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Abstract

This paper analyzes the extent to which information in commodity futures markets is useful for out-of-sample forecasting of commodity currencies. In the earlier literature, commodity price changes are documented to be weak out-of-sample predictors of commodity currency return. In contrast, we find that the basis of several commodities may contain useful information, but the usefulness of any particular commodity basis varies over time and depends on the nature of the commodity. In particular, it seems the basis of commodities with relatively high storage costs tend to be more useful. We argue that high storage costs will tend to make the basis more prone to fluctuations in commodity risk and therefore provide information about the risk premium for commodity currencies. We implement forecast combination strategies that take full advantage of the properties of the different bases and find large predictive gains.

JEL codes: C22, C52, C53, F31.
Keywords: Exchange rate predictability, commodity futures market, commodity currencies, forecast combinations.

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1 Introduction

This paper asks if commodity futures prices contain valuable information for forecasting commodity currency returns. Our answer is yes. We document that the futures price of several commodities contain information that is useful for forecasting commodity currency exchange rates. More precisely, we show that the commodity basis – the difference between the spot price and the price of a long-term futures contract – may contain useful information. At the same time, we show that changes in commodity prices do not contain useful information in the same out-of-sample forecasting exercise.

The paper is motivated by the mushrooming literature on the out-of-sample forecasting ability of economic models following the seminal contributions of Meese and Rogoff (1983a,b, 1988). After decades of research, the literature has still not found economic models that explain exchange rate movements, even ex post (see, e.g., Chen and Rogoff (2012)). Our paper is related to the particular strand of the exchange rate literature that has focused on commodity prices and so-called commodity currencies. The latter refers to currencies that co-move with commodity prices because the commodity is important for that country's export revenues (see, e.g., Chen and Rogoff (2012)). Movements in the exchange rate can, to some extent, be explained by commodity prices, but models based on those prices do not consistently outperform a random walk in out-of-sample forecasting (see, e.g., Chen and Rogoff (2003, 2012)). Most closely related to our study are Ferraro, Rogoff, and Rossi (2015), who focus on the out-of-sample predictive ability of commodity prices for exchange rate movements of commodity currencies. They find evidence for "out-of-sample fits" in daily data for some exchange rate-commodity pairs, but the predictive ability tends to fade after moving to monthly and quarterly data. Moreover, even in daily frequencies, they fail to find evidence for true "out-of-sample" forecasting ability. In our study, we focus on monthly frequencies and true out-of-sample forecasts. Our work differs from Ferraro et al.'s by including a wider range of commodities – more precisely, agricultural products – and by considering the commodity basis.

Recent studies attempt to explain the Meese–Rogoff puzzle from a different perspective. Engel and West (2005) argue that exchange rates and their fundamentals are linked in a way that is broadly consistent with asset-pricing models according to which the exchange rate is the expected discounted value of (linear) combinations of observable fundamentals and shocks.[1] In this case, when the discount factor approaches unity and the fundamentals have unit roots, the asset price will follow a process that is arbitrary close to a random walk.[2]

Consistent with Engel and West (2005) and the literature on commodity-currency forecasting, we find that models based on price changes of commodities cannot outperform the random walk benchmark in out-of-sample forecast of commodity currencies. We do, however, find evidence that models using the commodity basis can beat the random walk, and the forecast performance improves as we move to longer horizons. The latter is consistent with the results of Engel, Wang, and Wu (2010) (see also Engel (2014)). They extend Engel and West's framework to the case where stationary fundamentals co-exist along with non-stationary ones. In that case, the long-run level of asset prices are determined by the I(1) fundamentals, while stationary fundamentals explain deviations of the asset price from its long-run level. The authors show that in the presence of stationary fundamentals, the predictive ability improves for longer horizons. One prominent example of such stationary variables is the risk premium in the uncovered interest rate parity.

Interestingly, our analysis suggests that the usefulness of basis-models varies considerably across commodities. First, the usefulness of a commodity basis tends to be higher for commodities that are important for the commodity country. Second, storage costs seem to matter and, more precisely, the basis of commodities with high storage costs tends to be more useful. We set up a theoretical model to motivate how storage costs affect information in the commodity basis and in a nutshell, our explanation is as follows. The basis depends on the so-called convenience yield – the value of having the commodity in storage as opposed to owning a futures contract with a given maturity. This yield is an option value, since before maturity the investor has the right (but not the obligation) to sell the commodity and liquidate the futures con-

[1] See also Frankel and Mussa (1985); Obstfeld and Rogoff (1996).

[2] See also Bacchetta and van Wincoop (2013), who adopt an asset-pricing setup similar to that of Engel and West (2005). They show that, in the presence of parameter uncertainty, the relationship between exchange rates and macro fundamentals is determined by expectations about structural parameters and unobserved fundamentals. The existence of the latter makes inference difficult, especially in the short and medium run. Another potential explanation of the Meese–Rogoff puzzle can be found in Rossi (2005). She shows that for highly persistent series which are not exactly co-integrated, the parameter estimation error is a serious problem, especially for long horizons.

tract. This will be beneficial to the investor if the future spot price becomes sufficiently large relative to the relevant futures price. As for any option, the value is increasing in the volatility of the underlying asset, which in this case is the basis. A small storage cost will limit the volatility of the basis and thereby reduce the convenience yield. This, in turn, will limit how much information there is in the basis about commodity market risk factors, which is useful information for forecasting commodity currency return.

Moreover, our exercise reveals that the predictive ability of different bases varies over time. We associate this factor to variations in the price and quantity of risk. We argue that changes in the price of risk result in a positive relationship between currency returns and the basis, while changes in the quantity of risk imply a negative relationship. As a result, we should find predictive gains when changes in currency return and the basis are dominated by either the price or the quantity of risk.

To account for the uncertainty related to the ex-ante choice of basis and the documented time variation in their performance, we apply forecast combination strategies and combine individual forecasts. Time variation in model performance has recently been suggested as a possible solution to the Meese–Rogoff puzzle, see, for example, Byrne, Korobilis, and Ribeiro (2016). Our findings are encouraging. For almost all horizons and currencies in our sample, forecast combinations provide smaller mean squared forecast errors than the benchmark, smaller, in fact, than any individual model. On the other hand, selection of the best ex-ante model produces no gain relative to the benchmark for any of our cases.

The structure of the paper is as follows: Section 2 presents the theoretical background, while Section 3 describes the data. The econometric methodology is described in Section 4 and Section 5 presents our main empirical results. Finally, Section 6 considers forecast combinations and Section 7 concludes.

2 Theory Background

We consider a popular theory of commodity pricing, namely the theory of storage, but we cast it in an asset-pricing setup. First, we define the relative basis, $b_{t,n}^{j}$, of commodity j associated with the maturity n dollar futures price,

$F^j_{t,n}$, as

$$b^j_{t,n} \equiv p^j_t - f^j_{t,n}, \tag{1}$$

where P^j_t is the period t dollar spot price of commodity j and small letters denote the natural log of the variables. For future reference, we also define the n-period price difference as:

$$\Delta^n p^j_t \equiv p^j_t - p^j_{t-n}, \tag{2}$$

where $\Delta^n = (1 - L^n)$ with L denoting the lag operator.

Next, we develop the theory of storage. To this end, we consider the return of an investor that buys commodity j in period t in the spot market and stores it. We further assume the investor sells the commodity short in the futures market for delivery in period $t + n$. Using the pricing kernel $M_{t,t+n}$ to price the return in the commodity market, we get:

$$1 = E_t \left\{ M_{t,t+n} \left(cy^j_{t,n} - sc^j_{t,n} + \frac{F^j_{t,n}}{P^j_t} \right) \right\}, \tag{3}$$

where $cy_{t,n}$ and $sc_{t,n}$ are the convenience yield and the storage cost between periods t and $t+n$. The former is the value of having the commodity in storage as opposed to owning a futures contract for delivery in period $t+n$. We return to this option value shortly.

Next, since the interest rate on an n-period risk-free bond, $r_{t,n}$, is linked to the pricing kernel by $1 + r_{t,n} = 1/E_t(M_{t,t+n})$, equation (3) can be written as

$$r_{t,n} = \frac{E_t \left\{ M_{t,t+n} cy^j_{t,n} \right\}}{E_t(M_{t,t+n})} - sc^j_{t,n} + \left[\frac{F^j_{t,n}}{P^j_t} - 1 \right], \tag{4}$$

where we, for simplicity, have assumed that the storage cost is certain. Last, using the definition of the covariance, we can write

$$b^j_{t,n} = E_t \left\{ cy^j_{t,n} \right\} - sc^j_{t,n} - r_{t,n} - \mu^{cy,j}_{t,n}, \tag{5}$$

where $\mu^{cy,j}_{t,n}$ is the risk premium related to the stochastic nature of the convenience yield.[3] Equation (5) implies that the commodity basis depends on the expected convenience yield net of so-called carry charges (i.e. storage and financing costs). This is related to Kaldor's (1939) theory of storage. He argues that the convenience yield is related to the benefit of being able to use the commodity whenever desired, and carry charges are the opportunity costs of buying the commodity in the spot market rather than in the futures market. The convenience yield is therefore an option value. At every point in time $t + k$ (as long as $k < n$) the investor could sell the commodity and liquidate the futures contract (i.e. go long in the futures market with delivery in period $t+n$). Executing the option will give a positive payoff as long as the spot price (plus savings in carry charges) is higher than the futures price. The basis plus savings in carry charges thus corresponds to the underlying asset, while the so-called strike price is zero.

The convenience yield will include a value of waiting – or time value – since executing the option is irreversible. It is normally not optimal to execute an option when it is at the money (i.e. when the strike price equals the value of the underlying asset), since the option may give a positive payoff in the future and you can only collect the payoff once. This time value must be an increasing function of the volatility of the underlying asset – in this case the basis and the carry charges. The reason is that payoff is convex in the value of the underlying asset since the owner has no obligation to execute the option when payoff is negative (and thereby insuring the owner a minimum of zero payoff). This also implies that the convenience yield will depend negatively on the level of inventories and of the flexibility of production, since high inventories or very flexible production will limit the potential volatility of the basis in the future, which will reduce the option value. As a consequence, the convenience yield will be higher for commodities that have high storage costs and have inflexible production.

Another way of writing equation (5) above is as follows:

$$- b^j_{t,n} + E^*_t \left\{ cy^j_{t,n} \right\} = r_{t,n} + sc^j_{t,n} \tag{6}$$

where the expectation operator E^*_t uses risk-adjusted probabilities. This re-

[3] More precisely, we have $\mu^{cy,j}_{t,n} \equiv -\frac{Cov_t\{M_{t,t+n}, cy^j_{t,n}\}}{E_t\{M_{t,t+n}\}} + \mu^{app,j}_{t,n}$, where the latter term corrects for the fact that equation (4) implies a function for the percentage difference between the futures price and the spot price, while equation (5) uses the log difference.

sembles the theory of storage used in the literature (see, e.g., Gospodinov and Ng 2013). Notice, however, that the convenience yield does not enter the equation directly, but rather its risk-adjusted expected value. The left-hand side represents the risk-adjusted benefit of buying the commodity – the difference in price in the spot market and the futures market and the convenience yield. The right-hand side is the costs – the interest rate and the storage cost.

We can also use the stochastic return from an open position to price the commodity. The pricing equation for the open position can be written as:

$$E_t^* \left\{ \Delta^n p_{t+n}^j \right\} = r_{t,n} + sc_{t,n}^j, \tag{7}$$

where we have used risk-adjusted probabilities. This has a useful interpretation: it implies that the expected price change will equal the carry charges plus a compensation for risk. If storage is costless, the left-hand side of equation (7) will equal the risk-free nominal interest rate. In this case, the risk-adjusted expected price increase will just compensate for the financial cost of storage, and the commodity spot price will behave like what we could call a pure asset price. The current spot price will be a simple discounted value of the future risk-adjusted expected price. If, on the other hand, there is storage cost, this will drive a wedge between the risk-adjusted expected price increase and the nominal interest rate.

We can combine equations (6) and (7) to get

$$E_t^* \left\{ p_{t+n}^j \right\} = f_{t,n}^j + E_t^* \left\{ cy_{t,n}^j \right\} \tag{8}$$

which resembles the theory of normal backwardation, see, e.g. Gospodinov and Ng (2013). We see that the convenience yield introduces a wedge between the (risk-adjusted) expected future spot price and the futures price. The reason is simple: when commodity investors go short in the futures market, they are willing to accept a discounted price because they are assured a minimum price.

Our ultimate aim is to use information embedded in commodity markets to forecast commodity currencies. To this end, we consider exchange rates using a similar asset-pricing framework (see, e.g., Backus, Foresi and Telmer 2001). Letting $1/S_t$ denote the dollar price of the commodity currency, the standard uncovered interest rate parity (UIP) reads

$$-E_t\left\{\Delta^n s_{t+n}\right\} + r^c_{t,n} - \mu^{\Delta s}_{t,n} = r_{t,n}, \tag{9}$$

where $r^c_{t,n}$ is the commodity currency n-period risk-free interest rate and $\mu^{\Delta s}_{t,n}$ is the risk premium associated to the stochastic nature of the nominal currency return.[4] The equation has a standard interpretation: the risk-adjusted return from investing in a commodity currency bond must equal the risk-free return from a USD investment. If we solve with respect to the currency return, we therefore get

$$-E_t\left\{\Delta^n s_{t+n}\right\} = -(r^c_{t,n} - r_{t,n}) + \mu^{\Delta s}_{t,n}. \tag{10}$$

We see that the expected currency return depends on the interest rate differential and the risk premium. Therefore, finding proxies for the risk premium would help in forecasting commodity currency return. Our idea is to use information in the commodity futures market and, in particular, the commodity basis.

It is useful to relate the basis and currency return to the price and quantity of risk. First, consider an increase in the price of risk, for example an increase in risk aversion of the international investor. This implies that these investors will demand higher compensation for taking on the risk. This will be so for all risky assets and portfolios, including the commodity portfolio. The basis, which is the price of that portfolio, should then fall. Also, currency retursn should then increase. We therefore expect there to be a negative relationship between currency returns and the basis, that is, a positive relationship between $E_t\left\{\Delta^n s_{t+n}\right\}$ and $b_{t,n}$. What about the relationship between currency returns and the price difference of the commodity, which in earlier literature has been used to predict currency return? Since prices of all assets fall, the same should be true of commodity prices, and there should be a negative relationship between the change in the spot price and currency returns as well.

Consider next an increase in the uncertainty about future commodity prices, that is, an increase in the quantity of risk. Commodity currencies will then become more risky since they tend to follow the development of commodity prices. Investors will therefore demand a higher currency return. At the same

[4]Note that the risk-premium will be a function of the pricing kernels in both countries, see, e.g., Backus et al. (2001)

time, the basis will increase because the option value should increase. This should give a positive relationship between the basis and currency return, that is, a negative relationship between $E_t\{\Delta^n s_{t+n}\}$ and $b_{t,n}$. As far as the price difference is concerned, commodity prices should fall to compensate for the increase in risk. We should therefore expect a negative relationship.

At first glance, it seems that the price difference rather than the basis should be the better indicator of future currency return, since changes in both the price of risk and the quantity of risk result in the same negative relationship between price changes and currency returns. If we observe a fall in commodity prices, it should be an indication of a higher expected currency return, irrespective of whether the price has fallen due to a change in the price or the quantity of risk. This is not true for the basis, whose relationship with currency returns differs depending on the source of variation. Unfortunately, the price difference will also be driven by current and future expected changes in commodity demand or supply, or cash flow for short. Changes cash flow will cause commodity prices to move up and down. Due to the high contemporaneous relationship between commodity prices and commodity currencies, the exchange rate will also fluctuate, but there is no reason why it should affect currency return (unless there is a change in the uncertainty regarding future commodity prices). The commodity basis, however, should be much less affected by changes in cash flow, since both the spot price and the futures price will be affected. As a matter of fact, spot prices and futures prices are highly correlated, which indicates that changes in cash flow are persistent and/or that the market smoothens prices using inventories or the flexibility of production.

All in all, we argue that the basis could be a useful indicator of future currency returns in periods where movements in the basis are dominated wither by changes in the price of risk or in the quantity of risk. What about storage costs? We have seen that the basis will only fluctuate if there are some limitations to intertemporal substitution. This can be seen from equations (5) or (6) above. A small storage cost (or a very flexible production) will limit the volatility of the basis and reduce the convenience yield and thereby limit the amount by which both the price and the quantity of risk can influence the basis. In the limit, when storage is costless (or production is fully flexible), agents can use storage (or production) to fully smooth prices over time and the basis will just equal the financial cost. We therefore expect commodities with higher storage costs (and less flexible production) to be more useful when predicting commodity currency returns.

Our framework is related to Engel and West (2005) and Engel, Wang, and Wu (2010). As Engel and West argue, many theoretical macroeconomic models imply that exchange rates are related to their fundamentals in a way that is consistent with asset-pricing models according to which the exchange rate is the expected present discounted value of fundamentals. More precisely, many models imply a reduced-form exchange rate equation of the following form:[5]

$$s_t = (1-b)y_{1t} + by_{2t} + bE_t\left\{s_{t+1}\right\}, \tag{11}$$

where $0 < b < 1$ is a discount factor and the two variables y_{1t} and y_{2t} are some linear combinations of economic fundamentals. This equation can be solved forward to yield:

$$s_t = (1-b)\sum_{j=0}^{\infty} b^j y_{1t} + b\sum_{j=0}^{\infty} b^j y_{2t}. \tag{12}$$

Engel and West (2005) show that when the discount factor approaches unity and the fundamentals contain a unit root (either y_{1t}, when $y_{2t} = 0$, or y_{2t}), the exchange rate will follow a process that is arbitrarily close to a random walk. The intuition is as follows. When the discount factor is close to unity, the model puts weight on all future expected fundamentals and a very small weight on the recent change in fundamentals; and future expected fundamentals will be dominated by the unit root as the horizon increases. By implication, then, the exchange rate cannot be predicted, even if we have the right model.

Engel, Wang, and Wu (2010) extend Engel and West and consider the case where y_{2t} contains stationary fundamentals along with non-stationary ones. In this case, the long-run level of exchange rates is determined by I(1) fundamentals, while stationary fundamentals explain the deviation of exchange rates from their long-run level. The risk premium in equation (9) is one possible stationary fundamental.

3 Data

In the following we describe the data set and the choice of sample periods before discussing how we resolve the empirical issues related to using the commodity

[5] See also Engel (2014).

basis to predict exchange rates due to its correlation with the risk-free interest rate.

3.1 Data description

We focus on five commodity exporting countries, namely Australia, Canada, Chile, Norway, and South Africa. The currencies of these countries are typically classified as commodity currencies. Chen, Rogoff, and Rossi (2010) argue that commodity currencies co-move with world prices of primary commodities due to these countries' great dependence on commodity exports. We consider monthly data, which start in January 1990 for Canada, Australia, and Chile; in January 1995 for South Africa, and in January 2001 for Norway.[6] The sample ends in March 2014.

The data on commodity futures were obtained from the Commodities Research Bureau (CRB) data set. We focus on commodities traded at the four North American stock exchanges (NYMEX, NYBOT, CBOT, and CME). The sample of commodities was selected according to the availability of futures contracts and their shares in the export revenue of the countries we are considering. We select commodities with about a 3 percent or higher share of export revenues of a given country. We exclude some commodities which have considerable export shares but lack sufficient futures data. Table 1 lists commodities and their corresponding weights in total export of each country. The export weights for Australia, Canada, and South Africa are taken from Chen, Rogoff, and Rossi (2010); for Chile we use the IMF (2011) country report, and for Norway the authors' own calculations based on data from the Norwegian Ministry of Petroleum and Energy. Notice that the data for natural gas are limited to 1990:4-2014:3. Table 2 contains a description of selected commodities.

A commodity futures contract is an agreement to trade a unit of the commodity at a future date and for a fixed price. We follow the literature in using the first nearby futures contract[7] as a proxy for the spot price (see, e.g., Fama and French (1987); Gospodinov and Ng (2013); Gorton, Hayashi, and Rouwenhorst (2013)) and combine it with a futures contract with long maturity

[6]Norwegian data are available from January 1990, but we restrict the sample since Norges Bank formally adopted inflation targeting in March 2001. For South Africa we picked the date of the liberalization of the capital account.

[7]The contract with the closest settlement date is called the nearby futures contract.

to construct the basis. We choose the longest available maturity with sufficient liquidity for each commodity, and the longest maturity contract used in our study is therefore a 12-month contract. The reason is that futures contracts with longer maturities than one year are usually not considered informative due to lack of liquidity (see, e.g., Alquist and Kilian (2010) and Yang (2013)).

The exchange rate is defined as the price in U.S. dollars of a unit of the commodity currency. We use IMF's International Financial Statistics (IFS) to obtain both exchange rates and money market rates as a measure of short-term interest rates. The U.S. treasury bills rates are obtained from Datastream. We use end-of-the-month observations for all series.

3.2 The interest rate-adjusted basis

We consider two intertemporal prices, namely the basis and the nominal exchange rate. Both are defined in Section 2 above. Equation (6) implies that the nominal interest rate is an important fundamental for the basis and, moreover, as we see from equation (9), the interest rate is a major fundamental for the exchange rate as well. Therefore, in order to avoid that predictability of currency return comes from the interest rate, we clean the interest rate from the basis in our empirical analysis. As a first step, however, we check the relationship between the interest rate and basis using the Fama and French (1987) test:[8]

$$b_{t,n} = \sum_{m=1}^{12} \alpha_m d_m - \beta r_{t,n} + \epsilon_t. \tag{13}$$

where d_m are monthly dummies that equal 1 if the futures contract matures in month m and 0 otherwise. The dummies are assumed to capture variations in (risk-adjusted expected) net convenience yields due to seasonality in production or demand. The hypothesis of the test is that after controlling for seasonal variations in the basis, it should move one-for-one with (the negative of) interest rates.

Table 3 presents the results. To a large extent they are consistent with those of Fama and French (1987), but two observations are worth mentioning.

[8]Notice Fama and French (1987) define the basis as the (log) futures price minus the (log) spot price, which explains why there the interest rate term enters with a negative sign in our equation but not in theirs.

First, for two-thirds of the commodities the relationship between the basis and the interest rate is not statistically significant. Second, in most of the cases the coefficients are different from unity. Only the metals bases have statistically significant relationships with the interest rate. For gold, variations in interest rates explain about 75 percent of the variation in the basis, while the R^2 is much lower for copper and platinum.

One important implication of these results is that the standard practice of considering a naïve interest-rate adjustment, that is $b_{t,n}^{adj} = b_{t,n} + r_{t,n}$, does not clean the basis for correlation with interest rates.[9] In fact, in some cases the method would create more correlation. In what follows, we adjust the basis for metals, that is those commodities with statistically significant coefficients in Table 3. For those commodities we use the residual from a recursive estimation of the basis on the interest rate. For the remaining commodities we use the non-adjusted basis.

4 Empirical Framework

In this section, we explain the econometric methodology used in our forecast exercise and discuss some technical issues. Thereafter, we explain our out-of-sample forecast evaluation methods.

4.1 Long-horizon regressions

Our aim is to forecast exchange rate returns between time t and $t+h$, using information up to time t. We use ordinary least squares to estimate coefficients of the model using $60+h$ observations in a rolling window scheme:

$$\Delta^h s_{t+h} = \alpha_{t,h} + X_t \beta_{t,h} + \varepsilon_{t+h}, \tag{14}$$

where vector X_t contains predictors used to estimate the model. The out-of-sample forecasts are obtained using estimated coefficients from equation (14) in the following way:

$$\Delta^h \hat{s}_{t+h} = \hat{\alpha}_{t,h} + X_t \hat{\beta}_{t,h}. \tag{15}$$

[9] See Gospodinov and Ng (2013) for an example of studies that use the interest rate-adjusted basis.

Equation (14) is known as a long-run regression and is the prevalent framework for predicting financial returns. The general view is that the predictability of returns increases with the forecast horizon and we therefore consider both short and long horizons. High-frequency return series have time-varying and persistence volatility and it can be argued that the series is dominated by noise components in the short run, but that as we move toward a longer horizon the noise disappear. As we discussed in Section 2, this is related to Engel, Wang, and Wu (2010), who analyze the predictive power of long-run regressions when the exchange rate can be described as in equation (14). They show that under some conditions and in the presence of stationary fundamentals, the predictive power of long-run regressions improves with the horizon.

There are some caveats regarding the use of equation (14), however. The most important issue is discussed by Valkanov (2003). He argues that when the time series grows more persistent, it will start to behave (asymptotically) as an integrated series of order one as the analysis moves into longer horizons. For this reason, long-horizon regression tests are criticized for being biased in favor of finding predictability. We therefore check for unit roots and persistence in the exchange rate returns. We find significant evidence in favor of a unit root for exchange rate returns for horizons beyond 12 months for most of the countries.[10] For this reason, we restrict our analysis to horizons that are than a year.

We also check for unit root and persistence in the basis of the different commodities and the results are reported in the last two columns of Table 2. The basis of most commodities is persistent, but stationary. **We only find evidence of unit root in the gold and platinum bases, but less so for the interest rate-adjusted series.**

4.2 Out-of-sample forecast comparisons

In order to evaluate the out-of-sample performance of the models relative to the benchmark, we calculate three forecast evaluation statistics. The first statistic is the Mean Squared Forecast Error (MSFE) of the model relative to that of the benchmark. The second is the Clark and West (2006, 2007) test on MSFE differences. The null hypothesis of the test implies that MSFE of a model equals to that of the benchmark versus the alternative that a MSFE of

[10]The results are available upon request.

the model is smaller than that of the benchmark. The last statistic that we consider is the Cumulative Sum of Squared forecast Error Difference (CSSED) introduced by Welch and Goyal (2008):

$$CSSED_{m,\tau} = \sum_{\tau=R}^{T} (\hat{e}^2_{bm,\tau} - \hat{e}^2_{m,\tau}), \tag{16}$$

where $\hat{e}_{bm}$ denotes the forecast error of the benchmark, while $\hat{e}_m$ is the corresponding error of the alternative model. Parameters R and T indicate the beginning and end of the forecast evaluation period, respectively. At each point in time, an increase in CSSED indicates that the alternative model is outperforming the benchmark, while a decrease in CSSED has the opposite interpretation.

5 Empirical Results

This section presents the empirical results of the out-of-sample forecast performance tests for the two forecast competitors – the basis and the price change – using the framework described in Section 4. We start by discussing the aggregate measure of out-of-sample forecast performance by comparing the relative MSFE of the models. Next, we evaluate performance over time by tracing the movements of the CSSED. Last, we present in-sample evidence before – as a robustness exercise – considering an alternative benchmark.[11]

5.1 Overall forecast performance

Table 4 presents the relative MSFE from models using the basis of different commodities for the sample period ending in 2014:3. Our first observation is that the basis of several commodities offers forecast gains for some or all horizons. For Australia, two of the five commodities give forecast gains for some horizons, while for Canada, all the commodities offer forecast gains. Furthermore, and in particular for longer horizons, the copper basis and the gold

[11] Meese and Rogoff (1983a) consider both a random walk with drift and a drift-less random walk, while Mark (1995) consider a random walk with drift as the benchmark. We follow Ferraro, Rogoff, and Rossi (2015) and consider both models in our analysis. We present results relative to the random walk with drift in the main section because we find larger predictability for that model than the drift-less random walk, in particular for the Canadian dollar, due to the strong mean reverting feature of the exchange rates during our sample.

and platinum bases help forecasting currency returns for the Chilean Peso and South African Rand, respectively. Last, the natural gas basis gives some forecast gains for short horizons for the Norwegian Krone. These observations are interesting and important not least because the general view in the literature is that commodity prices are not useful for predicting commodity currency returns.

Our second observation in Table 4 regards the usefulness of the different commodities. There is a tendency for bases for different metals to offer little forecast gains, while the commodities that do offer such gains are either agricultural or energy products. These commodities are generally viewed as having high storage costs and low storage capacity. Consider Australia which exports a wide variety of different commodities. Neither gold nor copper offer any forecast ability, even though both have significant export weight. In fact, gold is the commodity with the highest export weight of the commodities we consider, but using the gold basis does not help in forecasting the Australian Dollar. The export weight of wheat is about the same as that of gold (8.3 percent and 9.4 percent, respectively), but the wheat basis offers forecast gains for all horizons. The copper basis does offer forecast gains for the Chilean Peso, and the gold basis helps forecasting the South African Rand, but the gains are modest. This is surprising given the fact that they both have an export weight of about 50 percent. The only exception is the platinum basis, which offers forecast gains for South Africa. We return to this below when we consider a shorter sample that excludes the recent financial crises.

So far, we have provided evidence of forecast gains from using the basis of different commodities compared to a conventional benchmark in the literature. In addition, we have argued that commodities with high storage costs and low storage capacity are particularly helpful. In principle, these results could be due to factors such as financialization of commodity markets or higher demand for commodities, or, more generally, to factors that affect commodity prices in general. In Table 5 we therefore produce similar forecast-comparison tests when the alternative model is based on the first order difference of log commodity prices. The difference between the two tables is remarkable. Compared to Table 4, there are few stars in Table 5 and there are little or no forecast gains from using the price difference. This is true all across our sample currencies and commodities. The only indications of predictability are found when the natural gas basis is used for Australia for the one-month horizon and the crude oil basis for Canada for the three-month horizon. In both cases, however, the size of the forecast gain is small.

Our sample period is characterized by several factors that have influenced the commodity markets in important ways. There commodity futures markets have seen several structural changes since 2003 (see, e.g., Irwin and Sanders 2012) and large capital inflows into those markets (see, e.g., Tang and Xiong 2012). There have also been large demand shocks from Asian countries, as shown in Kilian and Hicks (2013), and the world economy has been influenced by the U.S. financial crisis and the European debt crisis. Such large changes – both in the form of structural changes and economic disturbances – are likely to influence our findings in important ways and could even obscure the relationships we are seeking to establish (see, e.g., the discussion in Rossi 2012). Before evaluating the forecast performance over time in the next subsection, we therefore report relative forecast comparisons for a sample ending in January 2008. The results are shown in Tables 6 and 7.

Overall, the results in the two tables seem to confirm our earlier results. While forecasts using the basis of different commodities seem to outperform the benchmark, the same is not true of forecasts using the price difference of those commodities. However, there are some differences compared to the earlier results that are worth mentioning. First, forecasts using energy bases offer only small gains compared to the benchmarks for Australia and Canada. The forecast gain using the natural gas basis is significant, but small, for both countries for some horizons, and the crude oil basis forecast of the Canadian Dollar performs worse than the benchmark for all horizons. For Australia, the cotton basis now offers forecast gains; hence for both countries only the agriculture bases offer sizable forecast gains. Second, the basis of precious metals – gold and platinum – no longer offers significant and sizable forecast gains for the South African Rand for any horizon. The gold basis performs worse than the benchmark for all horizons, while the platinum basis offers a significant, but very small, forecast gain for the nine-month horizon. We conjecture that the forecast gains we observe using energy and precious metals bases from the whole sample are a result of the special circumstances during the financial crises.

5.2 Alternative benchmarks

In the previous section we used the random walk with drift as the benchmark. However, in the literature, it is also common to consider the driftless random walk. Following Ferraro, Rogoff, and Rossi (2015), as a robustness check, we therefore redo our tests using the driftless random walk. Table 8 reports the results of our forecast comparison using the new benchmark over the full sample for horizons $h = 1$ and 3. The results are qualitatively similar to those in tables 4 and 5: several bases provide statistical significant reductions in MSFE for several forecast horizons. Agricultural commodities, such as wheat and lumber, and the energy commodity natural gas, all of which all have high storage costs and low storage capacity, give higher forecast accuracy than the benchmark. Interestingly, the alternative model performs worse (relative to the benchmark) for the Chilean Peso and the South African Rand. This means that models based on metals such as copper and gold no longer offer any forecast gains.[12] As in the main analysis, price changes do not offer predictability.

5.3 Forecast performance over time

The previous sections provide support for the view that models using commodity bases might be useful for forecasting commodity currencies. In this section, we analyze forecast performance over time by computing CSSEDs of bases and price changes for a selected group of commodities.[13] The results are reported in Figure 1. Increases (decreases) in the CSSED imply that the model performs better (worse) than the benchmark.

Figure 1 clearly shows that all the three bases outperform the benchmark for several periods of time. This is true both for the one-month and the three-month horizons. The same is not true for the price difference. Importantly, for all the three exchange rate-commodity pairs in Figure 1, the price difference is consistently outperformed by the benchmark, in particular for the shortest horizon, but also for the three-month horizon. However, for shorter periods of time, the price difference does outperform the benchmark. We interpret the two observations in the following way. In periods with stable demand and production, changes in quantity and price of risk will dominate movements

[12] Results are robust to the sample ending in 2008:1.

[13] We restrict attention to three commodity-exchange rate pairs, but report the remaining pairs in Table 4 in the appendix.

in both commodity prices and exchange rate returns. Price changes should then, in principle, be useful for predicting currency return. In periods when commodity prices are largely driven by changes in demand or production, this will no longer be true. In the period running up to the financial crisis, both wheat and copper experienced tremendous price gains, a significant part of which it seems natural to attribute to changes in demand.

Models using bases to forecast currency returns seem to avoid long periods where forecast performance is worse than the benchmark. We attribute this to the fact that the basis is less influenced by demand disturbances since spot prices and futures prices will tend to move together. Figure 1 seems to indicate that both for wheat and the Australian Dollar and copper and the Chilean Peso, the basis forecasts do virtually just as well as the benchmark for extended periods of time, while they do better than the benchmark for some periods.

The performance over time of the one-month lumber-basis forecasts of the Canadian Dollar currency return is worth commenting. Over the five-year period up to 2010, the basis consistently outperforms the benchmark, while the opposite is true between 2010 and 2013.[14] The former period covers both the run up to the U.S. financial crisis and the crisis itself, but also the fourth U.S.-Canadian lumber dispute. One possible interpretation of our finding is therefore that the source of variations in the basis changed considerably between 2005 and 2014. In the beginning, uncertainty in the lumber market was important due to the lumber dispute, while the movements in the basis at the end of the sample were more affected by the risk appetite of the international investor. In other words, a change in the relationship between the basis and expected currency return could make our rolling-window forecast perform badly in the beginning of this decennium. We will return to this in the in-sample analysis below.

5.4 In-sample evidence

So far, our findings document the out-of-sample forecast ability for commodity currencies using bases for different commodities. In this section, we investigate the sign and evolution of the coefficients (β) in the predictive regression (14).

The U.S. financial crisis was a major event influencing all the commodity

[14]There is a somewhat similar pattern for the three-months forecasts.

(and other) markets at the same time. We therefore start by splitting the regression sample into a pre-crisis sample ending in 2008:1 and a post-crisis period starting the following month. Table 9 reports β's from our predictive one-step-ahead regression (14). We find two important results. First, several coefficients are statistically significant. More precisely, this is true for wheat for Australia, lumber for Canada, and copper for Chile in the pre-crisis sample, while the coefficients are significant for wheat and natural gas for Australia, natural gas for Canada, and crude oil and natural gas for Norway in the post-crisis sample. Importantly, these coefficients are associated with bases that offer forecast ability in Tables 4 and 6. Second, all the coefficients that are statistically different from zero in the pre-crisis sample have a negative sign, but a positive sign in the post-crisis sample, with gold being the only exception in the post-crisis sample. We interpret these findings as follows. Before the financial, crisis commodity prices were influenced largely by changes in demand for commodities from Asian countries, or, more generally, by sector-specific factors. Changes in the quantity of risk were therefore an important driver of commodity prices during this period, which rationalizes the negative relationships. In the aftermath of the financial crisis, changes in the risk appetite of the international investor became an important factor for currency returns, implying a positive relationship. The only exception is gold, where the post-crisis coefficient is negative, large, and statistically different from zero. The fact that gold typically is considered a safe haven when currency markets are volatile can rationalize this finding.

Table 9 splits the sample before and after the US financial crisis, but changes could be associated to other events and could differ across bases. To account for this, Figure 2 plots the rolling window estimation of β along with the 90% confidence interval[15] for the same selected group of commodities in Figure 1. Similar to the out-of-sample analysis, we use a 60-observation rolling window and, therefore, the plot of coefficient discards the initial five years. In general, we observe instabilities in magnitude and sign of coefficients.

[15]The t-statistics is computed with Newey-West estimator.

6 Forecast Combinations

We show that the basis of commodities with high storage costs provides useful information for predicting exchange rate returns. However, we also show that, for Australia, Canada, Norway, and South Africa, there is more than one commodity that delivers statistically superior forecasts than the benchmark. Moreover, their predictive power seems to vary over time, with periods with one basis providing more accurate information and others when other bases contain more useful information. We rationalize this finding by the fact that a basis will be a useful indicator for future currency returns in periods where movements in the basis are dominated by changes in either the price of risk or the quantity of risk. This creates issues regarding the choice basis and might question whether our strategy is robust to ex-ante decisions. Therefore, to account for the uncertainty in the choice of basis, we apply forecast combination strategies for the listed four countries and combine individual forecasts as:

$$\Delta^h \hat{s}_{t+h} = \sum_{i}^{n} w_{t,h}^i \Delta^h \hat{s}_{t+h}^i \tag{17}$$

where $w_{t,h}^i$ is the combination weight assigned to the individual forecast $\Delta^h \hat{s}_{t+h}^i$, $i = 1, \ldots, n$ using information up to time t. We consider three types of weights. First, we assume equal weights, that is $w_{t,h}^i = 1/n$, which we label FC_ EW. Second, we compute the weights $w_{t,h}^i+$ as the inverse mean square forecast error of model i up to time t for horizon h, normalized such that the weights for a given country and horizon sum up to 1. We label it FC_SFE. Finally, we also consider a selection strategy where the whole weight at time t for prediction of the value $t+h$ is given to the model with the lower mean square forecast error up to time t for horizon h, that is $w_{t,h}^l = 1$ and $w_{t,h}^j = 0$, $j = 1, \ldots, n$, $j \neq l$. The latter is labeled SEL. Timmermann (2006) discusses the benefits of the three methods and provides several macroeconomic and financial examples where the methods provide accurate forecasts relative to individual models. Time variation in model performance and the uncertainty associated to it have recently been indicated as a possible solution to the Meese–Rogoff puzzle (see, e.g., Byrne, Korobilis, and Ribeiro (2016)).

We combine forecasts based on gold, wheat, natural gas, copper, and cotton bases for Australia; crude oil, lumber, natural gas, and wheat bases for Canada; crude oil and gas bases for Norway; and gold and platinum bases for South

Africa. Table 10 reports results relative to the benchmark model for the full samples ending in March 2014.

The results are encouraging: for Australia, Canada, and Norway, and for all horizons, the forecast combinations based on equal weights or inverse MSPE weights provide mean square forecast errors smaller than the benchmark. For South Africa this is true for horizons $h = 3$, 6, and 9. In particular, the combination FC_ SFE provides the most accurate forecasts for all the entries in the table. The gains for Australia are 1 percent at the one-month horizon and 11 percent at the nine-month horizon; for Canada are 1 percent at the one-month horizon and 12 percent at the nine-month horizon; for South Africa the results are 0 percent at the one-month horizon and 8 percent at the nine-month horizon; and for Norway they are 1 percent at the 1-month horizon and 4 percent at the nine-month horizon. These gains are larger than those of any individual model reported in Table 4. The gains are statistically significant for long horizons, but not for the one-month horizon where wheat and natural gas for Australia and natural gas for Norway were providing statistically more accurate forecasts than the benchmark.

The strategy that does not work is selection. This method provides no gains relative to the benchmark at any horizon, confirming evidence in, e.g., Clark and McCracken (2008), Bjørnland, Gerdrup, Jore, Smith, and Thorsrud (2012), Aastveit, Gerdrup, Jore, and Thorsrud (2014), Aastveit, Ravazzolo, and van Dijk (2015), that selecting the best ex-ante individual model can result in large ex-post losses.

Figure 3 displays the weights in the combination scheme FC_SPE for the three countries at different horizons. These plots provide insights into why combinations result in large forecast gains. The general finding is that the relative size of the weights varies substantially over time. Models that provide more accurate forecasts for a period receive higher weights, but when their performance deteriorates the weights fall drastically. The plots indicate that a dominant model is not found in Australia and Canada, providing further evidence against selection. For South Africa, platinum receives the higher weight for the full sample period at the one-month horizon and for most of the sample at the three-month horizon. For the six and nine-month horizons, there is more variation between gold and platinum. For Norway, natural gas receives the highest weight for most of the sample at horizons $h = 1$ and 3, whereas there is more variation between them for horizon $h = 6$, and oil has a higher weight for most of the sample for $h = 9$. We notice that no model receives zero weight, again confirming that discarding them is not beneficial. It also means that each model contains some predictive power, which forecast combinations can exploit even if the overall performance of a single model is inferior to the benchmark model.

Focusing on individual countries, we find that wheat and natural gas receive the higher weights for the prediction of the Australian dollar at all horizons. Natural gas has the higher weight in the sample period at the beginning of 2000 and from 2010 to the end of the sample. Wheat has the higher weight from 2005 to 2009. Copper has the lower weight for most of the sample for horizons $h = 1$ and $h = 6$; whereas gold has the lower weight for most of the sample for horizons $h = 3$ and $h = 9$. We notice that for longer forecast horizons, gold has the higher weight at the beginning of the sample.

For Canada, the evidence is more mixed. Oil receives a higher weight for all horizons up to 2000, but afterwards lumber has the higher weight for short horizons, $h = 1$ and $h = 3$, and wheat for long horizons, $h = 6$ and $h = 9$. For all horizons, weights seem to converge to equal weighting from 2011.

As we wrote above, for South Africa and Norway, we have just two individual forecasts, and at shorter horizons one of them seems dominant. For South Africa, platinum receives the higher weight in the whole sample at horizon $h = 1$ and for most of the sample at horizon $h = 3$. At horizons $h = 6$ and 9, gold has the higher weight for a few months in 2007 and in the years 2011 and 2012. For Norway natural gas receives the higher weight for most of the sample at horizons $h = 1$ and 3, while at horizon $h = 6$, oil has the highest weight in the years 2008 and 2009. For $h = 9$, it has the higher weight for most of the years from 2008 to 2014.

Finally, we notice the difference in model weights ranges from 10 to 30 percent across countries and horizons, meaning that any individual model could receive up to a 30 percentage points higher weight than implied by equal weighting. Other combination schemes could be considered to discriminate more strongly across models, for example, a full distribution of the weights as in Billio, Casarin, Ravazzolo, and van Dijk (2013) could be derived.

7 Conclusion

This paper demonstrates that commodity futures prices contain valuable information for forecasting commodity currency returns. More precisely, we find that the commodity basis, i.e. the difference between the spot price and the price of a longer-term futures contract, provides more accurate out-of-sample forecasts than the random walk. At the same time, we show that changes in commodity prices do not contain useful information in the same out-of-sample forecasting exercise.

The usefulness of any particular basis depends on the nature of the commodity. The basis of commodities with relatively high storage costs tend to be more useful. We develop a theoretical model to show that high storage costs will tend to make the basis more prone to fluctuations in commodity risk and therefore provide information about the risk premium for commodity currencies.

We also find that the performance of different bases varies over time, something we relate to variations in the price and quantity of risk, affecting the commodity basis and its relationship to currency returns. This can create uncertainty regarding which basis to choose ex-ante. We apply forecast combinations to deal with such uncertainty and document large forecast gains.

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Table 1: Sample of commodities and export weights

Country	Commodity	Weight
Australia	Gold	9.4
	Wheat	8.3
	Natural Gas	4.8
	Copper	2.8
	Cotton	2.8
Canada	Crude Oil	21.4
	Lumber	13.6
	Natural Gas	10.7
	Wheat	3.4
South Africa	Gold	48
	Platinum	30
Chile	Copper	50
Norway	Crude Oil	30
	Natural Gas	16

Notes: The table presents the list of commodities and their export share (weight) in each country. The weights for Australia, Canada, South Africa are taken from Chen, Rogoff, and Rossi (2010), while that for Chile is from IMF's Country Report. The weights for Norway are the authors' own calculations based on data from Ministry of Petroleum and Energy.

Table 2: Description of selected commodities

Commodity	Exchange	Symbol	Delivery	S&P GSCI	DJ UBSCI	Basis AR(1)	Basis Test
Energy							
Crude oil (WTI)	NYMEX	CL	All Months	40.6	15.0	0.87	0.00
Crude oil (Brent)	ICE	CB	All Months	0	0	0.88	0.00
Natural Gas	NYMEX	NG	All Months	7.6	16.0	0.75	0.00
Metal							
Copper	NYMEX	HG	H,K,N,U,Z	2.6	6.7	0.91	0.01
Gold	NYMEX	GC	G,J,M,Q,V,Z	1.5	6.1	0.96	0.06
Platinum	NYMEX	PL	F,H,J,K,N,V	0	0	0.85	0.01
Agricultural							
Cotton	ICE	CT	H,K,N,V,Z	0.7	2.2	0.85	0.00
Lumber	CME	LB	F,H,K,N,U,X	0	0	0.73	0.00
Wheat	CBOT	W-	H,K,N,U,Z	3.0	3.4	0.84	0.00

Notes: The table presents descriptive information about the commodity futures contracts used in the analysis: exchange and month of delivery (January (F), February (G), March (H), April (J), May (K), June (M), July (N), August (Q), September (U), October (V), November (X) and December (Z)). The notation for futures exchanges is: CME = Chicago Mercantile Exchange, CBOT = Chicago Board of Trade, NYMEX = New York Mercantile Exchange, SFE =Sydney Futures Exchange, and ICE = Intercontinental Exchange. The data source is the Commodity Research Bureau (CRB). The columns S&P GSCI and DJ UBSCI show the weights of each commodity in the S&P GS and DJ-UBS commodity indices reported by Tang and Xiong (2012). The columns labeled "AR(1)" and "Test" present the coefficients of the first order autoregressive model of the basis and the Philip-Perron unit root test. The lag truncation parameter of the test is adjusted for sample size and the length of memory of the series.

Table 3: The Fama and French regression (1990:1-2014:3)

	Commodity	Obs.	β	t-stat	$\bar{R}_1^2$	$\bar{R}_2^2$
Energy	Crude Oil(WTI)	291	-0.76	(-1.19)	0.03	0.02
	Crude Oil (Brent)	159	0.39	(0.48)	0.00	0.00
	Natural Gas	288	-1.33	(-1.20)	0.23	0.00
Metal	Copper	291	**-0.77**	(-2.33)	0.24	0.18
	Gold	291	**0.41**	(21.11)	0.95	0.85
	Platinum	291	**0.12**	(2.53)	0.13	0.07
Agriculture	Cotton	291	-0.08	(-0.12)	0.08	0.00
	Lumber	291	-0.32	(-0.65)	0.26	0.02
	Wheat	291	-0.24	(-0.48)	0.30	0.00

Notes: The table presents a summary results of the Fama and French (1987) test. $\bar{R}_1^2$ is the adjusted R squared from the regression allowing for monthly seasonal dummies, and $\bar{R}_2^2$ is related to the modification without dummies. β is taken from the regression that includes the monthly seasonal dummies. Standard errors of the coefficient are calculated using the Newey-West HAC method in order to account for error serial autocorrelation with a bandwidth adjusted for 12 months. Statistically significant coefficients at the 5% level are reported in bold numbers.

Table 4: Relative MSFE: Basis compared to a random walk with drift (until 2014:3)

Benchmark: $\Delta^h \hat{s}_{t+h} = \hat{\delta}_{t,h}$

Alternative: $\Delta^h \hat{s}_{t+h} = \hat{\alpha}_{t,h} + \hat{\beta}_{t,h} b_t$

		Forecast Horizon				
		h=1	h=3	h=6	h=9	wght
Australia	Gold	1.04	1.03	1.04	1.04	9.4
(1990:1)	Wheat	0.98**	0.95***	0.94**	0.92**	8.3
	Natural Gas	0.99*	0.93***	0.92**	0.92**	4.8
	Copper	1.02	1.04	1.04	1.04	2.8
	Cotton	1.01	1.05	1.08*	1.03*	2.8
Canada	Crude Oil	1.01	1.00*	0.93**	0.92**	21.4
(1990:1)	Lumber	1.00	0.98*	0.97*	0.98*	13.6
	Natural Gas	1.01	0.98**	0.97**	0.95**	10.7
	Wheat	1.01	0.99	0.98*	0.95**	3.4
Chile	Copper	0.99**	0.98**	0.98**	0.98**	50
(1990:1)						
South Africa	Gold	1.03	1.00*	0.99**	0.98**	48
(1995:1)	Platinum	1.01	0.98**	0.96**	0.94**	30
Norway	Crude Oil	1.02	1.01	1.03	1.00	30
(1999:1)	Natural Gas	0.99*	0.97**	1.01*	1.02*	16

Notes: The numbers are mean squared forecast error (MSFE) of the alternative model relative to the benchmark for exchange rate returns over a period of 1 to 9 months. A ratio smaller than unity implies that the model beats the benchmark. One star, *, two stars, **, and three stars, ***, indicate that the model significantly outperforms the benchmark at 10%, 5%, 1% significance level, respectively, based on the Clark–West test. The dates placed below each country are the starting dates of the evaluation; therefore, with a rolling window size equal to $60 + h$ observations, the first out-of-sample forecast is generated 5 years after those dates. The column labeled wght presents the export weight cited from Table 1.

Table 5: Relative MSFE: Price change compared to a random walk with drift (until 2014:3)

Benchmark: $\Delta^h \hat{s}_{t+h} = \hat{\delta}_{t,h}$
Alternative: $\Delta^h \hat{s}_{t+h} = \hat{\alpha}_{t,h} + \hat{\beta}_{t,h} \Delta p_t$

		Forecast Horizon				
		h=1	h=3	h=6	h=9	wght
Australia	Gold	1.02	1.01	1.01	1.01	9.4
(1990:1)	Wheat	1.02	1.01	1.01	1.02	8.3
	Natural Gas	0.99**	1.03	1.02	0.99	4.8
	Copper	1.03	0.99	1.02	1.01	2.8
	Cotton	1.02	1.01	1.01	1.02	2.8
Canada	Crude Oil	1.01	0.99*	1.02	1.00	21.4
(1990:1)	Lumber	1.03	1.02	1.02	1.02	13.6
	Natural Gas	1.01	1.02	1.01	1.00	10.7
	Wheat	1.04	1.02	1.02	1.02	3.4
Chile	Copper	1.04	1.02	1.00	1.00	50
(1990:1)						
South Africa	Gold	1.01	1.02	1.02	1.01	48
(1995:1)	Platinum	1.08	1.01	1.03	1.02	30
Norway	Crude Oil	0.99	1.01	1.03	1.00	30
(1999:1)	Natural Gas	1.01	1.04	1.01	1.00	16

Notes: See description in Table 4.

Table 6: Relative MSFE: Basis compared to a random walk with drift (until 2008:1)

Benchmark: $\Delta^h \hat{s}_{t+h} = \hat{\delta}_{t,h}$
Alternative: $\Delta^h \hat{s}_{t+h} = \hat{\alpha}_{t,h} + \hat{\beta}_{t,h} b_t$

		Forecast Horizon				
		h=1	h=3	h=6	h=9	wght
Australia	Gold	1.03	1.02	1.01	1.01	9.4
(1990:1)	Wheat	0.98*	0.92**	0.89**	0.89**	8.3
	Natural Gas	1.02	0.99	0.99	0.98*	4.8
	Copper	1.01	1.02*	1.02*	1.02	2.8
	Cotton	1.00	1.02	0.95**	0.95**	2.8
Canada	Crude Oil	1.01	1.03	1.04	1.07	21.4
(1990:1)	Lumber	0.97**	0.94**	1.00	0.99*	13.6
	Natural Gas	1.02	1.02	1.01	0.99*	10.7
	Wheat	1.01	0.99	0.95*	0.89**	3.4
Chile	Copper	0.98**	0.92***	0.90***	0.89***	50
(1990:1)						
South Africa	Gold	1.03	1.05	1.06	1.02	48
(1995:1)	Platinum	1.00	1.00*	1.00*	0.98**	30

Notes: See description in Table 4.

Table 7: Relative MSFE: Price change compared to a random walk with drift (until 2008:1)

Benchmark: $\Delta^h \hat{s}_{t+h} = \hat{\delta}_{t,h}$
Alternative: $\Delta^h \hat{s}_{t+h} = \hat{\alpha}_{t,h} + \hat{\beta}_{t,h} \Delta p_t$

		Forecast Horizon				
		h=1	h=3	h=6	h=9	wght
Australia	Gold	1.02	1.02	1.02	1.01	9.4
(1990:1)	Wheat	1.01	1.01	1.00	1.00	8.3
	Natural Gas	0.97**	1.01	1.02	1.02	4.8
	Copper	1.02	1.01	1.01	1.01	2.8
	Cotton	1.00	1.01	1.01	1.01	2.8
Canada	Crude Oil	1.01	1.00	1.00	1.00	21.4
(1990:1)	Lumber	1.01	1.01	1.01	1.02	13.6
	Natural Gas	1.00	1.01	1.01	1.01	10.7
	Wheat	1.02	1.03	1.01	0.99	3.4
Chile	Copper	1.01	1.00	1.00*	1.00*	50
(1990:1)						
South Africa	Gold	1.00	1.02	1.01	1.00	48
(1995:1)	Platinum	1.02	1.01	1.04	1.01	30

Notes: See description in Table 4.

Table 8: Relative MSFE: Driftless random walk benchmark (until 2014:3)

Benchmark: $\Delta^h \hat{s}_{t+h} = 0$
Alternative: $\Delta^h \hat{s}_{t+h} = \hat{\alpha}_{t,h} + \hat{\beta}_{t,h} X_t$

		Basis		Price change	
		h=1	h=3	h=1	h=3
Australia	Gold	1.05	1.04	1.04	1.03
(1990:1)	Wheat	1.00*	0.96***	1.04	1.03
	Natural Gas	1.00	0.95**	1.00*	1.05
	Copper	1.04	1.06	1.04	1.01
	Cotton	1.03	1.06*	1.01	1.02*
Canada	Crude Oil	1.02	1.00*	1.03	0.99*
(1990:1)	Lumber	1.01	0.97**	1.04	1.02
	Natural Gas	1.02	0.98**	1.01	1.03
	Wheat	1.02	0.99*	1.05	1.02
Chile	Copper	1.08	1.08	1.06	1.05
(1990:1)					
South Africa	Gold	1.05	1.04	1.04	1.05
(1995:1)	Platinum	1.04	1.01	1.11	1.05
Norway	Crude Oil	1.03	1.02	1.00	1.02
(1999:1)	Natural Gas	1.01	0.98**	1.03	1.05

Notes: See description in Table 4.

Table 9: Basis: In-sample predictive regressions (1990:1-2008:6 & 2008:7-2014:3)

		Pre-crisis		Post-crisis		
		β	t-stat	β	t-stat	Wght
Australia	Gold	0.24	(1.54)	-3.55*	(-1.76)	9.4
(1990:1)	Wheat	-0.01*	(-1.85)	0.08*	(1.69)	8.3
	Natural Gas	0.01	(1.63)	0.03***	(3.04)	4.8
	Copper	-0.01	(-0.66)	0.18	(0.71)	2.8
	Cotton	0.01	(1.34)	-0.032	(-1.48)	2.8
Canada	Crude Oil	-0.01	(-1.51)	0.03	(1.42)	21.4
(1990:1)	Lumber	-0.03**	(-2.20)	0.05	(1.02)	13.6
	Natural Gas	0.003	(1.15)	0.02***	(2.96)	10.7
	Wheat	0.003	(0.58)	0.05	(1.54)	3.4
Chile	Copper	-0.034**	(-2.25)	0.20	(1.12)	50
(1990:1)						
South Africa	Gold	0.18	(0.61)	-2.30	(-0.99)	48
(1995:1)	Platinum	-0.012	(-0.86)	-1.51	(-0.57)	30
Norway	Crude Oil	–	–	0.03*	(1.87)	30
(1999:1)	Natural Gas	–	–	0.02**	(2.45)	16

Notes: The table reports β's from our predictive one-step ahead regression (14). The numbers in parenthesis are t-statistics adjusted for heteroskedasticity and serial autocorrelation by the Newey–West method, with bandwidth equal to $T^{\frac{1}{3}}$.

Table 10: Relative MSFE: Forecast combinations (until 2014:3)

Benchmark: $\Delta^h \hat{s}_{t+h} = \hat{\delta}_{t,h}$
Alternative: $\Delta^h \hat{s}_{t+h} = \sum_i^n w_{t,h}^i \Delta^h \hat{s}_{t+h}^i$

		Forecast Horizon			
		h=1	h=3	h=6	h=9
Australia	FC_EW	0.99	0.93***	0.91**	0.90***
(1990:1)	FC_SFE	0.99	0.93***	0.90**	0.89***
	SEL	1.01	1.05	1.08	1.04
Canada	FC_EW	0.99	0.95**	0.92**	0.89***
(1990:1)	FC_SFE	0.99	0.95**	0.91**	0.89***
	SEL	1.01	1.10	1.06	1.06
South Africa	FC_EW	1.00	0.96	0.93*	0.92**
(1999:1)	FC_SFE	1.00	0.96	0.93*	0.92**
	SEL	1.03	1.06	1.10	1.02
Norway	FC_EW	0.99	0.94*	0.98	0.96
(1999:1)	FC_SFE	0.99	0.94*	0.97	0.96
	SEL	1.01	1.01	1.05	1.05

Notes: The numbers are mean squared forecast errors (MSFE) of the forecast combination schemes relative to the benchmark reported above for exchange rate returns over a period of 1 to 9 months. The three schemes are: equal weights (FC_ EW), recursive inverted mean square weights (FC_ SFE); selection of the best model in terms of minimum square prediction errors for each vintage (SEL). See also description in table 4.

Figure 1: Cumulative sum of squared forecast error differences

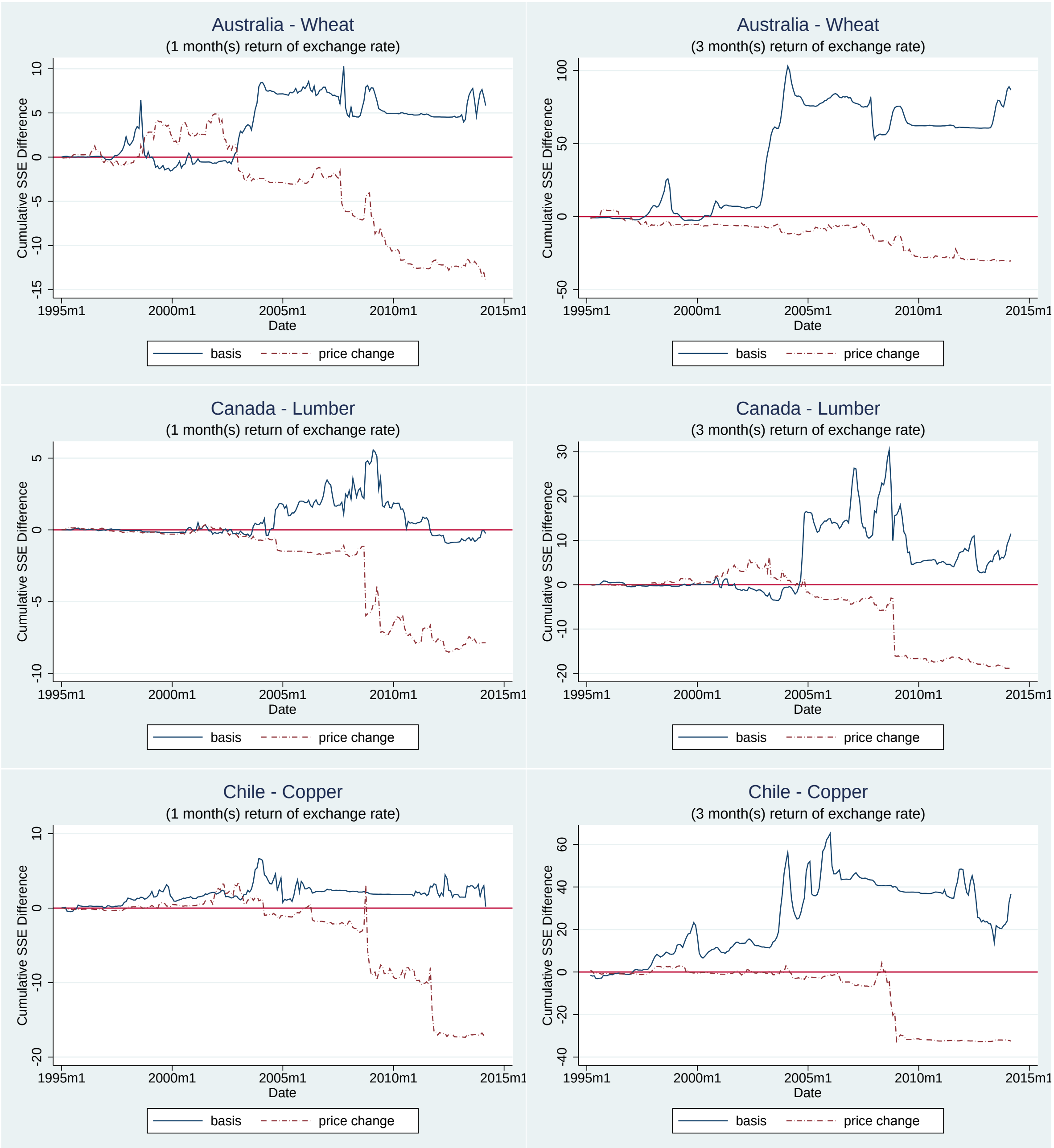


Figure 2: Rolling-window estimation of predictive-regressions coefficients

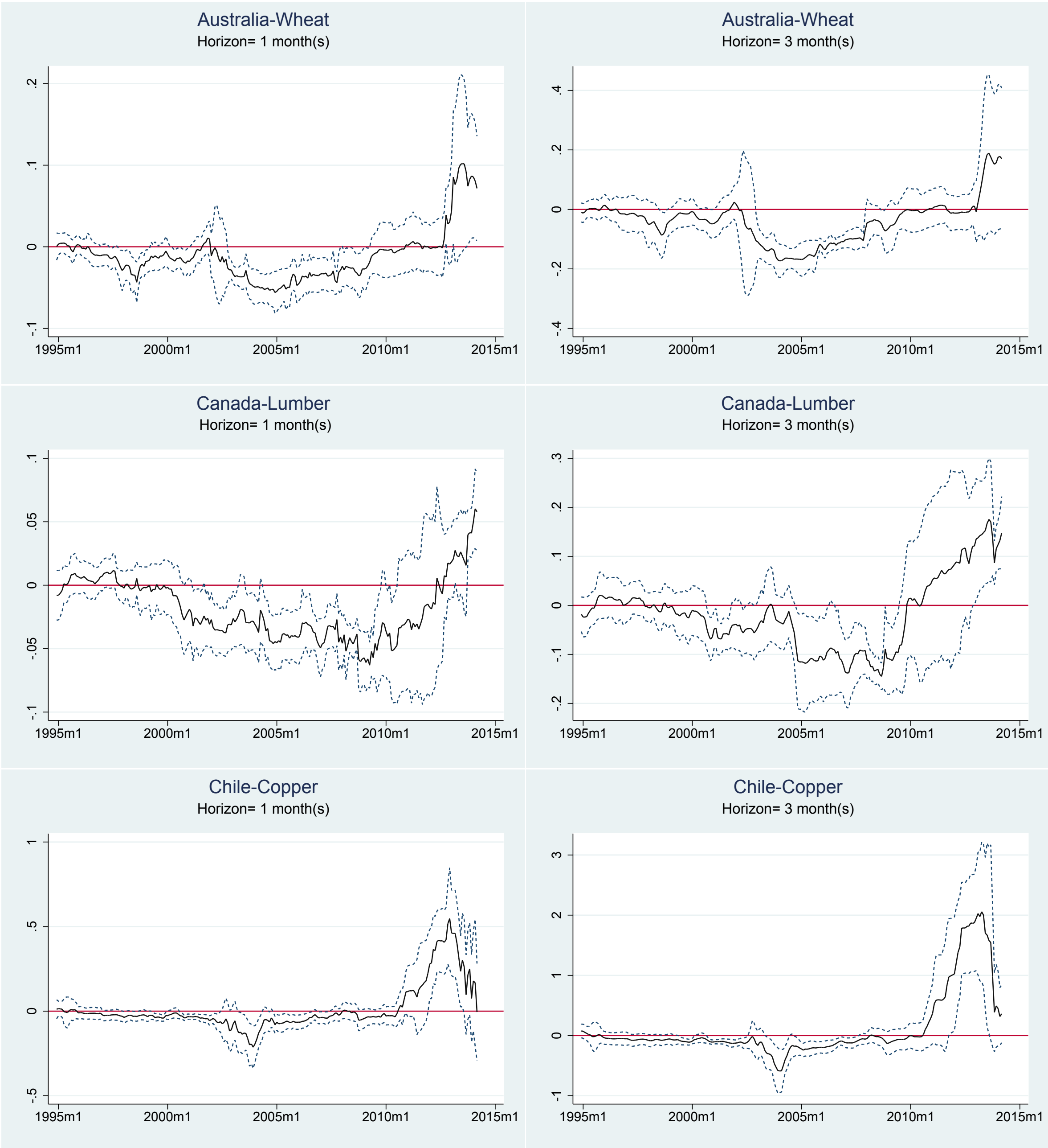
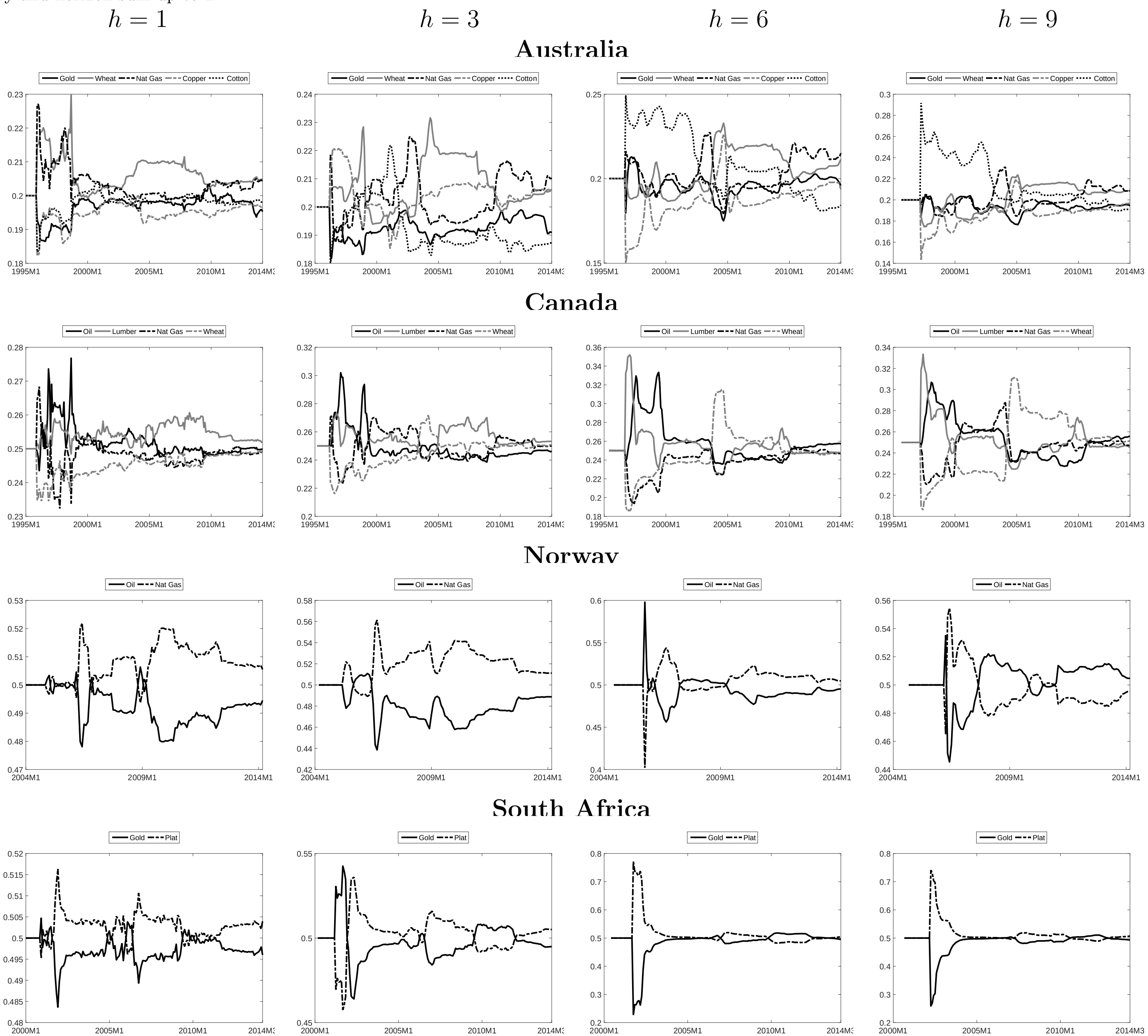


Figure 3: Combination weights for different countries and horizons

The graphs show the weights for the combination scheme FC_SFE for Australia, Canada, Norway and South Africa for different forecast horizons h. The weights at time t are computed as the inverse mean square forecast error of model i up to time t for horizon h months, normalized such that weights for given country and horizon sum up to 1.



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