

Exchange rate forecasting is easier than commonly believed.

Michał Rubaszek SGH Warsaw School of Economics

1



Michał Rubaszek

SGH Warsaw School of Economics

Exchange rate forecasting is easier than commonly believed

Based on:

1. Exchange rate forecasting on a napkin

ECB Working Paper 2151(with M. Ca' Zorzi)

2. Exchange rate forecasting with DSGE models

Journal of International Economics 107: 127-146, 2017 (with M. Ca' Zorzi & M. Kolasa)

3. RER forecasting and PPP: This time the random walk loses

Open Economies Review 27(3): 585-609, 2016 (with M. Ca' Zorzi & J. Mućk)

4. Bayesian forecasting of real exchange rates with a Dornbusch prior

Economic Modelling 46(C): 53-60, 2015 (with M. Ca' Zorzi & A. Kocięcki)

Motivation

ER forecasting horse race:

bird's eye view on the literature

Meese & Rogoff (1983):

exchange rates are not forecastable: start of the ER forecasting race

Mark (1995); Chinn & Meese (1995):

RW can be beaten at longer horizons by theoretical models

Cheung, Chinn & Pascual (2005):

none of standard models able to consistently outperform RW

Engel, Mark & West (2008):

ER models are not as bad as you think: part of the dismal forecasting performance of macro models can be attributed to estimation rather than mis-specification error

Rogoff (2009), Rossi (2013), Cheung et al. (2018):

the unpredictability of (nominal) exchange rates is likely to remain the consensus view for the conceivable future



- 1. Present the evidence that RERs are predictable, especially in the long run
- 2. Explain the why some models succeed or fail in outperforming the random walk in RER forecasting
- 3. Show that RER forecasts can be exploited in predicting NER.
- 4. Present evidence that problems in forecasting NER can be attributed to inability to predict changes relative price indices



Is RW really a tough benchmark for RER?

Forecast race No. 1: RW vs BVAR

Bayesian forecasting of real exchange rates with a Dornbusch prior, Economic Modelling 2015

Competing models:

RW - Random WalkVAR1 - BVAR with RW priorVAR2 - BVAR with Dornbusch prior

RID stationarity: Dornbusch prior:

$$rid_{t} = \theta rid_{t-1}$$
$$rer_{t} = \overline{rer} + \frac{1}{1-\theta} rid_{t}$$

Four countries:EA, UK, CHF, JP (vis-a-vis US)Data:rer, ridSample:1975:1-2011:7, forecasts for 1990:1-2011:7Forecasting scheme:rolling (R = 180 monthly data)

RMSFE comparison

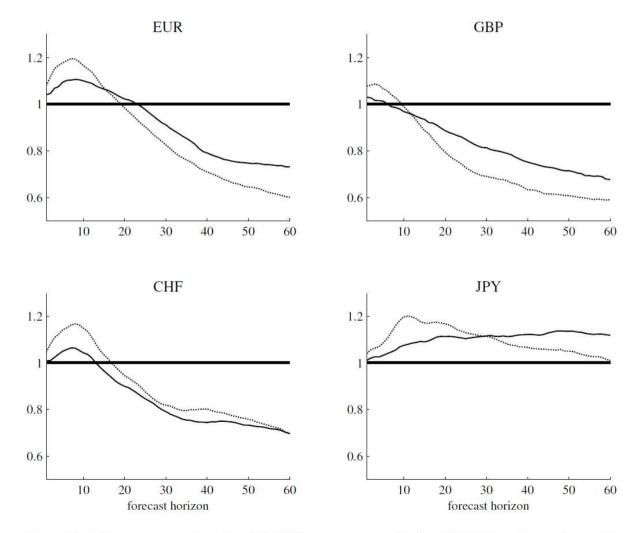
- > VAR2 (with Dornbusch prior) best performing at longer horizons
- RW wins at shorter horizons

h	RW	VAR1	VAR2	RW	VAR1	VAR2	RW	VAR1	VAR2	RW	VAR1	VAR2
		EUR			GBP			CHF			JPY	
1	0.031	1.04	1.08	0.027	1.03	1.08	0.033	1.01	1.05	0.031	1.01	1.04
6	0.077	1.10	1.19	0.075	1.00^{*}	1.06^{*}	0.079	1.06	1.15	0.080	1.04	1.11
12	0.106	1.09	1.14^{*}	0.095	0.96**	0.95**	0.105	1.02^{*}	1.11*	0.105	1.08	1.20
24	0.150	0.99^{*}	0.92^{**}	0.127	0.86**	0.74^{**}	0.145	0.86**	0.89^{**}	0.161	1.11	1.14
36	0.178	0.84**	0.75**	0.133	0.78**	0.66**	0.167	0.75**	0.80**	0.192	1.11	1.08^{*}
60	0.238	0.73**	0.60**	0.136	0.68**	0.59**	0.213	0.70**	0.70**	0.185	1.12	1.01**

Table 2: Root Mean Squared Forecast Errors (RMSFEs)

Notes: For the RW model RMSFEs are reported in levels, whereas for the remaining methods they appear as the ratios to the corresponding RMSFE from the RW model. Asterisks ** and * denote the rejection of the null of the Clark and West (2006) test, stating that the Random Walk is the true data generating process, at 1%, 5% significance level, respectively.

RMSFE comparison

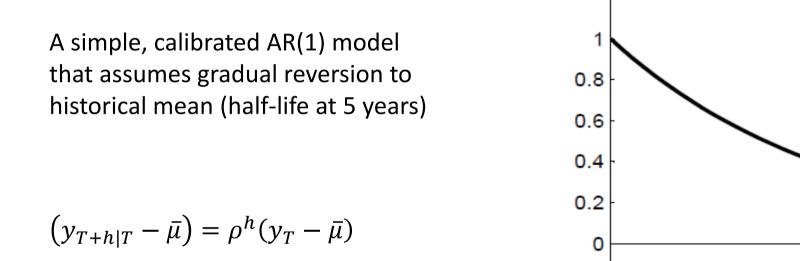


Notes: Each line represents the ratio of RMSE from a given method to RMSE from the random walk, where values below unity indicate better accuracy of point forecasts. The straight and dotted lines stand for VAR1 and VAR2, respectively. The forecast horizon is expressed in months.

A really tough benchmark: AR fixed model



A tough benchmark: HL / AR fixed model



Interpretation: a simple gliding path between an initial value and an end point, long-term forecast (PPP proxied by sample mean)

-0.2

8

4

12

16

20

24

> Faust and Wright (2013) have successfully used it for inflation forecasting!

Forecast race 2: RW - HL - AR

RER forecasting and PPP: This time the Random Walk loses, Open Economies Review 2016

Competing models:	RW model:	$y_{T+h T}^{RW} = y_T$
	HL model:	$y_{T+h T}^{HL} = \bar{\mu} + \bar{\rho}^h (y_T - \bar{\mu})$
	Estimated AR:	$y_{T+h T}^{AR} = \hat{\mu} + \hat{\rho}^h (y_T - \hat{\mu})$

AUD, CA, EA, JP, MX, NZ, CH, UK and US
real effective ER (BIS indices)
1975:1-2012:3, forecasts for 1990:1-2012:3
rolling (R = 180 monthly data)

MSFE: HL beats RW for 6 out of 9 currencies

h	RW	HL	AR	RW	HL	AR	RW	HL	AR
		AUD			CAD			EUR	
1	0.05	1.01	1.02^{*}	0.02	1.02	1.03^{*}	0.02	1.00	1.04^{**}
6	0.44	1.03	1.06^{*}	0.23	1.03	1.11**	0.19	0.96	1.12^{*}
12	0.82	1.06	1.09^{*}	0.46	1.06	1.20^{**}	0.43	0.92^{*}	1.14^{*}
24	1.53	1.10^{*}	1.09	0.94	1.10	1.19^{*}	0.89	0.83^{**}	1.18^{**}
36	2.10	1.12	1.06	1.58	1.06	1.20^{*}	1.28	0.77^{**}	1.13^{*}
60	3.00	1.11	1.06	3.02	0.94	1.45^{**}	2.06	0.66**	0.91
		JPY			MXN			NZD	
1	0.06	1.00	1.01	0.12	0.99	0.99	0.03	1.00	1.03^{*}
6	0.59	0.98	1.04	0.83	0.96^{*}	0.92	0.32	0.96	1.06
12	1.00	0.97	1.10^{*}	1.55	0.92^{*}	0.87^{*}	0.72	0.92^{*}	1.03
24	2.34	0.91	1.17^{**}	3.01	0.84^{**}	0.78^{*}	1.59	0.83^{**}	0.89^{*}
36	3.53	0.86	1.19^{**}	3.66	0.78^{**}	0.74^{**}	2.44	0.74^{**}	0.74^{**}
60	3.12	0.89	1.19^{*}	3.56	0.74^{**}	0.72^{*}	3.01	0.64^{**}	0.62^{**}
		CHF			GBP			USD	
1	0.02	1.00	1.06	0.03	1.00	1.02	0.02	1.00	1.03^{*}
6	0.12	0.98	1.22^{*}	0.24	0.97	1.04	0.19	0.96	1.10^{*}
12	0.25	0.97	1.16	0.47	0.95	1.03	0.31	0.93	1.21^{**}
24	0.50	0.88^{*}	0.99	1.06	0.87^{*}	0.98	0.55	0.84^{*}	1.21^{*}
36	0.72	0.80**	0.78^{**}	1.49	0.82**	0.93	0.69	0.72^{**}	1.13
60	0.79	0.72^{**}	0.69**	1.98	0.67**	0.70**	1.41	0.53^{**}	0.91

Michał Rubaszek, Exchange Rate Forecasting

Understanding the results

The variance of forecast from model $M \in \{RW, HL, AR\}$ can be decomposed into:

$$E\{(y_{T+h} - y_{T+h|T}^{M})^{2}\} = E\{(y_{T+h} - y_{T+h|T})^{2}\} + E\{(y_{T+h|T} - y_{T+h|T}^{M})^{2}\} + 2E\{(y_{T+h} - y_{T+h|T})(y_{T+h|T} - y_{T+h|T}^{M})\}$$

- 1. Random component (the same for all models)
- **2.** Estimation / calibration component
- 3. Remaining component (null for all models if random term is really random)

In the article we present analytical derivation for all components and show that:

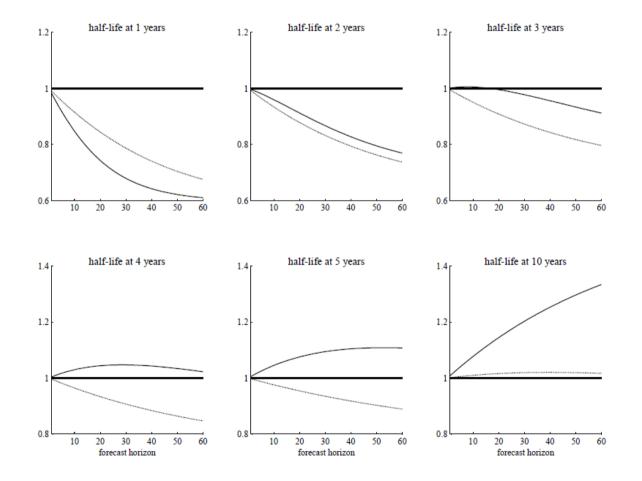
- for DGP HL up to 1Y:
- for DGP HL from 1Y to 3Y:
- ➢ for DGP HL from 3Y to 5Y:
- ➢ for DGP HL over 10Y:

AR outperforms HL and RW

- AR outperforms RW, but not HL
- HL outperforms RW, which is better than AR
- RW outperforms HL and AR



Theoretical MSFE ratios for various DGP HL



Notes: Each line represents the ratio of MSFE from a given method to MSFE from the random walk, where values below unity indicate better accuracy of point forecasts. The straight and dotted lines stand for AR and HL, respectively. The forecast horizon is expressed in months.



Main takeaways

Our results tell the following story:

If the true DGP is AR(1) with HL above 3 years, estimated AR usually will not outperform RW because the estimation error outweighs the accuracy loss due to misspecification of the RW.

The remedy: Employ a reasonably calibrated HL model assuming a gradual mean reversion to the sample mean



More sophisticated competitors:

DSGE and BVAR models



Forecast race 3: RW – HL – BVAR – DSGE

Exchange rate forecasting with DSGE models, Journal of International Economics 2017

Two Macro models:	2 DSGEs Justiniano and Preston, JAE (allowing / not allowing for RER trend)
Three time series models:	LBVAR - level BVAR DBVAR - differenced BVAR MBVAR - mean-reverting BVAR
A-theoretical benchmarks:	Random Walk AR fixed / HL model
Five countries:	US, EA, UK, CAN, AUS
Data for DSGE/BVAR:	y,y*,p,p*,i,i*,ca,rer
Sample:	1975-2013, forecasts for 1995-2013
Forecasting scheme:	recursive

RMSFE for RER

Main findings:

- AR fixed and DSGE no trend are clear winners
- Both models are meanreverting and forecast
 `conservative' dynamics
- MSBVAR also performs well at longer horizons (only mean-reversion)

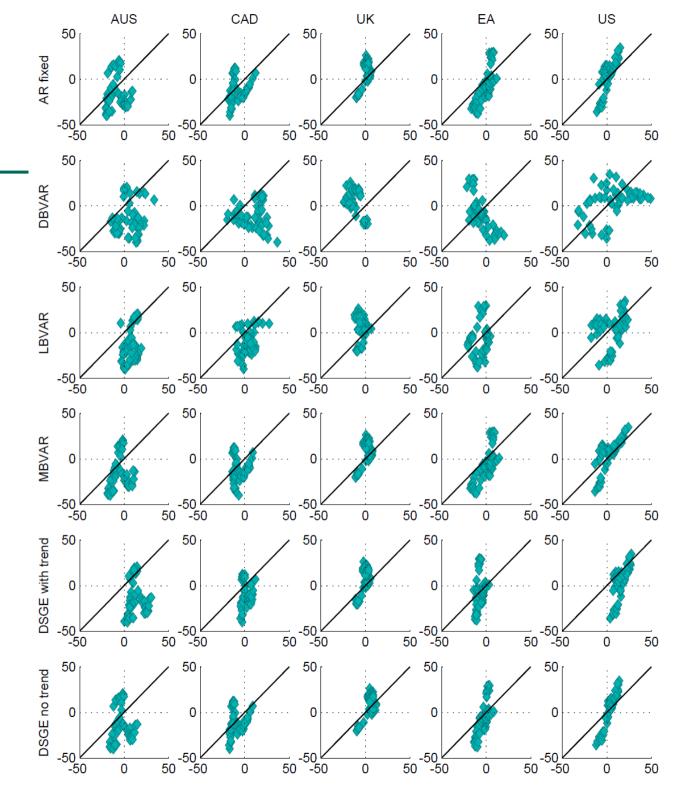
	H=1	H=2	H=4	H=8	H=12	H=24
			Unite	d States		
AR fixed	0.99	0.98	0.94	0.89	0.87	0.73**
DBVAR	1.04	1.15	1.13	1.19	1.13	1.28
LBVAR	1.01	1.09	1.15	1.29^{*}	1.36*	1.03
MBVAR	0.99	1.02	0.96	0.86	0.77	0.68**
DSGE with trend	1.12^{*}	1.15	1.22	1.21	1.21	1.01
DSGE no trend	1.03	1.02	1.00	0.92	0.83	0.66***
			Euro	o Area		
AR fixed	1.00	1.00	0.97	0.92	0.87	0.76**
DBVAR	1.05	1.12^{*}	1.20^{***}	1.30***	1.36***	1.36**
LBVAR	1.05	1.12	1.22	1.31	1.25	0.93
MBVAR	1.02	1.05	1.07	1.01	0.93	0.75**
DSGE with trend	0.99	0.98	0.98	1.01	1.00	0.90
DSGE no trend	0.99	0.98	0.96	0.95	0.91	0.77**
			United	Kingdor	n	
AR fixed	1.00	0.98	0.95	0.88**	0.86**	0.83**
DBVAR	1.06	1.18	1.23**	1.31**	1.43***	1.82**
LBVAR	1.12**	1.21**	1.24^{*}	1.14	1.13	1.23^{*}
MBVAR	1.02	1.06	1.00	0.89	0.86^{*}	0.82^{**}
DSGE with trend	1.01	0.98	0.94	0.84^{**}	0.80^{***}	0.86**
DSGE no trend	1.02	0.99	0.94	0.84	0.78^{**}	0.67**
			Ca	nada		
AR fixed	1.01	1.00	1.00	1.03	1.02	0.80
DBVAR	0.99	1.07^{*}	1.15*	1.31*	1.41**	1.61**
LBVAR	1.04	1.09^{*}	1.13**	1.09	1.03	1.10
MBVAR	0.99	1.03	1.05	1.07	1.07	0.88
DSGE with trend	1.02	1.02	1.03	1.08	1.08	1.04
DSGE no trend	1.03	1.03	1.04	1.08	1.05	0.79
			Aus	stralia		
AR fixed	1.01	1.00	1.00	1.02	1.03	0.88
DBVAR	1.03	1.10	1.12	1.05	0.98	1.18
LBVAR	1.02	1.06	1.09	1.07	1.07	1.22^{**}
MBVAR	1.04^{*}	1.08^{*}	1.10^{*}	1.07	1.06	0.92
DSGE with trend	1.07^{*}	1.10	1.18**	1.34***	1.46***	1.55***
DSGE no trend	1.03	1.03	1.04	1.10	1.14	1.01

Michał Rubaszek, Exchange Rate Forecasting

Scatter-plot for H=24

Main findings:

- High correlation of forecasts and realizations from AR fixed / MBVAR / DSGE no trend
- However, for the above models, in most cases forecasts underpredict realizations...
- DBVAR forecasts are the most `brave', but of wrong sign



Michał Rubaszek, Exchange Rate Forecasting

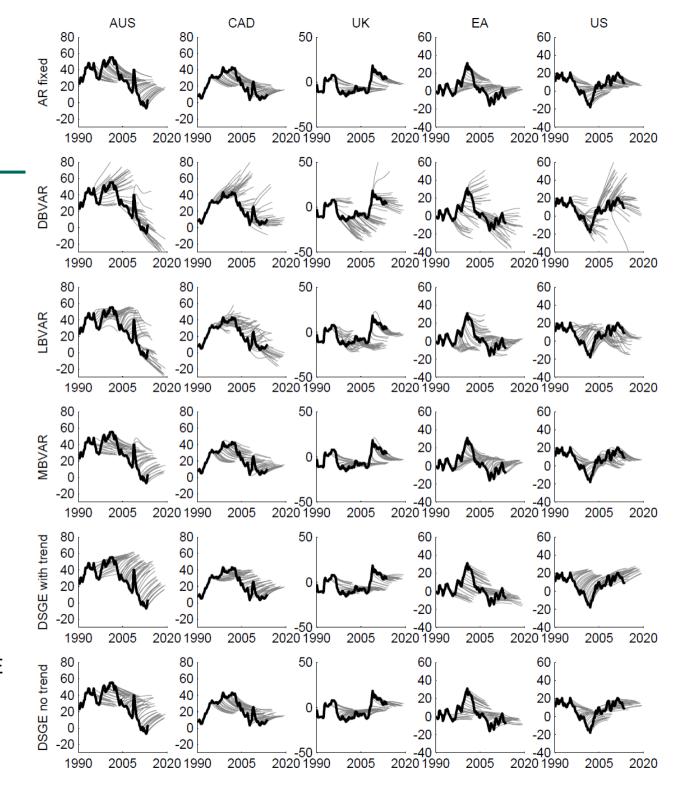
Comparison of forecasts and realizations

	1-0	luarter	r ahead	d forecas	\mathbf{sts}	24	-quarte	r ahead	l foreca	\mathbf{sts}	
	US	EA	UK	CAN	AUS	US	EA	UK	CAN	AUS	
		Correct sign $(\%)$									
AR-fixed	47	46	58	49	47	70***	70***	87***	64**	55	
DBVAR	66***	65**	53	46	51	76***	53	15^{***}	47	53	
LBVAR	54	63**	47	47	47	51	53	34^{**}	47	38^{*}	
MBVAR	59	53	55	59	47	76 ^{***}	68***	83***	64^{**}	45	
DSGE (with RER trend)	42	54	57	50	$\overline{43}$	74^{***}	76***	7 9***	51	23^{***}	
DSGE (no RER trend)	53	4 9	54	54	47	93 ^{***}	7 9***	96 ^{***}	70^{***}	43	
				of whic	h unde	erpredic	ction (%	6)			
AR-fixed	83	94	82	81	83	92	89	80	74	83	
DBVAR	66	82	75	83	85	38	50	75	40	79	
LBVAR	81	75	72	78	78	44	61	89	76	85	
MBVAR	80	83	74	89	81	85	89	71	82	88	
DSGE (with RER trend)	69	98	77	82	79	23	83	86	89	83	
DSGE (no RER trend)	83	97	71	83	81	92	81	67	76	100	

Hedgehog graphs

Models are inaccurate if:

- a lot of weight to dynamics in-sample, which deteriorates the out-ofsample accuracy in line with the "shrinkage principle" of Diebold (BVAR models)
- They ignore mean reverting tendencies of the RER and extrapolate too much past trends (DBVAR, LBVAR, DSGE with trend)



Michał Rubaszek, Exchange Rate Forecasting



Main takeaways

- Be cautious in including trends in RER in DSGE models: it might be counterproductive
- > Be cautious while differentiating the RER in BVAR
- Forecast RERs with a mean reverting pattern and conservative short-term dynamics.



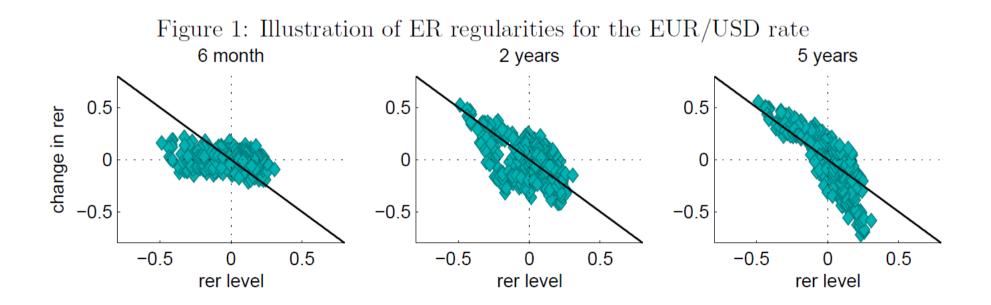
Returning to simplicity

Direct AR forecasts for RER

Direct forecasts

Exchange rate forecasting on a napkin, ECB Working Paper Series

We check mean-reversion of RER with Direct Forecast (DF) regression:



Direct forecasts

Exchange rate forecasting on a napkin, ECB Working Paper Series

We check mean-reversion of RER with DF regression:

	6	month		<u> </u>	years		5	5 years	
	α_h	β_h	R^2	α_h	β_h	R^2	α_h	β_h	R^2
		Esti	mates	of Δre	$r_{t,h} = \alpha$	$a_h + \beta_h$	rer_{t-h} -	$+ \epsilon_t$	
AUD	0.00	-0.11	0.06	-0.01	-0.41	0.22	-0.02	-0.92	0.44
CAD	0.00	-0.08	0.04	-0.01	-0.38	0.21	-0.02	-0.98	0.51
JPY	0.00	-0.12	0.06	0.01	-0.52	0.27	0.02	-0.85	0.43
NZD	0.00	-0.11	0.05	0.01	-0.51	0.25	0.00	-1.07	0.48
CHF	0.00	-0.14	0.07	0.01	-0.57	0.29	0.00	-1.05	0.52
GBP	0.00	-0.20	0.09	0.00	-0.84	0.39	0.00	-1.41	0.69
EUR	0.00	-0.13	0.06	-0.01	-0.59	0.29	-0.02	-1.35	0.70
KRW	0.00	-0.17	0.08	0.00	-0.63	0.31	-0.01	-1.16	0.62
NOK	0.00	-0.15	0.07	-0.01	-0.58	0.26	-0.01	-1.36	0.65
SEK	-0.01	-0.09	0.04	-0.02	-0.45	0.21	-0.04	-1.04	0.55

Table : Regressions for ER regularities



Forecast race 4: checking the quality of DF forecasts

Models: Autoregression (AR): $y_{t+h}^f = \hat{\mu} + \hat{\rho}^h (y_t - \hat{\mu}).$ Half-life (HL): $y_{t+h}^f = \overline{\mu} + \overline{\rho}^h (y_t - \overline{\mu}).$ Direct forecast (DF): $y_{t+h}^f = y_t + (\hat{\alpha}_h + \hat{\beta}_h x_t)$

Benchmark: Random walk

USD rates against:AUD, CAD, JPY, NZD, CHF, GBP, EUR, KRW, NOK, SEKSample:1975-2017, forecasts for 1995-2017Forecasting scheme:recursive

RMSFE for RER

Models:

 $\begin{array}{ll} \text{Autoregression (AR):} & y_{t+h}^f = \hat{\mu} + \hat{\rho}^h (y_t - \hat{\mu}). \\ \text{Half-life (HL):} & y_{t+h}^f = \overline{\mu} + \overline{\rho}^h (y_t - \overline{\mu}). \\ \text{Direct forecast (DF):} & y_{t+h}^f = y_t + (\hat{\alpha}_h + \hat{\beta}_h x_t) \end{array}$

		1 montl	ıs	Ĩ	6 montl	ns		2 years			5 years	
					real exchange rate							
	AR	\mathbf{DF}	HL	AR	DF	HL	AR	DF	HL	AR	DF	HL
AUD	1.01	1.01	1.00	1.03	1.04	1.00	1.02	1.11	0.96	0.97	1.08	0.92
CAD	1.01	1.01	1.00	1.05	1.05	1.01	1.07	1.15	0.99	1.16	1.15	0.88*
JPY	1.01	1.01	1.00	1.04	1.05	1.00	1.05	1.15	0.97	1.01	1.19	0.88*
NZD	1.01	1.01	1.00	1.05	1.05	0.99	1.03	0.96	0.90*	0.87**	0.98	0.81^{**}
CHF	1.01	1.01	1.00	1.06	1.06	0.98	1.04	1.04	0.90*	0.85**	1.01	0.75**
GBP	1.01	1.01	1.00	1.01	1.02	0.97^{*}	0.85**	0.76^{**}	0.85**	0.66**	0.68**	0.71**
EUR	1.02	1.01	1.00	1.07	1.07	0.97	1.03	0.92	0.87**	0.76**	0.67^{**}	0.69**
KRW	1.00	1.00	0.99	1.01	0.98	0.96**	1.05	0.87*	0.86**	1.60	0.79**	0.75**
NOK	1.01	1.01	1.00	1.05	1.05	0.97	0.99	0.93	0.89**	0.78**	0.71**	0.73**
SEK	1.01	1.01	1.00	1.04	1.05	0.98	1.05	0.93	0.88*	0.94	0.91	0.79**

Notes: The table shows the ratio of RMSFE from a given model in comparison to the RMSFE from a RW. Asterisks ** and *denote the 1% and 5% significance levels of the one-sided Diebold-Mariano test with the alternative that RMSFE from a given model is lower than that from the RW.



Forecasting relative price index (RPI)

Back to forecast race 3.

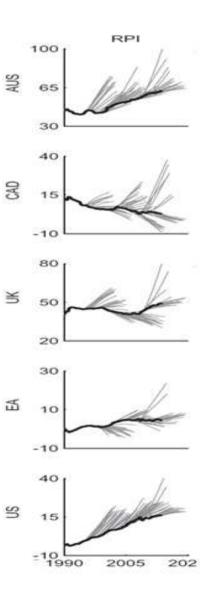
DSGE fails to forecast RPI well...

$$\widetilde{rpi}_{t+h}^{f} - \widetilde{rpi}_{t} = h\underbrace{(\mu_{\pi} - \mu_{\pi}^{*})}_{trend} + \sum_{i=1}^{h}\underbrace{\left(\pi_{t+i}^{f} - \pi_{t+i}^{*f}\right)}_{cycle}$$

DSGE (no RPI trend): includes only the *cycle*,DSGE (no RPI cycle): includes only the *trend*,RW: excludes both the *trend* and the *cycle*.

	H=1	H=2	H=4	H=8	H=12	H=24
			Unit	ed States		
DSGE	0.92	0.97	0.95	1.11	1.28	1.50^{***}
DSGE (no RPI trend)	0.92	0.97	0.93	1.08	1.26	1.47***
DSGE (no RPI cycle)	1.01	1.03	1.04	1.04	1.02	0.99
A.C			Eu	iro area		
DSGE	1.28	1.58	1.87	1.93*	2.04^{**}	2.32***
DSGE (no RPI trend)	1.28	1.56	1.83	1.85	1.97*	2.10^{***}
DSGE (no RPI cycle)	1.20***	1.31^{***}	1.55^{***}	1.72^{***}	1.76^{***}	1.97***
			United	d Kingdor	n	
DSGE	1.19	1.35^{*}	1.51**	1.76***	1.97^{***}	2.47***
DSGE (no RPI trend)	1.16	1.29^{*}	1.42^{**}	1.60^{***}	1.75***	2.17^{***}
DSGE (no RPI cycle)	1.05	1.09	1.12	1.19	1.25^{*}	1.64***
			C	anada		
DSGE	1.29**	1.59^{**}	2.13**	2.96^{***}	3.71***	4.06^{***}
DSGE (no RPI trend)	1.28**	1.56^{**}	2.06**	2.82***	3.53***	3.68***
DSGE (no RPI cycle)	1.09**	1.15^{**}	1.26^{**}	1.34***	1.41***	1.71***
			A	ustralia		
DSGE	1.03	1.12	1.32	1.60	1.78	1.54
DSGE (no RPI trend)	1.01	1.07	1.21	1.40	1.50	1.09
DSGE (no RPI cycle)	0.93	0.93	0.93	0.90	0.84	0.54***

Table : RMSFE for the RPI



Michał Rubaszek, Exchange Kate Forecasting

... because of the lack in price comovment.

		D	SGE m	odel				Data	-	
	H=1	H=4	H=8	H=12	H=24	H=1	H=4	H=8	H=12	H=24
C	orrelation	of chang	ges in p	rice indic	ces: $cor(j$	$\widetilde{p}_t^* - \widetilde{p}_{t-}^*$	$h, \widetilde{p}_t - j$	\tilde{p}_{t-h}		
United States	0.06	0.08	0.10	0.11	0.13	0.80	0.87	0.90	0.93	0.98
Euro area	0.03	0.05	0.06	0.06	0.06	0.87	0.92	0.93	0.94	0.97
United Kingdom	0.09	0.14	0.17	0.19	0.21	0.80	0.90	0.93	0.94	0.97
Canada	0.13	0.19	0.21	0.22	0.23	0.81	0.89	0.92	0.95	0.97
Australia	0.13	0.18	0.20	0.21	0.22	0.67	0.77	0.80	0.84	0.89
	Standa	rd devi	ation of	RPI cha	nges: sta	$l(\widetilde{rpi}_t -$	\widetilde{rpi}_{t-h}	(
United States	1.1	3.4	6.0	8.4	15.1	0.5	1.4	2.3	2.7	3.2
Euro area	1.1	3.8	7.1	10.3	19.4	0.4	1.2	2.1	2.8	3.6
United Kingdom	1.4	3.9	6.6	9.2	16.3	0.8	2.1	3.5	4.4	6.4
Canada	1.1	3.2	5.6	7.8	14.1	0.5	1.4	2.2	2.8	4.4
Australia	1.1	3.2	5.6	7.9	14.2	0.8	2.2	3.7	4.8	7.4

Back to forecast race 4.

RPI does not adjust to RER misalignment...

RPI does not play any role in RER adjustment, in a regression:

	6	month	ıs	1	2 years	;		5 years	;
	α_h	β_h	R^2	α_h	β_h	R^2	α_h	β_h	R^2
	1	Estin	mates	of Δrpi	$\dot{a}_{t,h} = \alpha_{b}$	$h + \beta_h \Delta$	$\Delta rer_{t,h}$	$+ \epsilon_t$	
AUD	0.01	-0.01	0.00	0.02	0.01	0.00	0.04	0.00	0.00
CAD	0.00	0.00	0.00	0.00	0.03	0.01	0.00	0.02	0.01
JPY	-0.01	0.03	0.05	-0.04	0.02	0.02	-0.12	0.01	0.00
NZD	0.01	0.01	0.00	0.03	0.09	0.06	0.08	0.06	0.01
CHF	-0.01	0.00	0.00	-0.04	0.01	0.00	-0.09	0.07	0.05
GBP	0.00	-0.02	0.01	0.01	-0.01	0.00	0.02	-0.01	0.00
EUR	0.00	-0.02	0.02	0.00	-0.03	0.04	-0.01	-0.05	0.13
KRW	0.01	-0.03	0.01	0.04	-0.04	0.01	0.09	-0.05	0.01
NOK	0.00	-0.01	0.00	0.01	-0.01	0.00	0.02	0.00	0.00
SEK	0.00	-0.01	0.00	0.01	0.01	0.00	0.02	0.03	0.01

and is best predicted by the RW process...

Models: Autoregression (AR): $y_{t+h}^f = \hat{\mu} + \hat{\rho}^h (y_t - \hat{\mu}).$ Half-life (HL): $y_{t+h}^f = \overline{\mu} + \overline{\rho}^h (y_t - \overline{\mu}).$ Direct forecast (DF): $y_{t+h}^f = y_t + (\hat{\alpha}_h + \hat{\beta}_h x_t)$

- For HL model, we follow Faust and Wright (2013) and set mean to 0 and half-life of inflation differential to six months
- For DF model, x = rer

	1 months				6 month	s		2 years			5 years		
	Relative price indices												
	AR	DF	HL	AR	DF	HL	AR	DF	HL	AR	DF	HL	
AUD	1.04	1.05	1.01	1.22	1.39	1.06	1.71	2.42	1.07	2.52	3.49	1.08	
CAD	1.01	1.03	1.02	1.06	1.19	1.09	1.21	1.73	0.93	1.34	2.23	0.95	
JPY	0.92**	0.94**	0.93**	0.76**	0.78**	0.76**	0.58**	0.66**	0.77^{**}	0.39**	0.49^{**}	0.87**	
NZD	1.19	1.12	1.02	1.80	1.75	1.08	3.23	3.71	1.03	5.00	6.52	1.03	
CHF	0.97*	1.01	0.96**	0.88	1.10	0.79**	0.79^{*}	1.09	0.77**	0.59**	0.79^{*}	0.90**	
GBP	1.01	1.01	1.00	1.05	1.06	0.99	1.23	1.32	0.91^{*}	1.57	1.70	0.96	
EUR	1.02	1.00	1.01	1.01	1.05	1.08	1.02	1.07	1.04	1.12	1.31	1.01	
KRW	0.91*	0.99	0.98	0.91	0.94	0.95	0.78*	0.88	0.87*	0.76*	0.89	0.88**	
NOK	1.01	1.02	1.02	1.10	1.11	1.04	1.40	1.66	1.02	1.92	2.83	1.05	
SEK	1.00	1.02	0.99	1.09	1.16	0.94	1.42	1.49	0.85**	1.80	2.22	0.94**	

Table: RMSFE for RPI with respect to the RW



Forecasting nominal exchange rates (NER)



Ad-hoc ``partial" forecast for NER:

- 1. We forecast RER from a given model: $rer_{T+h|T}^{M}$
- 2. For NER we assume that

$$ner_{T+h|T}^{M} - ner_{T} = rer_{T+h|T}^{M} - rer_{T}$$

Competing models:

- RW random walkHL fixed AR (half-life model)
- AR estimated AR

MSFE comparison:

HL beta RW forecasts for 6 out of 9 currencies

h	RW	HL	AR	RW	HL	AR	RW	HL	AR	
		AUD			CAD		EUR			
1	0.05	1.01	1.02^{*}	0.02	1.02	1.03^{*}	0.02	1.00	1.04^{*}	
6	0.44	1.02	1.06^{*}	0.24	1.03	1.11**	0.19	0.97	1.12^{*}	
12	0.78	1.06	1.11**	0.47	1.06	1.22^{**}	0.40	0.93	1.15^{*}	
24	1.30	1.12 *	1.13^{*}	0.86	1.10	1.26^{**}	0.81	0.85^{*}	1.20**	
36	1.70	1.16 *	1.10	1.42	1.05	1.29^{**}	1.13	0.78**	1.16**	
60	2.23	1.21 *	1.09	2.72	0.91	1.56^{**}	1.78	0.66**	0.93	
		JPY			MXN			NZD		
1	0.06	1.00	1.01	0.12	1.00	1.00	0.03	1.00	1.03^{*}	
6	0.57	0.99	1.03	1.23	0.98	0.95	0.32	0.96	1.06	
12	1.03	0.99	1.08^{*}	2.92	0.95^{*}	0.91	0.69	0.91^{*}	1.03	
24	2.55	0.93	1.11*	7.19	0.90**	0.84^{*}	1.41	0.81^{**}	0.89^{*}	
36	3.98	0.88	1.11^{*}	11.86	0.87^{**}	0.81^{**}	2.17	0.70^{**}	0.74^{**}	
60	3.51	0.99	0.95	25.53	0.88^{**}	0.82^{**}	2.69	0.60**	0.59^{**}	
		CHF			GBP		USD			
1	0.02	1.00	1.06 *	0.03	1.00	1.02^{*}	0.03	1.00	1.03^{*}	
6	0.13	1.00	1.22 *	0.23	0.99	1.06	0.25	0.97	1.09 *	
12	0.29	0.99	1.19	0.49	0.98	1.06	0.45	0.95	1.17**	
24	0.62	0.93^{*}	1.01	1.12	0.92	1.02	0.90	0.88^{*}	1.15^{**}	
36	0.90	0.87^{**}	0.85^{*}	1.69	0.88^{*}	0.98	1.26	0.81^{*}	1.05	
60	1.12	0.87^{**}	0.83^{*}	2.42	0.74^{**}	0.79^{**}	2.52	0.67^{*}	0.87**	

Michał Rubaszek, Exchange Rate Forecasting

Back to forecast race 3:

partial model is better than the full model

Partial DSGE model: with RER fcts from DSGE we compute $ner_{T+h|T}^{M} - ner_{T} = rer_{T+h|T}^{M} - rer_{T}$ **Full DSGE model:** forecasts for NER are calculated using full DSGE model

	H=1	H=2	H=4	H=8	H=12	H=24				
			United	d States						
AR fixed	1.00	0.98	0.95	0.90	0.87	0.76**				
DSGE partial	1.02	1.00	0.96	0.86	0.76^{*}	0.67***				
DSGE full	1.03	1.03	1.05	1.01	0.97	0.78				
			Euro	o Area						
AR fixed	1.01	1.00	0.98	0.93	0.89	0.77**				
DSGE partial	0.99	0.98	0.97	0.96	0.93	0.78**				
DSGE full	1.01	1.01	1.01	1.00	0.98	0.89				
	United Kingdom									
AR fixed	1.01	1.01	0.99	0.94	0.93	0.88**				
DSGE partial	1.03	1.02	0.98	0.90	0.87	0.77***				
DSGE full	1.06**	1.05^{*}	1.05	1.04	1.08	8 0.89 3 0.88** 7 0.77**				
			Ca	nada						
AR fixed	1.01	1.00	1.00	1.03	1.01	0.79				
DSGE partial	1.02	1.03	1.03	1.07	1.02	0.77				
DSGE full	1.04	1.06	1.12*	1.21*	1.21	0.86				
	Australia									
AR fixed	1.01	1.00	1.01	1.05	1.09	1.01				
DSGE partial	1.02	1.02	1.03	1.09	1.14^{*}	1.07				
DSGE full	1.06*	1.08*	1.14*	1.28**	1.38**	1.37**				

Table: RMSFE for nominal exchange rate

Michał Rubaszek, Exchange Kate Forecasting

Back to forecast race 4:

NER adjusts to RER misalignment...

NER is the driving force behind RER adjustment!!!

$$\Delta ner_{t,h} = \alpha_h + \beta_h \Delta rer_{t,h} + \epsilon_t$$

	6	month	s	2	years		5	years			
	α_h	β_h	R^2	α_h	β_h	R^2	α_h	eta_{h} .	R^2		
	Estimates of $\Delta ner_{t,h} = \alpha_h + \beta_h \Delta rer_{t,h} + \epsilon_t$										
AUD	-0.01	1.01	0.96	-0.02	0.99	0.93	-0.04	1.00	0.92		
CAD	0.00	1.00	0.96	0.00	0.97	0.94	0.00	0.98	0.95		
JPY	0.01	0.97	0.98	0.04	0.98	0.97	0.12	0.99	0.97		
NZD	-0.01	0.99	0.94	- <mark>0.03</mark>	0.91	0.87	- <mark>0.</mark> 08	0.94	0.76		
CHF	0.01	1.00	0.98	0.04	0.99	0.95	0.09	0.93	0.91		
GBP	0.00	1.02	0.96	- <mark>0.01</mark>	1.01	0.95	-0.02	1.01	0.93		
EUR	0.00	1.02	0.98	0.00	1.03	0.98	0.01	1.05	0.98		
KRW	-0.01	1.03	0.94	-0.04	1.04	0.89	- <mark>0.</mark> 09	1.05	0.81		
NOK	0.00	1.01	0.96	-0.01	1.01	0.93	-0.02	1.00	0.90		
SEK	0.00	1.01	0.97	- <mark>0.</mark> 01	0.99	0.95	-0.02	0.97	0.91		

... hence part of future NER changes is predictable (as long as RER is predictable)

Models: Autoregression (AR): $y_{t+h}^f = \hat{\mu} + \hat{\rho}^h (y_t - \hat{\mu})$. Half-life (HL): $y_{t+h}^f = \overline{\mu} + \overline{\rho}^h (y_t - \overline{\mu})$. Direct forecast (DF): $y_{t+h}^f = y_t + (\hat{\alpha}_h + \hat{\beta}_h x_t)$

		1 montl	ns	. A.	6 month	s	2 years			5 years			
	nominal exchange rate												
RER		HL	HL	1	HL	HL	1	HL	HL		HL	HL	
RPI		RW	HL		RW	HL		RW	HL		RW	HL	
NER	DF			DF			DF			DF			
AUD	1.01	1.00	1.01	1.04	0.99	1.01	1.05	0.95	0.97	0.99	0.89*	0.90*	
CAD	1.01	1.00	1.01	1.05	1.01	1.03	1.08	1.00	1.01	0.94	0.87^{*}	0.87*	
JPY	1.01	1.00	1.00	1.05	1.01	1.00	1.12	0.97	0.98	1.08	0.89	0.88*	
NZD	1.01	1.00	1.00	1.04	0.99	1.01	0.98	0.91*	0.92	1.28	0.80**	0.81**	
CHF	1.01	1.00	1.00	1.04	0.99	0.99	0.93	0.94	0.93	0.80*	0.87^{*}	0.85**	
GBP	1.01	1.00	1.00	1.03	0.97^{*}	0.99	0.78^{**}	0.85^{**}	0.84^{**}	0.86*	0.75**	0.74**	
EUR	1.02	1.00	1.00	1.07	0.97	0.99	0.91	0.87**	0.88**	0.68**	0.68**	0.68**	
KRW	1.00	0.99	1.00	0.97	0.97**	0.97^{*}	0.85*	0.88**	0.88**	0.63**	0.80**	0.78**	
NOK	1.01	1.00	1.00	1.05	0.98	0.98	0.93	0.91**	0.91**	0.77**	0.75^{**}	0.76**	
SEK	1.01	1.00	1.00	1.05	0.97	1.00	0.88	0.86**	0.88*	0.67**	0.69**	0.71**	

Table : RMSFE for NER with respect to the RW



Conclusions



- 1. The consensus view `*ER theories are of little help in ER forecasting*' is not true
- 2. We can forecast RERs with ``conservative'' and mean-reverting models. AR fixed is a good candidate (for its simplicity)
- 3. We encountered problems in forecasting changes in the relative price indices (from large and small models)
- 4. The best forecast for the NER is to assume that in the forecast horizon its change will be equal to the change in RER. This is the predictable part of future NER movements
- 5. Method from point 4 gives accurate forecasts and can be easily done in a spreadsheet.



Other takeaways

- Be careful while including trends in RER equation in DSGE models: it might be counterproductive out-of-sample
- > Be cautious while differentiating data in BVAR
- Forecast RERs with a mean reverting pattern and conservative short-term dynamics.
- > Forecast NER using forecasts for RER rather than using the entire model