Industry Cycles in the US Softwood Lumber Industry: 1985 through 2010

Shiv N. Mehrotra
Shashi Kant
Indrajit Majumdar

Abstract

Cyclical patterns in business activity are a common feature of industry in market economies. This study identifies and describes industry cycles in the US softwood lumber industry from 1985 to 2010. Statistical decomposition and filtering procedures are applied to time series data on sales volumes to extract the cyclical component, and nonparametric techniques are used to date the industry cycles. The study identifies four softwood lumber industry cycles: three coincident with business cycles and one attributable to developments in the US–Canada softwood lumber trade dispute. Softwood lumber industry cycle durations ranged between 5 and 6 years. Decline in seasonally adjusted softwood lumber industry business activity caused by cyclic contractions averaged 13 percent for the period under study, with the most recent contraction (January 2006 to March 2009) contributing a 22 percent decline in business activity.

Business activity in market economies tends to exhibit cyclical patterns over time, both economy-wide as well as in individual industrial sectors. Periods of sustained contraction in business activity are succeeded by periods of sustained expansion and vice versa. The cyclical patterns in economy-wide business activity over time are called business cycles and are a subject of great interest to macroeconomics. Among other areas of interest, research is directed at understanding the causes of business cycles, predicting the timing and severity of recessionary and inflationary phases, and developing prescriptions for reducing their severity and frequency.

Cyclical patterns of business activity in individual industry sectors (called industry cycles) can differ from economy-wide business cycle fluctuations. For example, some industries exhibit strong cyclical changes in business activity, while others exhibit weak industry cycles. The timing of fluctuations also varies widely—some industry cycles precede business cycles, while others coincide with or lag business cycles. Forest products industries also experience cyclical behavior in the level of their business activity over time. Table 1 reproduces correlation of a business activity indicator (industry final demand) for selected US forest product industries with business cycles (captured by US gross domestic product), reported in Berman and Pfleeger (1997).

To explain the high correlations found for industries like household furniture, Berman and Pfleeger (1997) argue that these industries provide goods that consumers and businesses can postpone purchasing during recessionary periods. For industries that exhibit moderate to low correlation, the study argues that they provide necessities or public goods, demand for which remains relatively less impacted by business cycles. On the other hand, Petersen and Strongin (1996) attribute the diversity in cyclical behavior between industries principally to differences in durability of output, finding that durable goods industries are approximately three times more cyclical than nondurable goods industries. Other determinants of cyclical behavior identified by the study include energy intensity, the proportion of variable and quasi-fixed factors, the extent of labor hoarding, and the degree of market concentration.

Among other studies that deal with industry cycles in forest products industries, Alajoutsijärvi et al. (2001) study the fine paper manufacturing industry and argue for the importance of customer relationship strategies in smoothing industry cycles. Alajoutsijärvi et al. (2005) describe historical cyclicity in prices, demand, and production levels in Finnish and Swedish sawmills and discuss structures and

The authors are, respectively, Resource Economics Consultant, Sault Ste. Marie, Ontario, Canada (shiv.mehrotra@gmail.com); Professor, Faculty of Forestry, Univ. of Toronto, Toronto, Ontario, Canada (shashi.kant@utoronto.ca [corresponding author]); and Economics Specialist, Ontario Ministry of Natural Resources, Sault Ste. Marie, Ontario, Canada (Indrajit.Majumdar@ontario.ca). This paper was received for publication in December 2013. Article no. 13-00090.

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Table 1.—Historical correlation coefficients for US gross domestic product (GDP) and industry final demand by selected industries for 1977 to 1993 (Berman and Pfleeger 1997).

Industry	GDP to industry final demand correlation
Household furniture	0.7713
Miscellaneous publishing	0.6307
Books	0.5240
Pulp, paper, and paperboard mills	0.5161
Wood containers and miscellaneous wood products	0.5066
Wood buildings and mobile homes	0.5045
Paperboard containers and boxes	0.4725
Newspapers	0.1271
Logging	−0.0640
Converted paper products except containers	−0.1651
Millwork, plywood, and structural members	−0.3770
Sawmills and planning mills	−0.4131
Forestry, fishing, hunting, and trapping	−0.5862

processes that may have caused or contributed to it. Buzzelli and Harris (2003) examine the transience of house builders in Ontario from 1978 to 1998 and find that the business cycle speeds and slows house building activity but attribute the flux primarily to the turnover of small builders. Berends and Romme (2001) study the paper industry and argue that the cause of strong cyclicality in capital intensive industries could be the lag between investment decisions and commissioning of manufacturing facilities.

Currently there are no studies that use time series analysis tools to study forest products industry cycles with the aim of describing their characteristics like incidence, frequency, intensity, and length of phases. This study applies time series analysis tools of decomposition and filtering to extract industry cycles experienced by the US softwood lumber manufacturing industry and uses nonparametric techniques to identify the cycle phases. Industry cycles represent volatility in the level of business activity in an industry. Business activity in the US softwood lumber industry can be expected to be volatile because of the low level of concentration in the industry and a very high dependence for sales on the domestic construction industry (US International Trade Commission 1999). The softwood lumber industry is the largest US forest sector industry by timber volumes processed and employment generated (Howard 2007). In 2007, there were approximately 1,700 softwood sawmill establishments in the United States, employing about 50,000 employees. The sector is characterized by a proliferation of small-scale operations, with approximately 55 percent establishments employing fewer than 20 employees (US Census Bureau 2007, Hardwood Market Report 2008, Spelter et al. 2009). It is also characterized by a significant concentration of demand for its output, with residential construction (including repair and remodeling) accounting for about 60 percent of domestic consumption and an additional 10 percent (approximately) used for nonresidential construction (Howard and McKeever 2011). Softwood lumber export volumes are a small fraction of total demand, ranging from a high of about 6.5 percent of total demand in 1991 to a low of about 1 percent in 2005 (Resource Information Systems Inc. [RISI] 2011). US domestic softwood lumber demand peaked at approximately 150 million m^3 in 2005. Installed capacity at US softwood sawmills rose from 83 million m^3 in 1995 to peak at 103 million m^3 in 2006 (Spelter et al. 2009). Softwood lumber import volume has averaged approximately 30 percent of total demand since 1985, peaking at about 39 percent in 2005 (Fig. 1). Canada is the source of more than 90 percent of the total volume of softwood lumber imported (Howard 2007, RISI 2011).

Analyzing US softwood lumber industry shipment data for the period 1985 to 2010, this study finds that the industry experienced four cycles. While three industry cycles overlapped business cycles, the fourth industry cycle could be explained by developments in the US–Canada softwood lumber trade dispute. The average length of the four industry cycles was between 5 and 6 years, with contraction phases lasting 20 months on average and contributing to a 13 percent average decline in seasonally adjusted softwood lumber industry business activity.

Definitions and Methodology

Economic time series tend to exhibit patterns that are distinguishable from irregular components. The components of these patterns are identified as trend, cycles, and seasonality. Seasonality refers to regular, periodic fluctuations of constant length caused by factors like temperature fluctuations, or the timing of holidays, while the trend and cycle are longer term changes in the level of the time series (Makridakis et al. 1997). The trend is the permanent component of a time series, as opposed to the cycles that are transitory components (Beveridge and Nelson 1981). The cyclic component of time series data on aggregate economic activity for an economy are called business cycles. Burns and Mitchell (1946) adopt the following definition of business cycles:

> Business cycles are a type of fluctuation in the aggregate economic activity of nations that organize their work mainly in business enterprises: a cycle consists of expansions occurring at about the same time in many economic activities, followed by similarly general recessions, contractions and revivals which merge into the expansion phase of the next cycle; this sequence of changes is recurrent but not periodic; in duration business cycles vary from more than one year to ten or twelve years; they are not divisible into shorter cycles of similar character with amplitudes approximating their own. (Burns and Mitchell 1946, p. 3)

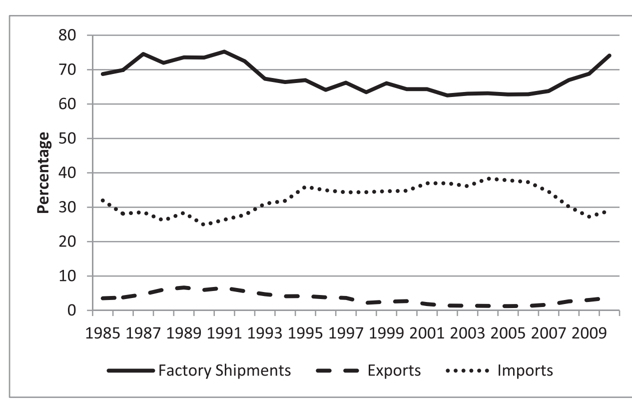

Figure 1.—US softwood lumber factory shipment, import, and export volumes as percent total demand: 1985 to 2010. Source: Resource Information Systems Inc.

The classic definition of cycles differs from a closely related phenomenon called growth cycles (Zarnovitz and Ozyildirim 2006). According to the classic definition, the cycles are a sequence of expansions and contractions in the levels of economic time series data, that is, they track declines and rebounds in absolute levels of economic activity. On the other hand, growth cycles are measured as deviations from the trend rate. Thus, while the identification of growth cycles from time series data requires trend estimation and elimination, it is not required for the identification of the classical cycle.

Tan and Mathews (2010) use the growth cycles approach for identification of industry cycles, arguing that in comparison with economy-wide data, industry level data tends to be dominated by stronger trends that suppress the classical cycles. The study defines industry cycles as

> cyclical patterns in the industrial data of the industry, including sales, price, capital investment and capacity. These cycles display as recurrent deviations from the long-term trend. The duration of an industry cycle's phases (upturn or downturn) lasts more than a few months. (Tan and Mathews 2010, p. 455)

Following Tan and Mathews (2010), this study uses the growth cycles approach for identifying softwood lumber industry cycles.

The time series decomposition method for identification of industry cycles from time series data comprises of three stages. In the first stage, the trend-cycle (a composite of the trend and the cycles) is extracted from the data by eliminating the irregular and seasonal components (a process known as seasonal adjustment). In the next stage, the cycle is extracted from the trend-cycle by modeling and eliminating the trend in a process known as detrending. The last step comprises identification of cycles, phases, peaks, and troughs in the extracted cyclical component. An alternate approach to separation of the cyclical component transforms the time series to the frequency domain and models the cycles as sine waves of different frequencies, amplitudes, etc. (Hamilton 1994). While both methods have their merits (see Tan and Mathews 2010 for a discussion), we chose the time series decomposition method with nonparametric cycle identification for this study for its transparency and ease of understanding.

Seasonal adjustment

Time series decomposition describes the process of separating the different components of a time series by statistical means. Time series decomposition is based on the assumption that time series data are composed of independent patterns and an irregular component, i.e.,

$$y_t = f(\tau_t, c_t, s_t, \varepsilon_t), \qquad t = 1, 2, \ldots, T \tag{1}$$

where y_t is the time series data with subscript t indexing time; τ_t, c_t, and s_t are, respectively, the trend, cycle, and seasonal component of patterns in the data; and ε_t is the irregular component (Makridakis et al. 1997). The data model is either additive ($y_t = \tau_t + c_t + s_t + \varepsilon_t$) or multiplicative ($y_t = \tau_t \times c_t \times s_t \times \varepsilon_t$, useful when the seasonality increases with level of series). Classical decomposition is accomplished through a procedure called smoothing, which in its simplest form consists of applying a moving average. The moving average technique also forms the basis of the more sophisticated and popular smoothing procedure, Census X-12-ARIMA, used by the US Census Bureau.[1] Franses et al. (2005) compares the performance of several seasonal adjustment procedures and recommends the Census X-12-ARIMA technique for its robustness. In this study, we use the Census X-12-ARIMA technique for extracting the trend-cycle from the time series data.

The classical decomposition technique extracts the trend-cycle from the time series data by applying a centered moving average of appropriate length (e.g., 12 for monthly data, 4 for quarterly data).[2] The Census X-12-ARIMA technique improves on the classical decomposition by using an iterative procedure to refine estimates and includes routines to exclude outliers and impute missing data (Makridakis et al. 1997, pp. 114–119).

Detrending

Several statistical procedures are available for separating the cyclical component from the trend. Canova (1994, 1999) compares 12 detrending procedures and concludes that the HP filter developed in Hodrick and Prescott (1997) and the band-pass BK filters developed in Baxter and King (1999) most closely reproduce cycles of the National Bureau of Economic Research benchmark (NBER 2010). In this study we use the HP filter as the BK filter is sensitive to user-determined filter bands.

The HP filter extracts the cycle c_t from the trend-cycle $\hat{y}_t = \tau_t + c_t$ by solving the minimization problem

$$\min_{\{\tau_t\}_{t=1}^{T}} \sum_{t=1}^{T} (\hat{y}_t - \tau_t)^2 + \lambda \sum_{t=2}^{T-1} [(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]^2 \tag{2}$$

where λ is an arbitrary constant that penalizes the variability in the smoother. When $\lambda = 0$ the smooth component is the data itself, i.e., no smoothing takes place, while as λ grows, the smooth component approximates a linear trend. Hodrick and Prescott (1997) recommend using $\lambda = 14{,}400$ for monthly data. However, subsequent research recommends using higher values for monthly data, in the range of 80,000 to 160,000 (Mills 2003). Ravn and Uhlig (2002) study the appropriate value for λ and recommend $\lambda = 129{,}600$ for monthly data, which is used in this study.

Identification of cycles

Harding and Pagan (2003, p. 1695) highlight the ambiguity involved in the identification of a turning point in business cycles when they argue that it revolves on the definition of a recession, the generally accepted version of which is simply a ''decline in the level of economic activity that lasts for some time.'' Procedures for identification of turning points in the cyclical component can be categorized as parametric and nonparametric. Harding and Pagan (2002) compare Markov-Switching models (a parametric proce-

[1] A full description of the Census X-12-ARIMA procedure with software for its implementation and software manuals is available from http://www.census.gov/srd/www/x12a/.

[2] A moving average procedure replaces each observation of the original time series with a weighted average of the observation and a constant number of its neighboring observations (an unweighted average implicitly uses 1 as the common weight). A centered moving average is constructed by averaging consecutive observations of a series to which an even order moving average has been applied.

Table 2.—Business cycles identified by National Bureau of Economic Research for 1985 to 2010 (www.nber.org/cycles/).

Reference dates		Duration (mo)			
		Contraction phase	Expansion phase	Cycle	
Peak	Trough	Peak to trough	Previous trough to this peak	Trough from previous trough	Peak from previous peak
Jul 1990	Mar 1991	8	92	100	108
Mar 2001	Nov 2001	8	120	128	128
Dec 2007	Jun 2009	18	73	91	81
Avg.		11	95	106	106

dure) with nonparametric algorithms and conclude that the dependence of parametric procedures on the validity of the adopted statistical model renders them less robust than nonparametric procedures. Nonparametric procedures for dating of cycles based on a set of rules were first proposed by Burns and Mitchell (1946) and later developed in Bry and Boschan (1971). The rules are a set of constraints on the minimum duration of a cycle and its phases. This study adopts the cycle dating rules used by Artis et al. (1995) to identify almost identical turning points for business cycles in the G-7 countries. The industry cycle identification rules used in this study are as follows:

1. A peak must be followed by a trough, and vice versa.
2. The minimum duration of a phase (peak to following trough or vice versa) must be 9 months.
3. The minimum duration of a cycle (peak to peak and trough to trough) must be 24 months.
4. A turning point must be the most extreme point between two phases.
5. Turning points are not identified within 9 months of either end of the time series.

Data and Results

The study investigates industry cycles in the US softwood lumber industry during the period 1985 to 2010. This period covers three business cycles identified by the NBER (see Table 2).

Historical data on price and sales volumes were considered for representing business activity in the US softwood lumber industry. Data on sales volume were considered more reliable and used for the study as sales volumes are real observed values, while the US-wide softwood lumber price index is a statistical construct (constructed by averaging regional and heterogenous product prices). The lowest frequency historical data set on US softwood lumber sales volumes was located with RISI. The data set commences from 1985 and reports quarterly shipments by US softwood lumber manufacturers in units of billion board feet (bbf). The quarterly data on US softwood lumber industry shipments for the period 1985 Q1 to 2010 Q4 are used to represent US softwood lumber industry business activity for this study.[3]

Temporal disaggregation was applied to the quarterly data on US softwood lumber industry shipments to obtain higher frequency monthly data, in order to improve the resolution.[4] Temporal disaggregation or the interpolation of time series data is the process of converting low-frequency (e.g., annual) data into higher frequency data (e.g., quarterly). Temporal disaggregation techniques have been used in the study of business cycles to extend the power and accuracy of data (Lahiri et al. 2011) or to overcome the shortage of high-frequency data (Abeysinghe and Rajaguru 2004). Several techniques have been developed for temporal disaggregation, including linear interpolation (e.g., Lisman and Sandee 1964), model-based regression (e.g., Chow and Lin, 1971), model-based ARIMA (e.g., Guerrero 1990), and least-squares regression (e.g., Stram and Wei 1986).[5] This study required distribution of low-frequency flow data into higher frequency intervals subject to a summing up constraint (i.e., the monthly values obtained must sum up to the aggregate value for their corresponding quarter). For this purpose, this study uses the proportional Denton method. Bloem et al. (2001, pp. 82–118) discusses the method in detail, describing it as robust. The proportional Denton method is a model-based regression technique that involves the use of a high-frequency indicator series that is highly correlated with the low-frequency series. The method uses a least-squares with constraints approach that is expressed mathematically as

$$\min_{(x_1,\ldots x_T)} \sum_{t=2}^{T} \left[\frac{x_t}{i_t} - \frac{x_{t-1}}{i_{t-1}}\right]^2, \qquad t \in \{1, \ldots, T\}$$

$$\text{subject to} \sum_{t=1}^{F} x_t = a_z, \qquad z \in \{1 \ldots \beta\} \qquad (3)$$

Here t indexes time in high-frequency units (months or quarters) and z indexes time in low-frequency units (quarters or years), x_t is the derived high-frequency estimate, i_t denotes the value of the high-frequency indicator series, and T represents the last high-frequency period for which data is available. For the summing up constraint, a_z represents the value of the low-frequency data, β represents the last period for which a low-frequency value is available, and F represents the number of subperiods in the high-frequency series corresponding to a single period of the low-frequency series (e.g., 12 for monthly series, 4 for quarterly series).

[3] The quality of data reported by RISI was confirmed by testing the correlation of historical data on quarterly softwood lumber import volumes into US from Canada reported by RISI (in bbf) with data on softwood lumber exports to US from Canada reported by Statistics Canada (2013; in m^3). The two data sets were strongly correlated with a 0.99 correlation coefficient.

[4] Results obtained with the quarterly data set were identical to those obtained with the disaggregated monthly data set in terms of number and timing of industry cycles. Temporal disaggregation improved the resolution of the results.

[5] Kladroba (2005) provides a classification and description of temporal disaggregation techniques.

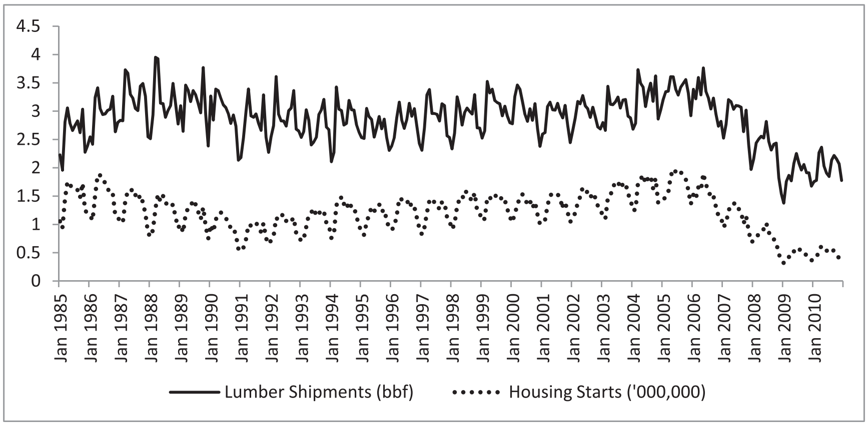

Figure 2.—Quarterly time series plots of US softwood lumber shipments and housing starts (1985 Q1 to 2010 Q4).

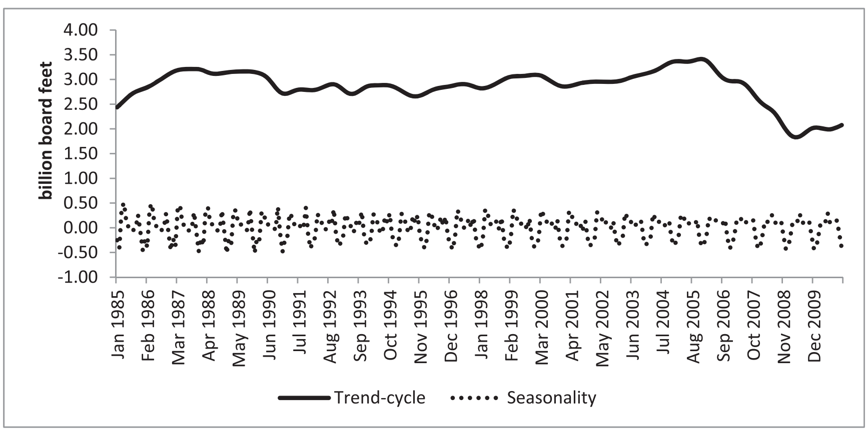

Figure 3.—US softwood lumber shipments trend-cycle and seasonal components (1985 to 2010 monthly time series).

Monthly data on US housing starts (US Census Bureau 2012) was used as the high-frequency indicator series for disaggregation of the quarterly softwood lumber shipment data. Value of the correlation coefficient between the two quarterly data series for the period under study was 0.82. A graph of the two data series (Fig. 2) displays a high level of comovement and a conspicuous seasonal pattern that corresponds with construction activity that peaks in the third quarter. Also, the seasonality in the softwood lumber shipment data appears to remain unchanged with respect to the level of the series.

STATA statistical software was used to apply the proportional Denton method for disaggregating the quarterly softwood lumber shipments data to monthly data.[6] The value of the correlation coefficient for the resulting monthly softwood lumber shipment data series and monthly housing starts data for the period is 0.80. The trend-cycle was extracted from the monthly softwood lumber shipment data series by means of the Census X-12-ARIMA procedure. The procedure was implemented in Eviews statistical software. Since the seasonality does not appear to change with the level of the series, the additive model was chosen for the decomposition. Default settings were used for the moving average filters. The resulting trend-cycle and seasonal components are plotted in Figure 3.

The cyclic component was extracted from the trend-cycle by applying the HP filter in Eviews software with $\lambda = 129{,}600$.[7] The extracted trend and cyclic components are plotted in Figure 4. In Figure 5 the softwood lumber industry cyclic component is compared with business cycle recessions identified by NBER. Softwood lumber industry cycles and phases were identified from the cyclic component using the dating rules listed earlier (plotted in Fig. 6). Detailed descriptions of identified cycles and phases are presented in Table 3.

The last column of Table 3 presents the amplitude of the identified softwood lumber industry cycles. Artis (2002) defines amplitude as the average of the percent increase in expansion and decline in contraction phases. In this study we chose to focus on the contraction phase and define the amplitude of the softwood lumber industry cycles as the percent decline experienced in the contraction phase of a cycle (last peak to this trough), which is calculated as

[6] STATA module ‘‘denton’’ was used for applying the proportional Denton method. It has been developed by Christopher F. Baum and Silvia Hristakeva of Boston College, Boston, Massachusetts.

[7] Census X-12-ARIMA and the HP filter procedures are in-built options in the Eviews 7.0 statistical software.

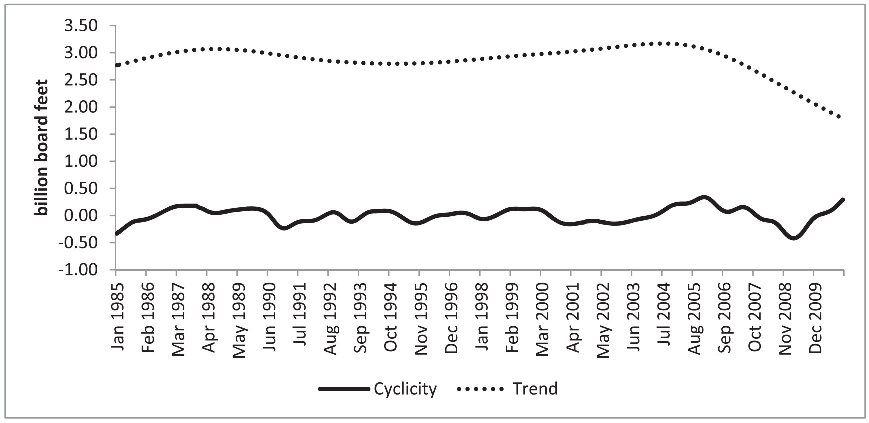

Figure 4.—US softwood lumber shipments cyclic and trend components (1985 to 2010 monthly time series).

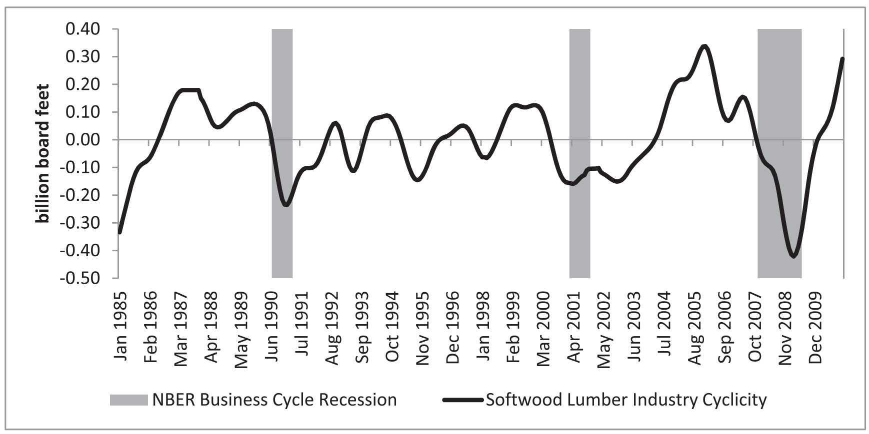

Figure 5.—National Bureau of Economic Research dated business cycle recessions compared with US softwood lumber industry cyclicity (1985 to 2010).

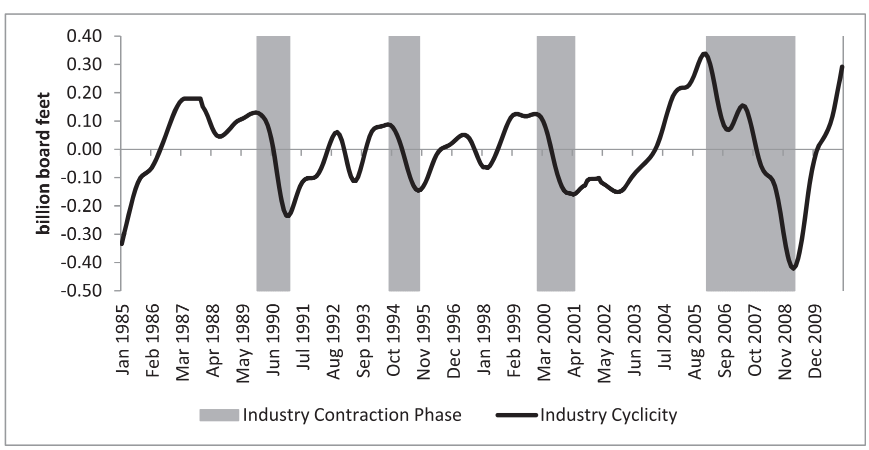

Figure 6.—US softwood lumber industry cycles and phases (1985 to 2010).

$$\frac{\begin{array}{c}\text{Magnitude of decline of measured}\\ \text{value in contraction phase}\end{array}}{\text{Value at last peak of trend-cycle}} \times 100 \qquad (4)$$

Therefore, the amplitude measures the intensity of the cycle as reflected in the decline in magnitude of shipments over the cycle. By measuring the magnitude of decline with reference to the trend-cycle, the amplitude captures the displacement of the trend caused by the cyclical contraction.

Figure 6 and Table 3 show that using the dating rules results in identification of a total of four cycles for the period, one more than the number of business cycles over the same period. To investigate the possible cause of the extra cycle C2, the US softwood lumber industry cyclicity was compared with cycles in softwood lumber imports from

Table 3.—Description of US softwood lumber industry cycles (1985 to 2010).

Softwood lumber industry cycle no.[a]	Reference dates		Duration (mo)				Amplitude	
			Contraction phase	Expansion phase	Cycle		Sales contraction	
	Peak	Trough	Peak to trough	Previous trough to this peak	Trough from previous trough	Peak from previous peak	Absolute (bbf)	% peak trend-cycle value
C1*	Nov 1989	Jan 1991	14	NA[b]	NA	NA	0.37	12
C2	Aug 1994	Sep 1995	13	43	56	57	0.23	8
C3*	Dec 1999	Apr 2001	16	51	67	64	0.28	9
C4*	Jan 2006	Mar 2009	38	57	95	73	0.76	22
Avg.			20	50	73	65	0.41	13

[a] Softwood lumber industry cycles that overlap business cycles are identified with an asterisk.
[b] NA = not applicable.

Canada (see Fig. 7). Figure 7 shows that the contraction phase in C2 (August 1994 to September 1995) overlaps with a cyclic expansion phase in softwood lumber imports from Canada. This period immediately precedes the softwood lumber agreement signed between the two countries in May 1996 (Random Lengths 2012). In August 1994, the United States lost its case on alleged subsidies provided by Canada to its softwood lumber producers before the Extraordinary Challenge Committee constituted under terms of the US–Canada free trade agreement. The resulting stoppage of collection of duty by the United States on softwood lumber imports from Canada was followed by a surge in imports that continued until May 1996. Therefore, a likely explanation for the contraction phase of the C2 cycle is that surging imports of softwood lumber from Canada depressed demand for and production of US softwood lumber.

The average contraction phase duration of softwood lumber industry cycles overlapping the business cycles (C1, C3, and C4) is 23 months. In comparison, the contraction phase duration of the C2 cycle is shorter at 13 months. Similarly, the amplitude of the C2 cycle is lower (at 8%) than the amplitudes of C1, C3, and C4 cycles (average, 14%). This appears to indicate that softwood lumber industry cyclic contractions that coincide with business cycle recessions tend to be longer and more intense. Economy-wide business conditions appear to have a stronger impact on softwood lumber industry cycles than industry-specific developments.

The average duration of softwood lumber industry cycles ranged between 65 months (5 years 5 months) and 73 months (6 years 1 month). In comparison, the average business cycle duration is 106 months (nearly 9 years). Frequent cycles are indicators of volatility in the industry. For comparison, Tan and Mathews (2010) identify three semiconductor industry cycles between 1986 and 2000, one more than the two cycles experienced by the US softwood lumber industry in the same period.

By comparing Tables 2 and 3 and referring to Figure 5, we see that the softwood lumber industry cycles that coincide with business cycles tend to lead them. For example, in comparison with the last business cycle recession phase lasting from December 2007 to June 2009, the corresponding softwood lumber industry contraction phase (C4) started 23 months earlier, in January 2006, and ended 3 months earlier in March 2009. This observation agrees with the use of housing starts as a lead indicator of business cycles by the NBER (Zarnovitz 1992, Stock and Watson 1993), with which business activity in the US softwood lumber industry is closely correlated (Fig. 2). However, it is important to note that NBER adopts a different methodology for identification of cycles, which is best summed up in the following quotation (from www.nber.org/cycles/recessions.html):

> The (NBER) Committee applies its judgment based on . . . definitions of recessions and expansions and has no fixed rule to determine whether a contraction is only a short interruption of an expansion, or an expansion is only a short interruption of a contraction. The Committee does not have a fixed definition of economic activity. It examines and compares the behavior of various measures of broad activity: real GDP measured on the product and

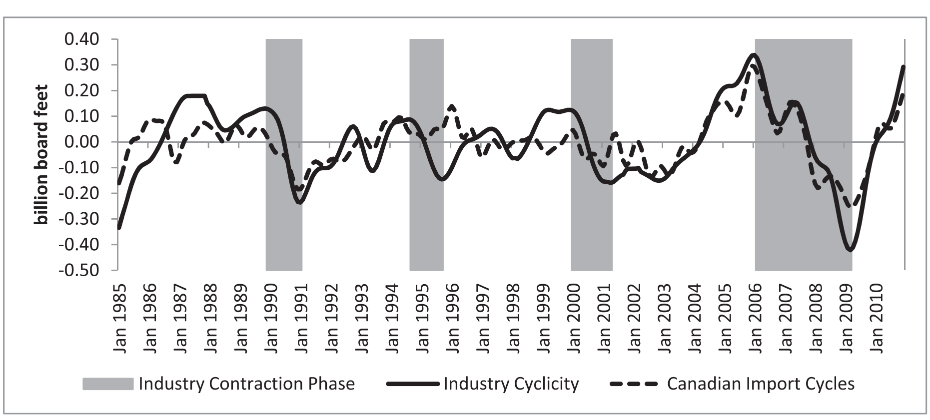

Figure 7.—Impact of cycles in imports from Canada on US softwood lumber industry cycles (1985 to 2010).

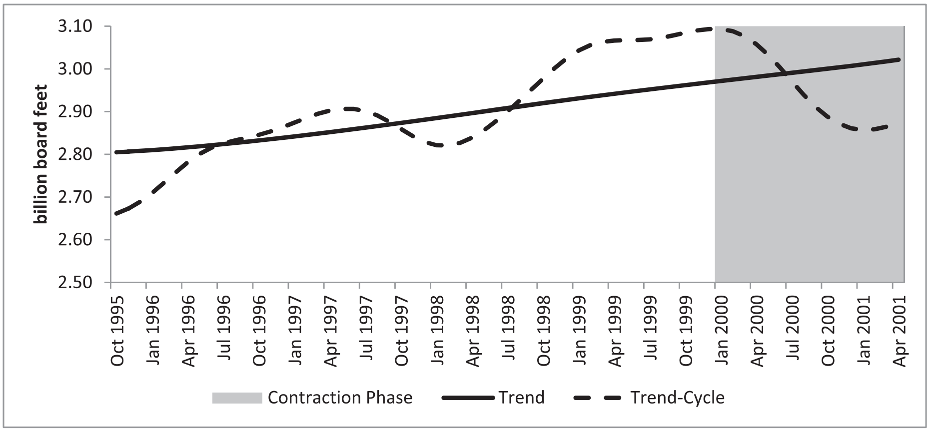

Figure 8.—Trend and trend-cycle through softwood lumber industry cycle C3 (trough to trough): September 1995 to April 2001.

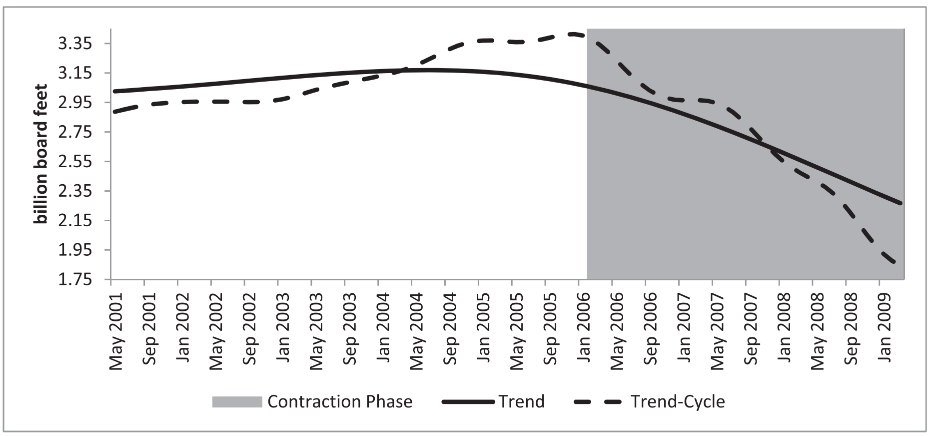

Figure 9.—Trend and trend-cycle through softwood lumber industry cycle C4 (trough to trough): April 2001 to March 2009.

income sides, economy-wide employment, and real income. The Committee also may consider indicators that do not cover the entire economy, such as real sales and the Federal Reserve's index of industrial production (IP). The Committee's use of these indicators in conjunction with the broad measures recognizes the issue of double-counting of sectors included in both those indicators and the broad measures. Still, a well-defined peak or trough in real sales or IP might help to determine the overall peak or trough dates, particularly if the economy-wide indicators are in conflict or do not have well-defined peaks or troughs.

The average amplitude of the softwood lumber industry cycle (Table 3) is 13 percent and ranges from 8 to 22 percent. This means that, on average, cyclic contractions during the period caused a 13 percent reduction in softwood lumber industry business activity. However, the impact of a cyclic contraction depends on the behavior of the trend for the relevant period. In Figure 8 the trend and trend-cycle components are plotted for the softwood lumber industry over the duration of C3 cycle (trough from previous trough) lasting from October 1995 to April 2001. It can be observed that over the duration of the contraction phase of this cycle (January 2000 to April 2001) the rising trend absorbed the impact of the cyclic contraction such that no absolute decline is experienced (the trend-cycle remains above the level of the last trough). In contrast, in Figure 9 the trend is declining over the contraction phase (January 2006 to March 2009) of the softwood lumber industry cycle C4 (trough from previous trough) lasting from May 2001 to March 2009. The declining trend accentuates the impact of the cyclic contraction.

It must be noted that a sharp and sustained change in future level of business activity in the US softwood lumber industry would have a significant impact on the C4 cycle. That is, for example, if a sharply rising trend were to be recorded in the years following 2010 it would result in reduction of the steepness of the decline in the trend recorded in the years leading to year 2010 in this study. In turn, this would increase the amplitude (deepen the trough) of the C4 cycle captured by the extended series, relative to this study. Cycles located early in the analyzed time period (C3, C2, C1) escape any significant impact from extension of the time series.

Discussion

Business cycles are a widely studied and reported phenomenon, but interest in the study of industry cycles is more recent. Industry cycles contribute to the business cycle but are independent of them in terms of incidence, frequency, duration, and intensity. The US softwood lumber industry is characterized by conditions conducive to volatility in levels of business activity. Several studies have concluded that persistent and high volatility in business activity contributes to the creation of a low value economy by discouraging long-term investment in productivity (e.g., Aizenman and Marion 1999). Volatility in business activity in the softwood lumber industry is also harmful for rural communities that are dependent on it for employment. The four cycles identified for the period 1985 to 2010, each occurring over 5 to 6 years, are indicators of the level of volatility in the US softwood lumber industry. Contraction phases with an average length of 20 months that results in an average 13 percent decline in seasonally adjusted business activity indicate the severity of the softwood lumber industry cycles.

What explains the behavior of industry cycles in the US softwood lumber industry? Dynamics of the residential and commercial construction and improvement activity, which are major sources of softwood lumber demand, can be expected to be a major influence on industry cycles in the softwood lumber industry. A related explanation is found in Jones et al. (2002), which models the dynamics of the sawmill industry to conclude that it has the potential to overshoot the resource constraint (timber supply) in expansionary phases, leading to instability. Expanding on this argument, since entry into the industry is possible at a relatively small-scale level and therefore relatively easier, there could be a tendency for production capacity to surge in the cyclic expansion phases. However, this growth in production disregards the capacity for expansion of timber supply in the short run (including harvesting capacity and transportation constraints), resulting in higher cost of production and low margins all around. Inevitably, when the markets for softwood lumber contract, the surplus production capacity is quickly exposed and rapidly shed, serving to exacerbate the intensity of the cycle. However, the short-run resource constraint argument for softwood lumber industry cycles is not supported by empirical studies and could be a subject for future research.

The influence of the softwood lumber trade dispute between the United States and Canada, developments in which are traced by the C2 cycle, is a significant finding of this study. If, as the analysis suggests, the trade dispute is contributing to significant volatility, it provides an important reason for the parties to the dispute to seek a stable solution. Future research could validate this finding by comparing industry cycles in other sectors of the US forest products industry with the results of this study for US softwood lumber industry.

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