# Exchange Rates and Price Misalignment: Evidence on Long-Horizon Predictability

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# Introduction

- The failure of open-economy macro theory to explain exchange rate behavior using economic fundamentals has prevailed in the international economics literature since the seminal papers by Meese and Rogoff (1983).
- A number of studies have found evidence of greater predictability of economic exchange rate models at longer horizons (Mark, 1995).

  Econometric issues questioned: Kilian (1999), Berkowitz and Giorgianni (2001), Cheung, Chinn and Pascual (2005).
- Short-horizon forecasting: Gourinchas and Rey (2007), Molodtsova and Papell (2008), Engel, Mark and West (2007).

  Important caveats: Rogoff and Stavrakeva (2008).

# Introduction

- Forecasting nominal exchange rates remains a remarkably difficult task, despite the development of more sophisticated econometric tests.
- However, most practitioners and policymakers do not believe that the random walk model is the true model (Engel and West, 2005). The model is simply used as a dummy for a frame of reference to measure the forecast accuracy of the structural model.

## Dual Role of Exchange Rates

- Most exchange rate movements in the short run seem to reflect changes in expectations about future monetary or real conditions.
- When prices are sticky, however, nominal exchange rate movements directly have impacts on terms of trade.
- When exchange rate changes are primarily forward-looking, relative prices would be forced to incorporate these expectation effects, and the terms of trade or other international prices may be badly misaligned in the short run (Devereux and Engel, 2006, 2007).

## Exchange Rates and Price Misalignments

- The relative price misalignment has welfare implications as it would trigger adjustment in consumption and employment.
- It may also help to predict subsequent re-evaluation of the nominal exchange rate.
- If a currency is overvalued, it would cause the relative price of goods in the domestic country to be more expensive than foreign in the short term. When there is a tendency for the currency to depreciate, such price misalignment might be useful to predict the subsequent depreciation.

# This Paper

- This paper studies whether price misalignments arising from this dual role of exchange rates have predictive power for future exchange rate movements.
- Previous studies have shown weak predictability at the aggregate level of price misalignments (PPP fundamentals). However, there is significant heterogeneity for prices at the good level.
- We collect good-level price data across borders to construct deviations from the Law of One Price (LOOP) as a measure of price misalignments at disaggregated level, with which we examine their predictive power for several bilateral exchange rates.
  - U.S. dollar and Japanese Yen rate: 1973:03 – 2009:08, 67 goods
  - U.S. dollar and British pound rate: 1987:01 – 2009:08, 48 goods

# This Paper

- In-sample and out-of-sample forecasting analysis for nominal exchange rate changes:
    - In-sample empirical work gives us some sense whether *ex post* price misalignments are essential indicators.
    - With out-of-sample analysis, we can study whether there are evidence to support that they are in fact indicators with *ex ante* predictive power.
- Test of superior predictive ability (Hansen, 2005): to correct for data mining by comparing the mean square prediction error (MSPE) under the null model (random walk with or without drift) to the MSPE under alternative models (price misalignment models).

# Preliminary Results

- U.S. dollar/Japanese Yen Rate:
  - Estimates of the slope coefficient is positive over all horizons for almost all goods. The bias-adjusted slope coefficients and R-squares both increase with the forecast horizon.
  - The out-of-sample SPA tests suggest that our price mislignment model generally outperforms random walks either with or without drift at the five percent level of significance over long horizons (12 months).
- U.S. dollar/UK pound Rate:
  - Estimates of the slope coefficient is positive over all horizons for almost all goods. The bias-adjusted slope coefficients and R-squares both increase with the forecast horizon.
  - Only a few good-level price misalignment shows out-of-sample predictability either at short or long horizon, possibly related to the limited length of UK data.

# Econometric Methodology

- Our empirical analysis centers on the following simple forecasting regression over a $k$-period horizon:

$$s_{t+k} - s_t = \alpha_k + \beta_k z_{i,t} + u_{t,t+k}$$

$s_t$ — log the nominal exchange rate defined as the U.S. dollar per foreign currency.

$z_{i,t}$ — deviation from LOOP for an individual good $i$, $z_{i,t} \equiv p_{i,t} - p^*_{i,t} - s_t$.

# Bootstrapping

- We rely on bootstrapping for small sample inferences in long horizon regressions to mitigate size distortions.

  The data generating process (DGP) under the null hypothesis that the exchange rate is unpredictable is as follows:

$$\Delta s_t = c_s + \varepsilon_{s,t}$$
$$z_{i,t} = c_z + \phi_1 z_{i.t-1} + \ldots + \phi_p z_{i.t-p} + \varepsilon_{z,t}$$

- When performing out-of-sample analysis against the random walk model without drift, we restrict the estimate of the drift term in the equation for $s_t$ (i.e. $c_s$) to zero in generating a sequence of pseudo observations.
- When the equation for $z_{i,t}$ is estimated, the small-sample bias correction is taken into account (Shaman and Stine, 1988).
- Robustness check: bootstrapping under the restricted Vector Error Correction Model (VECM) of $s_t$ and $z_{i,t}$ as the null DGP (Kilian, 1999).

## Data

- US: monthly good-level price data are obtained from the Bureau of Labor Statistics. Price indexes are available for major groups of consumer expenditures (food and beverages, housing, apparel, transportation, medical care, recreation,education and communications, and other goods and services).
- Japan: the source of Japanese data is from the Japan Statistics Bureau. Goods and services are classified so that each item encompasses similar products in terms of usage, function, etc., and prices within each item are expected to move parallel with each other for long spells.
- UK: good-level price data are obtained from the Office for National Statistics. The data set includes details on all consumer spending on goods and services by members of UK households.
- The monthly U.S. dollar per Japanese Yen and U.S. dollar per British pound exchange rates are obtained from the DRI (Global Insight) Database.

# Description of Goods – U.S. and Japan

| Good No. | Good | Good No. | Good |
|---|---|---|---|
| Good 01 | Beef and veal | Good 35 | Repair of household Goods |
| Good 02 | Pork chops | Good 36 | Electricity |
| Good 03 | Poultry | Good 37 | Water and sewerage maintenance |
| Good 04 | Bacon, breakfast sausage, and related products | Good 38 | Utility (piped) gas service |
| Good 05 | Ham | Good 39 | Fuel oil and other fuels |
| Good 06 | Frozen fish and seafood | Good 40 | Domestic services |
| Good 07 | Fresh fish and seafood | Good 41 | Household cleaning products |
| Good 08 | Canned fish and seafood | Good 42 | Household paper products |
| Good 09 | Fresh whole milk | Good 43 | Bedroom furniture |
| Good 10 | Butter | Good 44 | Floor coverings |
| Good 11 | Cheese and related products | Good 45 | Window coverings |
| Good 12 | Ice cream and related products | Good 46 | Other linens |
| Good 13 | Other dairy and related products | Good 47 | Major appliances |
| Good 14 | Eggs | Good 48 | Clocks, lamps, and decorator Goods |
| Good 15 | White bread | Good 49 | Dishes and flatware |
| Good 16 | Fresh biscuits, rolls, muffins | Good 50 | Nonelectric cookware and tableware |
| Good 17 | Rice, pasta, cornmeal | Good 51 | Tools, hardware and supplies |
| Good 18 | Flour and prepared flour mixes | Good 52 | Women's apparel |
| Good 19 | Bananas | Good 53 | Men's apparel |
| Good 20 | Juices and non-alcoholic drinks | Good 54 | Infants' and toddlers' apparel |
| Good 21 | Tomatoes | Good 55 | Women's footwear |
| Good 22 | Lettuce | Good 56 | Men's footwear |
| Good 23 | Canned fruits | Good 57 | Boys' and girls' footwear |
| Good 24 | Canned vegetables | Good 58 | Laundry and dry cleaning services |
| Good 25 | Sugar and sweets | Good 59 | New vehicles |
| Good 26 | Margarine | Good 60 | Gasoline (all types) |
| Good 27 | Other fats and oils including peanut butter | Good 61 | Tires |
| Good 28 | Coffee | Good 62 | Motor vehicle maintenance and repair |
| Good 29 | Other beverage materials including tea | Good 63 | Motor vehicle insurance |
| Good 30 | Spices, seasonings, condiments, sauces | Good 64 | State and local registration and license |
| Good 31 | Full service meals and snacks | Good 65 | Parking and other fees |
| Good 32 | Food at employee sites and schools | Good 66 | Intracity transportation |
| Good 33 | Rent of primary residence | Good 67 | Airline fare |
| Good 34 | Tenants' and household insurance | | |

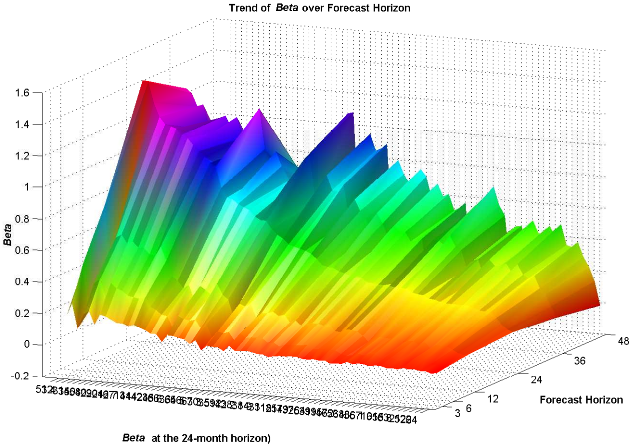
# Empirical Results

# U.S. dollar/Japanese Yen Rate

# In-sample Regression Results

- Estimates of the slope coefficient is positive over all horizons for almost all goods.
- Both the estimate of the slope coefficient and the R-square tend to increase with the forecast horizon for most of goods.
- t-statistic is based on the Newey-West's (1987) HAC covariance matrix estimator with Andrew's (1991) procedure for selecting a truncation lag; the p-value is derived from the bootstrap distribution.
- Among 67 goods considered, there are 24, 24, 22, 36, 43, and 33 goods at the 3, 6, 12, 24, 36, and 48-month forecast horizons, respectively, for which the estimates of the slope coefficient is statistically significant at the 10% level.

# In-sample Regression Coefficient $\beta$



# In-sample Regressions – 36 months

| Goods | R-sq | Beta | Tr(A) | p-(A) | Goods | R-sq | Beta | Tr(A) | p-(A) |
|---|---|---|---|---|---|---|---|---|---|
| Good 01 | 0.344 | 0.183 | 2.535 | 0.159 | Good 35 | 0.528 | 0.400 | 5.831 | 0.048 |
| Good 02 | 0.596 | 0.299 | 3.300 | 0.054 | Good 36 | 0.932 | 0.476 | 6.051 | 0.023 |
| Good 03 | 0.752 | 0.319 | 2.890 | 0.143 | Good 37 | 0.452 | 0.235 | 2.542 | 0.101 |
| Good 04 | 1.160 | 0.586 | 11.393 | 0.003 | Good 38 | 0.532 | 0.335 | 3.701 | 0.068 |
| Good 05 | 0.807 | 0.426 | 4.768 | 0.034 | Good 39 | 0.486 | 0.178 | 3.180 | 0.102 |
| Good 06 | 0.894 | 0.368 | 3.530 | 0.075 | Good 40 | 1.132 | 0.715 | 11.008 | 0.006 |
| Good 07 | 1.180 | 0.738 | 14.994 | 0.001 | Good 41 | 0.786 | 0.585 | 10.655 | 0.004 |
| Good 08 | 0.280 | 0.161 | 1.795 | 0.170 | Good 42 | 0.831 | 0.768 | 13.178 | 0.005 |
| Good 09 | 0.524 | 0.276 | 3.949 | 0.064 | Good 43 | 0.554 | 0.327 | 3.771 | 0.042 |
| Good 10 | 0.292 | 0.176 | 3.369 | 0.077 | Good 44 | 0.920 | 0.657 | 11.648 | 0.005 |
| Good 11 | 0.486 | 0.244 | 3.391 | 0.080 | Good 45 | 0.739 | 0.572 | 11.911 | 0.005 |
| Good 12 | 0.598 | 0.284 | 4.594 | 0.071 | Good 46 | 0.497 | 0.218 | 2.126 | 0.265 |
| Good 13 | 0.922 | 0.597 | 11.730 | 0.006 | Good 47 | 0.283 | 0.270 | 3.580 | 0.172 |
| Good 14 | 0.441 | 0.174 | 2.590 | 0.102 | Good 48 | 0.361 | 0.272 | 2.455 | 0.429 |
| Good 15 | 0.405 | 0.183 | 3.151 | 0.092 | Good 49 | 0.211 | 0.060 | 1.061 | 0.412 |
| Good 16 | 0.710 | 0.492 | 5.528 | 0.036 | Good 50 | 0.781 | 0.367 | 4.107 | 0.102 |
| Good 17 | 0.455 | 0.224 | 3.592 | 0.049 | Good 51 | 1.281 | 0.793 | 9.196 | 0.007 |
| Good 18 | 0.432 | 0.238 | 2.681 | 0.090 | Good 52 | 0.169 | 0.108 | 1.363 | 0.255 |
| Good 19 | 0.418 | 0.084 | 2.561 | 0.151 | Good 53 | 0.356 | 0.201 | 2.064 | 0.140 |
| Good 20 | 1.114 | 0.732 | 10.506 | 0.008 | Good 54 | 0.425 | 0.331 | 4.464 | 0.018 |
| Good 21 | 0.203 | 0.085 | 2.009 | 0.174 | Good 55 | 0.283 | 0.172 | 1.771 | 0.181 |
| Good 22 | 0.092 | 0.026 | 1.946 | 0.082 | Good 56 | 0.323 | 0.211 | 2.092 | 0.143 |
| Good 23 | 0.734 | 0.515 | 10.448 | 0.008 | Good 57 | 0.324 | 0.229 | 2.303 | 0.119 |
| Good 24 | 0.988 | 0.687 | 11.413 | 0.006 | Good 58 | 1.107 | 0.657 | 9.726 | 0.009 |
| Good 25 | 0.439 | 0.156 | 1.842 | 0.217 | Good 59 | 0.668 | 0.345 | 5.018 | 0.015 |
| Good 26 | 0.450 | 0.203 | 3.161 | 0.107 | Good 60 | 0.346 | 0.134 | 2.328 | 0.150 |
| Good 27 | 0.943 | 0.559 | 9.672 | 0.010 | Good 61 | 0.345 | 0.205 | 2.895 | 0.094 |
| Good 28 | 0.472 | 0.208 | 3.255 | 0.116 | Good 62 | 0.262 | 0.192 | 2.798 | 0.073 |
| Good 29 | 1.042 | 0.681 | 9.181 | 0.010 | Good 63 | 0.025 | 0.002 | 0.335 | 0.437 |
| Good 30 | 0.709 | 0.342 | 5.116 | 0.027 | Good 64 | 0.625 | 0.399 | 5.612 | 0.054 |
| Good 31 | 1.180 | 0.730 | 9.493 | 0.009 | Good 65 | 0.743 | 0.534 | 11.785 | 0.002 |
| Good 32 | 1.232 | 0.664 | 8.307 | 0.013 | Good 66 | 0.714 | 0.409 | 5.267 | 0.012 |
| Good 33 | 0.484 | 0.316 | 3.720 | 0.029 | Good 67 | 0.253 | 0.070 | 1.341 | 0.248 |
| Good 34 | 1.017 | 0.541 | 8.162 | 0.015 | | | | | |

## Out-of-sample Tests of Predictability

- We report the results from the out-of-sample analysis of the regression model against two alternatives: (1) the Random Walk (RW) without drift and (2) the RW with drift.
- t-statistic is computed using Clark and West (2006)'s procedure, and is based on Newey-West's (1987) HAC covariance matrix estimator with Andrew's (1991) procedure for selecting a truncation lag so as to account for serial correlations arising from the forecast horizon being more than one period.

# Out-of-sample Tests of Predictability – 36 months

| | RW w/o Drift | | RW with Drift | | | RW w/o Drift | | RW with Drift | |
|---|---|---|---|---|---|---|---|---|---|
| Goods | CW(A) | p-(A) | CW(A) | p-(A) | Goods | CW(A) | p-(A) | CW(A) | p-(A) |
| Good 01 | 2.063 | 0.064 | 3.458 | 0.016 | Good 35 | 0.734 | 0.401 | 0.055 | 0.469 |
| Good 02 | 2.981 | 0.023 | 3.332 | 0.026 | Good 36 | 2.828 | 0.031 | 2.835 | 0.037 |
| Good 03 | 3.242 | 0.023 | 2.941 | 0.029 | Good 37 | 2.871 | 0.024 | 2.607 | 0.042 |
| Good 04 | 0.982 | 0.363 | 3.190 | 0.157 | Good 38 | 1.933 | 0.080 | 2.282 | 0.058 |
| Good 05 | 3.674 | 0.038 | 1.723 | 0.177 | Good 39 | 3.267 | 0.024 | 2.043 | 0.101 |
| Good 06 | 4.356 | 0.005 | 1.913 | 0.082 | Good 40 | 1.412 | 0.302 | 4.046 | 0.113 |
| Good 07 | 1.547 | 0.299 | 3.206 | 0.161 | Good 41 | 0.901 | 0.370 | 0.899 | 0.383 |
| Good 08 | -0.985 | 0.696 | 1.203 | 0.155 | Good 42 | 1.691 | 0.315 | 4.330 | 0.025 |
| Good 09 | 2.127 | 0.061 | 2.574 | 0.052 | Good 43 | 0.082 | 0.419 | 2.271 | 0.047 |
| Good 10 | 1.075 | 0.162 | 1.890 | 0.090 | Good 44 | 1.623 | 0.289 | 2.642 | 0.191 |
| Good 11 | 0.042 | 0.438 | 1.709 | 0.090 | Good 45 | 1.014 | 0.349 | 1.046 | 0.343 |
| Good 12 | 1.079 | 0.175 | 1.685 | 0.100 | Good 46 | -0.367 | 0.506 | 0.887 | 0.373 |
| Good 13 | 1.074 | 0.357 | 1.292 | 0.359 | Good 47 | 0.386 | 0.413 | -0.572 | 0.522 |
| Good 14 | 2.153 | 0.059 | 2.478 | 0.051 | Good 48 | 0.588 | 0.371 | 3.036 | 0.069 |
| Good 15 | 2.714 | 0.036 | 2.289 | 0.066 | Good 49 | -0.201 | 0.491 | 0.953 | 0.359 |
| Good 16 | 1.687 | 0.312 | 4.151 | 0.027 | Good 50 | 0.380 | 0.426 | 1.304 | 0.338 |
| Good 17 | 0.602 | 0.297 | 1.852 | 0.077 | Good 51 | 2.062 | 0.283 | 4.879 | 0.017 |
| Good 18 | -0.135 | 0.465 | 1.652 | 0.092 | Good 52 | -0.967 | 0.700 | -0.679 | 0.600 |
| Good 19 | 1.833 | 0.073 | 2.978 | 0.023 | Good 53 | -0.570 | 0.582 | 1.856 | 0.070 |
| Good 20 | 1.493 | 0.298 | 3.866 | 0.121 | Good 54 | 0.916 | 0.204 | 2.444 | 0.047 |
| Good 21 | 1.982 | 0.070 | 1.879 | 0.085 | Good 55 | -0.857 | 0.653 | 1.499 | 0.111 |
| Good 22 | 1.808 | 0.098 | 1.878 | 0.102 | Good 56 | -0.726 | 0.622 | 2.093 | 0.054 |
| Good 23 | 1.043 | 0.346 | 1.004 | 0.347 | Good 57 | -0.815 | 0.647 | 2.232 | 0.047 |
| Good 24 | 1.425 | 0.306 | 3.566 | 0.133 | Good 58 | 1.267 | 0.319 | 3.030 | 0.162 |
| Good 25 | 4.361 | 0.005 | 1.774 | 0.099 | Good 59 | 1.488 | 0.114 | 2.755 | 0.037 |
| Good 26 | 2.155 | 0.070 | 2.135 | 0.081 | Good 60 | 4.300 | 0.005 | 1.541 | 0.117 |
| Good 27 | 1.123 | 0.335 | 1.537 | 0.289 | Good 61 | 1.347 | 0.114 | 2.632 | 0.040 |
| Good 28 | 1.409 | 0.126 | 2.588 | 0.047 | Good 62 | 0.766 | 0.239 | 2.238 | 0.055 |
| Good 29 | 1.345 | 0.324 | 3.663 | 0.122 | Good 63 | 1.836 | 0.065 | 0.117 | 0.365 |
| Good 30 | 2.569 | 0.039 | 2.103 | 0.064 | Good 64 | 1.247 | 0.324 | 1.238 | 0.318 |
| Good 31 | 1.462 | 0.297 | 4.600 | 0.094 | Good 65 | 1.051 | 0.362 | 0.849 | 0.382 |
| Good 32 | 1.890 | 0.276 | 5.065 | 0.059 | Good 66 | 1.793 | 0.068 | 2.790 | 0.029 |
| Good 33 | 1.348 | 0.115 | 2.507 | 0.042 | Good 67 | 2.332 | 0.042 | 1.132 | 0.157 |
| Good 34 | 1.081 | 0.357 | 2.330 | 0.221 | | | | | |

## Out-of-sample Tests of Predictability

- There are 16, 9, 5, 18, 22, and 8 goods over the 3, 6, 12, 24, 36, and 48-month forecast horizons, respectively, that perform better than the RW with no drift at the 10% level of significance.
- There are 13, 10, 7, 23, 41, and 30 goods over the 3, 6, 12, 24, 36, and 48-month forecast horizons, respectively, that perform better than the RW with drift at the 10% level of significance.

# RW with or without Drift

- RW without drift model seems to be a better representation of the U.S. dollar per Japanese Yen rate than RW with drift model over longer horizons.

**The Ratio of RMSPE for RW without Drift to RMSPE for RW with Drift**

| Starting Date | First Forecast | 3-month | 6-month | 12-month | 24-month | 36-month | 48-month |
|---|---|---|---|---|---|---|---|
| 1973.03 | 1983.01 | 1.003 | 1.004 | 1.006 | 0.997 | 0.987 | 0.983 |
| 1977.12 | 1983.01 | 1.000 | 0.998 | 0.992 | 0.970 | 0.944 | 0.924 |
| 1978.01 | 1983.01 | 1.000 | 0.998 | 0.993 | 0.971 | 0.945 | 0.925 |
| 1980.01 | 1994.10 | 0.980 | 0.956 | 0.895 | 0.831 | 0.727 | 0.510 |
| 1997.12 | 2003.10 | 0.994 | 0.984 | 0.985 | 0.907 | 0.849 | 0.966 |

## Testing for Superior Predictive Ability (SPA)

- Since we are simultaneously testing multiple out-of-sample hypotheses in terms of different goods prices, the inference based on conventional p-values is likely to be contaminated. As a result of an extensive specification search, data mining is likely to take place.
- Hansen (2005): test of superior predictive ability (SPA).
- The SPA test examines the composite null hypothesis that the benchmark model is not inferior to any of the alternatives against the alternative hypothesis that at least one of the linear economic models has superior predictive ability.

# SPA Test Groups

| Case | Group of Goods | Observations | Sample used for out-of-sample analysis | Date of First Forecast |
|---|---|---|---|---|
| 1 | 25 goods | first observation at 1973:03 | All available | 1983.01 |
| 2 | 13 goods | first observation at 1977:12 | All available | 1983.01 |
| 3 | 26 goods | first observation at 1997:12 | All available | 2003.10 |
| 4 | 38 goods | group 1 and 2 | All available | 1983.01 |
| 5 | 64 goods | group 1, 2 and 3 | All available | 2003.10 |
| 6 | 64 goods | group 1, 2 and 3 | from 1997:12 and onwards | 2003.10 |

# SPA Test Results

**Case 6: 64 goods**

| | | Benchmark model: RW without Drift | | | | Benchmark model: RW with Drift | | | |
|---|---|---|---|---|---|---|---|---|---|
| Horizon | | Stat. | p-value | 5% C.V. | 1% C.V. | Stat. | p-value | 5% C.V. | 1% C.V. |
| 3 | Lower | 3.026 | 0.022 | 2.646 | 3.311 | 3.292 | 0.014 | 2.673 | 3.396 |
| | Consistent | | 0.025 | 2.720 | 3.376 | | 0.014 | 2.712 | 3.406 |
| | Upper | | 0.025 | 2.720 | 3.376 | | 0.015 | 2.744 | 3.426 |
| 6 | Lower | 3.354 | 0.009 | 2.624 | 3.295 | 3.889 | 0.002 | 2.725 | 3.321 |
| | Consistent | | 0.009 | 2.653 | 3.305 | | 0.002 | 2.738 | 3.328 |
| | Upper | | 0.009 | 2.653 | 3.305 | | 0.002 | 2.738 | 3.328 |
| 12 | Lower | 4.312 | 0.001 | 2.581 | 3.330 | 3.884 | 0.002 | 2.670 | 3.311 |
| | Consistent | | 0.001 | 2.623 | 3.330 | | 0.003 | 2.706 | 3.354 |
| | Upper | | 0.001 | 2.658 | 3.332 | | 0.003 | 2.725 | 3.379 |
| 24 | Lower | 6.044 | 0.000 | 2.573 | 3.264 | 6.133 | 0.000 | 2.662 | 3.367 |
| | Consistent | | 0.000 | 2.576 | 3.264 | | 0.000 | 2.680 | 3.367 |
| | Upper | | 0.000 | 2.576 | 3.264 | | 0.000 | 2.680 | 3.367 |
| 36 | Lower | 4.981 | 0.000 | 2.506 | 3.153 | 6.047 | 0.000 | 2.659 | 3.328 |
| | Consistent | | 0.000 | 2.518 | 3.153 | | 0.000 | 2.665 | 3.333 |
| | Upper | | 0.000 | 2.518 | 3.153 | | 0.000 | 2.665 | 3.333 |
| 48 | Lower | 4.223 | 0.000 | 2.281 | 2.989 | 3.888 | 0.002 | 2.427 | 3.182 |
| | Consistent | | 0.000 | 2.431 | 3.082 | | 0.002 | 2.493 | 3.221 |
| | Upper | | 0.001 | 2.538 | 3.208 | | 0.002 | 2.539 | 3.248 |

## SPA Test Results

- We can reject the null of RW either with or without drift at the 5% level of significance over long horizons (12 months and above) for all cases.
- The SPA test results indicate that at least one of our price misalignment models has superior predictive ability in the long run over the RW model both with and without drift.

# Discussion: Which Good Price Misalignment Can Predict Exchange Rate Changes?

| Horizon | Good Description | Horizon | Good Description |
|---|---|---|---|
| 3 | Frozen fish and seafood<br>Fresh fish and seafood<br>Juices and non-alcoholic drinks<br>Canned vegetables<br>Other beverage materials including tea<br>Full service meals and snacks<br>Food at employee sites and schools<br>Electricity<br>Domestic services<br>Laundry and dry cleaning services | 24 | Pork chops<br>Ham<br>Frozen fish and seafood<br>Spices, seasonings, condiments, sauces<br>Rent of primary residence<br>Electricity<br>Utility (piped) gas service<br>New vehicles<br>Intracity transportation |
| 6 | Frozen fish and seafood<br>Spices, seasonings, condiments, sauces<br>Food at employee sites and schools<br>Electricity<br>Utility (piped) gas service<br>Intracity transportation | 36 | Pork chops<br>Frozen fish and seafood<br>Fresh whole milk<br>White bread<br>Spices, seasonings, condiments, sauces<br>Electricity<br>Utility (piped) gas service<br>Intracity transportation |
| 12 | Frozen fish and seafood<br>Electricity | 48 | Eggs<br>Bananas<br>Electricity |

# Discussion

- Only tradable good price misalignments across countries have predictive power for future exchange rate movements?

  ***No!*** electricity, utility gas service, intracity transportation.

- The price dispersions of goods with more sticky prices are better at forecasting nominal exchange rates?

  ***No!***

**Frequency of Price Changes**

| Good | Mean duration between price changes |
|---|---|
| Pork chops | 1.5 |
| Fish (excl canned) | 1.8 |
| Fresh whole milk | 2.4 |
| White bread | 3.4 |
| Salt and other seasonings and spices | 5.2 |
| Lettuce | 1.0 |
| Electricity | 1.8 |
| Utility natural gas service | 1.0 |
| Intercity bus fare | 4.4 |
| Weighted Statistics: Median 4.3 Mean 3.3 | |

Source: Bils and Klenow (2004).

# U.S. dollar/UK pound Rate

# In-sample Regression Results

- Estimates of the slope coefficient is positive over all horizons for almost all goods.
- Both the estimate of the slope coefficient and the R-square tend to increase with the forecast horizon for most of goods.
- Among 48 goods considered, there are 21, 18, 18, 25, 13, and 22 goods at the 3, 6, 12, 24, 36, and 48-month forecast horizons, respectively, for which the estimates of the slope coefficient is statistically significant at the 10% level.

# In-sample Regressions – 24 months

| Goods | R-sq | Beta | Tr(A) | p-(A) | Goods | R-sq | Beta | Tr(A) | p-(A) |
|---|---|---|---|---|---|---|---|---|---|
| Good 01 | 0.234 | 0.445 | 3.153 | 0.196 | Good 25 | 0.240 | 0.698 | 4.225 | 0.020 |
| Good 02 | 0.161 | 0.432 | 3.595 | 0.088 | Good 26 | 0.142 | 0.330 | 2.436 | 0.184 |
| Good 03 | 0.487 | 1.025 | 6.819 | 0.005 | Good 27 | 0.224 | 0.804 | 3.020 | 0.185 |
| Good 04 | 0.284 | 0.410 | 3.584 | 0.091 | Good 28 | 0.304 | 0.726 | 5.502 | 0.053 |
| Good 05 | 0.458 | 1.037 | 5.957 | 0.036 | Good 29 | 0.081 | 0.215 | 1.496 | 0.326 |
| Good 06 | 0.142 | 0.540 | 1.948 | 0.312 | Good 30 | 0.414 | 1.069 | 6.605 | 0.019 |
| Good 07 | 0.341 | 0.712 | 3.894 | 0.077 | Good 31 | 0.127 | 0.330 | 2.287 | 0.185 |
| Good 08 | 0.112 | 0.207 | 1.504 | 0.305 | Good 32 | 0.243 | 0.412 | 2.869 | 0.347 |
| Good 09 | 0.254 | 0.689 | 3.795 | 0.073 | Good 33 | 0.407 | 0.782 | 4.656 | 0.076 |
| Good 10 | 0.185 | 0.446 | 3.339 | 0.054 | Good 34 | 0.460 | 0.781 | 6.407 | 0.011 |
| Good 11 | 0.265 | 0.383 | 3.112 | 0.259 | Good 35 | 0.342 | 0.760 | 4.795 | 0.053 |
| Good 12 | 0.525 | 1.414 | 6.483 | 0.030 | Good 36 | 0.431 | 0.793 | 7.178 | 0.010 |
| Good 13 | 0.385 | 0.646 | 4.621 | 0.076 | Good 37 | 0.023 | 0.117 | 1.106 | 0.347 |
| Good 14 | 0.121 | 0.221 | 1.777 | 0.315 | Good 38 | 0.091 | 0.225 | 2.176 | 0.226 |
| Good 15 | 0.277 | 0.407 | 3.321 | 0.051 | Good 39 | 0.096 | 0.349 | 2.588 | 0.206 |
| Good 16 | 0.163 | 0.224 | 2.144 | 0.184 | Good 40 | 0.116 | 0.338 | 2.237 | 0.247 |
| Good 17 | 0.359 | 0.589 | 4.036 | 0.088 | Good 41 | 0.020 | 0.076 | 1.044 | 0.366 |
| Good 18 | 0.322 | 0.795 | 4.636 | 0.026 | Good 42 | 0.379 | 0.828 | 6.095 | 0.029 |
| Good 19 | 0.661 | 1.145 | 5.567 | 0.057 | Good 43 | 0.068 | 0.075 | 1.249 | 0.481 |
| Good 20 | 0.086 | 0.243 | 2.152 | 0.259 | Good 44 | 0.638 | 1.136 | 5.137 | 0.069 |
| Good 21 | 0.167 | 0.477 | 2.824 | 0.220 | Good 45 | 0.001 | 0.008 | 0.241 | 0.686 |
| Good 22 | 0.489 | 0.650 | 7.597 | 0.009 | Good 46 | 0.199 | 0.465 | 3.026 | 0.123 |
| Good 23 | 0.206 | 0.399 | 2.700 | 0.168 | Good 47 | 0.500 | 0.803 | 7.861 | 0.010 |
| Good 24 | 0.440 | 0.406 | 5.534 | 0.018 | Good 48 | 0.404 | 0.800 | 6.653 | 0.071 |

# Out-of-sample Tests of Predictability

- We report the results from the out-of-sample analysis of the regression model against two alternatives: (1) the Random Walk (RW) without drift and (2) the RW with drift.
- The results suggest that:
  - There are 4, 1, 1, 1, 2, 0 and 0 goods over the 1, 3, 6, 12, 24, 36, and 48-month forecast horizons, respectively, that perform better than the RW with no drift at the 10% level of significance.
  - There are 7, 2, 1, 1, 5, 1 and 4 goods over the 1, 3, 6, 12, 24, 36, and 48-month forecast horizons, respectively, that perform better than the RW with drift at the 10% level of significance.
- Data length might be an issue: price misalignment data starts from 1987:01 or 1999:12 in some cases, date of first forecast at 1998:04 or 2003:10.

# Conclusion

- This paper studies whether price misalignments arising from the dual role of exchange rates have predictive power for future exchange rate movements.
- We use good-level price data to construct deviations from the Law of One Price and examine several bilateral nominal exchange rates. To account for small sample bias and data mining issues, inference is drawn from bootstrap distributions and tests of superior predictive ability (SPA) are performed.
- Our results suggest that the bias-adjusted slope coefficients and R-squares increase with the forecast horizon, and for the U.S. dollar/Japanese Yen rate, our price misalignment model generally outperforms random walks either with or without drift at the five percent level of significance over long horizons.