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Real price appreciation forecast tool: Two delivered log market price cycles in the Puget Sound markets of western Washington, USA, from 1992 through 2019

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ABSTRACT

Delivered log prices represent stochastic values exchanged in competitive marketplaces, responsive to unfolding macroeconomic forces operating through shifts in supply and demand. Major market disruption events, experienced as price appreciation or devaluation, shape into predictable cycles to balance at market price equilibrium.

Monthly delivered log price records of a single grade/sort in the United States of America, Washington state's Puget Sound, from January 1989 through October 2019, are considered. The price series is analyzed during two market disruption and recovery events, reveal characteristics of a Markov-chain of order following a random-walk with ultimate return to base price levels. The Real Price Appreciation Forecast tool is guided by commodity real price disruption event severity in terms of how significant the price change is and how long it takes for the price disruption to initially peak or trough. The path of real price recovery to stable market equilibrium levels is predicted through the Real Price Appreciation Forecast tool presented in this manuscript. Within this price forecasting analysis, shocks, white noise, and other short-duration market events are viewed as peripheral factors when observing the ultimate market real equilibrium price level. The Real Price Appreciation Forecast tool gives the practitioner a mathematical model to analyze delivered log market data to predict the equilibrium price range shaped by the Markov-chain of order random-walk.

1. Introduction

While biologic parameters of forest growth and timber maturation are readily formulated (Arney, 2016; Prodan, 1968), timber commodity price predictions appear to be more challenging. Delivered log prices, responding to various competitive market-influencing forces, persistently fluctuate, frustrating the accuracy of price prediction claims.

Near-term commodity price projections generally favor assumptions that prices tomorrow will be about what they are today (Rinaldi and Jonsson, 2013). Commodity price forecasting directly impacts forestland ownership decisions when profitability is evaluated. Even forestland owners who do not plan to harvest timber on their property in the near-term but will eventually sell or purchase forestlands, must be able to appraise their forestland assets with attention given to changing timber commodity values on subject properties (USPAP, 2018; IVCS, 2017). Tradeoffs between competitive timber market values, other commodity markets, and non-commodity valuation, determine financial opportunities to define the highest and best use value of each property asset (PropEx, 2003). These activities necessitate an obvious need for accurate timber commodity price forecasts.

This has led to matching timber commodity price prediction methods with well-developed growth and yield estimates. Forestland value changes through time as trees mature and as price cycles appreciate or devalue, affecting forestland appraisals (USPAP, 2018; IVCS, 2017), financially optimal timber harvest timing (Schlosser, 2014), and asset return on investment considerations (Bare and Waggener, 1980).

The Real Price Appreciation (RPA) Forecast tool analysis was initiated in 2009 in the aftermath of the Great Recession (NBER, 2017). Monthly market data were synchronized with federal economic statistics, to integrate Markov-chain random-walk principles into delivered log market price predictions.

1.1. Theory of Markov processes

The Russian mathematician, Andrei A. Markov (1856–1922), formulated what has become known as the "Markov process" (Whitt,

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2013). His research combined probability theory and statistics to describe stochastic variables satisfying certain properties: future prices are determined only by current events, not based on past performance (Sigman, 2009). On the other hand, there is flexibility when defining event duration to eclipse a price point by encompassing several consecutive events. More recently, various forms of memory have been added to the basic Markov model (Gintis, 2013), giving form to the “Markov-chain of order”: a Markov-chain with memory of ‘m’ – time periods (Sipos et al., 2016).

Price time-series are often modeled as a Markov process or random walks, which, in some circumstances are the same thing. The forecast horizon takes advantage of reasoned intertemporal influences on the dependent variable: competitive market equilibrium price. Macroeconomic researchers have used Markov-chain random-walk theory with prediction smoothing and error adjustment techniques to exogenously model equilibrium price predictions in competitive markets. The Markov-chain with memory theory can be used as a method for performing a random-walk model, with cycle return to price initiation levels, as applicable to commodity price forecasting (Franco et al., 2012).

In the Markov-chain random-walk context, price series are mean-reverting, at any given instant price changes are random, but over time the series will migrate to the mean (Armstrong et al., 2002). The concept of prices returning to the cycle's price-starting point articulates real price values as exogenous variables while negotiating macroeconomic modalities in their current expressive terms. The process described in this paper involves a Markov-chain random-walk with discrete real price mean reversion (Meucci, 2017).

In probability theory, a mathematical model using identifiably finite non-negative values, with an exponential distribution, describes a potentially viable Markov decision horizon (Fogarasi and Levendovszky, 2013). Future behaviors predicted by the model develop response on the parameters of an economic disruption event initiating the cycle (Norris, 1997). A Markov-chain discrete-time with memory of ‘m’ variation proves applicable to competitively priced delivered timber log commodities because this process defines a sequence, or chain of states, partially based on historic patterns (Whitt, 2013). Competitively priced delivered log prices possess these Markov properties.

1.2. Input commodity data

Log market price forecasting has been considered by many analysts. In United States of America's Pacific Northwest, the US Forest Service (USFS) has published monthly stumpage price reports since about 1975 (Haynes, 1998), in annual reports derived from publicly owned timber stumpage sales data. While stumpage market data can identify trends and cycles in timber commodity markets, they are specifically based only on stumpage market transactions.

Delivered log market commodities represent a stage of timber production with logs delivered to raw material buyers, generally lumber mills. Logs are measured to specific lengths, “greater than” small-end diameters, and of specific species for each sort, with volume of each log defined by the governing log scaling bureau (NLRAG, 2011). Competitive market value represents the price paid to sellers for timber based on volume as graded and scaled logs. Stumpage sale buyers build roads, harvest timber, merchandise it, and load it onto logging trucks where they ultimately sell the timber to log-processing buyers, generally lumber mills, as logs. At this transaction point, commodities are sold in delivered log markets with each log sorted, graded, and scaled according to the state's log scaling rules (PSLSGB, 1948).

The Washington Department of Natural Resources (WaDNR), publishes monthly “mill log prices” detailing transactions of seven to nine species, each with multiple grades and in different market areas (WaDNR, 2019). This manuscript addresses delivered log market price forecasting in the Puget Sound region of western Washington, USA. Logs are measured by state licensed scalers using Scribner board foot, decimal C. scale as administered by the Puget Sound Log Scaling and Grading Bureau (PSLSGB, 1948) and measured in thousand board feet (MBF). Monthly prices in this analysis are collected as nominal prices per MBF by sort and grade (WaDNR, 2019), then converted to real prices by translating effects of inflation in the USA economy into current terms (BLS, 2019).

Log characteristics are defined by sorts and grades to express wood quality, small-end log diameter (inside bark), length of each log (plus trim), all these being reduced to net measurements for any defect losses (NLRAG, 2011). Douglas-fir (*Pseudotsuga menziesii* var. *menziesii* (Mirb.) Franco)) log sorts generally include in increasing value: pulp, 4-Sawmill, 3-Sawmill, 2-Sawmill, and Saw Mill and Better (SM & Better).

Douglas-fir logs dominate domestic and export markets from the Puget Sound region and have since before 1960 (Daniels, 2005). Washington state's Puget Sound region is oftentimes called the Douglas-fir Region (Darr et al., 1980), because of the market dominance for log value and volume traded.

This manuscript expresses Douglas-fir sort, 2-Sawmill grade log prices to model price prediction migration trends in Washington's Puget Sound marketplace. The dominance of this sort/grade commodity in commercial market transactions (Haynes et al., 1988; Adams, 1974) is founded on marketplace longevity and commercial availability in adjoining marketplaces west of the Cascade Mountain range in Washington, Oregon, northern California, and southwestern British Columbia, Canada. This sort and grade represent high quality logs which when milled are converted into high-quality lumber (Haynes and Fight, 2004). Production of Douglas-fir logs for sale to regional lumber mills in the grade of 2-Sawmill is competitive and favored by many log buyers (RISI, 2017).

1.3. Competitive timber markets

Log prices have both a regional and a very intense local dimension, reflecting the fluid structure in commodity value relationships existing in timber harvesting costs, timber log transaction value, wood products, and forestland markets. While variations in log prices are linked to supply factors, major determinant moves to the demand side: log and timber prices are strongly influenced by derived demand for lumber and other wood products (Haim et al., 2014; FAO, 2009).

Forecasting competitive log prices frustrates forestland owners who may not be involved in perpetual log marketing negotiations. Even when the log seller is a qualified agent of the timber owner, competitive market price forecasting is still complicated by imperfect knowledge.

1.4. Delivered log prices

Non-volume weighted delivered log price records presented in this analysis were purchased from RISI loglines (2017) for monthly prices from 1989 through 2010, then from 2011 through 2019 they were acquired from the WaDNR (2019). Conversion of these nominal prices into real prices is made using the Producer Price Index (PPI) values provided by the Bureau of Labor Statistics (BLS, 2019) and are stated in October 2019 real terms, using PPI data published 14 November 2019 (Fig. 1, Fig. 2, Fig. 3).[1]

Commodity market price migrations often follow probabilistically distributed temporal patterns, where return to base-price levels is governed by discrete probability distributions (Heaney, 2006). Discrete-time commodity price series have been extensively considered, yielding the quantitative approach to making time-series predictions. Commodity price data are often found within the realm of upper and lower market price parameters, confining the measurements to non-negative values, as determined by derived demand pricing of ultimate

[1] Real-prices in this manuscript and displayed on all figures represent 201910, meaning the year 2019 and the month 10 (October).

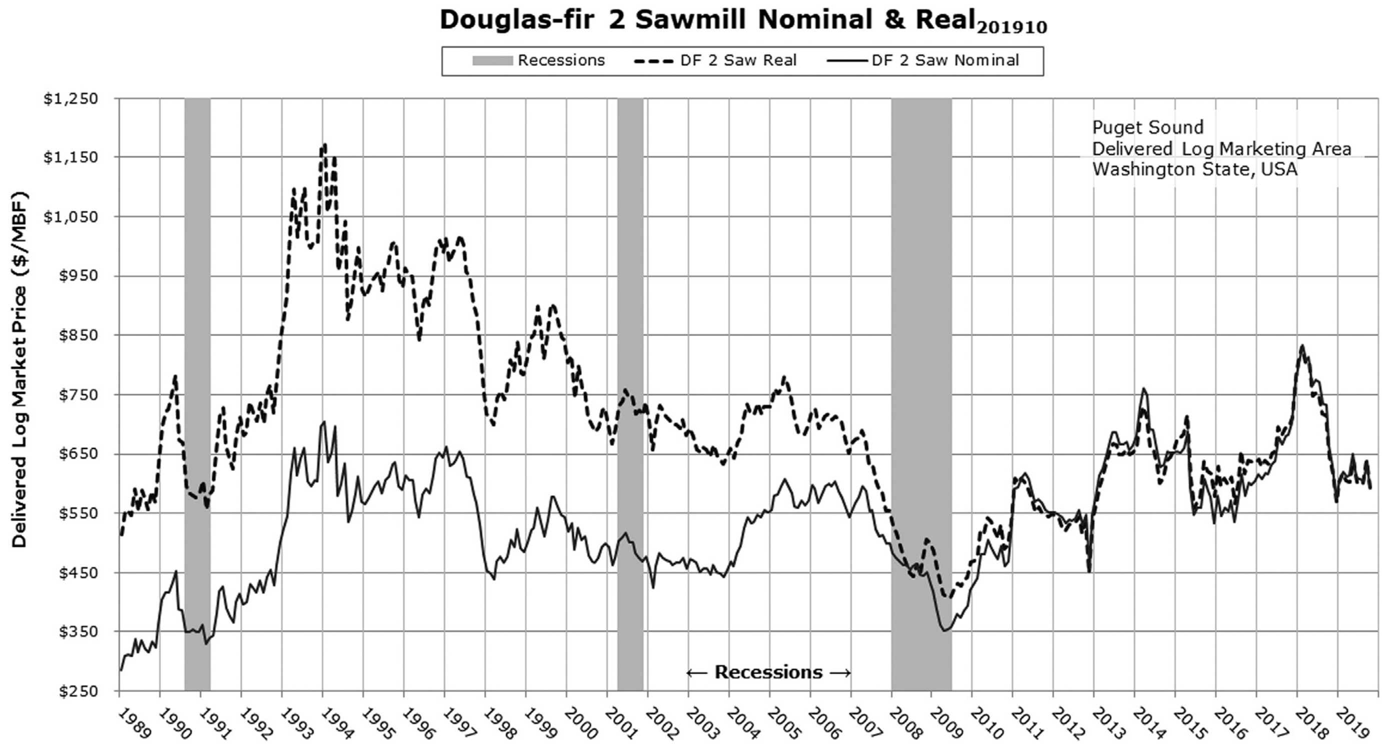

Fig. 1. Douglas-fir grade, 2-Sawmill sort, nominal and real delivered log prices, Puget Sound market (1989–2019).

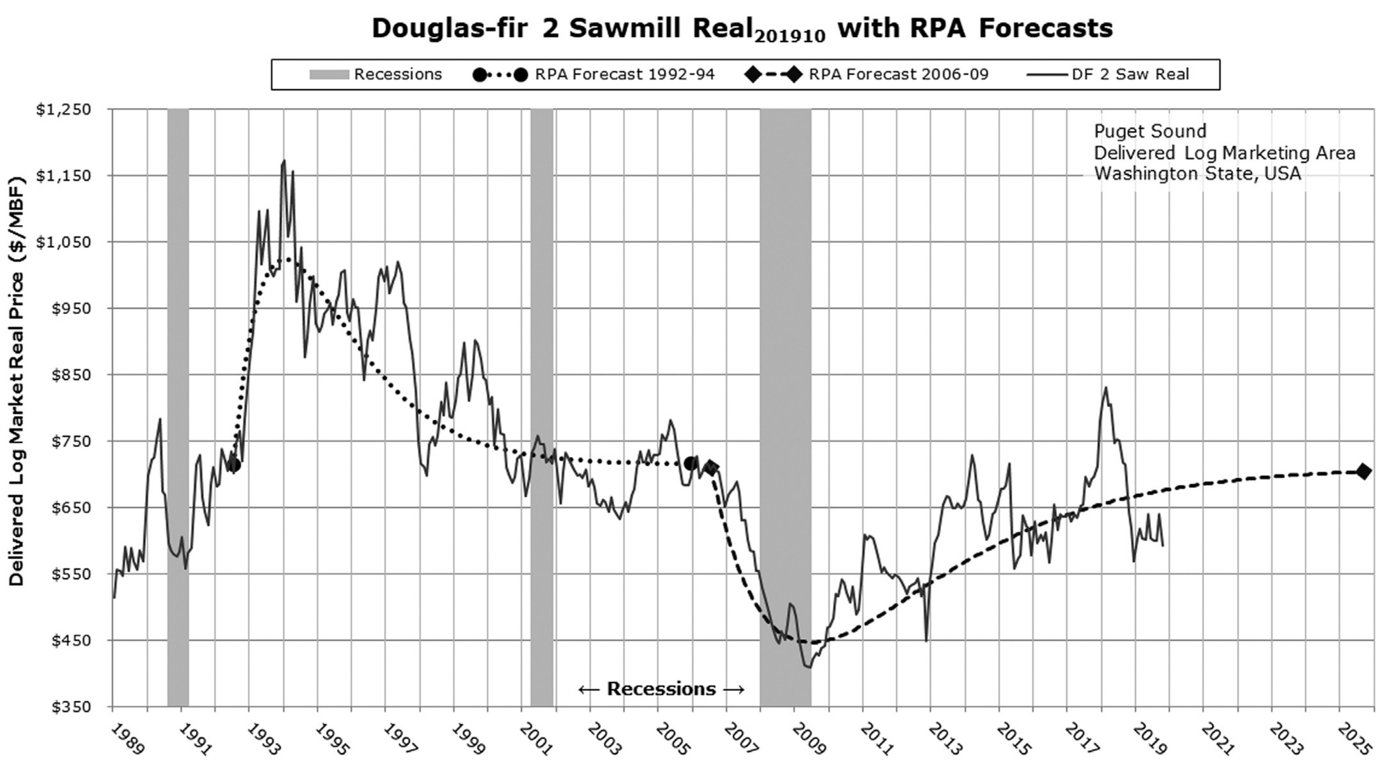

Fig. 2. Douglas-fir 2-Sawmill delivered log prices 1989–2025 in April 2019 real terms with RPA Forecast tool price predictions.

consumer products, such as lumber, veneer, and wood fiber (Prestemon et al., 2018). These parameters create discrete-value expectations, bound within the scope of market parameters, even when interrupted by macroeconomic price disruptions.

Long-term price changes occur, and they can be predictable (Russell and Taylor, 2018). Major timber management firms are likely to have in-house analysts who make timber commodity price predictions, sometimes based on sophisticated econometric modeling. But typical small or medium sized forestland owners, and most public forestland managers, may not have the resources to support a dedicated analytics unit to track and predict delivered log prices in their market(s).

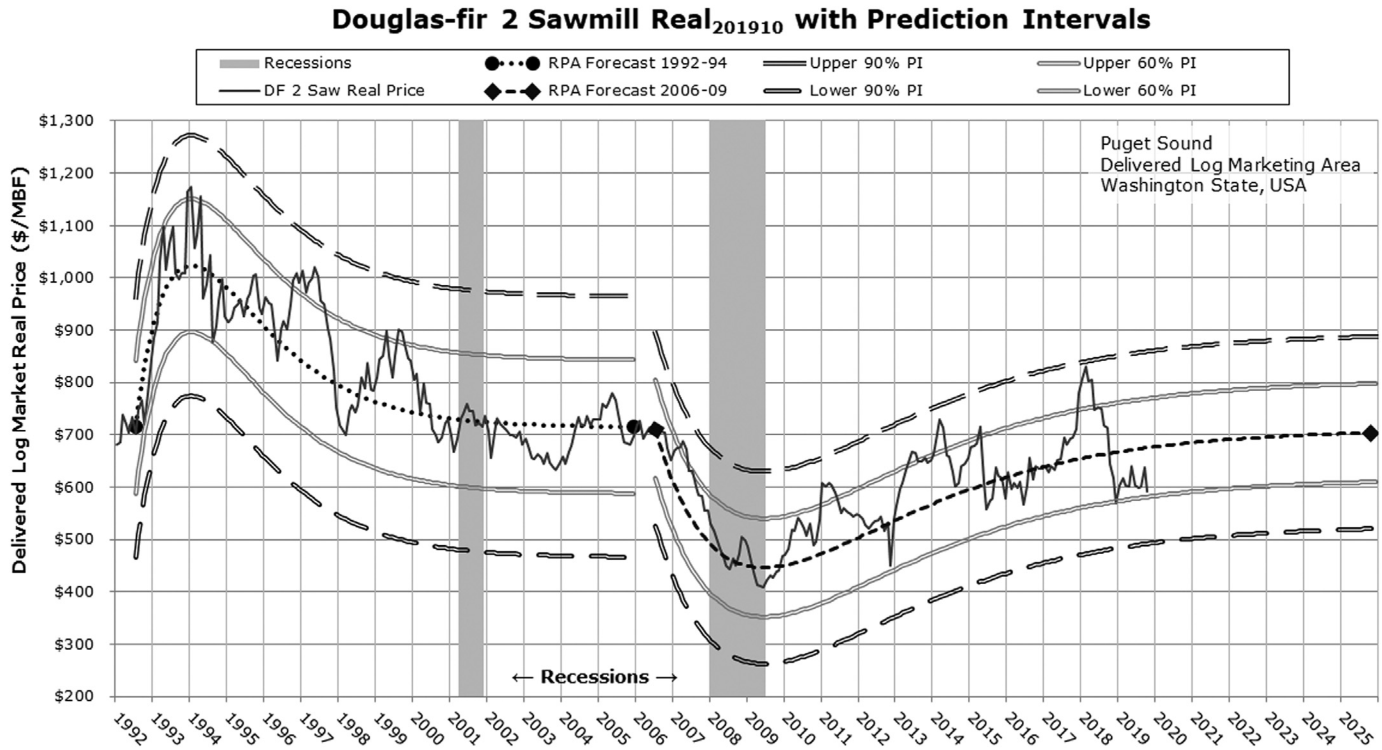

Fig. 3. Douglas-fir 2-Sawmill, Prediction Interval statistical differences between stochastic prices and the RPA Forecast tool price predictions.

1.5. Real price movements

Commodity price forecasting begins by observing past prices linked with economic forces embedded in the macroeconomy, where prices are influenced by the interaction of supply and demand. Log real price equilibrium implies that supply and demand factors consistently and efficiently interact. Long running economic relationships are fundamentally influenced by consumer behavioral patterns, weakening strict cause and effect, or supply and demand responses, even in efficient competitive markets.

Macroeconomic forces exert commodity transaction influences within nations and between international trading partners (Carbaugh, 2015). In the USA, when an economic recession happens, it is ultimately declared by the federal economic authority (NBER, 2017). Recession events are often displayed on economic graphs as vertical grey bars (Fig. 2, Fig. 3) showing the time-span of economic recession events. A period of recovery, often considered an economic expansion, begins after the recession concludes.

Commodity real price devaluation can happen synchronously with recession events, but this is not obligatory. Economic expansion and recession interact with land use policy changes, demographic shifts, and international competitive market forces to shape real commodity price changes. These price changes over time can be lumped into three categories: 1) seasonal, 2) shocks and random noise, or 3) shifts and trends (Alagidede, 2009).

Seasonal price fluctuations include price swings associated with annual home construction season demand effects on lumber prices, and thus timber prices (derived demand). Long-duration timber harvest contract lengths mean that seasonality effects are often muted in these markets even though prices are often negotiated daily (Bowers, 2014).

Shocks and random noise are non-patterned, generally unpredictable, one-time or short-term price changes. Timber market random noise includes recognizable price appreciation and devaluation, stemming from transitory mill inventory changes, or abrupt trade policy adjustments (Perry, 2006).

A market shock pattern was seen in Puget Sound delivered log market prices instigated by a significant change in lumber trade policies when USA trade tariffs/duties were imposed in 2017, specifically against Canada lumber (Buongiorno and Johnston, 2018). Delivered Douglas-fir 2-Sawmill logs were traded at $639/MBF ($655/MBF real) in June 2017, as the USA tariff was imposed on Canada lumber (Fig. 1). Prices peaked in February 2018 at $834/MBF ($831/MBF real), then followed a downward price devaluation to $576/MBF ($569/MBF real) in December 2018. The real price climb, peak and devaluation is seen graphically as a symmetrical chevron shape spanning thirty-one months (June 2016 through December 2018) (Fig. 2).

The distinction between random noise and price shock is one of degree, and the boundary between the two can be hazy (Kondor et al., 2014).

Shifts and trends are driven by longer running, fundamental changes in the economy, they are one-time changes in underlying factors; more fundamental and persistent in their consequences they are different from shocks. Trends are formed in response to long-term shifts such as population growth or consistent modernization technology changes (Parr-Rud, 2012). Trends and shifts are easily observable in retrospect, but often hard to predict for the future.

Price predictions presented in this paper have been created within interactions of all three price interruption movements, often happening simultaneously as commodity price disruption events unfold.

1.6. Price cycles

Specific commodity price patterns, in response to disruption events, are revealed through market data price cycles. The ability to recognize price-shock events as opposed to market disruption episodes aids the validity of prediction horizons. Real price forecasts presented, rely on mathematical structure and thereby uniformity in price prediction models (Manzan, 2007).

Fundamentally, price prediction models attempt stochastic system anticipation. Price predictions are destined to be disrupted by unpredictable shocks and random noise: although monthly prices may spike above or below a predicted cycle trajectory, they ultimately revert to the real monthly price cycle, if market adjustment factors remain consistent. Increases in a commodity's real price are referred to as price appreciation, and real price decrease as price devaluation, to distinguish them from the broader macroeconomic terms of inflation and deflation.

Price forecasting can be analyzed through various algorithms, statistical and graphical techniques (Guidolin and Ono, 2006). Generally, forestland owners (including federal, state, tribal, industrial, and non-industrial private forestland owners) are price takers in delivered log markets (Hyde, 2012). One landowner usually lacks market supply dominance to dictate prices to buyers.

2. Materials and methods: arranging Markov-chain predictions

This process evaluates delivered Douglas-fir 2-Sawmill log real prices in the Puget Sound region of western Washington, USA. The approach applied at the core of the RPA Forecast tool formula demonstrates the veracity of the “Markov-chain with memory predictive model” for log prices viewed as stochastic events.

Price predictions begin by examining information contained in the history of a market's delivered log prices. Armstrong (2001) recommends using as much historic data as can be assembled to increase robustness of projection horizons. The method proposed here has two initial steps. In step one, the analyst examines a specific (sort and grade) delivered log real price history through a sufficiently long time horizon to identify the price series' disruption event's “initiation date and real value” and the event's “turning point date and real value”. In the second step, these observations are converted to real price forecasts using the RPA Forecast tool.

2.1. Models

The Markov-chain of order random-walk and real price return to baseline levels is modeled through a mathematical formula. Market cycles begin with an economic disruption of the status-quo: equilibrium prices may move higher or lower than anticipated prices, but the disruption will be more systemic as compared to price shocks discussed earlier. The driving variables of this model hinge on the magnitude of the real price disruption event and the longevity of the price destabilization incident: hence, its manipulation by broad-based macroeconomic factors.

2.2. Determining significant real price disruption events

As an intuitive guide of practice, real price appreciation or devaluation events that leave a period of real price stability to eclipse competitive market price by 50% in real terms and takes longer than 12 months to peak or trough, can be considered as a potential new price disruption event. Within these conditions, real price return to the level of real price stability can be predicted by the RPA Forecast Tool scenario.

2.2.1. Initiation point

Competitive real prices within the commodity market should be established for a period of consistent real price stability not less than 4 consecutive months, longer is better. Real prices in this period of price stability should present within a range of about 5%. These conditions define the relatively stable price initiation point.

2.2.2. Turning point

The appreciation peak or devaluation trough should record the real price and date of the event. Generally, these are single point incidents where an extreme is reached to signal the beginning of return to the stable initiation price.

It is under these conditions that price recovery using the RPA Forecast Tool can be best applied. Recognition of real price stability and market disruption event significance are fundamentally heuristic skills.

3. Results: forecast tool

3.1. Delivered log real price 1992–94 cycle disruption

In the western Washington Puget Sound delivered log market, a price disruption event initiated in July 1992, when competitive market price of Douglas-fir 2-Sawmill grade logs was \$417/MBF nominal (RISI, 2017) (\$701/MBF real) (Fig. 1). A price appreciation event initiated and continued through January 1994 when prices peaked at \$704/MBF nominal (\$1173/MBF real). This created a 1-year 6-month real price appreciation event.

Putting these price events into context of the aforementioned analysis criteria, the starting point value has been time-weighted based on four months of prices preceding and including the July 1992 price point (April through July) (Formula 1). This approach applies the view of Baier et al. (1999) when determining Markov-chain initiation price memory. A.C. Harvey (1990, 25) made recommendations to consider “putting more weight on the most recent observations”. Formula 1 numerator sums fractional-weights, creating a time-weighted average price. While calculating a time-weighted average price is not obligatory to this analysis technique, it recognizes the importance of establishing the initial equilibrium real price level that will serve as the Markov-chain random-walk base level and the ultimate cycle's return price.

Formula 1. Time-weighted initiation real price.

$$IP_t^{\$} = \left(\left[\sum_{t=i}^{n} (d_t \times Price_t) \right] / \sum_{t=1}^{n} (d_t) \right) \tag{1}$$

where:

$d_1 = 0.60,\ d_2 = 0.70,\ d_3 = 0.80,\ d_4 = 0.90.$

Real $Price_t$ for [$t = 1$ (April 1992)] through [$t = 4$ (July 1992)] = \$720, \$704, \$735, \$701 (real)

In this market and for this commodity, initiation time-weighted real price is calculated at \$715/MBF (Formula 2), using the Formula 1 technique.

Formula 2. Time-weighted, 1992–94 cycle's initiation-point real price.

$$IP_t^{\$} = \frac{\begin{bmatrix} (0.60 \times 720) + (0.70 \times 705) \\ (0.80 \times 735) + (0.90 \times 701) \end{bmatrix}}{(0.60 + 0.70 + 0.80 + 0.90)} = \$715/MBF \tag{2}$$

The turning-point nominal price in this market cycle was captured at \$704/MBF (\$1173/MBF real) in January 1994, as prices reached the disruption's apex value. The real price appreciation incident of Douglas-fir 2-Sawmill logs in the 1992–94 disruption event initiated at \$701/MBF (Formula 2) with the turning point real price (\$1173/MBF), is seen in comparative real price appreciation between the time-bounded points (Formula 3). Real values for this specific commodity during this 1.5-year price appreciation event, reveal a 39.15% per year price appreciation rate for this commodity in this economic disruption event (Formula 4).

Formula 3. Price appreciation or devaluation rate for a commodity.

$$RPA\Big/_{yr} = \left[\sqrt[LNV]{\frac{TP_t^{\$}}{IP_t^{\$}}} - 1 \right] \tag{3}$$

Where:

$RPA\big/_{yr}$ = Real Price Appreciation/devaluation rate per year

LNV = the change in years between the starting date and turning point date

$TP_t^{\$}$ = Turning-point real price

$IP_t^{\$}$ = Initiation-point real price (Formula 2)

Formula 4. Real price appreciation rate: July 1992 to January 1994 (using Formula 3).

$$RPA/_{yr} = \sqrt[1.50]{\frac{\$1173/_{MBF}}{\$715/_{MBF}}} - 1 = 0.3915 = 39.15\%/year \quad (4)$$

3.2. Delivered log real price 2006–09 cycle disruption

A subsequent market cycle disruption initiated in July 2006 when the price of Douglas-fir 2-Sawmill logs was \$595/MBF nominal (\$708/MBF real) (Fig. 2). This was identified as the starting point of a 2.92-year devaluation event that turned in June 2009 when the nominal price reached \$358/MBF (\$408/MBF real).

The initiation-date 4-month time-weighted real prices for the April–July 2006 period were \$702, \$714, \$717, and \$708/MBF, to generate the time-weighted initiation real price (Formula 1) of \$711/MBF (Formula 5).

Formula 5. Time-weighted, 2006–09 cycle's initiation-point real price.

$$IP_t^{\$} = \frac{\begin{bmatrix}(0.60 \times 702) + (0.70 \times 714) \\ (0.80 \times 717) + (0.90 \times 708)\end{bmatrix}}{(0.60 + 0.70 + 0.80 + 0.90)} = \$711/MBF \quad (5)$$

Real price devaluation cycle of Douglas-fir 2-Sawmill logs, using the 2006–09 guiding values is revealed in comparative real price devaluation between the price points (Formula 3). Real-values for this specific commodity during this 2.92-year event, exposes a 17.29% per year devaluation rate (Formula 6).

Formula 6. Real price devaluation rate: July 2005 to June 2009 (using Formula 3).

$$RPA/_{yr} = \sqrt[2.92]{\frac{\$408/_{MBF}}{\$711/_{MBF}}} - 1 = -0.1729 = -17.29\%/year \quad (6)$$

When a commodity price increases in real terms, as it did in the 1992–94 disruption event (Formula 4), it is called a Real Price Appreciation. When the real prices drop, as they did in the 2006–09 cycle disruption event (Formula 6), it is called a Real Price Devaluation. Often, irrespective of whether it is appreciation or devaluation, the "RPA" title is applied using a negative value indicator "-" when it devalues.

Cycle disruption events analyzed indicate event patterns; additional considerations must be given to make price predictions following initial disruption events. Next, we examine market recovery segment of these cycles, which takes longer to unfold in time than its initial phase.

3.3. Real price appreciation forecast tool

This mathematical model (Formula 7) demonstrates a hyperbolic price recovery trajectory applicable to this timber commodity price profile (Barndorff-Nielsen, 1977). Cycle disruptions recover prices along trajectories progressing at a declining rate of change moving from the turning-point price to the initial real price level. The initial disruption and price recovery trajectories are not linear, and they are not symmetrical: price recovery takes longer then the initial disruption period.

Formula 7. RPA Forecast tool formula.

$$PF_t^{\$} = IP_t^{\$} \times \left\{1 + \left(\left[RPA/_{yr}\right] \times t \times 2^{\left[1-\left\{t/(LNV\times\{\ln(2)\})\right\}\right]}\right)\right\} \quad (7)$$

where:

$PF_t^{\$}$: RPA adjusted commodity real price forecast determined for time point "t"

$IP_t^{\$}$ = Cycle initiation real price (Formula 1)

$RPA/_{yr}$: Calculated RPA rate using date specific real price (Formula 3)

LNV = Longevity duration from initiation date to turning-point date (Formula 3)

t = Number of years from cycle initiation date to the date of price prediction

These components give enunciation of the Markov-chain random-walk with memory prediction model's hyperbolic price recovery trajectory.

3.4. Initiation/turning-point

The cycle's initiation real price (Formula 1), $IP_t^{\$}$, is the anchor which signifies the random-walk initiation and its return to the real price baseline level. The return to baseline price levels is founded in random-walk theories (Moosa and Burns, 2014), where economic smoothing has been applied. The furthest right side of Formula 7, $\left\langle 2^{\left[1-\left\{t/(LNV\times\{\ln(2)\})\right\}\right]} \right\rangle$ reduces to "0" by 2027 (after 21 years) in the 2006–09 event example (Formula 8) and will consistently reduce to "0" in all applications given sufficiently extended in time horizons. This portion of Formula 7, when combined with the remainder of multiplicative components, achieves $IP_t^{\$}$ and therefore the return to initiation real price.

3.5. RPA/yr and LNV term

The recovery path to the baseline price level is dictated by the severity of the RPA event and its duration in time, LNV (Formula 3), as real prices pivot to reverse the appreciation or devaluation incident. Event severity can be considered in terms of longevity exceeding 12 months. Simultaneously observing real price appreciation or devaluation exceeding 50% in the time elapsed can be used to identify the event as a commodity's real price disruption event.

3.6. Taylor series

The natural log of 2 {ln(2)}, placed in the denominator of the exponent to the number two (2) and added to one (1), gives steady disruption and recovery features to the RPA Forecast tool formula. Used in the Taylor series and subsequently applied by many (Duistermaat and Kolk, 2010), the application of {ln(2)} in this formula introduces a continuous compounding feature in order to recover the path to an original price level. Thereby, the return to the initial real price level is extended in time compared to the time elapsed during the initial phase of the disruption event.

3.7. Time forecast extent (t)

Modification of the time (t) variable (Formula 7), ushers price predictions to future dates. It is first multiplicative to the {*RPA/yr*} variable, and second, it is in the numerator of the value-reducing exponent of a constant (2). When 't' is a large number, the variable triggers this far right-side portion of the exponent's numerator to approach zero simultaneously resulting in its base ($2^{\times}$) approaching zero. As the far right-side of the clause is multiplicative of this feature (t), it also approaches zero and is summed with one (1), leading the entire cycle to revert to its baseline real price level: mean reverting Markov-chain.

4. Discussion

The RPA Forecast tool (Formula 7), being consistent with a multivariant discrete-time Markov-chain format relies in its design on some critical independent variables. There are four embedded variables and one equation modifier (Formula 7), arrays of PPI and log market price data to create real value predictions made here.

4.1. Price forecasting

This price forecast model (Formula 7), can be used to predict commodity price cycle values at time-specific cycle dates, but will not predict isolated price shocks, random noise, or seasonal fluctuations in competitive markets: it is applicable when predicting the underlying real price cycle as it recovers from price disruptions on a path to initial baseline level. Real price values diverting from this predicted path can be considered to determine if they are the result of shocks or random noise, or if cycle patterns are an indication of a new price cycle taking effect.

This conversion process (Formula 7) predicts future real prices from the date used to establish the cycle matching year and month “t” (Fig. 2). The July 1992 to January 1994 price disruption event displays how the RPA Forecast tool prediction seeks market price equilibrium through time. Return to real price base level ($715/MBF) took approximately 7 years (July 1999) to reacquire 95% of the real price level ($752/MBF), and 10 years (July 2002) to reacquire 99% of the real price level ($722/MBF) (Fig. 2). Several stochastic market price shock patterns are observed peaking exchange prices above and troughing below the RPA Forecast tool trend.

The trend line display (Fig. 2) was clipped at December 2005 for the purposes of clearing it for the next real price disruption event in 2006. The 1992–94 real price prediction forecast could have been extended further, but it fundamentally ends when a new commodity real price disruption event occurs. The RPA Forecast tool real price trend-line will asymptotically approach a horizontal line as real price forecasts are extended.

The 2006–09 disruption event's initiation time-weighted real value ($IP_t^{\$}$) was $711/MBF (Formula 5). The time from initiation to a future date (“t”), is projected 14 years to forecast this commodity's real price in July 2020: $682/MBF (Formula 8). This forecast price is approximately 96% of the initial base level projected by the RPA Forecast tool.

Formula 8. RPA price conversion of 2006–09 cycle disruption to July 2020 (Formula 7).

$$PF_{14.0}^{\$} = \$711 \times \{1 + (-0.1729 \times 14.0 \times 2^{[1-[14.0/(2.92\times\{\ln(2)\})]]})\} \tag{8}$$

$$= \$682/MBF$$

Real price forecasting from the 2006–09 disruption event displays (Fig. 2, Fig. 3) extend to 2025. The aforementioned return to baseline real price level ($711/MBF) will have attained 99% of equilibrium real price by 2025.

4.2. Forecast performance measures

The RPA Forecast tool (Formula 7) is not a regression analysis technique. It serves as an equation, computing price forecasts as a best fit approximation of delivered log market stochastic prices. Comparing on a monthly basis actual competitive market real prices with predicted trend line values gives insight to forecast accuracy. Time-series data, such as competitive market price data recorded at monthly intervals, showing non-stationary behavior with shocks, random noise, seasonality, shifts and trends, can be examined through the Box-Jenkins (Box and Jenkins, 1976) Autoregressive Integrated Moving Average (ARIMA) analyses (Adhikari and Agrawal, 2013) (Table 1).

A prediction interval (PI) estimate for each observed forecast (monthly) is graphically presented to describe forecast accuracy as observed since 1992, and as predicted through 2025 (Fig. 3). PI estimates involve a different, but conceptually similar type of probability statement from that implied by the more familiar confidence interval, which is traditionally applied to interval estimates for fixed but unknown parameters, such as regression analysis horizons (Box and Pierce, 1970).

ARIMA performance measures of efficiency and potential bias use traditional techniques when applied to price forecasting. The Mean Forecast Error (MFE) is a measure of the average deviation of forecasted values from the prices recorded monthly in the market, with minimum bias achieved when its value is as close to zero as possible. The Mean Absolute Error (MAE), also known as the Mean Absolute Deviation (MAD), measures the average absolute deviation of RPA Forecast tool to monthly marketplace values. The Mean Squared Error (MSE) emphasizes the deviation of total forecast error measures. MSE gives an overall measure of the amount of error occurring during forecasts (Adhikari and Agrawal, 2013).

Table 1
Performance measures for Douglas-fir 2-Sawmill log price predictions, expressed in October 2019 real terms.

Forecast performance measures	1992–94 disruption	2006–09 disruption
MFE: Mean Forecast Error, a.k.a. Forecast Bias	16.7058	34.2889
MAE: Mean Absolute Error, or MAD: Mean Absolute Deviation	54.4127	53.1196
MPE: Mean Percentage Error	1.1234	5.1622
MAPE: Mean Absolute Percentage Error	6.3950	8.5890
SSE: Sum of Squared Error	799,300	699,001
MSE: Mean Squared Error	5027	4369
SMSE: Signed Mean Squared Error	2767	3371
RMSE: Root Mean Squared Error	70.90	66.10
NMSE: Normalized Mean Squared Error	0.2812	0.5401
Theil's U Statistics	1.037×10^{-04}	1.928×10^{-04}
Number of Samples (n)	159	160
Sub-Population Mean ($\bar{x}$)	$826	$597
Sub-Population Variance (σ^2)	17,879	8088

PIs are broader as compared to confidence intervals, but both rely on the Student's t-statistic (Formula 9). Multiplication of the MSE by the variance estimate of each forecast amount contributes to the broader PI horizon (Formula 10). When creating PI segments, the square root of the sum of MSE and standard error (se) components convey the overall error of each segment analyzed and serves as a scaling factor when applied to Student's t-statistic tests of significance (Pardoe et al., 2018). PI horizons for both market disruption events are displayed using these criteria (Fig. 3).

Formula 9. Development of prediction interval around forecasted prices (general).

$$\text{Sample estimate} \pm (\text{t} - \text{multiplier}\times\text{cumulative error}) \tag{9}$$

Formula 10. Development of prediction interval around forecasted prices (specific).

$$\hat{y}_t = \pm t_{(\alpha/2, n-p)} \times \sqrt{MSE + [se(\hat{y}_t)]^2} \tag{10}$$

Other common forecast measures applied to ARIMA analyses (Table 1) provide an indication of the performance of both the ability of the RPA Forecast tool to predict prices in this marketplace, and the variability of this commodity's market prices. Student's t- statistic test with corresponding PI values can be applied to evaluate how closely the RPA Forecast tool formula follows the patterns of these stochastic real prices, as a normal distribution (Box and Jenkins, 1976). The Student's *t*-test is used here to determine if the RPA Forecast tool projections and the stochastic real price patterns, for matching time periods, are significantly different from each other (Mankiewicz, 2004).

4.3. 1992–94 disruption event

Application of the PI with Student's t-statistic test of the RPA Forecast tool formula observed in the marketplace versus real price events (Formula 10), indicates if they diverge significantly from each other. This 159-measurement segment of the time series has a mean of $826/MBF, and MAE of 54.41, MSE of 5027, and sub-population variance (σ^2) of 17,879 (Table 1).

Two tests of significance, 60% and 90% have been applied to these data during this period (Fig. 3). All real market prices within this market disruption event prediction were distributed within the 90% PI of the RPA Forecast tool. Simultaneously, approximately 89% (144 out of 162) real market prices were distributed within the 60% PI.

4.4. 2006–09 disruption event

This 160-measurement time-series segment has a mean of $597/MBF real, MAE of 53.12, MSE of 4369, and sub-population variance (σ^2) of 8088 (Table 1). All stochastic real prices have been distributed within the 90% PI of the RPA Forecast tool predictions (Formula 10). During this disruption event, approximately 14% (23 out of 160) stochastic market real prices have been recorded above the 60% PI (Fig. 3). Only one observed market real price dropped marginally below the 60% PI in December 2018.

As of October 2019, this market disruption event passed through 13.25 years to recapture approximately 95% of the real price baseline level. In July 2025 (19 years into this cycle) real prices are expected to approximate 99% of the projected base-price level at $704/MBF.

4.5. Prognostications

It is reasonable to assume that other significant market disruptions will be witnessed in this market before the return to base price level is settled. Such an event may be a technological advance of timber harvesting, lumber milling, home construction, building structure engineering, or it might come as new land use regulations changing supply patterns. Allen et al., (2002, 309) point out that “almost all economic relationships are behavioral rather than technical”. It is possible that a new cycle, instigated as behavioral (Lane, 2017) or technical changes (Hicks, 1932), will be introduced before the current cycle's base-line real price is reacquired.

When developing highly elaborate econometric forecast models of commodity price patterns, some researchers have separated vast arrays of potential independent variables into dozens or hundreds of simultaneous regression analysis algorithms to predict ultimate price effects on dependent commodity subjects. Zellner (1992) recognized the danger of over-complicating analysis rigor with what he called the KISS principle (Keep It Sophisticatedly Simple), while urging others to follow the “law of parsimony” (Soklakov, 2002). Decision makers are guided to seek simpler theories to explain phenomena as being the preferable approach to more complex and convoluted explanations (Baker, 2016). Independent variable parsimony has been the guiding theme while developing the Real Price Appreciation Forecast tool formula.

The RPA Forecast tool is not designed to precisely predict causal variables: it predicts neither monthly PPI values, nor changes in log demand or supply, nor the underlying demand for housing, nor interest rate changes. Monthly updates applied to these data arrays are limited to delivered log prices expressed nominally to be modified using another monthly updated variable, PPI values, allowing real price articulation in current terms.

The Markov-chain with random walk and return to base-level principles have fully supported the internal logic of the presented approach. Round log sellers can use these forecasts with current price data to contextualize their decision-making process based on the forecast price matrix and decide if it is time to sell their standing timber, or if holding it in anticipation of climbing prices is warranted. Timberland valuation analysts (appraisers) and financial officers are better assisted if they possess techniques to confidently project growing timber commodity values in unison with highly developed forest biometrician prognoses of merchandised timber volume.

4.6. Domestic and international market implications

Delivered log price forecasting has historically been elusive due to log market behavior unpredictability. The RPA Forecast tool results are expressed in real terms to apply to growing timber assets, referencing their financial value in sync with biometric growth and yield prognoses. This allows broad projected data fields extrapolated from these initial settings, to develop optimal harvest timing combinations.

Asset valuation is engaged through many forms of competitive market interactions found in local, domestic, and international market transactions. The RPA Forecast tool is an instrumental asset valuation application used to predict commodity price trends, extended beyond only current day transactions to capture migrating real commodity prices into the future. Price prediction trends extend into near- and mid-term forecasts, creating reserve price indicator horizons (Rosenkranz and Schmitz, 2007) where practitioners can consider their operational time value of money pressures.

While timber log markets transact at local and regional scales, these expand to competitive market forces across international markets. All timber is grown as single trees, assembled as timber stands. Timber stands accumulate to discrete properties which can be transacted between people, companies, organizations, and governments. Competitive market round log buyers and sellers use asset valuation protocols to anticipate transactable commodity prices and derivative forestland property value. Forestland value builds from timber log production possibilities of each timber stand where growing tree volume is expressed by forest biometricians around the world (Wykoff et al., 1982).

While these timber volume predictions are expressed with sometimes acute accuracy, the competitive market value of logs has been less predictable, especially when extended into time horizons passing annual periods. Commercial forestland asset value is topic of investigation by land appraisers (USPAP, 2018; IVCS, 2017), investment executives (Heaney, 2006), and forestland managers (Hyde, 2012). This price prediction mechanism provides financial insights to marketplace performance. As a policy tool for administrators, this reaches into taxation considerations, land use restrictions, employment levels across sectors, and financial returns to publicly owned forestlands. Commercial timberland owners will use these data to set asset valuation parameters and derivative stock prices, establish long- and short-term prices for timber log sale contracts, and schedule employment level predictions.

Application of the RPA Forecast tool where logs are transacted enables users to confidently predict short- and mid-term competitive market real prices.

Declaration of Competing Interest

None.

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