Optimal Inflation and the Phillips Curve

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The views expressed in this paper are those of the authors, and not necessarily those of the Bank of England or its committees
Is there a Phillips curve?

- **Inflation follows a seemingly exogenous process, unrelated to measures of slack.** E.g.,
  - Atkeson and Ohanian (2001)
  - Stock and Watson (2007, 2009)
  - Hall (2011)
  - Dotsey, Fujita and Stark (2017),
  - Cecchetti, Feroli, Hooper, Kashyap, and Schoenholtz (2017)
  - Forbes, Kirkham and Theodoridis (2017)
  - Uhlig (2018)

- **The Phillips Curve has flattened (or even disappeared).** E.g.,
  - Ball and Mazumder (2011)
  - IMF (2013)
  - Blanchard, Cerutti and Summers (2015)
  - Summers (2017)
  - Andolfatto (2017)
  - Blinder (2018)

- **Critical for the conduct of monetary policy**
  - Draghi (2017)
  - Carney (2017)
  - Powell (2018)
Stock taking by (some) academics

Harald Uhlig, 2018 *(based on empirics + quantitative models a la Smets and Wouters, 2007)*:

“Inflation, in essence, dances to its own music”

Bob Hall, 2013:

“Prior to the recent deep worldwide recession, macroeconomists of all schools took a negative relation between slack and declining inflation as an axiom. Few seem to have awakened to the recent experience as a contradiction to the axiom.”

This disconnect between inflation and slack poses a challenge to New Keynesian models, for which the Phillips curve is a key building block.
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Does the disconnect pose a challenge to the NK model?

On the contrary: this disconnect is exactly what a New Keynesian model with a welfare-optimizing Central Bank would predict.
A simple model of optimal inflation and the PC
Galí (2008); Woodford (2003); Clarida, Galí and Gertler (1999)

\[
Loss = E_0 \sum_{t=0}^{\infty} \beta^t (\pi_t^2 + \lambda x_t^2)
\]

Under discretion
\[
\min \pi_t^2 + \lambda x_t^2
\]
s.t.:
\[
\pi_t = \beta E_t \pi_{t+1} + \kappa x_t + u_t \quad \text{(PC)}
\]

Solution: Targeting rule
\[
\pi_t = -\frac{\lambda}{\kappa} x_t \quad \text{(TR)}
\]
Optimal inflation and the PC

\[ \text{Loss} = E_0 \sum_{t=0}^{\infty} \beta^t (\pi_t^2 + \lambda x_t^2) \]

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Solution: Targeting rule

\[ \pi_t = -\frac{\lambda}{\kappa} x_t \quad (\text{TR}) \]
Identification

\[ \min \pi_t^2 + \lambda x_t^2 \]

s.t.:
\[ \pi_t = \beta E_t \pi_{t+1} + \kappa x_t + u_t \quad \text{(PC)} \]

Solution: Targeting rule
\[ \pi_t = -\frac{\lambda}{\kappa} x_t \quad \text{(TR)} \]

Observed Inflation inherits properties of exogenous shock process:
\[ \pi_t = f(u_t) \]

If \( u_t = \rho u_{t-1} + v_t \),
\[ \pi_t = \frac{\lambda}{\kappa^2 + \lambda(1-\beta \rho)} u_t \]
Identification under commitment

Under commitment:

$$\min E_0 \sum_{t=0}^{\infty} \beta^t (\pi_t^2 + \lambda x_t^2)$$

s.t.:

$$\pi_t = \beta E_t \pi_{t+1} + \kappa x_t + u_t \quad \text{(PC)}$$

Solution: Targeting rule

$$p_t = -\frac{\lambda}{\kappa} x_t \quad \text{(TR)}$$

Observed inflation: inherits properties of exogenous shock process:

$$\pi_t = f(u_t, u_{t-1}, u_{t-2} \ldots)$$
Remarks

- Framework implies that equilibrium inflation rates should be uncorrelated with slack, as long as central banks are doing a sensible job.

- Challenge for econometricians, not for the model.

- Our point is distinct from most articulations of the “Fed view” on why the Phillips curve flattened (e.g. Williams, 2006; Mishkin, 2007; Bernanke, 2007, 2010).
  - They focus on the anchoring of inflation expectations weakening the reduced-form correlation between slack and inflation.
  - This paper: even in a setting in which expectations play no role, the structural relationship between slack and inflation can be masked by the conduct of monetary policy.
  - This is not to say that Fed policymakers were not aware of our point too, of course!

- Formulas: Barro and Gordon (1983)

- Interestingly, many papers on the PC flattening do not mention monetary policy. If they do, only to the extent that it affects expectations. E.g. Coibion and Gorodnichenko (2015).
Identification in graphs

\[ \pi_t = -\frac{\lambda}{\kappa} x_t - e_t \]  \hspace{1cm} (TR)

Identification improves as 
\[ \frac{\text{Var}(e_t)}{\text{Var}(u_t)} \text{ increases} \]
Identification in a big NK Model (COMPASS)

- **Big NK model at the BoE**
  - There is no single structural PC relation between inflation and slack. Multiple PC.
    - Still helpful for a policy maker to think about an average PC relation following demand shocks.
    - There is an underlying structural aggregate supply relation in the larger model.
    - The average PC gets closer to the underlying structural supply relation in a way that is more robust to model specification.

- Within COMPASS, run a stochastic simulation using all (18) shocks in the model.

- Exercise: Naïve estimation of the Phillips curve

- Two possibilities:
  - i) (estimated) Taylor rule
  - ii) discretionary optimal monetary policy (minimises loss function)
Naïve Phillips Curve in a big NK Model (COMPASS)
Phillips Curve in a big NK Model (COMPASS)

- Big NK model economy.
- Two assumptions on monetary policy
- **Separately conditioning on demand or supply shock**

<table>
<thead>
<tr>
<th></th>
<th>Taylor Rule</th>
<th>Optimal Monetary Policy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Supply Shock</td>
<td></td>
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<tr>
<td>Demand Shock</td>
<td></td>
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</table>
Naïve Phillips Curve in a big NK Model (COMPASS)

**Taylor Rule**

- Final output price markup shock
- Government spending shock

**Optimal Policy**

- Final output price markup shock
- Government spending shock
- Annual inflation
- Output gap

Supply shock

Demand shock
Identification strategies

- Control for supply shocks (Gordon, 1982)
  - Neither simple nor sufficient

- Instrumental variables
  - Lagged variables as instruments
  - Monetary policy shocks (Christiano, Eichenbaum and Evans, 1999; Romer and Romer, 2004)
    - Structural PC correlation can be recovered (Barnichon and Mesters, 2019)
    - MP shocks ideal IV: move output gap; not fully undone by MP. But some limitations (Boivin and Giannoni 2006, Ramey 2016).

- Regional data (Fitzgerald and Nicolini, 2014; Kiley, 2015; Babb and Detmeister, 2017)
  - MP does not offset regional demand shocks, so each region finds itself in a different segment of the PC.
  - Time-FE can absorb aggregate demand and supply shocks (e.g., oil shocks) and area-FE, regional diffs.
From model to data

**Note:** unemployment gap instead of output gap.

PC in $U_t$ is negatively sloped $U_t - U_t^* = -\theta x_t$
The PC: Aggregate US Data (1957-2018)
The PC: Standard OLS estimates suggest flattening

OLS equation: \( \pi_t = \alpha + \beta (U_t - U_t^*) + \sum_{i=1}^{3} \gamma_i \pi_{t-i} + \xi_t \)
## Regional panel data

- Use data on US cities: 23 metro areas; see also *Kiley (2013); Babb and Detmeister (2017)*.
- Semi-annual sample from 1990 H1 to 2018 H1 for most metro areas.

<table>
<thead>
<tr>
<th>Data series</th>
<th>Description (and source)</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Core inflation</td>
<td>Log change in CPI less food and energy (BLS via FRED).</td>
<td>NSA. Monthly data averaged over each half a year.</td>
</tr>
<tr>
<td>Unemployment rate</td>
<td>Unemployed as percentage of civilian labour force (BLS).</td>
<td>NSA. Monthly data averaged over each period. Some discrepancies in metro area definitions with CPI data.</td>
</tr>
<tr>
<td>Inflation expectations</td>
<td>12-month ahead price inflation expectations (Michigan Consumer Survey)</td>
<td>Geographical split into only 4 regions (North-Central, Northeast, South and West). Cities’ expectations assumed to be equal to the region average.</td>
</tr>
</tbody>
</table>
Largest three metro areas make up 35% of the labour-force in the sample:

- New York - 16%
- Los Angeles - 11%
- Chicago - 8%
Sample of cities covers around one-third of the US population (Babb and Detmeister, 2017).

Weighted by labour force, the aggregated panel data broadly match up to the true aggregate.
Table 3: US Metro area Phillips curve: 1990-2018

<table>
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<tr>
<th>Regression</th>
<th>(1) Pooled OLS</th>
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Robust standard errors (clustered by metro area) in brackets
*** p<0.01, ** p<0.05, * p<0.1

- Pooled OLS suggests flat Phillips curve.
Pooled OLS gives more precision than aggregate data (Kiley, 2013), but slope still flat.
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- Year FE: aggregate shocks.
Steeper slope with year FE: controlling for aggregate monetary policy and supply shocks.
Nearly 3 times the naïve slope once area and time FE are included.
Slope higher still with metro area fixed effects.

Need both sets to also control for cross-sectional variation in $U^*$.
Conclusions

- Of course everyone knows that the reduced-form PC depends on the mix of supply and demand shocks, and that monetary policy is one key factor that affects that mix.

- But much of the policy and academic discussion in recent years has ignored that, and estimated the PC by OLS. This led to unwarranted criticisms of the existing framework.

- Our paper is a call for a more careful identification that takes into account the endogenous monetary policy response.

- Encouragingly, new work doing so, e.g., Barnichon and Mesters; Galí and Gambetti; Jordà and Nechio.