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North American Oriented Strand Board Markets, Arbitrage Activity, and Market Price Dynamics: A Smooth Transition Approach*

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Abstract

Price dynamics for North American oriented strand board (OSB) markets are examined. The role of transactions costs are explored vis–à–vis the law of one price. Weekly data, February 3rd, 1995 through October 9th, 2009, are used in the analysis. Nonlinearities induced by unobservable transactions costs are modeled by estimating Time–Varying Smooth Transition Autoregressions (TV–STARs). Results indicate that nonlinearity and structural change are important features of these markets; price parity relationships implied by economic theory are generally supported by the estimated models. Implications for the efficiency of spatial market linkages and the dynamics associated with price adjustments are also examined.

Keywords: Law of one price, Oriented strand board, Nonlinear model; Time–varying smooth transition autoregression; Transactions costs, Unit root tests

JEL Classification Codes: E30; C22; C52; Q23; Q27

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1 Introduction

Over the years there has been considerable interest in and debate about the validity of the Law of One Price (LOP) as it pertains to markets for tradeable goods. On one hand, economists take it as being nearly axiomatic that freely functioning markets for traded, homogeneous products should ensure that prices are efficiently linked across regional markets, the implication being that no persistent opportunities for spatial arbitrage profits exist. This general concept is so fundamental that it often serves as an untested assumption that forms the starting point in models of exchange rate determination and regional trade. In spite of the prominent role played by the LOP in trade research, a number of qualifications to this general relationship exist. In particular, the strength of spatial linkages among commodity markets typically depends on the availability of reasonably accurate market information and the lack of significant impediments to spatial trade. Linkages that involve national borders also raise a number of issues pertaining to exchange rate pass–through and international trade policies. It is therefore common to examine commodities whose prices are denominated in a common currency, such as is the case with regional trade within national borders. An entire literature devoted to considerations of spatial market linkages within a country—the case of spatial market integration—has parallelled the Law of One Price studies.[1]

In any event, the general implication underlying these basic concepts is that prices for homogeneous products at different geographic locations in otherwise freely functioning markets should differ by no more than transport and transactions costs, the later including, for example, insurance, contracting fees, licensing fees, legal fees, and possibly a risk premium. On the other hand, there is substantial evidence that the adjustment lags required to restore arbitrage equilibrium are often found to be far longer than would seem natural based upon any reasonable understanding of the mechanics of physical trade as it pertains to the markets in question. Indeed, in some instances price differences have been observed to exhibit near unit root behavior, a condition that would most certainly be at odds with any typical rendering of efficient spatial arbitrage and/or

[1]Distinctions between tests of the "LOP" and "spatial market integration" are not especially meaningful. In both cases, the economic phenomena being evaluated—spatial market arbitrage—is identical. A survey of both strands of literature can be found in Fackler and Goodwin (2001).

the LOP.

What then is the empirical consensus regarding the LOP? In an extensive study that used disaggregate data for traded goods, Isard (1977) found rather conclusive evidence against the LOP. Isard's conclusions were, moreover, subsequently confirmed for a variety of commodities in a wide array of market settings by, among others, Richardson (1978), Thursby, Johnson, and Grennes (1986), Benninga and Protopapadakis (1988), and Giovannini (1988). Goodwin, Grennes, and Wohlgenant (1990) did, however, find some support for the LOP when it was specified in terms of price expectations as opposed to observed prices. A potential shortcoming of all of these studies is a general failure to explicitly consider the role of transactions costs and delivery lags. More recently, cointegration techniques have been used to rationalize the LOP as a long–run concept. By adopting this view of the LOP, numerous authors have found rather more compelling evidence in favor of the law, including, for example, Buongiorno and Uusivuori (1992) (U.S. pulp and paper exports), Michael, Nobay, and Peel (1994) (international wheat prices), Bessler and Fuller (1993) (U.S. regional wheat markets), and Jung and Doroodian (1994) (softwood lumber markets).

Most recently, economists have explored the implications of spatial arbitrage by using nonlinear models of various forms. The underlying motivation is that adjustments to equilibrium may not be linear, and that this nonlinearity may, in turn, be associated with hard–to–observe transactions costs associated with arbitrage. The theoretical underpinnings for transactions–costs–induced nonlinearity in the LOP have been put forward by Dumas (1992), although the basic idea dates back at least to the work of Heckscher (1916), who noted that transactions costs may define "commodity points" within which prices are not directly linked because the price differences are less than the costs of trade.[2]

Empirical investigations of the role of nonlinearity as pertains to the LOP have been reported by Goodwin and Piggott (2001), Lo and Zivot (2001), Sephton (2003), Balcombe, Bailey, and Brooks (2007), and Park, Mjelde, and Bessler (2007). The empirical work reported in these

[2]A good albeit brief review of the theory of nonlinearity induced by transactions costs vis–à–vis the LOP is reported in Lo and Zivot (2001).

studies has been conducted primarily by using variants of discrete threshold cointegration models of the sort introduced by Balke and Fomby (1997). In general these studies have found support for threshold effects, with the path of adjustment to equilibrium depending typically on the size if not the sign of the shock. Specifically, introducing nonlinearities in the form of threshold effects often provides much greater support for spatial market linkages of the sort implied by theory. In particular, large shocks that lead to profitable arbitrage opportunities net of transactions costs are quickly eliminated whereas smaller shocks, which may not be large enough to result in profitable arbitrage opportunities, may elicit a much smaller effect or even no adjustment at all.

The extent to which spatially distinct markets are efficiently linked may have important implications for overall market performance.[3] Here we consider regional North American markets for a prominent traded commodity—oriented strand board (OSB). OSB now accounts for the largest share of the overall panel wood products market, exceeding the production and use of plywood by a considerable extent. Spatial linkages in this market are of particular interest because it is a good that is widely traded across considerable distances within the North American continent. Consumption is widespread and spatially dispersed while production tends to be concentrated in particular regions such as the U.S. South and Eastern Canada. Depletion of old–growth timber stocks that traditionally served as a source for panel wood products brought about tremendous growth in the use of engineered wood products such as OSB. A burgeoning housing market (and its more recent contraction) have brought about a number of significant shocks to this rapidly expanding industry. Construction market responses to large hurricanes such as Andrew in 1992 and Katrina in 2005 are another source of OSB market price volatility that merits clearer understanding for better quantifying the economic impacts of these catastrophic events. These and related factors underscore the importance of understanding and quantitatively measuring linkages among regional OSB markets. Wood products are also bulky commodities, which are costly to

[3]Many different conceptual definitions of the notion of "spatial efficiency" are used in the literature and as a result the coherence of conclusions based upon empirical tests is often strained. Here we are interested in the extent to which price shocks in one location induce market reactions in another. This is consistent with conventional views of market efficiency—that is, an absence of persistent arbitrage opportunities. However, we do not explicitly pursue other aspects of efficiency that are often considered (especially in developing economy studies), such as the underlying structure and transportation linkages associated with regional commodity trade.

transport. This simple observation suggests that transactions costs should play a substantive role in shaping market linkages and reactions to market shocks for this particular good.

Other aspects of the OSB market make an investigation of spatial price linkages and price dynamics especially timely and interesting. The North American OSB market has been affected by a case involving allegations of price fixing behavior in violation of the Sherman Antitrust Act and related state antitrust laws. The source of the data used in our analysis—Random Lengths—played a role in the alleged conspiracy as a mechanism used by the OSB manufacturers to fix prices.[4] Any such actions on the part of producers, consumers, or middlemen who have market power may be reflected in spatial price linkages and adjustments to market shocks.

In this paper we apply a class of nonlinear, time–series models that allow for the possibility of gradual adjustments among price linkages and, moreover, for the possibility of structural change. Specifically, we focus on a class of models known as TV–STARs, or Time–Varying Smooth Transition Autoregressions. As the name implies, TV–STAR models allow for a (possibly) smooth transition in and out of a transactions cost band that segments markets. As noted by Taylor et al. (2000), this later feature may be important if agents operating in OSB markets are heterogenous, and each faces a slightly different and unique set of trading costs. Furthermore, by incorporating time–varying features it is possible to allow for structural change that may be associated with changes in production costs, changes in demand, or other changes that might, for example, be associated with non–competitive behavior. We present the results of an empirical study wherein we examine market linkages on a weekly basis for six price pairs derived from four important regional North American OSB markets. Initial test results indicate there is considerable evidence in every case in favor of nonlinearity in price linkages as well as structural change. And in every instance the estimated nonlinear models are superior to their linear counterparts. Moreover, the results show how ignoring transactions costs can lead to erroneous conclusions regarding the nature and the strength of OSB market linkages and the economic behavior underlying them.

[4]See Master File No. 06-826, OSB Antitrust Litigation, United States District Court For The Eastern District Of Pennsylvania.

2 The Economic Model

We present here a simple model of spatial price relationships that incorporates the effects of transaction costs. The conceptual model is based upon a framework developed by O'Connell and Wei (2002). To simplify, transaction costs are assumed to be entirely due to transport costs, which in turn are of the "iceberg" variety. Assume there is a homogenous commodity traded in two regional markets represented, respectively, by location indices *i* and *j*. The regional market prices for the good are given by p_i and p_j; moreover, assume for the moment that the good is ordinarily purchased in region *i* and sold in region *j*. The per–unit revenue to arbitragers selling in region *j* is therefore $(1-\kappa)p_j$, where κ denotes the per–unit loss in value for the commodity due to transaction (transport) costs, $0 < \kappa < 1$. In general the greater the distance between locations i and j, the closer is κ to one. We then have the following. Arbitrage from region i to region j is *not* profitable so long as $(1-\kappa)p_j - p_i \leq 0$ or conversely $(1-\kappa) \leq p_i/p_j$. Alternatively, if arbitrage is instead contemplated from j to i, it follows that this activity will *not* be profitable so long as $p_i/p_j \leq 1/(1-\kappa)$. Combining the inequalities associated with non–profitable arbitrage, we obtain

$$1/(1-\kappa) \geq p_i/p_j \geq (1-\kappa),$$

or, after taking natural logarithms,

$$-\,ln(1-\kappa) \geq y \geq ln(1-\kappa), \tag{1}$$

where $y = lnp_i - lnp_j$. The implication from (1) is there is a band, $[-ln(1-\kappa), ln(1-\kappa)]$, within which no profitable arbitrage activity will occur; arbitrage is, however, profitable when log relative prices, *y*, fall outside of the limits of the band. Over time we would expect that log relative prices within the limits of the band would follow something very close to a unit root process, likely without drift. But log relative prices that fall outside of the limits of the band should be mean reverting, perhaps strongly so. Among other things the implication is that standard unit root tests applied to y collected over time may be misleading in as much as the linear alternative employed in these tests is inconsistent with the presence of transaction costs (e.g., Lo and Zivot, 2001).

The relation in (1) implies a discrete transactions cost band, which has often been assumed in the literature (see., e.g., Balcombe, Bailey, and Brooks, 2007, or Goodwin and Piggott, 2001), and which typically yields an empirical model consistent with a threshold autoregression (TAR). Such an approach is reasonable if agents are largely homogeneous and they are geographically concentrated. But to the extent that agents (firms) are not geographically concentrated (i.e., they face differing transport costs), as is likely the case for the application considered here, the threshold approach may be limiting (Taylor et al., 2000). One reasonable alternative then, and one that we consider subsequently, is to allow for a continuum of transactions cost bands as might be implied, for example, by a smooth transition model.

3 The OSB Market and Price Data

Our focus here is on spatial price relationships for an important regionally–traded wood product: oriented strand board (OSB). OSB is a manufactured wood product that was first introduced in 1978 (the forerunner to oriented strand board was waferboard). OSB is engineered by using waterproof and heat cured resins and waxes, and consists of rectangular shaped wood strands that are arranged in oriented layers. OSB is produced in long, continuous mats which are then cut into panels of varying sizes. In this regard OSB is similar to plywood, although OSB is generally considered to have more uniformity than plywood and is, moreover, cheaper to produce. The Structural Board Association (SBA) reports that in 1980 OSB panel production in North America was 751 million square feet (on a $3/8^{th}$'s inch basis), but that by as early as 2005 this number had grown to 25 billion square feet. The SBA also reports that by 2000 OSB production exceeded that of plywood, and that by 2006 OSB production enjoyed a sixty–percent market share among all panel products in North America. Figure 1 illustrates the substantial growth in OSB use and the corresponding decline in consumption of plywood products. OSB is widely used in residential and commercial construction, with the bulk of OSB produced in North America originating in the Southern United States and Canada–in 2009 and 2010 Canada and the Southern U.S. produced nearly ninety–percent of all OSB produced in North America (Engineered Wood Product Association, 2010).

Considering the above, we focus on price relationships for OSB in four regional North American markets. Specifically, the regions examined are: (1) Eastern Canada (production deriving from plants in Ontario and Quebec); (2) North Central (production deriving from plants in Wisconsin, Michigan, and Minnesota);(3) Southeast (production deriving from plants in Georgia, Alabama, Mississippi, South Carolina, and Tennessee); and (4) Southwest (production deriving from plants in Texas, Louisiana, Arkansas, and Oklahoma). The result is there are six pairwise spatial price relationships that may be examined, with the market/price pairs identified, in order, in Table 1. The price data are for panels of $7/16^{th}$'s inch oriented strand board, and are expressed in U.S. dollars per thousand square feet. All price data are observed on a weekly basis and were obtained from the industry source Random Lengths.[5] The period covered is from February 3, 1995 through October 9, 2009, the result being there are 767 usable weekly observations. A plot of the regional OSB price data is reported in Figure 2; important events impacting North American OSB markets during the sample period are recorded in Table 2.

As noted previously, the sample period coincides with the growth and eventual dominance of OSB as a building material in North America. But specific episodes affecting regional OSB prices are as follows. First, the sample period coincides with an era of sustained growth in domestic housing markets (approximately 1991 through 2006), and most notably in several states in the Southeast region (i.e., Florida and Georgia). Second, the sample period also encompasses the more recent sharp contraction in U.S. new home construction (2006-2008) and the corresponding economic downturn. Third, and as previously noted, the sample period spans the time for which

[5] Random Lengths is an independent, privately owned price reporting service, providing information on commonly produced and consumed wood products in the U.S., Canada, and other countries since 1944. Reported open–market sales prices are based on hundreds of weekly telephone interviews with product buyers and sellers. These interviews are with producers, wholesalers, distributors, secondary manufacturers, buying groups, treaters, and some large retailers. The regional OSB price data used are FOB mill price averages.

a number of North American OSB manufacturers allegedly conspired to hold down production in a bid to increase prices (2002–2006). Fifth, five tropical cyclones, four of which were hurricanes, struck Florida in 2004, resulting in considerable property damage. Fifth, the sample period includes the immediate effects and aftermath of Hurricanes Katrina and Rita in 2005, of which Katrina alone was the second worst hurricane in terms of property damage in the past 105 years (Pielke et al., 2008). Finally, there were several notable periods of capacity expansion in OSB manufacturing. As reported by Kryzanowski (1996/1997), during 1996 and 1997 considerable new OSB production capacity came on–line in Canada with the result that OSB mill prices in Eastern Canada declined relative to other regions during much of the late 1990s and early 2000s (Figure 2). As well, from 2006–2007 considerable new production capacity came on–line in the Southeast at almost precisely the same time that conditions in the housing market, and most notably in the Southeast, started to weaken.[6] The net result is that during much of the period from 2007 on prices for OSB in the Southeast are below those for the remaining regions. See Figure 2. Taken together, these events raise interesting questions about how these various market "shocks" may have been transmitted among regional OSB prices and, moreover, what the role of structural change in regional price relationships might have been.

As implied previously, the basic unit of analysis used throughout this study is the natural logarithm of the price ratio, that is, $ln(p_{it}/p_{jt})$, where i and j are indices indicating regional location (i.e., $i, j = 1, \ldots, 4$) and a subscripted t is a time index such that $t = 1, \ldots, T$, where $T = 767$.[7] Plots of the six price pairs, expressed in logarithmic form, are presented in Figure 3. These plots reflect many of the patterns and events outlined above. For example, during the late 1990s prices in Eastern Canada were generally lower than those in other regions, due presumably to the expansion in production capacity in Canada during this time. As well, the plots in Figure 3 reveal that beginning in the fall of 2006 the relationship between prices in

[6]Monthly data on regional housing starts show that construction in the Atlantic States declined more rapidly then most other regions during much of the December, 2006 to May, 2010 period. Of the Atlantic States, Florida and Georgia experienced the steepest declines.

[7]The bulk of the empirical literature examining the LOP and, relatedly, purchasing power parity (PPP) utilizes relative price relationships in logarithmic form. Alternatively, price differences in levels could also be examined, although the strong kurtosis patterns observed in the data would only be exacerbated by doing so.

the Southeast versus those in other regions changed fundamentally, with prices in the Southeast becoming considerably cheaper. See panels (b), (d), and (f) in Figure 3. As well, the OSB price in Eastern Canada has been rising steadily relative to that of the Southwest throughout much of the sample period, presumably for some of the reasons described previously. Figure 3 also shows there is considerable volatility in price ratios, suggesting the potential for significant market interactions and reactions to shocks.

4 Econometric Methods

As noted in previous sections, for various reasons, including firm heterogeneity, we use a specific class of nonlinear time series models, the Time–Varying Smooth Transition Autoregression (TV–STAR), to examine the potential role of transactions costs and structural change in regional OSB markets. Specifically, our empirical analysis will focus on transactions costs being modeled according to a Quadratic STAR (QSTAR) or Exponential STAR (ESTAR) model. In this section we define the TV–STAR models used and, as well, discuss ways of testing for threshold effects and unit roots simultaneously in the context of provisional linear models.

4.1 STAR–Type Models

The fundamental building block of any nonlinear time series model is a linear model, and typically a linear autoregressive model. Let $y_t = ln(p_{it}/p_{jt})$ for some *i* and *j*. We may then specify a linear p^{th}–order autoregressive model for the price pair as

$$\Delta y_t \;=\; \phi_0 + \boldsymbol{\phi}^{'}\boldsymbol{x}_t + \theta y_{t-1} + \varepsilon_t, \tag{2}$$

where $\boldsymbol{\phi} = (\phi_1, \ldots, \phi_{p-1})$ and where $\boldsymbol{x}_t = (\Delta y_{t-1}, \ldots, \Delta y_{t-p+1})$.[8] As well, ε_t is a mean–zero *iid* error term with finite variance. Lag length p may be chosen by using, for example, a model

[8] In the ensuing discussion we assume that y_t is stationary in the levels, that is, is a mean–reverting process. As we shall see in subsequent sections this assumption is entirely consistent with our preliminary analysis of the OSB regional price data.

selection criterion such as Akaike's Information Criterion (AIC).

In the basic STAR modeling framework used to investigate the LOP, the linear autoregression in (2) is typically modified as follows

$$\Delta y_t \;=\; \widetilde{\boldsymbol{\phi}}_{\mathbf{1}}'\widetilde{\boldsymbol{x}}_t(1 - G(s_t;\gamma,\boldsymbol{c})) + \widetilde{\boldsymbol{\phi}}_{\mathbf{2}}'\widetilde{\boldsymbol{x}}_t G(s_t;\gamma,\boldsymbol{c}) + \varepsilon_t, \tag{3}$$

where $\widetilde{\boldsymbol{x}}_t = (1, \boldsymbol{x}_t, y_{t-1})$, $\widetilde{\boldsymbol{\phi}}_{\mathbf{1}} = (0, \boldsymbol{\phi}_{\mathbf{1}}, 0)'$, $\widetilde{\boldsymbol{\phi}}_{\mathbf{2}} = (\phi_{2,0}, \boldsymbol{\phi}_{\mathbf{1}}, \theta_2)'$, and where $\theta_2 < 0$ is required. As well $\boldsymbol{c}$ may either be scaler– or vector–valued. In (3) $G(s_t;\gamma,\boldsymbol{c})$ is the so-called "transition function" that varies in a potentially smooth manner between zero and one according to a "transition" variable s_t, and whose properties are determined by the values of the speed–of–adjustment parameter $\gamma > 0$ and the location parameter(s), $\boldsymbol{c}$. The transition variable s_t may be a function of nearly any observed variable, but in practice it is typically taken to be some function of the lagged dependent variable, y_t. For example, Killian and Taylor (2003), in their investigation of the behavior of real exchange rates based on PPP fundamentals, suggest using something like

$$s_t \;=\; \left(\frac{1}{D_{max}}\right)\sum_{d=1}^{D_{max}} y_{t-d}, \tag{4}$$

where D_{max} is a pre–specified lag limit. The specification in (4) is also consistent with the notion that profit opportunities occur when large deviations in relative prices occur from some moving average.[9] In what follows we use the specification for s_t in (4) with $D_{max} = 5$.

In (3) we have *a priori* imposed a set of restrictions that are commonly employed in price parity studies where transactions costs are a feature of the analysis. Specifically, we have imposed $\phi_{1,0} = \theta_1 = 0$ throughout, a set of restrictions that, moreover, have been employed by Michael, Nobay, and Peel (1997), Taylor, Peel and Sarno (2001), and Killian and Taylor (2003), among others.[10] The implication is that when the transition function $G(.)$ in (3) approaches zero

[9]We are grateful to a referee for suggesting this specification for the transition variable along with its interpretation/justification.

[10]Moreover, in the subsequent empirical analysis a test of these restrictions for each price pair never resulted in a *p*–value less than 0.05.

that log price differential will follow a unit root process without drift. Alternatively, when $G(.)$ approaches one the log price differential will exhibit mean–reverting behavior with, moreover, $\phi_{2,0}$ denoting the long–run equilibrium.

In any event (3) has a natural economic interpretation in terms of departures from equilibrium parity conditions. The transition variable determines the nature of adjustment (or transition). In our case, the transition variable represents a function of lagged differences in logarithmic prices at two distinct locations. The larger the (absolute) value of the transition variable, the bigger will be the difference in recently observed prices and thus the larger is the deviation from a presumed parity condition and potential gains from arbitrage. We anticipate that larger deviations will induce faster and/or larger market adjustments than will smaller deviations. In this manner the STAR specification accommodates potentially different market adjustments that approximately follow departures from spatial price parity. The overall implication is that large market shocks that lead to departures from the LOP at time $t-1$ should result in adjustments that tend to restore the LOP beginning at time t. Smaller shocks may indicate significantly different patterns of adjustment.

There are a number of candidates for the transition function $G(.)$ in (3). Even so, one that has been used extensively in price parity analysis is the the exponential or ESTAR model. See, for example, Kilian and Taylor (2003), Taylor, Peel, and Sarno (2001), Paya and Peel (2004), and Fan and Wei (2006). In this case the transition function embedded in (3) is specified as

$$G(s_t;\eta,c) \;=\; 1-\exp\{-\gamma(\eta)[(s_t-c)/\sigma_{s_t}]^{2\nu}\},\gamma(\eta)>0,\nu=1,2,\ldots, \tag{5}$$

where typically $\nu=1$ and where σ_{s_t} is the sample standard deviation of the transition variable, s_t–normalizing (s_t-c) by σ_{s_t} tends to make the speed–of–adjustment term, $\gamma(\eta)$, unit free. The exponential function in (5) differs from many prior specifications in that the speed–of–adjustment term, γ, is specified in turn as a function of an estimable parameter, η. It is, of course, required that $\gamma(\eta)$ be positive. This inequality restriction is satisfied here by specifying $\gamma=\exp(-\eta)$, and thereby estimating η in lieu of γ. The resultant exponential transition function is therefore given by

$$(6) \qquad G(s_t;\eta,c) \;=\; 1-\exp\{-\exp(-\eta)[(s_t-c)/\sigma_{s_t}]^{2\nu}\}, \nu = 1,2,\ldots.$$

In any event the exponential transition function includes one location parameter, c.[11] The combination of (3) and (6) when $\nu = 1$ yields the ESTAR model. Alternatively, when $\nu \neq 1$ we follow Holt (2010) and refer to (5) as the Generalized ESTAR, or GESTAR. In either case the parameters $\widetilde{\boldsymbol{\phi}}_1(1-G(s_t;\gamma,c)) + \widetilde{\boldsymbol{\phi}}_2 G(s_t;\gamma,c)$ change symmetrically about the parameter c in (5) with s_t, thereby allowing for the possibility of a transactions cost band. Both the ESTAR and GESTAR become linear as $\gamma \to 0$ but as well when $\gamma \to \infty$. The ESTAR setup is therefore capable of modeling a spatial market setting wherein there are transactions costs associated with altering trade flows and where, moreover, movements in or out of the band are potentially smooth. One potential limitation of the ESTAR is that, as such, it does not nest as a special case a three–regime self exciting threshold autoregression (SETAR). This later property is potentially useful in part because several previous studies of spatial price relationships have successfully employed three–regime SETAR models to account for nonlinearities introduced by transactions costs. See, for example, Goodwin and Piggott (2001). What is true, however, is that the GESTAR does nest a (restricted) three regime SETAR. Specifically, even for finite γ as $\nu \to \infty$ the GESTAR takes on SETAR properties. See Holt (2010) for additional details. In this regard the GESTAR is a reasonably flexible transition function, and one with a potentially wider range of application then its nested ESTAR counterpart.[12]

An alternative to the ESTAR/GESTAR setup that is also well–suited for examining questions

[11] A number of studies employing the ESTAR in the context of the LOP or PPP have added the additional restriction that $c = \phi_{2,0}$. See, for example, Killian and Taylor (2003). In the application considered here, however, this restriction was found to have little empirical support.

[12] The choice of ν may be determined by estimating the model for a wide range of power parameters and comparing, for example, AIC or likelihood function values. Since the value for ν does not affect the number of free parameters being estimated the model with the lowest AIC is typically chosen. See, for example, Pollak and Wales (1991). Holt (2010) also considers the case where ν can take on non-integer values and, moreover, can be freely estimated, possibly by employing grid search techniques.

related to price parity is the second–order or quadratic logistic function, proposed initially by Jansen and Teräsvirta (1996), where $\boldsymbol{c} = (c_1, c_2)$ are location parameters, and given by

$$(7) \qquad G(s_t; \gamma, \boldsymbol{c}) \;=\; [1 + \exp\{-\exp(-\eta)(s_t - c_1)(s_t - c_2)/\sigma^2_{s_t}\}]^{-1}, \gamma > 0, c_1 \leq c_2.$$

An interesting feature of (7) is that, when combined with (3), the parameters $\widetilde{\boldsymbol{\phi}}_1(1-G(s_t;\gamma,\boldsymbol{c}))+\widetilde{\boldsymbol{\phi}}_2 G(s_t;\gamma,\boldsymbol{c})$ change symmetrically as a function of s_t around $(c_1 + c_2)/2$, the quadratic logistic function's mid–point. In this manner the model that combines (3) and (7), the so-called "QSTAR," allows for the possibility of a transactions cost band wherein movements in or out of the band are potentially smooth. Note that as $\gamma \to 0$ the model in (3) becomes linear and, as well, as $\gamma \to \infty$, and assuming that $c_1 \neq c_2$, then $G(.)$ assumes a value of one for $s_t < c_1$ and $s_t > c_2$ and zero otherwise. In this manner the QSTAR, similar to the GESTAR, nests as a special case a three–regime SETAR. Even so, to date the QSTAR has not been explicitly used to examine the LOP or purchasing power parity (PPP).[13] Because each transition function involves three parameters the choice between a QSTAR and a GESTAR will generally be application specific, being determined by overall fit (i.e., AIC) as well as various model diagnostic measures.

There are several intuitive reasons to suspect that the patterns of price adjustment in regional markets might be smooth rather than discrete, even though the economic behavior underlying the adjustments is of a discrete nature (i.e., arbitrage is either profitable or it is not). Weekly prices of the sort used in our analysis are comprised of many transactions among many agents, all averaged (or otherwise aggregated) to obtain a single price. To the extent that agents are heterogeneous and markets are not entirely static within the week, differences will exist across individual transactions. Averaging or otherwise aggregating prices to obtain a weekly price quote smooths these differences and should result in smooth patterns of price adjustment. Thus, it is preferable to allow for the possibility that market shocks will result in smooth adjustments back to parity rather than *a priori* imposing discrete breaks that define market regimes (Taylor et al., 2000).

[13] Eklund (2003) considers QSTAR models in the context of PPP but does not directly estimate such models.

4.2 Modeling Structural Change

An essential feature of the LOP, as implemented in the context of transactions costs bands, is that the process explaining the logarithm of relative prices is mean reverting for all values of the transition function, $G(.) > 0$. In short, the intercept term $\phi_{2,0}$ in (3) defines the long–run equilibrium between price pairs. There is, however, no reason to suspect *a priori* that the long–run equilibrium term is constant over time. Changes, either temporary or permanent, in the marginal costs of producing OSB in one area relative to another could, for example, cause the value of $\phi_{2,0}$ to change. As well, changes in market structure, induced perhaps by a change in competitive behavior in one region relative to another, could also cause the long–run relationship between regional OSB prices to be altered.

Generally speaking structural change has not been a feature of models investigation either PPP or the LOP, at least when nonlinearity induced by transactions costs is considered. Even so, the model in (3) is easily modified to account for structural change, and indeed to account for multiple structural changes. Specifically, consider the following modified version of (3) that allows for up to $\tau \geq 1$ structural breaks:

$$(8)\quad \Delta y_t \;=\; \widetilde{\boldsymbol{\phi}}_{\mathbf{1}}' \widetilde{\boldsymbol{x}}_t (1 - G_1(s_t; \eta_1, \boldsymbol{c_1})) + \left[\widetilde{\boldsymbol{\phi}}_{\mathbf{2}}' \widetilde{\boldsymbol{x}}_t + \sum_{j=2}^{\tau} \phi_{j+1,0} G_j(t^*; \eta_j, \boldsymbol{c_j}) \right] G_1(s_t; \eta_1, \boldsymbol{c_1}) + \varepsilon_t,$$

where $t^* = t/T, t = 1, \ldots, T$.[14] In other words, $G_j(.)$ is a transition function where the transition variable s_t is the time index, t^*. As such, the specification in (8) is similar in spirit to the time–varying STAR, or TV–STAR, framework put forth originally by Lundberg, Teräsvirta, and van Dijk (2003). In the event that structural change is smooth over time and non–monotonic the transition function $G_j(.)$ could be specified to belong to the class of ESTAR or GESTAR models in (6). Alternatively, if structural change is either monotonic or discontinuous, $G_2(.)$ could be

[14]In general other parameters including the autocorrelation coefficients and the coefficient on the lagged dependent variable could change over time as well. In the subsequent empirical application, however, there was not much evidence that this was the case.

specified according to the following logistic function

$$G_j(t^*;\eta_j,c_j) \;=\; \left[1+\exp\{\exp(-\eta_j)[(t^*-c_j)/\sigma_{t^*}]^k\}\right]^{-1}, j=2,\ldots,s, \tag{9}$$

and where k could be any consecutive odd integer, but is typically set to $k=1$ or $k=3$. See Balagtas and Holt (2009) for additional details. In any event as $\gamma(\eta_j)=\exp(-\eta_j)\to\infty$ the relevant structural change becomes discrete (discontinuous). There are various ways to test for and fit models similar to (8), that is, for models that allow simultaneously for nonlinearity due to transactions costs and structural change. In what follows we employ a specific–to–general modelling strategy similar to that described by Lundberg, Teräsvirta, and van Dijk (2003). Specifically, a QSTAR or GESTAR is first fitted to the relevant data and then evidence of structural change is obtained via additional diagnostic testing.

4.3 A Combined Unit Root and Linearity Testing Framework

A key component of any study of spatial price relationships is: (1) testing for unit roots (i.e., stochastic trends) in the respective $ln(p_{it}/p_{jt})$ price pairs, and (2) testing for linearity against nonlinear alternatives. In as much as standard unit root tests (e.g., the augmented Dickey–Fuller, or ADF, tests) do not consider nonlinear alternatives, prior research has generally approached testing in a two–step process. First, stationarity is examined by using standard unit root tests. Second, the data are then examined for nonlinear features by specifying an appropriate linear model and testing this model against various nonlinear alternatives.

When considering the LOP it may be desirable to test the null of a linear model with a unit root against an alternative that incorporates nonlinear features *and* mean reversion. Eklund (2003), for example, presents a bootstrapping framework for testing a linear unit root model against a stationary STAR–type alternative, specifically, a QSTAR alternative. Rothe and Sibbertsen (2006) extend Phillips–Perron type tests of unit roots to consider a stationary ESTAR alternative. Finally, Bahmani–Oskooee, Kutan, and Su (2008) use tests developed by Kapetanios, Youngcheol, and Snell (2003) to to examine the unit root hypothesis against nonlinear, stationary alternatives consistent with an ESTAR specification.

Here we employ a testing approach similar to Eklund's (2003). Formally, consider that we wish to test the validity of the linear unit root model

$$\Delta y_t \;=\; \phi_0 + \boldsymbol{\phi}'\boldsymbol{x}_t + \varepsilon_t, \tag{10}$$

against a stationary GESTAR or QSTAR alternative

$$\Delta y_t \;=\; (\phi_{1,0} + \boldsymbol{\phi}_1'\boldsymbol{x}_t + \theta_1 y_{t-1})(1 - G(s_t;\gamma,\boldsymbol{\omega})) + (\phi_{2,0} + \boldsymbol{\phi}_2'\boldsymbol{x}_t + \theta_2 y_{t-1})G(s_t;\eta,\boldsymbol{\omega}) + \varepsilon_t, \tag{11}$$

where $\boldsymbol{\omega}$ denotes parameters in $G(.)$ other than γ (i.e., $\boldsymbol{\omega}$ includes one or more centrality parameters and, possibly, the power parameter η).[15] Luukkonen, Saikkonen, and Teräsvirta (1988), or LST, note that even in the absence of the unit root question it is not possible to directly test (10) against (11) by using standard tests. The reason is even under the null hypothesis of linearity, that is, under $H_0' : \gamma = 0$, the remaining parameter(s) in $G(.)$ as well as those in $\boldsymbol{\phi}_1$ and $\boldsymbol{\phi}_2$ are unidentified. Simply put, there are unidentified nuisance parameters under the null, the classical Davies (1977, 1987) problem; usual test statistics such as the log likelihood ratio have no known classical limiting distributions.

LST describe a practical approach to testing H_0'. Specifically, they replace $G(s_t;\gamma,\boldsymbol{\omega})$ in (11) with a suitable Taylor series approximation evaluated at $\gamma = 0$. For GESTAR or QSTAR models LST suggest using a first–order approximation to $G(.)$; however, Escribano and Jordá (1999) present evidence that a second–order approximation may have certain advantages. By using the later, and after substituting the resultant second–order approximation into (11) and collecting

[15] For purposes of unit root and linearity testing we assume under the alternative that both regimes contain a drift term, and that both contain the lagged level of the log price ratio. The reason for doing so is the testing framework, developed by employing suitable Taylor series approximations of $G(.)$, cannot also distinguish between (3) and (11).

terms, the following auxiliary regression is obtained

$$\Delta y_t \;=\; \delta_0 + \boldsymbol{\vartheta}'\boldsymbol{x}_t + \lambda_0 y_{t-1} + \sum_{i=1}^{4}\delta_i s_t^i + \sum_{i=1}^{4}\boldsymbol{\vartheta}_i'\boldsymbol{x}_t s_t^i + \sum_{i=1}^{4}\lambda_i y_{t-1}s_t^i + \xi_t. \tag{12}$$

The error term ξ_t is a linear function of the original error term ε_t in (11) plus approximation error. Even so, under H_0' approximation error is zero and $\xi_t = \varepsilon_t$.

We use (12) to test the null hypothesis that log relative price pairs for regional OSB markets are best characterized by a linear model containing a unit root. Specifically, by imposing the restrictions $\delta_1 = \ldots = \delta_4 = \lambda_0 = \ldots = \lambda_4 = \vartheta_{1,1} = \ldots = \vartheta_{4,p} = 0$ on (12), a linear unit root model is obtained. We refer to the null hypothesis being tested in this case as $H_{0,lur}$. Likewise, we refer to the resulting F statistic associated with testing $H_{0,lur}$ as F_{lur}, which in turn is associated with $(9 + 3p)$ and $T - (10 + 5p)$ degrees of freedom.

The F_{lur} test statistic will not be associated with a limiting F–distribution when the unit root hypothesis is also embedded in the restrictions being tested. We therefore approximate the limiting distribution of F_{lur} empirically by using nonparametric bootstrapping methods. See Balagtas and Holt (2009) for additional details.

5 Empirical Results

The econometric results obtained for the weekly OSB regional North American price data for the 1995–2009 period are presented in three parts. First, we discuss the results of linear unit root (i.e., ADF) tests applied to the price pairs. We then discuss the results for the tests of the linear unit root model versus a nonlinear and (possibly locally) stationary alternative. Finally, we present results for estimated STAR models for the six OSB price pairs.

5.1 ADF Test Results

ADF tests were performed for each unique $ln(p_{it}/p_{jt})$ where we focus exclusively on the case where the null model is a random walk with drift similar to (10) (i.e., the τ_μ test). The first nineteen observations are retained to determine the optimal lag length by using the AIC criterion, as well as for conducting further diagnostic analyses. The result is that after first–differencing we have a usable sample of 747 weekly observations for each market pair.

The ADF test results, including empirical p–values, obtained in each case by boostrapping the respective null model B = 999 times, are reported in the left–hand panel of Table 3. Overall there is little support for the unit root hypothesis in these data, at least when tested against linear alternatives. Among other things, the implication is that $ln(p_{it}) - ln(p_{jt})$ may be thought of as a cointegrating relationship for all i and j.[16]

Results of testing the unit root hypothesis against stationary but nonlinear alternatives are presented in the right–hand panel of Table 3 for each market pair. As indicated previously, the candidate transition variable, s_t, in each case is the average of the log price ratio for the previous five weeks as defined in (4). Again, empirical p–values are constructed by using 999 non–parametric bootstrap draws of the null model's residuals. Results in Table 3 indicate that the null of a unit root and linearity may be rejected in every case at conventional significance levels. Indeed, for four of the six price pairs the minimal p–value (0.001) is obtained. Given the results of the standard ADF tests, it seems reasonable to conclude that the results for the joint unit root and nonlinearity tests provide strong evidence in favor of nonlinearity in the data generating processes for each price pair, and most notably nonlinearity that is potentially consistent with a GESTAR or QSTAR specification.

5.2 TV–STAR Estimates

As specified, both the GESTAR model given by (3) and (6) and the QSTAR model given by (3) and (7) are nonlinear in parameters–nonlinear estimation methods are called for. Additional details regarding estimation may be found in van Dijk, Teräsvirta, and Franses (2002). Optimal lag lengths are determined by applying the AIC to the linear model (Teräsvirta, 1994). Finally, the

[16]Given that log relative prices are the basic unit of analysis, it follows that in this case the ADF test is equivalent to a test that $\boldsymbol{\beta} = (0, 1)$ is a cointegrating vector in the log–linear price relationship $ln(p_{it}) - \beta_0 - \beta_1 ln(p_{jt})$.

choice between the GESTAR and QSTAR specifications is determined by carefully examining the results of each model's fit statistics as well as various diagnostic tests. As well, Eitrheim and Teräsvirta's (1996) tests for parameter nonconstancy are applied to the initial STAR model estimates; in every instance there is evidence of structural change. Consequently, the STAR model with structural change described in (8) is employed. The choice of the form of $G_j(.)$ as well as the number of structural change transition functions, τ, were also determined on the basis of overall model fit criterion and model diagnostics. The parameter estimates along with a variety of model diagnostics are reported in Table 4 for each of the six final model specifications. Plots of the estimated transition functions are reported in Figure 4.

As indicated in Table 4, all price pairs save for pair (F), that is, between the Southeast and Southwest, employ a QSTAR to model nonlinearity due to transactions costs: for pair (F), nonlinearity is modeled using a GESTAR. Structural change is also modeled as either an LSTAR, GESTAR, or some combination of the two–see Figure 4–pairs (A), (C), and (D) are found to have multiple structural change features whilst the remaining pairs are associated with a single structural change transition. As reported in Table 4, for every price pair the estimated standard error for the TV–STAR model is smaller than that for the respective linear model. Although not reported in order to conserve space, in every case the respective TV–STAR model has a lower AIC than its linear counterpart. In this regard the estimated TV–STAR models represent an improvement in fit relative to their respective linear analogues. Results in Table 4 also indicate there is no evidence of skewness in each model's residuals, although in each case there is substantial evidence of excess kurtosis. Of course, such results are not surprising given that weekly price data are being employed. For these reasons the Lomnicki–Jarque–Bera (LJB) test overwhelmingly rejects the null hypothesis of normality of the estimated residuals in each case (Table 4). Correspondingly, diagnostic test results also reveal there is considerable evidence of ARCH–type heteroskedasticity in most instances.

The diagnostic tests developed by Eitrheim and Teräsvirta (1996) were also employed to test for any remaining autocorrelation as well as remaining nonlinearity and/or parameter nonconstancy. These tests are implemented as F–test versions of the respective Lagrange Multiplier (LM) tests. The results, also reported in Table 4, indicate that in each case there is little evidence of remaining autocorrelation and, as well, virtually no evidence of remaining nonlinearity. For pairs (A) and (C) there is some evidence of additional parameter nonconstancy, although attempts to fit additional strucutural change features were not successful.[17] Finally, the plots in Figure 4 indicate that for pairs (A)–(D) the estimated STAR models approach a SETAR. Alternatively, for pairs (E) and (F) the transition functions for s_t are smooth, implying there are no unique transactions cost bands.

5.3 Model Dynamics

While the model fit and diagnostic results indicate the estimated TV–STAR models for the regional OSB price relationships do a reasonable job of explaining the data, additional questions remain. In particular, what are the implications of the estimated nonlinear models for the dynamics of price linkages in each case? To obtain additional insights into the behavior of the estimated STAR models we perform stochastic forward simulations of the models by using a bootstrap routine similar to that suggested by Clements and Smith (1997) for use in SETAR models. In essence bootstrapping is used to perform numerical integration in order to obtain estimates of expected values of forward iterations once stochastic shocks are introduced. A representative draw (out of 1000 draws) for each price pair, iterated ahead for 400 weeks beginning with October 16, 2009, is recorded along with the actual observations over the February 3, 1995 through October 9, 2009 period in Figure 3. As well, the approximate transactions cost bands are reported as dashed horizontal lines in Figure 3.[18] In every instance it appears that the fitted TV–STAR models do a reasonable job of replicating the salient features of the data, including long swings in the

[17]Specifically, attempts to add additional structural change components in theses instances did not yield models with AIC values that were lower than those for the models reported here.

[18]In particular, the bands are approximate in panels (e) and (f) in that the underlying models in these cases are associated with smooth transition from one regime to another, as opposed to discrete transition.

price relationships.[19] Based on these results it seems reasonable to further assess the dynamic properties of the estimated models by examining each model's regime–dependent half–lives and by developing generalized impulse response functions.

We first consider regime–dependent half–lives, which are computed by evaluating $ln(0.5)/ln(\widehat{\rho})$, where $1-\widehat{\rho}$ is the coefficient on the lagged dependent variable in the (regime–dependent) regression. Imputed half–lives in turn represent the amount of time in weeks for one–half of a shock resulting in a movement away from equilibrium to dissipate. For the TV–STAR models these are constructed for the regime corresponding to $G(s_t;\gamma,c)=1$, since this regime corresponds to the one where log price differentials lie outside of the transactions cost band. The results for each OSB market/price pair are reported in Table 5. For purposes of comparison half–lives from the corresponding linear autoregressive model are reported as well. For all six market pairs the half–lives obtained from the TV–STAR model are less than those from the corresponding linear model, and in several instances substantially so. For example, and as may be inferred from Table 5, half lives for the linear model vis–á–vis those for the TV–STAR models (when $G(s_t;\gamma,c)=1$) imply that for the later the time necessary for one half of the shock to dissipate varies anywhere from two (for pair C) to nearly seven (for pair A) weeks faster relative to the former. In short, these findings correspond to a faster adjustment back to spatial equilibrium following a shock that moves price linkages away from equilibrium. As well, our finding that half–lives are smaller when nonlinearities are considered is consistent with the presence of unobserved transactions costs, which in turn may inhibit adjustments to smaller price shocks.

To further investigate the implications of transactions costs for regional OSB price relationships we now turn to an imputation of the generalized impulse response functions (GIRFs). GIRFs are obtained by simulating the model ahead both with and without a shock and for different histories. The basic methodology for obtaining GIRFs is developed in detail by Koop, Pesaran, and Potter (1996). In particular, let δ denote a specific shock, that is, let $\delta=\varepsilon_t$ for the initial period $t=0$. As well, let a given history of data associated with time *t* be given by

[19]Indeed, perhaps the only feature not adequately captured by the estimated TV–STAR models, and as noted above, is the fat tail feature of regional price–pair distributions.

$\Omega_{t-1} = \omega_{t-1}$. The GIRF for time period (i.e., history) t at forward iteration n is then given by

$$(13)\quad GIRF_{\Delta y}(n, \delta, \omega_{t-1}) \; = \; E[\Delta y_{t+n} | \varepsilon_t = \delta, \Omega_{t-1} = \omega_{t-1}] - E[\Delta y_{t+n} | \varepsilon_t = 0, \Omega_{t-1} = \omega_{t-1}].$$

where the histories are determined as follows. We randomly draw (with replacement) 187 histories (i.e., ω_{t-1}'s) from the 747 available histories, or approximately one quarter of the available histories, for each price pair. We then use normalized shocks taking on a range of values given by $\delta/\widehat{\sigma}_\varepsilon = 3.0, 2.8, \ldots, 0.2$, where $\widehat{\sigma}_\varepsilon$ denotes the estimated standard deviation of the residuals from the relevant TV–STAR model. For each combination of history and initial shock we compute $GIRF_{\Delta y}(n, \delta, \omega_{t-1})$ for $n = 0, 1, \ldots, 78$, or 1.5 years. The expectations in (13) are computed, both with and without the shock, by using 800 bootstrap draws of the model's estimated residuals. As well, All GIRFs are conditional in the sense that it was assumed that any structural change component was complete, that is, that $G_j(t^*) = 1$ for all *j* and t, $j = 1, \ldots, \tau$. Finally, impulse responses for the log levels of the price pairs are obtained by simply summing those obtained for the first differences, that is, by

$$(14)\qquad GIRF(n, \delta, \omega_{t-1}) \; = \sum_{i=0}^{n} GIRF_{\Delta y}(n, \delta, \omega_{t-1}).$$

Finally, because the estimated QSTAR and GESTAR functions are not necessarily symmetric around zero we also consider regime dependent shocks (i.e., shocks initiated when either $G_1(s_t) \geq 0.5$ or $G_1(s_t) < 0.5$) and, as well, we delineate between positive and negative shocks. The GIRFs associated with negative shocks are re–scaled by multiplying by -1 in order to facilitate comparisons with those obtained for positive shocks.

Estimated GIRFs for each TV–STAR model are illustrated in Figure 5. There are several noteworthy results. To begin, in each case the effects of a shock eventually dissipate, with the GIRFs eventually returning to zero, albeit at differing rates. There is also evidence that, at least in some instances, initial conditions matter. For example, when considering the relationship between prices in Eastern Canada and the Southeast, it is clear that negative shocks which occur when prices are initially within the transactions cost band dissipate more slowly than do the remaining shocks. In general this result is consistent with the findings reported in Table 5, where the half–life for the TV–STAR model associated with pair (B) is largest overall. Regarding the relationship between prices in Eastern Canada and the Southwest, Figure 5 shows there are substantively different rates of adjustment back to equilibrium levels depending on whether the initial shocks are positive or negative, with positive shocks resulting in much quicker adjustments to equilibrium overall. The GIRFs for pair (D), the price relationship between North Central and Southeast, also reveal considerable nonlinearities. In particular it seems that a positive shock associated with the initial state being within the transactions cost band vanishes much more slowly than shocks of other signs and in other initial states.

In the remaining cases there is not strong evidence that GIRFs are substantively influenced by either the initial state or the sign of the shock. Overall, the results of the generalized impulse response function analysis indicate that the effects of market shocks do eventually dissipate, signaling spatial market equilibrium, but apparently at a slower rate, at least within the transactions cost band, than would be implied by models that do not account for these costs.

6 Summary and Conclusions

We have reviewed and evaluated nonlinear smooth transition autoregressive models that can advance our understanding of spatial market integration in oriented strand board (OSB) markets. We consider spatial price linkages among several important North American regional markets. Our results show that all tested price pairs for oriented strand board in North America create stationary linear combinations, or cointegrated price pairs, and that these pairs also exhibit nonlinearities in the data generating process. Moreover, the nonlinearities in the price relationships support the application of QSTAR and ESTAR smooth transition autoregressive models to evaluate whether the nonlinearities derive from transactions costs, and therefore the threshold parameters in the DGP.

Over the sample period (1995–2005) there were a number of events that impacted OSB prices, and possibly regional OSB price relationships. These include, for example, new capacity that came on–line in 1996-1997 in Canada and in 2006–2007 in the Southeast. As well, an alleged price–fixing scheme among many leading OSB manufacturers was apparently in operation during much of the 2002–2006 period. For these reasons the basic smooth transition framework was augmented, where appropriate, with time–varying features that allowed for either permanent or transitory changes in regional price relationships. The result is that for each price pair considered a variant of a time–varying STAR, or TV–STAR model was ultimately fitted to the data. By using several measures of goodness–of–fit and model performance we find that the TV–STAR models do a superior job of explaining relative price movements compared to their linear counterparts. Aside from providing confirmation that the Law of One Price—augmented to account for transactions costs bands—holds for oriented strand board markets in North America, the TV–STAR results imply that market shocks are more persistent than linear models would suggest.

The primary implication of these findings is that market models that ignore the existence of transactions cost bands would tend to overestimate the rate of adjustment to market shocks brought about by catastrophic events or regional housing market shifts. For example, small shocks to local or regional housing markets would likely not transmit quickly to distant markets, but large shocks could register quickly, through a spatial arbitrage process. Another implication of our findings is that transmission of market shocks depends on initial price differentials, yielding rapid responses when prices are far apart but slow ones when they are not.

There are, of course, a number of limitations to the present study. Future research might focus, for example, on more direct ways of incorporating transactions costs into the estimation framework. As well, it might be useful to explore regional price relationships among all panel products, including plywood. It would be potentially useful to expand the modeling framework to include a post–sample forecasting exercise in an attempt to determine the extent to which modeling nonlinearities induced by transactions costs in a STAR–framework could lead to improved predictive performance. Finally, future research should focus on identifying the role of transactions costs in a multivariate STAR–model setting (i.e., all prices modeled together as part of a system), possibly in a manner consistent with the framework employed by, for example, Rothman, van Dijk and Franses (2001). These remain, however, as important issues for future investigation.

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Table 1: Definition of Six Regional OSB Price Pairs.

Pair	Market Pairs	Price Pairs
(A)	Eastern Canada–North Central	$ln(p_1/p_2)$
(B)	Eastern Canada–Southeast	$ln(p_1/p_3)$
(C)	Eastern Canada–Southwest	$ln(p_1/p_4)$
(D)	North Central–Southeast	$ln(p_2/p_3)$
(E)	North Central–Southwest	$ln(p_2/p_4)$
(F)	Southeast–Southwest	$ln(p_3/p_4)$

Note: Eastern Canada refers to prices from plants operating in Ontario and Quebec; North Central refers to prices from plants operating in Plants in Wisconsin, Michigan, and Minnesota; Southeast refers to prices from plants operating in Georgia, Alabama, Mississippi, South Carolina, and Tennessee; and Southwest refers to prices from plant operating in Texas, Louisiana, Arkansas, and Oklahoma.

Table 2: Major Events Impacting Regional OSB Markets.

Event	Description	Time Period
(1)	Steady growth in new home construction, most notably in the Southeast.	1991-2006
(2)	New production capacity comes online in Canada.	1996-1997
(4)	Price-fixing scheme allegedly engaged in by nine OSB manufacturers that account for 90–percent of U.S. production.	June, 2002 through February, 2006
(5)	Four hurricanes and one named storm make landfall in Florida, causing over $49 billion in damage (2005 dollars).	August, 2004 through September, 2004
(6)	Hurricanes Katrina and Rita make landfall. Combined they account for more than $90 billion in property damage (2005 dollars).	August, 2005 through September, 2005
(7)	New production capacity comes online in South Carolina and Georgia.	2006-2007
(8)	Significant weakening in new home construction, especially in Florida and the Atlanta metro region.	2006-2009

Note: Dollar figures for named storms were obtained from Pielke et al. (2008) and are based on their PL05 methodology.

Table 3: Results of Unit Root Tests Against Linear and STAR–Type Alternatives Applied to Six Regional OSB Price Pairs.

		Linear Alternative			Nonlinear Alternative			
Price Pair	Lag Length	$\widehat{\rho}$	τ_μ	p–value	$\widehat{\rho}$	τ_μ	F_{lur}	p–value
$ln(p_1/p_2)$	4	0.895	-5.590	0.001	0.703	-2.801	3.605	0.001
$ln(p_1/p_3)$	4	0.960	-3.299	0.013	1.010	0.238	2.198	0.013
$ln(p_1/p_4)$	1	0.902	-6.538	0.001	0.870	-3.161	5.635	0.001
$ln(p_2/p_3)$	3	0.952	-3.822	0.005	0.907	-2.847	3.992	0.001
$ln(p_2/p_4)$	1	0.865	-7.722	0.001	0.848	-4.445	9.297	0.001
$ln(p_3/p_4)$	8	0.961	-2.809	0.060	0.975	-0.613	1.840	0.013

Note: The first column indicates the optimal lag length for each price pair, determined by minimizing the AIC. $\widehat{\rho}$ is the estimated root. The test statistic τ_μ denotes t–ratios for $(\widehat{\rho} - 1)$, and corresponds to the case where the estimated model includes an intercept but no trend. Columns headed p–value record approximate p–value's based on $B = 999$ bootstrap simulations. In every instance involving a nonlinear alternative the transition variable, s_t, used is a rolling average of the five most recent log price pairs, that is, $s_t = \frac{1}{5}\sum_{j=1}^{5} y_{t-j}$. As well, a fourth–order approximation to the transition function is used in estimation and hypothesis testing.

Table 4: STAR Model Estimates for the Weekly OSB Regional Price Relationships.

Panel A, $y_t = ln(p_{1t}/p_{2t})$

$$\Delta y_t = [\underset{(0.039)}{0.044}\ \Delta y_{t-1} - \underset{(0.035)}{0.119}\ \Delta y_{t-2} - \underset{(0.036)}{0.034}\ \Delta y_{t-3} - \underset{(0.035)}{0.124}\ \Delta y_{t-4}] \times [1 - G_1(s_t;\eta_1,c_1,c_2)] + [-\underset{(0.880)}{7.668} + \underset{(0.093)}{0.253}\ \Delta y_{t-1} + \underset{(0.129)}{0.249}\ \Delta y_{t-2} - \underset{(0.156)}{0.113}\ \Delta y_{t-3} + \underset{(0.160)}{0.214}\ \Delta y_{t-4}$$

$$- \underset{(0.058)}{0.538}\ y_{t-1} + \underset{(1.131)}{7.940}\ G_2(t^*;\eta_2,c_3) - \underset{(1.048)}{3.915}\ G_3(t^*;\eta_3,c_4)] \times G_1(s_t;\eta_1,c_1,c_2) + \hat{\varepsilon}_t; \quad G_1(s_t;\eta_1,c_1,c_2) \ = \ [1 + \exp\{-\exp(\underset{(9.630)}{7.740})(s_t + \underset{(1.193)}{12.651})(s_t - \underset{(1.378)}{2.538})/\hat{\sigma}^2_{s_t}\}]^{-1};$$

$$G_2(t^*;\eta_2,c_3) \ = \ 1 - \exp\{-\exp(-\underset{(0.785)}{0.124})(t^* - \underset{(0.020)}{0.380})^{10}/\hat{\sigma}^{10}_{t^*}\}; \quad G_3(t^*;\eta_3,c_4) \ = \ [1 + \exp\{-\exp(\underset{(180.387)}{9.156})(t^* - \underset{(0.089)}{0.893})/\hat{\sigma}_{t^*}\}]^{-1}.$$

$R^2 = 0.175$, $\hat{\sigma}_{NL} = 2.093$, $\hat{\sigma}_{NL}/\hat{\sigma}_L = 0.946$, AIC $= 1.528$, SBC $= 1.814$, LJB $= 123.11\,(1.85 \times 10^{-27})$, $\text{LM}_{SC}(4) = 0.723\,(0.576)$, $\text{LM}_{ARCH}(4) = 2.399\,(0.049)$,
$\text{LM}_{NL}(s_{t-1}) = 0.510\,(0.728)$, $\text{LM}_{NL}(s_{t-2}) = 1.805\,(0.228)$, $\text{LM}_{NL}(s_{t-3}) = 1.925\,(0.158)$, $\text{LM}_{NL}(s_{t-4}) = 1.334\,(0.658)$, $\text{LM}_C = 2.540\,(0.009)$.

Panel B, $y_t = ln(p_{1t}/p_{3t})$

$$\Delta y_t = [\underset{(0.084)}{0.129}\ \Delta y_{t-1} + \underset{(0.085)}{0.056}\ \Delta y_{t-2} - \underset{(0.083)}{0.152}\ \Delta y_{t-3} + \underset{(0.080)}{0.039}\ \Delta y_{t-4}] \times [1 - G_1(s_t;\eta_1,c_1,c_2)] + [\underset{(0.961)}{2.343} - \underset{(0.041)}{0.029}\ \Delta y_{t-1} - \underset{(0.041)}{0.138}\ \Delta y_{t-2} - \underset{(0.041)}{0.072}\ \Delta y_{t-3}$$

$$- \underset{(0.042)}{0.071}\ \Delta y_{t-4} - \underset{(0.018)}{0.092}\ y_{t-1} - \underset{(0.962)}{3.209}\ G_2(t^*;\eta_2,c_3)] \times G_1(s_t;\eta_1,c_1,c_2) + \hat{\varepsilon}_t; \quad G_1(s_t;\eta_1,c_1,c_2) \ = \ [1 + \exp\{-\exp(\underset{(2.939)}{4.982})(s_t + \underset{(0.072)}{1.591})(s_t - \underset{(0.183)}{15.949})/\hat{\sigma}^2_{s_t}\}]^{-1};$$

$$G_2(t^*;\eta_2,c_3) \ = \ 1 - \exp\{-\exp(\underset{(0.519)}{4.068})(t^* - \underset{(0.009)}{0.599})^2/\hat{\sigma}^2_{t^*}\}.$$

$R^2 = 0.098$, $\hat{\sigma}_{NL} = 2.920$, $\hat{\sigma}_{NL}/\hat{\sigma}_L = 0.973$, AIC $= 2.186$, SBC $= 2.427$, LJB $= 184.70\,(7.81 \times 10^{-41})$, $\text{LM}_{SC}(4) = 1.221\,(0.300)$, $\text{LM}_{ARCH}(4) = 8.521\,(1.00 \times 10^{-6})$,
$\text{LM}_{NL}(s_{t-1}) = 1.550\,(0.440)$, $\text{LM}_{NL}(s_{t-2}) = 1.512\,(0.477)$, $\text{LM}_{NL}(s_{t-3}) = 1.765\,(0.256)$, $\text{LM}_{NL}(s_{t-4}) = 1.953\,(0.144)$, $\text{LM}_C = 2.050\,(0.089)$.

Panel C, $y_t = ln(p_{1t}/p_{4t})$

$$\Delta y_t = [\underset{(0.088)}{0.340}\ \Delta y_{t-1}] \times [1 - G_1(s_t;\eta_1,c_1,c_2)] + [-\underset{(0.963)}{1.787} + \underset{(0.040)}{0.147}\ \Delta y_{t-1} - \underset{(0.021)}{0.191}\ y_{t-1} + \underset{(2.461)}{9.834}\ G_2(t^*;\eta_2,c_3) - \underset{(2.061)}{8.538}\ G_3(t^*;\eta_3,c_4)] \times \ G_1(s_t;\eta_1,c_1,c_2) + \hat{\varepsilon}_t;$$

$$G_1(s_t;\eta_1,c_1,c_2) \ = \ [1 + \exp\{-\exp(\underset{(544.333)}{8.440})(s_t + \underset{(0.123)}{0.287})(s_t - \underset{(0.236)}{6.105})/\hat{\sigma}^2_{s_t}\}]^{-1}; \quad G_2(t^*;\eta_2,c_3) \ = \ [1 + \exp\{-\exp(\underset{(0.163)}{1.155})(t^* - \underset{(0.027)}{0.245})/\hat{\sigma}_{t^*}\}]^{-1};$$

$$G_3(t^*;\eta_3,c_4) \ = \ [1 + \exp\{-\exp(\underset{(0.298)}{2.916})(t^* - \underset{(0.010)}{0.201})^3/\hat{\sigma}^3_{t^*}\}]^{-1}.$$

$R^2 = 0.121$, $\hat{\sigma}_{NL} = 2.817$, $\hat{\sigma}_{NL}/\hat{\sigma}_L = 0.969$, AIC $= 2.106$, SBC $= 2.302$, LJB $= 169.47\,(1.59 \times 10^{-37})$, $\text{LM}_{SC}(4) = 0.610\,(0.656)$, $\text{LM}_{ARCH}(4) = 17.305\,(1.39 \times 10^{-13})$,
$\text{LM}_{NL}(s_{t-1}) = 1.360\,(0.545)$, $\text{LM}_{NL}(s_{t-2}) = 0.993\,(0.855)$, $\text{LM}_{NL}(s_{t-3}) = 0.824\,(0.937)$, $\text{LM}_{NL}(s_{t-4}) = 0.813\,(0.941)$, $\text{LM}_C = 2.431\,(0.052)$.

Table 3: Continued.

Panel D, $y_t = ln(p_{2t}/p_{3t})$

$$\Delta y_t = [-\underset{(0.044)}{0.012}\ \Delta y_{t-1} - \underset{(0.045)}{0.150}\ \Delta y_{t-2} - \underset{(0.044)}{0.071}\ \Delta y_{t-3}] \times [1 - G_1(s_t;\eta_1,c_1,c_2)] + [-\underset{(0.309)}{0.262} - \underset{(0.065)}{0.038}\ \Delta y_{t-1} + \underset{(0.064)}{0.008}\ \Delta y_{t-1} - \underset{(0.063)}{0.011}\ \Delta y_{t-1} - \underset{(0.021)}{0.114}\ y_{t-1}$$

$$+\underset{(1.607)}{7.200}\ G_2(t^*;\eta_2,c_3) - \underset{(1.652)}{5.399}\ G_3(t^*;\eta_3,c_4)] \times G_1(s_t;\eta_1,c_1,c_2) + \hat{\varepsilon}_t; \quad G_1(s_t;\eta_1,c_1,c_2) \ = \ [1+\exp\{-\exp(\underset{(2.971)}{14.185})(s_t + \underset{(0.001)}{6.685})(s_t - \underset{(0.135)}{5.651})/\hat{\sigma}^2_{s_t}\}]^{-1};$$

$$G_2(t^*;\eta_2,c_3) \ = \ [1+\exp\{-\exp(\underset{(3.045)}{13.758})(t^* - \underset{(0.001)}{0.555})/\hat{\sigma}_{t^*}\}]^{-1}; \quad G_3(t^*;\eta_3,c_4) \ = \ [1+\exp\{-\exp(\underset{(4.455)}{7.348})(t^* - \underset{(0.002)}{0.674})/\hat{\sigma}_{t^*}\}]^{-1}.$$

$R^2 = 0.102$, $\hat{\sigma}_{NL} = 2.820$, $\hat{\sigma}_{NL}/\hat{\sigma}_L = 0.968$, AIC $= 2.119$, SBC $= 2.374$, LJB $= 55.81\,(7.62 \times 10^{-13})$, LM$_{SC}(4) = 0.392\,(0.815)$, LM$_{ARCH}(4) = 4.153\,(0.002)$,
LM$_{NL}(s_{t-1}) = 2.188\,(0.079)$, LM$_{NL}(s_{t-2}) = 2.144\,(0.091)$, LM$_{NL}(s_{t-3}) = 1.982\,(0.150)$, LM$_{NL}(s_{t-4}) = 2.020\,(0.115)$, LM$_C = 2.540\,(0.015)$.

Panel E, $y_t = ln(p_{2t}/p_{4t})$

$$\Delta y_t = [\underset{(0.106)}{0.272}\ \Delta y_{t-1}] \times [1 - G_1(s_t;\eta_1,c_1,c_2)] + [-\underset{(0.479)}{1.393} + \underset{(0.072)}{0.127}\ \Delta y_{t-1} - \underset{(0.062)}{0.323}\ y_{t-1} + \underset{(0.614)}{1.702}\ G_2(t^*;\eta_2,c_3)] \times G_1(s_t;\eta_1,c_1,c_2) + \hat{\varepsilon}_t;$$

$$G_1(s_t;\eta_1,c_1,c_2) \ = \ [1+\exp\{-\exp(-\underset{(0.438)}{0.788})(s_t - \underset{(2.239)}{0.720})(s_t - \underset{(2.708)}{19.201})/\hat{\sigma}^2_{s_t}\}]^{-1}; \quad G_2(t^*;\eta_2,c_3) \ = \ [1+\exp\{-\exp(\underset{(0.582)}{1.905})(t^* - \underset{(0.038)}{0.404})/\hat{\sigma}_{t^*}\}]^{-1}.$$

$R^2 = 0.121$, $\hat{\sigma}_{NL} = 2.693$, $\hat{\sigma}_{NL}/\hat{\sigma}_L = 0.978$, AIC $= 2.008$, SBC $= 2.158$, LJB $= 76.27\,(2.74 \times 10^{-17})$, LM$_{SC}(4) = 1.764\,(0.134)$, LM$_{ARCH}(4) = 8.713\,(7.09 \times 10^{-7})$,
LM$_{NL}(s_{t-1}) = 1.990\,(0.202)$, LM$_{NL}(s_{t-2}) = 1.612\,(0.383)$, LM$_{NL}(s_{t-3}) = 1.512\,(0.458)$, LM$_{NL}(s_{t-4}) = 1.751\,(0.291)$, LM$_C = 2.373\,(0.062)$.

Panel F, $y_t = ln(p_{3t}/p_{4t})$

$$\Delta y_t = [-\underset{(0.056)}{0.098}\ \Delta y_{t-1} - \underset{(0.049)}{0.173}\ \Delta y_{t-2} - \underset{(0.051)}{0.168}\ \Delta y_{t-3} - \underset{(0.052)}{0.036}\ \Delta y_{t-4} - \underset{(0.050)}{0.023}\ \Delta y_{t-5} - \underset{(0.051)}{0.113}\ \Delta y_{t-6} - \underset{(0.051)}{0.055}\ \Delta y_{t-7} - \underset{(0.050)}{0.044}\ \Delta y_{t-8}] \times [1 - G_1(s_t;\eta_1,c_1)]$$

$$+[\underset{(0.187)}{0.216} + \underset{(0.062)}{0.262}\ \Delta y_{t-1} + \underset{(0.060)}{0.123}\ \Delta y_{t-2} - \underset{(0.065)}{0.077}\ \Delta y_{t-3} - \underset{(0.059)}{0.008}\ \Delta y_{t-4} - \underset{(0.059)}{0.026}\ \Delta y_{t-5} - \underset{(0.060)}{0.028}\ \Delta y_{t-6} - \underset{(0.058)}{0.012}\ \Delta y_{t-7} - \underset{(0.060)}{0.180}\ \Delta y_{t-8} - \underset{(0.027)}{0.160}\ y_{t-1}$$

$$-\underset{(0.449)}{2.140}\ G_2(t^*;\eta_2,c_3)] \times G_1(s_t;\eta_1,c_1) + \hat{\varepsilon}_t; \quad G_1(s_t;\eta_1,c_1) \ = \ 1-\exp\{-\exp(\underset{(0.538)}{2.942})(s_t - \underset{(0.230)}{0.646})^6/\hat{\sigma}^6_{s_t}\}; \ \ G_2(t^*;\eta_2,c_2) \ = \ [1+\exp\{-\exp(\underset{(8.190)}{7.399})(t^* - \underset{(0.001)}{0.826})/\hat{\sigma}_{t^*}\}]^{-1}.$$

$R^2 = 0.173$, $\hat{\sigma}_{NL} = 1.926$, $\hat{\sigma}_{NL}/\hat{\sigma}_L = 0.960$, AIC $= 1.373$, SBC $= 1.719$, LJB $= 162.14\,(6.20 \times 10^{-36})$, LM$_{SC}(4) = 1.145\,(0.334)$, LM$_{ARCH}(4) = 3.538\,(0.007)$,
LM$_{NL}(s_{t-1}) = 1.572\,(0.437)$, LM$_{NL}(s_{t-2}) = 1.809\,(0.190)$, LM$_{NL}(s_{t-3}) = 1.563\,(0.448)$, LM$_{NL}(s_{t-4}) = 1.651\,(0.342)$, LM$_C = 1.796\,(0.201)$.

Note: Asymptotic standard errors are given below parameter estimates in parentheses; R^2 is the unadjusted R^2; $\hat{\varepsilon}_t$ denotes the model's residual at time *t*; $\hat{\sigma}_{NL}$ denotes the STAR model's residual standard error; $\widehat{\sigma}_{NL}/\widehat{\sigma}_L$ is the ratio of the STAR model versus AR model residual standard error; and AIC is Akaike information criterion and SBC denotes Schwarz's Bayesian Criterion. As well, LJB is the Lomnicki–Jarque–Bera test of normality of residuals, with asymptotic p–values in parentheses. LM$_{SC}(4)$ denotes the F variant of Eitrheim and Teräsvirta's (1996) LM test of no remaining autocorrelation in the residuals based on four lags. Likewise, LM$_{ARCH}(4)$ denotes an LM test for ARCH–type heteroskedasticity based on four lags. As well, LM$_{NL}$ is the F variant of Eitrheim and Teräsvirta's (1996) LM tests for remaining nonlinearity, $(s_{t-1},\ldots,s_{t-4})$. Finally, LM$_C$ is the F variant of Lim and Teräsvirta's (1994) LM test for parameter constancy.

Table 5: Estimated Half Lives for the Estimated AR and STAR Models for Regional OSB Price Relationships.

Price Pair	Parameter	AR	TV–STAR
$\ln(p_1/p_2)$	$1-\widehat{\rho}$	-0.105	-0.538
	Half Life:	6.248	0.898
$\ln(p_1/p_3)$	$1-\widehat{\rho}$	-0.040	-0.092
	Half Life:	17.099	7.161
$\ln(p_1/p_4)$	$1-\widehat{\rho}$	-0.098	-0.191
	Half Life:	6.736	3.263
$\ln(p_2/p_3)$	$1-\widehat{\rho}$	-0.048	-0.114
	Half Life:	14.051	5.753
$\ln(p_2/p_4)$	$1-\widehat{\rho}$	-0.135	-0.323
	Half Life:	4.789	1.777
$\ln(p_3/p_4)$	$1-\widehat{\rho}$	-0.039	-0.160
	Half Life:	17.638	3.987

Note: $1-\widehat{\rho}$ is the estimated coefficient on the lagged level term in the respective model. Half lives for STAR models are constructed by using the estimated $1-\widehat{\rho}$ coefficient corresponding to the regime implied when $G_1(s_t;\eta,\boldsymbol{c})=1$. Half–lives are the weeks required for one–half of the deviation from equilibrium to be eliminated.

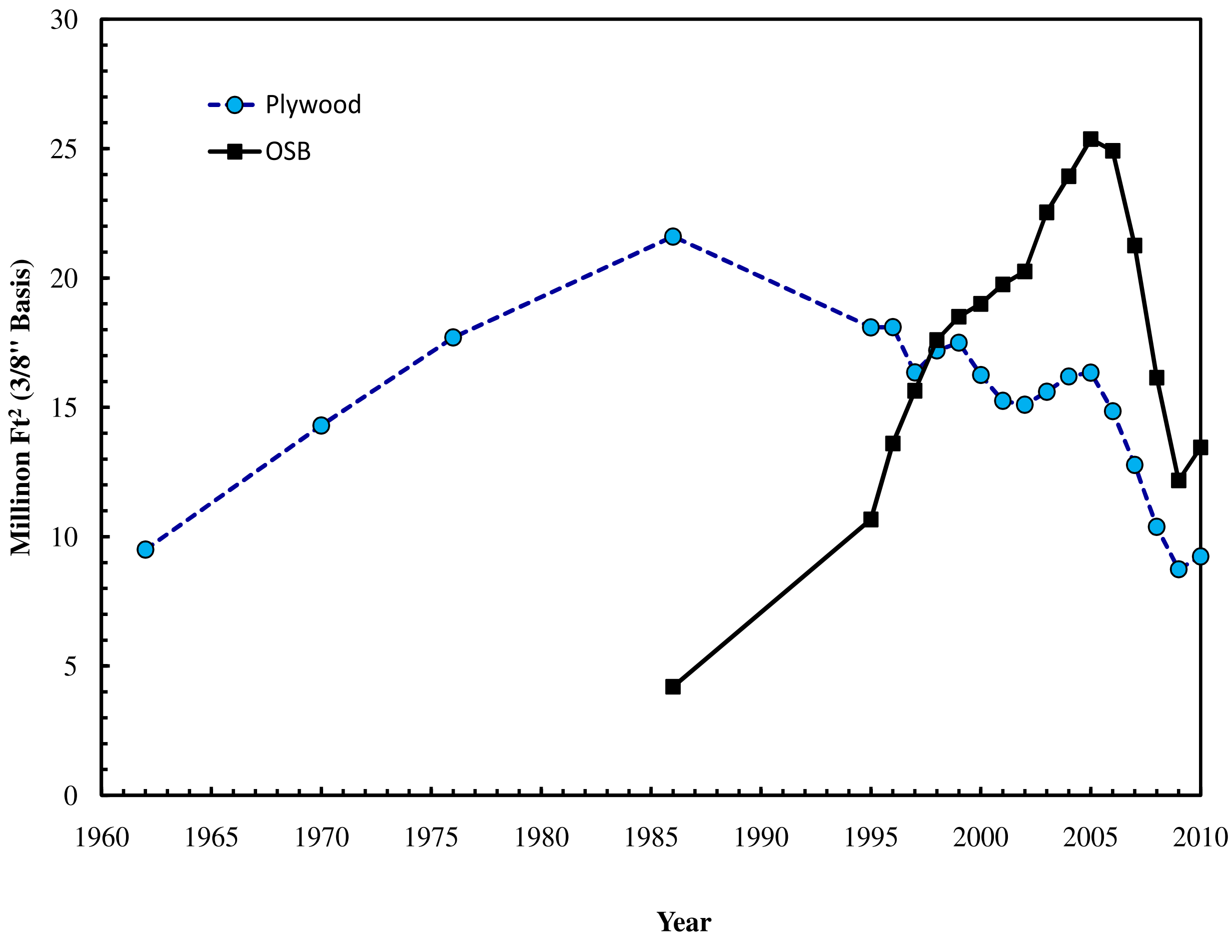


Figure 1: U.S. Plywood and OSB Consumption, 1958–2009 and Projected for 2010.

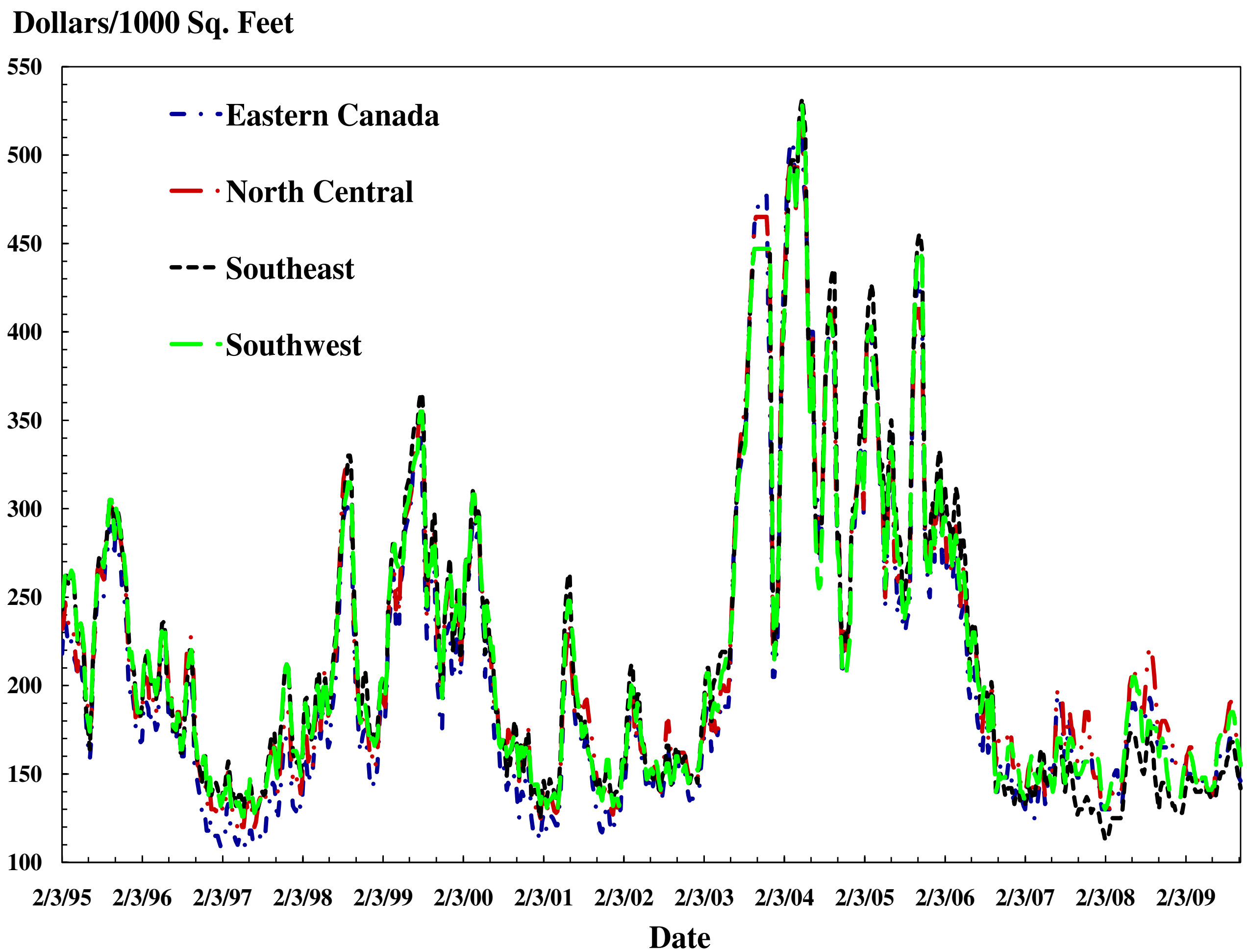


Figure 2: Regional Weekly OSB Prices, 1995–2009.

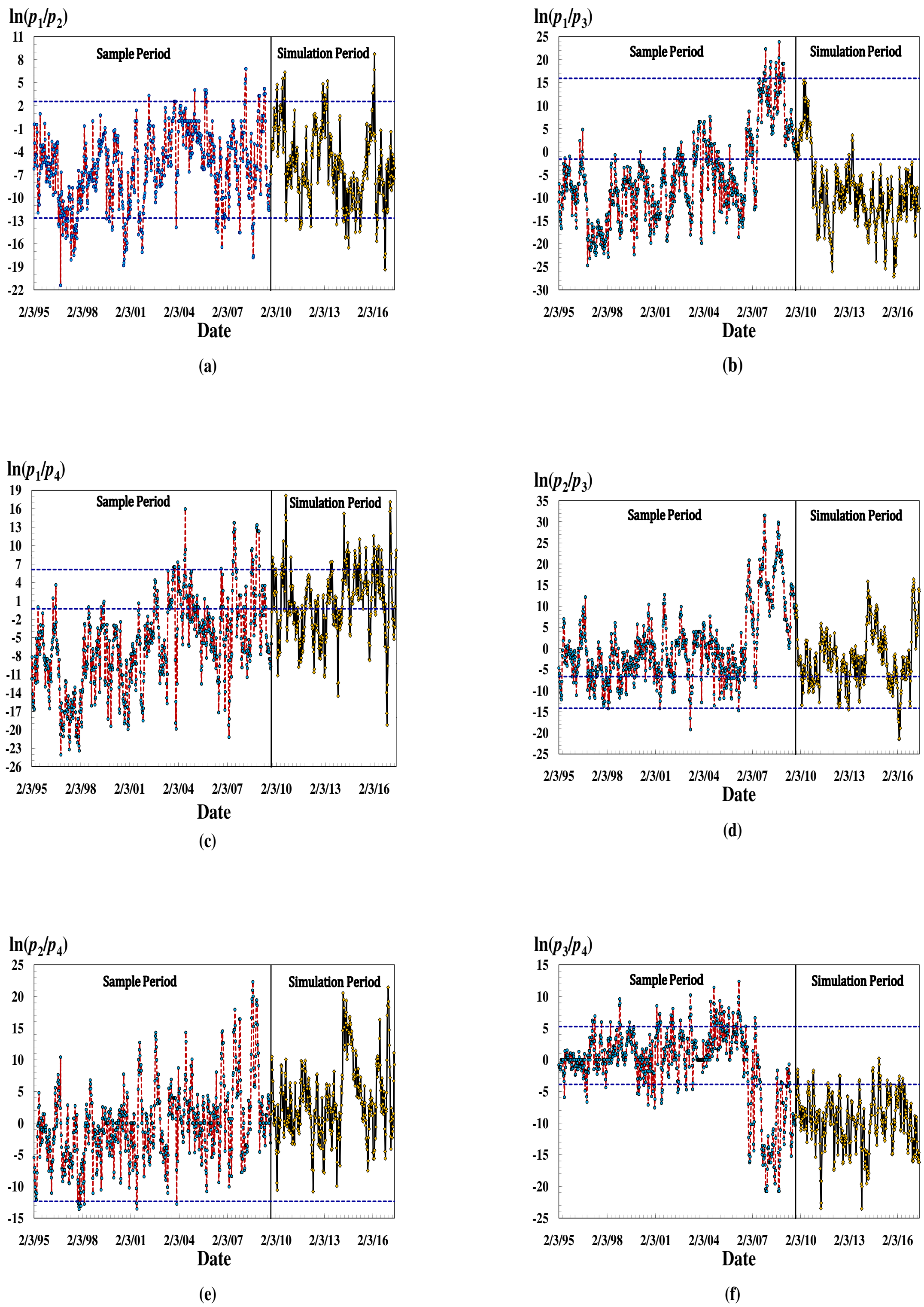
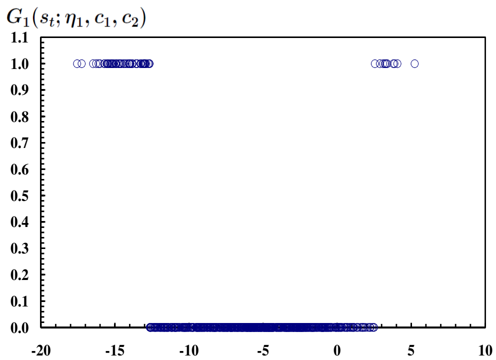
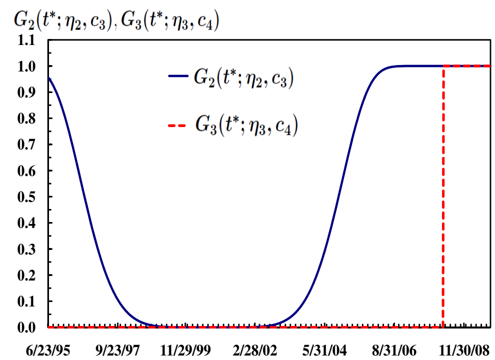


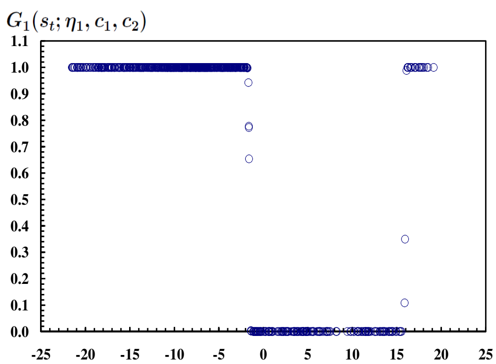
Figure 3: Time–Series Plots of Natural Logarithms of Sample (Dashed Line) and Bootstrap Simulated (Solid Line) Regional Relative Prices for Oriented Strand Board. Dashed horizontal lines denote approximately the transactions cost bands.



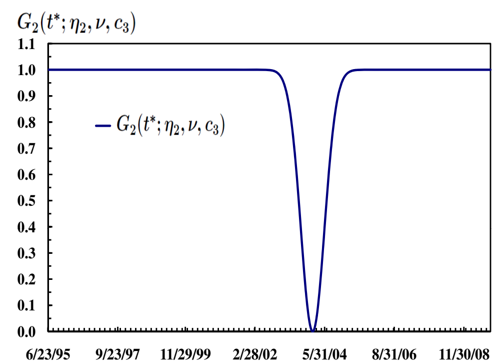
(a) s_t



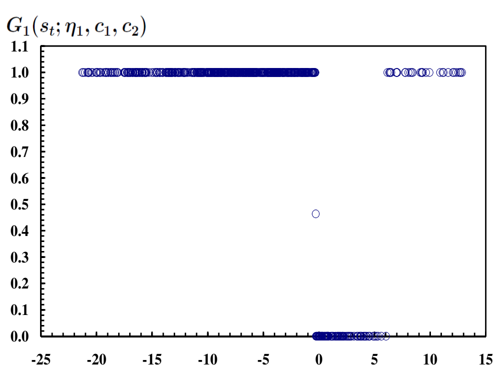
(a) Date



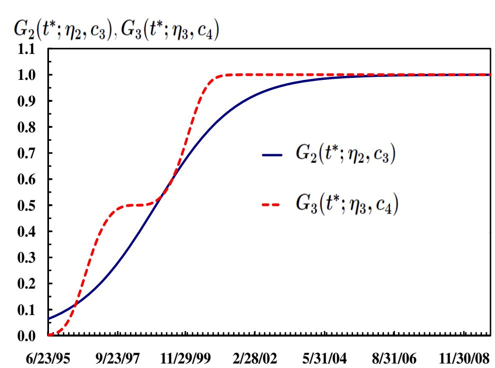
(b) s_t



(b) Date



(c) s_t



(c) Date

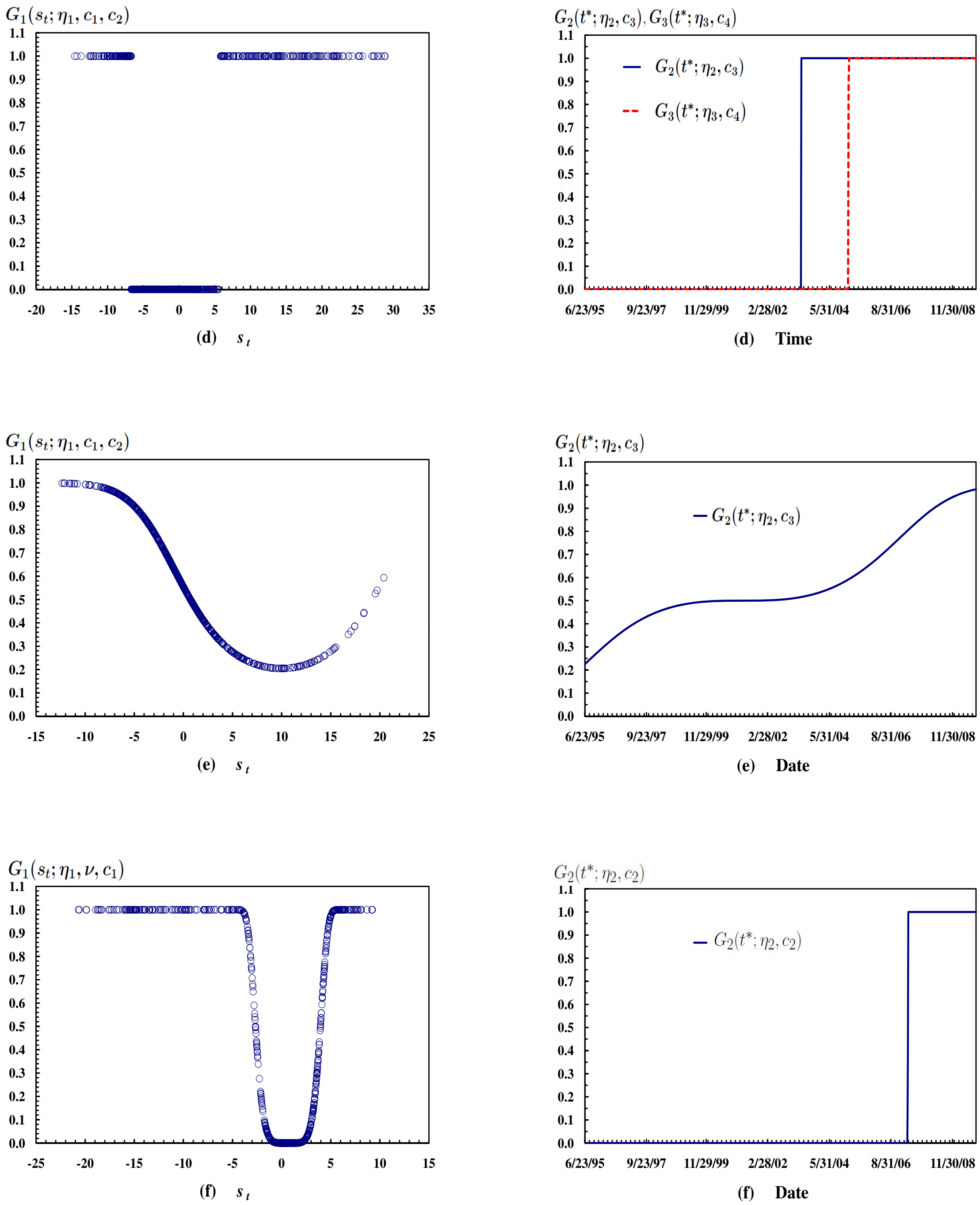


Figure 4: Transition Functions versus the Respective Transition Variable, $s_t = \frac{1}{5}\sum_{i=1}^{5} y_{t-i}$, (left–hand column) and Time–Varying Transition Functions Over Time (right–hand column) for Six OSB Regional Price Pairs.

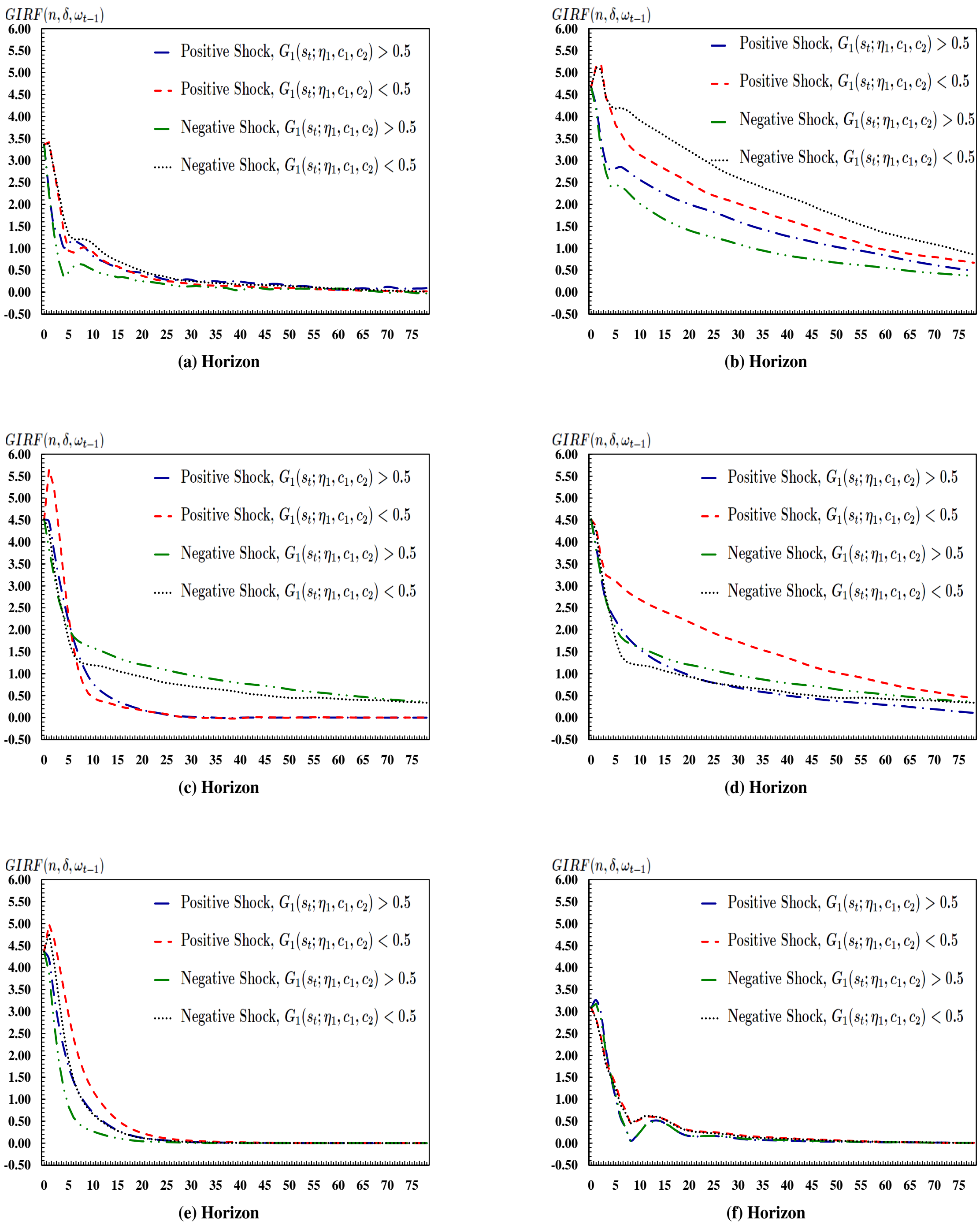


Figure 5: Estimated Generalized Impulse Response Functions for Six Regional Oriented Strand Board Price Relationships.