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Nonlinear exchange rate pass-through in timber products: The case of oriented strand board in Canada and the United States

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ABSTRACT

We assess exchange rate pass-through (ERPT) for U.S. and Canadian prices for oriented strand board (OSB), a structural wood panel product used extensively in U.S. residential construction. Because of its prominence in construction and international trade, OSB markets are likely sensitive to general economic conditions. In keeping with recent research, we examine regime-specific ERPT effects; we use a smooth transition vector error correction model. We also consider ERPT asymmetries associated with a measure of general macroeconomic activity. Our results indicate that during expansionary periods ERPT is modest, but during downturns, ERPT effects are larger.

1. Introduction

Questions regarding the extent of exchange rate pass-through (ERPT) into import prices, in other words, the degree to which exchange rate shocks evoke an equilibrating price response for traded commodities and goods, have long been of interest to economists and policy makers. Much of the recent interest in this topic can be traced to the observation that estimated ERPT effects are generally reported to be small (Goldberg & Knetter, 1997). For example, a widely cited rate of pass-through into aggregate import price is approximately 50%, as reported by Goldberg and Knetter (1997). In addition to relatively low rates of ERPT, there is also mounting evidence that they have been declining over time; see, for example, Bailliu and Fujii (2004), Campa and Goldberg (2005), and Marazzi and Sheets (2007), among others. Correspondingly, several strands of the ERPT literature have evolved. One is the so-called macro strand, where the focus is on determining the extent of ERPT to import prices at the aggregate level and, secondarily, the extent to which such responses are passed along to consumers (see, e.g., Gagnon & Ihrig, 2004). Another strand focuses on determining the extent to which ERPT impacts import prices at the industry or commodity level, where incomplete pass-through is often conjectured to be a function of the market structure of the industry being examined. Examples of work in this vain include Ahn, Park, and Park (2016), Knetter (1989), and Pollard and Coughlin (2004). Of interest is that empirical estimates of long-run ERPT at the industry or commodity level are often smaller than those obtained by using more aggregated data.

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Over the years, various theories and methodological refinements have been explored in an attempt to account for low or declining rates of ERPT. Of interest is that a number of recent studies have examined the possibility that there are asymmetries or nonlinearities in pass-through, that is, for example, that a currency depreciation could have different impacts on import prices than would an appreciation or, similarly, that large changes may have different effects than small ones. In one of the earliest studies of this sort, Mann (1986) found evidence of asymmetric pass-through effects. Likewise, by employing aggregate data for seven Asian Pacific countries, Webber (2000) reports substantial evidence of asymmetric pass-through effects for five of these. Bussiere (2007) considers pass-through into import and export prices in G7 countries, and finds substantial evidence of nonlinearities. Even so, Bussiere (2007) only tests for nonlinearity and does not otherwise estimate corresponding nonlinear models of pass through. Karoro, Aziakpono, and Cattaneo (2009) consider asymmetries in pass-through to import prices in South Africa; they find evidence that ERPT is higher during periods of rapid appreciation relative to deprecation. As well, Al-Abri and Goodwin (2009) update the data used by Campa and Goldberg (2005) and also allow for threshold effects with respect to ERPT into G7 country import prices. Overall, they find substantial evidence of nonlinearities in pass-through effects. In a closely related study, Larue, Gervais, and Rancourt (2010) examine the possibility asymmetric ERPT into export prices for pork meat from Canada to Japan and the U.S. by using threshold cointegration techniques. More recently, several studies, including those by Junttila and Korhonen (2012), Kiliç (2016), and Shintani, Terada-Hagiwara, and Yabu (2013), have focused on the effects of inflation regimes (i.e., whether or not the overall economy is in a high-inflation as opposed to a low-inflation period) on ERPT, with the results generally supporting regime-dependent behavior.

Many of the foregoing studies focused on estimating pass-through effects by using either import prices at the aggregate level or for specific industries. Comparatively few studies have focused on pass-through effects at the individual commodity level. In part, this is because commodities are typically homogeneous and are traded in something close to perfectly competitive market conditions. The implication is that the ability of exporting firms to exert any market power over pricing combined with the perfect arbitrage conditions of the “law of one price” (LOP) are thought to result in complete ERPT for commodity import prices. In short, commodities are thought to have flexible or flex import prices. Even so, in some instances there is evidence of incomplete pass-through for commodity prices. Jabara and Schwartz (1987) explore ERPT for Japanese import prices for five agricultural commodities, and find evidence of incomplete pass-through as well as evidence of asymmetric responses to exchange rate shocks for several commodities. As well, they find substantial evidence of asymmetric responses to exchange rates for several commodities. Likewise, Uusivuori and Buongiorno (1991) examine ERPT for a number of U.S. forest product exports to Europe and Japan, and find both that pass-through is incomplete and that its effects are asymmetric depending on whether the exchange rate is appreciating or depreciating. Parsley (1995) examines ERPT for five specific products exported from Japan to the United States. In this study, asymmetry in (real) exchange rate effects were also allowed for; the results show there are apparent declines in ERPT during periods of dollar appreciation. Finally, Larue et al. (2010) investigate ERPT for import prices of pork (from Canada) for U.S. and Japanese markets. They also use a threshold model to allow for nonlinearities (menu costs) in exchange-rate pass through and find evidence of incomplete ERPT, especially for several provinces in Japan.

In general, ERPT is an important indicator of the operation and performance of markets for internationally-traded commodities such as oriented strand board (OSB). A lack of pass-through may reflect imperfect arbitrage, inefficient trade, inflexible prices (perhaps due to contracts or menu pricing practices), price discrimination, high transactions costs, and the influences of government policies, among others. A lack of full pass-through indicates that standard arbitrage behavior, which is often assumed to hold in absolute terms in conceptual and empirical trade models, may not be supported by the empirical evidence. In any event, attaining deeper insights into the nature of ERPT at the primary commodity level is an important agenda in the modern empirical trade literature; there is scope for further work.

To begin, it is surprising that comparatively few studies have explored ERPT at the product or commodity level. As well, while there is mounting evidence that asymmetries or, more generally, nonlinearities are a feature of the exchange rate effect on import prices, it is also surprising that comparatively few studies have examined these effects by using modern time series methods, and especially so when ERPT is examined at the commodity level.[1] Finally, while recent studies have examined nonlinearities in ERPT as a function of either exchange rate or inflationary regimes, comparatively few studies have examined the relationship between ERPT and the business cycle.

Considering the above, the overall goals of this paper are then: (1) to examine ERPT in import prices for a highly traded, homogeneous commodity; (2) to examine in a general testing and estimation framework the role of nonlinearities in ERPT; and (3) to examine ERPT and regime-dependent behavior for commodity prices vis-à-vis the business cycle. Specifically, we examine the (potentially nonlinear) impacts of exchange rates on U.S. import prices and Canadian export prices for oriented strand board. OSB represents an interesting case study for which to examine ERPT at the product level. It is a homogeneous product that is widely used in residential and commercial construction throughout North America. As illustrated in Fig. 1, in recent years the U.S. has produced more OSB than Canada, but Canada exports both a far higher amount as well as a greater percentage of its total production than does the United States (on average 81% versus 1.9%). Moreover, as also illustrated in Fig. 1, the overwhelming majority of all Canadian OSB exports are destined for the United States. While prior work has examined pass-through issues for international trade in various timber products (see, e.g., Bolkesjø & Buongiorno, 2006; Uusivuori & Buongiorno, 1991), to our knowledge similar questions have not been addressed for manufactured wood products. Taken together, the evidence suggests that additional insights into ERPT at the product level can be attained by conducting a careful analysis of U.S. and Canadian OSB price relationships.

[1] Notable exceptions include, of course, Al-Abri and Goodwin (2009) and Larue et al. (2010), who do use threshold cointegration methods to estimate asymmetric pass-through effects.

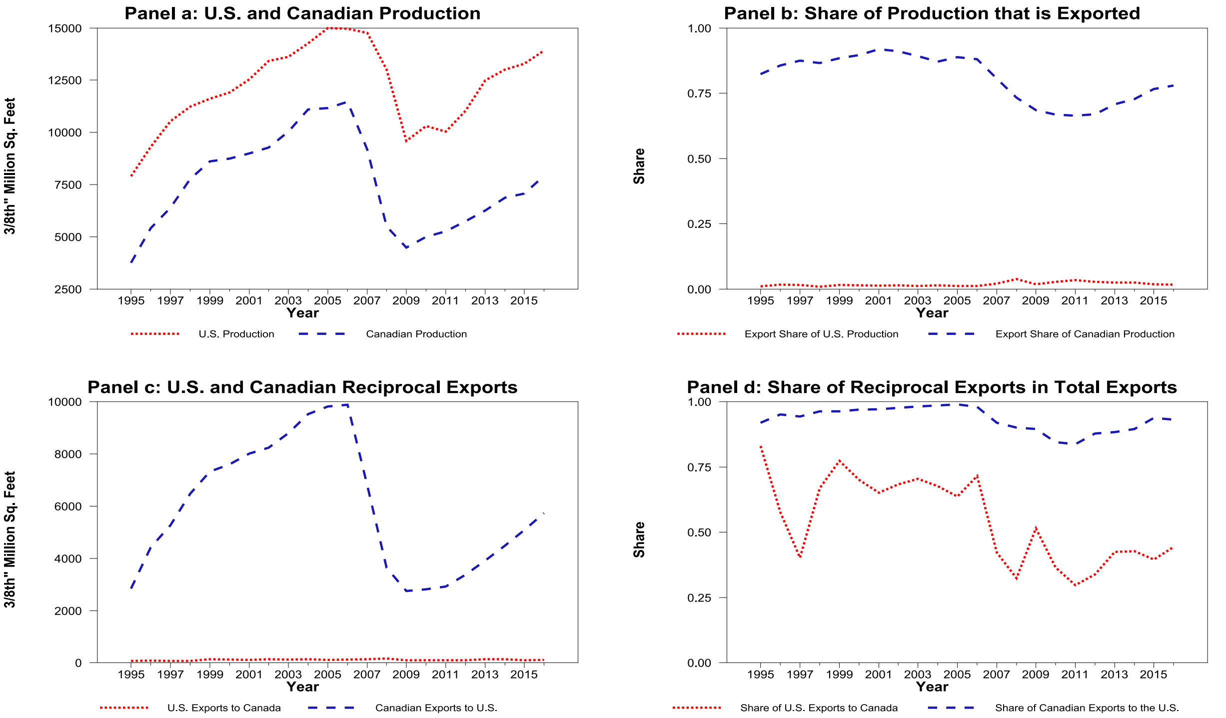

Fig. 1. Production and Export Trends for 3/8th" OSB in the United States and Canada, 1995–2016. The data were obtained from annual reports of the Structural Board Association (SBA).

2. Conceptual framework

There is an extensive literature that examines the LOP in the context of international price behavior; see Goodwin et al. (2011) for an example in the context of markets for North American OSB prices. The theoretical foundations underlying ERPT are closely related to those that motivate the LOP; however, investigations of ERPT highlight the separate effects of price and exchange rate shocks in commodities that are traded across markets with differing currencies.

In the pass-through literature (see, e.g., Goldberg & Knetter, 1997), a long-run price relationship is often specified as:

$$P_{it} = E_t^{\beta_1} P_{xt}^{\beta_2},\ \beta_1, \beta_2 > 0, \quad t = 1, \ldots, T, \tag{1}$$

where P_{it} is the good's (nominal) price in country i in period t (denominated in country i's currency); P_{xt} is the corresponding (nominal) price in country j (denominated in country j's currency); and E_t is the nominal exchange rate, expressed in terms of country i's currency relative to country j's. Here, β_1 and β_2 are parameters and $\beta_1 = \beta_2 = 1$ implies complete pass-through. Converting (1) to natural logarithmic form and adding a stochastic error term yields:

$$p_{it} = \beta_1 e_t + \beta_2 p_{xt} + \varepsilon_t, \tag{2}$$

where lower case letters denote variables in natural logarithm form and $\varepsilon_t \sim iid(0, \sigma^2)$ is an additive error term. In (2), a test of complete exchange rate pass-through is consistent with testing the hypothesis H_0: $\beta_1 = \beta_2 = 1$.

The foregoing assumes p_{xt} is measured in the exporter's currency. When exports are invoiced in the importer's currency, the exporter's price is written as $P_{xt} = \widetilde{P}_{xt}/E_t$, where $\widetilde{P}_{xt}$ is the export price expressed in the importing country's currency. In this case, (2) may be rewritten as:

$$p_{it} = (\beta_1 - \beta_2)e_t + \beta_2 \widetilde{p}_{xt} + \varepsilon_t. \tag{3}$$

Complete pass-through is again consistent with $\beta_1 = \beta_2 = 1$, which reduces (3) to a stochastic version of the LOP relationship. In other words, with common currency pricing complete pass-through implies that the exchange rate should have no long-term impact on the import price.

As is common in the ERPT literature (see, e.g., Campa, Goldberg, & Gonzalez-Minguez, 2005), the model could be modified to allow for the possibility that exporting firms, presumably operating in an imperfectly competitive market environment, maintain a fixed percentage markup over their marginal cost.[2] To modify the model to allow for imperfectly competitive behavior, rewrite $\widetilde{p}_{x,t}$ as:

$$\widetilde{p}_{xt} = mkup_{xt}(e_t) + mc_{xt}, \tag{4}$$

where $mkup_{xt}(e_t)$ denotes percentage markup and mc_{xt} denotes marginal cost, both in logarithmic form. As suggested by the notation in (4), the markup may vary with the exchange rate. In this case, (4) may be written as:

$$mkup_{xt}(e_t) = \phi + \Phi e_t, \tag{5}$$

whereϕ is the markup component that does not vary with the exchange rate.

When import prices are invoiced in importing firm's currency (i.e., local currency pricing), (4) and (5) may be substituted into (3) to obtain:

$$p_{it} = \alpha_0 + (\beta_1 + \beta_2(\Phi - 1))e_t + \beta_2 mc_{xt} + \varepsilon_t, \tag{6}$$

where $\alpha_0 = \phi\beta_2$. Even if $\beta_1 = \beta_2 = 1$ holds, incomplete pass-through occurs when exporting firms operate in an imperfectly competitive environment. As well, if (6) is viewed as a long-run relationship, then a non-zero intercept term exists if ϕ, the fixed mark-up parameter, is non-zero.[3] In the literature, variants of (6) have been used to estimate ERPT effects.

The basic framework may be further modified if ERPT effects are regime specific, that is, if the impact of exchange rates on import prices varies with either the magnitude or direction of adjustment of some other variable. For example, as Al-Abri and Goodwin (2009) and Larue et al. (2010) note, the markup equation in (5) might be such that the exchange rate response parameter, Φ, varies depending on the size (or sign) of an exchange rate adjustment. For relatively small moves, exporters may decide not to adjust the markup due to menu costs. But for a large exchange rate adjustment, exporting firms may be forced to change markups in order to maintain market share. Alternatively, with local currency pricing exporters still convert revenues earned in foreign currency into the home currency, and doing so involves transactions costs as well as costs that could vary with the magnitude of recent exchange rate movements.

In view of the foregoing, the model in (6) may be modified as follows:

$$p_{it} = \alpha_0 + (\beta_1 + \beta_2(\Phi_1(1 - I_{\{s_t > \theta\}}) + \Phi_2 I_{\{s_t > \theta\}} - 1))e_t + \beta_2 mc_{xt} + \varepsilon_t, \tag{7}$$

where θ is the threshold parameter, and where $I_{\{s_t > \theta\}}$ is a Heaviside indicator function such that $I_{\{s_t \leqslant \theta\}} = 1$ if $s_t > \theta$, 0 otherwise. Heres_t is the transition variable; it is the variable that, in conjunction with θ, determines the nature of nonlinear pass-through effects. The important point is the markup varies depending on recent movements ins_t and, therefore, ERPT effects may also vary with these changes.

As demonstrated independently by Balagtas and Holt (2009) and Enders and Holt (2012), there is substantial evidence that prices for many primary commodities adjust in ways that are consistent with asymmetric and/or regime-dependent behavior. As further demonstrated by Goodwin et al., 2011, there is additional evidence that regional OSB prices also behave in a way consistent with nonlinearity. In many ways, these results are not surprising. Specifically, OSB is a storable commodity and, as illustrated by Deaton and Laroque (1995), the impossibility of negative storage easily gives rise to nonlinear price relationships for these types of goods. Furthermore,Lewandrowski, Wohlgenant and Grennes (1994) highlight important linkages between storage and price behavior for softwood lumber, a commodity similar in many respects to OSB. In any event, there is substantial reason to believe that OSB prices behave in ways consistent with nonlinearity and, moreover, that the effects of ERPT on import prices may be regime dependent.

Regarding noninearity vis-à-vis ERPT, several studies have examined the impact of the business cycle on ERPT, but always in the context of aggregate price levels; see, for example, Chew, Ouliaris, and Tan (2011), Cheikh, Zaied, Bouzgarrou, and Nguyen (2018), and Nogueira and León-Ledesma (2011). Business cycle effects with respect to ERPT in North American OSB markets seem especially relevant given that residential construction – a primary end-use for OSB – is quite sensitive to economic downturns. Indeed, housing starts are often asserted to be an important leading indicator of overall economic activity; see, for example, Leamer (2007) and Stock and Watson (2003). As an empirical proposition then, it is entirely plausible that markups and hence ERPT could vary with the business cycle even when considering price response for a specific commodity such as OSB. In terms of (7), the idea is to links_t to one or more variables that transmit information regarding the stage of the business cycle.

3. Data

3.1. Data description

As indicated previously, our interest is on prices for OSB in Canada and the United States. OSB is a manufactured wood product

[2] The assumption of imperfectly competitive market conditions seems relevant for North American OSB markets. In 2006, a series of lawsuits were consolidated into a single case in the U.S. District Court in Pennsylvania on behalf of aggrieved parties involved in OSB purchases between June, 2002 and February, 2006. The suite alleged that a number of major North American OSB manufacturers, operating in both the United States and Canada, conspired to maintain artificially high prices for OSB during the June, 2002 through February, 2006 period. A settlement between plaintiffs and defendants was reached in 2008, and subsequently approved by the court in December, 2008. The cases against OSB manufacturers were subsequently dismissed.

[3] In addition, α_0 may also capture factors associated with the cost of trade if such factors are proportional to prices, an assumption that is common in empirical studies of price parity relationships.

that was introduced in 1978, and is widely used in residential and commercial construction, with the bulk of OSB produced in North America originating in the Southern U.S. and Canada. For example, from 2007 to 2014, Canada and the Southern U.S. produced 87 percent of all OSB otherwise produced in North America (Adair, 2010; APA, 2017). For example, in 2009 and 2010 Canada and the Southern U.S. produced nearly ninety-percent of all OSB otherwise produced in North America (Engineered Wood Product Association, 2010). OSB is constructed by using waterproof and heat cured resins and waxes, and consists of rectangular shaped wood strands that are arranged in oriented layers. As well, it is manufactured in long, continuous mats which are then cut into panels of varying sizes. As a structural panel product, OSB is similar to softwood plywood, although it is generally considered to have more consistency than plywood and is cheaper to produce. The Structural Board Association (SBA) reports that in 1980, OSB panel production in the U.S. was 135 million square feet (on a3/8th's inch basis) and in Canada was 616 million square feet. Comparable numbers for 2014 were 12,892 million square feet produced in the U.S. and 6676 million square feet in Canada. The SBA also reports that by 2000, OSB production exceeded that of softwood plywood, and that by 2014, OSB production enjoyed a 64 percent market share among all structural wood panel products in North America (Adair, 2010; APA, 2017). Fig. 1 illustrates the substantial growth in OSB production since 1995 as well as the sharp decline in OSB production following the collapse of the U.S. housing market in 2007–2008.

Our focus here, then, is on pass-through effects for OSB in two regional North American markets: (1) Eastern Canada (production deriving from plants in Ontario and Quebec); and (2) the Southeast U.S. (production deriving from plants in Georgia, Alabama, Mississippi, South Carolina, and Tennessee). The price data are for 7/16th's inch OSB panels and are expressed in U.S. dollars per thousand square feet; that is, Canadian mills engage in local currency pricing. All price data are observed on a weekly basis and were obtained from the industry source *Random Lengths*.[4] The regional OSB price data used are FOB mill price averages. The period covered is from October 9, 1998 through July 15, 2016, the result being there are 928 usable weekly observations. A plot of the regional OSB price data converted to natural log form is reported in Fig. 2. In the analysis we propose treating the (natural logarithm) of the Southeast U.S. as the effective import price (p_i) and, following Karoro et al. (2009) and Wickremasinghe, Banda, and Silvapulle (2004), using the observed (natural logarithm) of the FOB mill price in Eastern Canada (p_x) as a proxy for the exporter's price (marginal cost) in (6) or, respectively, (7). Doing so is reasonable in part because, although the bulk of OSB in the U.S. is produced in the Southeast, it is also the region with the largest demand growth; U.S. Census Bureau data on housing starts confirm that states in the Southeast have, since the late 1980s, dominated much of the rest of the country in terms of overall starts as well as growth in new home construction.

Aside from reasonable proxies for OSB import and export prices, the specification in Eq. (6) indicates that a relevant exchange rate is also needed. Here, we use the (reciprocal of) the week-ending average of the nominal Canadian dollar-to-U.S. dollar exchange rate as reported on the St. Louis Federal Reserve's Federal Reserve Economic Data (FRED) archive. A plot of the (natural logarithm) of the weekly exchange rate, e, over the sample period, that is, over the October 9, 1998 through July 15, 2016 period, is also recorded in Fig. 2. As illustrated there, the U.S. dollar tended to appreciate relative to the Canadian dollar during much of the sample period, with the 2012–2015 period being an exception.

As noted previously, internationally traded commodities may have price relationships that are sensitive to conditions in the aggregate economy. In the case of OSB, which is a principal building material used in residential and commercial construction, this is even more likely to be true. To allow for the possibility that changes in overall economic conditions may affect exchange rate pass-through for U.S. and Canadian OSB markets, an indicator of weekly changes in overall economic performance is needed. There are several options. One obvious choice, and a frequently cited indicator of the overall health of the economy, is the unemployment rate (Rothman, 1991). In particular, we consider weekly, end-of-period insured unemployment claims. Weekly unemployment claims are collected by the U.S. Department of Labor and are reported on the St. Louis Federal Reserve's FRED online database. The unemployment measure used here, *une*, is the percentage unemployment claims variable without seasonal adjustment. Alternatively, and as discussed in more detail by Estrella and Trubin (2006), the yield curve might also be used as an indicator of overall economic performance. In preliminary analysis, we also considered a measure of the weekly yield curve, *yld*, which was computed as a weekly average of daily spreads between the ten-year constant maturity and the corresponding two-year constant maturity Treasury rates, also obtained from the St. Louis Federal Reserve's FRED online database. Although not reported here (additional results are available upon request), this preliminary analysis indicated that weekly unemployment claims resulted in uniformly better overall model fit and performance relative to the yield curve variable. For this reason, and to conserve space, we proceed by focusing exclusively on U.S. weekly unemployment claims as our measure of overall economic activity. A plot of the unemployment variable over the sample period is reported in Fig. 3.

3.2. Data: preliminary properties

Having identified the series to be used in the empirical analysis, it is useful to examine some of their basic statistical properties. Specifically, we test the null hypothesis of a unit root for each series by using augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests (Dickey & Fuller, 1979; Phillips & Perron, 1988). In implementing the ADF test, we account for the potential effects of heteroskedasticity by using the modified test statistic suggested by Demetrescu (2010). As well, we choose lag lengths for the

[4] *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 producers, wholesalers, distributors, secondary manufacturers, buying groups, treaters, and large retailers.

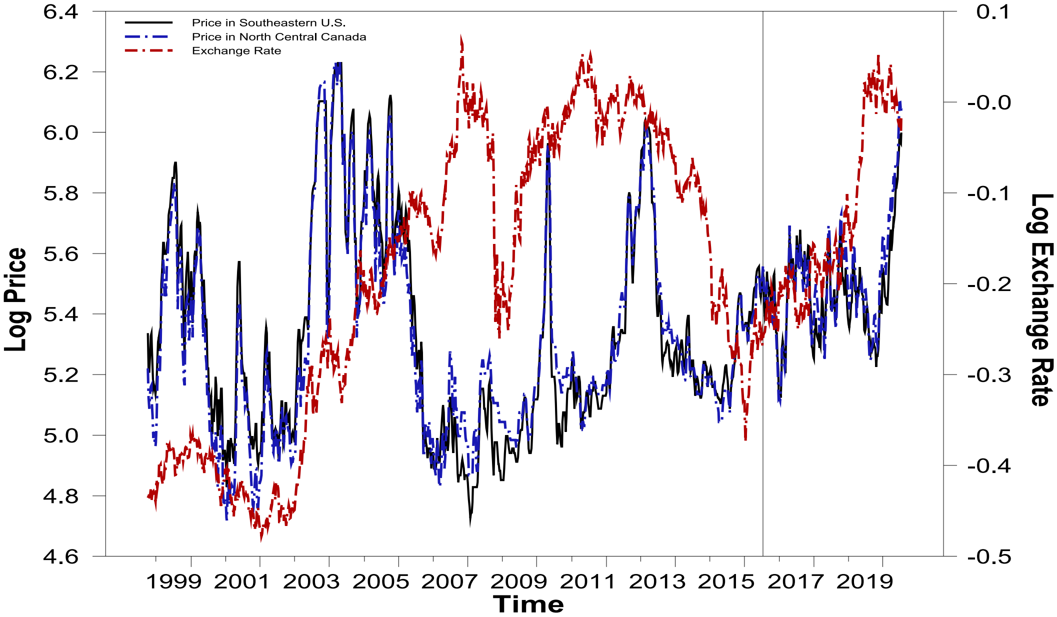

Fig. 2. Natural Logarithms of OSB Prices in Northeastern Canada and Southeastern U.S. along with the U.S.-Canadian Dollar Nominal Exchange Rate, Actual and Simulated, 1998–2020.

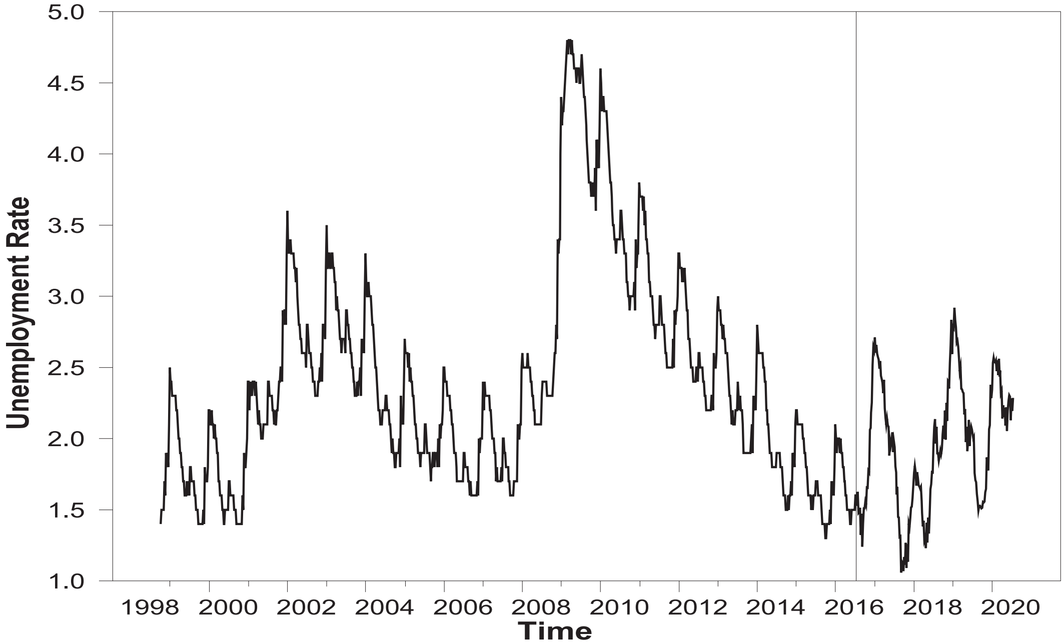

Fig. 3. Weekly U.S. Unemployment Claims, Actual and Simulated, 1998–2020.

autoregressive parameters in the ADF test by using the lag-length selection procedures outlined by Ng and Perron (1995); for the PP test, we choose a lag length based on the rule $int(12(T/100)^{0.25})$, which is 20 in the present case. Unit root test results are reported in upper panel of Table 1.

As recorded in the Table, the tests provide evidence of nonstationarity for each variable considered. In terms of the conceptual framework outlined in the previous section, the implication is that Eq. (6) should now be viewed as a cointegrating regression, thereby reflecting the long-run relationship between the two price variables and the exchange rate variable. Following Al-Abri and Goodwin (2009) and Balke and Fomby (1997), we estimate the (unrestricted) version of (6), although we employ the dynamic OLS cointegration estimator due to Stock and Watson (1993) in order to obtain efficient parameter estimates. In implementing the estimator, the AIC was used to choose the number of leads and lags-in this case, two-to include in the regression. The dynamic

Table 1
Unit Root and Cointegration Test Results for OSB Pass-Through Data.

Variable	ADF	PP
Unit Root:		
p_i	−2.380	−2.853
p_x	−2.783	−3.005
e	−1.824	−1.570
une	−1.915	−1.907
Critical Values:		
1-percent	−3.444	−3.444
5-percent	−2.867	−2.867
Cointegration:		
	−5.347	−6.434
Critical Values:		
1-percent	−4.309	−4.309
5-percent	−3.750	−3.750
10-percent	−3.459	−3.459

Note: p_i denotes the import price (Southeast U.S.); p_x the export price (Eastern Canada); e the nominal U.S. dollar/Canadian dollar exchange rate; and une the unemployment rate. The column headed ADF reports heteroskedasticity robust Augmented Dickey–Fuller test statistics. The column headed PP denotes Phillips–Perron unit root test statistics. Results labeled cointegration are for a unit root test of the residuals of an Engle–Granger cointegrating regression of the import price on the export price and the exchange rate. All critical values were obtained from MacKinnon (2010).

Table 2
Stock and Watson Dynamic OLS Cointegration Regression Results.

Parameter	Variable	Coefficient	Std. Error
α_0		−0.166	(0.116)
$\tilde{\beta}_1$	$p_{xt} + e_t$	1.022	(0.021)
$\tilde{\beta}_1$	e_t	−1.338	(0.047)
ψ_2	$\Delta(p_{xt+2} + e_{t+2})$	−0.049	(0.048)
ψ_1	$\Delta(p_{xt+1} + e_{t+1})$	−0.014	(0.032)
ψ_0	$\Delta(p_{xt} + e_t)$	−0.159	(0.046)
ψ_{-1}	$\Delta(p_{xt-1} + e_{t-1})$	0.090	(0.035)
ψ_{-2}	$\Delta(p_{xt-2} + e_{t-2})$	0.001	(0.040)
ζ_2	Δe_{t+2}	0.467	(0.173)
ζ_1	Δe_{t+1}	0.442	(0.182)
ζ_0	Δe_t	0.662	(0.226)
ζ_{-1}	Δe_{t-1}	0.193	(0.250)
ζ_{-2}	Δe_{t-2}	0.263	(0.229)

Note: Reported values are obtained by using Stock and Watson's (Stock & Watson, 1993) Dynamic OLS estimator of the cointegration relationship in (6). The dependent variable, p_{it}, is the price of OSB in the Southeast United States. Augmenting the model two leads and lags of the first difference of the right-hand-side variables was determined to be sufficient. The estimated standard errors are Newey-West (Newey & West, 1987) HAC standard errors.

regression results are reported in Table 2. The results there suggest there is incomplete exchange rate pass-through.[5]

Of course, the next step in the testing process is to test the resulting residual series from the cointegrating regression for the presence of a unit root. The results in this instance are reported in the lower panel of Table 1. Regardless of which test is employed (i.e., ADF or PP), it is clear that we reject the unit root hypothesis and conclude that OSB prices and the exchange rate are, in fact, cointegrated. This information will be fundamental in specifying and estimating the subsequent nonlinear model used to estimate ERPT effects, to which we now turn.

[5] In order to check the robustness of the Stock and Watson (1993) estimates of the cointegrating vector, we also used the maximum likelihood methods due to Johansen (1988). Specifically, we used Johansen's trace and eigenvalue tests where, respectively, four and six lags were used. In both instances, that is, irrespective of the number of lags used, one cointegrating vector was identified. Moreover, when both cointegrating vectors are normalized so that p_{it} is the left-hand-side variable, the results obtained are virtually identical to those reported in Table 2. These additional results are available upon request.

4. Modelling framework

A primary modelling question is how we might identify and capture the regime-specific behavior of exchange-rate pass through for Canadian and U.S. OSB prices as outlined in (7). Various approaches have been used in the literature. For example, threshold vector autoregression (VAR) and vector error correction (VECM) models, where the parameter(s) embedded in the Heaviside indicator function $I_{\{s_t > \theta\}}$ in (7) are identified and estimated, have been used extensively in the ERPT literature. See, for example, Al-Abri and Goodwin (2009), Aleem and Lahiani (2014), Donayre and Panovska (2016), Lin and Wu (2012), and Ghartey (2019), among others. Alternatively, a smooth transition process, where the Heaviside indicator function $I_{\{s_t > \theta\}}$ in (7) is replaced with a function that has the potential to change in a smooth, continuous manner between zero and one, depending on the value of s_t, have also been used to model ERPT effects. Studies that have used this so called smooth transition approach to model regime-dependent ERPT effects include Cheikh (2012), Nogueira and León-Ledesma (2011), Shintani et al. (2013), and Wu, Liu, and Yang (2017), among others. Prior efforts in this regard have not, however, been couched in the context of a vector error correction system, as we propose here.

4.1. Multivariate smooth transition models

The basic building block of our empirical analysis is a VECM model of the general form:

$$\Delta \boldsymbol{y_t} = \delta + \sum_{i=1}^{p-1} \boldsymbol{\Psi_i} \Delta \boldsymbol{y_{t-i}} + \alpha \hat{\varepsilon}_{t-1} + \upsilon_t, \tag{8}$$

where $\boldsymbol{y}_t = (p_{it}, p_{xt}, e_t)'; \hat{\varepsilon}_{t-1}$ is the lagged residual from the cointegrating regression described in the previous section, that is, the (lagged) departure from long-run equilibrium; δ and α are conformable parameter vectors, where α contains the so called speed-of-adjustment parameters or error correction coefficients; $\boldsymbol{\Psi}_i$ are conformable parameter matrices; and υ_t is a vector of mean zero, random, additive errors. Importantly, and as the notation makes clear, we treat the (lagged) error correction residual, $\hat{\varepsilon}_{t-1}$ as known. As discussed by Zivot and Wang (2006), doing so is common in estimating VECM models because estimates of the parameters in the cointegrating vector are super consistent. See, for example, Stock (1987) for additional details.

If nonlinear ERPT effects are not considered, then the system in (8) can be estimated and impulse response functions generated in order to determine the degree of pass-through. Alternatively, if nonlinearities of the sort described in previous sections are considered, then it is necessary to modify (8). In the spirit of the regime switching framework in (7), we could re-specify the VECM as:

$$\begin{aligned} \Delta \boldsymbol{y_t} = & \left[\delta_1 + \sum_{i=1}^{p-1} \boldsymbol{\Psi_{i1}} \Delta \boldsymbol{y_{t-i}} + \alpha_1 \hat{\varepsilon}_{t-1}\right](1 - \boldsymbol{G}(\boldsymbol{s_t}, \theta)) \\ & + \left[\delta_2 + \sum_{i=1}^{p-1} \boldsymbol{\Psi_{i2}} \Delta \boldsymbol{y_{t-i}} + \alpha_2 \hat{\varepsilon}_{t-1}\right] \boldsymbol{G}\left(\boldsymbol{s_t}, \theta\right) + \upsilon_t, \end{aligned} \tag{9}$$

where Δ is a difference operator such that $\Delta x_t = x_t - x_{t-1}$. In (9), the function $G(.)$, the so called transition function, now plays the role of the Heaviside indicator function defined previously, and θ denotes a vector of parameters that identifies the transition function. Importantly, similar to the Heaviside indicator function, the function $G(.)$ is bounded between zero and one. A primary difference, however, is that $G(.)$ can also assume intermediate values on the unit interval, that is, regime change can be gradual or smooth. For this reason, the model in (9) is referred to as a smooth transition VECM, or STVECM, and was introduced originally by Rothman, van Dijk, and Hans Franses (2001). Furthermore, the STVECM is a straightforward extension of the univariate smooth transition autoregressive (STAR) modelling framework introduced by Teräsvirta (1994). The model is, of course, nonlinear in parameters given that the parameters in θ must also be estimated; nonlinear estimation methods are employed.

To implement the STVECM, it is necessary to specify a form for the transition function, $G(.)$. In the present case if, for example, it is hypothesized that ERPT varies with the magnitude of the departure from long-run equilibrium, then it would be feasible to specify the transition function as:

$$G(s_t; \gamma, c_1, c_2) = [1 + \exp(-\gamma(s_t - c_1)(s_t - c_2)/\hat{\sigma}_{st}^2)]^{-1}, \; c_1 < c_2, \; \gamma > 0, \tag{10}$$

that is, the second-order logistic function, where $\theta = (\gamma, c_1, c_2)$, with γ being the speed-of-adjustment parameter and c_1 and c_2 are centrality parameters; and $\hat{\sigma}_{s_t}$ is the sample standard deviation of the transition variable, s_t. In (10), as $\gamma \to \infty$, and assuming that $c_1 \neq c_2$, as the transition variable, s_t, drops below c_1 or exceeds c_2, the function $G(.)$ approaches unity while, conversely, over the range $c_1 \leqslant s_t \leqslant c_2$ the function $G(.)$ approaches zero. The speed with which the transition from one extreme (regime) to the other occurs is dictated by the magnitude of theγ parameter. In this manner, the second-order logistic function is capable of approximating a three-regime threshold model of the sort employed by Al-Abri and Goodwin (2009) and Larue et al. (2010), albeit in a potentially smooth way. To abbreviate, we refer to a regression equation with an exponential transition function as an quadratic smooth transition regression equation, or QSTR.

Alternatively, a simpler version of (10) is the first-order logistic function or, more simply, the logistic function, which is simply specified as:

$$G(s_t; \gamma, c) = [1 + \exp(-\gamma(s_t - c)/\hat{\sigma}_{st})]^{-1}, \; \gamma > 0. \tag{11}$$

The first-order logistic function is another widely used specification for the transition function, $G(.)$, in the STVECM (see, e.g., Rothman et al., 2001). In (11), as s_t increases above the centrality parameter c, the function $G(.)$ will approach unity. Alternatively, for s_t below c the logistic function approaches zero. Again, the speed with which this transition occurs is determined by the relative magnitude of the parameter γ. By incorporating (11) into (9), it follows that the resulting STVECM can display asymmetric behavior depending on the value of the transition variable, s_t. For example, one option, and one largely unexplored in the ERPT literature, is to set s_t equal to some observed measure of real economic activity such as the unemployment rate in an attempt to mimic the business cycle. Here we refer to a regression equation that uses a first-order logistic transition function as a logistic smooth transition regression equation, or LSTR.

As specified in (9), it follows that each equation in the STVECM shares the same transition function. This is the approach most commonly applied in the literature; see, for example, Anderson and Vahid (1998), Camacho (2004), and Rothman et al. (2001). From an empirical perspective, such a specification may be overly restrictive. In other words, it is entirely possible that p_{it} will respond to s_t with a different speed than will p_{xt}. It is even possible that the various equations in the system will have different transition functions, that is, some mix of logistic and exponential functions. In this spirit, (9) may be generalized as follows:

$$\Delta \boldsymbol{y_t} = (\boldsymbol{I} - \boldsymbol{\Gamma_t})\left[\boldsymbol{\delta_1} + \sum_{i=1}^{p-1} \boldsymbol{\Psi_{i1}}\Delta \boldsymbol{y_{t-i}} + \boldsymbol{\alpha_1}\hat{\varepsilon}_{t-1}\right] + \boldsymbol{\Gamma_t}\left[\boldsymbol{\delta_2} + \sum_{i=1}^{p-1} \boldsymbol{\Psi_{i2}}\Delta \boldsymbol{y_{t-i}} + \boldsymbol{\alpha_2}\hat{\varepsilon}_{t-1}\right] + \upsilon_t, \tag{12}$$

where $\boldsymbol{I}$ is a 3×3 identity matrix and $\mathrm{diag}(\boldsymbol{\Gamma_t}) = (G_1(s_{1t}), G_2(s_{2t}), G_3(s_{3t}))$, with off diagonal terms equalling zero. In this manner the STVECM in (9) may be generalized to allow for different transition functions (and transition variables) for each equation in the system. He, Teräsvirta, and González (2008) considered a similar specification for a vector-autoregressive model, although they limited their analysis to the case where s_t simply equals the time index, t.

To our knowledge, the STVECM framework has not been used to model regime dependent exchange rate pass-through effects. This is surprising given that the STVECM clearly nests many of the more common specifications used to examine nonlinear responses in the empirical literature on exchange rate pass-through.

4.2. A testing strategy: single equations

As is evident from both (9) and (12), the nonlinear features of the provisional STVECM model will depend on the selection of the transition function(s) as well as the transition variable(s). In practice, there are typically a large number of options available during the model building phase. It is therefore desirable to have a testing strategy that reduces the number of nonlinear models to be estimated and compared. To date, there has been relatively little research on testing strategies for multivariate systems, with much of the focus being on testing in single equation models (e.g., Lundbergh, Teräsvirta, & van Dijk, 2003; Teräsvirta, 1994).

To gain insight into the testing problem, consider the case where (9) is reduced to a univariate smooth transition error correction model, that is, where $\boldsymbol{y_t} = \tilde{\boldsymbol{y}}_t$ is a scalar. In this case, we may re-write (9) as:

$$\Delta\tilde{y}_t = \boldsymbol{\varphi}_1'\tilde{\boldsymbol{x}}_t(1 - G(s_t;\theta)) + \boldsymbol{\varphi}_2'\tilde{\boldsymbol{x}}_t G(s_t;\theta) + \upsilon_t, \tag{13}$$

where $\tilde{\boldsymbol{x}}_t = (1, \Delta\boldsymbol{y}'_{t-1}, \ldots, \Delta\boldsymbol{y}'_{t-p+1}, \hat{\varepsilon}_{t-1})'$, a $(3 \times p + 1)$ vector, and where $\boldsymbol{\varphi}_1$ and $\boldsymbol{\varphi}_2$ are conformable parameter vectors. As well, assume that $G(.)$ is given by either (10) or (11). The problem, of course, is there are two ways to reduce (13) to a linear error correction model. On the one hand, if $\boldsymbol{\varphi}_1 = \boldsymbol{\varphi}_2$ the model becomes linear in parameters. Even so, it is not appropriate to simply test H_0: $\boldsymbol{\varphi}_1 = \boldsymbol{\varphi}_2$ given that the γ and c parameters embedded in $G(.)$ are unidentified. On the other hand, a standard test of H_0: $\gamma = 0$ is not appropriate given that, in this case, $\boldsymbol{\varphi}_1$ and $\boldsymbol{\varphi}_2$ are unidentified. The result in either case is the classical "Davies problem," outlined in a pair of papers by Davies (1977, 1987). The upshot is that tests of either null hypothesis will be associated with non-standard asymptotic distributions.

While various testing procedures have been proposed, a computationally convenient approach was put forth by Luukkonen, Saikkonen, and Teräsvirta (1988). Specifically, these authors advocate replacing the transition function $G(.)$ with a suitable Taylor series approximation, where the approximation is evaluated at $\gamma = 0$. If, for example, a third-order approximation is used, then a linear approximation to (13) is:

$$\Delta\tilde{y}_t = \boldsymbol{\psi}_1'\tilde{\boldsymbol{x}}_t + \boldsymbol{\psi}_2'\tilde{\boldsymbol{x}}_t s_t + \boldsymbol{\psi}_3'\tilde{\boldsymbol{x}}_t s_t^2 + \boldsymbol{\psi}_4'\tilde{\boldsymbol{x}}_t s_t^3 + \xi_t. \tag{14}$$

A test of linearity may now be conducted by simply testing H_0': $\boldsymbol{\psi}_2 = \boldsymbol{\psi}_3 = \boldsymbol{\psi}_4 = \boldsymbol{0}$ in (14). Note that while in general ξ_t contains both ε_t and an approximation error, under the null hypothesis of linearity the approximation error vanishes. In this case, $\varepsilon_t = \xi_t$, and standard Lagrange Multipler (LM) tests may be used. That is, if RSS_1 denotes the error sum of squares from the restricted version of (14) and RSS_2 denotes the corresponding measure for the unrestricted model, then an F-test version of the LM test of linearity is:

$$F_{LM} = \frac{(RSS_1 - RSS_2)/q}{RSS_2/(n-k)} \overset{approx}{\sim} F\left(q,\, T - p - 1\right), \tag{15}$$

where $q = 3(p + 1)$ are the number of restrictions implied by the null hypothesis H_0' and k are the number of free parameters estimated in the unrestricted version of (14).

Although the proposed linearity test is reasonable for detecting nonlinearity, several issues remain. For example, it does not directly determine which transition function, that is, the second-order or the first-order logistic, is most appropriate for a given application. Moreover, the nonlinearity test assumes that the transition variable, s_t, is known. While in some instances theory might dictate a likely candidate for s_t, in many instances this choice, too, must be part of the overall testing and model specification framework. Regarding the first issue, Teräsvirta and Anderson (1992) and Teräsvirta (1994) describes a testing sequence that can be employed to identify the transition function. Specifically, assuming the linear model is rejected, the following conditional tests may be performed:

$$\mathrm{H}_{04}\text{: } \boldsymbol{\psi}_4 = \mathbf{0}, \tag{16}$$

$$\mathrm{H}_{03}\text{: } \boldsymbol{\psi}_3 = bf0|\boldsymbol{\psi}_4 = \mathbf{0}, \tag{17}$$

$$\mathrm{H}_{02}\text{: } \boldsymbol{\psi}_2 = \mathbf{0}|\boldsymbol{\psi}_3 = \boldsymbol{\psi}_4 = \mathbf{0}, \tag{18}$$

where again it is appropriate to use suitable F-versions of the tests implied by (16)–(18).The logic of the above testing sequence is that an exponential function is likely best approximated by a quadratic in s_t. Therefore, if (17) is rejected while (16) and (18) are not, the second-order logistic function in (10) may be used.[6] Alternatively, if (16) or (18) are rejected while (17) is not, than the first-order logistic function in (11) may be tried.[7] Finally, there are few restrictions on candidates for the transition variable, s_t. Again, Teräsvirta (1994) suggests trying a slate of candidates and using the one associated with the strongest rejection of the linearity hypothesis, H_0'. Finally, once a candidate transition variable and transition function have been identified, provisional estimates of the smooth transition model in (13) can be obtained by employing nonlinear least squares (van Dijk et al., 2002). Finally, the diagnostic tests described by Eitrheim and Teräsvirta (1996) can be employed to examine model adequacy.

4.3. A testing strategy: multivariate systems

As noted previously, there is a paucity of studies that have explored nonlinearity testing in a multivariate setting, especially when a system such as (12) is examined with equation-specific transition functions. Even so, Camacho (2004) and Rothman et al. (2001) are notable exceptions, with each of these studies advancing a framework for testing nonlinearities in a multi-equation model. In principle, doing so is straightforward: the multivariate counterpart to (14) may be specified as:

$$\Delta \boldsymbol{y}_t = \mathrm{F}_1\boldsymbol{X}_t + \mathrm{F}_2\boldsymbol{X}_t\boldsymbol{s}_{1t} + \mathrm{F}_3\boldsymbol{X}_t\boldsymbol{s}_{2t} + \mathrm{F}_4\boldsymbol{X}_t\boldsymbol{s}_{3t} + \boldsymbol{\xi}_t,\ \boldsymbol{\xi}_t \sim N(\boldsymbol{0}, \boldsymbol{\Sigma}), \tag{19}$$

where in this case $\boldsymbol{X}_t$ is a $3 \times (p+1)$ matrix defined as $\boldsymbol{X}_t = \boldsymbol{\iota}\tilde{\boldsymbol{x}}_t'$, and where $\boldsymbol{\iota}$ is a (3×1) unit vector. As well, $\boldsymbol{s}_{it} = (s_{1t}^i, s_{2t}^i, s_{3t}^i)'$, $i = 1, 2, 3$, F_i, $i = 1, \ldots, 4$, are conformable parameter matrices, and where $\boldsymbol{\Sigma}$ is a symmetric, positive-definite error covariance matrix. The system nonlinearity test then involves a test of the hypothesis H_0'': $\mathrm{F}_2 = \mathrm{F}_3 = \mathrm{F}_4 = 0$, which will involve $M = 3[3 \times (p+1)]$ linear restrictions on the parameters of (19).

Following (Rao et al. (1973) p. 556), an F-version of the LM test of H_0'' in the multi-equation system may also be defined. Specifically, let $\hat{\boldsymbol{\Sigma}}_0$ denote the estimated residual covariance matrix for the model under the null and let $\hat{\boldsymbol{\Sigma}}_1$ be similarly defined for the model under the alternative. Also, let M denote the number of equations in the system (here $M = 3$). Furthermore, define m_r as the *number of restrictions per equation* under H_0'', that is, for the restricted model (relative to the unrestricted model). Finally, let k_u denote the number of parameters *per equation* in the unrestricted system in (19). To derive Rao's F, we begin by defining the standard likelihood ratio test as:

$$\lambda = T(\ln\det(\hat{\boldsymbol{\Sigma}}_0) - \ln\det(\hat{\boldsymbol{\Sigma}}_1)) \sim \chi^2(Mm_r),$$

where T denotes sample size. To introduce Rao's F, define Wilks's Lambda as:

$$\Lambda = \exp(-\lambda/T) = \det(\hat{\boldsymbol{\Sigma}}_0)/\det(\hat{\boldsymbol{\Sigma}}_1).$$

We may then define Rao's F, denoted as F_{LMS}, as:

$$F_{LMS} = \left(\frac{1-\Lambda^{1/s}}{\Lambda^{1/s}}\right)\left(\frac{hs-r}{m_rM}\right) \overset{approx}{\sim} F(m_rM, hs-r), \tag{20}$$

where h, s, r, and τ are defined as:

$$\tau = \sqrt{\frac{m_r^2M^2-4}{m_r^2+M^2-5}},$$

[6] Alternatively, and as described by van Dijk, Teräsvirta, and Hans Franses (2002), in this instance an exponential smooth transition function, given by $G(s_t;\gamma, c) = 1 - \exp(-\gamma(s_t - c)^2/\sigma_{s_t}^2)$, could also be considered. While the exponential function has one fewer free parameters than the double logistic function, and is therefore more parsimonious, it does not have the same range of flexibility in approximating various regimes as does the second-order logistic function. For this reason, we focus on the second-order logistic function as an alternative to its first-order counterpart.

[7] In the event that the testing sequence allows all hypotheses in (16)–(18) to be rejected, Teräsvirta (1994) suggests picking the transition function associated with the smallest p-value. For example, if a test of (17) yields the smallest p-value, the second-order logistic transition function would be used.

$$s = \begin{cases} \tau & \text{if } m_r^2 + M^2 - 5 > 0 \\ 1 & \text{otherwise} \end{cases},$$

$$h = T - k_u - \frac{1}{2}[M - m_r + 1],$$

and

$$r = \frac{1}{2} m_r M - 1.$$

While a value for F_{LMS} that exceeds the critical value from the $F(m_r M, hs - r)$ distribution is a clear indication of nonlinearity in the system, it says nothing about which equation(s) are appropriately nonlinear, nor does it suggest which transition function or set of transition variables are most applicable.

In principle, a multivariate version of the testing sequence in (16)–(18) could also be performed. While, as such, a richer, more detailed sequence of tests could be developed, the number of combinations of candidate transition variables and transition functions involved could quickly become overwhelming. We therefore propose a simple yet practical strategy for identifying the appropriate form of the STVECM in (12). Specifically, we propose using the single-equation testing framework outlined in the previous section for specifying the structure of each equation in the system. Furthermore, once a set of candidate transition variables has been identified, the test in (20) may be employed to evaluate system-wide nonlinearity.

5. Empirical results

5.1. Nonlinearity testing results

The testing and estimation methods described above are used to examine nonlinearity in exchange rate pass-through for U.S. and Canadian OSB prices. The approach first necessitates estimating a best-fitting linear error correction model for each equation. The explanatory variables used are lags of (first differences) of representative (logarithmic) OSB import and export prices and the first difference of the log of the U.S. dollar-Canadian dollar exchange rate. A systems version of Akaike's information criterion (AIC) is used to determine appropriate lag lengths.[8] The AIC indicated that up to six lags of the $\Delta \boldsymbol{y}_t$ vector are needed in each equation. Even so, four additional lags were called for to render the residuals of the foreign exchange equation white noise. Additional testing confirmed that exchange rates respond only to their own lags, and are therefore exogenous to OSB prices. As well, preliminary tests suggested that lagged changes in exchange rates are insignificant in the OSB price equations.[9]

The results of nonlinearity tests applied to the U.S. and Canadian OSB price equations are reported in Table 3. Candidates for the transition variables include various moving averages for the lagged weekly U.S. unemployment rate. Specifically, we consider

$$\widetilde{une}_t = \frac{1}{N} \sum_{i=1}^{N} une_{t-i}, \tag{21}$$

where $N = 8$, 12, 16, 20, 24, 28, 52, and, 104. The longer averages (i.e., $N = 52$ and 104) smooth out short-term and seasonal fluctuations in weekly unemployment rates, and therefore might be expected over time to send a reasonable signal of general economic conditions. The test results show that for the import price (i.e., Southeast U.S. OSB price), linearity is most convincingly rejected for the $\widetilde{une}_t$ variable when $N = 16$. Alternatively, for the export price (i.e., Eastern Canada OSB Price) linearity is most strongly rejected when $N = 20$. Moreover, the results of applying the testing sequence in (16)–(18) suggest that in both instances the transition function is likely a logistic as specified in (11). Even so, we fitted provisional LSTR models to each series by using the suite of candidate transition variables related to lagged unemployment. In so doing, we discovered the best overall model fit for both OSB price series occurred for $\widetilde{une}_t$ when $N = 104$, that is, when a two-year moving average of lagged unemployment rates was specified for s_t, the transition variable.[10] The implication then is that ERPT into OSB prices is likely asymmetric, and moreover that this asymmetry occurs in conjunction with a general indicator of the business cycle. This preliminary result is also consistent with recent work by Chew et al. (2011), Cheikh and Rault (2016), and da Silva Correa et al. (2010).

At this stage, several additional issues must be considered. First is the question of what transition variable is most likely associated with nonlinearity in the exchange rate equation, which contains an intercept and ten lags of the log difference of exchange rates. To this end, the nonlinearity tests were repeated for the exchange rate equation; the results are reported in the left-hand panel of Table 4. Of the transition variables considered, results in Table 4 indicate the presence of substantial nonlinearities in the exchange rate equation, with $s_t = \Delta e_{t-1}$ being associated with the strongest rejection of linearity; for this variable, the testing sequence suggests that a QSTR, as specified in (10), may be the most appropriate spe-cification. Even so, we repeated the provisional single-equation estimation strategy outlined for the OSB price equations by fitting QSTR models using all the candidates for the transition variable, s_t,

[8] Specifically, we use $\text{AIC} = ln(\det(\widehat{\Sigma})) + 2N/T$, where N denotes the number of estimated parameters in the model.

[9] Of course, this result does not preclude the possibility of ERPT into OSB prices, as the lagged cointegrating residuals, which incorporate the lagged exchange rate, remain in the specifications.

[10] A similar testing and specification strategy, including the use of longer-term moving averages of candidate transition variables, was employed by Shintani et al. (2013) in their study of exchange rate pass-through and inflation.

Table 3
Single-Equation Nonlinearity Test Results for Southeast U.S. and North Eastern Canada.

	Import Price-Southeast U.S.				Export Price-Eastern Canada			
s_t	H_0'	H_{04}	H_{03}	H_{02}	H_0'	H_{04}	H_{03}	H_{02}
$\frac{1}{8}\sum_{i=1}^{8} une_{t-i}$	3.78×10^{-3}	0.074	0.826	3.03×10^{-4}	0.197	0.451	0.886	0.015
$\frac{1}{12}\sum_{i=1}^{12} une_{t-i}$	1.02×10^{-3}	0.028	0.827	1.48×10^{-4}	0.118	0.321	0.850	0.012
$\frac{1}{16}\sum_{i=1}^{16} une_{t-i}$	4.81×10^{-4}	0.020	0.850	6.62×10^{-5}	0.060	0.200	0.810	7.97×10^{-3}
$\frac{1}{20}\sum_{i=1}^{20} une_{t-i}$	5.12×10^{-4}	0.025	0.898	3.88×10^{-5}	0.046	0.158	0.858	5.60×10^{-3}
$\frac{1}{24}\sum_{i=1}^{24} une_{t-i}$	1.10×10^{-3}	0.052	0.936	3.32×10^{-5}	0.073	0.260	0.902	4.70×10^{-3}
$\frac{1}{28}\sum_{i=1}^{28} une_{t-i}$	2.40×10^{-3}	0.119	0.946	3.00×10^{-5}	0.110	0.430	0.896	4.51×10^{-3}
$\frac{1}{52}\sum_{i=1}^{52} une_{t-i}$	6.93×10^{-3}	0.150	0.995	4.48×10^{-5}	0.057	0.247	0.882	3.60×10^{-3}
$\frac{1}{104}\sum_{i=1}^{104} une_{t-i}$	0.023	0.330	0.983	1.41×10^{-4}	0.065	0.174	0.821	0.011

Note: The column headed s_t defines the candidate transition variable. Entries are approximate p-values for the LM tests of nonlinearity (H_0'), and for the sequence of tests defined in (16)–(18) for determining whether the transition function is likely an exponential or a logistic.

Table 4
Single-Equation Nonlinearity Test Results for Exchange Rate and Unemployment Rate.

	Exchange Rate					Unemployment Rate			
s_t	H_0'	H_{04}	H_{03}	H_{02}	s_t	H_0'	H_{04}	H_{03}	H_{02}
Δe_{t-1}	2.72×10^{-17}	1.44×10^{-3}	3.41×10^{-9}	8.03×10^{-9}	Δune_{t-1}	7.14×10^{-42}	1.09×10^{-4}	3.29×10^{-7}	1.24×10^{-37}
$(e_{t-1} - e_{t-3})$	8.41×10^{-10}	2.09×10^{-3}	7.47×10^{-5}	3.24×10^{-5}	$(une_{t-1} - une_{t-3})$	4.63×10^{-34}	1.82×10^{-4}	3.22×10^{-3}	2.17×10^{-34}
$(e_{t-1} - e_{t-4})$	4.03×10^{-13}	0.012	3.38×10^{-5}	1.58×10^{-9}	$(une_{t-1} - une_{t-4})$	1.94×10^{-43}	3.50×10^{-6}	1.69×10^{-5}	1.80×10^{-39}
$(e_{t-1} - e_{t-5})$	3.76×10^{-11}	5.96×10^{-4}	1.12×10^{-3}	2.14×10^{-7}	$(une_{t-1} - une_{t-5})$	4.61×10^{-31}	3.36×10^{-6}	1.45×10^{-5}	2.59×10^{-25}
$(e_{t-1} - e_{t-6})$	9.96×10^{-11}	0.065	2.22×10^{-9}	1.02×10^{-3}	$(une_{t-1} - une_{t-6})$	1.22×10^{-39}	7.04×10^{-10}	9.69×10^{-3}	1.49×10^{-34}
$(e_{t-1} - e_{t-7})$	7.07×10^{-11}	0.061	7.76×10^{-8}	3.06×10^{-5}	$(une_{t-1} - une_{t-7})$	6.80×10^{-32}	2.24×10^{-5}	1.48×10^{-4}	1.09×10^{-28}
$(e_{t-1} - e_{t-8})$	9.58×10^{-12}	0.402	1.56×10^{-11}	4.78×10^{-4}	$(une_{t-1} - une_{t-8})$	1.27×10^{-31}	9.60×10^{-8}	1.27×10^{-3}	1.16×10^{-26}
$(e_{t-1} - e_{t-12})$	1.39×10^{-14}	1.73×10^{-8}	1.39×10^{-4}	1.90×10^{-5}	$(une_{t-1} - une_{t-12})$	1.65×10^{-25}	6.41×10^{-7}	3.46×10^{-3}	2.79×10^{-21}
					$(une_{t-1} - une_{t-53})$	8.21×10^{-8}	0.085	0.049	1.80×10^{-8}
					$\frac{1}{52}\sum_{i=1}^{52} une_{t-i}$	2.55×10^{-3}	0.578	1.25×10^{-3}	0.035
					$\frac{1}{104}\sum_{i=1}^{104} une_{t-i}$	4.11×10^{-4}	0.757	4.91×10^{-4}	3.56×10^{-3}

Note: The column headed s_t defines the candidate transition variable. Entries are approximate p-values for the LM tests of nonlinearity (H_0'), and for the sequence of tests defined in (16)–(18) for determining whether the transition function is likely an exponential or a logistic.

indicated in the left-hand panel of Table 4. In this case, the choice of $s_t = \Delta e_{t-1}$ was confirmed.

The preliminary evidence reported above suggests that a 104-week moving average of unemployment is a reasonable transition variable in both OSB price equations. Therefore, it is desirable to incorporate a fourth equation into the system to explain weekly unemployment rates. Moreover, prior work-see, for example, Deschamps et al. (2008) and van Dijk et al. (2002) — has found substantial evidence in favor of LSTR models for monthly U.S. unemployment rates. Even so, to our knowledge prior studies have not focused on modelling unemployment rates (based on unemployment claims) on a weekly basis. The base linear model we use is of the form:

$$\Delta\widetilde{y}_t = \lambda_0 + \sum_{i=1}^{3} (\eta_i \sin(2\pi t/f_i) + \kappa_i \cos(2\pi t/f_i)) + \sum_{i=1}^{p-1} \lambda_i \Delta\widetilde{y}_{t-i} + \rho y_{t-1} + \upsilon_t, \tag{22}$$

where $\widetilde{y}_t = une_t$ and $f_1 = 13, f_2 = 26$, and $f_3 = 52$. The sine-cosine terms are incorporated to account for the seasonal nature of unemployment claims. As well, we follow Skalin and Teräsvirta (2002) by including a lagged level term for the unemployment variable, which in turn implies that unemployment follows a "natural rate" (i.e., is mean reverting) as opposed to a "hysteresis" hypothesis.[11] Of course, once nonlinearities are considered unemployment rates could even display locally explosive behavior.

The linear model in (22) was fitted to the data. The (univariate) AIC indicated that up to eleven lags of Δune_t are needed to

[11] Even so, the results reported in Table 1 suggest that une_t behaves in a manner consistent with a unit root process (i.e., hysteresis). As Skalin and Teräsvirta (2002) report, it is often difficult reject the null of a unit root even when the underlying data were generated in a manner consistent with mean-reverting behavior in the presence of strong asymmetries.

Table 5
Single-Equation Model Assessment and Diagnostic Test Results.

	Southeast U.S. Price		Eastern Canada Price		Exchange Rate		Unemployment Rate	
Measure	Linear	STR Model	Linear	STR Model	Linear	STR Model	Linear	STR Model
Type	–	LSTR	–	LSTR	–	QSTR	–	LSTR
s_t	–	$\frac{1}{104}\sum_{i=1}^{104} une_{t-i}$	–	$\frac{1}{104}\sum_{i=1}^{104} une_{t-i}$	–	Δe_{t-1}	–	$une_{t-1} - une_{t-4}$
R^2	0.331	0.371	0.294	0.339	0.032	0.077	0.401	0.572
$\hat{\sigma}_\upsilon$	0.045	0.044	0.045	0.044	0.012	0.012	0.092	0.079
$\hat{\sigma}_{\upsilon,NL}/\hat{\sigma}_{\upsilon,L}$	–	0.978	–	0.976	–	0.984	–	0.854
AIC	−3.356	−3.380	−3.339	−3.368	−5.800	−5.806	−1.906	−2.196
AR(4)	0.543	0.686	0.109	0.776	0.235	0.965	0.662	0.441
AR(6)	0.398	0.834	0.177	0.709	0.389	0.506	0.668	0.136
AR(12)	0.428	0.899	0.163	0.824	0.206	0.708	0.204	0.028
ARCH(4)	2.22×10^{-13}	9.12×10^{-11}	3.59×10^{-17}	9.17×10^{-10}	4.01×10^{-26}	1.46×10^{-27}	4.91×10^{-16}	2.35×10^{-18}
ARCH(6)	2.21×10^{-8}	1.20×10^{-10}	0.036	6.52×10^{-12}	2.04×10^{-28}	6.22×10^{-29}	9.03×10^{-12}	5.15×10^{-17}
SK	−0.055	−0.032	0.065	0.271	−1.024	−1.034	0.800	0.513
EK	3.187	3.128	4.275	3.824	6.855	7.406	2.966	3.544
LJB	387.74	373.16	697.30	568.57	1294.40	1495.43	433.06	518.90

Note: The effective sample size, T, is 915. LSTR denotes logistic smooth transition and QSTR the quadratic smooth transition. Here s_t denotes the transition variable used. R^2 is the unadjusted R^2 and $\hat{\sigma}_\upsilon$ is the residual standard error. $\hat{\sigma}_{\upsilon,NL}/\hat{\sigma}_{\upsilon,L}$ is the ratio of the respective standard error from the nonlinear model relative to the linear model. SK is skewness, EK is excess kurtosis, and LJB is the Lomnicki-Jarque-Bera test of normality of the residuals (critical value from the χ_2^2 distribution is 13.82 at the 0.001 significance level). AR(j), j = 4, 6, 12, is the p-value from an F-version of the LM test for remaining autocorrelation up to lag j. Entries for ARCH(j), j = 4, 6 are similarly defined for ARCH errors up to lag j.

eliminate residual serial correlation. Results of applying linearity tests for the unemployment rate equation are recorded in the right-hand panel of Table 4. Consistent with prior studies, as well as with the asymmetries that may be detected by simply examining the data plot in Fig. 3, there is overwhelming evidence of nonlinearity in weely unemployment rates. Results in Table 4 suggest that linearity is rejected most convincingly for $(une_{t-1} - une_{t-4})$. Of interest is that the seasonal difference $(une_{t-1} - une_{t-53})$ and the 52- and 104-week moving averages, while indicating the presence of nonlinearities, are not the strongest candidates for a transition variable in the unemployment equation.[12] In all instances the testing sequence overwhelmingly indicates that an LSTR model is called for, a result that is, moreover, also consistent with prior research (van Dijk et al., 2002). As before, the choice of $s_t = (une_{t-1} - une_{t-4})$ as the transition variable was confirmed by estimating provisional LSTR models using the range of candidates for s_t indicated in Table 4.

5.2. Smooth transition model results

The foregoing suggests there is evidence of nonlinearity in each equation in the system, which, among other things, suggests that ERPT into OSB prices may be regime-dependent. As discussed in Section 4, as part of the STVECM model building process we first estimate suitable univariate smooth transition models for each equation.

The results of the univariate analysis are summarized in Table 5 – there we report model fit diagnostic measures for each of the estimated linear and nonlinear models for each variable in the system. As indicated in the Table, the results show that in every case the nonlinear model represents an improvement in fit relative to its linear counterpart, with the nonlinear unemployment equation yielding the biggest relative increase in fit and the exchange rate equation the smallest. In addition, there is little evidence of remaining autocorrelation in each model's residuals up to a twelve-week lag (the smooth transition model for unemployment at lags six and twelve being an exception). Results in Table 5 also indicate that the residuals for each estimated model are highly leptokurtic (i.e., they are associated with "fat tails"), which is not surprising given the frequency for which the data are observed (i.e., weekly). There is also evidence of ARCH errors in each case, a result that, moreover, might be anticipated given the weekly frequency of the data.

As a final check of the nonlinear specifications, the system nonlinearity test, as outlined in (20), was applied to what now constitutes the four-equation system. In conducting the test, the system in (19) was estimated where the transition variables identified for the univariate models in Table 5 are used. The resulting Rao's F_{LMS} test statistic is 3.956, which is extreme in the corresponding $F_{(168,3423)}$ distribution. Taken together, this result and those recorded in Table 5 suggest that nonlinearity is an important feature of the OSB price, Canadian Dollar-to-U.S. Dollar exchange rate, and U.S. weekly unemployment claims data.

The final step in constructing a model for assessing regime-dependent ERPT into North American OSB prices is to estimate the STVECM. The transition functions and transition variables used in specifying the univariate models are maintained; the parameter estimates obtained for the univariate models are used as starting values. The system estimation results, along with several summary

[12] Alternatively, and when using monthly U.S. unemployment data, van Dijk et al. (2002) and Deschamps et al. (2008) find that a lagged seasonal difference works quite well as a transition variable.

Table 6
STVECM Model Estimates.

Panel A: Southeast U.S. Price, $y_{1t} = ln(p_{it})$

$$\Delta y_{1t} = \Big[\underset{0.0010}{-0.0018} + \underset{(0.019)}{0.242}\Delta y_{1t-1} - \underset{(0.020)}{0.156}\Delta y_{1t-2} - \underset{(0.021)}{0.019}\Delta y_{1t-3} - \underset{(0.019)}{0.036}\Delta y_{1t-4} + \underset{(0.098)}{0.004}\Delta y_{1t-5} - \underset{(0.019)}{0.018}\Delta y_{1t-6} + \underset{(0.065)}{0.237}\Delta y_{2t-1} - \underset{(0.102)}{0.091}\Delta y_{2t-2}$$

$$+ \underset{(0.035)}{0.174}\Delta y_{2t-3} - \underset{(0.039)}{0.012}\Delta y_{2t-4} + \underset{(0.087)}{0.003}\Delta y_{2t-5} - \underset{(0.063)}{0.067}\Delta y_{2t-6} - \underset{(0.029)}{0.044}\hat{\varepsilon}_{t-1}\Big] \times \Big[1 - G_1\big(s_{1t}, \gamma_1, c_1\big)\Big] + \Big[\underset{(0.0015)}{0.0034} + \underset{(0.146)}{0.547}\Delta y_{1t-1} - \underset{(0.041)}{0.555}\Delta y_{1t-2}$$

$$- \underset{(0.110)}{0.205}\Delta y_{1t-3} - \underset{(0.071)}{0.003}\Delta y_{1t-4} - \underset{(0.171)}{0.089}\Delta y_{1t-5} + \underset{(0.060)}{0.026}\Delta y_{1t-6} + \underset{(0.108)}{0.546}\Delta y_{2t-1} + \underset{(0.093)}{0.223}\Delta y_{2t-2} + \underset{(0.061)}{0.232}\Delta y_{2t-3} - \underset{(0.104)}{0.075}\Delta y_{2t-4}$$

$$- \underset{(0.162)}{0.010}\Delta y_{2t-5} - \underset{(0.084)}{0.071}\Delta y_{2t-6} - \underset{(0.050)}{0.016}\hat{\varepsilon}_{t-1}\Big] \times G_1\big(s_{1t};\gamma_1, c_1\big) + \hat{\upsilon}_{1t}; G_1\big(s_{1t};\gamma_1, c_1\big) = \Big[1 + \exp\Big\{\underset{(2.791)}{-2.611}\big(s_{1t} - \underset{(0.080)}{2.662}\big)/\hat{\sigma}_{s_{1t}}\Big\}\Big]^{-1}, \ \mathrm{R}^2 = 0.358.$$

Panel B: Eastern Canada Price, $y_{2t} = ln(p_{xt})$

$$\Delta y_{2t} = \Big[\underset{0.0008}{-0.0013} + \underset{(0.021)}{0.193}\Delta y_{1t-1} - \underset{(0.035)}{0.113}\Delta y_{1t-2} + \underset{(0.028)}{0.079}\Delta y_{1t-3} + \underset{(0.032)}{0.017}\Delta y_{1t-4} - \underset{(0.053)}{0.021}\Delta y_{1t-5} + \underset{(0.016)}{0.049}\Delta y_{1t-6} + \underset{(0.021)}{0.339}\Delta y_{2t-1} - \underset{(0.035)}{0.125}\Delta y_{2t-2}$$

$$+ \underset{(0.025)}{0.051}\Delta y_{2t-3} - \underset{(0.034)}{0.077}\Delta y_{2t-4} - \underset{(0.059)}{0.035}\Delta y_{2t-5} - \underset{(0.019)}{0.038}\Delta y_{2t-6} + \underset{(0.020)}{0.033}\hat{\varepsilon}_{t-1}\Big] \times \Big[1 - G_2\big(s_{2t}, \gamma_2, c_2\big)\Big] + \Big[\underset{(0.0012)}{0.0031} + \underset{(0.131)}{0.345}\Delta y_{1t-1} - \underset{(0.024)}{0.583}\Delta y_{1t-2}$$

$$- \underset{(0.074)}{0.042}\Delta y_{1t-3} + \underset{(0.059)}{0.050}\Delta y_{1t-4} - \underset{(0.109)}{0.179}\Delta y_{1t-5} + \underset{(0.045)}{0.018}\Delta y_{1t-6} + \underset{(0.065)}{0.551}\Delta y_{2t-1} + \underset{(0.028)}{0.161}\Delta y_{2t-2} + \underset{(0.041)}{0.266}\Delta y_{2t-3} - \underset{(0.094)}{0.125}\Delta y_{2t-4}$$

$$- \underset{(0.109)}{0.020}\Delta y_{2t-5} + \underset{(0.049)}{0.086}\Delta y_{2t-6} - \underset{(0.038)}{0.089}\hat{\varepsilon}_{t-1}\Big] \times G_2\big(s_{2t};\gamma_2, c_2\big) + \hat{\upsilon}_{1t}; G_2\big(s_{2t};\gamma_2, c_2\big) = \Big[1 + \exp\Big\{\underset{(14.277)}{-123.74}\big(s_{2t} - \underset{(0.009)}{2.648}\big)/\hat{\sigma}_{s_{2t}}\Big\}\Big]^{-1}, \ \mathrm{R}^2 = 0.331.$$

Panel C: Exchange Rate, $y_{3t} = ln(e_t)$

$$\Delta y_{3t} = \Big[\underset{(0.0026)}{0.0090} - \underset{(0.325)}{0.983}\Delta y_{3t-1} + \underset{(0.168)}{0.293}\Delta y_{3t-2} + \underset{(0.133)}{0.432}\Delta y_{3t-3} + \underset{(0.115)}{0.077}\Delta y_{3t-4} - \underset{(0.125)}{0.029}\Delta y_{3t-5} - \underset{(0.109)}{0.071}\Delta y_{3t-6} - \underset{(0.111)}{0.031}\Delta y_{3t-7} - \underset{(0.108)}{0.007}\Delta y_{3t-8}$$

$$- \underset{(0.107)}{0.408}\Delta y_{3t-9} - \underset{(0.111)}{0.055}\Delta y_{3t-10}\Big] \times \Big[1 - G_3\big(s_{3t}, \gamma_3, c_3, c_4\big)\Big] + \Big[\underset{(0.0004)}{0.0002} - \underset{(0.030)}{0.020}\Delta y_{3t-1} - \underset{(0.028)}{0.088}\Delta y_{3t-2} - \underset{(0.029)}{0.083}\Delta y_{3t-3} - \underset{(0.030)}{0.014}\Delta y_{3t-4}$$

$$- \underset{(0.036)}{0.015}\Delta y_{3t-5} + \underset{(0.128)}{0.144}\Delta y_{3t-6} - \underset{(0.029)}{0.040}\Delta y_{3t-7} + \underset{(0.030)}{0.083}\Delta y_{3t-8} + \underset{(0.033)}{0.026}\Delta y_{3t-9} - \underset{(0.030)}{0.079}\Delta y_{3t-10}\Big] \times G_3\big(s_{3t}, \gamma_3, c_3, c_4\big) + \hat{\upsilon}_{3t};$$

$$G_3\big(s_{3t};\gamma_3, c_3, c_4\big) = \Big[1 + \exp\Big\{\underset{(--)}{-150.0}\big(s_{3t} - \underset{(0.0001)}{0.0063}\big)\big(s_{3t} - \underset{(0.0003)}{0.0099}\big)/\hat{\sigma}^2_{s_{3t}}\Big\}\Big]^{-1}, \ \mathrm{R}^2 = 0.077.$$

Panel D: Unemployment Rate, $y_{4t} = une_t$

$$\Delta y_{4t} = \Big[\underset{(0.008)}{0.039} + \underset{0.007}{0.063}\sin\big(2\pi t/52\big) + \underset{0.004}{0.036}\cos\big(2\pi t/52\big) + \underset{0.009}{0.040}\sin\big(2\pi t/26\big) - \underset{0.008}{0.106}\cos\big(2\pi t/26\big) + \underset{0.0049}{0.0004}\sin\big(2\pi t/13\big) + \underset{0.005}{0.030}\cos\big(2\pi t/13\big)$$

$$- \underset{(0.045)}{0.749}\Delta y_{4t-1} - \underset{(0.054)}{0.034}\Delta y_{4t-2} + \underset{(0.046)}{0.021}\Delta y_{4t-3} - \underset{(0.041)}{0.032}\Delta y_{4t-4} + \underset{(0.036)}{0.104}\Delta y_{4t-5} + \underset{(0.039)}{0.099}\Delta y_{4t-6} + \underset{(0.037)}{0.126}\Delta y_{4t-7} + \underset{(0.039)}{0.170}\Delta y_{4t-8}$$

$$+ \underset{(0.032)}{0.083}\Delta y_{4t-9} - \underset{(0.025)}{0.004}\Delta y_{4t-10} + \underset{(0.024)}{0.004}\Delta y_{4t-11} - \underset{(0.003)}{0.012}y_{4t-1}\Big] \times \Big[1 - G_4\big(s_{4t}, \gamma_4, c_4\big)\Big] + \Big[\underset{(0.010)}{0.047} - \underset{0.010}{0.009}\sin\big(2\pi t/52\big) + \underset{0.021}{0.064}\cos\big(2\pi t/52\big)$$

$$+ \underset{0.017}{0.037}\sin\big(2\pi t/26\big) + \underset{0.015}{0.025}\cos\big(2\pi t/26\big) + \underset{0.011}{0.067}\sin\big(2\pi t/13\big) + \underset{0.010}{0.071}\cos\big(2\pi t/13\big) - \underset{(0.045)}{0.291}\Delta y_{4t-1} - \underset{(0.058)}{0.317}\Delta y_{4t-2} - \underset{(0.058)}{0.296}\Delta y_{4t-3}$$

$$+ \underset{(0.063)}{0.199}\Delta y_{4t-4} + \underset{(0.056)}{0.778}\Delta y_{4t-5} + \underset{(0.060)}{0.303}\Delta y_{4t-6} + \underset{(0.068)}{0.212}\Delta y_{4t-7} + \underset{(0.054)}{0.355}\Delta y_{4t-8} + \underset{(0.072)}{0.240}\Delta y_{4t-9} - \underset{(0.062)}{0.004}\Delta y_{4t-10} + \underset{(0.077)}{0.315}\Delta y_{4t-11}$$

$$- \underset{(0.008)}{0.016}y_{4t-1}\Big] \times G_4\big(s_{4t}, \gamma_4, c_4\big) + \hat{\upsilon}_{4t}; G_4\big(s_{4t};\gamma_4, c_4\big) = \Big[1 + \exp\Big\{\underset{(0.460)}{-3.687}\big(s_{4t} - \underset{(0.010)}{0.109}\big)/\hat{\sigma}_{s_{4t}}\Big\}\Big]^{-1}, \ \mathrm{R}^2 = 0.573.$$

Panel E: Model Summary Statistics

$$\ln L = 4703.848, \ \widetilde{\mathrm{R}}^2 = 0.783, \ AIC_{NL} = -27.311, \ SBC_{NL} = -20.776, \ AIC_L = -26.963, \ SBC_L = -20.293, \ \det(\hat{\Sigma}_{NL})/\det(\hat{\Sigma}_L) = 0.617,$$

$$\hat{\sigma}_1^2 = \underset{(3.96\times10^{-5})}{1.90 \times 10^{-3}}, \ \hat{\sigma}_2^2 = \underset{(3.64\times10^{-5})}{1.91 \times 10^{-3}}, \ \hat{\sigma}_3^2 = \underset{(4.36\times10^{-6})}{1.45 \times 10^{-4}}, \ \hat{\sigma}_4^2 = \underset{(1.96\times10^{-4})}{5.95 \times 10^{-3}}, \ \hat{\sigma}_{12} = \underset{(3.90\times10^{-5})}{1.56 \times 10^{-3}}, \ \hat{\rho}_{12} = 0.817$$

Note: Asymptotic heteroskedasticity robust standard errors are given below parameter estimates in parentheses; R^2 is the squared correlation between actual and fitted values for each equation; $\hat{\upsilon}_{jt}$ denotes the jth equation's residual at time t, $j = 1, \ldots, 4$; $\widetilde{\mathrm{R}}^2$ denotes the likelihood system R^2 as defined by Magee (1990); AIC is the system Akaike information criterion and SBC denotes the system Schwarz's Bayesian Criterion. A subscripted L refers to the linear model and NL a nonlinear model. As well, $\det(\hat{\Sigma}_{NL})/\det(\hat{\Sigma}_L)$ denotes the ratio of the determinant of the covariance matrix for the STVECM relative to the VECM. $\hat{\sigma}_j^2$ denotes the estimated variance for equation j, $\hat{\sigma}_{12}$ is the estimated covariance term for the residuals between p_{it} and p_{xt}, and $\hat{\rho}_{12}$ is the corresponding correlation coefficient.

measures of model fit, are reported in Table 6. Plots of the corresponding estimated transition functions for each equation, both over time and with respect to each implied transition variable, are reported in Fig. 4. Additional tests revealed that covariance terms amongst the price variables and exchange rates and, likewise, the price variables and the unemployment rate were not significantly different from zero, as is the covariance term between the exchange rate and unemployment. These restrictions are incorporated in the estimates recorded for the STVECM reported in Table 6.

As indicated in Table 6, the STVECM provides a substantial improvement in fit relative to the linear VECM; for example, the ratio of the determinant for the STVECM's covariance matrix relative to its linear counterpart is 0.617. As well, the system AIC also

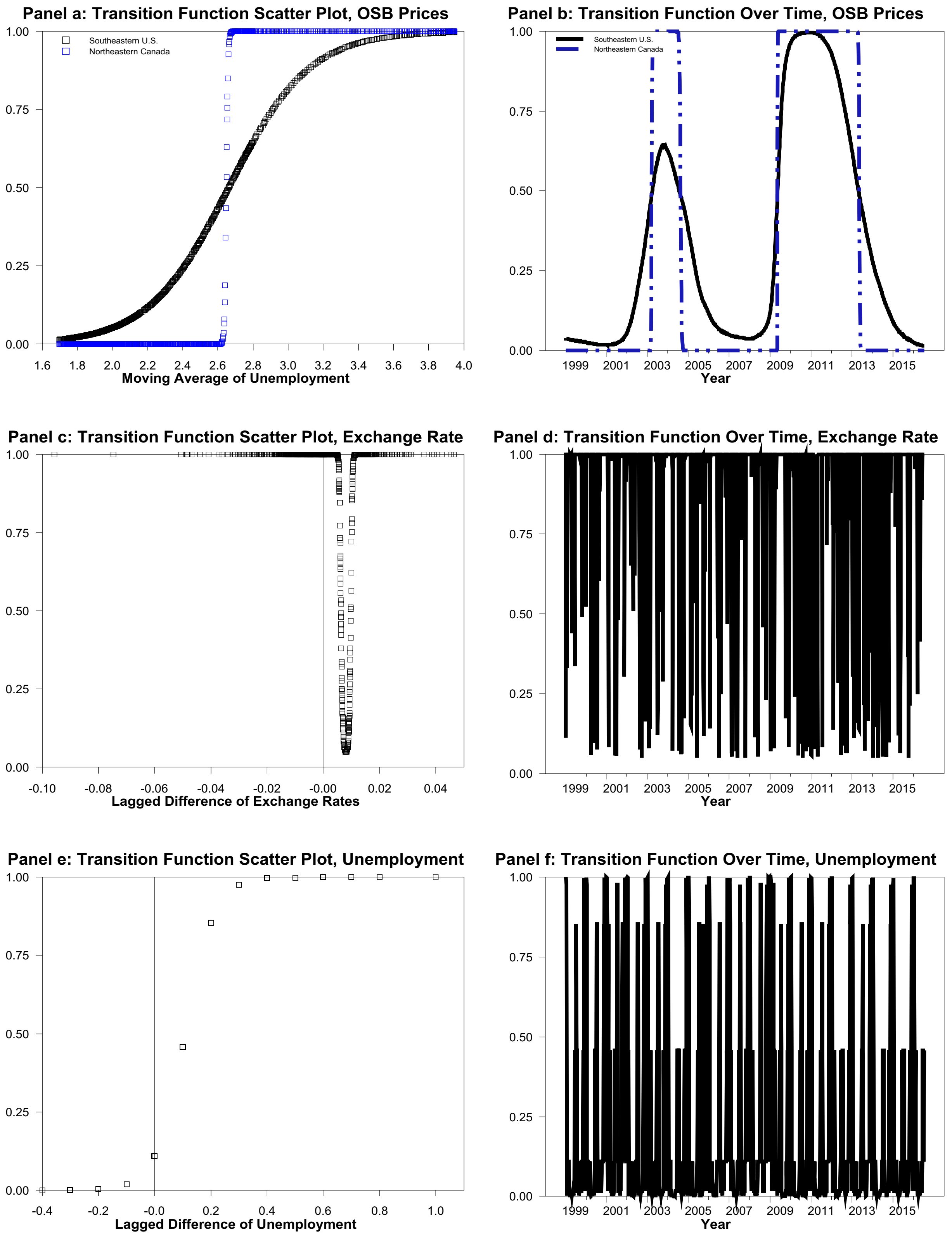

Fig. 4. Unconditional Generalized Impulse Response Functions for Unit Shocks to U.S.-Canadian Dollar Exchange Rate.

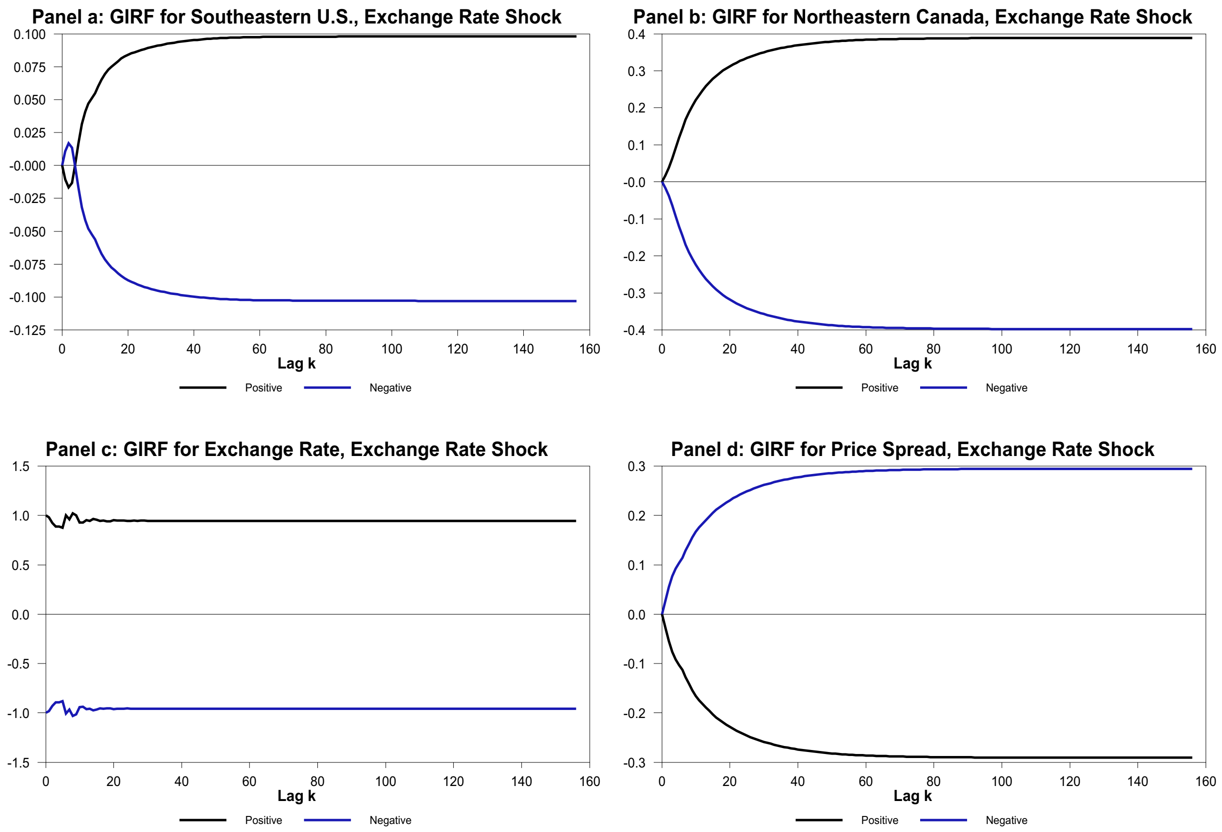

Fig. 5. Generalized Impulse Response Functions for Unit Shocks to U.S.-Canadian Dollar Exchange Rate Conditional on the Moving-Average of Weekly U.S. Unemployment Rates being Greater than (Less than) 2.91-Percent at Horizon $n = 0$.

indicates an improvement in fit for the STVECM relative to the linear VECM. Regarding the implied nonlinearities, the plots in Fig. 4 show that, with the exception of the transition function for the OSB price in Eastern Canada, the estimated transition functions imply a smooth response to changes in the respective transition variables. The plots in Fig. 4 also suggest that the transition functions for the OSB price equations, when plotted over time, do a reasonable job of tracking recent business cycle behavior. Finally, the parameter estimates reported in Table 6 suggest that, for each estimated equation, the estimated parameters change substantially with respect to the implied transition functions, including the speed-of-adjustment parameters associated with the lagged error correction terms in the OSB price equations. Furthermore, the STVECM apparently does a reasonable job of generating results for prices, the exchange rate, and the unemployment rate that are consistent with observed behavior. Along with the observed data, Figs. 2 and 3 show the realizations of a single Monte Carlo simulation of the model from the end of the sample period (August, 2016) through the middle of 2020. In each case, the simulated data seemingly depicts various features of the observed data, including asymmetries. Taken together, the results for the estimated STVECM suggest there is scope for ERPT into OSB prices to vary with the weekly U.S. unemployment rate and that, moreover, unemployment rates are, themselves, associated with a highly nonlinear process.

5.3. Generalized impulse response functions

To assess the effects of ERPT into OSB prices, it is useful to generate generalized impulse response functions (GIRFs). Specifically, Koop, Pesaran, and Potter (1996) define a set of procedures that may be applied to compute GIRFs for multivariate nonlinear models. A (multivariate) GIRF is defined by:

$$G_{\Delta y}(n, \delta, \omega_{t-1}) = E(\Delta \boldsymbol{y}_{t+n} \mid v_t = \delta, \Omega_{t-1} = \omega_{t-1}) - E(\Delta \boldsymbol{y}_{t+n} \mid v_t = \boldsymbol{0}, \Omega_{t-1} = \omega_{t-1}), \tag{23}$$

where n denotes the forecast horizon, δ is a vector of shocks, $\Omega_{t-1} = \omega_{t-1}$ denotes information available through period $t - 1$ (i.e., the history), and E is an expectation operator. To determine the initial conditions, we randomly draw (with replacement) 50 histories (i.e., ω_{t-1}'s) from the set of 915 available histories. As is common in the ERPT literature, we then consider unit shocks to the exchange rate equation (Cashin, Liang, & John McDermott, 2000) and, as well, to the unemployment rate. To evaluate the expectations in (23), we use 600 Monte Carlo draws from a multivariate random normal distribution with a variance-covariance matrix equal to that of the estimated STVECM. Impulse responses for the levels of the variables in the system are computed by summing those obtained for the first differences, that is, by constructing:

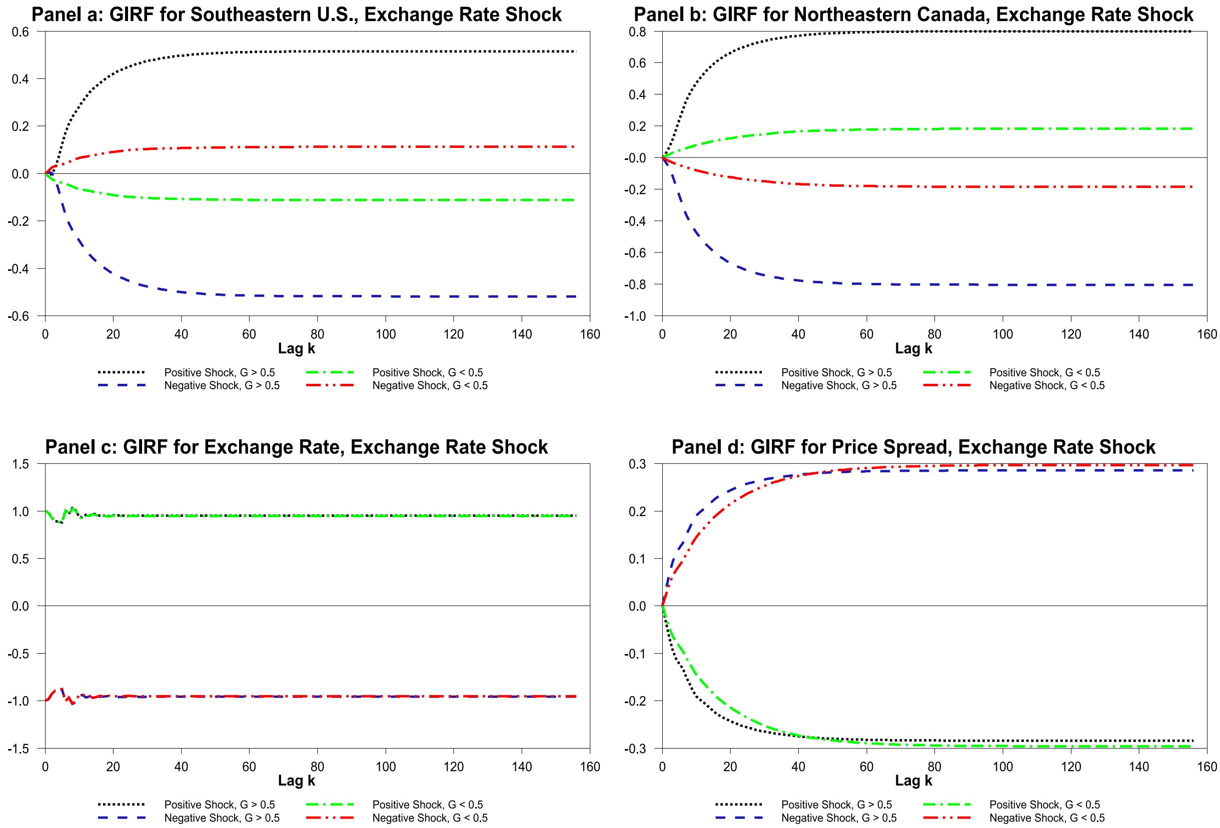

Fig. 6. Unconditional Generalized Impulse Response Functions for a One-Standard-Deviation Shock to the U.S. Weekly Unemployment Rate.

$$G_y(n, \delta, \omega_{t-1}) = \sum_{i=1}^{n} G_{\Delta y}(n, \delta, \omega_{t-1}). \tag{24}$$

Finally, it is also possible to construct regime-dependent GIRFs where, for example, shocks can be initiated only when $G_1(s_{1t}) \geqslant 0.5$ or $G_1(s_{1t}) < 0.5$. [13] In this manner, it is possible to examine the extent to which ERPT into OSB prices varies with the unemployment rate.

Unconditional GIRFs for a one-time unit shock (both positive and negative) to the U.S. dollar-Canadian dollar exchange rate, taken over a 156-week horizon, are reported in Fig. 5. As illustrated there, pass-through of such a shock into the U.S. OSB price is never complete, reaching at most 10-percent. As well, the GIRFs appear to be nearly symmetric with respect to positive versus negative exchange rate shocks. This result is reasonable given that: (1) unemployment is not impacted by nominal exchange rate movements (and therefore there is no systematic "regime change" for the OSB price equations); and (2) that nonlinearity in the exchange rate equation is associated with an QSTR, which is, moreover, close to being symmetric around zero.

A different picture emerges, however, when conditional GIRFs are computed for an exchange rate shock; see Fig. 6. As the Figure shows, when the 104-week moving average of unemployment (i.e., s_{1t}) is greater than 2.66-percent, that is, when $G_1(s_{1t}) \geqslant 0.5$, ERPT associated with a positive one-unit shock reaches 50-percent (i.e., is fifty-percent complete) after 43 weeks. Indeed, as depicted in Fig. 6, this GIRF stabilizes at a value less than unity – near 0.515, in fact – after approximately 1.65 years have elapsed. Conversely, the GIRFs conditional on the moving average of unemployment being less than 2.66-percent (i.e., $G_1(s_{1t}) < 0.5$) are now small (in absolute value) and, in fact, negative. As illustrated in the Figure, in this case pass-through is even slower to respond and, moreover, relatively incomplete, even after three years have elapsed; the long-run response to a positive unit shock in this case is about -0.11-percent. These results firmly establish that ERPT into prices for a primary home construction material, that is, oriented strand board, is highly regime dependent and that, moreover, the regimes themselves are apparently a function of the overall performance of the general economy.

Because of the nature of the model it is also possible to obtain GIRFs associated with an unemployment shock, in this case with respect to a one standard deviation shock to the weekly unemployment rate. The resulting unconditional GIRFs-in this case obtained over a six-year, or 312 week period-are reported in Fig. 7. They show, for example, that a positive shock to unemployment apparently causes unemployment rates themselves to continue to rise rapidly throughout the first 59 weeks, and then gradually return to zero

[13] Given the estimate for the centrality parameter, c_1, reported in Table 6, the conditional GIRFs in this case are consistent with the 104-week moving average of unemployment rates, $\widehat{une}_t$, being above or below 2.662.

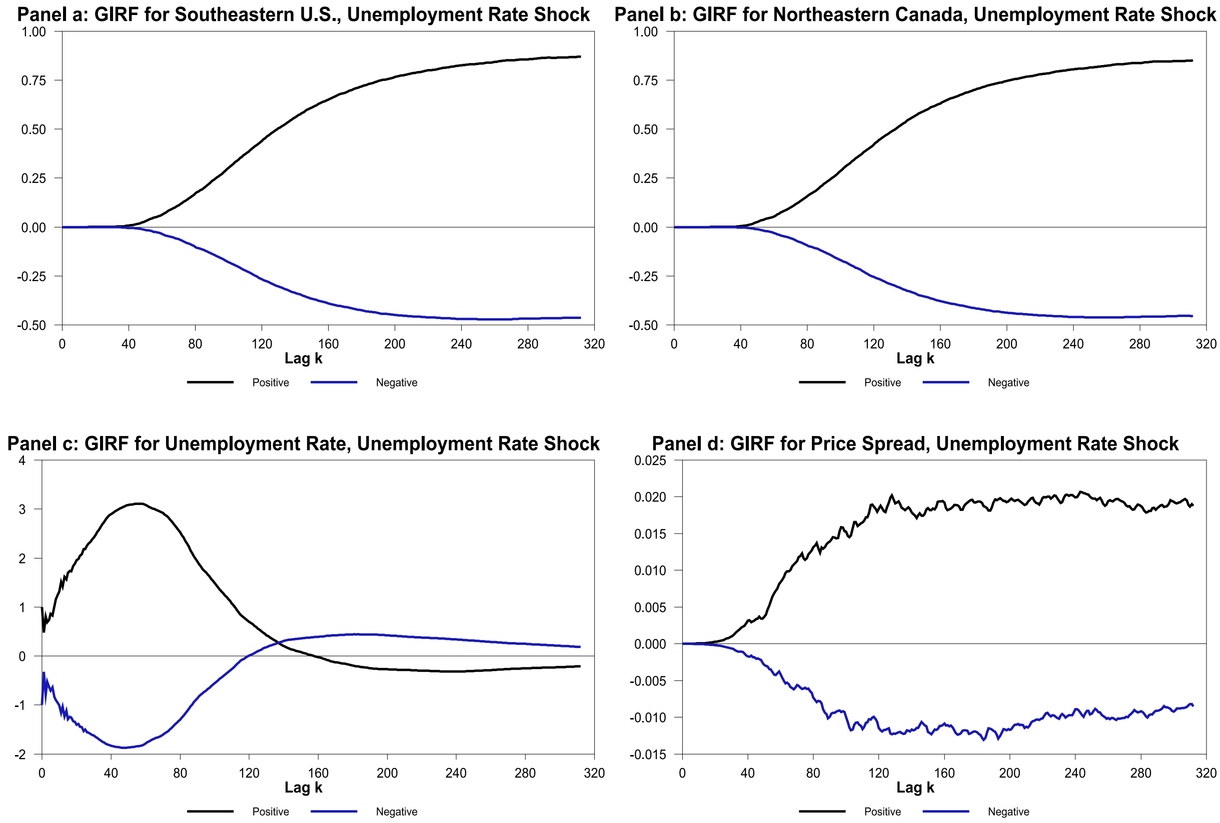

Fig. 7. Transition Functions for the Estimated STVECM Model. Panels in the left-hand column show estimated transition functions plotted against corresponding transition variables. Panels in the right-hand column show the estimated transition function values over time.

after slightly more than three years. Of further interest is that the effects of a positive versus a negative unemployment shock are not symmetric, with the GIRF, in absolute terms, associated with a negative shock being about two-thirds the size of the corresponding GIRF from a positive shock. A positive, one-time unemployment shock causes both OSB prices to increase throughout the simulation period, that is, they find a new, higher but stable equilibrium. Again, the GIRFs for OSB prices reveal that responses to positive and negative shocks are not symmetric, thereby further underscoring the importance of the nonlinear systems approach to modelling ERPT, as used here.

6. Summary and conclusions

In this study, we have examined exchange rate pass-through into oriented strand board, an important construction material produced and traded throughout much of North America. Indeed, Canada and the United States are leading producers of OSB, but historically Canada has exported more than 75-percent of its total OSB production to the United States. In the U.S., OSB is produced primarily in the Southeastern region of the country, although in recent decades this region has also experienced the most rapid growth in new home construction. To investigate ERPT into OSB prices, we obtained weekly mill-gate prices from *Random Lengths* for the 1998–2016 period. Specifically, the prices correspond to mill prices for OSB in Eastern Canada (prices for mills in Ontario and Quebec) and the Southeast U.S. (prices for mills in Georgia, Alabama, Mississippi, South Carolina, and Tennessee). Furthermore, the Canadian prices are recorded in U.S. dollars, that is, local currency pricing is employed.

Prior work by Goodwin et al. (2011) found evidence of nonlinearity in the LOP relationship between these prices, but otherwise they did not consider ERPT effects. Moreover, recent research has examined nonlinear and asymmetric ERPT into import prices by assuming that deviations from the underlying long-run equilibrium relationship will have a differential impact on estimated pass-through responses, depending on the overall magnitude of the deviations (see, e.g., Larue et al., 2010). More recently, several authors have investigated asymmetric effects of ERPT into prices as a function of overall macroeconomic activity (Chew et al., 2011; Cheikh & Rault, 2016; Kiliç, 2016; Shintani et al., 2013), albeit for aggregate price inflation and not for specific industries or commodity prices.

Building on prior work in this general area, we examine the asymmetric effects of long-term swings in weekly unemployment claims on ERPT into prices for OSB. We do so by proposing a feasible strategy for building and estimating a smooth transition vector error correction model wherein each equation is allowed to have its own built-in asymmetries (i.e., transition function and transition variables). Specifically, we estimate a four-equation STVECM where asymmetries in the OSB price equations are modeled by using logistic transition functions where, moreover, the transition variables are in both cases a 104-week moving average of the unemployment rate. Nonlinearities in the nominal U.S. dollar-Canadian dollar exchange rate are modeled by using a quadratic logistic transition function. And finally, in a manner consistent with prior work on modelling asymmetries in unemployment rates (see, e.g., Skalin & Teräsvirta, 2002), we model asymmetries in weekly unemployment rates by using a logistic smooth transition model.

An immediate implication of the estimated STVECM is as follows: not only is there the potential for direct asymmetric (nonlinear) ERPT into OSB prices, but also the potential for indirect effects due to the regime-dependent behavior identified separately for the exchange rate and unemployment equations. To our knowledge, no prior study has allowed for such a rich specification of nonlinearities when examining ERPT. To assess the nature of nonlinearities in ERPT, we employ the generalized impulse response function framework of Koop et al. (1996). Similar to prior work on this general topic, we find incomplete pass-through into OSB prices in both the U.S. and Canada. Moreover, for OSB prices in the Southeast U.S., pass-through effects are very small, reaching a long-run steady state of only about 0.10 (for a positive shock) after three years have elapsed. As well, these estimated effects depend in a striking way on overall macroeconomic conditions. Specifically, conditional GIRFs, that is, GIRFs obtained for when unemployment rates are high versus low, indicate that ERPT effects depend on overall macroeconomic performance. These results are, moreover, in keeping with prior work by Chew et al. (2011),iliç (2016) and others, who also find that pass-through effects change substantially during economic contractions versus expansions. Finally, because of the way the STVECM is specified, we can calculate GIRFs associated with unemployment shocks, that is, unemployment pass-through effects. We find these effects are generally larger than for exchange rate shocks, although they vary considerably over a six-year period, which in turn is roughly consistent with the observed span for post-war business cycle activity.

While this paper represents an important contribution to the ERPT literature, and especially so for timber products, more work remains. Specifically, in preliminary analysis we explored using a measure of the yield curve in lieu of unemployment as a transition variable, albeit finding that it had lower explanatory power. Even so, it might be useful to examine potential asymmetric ERPT responses to other measures of macroeconomic activity. Furthermore, in addition to nonlinear ERPT effects implied by regime-dependent behavior, it is not unreasonable to expect that structural change is also a potentially relevant feature of the model and the data. One way to proceed would be to use the time-varying smooth transition autoregressive (TV-STAR) methodology proposed by Lundbergh et al. (2003) to identify both structural change and asymmetric features in individual equations. From there, it would be possible to build a time-varying smooth transition VECM, or TV-STVECM model, that incorporates both structural change and nonlinearity as relevant features. Even so, we believe the work reported here provides a good starting point for subsequent studies on these and related topics.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, athttps://doi.org/10.1016/j.najef.2019.100989.

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