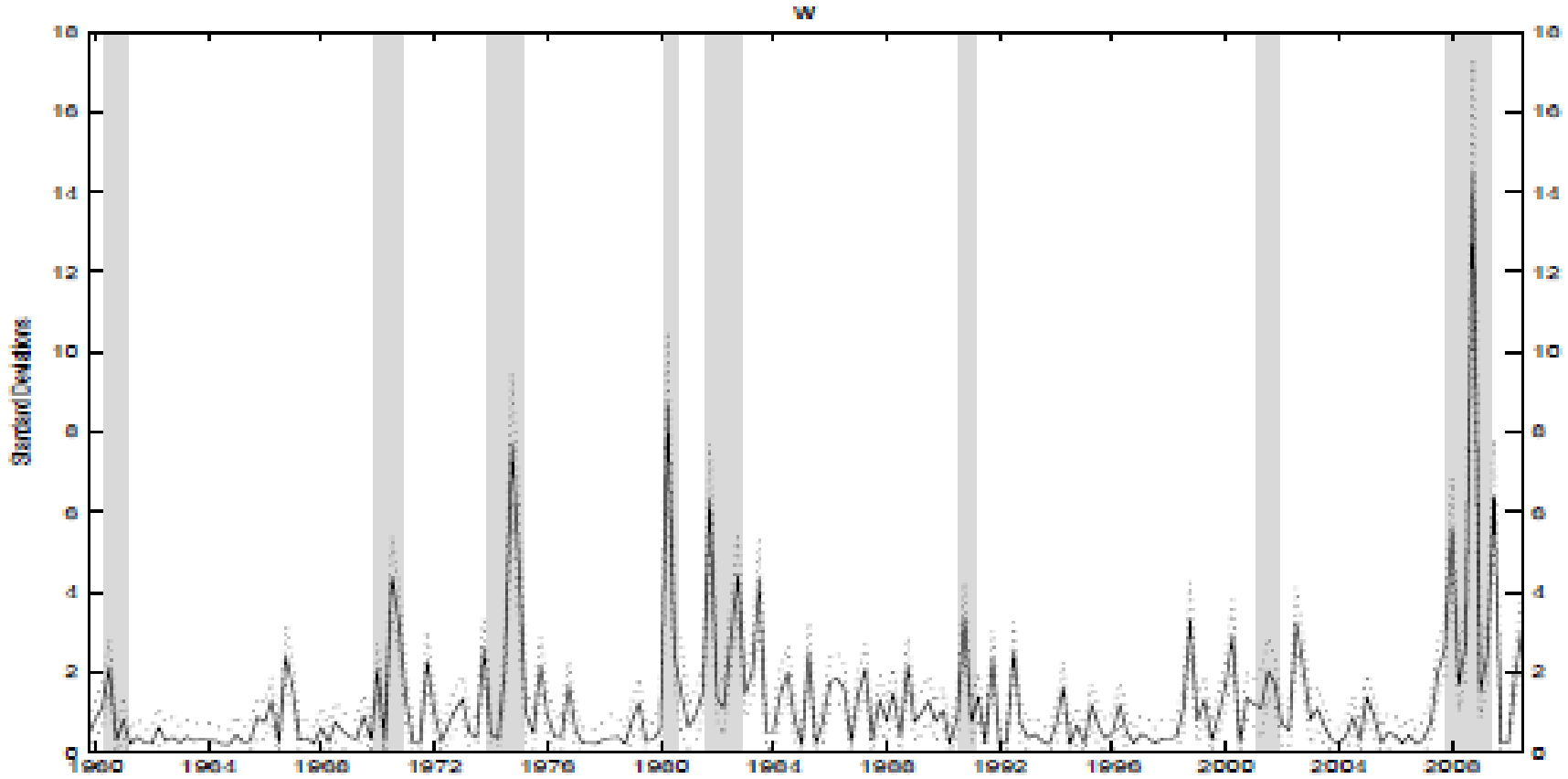
(2) Gradually time-varying volatility of shocks (**SV**)
$\hookrightarrow$ after a large shock we expect more large shocks

**(3) Abruptly time-varying volatility of shocks (RS)**

$\hookrightarrow$ a large shock can occur suddenly $\rightarrow$ like **t**

$\hookrightarrow$ after a large shock we expect more large shocks $\rightarrow$ like **SV**

Marco's paper: Fig.2a - enterpreneurial risk shock, assuming t distribution



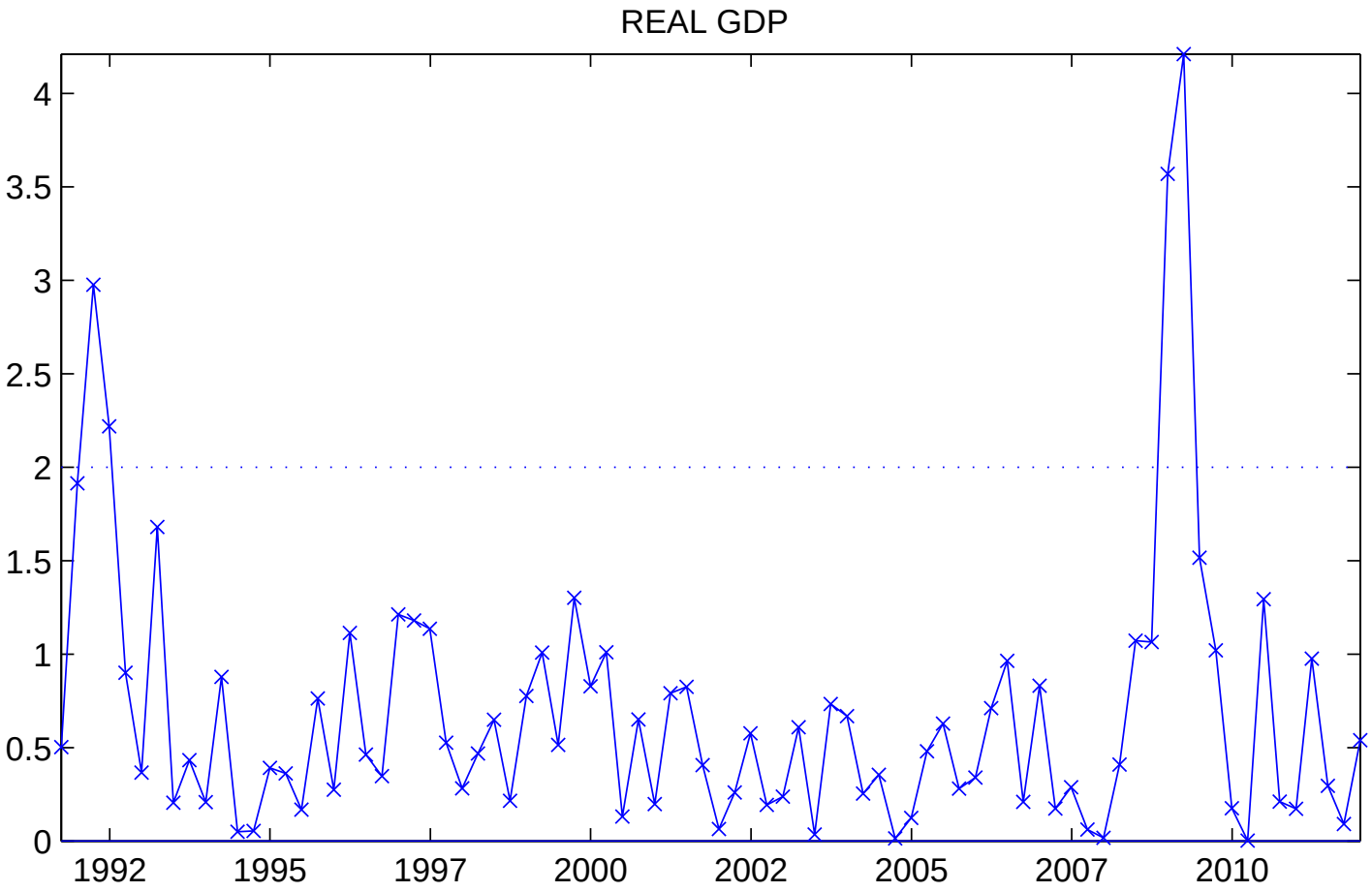
Other evidence (euro area):

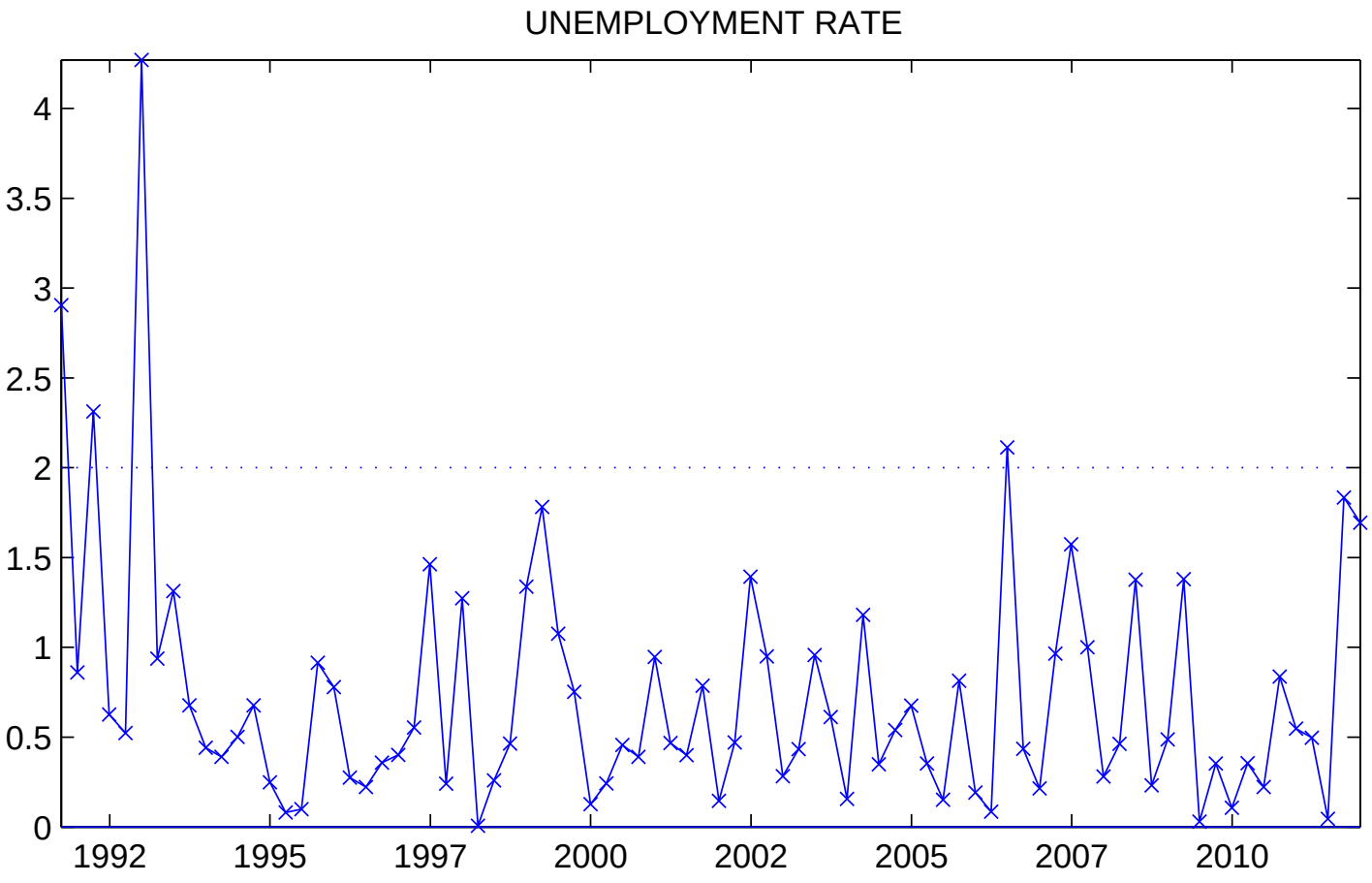
I estimate a reduced form Bayesian VAR for the euro area with 8 macroeconomic variables, assuming gaussian shocks, orthogonalize shocks using Choleski

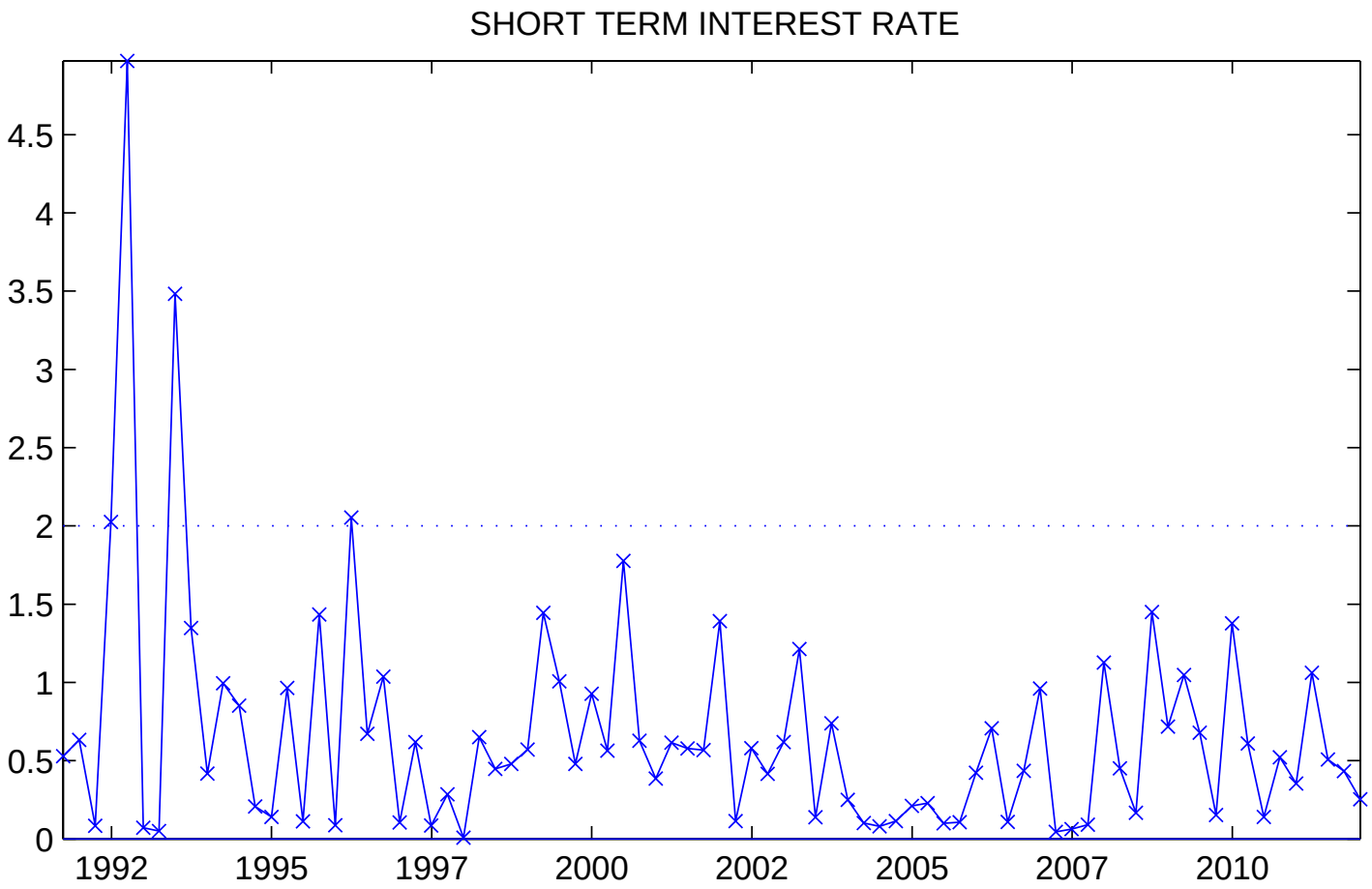
Findings:

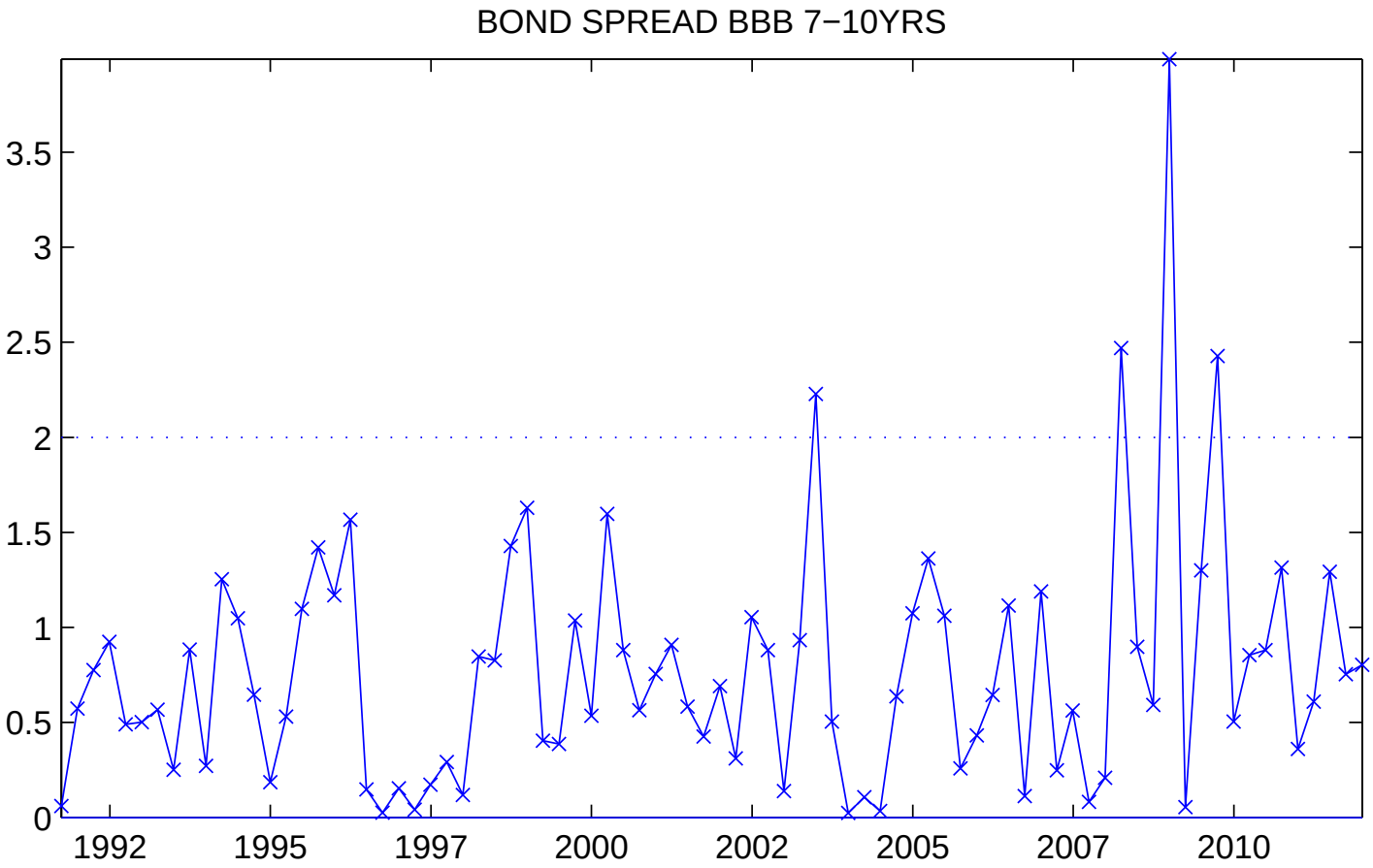
- shocks are sometimes large ($>>$ 2std)
- large shocks often come 2-3 in a row

Plots of some shocks:


REAL GDP
4
3.5
3
2.5
2
1.5
1
0.5
0
1992
1995
1997
2000
2002
2005
2007
2010


UNEMPLOYMENT RATE
4
3.5
3
2.5
2
1.5
1
0.5
0
1992
1995
1997
2000
2002
2005
2007
2010


SHORT TERM INTEREST RATE
4.5
4
3.5
3
2.5
2
1.5
1
0.5
0
1992
1995
1997
2000
2002
2005
2007
2010


BOND SPREAD BBB 7−10YRS
3.5
3
2.5
2
1.5
1
0.5
0
1992
1995
1997
2000
2002
2005
2007
2010

**Do these shocks look like i.i.d. t?**

No, we observe too many runs of large shocks

Monte Carlo:

- I generate 100,000 sequences of 200 draws each from **t**
- For each sequence I record the longest run of large (abs.$>$3std) draws with up to i) 0, ii) 1, iii) 2 small draws between any two large draws

Marco's paper: Fig.2a - enterpreneurial risk shock, assuming t distribution

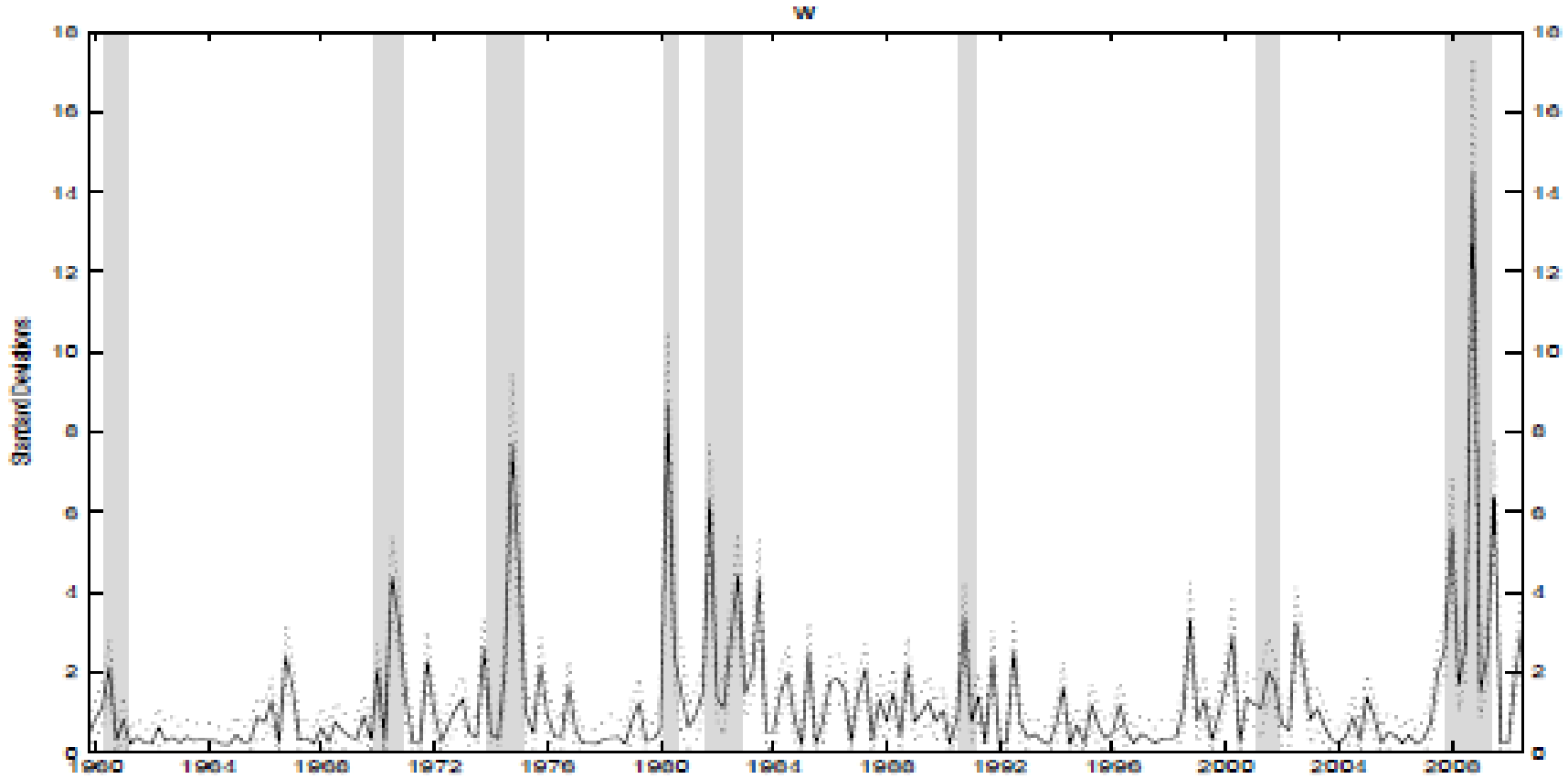


Table 1: Runs of realizations >3 stdev in 100,000 sequences of 200 draws, allowing up to 2 small draws between any two large draws within a run

| | run length | no. of sequences with the maximum run of this length | no. of sequences with more than one run of this length |
|---|---|---|---|
| | 0 | 90 | |
| | 1 | 86,036 | 79,722 |
| **t** | 2 | 13,353 | 462 |
| | **3** | **507** | **0** |
| | 4 | 14 | 0 |
| | 5 | 0 | 0 |

**RS with two regimes for the variance**

$$\varepsilon_t \sim N(0, \sigma^2_{s_t})$$

$$s_t = \{1, 2\}, \qquad \sigma^2_1 = 1, \qquad \sigma^2_2 = 10$$

$$p(s_{t+1} = 1 | s_t = 1) = p_{11}, \qquad p(s_{t+1} = 2 | s_t = 1) = 1 - p_{11}$$

$$p(s_{t+1} = 2 | s_t = 2) = p_{22}, \qquad p(s_{t+1} = 1 | s_t = 2) = 1 - p_{22}$$

I choose $p_{11}$ and $p_{22}$ so that
state 1 has expected duration of 40 quarters and
state 2 has expected duration of 4 quarters.

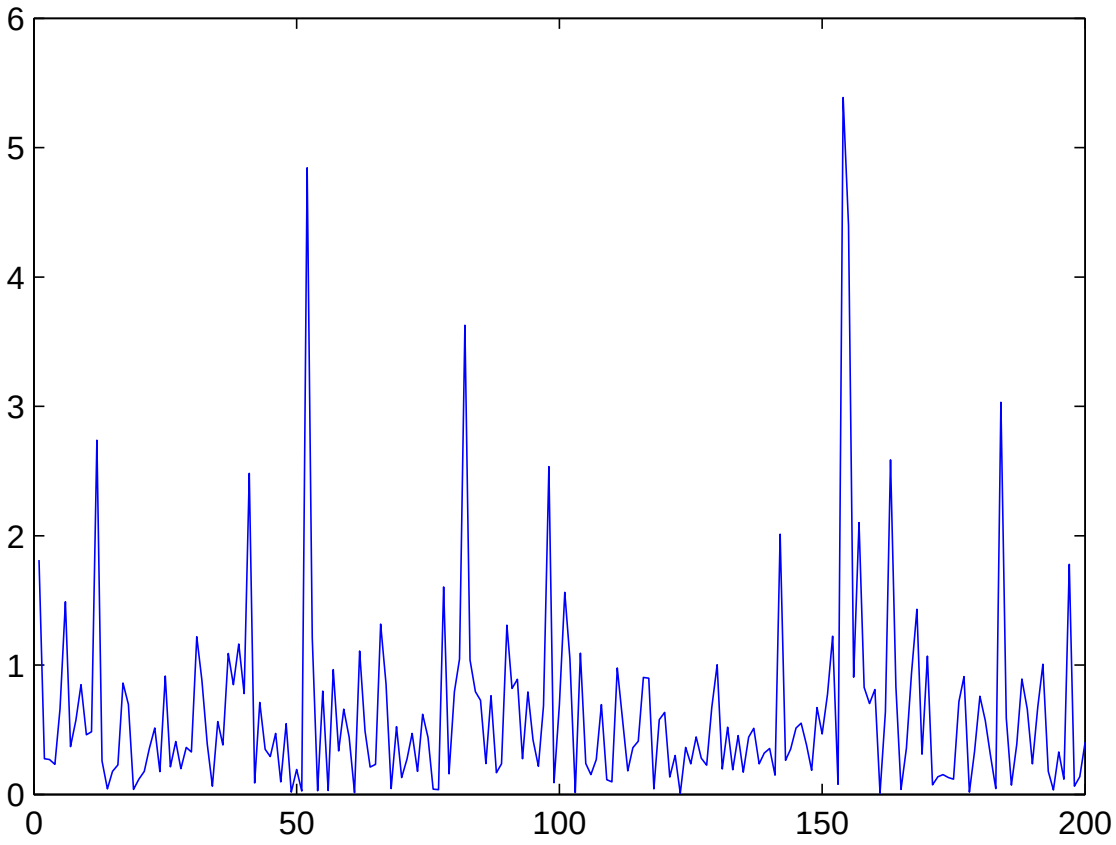
Table 2: Runs of realizations >3 stdev in 100,000 sequences of 200 draws, allowing up to 2 small draws between any two large draws within a run

| | run length | no. of sequences with the maximum run of this length | no. of sequences with more than one run of this length |
|---|---|---|---|
| | 0 | 90 | |
| | 1 | 86,036 | 79,722 |
| **t** | 2 | 13,353 | 462 |
| | **3** | **507** | **0** |
| | 4 | 14 | 0 |
| | 5 | 0 | 0 |
| | | | |
| | 0 | 514 | |
| | 1 | 10,193 | 8,124 |
| **RS** | 2 | 37,851 | 17,047 |
| | **3** | **30,732** | **2,929** |
| | 4 | 13,625 | 174 |
| | 5 | 4,850 | 5 |

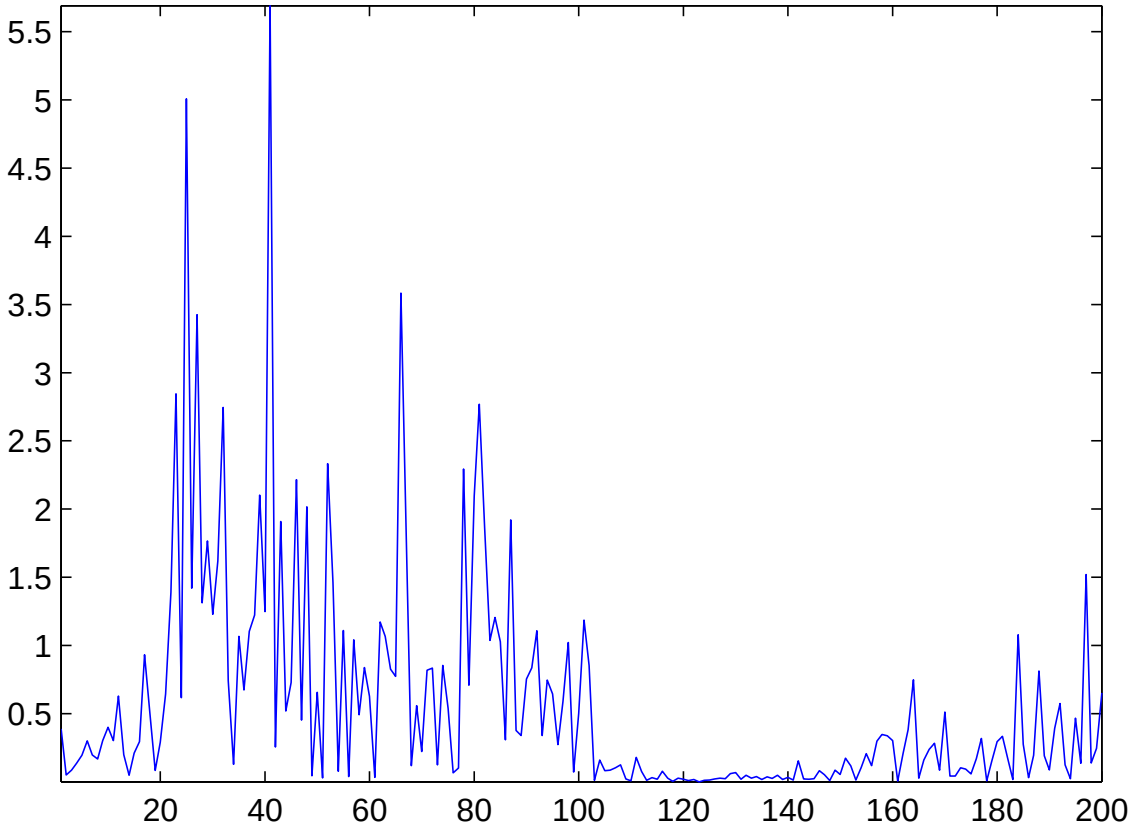
**What do t, SV and RS shocks look like?**

Plots of some *simulated* sequences of 200 shocks:

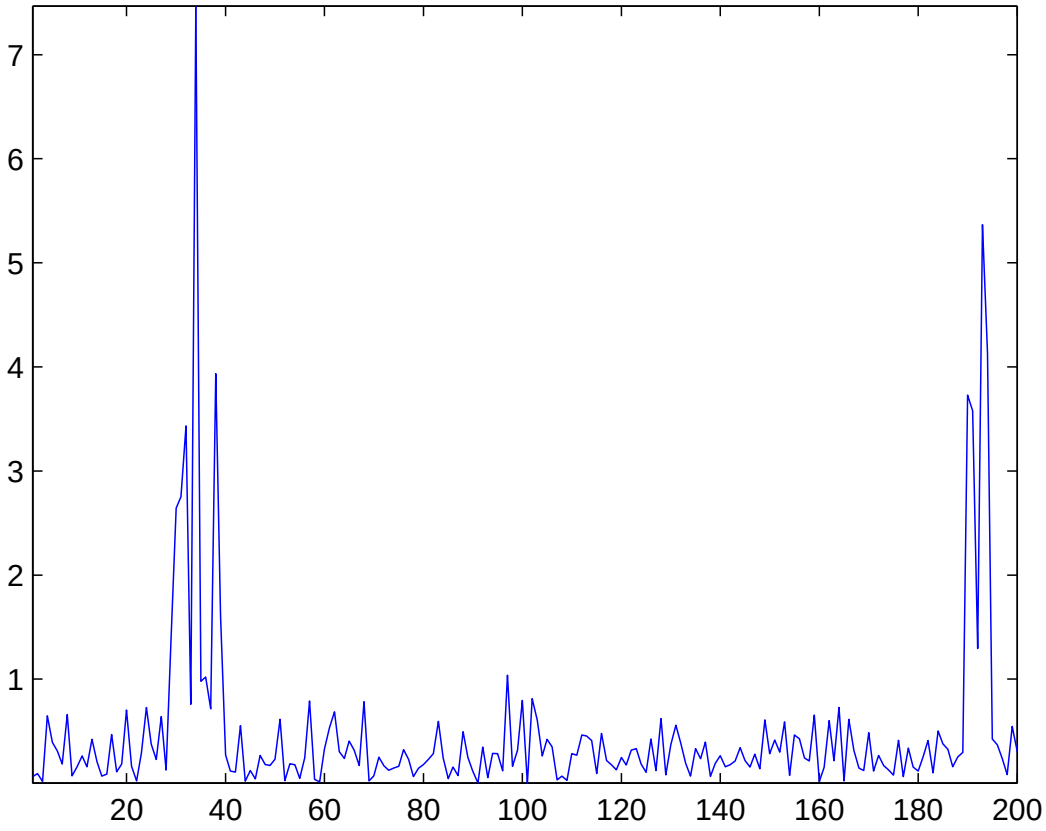
**t** - no runs



**SV** - has periods with very low volatility $\rightarrow$ we never observe such periods in the data



# RS



## Conclusions

- This paper reports convincing evidence on the importance of non-gaussian shocks
  - I confirm this evidence with euro area data

- **RS** is a natural alternative to **t** and **SV**

**Terminology and References for this discussion**

Terminology:

do simulations from the model look like the data? $\rightarrow$ 'prior predictive analysis'
maximum run length $\rightarrow$ 'checking function'

References:

Box, George (1980), Sampling and Bayes Inference in Scientific Modeling and Robustness, Journal of the Royal Statistical Society.

Geweke, John (2010), Bayesian Model Comparison and Validation, American Economic Review Papers and Proceedings.