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# ECONOMICS

# FORECASTING METALS RETURNS
# A BAYESIAN DECISION THEORETIC APPROACH

**by**

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**DISCUSSION PAPER 10.24**

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Abstract

Turning points in commodity returns are important for decisions of policy makers, commodity producers and consumers reliant on medium term outcomes. However, forecasting of turning points has been a neglected feature of forecasting, especially in commodity markets. I forecast turning points in metals price returns using Bayesian Decision Theory. The method produces a probabilistic statement about our belief of a turning point occurring in the next period which, combined with a decision rule based on a loss function generates optimal turning point forecasts. This method produces positive results in forecasting turning points in metals returns, with the simple linear models investigated producing more accurate turning point forecasts than naive models across a number of different evaluation methods for the general case and for the specific example of a producing firm.

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## 1. Introduction

The last decade has seen what has been classified as the largest commodity price boom in the last century (World Bank 2009). Although the combined amplitude and duration of this boom is of a magnitude not seen before, what is consistent between now and the past is the volatility and uncertainty in commodity markets, which can be costly to economies which depend on commodities – especially the developing world. Volatility can be effectively managed through entering futures markets; however uncertainty is more complicated to deal with. The major cause of uncertainty in economic actions is the temporal dislocation of decisions made today and payoffs obtained in the future[2] and in this light, uncertainty can be reduced through having accurate forecasts of the future payoffs. In its widest definition, a forecast can be any statement predicting a future event, and can range from absurdly simple statements such as "the sun will rise tomorrow" to the complex synthesis of data and models, both statistical and theoretic which characterise modern economic forecasting. Forecasting allows us to transform part of the *uncertain* future into a *risky* future by assigning a probability distribution over the possible outcomes[3].

Most economic forecasts are *point* forecasts, producing the "one" best estimate of the future value of the variable in question. Although this is very important for most decisions, some decisions are more sensitive to the direction of change at specific dates, i.e. turning points. This is especially the case in industries with long lead times between decisions being made and payoffs from those decisions, e.g. the primary resources industry, or when economic pressures from a variable only build in the medium term. Here, turning points in the series can be very influential to payoffs with the possibility of large, asymmetric outcomes.

Forecasting turning points in economic time series has been given relatively little attention. There are two main reasons for this: first is that at or near potential turning points there is large uncertainties making forecasting more difficult, secondly, some of the tools for forecasting turning points (e.g. simulation methods) were not developed until the late 1970's, and especially before the development of the personal computer. Some of the early works in forecast turning points are Wecker (1979), who is credited with the first computer based forecasting of turning points through simulation methods, Kling (1987), a series of papers by Zellner et al. (1990), Zellner et al. (1991) and Zellner and Min (1999) (from now on grouped as Zellner and co-authors) in the context of GDP and more recently Chin et al. (2000) looking at unemployment.

Forecasting commodity prices has recently been given attention by Chen et al. (2010) and Goren and Pasenti (2010), while past investigations include Fama and French (1987) and Just and Rausser (1981) *inter alia*, but no known attempt at forecasting turning points in commodity returns has been made[4]. It is important for policy institutions to distinguish between short term fluctuations and medium term trends/cycles as economic pressures arising in the medium term from commodity prices such as; i) Dutch Disease, ii) the pro-cyclicality of fiscal policy in commodity rich developing countries (Frankel 2010) and iii) inflation-

[2] As we can never see the future there always some uncertainty in surrounding it, no matter how "certain" we believe it to be.
[3] Part of the uncertainty would then lie in the question, is my forecast an accurate forecast, or is my model correct?
[4] Turning points have been studied in an historical context by Cashin et al. (2002), Roberts (2009) and Clements and Halperin (forthcoming).

ary/deflationary pressures that build in the medium term as price changes cannot be continually internalised, can be problematic for economies. The medium term can also be important for firms operating on the demand or (especially) supply side of primary commodity markets, as long lead times combined with high, non-recoverable costs means that profitable projects require sufficient expected revenues in the medium term to justify investment. These medium term problems are arguably more important than the oft sited issue of high price volatility as short term fluctuations can be hedged on commodity exchanges but medium term trends cannot.

In this paper I forecast turning points in the returns to six industrial metals traded on the London Metals Exchange (LME)[5] using the method of Zellner and co-authors. Their Bayesian method provides useful advantages over classical methods, especially in the context of forecasting turning points, through the explicit modelling of the uncertainty and easy inclusion of possible asymmetric outcomes[6]. The remainder of this paper is outlined as follows. Section 2 presents some of the past literature on commodity price determination while Section 3 outlines the model and method used to forecast commodity returns, both theoretically and the specific model used. Section 4 provides a brief summary of the data and model implementation. Section 5 presents the results from the turning point forecasting where the Bayesian method produces superior turning point forecasts over naive forecasts, while in Section 6 the method is more finely tuned for the example of a generic mining firm. Finally in Section 7 summary remarks and conclusions are presented.

## 2. Determinants of Commodity Prices

There is a long line of work which aims to identify the determinants of commodity prices. The short/medium term determinants of commodity prices can be classified in a number of ways[7], market based or financially based, macroeconomic or microeconomic. The relationship between market and financial determinants is based on the storability, homogeneity and liquidity (of trade) for the commodity. Commodities can be argued to be hybrids of *assets* and *goods* as they are storable, homogenous and traded on exchange but they also rely on flow demand and supply (Frankel and Rose 2009). If commodities are priced like assets, prices would be unpredictable – by the Efficient Markets Hypothesis – however, the hybrid nature of commodities combined with spot market frictions means that *spot* prices may be still predictable.

The microeconomic investigations have mostly been done in the context of agricultural commodities and incorporate four components; current demand and supply, storage (which is costly) and expectations (Deaton and Laroque 1992), where the current, *flow*, demand and supply can be adjusted through stored production. Minor manipulations of this theory to look at different markets involve placing different assumptions on the storability of production and the type of expectations held by producers and consumers. If storage is prohibitively costly and/or expectations are not met, seasonality can have an impact on shorter

[5] Aluminium, copper, lead, nickel, tin and zinc.

[6] The method was originally developed in the context of forecasting turning points in GDP growth rates, an interesting question is; does the method provide advantages in turning point forecasting in an economic series which is less “sticky” and more volatile?

[7] In the long term, there are two theories; Hotelling based on a Malthusian supply constraint says that commodity prices should increase at the rate of inflation, while the Prehbish-Singer hypothesis says they should decrease; see Frankel (2010).

term prices by creating short term excess demand or supply just before or after harvests. The ability to store and the incorporation of expectation into demand/supply analysis produces a potential relationship between current spot and futures prices. This can be in two ways, either the current futures price in an expectation of the future spot price (adjusted for a risk premium) or with the cost of storage being as the explanation of the difference between spot and futures prices (Fama and French 1987).

The theory of macroeconomic determination of commodity prices originates from the observed correlations amongst between different commodity classes (e.g. agriculture and metals) which cannot be explained by microeconomic forces. Typically the theory highlights the influence of three macroeconomic variables on commodity prices; monetary policy, exchange rates and economic output through industrial production. Industrial production has been shown to be a determinant of commodity price indices in a number of papers (e.g. Borenztien and Reinhart 1994). Industrial production is more heavily dependent on raw commodity inputs than general economic activity, and it has been argued that indices of industrial production can be used to model the general demand for raw commodities.

Monetary policy, especially US, has been shown to influence commodity prices (Frankel and Hardovelious 1985 and Akram 2009 *inter alia*). Higher interest rates produce an incentive for resource extraction today instead of tomorrow, reduce the demand for inventories and induce a shift away from capital investment towards investment in government bonds, all leading to lower commodity prices. Monetary policy can also act as a signal for future demand (lower interest rates stimulate demand, thus prices increase now because of the expectation of this) and through a Purchasing Power Parity argument on exchange rates. The USD is also used frequently as a determinant of commodity prices, particularly as most commodity prices are denominated in USD, thus the USD would produce a direct effect on the USD price of commodities.

Motivated by the high international trade of commodities, the interaction between exchange rates and commodity prices has been widely studied, especially for the “Commodity Currencies” (see Clements and Fry 2008). Though the literature is inconclusive on the theoretical direction of causation, Chen et al. (2010) show that country specific traded weighed exchange rate indices Granger-cause country specific indices of spot commodity prices. Also, Clements and Fry show that the spill over from currency returns to commodity returns is greater than commodities to currencies. These two papers therefore suggest that the commodity currencies have forecasting power for commodities.

Commodities are increasingly being included in portfolios as an alternative investment strategy. This has been used as a justification for the destabilising speculation theory for the recent commodity boom. Although the “jury is still out” on this explanation for the current boom, the increasing use of commodities as an investment strategy does highlight the fact that equity returns can have an impact on commodity returns through two possible channels; substitution between equity investments and commodity investments and using equity markets as a proxy for economic expectations through equity markets role as a leading economic indicator. Also, if commodities are considered as an investment class then there is the possibility of “bandwagon effects” where returns to a commodity “spill over” into returns to another which could potentially explain the most recent boom across the whole spectrum of commodities simultaneously (Frankel and Rose 2009).

## 3. Forecasting Turning points

The Bayesian method for forecasting turning points is intuitively simple. After classifying the potential turning points, the analyst estimates the probability of a turning point and makes an optimal forecast by minimising their expected loss if they were to make a forecasting error. However, as they say, the devil lies in the detail. In order to construct optimal turning point forecasts a number of components are needed; a definition of what constitutes a turning point, a model for the forecasts and an associated predictive probability function and a loss function for optimal forecasts (Zellner and co-authors).

*A Turning Point*

What is a turning point? It is a "point in time when a series which has been increasing [decreasing] reverses and, for a time, decreases [increases]" (Wecker 1979, p35). We will however require a finer definition of a turning point for operational purposes, one that can account for the four outcomes when forecasting turning points which are; upturns, downturns, no-upturns and no-downturns, which are mutually exclusive events. There are countless potential operational definitions of a turning point, but, in this paper a simple definition is used. First defining the log change in price (the return) for metal $i$ at time $t$ as $p_{it}$ the four outcomes for turning points are defined as:

*Upturn* at time $T$: $p_{iT-2} > p_{iT-1} > p_{iT} < p_{iT+1}$; *No-upturn* at time $T$: $p_{iT-2} > p_{iT-1} > p_{iT} \geq p_{iT+1}$

*Downturn* at time $T$: $p_{iT-2} < p_{iT-1} < p_{iT} > p_{iT+1}$; *No-downturn* at time $T$: $p_{iT-2} < p_{iT-1} < p_{iT} \leq p_{iT+1}$ [8].

If $p_{iT-2} > p_{iT-1} > p_{iT}$ then $T$ is an *upturn candidate* and if $p_{iT-2} < p_{iT-1} < p_{iT}$ then $T$ is a *downturn candidate*[9].

*A Model of Returns*

To forecast turning points, a model is required that relates the future value of metals returns to today's observed data. The model used is a linear autoregressive model augmented with economic leading indicator variables that are motivated by the literature on the determinants of commodity prices from the previous section. In general, the model takes the form: returns are distributed as $p_{it} \mid \mathrm{I}_{it} \sim t(\overline{p}_{it}, \tau_{it}, k_i)$, a student-t distribution[10] with mean $\overline{p}_{it}$ and precision (inverse of variance) $\tau_{it}$ and $k_i$ degrees of freedom, where

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[8] Preliminary testing was performed on a stricter turning point definition referencing to 0, e.g., a downturn occurs if $p_{it+1} < 0$. This did not significantly change the relative results, all models were less accurate but model rankings did not change.

[9] These definitions can easily be extended to include more steps before or after the date $T$. Then, higher order censoring rules (e.g. mean or trend) would be required to determine the classification of time $T$.

[10] As with many financial studies, metals returns are not normally distributed exhibiting what is known as "fat tails".

$$\bar{p}_{it} = \gamma_i + \sum_{j=1}^{q} \alpha_{ij} p_{i,t-j} + \sum_{l=1}^{m} \beta_{il} X_{l,t-1}^{(i)} = E(p_{it} \mid \mathrm{I}_{it}) \quad \text{and}$$
$$\ln(\tau_{it}) = \delta_{i0} + \sum_{h=1}^{v} \delta_{ih} Y_{h,t-1}^{(i)} \tag{3.1}$$

where $\mathrm{I}_{it}$ is the commodity specific information set at time $t$. The mean is modelled as a linear function of $q$ autoregressive terms and $m$ explanatory variables. The precision parameter is allowed to vary over time in response to $v$ explanatory variables to model shocks that effect out certainty of the expected returns, while the log specification ensures that $\tau_{it}$ cannot be negative. This produces the likelihood function which is used in conjunction with Bayes' Rule to derive the predictive density.

*The Predictive Density*

The next step after developing the model for returns is to compute the predictive probability density function (predictive pdf). The application of Bayes Rule obtains the posterior distribution for the parameters:

$p(\boldsymbol{\theta}|\boldsymbol{y},I) \propto \pi(\boldsymbol{\theta}|\boldsymbol{y},I)p(\boldsymbol{y}|\boldsymbol{\theta})$ where $p(\boldsymbol{y}|\boldsymbol{\theta})$ is the likelihood function, $\pi(\boldsymbol{\theta}|\boldsymbol{y},I)$ is the prior distribution, $\boldsymbol{\theta}$ is the vec-

tor of parameters, $\boldsymbol{y}$ is past data and $I$ is the information set. We also define $p(\omega|\boldsymbol{y},\boldsymbol{\theta},I)$ as the pdf for $\omega \equiv p_{it+1}$ the future return given $\boldsymbol{\theta}$, $\boldsymbol{y}$ and $I$. We combine the pdf for $\omega$ with the posterior to obtain the predictive pdf

$$p(\omega \mid \boldsymbol{y}, I) = \int_{\Theta} p(\omega \mid \boldsymbol{\theta}, \boldsymbol{y}, I) p(\boldsymbol{\theta} \mid \boldsymbol{y}, I) d\boldsymbol{\theta} \tag{3.2}$$

$\boldsymbol{\theta} \subset \Theta$[11]. Assuming we are at a potential upturn point ($p_{iT-2} > p_{iT-1} > p_{iT}$) the probability of an upturn at time $T$ is simply the probability that tomorrows value is above today's, it is the area underneath the predictive pdf for all values of ω greater than $p_{iT}$;

$$P_{UT} = P(\omega > p_{iT} \mid \boldsymbol{y}, I) = \int_{p_{iT}}^{\infty} p(\omega \mid \boldsymbol{y}, I) d\omega \tag{3.3}$$

The probability of no-upturn is $P_{NUT} = 1 - P_{UT}$, and by the events being mutually exclusive $P_{DT} = P_{NDT} = 0$. By the same logic the corresponding results for downturns where $P_{DT} = P(\omega < p_{iT} \mid \boldsymbol{y}, I)$ can be derived[12].

*The Loss Function*[13]

[11] This integration in effect removes the uncertainty of these parameters.
[12] This can easily be extended to the $g$ step ahead forecasts by evaluating the joint pdf for each $T+g$ (Zellner et al. 1990, p.379).
[13] The loss function provides economic justification for the use of Bayesian forecasting techniques. This is analogous to the decision making process imbedded in expected utility theory. Additionally, the Bayesian loss function can be considered the inverse of the utility-from-wealth function of Friedman and Savage (Geweke 2005, p17).

There is always a purpose to forecasting, forecasting is performed to inform the decision making process. It would therefore appear natural that an optimal forecast would depend on the reason for forecasting and the subsequent actions taken based on the forecast. This is done in Bayesian Econometrics through the incorporation of a loss function. Losses arise when forecasting from taking an action based on a forecast which is proved inaccurate *ex-post*. A forecaster wishes to minimise their *expected* loss from making a forecasting error. Formally this is

$$\min_{\boldsymbol{a}} E[L(\boldsymbol{a},\boldsymbol{\omega}) \mid \boldsymbol{y}, I] = \min_{\boldsymbol{a}} \int_{\Omega} L(\boldsymbol{a},\omega) p(\omega \mid \boldsymbol{y}, I)\, d\boldsymbol{\omega} \tag{3.4}$$

where $\boldsymbol{a}$ is the vector of actions and $\omega \in \Omega$. This framework is easily applied to forecasting turning points. When forecasting turning points, conditioned on the basis that we are at a potential turning point, $\boldsymbol{a}$ contains two possible actions, either forecasting a turning point or forecasting no turning point, $\boldsymbol{a}$=(*TP,NTP*). The forecaster chooses to forecast *TP* or *NTP* to minimise the expected loss from subsequent actions if the forecast is deemed to be inaccurate *ex-post*.

The simplest loss function is the constant loss function (Table 1). There is no loss if the forecast is correct, while losses are scaled such that if a turning point is forecast, but no-turning point occurs the loss is $C_1$ and conversely, if no-turning point is forecasted and a turning point actually occurs, the loss is $C_2$. In this sense we are only incurring a loss from a turning point error and removing the possibility of losses arising from making a *point* forecasting error (see Theil 1965, pp.28-31) and this possibility can be incorporated into the loss function as shown in Zellner et al. (1990, p375).

A decision maker is indifferent between forecasting a turning point or no turning point if the expected loss from each action is the same. That is, if $\hat{P}_{TP}.0+(1-\hat{P}_{TP})C_1=\hat{P}_{TP}.C_2+(1-\hat{P}_{TP})0$, where $\hat{P}_{TP}$ is the probability of a turning point which would make the forecaster indifferent between forecasting a turning point of not. This can be simplified to

$$1=\frac{C_2}{C_1}.\frac{\hat{P}_{TP}}{1-\hat{P}_{TP}} \qquad \text{or} \qquad \hat{P}_{TP}=\frac{C_1}{C_1+C_2} \tag{3.5}$$

which is the decision rule for forecasting turning points. The ratio $\hat{P}_{TP}$ is the cut-off probability for forecasting a turning point; a forecaster makes her decision (forecast a turning point or not) by comparing the estimated $P_{TP}$ in (3.3) with $\hat{P}_{TP}$. A turning point is forecasted if $P_{TP}>\hat{P}_{TP}$ and no turning point otherwise.

There are three significant features of this loss function which can help improve the decision making of organisations. First, the loss function may be asymmetric, i.e. $C_1$ does not have to (and most likely will not) equal $C_2$. Second, each individual organisation will have a different value for $C_1$ and $C_2$ based on the organisations' individual circumstances[14]. Finally the losses associated with an upturn situation do not have to be the same as those for the downturn case, which can be accounted for by reserving $C_1$ and $C_2$ for downturn candidates and creating two new costs, $C_3$ and $C_4$ to represent the losses from upturn candidates.

## 4. Data and Model Implementation

Summary statistics for the annualised metals returns are presented in Table 2, separating the data into two sub periods[15]. The early sub period (1989 to 2003) is used for model estimation, while the latter (2003 to 2009) is set aside for out-of-sample forecasting. In both periods there is substantial volatility in commodity returns, for instance, the 2 standard deviation confidence interval for aluminium (the metal with the lowest volatility) has a range of 86%. In the estimation sub-period all of the metals have returns which are significantly different from a normal distribution at the 1% significance level. Also as can be seen in Panel C, there is a statistical difference between the two sub-periods based on the simple t-test for the means and F-test for the variances. Only for two metals (aluminium and nickel) can we not reject the hypothesis of mean equality at a 10% level, and for three metals at a 5% level. The variance is significantly different between sub-periods for all metals[16].

The determinants of commodity prices outlined in Section 2 motivate the variables used for forecasting metals returns. The variables are; the US Federal Funds Rate and an index of OECD M3 money supply (modelling the US and international monetary environment), the Morgan Stanley Capital Index, MSCI, and the S&P Goldman Sachs Commodity Index, GSCI, (to model investment decisions), the CAD/USD real exchange rate (modelling both the effect of USD and commodity currencies)[17], G7 industrial production index, LME warehouse stocks (a proxy for microeconomic determinants of the cost of carry; Frankel and Rose (2009)), LME contract turnover (proxy for quantity traded in world market), three and fifteen month futures premiums (indicator of expectations; Fama and French (1987)) and a dummy variable for seasonality. This provides 11 variables as possible explanatory variables for future metals returns.

A number of different linear specifications of the model were examined by varying by the number of explanatory variables (*m, v* and *q*) in equation (3.1). The first dimension of model variation is in *q*, the number of lagged values of $p_{it}$ which takes the values of *q*=0, 1, 3. The second dimension is in the number of explanatory variables for $\bar{p}_{it}$ and $\tau_{it}$. Three combinations of values were investigated; i) *m*=*v*=0 ii) m=11 and

[14] The subjective nature improves individual decision making but means that there is no "one" best forecast across different individuals or institutions.
[15] A summary of data sources can be found in the appendix
[16] This provides a stronger test of the forecasting ability of the Bayesian method, if the period used to calibrate the model differs from the forecasting period then it makes it more difficult to obtain accurate forecasts.
[17] It would have been beneficial to include Australia and New Zealand in the analysis, but inflation data is only published quarterly for these countries, limiting the ability to incorporate these exchange rates into the monthly analysis in this paper. Also it would be useful to have commodity specific exchange rates (e.g. including the Peruvian Sol for copper) but data limitation and/or fixed exchange rate to the USD limits this inclusion from a commodity currency standpoint.

$v$=1 or iii) m=7 and $v$=1[18]. This provides eight models in total (the null model $q$=$m$=$v$=0 is meaningless) which are grouped for turning points analysis as the "Bayesian Models".

The models were estimated using the Gibbs Sampling algorithm which is a variant of the Markov Chain Monte Carlo simulation methods. The algorithm allows for the simulation of posterior distributions that are too complex to be derived analytically, those that are intractable. Although the models investigated are tractable (Zellner and co-authors solve a similar model analytically) the MCMC simulations were performed to outline a framework which can survive when defining more complex models which may potentially not have tractable solutions. In particular, the algorithm was run with a 1000 update "burn in" period, followed by 10 000 updates with two chains (showing good convergence); see Lunn et al. (2000).

To implement the Bayesian techniques the forecaster must specify a prior distribution for each coefficient of the models must be specified. Here, vague priors were used to indicate a lack of prior belief on the value of the coefficients. Thus the prior for coefficient $i$ in $\boldsymbol{\theta}$ is $\theta_i \sim N(0,\ 0.01)$, except for $k_i$ which is given a prior distribution of $k_i \sim \mathrm{U}(3,30)$[19].

## 5. Turning Point Results[20]

The first step in turning point forecasting is the classification of the dates as potential turning points or not; Table 3 presents the dates of potential turning points within the forecasting period. Over the forecasting period there are a total of 157 potential turning points across the six metals, 82 of which are potential downturns, and the remaining 75 potential upturns. Except for tin, each metal has more potential downturn points than upturn points (possibly owing to the boom in metals prices exhibited over the sub period). Listed next to each date is the estimated probability of a turning point occurring for a representative model using a symmetric loss function ($C_1 = C_2$ and $C_3 = C_4$) and the stars indicate whether the turning point forecast was correct or not. The forecasting results can be summarised as in Table 4 for each model and metal. There is a bias towards forecasting turning points, which most likely is derived from the high volatility of returns, with approximately 70% of turning points occurring out of the 157 potential turning points.

Five measures were used to compare the binary forecasting outcomes of the models. The first two measures are the proportion of correct forecasts (percentage correct) and the evaluation of the loss function *ex-post* for each forecasting event over the forecasting horizon and solely look at whether the model produces correct or incorrect forecasts. However, these two measures are sensitive to the cost ratio used and thus are not perfect. The other three evaluation methods are the "proper scoring rules", which evaluate the models based on the estimated probability of a turning points and whether the forecast is correct or not (Czardo et al.

[18]The $m$=7 variables remove the futures premiums, industrial production and GSCI variables. See results appendix.

[19]Alternative priors were investigated, e.g. $\theta_i \sim t(0,\ 0.01,\ 3)$ with little change in results.

[20] Some preliminary point forecasting results are presented in the appendix.

2009). The three scores are the Brier Score (*BS*), the Log Score (*LS*) and the Spherical Score (*SS*). For binary outcomes, these are calculated as;

$$BS = \frac{1}{N}\sum_{i=1}^{N} 2(P_i - R_i)^2, \quad LS = -\frac{1}{N}\sum_{i=1}^{N} \ln(X_i), \quad SS = \frac{1}{N}\sum_{i=1}^{N} \frac{X_i}{\sqrt{P_i^2 + (1-P_i)^2}} \tag{5.1}$$

where $R_i = 1$ if event *i* is correctly forecasted and zero if not and $X_i = P_i$ if is event *i* correctly forecast and $X_i = 1 - P_i$ if incorrect. A lower *BS* and *LS* and a higher *SS* indicate higher accuracy. The proper scoring rules are preferred for model comparison as they are invariant to the cost ratio, focusing in on the accuracy of the probabilistic forecast, but this does not mean that the evaluation of the loss function or percentage correct should be ignored, this are still valid if we fix on the cost ratio.

To ascertain if the Bayesian models provide a forecasting improvement we must compare their results to a base case, that is, naive models. Five naive models are included for comparative purposes, these include three certainty forecasts: the optimist ($P_{UT} = P_{NDT} = 100\%$), the pessimist ($P_{NUT} = P_{DT} = 100\%$) and forecasting "always a turning point" ($P_{UT} = P_{DT} = 100\%$) and two probability forecasts, the coin flipper (forecast a turning point with 50% probability) and forecasting a turning point with the probability based on the frequency of turning points occurring previously ("past").

As the proper scoring rules are the preferred comparison measure, they will be discussed before the other two and as the *BS* is argued as the most appropriate measure for time series evaluations (Kling 1987) this will be discussed first. All of the Bayesian models have a lower *BS* than the naive forecasts (see Table 5). The best of the naive models is the "past model" with a *BS* of approximately 0.41 while the worst of the Bayesian models has a score of 0.37, and the best of 0.34, which is a narrow range indicating little differences between the Bayesian models. The same outcomes are also apparent when we break down the forecast to investigate downturn and upturns separately, with the highest *BS* for the Bayesian models being less than the lowest naive model for both downturns and upturns. The exact same patters are seen in the *SS*, where the minimum *SS* for the Bayesian models are all greater than those for the naive models across both downturns and upturns. Finally the *LS*; it is apparent that the models again do well in comparison to the naive models included[21] outperforming the naive models, but to a lesser extent, in both overall forecasting and when looking at upturns individually. However, when forecasting downturns, three of the models are outperformed by the "past" naive model. By these proper scoring rules the Bayesian models are shown to provide more accurate forecasts than the naive models.

We now look at the percentage correct evaluation measure. As was noted earlier, the percentage correct and loss function evaluation methods are variant when the cost ratio changes[22]. Figure 1 Panel A shows the

[21] The certainty naive models have undefined log scores; $\ln(x) \to -\infty$ as $x \to 0$.

[22] Also, for evaluation purposes, it is assumed that relative costs, and therefore the cut-off probabilities do not vary over time.

percentage correct across all 157 potential turning points (fixing $\hat{P}_{UT} = \hat{P}_{DT}$ for visual clarity). Again, as with the proper scoring rules, the Bayesian models outperform the optimist and pessimist naive models for all $\hat{P}_{UT} = \hat{P}_{DT}$, however, the models only outperform the "always a turning point" naive forecast for the cut-off probabilities $\hat{P}_{UT} = \hat{P}_{DT} \leq 63\%$. The percentage of time that the Bayesian models are correct falls considerable once the cut-off probability for a turning point exceeds roughly 60%, due to the large proportion of turning points which actually occur out of the total potential turning points. When looking at upturns (Panel B) and downturns (Panel C) individually, the same patterns appear as with the combined case. Upturn forecasting is more accurate, but, the Bayesian models provide a greater improvement over the naive models when forecasting downturns.

The final measure is the evaluation of the loss function. This has two independent variables, the two cut-off probabilities, thus a visual representation is in three dimensional, such as Figure 2 for a representative model. However, there is a problem with the loss function evaluations, total costs are varied based on which cost is kept fixed, either fixing the cost of a turning points error ($C_1 = C_3 = 1$) or the cost of a no-turning point error ($C_2 = C_4 = 1$). This is best shown by Figure 3 which depicts the results for the "always a turning point" naive forecast; when $C_1 = C_3 = 1$, there is no change in total costs, where as when $C_2 = C_4 = 1$ the total cost changes with the cut-off probabilities. This might cause a problem if we were interested in the absolute costs (which would be relevant if using the loss function for compensation purposes), but, as we as focusing on model comparisons we can look at the comparative model rankings and the ranking of the different models are maintained under each cost regime which maintains the usefulness of the measure. For the majority of cut-off probabilities the Bayesian models outperform (have a lower cost) than the naive turning point forecasting models, as shown in Figure 4, (again fixing $\hat{P}_{UT} = \hat{P}_{DT}$ for visual clarity). As mirrored with the percentage correct measure, upturn forecasting incurs lower overall costs, but the Bayesian models produce greater gains over the naive forecasts when forecasting downturns.

In summary, across all measures the Bayesian method produces superior forecasts of commodity returns turning points than naive models. It is interesting to note that the proper scoring rules indicate that the Bayesian models provide a larger improvement over the naive models when forecasting upturns over downturns, but, the evaluation of the loss function and the fraction of correct forecasts indicates the opposite, that the improvement is in the forecasting of downturns.

## 6. Optimal Decision Making

In the previous section we varied the cost function (and therefore the cut-off probabilities) in order to ascertain whether the Bayesian process provides more accurate forecasts than naive models across a range of possible cost ratios, and this was shown to be the case. However, this is not how the decision making process works in reality where the costs $C_1$, $C_2$, $C_3$ and $C_4$ would be known, at least roughly, before forecasting[23]. An institution would want the model which forecasts most accurately *given* the particular cost structure they face. This is best outlined with an example of a mining firm and can be easily replicated for any institution (firm or policy).

Mining firms (producers of metals) are likely to have a larger cost of forecasting increasing metals returns (forecasting an upturn or no-downturn) and being wrong than being wrong when forecasting decreasing returns (forecasting a downturn or no-upturn). Why is this so? The natural inclination for a firm is to expand operations based on the expectation of increasing returns, but, if the forecast is wrong and returns actually fall occurs the expansion can leave the firm with large debts and unproductive infrastructure which can potentially lead to the bankruptcy of the firm – i.e. "the project that ruined the firm". In the other situation, forecasting falling returns but actually having higher returns occurring can be seen as an opportunity loss (i.e. "the one that got away"), though this would be distressing for shareholders, it should not lead to the bankruptcy of the firm. In many business decisions the possibility of bankruptcy is a key determinant of the asymmetric possibilities. Based on this logic it would seem appropriate that a mining firm would have $C_1 < C_2$ and $C_3 > C_4$, indicating that he cut-off probability to forecast an upturn will be greater than 50% while the cut-off for downturns will be less than 50%. Thus a mining company would (should) be cautious when forecasting increasing returns because the cost of getting it wrong are higher than the costs of wrongly forecasting lower returns.

Let's conservatively assume, based on the above logic, that $2C_1 = C_2$ and $C_3 = 2C_4$, which translates into cut-off probabilities of $\hat{P}_{DT} = 33\%$ and $\hat{P}_{UT} = 67\%$. From earlier we know that the proper scoring rules from (5.1) are invariant to the cut-off probabilities and that the Bayesian models outperform the naive models for each of these scoring rules (Table 5); thus they are still better than the naive models for this cost structure. However, a firm is most likely interested in their *actual* losses from being wrong, not an abstract scoring rule, so, a firm would want to evaluate the loss function based on this cost structure. The results of this are shown in Table 6, where it is evident again that the Bayesian models all outperform the naive forecasting models. The range of outcomes for the Bayesian models is again small, between 33 and 37 units when $C_1 = C_3 = 1$ and between 33 and 39 units when $C_2 = C_4 = 1$, while the lowest cost when using the naive models is 46 and 61 units respectively when using the "always a turning point" model. On the final evaluation measure, the percentage correct, the Bayesian models continue to produce more accurate forecasts for downturns, but, at these cut-off probabilities the naive models are more accurate in forecasting upturns. The Bayesian models still produce at least as accurate forecasts by this measure when looking at combined upturn and downturn forecasting.

Which model is best? The Bayesian method provides improvements in forecasting performance over the naive models, however, the Bayesian model which performs the best is not certain. There is very little dif-

[23] A firm could easily include uncertainty over costs by placing a probability distribution over the relative costs.

ference between Bayesian models, but, on average, the two models that perform the best are the $q$=1, $m$=$v$=0 model (simple AR(1) process) and the $q$=0, $m$=7 $v$=1 model. However, the small differences between the models are not significant.

## 7 Conclusion

The most recent boom-bust and now boom again has ignited research and public discourse on commodity prices. The recent economic research has focused on the impacts of the commodity price boom on developing countries (e.g. World Bank 2009, Frankel 2010) and on the determinants of commodity prices, focusing in on the possibility of joint macroeconomic determinants (e.g. Frankel and Rose 2009) with only a few forecasting commodity prices (Chen et al. 2010, Goren and Pasenti 2010). As commodities increasingly trade on exchanges, returns may be argued to be unpredictable, especially futures returns, however, commodity *spot* returns may still be predictable as market frictions may inhibit intertemporal arbitrage and transmission of micro and macroeconomic shocks. For this purpose, the spot returns for the six non-ferrous metals traded on the London Metals Exchange provide a good laboratory as they provide for spot trading.

This paper presented a new application of the turning point forecasting method of Zellner and co-authors (1990, 1991, 1999) to forecasting turning points in commodity (in specific metals) returns. Forecasting is generally performed to help inform a decision by gaining insight into what is expected to occur in the future and the Bayesian method provides a framework for the inclusion of this through the use of a loss function which can be calibrated to any situation and can improve decisions. The Bayesian method also provides other advantages in forecasting turning points over classical techniques, through the explicit modelling of uncertainty and the production of probability distributions which are easily used for both turning point forecasting and point forecasting.

The results outlined in Sections 5 and 6 provides evidence of the ability for the Bayesian method to improve the forecasting of turning points in metals returns, with the Bayesian method combined with the simple linear models consistently outperforming naive models across various evaluation methods. The gains here, measured by the improvement over the naive models, are more modest than those of Zellner and co-authors, partially owing to the bias towards turning points occurring. The models investigated are not complex to any degree, they are simple linear models and this adds to the viability of the turning point forecasting method. As with any exercise in forecasting, there are a number of possible extensions that can be made to further refine the model used and improve forecasting performance, but what is clear is that the method presented for forecasting turning points does provide a substantive improvement in forecasting performance for these six metals[24].

As Frankel (2010) has argued, better institutions in the developing world are needed if these countries are to effectively manage their natural resources, especially during booms. However, the development of institu-

[24] The one extension that could prove fruitful is creating commodity specific trade weighted indices for both industrial production and real exchange rates (see Sjasstad and Scacciavillai 1996) to target producers and consumers of the metals.

tions is extremely difficult. In the mean time, greater information through better forecasting, especially of turning points, is essential to the well being of these countries through improved resource management. For the developed world (especially those with inflation targets) commodity prices have been shown to contain information that can improve monetary policy (Cody and Mills 1991), and as commodity prices influence on inflation is likely to be a medium term phenomenon, the forecasting of turning points could have positive impacts for the effectiveness of monetary policy.

## Appendix

*Data*

The data set comprises of monthly data from July 1989 to September 2009, with 242 observations of log changes (see Table A1 for data sources). Nominal metals prices were converted to 2005 USD values using the US CPI inflation figures. None of the variables were seasonally adjusted as this may have the potential to remove meaningful price changes. The market based data (from Datastream) was converted to monthly frequency using the average for the month. Returns are calculated as log changes to account for base drift. The real CAD/USD exchange rate is calculated with the US being the home country.

*Results*

As a very preliminary analysis, correlations between next month's metals spot returns and the log changes in the variables (except for the Federal Funds Rate) are presented in Table A2. Most of the correlations are not strong, the strongest being the negative correlation between returns and changes in LME warehouse stocks[25]. The correlations between the metals returns and the futures premiums are calculated to conform to the theoretical underpinnings of the expectations hypothesis; that the futures premium indicates the expected change in commodity price over the futures contract horizon. Therefore, the correlation is comparing $f_h$ with the subsequent $h$ period return. By this we can see that the futures premia are not a good indicator of subsequent returns, although the 15 month premium is (slightly) better than the three month.

One of the benefits of the Bayesian forecasting process is that without changing the model specifications it is possible to conduct both *point* and *turning point* forecasting at the same time. The turning point results are presented in text, here I will outline initial point forecasting results of the eight models and compare them to the two standard naive forecasting benchmarks, the random walk in the price *levels* ($p_{it+1} = 0$) and the random walk in *returns* ($p_{it+1} = p_{it}$).

First however, the estimates of the coefficients (the means of the posterior distributions) for each model across each metal are presented in Table A3. The majority of estimates for the coefficients are relatively stable across the different models, and they generally (except for the model with $q$=0, $m$=11 and $v$=1) conform the theory presented in Section 2. As can be seen, the difference between the $m$=11 and $m$=7 models is the

[25] This negative correlation indicates that the LME buys when the price is low and sells when the price is high with statistical consequences for the future returns.

inclusion/exclusion of the two futures premiums, industrial production and the GSCI as economic predictors of metals returns. These variables were removed for a number of reasons including; the correlation results form Table A2, the values of the coefficients in Table A3 and through trial and error the root mean squared errors (RMSE) of the forecasts was improved. A possible explanation for the insignificant results for industrial production is that most of the growth in demand for raw commodities over the last decade has been from China and India, which are not part of the G7 for which the index is constructed from.

The RMSE results are presented in Table A4, where the last two lines represented the median and mean of the RMSE across the metals. Testing the forecasting ability of a model involves a two-step test: can the model beat a random walk, and if so, can the model beat a simple autoregressive model. Each of the models with economic variables ($m$=7 or $m$=11 and $v$=1) perform better than the two naive random walk forecasts for each of the metals, but, as has been shown by others (e.g. Goren and Pesenti 2009) the models which include economic predictors do not consistently perform better than the simple autoregressive models. When taking the median across metals, three models perform better than the autoregressive models, but not significantly so.

Table 1 – Loss Structure

| | Actual | |
|---|---|---|
| Forecast | Turning Point | No Turning Point |
| Turning Point | 0 | $C_1$ |
| No Turning Point | $C_2$ | 0 |

Table 2 – Summary Statistics

| | Aluminium | Copper | Lead | Nickel | Tin | Zinc |
|---|---|---|---|---|---|---|
| | | | A. 1989:08 to 2003:09 | | | |
| Mean (%) | -4.33 | -5.18 | -4.79 | -4.28 | -7.66 | -7.84 |
| Std Dev (%) | 15.68 | 17.40 | 20.07 | 24.50 | 14.32 | 18.55 |
| JB | 9.03 | 8.48 | 190.19 | 9.29 | 25.14 | 71.83 |
| (p-value) | (0.01) | (0.01) | (0) | (0.01) | (0) | (0) |
| | | | B. 2003:10 to 2009:09 | | | |
| Mean (%) | 1.83 | 18.27 | 21.49 | 6.90 | 15.86 | 11.37 |
| Std Dev (%) | 21.54 | 32.74 | 36.97 | 40.16 | 26.05 | 30.12 |
| JB | 13.60 | 32.65 | 10.70 | 2.99 | 7.44 | 4.45 |
| (p-value) | (0) | (0) | (0) | (0.22) | (0.02) | (0.11) |
| | | | C. Tests of Equality (p-values) | | | |
| Mean (t-test) | 0.51 | 0.04 | 0.04 | 0.41 | 0.01 | 0.08 |
| Variance (F-test) | 0 | 0 | 0 | 0 | 0 | 0 |

Mean and standard deviations are annualised.
The Jaque-Bera (JB) statistic tests the null hypothesis of the data being drawn from a normal distribution.
All p-values are rounded to 2 decimal places.

Table 3 – Potential Turning Point Dates (time= $T$ )and the Probability of a Turning Point Occurring From a Representative Model

| Aluminium | | | | Copper | | | | Lead | | | | Nickel | | | | Tin | | | | Zinc | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Downturn | | Upturn | | Downturn | | Upturn | | Downturn | | Upturn | | Downturn | | Upturn | | Downturn | | Upturn | | Downturn | | Upturn | |
| Date | $P_{TP}$ | Date | $P_{TP}$ | Date | $P_{TP}$ | Date | $P_{TP}$ | Date | $P_{TP}$ | Date | $P_{TP}$ | Date | $P_{TP}$ | Date | $P_{TP}$ | Date | $P_{TP}$ | Date | $P_{TP}$ | Date | $P_{TP}$ | Date | $P_{TP}$ |
| Oct 04 | 0.85* | Sep 03 | 0.77* | Oct 03 | 0.89 | Apr 04 | 0.85 | Oct 03 | 0.96* | Apr 04 | 0.99* | Oct 04 | 0.72* | Feb 04 | 0.53 | Sep 03 | 0.43* | Feb 04 | 0.33 | Oct 03 | 0.92* | Apr 04 | 0.89* |
| Mar 05 | 0.76* | Aug 04 | 0.66* | Jun 04 | 0.96* | May 04 | 0.94* | Jun 04 | 0.44* | Jan 05 | 0.65* | Jan 05 | 0.49* | Mar 04 | 0.91* | Oct 03 | 0.90* | Jun 04 | 0.80* | Sep 04 | 0.40* | Jul 04 | 0.79* |
| Jul 05 | 0.73 | May 05 | 0.98* | Jul 04 | 0.55* | Jan 05 | 0.63* | Jul 04 | 0.74* | Jul 05 | 0.94* | Feb 05 | 0.76* | Aug 04 | 0.85* | Apr 04 | 0.98* | Jan 05 | 0.98* | Oct 04 | 0.93* | Apr 05 | 0.88* |
| Aug 05 | 0.82* | Feb 06 | 0.27* | Mar 05 | 0.64 | May 05 | 0.77* | Mar 05 | 0.58* | Feb 06 | 0.43* | Dec 05 | 0.63* | Apr 05 | 0.52* | Aug 04 | 0.25* | Apr 05 | 0.89* | Jun 05 | 0.65* | Feb 06 | 0.26 |
| Nov 05 | 0.97 | Mar 06 | 0.63* | Sep 05 | 0.38 | Sep 06 | 0.45* | Sep 05 | 0.60 | Mar 06 | 0.76* | Aug 07 | 0.02* | Jul 05 | 0.85* | Sep 04 | 0.61* | Jul 05 | 0.94* | Nov 05 | 0.93 | Jun 06 | 0.96* |
| Dec 05 | 0.92* | Jun 07 | 0.82* | Oct 05 | 0.59* | Oct 06 | 0.68 | Oct 05 | 0.90* | Nov 06 | 0.18* | Sep 07 | 0.64* | Oct 05 | 0.96* | Nov 05 | 0.33* | Jun 06 | 0.97* | Dec 05 | 0.96* | Jan 07 | 0.97 |
| May 06 | 0.96* | Apr 08 | 0.66 | May 06 | 0.74 | Nov 06 | 0.82* | May 06 | 0.50* | Dec 06 | 0.20* | Aug 08 | 0.11 | Feb 06 | 0.39* | Dec 05 | 0.98* | Apr 07 | 0.55 | Apr 06 | 0.99* | Feb 07 | 0.99* |
| Oct 06 | 0.93* | May 08 | 0.75* | Aug 06 | 0.88* | Jun 07 | 0.78* | Aug 06 | 0.91 | Jan 07 | 0.58* | Dec 08 | 0.08* | Mar 06 | 0.57* | Oct 06 | 0.97* | May 07 | 0.51 | Oct 06 | 0.94 | Jun 07 | 0.91* |
| Oct 07 | 0.80 | | | Sep 06 | 0.99* | Apr 08 | 0.45* | Sep 06 | 0.96* | Dec 07 | 0.99* | Jan 09 | 0.79* | Jun 06 | 0.46 | Feb 08 | 0.81 | Jun 07 | 0.35 | Nov 06 | 0.92* | Sep 07 | 0.97* |
| Nov 07 | 0.75* | | | Mar 07 | 0.95 | May 08 | 0.8* | Mar 07 | 0.86* | Apr 08 | 0.84 | Apr 09 | 0.82* | Sep 06 | 0.58* | Mar 08 | 0.98* | Sep 07 | 0.62* | Apr 07 | 0.79* | Apr 08 | 0.95* |
| Feb 08 | 0.99* | | | Jun 07 | 0.98* | | | Jun 07 | 0.95 | May 08 | 0.99* | | | Apr 07 | 0.22* | May 09 | 0.99* | Dec 07 | 0.75* | Jan 08 | 0.69 | Jun 09 | 0.39* |
| Jul 08 | 0.79* | | | Jul 07 | 0.69* | | | Jul 07 | 0.99* | Sep 08 | 0.79 | | | May 07 | 0.32* | | | Mar 09 | 0.81* | Feb 08 | 0.76* | Jul 09 | 0.51* |
| Apr 09 | 0.62* | | | Oct 07 | 0.89 | | | Oct 07 | 0.97* | Oct 08 | 0.96* | | | Jun 07 | 0.98* | | | Jul 09 | 0.94* | Dec 08 | 0.37* | | |
| | | | | Feb 08 | 0.94* | | | Feb 08 | 0.97* | May 09 | 0.5* | | | Nov 07 | 0.55 | | | | | Jan 09 | 0.87* | | |
| | | | | Jul 08 | 0.61* | | | Jul 08 | 0.87* | | | | | Dec 07 | 0.98* | | | | | Apr 09 | 0.83* | | |
| | | | | Dec 08 | 0.01* | | | | | | | | | May 08 | 0.87 | | | | | | | | |
| | | | | Jan 09 | 0.81* | | | | | | | | | Jun 08 | 0.94* | | | | | | | | |
| | | | | Apr 09 | 0.88* | | | | | | | | | Oct 08 | 0.99* | | | | | | | | |

Model is when $q$=1, $m$=7 and $v$=1.

Table 4 – Turning Points Forecast Summary: A Representative Model

| | Correct | Incorrect | Total |
|---|---|---|---|
| | | A. Downturns | |
| DT | 55 | 15 | 70 |
| NDT | 10 | 2 | 12 |
| Total | 65<br>(79%) | 17<br>(21%) | 82<br>(100%) |
| | | B. Upturns | |
| UT | 50 | 11 | 61 |
| NUT | 10 | 4 | 14 |
| Total | 60<br>(80%) | 15<br>(20%) | 75<br>(100%) |

Model is when $q$=1, $m$=7 and $v$=1.
Calculated with symmetric loss function

Table 5 – Proper Scoring Rules

| | Brier Score | | | Spherical Score | | | Log Score | | |
|---|---|---|---|---|---|---|---|---|---|
| Models | UT | DT | Combined | UT | DT | Combined | UT | DT | Combined |
| | | | | A. Naive Models | | | | | |
| Always a TP | 0.61 | 0.56 | 0.59 | 0.72 | 0.70 | 0.71 | - | - | - |
| Optimist | 0.61 | 1.44 | 1.01 | 0.72 | 0.30 | 0.50 | - | - | - |
| Pessimist | 1.39 | 0.56 | 0.99 | 0.28 | 0.70 | 0.50 | - | - | - |
| Coin Flip | 0.50 | 0.50 | 0.50 | 0.71 | 0.71 | 0.71 | 0.69 | 0.69 | 0.69 |
| Past | 0.40 | 0.43 | 0.41 | 0.78 | 0.76 | 0.77 | 0.58 | 0.62 | 0.60 |
| | | | | B. Bayesian Models | | | | | |
| $m$=0, $v$=0, $q$=1 | 0.30 | 0.38 | 0.34 | 0.83 | 0.79 | 0.81 | 0.48 | 0.61 | 0.54 |
| $m$=0, $v$=0, $q$=3 | 0.30 | 0.38 | 0.35 | 0.83 | 0.79 | 0.81 | 0.48 | 0.61 | 0.57 |
| $m$=11, $v$=1, $q$=1 | 0.34 | 0.39 | 0.37 | 0.81 | 0.79 | 0.80 | 0.51 | 0.64 | 0.58 |
| $m$=11, $v$=1, $q$=3 | 0.33 | 0.41 | 0.37 | 0.81 | 0.77 | 0.81 | 0.49 | 0.65 | 0.55 |
| $m$=11, $v$=1, $q$=0 | 0.33 | 0.39 | 0.36 | 0.82 | 0.79 | 0.80 | 0.51 | 0.67 | 0.59 |
| $m$=7, $v$=1, $q$=1 | 0.32 | 0.37 | 0.34 | 0.82 | 0.80 | 0.81 | 0.49 | 0.60 | 0.55 |
| $m$=7, $v$=1, $q$=3 | 0.31 | 0.38 | 0.35 | 0.82 | 0.79 | 0.79 | 0.49 | 0.59 | 0.58 |
| $m$=7, $v$=1 $q$=0 | 0.31 | 0.37 | 0.34 | 0.83 | 0.80 | 0.81 | 0.50 | 0.64 | 0.55 |

The Log Score is not defined for the “absolute” naive forecast. “Combined” is the weighted average of the UT and DT results.

Table 6 – Results for Mining Firm Example

| | | Naive Models | | | AR Models | | With Economic Variables | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Always a TP | Optimist | Pessimist | $m$=0, $v$=0 | | $m$=11, $v$=1 | | | $m$=7, $v$=1 | | |
| | | | | | $q$=1 | $q$=3 | $q$=1 | $q$=3 | $q$=0 | $q$=1 | $q$=3 | $q$=0 |
| $C_1 = C_3 = 1$ | DT | 25 | 116 | 25 | 22 | 23 | 23 | 24 | 23 | 23 | 23 | 22 |
| | UT | 21 | 21 | 27 | 11 | 12 | 14 | 13 | 13 | 12 | 13 | 11 |
| | Combined | 46 | 137 | 52 | 33 | 35 | 37 | 37 | 36 | 35 | 36 | 33 |
| $C_2 = C_4 = 1$ | DT | 12 | 57 | 12 | 11 | 11 | 11 | 12 | 11 | 11 | 11 | 11 |
| | UT | 43 | 43 | 54 | 22 | 25 | 28 | 26 | 27 | 24 | 26 | 23 |
| | Combined | 55 | 100 | 66 | 33 | 36 | 39 | 38 | 38 | 35 | 37 | 34 |
| Correct (%) | DT | 69 | 30 | 69 | 74 | 73 | 73 | 72 | 73 | 73 | 73 | 74 |
| | UT | 72 | 72 | 28 | 75 | 71 | 69 | 71 | 71 | 75 | 72 | 76 |
| | Combined | 71 | 50 | 50 | 75 | 72 | 71 | 71 | 72 | 74 | 73 | 75 |

Calculated for $\hat{P}_{DT} = 33\%$ and $\hat{P}_{UT} = 67\%$

Table A1 – Data Sources

| Source | Variable |
|---|---|
| Thompson Reuters DataStream | LME Data: prices (spot and futures), quantity traded, warehouse stocks<br>CAD/USD nominal exchange rate<br>Morgan Stanley Capital Index<br>S&P Goldman Sachs Commodity Index |
| OECD | G7 Industrial Production<br>OECD M3 Index<br>Canadian CPI<br>US CPI |

Table A2 – Correlation of Metals Returns to Lagged Economic Variables

| Metal | Federal Funds Rate | GSCI | Money Growth | Industrial Production | Real CAD/USD | MSCI | Turnover | Warehouse Stocks | Lagged Premia | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | 3 Month | 15 Month |
| Aluminium | -0.15 | 0.19 | -0.20 | 0.20 | -0.16 | 0.17 | 0.15 | -0.31 | 0.03 | 0.02 |
| Copper | -0.18 | 0.24 | -0.25 | 0.07 | -0.21 | 0.19 | 0.15 | -0.31 | 0.00 | 0.22 |
| Lead | -0.14 | 0.03 | -0.14 | 0.04 | -0.17 | 0.19 | 0.17 | -0.28 | -0.17 | 0.34 |
| Nickel | -0.18 | 0.00 | -0.17 | 0.04 | -0.03 | 0.12 | -0.04 | -0.35 | 0.00 | 0.11 |
| Tin | -0.18 | 0.19 | -0.22 | 0.11 | -0.13 | 0.19 | -0.04 | -0.32 | -0.14 | -0.08 |
| Zinc | -0.18 | -0.04 | -0.18 | 0.01 | -0.08 | 0.21 | 0.12 | -0.35 | 0.16 | 0.35 |

Table A3 – Posterior Means of Coefficient Distributions

| Variables | AR Models $m$=0, $v$=0 | | With Economic Variables $m$=11, $v$=1 | | | With Economic Variables $m$=7, $v$=1 | | | AR Models $m$=0, $v$=0 | | With Economic Variables $m$=11, $v$=1 | | | With Economic Variables $m$=7, $v$=1 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $q$=1 | $q$=3 | $q$=1 | $q$=3 | $q$=0 | $q$=1 | $q$=3 | $q$=0 | $q$=1 | $q$=3 | $q$=1 | $q$=3 | $q$=0 | $q$=1 | $q$=3 | $q$=0 |
| | A. Aluminium | | | | | | | | B. Copper | | | | | | | |
| i) $\overline{p}_{it} = \gamma_i + \sum_{j=1}^{q} \alpha_{ij} p_{i,t-j} + \sum_{l=1}^{m} \beta_{il} X_{l,t-1}^{(i)}$ | | | | | | | | | | | | | | | | |
| $\gamma$ | 0.00 | 0.00 | 0.01 | 0.01 | 0.01 | 0.03 | 0.03 | 0.03 | 0.00 | -0.01 | 0.01 | 0.02 | 0.02 | 0.01 | 0.02 | 0.02 |
| $p_{t-1}$ | 0.24 | 0.29 | 0.26 | 0.27 | - | 0.14 | 0.20 | - | 0.31 | 0.34 | 0.24 | 0.26 | - | 0.25 | 0.27 | - |
| $p_{t-2}$ | - | -0.11 | - | -0.04 | - | - | -0.14 | - | - | -0.10 | - | -0.08 | - | - | -0.05 | - |
| $p_{t-3}$ | - | -0.04 | - | 0.07 | - | - | 0.00 | - | - | -0.10 | - | -0.18 | - | - | -0.19 | - |
| Real CAD/USD | - | - | 0.05 | -0.01 | 0.29 | 0.26 | 0.24 | 0.24 | - | - | -0.08 | -0.07 | 0.30 | -0.09 | -0.07 | -0.19 |
| Season Dummy | - | - | 0.02 | 0.02 | 0.01 | 0.02 | 0.02 | 0.02 | - | - | 0.01 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 |
| Turnover Volume | - | - | 0.01 | 0.01 | 0.02 | 0.01 | 0.01 | 0.02 | - | - | -0.04 | -0.05 | 0.02 | -0.04 | -0.06 | -0.03 |
| Warehouse Stocks | - | - | -0.08 | -0.08 | 0.03 | -0.05 | -0.03 | -0.07 | - | - | -0.07 | -0.07 | 0.03 | -0.07 | -0.06 | -0.10 |
| Fed Funds Rate | - | - | -0.22 | -0.19 | 0.12 | -0.16 | -0.21 | -0.18 | | - | 0.04 | -0.09 | 0.26 | -0.08 | -0.12 | -0.10 |
| MSCI | - | - | -0.04 | -0.06 | 0.10 | 0.01 | 0.00 | 0.02 | - | - | 0.04 | 0.05 | 0.11 | 0.07 | 0.06 | 0.08 |
| OECD M3 Index | - | - | -1.80 | -1.69 | 1.83 | -3.35 | -3.33 | -3.46 | - | - | -2.24 | -2.69 | 2.13 | -1.52 | -2.44 | -2.13 |
| 3 Mth Premium | - | - | -0.45 | -0.36 | 0.29 | - | - | - | - | - | 0.00 | 0.00 | 0.16 | - | - | - |
| 15 Mth Premium | - | - | 0.32 | 0.32 | 0.09 | - | - | - | - | - | 0.02 | 0.00 | 0.03 | - | - | - |
| Industrial Prod | - | - | -0.07 | -0.08 | 0.06 | - | - | - | - | - | -0.12 | -0.09 | 0.08 | - | - | - |
| GSCI | - | - | -0.03 | -0.03 | 0.09 | - | - | - | - | - | 0.02 | 0.05 | 0.09 | - | - | - |
| ii) $\ln(\tau_{it}) = \delta_{i0} + \sum_{h=1}^{v} \delta_{ih} Y_{h,t-1}^{(i)}$ and $p_t \sim t(\overline{p}_t, \tau_t, k)$ | | | | | | | | | | | | | | | | |
| $\delta_0$ | - | - | 6.59 | 6.55 | 0.15 | 6.52 | 6.55 | 6.51 | - | - | 6.38 | 6.54 | 0.15 | 6.42 | 6.54 | 6.32 |
| Turnover Volume | - | - | -1.06 | -1.17 | 0.81 | -2.06 | -1.85 | -2.21 | - | - | -0.73 | -0.75 | 0.53 | -0.77 | -0.84 | -1.03 |
| $k$ | 17.25 | 17.57 | 15.01 | 16.49 | 7.11 | 15.64 | 14.97 | 15.41 | 9.472 | 9.69 | 13.85 | 9.63 | 7.15 | 12.91 | 9.79 | 15.36 |
| $\tau$ | 596.8 | 606.8 | - | - | - | - | - | - | 622.5 | 627.9 | - | - | - | - | - | - |

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Table A3 – Posterior Means of Coefficient Distributions (continued)

| | AR Models | | With Economic Variables | | | | | | AR Models | | With Economic Variables | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $m$=0, $v$=0 | | $m$=11, $v$=1 | | | $m$=7, $v$=1 | | | $m$=0, $v$=0 | | $m$=11, $v$=1 | | | $m$=7, $v$=1 | | |
| | $q$=1 | $q$=3 | $q$=1 | $q$=3 | $q$=0 | $q$=1 | $q$=3 | $q$=0 | $q$=1 | $q$=3 | $q$=1 | $q$=3 | $q$=0 | $q$=1 | $q$=3 | $q$=0 |
| | C. Lead | | | | | | | | D. Nickel | | | | | | | |
| i) $\overline{p}_{it} = \gamma_i + \sum_{j=1}^{q} \alpha_{ij} p_{i,t-j} + \sum_{l=1}^{m} \beta_{il} X_{l,t-1}^{(i)}$ | | | | | | | | | | | | | | | | |
| $\gamma$ | 0.00 | 0.00 | -0.02 | -0.02 | 0.02 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.03 | 0.03 | 0.02 | 0.03 | 0.02 | 0.04 |
| $p_{t-1}$ | 0.14 | 0.14 | 0.08 | 0.07 | - | 0.07 | 0.06 | - | 0.30 | 0.32 | 0.30 | 0.31 | - | 0.24 | 0.29 | - |
| $p_{t-2}$ | - | -0.01 | - | 0.03 | - | - | 0.01 | - | - | -0.07 | - | -0.03 | - | - | -0.10 | - |
| $p_{t-3}$ | - | -0.01 | - | -0.01 | - | - | -0.02 | - | - | -0.02 | - | 0.03 | - | - | 0.00 | - |
| Real CAD/USD | - | - | -0.41 | -0.38 | 0.30 | -0.28 | -0.25 | -0.32 | - | - | -0.28 | -0.31 | 0.46 | -0.12 | -0.19 | -0.42 |
| Season Dummy | - | - | 0.03 | 0.03 | 0.01 | 0.03 | 0.03 | 0.03 | - | - | 0.02 | 0.02 | 0.02 | 0.04 | 0.03 | 0.04 |
| Turnover Volume | - | - | -0.02 | -0.02 | 0.01 | -0.02 | -0.02 | -0.02 | - | - | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 |
| Warehouse Stocks | - | - | -0.10 | -0.11 | 0.05 | -0.11 | -0.12 | -0.12 | - | - | 0.02 | 0.02 | 0.04 | 0.05 | 0.05 | 0.00 |
| Fed Funds Rate | - | - | 0.40 | 0.39 | 0.25 | -0.07 | -0.11 | -0.07 | - | - | -0.39 | -0.39 | 0.18 | -0.40 | -0.36 | -0.42 |
| MSCI | - | - | 0.16 | 0.16 | 0.11 | 0.21 | 0.21 | 0.22 | - | - | 0.00 | -0.02 | 0.15 | -0.01 | 0.00 | 0.02 |
| OECD M3 Index | - | - | -1.99 | -2.20 | 2.26 | -0.26 | -0.99 | -0.35 | - | - | -0.62 | -0.47 | 2.90 | -1.97 | -0.31 | -4.01 |
| 3 Mth Premium | - | - | -0.09 | -0.11 | 0.14 | - | - | - | - | - | -0.81 | -0.76 | 0.52 | - | - | - |
| 15 Mth Premium | - | - | 0.08 | 0.08 | 0.03 | - | - | - | - | - | 0.20 | 0.20 | 0.12 | - | - | - |
| Industrial Prod | - | - | -0.09 | -0.08 | 0.07 | - | - | - | - | - | -0.14 | -0.14 | 0.10 | - | - | - |
| GSCI | - | - | -0.07 | -0.07 | 0.09 | - | - | - | - | - | -0.12 | -0.12 | 0.13 | - | - | - |
| ii) $\ln(\tau_{it}) = \delta_{i0} + \sum_{h=1}^{v} \delta_{ih} Y_{h,t-1}^{(i)}$ and $p_t \sim t(\overline{p}_t, \tau_t, k)$ | | | | | | | | | | | | | | | | |
| $\delta_0$ | - | - | 6.31 | 6.29 | 0.20 | 6.33 | 6.33 | 6.33 | - | - | 5.66 | 5.64 | 0.17 | 5.74 | 5.70 | 5.72 |
| Turnover Volume | - | - | -1.54 | -1.50 | 0.56 | -1.43 | -1.40 | -1.47 | - | - | -0.73 | -0.77 | 0.63 | -0.72 | -0.79 | -0.83 |
| $k$ | 6.168 | 6.02 | 9.39 | 9.74 | 5.63 | 7.81 | 7.945 | 8.337 | 14.75 | 15.76 | 16.27 | 16.30 | 7.21 | 10.67 | 12.66 | 9.53 |
| $\tau$ | 518.9 | 512.6 | - | - | - | - | - | - | 266.1 | 264.9 | - | - | - | - | - | - |

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Table A3 – Posterior Means of Coefficient Distributions (continued)

| | AR Models | | With Economic Variables | | | | | | AR Models | | With Economic Variables | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *m*=0, *v*=0 | | *m*=11, *v*=1 | | | *m*=7, *v*=1 | | | *m*=0, *v*=0 | | *m*=11, *v*=1 | | | *m*=7, *v*=1 | | |
| | *q*=1 | *q*=3 | *q*=1 | *q*=3 | *q*=0 | *q*=1 | *q*=3 | *q*=0 | *q*=1 | *q*=3 | *q*=1 | *q*=3 | *q*=0 | *q*=1 | *q*=3 | *q*=0 |
| | E. Tin | | | | | | | | F. Zinc | | | | | | | |
| i) $\overline{p}_{it} = \gamma_i + \sum_{j=1}^{q} \alpha_{ij} p_{i,t-j} + \sum_{l=1}^{m} \beta_{il} X_{l,t-1}^{(i)}$ | | | | | | | | | | | | | | | | |
| $\gamma$ | 0.00 | 0.00 | 0.02 | 0.01 | 0.01 | 0.02 | 0.02 | 0.02 | 0.00 | 0.00 | -0.01 | -0.02 | 0.02 | 0.01 | 0.01 | 0.01 |
| $p_{t-1}$ | 0.16 | 0.13 | 0.05 | 0.06 | - | 0.00 | -0.01 | - | 0.17 | 0.19 | 0.10 | 0.13 | - | 0.06 | 0.05 | - |
| $p_{t-2}$ | - | 0.02 | - | 0.02 | - | - | -0.05 | - | - | 0.00 | - | 0.14 | - | - | 0.04 | - |
| $p_{t-3}$ | - | -0.04 | - | 0.00 | - | - | -0.01 | - | - | 0.04 | - | 0.08 | - | - | 0.00 | - |
| Real CAD/USD | - | - | -0.14 | -0.14 | 0.23 | -0.21 | -0.22 | -0.21 | - | - | -0.28 | -0.32 | 0.30 | -0.14 | -0.14 | -0.16 |
| Season Dummy | - | - | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | - | - | 0.01 | 0.02 | 0.01 | 0.01 | 0.01 | 0.01 |
| Turnover Volume | - | - | 0.00 | 0.00 | 0.01 | -0.01 | 0.00 | -0.01 | - | - | 0.01 | 0.02 | 0.01 | 0.02 | 0.02 | 0.02 |
| Warehouse Stocks | - | - | -0.11 | -0.11 | 0.03 | -0.08 | -0.10 | -0.08 | - | - | -0.10 | -0.12 | 0.05 | -0.05 | -0.09 | -0.06 |
| Fed Funds Rate | - | - | -0.23 | -0.23 | 0.11 | -0.10 | -0.13 | -0.11 | - | - | 0.04 | 0.20 | 0.20 | -0.17 | -0.17 | -0.18 |
| MSCI | - | - | -0.03 | -0.03 | 0.08 | -0.03 | -0.03 | -0.04 | - | - | 0.10 | 0.08 | 0.10 | 0.17 | 0.16 | 0.17 |
| OECD M3 Index | - | - | -1.69 | -1.43 | 1.48 | -2.36 | -2.48 | -2.25 | - | - | -0.85 | -0.11 | 1.80 | -0.30 | -0.10 | -0.18 |
| 3 Mth Premium | - | - | -0.81 | -0.85 | 0.47 | - | - | - | - | - | 0.07 | -0.12 | 0.17 | - | - | - |
| 15 Mth Premium | - | - | 0.34 | 0.36 | 0.14 | - | - | - | - | - | 0.10 | 0.23 | 0.08 | - | - | - |
| Industrial Prod | - | - | 0.02 | 0.01 | 0.05 | - | - | - | - | - | -0.06 | -0.07 | 0.07 | - | - | - |
| GSCI | - | - | 0.02 | 0.03 | 0.06 | - | - | - | - | - | -0.10 | -0.11 | 0.08 | - | - | - |
| ii) $\ln(\tau_{it}) = \delta_{i0} + \sum_{h=1}^{v} \delta_{ih} Y_{h,t-1}^{(i)}$ and $p_t \sim t(\overline{p}_t, \tau_t, k)$ | | | | | | | | | | | | | | | | |
| $\delta_0$ | - | - | 7.10 | 7.07 | 0.25 | 7.03 | 7.06 | 7.03 | - | - | 6.38 | 6.35 | 0.20 | 6.44 | 6.43 | 6.45 |
| Turnover Volume | - | - | -1.09 | -1.07 | 0.67 | -0.83 | -0.96 | -0.84 | - | - | -1.49 | -1.41 | 0.67 | -1.76 | -1.54 | -1.79 |
| $k$ | 6.44 | 6.20 | 6.47 | 6.77 | 4.98 | 7.04 | 6.683 | 7.16 | 5.795 | 5.87 | 10.47 | 12.08 | 6.24 | 8.27 | 8.135 | 8.015 |
| $\tau$ | 1039 | 1040 | - | - | - | - | - | - | 625.7 | 623.6 | - | - | - | - | - | - |

Table A4 – RMSE of Point Forecasts (percent)

| Metals | Naive Models: RW: Levels | Naive Models: RW: Returns | Simple AR Models ($m=0$ $v=0$): $q=1$ | Simple AR Models ($m=0$ $v=0$): $q=3$ | Models with Economic Variables ($m=11$ $v=1$): $q=1$ | ($m=11$ $v=1$): $q=3$ | ($m=11$ $v=1$): $q=0$ | ($m=7$ $v=1$): $q=1$ | ($m=7$ $v=1$): $q=3$ | ($m=7$ $v=1$): $q=0$ |
|---|---|---|---|---|---|---|---|---|---|---|
| Aluminium | 6.18 | 6.89 | 5.80 | 5.97 | 6.25 | 6.28 | 6.37 | 5.78 | 5.95 | 5.99 |
| Copper | 9.51 | 9.56 | 8.50 | 8.69 | 8.39 | 8.42 | 8.83 | 8.38 | 8.49 | 8.97 |
| Lead | 10.75 | 12.48 | 10.43 | 10.47 | 10.51 | 10.49 | 10.66 | 10.23 | 10.24 | 10.35 |
| Nickel | 11.53 | 13.04 | 10.80 | 10.84 | 11.07 | 11.08 | 11.47 | 10.84 | 11.01 | 11.19 |
| Tin | 7.58 | 8.52 | 7.29 | 7.31 | 7.78 | 7.72 | 7.85 | 7.55 | 7.75 | 7.56 |
| Zinc | 8.69 | 9.38 | 8.23 | 8.16 | 8.22 | 8.37 | 8.35 | 8.27 | 8.12 | 8.52 |
| Median | 9.10 | 9.47 | 8.37 | 8.43 | 8.31 | 8.40 | 8.59 | 8.33 | 8.31 | 8.75 |
| Mean | 9.04 | 9.98 | 8.51 | 8.57 | 8.70 | 8.73 | 8.92 | 8.51 | 8.59 | 8.76 |

The variables $q$, $m$ and $v$ come from the equations $\overline{p}_{it} = \gamma_i + \sum_{j=1}^{q} \alpha_{ij} p_{i,t-j} + \sum_{l=1}^{m} \beta_{il} X_{l,t-1}^{(i)}$ and $\ln(\tau_{it}) = \delta_{i0} + \sum_{h=1}^{v} \delta_{ih} Y_{h,t-1}^{(i)}$ .

Figure 1 – Percent Correct

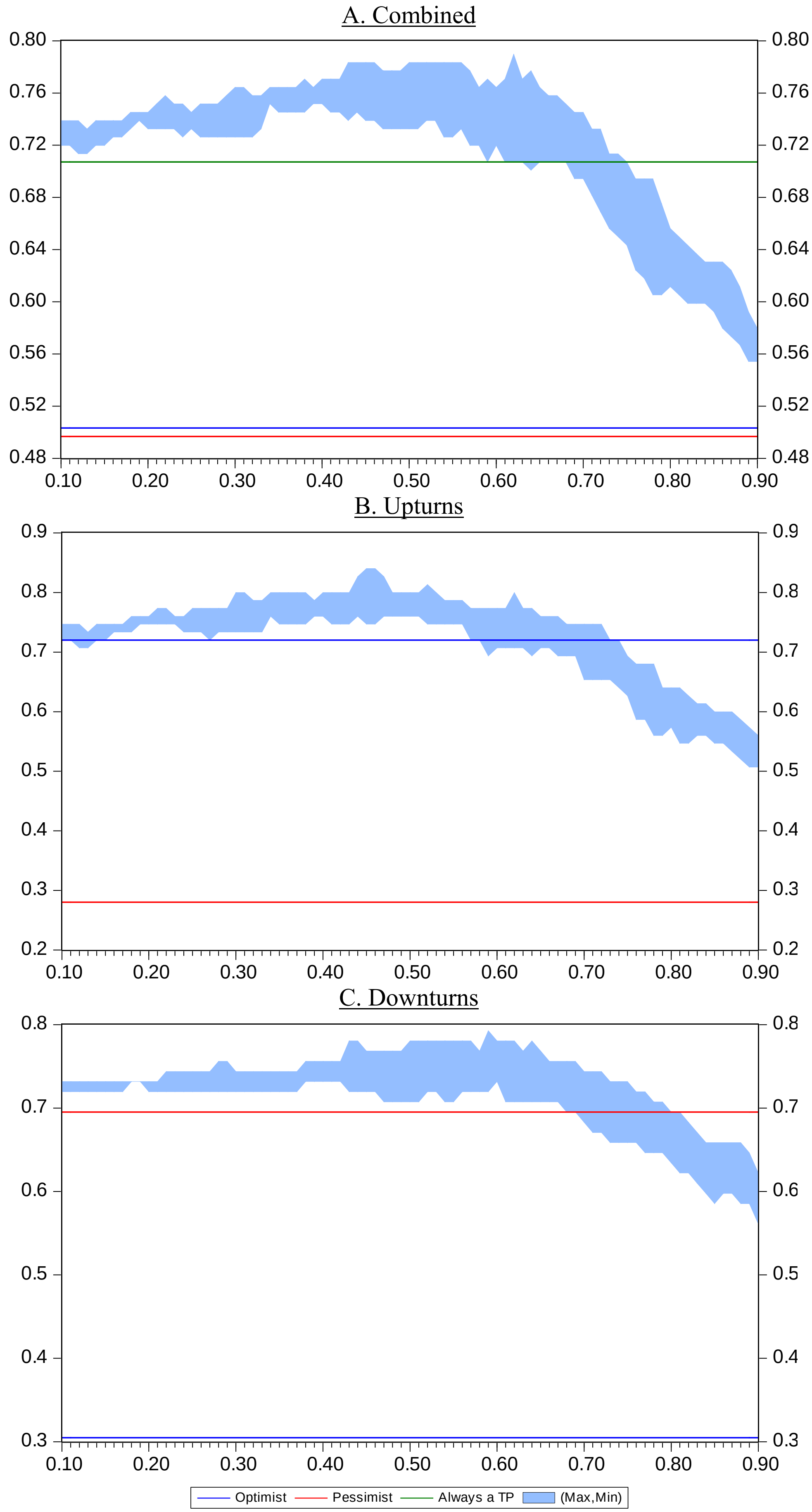


Figure 2 – Loss Function For Combined Decision Making

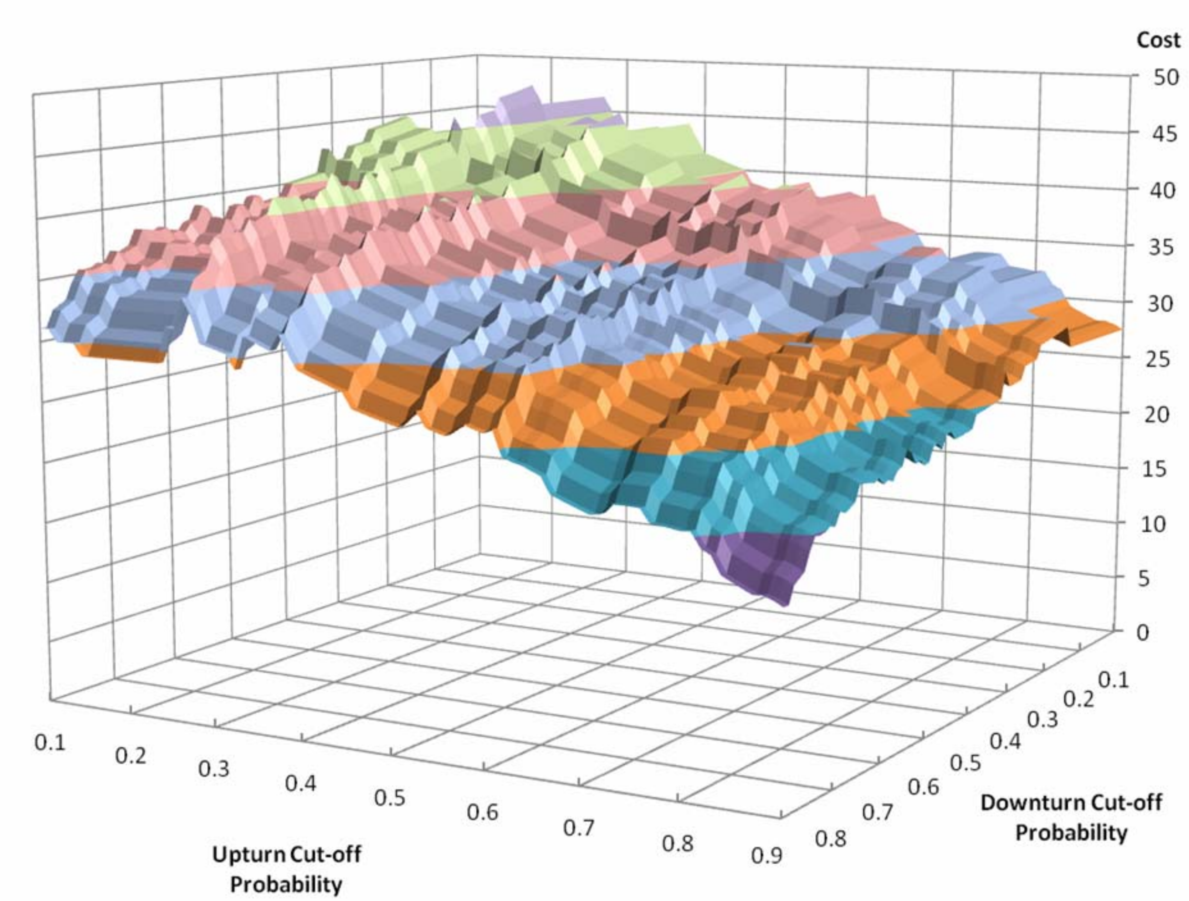



Figure 3 – Bias in Loss Function Evaluation

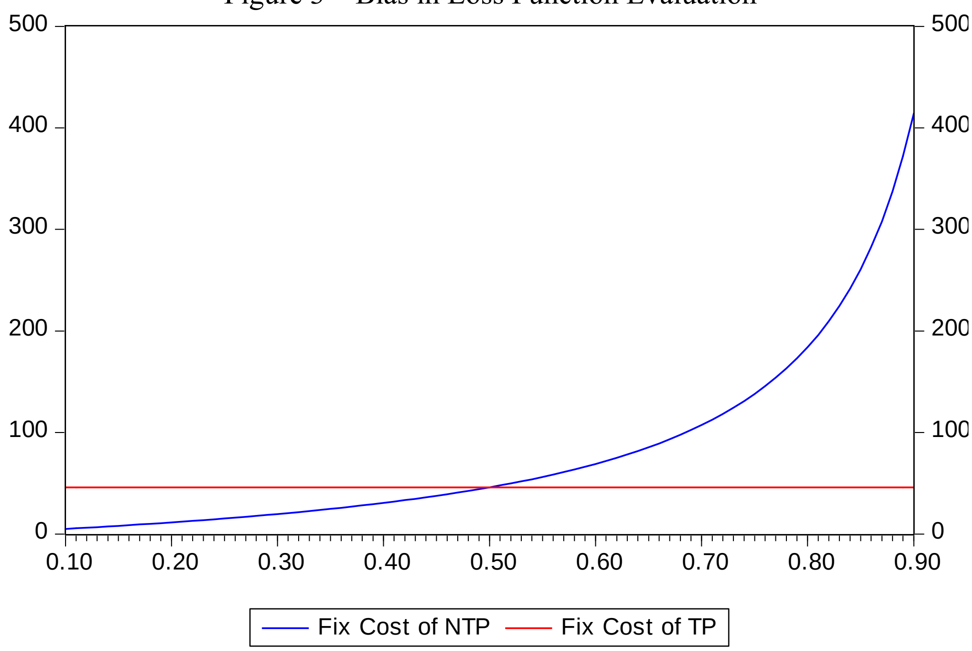
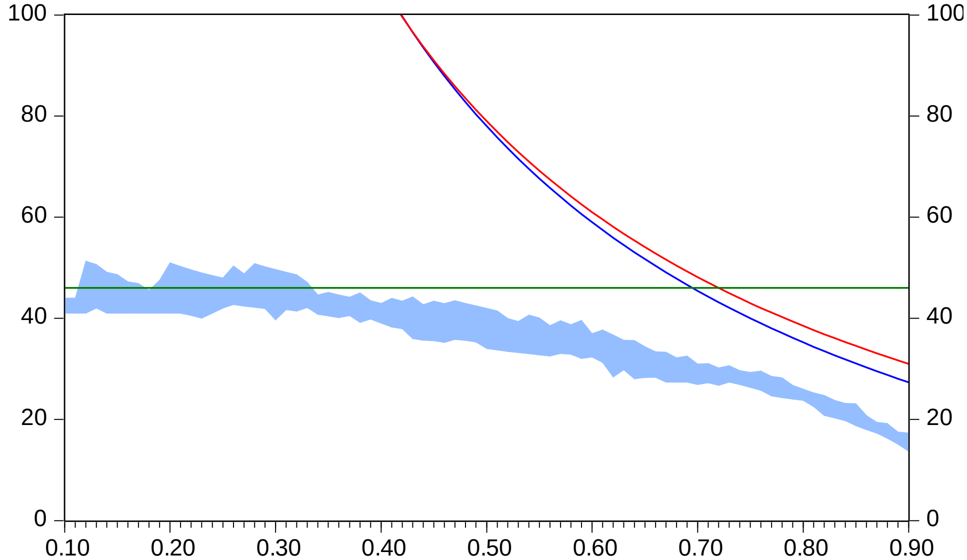
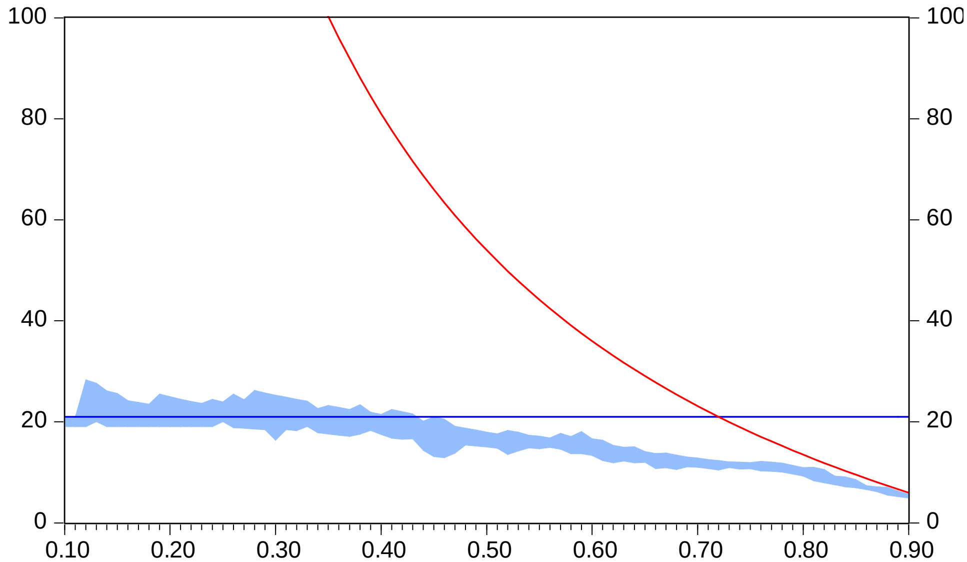


Figure 4 – Total Cost Comparisons

A. Combined



B. Upturn



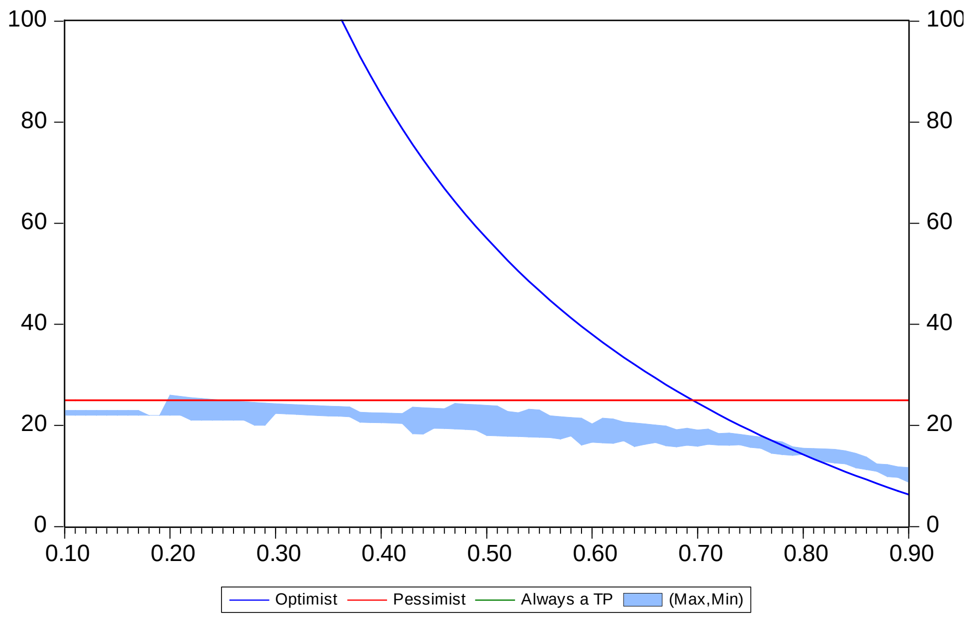
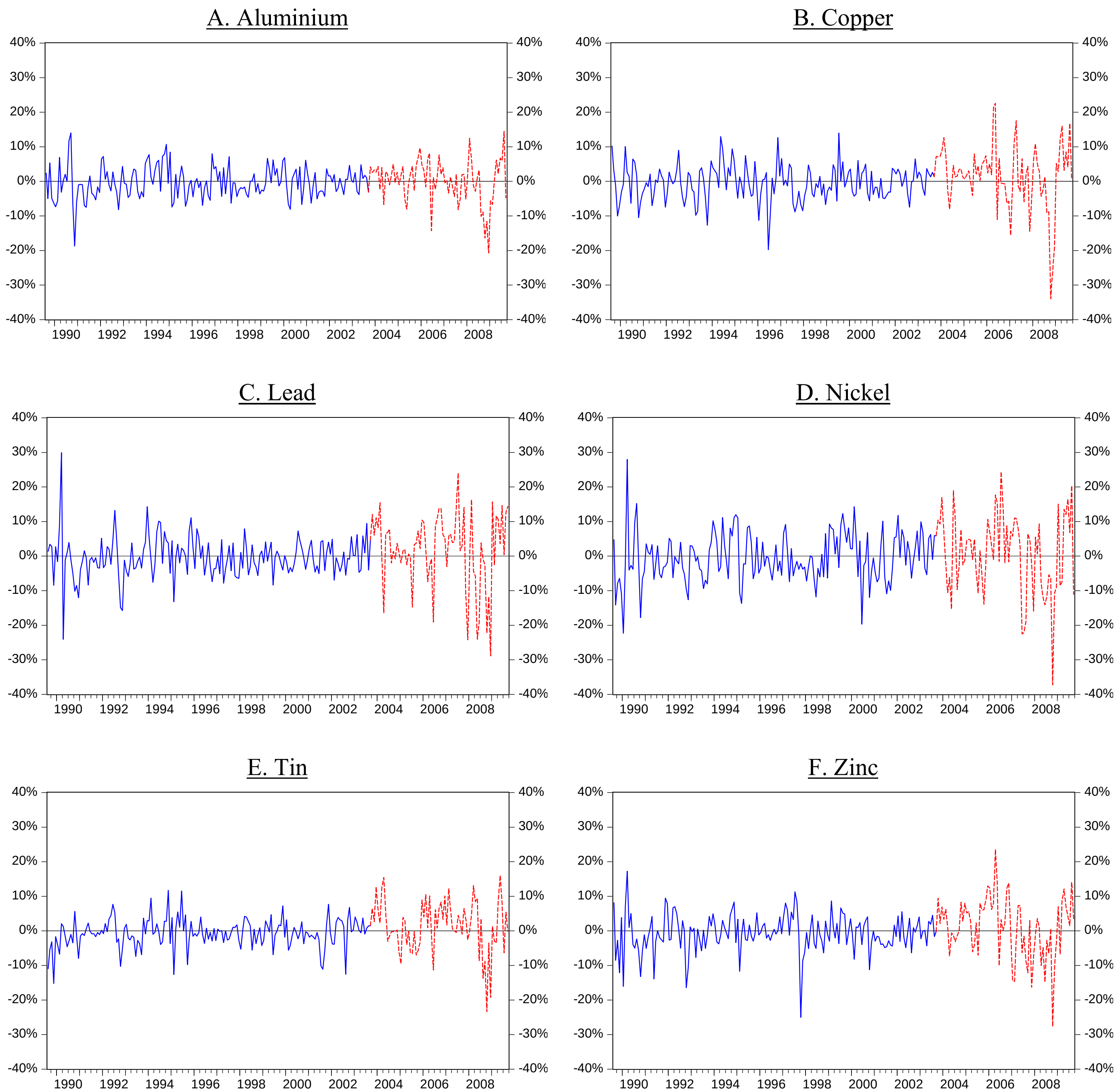


Figure A1 – Commodity Returns



## References


Akram, Q.F, 2009 “Commodity Prices, Interest Rates and the Dollar”, *Energy Economics 31*: 838-51

Borensztein, E and Reinhart, C.M, 1994 “The Macroeconomic Determinants of Commodity Prices”, *IMF Staff Papers 41:* 236-61.

Cashin, P, McDermott, C.J and Scott, A, 2002, “Booms and Slumps in World Commodity Prices”, *Journal of Developmental Economics 69*: 277-96.

Chen, Y.C, Rogoff, K. and Rossi, B, 2010, “Can Exchange Rates Forecast Commodity Prices?” *Quarterly Journal of Economics*, *125*: 1145-94

Chin, D, Geweke, J, and Miller, P, 2000, “Predicting Turning Points”, *Technical Paper Series*, Congressional Budget Office, Washington DC.

Clements, K.W and Halperin, D (2010). "Metals Markets Cycles." Forthcoming working paper, Business School, The University of Western Australia.

Clements, K and Fry, R, 2008, “Commodity Currencies and Currency Commodities”, *Resources Policy 33*: 55-73

Cody, B.J and Mills L.O, 1991, “The Role of Commodity Prices in Formulating Monetary Policy”, *The Review of Economics and Statistics 73*: 358-65.

Czardo, C, Gneitning T, and Held, L, 2009, “Predictive Model Assessment for Count Data”, *Biometrics*, 65: 1254-61.

Deaton, A and Laroque, G, 1992, “On the Behaviour of Commodity Prices”, *The Review of Economic Studies 59*:1-23.

Fama, E.F and French, K.R, 1987, “Commodity Futures Prices: Some Evidence on Forecast Power, Premiums and the Theory of Storage” *The Journal of Business 60*: 55-73.

Frankel, J.A, 2010, “The Natural Resource Curse: A Survey”, *NBER Working Paper w15836*.

Frankel, J.A and Hardouvelis, G, 1985, “Commodity Prices, Money Surprises and Fed Credibility”, *Journal of Money, Credit and Banking*, *17*: 427-38.

Frankel, J.A. and Rose, A.K, 2009, “Determinants of Agricultural and Mineral Commodity Prices” in: Fry, R, Jones, C, and Kent, C, (eds.), 2010, Inflation in an Era of Relative Price Shocks, RBA, Sydney.

Friedman, M, 1953, “The Methodology of Positive Economics”, In Essays in Positive Economics, University of Chicago Press, 3-43.

Geweke, J, 2005, Contemporary Bayesian Econometrics and Statistics. Hoboken, N.J, Wiley-Interscience.

Goren, J.J, and Pesenti, P.A, 2010, “Commodity Prices, Commodity Currencies, and Global Economic Developments”, *NBER Working Paper 15743*

Just, R.E and Rausser, G.C, 1981, “Commodity Price Forecasting with Large-Scale Econometric Models and the Futures Market, *Americal Journal of Agricultural Economics 63: 197-208.*

Kling, J.L, 1987, “Predicting the Turning Points of Business and Economic Time Series”, *Journal of Business 60*: 201-38

Lunn, D.J, Thomas, A, Best, N, and Spiegelhalter, D, 2000, “Winbugs – A Bayesian Modelling Framework: Concepts, Structure, and Extensibility”, *Statistics and Computing 10*: 325-37.

Roberts, M.C. 2009 “Duration and Characteristics of Metals Price Cycles”, *Resources Policy 34*:87-102.

Sjaastad, L and Scacciavillani, F, 1996, “The Price of Gold and the Exchange Rate”, *Journal of International Money and Finance 15*: 331-46.

Theil, H, 1965, Economic Forecasts and Policy 2nd Revised Ed. North-Holland Publishing, Amsterdam.

Wecker, W.E, 1979, “Predicting Turning Points of a Time Series”, *Journal of Business 52*: 35-50.

Zellner, A, 1985, “Bayesian Econometrics”, *Econometrica 53*: 253-69.

Zellner, A, Hong, C and Gulati, G.M, 1990, “Turning Points in Economic Time Series, Loss Structures and Bayesian Forecasting”, in: Geisser, S, Hodges, J, Press, J.S and Zellner, A, eds., Bayesian and Likelihood Methods in Statistics and Econometrics: Essays in Honour of George A. Barnard (North-Holland, Amsterdam) 371-93.

Zellner, A, Hong, C and Min, C, 1991, “Forecasting Turning Points in International Output Growth Rates Using Bayesian Exponentially Weighted Autoregression, Time-Varying Parameter, and Pooling Techniques”, *Journal of Econometrics 49*: 275-304.

Zellner, A and Min, C, 1999, “Forecasting Turning Points in Countries’ Output Growth Rates: A Response to Milton Friedman”, *Journal of Econometrics 88*: 203-06.

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