

Some Comments on Cieslak and Povala's

Expecting the Fed

FRB SF

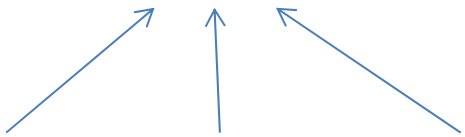
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Contributions

$$(1) \quad i_{t+h} - i_t = (\text{Fcst of } i_{t+h} - i_t) + \beta' (\text{lags of } i_t) + \text{error}$$

Yield Curve, Surveys, Greenbook



$\beta \neq 0$

(2) Implications and interpretation ...

Selected Evidence from Paper (t indexes quarters in my slides)

(1) Long-sample short-rate regressions

$$\text{Table 1: } i_{t+4} - i_t = \beta_0 + \delta_0 i_t + \delta_1 i_{t-\text{lag}1} + \delta_2 i_{t-\text{lag}2} + \delta_3 i_{t-\text{lag}3} + \text{error}$$

$$\text{Table 2: } i_{t+4} - i_t = \beta_0 + \sum_{j=1}^j \beta_j PC_{j,t} + \delta_1 i_{t-\text{lag}1} + \delta_2 i_{t-\text{lag}2} + \text{error}$$

Regressions lags are long, for some sample periods (1952-1979 and 1984-2011), δ 's are statistically significant, marginal R^2 from lags is large. Some instability across these two periods.

(2) Post 1983 regressions using Fed Funds Rate (FFR)

$$FFR_{t+h} - FFR_t = \beta_0 + \beta_1 [E_t^*(FFR_{t+h}) - FFR_t] + \delta FFR_{t-4}^c + \text{error}$$

$$\text{with } FFR_t^c = FFR_t - \hat{\beta} \gamma(L) \pi_t; \gamma(L) = \gamma \sum_{i=0}^{120} (.9865)^i L^i$$

δ is statistically significant and marginal R^2 is large. Estimated value of δ and marg. R^2 increase as h increases from $h = 1$ to $h = 4$.

Complications with evaluating evidence:

$$(1) i_{t+4} - i_t = \beta_0 + \delta_0 i_t + \delta_1 i_{t-\text{lag}1} + \delta_2 i_{t-\text{lag}2} + \delta_3 i_{t-\text{lag}3} + \text{error}$$

- i_t is persistent
- rhs is $i_{t+4} - i_t$, so error is serially correlated. Newey-West (6 lags) used.
- $lags$ are long

$$(2) FFR_{t+h} - FFR_t = \beta_0 + \beta_1 [E_t^*(FFR_{t+h}) - FFR_t] + \delta FFR_t^c + \text{error}$$

- FFR_t is persistent
- rhs is $FFR_{t+h} - FFR_t$ so error is serially correlated. Newey-West (6 lags) used.
- $FFR_t^c = FFR_t - \hat{\beta} \gamma(L) \pi_t$; $\gamma(L) = \gamma \sum_{i=0}^{120} (.9865)^i L^i$

(1) Long-sample short-rate regressions

Table 1: $i_{t+4} - i_t = \beta_0 + \delta_0 i_t + \delta_1 i_{t-\text{lag}1} + \delta_2 i_{t-\text{lag}2} + \delta_3 i_{t-\text{lag}3} + \text{error}$

Table 2: $i_{t+4} - i_t = \beta_0 + \sum_{j=1}^j \beta_j PC_{j,t} + \delta_1 i_{t-\text{lag}1} + \delta_2 i_{t-\text{lag}2} + \text{error}$

- i_t is persistent
 - Familiar “Dickey-Fuller” problems
 - “Mean Reversion” bias in OLS
 - non-normal t -stat
 - $R^2 \sim O_p(T^{-1})$ (as usual)

(1) Long-sample short-rate regressions

Table 1: $i_{t+4} - i_t = \beta_0 + \delta_0 i_t + \delta_1 i_{t-\text{lag}1} + \delta_2 i_{t-\text{lag}2} + \delta_3 i_{t-\text{lag}3} + \text{error}$

Table 2: $i_{t+4} - i_t = \beta_0 + \sum_{i=1}^j \beta_j PC_{j,t} + \delta_1 i_{t-\text{lag}1} + \delta_2 i_{t-\text{lag}2} + \text{error}$

- *rhs* is $i_{t+4} - i_t$ so error is serially correlated. Newey-West (6 lags) used.
 - $i_{t+4} - i_t = \Delta i_{t+1} + \Delta i_{t+2} + \Delta i_{t+3} + \Delta i_{t+4}$, so OLS bias is multiplied by 4
 - Effect on *t*-stat depends on details of HAC estimator

(1) Long-sample short-rate regressions

Table 1: $i_{t+4} - i_t = \beta_0 + \delta_0 i_t + \delta_1 i_{t-\text{lag}1} + \delta_2 i_{t-\text{lag}2} + \delta_3 i_{t-\text{lag}3} + \text{error}$

Table 2: $i_{t+4} - i_t = \beta_0 + \sum_{i=1}^j \beta_j PC_{j,t} + \delta_1 i_{t-\text{lag}1} + \delta_2 i_{t-\text{lag}2} + \text{error}$

- lags are long: $\Delta y_{t+1} = \rho_1 y_t + \rho_2 y_{t-k} + \varepsilon_t$

- y_t, y_{t-k} , nearly collinear if k is small. When y is very persistent, $(X'X)$ has one eigenvalue that is $O_p(T^2)$ and one that is $O_p(T)$. Persistence in regressors affects $\hat{\rho}_1 + \hat{\rho}_2$ but not other linear combinations of $\hat{\rho}_1$ and $\hat{\rho}_2$, which behave as if data were “iid”.

- y_t, y_{t-k} , not as collinear if k is large. $(X'X)$ has two eigenvalues that are $O_p(T^2)$. Persistence in regressors affects all linear combinations of $\hat{\rho}_1$ and $\hat{\rho}_2$.

- Whether lags are “Large” or “Small” depends on (lag/T) .

Selected CP Empirical results:

Table 1: $i_{t+4} - i_t = \beta_0 + \delta_0 i_t + \delta_1 i_{t-\text{lag}1} + \delta_2 i_{t-\text{lag}2} + \delta_3 i_{t-\text{lag}3} + \text{error}$

($1 \leq \text{lag}1 \leq 4$, $5 \leq \text{lag}2 \leq 8$, $13 \leq \text{lag}3 \leq 26$)

Sample	T	δ_0 (tstat)	δ_1 (tstat)	δ_2 (tstat)	δ_3 (tstat)	R^2	R^2 (no lags)
1951-2011	240	-0.01 (-0.10)	-0.27 (-1.88)	0.04 (0.38)	0.14 (1.59)	0.13	0.06
1951-1979	116	-0.52 (-3.47)	-0.37 (-2.78)	0.34 (3.26)	0.51 (3.71)	0.39	0.04
1984-2011	112	0.02 (0.27)	-0.47 (-3.63)	-0.01 (-0.10)	0.23 (3.16)	0.41	0.11

Similar results for

Table 2: $i_{t+4} - i_t = \beta_0 + \sum_{i=1}^j \beta_j PC_{j,t} + \delta_1 i_{t-\text{lag}1} + \delta_2 i_{t-\text{lag}2} + \text{error}$

Distribution of statistics for based on $\Delta i_t = \varepsilon_t$

Regression: $\Delta i_{t+1} = \beta_0 + \delta_0 i_t + \varepsilon_t$ – “Dickey-Fuller”

	T = 240				T = 115		
	50%	95%	99%		50%	95%	99%
tstat	1.6	2.9	3.4		1.6	2.9	3.5
R ²	1%	3%	4%		1%	6%	9%

Regression: $i_{t+4} - i_t = \beta_0 + \delta_0 i_t + u_t$ – “DF + Longer lead of LHS”

	T = 240				T = 115		
	50%	95%	99%		50%	95%	99%
tstat ^{NW}	1.8	3.7	4.7		2.0	4.3	5.7
R ²	4%	12%	17%		7%	23%	31%

Regression: $i_{t+4} - i_t = \beta_0 + \delta_0 i_t + \delta_1 i_{t-16} + u_t$ – “DF + LL LHS + Longer Lags RHS”

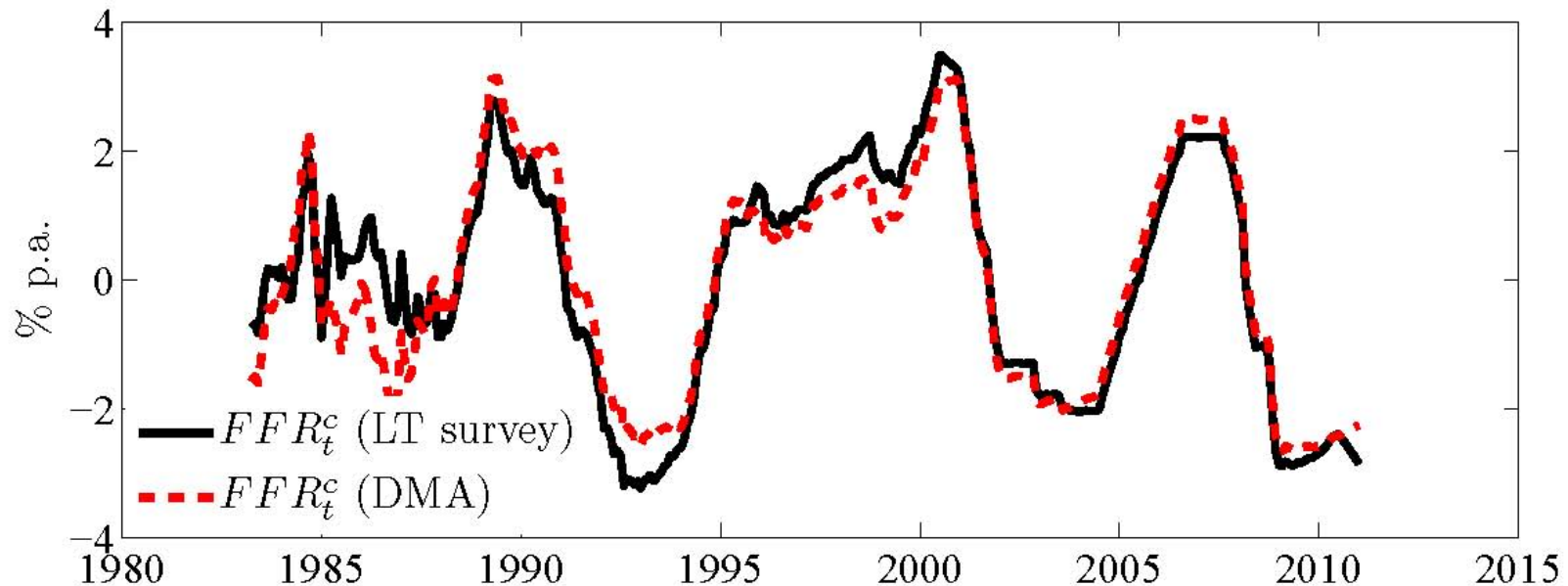
	T = 240				T = 115		
	50%	95%	99%		50%	95%	99%
tstat ₀ ^{NW}	1.3	3.6	4.8		1.9	4.4	5.9
tstat ₁ ^{NW}	0.9	2.7	3.6		1.0	3.1	4.4
R ² (no lags)	4%	12%	17%		7%	23%	31%
Marg. R ²	0%	6%	11%		1%	13%	21%

$$(2) FFR_{t+h} - FFR_t = \beta_0 + \beta_1 [E_t^*(FFR_{t+h}) - FFR_t] + \delta FFR_{t-4}^c + error$$

- FFR_t is persistent
- rhs is $FFR_{t+h} - FFR_t$ so error is serially correlated. Newey-West (6 lags) used.

- $FFR_t^c = FFR_t - \hat{\beta} \gamma(L) \pi_t$; $\gamma(L) = \gamma \sum_{i=0}^{120} (.9865)^i L^i$

- This “detrending” leaves a persistent component in FFR^c (compare the demeaning)



Selected CP Empirical results: Table IV (1983-2010, $T = 112$)

$$FFR_{t+h} - FFR_t = \beta_0 + \beta_1[E_t^*(FFR_{t+h}) - FFR_t] + \delta FFR_{t-4}^c + error$$

	$h = 1$	$h = 2$	$h = 3$	$h = 4$
$\hat{\delta}$ (<i>tstat</i>)	-0.1 (-3.2)	-0.2 (-3.8)	-0.4 (-4.9)	-0.6 (-6.1)
Marg. R^2	4%	10%	17%	25%

An experiment: $\Delta y_t = \varepsilon_t$, $\varepsilon_t \sim \text{iidN}(0,1)$ and $x_t = y_t + a_t$, $a_t \sim \text{iidN}(0,4)$

$$y_t^c = y_t - \hat{\beta}\gamma(L)x_t$$

Regression: $y_{t+h} - y_t = \alpha + \delta y_t^c + u_t$

Quantiles of distribution for selected statistics ($T = 115$)

	$h = 1$			$h = 4$		
	50%	95%	99%	50%	95%	99%
$-\hat{\delta}$	0.07	0.17	0.23	0.24	0.57	0.73
$-tstat^{NW}$	2.2	4.1	5.1	2.6	5.4	6.9
R^2	3%	9%	12%	12%	31%	39%

Some problems with my discussion:

- Numerical results computed for $I(1)$ stochastic process, which does not characterize i_t . And many other important features of stochastic process (instability, stochastic volatility, etc.) were ignored.
- CPs analysis includes many other empirical exercises that I haven't discussed.
Example: regressions:

$$y_{t+h} - y_{t,t+h}^s = \beta_0 + \beta_1(y_{t,t+h}^s - y_{t-1,t+h}^s) + error$$

$\hat{\beta}_1$ is positive and statistically significant ...

Nordhaus (1987) – Empirical result

Elliott, Komunjer, Timmermann (2005) – Loss function

Engleberg, Manski, Williams (2009) – Survey Panels

Coibion-Gorodnichenko (2012) – Stickiness

Kirchgässner-Müller (2006) – Stability