Are the Commodity Currencies an Exception to the Rule?

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Plan for Today's Talk

Commodity Currencies: Why, Who, How, & What

- Do Commodity Prices Drive Real Exchange Rates?
  - The Need for Local-to-Unity Asymptotics
- What are the Possible Transition Mechanisms?
  - Different dynamic implications
- What Explains Exchange Rate Dynamics?
  - Incorporate Model Uncertainty- e.g. Bayesian Model Averaging, in predictive and forecast exercises

Motivation:

- Empirical disconnect between macroeconomic fundamentals and the behavior of major OECD floating currencies at short- to medium-horizons, as evident in various exchange rate puzzles.

Quotes from the literature:

- Frankel and Rose (1995, Handbook of International Economics) conclude with doubts *“in the value of further time-series modeling of exchange rates at high or medium frequencies using macroeconomic models.”*

Lyons (2002):

“At horizon less than two years, the explanatory power of macro-fundamental-based exchange rate models is essentially zero.”

Our Approach: A Missing Shock?

- Look at “commodity economies” where a significant share of the production and exports are in primary commodity products
- The “world prices” for their major exports can be easily observed in the centralized international commodity markets
- This allows for a clean identification strategy to test how exchange rates respond to exogenous terms of trade shocks

Who

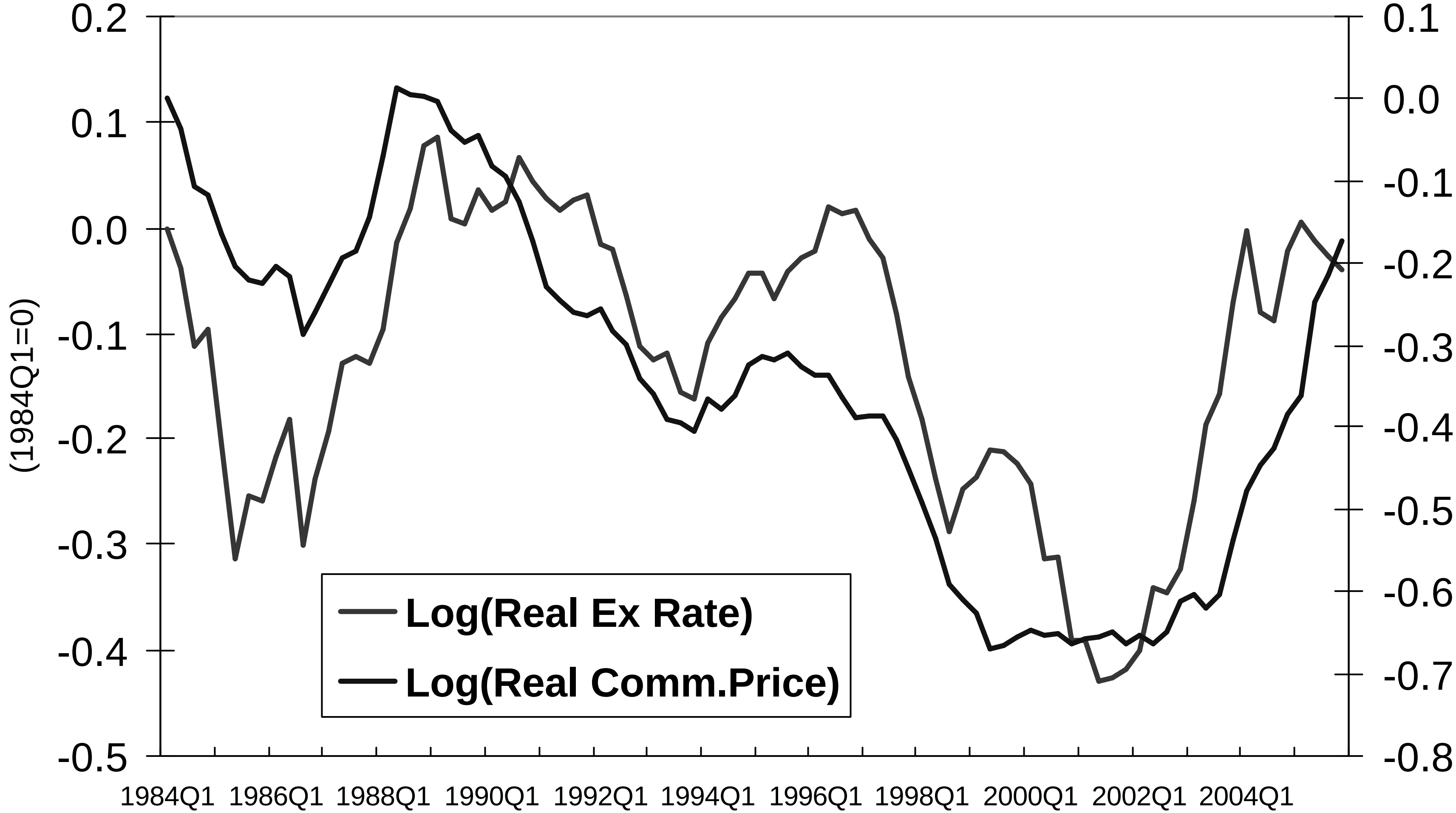
- Cashin et al (2004) identified 73 countries with significant commodity exports

We focus on:

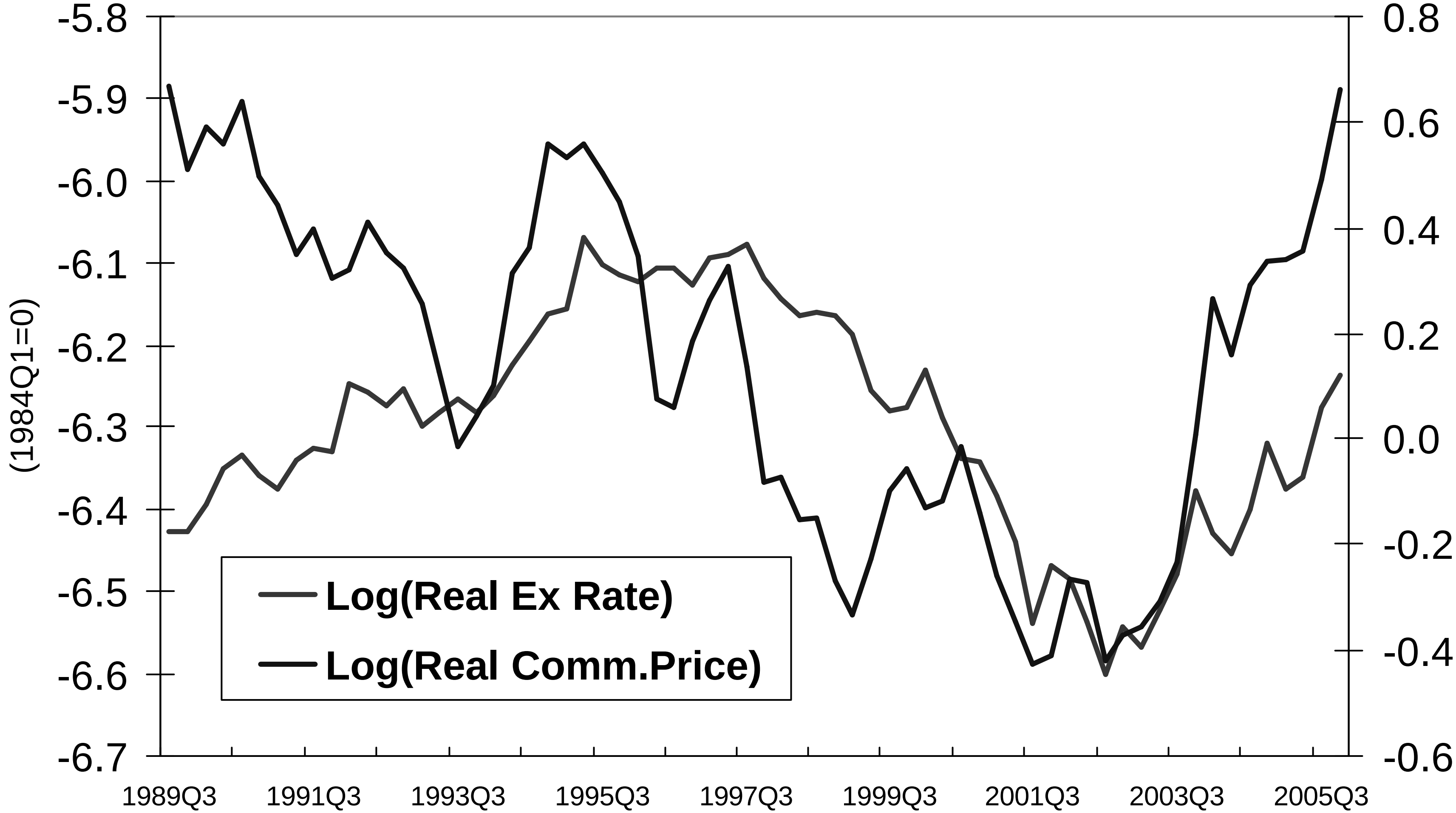
- Small open economy: little capital control, free trade
- Have sufficiently long history of free floating/market-based exchange rates

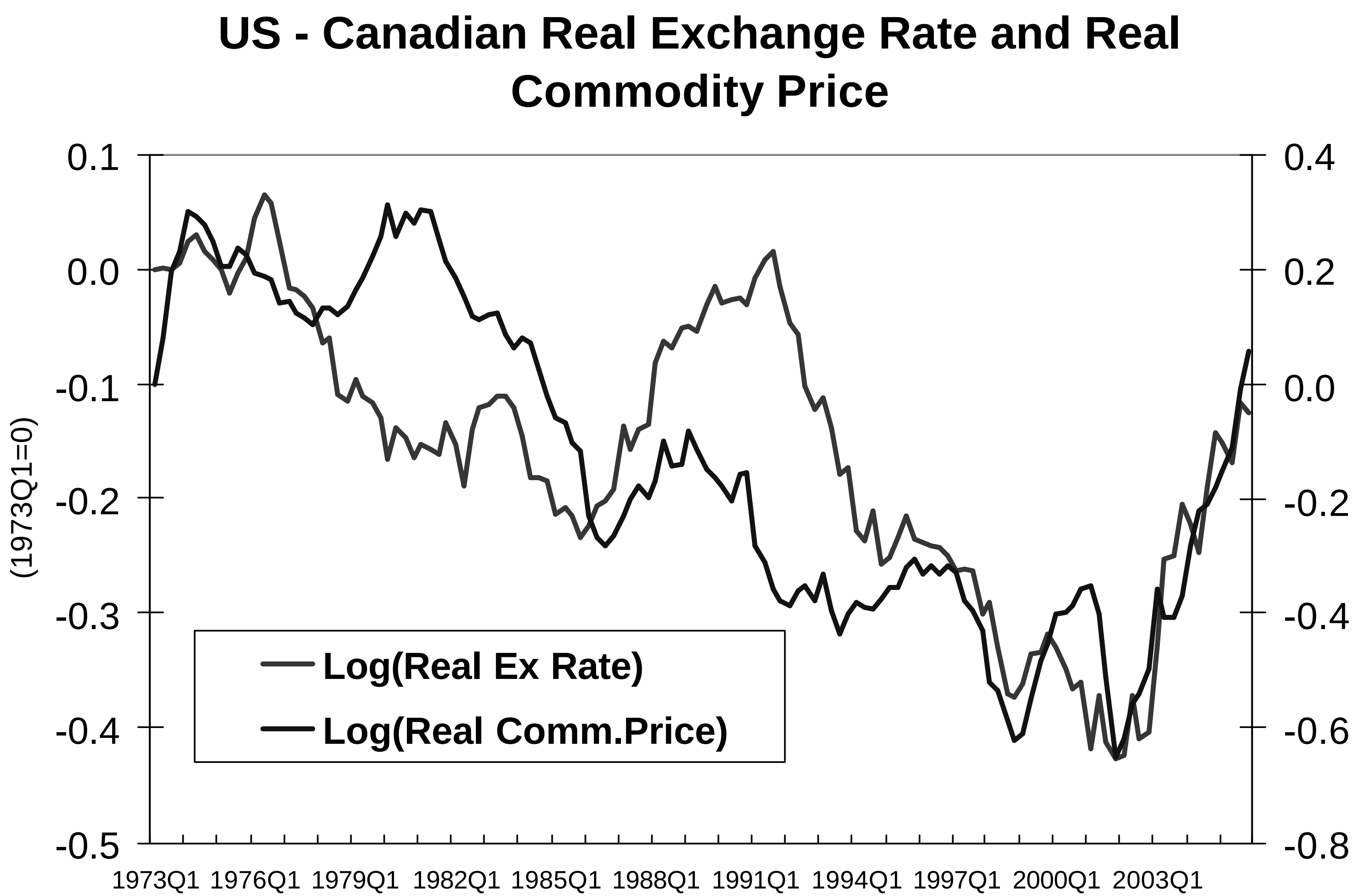
$\Rightarrow$ Australia (1984-), Canada (1973-), Chile (1989-), New Zealand (1987-), and South Africa (1994-)

US - Australian Real Exchange Rate and Real Commodity Price



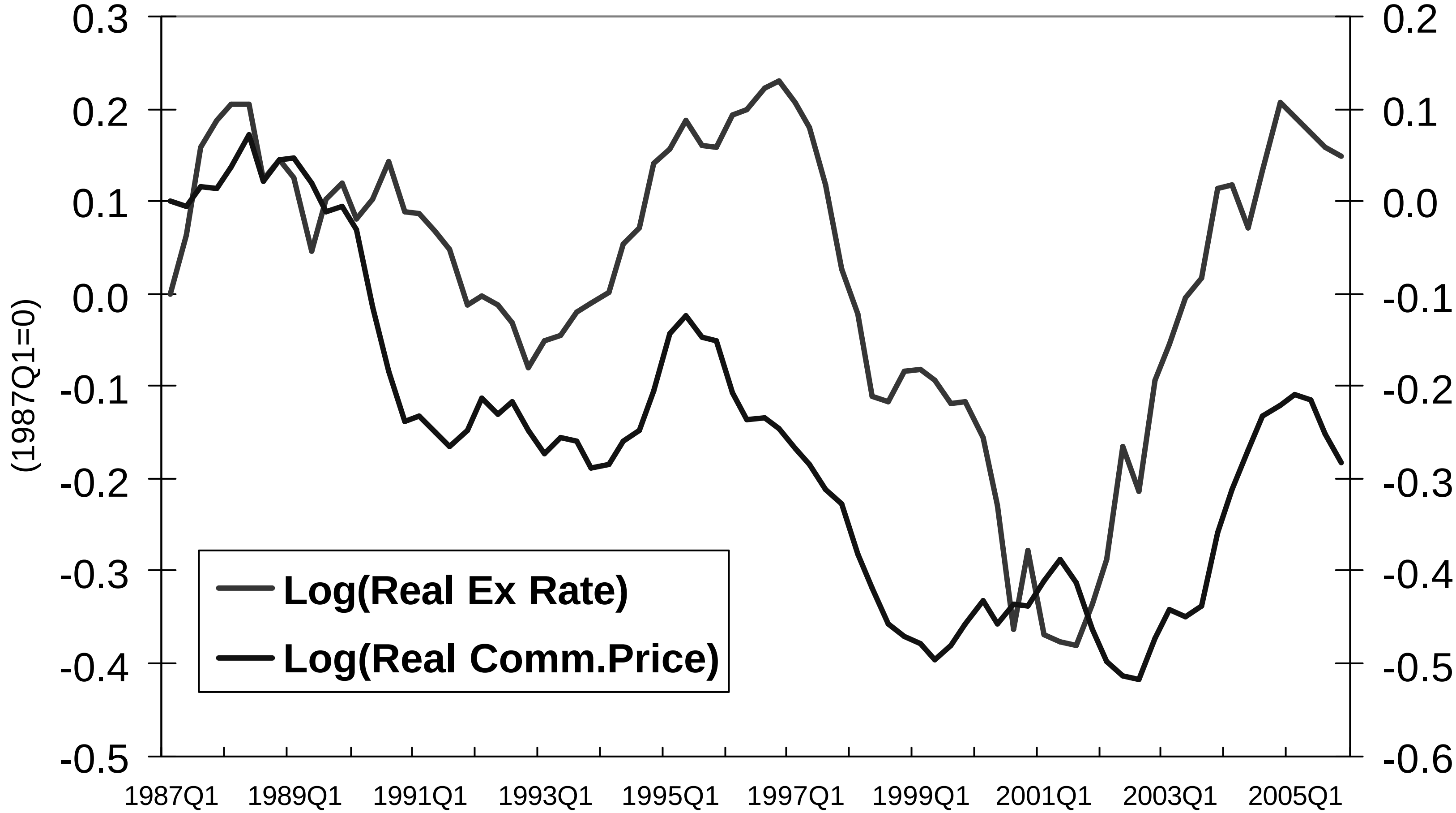
US - Chilean Real Exchange Rate and Real Commodity Price

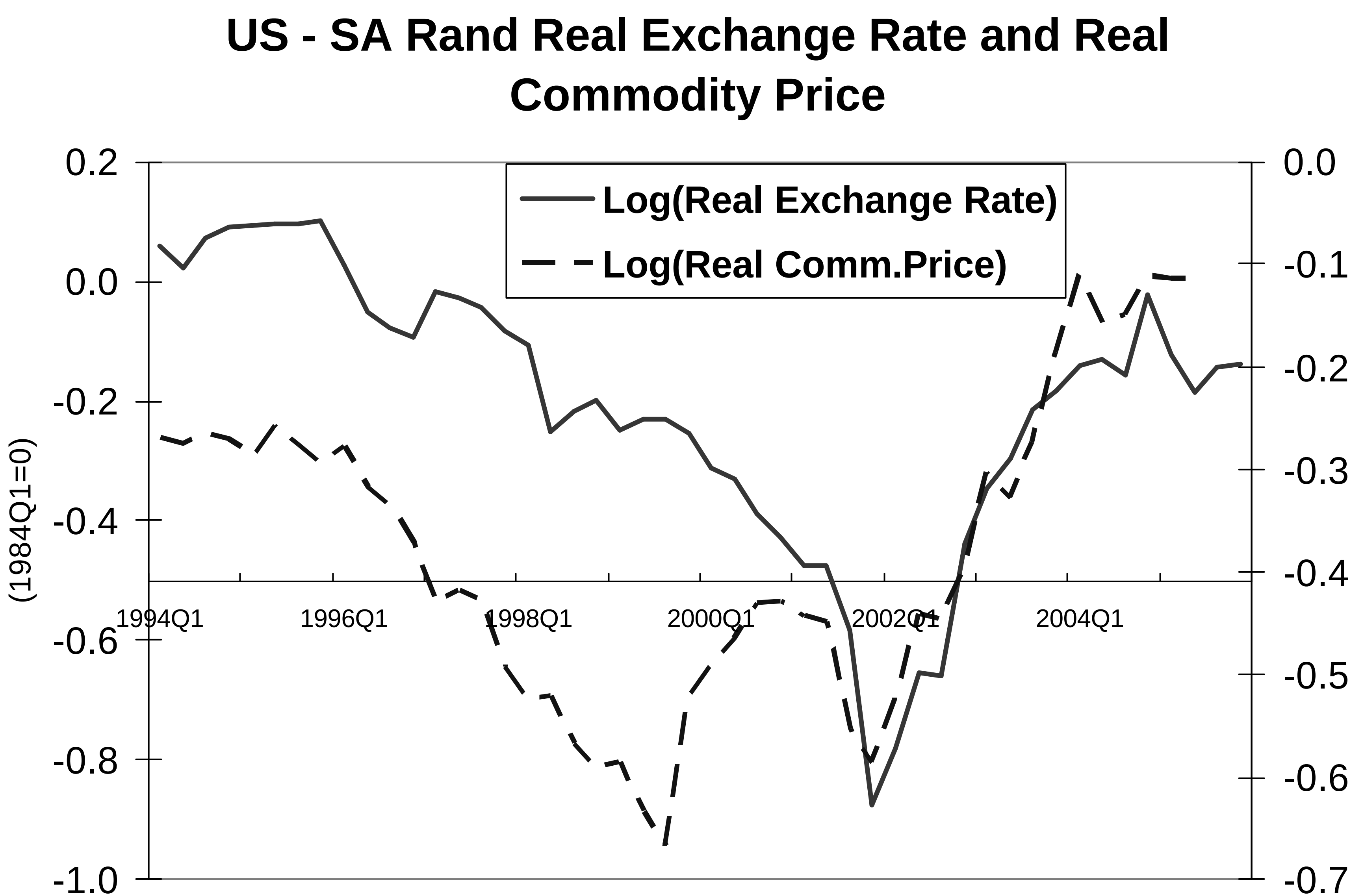




US - Canadian Real Exchange Rate and Real Commodity Price
0.1
0.0
-0.1
-0.2
-0.3
-0.4
-0.5
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
(1973Q1=0)
Log(Real Ex Rate)
Log(Real Comm.Price)
1973Q1
1976Q1
1979Q1
1982Q1
1985Q1
1988Q1
1991Q1
1994Q1
1997Q1
2000Q1
2003Q1

US - New Zealand Real Exchange Rate and Real Commodity Price




US - SA Rand Real Exchange Rate and Real Commodity Price
Log(Real Exchange Rate)
Log(Real Comm.Price)
(1984Q1=0)
0.2
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
0.0
-0.1
-0.2
-0.3
-0.4
-0.5
-0.6
-0.7
1994Q1
1996Q1
1998Q1
2000Q1
2002Q1
2004Q1

Do Commodity Prices Drive RER?

- Consider the linear model:

$$\ln RER_t = a + ß\ln(RCP)_t + \mu_t$$

$$\ln(RCP)_t = ? + ?\ln(RCP)_{t-1} + e_t$$

Parameter of interest: *ß*

- Standard economic models predict stationary real exchange rates

- But in data, hard to reject unit root

1) Claim I(0) based on theory and use first-order asymptotics:

But, it is well known that when the regressor (lnRCP) is persistent and its innovations are correlated with lnRER,

- large sample theory provides poor approximation to finite sample distribution of test statistics
- e.g. Mankiw-Shapiro (1986), Elliott and Stock (2001), Stambaugh (1999)…etc.

2) **Claim AR root is exactly 1 and use the cointegration framework**

BUT, e.g. Elliott (1998) show that:

- If variables do not have an EXACT unit root (nearly but not exactly cointegrated), the null of no cointegration may be rejected too often.
- Slight deviation from ?=1 can cause large size distortion
- Size of bias depends on T, ?, and the zero frequency correlation of e_t and μ_t

3) “No doubt unity is something to be desired… but it cannot be willed into being by mere declarations.”

- Theodore Bikel

- **Solution: Use Local-to-Unit Root Asymptotic Theory**
- Agnostic as to whether a time series is I(1) or stationary with a root very close to 1.
- Use finite-sample results to construct robust test statistics that work regardless of the order of integration
- Follow Campbell and Yogo (2005), obtain correct coverage probability with Modified Bonferroni intervals.
- Other recent research: Elliott (1998), Wright (2000), Elliott and Stock (2001), Lanne (2000), and Miyanishi (2005)

Country: Canada

Dep Var:Log CPI-Real Exchange Rate

(1973Q1 - 2005Q4; IT = 1991)

$$Q_t = a + ßCP_t + \mu_t$$
$$CP_t = ? + ?CP_{t-1} + e_t$$

	N	Time Period	p (BIC lag length)	d (innovation correl)	95% CI: ?	ß-hat	t-stat	90% CI Q-test
vs.USD	132	Full Sample	2	-0.045	[0.935,1.027]	0.312	10.69	[0.262,0.360]
	68	- Pre-IT	1	0.197	[0.933,1.064]	0.172	3.232	[0.056,0.243]
	64	- Post-IT	2	-0.151	[0.868,1.058]	0.546	6.26	[0.473,0.767]
vs.UKP	132	Full Sample	2	-0.168	[0.935,1.027]	0.435	8.844	[0.365,0.537]
	68	- Pre-IT	1	-0.077	[0.933,1.064]	0.018	0.149	[-0.166,0.235]
	64	- Post-IT	2	-0.179	[0.868,1.058]	0.268	3.011	[0.196,0.497]
vs.JPY	132	Full Sample	2	-0.168	[0.935,1.027]	0.821	16.078	[0.745,0.923]
	68	- Pre-IT	1	-0.175	[0.933,1.064]	0.806	6.869	[0.631,1.042]
	64	- Post-IT	2	-0.063	[0.868,1.058]	0.529	3.896	[0.373,0.825]

Bivariate Regressions show:

- Contemporaneous elasticity of exchange rate response mostly in the range of 0.2 to 1
- Results robust across country pairs, and appear stronger post-inflation targeting
- However, there appears to be little detectable dynamic responses...

Dep Var: First-Differenced Log CPI-Real Exchange Rate

$dQ_t = a + ßCP_{t-1} + \mu_t$

$CP_t = ? + ?CP_{t-1} + e_t$

	N	Time Period	p (BIC lag length)	d (innovation correl)	95% CI: ?	ß-hat	90% CI Q-test
vs.USD	131	Full Sample	2	0.076	[0.935,1.028]	-0.003	[-0.019,0.009]
	68	- Pre-IT	1	0.033	[0.933,1.064]	-0.029	[-0.054,-0.005]
	63	- Post-IT	2	0.132	[0.850,1.056]	0.013	[-0.054,0.050]
vs.UKP	131	Full Sample	2	0.058	[0.935,1.028]	0.008	[-0.024,0.035]
	68	- Pre-IT	1	0.082	[0.933,1.064]	0.023	[-0.053,0.086]
	63	- Post-IT	2	-0.045	[0.850,1.056]	0.065	[-0.031,0.139]
vs.JPY	131	Full Sample	2	0.092	[0.935,1.028]	0.006	[-0.034,0.038]
	68	- Pre-IT	1	0.167	[0.933,1.064]	0.022	[-0.072,0.087]
	63	- Post-IT	2	-0.037	[0.850,1.056]	0.101	[-0.009,0.209]

How should commodity price shocks affect real exchange rates?

1) Income Effect
2) Modified Balassa-Samuelson Model (e.g. Chen-Rogoff 2003, Cashin-Cespedes-Sahay 2004)
3) Open capital market + short-run fixed factor model (Rogoff 1992)
4) Capital-adjustment cost model (Obstfeld-Rogoff 1996)
5) Can incorporate stick prices, inflation targeting

These Various Transmission Channels:

- all imply a levels relation between RER and ToT shock similar to what we observed in the data
- However, they have different dynamic implications
- Can a more general dynamic predictive equation help shed light on the channel of transmission?

Exchange Rate Predictive Regressions

Consider the following linear in-sample predictive equation:

$$\ln RER_{\mathbf{t+1}} = \mathbf{a} + b'\mathbf{X}_{\mathbf{t}} + e_{\mathbf{t+1}}$$

where X_t is a vector of candidate predictors (e.g. $\ln RER_{\mathbf{t}}$, $\ln CP_{\mathbf{t}}$, $(i - i^*)_{\mathbf{t}}$…etc.)

and will be model dependent

Question: what is the correct model??

Addressing “Model Uncertainty”:

- We simply do NOT know what the correct structural model is for exchange rate determination

- We should incorporate this uncertainty into our inference procedure to avoid under-estimating forecast uncertainty

- How?

Proposal: Model Averaging

Use a weighted average of forecasts over a large number of different models,

Choosing weights as:

- Bayesian Posterior (Bayesian Model Averaging; Raftery, Madigan and Hoeting 1997; Hoeting, Madigan, Raftery and Volinsky 1999)
- Based on information criterion (Buckland, Bunham, Augustin 1997)

Basic idea (interpretation 1: for frequentists):

- Many candidate variables could contain useful information for forecast
- The trick is to judiciously combine these information and avoid having to estimate a large number of unrestricted parameters
- Recent literature has found this approach to give consistently good forecast results (Stock and Watson 2001; Wright 2005; Bernanke and Boivin 2003)

Basic idea (interpretation 2: for Bayesians):

Conceptually: prediction process should take into account researcher's uncertainty about the true model, and consider all candidate models.

e.g. BMA: Starting from a prior, we can estimate the posterior probabilities of each model and use them as weights to "combine information" as discussed above

Wright(2005) shows that the BMA consistently outperforms simple equal weight averaging for predicting US inflation across different time periods

1) In-Sample Predictive Regression Results:

- $$dQ_{t+1} = bX_t + e_{t+1}$$

Next slide:

- Predictive Analysis using Bayesian Model Averaging
- Country: Australia

18 models were selected

Best 18 models (cumulative posterior probability = 1):

The Top 5 selected models:

(Coeff = OLS estimates)

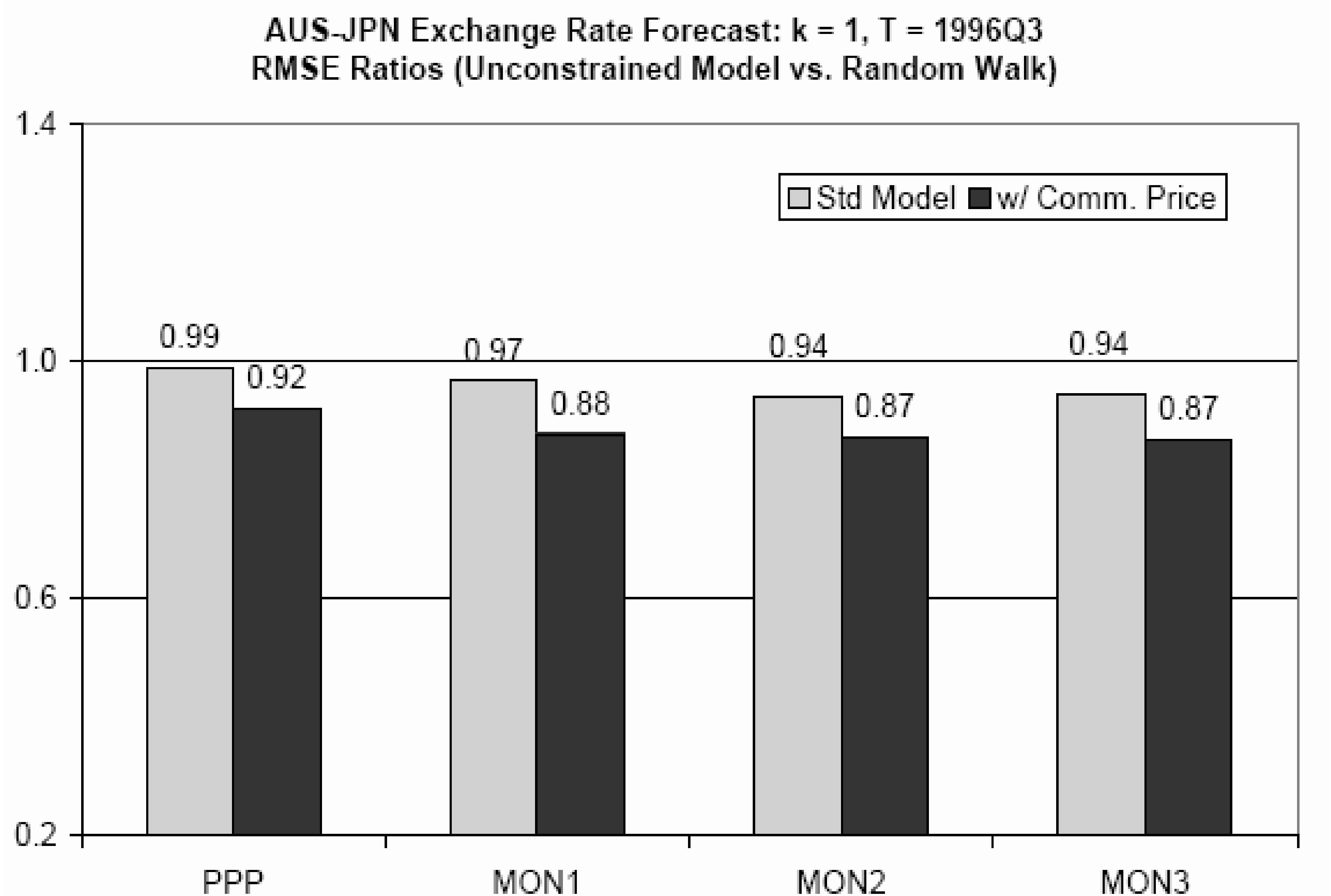
	Posterior Prob of Coeff ß? 0	**Posterior Mean of Coeff**	**Posterior Std Dev of Coeff**	model 1	model 2	model 3	model 4	model 5
Intercept	100	-0.2890	0.107	-2.90E-01	-3.30E-01	-2.41E-01	-2.86E-01	-3.05E-01
lRER	100	0.9263	0.036	9.30E-01	9.17E-01	9.26E-01	9.32E-01	9.21E-01
d(short rate)	6.1	-0.0001	0.001	.	.	.	.	.
d(long rate)	17.2	0.0011	0.003	.	.	5.25E-03	.	.
d(inflation)	8.5	-0.0001	0.001	.	.	.	.	-8.78E-04
dCApY	6.3	-0.0001	0.001	.	.	.	.	.
dGpY	9.8	-0.0001	0.001	.	.	.	-1.50E-03	.
dlrY	100	1.9800	0.407	2.08E+00	1.79E+00	1.86E+00	2.12E+00	2.13E+00
lRCP	7.2	-0.0030	0.020	.	.	.	.	.
lFuture	5.7	-0.0011	0.016	.	.	.	.	.
dlProd	100	0.2885	0.078	3.17E-01	2.46E-01	2.45E-01	3.16E-01	3.32E-01
dlStock	24.5	0.0112	0.025	.	3.96E-02	.	.	.
nVar				3	4	4	4	4
r2				0.93	0.932	0.931	0.931	0.93
BIC				-2.10E+02	-2.08E+02	-2.07E+02	-2.06E+02	-2.06E+02
Posterior Prob of Model				0.342	0.114	0.089	0.061	0.044

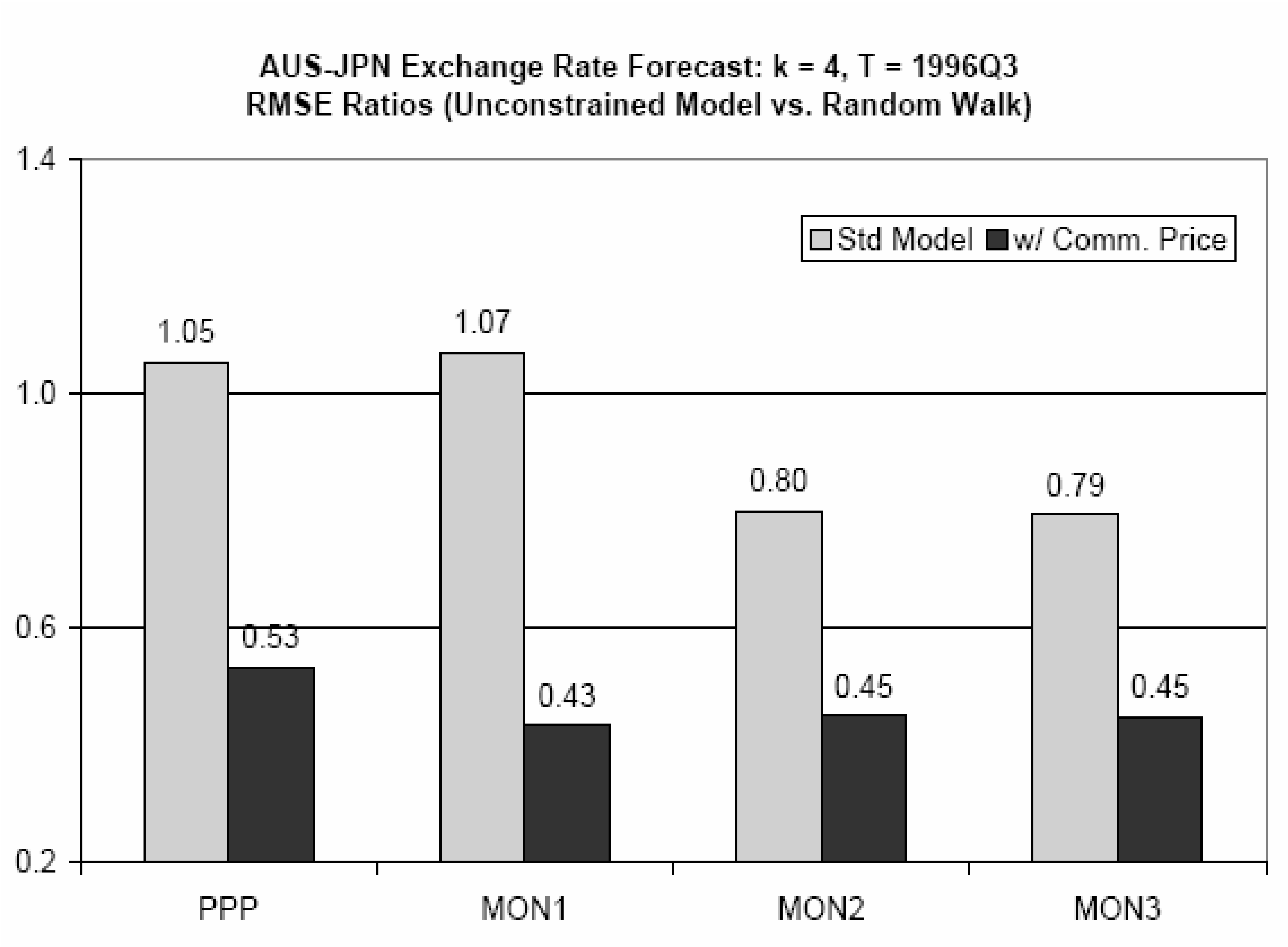
1) In-Sample Predictive Regression Results

- Fundamentals appear useful for predicting exchange rate movements (e.g. real income differences for Australia, commodity prices for Canada in the 1973-2001 period…etc.)
- While the current level of RER appears the most robust predictor of future level (always selected by BMA), the pure AR process is dominated by models with fundamentals.
- No clear model is consistently selected… Is there a clear structural transmission pattern in here?

2) Simulated Out-of-Sample Forecasts:

- Especially since in-sample analyses support "model uncertainty," it suggests out of sample forecasts may gain from "forecast combining"
- Don't have BMA results yet, but optimistic
- Chen (2004) shows that for nominal exchange rate models, incorporating a commodity price term can drastically improve their performance


AUS-JPN Exchange Rate Forecast: k = 1, T = 1996Q3
RMSE Ratios (Unconstrained Model vs. Random Walk)
Std Model
w/ Comm. Price
1.4
1.0
0.6
0.2
0.99
0.92
0.97
0.88
0.94
0.87
0.94
0.87
PPP
MON1
MON2
MON3


AUS-JPN Exchange Rate Forecast: k = 4, T = 1996Q3
RMSE Ratios (Unconstrained Model vs. Random Walk)
Std Model
w/ Comm. Price
1.4
1.0
0.6
0.2
1.05
0.53
1.07
0.43
0.80
0.45
0.79
0.45
PPP
MON1
MON2
MON3