Lies, Damned Lies, and Statistics?

Examples From Finance & Economics

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A host of modern statistical tools are constantly being developed to cope with a wealth of new data.

Some methods need to be tailored to cope with different environments. (Not all ailments are cured by the same medicine!)

Today's "backyard" will be financial econometrics and empirical macroeconomics. In particular:

1. Statistical distribution theory: how to quantify randomness.

   Option-pricing requires the specification of a distribution of likely future prices. An arbitrarily-chosen form will give misleading results.

   "You can't fix by analysis what you bungled by design"
   Light, Singer, and Willett (1990).

   We need new flexible specifications for distributions.

2. The relation between interest rates on different maturities, now and in the future; the "term structure of interest rates":

   (a) Rare uncharacteristic events can generate one-off "outliers".
   They have distortionary effects on traditional methods of estimating relations between these interest rates.

   (b) Short-term interest rates do *not* have the "Markovian" dynamics that prevail in the literatures on finance and time series.
   We first need new methods to deal with such time-series data.

3. These new dynamics arise from a general-equilibrium economic model.

Because of this link, it turns out that exchange rates, stock market indexes, and all macroeconomic variables are well characterized by this new process.

Implications for trading (momentum, cycles, etc.),
but also for macroeconomic stabilization.

1. Flexible specification of probability distributions

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Loosely speaking, a probability density function (or simply "density") depicts the relative frequency of outcomes for a variable.

A flexible parametric form for densities is needed to:

1. cover a wide range of possible descriptions and shapes;
2. achieve efficiency gains over nonparametric estimation, gains that are useful for cases where there is not a lot of data.

This is needed for many statistical applications, well beyond the current context of option pricing.

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Its value depends on the distribution of likely future prices.

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Let x_t be the price of an asset at time t. Assume, for the moment, that the asset does not pay dividends. Suppose that this asset is underlying a European call option with expiration date T and strike price k.

Then, the intrinsic value of this option at expiration is $\max\{x_T - k, 0\}$. In an arbitrage-free economy, there exists a risk-neutral density f such that the price of this call option at time t can be written as

$$c_t(k) = \mathrm{e}^{-(T-t)r}\mathrm{E}_t\left(\max\{x_T - k, 0\}\right) \equiv \mathrm{e}^{-(T-t)r}\int_k^\infty (u-k)\, f(u)\, \mathrm{d}u,$$

where r is the continuously-compounded risk-free interest rate and E_t is the expectation taken at time t.

Differentiating the integral gives

$$\frac{\mathrm{d}c_t\left(k\right)}{\mathrm{d}k}=-\mathrm{e}^{-(T-t)r}\int_k^{\infty}f\left(u\right)\mathrm{d}u\equiv-\mathrm{e}^{-(T-t)r}\left(1-F\left(k\right)\right),$$

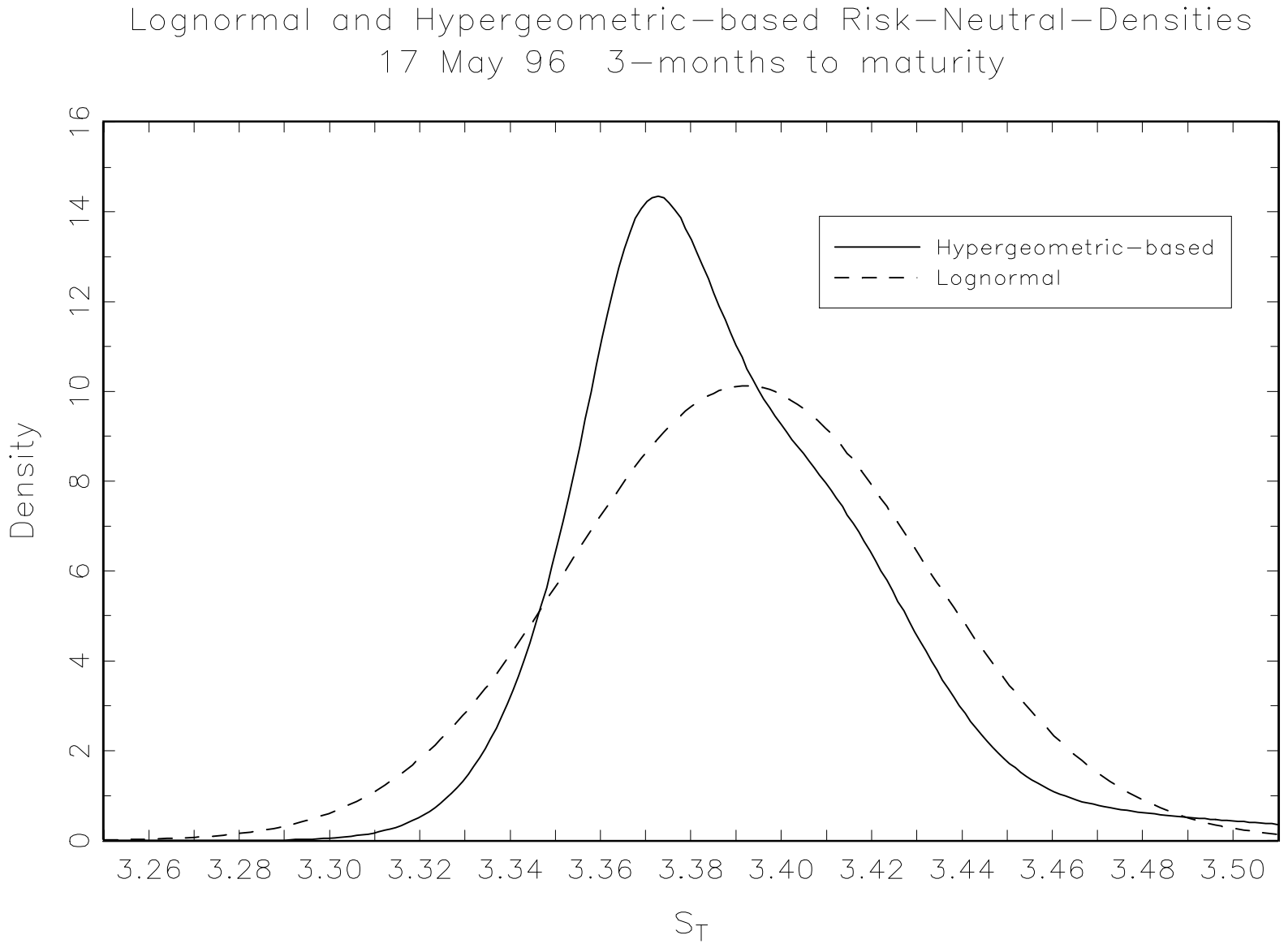
where F is the c.d.f. corresponding to the p.d.f. f. The second derivative is given by

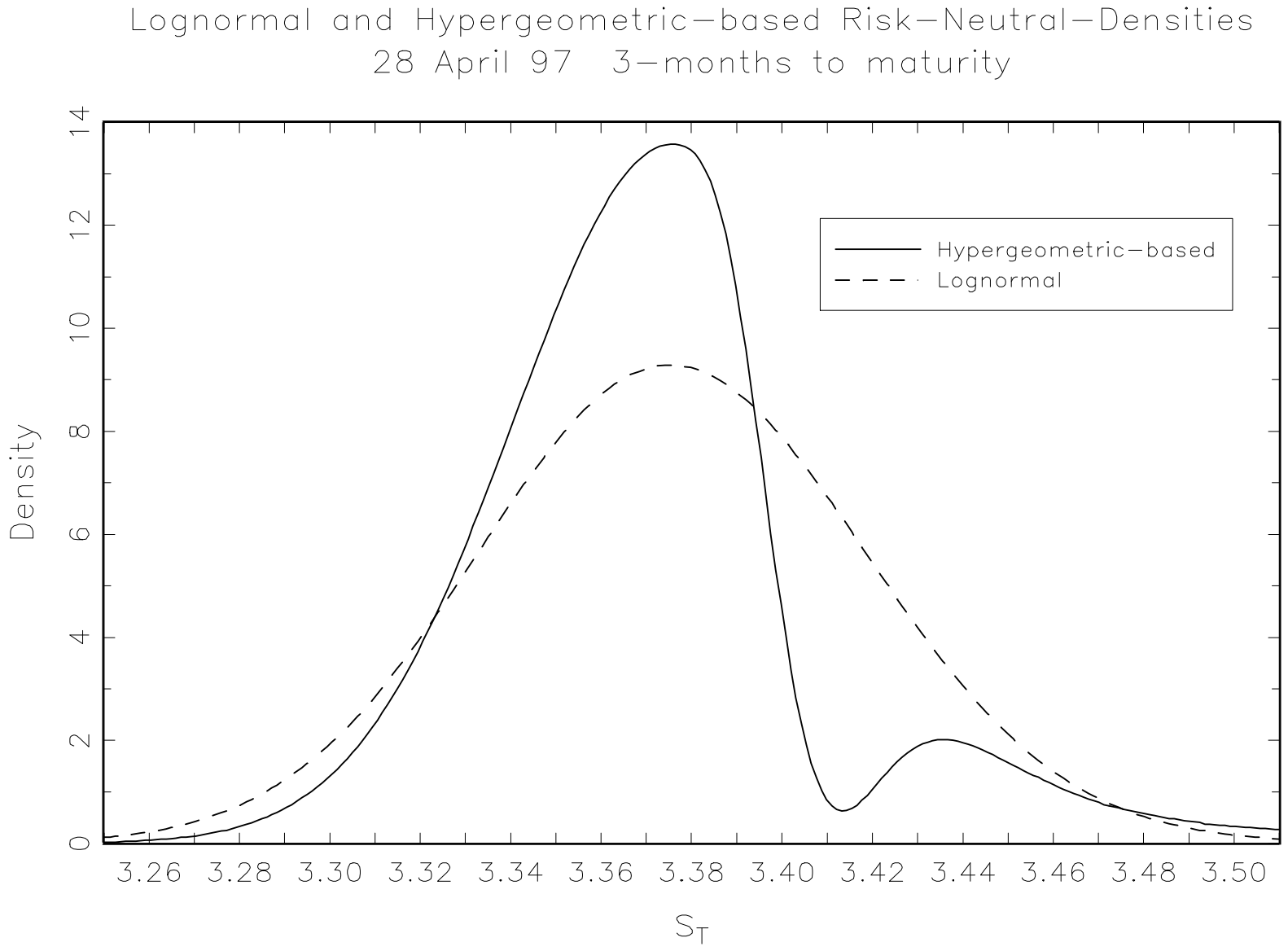
$$\left.\frac{\mathrm{d}^2c_t\left(k\right)}{\mathrm{d}k^2}\right|_{k=u}=\mathrm{e}^{-(T-t)r}f\left(u\right),$$

which reveals the required density f. If the asset pays a dividend yield of $r^{\dagger}$, then it should be subtracted from r and the RHSs should be multiplied by $\mathrm{e}^{(T-t)r^{\dagger}}$.

The Black-Scholes (1973, *JPE*) and Garman-Kohlhagen (1983, *JIMF*) models assume that f is log-normal.

Using a construction from special functions in mathematics ("hypergeometric functions"), first introduced in Abadir and Rockinger (2003, *ET*), we get the following densities about future asset prices (exchange rates and S&P500), as implied by current option prices...


Lognormal and Hypergeometric−based Risk−Neutral−Densities
17 May 96 3−months to maturity
Density
0
2
4
6
8
10
12
14
16
3.26
3.28
3.30
3.32
3.34
3.36
3.38
3.40
3.42
3.44
3.46
3.48
3.50
S_T
Hypergeometric−based
Lognormal


Lognormal and Hypergeometric−based Risk−Neutral−Densities
28 April 97 3−months to maturity
Density
0
2
4
6
8
10
12
14
3.26
3.28
3.30
3.32
3.34
3.36
3.38
3.40
3.42
3.44
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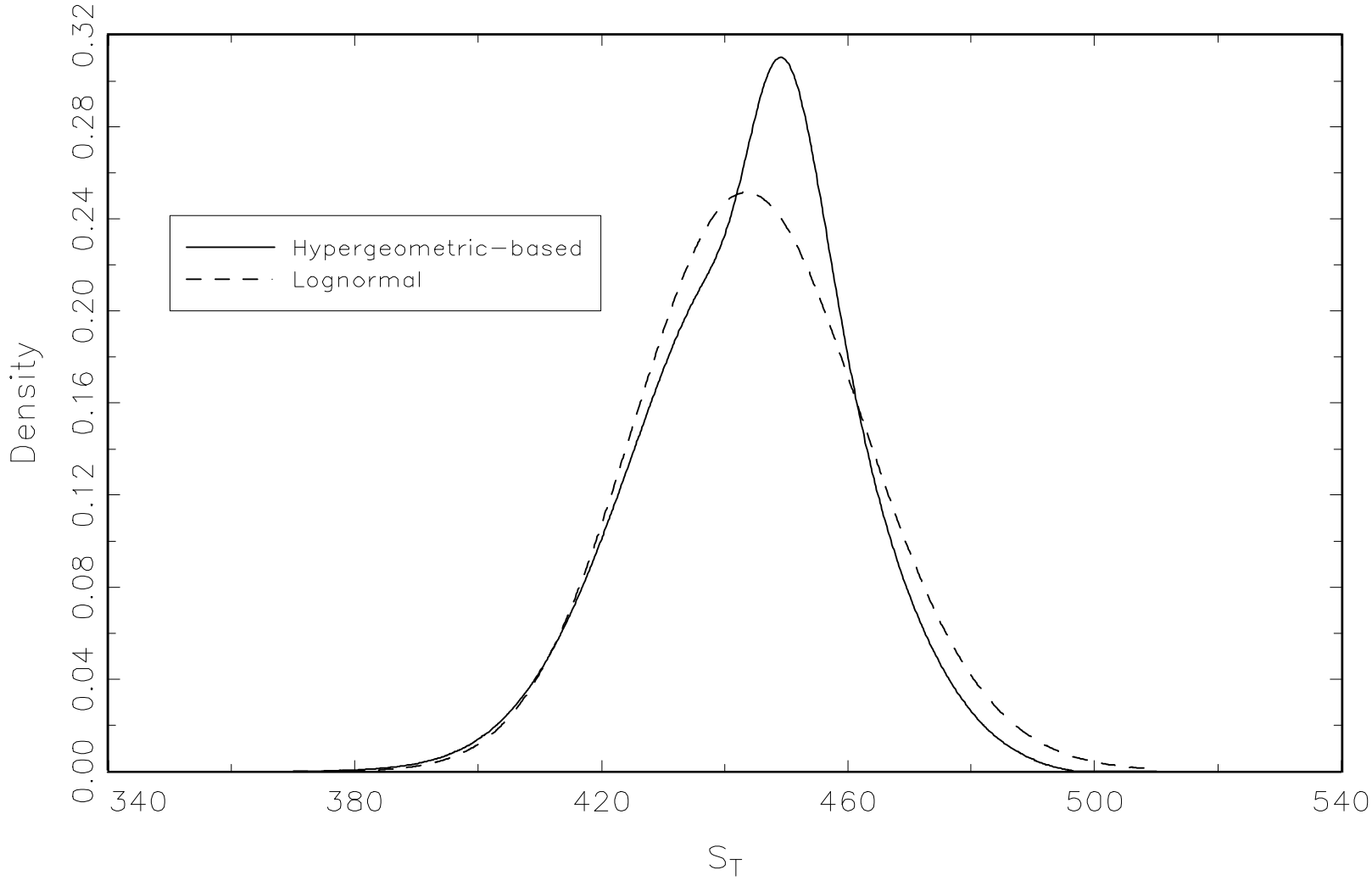
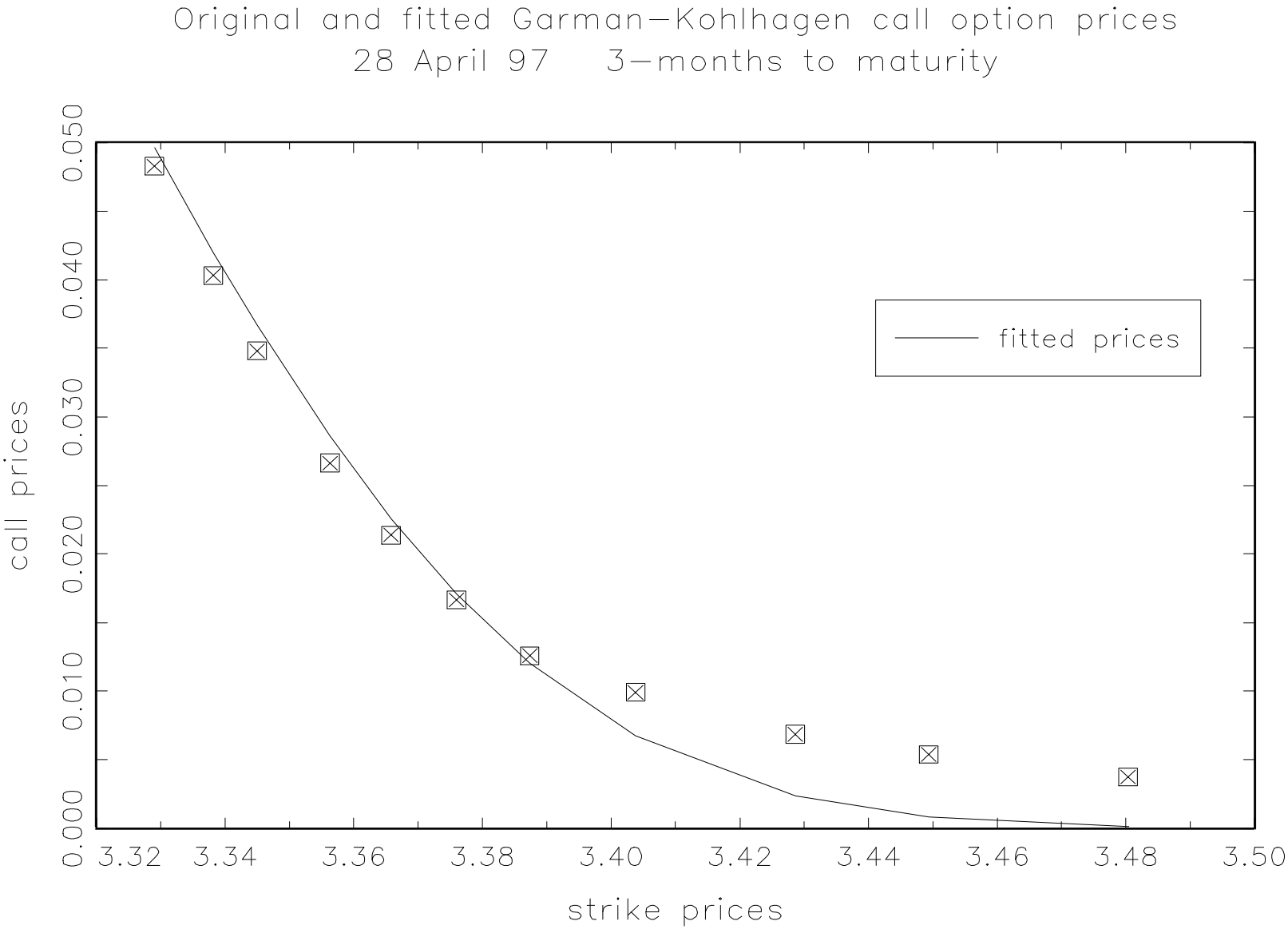
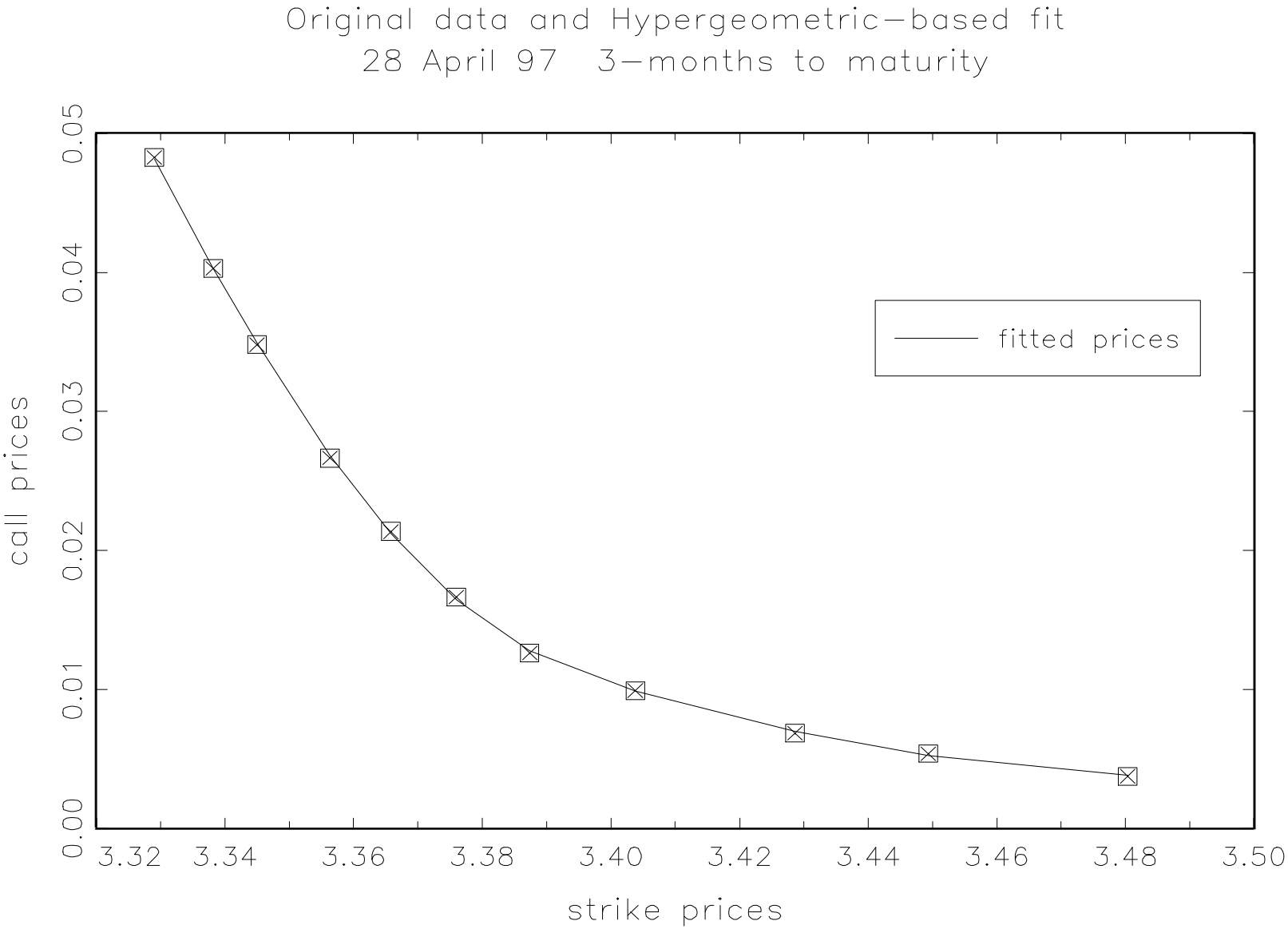
Lognormal


Lognormal and Hypergeometric−based Risk−Neutral−Densities
S&P500 index options, 3 May 1993, 46−days to maturity
Density
0.00
0.04
0.08
0.12
0.16
0.20
0.24
0.28
0.32
340
380
420
460
500
540
S_T
Hypergeometric−based
Lognormal

The representative fit for option prices implied by these densities, as opposed to the Garman-Kohlhagen (1983, *JIMF*) or Black-Scholes (1973, *JPE*) benchmark is...


Original and fitted Garman–Kohlhagen call option prices
28 April 97 3–months to maturity
call prices
0.000
0.010
0.020
0.030
0.040
0.050
3.32
3.34
3.36
3.38
3.40
3.42
3.44
3.46
3.48
3.50
strike prices
fitted prices


Original data and Hypergeometric−based fit
28 April 97 3−months to maturity
call prices
0.00
0.01
0.02
0.03
0.04
0.05
3.32
3.34
3.36
3.38
3.40
3.42
3.44
3.46
3.48
3.50
strike prices
fitted prices

There are other methods too. But they do not fit as well, and they do not detect the:

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2. negative skew of the density of S&P500 (higher prevalence of negative corrections in shares).

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Also, other methods force unjustified features on the estimates (e.g. number of modes, oscillatory tails,...) or have no explicit structure (a drawback when forecasting and/or analyzing tails, i.e. extreme events).

The new method does very well, and uniformly so for:

1. volatile days, as well as for quiet ones;
2. different maturities; and
3. options on very different underlying assets.

The estimated densities' functional forms (i.e. shapes) vary over the dates, maturities, and assets. Therefore, other parametric methods which restrict functional forms will not do uniformly well.

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The estimates are stable and robust, as revealed by sensitivity analysis to bid-ask spread, dependence on each data point, etc.

Talking of robustness...

2. The term structure of interest rates

a. The expectation hypothesis (EH)

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But is this really the case? If so, what causes EH to break down?

It will turn out that the empirical rejection of the EH is largely due to a handful of outliers, corresponding to a couple of rare events that are mostly politically-driven.

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Let us focus on the following version of EH:

forward rates are unbiased predictors of futures rates.

Define $f(t,u)$ as the instantaneous forward rate that satisfies the pricing

$$P(t,T) = \exp\left(-\int_t^T f(t,u)\mathrm{d}u\right), \quad T > t,$$

for a zero-coupon bond with face value 1.

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The EH with constant risk premium states that $\pi(t,u) = \bar{\pi}$, hence

$$y(t,T) = \frac{\int_t^T \left(\mathrm{E}_t\left[r(u)\right] + \bar{\pi}\right)\mathrm{d}u}{T-t} = \bar{\pi} + \frac{\int_t^T \mathrm{E}_t\left[r(u)\right]\mathrm{d}u}{T-t},$$

where $y\left(t,T\right)$ is the yield at time t of a bond maturing at time T.

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A discretization gives a restriction that has been extensively tested:

$$y\left(t,t+n\right) = \bar{\pi} + \frac{\sum_{i=1}^{n} \mathrm{E}_t\left[y\left(t+i-1,t+i\right)\right]}{n}, \tag{1}$$

where $n := T - t$ is the time to maturity.

Reproducing (1),

$$y\left(t,t+n\right)=\bar{\pi}+\frac{1}{n}\sum_{i=1}^{n}\mathrm{E}_{t}\left[y\left(t+i-1,t+i\right)\right],$$

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Here, changes in yields can only be explained by changes in the expectation of the future interest rates.

If the risk premium were time-varying, yields would also depend on changes of attitudes towards risk or changes in interest rate volatility.

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Two relations can be derived from (1). One of them is

$$\mathrm{E}_t[y\,(t+1,T)] - y\,(t,T) = \alpha_n + \beta_n \frac{y\,(t,T) - y\,(t,t+1)}{n-1},$$

where $\beta_n = 1$ if EH is satisfied. A positive risk premium translates into negative values for α, while Jensen's convexity effect increases α.

The equation relates future changes in long-term interest rates (call this LHS z) to the slope of the term structure (call this RHS fraction x) after correction for a constant term premium.

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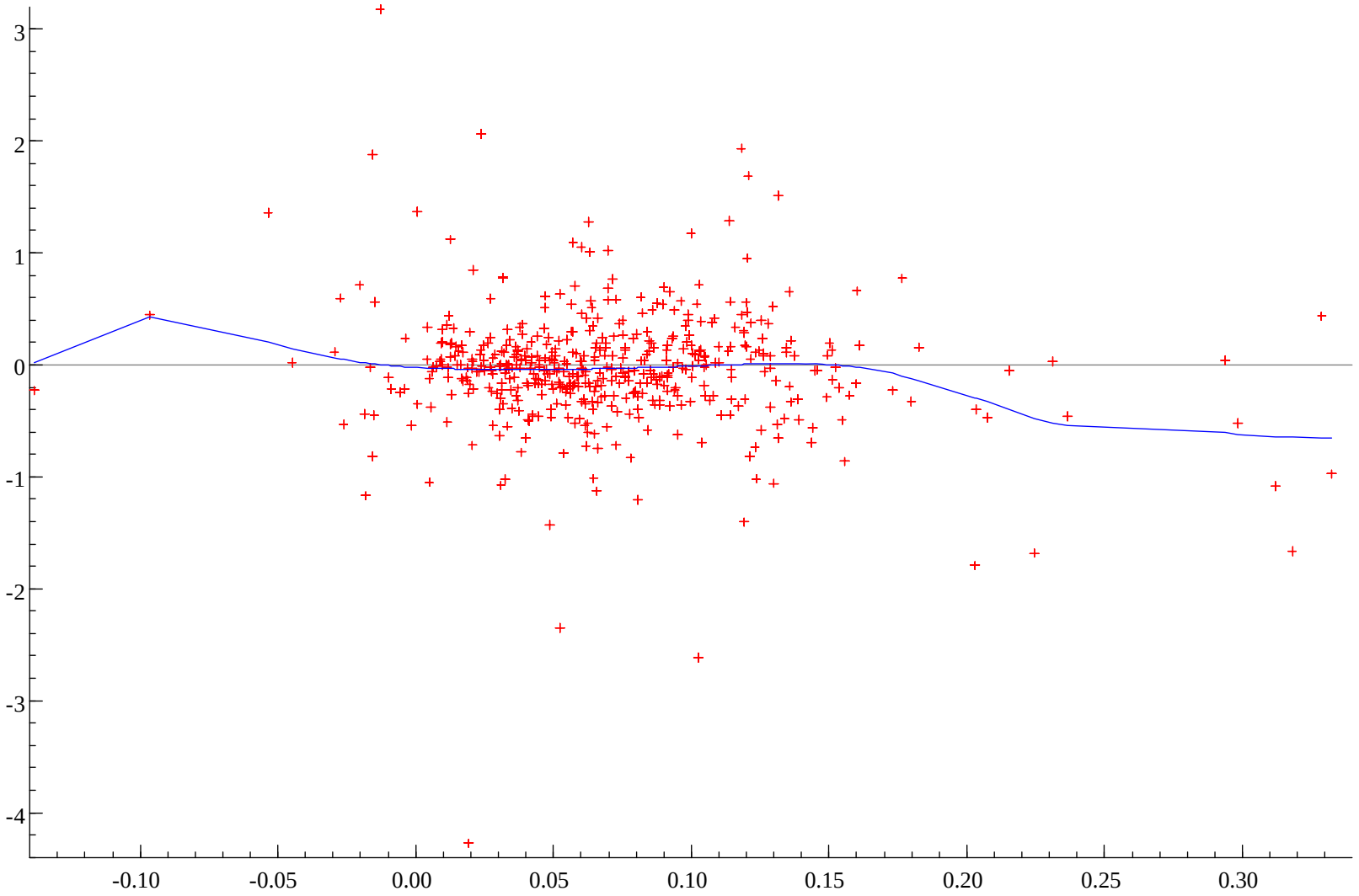
Nonparametric (NP) kernel regression reveals the functional form of the conditional expectation and how far it deviates from linearity and from $\beta_n = 1$.

Being a local-LS device, it also reveals the extent to which earlier results in the literature depended on a handful of extreme observations driven by unusual events: in 1981/1982 (the Volcker experiment) and 1987 (the stock market crash).

From the CRSP database, one can get monthly yields on Treasury Bills with 1 to 12 months to maturity from January 1959 to December 2000, and yields on artificial zero-coupon Treasury bonds with 1 to 10 years to maturity.

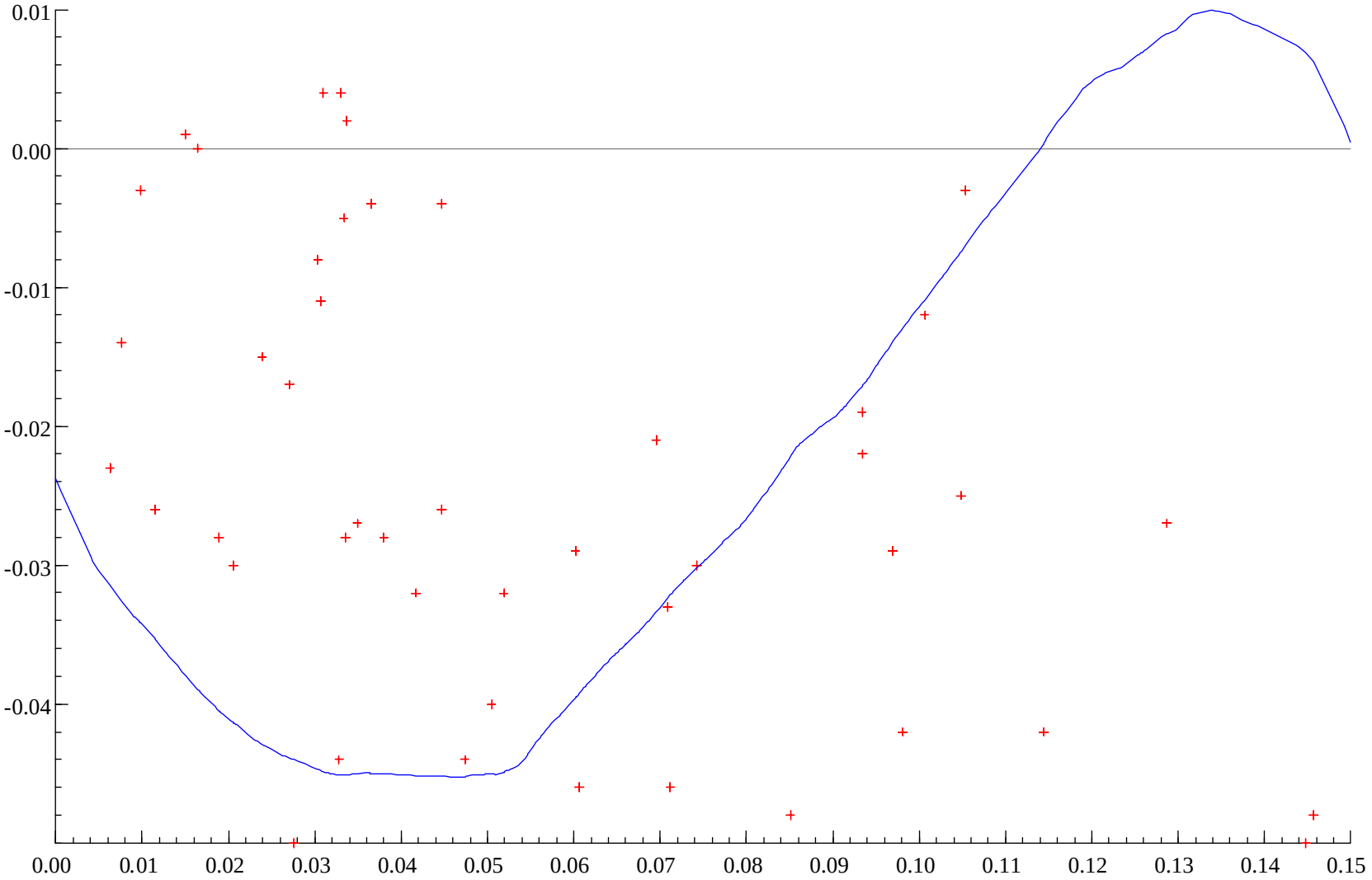
The results are qualitatively similar across the board, so only one-year estimates are reported.

Two graphs for the same NP regression will follow: one showing all the data points, the other zooming into the same picture to show in more detail the fitted NP regression curve for the bulk of the data.



It looks like a flat line, except for a handful of outliers at each extremity.

Actually, it is even better (for EH) if we zoom into the body of the graph and enlarge it...



For the x-axis ranging from 0.05 to 0.12, the NP regression is amazingly linear (this has not been imposed at the outset) with a slope of just over 0.7. Even when taking all the points on the last graph, the "average" slope is little changed.

This is in sharp contrast to the massively negative number obtained by LS regression, namely -1.2 with a standard error of 0.45 leading to the rejection of EH.

We can now see that the puzzling LS result was due to the handful of extreme values (in the first figure) that are driving the "average" slope down, and that the slope for the bulk of the data is statistically indistinguishable from the unit coefficient that is implied by EH.

b. Up & down it goes (dynamics of the short rate)

It is well known that interest rates are persistent.

Further, it has been acknowledged relatively recently that the short-rate process contains nonlinearities. For example, Aït-Sahalia (1996, *RFS*) finds nonparametrically that the process is:

1. very persistent when rates are close to their historical norm;
2. more mean-reverting when rates are far from their norm.

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To add to the troubles, we will see that the process is not Markovian:

1. one cannot summarize the bulk of the dynamics by conditioning on a fixed number of previous values;
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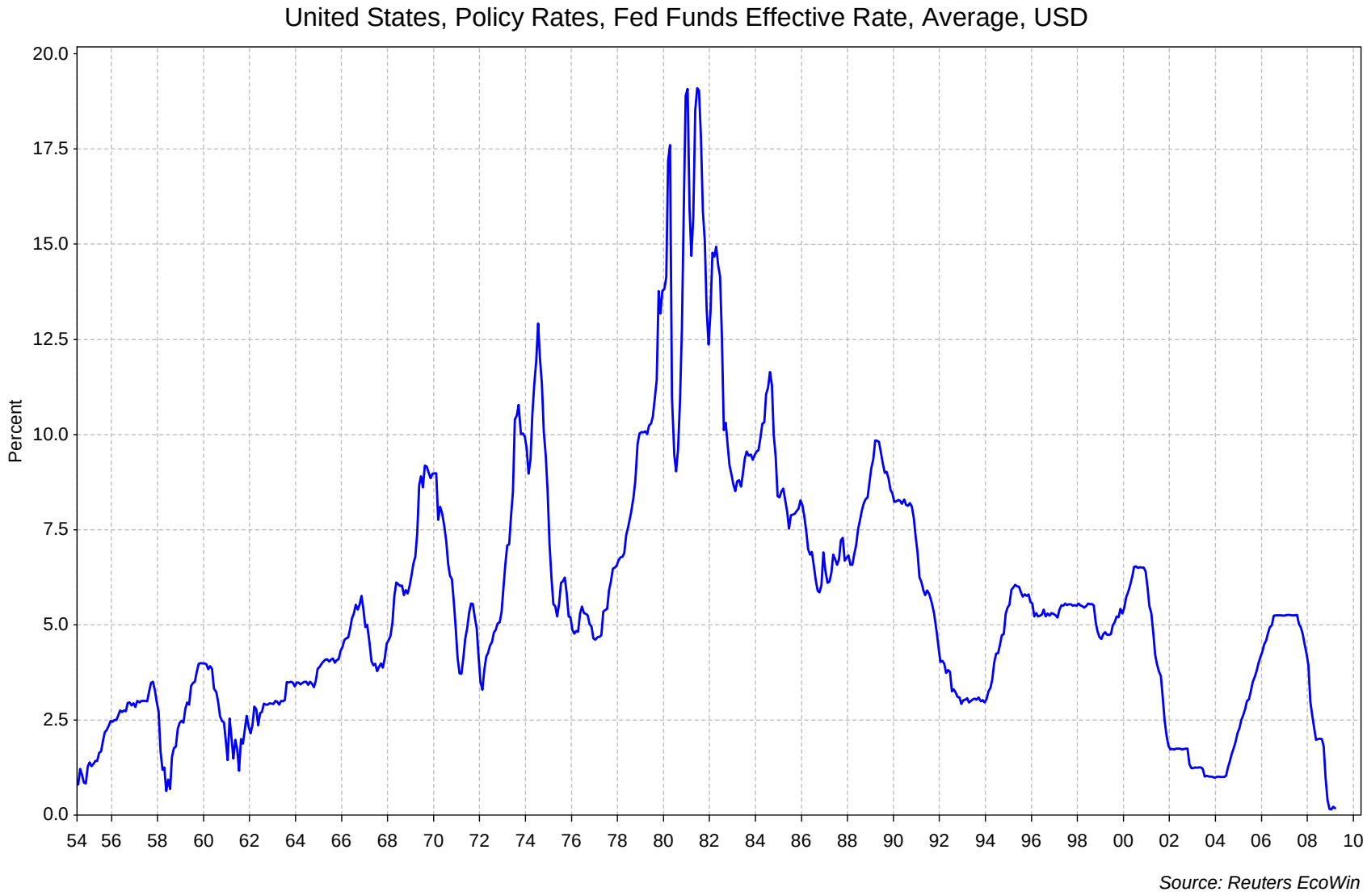
Furthermore, the process does not look like any existing non-Markovian model that we can pull off the shelf: we need new technology!

Here is a picture illustrating what we're up against...



Source: Reuters EcoWin

What a horrible animal! All jagged and seemingly patternless.

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Really?!

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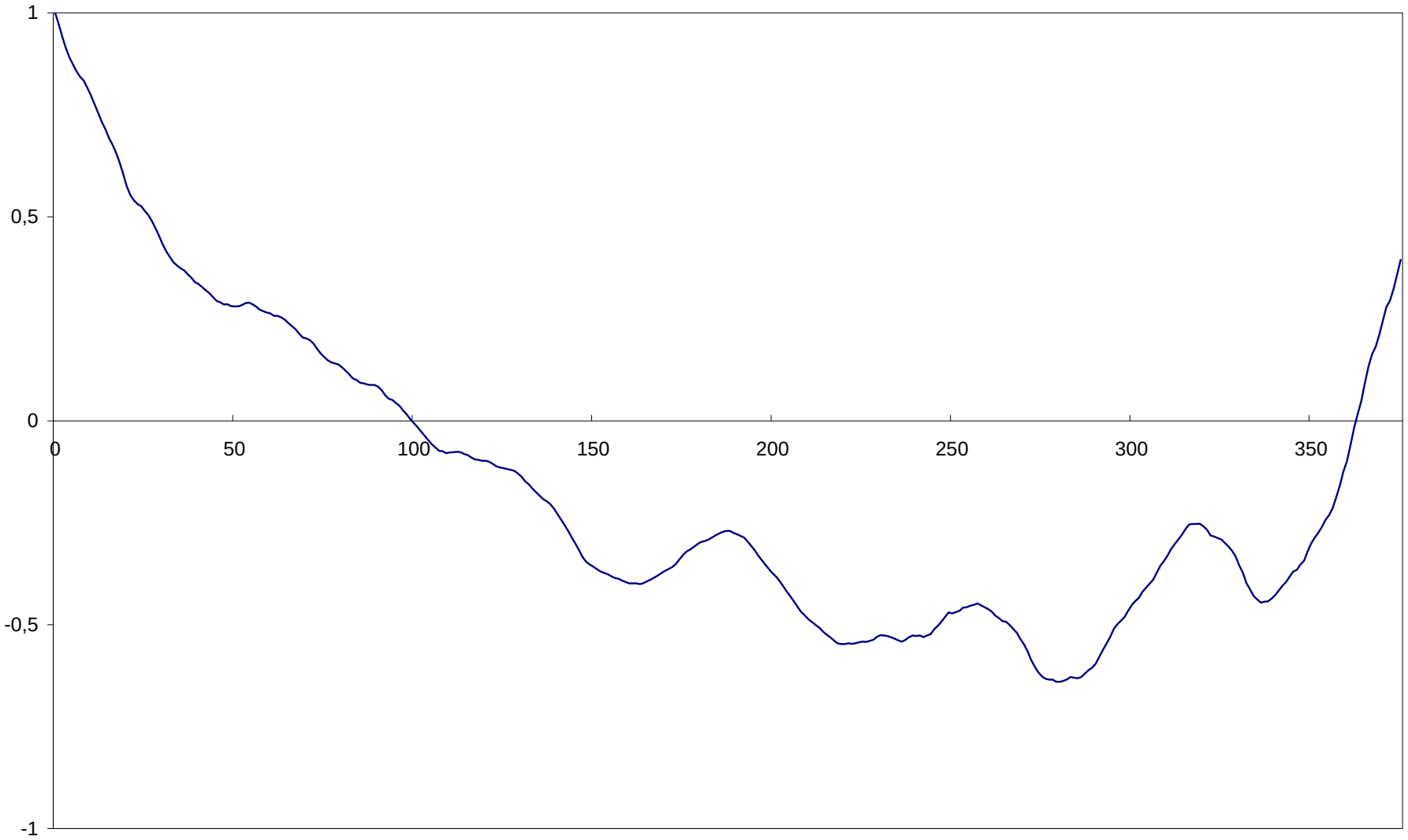
Really?!

Here is how each point correlates with the previous values (the auto-correlation function or ACF)...

... a smoothie (with a wiggly tail)!



Interest rates go in long cycles.

"The evidence in Fama and Bliss (1987) that forward interest rates forecast future spot interest rates for horizons beyond a year repeats in the out-of-sample 1986–2004 period. But the inference that this forecast power is due to mean reversion of the spot rate toward a constant expected value no longer seems valid. Instead, the predictability of the spot rate captured by forward rates seems to be due to mean reversion toward a time-varying expected value that is subject to a sequence of apparently permanent shocks that are on balance positive to mid-1981 and on balance negative thereafter."

Eugene Fama (2006, *RFS*)

What next?!

It turns out that this interest-rate process has a parsimonious representation in the ACF and frequency domains. The ACF is

$$\rho_\tau := \frac{\operatorname{cov}(z_t, z_{t-\tau})}{\sqrt{\operatorname{var}(z_t)\operatorname{var}(z_{t-\tau})}} \approx \frac{\cos(\omega\tau)}{(1+b\tau)^c} \qquad (b, c > 0).$$

Its Fourier-inversion produces a spectrum $f(\lambda)$ that is proportional to $|\lambda - \omega|^{c-1}$; that is, at frequency ω, there is a singularity when $c \in (0, 1)$.

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For linear ARIMA(p, d, q) processes having $d \in (0, \frac{1}{2})$, the spectrum has a singularity at the origin that is proportional to $|\lambda|^{-2d}$, giving the correspondence $c = 1 - 2d$ if $\omega = 0$ but *not* otherwise!

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This representation is not arbitrarily chosen.
It arises from a general-equilibrium economic model that allows for heterogeneity of firms, introduced by Abadir and Talmain (2002, *REStud*).
Not surprisingly, most macroeconomic series and financial aggregates share this common structure, to which we now turn.

3. The new evolution

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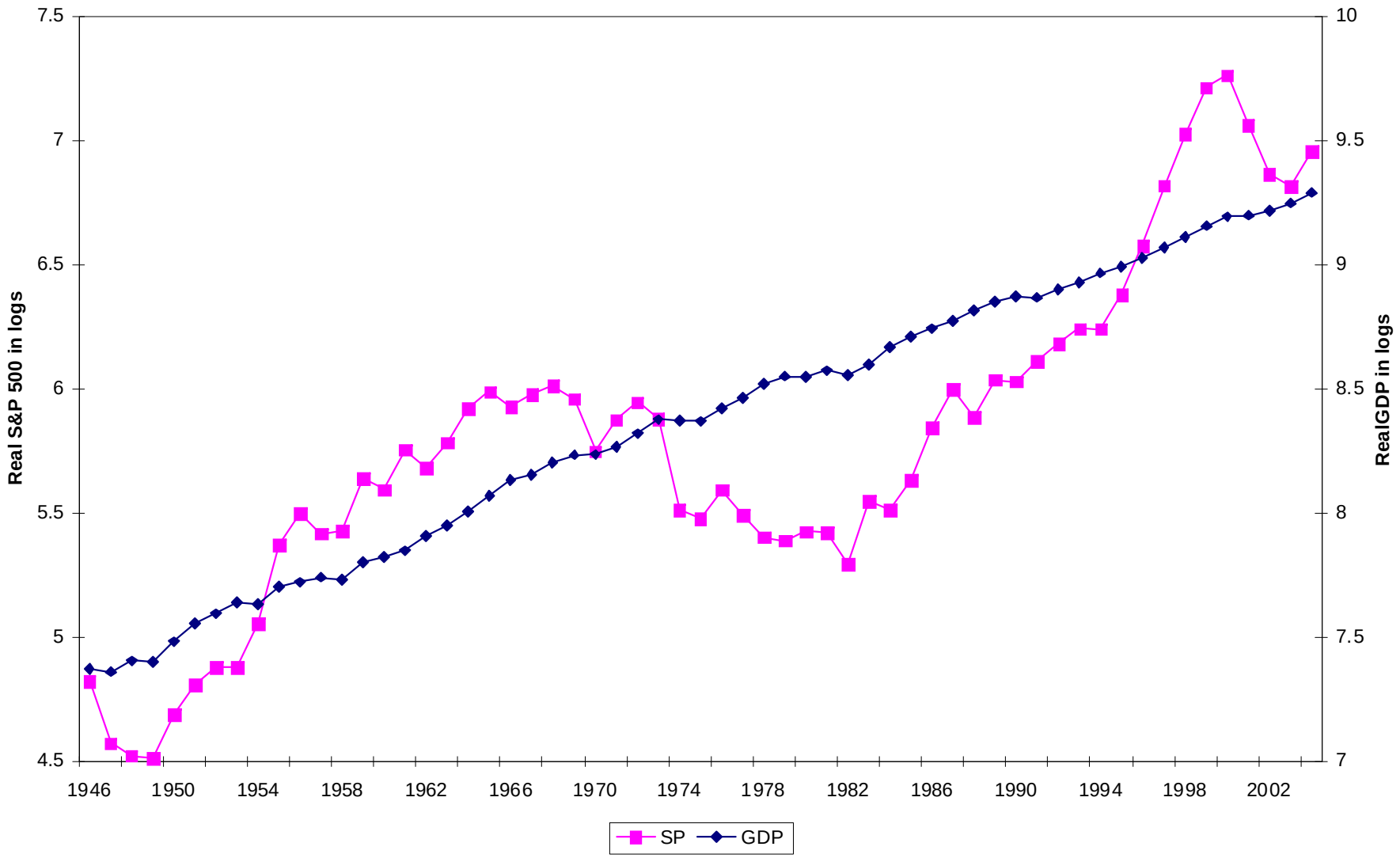
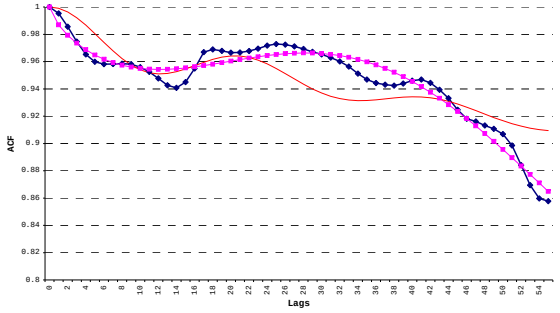
First, we can illustrate this in the time domain in the next graph, where we see that the variables are evolving around a time trend, well within finite variance bounds that don't expand over time (unlike unit-root processes).

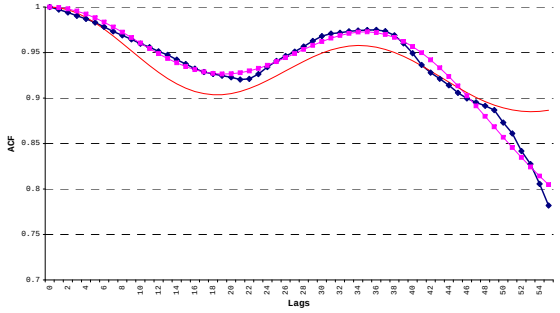

Real S&P 500 in logs
RealGDP in logs
7.5
7
6.5
6
5.5
5
4.5
10
9.5
9
8.5
8
7.5
7
1946
1950
1954
1958
1962
1966
1970
1974
1978
1982
1986
1990
1994
1998
2002
SP
GDP

Second, we represent this evolution parametrically and give the following pictures, using ACFs as viewing glasses.

They compare the actual ACF to two possible models by fitting:

1. a formula similar to the one given at the end of the previous section;
2. the best AR(p) model.


ACF
Lags
Government Expenditure (real)
AT_fit
AR_fit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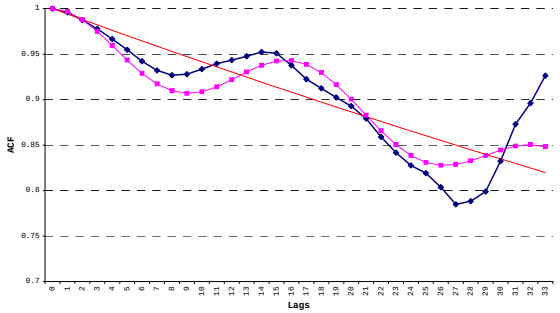
Lags
Tax Receipts (real)
AT_fit
AR_fit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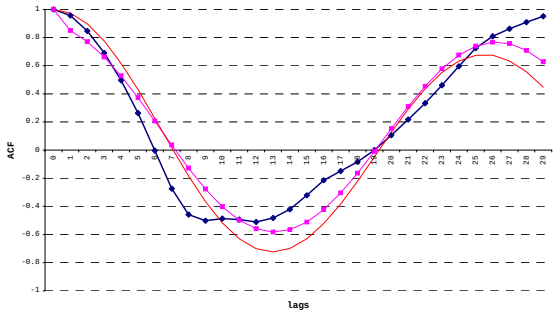
Lags
Money stock (real)
AT_fit
AR_fit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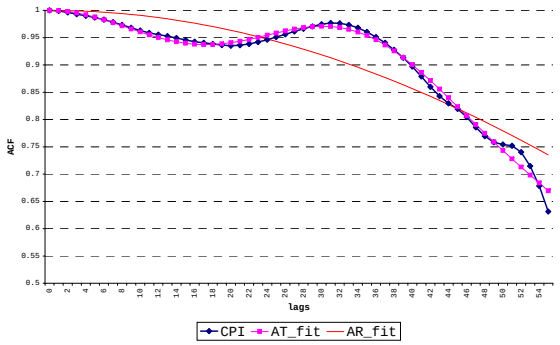
lags
Wages (real)
AT_fit
AR_fit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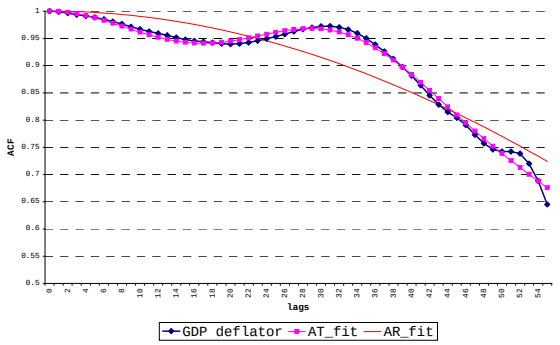
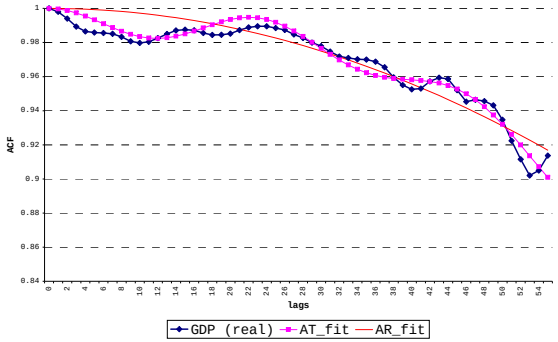
lags
CPI
AT_fit
AR_fit


ACF
lags
GDP deflator
AT_fit
AR_fit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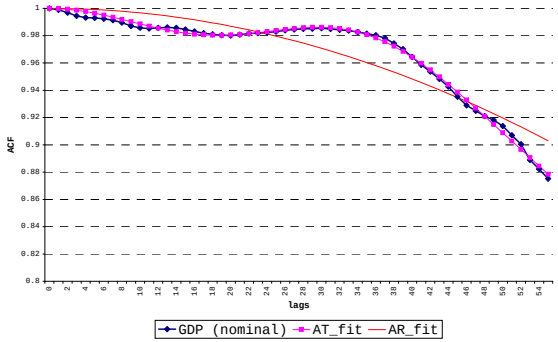
lags
GDP (real)
AT_fit
AR_fit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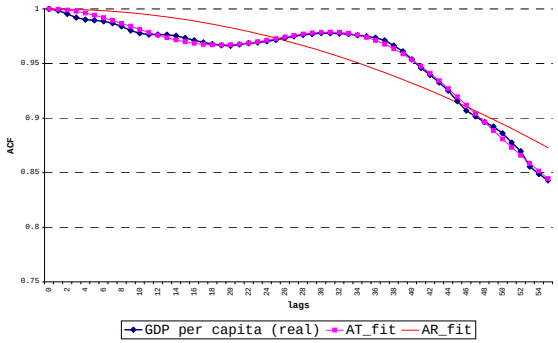
lags
GDP (nominal)
AT_fit
AR_fit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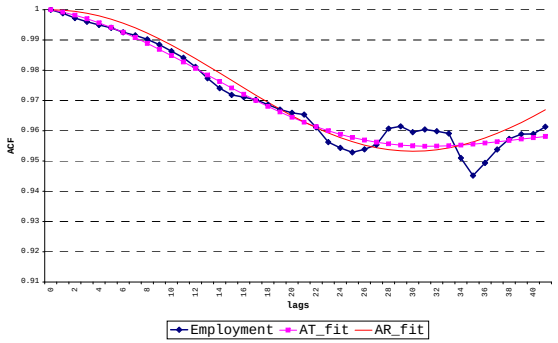
lags
GDP per capita (real)
AT_fit
AR_fit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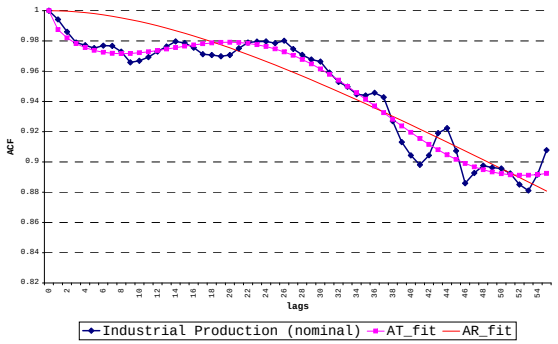
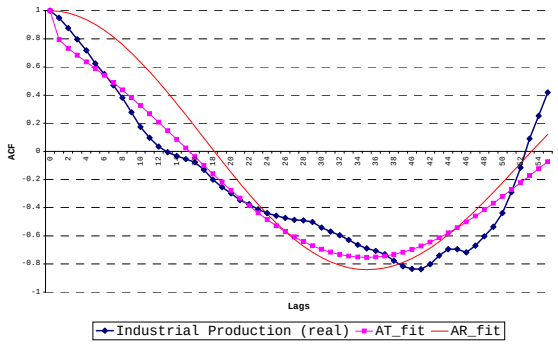
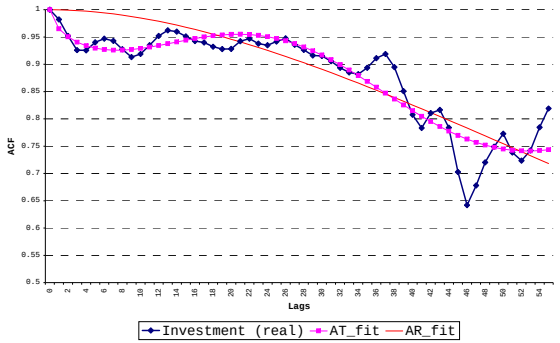
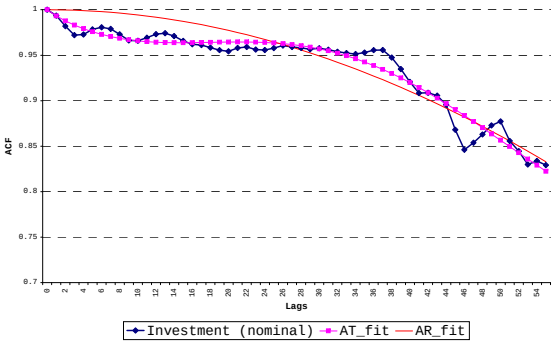
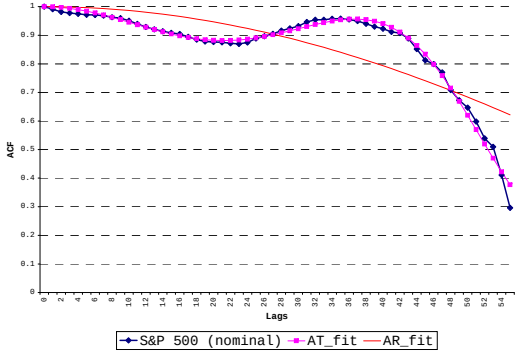
lags
Employment
AT_fit
AR_fit

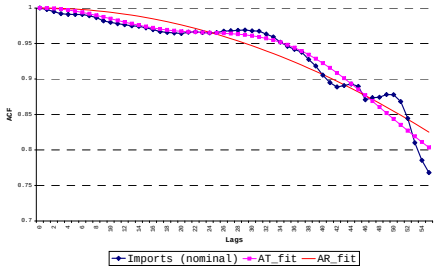

ACF
lags
Industrial Production (nominal)
AT_fit
AR_fit

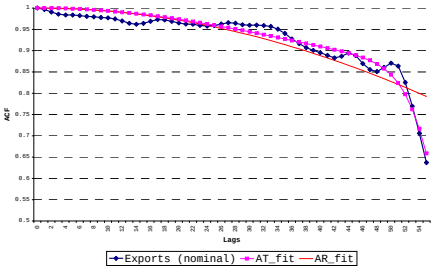

ACF
Lags
Industrial Production (real)
AT_fit
AR_fit

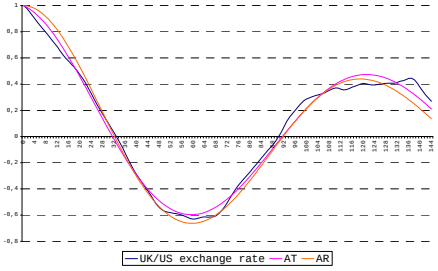

ACF
Lags
Investment (real)
AT_fit
AR_fit

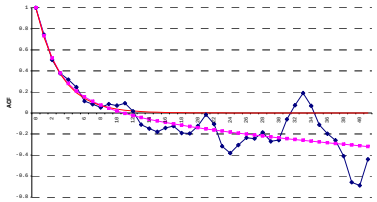

ACF
Lags
Investment (nominal)
AT_fit
AR_fit


ACF
Lags
S&P 500 (nominal)
AT_fit
AR_fit

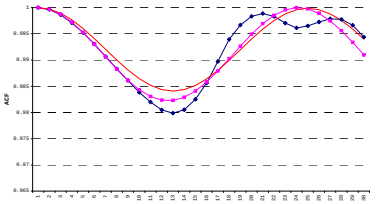

ACF
Lags
Imports (nominal)
AT_fit
AR_fit


ACF
Lags
Exports (nominal)
AT_fit
AR_fit

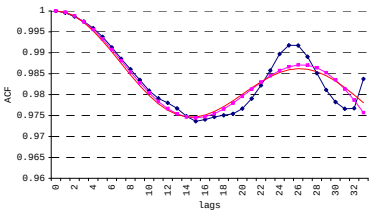

UK/US exchange rate
AT
AR



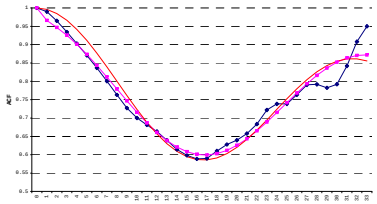
Unemployment AT_fit AR_fit



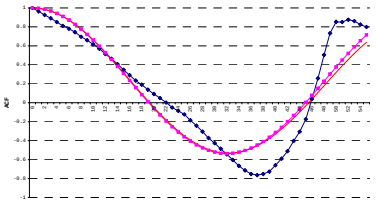
Wages (nominal) AT_fit AR_fit



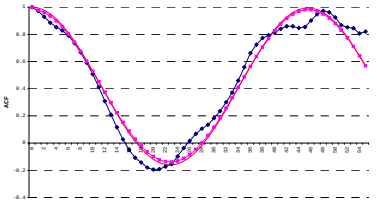
Money stock (nominal) AT_fit AR_fit



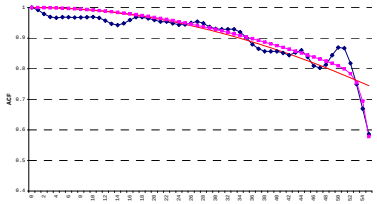
Velocity AT_fit AR_fit



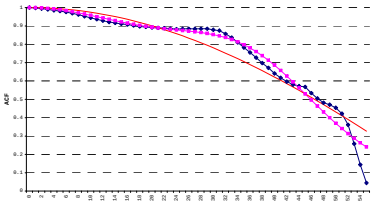
Bond yield (nominal) AT_fit AR_fit



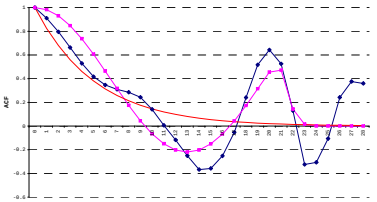
Bond yield (real) AT_fit AR_fit



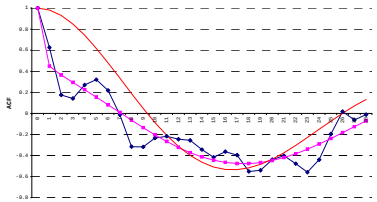
Exports (real) AT_fit AR_fit



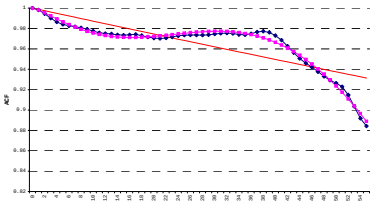
Imports (real) AT_fit AR_fit



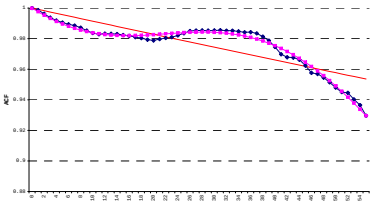
Wages growth (nominal) AT_fit AR_fit



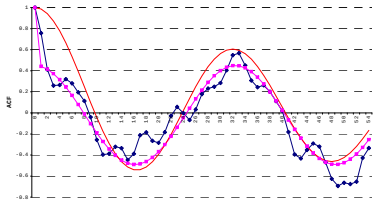
Wages growth (real) AT_fit AR_fit



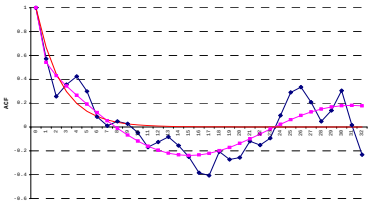
Government Expenditure (nominal) AT_fit AR_fit



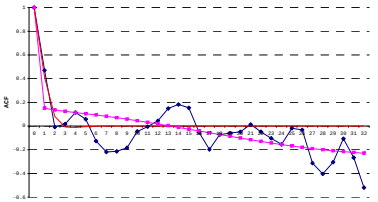
Tax Receipts (nominal) AT_fit AR_fit



Inflation AT_fit AR_fit



Money growth (nominal) AT_fit AR_fit



Money growth (real) AT_fit AR_fit

The dominance over traditional models remains even when we:

- take structural breaks into account;
- consider different sample periods.

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Through the ACFs, we can see that:

1. impulses decay very slowly and these variables takes a long time to alter directions;
2. once they do, the change is abrupt and accelerates.

In the context of financial variables, these two features are the (short-run) momentum and (medium-run) cycles that are often noted empirically, but not captured within a single model.

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In the context of macroeconomic stabilization, the features imply that, if an intervention takes place (e.g. change in interest rates), it should:

1. occur as soon as possible to give time to the policy to operate;
2. impart a stimulus sufficient to achieve the objective, taking into account the increments due to the persistent dynamics; and
3. revert to a neutral stance well before its objective is achieved, letting the economy ease onto its intended path.

Unfortunately, counterexamples to this course of action still exist.