MAGKS

Joint Discussion Paper
Series in Economics

by the Universities of

Aachen · Gießen · Göttingen
Kassel · Marburg · Siegen

ISSN 1867-3678

No. 12-2018

Martin Baumgärtner and Jens Klose

Forecasting Exchange Rates with Commodity Prices - A Global Country Analysis

This paper can be downloaded from
http://www.uni-marburg.de/fb02/makro/forschung/magkspapers

Coordination: Bernd Hayo • Philipps-University Marburg
School of Business and Economics • Universitätsstraße 24, D-35032 Marburg
Tel: +49-6421-2823091, Fax: +49-6421-2823088, e-mail: hayo@wiwi.uni-marburg.de

Forecasting Exchange Rates with Commodity Prices - A Global Country Analysis

Martin Baumgärtner*, Jens Klose†

Abstract

This paper investigates the predictive properties of import and export prices of commodities on the exchange rates. A period from 1993 to 2016 is considered. We find that forecasts of the exchange rate adding commodity export and import prices are superior to those neglecting these variables. This holds irrespective of whether the countries are net exporters or importers of commodities. However, the forecasting power was even better in the 1990s and seems to have decreased since that that time. Nevertheless forecasts can even today be improved considerably by adding commodity prices.

Keywords: Exchange Rate, Commodity Prices, Forecast, Panel-Analysis

JEL-codes: F17, F31, F47, C23

*THM Business School, Wiesenstraße 14, 35390 Gießen, Tel.: +49 641 309 2764, E-Mail: martin.baumgaertner@w.thm.de

†Corresponding Author, THM Business School, Wiesenstraße 14, 35390 Gießen, Tel.: +49 641 309 4006, E-Mail: Jens.Klose@w.thm.de

1 Introduction

In economic forecast commodity prices serve as early indicators for future developments. The prices for oil or copper are used to determine how the supply and demand of the industry will develop. They are also of interest for monetary policy, as commodity prices are frequently used to forecast the exchange rates of various countries. Meese and Rogoff (1983) were the first to study the forecasting properties of commodities on exchange rates. However, they were unable to beat the random walk, which is why they concluded that commodities are not suitable for forecasting exchange rates. Subsequent studies found the opposite effect (Mark 1995, Chen and Chen 2007, Ferraro et al. 2015, Bouoiyour et al. 2015). Thus, there is still no consensus in literature upon this issue. The results vary heavily depending on the period under investigation and the countries used in the sample.

Based on the methodology of Chen and Rogoff (2003) and Kohlscheen et al. (2017), this work provides a comprehensive picture of the predictive properties of commodity prices for a number of 126 countries over a period from 1993 to 2016. While many studies concentrate only on a relatively limited sample of countries, e.g. countries mostly exporting commodities, every country with a sufficient database is considered here. This broader approach makes it possible to show that commodities are generally suitable for forecasting exchange rates for our period under consideration. In addition to the usual export price index of each country, also an import price index is calculated, which allows good forecasts to be made even for countries without strong commodity exports. It has the same sign as the export price index, which contradicts the theory but is in line with other empiric results. By dividing the sample into two periods we gain insight whether the prediction power changes over time.

The remainder of the paper proceeds as follows: Section 2 describes the economic channels how commodity prices influence the exchange rate. Section 3 gives a literature review over studies in this field so far. Section four describes the data used in this study, while section five presents our estimation and forecasting approach. The results are shown in section six while section seven finally concludes.

2 Economic Channels

According to economic theory, exchange rates and commodity prices are interrelated. We identify four channels in which both variables are connected with each other. Most studies investigate the effect of individual commodity prices, such as oil prices, on the exchange rate. The transfer of these results to other commodities should, however, be possible without major restrictions because all of them are traded in US-dollar nowadays (Habib et al. 2016).

The first channel is the expectations channel (Chen et al. 2010). While transaction costs can cause arbitrage transactions not leading to a complete price compensation, investors should rationally try to anticipate future market developments and adapt their behaviour accordingly. This has an effect of commodity prices on the exchange rates. If an investor expects rising commodity prices, he will invest more in commodity producing countries which export commodities, as interest rates tend to rise in these countries. The induced capital inflows lead to an appreciation of the exchange rate due to higher demand for domestic currency.

Secondly, the terms of trade channel describes the effect of a price increase of a traded good on the economy in general and the exchange in specific. The channel works as follows: A rise in world commodity prices increases the production costs of companies which rely on imports of these commodities. This price increase leads to higher inflation rates as the producer pass it through into the consumer prices. In this case the general price level in a country which is dependent on commodities rises more strongly than in a more self-sufficient country whose industry is not affected by this price increase. As a result, inflation rates in countries are differently and the real exchange rate changes (Beckmann et al. 2017). On the one hand, companies depending on commodities lose competitiveness. On the other hand companies independent of commodities become more competitive on the world market. Thus, in theory a price shock for commodities leads to a real devaluation of the exchange rate for net importers.

The third important channel is the portfolio and wealth channel developed by Krugman (1980). The portfolio channel has a short-term effect. Starting point is again a rise in commodity prices. Thus, the import costs for commodity scarce countries will initially increase, which deteriorates their current account balance. At the same time, the investments from commodity exporting countries are increasing due to higher profits. This increases the capital account balances of industrialized countries. The degree of exchange rate variability thus depends on the investment behaviour of the commodity exportering countries (Lane and Shambaugh 2010). The dampening portfolio effect is usually not fully converted into the domestic currency, but are mostly invested abroad by state-controlled funds. E.g. most oil-exporting countries have high foreign currency reserves, which are invested worldwide (Habib et al. 2016).

In the medium term, there is a fourth channel - the wealth channel. Commodity exporting countries adapt their consumption to the increased income resulting from the commodity price increases, while investments into foreign assets are falling. The net effect is no longer dependent on the distribution of assets into domestic and foreign, but on which country produces the goods and services the commodity exporting countries demand. This leads to increased current account surpluses for those countries producing the demanded goods and services and revaluates the domestic currency if the foreign currencies are changed into domestic ones (Beckmann et al. 2017). Although the effect appears intuitive at first sight, it is more complex on closer inspection. For example, a distinction must be made between demand and supply shocks which push the commodity price upwards. While demand shocks increase producers' profits and incomes, supply shocks also involve higher costs for producers. For example, new extraction methods could require machinery which is more expensive. If this machinery has to be imported this would immediately lead to capital outflows and dampen the effect on the current account (Habib et al. 2016). Therefore, the wealth effect could only be observed to a lesser extent (Basher et al. 2016).

3 Literature Review

In literature, it is a controversial whether commodities are suitable for forecasting exchange rates. Due to its importance, crude oil as an individual commodity is usually the main focus. The results of studies concerning this particular commodity vary widely, depending on the sample period and countries considered. Beckmann et al. (2017) provides a comprehensive overview of this. The most important ones are presented below.

Meese and Rogoff (1983) provide one of the first works which tries to predict the exchange rate with structural models. Using data from 1973 to 1981, they investigate the predictive properties of structural models on the US-dollar/Mark, US-dollar/Yen and US-dollar/Pound exchange rate. They come to the conclusion that their models are not able to beat the random walk in an out-of-sample comparison. At the same time, they establish a pseudo out-of-sample prediction method by which the predictive properties of a model can be evaluated.

Ferraro et al. (2015) consider the relationship between the Canadian-dollar exchange rate and the oil price with daily, monthly and quarterly data from 1984 to 2010. The authors receive similar results for other countries exporting commodities. Using monthly and quarterly data, there are only minor correlations, whereas daily data have good forecasting properties. They conclude from this that price effects, such as an oil price shock, have only a short-term influence on the exchange rate, which is why a high frequency of data is important. Similar results are also found in Bouoiyour et al. (2015). Chen and Chen (2007) find even some long-term predictability of crude oil prices on exchange rates.

Akram (2004) suggests that commodity prices may have an asymmetric effect on the exchange rate. Therefore, he estimates a non-linear model. He uses dummy variables, which are defined by certain oil price levels. This allows him to model different effects at different price levels. For the period from 1986 to 1998 he is able to beat the random walk in the out-of-sample forecast in Norway. His results indicate that the influence of the oil price on the exchange rate is higher when the price is low. However, this effect could also be due to the central bank response which may react differently to devaluations and appreciations (Akram 2004).

Other authors find further evidence of a non-linear relationship also for other countries. See e.g. Bal and Rath (2015) and Wang and Wu (2012) for studies concerning India and China[1]. The result of Bal and Rath (2015) is controversial, since Vita and Trachanas (2016) are unable to replicate it. The data for China and India are not integrated, which is why no permissible cointegration model could be estimated. In general, the number of studies which can derive a cointegration relationship between commodity prices and exchange rates for different countries predominates (Amano and van Norden 1998; Chaudhuri and Daniel 1998; Bénassy-Quéré et al. 2007; Chen and Chen 2007; Coudert et al. 2008; Bodart et al. 2012; Beckmann et al. 2017).

Ahmad and Moran Hernandez (2013) have a larger sample of six countries. They only investigate countries which have a de jure free exchange rate, even though they point out that reality may be different. The sample period is 1970 to 2012. For Brazil, South Korea, Mexico, Nigeria, the United Kingdom and the Eurozone, they are able to find a cointegration relationship between commodity prices and exchange rates. Four of these countries, Brazil, the Eurozone, Nigeria and the UK,

[1] By contrast, Ghosh (2011) observes symmetrical effects in the case of India.

are asymmetric in this relationship. A positive shock usually had a larger effect on the exchange rate than a negative shock.

4 Data

In this study basically two variables are needed. The one is the exchange rate and the other are some kind of commodity prices. We collected those data for the sample period 1993 to the end of 2016 using montly data. The exchange rates are collected from various central banks, the International Monetary Fund (IMF) and the World Bank. In some cases, the data are obtained from plattforms such as Google or Quandl. Where possible, the plausibility of the data is checked by comparing the information from different sources[2].

The exchange rates are the monthly mean of daily rates of the currency and are always indirect quotation, thus the domestic currency is always in the denominator. This has the advantage that an increase in the exchange rate can be interpreted as an appreciation of the domestic currency and vice versa, thus simplifying the interpretation of our results. Performing exchange rate forecasts makes only sense for countries-pairs having a at least a minimum degree of flexibility in it. The IMF assesses the exchange rate regimes of the individual countries. They evaluate specific information on interventions, foreign exchange reserves and other macroeconomic variables. All IMF countries are covered, making a large part of the Comtrade dataset suitable for examination. In general, we try to keep the data set as wide as possible. For this reason, the assessment of the IMF from the Annual Report on Exchange Arrangements and Exchange Restrictions is studied. In the case of hybrid forms, the country is retained in the dataset. E.g. a country with a crawling peg has still some room in the foreign exchange market and thus could still influence the exchange rate in certain directions, e.g. in case of changing commodity prices.

[2] The review underpins the validity of the data

As our forecast is made on a country-by-country basis, the results of other countries are not influenced by this choice of data. In the worst-case scenario, it turns out that a countries commodity price index is not suitable for forecasting. If the exchange rate policy is not applied in a fully consistent manner, an effect could nevertheless be observed. A change in exchange rate policy was also considered. Countries which had only a temporary dollar commitment were included in the data for the entire period if possible.

The most detailed commodity price data, i.e. price data on a daily or even hourly basis, is best suited for this work. With those it would also be possible to observe short-term effects of price changes on exchange rates. However, a sample period using only these detailed data is too short. For this reason, this paper uses monthly price data for commodities. One central assumption is that the law of one price applies to commodity prices (Ardeni 1989). Commodities from one or another country are assumed to be perfect substitutes, which is why each country has at best a limited price setting power (Ardeni 1989). Therefore, every single country appears to be a price taker on the world market. However, whether this condition holds in the world markets is still an open research question. Arbitrage transactions are not always profitable due to transaction costs, which is why deviations from the rule of one price can be empirically observed (Ardeni 1989). But Sarno et al. (2004) assume these deviations to be only temporary and do not allow for permanent price differences. Some countries, however, are influencing prices in certain markets, but on the whole commodities market these countries are also the price takers (Chen et al. 2010).

This allows one world market price for commodities to be assumed for all countries. The data used here are collected from the IMF. The IMF data are the arithmetic means of commodity prices over one month. The price for the largest exporter of this commodity is used as an approximation for the world market price. Prices are always in US-dollars. In total there are 63 different prices, which are available in the dataset. Unfortunately, the IMF data does not cover all commodity categories in the Comtrade data set. Therefore, where no IMF data is available, the gaps are filled with US data import prices of commodities from the Federal Reserve Economic Data Record. Since commodities are assumed to be perfect substitutes, this should not alter our results significantly (Ardeni 1989). A comparison of prices available in both databases shows a very high correlation, which also empirically supports this theoretical argument.[3] Some data were only available on a quarterly basis in the early 1990s (1992-1995). To obtain a homogeneous picture of monthly price data, smaller gaps, i. e. where a maximum of 2 data points are missing, were interpolated linearly.

Finally, we need country data on imports and exports for each commodity. The United Nations (UN) collects these data in the United Nations Commodity Trade Statistics Database (Comtrade). The harmonized system (HS), developed by the World Customs Organization (WCO), can be used to separate the individual commodity groups. It is a standardised system which assigns identification numbers to certain commodities and organizes them on this basis and forms larger aggregates. In principle, a HS code consists of 6 digits. This is determined by WCO for commodities. The first two digits indicate the category of the commodity. The next two digits indicate a specific commodity in the previous category. The last two digits allow to distinguish between different processing states. All further numbers beyond these 6 are country-specific, which allow countries to refine their statistics individually. Since detailed price data are unfortunately not available, this work concentrates on the first four digits of the HS codes. In addition, it is unlikely that a more precise classification would significantly influence the result, since prices for different processing methods differ, if at all in level, but should have the same trend. Since the database delivers country data only, while the target value exchange rate may

[3] Copper and maize, for example, both have a correlation of more than 0.98. Gas has the lowest correlation of all the commodities compared and still has a very high value of 0.91.

represent a currency area, some data are aggregated for those by simply summing up the individual country data. This is possible without any problems, as absolute numbers are given in the database. With this method the following currency areas are created, and the corresponding individual countries are replaced:

—Table 1 about here—

The construction of the commodity price index is based on the paper by Kohlscheen et al. (2017). A specific price index is constructed for each country, which is used to forecast the exchange rate. Literature shows that commodities with a high trading weight have a stronger effect on the exchange rate (Bodart et al. 2012). Due to the construction of this broad commodity price index, the relationship is not exclusively based on oil prices. So it is possible to look at countries which are not very dependent on oil imports or exports. In this paper this idea is expanded in three ways. First, the restriction to commodity-exporting countries is abandoned. Second, the imports of the countries are also taken into account. Third, the period of observation is extended back to the 1990s. Each HS code is assigned to a commodity. In total, we consider 64 different commodities. 29 of them are agricultural products, 14 are metals and 5 are energy. The remaining 16 cannot be categorized into one of these groups. For example, they contain simple precursors such as glass, paper or chemicals. Kohlscheen et al. (2017) have a slightly higher number of categories due to more types in the category metal.

The weights of each commodity are build using a Lowe price index. Those are calculated from the total trade of the individual countries in US-dollar. This has the advantage that, despite a strong aggregation of the individual types of commodities, comparability is given. The use of value weights means that commodities with the largest product of quantity and price are most important. Accordingly, this index weighting means that expensive commodities which are traded in large quantities, such as oil, have a large effect on the price index. However, these commodities are also likely to have the largest impact on exchange rates. The basket of commodities is fixed over the entire sample period and weights are fixed as current information on current weights is usually only available with a long delay.

But at which period should we fix the weights? We decided that this period is not a real observation. We therefore construct a mean that is calculated for each commodity over all periods, thus calculating the average import and export over time. Doing so we end up with properties like those of a midyear index (IMF 2004). Chen and Rogoff (2003) and Kohlscheen et al. (2017) use the same concept.

As the Comtrade database provides information on both imports and exports of a country, it is possible to create a separate price index for both imports and exports. So it is also possible to investigate the less studied effect of import price changes on the exchange rate. This area is cited by many authors as noteworthy but has not yet been researched in literature (Chen et al. 2010). The fact that the Comtrade database issues annual data, but that the price data is collected on a monthly basis, may initially appear problematic. In literature, however, it is regarded as practicable (International Monetary Fund 2004).

In addition to the two price indices used here, two net price indices are also calculated. For each country, the mean is calculated for exports and imports of each commodity. These are used to calculate the difference between exports and imports, which can be used to determine whether a country has been a net importer or exporter of the commodity during the period under investigation. If a country is a net exporter (importer) of a commodity, this commodity appears in the country's export (import) price index. The results do not differ significantly from the normal index, so that only the first is considered in the further analysis.[4]

Although a broad sample is aimed for, some countries have to be dropped out of the dataset. All countries which have fixed their exchange rates to the US-dollar and this is clearly evident in the data have not been considered. As a result, 27

[4] The results for the net commodity price indices are available from the authors upon request.

countries are taken out of the dataset, most of them smaller island states in the Pacific and Atlantic. Saudi Arabia and the United Arab Emirates are therefore also not considered. These countries would be very interesting for the study because of their great importance in oil exports. China is also interesting as one of the largest importers of commodities, but has quasi fixed its exchange rate (Ahmad and Moran Hernandez 2013; Lipman 2011). Furthermore, all countries which use the US-dollar as their currency for the entire period were removed. Ecuador and El Salvador remain in the data set, as the US-dollar was not introduced until January 2000 and January 2001, respectively (Rennhack and Nozaki 2006). Because of these different circumstances, the dataset does not contain the same years T for each country. 126 countries covering a period of 48 to 288 periods are considered. The data set contains a total of 28298 observations. On average, each country has 224 observations.

To prevent distortion of the estimate, it is examined whether the time series have a unit root. Since it is possible that the residuals are serial correlated, the Augmented Dickey-Fuller (ADF) test is used (Dickey and Fuller 1979). The optimum number of lags was determined by the Akaike Information Criterion (AIC). The power of the test is particularly dependent on the number of observations. For time series with a number of observations above 100, this is less problematic (Fedorová 2016). Our results for those countries indicate that the exchange rate and the price indices are not stationary. Is the number of observations below 100, the test loses power. The time series of euro area countries which joined the euro in 1999 and some others have only 73 data points per country. Hence, the risk of misspecification is larger for these countries than for other. Therefore, a variance ratio test is carried out for these borderline cases (Breitung 2002). This is a non-parametric test, so the assumptions are less restrictive. For small time series it provides better results than the ADF test, which is why it is well suited here. The null hypothesis is that the time series is integrated. It can be rejected in all countries with low number of observations, so it is assumed that all exchange rates are integrated. Therefore, the logarithmic first differences of the series are calculated. These exchange rate changes and the changes in both price indices are now stationary for all countries.

5 Estimation Equation

In this section we will present our estimation equations and the forecasting procedure for the exchange rate. Results of both will be shown in the next section.

5.1 Regression analysis

First, we evaluate whether there is a relationship between commodity prices and exchange rates. Kohlscheen et al. (2017) use a panel data model with fixed effects for their analysis. To be able to compare our with these results, we follow a somehow similar approach. The panel data are examined for autocorrelation in the residuals using the Breusch-Godfrey test. The null hypothesis that there is no autocorrelation can be clearly rejected. Accordingly, it can be assumed that the residuals influence each other and thus violate the assumptions of the Gauss-Markov theorem. The method of least squares is still efficient, but the standard errors are no longer valid. There are two possible reasons for this: On the one Hand it could be an indication that other factors influence the exchange rate. This seems realistic since many other factors such as monetary policy or economic cycles are not included in our estimation equation. On the other hand our estimation equation may be misspecified and a linear model is not sufficient. Inclusion of all variables seems unrealistic because we would loose too many degrees of freedom in order to generate robust results, which is why the robust standard errors calculated by Newey and West (1987) are used here modified by Driscoll and Kraay (1998) to apply to panel data.

Another factor that could influence the estimation is heteroscedasticity. The null hypothesis of the Breusch-Pagan test cannot be rejected, which is why homoskedasticity is assumed.[5]

The solution for a consistent estimation would be a fixed (FE) or random effects (RE) panel-estimator. While FE models are consistently estimated but not efficient, a RE model is also efficient when there are individual differences between countries. However, a RE estimator is not consistent if the explanatory variables and the residuals are correlated with the explanatory variables. A Hausman test is performed to empirically validate which estimator is suitable in order case. The test compares the coefficients between the random and fixed effects estimation and tests whether the residuals are correlated with the regressors. If it is, both estimates are consistent and the difference is relatively small, so the RE estimator should be used as it is also efficient. Here, the null hypothesis of no correlation cannot be rejected again, so the RE estimator will be used. This holds even more as the Breusch Pagan test can be used to test whether panel regressions the variance of the random effects is zero. The null hypothesis is therefore that the pooling model is consistent. This can be rejected here, which is robust evidence that a RE estimator is to be used. So our RE estimator concerning commodity export prices takes thus following form:

$$\Delta WK.average_{i,t} = \beta_0 + \beta_1 * \Delta PEX_{i,t} + \zeta_i + \theta_t \tag{1}$$

In this context, $\Delta WK.average_{i,t}$ describes the change in the exchange rate of country i in period t. $\Delta PEX_{i,t}$ correspondingly represents the change in the commodity price index of country i in the period t. The random effects are described by ζ_i. θ_t contains the different years, as dummy variables. In order to save degrees of freedom, periods are chosen instead of years. We classify four groups in this respect: First, before the turn of the millennium, second, until the financial crisis in 2007 hit, third until the European debt crisis emerged in 2011 and fourth, the period thereafter. The very same procedure is implemented with respect to the commodity

[5] The Breusch-Pagan-Test was carried out with the test statistics of Koenker (1981)

import price index shown in equation (2):

$$\Delta WK.average_{i,t} = \beta_0 + \beta_1 * \Delta PIM_{i,t} + \zeta_i + \theta_t \tag{2}$$

Since both imports and exports should theoretically influence a country's exchange rates the two variables $\Delta PIM_{i,t}$ and $\Delta PEX_{i,t}$ are simultaneously added to one equation as the third strategy in equation (3):

$$\Delta WK.average_{i,t} = \beta_0 + \beta_1 * \Delta PEX_{i,t} + \Delta PIM_{i,t} + \zeta_i + \theta_t \tag{3}$$

All three equations can now be estimated for different time periods and countries combinations. We will add further evidence by concerning two time periods 1993-2003 and 2004-2016 on the one hand and between countries whose foreign trade is dominated by commodities and others where commodities do not have an exposed position on the other. This allows the results to be compared with the work of Kohlscheen et al. (2017).

5.2 Forecasting

In the next step, a structural forecasting model will be developed. Two different approaches are chosen: A recursive window (ReW) model and a rolling window (RoW) model. All models make forecasts for different time intervals. The forecasting power for the next month is checked. The first forecast is made for January 1996, so that there is a sufficient number of observations available. In this case the number of observations is T=36.[6] For the RoW model, the value is kept constant at T=36 for all other forecasts, whereas for the ReW model, the window starts with T=36 in January 1996 and then increases as more data become available, thus using always the full set of information up to the respective point in time (Figure 1). All in all,

[6]Note that, the forecasting periods do not in all countries start in January 1996 due to data availability. However, the first 36 available values are always used for the first estimate.

up to 251 monthly forecasts can be made per country, depending on the forecasting period and data availability.

— *Figure 1 about here* —

It should be noted that rational expectations are assumed in the pseudo out of sample procedure. A forecast for t+1 is estimated using a model which has been calibrated on all data up to period t. The actual values for $\Delta PEX_{i,t+1}$ and $\Delta PIM_{i,t+1}$ are then used with this model. Meese and Rogoff (1983) use the very same approach. In practice, the values $\Delta PEX_{i,t+1}$ and $\Delta PIM_{i,t+1}$ would have to be predicted before the prediction for $\Delta WK.average_{i,t+1}$ can be made. By using the actual value from period t+1, it is assumed that the explanatory variable can be perfectly predicted. All the problems which now arise with this prediction can therefore be attributed to the lack of information in $\Delta PEX_{i,t}$ or $\Delta PIM_{i,t}$.

It is not only possible to consider whether commodity prices have predictive power for exchange rates, but also which model, RoW or ReW, performs better. In addition, it can also be observed which of the equations (1) to (3) is best suited to forecast each country. Each forecast requires a comparative value on which the quality of the forecast can be checked. For this reason, the forecast error is generally represented by a loss function $g(e_t)$. A loss function is a function which assumes the value 0 if there is no error. As the forecasting error increases, so does the loss function (Elliott and Timmermann 2004). A special loss function and one of the standard measures in the forecast is the mean square error (MSE).

Since the work of Meese and Rogoff (1983), the random Walk in exchange rate forecasting has been the first step in evaluating the forecasting ability of a model. It is assumed that the value today will continue to be the best forecast in the future. A lower forecast error than the random walk is not yet a criterion which constitutes a good forecast model. The Diebold Mariano test (Diebold and Mariano 1995) can be used to check whether the differences between the models are significant. It compares the loss functions $g(e_t)$ of the forecasts, where e_t describes the prediction error. The Diebold Mariano test also allows asymmetrically distributed errors and allows autocorrelation in the residuals (Enders 2010). Its null hypothesis is that there is no deviation between the two prediction errors. Harvey et al. (1997) developed a modified version. Here, the test assumptions became even more realistic. It is no longer necessary to assume that the prediction errors are undistorted. This is especially useful for comparing forecasts which go beyond the period of one period. The minimum of the MSE is used to select the best specification. Simulations show that with stable parameters the ReW window should be superior (Pesaran and Timmermann 2007). If the values of RoW and ReW are different for individual countries, this would be a first indication of local structural breakdowns affecting those. A general improvement in the forecasting power of the RoW across most countries would suggest a major structural disruption.

6 Results

The Panel regression lead to interesting results as shown in Table 2. For the period considered by Kohlscheen et al. (2017) the observed coefficients are quite similar. If we look at another sample period, a different country sample or a different parameter combination, we are able to derive further interesting results. When estimating equation (1) for commodity exporting countries[7] and the sample period 2004 - 2016 the results are very similar to those of Kohlscheen et al. (2017), i.e. we estimate a significantly positive coefficient of $\Delta PEX_{i,t}$. However, the coefficient is slightly higher and R^2 is twice as high. However, when this equation is only estimated for the period 1993-2003 (column (2) in Table 2), where there is no significant effect for $\Delta PEX_{i,t}$ and a much smaller part of the variance can be explained by this specification. Column (3) uses the import price index as an independent variable.

[7] Australian Dollar area, Canada, Norway, Brazil, Chile, Colombia, Mexico, Peru, Common Monetary Area, Russian Federation and Malaysia

For the added variable $\Delta PIM_{i,t}$ a contra intuitive behaviour can be observed. It has a positive sign in all cases, even if it is integrated into the Column (4) together with $\Delta PEX_{i,t}$. Of course, due to the high correlation between $\Delta PEX_{i,t}$ and $\Delta PIM_{i,t}$ there is a problem of high multicollinearity in some countries. This does not directly affect the estimate. Least Squares estimator remains the Best Linear Unbiased Estimator. However, the high correlation is reflected in the standard deviation of the coefficients. This can lead to the fact that it is no longer possible to reject the null hypothesis, although there is an effect. The test is losing power. The results from equation (3) are similar to those of the study by Beckmann and Czudaj (2013). There the authors also find no theoretically expectable behavior. They observe no difference between commodity prices and exchange rates between importing and exporting countries.

— *Table 2 about here* —

Columns (5) and (6) in Table 2 vary the countries under consideration. All countries except countries which export commodities are considered here. The effect of $\Delta PEX_{i,t}$ seems to be smaller in both specifications. The adjusted R^2 is, however, considerably higher for countries with strong exports than for countries in (5) and (6). Looking at the influence of $\Delta PEX_{i,t}$ and $\Delta PIM_{i,t}$, the former has more influence on commodity exporters, whereas the latter have more influence in other countries. This can be seen by comparing the coefficients in column (4) and (6).

6.1 Forecasting results

Figure 2 shows the percentage improvement of our forecast using the RoW model compared to the random walk (red line) for the forecasting periods 1993-2003 and 2004-2016. The ReW model provides similar results[8]. For most countries a lower MSE value than the random walk forecast is achieved. Only in 8 countries does our

[8] The results for the ReW model are available from the authors upon request.

forecast lead to a higher MSE value than the random walk. In all other countries it is possible to achieve a better forecast. It is striking that in the period 1993-2003 it is possible to make considerably better forecasts than in the period 2004-2016. Overall it is also evident that for the latter period commodity prices can be suitable for forecasting the exchange rate.

— *Figure 2 about here* —

To examine the difference more closely and determine the best method for each country, the forecasting errors are compared. First, the ReW and RoW forecasts are compared with the random walk. The null hypothesis of the Diebold Mariano test is here (Harvey et al. 1997) : H_0*: ReW (RoW) has the same explanatory power as the random walk.* If this can be rejected, it is concluded that commodities contain useful information for forecasting exchange rates. If this is true, we try to evaluate whether the ReW or RoW forecasts perform better. To find the best specification in this respect, Diebold Mariano are again performed with the null hypothesis: H_0*: ReW has the same explanatory power as RoW* or H_0*: RoW has the same explanatory power as ReW.* A test with the first (second) hypothesis indicates that the ReW (RoW) model has better predictive properties. Based on the results, countries can be divided into four different groups: : First, countries where we are unable to beat the random walk, second, countries where the RoW forecasts perform best, third, countries where the ReW forecasts are best and fourth, countries where both RoW and Rew beat the random walk and perform equally good.

— *Tables 3 and 4 about here* —

Tables 3 and 4 show the classification of the individual countries into the categories for the periods 1993-2003 and 2004-2016, respectively. Overall, it is not possible to determine one ideal system for all countries. In many cases there is no significant difference between the RoW and ReW model. It turns out that it is possible to beat the random walk for more countries in the period 1993-2003. The information content of the commodity indices has thus partially decreased. Nevertheless, it remains relevant for many countries. This is especially true for countries where commodities exports are a great economic factor.

7 Conclusion

In this paper we examined the information content of commodity prices when forecasting exchange rates. The panel data analysis clearly indicates that commodity prices are suitable for exchange rate forecasts. In fact, for a large number of countries, the random walk can be beaten with our forecasting approach. We thus conclude that commodity prices contain information which is useful for forecasting exchange rates. The forecast for the sample period 1993-2003 is more successful across all countries than for the sample period 2004-2016. This leads to the conclusion that the information value of the commodity price index has decreased over time. One possible explanation would be the increased influence of other factors influencing the exchange rate especially during the financial crisis such as monetary and fiscal policies. This result does not only apply to countries with a large relative share of commodity exports but also to other countries. While in the literature results on predictability of commodity prices depend strongly on the selected countries and the sample period, we find that predictions for almost all countries can be improved with a combination of import and export prices. However, for countries with relatively strong commodity exports, the export index seems to be more important. The reverse applies to all other countries.

While our study gives a first indication of the usefulness of commodity prices in exchange rate forecasts for a large set of countries, further research is needed in this area. One approach would be to investigate this phenomenon with high frequency data. The information content tends to increase further in the short term, which is why these results could become even more clear. Furthermore, a stronger disaggregation of price data could provide a more accurate picture of which raw materials are particularly suitable for forecasting individual exchange rates. It is conceivable, for example, that individual commodities should be given a higher importance than is attributed to them in our index. It can thus be concluded that both monthly export and import commodity prices for most of the countries considered in the period include information that is useful for forecasting exchange rate. They should therefore be regarded as a leading indicator whose integration in forecasting models could even contribute to improvements in forecasting at the monthly level.

References

[1] Q. F. Akram. Oil prices and exchange rates: Norwegian evidence. *The Econometrics Journal*, 7(2):476–504, 2004.

[2] A. H. Ahmad and Ricardo Moran Hernandez. Asymmetric adjustment between oil prices and exchange rates: Empirical evidence from major oil producers and consumers. *Journal of International Financial Markets, Institutions and Money*, 27:306–317, 2013.

[3] R. A. Amano and S. van Norden. Exchange rates and oil prices. *Review of International Economics*, 6(4):683–694, 1998.

[4] P. G. Ardeni. Does the law of one price really hold for commodity prices? *American Journal of Agricultural Economics*, 71(3):661-669., 1989.

[5] D. P. Bal and B. N. Rath. Nonlinear causality between crude oil price and exchange rate: A comparative study of china and india. *Energy Economics*, 51:149–156, 2015.

[6] S. A. Basher, A. A. Haug, and P. Sadorsky. The impact of oil shocks on exchange rates: A markov-switching approach. *Energy Economics*, 54:11–23, 2016.

[7] J. Beckmann, R. Czudaj, and V. Arora. The relationship between oil prices and exchange rates: Theory and evidence. *EIA Working Papers*, 2017.

[8] A. Bénassy-Quéré, V. Mignon, and A. Penot. China and the relationship between the oil price and the dollar. *Energy Policy*, 35(11):5795–5805, 2007.

[9] V. Bodart, B. Candelon, and J.-F. Carpantier. Real exchanges rates in commodity producing countries: A reappraisal. *Journal of International Money and Finance*, 31(6):1482–1502, 2012.

[10] J. Bouoiyour, R. Selmi, A. K. Tiwari, and M. Shahbaz. The nexus between oil price and russia's real exchange rate: Better paths via unconditional vs conditional analysis. *Energy Economics*, 51:54–66, 2015.

[11] J. Breitung. Nonparametric tests for unit roots and cointegration. *Journal of Econometrics*, 108(2):343–363, 2002.

[12] K. Chaudhuri and B. C. Daniel. Long-run equilibrium real exchange rates and oil prices. *Economics Letters*, 58(2):231–238, 1998.

[13] S.-S. Chen and H.-C. Chen. Oil prices and real exchange rates. *Energy Economics*, 29(3):390–404, 2007.

[14] Y. Chen and K. Rogoff. Commodity currencies. *Journal of International Economics*, 60(1):133–160, 2003.

[15] Y. Chen, K. Rogoff, and B. Rossi. Can exchange rates forecast commodity prices?. *Quarterly Journal of Economics*, 125(3):1145–1194, 2010.

[16] V. Coudert, C. Couharde, and V. Mignon. Do terms of trade drive real exchange rates? comparing oil and commodity currencies. *CEPII research center Working Papers*, 32, 2008.

[17] D. A. Dickey and W. A. Fuller. Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica*, 49(4):1057–1072, 1981.

[18] F. X. Diebold and R. S. Mariano. Comparing predictive accuracy. *Journal of Business & Economic Statistics*, 13(3):253–263, 1995.

[19] J. C. Driscoll and A. C. Kraay. Consistent covariance matrix estimation with spatially dependent panel data. *The Review of Economics and Statistics*, 80(4):549–560, 1998.

[20] G. Elliott and A. Timmermann. Optimal forecast combinations under general loss functions and forecast error distributions. *Journal of Econometrics*, 122(1):47–79, 2004.

[21] D. Ferraro, K. Rogoff, and B. Rossi. Can oil prices forecast exchange rates? an empirical analysis of the relationship between commodity prices and exchange rates. *Journal of International Money and Finance*, 54:116–141, 2015.

[22] D. Fedorová. Selection of unit root test on the basis of length of the time series and value of ar (1) parameter. *Statistica*, 96(3):3, 2016.

[23] M. M. Habib, S. Bützer, and L. Stracca. Global exchange rate configurations: Do oil shocks matter? *IMF Economic Review*, 64(3):443–470, 2016.

[24] D. Harvey, S. Leybourne, and P. Newbold. Testing the equality of prediction mean squared errors. *International Journal of forecasting*, 13(2):281–291, 1997.

[25] International Monetary Fund. Producer price index manual: Theory and practice. Washington, DC, 2004.

[26] E. Kohlscheen, F. Avalos and A. Schrimpf. When the walk is not random: Commodity prices and exchange rates. *International Journal of Central Banking*, 13(02):121–158, 2017.

[27] P. Krugman. Oil and the Dollar. *NBER Working Papers*, 0554, Cambridge, MA, 1980.

[28] P. R. Lane and J. C. Shambaugh. Financial exchange rates and international currency exposures. *American Economic Review*, 100(1):518–540, 2010.

[29] J. K. Lipman. Law of yuan price: Estimating equilibrium of the renminbi. *Michigan Journal of Business*, 4(2), 2011.

[30] R. A. Meese and K. Rogoff. Empirical exchange rate models of the seventies. *Journal of International Economics*, 14(1-2):3–24, 1983.

[31] W. K. Newey and K. D. West. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, 55(3):703–708, 1987.

[32] M. H. Pesaran and A. Timmermann. Selection of estimation window in the presence of breaks. *Journal of Econometrics*, 137(1):134–161, 2007.

[33] R. Rennhack and M. Nozaki. Financial dollarization in latin america. *IMF Working Papers*, 06(7):1, 2006.

[34] L. Sarno, M. P. Taylor, and I. Chowdhury. Nonlinear dynamics in deviations from the law of one price: A broad-based empirical study. *Journal of International Money and Finance*, 23(1):1–25, 2004.

[35] G. de Vita and E. Trachanas. 'nonlinear causality between crude oil price and exchange rate: A comparative study of china and india' — a failed replication (negative type 1 and type 2). *Energy Economics*, 56:150–160, 2016.

[36] Y. Wang and C. Wu. Energy prices and exchange rates of the u.s. dollar: Further evidence from linear and nonlinear causality analysis. *Economic Modelling*, 29(6):2289–2297, 2012.

Tables

Table 1: Country allocation

Currency Area	Shortcut	Countries
France	Franc	Andorra, France, French Guinea, Guadeloupe, Martinique, Mayotte and Réunion
Belgium-Luxembourg	Belux	Belgium and Luxembourg
Denmark	Den	Denmark, Faroe Islands and Greenland
Euro zone	Euro	Andorra, Austria, Belgium, Finland, Finland, France, Guinea, France, Germany, Guadeloupe, Ireland, Italy, Luxembourg, Martinique, Netherlands, Portugal, Réunion and Spain, Greece (from 2001), Slovenia (from 2007), Malta and Cyprus (from 2008), Slovakia (from 2009), Estonia (from 2011), Latvia (from 2014) and Lithuania (from 2015)
CFA-Franc BEAC Area	CFABEAC	Cameroon, Central African Republic, Chad, Republic of Congo and Gabon
CFA-Franc BCEAO Area	CFABCEAO	Benin, Côte d' Ivoire, Malie, Niger, Guinea-Bissau, Senegal, Togo and Burkina Faso
CFP-Franc Area	CFP	French Polynesia, New Caledonia and Wallis and Futuna
Australian Dollar Area	AUD	Australia, Kiribati and Tuvalu
Common Monetary Area	CMA	South Africa, Lesotho, Swaziland and Namibia

Notes: BEAC= Banque des Etats de l'Afrique Centrale;
BCEAO= Banque Centrale des États de l'Afrique de l'Ouest

Table 2: Estimation results

	Dependent variable:					
	Exchange Rate					
	(1)	(2)	(3)	(4)	(5)	(6)
Sample Period	2004 - 2016	1993 - 2003	2004 - 2016	2004 - 2016	2004 - 2016	2004 - 2016
Countries	exporting	exporting	exporting	exporting	non exporting	non exporting
PEX	0.241***	0.062		0.148***	0.143***	0.040*
	(0.041)	(0.050)		(0.028)	(0.025)	(0.022)
PIM			0.286***	0.129***		0.168***
			(0.050)	(0.040)		(0.030)
2001-2003		0.007*				
		(0.004)				
2007-2011	0.003		0.003	0.003	0.001	0.002
	(0.003)		(0.003)	(0.003)	(0.003)	(0.003)
2011-2016	−0.003		−0.003	−0.002	−0.001	−0.0001
	(0.003)		(0.003)	(0.003)	(0.002)	(0.002)
Constant	−0.002	−0.008***	−0.002	−0.002	−0.002	−0.003
	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
Observations	1,704	1,376	1,704	1,704	15,779	15,779
Adjusted R^2	0.226	0.007	0.217	0.235	0.007	0.010
F Statistic	166.496***	5.578***	158.142***	131.737***	38.225***	40.777***
	(df = 3; 1700)	(df = 2; 1373)	(df = 3; 1700)	(df = 4; 1699)	(df = 3; 15775)	(df = 4; 15774)

Note: Exporting: Australian Dollar area, Canada, Norway, Brazil, Chile, Colombia, Mexico, Peru, Common Monetary Area, Russian Federation and Malaysia; Non Exporting: all remaining countries; standard errors in parenthesis, */**/*** denote significance at the 10%/5%/1% level.

Table 3: Country allocation 1993-2003

Random	RoW	ReW	RoW/ReW
Armenia, Austria, Belarus, Belgium-Luxembourg, Botswana, Brazil, Bulgaria, Cabo Verde, Common Monetary Area, Den, Dominican Rep., Ecuador, El Salvador, Euro zone, Fiji, Finland, Franc, Georgia, Germany, Indonesia, Iran, Italy, Japan, Kazakhstan, Kuwait, Kyrgyzstan, Latvia, Madagascar, Malaysia, Mauritania, Mexico, Mozambique, Netherlands, Nigeria, Norway, Portugal, Rep. of Korea, Rep. of Moldova, Russian Federation, Sao Tome and Principe, Singapore, Spain, Thailand, Tonga, Turkey, Ukraine, Viet Nam	Algeria, CFA-Franc BCEAO Area, CFA-Franc BEAC Area, Comoros	Bangladesh, Cyprus, Guatemala, Iceland, Seychelles, Sierra Leone, Trinidad and Tobago, Uruguay	Albania, Australian dollar Area, Bhutan, Bolivia (Plurinational State of), Brunei Darussalam, Burundi, Canada, CFP-Franc Area, Chile, Colombia, Costa Rica, Croatia, Czechia, Egypt, Estonia, Ethiopia, Gambia, Greece, Guinea, Guyana, Honduras, Hungary, India, Ireland, Israel, Jamaica, Kenya, Lithuania, Malawi, Maldives, Malta, Mauritius, Mongolia, Morocco, Nepal, New Zealand, Nicaragua, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Rwanda, Slovakia, Slovenia, Solomon Isds, Sri Lanka, Sweden, Switzerland, Tunisia, Uganda, United Kingdom, United Rep. of Tanzania, Vanuatu, Zambia

Table 4: Country allocation 2004-2016

Random	RoW	ReW	RoW/ReW
Afghanistan, Algeria, Angola, Argentina, Armenia, Bangladesh, Belarus, Bolivia (Plurinational State of), Brazil, Costa Rica, Dominican Rep., Egypt, Ethiopia, Gambia, Georgia, Ghana, Guatemala, Guinea, Guyana, Honduras, Iceland, Jamaica, Japan, Kazakhstan, Kenya, Kuwait, Kyrgyzstan, Libya, Madagascar, Malawi, Maldives, Mauritania, Mongolia, Mozambique, Nicaragua, Nigeria, Pakistan, Papua New Guinea, Paraguay, Peru, Rep. of Moldova, Russian Federation, Seychelles, Sri Lanka, Syria, Thailand, Trinidad and Tobago, Uganda, Ukraine, United Rep. of Tanzania, Uruguay, Yemen, Zambia	Bhutan, Rwanda	Bulgaria, Burundi, Cabo Verde, CFA-Franc BCEAO Area, CFP-Franc Area, Fiji, Hungary, Morocco, Switzerland, United Kingdom	Albania, Australian dollar Area, Bosnia Herzegovina, Botswana, Brunei Darussalam, Canada, CFA-Franc BEAC Area, Chile, Common Monetary Area, Colombia, Comoros, Croatia, Cyprus, Czechia, Den, Estonia, Euro zone, India, Indonesia, Iran, Iraq, Israel, Latvia, Lithuania, Malaysia, Malta, Mauritius, Mexico, Nepal, New Zealand, Norway, Philippines, Poland, Rep. of Korea, Romania, Samoa, Sao Tome and Principe, Sierra Leone, Singapore, Slovakia, Solomon Islands, Sweden, Tonga, Tunisia, Turkey, Vanuatu, Viet Nam

Figures

Figure 1: Recursive and rolling prediction methods

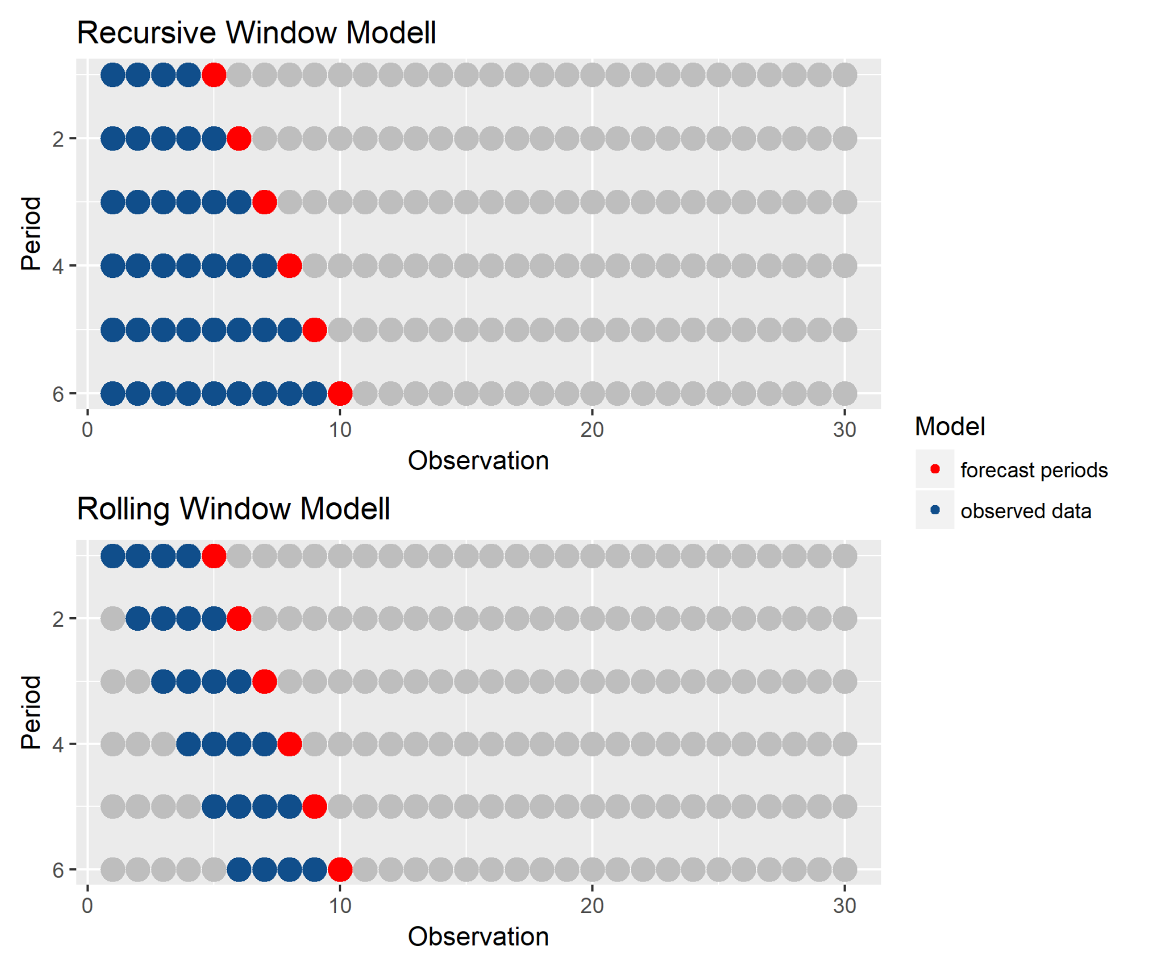

Figure 2: Percentage improvement over random walk (RoW)