Monetary Policy Rule as a Bridge: Predicting Inflation Without Predictive Regressions

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Overview

*It is difficult to predict, especially the future.*— Neils Bohr

- Predicting inflation is important for monetary policy..., but extremely difficult to do *well*.

- Virtually all *predictive regressions* fail to beat random walk *out of sample* — Stock & Watson (2007, 2010), Faust & Wright (2013).

- Predictive regressions also perform poorly in out-of-sample tests in predicting *interest rates* (Duffee (2002, 2013)), *exchange rates* (Engel & West (2005)), other persistent series

- Inference issues with predictive regressions are well known (Phillips, 2013).
  - This is important when inferring dynamic behaviors from predictive regression estimates

- Our focus is on out-of-sample forecasting performance.
  - An important metric for many practical applications.
Why do predictive regressions fail in out-of-sample tests?

Even if the predictors are truly informative, it is difficult to estimate the predictive relation with accuracy via predictive regressions.

- Many predictive regressions have low $R^2$ by nature.
- The low $R^2$ by itself is not an issue, the issue is its implication on the standard error of the coefficient estimates.
- Rolling-window predictive regressions often generate large sample variations on the estimates, which tend to add more noise than information to out-of-sample prediction.
- The net result is a prediction worse than no-prediction (random walk).

Can we think of alternative ways of determining a predictive relation, rather than via a predictive regression?
We propose to predict inflation without running any predictive regressions: Link the inflation rate to a short-term interest rate, and rely on the forward interest rate curve to predict future path of short-term interest rates.

1. Monetary policy rules provide a theoretical basis for a strong link between policy interest rate and inflation rate.
   - This is a *strong contemporaneous relation* – We may have a chance of estimating the coefficients with more accuracy.

2. Use the forward rate curve to predict the future path of short-term interest rates across different horizons.
   - Remove the average bias induced by risk premium and convexity via a *moving average*, rather than a predictive regression.
   - The expectation hypothesis predictive regression performs much worse.

Combining the two elements generates a predictive relation that predicts future inflation rate changes with the forward-spot interest rate differential:

- The predictive relation is not estimated by a predictive regression.
Monetary policy rule as a bridge

- The large literature on *monetary policy rules* provides the theoretical basis for linking the expected inflation rate \( \pi_t \) to the short-term interest rate \( r_t \):

\[
 r_t = \alpha + \beta \pi_t + o_t 
\]  

(1)

- \( o_t \) denotes other policy considerations or policy surprises.
- The less emphasis the policy puts on “other considerations \( o_t \),” the stronger the link between the policy rate and the expected inflation.

- We propose to turn the policy rule around and estimate the policy response via:

\[
 p_t \equiv \ln(P_t/P_{t-1}) = a + br_t + e_t 
\]  

(2)

- \( P_t \) denotes some price index level, \( p_t \) the realized inflation rate over period \( (t - 1, t) \), and \( r_t \) the average short rate within the same period.
- The reversed regression mitigates the EIV problem, with \( \beta = 1/b \).

- The estimated linkage transforms the task of forecasting inflation to the task of forecasting future short rates,

\[
 \hat{p}_{t+h|t} - p_t = \hat{b} (\hat{r}_{t+h|t} - r_t) . 
\]  

(3)
The forward curve \( f_t^h \) contains 3 components: (i) expectation \( \mathbb{E}_t[r_{t+h}] \), (ii) risk premium \( \uparrow \), and (iii) convexity \( \downarrow \).

Example: Vasick (1977) model
\[
f_t^h = \left[ \theta(1 - e^{-\kappa h}) + r_t e^{-\kappa h} \right] - \left[ \frac{1-e^{-\kappa h}}{\kappa} \sigma \lambda \right] - \left[ \frac{1}{2} \frac{(1-e^{-\kappa h})^2}{\kappa^2} \sigma^2 \right]
\]

We exploit (i) for our forecast while removing the average bias induced by (ii) and (iii):

\[
\hat{r}_{t+h} - r_t = (f_t^h - r_t) - (f_t^h - r_t),
\] (4)

with \((f_t^h - r_t)\) denoting a moving average of the forward-spot differential.

The expectation hypothesis (EH) literature often performs a forecasting regression of the type:

\[
r_{t+h} - r_t = a + b(f_t^h - r_t) + e_{t+h}
\] (5)

- The null of EH is \( a = 0, b = 1 \).
- The regression is used as a way of testing “time-varying risk premium.”
- Our simple average-bias removal approach avoids running this predictive regression.
Combining the two steps lead to the following predictive relation:

$$\hat{p}_{t+h|t} - p_t = \hat{b} \left( f_t^h - r_t - (f_t^h - r_t) \right).$$  \hspace{1cm} (6)

One could, in principle, estimate the relation with a predictive regression:

$$\hat{p}_{t+h} - p_t = c + b \left( f_t^h - r_t \right) + e_{t+h}.$$  \hspace{1cm} (7)

Instead,

- We determine the slope coefficient $\hat{b}$ via a much stronger contemporaneous relation.
- We determine the intercept via a moving average bias correction.

Avoiding the predictive regression helps out-of-sample performance.
Data and implementation details

- Form year-over-year (YoY) realized inflation rates using 4 monthly observed prices indexes, CPI, CCPI, PCE, CPCE.
  - June 1962 to June 2012.
- Stripped spot and forward Treasury rates from 3 months to 6 years over the same sample period.
  - Use 3-month rate as a proxy for the short rate $r$.
  - Use annual averages of daily short rates to match YoY inflation rates.
  - Construct 1-5 year forward rates on the 3-month rate, for forecasting 3-month rate and inflation rates over horizons from 1 to 5 years.

Rolling-window estimation and out-of-sample estimation
- Relations are estimated with a 10-year rolling window – Balance between sample size (cycles) and policy variation
- Out-of-sample forecasting performance measure: $e_{t+h} = p_{t+h} - \hat{p}_{t+h|t}$.

$$MSFE = \frac{1}{T} \sum_{t=1}^{T} e_{t+h}^2$$

$$R^2 = 1 - \frac{MSFE}{MSFE_0}, \text{ with } MSFE_0 \text{ defined on } e_{t+h} = p_{t+h} - p_t.$$ 

Diebold-Mariano $t$-statistics on squared forecasting error difference
Interest rates and inflation rates co-move.
Policy linkage: Full-sample estimates

Full-sample estimates of policy linkage: $p_t = a + br_t + e_t$

<table>
<thead>
<tr>
<th>Price Index</th>
<th>$\hat{a}$</th>
<th>$\hat{b}$</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>CPI</td>
<td>0.65 (0.59)</td>
<td>0.62 (0.14)</td>
<td>0.47</td>
</tr>
<tr>
<td>CCPI</td>
<td>0.37 (0.45)</td>
<td>0.66 (0.10)</td>
<td>0.62</td>
</tr>
<tr>
<td>PCE</td>
<td>0.69 (0.48)</td>
<td>0.53 (0.11)</td>
<td>0.46</td>
</tr>
<tr>
<td>CPCE</td>
<td>0.61 (0.36)</td>
<td>0.53 (0.07)</td>
<td>0.58</td>
</tr>
</tbody>
</table>

- Contemporaneous regression generates high $R^2$, due to strength of relation.
- Slope estimates suggest a strong policy reaction to inflation ($\beta = 1/b = [1.5, 1.9]$).
- Estimates similar to those in the literature Taylor (1999); Clarida, Gali, Gertler (2000)).
### Policy linkage: Regime switches

<table>
<thead>
<tr>
<th>Price Index</th>
<th>( \hat{a} )</th>
<th>( \hat{b} )</th>
<th>( R^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>B. 1962:6 – 1979:9</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CPI</td>
<td>-3.97 (0.71)</td>
<td>1.62 (0.14)</td>
<td>0.87</td>
</tr>
<tr>
<td>CCPI</td>
<td>-3.14 (0.63)</td>
<td>1.43 (0.11)</td>
<td>0.83</td>
</tr>
<tr>
<td>PCE</td>
<td>-3.03 (0.90)</td>
<td>1.37 (0.18)</td>
<td>0.79</td>
</tr>
<tr>
<td>CPCE</td>
<td>-2.03 (0.86)</td>
<td>1.15 (0.15)</td>
<td>0.74</td>
</tr>
<tr>
<td><strong>C. 1979:10 – 2012:6</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CPI</td>
<td>0.82 (0.60)</td>
<td>0.50 (0.14)</td>
<td>0.49</td>
</tr>
<tr>
<td>CCPI</td>
<td>0.47 (0.47)</td>
<td>0.57 (0.11)</td>
<td>0.71</td>
</tr>
<tr>
<td>PCE</td>
<td>0.75 (0.50)</td>
<td>0.43 (0.11)</td>
<td>0.54</td>
</tr>
<tr>
<td>CPCE</td>
<td>0.59 (0.39)</td>
<td>0.46 (0.07)</td>
<td>0.72</td>
</tr>
</tbody>
</table>

- Policy was inflationary before 1979 \( (\beta = 1/b < 1) \).
- Policy response to inflation has been a lot stronger since Volker, leading to lower inflation.
Rolling-window slope estimates reflect the policy changes of the switched regimes.

One can in principle modify the estimates based on policy announcements.
Out-of-sample interest rate forecasting: $R^2$

- Full-sample EH predictive regression slope estimates may be useful in revealing the time-series behavior of risks and risk premiums,
- but using rolling-window EH predictive regression to do out-of-sample prediction fails miserably, much worse than no prediction (random walk).
- Directly using the forward-spot differential with an average bias removal works much better, can generate up to 30% out-of-sample $R^2$. 
### Out-of-sample interest rate forecasting: DM tests

<table>
<thead>
<tr>
<th>Horizon Years</th>
<th>A. EH regression</th>
<th></th>
<th>B. MV bias correction</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$R^2$</td>
<td>DM</td>
<td>$R^2$</td>
<td>DM</td>
</tr>
<tr>
<td>1</td>
<td>-0.12</td>
<td>-1.06</td>
<td>-0.01</td>
<td>-0.07</td>
</tr>
<tr>
<td>2</td>
<td>-0.17</td>
<td>-0.71</td>
<td>0.11</td>
<td>0.72</td>
</tr>
<tr>
<td>3</td>
<td>-0.14</td>
<td>-0.28</td>
<td>0.23</td>
<td>1.69</td>
</tr>
<tr>
<td>4</td>
<td>-0.27</td>
<td>-0.39</td>
<td>0.28</td>
<td>1.96</td>
</tr>
<tr>
<td>5</td>
<td>-0.58</td>
<td>-0.78</td>
<td>0.21</td>
<td>1.25</td>
</tr>
</tbody>
</table>

- Directly using the forward-spot differential with an average bias removal can generate statistically significant outperformance over random walk.
Large sample variation across both time and horizons, all round the null hypothesis of 1 (no risk/risk premium variation).

Even if risk/risk premium is time varying, it is difficult to nail down the coefficients via rolling window estimation.

Moving average bias removal is a much more efficient way of removing the average bias.
Out-of-sample forecasting $R^2$ can be as high as 40-60% at 3.5-year forecasting horizon.

Outperformance over random walk is large for all four series and over a wide range of forecasting horizons.
Predicting inflation *without* predictive regressions

DM tests on out-of-sample forecasting squared difference over random walk:

<table>
<thead>
<tr>
<th>Horizon Years</th>
<th>CPI $R^2$</th>
<th>DM</th>
<th>CCPI $R^2$</th>
<th>DM</th>
<th>PCE $R^2$</th>
<th>DM</th>
<th>CPCE $R^2$</th>
<th>DM</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.14</td>
<td>1.36</td>
<td>-0.02</td>
<td>-0.12</td>
<td>0.13</td>
<td>1.10</td>
<td>-0.07</td>
<td>-0.42</td>
</tr>
<tr>
<td>2</td>
<td>0.37</td>
<td>2.09</td>
<td>0.31</td>
<td>1.65</td>
<td>0.33</td>
<td>1.95</td>
<td>0.21</td>
<td>1.21</td>
</tr>
<tr>
<td>3</td>
<td>0.52</td>
<td>1.83</td>
<td>0.51</td>
<td>1.75</td>
<td>0.49</td>
<td>1.84</td>
<td>0.39</td>
<td>1.69</td>
</tr>
<tr>
<td>4</td>
<td>0.51</td>
<td>1.55</td>
<td>0.56</td>
<td>1.52</td>
<td>0.49</td>
<td>1.53</td>
<td>0.44</td>
<td>1.47</td>
</tr>
<tr>
<td>5</td>
<td>0.38</td>
<td>1.07</td>
<td>0.40</td>
<td>1.11</td>
<td>0.35</td>
<td>1.06</td>
<td>0.32</td>
<td>1.06</td>
</tr>
</tbody>
</table>

- Out-of-sample forecasting $R^2$ is highest at 3-4 year horizon.
- DM tests are the most significant at 2-4 year horizon.
Predicting inflation *with* predictive regressions

- We have proposed to predict future inflation rate changes with the current forward-spot interest rate differential:
\[
\hat{p}_{t+h|t} - p_t = \hat{b} \left( f^h_t - r_t - (f^h_t - r_t) \right).
\]
- We arrive at this relation by combining a monetary policy rule with the decomposition of the forward interest rate curve.
- Slope is determined by the policy rule.
- Intercept is determined by a moving average removal of the average bias induced by convexity effects and risk premium.
- We can estimate the same predictive relation *with predictive regressions*:

\[
\begin{align*}
A_1 &: \quad p_{t+h} - p_t = c^h_t + b^h_t (f^h_t - r_t) + e_{t+h}, \\
A_2 &: \quad p_{t+h} - p_t = b^h_t \left( f^h_t - r_t - (f^h_t - r_t) \right) + e_{t+h}, \\
A_3 &: \quad p_{t+h} - p_t = b^h_t \left( f^h_t - r_t - (f^h_t - r_t) \right) + e_{t+h},
\end{align*}
\]

- \( A_1 \): Separate predictive regression at each horizon
- \( A_2 \): Separate predictive regression without intercept
- \( A_3 \): Pooled predictive regression without intercept

In theory it is the same relation, in practice ...
## Out-of-sample performance of predictive regressions

<table>
<thead>
<tr>
<th>Horizon</th>
<th>CPI</th>
<th>CCPI</th>
<th>PCE</th>
<th>CPCE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$R^2$</td>
<td>DMR</td>
<td>DMN</td>
<td>$R^2$</td>
</tr>
<tr>
<td>Years</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>$-0.14$</td>
<td>$-1.23$</td>
<td>$-2.30$</td>
<td>$-0.31$</td>
</tr>
<tr>
<td>3</td>
<td>$0.14$</td>
<td>$0.23$</td>
<td>$-0.87$</td>
<td>$0.07$</td>
</tr>
<tr>
<td>5</td>
<td>$-0.46$</td>
<td>$-1.80$</td>
<td>$-1.47$</td>
<td>$-0.85$</td>
</tr>
</tbody>
</table>

$A_1$: Predictive regression estimation of intercept and slope

$A_2$: Predictive regression estimation of slope without intercept

$A_3$: Stacked predictive regression estimation of common slope without intercept

- DMR is against random walk: negative or insignificantly positive.
- DMN is against our proposal: All negative, some significantly so.
- $A_3 > A_2 > A_1$. More constraints generate slightly better results.
Extensions and robust checks

- UK inflation rate prediction: similar findings
  - Up to 40% R-squared at three year horizon.
  - Forward curve predicts future short rate with moving average bias correction: up to 20% R-squared, versus complete breakdown of EH regression

- Robustness checks
  - Different performance measures
  - Different rolling window sizes
  - Different short rate proxy
Even with the same predictive relation, out-of-sample performance can greatly vary depending on how the relation is estimated.

Predictive regressions are often the most apparent approach for estimating a predictive relation, but they tend to be the least likely to generate stable estimates for robust out-of-sample performance.

For future research, it is equally important to
- Search for predictive instruments
- Identify robust methods to estimate predictive relations without resorting to predictive regressions

Example: surveys
- More accurate than regression forecasts, but very sparse and sporadic.
- Do not use surveys as predictive regressors, but as calibrators of predictive relations

Example: Forward-looking derivatives (e.g. inflation swaps)
- Remove bias (risk premium) via average bias correction