XXXII Encuentro de Economistas - Banco Central de Reserva del Perú

Inferring inflation expectations from fixed-event forecasts

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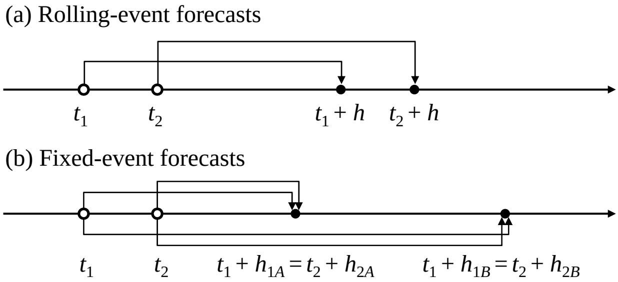
November 2014

Outline

Motivation

- Inflationary expectations are key for empirical macroeconomic analysis (e.g., Phillips curve, real interest rate, inflation targeting).
- Macroeconomic models often treat expectations as rolling-event forecasts (e.g., Livingston Survey, Gallop Poll).
- Data on fixed-event forecasts widely available for a much larger number of countries (e.g., *Consensus Forecasts*, IMF's *World Economic Outlook*, World Bank's *Global Economic Prospects*, OECD's *Economic Outlook*).
- Rolling-event forecasts may be inferred from fixed-event forecasts.
  However, there is no obvious way to do this.
  The purpose of the paper is to develop an empirical model to bridge this gap.

Motivation: Data structures



- Rolling-event forecasts: Survey collects h-period ahead inflation forecasts. Every new release the "event" to be forecast "rolls' forward. The horizon h is fixed, and the target date is always separated h periods from the forecast origin.

- Fixed-event forecasts: In period t_1, survey participants are asked to forecast inflation for period $t_1 + h_1$, an h_1-period ahead prediction; later on, in period $t_2 > t_1$ they are asked for a forecast *for the same date*, which now corresponds to an h_2-period ahead forecast, where $h_2 = h_1 - (t_2 - t_1)$. The forecast event is kept fixed throughout, and the forecasting horizon *shrinks* as the time line approaches the event, $h_2 < h_1$.

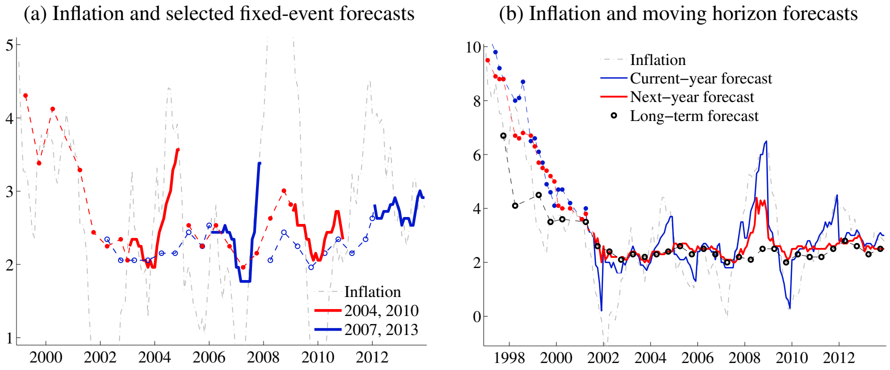
Outline

Data: *Latin American Consensus Forecasts*

- Highly reputed.
- Bi-monthly (alternate months) between March 1993 and April 2001 and monthly thereafter.
- Each issue provides forecasts for current-year and next-year inflation ("short-term" forecasts).
- April and October issues include also "long-term" forecasts (up to 10 years ahead).
- Survey are usually taken by the middle of the month. Thus, participants in period t have already observed inflation in period $t-1$.
- Our sample: Reports from February 1997 to December 2013.
  - 169 "short-term" forecasts: current year (1) and next year (2).
  - 31 "long-term" forecasts: years 3 to 6.
- Latin American inflation targeters: Chile, Colombia, Mexico and Peru.

Glimpse of the data

Peru: Inflation and survey data from the Latin American Consensus Forecasts



Notes: The dots in the figure represent forecasts that are irregularly sampled (long-term forecasts throughout all the sample period, and short-term forecasts until April 2001). To ease visualization, these dots are connected with linearly interpolated values depicted as discontinuous lines. The interpolations are not used in the estimations.

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Shifting-endpoint model for inflation

- Adaptation of Kozicki and Tinsley (2012).
- Limiting conditional forecast of inflation (the *endpoint*) is given by

$$\mu_t = \lim_{h \to \infty} \pi_{h\,|\,t}\,, \tag{1}$$

where t denotes the time subscript of the information set on which expectations are conditioned.

- Long-term forecasts are formed in a weakly rational manner: changes in perception are unpredictable (if agents can anticipate future changes to their long-run perceptions, then such changes should be immediately incorporated in their current perceptions):

$$\mu_t = \mu_{t-1} + \nu_t\,, \tag{2}$$

where ν_t is an innovation. The endpoint μ_t is treated as an unobservable variable, and the main purpose of the analysis is to infer about its state using inflation and survey data.

Shifting-endpoint model for inflation (2)

- Inflation dynamics:
$$\pi_t = \rho\, \pi_{t-1} + (1-\rho)\mu_{t-1} + \epsilon_t\,, \tag{3}$$
where ϵ_t is an inflation shock, assumed to be uncorrelated with ν_t at all lags and leads.

- Given the information up to period $t-1$, inflation is expected to converge to μ_{t-1} as the forecast horizon increases. Thus, the dynamic specification (3) allows us to disentangle the effects of the shifting-endpoint from short-run fluctuations.

- Multistep forecasts of inflation based on this model:
$$\pi_{t+h\,|\,t-1} = \rho^{h+1}\pi_{t-1} + (1-\rho^{h+1})\mu_{t-1}\,. \tag{4}$$

- In the paper: Expectations conditioned on an arbitrary period in the past (μ_{t-n} appears in equation 3). Also, (3) follows an arbitrary AR(p) structure.

Shifting-endpoint model for inflation (3)

- Survey data: m different forecasts F_{it}, each associated to a fixed-event, which in turn implies a time-varying horizon h_{it} ($i = 1, 2, \ldots, m$).
- For fixed-event forecasts, h_{it} varies with t in a deterministic fashion.
  In the *Latin American Consensus Forecasts*, the data from month M_t refer to forecasts by the end of year i, with $i = 1$ being the current year, so the forecast horizons (in months) evolve deterministically as $h_{it} = 12i - (M_t - 1)$.
- The conditional inflation forecast from the shifting-endpoint model provides an approximation of the survey expectation:

$$F_{it} = \pi_{t+h_{it}\,|\,t-1} + \varepsilon_{it}\,, \tag{5}$$

  where ε_{it} is an approximation error that reflects differences between the implicit forecasting model of survey participants and the shifting-endpoint model.
  It also captures possible measurement errors in survey data.

Shifting-endpoint model for inflation (4)

- State space form: Measurement equations (time-varying),

$$\begin{bmatrix} \pi_t \\ F_{1t} \\ F_{2t} \\ \vdots \\ F_{mt} \end{bmatrix} = \begin{bmatrix} \rho \\ \rho^{h_{1t}+1} \\ \rho^{h_{2t}+1} \\ \vdots \\ \rho^{h_{mt}+1} \end{bmatrix} \pi_{t-1} + \begin{bmatrix} 0 & 1-\rho \\ 0 & 1-\rho^{h_{1t}+1} \\ 0 & 1-\rho^{h_{2t}+1} \\ \vdots & \vdots \\ 0 & 1-\rho^{h_{mt}+1} \end{bmatrix} \begin{bmatrix} \mu_t \\ \mu_{t-1} \end{bmatrix} + \begin{bmatrix} \epsilon_t \\ \varepsilon_{1t} \\ \varepsilon_{2t} \\ \vdots \\ \varepsilon_{mt} \end{bmatrix} . \qquad (6)$$

- State space form: State equations (time-invariant),

$$\begin{bmatrix} \mu_t \\ \mu_{t-1} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 1 & 0 \end{bmatrix} = \begin{bmatrix} \mu_{t-1} \\ \mu_{t-2} \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix} \nu_t . \qquad (7)$$

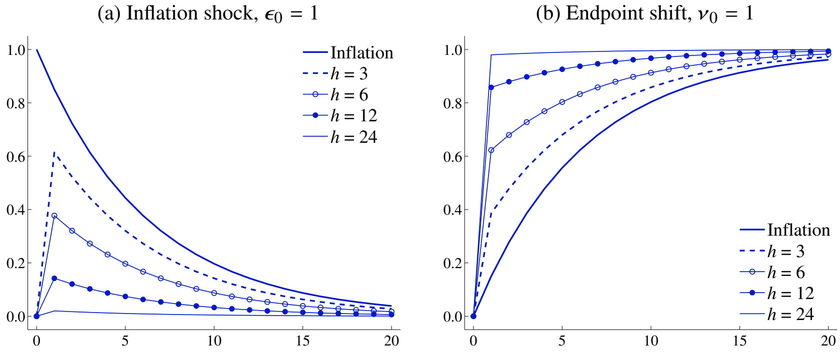
- Interpolation: The model uses all available observations from surveys, which are irregularly sampled and are associated to time-varying forecast horizons.
  Once the model is estimated, it can be used to estimate a complete term structure of expected inflation, by simply evaluating:

$$\hat{\pi}_{t+h\,|\,t-1} = \hat{\rho}^{h+1}\pi_{t-1} + (1-\hat{\rho}^{h+1})\hat{\mu}_{t-1} .$$

Shifting-endpoint model for inflation (5)

- Expected inflation is a linear combination of the latest realization of inflation π_{t-1} and the perceived long-run level μ_{t-1}.
  As h increases, the expectations converge from a short-term forecast dominated by recent history to the endpoint.

Inflation and expectations responses to shocks



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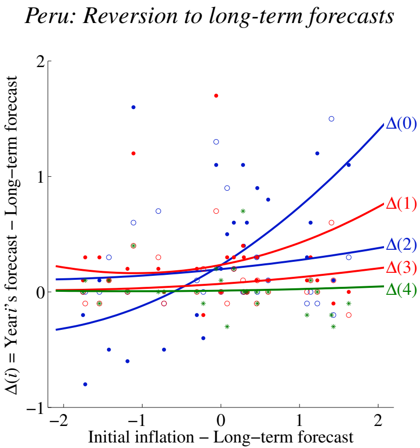
Mean reversion



Notes: Regression lines of the deviation of Year i's forecast from the long-term forecast on the deviation of the latest inflation observation on the long-term forecast.

Mean reversion (2)

Mean reversion of forecasts

		$F_1 - F_6$	$F_2 - F_6$	$F_3 - F_6$	$F_4 - F_6$	$F_5 - F_6$
Chile	α	0.257 (0.147)*	0.181 (0.070)*	0.083 (0.047)*	0.055 (0.039)	0.013 (0.023)
	β	0.565 (0.119)*	0.116 (0.035)*	0.026 (0.027)	0.007 (0.021)	0.004 (0.016)
Colombia	α	0.525 (0.201)*	0.451 (0.194)*	0.276 (0.180)	0.166 (0.163)	0.036 (0.096)
	β	0.696 (0.090)*	0.413 (0.110)*	0.262 (0.128)*	0.159 (0.112)	0.066 (0.048)
Mexico	α	0.101 (0.113)	0.005 (0.085)	0.028 (0.054)	0.019 (0.037)	0.016 (0.034)
	β	0.732 (0.058)*	0.395 (0.032)*	0.204 (0.020)*	0.096 (0.016)*	0.037 (0.017)*
Peru	α	0.422 (0.156)*	0.357 (0.143)*	0.201 (0.099)*	0.077 (0.053)	0.015 (0.046)
	β	0.544 (0.111)*	0.191 (0.095)*	0.059 (0.062)	0.045 (0.032)	0.015 (0.032)

Notes: Least squares estimates of equation

$$F_{it} - F_{6t} = \alpha_i + \beta_i(\pi_{t-1} - F_{6t}) + \text{error}_t\,,$$

using the 34 available observations for long-term forecasts.
HAC standard errors in parenthesis. "*" denotes coefficients different from zero at a 5% significance level.

Model variants

CE: Constant endpoint model: $\mu_t = \mu$.

UR: Unit root model: $\rho = 1$. In this case, the limiting forecast is π_{t-1} (more generally, a moving average of the latest inflation data).

LL: Local level model: Univariate model that ignores survey information.

Model estimation

Estimation results (model variants)

		Model specification				RMSE	RMSE survey forecasts			
		ρ	std(ϵ_t)	std($\Delta\mu_t$)	std(ε_t)	Inflation	1	2	3	≥ 4
Chile	CE	0.931 (0.022)	0.379	0.000	0.473	0.38	0.88	0.93	0.36	0.24
	UR	1.000 (0.000)	0.387	0.000	1.417	0.39	1.07	1.37	1.62	1.64
	LL	0.544 (0.043)	0.311	0.286	1.038	0.46	0.64	1.06	1.17	1.24
	SE	0.677 (0.040)	0.405	0.175	0.844	0.43	0.57	0.78	0.56	0.54
Colombia	CE	0.979 (0.011)	0.309	0.000	1.322	0.33	0.99	0.98	1.50	1.62
	UR	1.000 (0.000)	0.333	0.000	1.570	0.34	1.07	1.03	1.44	1.69
	LL	0.480 (0.054)	0.242	0.257	1.122	0.43	0.41	0.83	1.11	1.45
	SE	0.713 (0.051)	0.324	0.193	0.925	0.36	0.53	0.62	0.77	1.06
Mexico	CE	0.981 (0.007)	0.278	0.000	0.798	0.28	0.60	0.72	0.60	0.80
	UR	1.000 (0.000)	0.292	0.000	1.750	0.29	0.82	1.29	1.80	2.21
	LL	0.564 (0.051)	0.219	0.241	1.263	0.34	0.58	1.01	1.68	2.08
	SE	0.790 (0.031)	0.291	0.161	0.987	0.30	0.51	0.66	0.76	1.01
Peru	CE	0.949 (0.015)	0.334	0.000	0.745	0.34	0.94	0.91	0.76	0.59
	UR	1.000 (0.000)	0.346	0.000	1.037	0.35	0.97	0.96	1.26	1.25
	LL	0.511 (0.041)	0.268	0.234	0.819	0.41	0.50	0.82	1.05	1.11
	SE	0.693 (0.038)	0.369	0.143	0.606	0.39	0.50	0.60	0.78	0.74

Notes: Maximum likelihood estimates, using data from February 1997 to December 2013. All models use $p = 13$. ρ: sum of the autoregressive coefficients (robust standard errors in parentheses); std(ϵ_t): standard deviation of the inflation shock; std($\Delta\mu_t$): standard deviation of the endpoint shock; std(ε_t): *average* standard deviation of the approximation errors of the $m = 6$ survey measures; "RMSE" is the root mean square error of the one-step ahead predictions (produced by the Kalman filter) for inflation and survey forecasts for years 1 (current), 2 (next), 3 and ≥ 4 (subsequent).

Signal extraction: The workings of the Kalman Filter

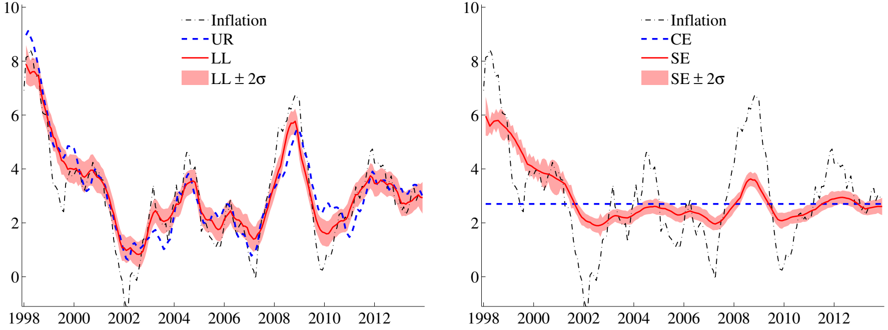
Kalman gains (from prediction errors to updated predictions of μ_t)

	Inflation	F_1	F_2	F_3	F_4	F_5	F_6
February 2001	0.1036	0.1767	0.1661	0	0	0	0
March 2001	0.1187	0	0	0	0	0	0
April 2001	0.0654	0.1410	0.0720	0.0167	0.0364	0.0669	0.1364
September 2006	0.0640	0.0985	0.0947	0	0	0	0
October 2006	0.0528	0.0992	0.0550	0.0160	0.0220	0.0568	0.1034
March 2013	0.0621	0.1047	0.0993	0	0	0	0
April 2013	0.0492	0.1062	0.0542	0.0126	0.0274	0.0504	0.1028

- The Kalman gain is zero for missing observations.
- Whenever long-term forecasts are available, the Kalman filter places more weight to them, and less to short-term forecasts, to predict the unobserved endpoint μ_t.

Peru: Alternative endpoints

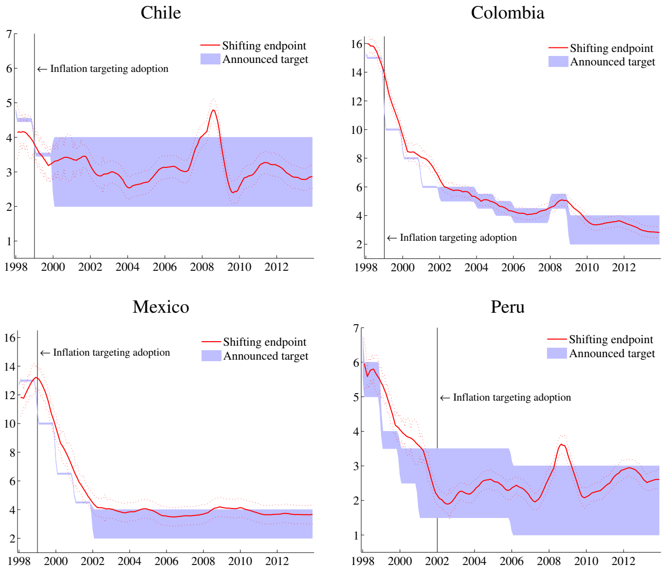
Peru: Predicted endpoints by model variant



Notes: CE: Constant endpoint model; UR: Unit root model; LL: Local level model; SE: Shifting-endpoint model. For the CE, the figure displays the estimated value of μ. For the UR, the moving average endpoint is $\mu_t = e'Cz_t$ (see paper). Only the point estimates are reported for these models to avoid clutter. For the LL and SE models, the figure shows the smoothed predictions and a 95% confidence interval.

Latin America: Inflation targeting

Predicted endpoints and the announcement of inflation targets in Latin America



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Closing remarks

- Fixed-event forecasts provide a widespread, yet unexplored, source of inflation expectations in many countries. The main difficulty is that the very structure of the FEFs, especially the fact that they correspond to moving forecast horizons, hinders their direct applicability in empirical work.
- To overcome this hindrance, and to infer about the term structure of inflation expectations from FEFs, we have proposed an extended version of the shifting-endpoint model of Kozicki and Tinsley (2012).
- Our empirical exploration also suggests that survey FEFs provide a valuable source of information on expected inflation, complementary to that contained in historical records of inflation.
- Given the availability of FEFs, exploring alternative methods to readily and effectively use such data in econometric models is likely to have important practical implications.