Information Rigidity, Tenure Effects, and Persistence in the Survey of Professional Forecasters

Jane Ryngaert

University of Texas

September 1, 2016
Outline

1. **Introduction**
   - First contribution - A new estimation equation

2. **Results from the Data**
   - Some Facts from the Data

3. **Individual Heterogeneity**
   - Random Coefficients
   - Tenure Effects

4. **Time Variation and Persistence**
   - Effect of Time-Varying Process Persistence
Why do we care about information rigidities?

- They are important for price and wage setting decisions, for determining optimal monetary policy, etc.
- Lower rigidity lead to faster recovery in impulse responses and therefore a different response of monetary policy.
- I’m going to argue that it’s very important we correctly measure these rigidities and understand their interactions with process persistence.
## Related Literature

### Measuring Information Rigidity
- Coibion and Gorodnichenko (2012 JPE, 2015 AER)
- Dovern, Fritsche, Loungani, Tamirisa (2014)

### Lagged Dependent Variable Models in Panel Data

### Persistence of US inflation over time
- Gamber, Liebner, Smith (2013)
- Blanchard and Gali (2007)
I focus on two equations for testing the degree of information rigidity. The first is my specification

**Using individual forecast errors**

If we assume that agents do not observe realized inflation for at least one period following each forecast.

\[
\tilde{x}_t(i) - x_t = \rho(1 - p)(\tilde{x}_{t-1}(i) - x_{t-1}) + \epsilon_{it}
\]

(1)

Where \( p \) is the gain from the Kalman filter, \( x_t \) is some economic variable and \( \tilde{x}_t(i) \) is agent \( i \)'s forecast of that variable.
Preliminary Estimation Equations

Using aggregate forecast errors

This follows from Coibion and Gorodnichenko (2012)’s specification for mean level forecasts.

\[ \tilde{x}_t(i) - x_t = \rho(1 - p)(\tilde{x}_{t-1}(i) - x_{t-1}) + \epsilon_t \]  

(2)
How Do These Variables Relate to Each Other?

In the following equation,

\[ \tilde{x}_t(i) - x_t = \rho(1 - p)(\tilde{x}_{t-1}(i) - x_{t-1}) + \epsilon_{it} \]  

(3)

- Persistence \((\rho)\), information rigidity \((1-p)\), and the variance of an agent’s signal noise \((\sigma^2_{\nu_{it}})\) are interdependent.
- Information rigidity is decreasing in process persistence and increasing in signal noise.
Linking these equations to the data. What are we testing?

**Regression Equations**

My pooled OLS specification

\[ FE_t(i) = \beta_0 + \beta_1(FE_{t-1}(i)) + \epsilon_{it} \]  \hspace{1cm} (4)

Aggregate regression specification:

\[ \overline{FE}_t = \beta_0 + \beta_1(\overline{FE}_{t-1}) + \epsilon_t \]  \hspace{1cm} (5)

Taking these to the data and assuming \( \rho = 1 \) should recover \( \beta_0 = 0 \) and \( \beta_1 \) equal to the underlying degree of information rigidity, \( 1 - p \), in the survey. If \( \rho < 1 \), the implied degree of information rigidity will be higher than the estimated \( \beta_1 \).
## Results for Two Variables

### Aggregate Regressions

<table>
<thead>
<tr>
<th></th>
<th>Real GDP</th>
<th>Inflation</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_0$</td>
<td>-0.012 (0.078)</td>
<td>-0.015 (0.034)</td>
</tr>
<tr>
<td>$\beta_1$</td>
<td>0.749*** (0.049)</td>
<td>0.889*** (0.033)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.56</td>
<td>0.80</td>
</tr>
<tr>
<td>N</td>
<td>183</td>
<td>183</td>
</tr>
</tbody>
</table>

### Pooled Regressions

<table>
<thead>
<tr>
<th></th>
<th>Real GDP</th>
<th>Inflation</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_0$</td>
<td>-0.06 (0.024)</td>
<td>0.005 (0.014)</td>
</tr>
<tr>
<td>$\beta_1$</td>
<td>0.688*** (0.013)</td>
<td>0.780*** (0.011)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.47</td>
<td>0.61</td>
</tr>
<tr>
<td>N</td>
<td>3,078</td>
<td>2,994</td>
</tr>
</tbody>
</table>
If $\beta_{i,t} = \beta \ \forall \ i, \ \forall \ t$, both estimation equations should recover $\beta$ and should therefore be equal to each other. We know that they are not.

- Absolute forecast errors decline with tenure
- Absolute forecast errors decline with time
- The coefficient on lagged forecast errors in the pooled regression decreases over time.
Performance of Estimators in an Unbalanced Panel

Figure 2: Coefficients - Inflation
Figure 3: Coefficients - Inflation
Forecast Errors Over Tenure

Figure 4: Coefficients - Inflation
Forecast Errors Over Time

Figure 5: Coefficients - Inflation
Forecast Errors Over Time

Figure 6: Coefficients - Inflation
\( \beta \) has been declining over time

Running the regression:

\[
FE_t(i) = \beta_0 + \beta_1 FE_{t-1}(i) + \beta_2 year + \beta_3 (\text{year} \times FE_{t-1}(i)) + \epsilon_{it} \quad (6)
\]

A reduction in our \( \rho(1 - p) \) parameter means this regression would mean that this regression returns a \( \beta_3 < 0 \).
What if individuals have different Kalman gains?

- Both the pooled OLS and the aggregate time series depend on the assumption that the underlying data generating process and parameters are constant across agents.
- Suppose, however, that agents do not have the same Kalman gain and some agents actually incorporate new information more quickly than others.

### A Random Coefficients Model

Let $\beta + \beta_i = 1 - p_i$, where $p_i$ is Agent $i$’s Kalman gain.

$$\tilde{x}_t(i) - x_t = (\beta + \beta_i)(\tilde{x}_{t-1}(i) - x_{t-1}) + \epsilon_{it}$$  (7)

Where $\beta_i \sim N(0, \sigma_i)$ and is independent of the noise in agent signals.
What if individuals have different Kalman gains?

- If this is the case, both the Pooled OLS and aggregate regressions will produce biased results due to the dynamic panel structure of the regression equation. (Pesaran and Smith).
- With a dynamic equation structure over panel data, Pesaran and Smith’s recommendation is to go ahead and run the random coefficients specification and test the null that the coefficients are equal across individuals.
- The random coefficients specification should consistently return the true value in cases of homogeneity or heterogeneity and allows for a direct test of the constancy of coefficients across individuals.
Random Coefficients Doesn’t Seem to Solve the Problem
Random Coefficients Doesn’t Seem to Solve the Problem

Figure 8: Difference in Coefficients - Inflation
Systematic individual heterogeneity involves forecasters gaining better signals for each period they are in the survey.

As agent’s get signals with lower noise (given a constant persistence parameter), her Kalman gain \((p)\) increases, causing her information rigidity measure \((1-p)\) to decrease.

There are a couple ways to implement this - we could have constant, linear tenure effects, or nonlinear effects that look like a huge gain to the first few periods that eventually levels off.
Systematic Tenure Effects

Linking these equations to the data. What are we testing?

**Linear Tenure Effects**

\[ FE_t(i) = \rho(1 - p - \delta \times tenure)FE_t(i) + \epsilon_{it} \]  \hspace{1cm} (8)

**Nonlinear tenure effects**

\[ FE_t(i) = \rho(1 - p(tenure))FE_t(i) + \epsilon_{it} \]  \hspace{1cm} (9)

where \( p \) is an increasing function of tenure.
Nonlinear Learning Response

Figure 9: Coefficients - Inflation
Nonlinear Learning Response

Figure 10: Coefficients - Inflation
In the following equation,

\[ \tilde{x}_t(i) - x_t = \rho(1 - p)(\tilde{x}_{t-1}(i) - x_{t-1}) + \epsilon_{it} \]  

(10)

- We can also influence our \( \beta \) term by adjusting \( \rho \). Lower levels of persistence may create the same results we see in the data.
How does this work?

Assume for a moment that, without changing the agents’ signal noise parameter.

\[ FE_t(i) = \rho_t(1 - p)FE_{t-1}(i) + \epsilon_{it} \]  

(11)

- Again, there are a couple of ways we can do this. The change in \( \rho_t \) could continuous - either linear or nonlinear. It could also take the form of regime changes - discrete changes in \( \rho \) at a couple of points in the sample that hold for some length of time.

- Also have to consider whether or not the agents know that persistence is changing. If they do, they will incorporate it into their gain.
Regime Changes in Persistence

Figure 11: Betas Over Time - Inflation
Regime Changes in Persistence

Figure 12: Coefficients - Inflation
Regime Changes in Persistence

Figure 13: Difference - Inflation
Regime Changes in Persistence - Absolute Value of FE over Tenure
Regime Changes in Persistence - Absolute Value of FE over Time
Regime Changes in Persistence - Coefficients on Period

Figure 16: Coefficients - Inflation
Conclusions

- Using both time series and pooled OLS regressions of forecast errors on their own lags gives us data suggesting that something odd is happening.
- Unbalanced panels, random coefficients, and tenure effects cannot create the kinds of empirics we see in the inflation data.
- Time-varying persistence seems a promising direction for generating these persistence.
- Of potential forms of time variation, regime changes (as opposed to continuous changes in persistence) best match the observed empirics.
The Kalman Filter Model

Inflation follows the following AR(1) process:

$$\pi_t = \rho \pi_{t-1} + w_t$$  \hspace{1cm} (12)

Agents each receive a private signal about inflation:

$$z_{it} = \pi_t + v_{it}$$  \hspace{1cm} (13)

Agents will process this information about inflation as
Average Forecast Errors Over Time

Figure 18: Coefficients - Inflation
Average Absolute Forecast Errors Over Time

Figure 19: Coefficients - Inflation
Figure 20: Coefficients - Inflation

Continuous Changes in Persistence
Continuous Changes in Persistence

Figure 21: Difference - Inflation
Individual Coefficients for Random Coefficients

Figure 22: Coefficients - Inflation
Figure 23: Coefficients - Inflation