

Trend analysis

A relevant tool to assess post-regulation impacts

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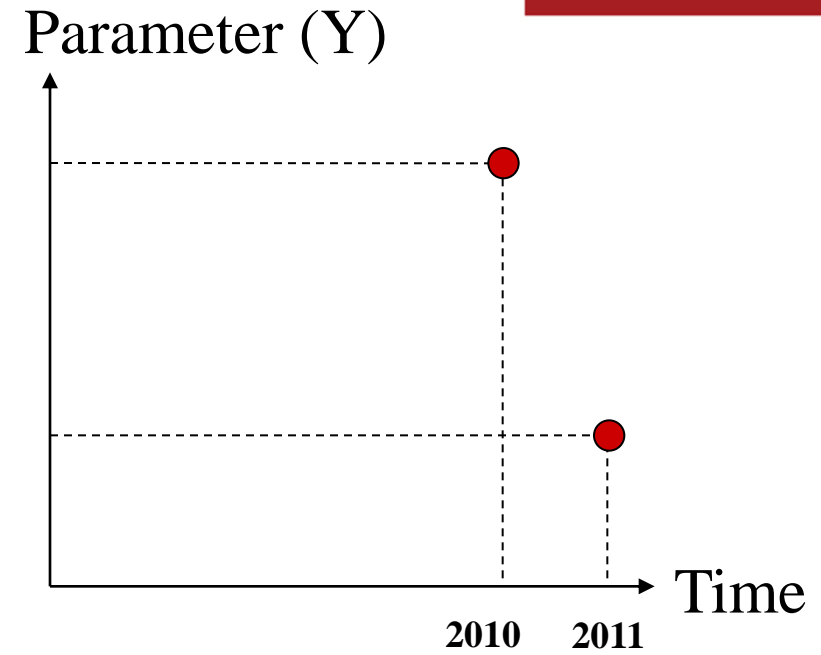
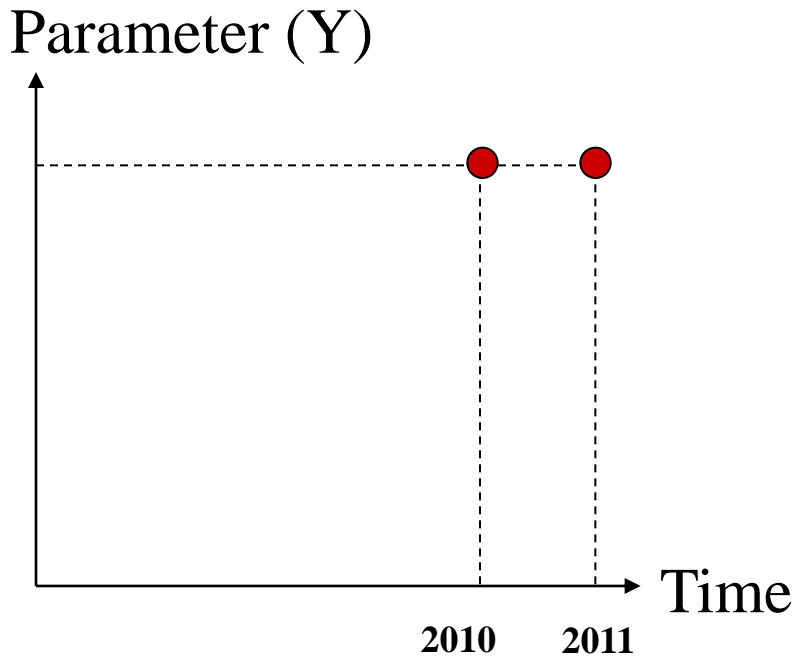
Context

- Following new regulations, conclusions are often rapidly drawn to prove their positive impacts
 - LIP regulation on smoking fire death number (e.g. Finland, USA)
 - Public smoking bans on rates of hospital admission
- These conclusions are often based on few data; comparison of data obtained the years before and after the implementation of the regulation without taking into account the trend, seasonality and irregular components

Objective

- Assess the impact of new regulation using appropriate tools
-

What You Can and Can't Say

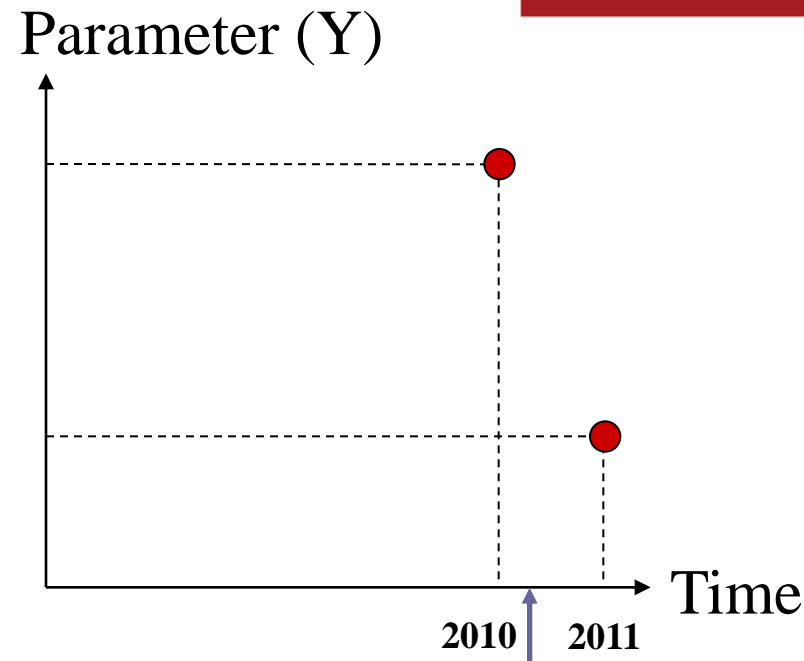
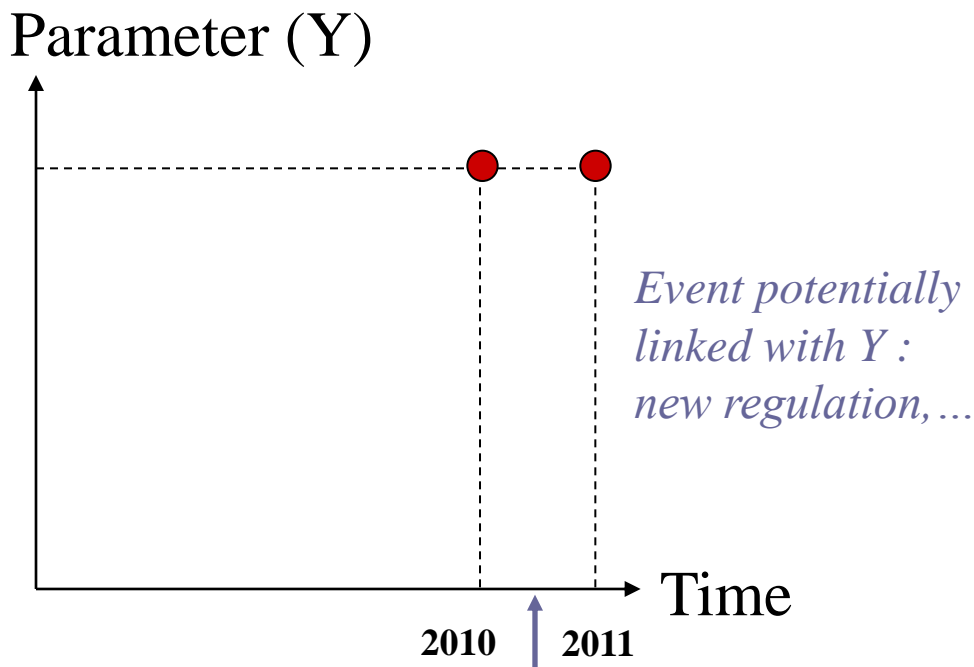


We can say

No difference between 2010 and 2011

A reduction of X% between 2010 and 2011

What You Can and Can't Say



We can say

No difference between 2010 and 2011

A reduction of X% between 2010 and 2011

We can not say

The evolution is due to the event occurring between the two dates

For that, we need more information

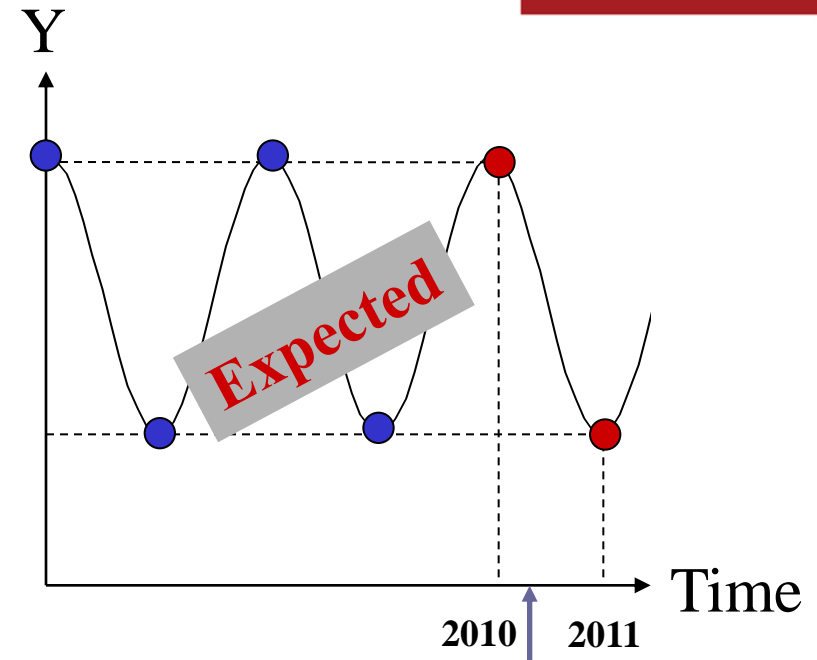
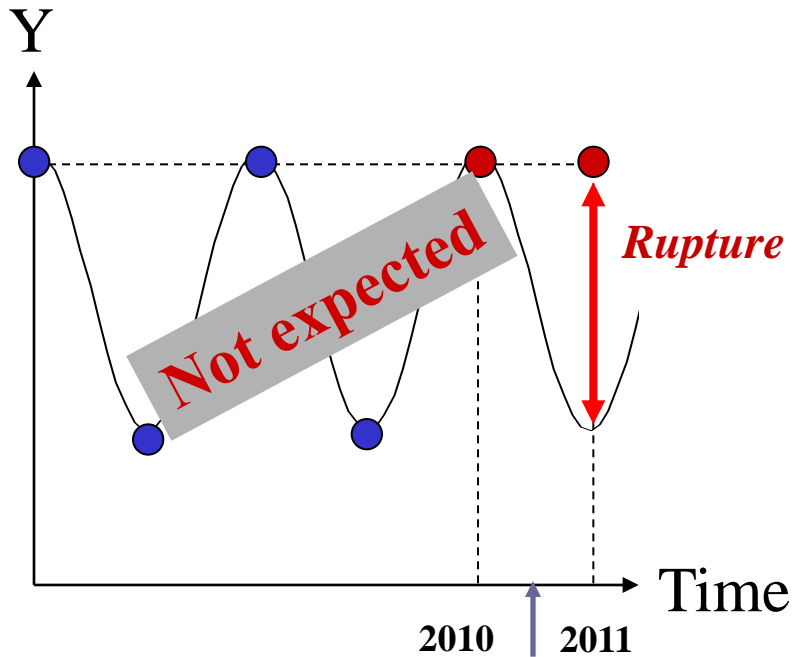
Which kind of information, do we need?

If we want to associate the variation to an external event, we need to know:

- The trend
- The season/cyclic information (short period/long period)
- The random variation

We can conclude that an external event has a significant impact on a process if we have a rupture/break of trend and/or seasonality higher than the random variation.

What You Can and Can't Say



We can say

No difference between 2010 and 2011

A reduction of X% between 2010 and 2011

We can not say

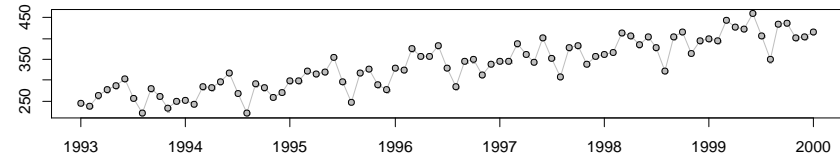
The evolution is due to the event that took place between the two dates

Information and tools to manage data are crucial

Time series definition

Information

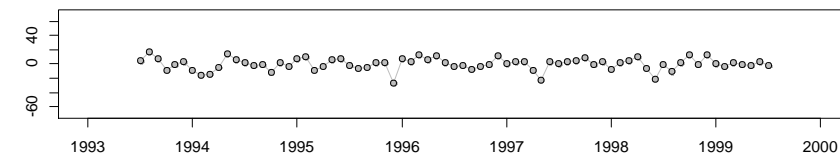
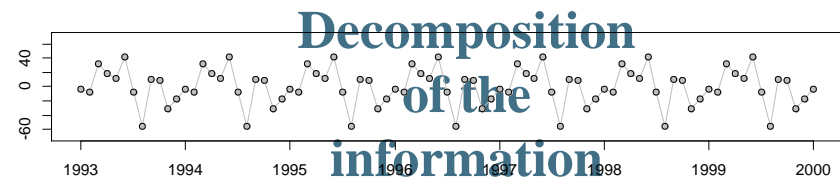
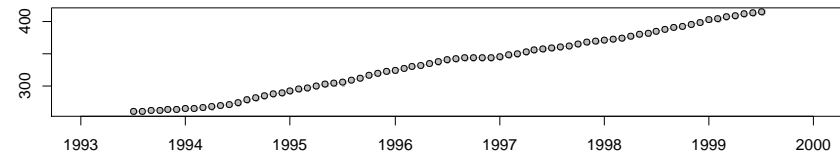
Time series is a sequence of data points, measured typically at successive time instants spaced at uniform time intervals.



Tools to manage data

Mathematical filtering procedures for decomposing a time series into trend, Seasonal and remainder components:

- **Trend component:** the low frequency variation in the data together with no stationary, long-term changes in level.
- **Seasonal component:** variation in the data at or near the seasonal frequency.
- **Remainder component:** remaining variation in the data beyond that in the seasonal and trends components.



Decomposition
of the
information

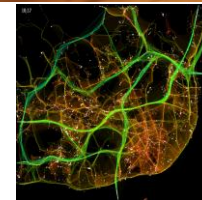
Time series

Objectives

- **Predict** the future values of a variable by using the observed past and present values of this same variable.
- **Estimate a trend**, in order to know if a variation of a variable (for example unemployment rate) is the consequence of seasonal component or reflect of a trend.
- **Detect break or rupture**, in order to evaluate the impact of a new regulation on a variable of interest (influence of the security belt in car on the number of road death).

The time series are widely used in several fields:

- Financial area (share evolution, interest rate...)
- Economy (unemployment, GNP...)
- Ecology (Ozone or CO₂ pollution)
- Logistic (airport traffic...)
- Demography



Time series

AR PROBABILISTIC METHODS
ETS SMOOTHING METHODS
GARCH ARIMA SARIMA VARIMA LM SEM MA ARMAX
FILTER LOESS ARMA

▪ Extrapolation methods:

Methods that use only the past of the variable itself to make prediction

- Smoothing methods :

moving average, LOESS, exponential smoothing...*

- Probabilistic models:

AutoRegressive and Moving Average modeling approach

▪ Explanatory methods:

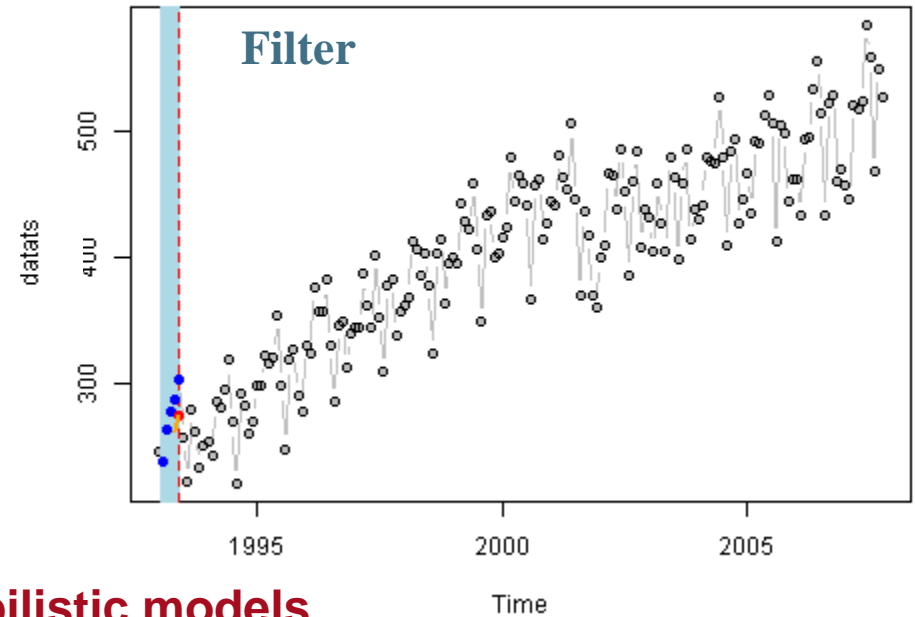
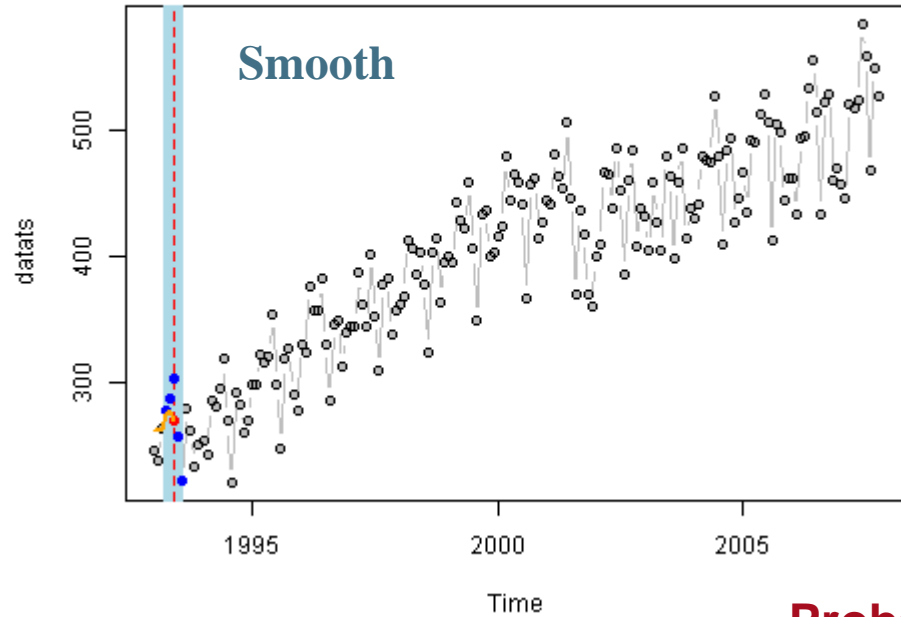
Methods that use the past and/or the present of one of several variables simultaneously.

- Linear regression
- Structural equation modeling

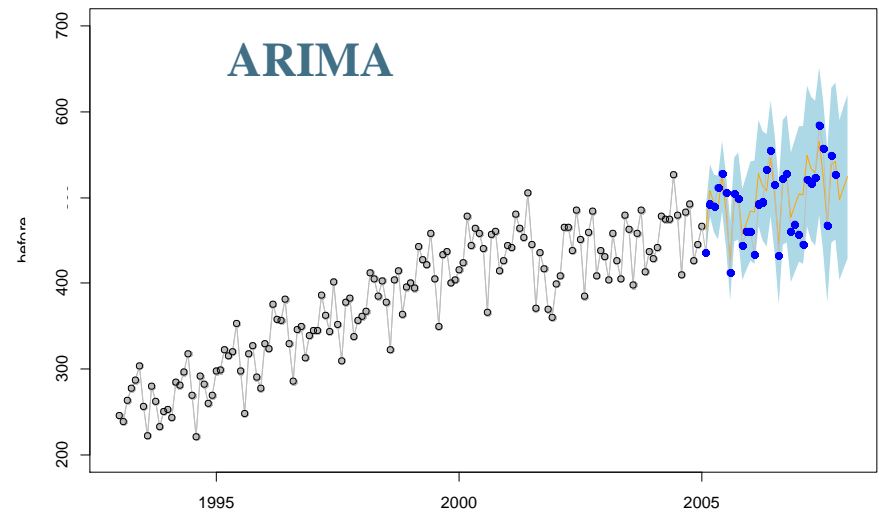
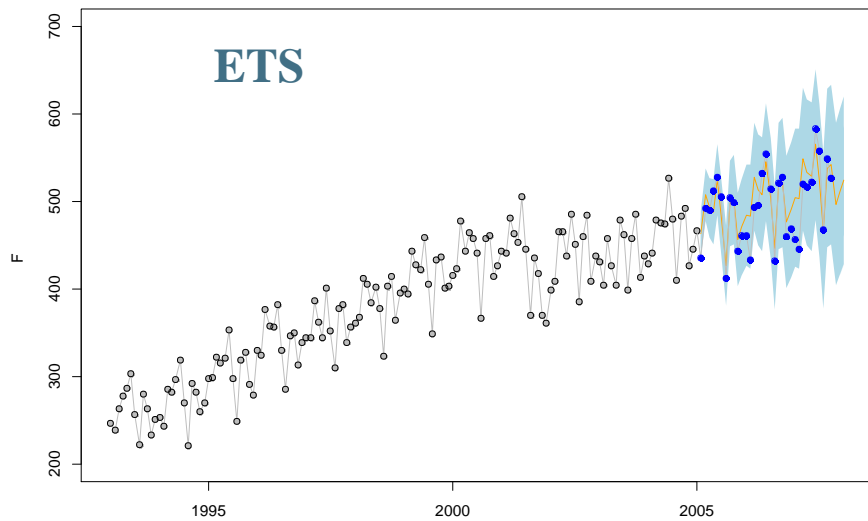
**LOESS, or LOWESS (locally weighted scatterplot smoothing),*

Examples

Smoothing methods

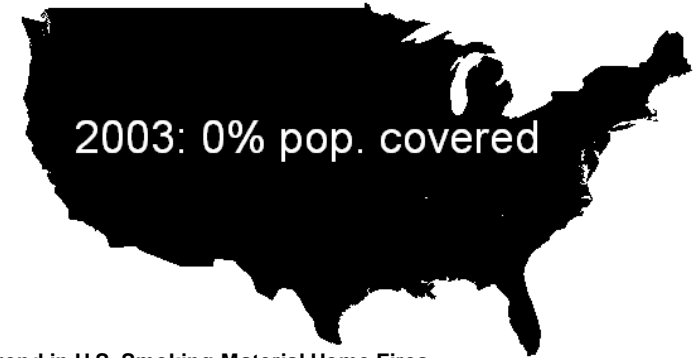


Probabilistic models

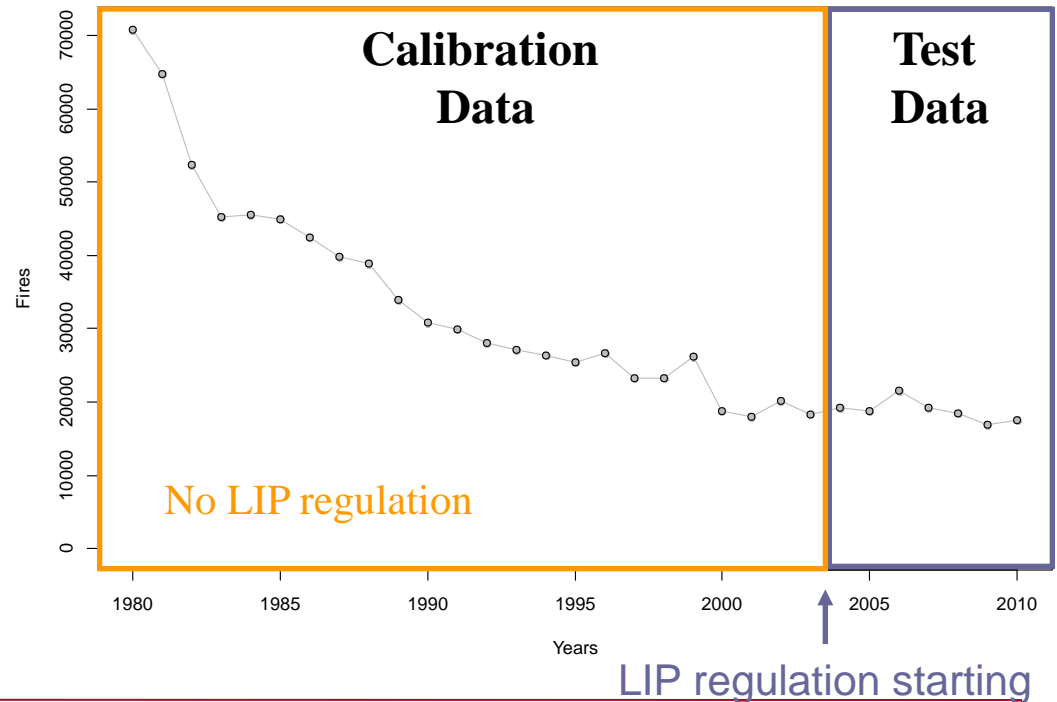


Application on USA LIP data

Year	Smoking-material Structure Fires	Number of civilian deaths	Cig. Consumed
1980	70800	1820	632
1981	64700	1980	640
1982	52400	1680	634
1983	45300	1510	600
1984	45600	1480	600
1985	44900	1580	594
1986	42500	1350	584
1987	39800	1380	575
1988	38900	1570	563
1989	34000	1190	540
1990	30800	1150	525
1991	29900	880	510
1992	28000	1000	500
1993	27200	980	485
1994	26300	840	486
1995	25400	1040	487
1996	26600	1090	487
1997	23300	870	480
1998	23200	850	465
1999	26200	830	435
2000	18800	860	430
2001	18000	760	425
2002	20100	610	415
2003	18300	690	400
2004	19300	710	388
2005	18700	740	376
2006	21600	690	372
2007	19200	650	NA
2008	18400	620	NA
2009	16900	590	NA
2010	17500	540	NA



Trend in U.S. Smoking-Material Home Fires



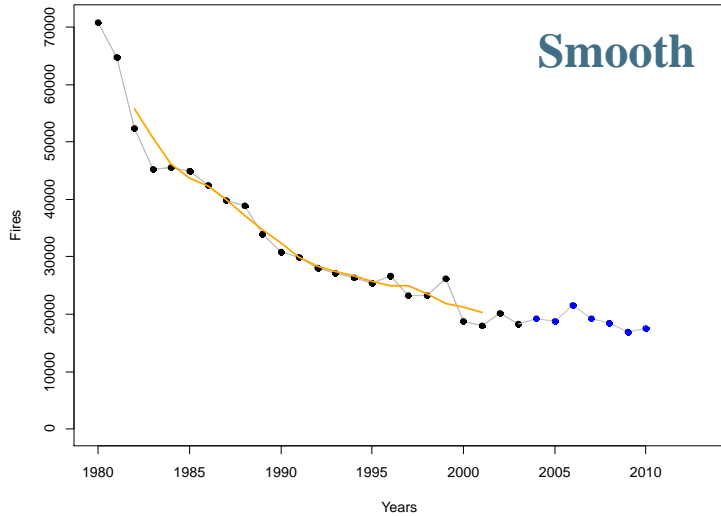
Reference:

The smoking-material fire problem, National Fire Protection Association, March 2012

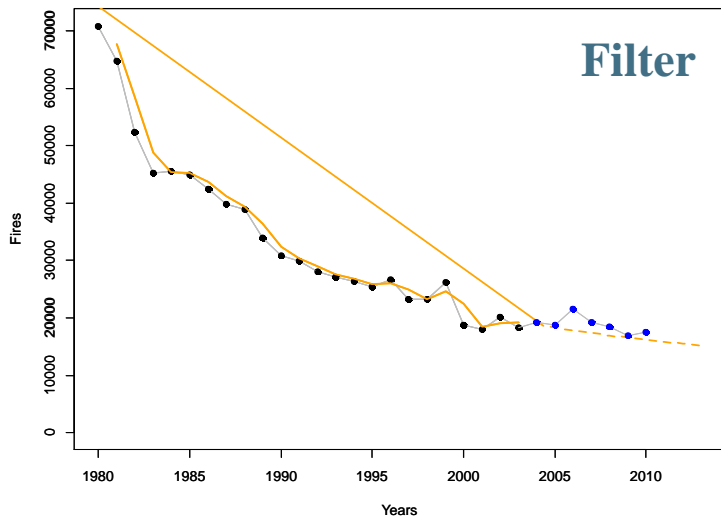
Basic trend decomposition



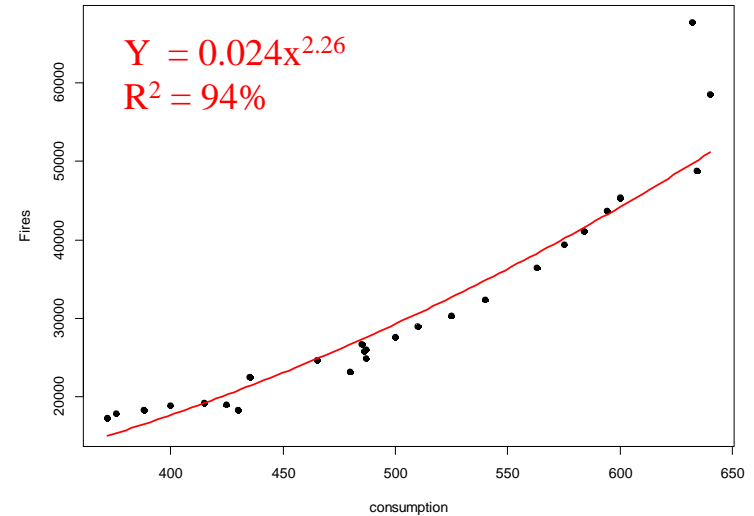
Trend in U.S. Smoking-Material Home Fires



Trend in U.S. Smoking-Material Home Fires



Relation Trend vs Consumption



Without any new regulation:

A decrease of the consumption

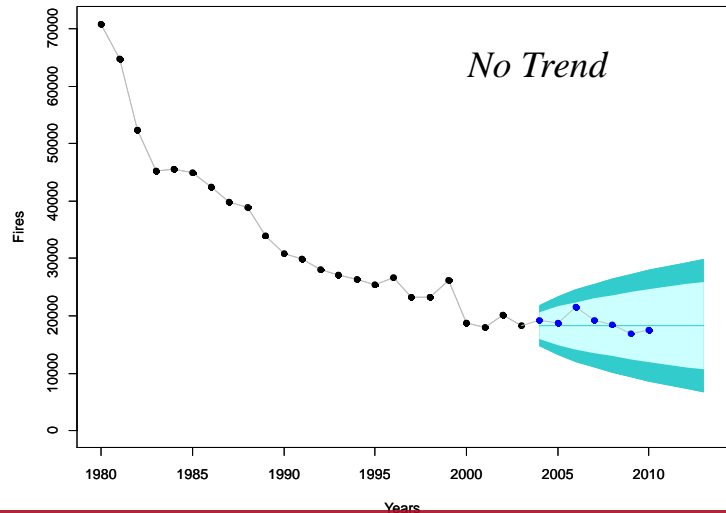


A decrease of the number of fires

Modeling approaches

Exponential Smoothing

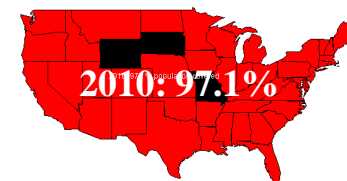
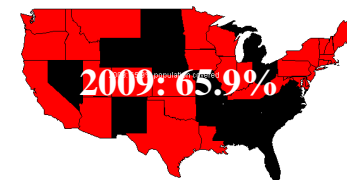
No Trend



Predicted values & IC, if no regulation implemented

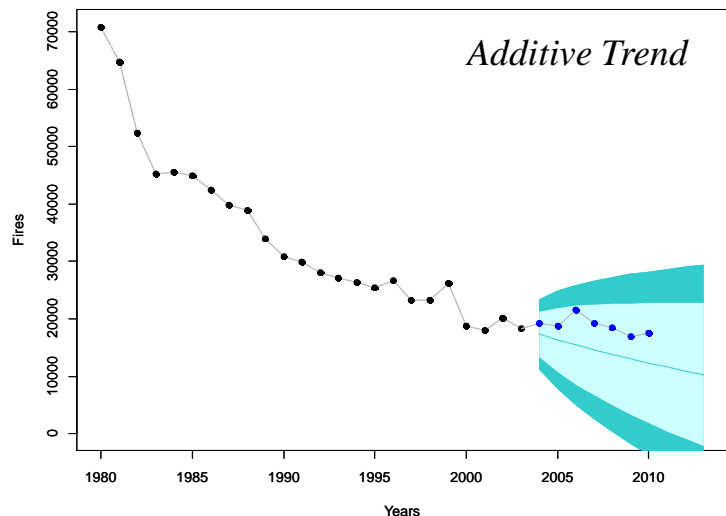
VS

Observed data with spreading of Regulation

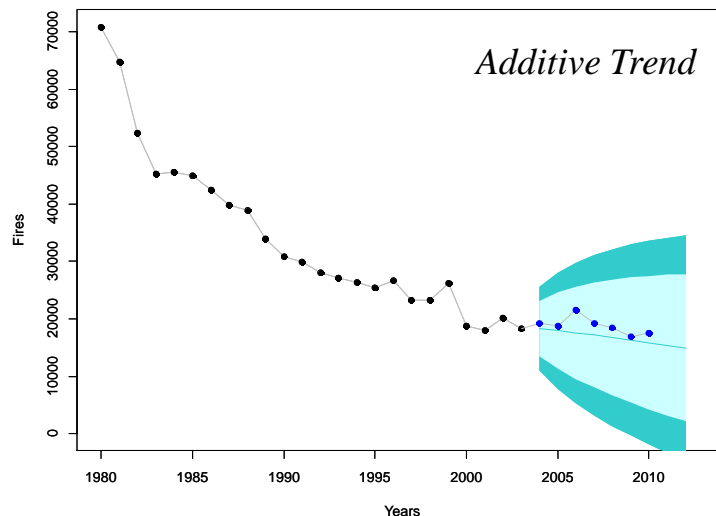


Observations are slightly higher than prediction based on “any regulation changes”
 From model predictions there is no evidence that LIP regulation reduced smoking fires

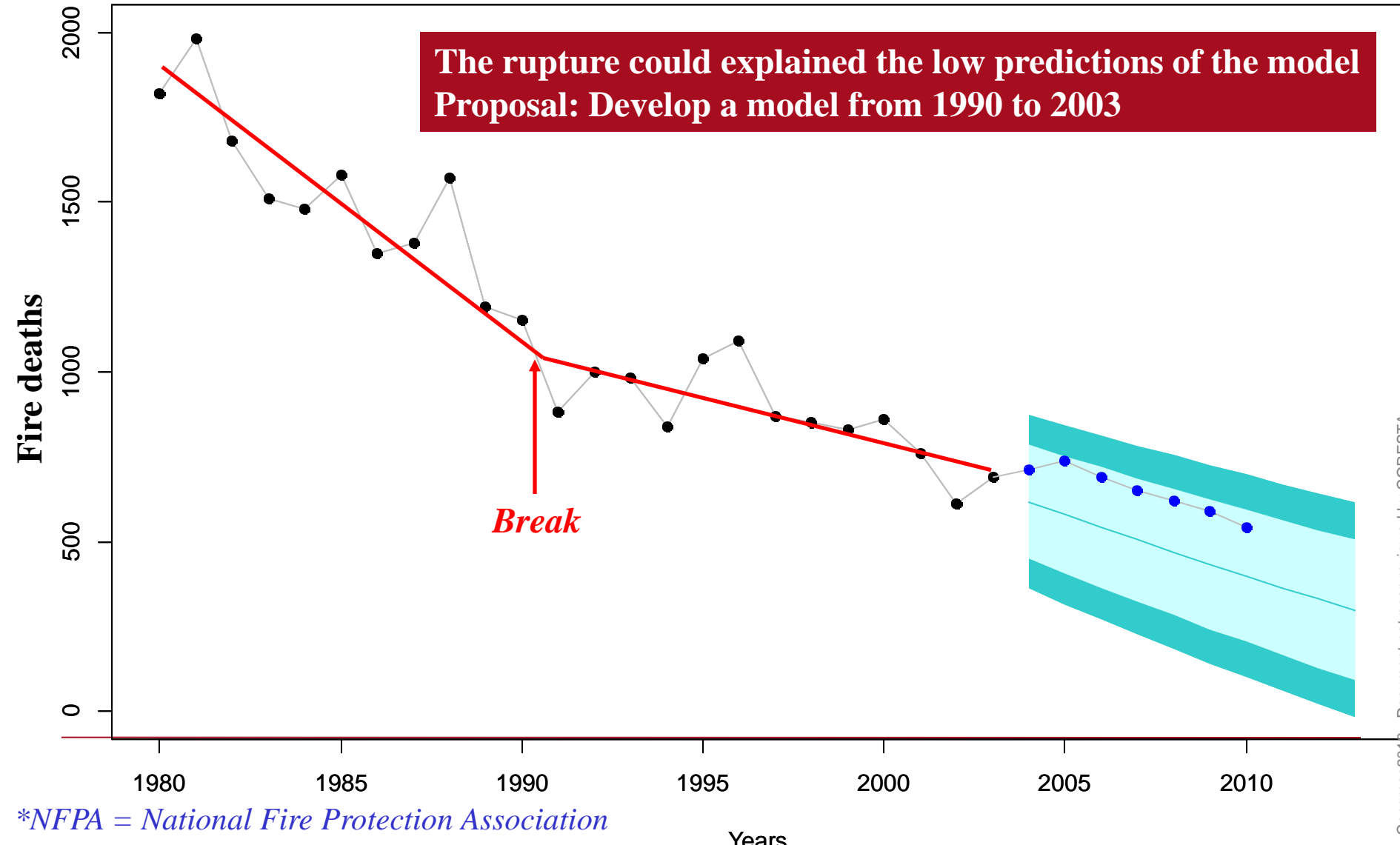
Additive Trend



Additive Trend



Exponential Smoothing: Deaths



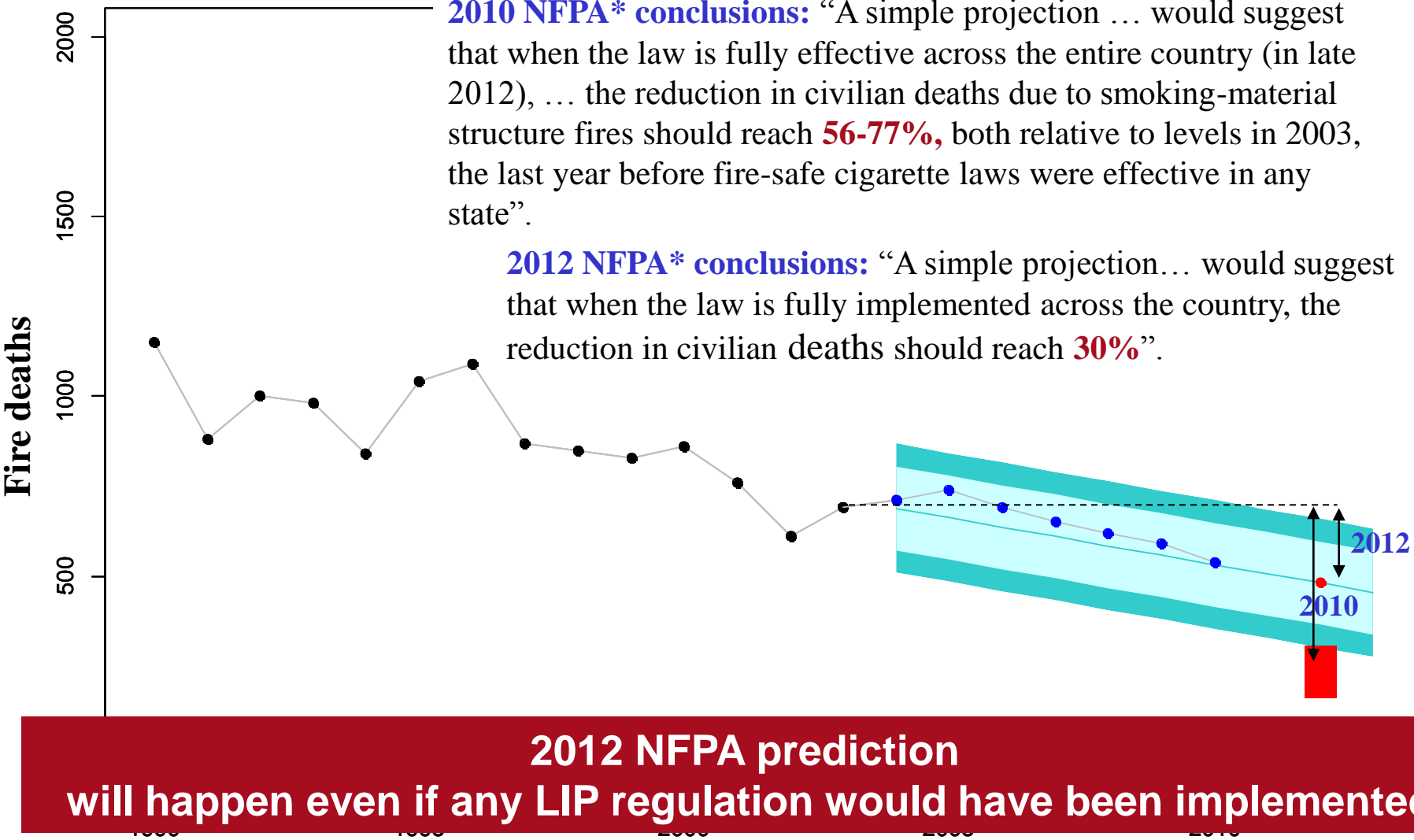
*NFPA = National Fire Protection Association

ETS 1990-2003: Deaths



2010 NFPA* conclusions: “A simple projection ... would suggest that when the law is fully effective across the entire country (in late 2012), ... the reduction in civilian deaths due to smoking-material structure fires should reach **56-77%**, both relative to levels in 2003, the last year before fire-safe cigarette laws were effective in any state”.

2012 NFPA* conclusions: “A simple projection... would suggest that when the law is fully implemented across the country, the reduction in civilian deaths should reach **30%**”.



2012 NFPA prediction will happen even if any LIP regulation would have been implemented

*NFPA = National Fire Protection Association

Years

Conclusions

- ***Trend Analysis***

- ✓ A time series must be analyzed using specific models.
- ✓ Some assumptions must be checked such as the independence of the observations (no correlation) and stationary of the series.

- ***LIP data***

- ✓ The results of the models do not allow to conclude that the reduction of smoking fires and smoking fire deaths in USA after 2003 is the consequence of LIP regulation.

Perspective: Break point analysis (retrospective identification)
