Evaluating Direct and Iterated Multistep Smooth Transition Autoregressive Methods for Commodity Price Forecasting

Abstract

Among nonlinear time series models, smooth transition autoregressive (STAR) framework has become particularly popular in commodity price analysis. In many instances, this modeling framework helps capture essential features of complex price dynamics. The question is, does the improved in-sample fit result in more accurate forecasts? One can generate intermediate-term forecasts either by iterating forward an estimated one-step model—i.e., the iterated method—or by directly estimating a horizon-specific model—i.e., the direct method. Iterated method is more efficient—and thus preferred—when a one-step model is correctly specified; otherwise, the direct method may lead to more accurate forecasts. In the STAR framework, when a one-step model is estimated, a bootstrap simulation is necessary to numerically approximate multistep forecasts; alternatively, a horizon-specific nonlinear model needs to be estimated for each horizon to generate direct multistep forecasts. Such a trade-off in computational, and indeed judgmental burden amplifies the need for better understanding of any advantage one method may have over another. The findings of this study, which are based on 36 agricultural and non-agricultural commodity prices, suggest that even when the STAR models well approximate complex commodity price dynamics, they offer little advantage, and indeed, in most instances appear to be an inferior alternative to the basic autoregressive framework for multistep commodity price forecasting.

Keywords: Commodity Prices; Direct Forecasts; Interval Forecasts; Iterated Forecasts; Multistep Forecasts; Point Forecasts; Smooth Transition Autoregression

JEL Classification: C53; E37; Q02

1 Introduction

Smooth transition autoregressive (STAR) models have been successfully deployed to approximate the complex commodity price dynamics (e.g., Holt and Craig, 2006; Balagtas and Holt, 2009; Enders and Holt, 2012; Hood and Dorfman, 2015; Ubilava, 2018). This line of empirical research is important and relevant, as commodity price dynamics can be asymmetric because of transactions costs in spatial and temporal arbitrage, the market structure, or simply due to the peculiar nature of production processes. The previous studies have demonstrated that STAR models can capture essential features of price dynamics.

The question remains whether the improved in-sample fit, due to the nonlinear modeling, manifests into a better forecast performance, particularly at longer horizons; and whether the direct or the iterated multistep forecasting method yields more accurate forecasts from a STAR-type model. The answers to these questions can benefit market participants who make their decisions based on prices set to be realized several months into the future.

The iterated multistep method fits a one-step model—thus minimizing the squares of one-step ahead residuals—to generate a multistep forecast by recursively substituting the intermediate forecasts into the projection up to horizon h. The direct multistep method fits an h-step model—thus minimizing the squares of h-step ahead residuals—which directly generates a multistep ahead forecast at the desired horizon. The theory suggests that while iterated multistep forecasts are more efficient when the (one-step) model is correctly specified, direct multistep forecasts can be more robust to model misspecification (Weiss, 1991; Stock and Watson, 1998).

The foregoing trade-off—usually examined in the context of linear models (e.g., Chevillon and Hendry, 2005; Marcellino et al., 2006)—is also applicable to nonlinear models. To that end, the STAR modeling framework offers an additional set of peculiarities. On the one hand, an iterated method necessitates a numerical approximation to generate forecasts from nonlinear models, because a simple extrapolation—commonly applied to generate forecasts from linear models—results in biased multistep forecasts (e.g., Teräsvirta et al., 2010). On the other hand, a direct method requires selection and estimation of the preferred nonlinear specification at each considered horizon, which brings on a computational burden of its own (e.g., Teräsvirta, 2006).

A number of studies have examined direct multistep forecasts vis-à-vis iterated multistep forecasts, primarily in linear univariate or multivariate settings (see, for example, Chevillon, 2007, for the survey of the literature). More recently, Chevillon (2016) compared the two multistep forecasting methods in presence of structural breaks in time series, while Enders and Pascalau (2015) proposed a pre-testing procedure to investigate the potential benefit of forecasting from STAR-type models. The present study builds on the previous research and contributes to the literature by comparing direct and iterated multistep forecasts of a large set of primary commodity prices from models that can be characterized by STAR-type of regime–switching dynamics.

This study finds that in general, the iterated method is preferred to the direct method, when STAR-type nonlinearity is the underlying feature of the time series. Barring a few exceptions, this study also finds that forecasts generated from linear models are more accurate than those from nonlinear models, even when the linearity tests of Teräsvirta (1994)—including its multistep variant of Enders and Pascalau (2015)—point to STAR-type dynamics in the time series.

The findings of this study shed light on the potential advantage in generating accurate multistep forecasts of the iterated method over the direct method when the underlying modeling framework is nonlinear, as well as that of the smooth transition autoregressive models vis-à-vis their linear counterparts. Overall, the present study concludes that while STAR modeling framework is well suited to unveil nonlinear intricacies of commodity price series—as evidenced by previous studies, as well as the present study—when it comes to multistep forecasting, the framework doesn't offer an advantage, and indeed, in most instances appears to be an inferior alternative to the basic autoregressive framework.

2 The Smooth Transition Autoregression

The evolution of STAR type econometric models began with Bacon and Watts (1971), who pioneered the concept of a smooth transition regression. Subsequently, Chan and Tong (1986) advocated this model in a time series context. Luukkonen et al. (1988) and Teräsvirta (1994) introduced and developed smooth STAR modeling and testing frameworks. In what follows, I will briefly outline the key characteristics of a STAR model.

To begin, consider a linear autoregressive model of order p, AR(p):

$$y_t = \beta_0 + \sum_{i=1}^{p} \beta_i y_{t-i} + \varepsilon_t \tag{1}$$

where y_t is the dependent variable in period t; β_i, $i = 0, \ldots, p$, are parameters defining the dynamic properties of the model; and ε_t is a white noise process.

The linearity restriction in the foregoing model can be relaxed in a number of different ways. One such way is the smooth transition autoregressive modeling framework of Teräsvirta (1994). This framework introduces a specific type of regime–dependency in the model:

$$y_t = \beta_{10} + \sum_{i=1}^{p} \beta_{1i} y_{t-i} + \left[\beta_{20} + \sum_{i=1}^{p} \beta_{2i} y_{t-i}\right] G\left(s_t; \gamma, c\right) + \varepsilon_t \tag{2}$$

where $G(s_t; \gamma, c)$ is the transition function, bounded by zero and one. The value of this function is attained depending on the transition variable (s_t), and the smoothness (γ) and centrality (c) parameters. The transition variable can be any variable. In practice, often, it is the lagged dependent variable, in which case the model falls within the family of self-exciting autoregressive models. The non-negative smoothness parameter determines the speed-of-transition between the regimes, wherein the regimes are centered around the centrality parameter. For the low values of γ the transition between the regimes is gradual; as $\gamma \to \infty$, depending on the functional form of $G(\cdot)$, the switch between the regimes becomes instantaneous, or the model reduces to a linear one.

Two of the possible choices for the transition functions, and certainly the most popular ones, are the logistic and exponential functions, respectively given by:

$$G\left(s_t; \gamma, c\right) = \left\{1 + \exp\left[-\gamma\left(\frac{s_t - c}{\sigma_s}\right)\right]\right\}^{-1} \qquad \text{(logistic)} \tag{3}$$

$$G\left(s_t; \gamma, c\right) = 1 - \exp\left[-\gamma\left(\frac{s_t - c}{\sigma_s}\right)^2\right] \qquad \text{(exponential)} \tag{4}$$

The sigmoid-shaped logistic function is suitable in situations where asymmetries in autoregressive dynamics in relation to the transition variable are suspected. In this case, the centrality parameter is the inflection point of the transition function. The inverted bell-shaped exponential function is useful for situations where nonlinearity in dynamics is linked to the deviation of s_t from the centrality parameter. Both these functions are normalized by the sample standard deviation of the transition variable (σ_s), which makes the smoothness parameter unit–free.

Whether a logistic or an exponential transition function is better suited to approximate the regime–dependent dynamics of the time series, or whether the time series is, indeed, characterized by a STAR–type nonlinearity, are testable hypotheses. However, the tests need to be carried out in an auxiliary regression setting—as proposed by Luukkonen et al. (1988)—to circumvent the unidentified nuisance parameter issue, better known as the Davies' problem (Davies, 1977, 1987). The auxiliary regression is the result of the Taylor series expansion of the transition function around $\gamma = 0$ that, in effect, interacts the polynomials of the transition variable with the lagged dependent variables of the linear autoregressive model. That is:

$$y_t = \phi_0 + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{k=1}^{3} \sum_{i=1}^{p} \varphi_{ki} y_{t-i} s_t^k + \upsilon_t, \tag{5}$$

where υ_t combines the original error term, and the approximation error due to the Taylor series expansion. The null of linearity is equivalent to the joint hypothesis test of $\varphi_{ki} = 0, \;\; \forall \; k, i$. The framework is also suited to decide on the type of the transition function. The test against the logistic STAR is equivalent to tests of $\varphi_{3i} = 0$ and $\varphi_{1i} = 0 \mid \varphi_{ki} = 0, \;\; k = 2, 3, \;\; i = 1, \ldots, p$; while the test against the exponential STAR is equivalent to a test of $\varphi_{2i} = 0 \mid \varphi_{3j} = 0$, $i = 1, \ldots, p$.

The testing framework is similar in the case of multistep models, with an exception that the vector of the lagged dependent variables, on the right-hand-side, becomes $\{y_{t-h}, \ldots, y_{t-p-h+1}\}$, where h is the horizon for which a multistep forecast is to be generated. See Enders and Pascalau (2015) for further details of such testing procedure.

3 Iterated and Direct Multistep Forecasting Methods

For a time series $\{y_t: \ t = 1, \ldots, T\}$, a one-step-ahead point forecast—regardless of the econometric model (i.e., linear vs. nonlinear), or the forecasting method (i.e., direct vs. iterated)—is given by:

$$\hat{y}_{T+1} = \tilde{g}\left(y_T, y_{T-1}, \ldots | \hat{\theta}_1\right),$$

where $\tilde{g}(\cdot)$ is the functional form our best guess of the true model, $y_T, y_{T-1}, \ldots$ is the information set, and $\hat{\theta}_1$ is the vector of parameter estimates.

If $\tilde{g}(\cdot)$ is a linear model, a multistep iterated point forecast can be obtained recursively by naïve extrapolation, i.e., by substituting the forecasts from the preceding horizons into the model. For example, in the case of a linear autoregressive model, an h-step-ahead iterated point forecast is:

$$\hat{y}_{T+h} = \hat{\alpha}_1 + \sum_{i=1}^{p} \hat{\beta}_{1i}\hat{y}_{T+h-i}, \tag{6}$$

where for $h \leq i$, $\hat{y}_{T+h-i} = y_{T+h-i}$, and where $\hat{\alpha}_1$ and $\hat{\beta}_{1i}$, $i = 1, \ldots, p$, are the parameter estimates from regressing y_t on $y_{t-1}, \ldots, y_{t-p}$.

When $\tilde{g}(\cdot)$ is a nonlinear model, however, such naïve extrapolation could lead to biased multistep forecasts (e.g., Teräsvirta, 2006). This bias can be avoided via a numerical approximation, which involves a bootstrap procedure. Each iteration of the procedure involves 'disturbing' the forecast path with a sequence of bootstrapped forecast errors, $e^b_{T+1}, \ldots, e^b_{T+h}$, which are sampled (with replacement) from the residuals of the estimated model. A multistep iterated point forecast from a nonlinear model then is the mean of the array of forecast paths at a given horizon. For example, in the case of a smooth transition autoregressive model, an h-step-ahead point forecast is:

$$\hat{y}^i_{T+h} = \frac{1}{B}\sum_{j=1}^{B} \hat{y}^b_{T+h}, \quad \text{where}$$

$$\hat{y}^b_{T+h} = \left(\hat{\beta}_{10} + \sum_{i=1}^{p} \hat{\beta}_{1i}\hat{y}^b_{T+h-i}\right) + \left(\hat{\beta}_{20} + \sum_{i=1}^{p} \hat{\beta}_{2i}\hat{y}^b_{T+h-i}\right) G\left(y^b_{T+h-j}; \hat{\gamma}, \hat{c}\right) + e^b_{T+h}, \tag{7}$$

and where $G(\cdot)$ is the transition function, as outlined in the previous section.

The direct forecasting method is applicable both for linear and nonlinear models. For example, in the case of a linear autoregressive model, an h-step-ahead direct forecast is:

$$\hat{y}^d_{T+h} = \hat{\beta}_{0h} + \sum_{i=1}^{p} \hat{\beta}_{ih} y_{T+1-i}, \tag{8}$$

where $\hat{\beta}_{jh}$ $j = 0, \ldots, p$, are the parameter estimates from regressing y_t on $y_{t-h}, \ldots, y_{t-h-p}$. Alternatively, in the case of a smooth transition autoregressive type of nonlinear model, an h-step-ahead direct forecast is:

$$\hat{y}^d_{T+h} = \left(\hat{\beta}_{10h} + \sum_{i=1}^{p} \hat{\beta}_{1ih} y_{T+1-i}\right) + \left(\hat{\beta}_{20h} + \sum_{i=1}^{p} \hat{\beta}_{2ih} y_{T+1-i}\right) G\left(y_{T+1-j}; \hat{\gamma}_h, \hat{c}_h\right), \tag{9}$$

where $G(\cdot)$, as before, is the transition function, bounded by zero and one, and which depends on the realized transition variable. With direct forecasts, in order to obtain point forecasts, there is no need to generate empirical distributions of the forecast; however, the option is available if desired.

4 Model Selection and Forecasting

This study applies monthly primary commodity price series sourced from the online portals of the World Bank and the International Monetary Fund. The original data consisted of 53 commodity price series spanning the January 1980 – December 2019 period. From these, I retained 36 commodity prices that exhibited STAR-type nonlinear dynamics, based on Teräsvirta (1994)'s linearity test applied to the complete time series. The retained list consists of several important commodity groups, including cereal grains, vegetable oils, and industrial and rare metals. Figure 1 illustrates the log-transformed nominal price series (henceforth denoted by y_t).

For each price series, I decided on the order of integration (based on the augmented Dickey–Fuller test), and the autoregressive lag length (based on the Schwartz Information Criterion subject to no remaining residual autocorrelation) using the data ranging the January 1982 – December 2019 period. That is, the series exclude first 24 months, which were reserved for lag selection and for testing linearity against multistep STAR models. I tested the null hypotheses of linearity against

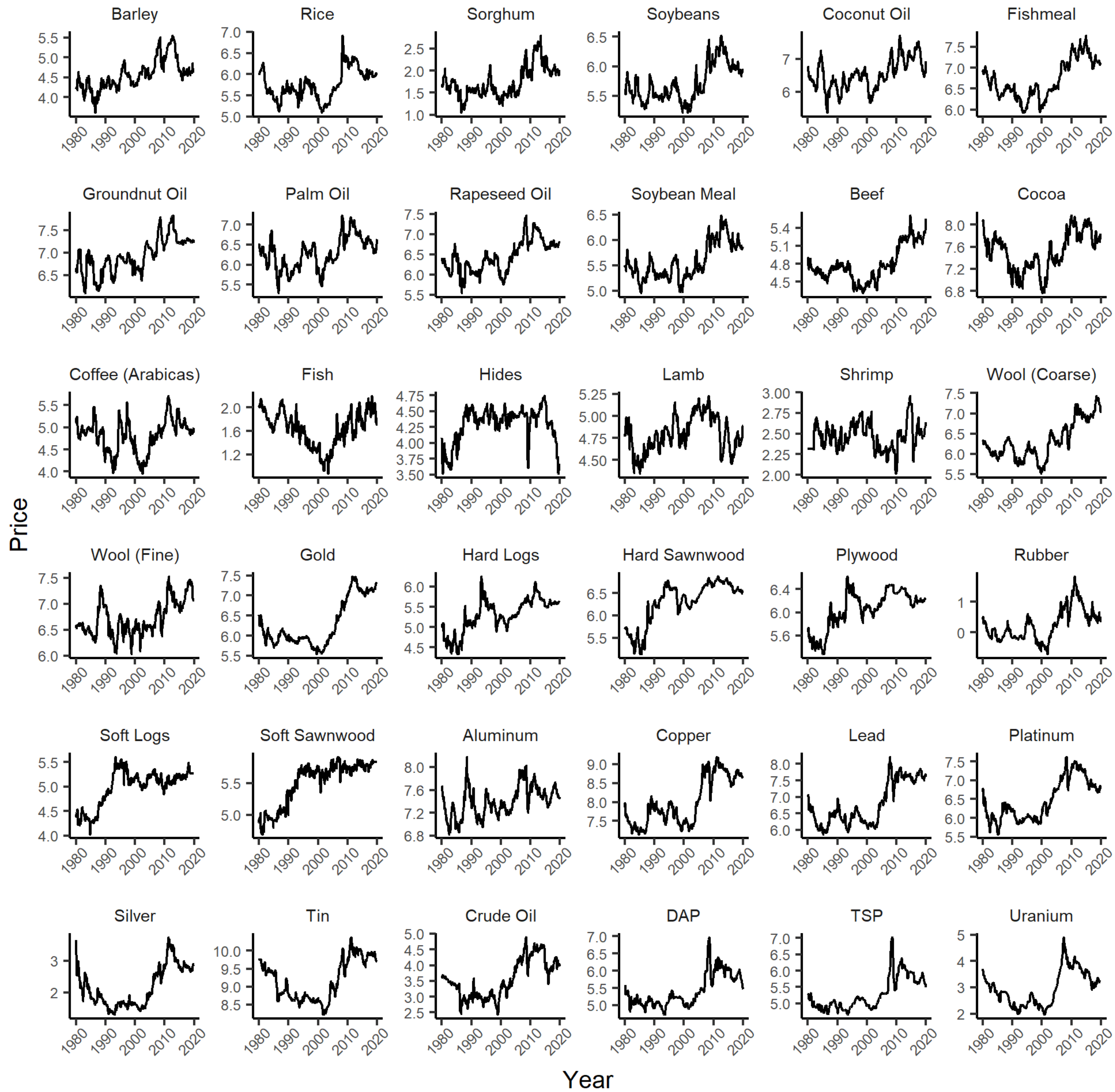

Figure 1: Time Series of the Commodity Prices Used in the Analysis
Note: The price series are log-transformed. Appendix Table A1 presents the description, including the units of measurement, of these commodity prices.

STAR alternatives using lagged dependent variables, up to the selected autoregressive order, as candidate transition variables. This is to decide on a suitable transition variable, as well as the form of a transition function—logistic or exponential—as discussed in the previous section. Using the same order of integration and the autoregressive order, I also tested the null hypotheses of linearity against multistep STAR alternatives to decide on the horizon–specific suitable transition variables and the form of transition functions. The resulting functional forms are then imposed onto the commodity price series in each and every rolling window. That is, in any rolling window, and for a given horizon, forecasts are obtained assuming the same STAR specification. Figure 2 illustrates the estimated transition functions plotted against to the selected transition variables (denoted by s_t, which can be either y_{t-d} or Δy_{t-d+1}, where $d \in 1, \dots, p$.)

To set up a forecasting routine, I use 80 percent of the price series (360 observations) for model estimation, and the remaining 20 percent of the series (84 observations) for out-of-sample evaluation of one-to-twelve-months-ahead forecasts.[1] Throughout I use a rolling window approach. Thus, the first estimation window spans the January 1982 – December 2011 period, yielding forecasts for months of January 2012 through December 2012. The second estimation window spans the February 1982 – January 2012 period, yielding forecasts for February 2012 through January 2013. All the subsequent estimation windows are rolled in a similar fashion, the very last estimation window yielding forecasts for months of December 2018 through November 2019.

For each rolling window, I generate iterated multistep forecasts from a one-step STAR model, by iterating forward 5,000 projections, using the bootstrap procedure outlined in the previous section; the horizon-specific averages of these projections form the iterated multistep forecasts. I also generate direct multistep forecasts from horizon-specific STAR models.

Note that for the I(1) series, I slightly modify equations (6) and (7) (for iterated forecasts) and equations (8) and (9) (for direct forecasts). In the case of the iterated method, first I obtain the forecast path up to horizon h of the first-differenced series; then I calculate an h-step-ahead forecast: $\hat{y}^i_{T+h} = y_T + \sum_{j=1}^{h} \Delta\hat{y}^i_{T+j}$, where Δ is the first-difference operator, and $\Delta\hat{y}^i_{T+j}$, $j = 1, \dots, h$, are obtained iteratively, as described above, using parameter estimates of a regression

[1] As a robustness check, I repeated the forecasting exercise for the 75/25 and the 85/15 sample splits. The results of this check are available in the Appendix.

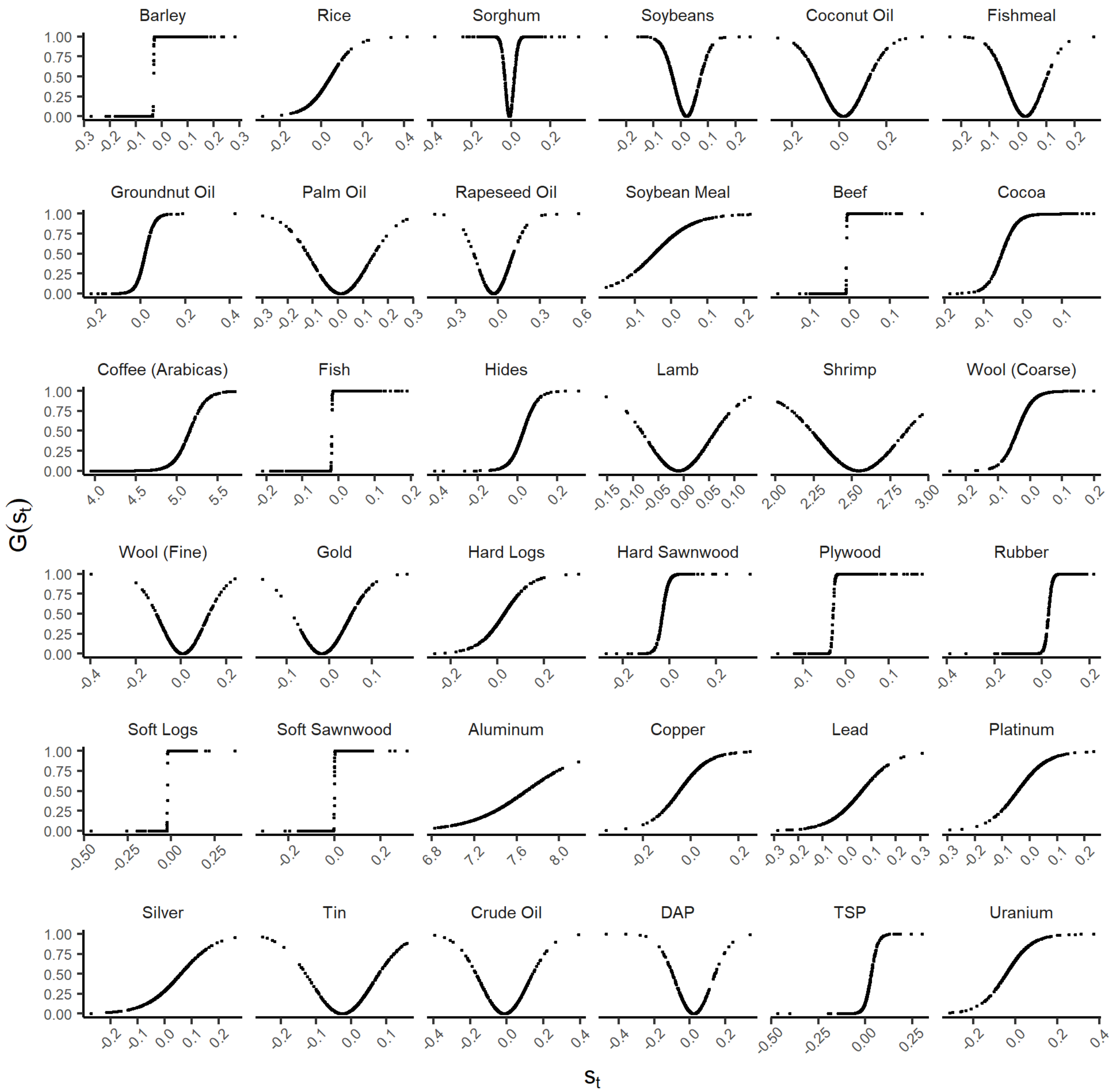

Figure 2: Estimated Transition Functions Against Selected Transition Variables
Note:

of Δy_t on $\Delta y_{t-1}, \ldots, \Delta y_{t-p+1}$. In the case of direct method, an h-step-ahead forecast becomes: $\hat{y}^d_{T+h} = y_T + \hat{x}_{T+h}$, where the second term is the point forecast of $x_{T+h} = y_{T+h} - y_T$, which is obtained by first regressing x_t on $\Delta y_{t-h}, \ldots, \Delta y_{t-h-p+2}$, and then applying the parameter estimates of this regression on $\Delta y_t, \ldots, \Delta y_{t-p+2}$.

Thus, for each commodity price series, and for each considered horizon, $h = 1, \ldots, 12$, I generate two sets of forecasts, $\hat{y}^{i,n}_{T+h}$ and $\hat{y}^{d,n}_{T+h}$, from STAR specifications. In addition, I generate two sets of forecasts, $\hat{y}^{i,l}_{T+h}$ and $\hat{y}^{d,l}_{T+h}$, using AR specifications (i.e., the linear counterparts of the previous two forecasts). This yields 84 point forecasts for each horizon, for the out-of-sample period from January 2012 onward.

5 Forecast Evaluation and Discussion

I evaluate forecast accuracy under the assumption of a quadratic loss—a widely accepted loss function, particularly as it relates to the implicit criterion for in-sample fitting of the data (i.e., minimizing the sum of squared residuals). In particular, for a given forecast, $\hat{y}_{T+h}$, the out-of-sample forecast error is $e_{T+h} = y_{T+h} - \hat{y}_{T+h}$ (here, and in what follows, I omit the method and model superscripts for ease of notation). The quadratic loss leads to the root mean squared forecast error (RMSFE), given by:

$$\text{RMSFE} = \sqrt{\frac{1}{T_2 - T_1 + 1} \sum_{T=T_1}^{T_2} e^2_{T+h}},$$

where T_1 denotes the period at which the first forecast is made, and T_2 denotes the period at which the last forecast is made. For each commodity price series, and each horizon, I assess the accuracy of forecasts from two competing methods (or models) by comparing the respective RMSFEs. To get further insights for the degree (or, rather, the statistical significance) of the differences in RMSFEs, I perform horizon–specific tests for the equal predictive accuracy as per Diebold and Mariano (1995), using Harvey et al. (1997)–modified test statistics. In addition, as a single measure of multi-horizon accuracy, I apply the average superior predictive ability method of Quaedvlieg (2021) for each considered horizon (i.e., for horizons 2 to 12).

To begin, I compare RMSFEs of forecasts from iterated and direct STAR methods. Table 1 presents the relative RMSFEs, together with the single-horizon and multi-horizon statistical significance identifiers. Overall, the iterated STAR method appears to be more accurate than the direct STAR method in multistep commodity price forecasting (e.g., rice, soybeans, shrimp, and the wood varieties), but there are also instances when the opposite appears to be the case (e.g., groundnut oil, beef, and some metals). Notably, there are instances when one-step-ahead forecasts from STAR models do not outperform a simple random walk specification—a feature that appears to be more common for metals.

Next, I evaluate the forecast accuracy of the iterated STAR method relative to the direct AR method. This is of specific interest to the present study as one of the main arguments for the use of a direct method to generate forecasts is when the one-step model is believed to be misspecified. Table 2 presents this comparison, as before accompanied by the associated statistical significance tests. One key general take-away from these results is that the iterated STAR method outperforms the direct AR method in forecasting most agricultural commodity prices; however, the direct AR method is preferred to the iterated STAR method in forecasting metal and other non-agricultural commodity prices, even though the STAR-type nonlinearity is the characterizing feature of these price dynamics.

At this point, a question is whether the nonlinear modeling facilitates more accurate forecasting of the considered commodity prices. Table 3 addresses this question by presenting the ratios of RMSFEs from the iterated STAR method relative to the iterated AR method. In some agricultural commodities, specifically soybeans and coffee, there is evidence of improved forecast accuracy, particularly at longer horizons. An improved forecast accuracy, albeit not statistically significant, is also observed in several other agricultural commodities, such as fishmeal, soybean meal, coconut oil, and rapeseed oil. For non-agricultural commodities, there is hardly any evidence that the nonlinear modeling benefits price forecasting; indeed, in most instances, there is strong evidence that AR models outperform STAR models in generating accurate multistep forecasts. This is not an unusual finding, and indeed, it accords with the existing literature; the possible explanations include parameter non-constancy in the time series, as well as misspecification and over-fitting of the nonlinear model (Teräsvirta, 2006).

Table 1: Relative RMSFEs of Iterated STAR vs. Direct STAR Methods

Commodity	*horizon*											
	1	2	3	4	5	6	7	8	9	10	11	12
Barley	0.976	0.975	0.952	0.976	0.980	0.996	1.004	1.017	1.001	0.987	1.003	0.983
Rice	1.023	0.996	1.015	0.965	0.971	0.949*	0.924*	0.920	0.905*†	0.901†	0.917†	0.949†
Sorghum	1.077	0.988	1.052	0.984	1.052	1.036	1.071	1.024	1.048	0.991	1.025	0.979
Soybeans	1.017	0.980	0.982†	0.997	1.002	0.993	0.986	0.963	0.936*	0.946†	0.939†	0.929†
Coconut Oil	1.022	1.007	1.009	1.037	1.055	1.051	1.029	1.006	1.001	1.010	0.997	1.000
Fishmeal	0.902*	1.013	1.015	1.002	0.999	1.009	1.011	1.005	1.019	1.008	1.015	1.012
Groundnut Oil	0.889	1.021	1.014	1.013*	1.035*	1.032†	1.053	1.041	1.037	1.035	1.035	1.043
Palm Oil	0.949*	1.039	0.996	1.021	0.978	0.979	0.991	0.976	0.959	0.959	0.956	0.950
Rapeseed Oil	1.001	1.002	1.021	0.987	0.962	0.972	0.943	0.941*	0.933	0.918	0.901	0.896
Soybean Meal	0.910	0.965	0.991	0.954	0.963	0.955	0.967	0.972	0.978	0.982	0.977	1.026
Beef	0.955	0.999	1.020	1.037	1.048	1.041	1.053	1.043	1.032	1.028	1.003	1.024*
Cocoa	0.961	0.964	0.979	0.939	0.944	0.953	0.978	0.989	0.992	0.992	1.001	1.023
Coffee (Arabicas)	0.935	0.997	1.007	1.004	1.005	0.977	1.022	1.064	1.026	1.086	1.131	1.124
Fish	1.031	0.961	0.967	0.982	0.980	0.987	0.985	0.983	0.976	0.972	0.974	0.965
Hides	0.945	0.996	0.978	0.979	0.994	0.996	0.996	0.976	0.994	1.012	1.032	1.034
Lamb	0.884*	1.002	0.984	0.996	0.959	0.959	0.964	0.962	0.964	0.964	0.950	0.943
Shrimp	0.769	0.930*†	0.902†	0.900*†	0.961†	0.847†	0.859	0.936	0.991	1.026	0.976	0.988
Wool (Coarse)	0.982	0.994	1.003	0.984	0.985	0.975	0.992	1.004	0.969	0.970	0.973	0.972
Wool (Fine)	0.982	0.979	0.973*†	0.979	0.987	1.004	0.981	0.984	0.963	0.941	0.940	0.969
Gold	0.996	0.988	0.999	0.997	0.999	0.988	0.992	0.993	0.994	0.984	0.975	0.971
Hard Logs	1.021	1.025	0.956	0.929	0.952	0.982	0.970	0.940	0.867	0.865	0.859	0.853
Hard Sawnwood	1.108*†	1.020*†	0.970	0.887*†	0.937*†	0.960*†	0.976†	0.995†	0.977†	1.018	0.961	1.018
Plywood	0.996	0.997	0.958†	0.982†	0.956	0.968	0.969	0.982	0.985	0.970*†	0.941*†	0.949*†
Rubber	1.022	1.010	1.001	1.012	1.029	1.008	1.013	1.023	1.032	1.031	1.016	1.038
Soft Logs	0.986	1.005	0.998	0.993	1.005	0.965*	1.011	0.966	0.989	0.934*	0.955*	0.987
Soft Sawnwood	0.986	1.010	0.993	0.995	1.024	1.014	1.007	0.993	0.955	1.008	1.000	0.982
Aluminum	1.065*	1.027	1.088	1.077*	1.021	1.045	1.065	1.037	1.083	1.049	1.044	1.086
Copper	0.987	0.969*†	0.978	0.977	0.965	0.964	0.968	0.955	0.948	0.966	0.964	0.958
Lead	1.072	1.021*†	1.014	0.991	0.984	0.977	0.999	0.983	0.995	0.991	0.986	1.002
Platinum	1.017	1.018*†	1.014	1.022	1.041	1.045	1.039	1.037	1.028	1.062	1.075	1.067
Silver	0.991	0.981	1.007	0.992	0.976	0.971	0.932*	0.972	0.965	0.966	0.968	0.966
Tin	1.017	1.009	1.032	1.057	1.048	1.030	1.039	1.056	1.023	1.034	1.056	1.073*
Crude Oil	0.944	0.989	0.994	1.023	1.011	1.016	1.002	1.001	1.008	1.005	0.997	0.985
DAP	0.972	0.977	0.952	1.000	1.013	1.009	1.017	1.029	1.041	1.025	1.012	1.023
TSP	1.028	1.003	1.024	1.032	1.032	1.002	1.009	0.962	0.911	0.956	0.973	0.987
Uranium	1.005	1.040*†	1.061†	1.085	1.048	1.038	1.018	0.999	0.985	0.978	0.960	0.973

Note: The entries for the horizon 1 are the RMSFEs of a STAR model relative to the random walk; the entries for the horizons 2 to 12 are the RMSFEs of the iterated STAR method relative to the direct STAR method; * denotes 5% statistical significance of the loss differential of the given horizon, and † denotes 5% statistical significance of the sum of loss differentials up to a given horizon, as per Quaedvlieg (2021); both tests are based on the heteroskedasticity and autocorrelation consistent t distribution of the Harvey et al. (1997)–modified Diebold and Mariano (1995) statistic.

Table 2: Relative RMSFEs of Iterated STAR vs. Direct AR Methods

Commodity	*horizon*											
	1	2	3	4	5	6	7	8	9	10	11	12
Barley	1.003	0.985	0.979	0.989	1.002	1.009	1.019	1.018	1.008	1.005	1.003	0.997
Rice	1.075*†	1.036	1.019	1.010	1.001	0.983	1.001	1.005	1.009	0.998	0.994	1.007
Sorghum	1.038	0.967	1.041	1.006	1.068	1.044	1.075	1.029	1.051	1.013	1.033	0.990
Soybeans	1.007	0.999	0.985	0.982	0.978	0.961	0.962	0.970	0.952	0.954	0.953	0.950
Coconut Oil	1.005	1.018	1.014	1.024	1.043	1.029	1.016	1.004	0.996	1.003	0.986	0.982
Fishmeal	0.990	0.979	0.984	0.970	0.977	0.987	0.980	0.971	0.975	0.972	0.981	0.974
Groundnut Oil	1.013	1.014	1.005	0.996	1.010	1.009	0.999	1.011	1.019	1.036	1.055	1.071
Palm Oil	1.013	1.032	1.034	1.025	0.998	0.990	0.992	0.988	0.983	0.978	0.981	0.991
Rapeseed Oil	0.985	0.999	1.016	1.004	0.985	0.978	0.992	0.972	0.971	0.959	0.948	0.951
Soybean Meal	0.997	0.986	0.981	0.983	0.987	0.989	0.995	0.998	0.995	0.998	0.997	0.997
Beef	1.019	1.001	1.003	1.014	1.026	1.036	1.044	1.043	1.035*	1.032	1.029	1.033
Cocoa	0.978	0.975	0.980	0.962	0.973	0.978	0.992	1.000	1.004	1.016	1.016	1.034
Coffee (Arabicas)	0.988	0.981	0.983	0.978	0.972	0.962	0.955*	0.952*	0.948*	0.937	0.924*†	0.923
Fish	1.017	0.993	0.996	1.012	1.011	1.016	1.012	1.011	1.015	1.008	1.016	1.012
Hides	1.011	1.012	1.015	1.004	1.004	0.999	0.989	0.980	0.992	1.004	1.018	1.015
Lamb	0.987	0.993	0.989	0.969*	0.957*†	0.940*†	0.941*†	0.942†	0.943	0.953	0.964	0.960
Shrimp	1.029*†	1.018	1.019	1.018	1.015	1.016	1.018	1.019	1.014	1.022	1.030	1.034
Wool (Coarse)	1.011	1.011	1.013	1.008	1.004	1.010	1.020*	1.020	1.005	1.010	1.009	1.002
Wool (Fine)	1.021	1.025	1.037	1.035	1.055	1.070	1.060	1.045	1.011	0.988	0.983	0.992
Gold	0.999	0.994	1.008	0.997	0.997	0.996	0.994	0.993	0.996	0.993	0.989	0.984
Hard Logs	1.009	1.008	0.989	0.981	0.975	0.968	0.964	0.968	0.933*	0.936	0.918	0.910
Hard Sawnwood	1.056*†	1.030	1.002	0.972	0.987	0.994	0.990	0.985	0.979	0.986	0.948	0.963
Plywood	0.998	0.987	0.984	0.984	0.984	0.992	0.998	0.997	0.998	0.984	0.978	0.982
Rubber	1.053*†	1.037	1.017	1.026	1.038*	1.043*†	1.040†	1.047*†	1.050*†	1.046*†	1.031†	1.039*†
Soft Logs	1.024*†	1.023*†	1.003	0.997	0.999	1.004	1.005	0.991	0.996	1.000	1.006	1.002
Soft Sawnwood	0.988	1.005	1.010	1.033	1.032	1.028	1.022	1.020	1.012	1.044	1.023	1.011
Aluminum	1.057*†	1.090*†	1.111*†	1.131*†	1.127*†	1.126*†	1.145*†	1.156*†	1.156*†	1.171*†	1.207*†	1.192*†
Copper	1.005	1.000	1.007	1.016	1.016	1.009	1.006	0.988	0.996	0.987	0.981	0.995
Lead	1.071*†	1.048*†	1.043*†	1.018†	1.015	1.010	1.009	1.018	1.024	1.020	1.008	1.025
Platinum	1.011	1.017	1.024	1.028	1.040*	1.046*	1.047*†	1.046*†	1.042*†	1.056*†	1.056*†	1.048*†
Silver	0.998	0.993	0.993	0.993	0.985	0.984	0.980	0.999	0.975	0.984	0.983	0.991
Tin	1.024	1.034	1.050	1.061	1.070	1.074	1.086	1.100	1.080	1.084	1.072	1.095*
Crude Oil	0.994	1.011	1.013	1.025	1.020	1.013	1.009	0.999	1.012	1.010	0.996	0.989
DAP	0.957	0.967	0.970	0.975	0.969	0.990	1.004	1.012	1.025	1.016	1.020	1.030*
TSP	1.046	1.045	1.035	1.037	1.026	1.007	1.025	1.019	1.020	1.026	1.029	1.032
Uranium	1.077	1.060	1.027	1.000	0.994	1.026	1.042	1.044	1.034	1.029	1.015	1.019

Note: The entries are the RMSFEs of the iterated STAR method relative to the direct AR method (for the horizon 1, the entries, by default, are the RMSFEs of a STAR model relative to an AR model); * denotes 5% statistical significance of the loss differential of the given horizon, and † denotes 5% statistical significance of the sum of loss differentials up to a given horizon, as per Quaedvlieg (2021); both tests are based on the heteroskedasticity and autocorrelation consistent t distribution of the Harvey et al. (1997)–modified Diebold and Mariano (1995) statistic.

Table 3: Relative RMSFEs of Iterated STAR vs. Iterated AR Methods

Commodity	*horizon*											
	1	2	3	4	5	6	7	8	9	10	11	12
Barley	1.003	0.993	0.998	1.005	1.011	1.014	1.018	1.022	1.021	1.017	1.015	1.015
Rice	1.075*†	1.038	1.019	1.011	1.005	1.000	1.008	1.013	1.009	1.005	1.008	1.013
Sorghum	1.038	0.965	1.025	0.990	1.035	1.003	1.043	1.008	1.041*	1.004	1.039	0.996
Soybeans	1.007	1.005	0.989	0.978	0.971	0.964	0.962*	0.968	0.958	0.952	0.947*	0.944*†
Coconut Oil	1.005	1.006	0.992	0.988	0.989	0.986	0.985	0.985	0.984	0.983	0.982	0.982
Fishmeal	0.990	0.985	0.988	0.982	0.982	0.984	0.980	0.976	0.974*	0.974	0.978	0.979
Groundnut Oil	1.013	1.014	1.006	0.998	1.002	1.010	1.017	1.025	1.041	1.055	1.061	1.063
Palm Oil	1.013	1.033	1.033	1.015	1.005	1.003	1.007	1.005	1.002	1.001	0.999	1.001
Rapeseed Oil	0.985	1.002	1.013	0.997	0.992	0.982	0.982	0.979	0.980	0.975	0.972	0.970
Soybean Meal	0.997	0.990	0.982	0.984	0.987	0.986	0.986	0.986	0.985	0.985	0.984	0.982
Beef	1.019	1.001	1.004	1.005	1.011	1.018	1.024*	1.026*	1.027*†	1.028*†	1.024*†	1.019*†
Cocoa	0.978	0.977	0.980	0.971	0.974	0.984	0.989	0.992	0.996	1.003	1.007	1.014
Coffee (Arabicas)	0.988	0.985	0.979	0.974	0.966	0.959	0.952*	0.944*	0.940*	0.936*	0.932*†	0.929*†
Fish	1.017	0.993	0.996	1.008	1.013	1.011	1.000	0.994	0.999	1.007	1.010	1.010
Hides	1.011	1.015	1.021	1.021	1.022*	1.031*	1.031*†	1.033†	1.037†	1.042†	1.049†	1.054†
Lamb	0.987	0.999	0.997	0.993	0.990	0.986	0.986	0.988	0.990	0.989	0.988	0.988
Shrimp	1.029*†	1.026	1.032	1.036	1.036	1.035	1.035	1.036	1.038	1.041	1.040	1.036
Wool (Coarse)	1.011	1.004	1.001	0.999	0.998	0.999	0.998	0.999	1.002	1.001	0.998	1.000
Wool (Fine)	1.021	1.029	1.043	1.045	1.046	1.048	1.041	1.031	1.014	0.997	0.992	0.992
Gold	0.999	0.994	1.001	0.997	0.997	0.999	1.000	1.000	0.998	0.997	0.998	0.999
Hard Logs	1.009	0.999	0.992	0.986	0.983	0.980	0.981	0.984	0.985	0.987	0.989	0.992
Hard Sawnwood	1.056*†	1.038†	1.025	1.007	0.999	0.997	0.995	0.991	0.985	0.983	0.982	0.980
Plywood	0.998	0.985	0.986	0.987	0.990	0.992	0.992	0.992	0.994	0.994	0.995	0.996
Rubber	1.053*†	1.040†	1.019	1.015	1.022	1.027	1.031	1.040*	1.045*	1.043*	1.039*	1.040*
Soft Logs	1.024*†	1.019*†	1.010†	0.998	0.994	0.996	0.994	0.993	0.999	0.995	0.998	1.000
Soft Sawnwood	0.988	1.004	0.997	1.003	1.002	1.001	0.994	0.995	0.994	0.997	0.998	0.988
Aluminum	1.057*†	1.098*†	1.118*†	1.135*†	1.129*†	1.138*†	1.144*†	1.136*†	1.141*†	1.144*†	1.156*†	1.162*†
Copper	1.005	1.002	1.003	1.008	1.013	1.012	1.010	1.011	1.012*	1.014*	1.014	1.011
Lead	1.071*†	1.046*†	1.035*†	1.022†	1.019†	1.024*†	1.024†	1.020†	1.015	1.018	1.016	1.021
Platinum	1.011	1.018	1.025	1.032	1.041	1.043	1.041	1.041	1.047	1.050	1.054*	1.054*
Silver	0.998	0.996	1.001	1.000	0.994	0.991	0.990	0.991	0.987	0.986	0.987	0.988
Tin	1.024	1.034	1.045	1.051	1.054	1.064	1.076	1.083*†	1.078*†	1.084*†	1.080*†	1.073*†
Crude Oil	0.994	1.012	1.009	1.013	1.016	1.011	1.003	1.001	1.002	1.004	1.003	1.002
DAP	0.957	0.962	0.963	0.962	0.972	0.983	0.988	0.986	0.985	0.988	0.993	0.997
TSP	1.046	1.040	1.034	1.029	1.025	1.023	1.023	1.022	1.019	1.015	1.014	1.013
Uranium	1.077	1.057	1.018	0.983	0.976	1.013	1.047	1.058	1.053	1.038	1.025	1.020

Note: The entries are the RMSFEs of the iterated forecasts from a STAR model relative to an AR model; * denotes 5% statistical significance of the loss differential of the given horizon, and † denotes 5% statistical significance of the sum of loss differentials up to a given horizon, as per Quaedvlieg (2021); both tests are based on the heteroskedasticity and autocorrelation consistent t distribution of the Harvey et al. (1997)–modified Diebold and Mariano (1995) statistic.

6 Conclusion

This study empirically investigates the possible advantage of an iterated multistep method over a direct multistep method in forecasting primary commodity prices using smooth transition autoregressive models. From an array of 53 primary commodity prices, the analysis focuses on 18 price series, which present strong evidence of STAR-type nonlinear dynamics. Overall, the findings indicate that while STAR models can well approximate nonlinear dynamics of commodity price series, when it comes to multistep forecasting, the framework doesn't offer an advantage, and indeed, in most instances appears to be an inferior alternative to the basic autoregressive framework. While for select individual commodities a case can be made for either of the considered methods, general recommendation—based on the results of this study—is that linear methods are to be seen as safer approach for their multistep forecasting.

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A Tables

Table A1: The Details of the Commodity Price Series Used in the Analysis

Abbrev	Description and Origin
ALMN	Aluminum, 99.5% minimum purity, LME spot price, CIF UK ports, \$/mt
BEEF	Beef, Australian and New Zealand 85% lean fores, CIF U.S. import price, c/lb
CARB	Coffee, Other Mild Arabicas, ICO New York cash price, ex-dock New York, c/lb
CCOA	Cocoa beans, ICO cash price, CIF U.S. and European ports, \$/mt
COIL	Crude Oil (petroleum), West Texas Intermediate 40 API, Midland Texas, \$/barrel
CPPR	Copper, grade A cathode, LME spot price, CIF European ports, \$/mt
CRBS	Coffee, Robusta, ICO New York cash price, ex-dock New York, c/lb
DAPP	DAP (diammonium phosphate), spot, FOB U.S. Gulf
FSML	Fishmeal, Peru Fish meal/pellets 65% protein, CIF, \$/mt
GNOL	Groundnut oil, U.S. crude, FOB SE beg. 1999; prev. any origin, CIF Rotterdam.
GOLD	Gold (UK), 99.5% fine, London afternoon fixing, average of daily rates
HIDE	Hides, heavy native steers over 53 pounds, wholesale dealer's price, Chicago FOB Shipping Point, c/lb
LEAD	Lead, 99.97% pure, LME spot price, CIF European Ports, \$/mt
LGHD	Hard Logs, Best quality Malaysian meranti, import price Japan, \$/m^3
LGST	Soft Logs, Average Export price from the U.S. for Douglas Fir, \$/m^3
OVOL	Olive Oil, extra virgin less than 1% free fatty acid, ex-tanker price U.K., \$/mt
PLAT	Platinum (UK), 99.9% refined, London afternoon fixing
PLWD	Plywood (Africa and Southeast Asia), Lauan, 3-ply, extra, 91cm$\times$182cm$\times$4mm, wholesale price, spot Tokyo
PMOL	Palm oil (Malaysia), RBD, CIF Rotterdam beg. Dec 2001; prev. 5%, CIF NW Europe, bulk, nearest forward
RICE	Rice, 5 percent broken milled white rice, Thailand nominal price quote, \$/mt
RPOL	Rapeseed oil, crude, fob Rotterdam, \$/mt
RUBR	Rubber (any origin), Ribbed Smoked Sheet (RSS) no.1, in bales, RTA, spot, New York
SBOL	Soybean oil, Dutch crude degummed, FOB NW Europe beg. 1999; prev. FOB ex-mill Netherlands, nearest forward
SRGM	Sorghum; U.S., Number 2 yellow, fob Gulf of Mexico, c/lb
SRMP	Shrimp (US), brown, shell-on, headless, 26–30 count/lb, wholesale Gulf of Mexico beg. 2004; prev. New York.
SWHD	Hard Sawnwood, Dark Red Meranti, select and better quality, C&F U.K port, \$/m^3
SWST	Soft Sawnwood, average export price of Douglas Fir, U.S. Price, \$/m^3
TINN	Tin, standard grade, LME spot price, \$/mt
TSPP	TSP (triple superphosphate), spot, import U.S. Gulf
URAN	Uranium, NUEXCO, Restricted Price, Nuexco exchange spot, \$/lb

Table A2: Linearity Test Results

Commodity	*horizon*											
	1	2	3	4	5	6	7	8	9	10	11	12
Barley	0.005	0.053	0.070	0.160	0.311	0.613	0.776	0.616	0.453	0.415	0.545	0.863
Rice	0.001*	0.001*	0.001*	0.001	0.001*	0.001*	0.001*	0.014	0.069	0.088	0.051	0.084
Sorghum	0.001*	0.001*	0.001*	0.001*	0.001*	0.011	0.036	0.105	0.175	0.157	0.123	0.021
Soybeans	0.001*	0.002	0.005	0.009	0.014	0.025	0.036	0.018	0.083	0.024	0.021	0.005
Coconut Oil	0.044	0.007	0.102	0.068	0.039	0.019	0.035	0.061	0.051	0.043	0.009	0.007
Fishmeal	0.003	0.003	0.001	0.001*	0.001	0.002	0.001	0.002	0.005	0.026	0.047	0.026
Groundnut Oil	0.001*	0.001*	0.001*	0.001*	0.001*	0.003	0.003	0.013	0.024	0.092	0.137	0.086
Palm Oil	0.001*	0.006	0.033	0.142	0.273	0.275	0.610	0.568	0.423	0.697	0.685	0.665
Rapeseed Oil	0.001*	0.001*	0.007	0.001	0.001*	0.005	0.099	0.089	0.370	0.374	0.254	0.242
Soybean Meal	0.017	0.025	0.190	0.065	0.040	0.160	0.312	0.292	0.411	0.184	0.085	0.043
Beef	0.001*	0.021	0.008	0.004	0.009	0.076	0.184	0.060	0.058	0.104	0.116	0.051
Cocoa	0.017	0.034	0.178	0.534	0.549	0.611	0.569	0.578	0.352	0.182	0.219	0.378
Coffee (Arabicas)	0.009	0.007	0.004	0.006	0.006	0.009	0.012	0.006	0.003	0.001*	0.001*	0.001*
Fish	0.030	0.035	0.168	0.141	0.231	0.418	0.448	0.487	0.306	0.274	0.222	0.240
Hides	0.001*	0.001*	0.001*	0.002	0.002	0.001	0.001	0.002	0.001*	0.001*	0.001*	0.001*
Lamb	0.002	0.001*	0.002	0.016	0.002	0.001	0.007	0.034	0.060	0.046	0.042	0.028
Shrimp	0.001*	0.001*	0.001*	0.001*	0.001*	0.001*	0.001*	0.001*	0.001*	0.001*	0.001*	0.001*
Wool (Coarse)	0.022	0.597	0.788	0.737	0.381	0.119	0.082	0.071	0.033	0.014	0.007	0.004
Wool (Fine)	0.033	0.028	0.008	0.008	0.008	0.011	0.013	0.054	0.054	0.029	0.023	0.014
Gold	0.003	0.038	0.360	0.939	0.842	0.395	0.549	0.518	0.266	0.178	0.490	0.172
Hard Logs	0.001*	0.001*	0.001*	0.001*	0.001*	0.001	0.001*	0.001*	0.001*	0.003	0.033	0.065
Hard Sawnwood	0.001*	0.010	0.001*	0.001*	0.001*	0.001*	0.001	0.002	0.001*	0.001*	0.001*	0.001*
Plywood	0.001	0.024	0.033	0.015	0.087	0.147	0.322	0.270	0.282	0.371	0.415	0.357
Rubber	0.001*	0.001*	0.032	0.009	0.033	0.021	0.003	0.001*	0.001*	0.001*	0.001*	0.001*
Soft Logs	0.001*	0.001*	0.009	0.011	0.026	0.011	0.036	0.049	0.022	0.061	0.178	0.175
Soft Sawnwood	0.001*	0.001*	0.001*	0.008	0.005	0.042	0.069	0.009	0.128	0.027	0.126	0.228
Aluminum	0.001*	0.004	0.001	0.001*	0.001*	0.001*	0.001*	0.001*	0.001*	0.001*	0.001*	0.001*
Copper	0.001*	0.007	0.002	0.001*	0.001*	0.001*	0.001*	0.001*	0.001*	0.001*	0.001*	0.001*
Lead	0.001*	0.008	0.010	0.019	0.015	0.044	0.059	0.012	0.004	0.002	0.001	0.007
Platinum	0.002	0.003	0.007	0.034	0.010	0.002	0.001*	0.001*	0.001*	0.001*	0.004	0.004
Silver	0.010	0.040	0.147	0.076	0.016	0.007	0.008	0.056	0.321	0.186	0.119	0.060
Tin	0.001*	0.058	0.079	0.040	0.094	0.234	0.366	0.178	0.185	0.254	0.251	0.261
Crude Oil	0.032	0.031	0.179	0.047	0.049	0.031	0.012	0.008	0.002	0.003	0.006	0.014
DAP	0.001*	0.001*	0.001	0.004	0.001*	0.001*	0.001*	0.009	0.028	0.099	0.064	0.061
TSP	0.001	0.118	0.356	0.298	0.339	0.318	0.265	0.079	0.002	0.001*	0.001*	0.001*
Uranium	0.001*	0.001*	0.001*	0.001*	0.001*	0.001*	0.001	0.002	0.001	0.002	0.001*	0.001*

Note: The entries are probability values of Teräsvirta (1994)'s linearity test and its Enders and Pascalau (2015) multistep variant. * denotes probability values that are smaller than those presented in the table.

Table A3: Relative RMSFEs of Iterated STAR vs. Direct STAR Methods (75/25 split)

Commodity	*horizon*											
	1	2	3	4	5	6	7	8	9	10	11	12
Barley	0.978	0.978	0.933	0.969	0.968	0.985	0.993	1.012	0.986	0.980	0.999	0.984
Rice	0.991	1.034	1.015	0.966	0.955	0.943	0.917	0.908	0.903	0.890	0.912	0.950
Sorghum	1.071	0.996	1.041	0.988	1.026	0.999	1.025	1.010	1.036	1.003	1.005	0.980
Soybeans	1.002	0.995	0.987	1.022	1.026	1.021	0.991	1.006	0.988	0.987	0.986	1.005
Coconut Oil	0.982	1.000	1.019	1.026	1.048	1.047	1.030	1.022	1.027	1.013	1.018	1.017
Fishmeal	0.907	1.010	1.009	1.001	0.998	0.998	0.995	1.002	1.012	1.004	1.011	0.995
Groundnut Oil	0.837	1.029	1.028	1.021	1.025	1.026	1.020	0.995	0.995	0.985	0.952	0.958
Palm Oil	0.937	0.988	1.024	1.048	1.049	1.031	1.039	1.024	1.019	0.994	1.015	1.001
Rapeseed Oil	0.970	1.003	1.036	0.991	0.985	1.002	0.996	1.003	0.976	0.986	0.978	0.982
Soybean Meal	0.919	0.983	0.977	0.968	0.962	0.961	0.962	0.968	0.986	0.970	0.975	1.014
Beef	0.969	1.012	1.040	1.047	1.054	1.035	1.031	1.018	1.011	1.003	0.993	0.986
Cocoa	0.954	0.958	0.978	0.944	0.959	0.953	0.971	0.976	0.986	0.986	1.000	1.008
Coffee (Arabicas)	1.061	1.073	1.071	1.066	1.059	0.956	0.968	0.922	0.915	0.899	0.878	0.812
Fish	1.010	0.970	0.956	0.951	0.967	0.953	0.954	0.955	0.952	0.968	0.970	0.958
Hides	0.957	0.985	0.963	0.976	0.987	1.006	1.013	0.979	0.994	1.012	1.031	1.044
Lamb	0.924	1.013	0.991	1.005	0.967	0.965	0.957	0.952	0.959	0.975	0.959	0.970
Shrimp	0.812	0.967	0.928	0.909	0.969	0.884	0.874	0.992	0.976	1.013	0.999	1.002
Wool (Coarse)	0.968	0.987	0.978	0.967	0.971	0.973	0.978	0.972	0.968	0.977	0.973	0.977
Wool (Fine)	0.946	0.982	0.967	1.002	0.997	0.972	0.970	0.972	0.957	0.941	0.945	0.954
Gold	0.976	0.990	0.983	0.990	1.005	0.998	1.000	0.999	1.002	0.999	1.003	1.002
Hard Logs	0.914	1.012	1.000	0.966	0.990	1.015	0.959	0.992	0.960	0.951	0.951	0.948
Hard Sawnwood	1.065	1.014	0.954	0.944	0.969	0.970	1.018	1.019	0.993	1.004	0.992	1.009
Plywood	1.010	0.995	0.965	0.955	0.958	0.974	0.973	0.991	0.996	1.008	0.975	0.979
Rubber	1.010	1.014	1.017	1.015	1.029	1.012	1.006	1.017	1.012	1.012	1.014	1.056
Soft Logs	0.985	0.994	0.989	0.982	0.978	0.977	1.013	0.957	0.997	0.958	0.972	0.975
Soft Sawnwood	0.951	1.014	1.000	0.994	1.021	1.020	1.012	1.009	0.966	1.005	1.024	0.968
Aluminum	1.009	0.982	0.898	0.918	0.887	0.910	0.905	0.915	0.925	0.912	0.943	0.919
Copper	0.988	0.984	0.999	1.000	0.982	0.976	0.982	0.982	0.968	0.980	0.969	0.965
Lead	1.057	1.007	0.993	0.988	0.985	0.971	0.993	0.977	0.979	0.996	0.994	1.006
Platinum	1.008	1.009	0.987	1.000	1.013	1.019	1.004	1.010	1.014	1.023	1.042	1.035
Silver	0.996	0.991	1.006	1.007	0.997	0.962	0.962	0.976	0.970	0.978	0.975	0.973
Tin	0.989	1.003	1.014	1.015	0.995	0.995	0.971	0.971	0.966	0.989	0.967	0.968
Crude Oil	0.962	0.987	0.976	0.998	0.999	1.003	0.987	0.990	1.002	1.000	1.002	0.987
DAP	1.077	0.973	0.953	1.008	0.977	0.981	0.969	0.966	0.905	0.963	0.961	0.981
TSP	1.022	1.001	1.008	1.025	1.021	0.978	0.959	0.951	0.869	0.869	0.897	0.918
Uranium	0.982	1.044	1.056	1.047	1.034	1.022	1.029	1.013	1.014	0.995	0.989	1.001

Note: The entries for the horizon 1 are the RMSFEs of a STAR model relative to the random walk model; the entries for the horizons 2 to 12 are the RMSFEs of the iterated STAR method relative to the direct STAR method; * denotes 5% statistical significance of the loss differential of the given horizon, and † denotes 5% statistical significance of the sum of loss differentials up to a given horizon, as per Quaedvlieg (2021); both tests are based on the heteroskedasticity and autocorrelation consistent t distribution of the Harvey et al. (1997)–modified Diebold and Mariano (1995) statistic.

Table A4: Relative RMSFEs of Iterated STAR vs. Direct AR Methods (75/25 split)

Commodity	*horizon*											
	1	2	3	4	5	6	7	8	9	10	11	12
Barley	0.992	0.970	0.972	0.981	0.998	1.006	1.004	1.012	1.001	0.997	1.001	1.002
Rice	1.054	1.040	1.023	1.016	1.013	1.008	1.006	1.003	1.011	0.995	0.997	1.009
Sorghum	1.033	0.976	1.026	1.001	1.039	1.018	1.051	1.006	1.030	1.003	1.009	0.996
Soybeans	1.007	0.999	0.990	0.989	0.991	0.990	0.982	0.997	1.001	0.999	0.995	1.008
Coconut Oil	0.990	1.011	1.019	1.016	1.020	1.006	1.003	0.999	1.007	0.990	0.987	0.985
Fishmeal	0.987	0.978	0.981	0.973	0.974	0.979	0.972	0.967	0.974	0.974	0.980	0.976
Groundnut Oil	0.989	1.013	1.008	1.006	1.019	1.018	1.020	0.997	1.008	1.014	0.990	1.004
Palm Oil	1.001	1.004	1.027	1.039	1.050	1.035	1.040	1.021	1.028	1.015	1.015	1.024
Rapeseed Oil	0.939	0.975	0.973	0.969	0.976	0.979	0.996	0.995	0.985	0.990	0.989	0.999
Soybean Meal	1.012	0.998	0.993	0.996	0.995	1.000	0.991	0.994	0.997	0.987	0.996	1.002
Beef	1.036	1.025	1.028	1.029	1.036	1.043	1.036	1.025	1.020	1.019	1.012	1.003
Cocoa	0.974	0.967	0.974	0.965	0.966	0.980	0.989	0.986	1.000	1.007	1.007	1.013
Coffee (Arabicas)	1.095	1.122	1.145	1.151	1.145	1.142	1.124	1.118	1.109	1.096	1.076	1.049
Fish	1.020	0.991	0.980	0.994	0.986	0.991	0.988	0.987	0.986	0.990	0.994	0.996
Hides	1.009	0.999	1.001	0.991	0.990	0.999	0.998	0.988	0.993	1.006	1.021	1.027
Lamb	1.019	1.013	1.001	0.981	0.973	0.952	0.944	0.943	0.951	0.961	0.963	0.974
Shrimp	1.056	1.047	1.040	1.019	0.999	0.997	0.999	1.005	1.006	1.008	1.012	1.006
Wool (Coarse)	1.018	1.012	1.016	1.019	1.018	1.011	1.012	1.004	1.004	1.010	1.002	1.005
Wool (Fine)	1.008	0.999	1.004	1.010	1.009	1.013	1.007	1.008	0.994	0.983	0.984	0.989
Gold	0.987	0.983	0.994	0.992	0.998	1.001	1.001	1.001	1.000	0.997	1.003	1.010
Hard Logs	1.027	1.015	1.011	1.001	1.002	1.003	1.007	1.007	1.005	0.997	0.995	0.993
Hard Sawnwood	1.055	1.033	1.014	1.006	1.001	1.012	1.004	0.995	0.972	0.972	0.955	0.955
Plywood	1.011	0.996	0.984	0.979	0.975	0.985	0.990	0.997	0.997	1.016	0.996	0.993
Rubber	1.047	1.033	1.013	1.012	1.030	1.040	1.040	1.040	1.033	1.028	1.028	1.043
Soft Logs	1.003	1.008	0.994	0.993	0.990	0.998	0.997	0.991	0.990	1.010	1.007	1.016
Soft Sawnwood	0.969	1.000	1.014	1.035	1.037	1.032	1.028	1.026	1.002	1.035	1.030	0.993
Aluminum	1.010	0.994	0.983	0.978	0.959	0.960	0.946	0.953	0.938	0.936	0.955	0.967
Copper	0.999	1.015	1.020	1.017	1.014	1.004	1.006	0.998	0.991	0.994	0.991	1.002
Lead	1.054	1.035	1.009	1.009	0.993	0.986	0.991	1.000	0.993	1.019	1.018	1.037
Platinum	0.992	1.002	1.017	1.018	1.025	1.035	1.027	1.024	1.028	1.024	1.033	1.021
Silver	1.009	0.999	1.015	1.017	1.005	0.995	0.990	0.993	0.983	0.987	0.983	0.975
Tin	0.986	1.003	1.023	1.038	1.049	1.047	1.048	1.040	1.042	1.042	1.045	1.051
Crude Oil	0.994	1.002	1.007	1.020	1.016	1.012	1.003	1.003	1.012	1.007	1.006	0.991
DAP	1.019	1.017	0.998	1.009	0.987	0.990	1.004	1.010	1.005	1.004	0.991	1.001
TSP	1.020	1.015	1.007	1.019	1.008	0.992	0.987	0.993	1.002	0.993	0.989	0.980
Uranium	1.043	1.055	1.018	0.993	1.006	1.039	1.074	1.083	1.090	1.075	1.072	1.074

Note: The entries are the RMSFEs of the iterated STAR method relative to the direct AR method (for the horizon 1, the entries, by default, are the RMSFEs of a STAR model relative to an AR model); * denotes 5% statistical significance of the loss differential of the given horizon, and † denotes 5% statistical significance of the sum of loss differentials up to a given horizon, as per Quaedvlieg (2021); both tests are based on the heteroskedasticity and autocorrelation consistent t distribution of the Harvey et al. (1997)–modified Diebold and Mariano (1995) statistic.

Table A5: Relative RMSFEs of Iterated STAR vs. Iterated AR Methods (75/25 split)

Commodity	*horizon*											
	1	2	3	4	5	6	7	8	9	10	11	12
Barley	0.992	0.977	0.990	1.002	1.003	1.006	1.011	1.014	1.013	1.010	1.009	1.009
Rice	1.054	1.031	1.017	1.006	0.998	0.989	0.989	0.992	0.992	0.994	0.998	1.001
Sorghum	1.033	0.979	1.021	0.994	1.031	1.007	1.039	1.009	1.035	1.007	1.035	1.003
Soybeans	1.007	1.003	0.992	0.987	0.986	0.987	0.985	0.988	0.983	0.982	0.979	0.973
Coconut Oil	0.990	0.999	0.995	0.987	0.986	0.980	0.981	0.983	0.982	0.982	0.979	0.979
Fishmeal	0.987	0.983	0.984	0.980	0.979	0.980	0.976	0.974	0.973	0.974	0.978	0.978
Groundnut Oil	0.989	1.009	1.013	1.012	1.014	1.016	1.008	0.995	0.989	0.986	0.981	0.978
Palm Oil	1.001	1.006	1.021	1.032	1.042	1.039	1.037	1.033	1.032	1.029	1.026	1.023
Rapeseed Oil	0.939	0.967	0.978	0.975	0.979	0.983	0.988	0.990	0.990	0.990	0.990	0.990
Soybean Meal	1.012	1.008	0.999	0.998	0.996	0.991	0.988	0.988	0.987	0.987	0.986	0.985
Beef	1.036	1.030	1.030	1.023	1.024	1.024	1.024	1.017	1.011	1.010	1.007	1.003
Cocoa	0.974	0.966	0.973	0.974	0.977	0.982	0.984	0.987	0.994	1.002	1.006	1.010
Coffee (Arabicas)	1.095	1.123	1.139	1.148	1.152	1.148	1.134	1.120	1.098	1.080	1.062	1.046
Fish	1.020	0.991	0.984	0.987	0.988	0.988	0.982	0.979	0.984	0.990	0.992	0.993
Hides	1.009	1.006	1.009	1.008	1.013	1.027	1.032	1.038	1.045	1.053	1.060	1.067
Lamb	1.019	1.016	1.007	1.002	0.998	0.992	0.991	0.993	0.993	0.993	0.992	0.992
Shrimp	1.056	1.048	1.042	1.027	1.017	1.014	1.019	1.026	1.029	1.026	1.016	1.005
Wool (Coarse)	1.018	1.013	1.014	1.016	1.015	1.009	1.005	1.005	1.007	1.008	1.005	1.005
Wool (Fine)	1.008	0.999	1.007	1.012	1.012	1.011	1.006	1.001	0.994	0.990	0.990	0.992
Gold	0.987	0.984	0.997	0.993	0.995	0.998	0.999	1.000	0.999	0.998	0.999	1.001
Hard Logs	1.027	1.018	1.011	1.004	1.003	1.004	1.005	1.003	1.001	1.001	1.000	1.000
Hard Sawnwood	1.055	1.036	1.033	1.018	1.014	1.011	1.004	1.000	0.994	0.993	0.992	0.990
Plywood	1.011	0.994	0.996	0.992	0.993	0.997	1.000	1.000	1.001	1.002	1.005	1.006
Rubber	1.047	1.032	1.017	1.012	1.016	1.024	1.031	1.038	1.038	1.036	1.034	1.041
Soft Logs	1.003	1.006	1.000	0.991	0.992	0.998	0.996	0.999	1.004	0.999	1.001	1.004
Soft Sawnwood	0.969	1.000	1.002	1.010	1.010	1.006	1.000	1.000	0.993	0.997	1.000	0.990
Aluminum	1.010	1.004	0.992	0.983	0.974	0.973	0.966	0.961	0.962	0.967	0.976	0.984
Copper	0.999	1.009	1.012	1.015	1.014	1.012	1.009	1.008	1.007	1.007	1.007	1.005
Lead	1.054	1.038	1.012	1.008	1.003	1.001	1.010	1.010	1.012	1.019	1.017	1.023
Platinum	0.992	1.000	1.014	1.020	1.026	1.030	1.030	1.029	1.035	1.041	1.045	1.046
Silver	1.009	1.000	1.007	1.013	1.006	0.994	0.990	0.991	0.992	0.991	0.990	0.988
Tin	0.986	1.003	1.018	1.038	1.045	1.056	1.059	1.051	1.046	1.043	1.043	1.039
Crude Oil	0.994	1.001	1.001	1.009	1.010	1.006	1.000	1.000	1.003	1.005	1.005	1.005
DAP	1.019	1.016	1.003	1.001	1.002	1.004	1.002	1.001	0.999	0.999	1.002	1.002
TSP	1.020	1.013	1.008	1.010	1.006	1.005	1.004	1.004	1.001	0.996	0.994	0.991
Uranium	1.043	1.053	1.016	0.995	1.007	1.041	1.079	1.093	1.093	1.085	1.078	1.075

Note: The entries are the RMSFEs of the iterated forecasts from a STAR model relative to an AR model; * denotes 5% statistical significance of the loss differential of the given horizon, and † denotes 5% statistical significance of the sum of loss differentials up to a given horizon, as per Quaedvlieg (2021); both tests are based on the heteroskedasticity and autocorrelation consistent t distribution of the Harvey et al. (1997)–modified Diebold and Mariano (1995) statistic.

Table A6: Relative RMSFEs of Iterated STAR vs. Direct STAR Methods (85/15 split)

Commodity	*horizon*											
	1	2	3	4	5	6	7	8	9	10	11	12
Barley	0.998	0.973	0.969	0.975	0.990	1.026	1.007	1.054	1.018	1.025	1.032	0.979
Rice	1.054	1.026	1.055	0.990	0.988	0.977	0.969	0.941	0.868	0.923	0.944	0.954
Sorghum	0.991	1.008	1.025	1.006	1.045	1.053	1.061	1.070	1.053	1.047	1.041	1.068
Soybeans	1.037	0.989	0.999	0.994	0.992	1.000	0.991	1.001	0.983	0.969	0.976	0.966
Coconut Oil	0.996	1.019	1.000	1.030	1.028	1.038	1.022	1.021	1.036	1.043	1.043	1.064
Fishmeal	0.873	1.018	1.024	1.005	1.016	1.021	1.030	1.029	1.026	1.021	1.016	1.001
Groundnut Oil	0.917	0.995	1.008	1.034	1.033	1.034	1.109	1.059	1.083	1.112	1.144	1.140
Palm Oil	0.929	1.029	0.955	0.957	0.968	0.945	0.954	0.958	0.955	1.034	0.971	1.009
Rapeseed Oil	0.997	0.963	1.015	1.001	0.996	1.007	0.994	0.990	1.017	0.980	0.982	0.998
Soybean Meal	0.891	0.959	0.964	0.909	0.931	0.924	0.937	0.942	0.966	0.954	0.974	1.002
Beef	0.958	1.002	1.032	1.049	1.052	1.038	1.051	1.045	1.026	1.015	0.992	1.034
Cocoa	0.942	0.961	0.981	0.940	0.931	0.954	0.970	0.992	0.969	0.969	0.985	0.981
Coffee (Arabicas)	0.958	1.007	1.004	1.008	1.003	0.929	0.961	0.960	0.977	1.024	1.056	1.104
Fish	1.004	0.984	0.943	0.956	0.935	0.947	0.954	0.944	0.925	0.913	0.910	0.907
Hides	0.900	0.976	0.966	0.972	0.980	1.001	1.002	0.979	1.000	1.027	1.042	1.060
Lamb	0.922	1.002	0.995	1.001	0.980	0.992	0.986	0.961	0.974	0.996	0.966	0.979
Shrimp	0.778	0.935	0.910	0.919	1.008	0.875	0.904	0.992	1.048	1.125	1.051	1.054
Wool (Coarse)	0.959	0.976	0.981	0.980	0.989	0.990	0.996	0.979	0.982	0.970	0.989	0.979
Wool (Fine)	1.025	0.983	0.977	0.942	0.918	0.931	0.894	0.905	0.915	0.918	0.927	0.947
Gold	0.993	0.996	1.014	1.012	0.986	0.982	0.977	0.967	0.954	0.940	0.926	0.925
Hard Logs	1.010	1.003	0.946	0.985	0.993	1.027	1.017	0.954	0.904	0.910	0.920	0.913
Hard Sawnwood	1.103	1.011	0.972	0.900	0.903	0.913	0.920	0.925	0.940	0.952	0.937	0.962
Plywood	0.963	1.000	0.964	0.998	0.971	0.982	0.970	1.002	0.980	0.981	0.943	0.946
Rubber	0.996	0.996	0.990	0.991	1.014	0.982	0.978	1.000	1.005	0.996	1.001	1.029
Soft Logs	1.014	0.996	0.990	0.981	0.997	0.974	1.004	0.988	1.007	0.969	0.980	1.001
Soft Sawnwood	0.957	1.011	1.001	0.984	0.992	0.997	0.998	1.010	1.005	1.019	1.022	0.987
Aluminum	1.018	1.011	1.048	1.022	1.123	1.079	1.035	1.006	1.072	1.093	1.061	0.996
Copper	0.975	0.966	0.977	0.994	0.970	0.961	0.964	0.958	0.942	0.952	0.963	0.953
Lead	1.022	1.007	1.001	0.983	0.981	0.982	1.023	1.001	1.035	1.015	1.014	1.029
Platinum	1.014	1.020	1.030	1.054	1.078	1.062	1.044	1.035	1.029	1.043	1.055	1.056
Silver	1.040	0.995	1.035	1.013	1.017	1.000	0.995	0.990	0.982	0.994	0.991	0.996
Tin	1.003	1.011	1.034	1.046	1.028	1.011	1.017	1.022	1.023	1.039	1.050	1.071
Crude Oil	0.940	0.996	1.004	1.029	1.011	1.014	0.987	1.003	1.006	1.005	0.999	0.981
DAP	0.890	0.999	0.962	1.029	1.006	1.011	0.988	0.999	1.018	0.985	0.997	0.980
TSP	1.004	1.015	1.002	1.001	0.997	0.966	0.963	1.003	0.939	0.935	0.951	1.005
Uranium	1.023	1.033	1.060	1.082	1.043	1.038	1.026	1.026	1.025	1.023	0.999	0.996

Note: The entries for the horizon 1 are the RMSFEs of a STAR model relative to the random walk model; the entries for the horizons 2 to 12 are the RMSFEs of the iterated STAR method relative to the direct STAR method; * denotes 5% statistical significance of the loss differential of the given horizon, and † denotes 5% statistical significance of the sum of loss differentials up to a given horizon, as per Quaedvlieg (2021); both tests are based on the heteroskedasticity and autocorrelation consistent t distribution of the Harvey et al. (1997)–modified Diebold and Mariano (1995) statistic.

Table A7: Relative RMSFEs of Iterated STAR vs. Direct AR Methods (85/15 split)

Commodity	*horizon*											
	1	2	3	4	5	6	7	8	9	10	11	12
Barley	1.011	0.999	0.996	1.006	1.001	1.016	1.024	1.030	1.028	1.031	1.018	1.010
Rice	1.083	1.048	1.036	1.017	1.037	1.050	1.084	1.108	1.059	1.035	1.041	1.045
Sorghum	0.968	0.983	1.015	1.045	1.064	1.079	1.094	1.092	1.070	1.096	1.086	1.086
Soybeans	1.008	1.014	1.001	1.005	0.992	0.995	0.985	1.004	1.003	0.987	0.984	0.988
Coconut Oil	0.969	0.990	0.999	1.011	1.019	1.014	1.009	1.010	1.018	1.022	1.015	1.027
Fishmeal	0.963	0.978	0.999	0.983	0.988	0.991	0.995	0.982	0.982	0.987	0.984	0.971
Groundnut Oil	1.034	1.041	1.052	1.039	1.046	1.049	1.051	1.031	1.036	1.079	1.179	1.182
Palm Oil	0.996	0.998	0.994	0.964	0.955	0.943	0.960	0.964	0.966	0.994	0.991	1.035
Rapeseed Oil	0.956	0.986	1.009	0.997	1.019	1.019	1.013	1.001	1.011	1.003	1.015	1.002
Soybean Meal	0.985	0.974	0.964	0.967	0.972	0.977	0.986	0.988	0.983	0.981	0.991	0.987
Beef	1.028	1.009	1.019	1.029	1.032	1.036	1.043	1.037	1.048	1.050	1.053	1.052
Cocoa	0.964	0.970	0.975	0.959	0.959	0.977	0.993	0.990	0.992	1.002	0.999	1.004
Coffee (Arabicas)	1.004	0.993	0.987	0.985	0.973	0.963	0.930	0.921	0.935	0.920	0.890	0.880
Fish	1.001	0.976	0.965	0.980	0.977	0.989	0.994	0.989	0.993	0.988	0.982	0.975
Hides	0.969	0.979	0.996	0.989	0.985	0.989	0.985	0.975	0.987	1.006	1.019	1.024
Lamb	0.991	0.986	0.980	0.971	0.959	0.950	0.945	0.955	0.948	0.975	0.974	0.976
Shrimp	1.049	1.047	1.054	1.067	1.076	1.092	1.100	1.098	1.088	1.096	1.098	1.110
Wool (Coarse)	0.992	0.989	0.993	0.994	0.988	0.998	1.000	0.987	0.999	1.004	1.004	0.997
Wool (Fine)	1.035	1.049	1.059	1.045	1.035	1.017	0.988	0.986	0.976	0.966	0.968	0.977
Gold	1.007	0.991	0.994	0.991	0.989	0.988	0.980	0.975	0.968	0.957	0.958	0.965
Hard Logs	1.005	1.006	0.995	0.999	0.997	0.997	1.000	0.980	0.962	0.968	0.984	0.978
Hard Sawnwood	1.058	1.022	0.987	0.973	0.969	0.960	0.941	0.934	0.933	0.925	0.915	0.894
Plywood	1.002	0.990	0.986	0.999	0.993	1.000	0.999	1.008	0.992	0.996	0.990	0.985
Rubber	1.042	1.006	1.004	1.003	1.015	1.018	1.012	1.027	1.026	1.020	1.027	1.037
Soft Logs	1.008	1.017	1.010	1.000	0.992	1.002	1.007	0.998	1.006	1.008	1.019	1.017
Soft Sawnwood	0.990	1.002	0.985	0.991	0.986	1.011	1.008	1.027	1.025	1.021	1.018	0.984
Aluminum	1.024	1.031	1.054	1.081	1.107	1.109	1.129	1.151	1.164	1.188	1.187	1.216
Copper	1.003	0.999	1.002	1.015	1.003	0.995	0.995	0.984	0.984	0.975	0.989	0.992
Lead	1.037	1.030	1.020	1.006	1.013	1.004	1.020	1.014	1.037	1.018	1.019	1.036
Platinum	1.012	1.025	1.044	1.048	1.051	1.048	1.038	1.040	1.033	1.031	1.038	1.035
Silver	1.013	1.021	1.021	1.007	1.008	1.006	1.012	1.011	1.003	1.000	1.002	1.017
Tin	1.043	1.037	1.053	1.057	1.055	1.045	1.029	1.032	1.036	1.051	1.052	1.072
Crude Oil	0.988	1.017	1.015	1.023	1.024	1.011	0.997	1.003	1.008	1.009	1.002	0.986
DAP	0.963	0.970	0.985	0.988	0.981	1.010	0.994	0.998	1.016	0.988	1.007	0.988
TSP	1.040	1.022	1.016	1.016	1.006	1.007	1.000	1.020	1.032	1.020	1.033	1.030
Uranium	1.048	1.057	1.026	0.996	0.993	1.035	1.068	1.065	1.076	1.071	1.056	1.046

Note: The entries are the RMSFEs of the iterated STAR method relative to the direct AR method (for the horizon 1, the entries, by default, are the RMSFEs of a STAR model relative to an AR model); * denotes 5% statistical significance of the loss differential of the given horizon, and † denotes 5% statistical significance of the sum of loss differentials up to a given horizon, as per Quaedvlieg (2021); both tests are based on the heteroskedasticity and autocorrelation consistent t distribution of the Harvey et al. (1997)–modified Diebold and Mariano (1995) statistic.

Table A8: Relative RMSFEs of Iterated STAR vs. Iterated AR Methods (85/15 split)

Commodity	*horizon*											
	1	2	3	4	5	6	7	8	9	10	11	12
Barley	1.011	0.997	0.998	1.004	1.010	1.015	1.021	1.027	1.026	1.022	1.024	1.024
Rice	1.083	1.044	1.032	1.022	1.017	1.008	1.007	1.007	0.994	0.981	0.985	0.997
Sorghum	0.968	0.981	1.001	1.011	1.028	1.037	1.047	1.048	1.052	1.056	1.061	1.062
Soybeans	1.008	1.012	1.001	1.001	0.998	0.994	0.994	0.993	0.993	0.986	0.979	0.979
Coconut Oil	0.969	0.982	0.983	0.985	0.987	0.987	0.988	0.988	0.988	0.988	0.987	0.987
Fishmeal	0.963	0.983	1.000	0.995	0.992	0.993	0.989	0.984	0.982	0.982	0.984	0.983
Groundnut Oil	1.034	1.036	1.037	1.029	1.038	1.056	1.074	1.085	1.095	1.107	1.107	1.084
Palm Oil	0.996	1.003	0.987	0.955	0.940	0.945	0.957	0.960	0.963	0.974	0.983	0.989
Rapeseed Oil	0.956	0.975	1.000	0.996	1.012	1.004	1.007	1.001	1.003	0.997	0.987	0.981
Soybean Meal	0.985	0.979	0.971	0.972	0.977	0.979	0.979	0.980	0.981	0.980	0.980	0.980
Beef	1.028	1.018	1.019	1.019	1.022	1.025	1.028	1.032	1.036	1.042	1.043	1.038
Cocoa	0.964	0.970	0.972	0.966	0.970	0.980	0.987	0.993	0.998	1.004	1.009	1.014
Coffee (Arabicas)	1.004	0.995	0.985	0.978	0.970	0.955	0.941	0.930	0.921	0.909	0.889	0.881
Fish	1.001	0.972	0.967	0.978	0.982	0.987	0.980	0.975	0.979	0.986	0.983	0.983
Hides	0.969	0.993	1.007	1.013	1.018	1.026	1.030	1.033	1.038	1.044	1.051	1.057
Lamb	0.991	0.984	0.982	0.979	0.974	0.967	0.967	0.971	0.974	0.974	0.972	0.974
Shrimp	1.049	1.054	1.065	1.077	1.086	1.095	1.102	1.101	1.099	1.102	1.100	1.092
Wool (Coarse)	0.992	0.983	0.984	0.986	0.987	0.988	0.990	0.994	0.997	0.998	0.997	0.998
Wool (Fine)	1.035	1.046	1.053	1.047	1.035	1.015	0.992	0.983	0.977	0.972	0.976	0.978
Gold	1.007	0.995	1.000	0.996	0.995	0.998	1.001	1.000	0.998	0.995	0.998	1.002
Hard Logs	1.005	1.006	1.000	0.990	0.979	0.976	0.976	0.979	0.979	0.980	0.980	0.982
Hard Sawnwood	1.058	1.029	1.005	0.994	0.982	0.969	0.961	0.958	0.952	0.948	0.946	0.940
Plywood	1.002	0.987	0.989	0.992	0.993	0.994	0.996	0.995	0.994	0.994	0.993	0.993
Rubber	1.042	1.008	0.998	0.997	0.997	1.001	1.009	1.022	1.026	1.022	1.018	1.019
Soft Logs	1.008	1.019	1.010	1.001	0.996	0.998	1.006	0.999	1.000	0.997	1.001	0.999
Soft Sawnwood	0.990	1.000	0.988	0.991	0.993	1.005	0.995	0.994	0.995	0.995	0.993	0.984
Aluminum	1.024	1.036	1.061	1.081	1.090	1.104	1.112	1.133	1.149	1.158	1.168	1.178
Copper	1.003	1.001	1.000	1.003	1.002	1.000	1.000	1.002	1.003	1.005	1.004	1.002
Lead	1.037	1.029	1.023	1.009	1.005	1.012	1.016	1.014	1.010	1.011	1.012	1.016
Platinum	1.012	1.025	1.040	1.046	1.054	1.050	1.042	1.040	1.045	1.046	1.046	1.044
Silver	1.013	1.028	1.024	1.015	1.007	1.013	1.017	1.013	1.005	1.002	1.007	1.010
Tin	1.043	1.034	1.057	1.057	1.054	1.055	1.048	1.048	1.043	1.049	1.050	1.050
Crude Oil	0.988	1.015	1.012	1.016	1.018	1.012	1.004	1.003	1.005	1.005	1.004	1.003
DAP	0.963	0.973	0.967	0.970	0.979	0.991	0.995	0.995	0.992	0.991	0.993	0.996
TSP	1.040	1.029	1.021	1.014	1.010	1.009	1.009	1.010	1.008	1.005	1.004	1.004
Uranium	1.048	1.060	1.026	0.984	0.979	1.031	1.075	1.086	1.085	1.075	1.064	1.055

Note: The entries are the RMSFEs of the iterated forecasts from a STAR model relative to an AR model; * denotes 5% statistical significance of the loss differential of the given horizon, and † denotes 5% statistical significance of the sum of loss differentials up to a given horizon, as per Quaedvlieg (2021); both tests are based on the heteroskedasticity and autocorrelation consistent t distribution of the Harvey et al. (1997)–modified Diebold and Mariano (1995) statistic.