Dynamics of U.S. Housing and Primary Building Materials in the Presence of Structural Breaks

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Abstract

The objective of this study is to explain the dynamic relationship between the housing market and the markets for primary building materials in the U.S. by allowing a single structural break that may have risen in response to macroeconomic shocks, specifically the housing market crisis started in 2007. In particular, using a vector error correction model (VECM), Granger–causality test, and impulse response analysis, the dynamics of housing prices and prices of concrete, lumber, plywood, and oriented strand board are investigated in two macroeconomic conditions of the economy: during the presence of structural break as well as before and after it. The data used in the analyses cover monthly time–series observations over the period of 1995-2015. Using the Qu and Perron (2007) methodology in a VECM with certain parameter restrictions shows that there is a strong single structural break in September 2007, which is a close estimation for the start of the Great Recession in December 2007. Thus, the data are split into two segments. The time–series analyses across segments suggest that most of the bidirectional Granger–causalities and dynamic linkages between housing prices and the prices of building materials have weakened or even disappeared after the housing market crisis.

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1 Introduction

In advanced countries, recessions are often associated with global financial crises. Specifically, these recessions are accompanied by severe financial disruptions, including credit crunches, housing and equity price busts, and outright banking crises in some countries. Recently, some researchers have attempted to analyze the reasons and policy lessons of the financial crisis in 2007, the Great Recession. Concerning economic impact, the International Monetary Fund states that it is the worst global recession in the developed world history since the 1930s (i.e., the Great Depression).

Some economists (e.g., Karl Case and Robert Shiller are among the first) had warned about the impending crash in the housing market even many years before it started (Case and Shiller, 2003).[1] They point out that the dynamics of U.S. housing prices are mainly driven in micro–level by price expectations, anticipations of capital gains on housing property, and public policies favor private home ownership (Rötheli, 2010). On the other hand, a vast majority of studies in the literature have treated housing as one of the many consumption goods before the Great Recession. Only a few studies have linked the housing market to macroeconomics (Iacoviello, 2000, 2002). Moreover, in a detailed literature survey, Leung (2004) shows the lack of connection between macroeconomics and housing market. Thus, it can be said that there has been an apparent disconnect between macroeconomics and housing research.

However, after the Great Recession, the bursting of the housing bubble in the U.S. has often been mentioned by researchers as the factor triggered the financial crisis. It is because players in the housing market had been effectively speculating on the ever–increasing housing prices by lending to financial institutions and individuals with poor credit scores as well as investors in mortgage–backed securities until the housing market started to crumble in 2006. These reasons have led researchers to investigate: (1) the macroeconomic determinants of housing prices; (2) the interrelationship between housing prices and macroeconomic fluctuations; and (3) the dynamic relationships between the housing market and macroeconomic variables such as gross domestic product, consumption, income, unemployment, investment, interest rate, money supply, and inflation.[2]

Although there is plenty of evidence in the literature suggesting that the housing market is linked to the aggregate economic activity, to the best of our knowledge, there is still no study that examines the dynamic link between the housing market and the markets for primary building materials. Instead, the literature has mainly focused on the spatial market and price linkages of

[1] Figure 1a displays the course of the S&P CoreLogic Case–Shiller U.S. National Home Price Index.

[2] See, among others, Adams and Füss (2010), Beltratti and Morana (2010), Claessens et al. (2010), Duca et al. (2010), Agnello and Schuknecht (2011), Kuethe and Pede (2011), Inglesi-Lotz et al. (2012), Ahamada and Diaz Sanchez (2013), and Milcheva and Sebastian (2016).

specific types of wood building materials such as lumber[3], oriented strand board[4], and timber[5] using cointegration and causality tests as well as the copula and time–varying smooth transition autoregressive models.

Instead of examining the relationship between aggregate economic activity and the housing market or the spatial price linkages among various building materials, this study diverges from the primary focus of the literature. It seeks to explain the dynamic relationship between the housing market and the markets for primary building materials in the U.S. by allowing a single structural break that may have risen in response to macroeconomic shocks, specifically the housing market crisis. In particular, the dynamics of housing prices, oil prices as a proxy of transportation and production cost, and prices of building materials such as concrete, lumber, plywood, and oriented strand board are investigated in two macroeconomic conditions of the economy: during the presence of structural break (i.e., housing market crisis) as well as before and after it.[6]

Understanding the dynamic links between these markets can help real estate industry, building material producers, policymakers, and investors to take positions in advance if a housing market crash ever occurs again in the future. Moreover, examining the price dynamics between these markets is also relevant considering the Canada–U.S. softwood lumber dispute, which is one of the most enduring and significant trade disputes between both nations. Although the argument dates back many decades, it has heated up significantly since 1982. The difference of how the prices charged to harvest timber (i.e., stumpage fee) between two countries is the hearth of the dispute. The majority of U.S. softwood lumber is manufactured from trees grown on privately owned land. However, in Canada, most of the softwood lumber is produced from trees grown on government–owned land with a low stumpage fee set by federal and provincial governments, rather than a high one set through market forces in the United States. The U.S. claims that low prices charged to Canadian softwood lumber producers constitutes an unfair subsidy; and thus, it is subject to U.S. trade remedy laws, a countervailing duty tariff which brings the commodity price back up to market rates. The dispute still continues although there have been several agreements between two nations to end it by raising the price of Canadian softwood lumber, which led to higher lumber and housing prices in the U.S. (Lindsey et al., 2000; Zhang, 2001, 2006).

In summary, the dynamics of these markets are investigated in three steps. In the first step, unit root, stationary, cointegration, and causality tests are performed assuming no structural break and using the entire data. Then, a vector error correction model is estimated to understand the short–run and long–run relationships between the prices in these markets. Finally, to evaluate the nature of dynamic relations inherent in the estimates of the vector error correction model,

[3]See, among others, Jung and Doroodian (1994), Luppold and Prestemon (2003), Yin and Xu (2003), Yin and Baek (2005), and Shahi and Kant (2009).

[4]See, among others, Goodwin et al. (2011, 2013).

[5]See, among others, Prestemon and Holmes (2000) and Hood and Dorfman (2015).

[6]Figure 2 and Figure 3 display that prices in these markets move together since 1995.

impulse response analysis is performed. In the second step, a series of structural break tests are performed to estimate a single structural break date in the entire data. Specifically, to investigate structural breaks in each variable separately, various univariate structural break tests are applied only to the mean of each price series. Then, a single structural break is endogenously estimated for the vector error correction model performed in the first step using the Qu and Perron (2007) methodology[7]. In the third step, the data are split into two segments on the estimated single break date, and the same analyses explained in the first step are performed for each segment.

The primary results of this study can be summarized as follows: (1) the application of Qu and Perron (2007) methodology in a vector error correction model with certain valid restrictions on the model parameters concludes that there is a single structural break in 09-2007 (i.e., the 9$^{\text{th}}$ month of 2007), which appears to have affected the dynamic price linkages between the housing market and the market for primary building materials; and (2) the time–series analyses across segments suggest that most of the bidirectional Granger–causalities and dynamic linkages between housing prices and the prices of building materials have weakened or even disappeared after the housing market crisis.

The paper proceeds as follows: Section 2 presents the relevant data sources; Section 3 presents the empirical methods; Section 4 provides the estimation and results for the entire data; Section 5 presents the structural break tests and provides the results; Section 6 provides the estimation and results for each segment; Section 7 discusses the results; and Section 8 concludes.

2 Data Descriptions

The analyses of this study are conducted with a monthly dataset created by combining four time series data sources. Table 1 presents the descriptive summary of data along with the sources and number of observations in the raw data.

The S&P CoreLogic Case–Shiller U.S. National Home Price Index from Standard & Poor's is used to capture shocks in the housing market. From now on, it is called *Shiller Index*. Based on the pioneering study of Robert J. Shiller and Karl E. Case, *Shiller Index* is considered as the leading measure of U.S. residential real estate prices. By tracking changes in the total value of all existing residential real estate nationally, *Shiller Index* measures the average change in housing market prices given a constant level of quality (S&P, 2016a). It is calculated monthly with a three–month moving average algorithm. This averaging methodology is necessary to offset the delays that can occur in the flow of sales price data from county deed recorders as well as to keep sample sizes large enough to create meaningful price change averages (S&P, 2016a). *Shiller Index* used in this study is a composite of home price indices for the nine U.S. Census divisions. It has monthly observations with a base month of 01-2001.

In order to control for energy and transportation–related costs, the Crude Oil Brent/Global

[7] See Section 5.2 for the details of the Qu and Perron (2007) methodology.

Spot Price in Intercontinental Exchange is obtained from Commodity Research Bureau (CRB) as a proxy. From now on, it is called *Oil Price*. Monthly observations on *Oil Price* are calculated by simple averages of daily observations in a given month.[8]

As a control variable for concrete related building materials, Concrete Block and Brick Producer Index is collected from the U.S. Bureau of Labor Statistics. From now on, it is called *Concrete Price Index*. It had monthly observations with a base month of 01-1982 but converted to 01-2001 to match the base month of *Shiller Index*.

Three types of wood prices are obtained from Random Lengths (RL): Lumber, Plywood, and Oriented Strand Board (OSB) prices. From now on, they are called *Lumber Price*, *Plywood Price*, and *OSB Price* respectively. Monthly observations of wood prices are calculated by simple averages of weekly observations in a given month.

All datasets mentioned above are merged using the year and month numbers of the observation dates. The resulting merged data are subsetted by excluding observations before the first observation of RL data and after the last observation of CRB data to achieve a complete time series dataset. Then, for plotting and estimation purposes, a date variable for each observation is generated by assigning each monthly observation to the first date of the respective month and year number. The final merged data covers six variables from 01-1995 to 11-2015.

Finally, all variables in the merged dataset are processed applying the natural logarithmic transformation, and only the transformed forms are used for analyses. One reason for this approach is that transformations such as logarithms can help to stabilize the variance of a time series variable[9]. Another reason is that the Maximum Likelihood (ML) estimation of vector error correction model requires normally distributed dependent variables. Moreover, Tabachnick et al. (2001) suggest using logarithmic transformation in case of positively skewed variables which applies to most of the variables in the merged time series data.

In order to assess the effect of seasonality in each series, the X-13ARIMA-SEATS seasonal adjustment procedure developed by the U.S. Census Bureau is used (Census Bureau, 2017). The procedure first tests seasonality in each series using the QS statistic.[10] Then, it adjusts each series for seasonality. According to the results, only the transformed forms of *Shiller Index* and *Concrete Price Index* are found to have seasonality. These two series are adjusted for seasonality using the default options of the X-13ARIMA-SEATS procedure, and the rest of the estimation methods are performed. However, the difference between the estimation results with seasonally adjusted and unadjusted series is trivial. Therefore, non of the series are adjusted for seasonality.

Table 2 presents the summary statistics of variables including the transformed forms. As it can be seen from Table 2, the transformed variables are in the range of rules of thumb for

[8]The results of the Granger–causality tests and impulse response analyses presented in Section 4 and Section 6 show that *Oil Price* acts as an exogenous variable. Therefore, *Oil Price* is omitted during the interpretation of results.

[9]Throughout this study, *time series variable*, *variable*, and *series* are used interchangeably to refer to an individual time series in the merged data.

[10]The QS statistic looks for positive seasonal autocorrelation in a series to test the null hypothesis of no seasonality (Gómez and Maravall, 1996). It checks seasonality not only in the original series but also in the seasonally adjusted series. For more information, see URL: `https://goo.gl/8DEheD` (visited on Jan. 30, 2017)

normality[11]. Figure 1 presents plots of all variables.[12] For easy comparison, non–wood variables (i.e., *Shiller Index*, *Oil Price*, and *Concrete Price Index*) and wood variables (i.e., *Lumber Price*, *Plywood Price*, and *OSB Price*) are plotted together in Figure 2 and Figure 3 respectively. In these plots, boundaries of the red shaded area indicate the starting and ending months of the Great Recession.[13] The blue dotted line indicates the estimated single structural break date, 09-2007, using the Qu and Perron (2007) methodology.

In order to prevent repetition, in the text, tables, and figures of the subsequent sections, a symbol is designated to the natural logarithmic form of each variable. These symbols are *Shiller* for Shiller Index, *CB* for Oil Price, *WPU1331* for Concrete Price Index, *LAES* for Lumber Price, *PAAB* for Plywood Price, and *PACS* for OSB Price.

All analyses performed in this study, including the data cleaning and merging parts, are completed using open source software R. Appendix A presents the R version information along with the used packages. GAUSS software is used only for estimating the single structural break date with the Qu and Perron (2007) methodology. Appendix B presents the GAUSS version information.

3 Empirical Methods

This section presents the empirical methods performed on the entire data as well as on each segment after the data are split into two. The section proceeds as follows: Section 3.1 presents the unit root and stationary tests; Section 3.2 briefly summarizes the vector autoregressive model; and Section 3.3 through Section 3.7 cover the details of vector error correction model along with the cointegration, causality, and model diagnostic tests as well as the impulse response analysis for interpreting the dynamics of the model.

3.1 Unit Root and Stationary Tests

Unit root testing of a time series variable is often the first step in time series analyses. If any of the variables in a time series regression has a unit root[14], then there might be a spurious regression problem as pointed out by Granger and Newbold (1974) and Phillips (1986). In order to avoid the spurious regression problem, a non–stationary process should be transformed into a

[11]The conservative guidelines of Tabachnick et al. (2001) recommend using ±2 for both skewness and kurtosis. West et al. (1995) is more liberal and suggest using ±2 for skewness and ±7 for kurtosis. Note that throughout this paper, *kurtosis* refers to *excess kurtosis* which is the kurtosis minus three and provides a comparison to the normal distribution.

[12]Figure 7 presents plots for the same variables in the natural logarithmic form.

[13]According to the U.S. National Bureau of Economic Research (i.e., the official arbiter of U.S. recessions), the Great Recession began in 12-2007 and ended in 06-2009. See URLs: `https://goo.gl/UBg0Me` and `https://goo.gl/yCC846` (visited on Mar. 30, 2017).

[14]In the time series literature, the following groups of concepts are used interchangeably: (1) *stationary* and *integrated order of zero* (i.e., $I(0)$); and (2) *unit root*, *non–stationary*, and *integrated order of one* (i.e., $I(1)$) assuming that the variable of interest has a single unit root.

stationary process. Detrending and differencing can help to stabilize the mean of a time series by eliminating trend and seasonality. Thus, these methods can yield a stationary process. However, the correct transformation method depends on whether the series is a trend–stationary process (TSP) or a difference–stationary process (DSP). A DSP should be differenced whereas a TSP should be detrended by regressing it on deterministic functions of time. Applying a wrong method might cause over or under differencing depending on the true data generating process (DGP) and result in specification error in time series regressions.

Before testing each series for unit root, it is better to investigate whether there is a seasonal unit root in the variable of interest. Two methods performed for testing seasonal unit root are Osborn–Chui–Smith–Birchenhall test by Osborn et al. (1988) and Canova–Hansen test by Canova and Hansen (1995).

A joint application of two groups of tests is conducted to test each series for unit root. In the first group, commonly used unit root tests are applied. These tests are Augmented Dickey–Fuller (ADF) unit root test by Dickey and Fuller (1979, 1981), Phillips–Perron (PP) unit root test by Phillips and Perron (1988), and Elliott–Rothenberg–Stock (ERS) unit root test by Elliott et al. (1996).[15] In the second group, Kwiatkowski–Phillips–Schmidt–Shin stationary test by Kwiatkowski et al. (1992) is performed.[16] This joint application is implemented as a confirmatory analysis such that a non–rejection in the first group of tests confirms a rejection in the second group of tests.

An important practical issue for the unit root and stationarity tests is the selection of the lag length p. If p is too small, then the remaining serial correlation in errors will bias the test whereas if p is too large, then the power of a test will suffer. Therefore, various lag length selection criteria are considered and employed in all tests.

The conventional unit root tests presented above require prior knowledge about the DGP. For instance, inappropriate exclusion of an intercept or a trend leads to biased coefficient estimates and causes size problems whereas inappropriate inclusion reduces the power of a test. Thus, these unit root tests work better when there is a priori knowledge about the DGP. Since the form of the DGP is entirely unknown to this study, Enders' ADF Procedure (EAP) by Enders (2004) is applied to reveal whether the variable of interest is a DSP or a TSP while testing for unit root as well. In summary, EAP performs several ADF unit root tests in a nested fashion. It starts with the least restrictive model (i.e., with intercept and trend) and proceeds sequentially until the most restrictive model (i.e., without any deterministic parts).[17]

For each series, EAP is performed with three lag length selection criteria which are Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Ng–Perron–Schwert

[15] In ADF, PP, and ERS unit root tests, the null hypothesis is that *series is non–stationary*.

[16] In KPSS stationary test, the null hypothesis is that *series is stationary*.

[17] The whole procedure can be found in "Supplementary Manual to Accompany, Applied Econometric Time Series (4th Edition) by Walter Enders" at page 63-66 (see URL: `https://goo.gl/hd7uHN`) and in Enders (2004) at page 194-198.

(NPS).[18] The NPS is a backward lag length selection procedure performed in several steps: (1) define an upper bound, p_{max}, for the lag length p and set $p = p_{max}$, then use Schwert (1989)'s rule of thumb to determine the p_{max} with the integer of $12\sqrt[4]{N/100}$ value, where N is the length of a series; (2) estimate ADF unit root test regression with p; and (3) if $|\text{t-value}_{(p)}| > 1.6$, perform ADF unit root test with p; otherwise, reduce p by one and go back to the previous step.

PP unit root test is essentially a modification of ADF unit root test. It is based on a nonparametric correction to account for serial correlation. Although ADF and PP unit root tests are asymptotically equivalent, they might differ substantially in finite samples due to the different ways of correcting serial correlation. PP unit root test tends to be more powerful than ADF unit root test. On the other hand, PP unit root test is more sensitive to model misspecification, and it can have severe size distortions when autocorrelation of the error terms is negative. In this study, PP unit root test is performed under two models (i.e., a model with constant or trend) and with four lag lengths. Additional to AIC and BIC, two other methods are employed for selecting the lag length. These methods are commonly used in the literature and defined as *Long* and *Short* with the integer of $12\sqrt[4]{N/100}$ and $4\sqrt[4]{N/100}$ values respectively, where N is the length of a series.

ERS unit root test is another modification of ADF unit root test. It first detrends a time series with Generalized Least Squares and then applies ADF unit root test. ERS unit root test is considered as an efficient unit root test since it has substantially higher power than ADF and PP unit root tests especially when the root is close to unity and an unknown mean or trend is present. Elliott et al. (1996) show that it has the best overall performance concerning small–sample size and power. Thus, ERS unit root test is performed under two models and with four lag lengths as in the PP unit root test.

Power of ADF and PP unit root tests are low if the variable of interest is a stationary process with a root close to the non–stationary boundary. One way to get around the problem is to use a stationarity test such as KPSS stationary test. Thus, KPSS stationary test is performed under two models and with four lag lengths as in the PP and ERS unit root tests. In KPSS stationary test; however, *Long* and *Short* indicate the lag length decided with the integer of $10\sqrt{N}/14$ and $3\sqrt{N}/13$ values respectively, where N is the length of a series.

3.2 Vector Autoregressive Model

The Vector autoregressive model (VAR) was introduced by Sims (1980) as a technique to characterize the joint dynamic behavior among a set of variables. It has become a prevalent method of time series modeling since then.[19] VAR is often considered as an alternative to a large simultaneous equations model that does not account for the rich dynamic structure in time series data (Lütkepohl, 2006).

[18] See Akaike (1974, 1998) for AIC, Schwarz et al. (1978) and Rissanen (1978) for BIC, and Schwert (1989) and Ng and Perron (2001) for NPS.

[19] For a detailed literature review of VAR, see Watson (1994) and Lütkepohl (2005, 2011).

VAR typically treats all variables as a priori endogenous. Hence, it accounts for Sims' critique that the exogeneity assumptions for some variables in a simultaneous equations model are *ad hoc* and often not backed by fully developed theories. The only prior knowledge required in a VAR is a set of variables which can be hypothesized to affect each other intertemporally. Therefore, the estimation of VAR does not require as much information about the forces affecting a variable as do structural models with simultaneous equations. Based on this feature, Sims (1980) advocates the use of VAR as a theory–free method to estimate economic relationships.

VAR is a k-variable and k-equation linear model in which each variable is in turn explained by the lagged values of all variables and the error term. So, it is a multivariate version of a univariate autoregressive model with a single equation. The simple framework of VAR provides a systematic way to capture rich dynamics in multiple time series along with a statistical toolkit (e.g., impulse response analysis) that is easy to use and interpret.

A k-dimensional p^{th}-order VAR can be defined as

$$\mathbf{y_t} = \mathbf{c} + A_1\mathbf{y_{t-1}} + \cdots + A_p\mathbf{y_{t-p}} + \boldsymbol{\varepsilon}_\mathbf{t} \tag{1}$$

where p is the lag length; T is the sample size; t indicates a temporal observation for $t = (1, \ldots, T)$; k is the number of endogenous time series variables and the total number of equations; $\mathbf{y_t} = (y_{1t}, \ldots, y_{kt})'$ is a $k \times 1$ vector for a set of k endogenous time series variables; $\mathbf{c} = (c_1, \ldots, c_k)'$ is a $k \times 1$ vector of constants allowing for the possibility of a nonzero mean $E(\mathbf{y_t})$; A_i's are $k \times k$ coefficient matrices for $i = (1, \ldots, p)$; and $\boldsymbol{\varepsilon}_\mathbf{t} = (\varepsilon_{1t}, \ldots, \varepsilon_{kt})'$ is a $k \times 1$ vector of errors with zero mean white noise process and time invariant positive definite covariance matrix $E(\boldsymbol{\varepsilon}_\mathbf{t}\boldsymbol{\varepsilon}_\mathbf{t}') = \Sigma_\varepsilon$, that is $\boldsymbol{\varepsilon}_\mathbf{t} \overset{iid}{\sim} (0, \Sigma_\varepsilon)$.[20] It is possible to add additional exogenous variables (e.g., time trends and seasonal dummies) to any multiple–equation time series model. However, throughout this study, only the constant is included as an exogenous variable. The model in Eq. 1 is briefly called VAR(p) and can be estimated with standard ordinary least squares (OLS) and ML methods.

The process of choosing the lag length of VAR requires particular attention since coefficient inference, impulse response analysis and other formal tests depend on it. Choosing a lag length too small can lead to size distortions in formal tests whereas a too large lag length may imply reductions in power (Lütkepohl, 2005). Therefore, considering various lag lengths may provide useful insights. In the literature, information criteria such as AIC and BIC are often used for selecting the lag length of VAR. However, the present study considers only BIC for the lag length selection in all of the time series models and the related formal tests since AIC often estimates a lag length that is too large. For the VAR presented in Eq. 1, BIC is defined as

$$\text{BIC}(p) = \ln\det\left(\hat{\Sigma}_\varepsilon(p)\right) + \frac{\ln T}{T} p k^2 \tag{2}$$

[20] Vectors are assigned by small bold letters and matrices by capital letters. Scalars are written out in small letters which are possibly subscripted.

where $\hat{\Sigma}_\varepsilon(p) = T^{-1}\sum_{t=1}^{T}\hat{\varepsilon}_\mathbf{t}\hat{\varepsilon}_\mathbf{t}'$; and the other notations are as in Eq. 1.

Traditionally, VAR is designed for stationary variables. The underlying reason for this convention relates to one of the critical characteristics of VAR, that is, the stability of the model. VAR is stable if the following condition holds.

$$\det(I_k - A_1 z - \cdots - A_p z^p) \neq 0 \quad \text{for } |z| \leq 1 \tag{3}$$

where I_k is a $k \times k$ identity matrix; and the other notations are as in Eq. 1. The condition states that VAR is stable if the polynomial defined in Eq. 3 has no roots in and on the complex unit circle, which can be satisfied by having stationary variables only. Whereas, VAR is not stable, if the polynomial has a unit root (e.g., the determinant is zero for $z = 1$) due to some non–stationary variables in the model. Therefore, all variables have to be stationary to ensure the stability of VAR.

In practice, VAR with all $I(0)$ variables is called *VAR in levels*. Alternatively, VAR with all $I(1)$ variables can be performed as long as their first differences are used in the estimation. This model is known as *VAR in first differences*. The other possibility is that if all variables are $I(1)$ but some of them are cointegrated (i.e., there exists a linear combination of them that is stationary) then an error correction term should be included into VAR. Such a model is called vector error correction model (VECM).

3.3 Vector Error Correction Model

In the 1980s, the discovery of the importance of stochastic trends in economic variables and the development of the cointegration concept by Engle and Granger (1987) and Johansen (1995) have shown that stochastic trends can also be captured by VAR (Lütkepohl, 2011). If there are common trends between some variables, it may be desirable to separate the long–run relations from the short–run dynamics of these variables. From this aspect, VECM offers a convenient framework for separating long–run and short–run components of the DGP when the variables are $I(1)$ but cointegrated. More specifically, VECM has an error correction term that ensures the long–run behavior of the endogenous variables to converge to their cointegration relations while allowing for short–run adjustment dynamics.

The VECM representation of a dynamic system is obtained as a simple rearrangement of VAR. Any k-dimensional p^{th}-order VAR can be converted to a k-dimensional $(p-1)^{\text{th}}$-order VECM, and called VECM$(p-1)$. Using simple algebra by subtracting some terms and rearranging, two forms of VECM can be delineated from Eq. 1.

The first form of VECM can be obtained by subtracting the $\mathbf{y_{t-1}}$ term from both sides of Eq. 1 and rearranging terms. The cointegration term $\Pi\mathbf{y_{t-p}}$ enters the system with lag $t-p$, and the model is defined as

$$\Delta \mathbf{y_t} = \mathbf{c} + \Pi \mathbf{y_{t-p}} + \Gamma_1 \Delta \mathbf{y_{t-1}} + \cdots + \Gamma_{p-1} \Delta \mathbf{y_{t-p+1}} + \boldsymbol{\varepsilon}_\mathbf{t} \tag{4a}$$

$$\Gamma_i = -(I_k - A_1 + \cdots + A_i) \quad \text{for } i = 1, \ldots, p-1 \tag{4b}$$

$$\Pi = -(I_k - A_1 - \cdots - A_p) \tag{4c}$$

where I_k is a $k \times k$ identity matrix; and the other notations are as in Eq. 1. Since the matrix Γ_i in Eq. 4b contains the cumulative long–run impacts, this form of VECM in Eq. 4a is often referred to as *long–run form VECM*.

The second form of VECM can be obtained by subtracting the $\mathbf{y_{t-p+1}}$ term from both sides of Eq. 1 and rearranging terms. The cointegration term $\Pi \mathbf{y_{t-1}}$ enters the system with lag $t-1$, and the model is defined as

$$\Delta \mathbf{y_t} = \mathbf{c} + \Pi \mathbf{y_{t-1}} + \Gamma_1 \Delta \mathbf{y_{t-1}} + \cdots + \Gamma_{p-1} \Delta \mathbf{y_{t-p+1}} + \boldsymbol{\varepsilon}_\mathbf{t} \tag{5a}$$

$$\Gamma_i = -(A_{i+1} + \cdots + A_p) \quad \text{for } i = 1, \ldots, p-1 \tag{5b}$$

$$\Pi = -(I_k - A_1 - \cdots - A_p) \tag{5c}$$

where I_k is a $k \times k$ identity matrix; and the other notations are as in Eq. 1. Since the matrix Γ_i in Eq. 5b measures the transitory effects, this form of VECM in Eq. 5a is often referred to as *transitory form VECM*.

The cointegration term (e.g., the matrix $\Pi \mathbf{y_{t-1}}$ in Eq. 5a) is also known as the *error correction term* or *long–run term* since the deviation from the long–run equilibrium is gradually corrected through a series of partial short–run adjustments. In both forms of VECM, the $k \times k$ matrix Γ_i is often called *short–run parameters matrix* which measures the short–run changes occurring due to previous changes in variables. Whereas the $k \times k$ matrix Π is called *composite matrix* that contains the parameters pertaining to the long–run relationships among variables. Since the matrix Π is the same in both forms, cointegration tests conducted and inferences drawn on the matrix Π are the same regardless of the form chosen. The parameters of both forms of VECM can be estimated with ML by Johansen (1995). Moreover, both forms of VECM gives identical results when converted back to VAR.[21] In the literature, the transitory form VECM is used more often than the long–run form. Therefore, this study follows the literature and performs only the transitory form VECM presented in Eq. 5a.

3.4 Cointegration Tests

The concept of cointegration was introduced by Granger (1981), and the general case was constructed by Engle and Granger (1987) in their seminal paper. The main idea behind the

[21] Any k-dimensional VECM$(p-1)$ can be converted back to a k-dimensional VAR(p). In conversion, Eq. 4a through Eq. 4c or Eq. 5a through Eq. 5c should be used.

cointegration is to find a linear combination between two $I(d)$ variables that yields a variable with a lower order of integration. For instance, suppose we have two $I(1)$ series X and Y such that some linear combination of them is $I(0)$, then it can be said that X and Y are cointegrated. Thus, we can think of cointegration as describing a particular kind of long–run equilibrium relationship.

Testing for cointegration is an important step to prevent spurious regression problem in estimating VECM. Without any statistically significant cointegration between series, the long–run relationship found in VECM will be invalid due to the spurious regression problem even if the estimates are statistically significant and R^2 is very high. Various procedures have been proposed by the literature to determine cointegration between the variables of interest. They include single–equation methods such as Engle–Granger test by Engle and Granger (1987) and Phillips–Ouliaris test by Phillips and Ouliaris (1990). However, empirical researchers have relied more on the multiple–equation methods such as the frequently used Johansen *trace* and *maximum eigenvalue* cointegration tests by Johansen (1988), Johansen and Juselius (1990), and Johansen (1991). In this study, Johansen trace cointegration test is used due to its superior power in small sample sizes (Lütkepohl et al., 2001) and its current popularity in empirical applications.

Traditionally, the individual components of $\mathbf{y_t}$ are all $I(1)$ by the construction of VECM. Therefore, all first–differenced terms (i.e., $\Delta\mathbf{y_t}, \ldots, \Delta\mathbf{y_{t-p+1}}$) on each side of equations are stationary. Moreover, the cointegration term (e.g., the matrix $\Pi\mathbf{y_{t-1}}$ in Eq. 5a) has to be stationary; otherwise, VECM does not balance. The stationarity of this matrix is satisfied by having at least one cointegration relation between variables which ensures that the linear combinations of $I(1)$ variables are $I(0)$. Therefore, the unit root of series and cointegration relations between them have to be satisfied before estimating VECM.

The hypothesis of cointegration for the process $\mathbf{y_t}$ can be performed by testing the rank of the matrix Π. When the null hypothesis is that the cointegration rank is equal to r, Johansen trace cointegration test statistic (i.e., λ_{tr}) is defined as

$$\lambda_{tr} = -T \sum_{i=r+1}^{k} \ln(1 - \lambda_i) \tag{6}$$

where k is the number of endogenous time series variables; r is the cointegration rank; and λ_i is the i^{th} largest eigenvalue associated to the matrix Π. Johansen trace cointegration test is a collection of nested sequential tests. The sequential testing starts with the null hypothesis that is $r = 0$. If it is rejected, one should continue to test $r \leq 1$ and stop testing when the first time it is not rejected or just after the null hypothesis $r \leq k - 1$ is rejected. Therefore, Johansen trace cointegration test can yield three distinct results which are

- **Case 1**: $rk(\Pi) = k$
- **Case 2**: $rk(\Pi) = 0$

- **Case 3**: $0 < rk(\Pi) = r < k$

where $rk(.)$ assigns the rank of a matrix. In the first case, the matrix Π has full rank, and all k linearly independent combinations must be stationary. It indicates that the process $\mathbf{y_t}$ is *level stationary* and VAR in levels should be performed. In the second case, the rank of the matrix Π is zero, and no linear combination exists to make the matrix $\Pi\mathbf{y_{t-1}}$ stationary. Thus, the second case indicates that the process $\mathbf{y_t}$ is *difference stationary* and VAR in first differences should be performed.

The desired case is the third one where the stationarity of the matrix $\Pi\mathbf{y_{t-1}}$ is satisfied. If the condition $0 < rk(\Pi) = r < k$ holds, the matrix Π can be written as $\Pi = \alpha\beta'$, where α and β are $k \times r$ matrices with $rk(\alpha) = rk(\beta) = r$. The matrix β has a property that makes $\beta'\mathbf{y_{t-1}}$ stationary even though the process $\mathbf{y_t}$ itself is non–stationary. For instance, consider the k-dimensional transitory form VECM($p-1$) presented in Eq. 5a. Substituting $\Pi = \alpha\beta'$ into Eq. 5a and rearranging terms gives

$$\alpha\beta'\mathbf{y_{t-1}} = \Delta\mathbf{y_t} - \mathbf{c} - \Gamma_1\Delta\mathbf{y_{t-1}} - \cdots - \Gamma_{p-1}\Delta\mathbf{y_{t-p+1}} - \varepsilon_\mathbf{t} \tag{7}$$

Since the right–hand side of Eq. 7 involves stationary terms only, the $\alpha\beta'\mathbf{y_{t-1}}$ term must also be stationary. It remains stationary upon premultiplication by $(\alpha'\alpha)^{-1}\alpha'$. It is because premultiplying a stationary matrix by some other matrix results again in a stationary process (Lütkepohl and Krätzig, 2004). In other words, $\beta'\mathbf{y_{t-1}}$ is stationary since it can be obtained by premultiplying the matrix $\Pi\mathbf{y_{t-1}} = \alpha\beta'\mathbf{y_{t-1}}$ with $(\alpha'\alpha)^{-1}\alpha'$. As a result, if the condition $0 < rk(\Pi) = r < k$ holds, the k-dimensional transitory form VECM($p-1$) presented in Eq. 5a is valid and should be performed.[22]

In the time series literature, the matrix β is referred to as *cointegration matrix* since $\beta'\mathbf{y_{t-1}}$ contains cointegration relations. On the other hand, the matrix α is called *adjustment matrix* which contains the weights attached to the cointegration relations in individual equations of VECM (Lütkepohl, 2005). Its elements determine the average speed of adjustment towards the long–run equilibrium. The rank of the matrix Π is known as *cointegration rank* of the process $\mathbf{y_t}$, which indicates that there are r linearly independent cointegration relations among the components of $\mathbf{y_t}$. It also means that there are r linear independent columns of β called *cointegrating vectors* and r columns of α called *adjustment vectors*. Each column of β represents one long–run relationship between the individual series of $\mathbf{y_t}$.

It is important to recognize that the factorization of the matrix Π (i.e., $\Pi = \alpha\beta'$) is not unique unless $r = 1$. In fact, for any non–singular $r \times r$ matrix Θ, we can define $\alpha^* = \alpha\Theta'$ and $\beta^* = \beta\Theta^{-1}$ and get $\Pi = \alpha^*\beta^{*\prime}$ (Lütkepohl, 2005). Hence, the factorization of the matrix Π uniquely identifies only the space spanned by the cointegration relations but not the matrices α and β. This non–unique factorization of the matrix Π shows that the cointegration relations are not unique as well. It is necessary to impose identifying restrictions on α and β to obtain unique

[22]The same conclusion applies to the k-dimensional long–run form VECM($p-1$) presented in Eq. 4a.

cointegration relations. Without such restrictions, only the cointegration matrix $\Pi = \alpha\beta'$ can be estimated uniquely.[23] The simplest method of identifying restrictions that has received some attention in the literature is called *normalization*. It assumes that the first part of β is an identity matrix such that $\beta' = [I_r : \beta^{*\prime}]$, where β^* is a $(k-r) \times r$ matrix. For instance, normalizing the matrix β yields the coefficient of the first variable to be one when $r = 1$ (Lütkepohl, 2006). The rest of the parameters of β (i.e., $\beta_{(k-r)}$) can be identified using the normalization so that inference becomes possible. The estimation of the matrix α is adjusted accordingly on the normalization of the matrix β. Hence, it depends on the matrix β.[24]

After estimating VECM$(p-1)$, while the number of cointegration relations is imposed, it can be converted back to VAR(p) form for model diagnostic tests and impulse response analysis. The converted form is often called *VECM in level–VAR form* in the literature.

3.5 Granger–Causality Tests

The concept of Granger–causality was introduced by Granger (1969) and became quite popular in the time series literature due to its easy application in the context of VAR. According to Granger–causality, if a time series y_{1t} Granger–causes a time series y_{2t}, then the past values of y_{1t} should contain information that helps to predict y_{2t} above and beyond the information contained in the past values of y_{2t} alone. In a general sense, it is a statistical hypothesis test (e.g., through a series of F–tests on the lagged values of y_{1t} and y_{2t}) for determining whether the series y_{1t} is useful in forecasting y_{2t}.

To test for Granger–causality between two stationary time series, consider a 2–dimensional version of VAR(p) presented in Eq. 1 and rewrite it with the matrix notation as follows:

$$\begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + \sum_{i=1}^{p} \begin{bmatrix} A_{11,i} & A_{12,i} \\ A_{21,i} & A_{22,i} \end{bmatrix} \begin{bmatrix} y_{1,t-i} \\ y_{2,t-i} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} \tag{8}$$

Then, y_{2t} does not Granger–cause y_{1t} if and only if the hypothesis

$$H_0 : A_{12,i} = 0 \quad \text{for} \quad i = 1, \dots, p \tag{9}$$

is true. Similarly, y_{1t} does not Granger–cause y_{2t} if and only if the hypothesis

$$H_0 : A_{21,i} = 0 \quad \text{for} \quad i = 1, \dots, p \tag{10}$$

is true. In each case, a rejection of the null hypothesis implies there is Granger–causality. A Wald test is a standard choice for testing the above hypotheses since a set of liner restrictions

[23] Although the inference for α and β separately requires identifying restrictions, such constraints for α and β are not necessary for the impulse response analysis (Lütkepohl, 2006).

[24] For the ML estimators of the matrices α and β, see Johansen (1988, 1991, 1995) and Johansen and Juselius (1990).

should be tested simultaneously. Under the null hypothesis, the Wald test statistic follows a usual asymptotic χ^2 distribution with p degrees of freedom.

Unfortunately, if any of the time series are non–stationary (whether or not they are cointegrated), then the Wald test statistic does not follow its usual asymptotic χ^2 distribution under the null hypothesis. Thus, the standard Granger–causality test inference would be invalid (Engle and Granger, 1987). However, these problems can be easily overcome as pointed out by (Toda and Yamamoto, 1995; Dolado and Lütkepohl, 1996). They introduce a modified Wald test based on lag–augmented VAR. This procedure is found to be superior to the standard Granger–causality test since it does not require stationary series. Specifically, it can be applied regardless of whether a series is stationary, non–stationary (i.e., integrated with an arbitrary order), or cointegrated. From now on, this procedure is called TYDL and the Granger–causality test performed with this procedure is called TYDL Granger–causality test.

TYDL Granger–causality test can be performed in four steps: (1) define the maximum order of integration, d_{max}, among the series[25]; (2) specify a k–dimensional VAR(p) in levels; (3) intentionally over–fit the underlying model with additional d_{max} lags, that is, fit lag–augmented VAR($p + d_{max}$); and (4) perform a standard Granger–causality test on the A_i only with p lags (i.e., ignore the extra parameters associated with the additional d_{max} lags). Overfitting the model and ignoring the extra parameters in testing for Granger–causality ensure that the Wald test statistic follows a usual asymptotic χ^2 distribution under the null hypothesis (Dolado and Lütkepohl, 1996).

It is important to note that if there is a cointegration relation between two time series, then there must be a Granger–causality between them in at least one direction. However, the converse is not true. Therefore, to assess the causality between variables and also to verify the cointegration relations suggested by formal tests, TYDL Granger–causality test is performed.

3.6 Diagnostic Tests

Once a VAR is estimated, it is of central interest to test whether the residuals obey the model assumptions with a set of diagnostic tests. That is, one should check for the absence of autocorrelation and heteroskedasticity in the model residuals, and see whether the error process is normally distributed. Therefore, univariate and multivariate versions of formal tests for residual autocorrelation, conditional heteroskedasticity, and non–normality are conducted. The univariate diagnostic tests are applied to the residuals of the individual equations whereas the multivariate versions are used to diagnose the residual vector of VAR.

Ljung–Box (LB) test by Ljung and Box (1978) is a standard tool for checking autocorrelation of residuals in VAR.[26] The null hypothesis of LB test is that all of the residual autocovariances are zero (i.e., no serial correlation). LB test jointly examines the first h lags of serial correlation

[25]For instance, if three variables are found to be $I(0)$, $I(1)$, and $I(2)$, then d_{max} would be two.

[26]The univariate LB test has been generalized to the multivariate case by Hosking (1980, 1981) and Li and Mcleod (1981).

in residual. The choice of the lag length h is crucial for the small sample properties of the test. If h is chosen too low, then the approximation to the null distribution may be poor whereas a large h reduces the power of the test. In practice, the choice of h may affect the performance of the test. However, in the literature, there is little practical advice about how to choose h for LB test; and thus, using various h values is not uncommon in practice. Therefore, several h values are employed in all of the LB tests performed in this study. One condition for the multivariate LB test is that the h value should not be less than the lag length p in VAR(p). Therefore the following h values are selected for all of the LB tests: (1) the lag length p in VAR(p); (2) $\ln(T)$ which provides better power performance as suggested by some simulation studies (Tsay, 2005); (3) ten since it is indicated by Hyndman and Athanasopoulos (2014) conducting several simulation tests; (4) the frequency of the time series data; and (5) some other arbitrarily selected values.

For testing heteroskedasticity in the univariate and multivariate cases, the autoregressive conditional heteroskedasticity Lagrange multiplier (ARCH) test is performed (Engle, 1982; Hamilton, 1994; Lütkepohl, 2005). The null hypothesis of ARCH test is that there is no ARCH effect from lag 1 to lag h; and hence, residuals are homoskedastic. Conditional heteroskedasticity is often a concern for models based on time series data with monthly or higher frequency. Therefore, to investigate the ARCH effect in the model residuals, same h values used in the LB tests are employed.

Normality test is often used for model diagnosis although it is not a necessary condition for the validity of the statistical tests or estimators pertaining to VAR. However, non–normality of the residuals may indicate other model deficiencies such as non–linearities or structural change (Lütkepohl, 2011). Therefore, Jarque–Bera (JB) normality test by Jarque and Bera (1987) is applied to test for normality of the residuals in the univariate and multivariate cases. Moreover, separate tests for only skewness and only kurtosis is performed for each case.

3.7 Impulse Response Analysis

In VAR, coefficient estimates are rarely the focus of the analysis since their interpretation is often hard due to the multidimensional system. Therefore, following Sims (1980)'s seminal paper, it is often of interest to analyze the dynamic relationships among the variables via impulse response analysis. It explains how an external one–time shock affects the dynamic path of a set of variables in a system. These dynamic paths are defined by impulse response functions (IRFs). More specifically, IRF measures the *response* of a variable as a function of time to an *impulse* in another variable, holding all else constant.

Impulse response analysis is often performed in terms of the moving average (MA) representation. For instance, the MA representation of the k-dimensional stable VAR(p) presented in Eq. 1 is given as

$$\mathbf{y_t} = \mathbf{c} + \sum_{i=0}^{\infty} \Phi_i \varepsilon_{\mathbf{t-i}} \tag{11}$$

where $\Phi_0 = I_k$; and Φ_i's are $k \times k$ matrices which contain the impulse responses. The Φ_s matrices can be computed recursively as

$$\Phi_s = \sum_{j=1}^{s} \Phi_{s-j} A_j \quad \text{for} \quad s = 1, 2, \ldots \tag{12}$$

where $A_j = 0$ for $j > p$; and s indicates the time ahead from the impulse[27]. The $(i, j)^{\text{th}}$ coefficients of the matrix Φ_s is interpreted as the expected response of variable $y_{i,t+s}$ to a unit shock in variable y_{jt}. Thus, the matrix $\Phi_{ij,s} = \frac{\partial y_{i,t+s}}{\partial \varepsilon_{jt}}$ as a function of s is called the impulse response function. An important note is that if VAR is stable, then the IRFs should converge to zero as the time from the impulse s gets large, that is, the effect of an impulse is *transitory*. However, the impact of a one–time shock in VECM may lead to *permanent* changes in some or all of the variables, that is, it shifts the system to a new equilibrium (Lütkepohl and Reimers, 1992; Lütkepohl, 2005).

In order to evaluate the dynamic relationships among the variables of a model, the standard IRFs are used with a 90% confidence interval generated with 10000 bootstrap replications.

4 Estimation and Results for the Entire Data

Using the entire data and assuming no structural break, this section presents the results of all empirical methods explained in Section 3. One important point is that the reliability of these results is in question due to the assumption of no structural breaks. However, these results can still be considered helpful to compare the internal dynamics of the system to the cases before and after the structural break occurred.

Before testing each series for unit root, the seasonal unit root tests are performed. None of the series are found to have a seasonal unit root in the Osborn–Chui–Smith–Birchenhall and the Canova–Hansen seasonal unit root tests. Thus, there is no need for seasonal differencing in any of the series.

The EAP is first used to reveal whether each series is a TSP or a DSP. These results are omitted since none of the series with any lag lengths are found to be a TSP at the 5% significance level. Thus, all series are concluded to be either a stationary process or a DSP. This conclusion suggests that if any of the series are found to be a unit root process in formal tests, the first differencing method should be used to generate a stationary series. Table 3 presents the ADF unit root test results with EAP for each series. All series except *PACS* show evidence for having a unit root at the 5% significance level. The PP unit root test results for each series are presented in Table 4. These results indicate that *Shiller*, *CB*, and *WPU1331* have a unit root since the null hypothesis cannot be rejected at any conventional significance levels. However, the rest of the

[27] In VAR, an impulse in a variable is induced through the residual vector $\varepsilon_{\mathbf{t}} = (\varepsilon_{1t}, \ldots, \varepsilon_{kt})'$. For instance, a non–zero element of $\varepsilon_{\mathbf{t}}$ yields an equal change in the associated left–hand side variable. Then, it induces further changes in the other variables of the system in the next periods.

variables seem to be stationary. Table 5 presents the ERS unit root test results for each series, which are similar to the PP unit root test results. The KPSS stationary test results for each series are presented in Table 6. These results are substantially different from the results of the previous two tests. In almost all of the tests, *Shiller*, *CB*, *WPU1331*, *LAES*, and *PAAB* have a unit root since the null hypothesis is rejected at the 1% significance level. However, *PACS* seems to be stationary only when a trend is used as the deterministic part.

When the results of the unit root and stationary tests are considered, it is decided that all of the series exhibit a unit root process. In order to confirm this conclusion, the unit root and stationary tests are employed once again for the first–differenced series.[28] Table 27 through Table 30 present the ADF, PP, and ERS unit root tests and KPSS stationary test results of the first–differenced series. The results of these tests confirm each other and suggest that all of the first–differenced series are stationary, except *Shiller*. According to the ADF unit root and KPSS stationary test results, the first–differenced *Shiller* is still non–stationary. However, some of the PP and ERS unit root test results suggest that it is stationary.

In solving the puzzle created with these conflicting results, some of the previous studies in the economics literature are utilized. Using the quarterly housing prices data from 1976 to 1999 for the U.S., Meen (2002) finds that housing prices follow a DSP and should be first–differenced. Moreover, in an influential paper, Nelson and Plosser (1982) provide statistical evidence that many U.S. macroeconomic time series exhibit a unit root process. Therefore, following the literature and considering the results presented above, it is concluded that all of the series are $I(1)$.

After all of the series are confirmed to exhibit a unit root process, the Johansen trace cointegration and TYDL Granger–causality tests are performed. However, before turning to the multidimensional system (i.e., 6-dimensional VECM), cointegration tests on all pairs of series are applied. It is because that cointegration tests tend to have relatively low power, especially in multidimensional systems. Thus, performing tests on bivariate systems first works as a check procedure for the overall consistency of the results obtained in the multidimensional system (Lütkepohl and Krätzig, 2004). Similarly, to assess causalities between the pairs of series, pairwise TYDL Granger–causality tests are performed. As noted before, BIC is used to determine the lag length for each pair in both tests. Table 31 and Table 32 present the pairwise Johansen trace cointegration and TYDL Granger–causality test results. What stands out in these tables is that *Shiller* has a cointegration relation with all of the building materials (i.e., *LAES*, *PAAB*. *PACS*, and *WPU1331*). In overall, it is also confirmed by the TYDL Granger–causality tests that there are bidirectional Granger–causalities between *Shiller* and these variables. Therefore, it can be said that there should be some cointegration relations and related Granger–causalities between these variables in the multidimensional system as well.

The Johansen trace cointegration test is performed to determine the number of cointegration

[28]The first differencing method is used instead of detrending since it is the most commonly used method of making series stationary in the literature and the EAP suggested that all of the series are a DSP.

relations in the multidimensional system. One important point is that cointegration tests are sensitive to the lag length selection. Therefore, the Johansen trace cointegration test is conducted with arbitrarily selected lag lengths to investigate the number of cointegration in the multidimensional system as a robustness check. As it can be seen in Table 7, there are only two cointegration relations up to six lags at the 5% significance level. Hence, using BIC for the lag length selection and choosing the respective number of cointegration relation in Table 7, it is decided that the multidimensional system has one lag and two cointegration relations. A TYDL Granger–causality test is performed to confirm the cointegration relations found in the Johansen trace cointegration test. Similar to the pairwise case, Table 8 shows that there are bidirectional Granger–causalities between *Shiller* and the building materials in overall. Moreover, the results also suggest a bidirectional Granger–causality between *WPU1331-PAAB* and a unidirectional one between *PACS-WPU1331*.

The two preconditions of VECM are satisfied since there is statistical evidence that all of the variables are $I(1)$ and some of them are cointegrated. Hence, a 6-dimensional VECM is estimated with one lag and imposing the two cointegration relations (i.e., VECM(1)). Table 9 presents the VECM(1) results along with some model statistics. The adjustment matrix α, cointegration matrix β, and composite matrix Π are shown in Table 33, Table 34, and Table 35 respectively. Then, the VECM(1) is converted back to VAR for model diagnostic tests and impulse response analysis. Table 10 presents the coefficient estimates of VECM(1) in level–VAR form.

A series of multivariate and univariate diagnostic tests for the model residuals are presented in Table 11. According to the results, there appears to be a statistically significant serial correlation, conditional heteroskedasticity, and non–normality in the multivariate case, except the ARCH test with twelve lags concludes that the residuals are homoskedastic. The results for the univariate case is similar for the *Shiller*, *PAAB*, and *PACS* equations. In other equations; however, it seems that there is no serial correlation in the residuals. Moreover, *WPU1331* and *LAES* equations have homoskedastic residuals for only some lag lengths. In general, these results suggest that the lag length specified for the VECM(1) should be increased. Therefore, the same model is estimated with various higher lag lengths. However, the TYDL Granger–causality test results and impulse responses stay almost the same, but only the number of cointegration relations increased to three. Therefore, impulse response analysis is conducted on the above–presented model.

As noted before, it is difficult to interpret the coefficient estimates in multidimensional systems. Therefore, the standard IRFs are applied to the estimates of the VECM(1) in level–VAR form to compute responses over time in all variables to a one-unit positive shock in one of the variables. An important point is that all variables are employed in the natural logarithmic form in the estimation of VECM(1). Thus, a one-unit positive shock in natural logarithmic form can be approximated by a 1% positive shock in levels. Using the approximation, all IRFs in this study are interpreted in percentages.

Figure 4 illustrates the responses of all variables to a 1% positive shock in each variable individually.[29] What stands out in these results is that all responses are positive, and after some time they become permanent effects (i.e., they reach a new long–run equilibrium) as expected due to the cointegration relations in the system. Among all of the variables, *Shiller Index* has the most substantial impacts on all variables, including itself. Specifically, a 1% positive shock in *Shiller Index* results in a gradually increasing effect on itself, and then it turns into a permanent impact around 7.5% level. On the other hand, the same shock causes immediate 7%, 2.5%, and 6% increases in *Lumber Price*, *Plywood Price*, and *OSB Price* respectively, and then the responses become permanent around 7.5%, 7%, and 7.5% levels. The impacts on *Plywood Price* and *OSB Price* become statistically insignificant after nine and two months respectively whereas it stays statistically significant for *Lumber Price*. One interesting result is that the same impulse creates a small impact, approximately a 1% rise, on *Concrete Price Index* and stays statistically significant in the next months.

The results indicate that a 1% positive shock in *Concrete Price Index* generates statistically significant responses only in *Shiller Index*, *Lumber Price*, and itself. The responses in *Shiller Index* and *Concrete Price Index* gradually increase and turn into permanent impact around 2% and 1% levels respectively. However, the immediate rise in *Lumber Price*, around 3%, becomes statistically insignificant after the first month.

The intriguing impulse responses are among *Lumber Price*, *Plywood Price*, and *OSB Price*. A 1% positive shock in *Lumber Price* generates immediate 0.35% and 0.7% increases in *Plywood Price* and *OSB Price* respectively, which become permanent around 0.55% and 0.4% levels. The response of *Lumber Price* to its own impulse gradually decreases and reaches a permanent impact around 0.6% level. The effect of *Lumber Price* on *Shiller Index* starts from a low positive level and gradually increases until 0.2% in the next months. A similar shock in *Plywood Price* results in immediate 0.75% and 1.75% increases in *Lumber Price* and *OSB Price* respectively. However, they turn into permanent impacts around 0.5% and 1.6% levels. Its own response stays almost same throughout the months considered. A 1% positive shock in *OSB Price* generates a 0.4% increase in *Plywood Price* and stays the same in the next months. However, the same impulse results in an immediate 0.3% rise in *Lumber Price*, but it gradually decreases to 0.15% level and becomes statistically insignificant after five months. Moreover, it seems that *Shiller Index* has a small positive but gradually increasing response, about 0.1%, to the same impulse in *OSB Price*. An interesting result is that *Concrete Price Index* has a small but gradually increasing response, around a 0.1% rise, to the impulses in *Lumber Price*, *Plywood Price*, and *OSB Price* separately.

[29] Since the ultimate aim of this paper is to understand the dynamic relations between housing prices and building materials, the focus will be on those variables while interpreting the impulse responses. Also, all the reported responses are positive and statistically significant unless stated otherwise.

5 Structural Break Tests

A structural break occurs when there is an abrupt change in a time series, a regression or even a system of equations in a point of time. It can involve a change in mean and a change in the other parameters of the process of interest which in turn reduces the reliability of the empirical analyses.

Before testing for a single structural break in the multivariate system (i.e., 6-dimensional VECM(1) presented in Section 4), each variable is individually tested for structural breaks through various univariate structural break tests, which are conducted only on the mean of the variable of interest. The reasoning of performing these tests is to see whether each variable individually exhibits some breaks which are close to the single break found in the multivariate system. One important note is that, following the literature, the present study assumes that all of the structural breaks detected by formal tests are immediate. The following subsections briefly describe all of the structural break tests applied and then presents the results.

5.1 Univariate Structural Break Tests

As noted above, a break in only the mean of the variable of interest is tested in the univariate structural break tests. That is, each variable is regressed only on the intercept and then tested for structural breaks. The univariate structural break test procedure for each variable is conducted in three steps with three sets of tests which are Empirical Fluctuation Process (EFP) test, F–Statistics (FS) based tests, and maximum likelihood score (MLS) tests.[30]

In the first step, four tests are conducted to find evidence of at least one structural break. These tests are Rec–CUSUM test[31] by Brown et al. (1975) and a set of FS–based tests[32] by Andrews (1993) and Andrews and Ploberger (1994). The results are presented in Table 12. All of the tests suggest strong statistical evidence of at least one structural break for each variable.

In the second step, the total number of breaks and the single break date is estimated using Bai–Perron (BP) structural break test by Bai and Perron (1998, 2003a,b, 2004). The total number of breaks are determined by BIC and residual sum of squares, where the maximum number of breaks allowed is five. Similarly, the single brake date is estimated by fixing the maximum number of breaks to one. Table 13 presents the BP structural break test results which confirm the conclusion given in the first step, that is, there is at least one structural break for each variable. The single break dates for all variables are clustered around the first half of the 2000s. Specifically, *Shiller* has the earliest break date (i.e., 04-2002) whereas *PACS* has the latest break date (i.e., 06-2006). One important point is that the single break date for the variables other than *Shiller* and *PAAB* are clustered between the second half of 2004 and 2006. Moreover, the single break dates for the building material variables are later than it is with *Shiller*. It is an expected

[30] See Zeileis (2005) and Zeileis et al. (2005) for a detailed literature review and application of these tests.
[31] The Rec–CUSUM test is an EFP test based on the cumulative sums of recursive residuals.
[32] These are SupF, ExpF, and AveF tests.

result since any break in housing prices eventually affects the building material prices in the later periods.

In the third step, the break dates determined by the BP structural break tests are once again tested for structural breaks using Chow structural break test (i.e., an FS–based test) by Chow (1960) and Nyblom–Hansen Stability (NHS) test[33] (i.e., an MLS based test) by Nyblom (1989) and Hansen (1992). For each variable, tests conclude that these break dates are statistically significant at all conventional significance levels.[34] Finally, each variable is tested for a structural break on the single break date identified for VECM (i.e., 09-2007) using Chow structural break test and NHS test.[35] Table 14 presents the results with additional dates, one month before and after the date of interest[';]. The results of both tests suggest that the break on 09-2007 is statistically significant in all conventional levels for each variable individually.

Figure 8 through Figure 13 present two plots for each variable. The first plot displays the break dates when the maximum number of breaks is fixed to one versus five. This plot also illustrates the mean of the variable of interest without any break versus means before and after the single break date. The second plot displays the F–Statistics found in the FS–based tests as well as the date with the highest F–Statistics. These two plots visually support the results of all structural break tests and most importantly they show that a single structural break in each variable has occurred earlier than the start of the Great Recession, 12-2007.

5.2 Structural Break Tests in VECM

Issues related to structural breaks in regressions have been extensively studied in the econometrics literature.[36] Various methods for identifying structural breaks in a single regression model have been well documented in Bai and Perron (1998, 2003a,b, 2004) and Perron and Qu (2006). However, only a few studies such as Bai et al. (1998, 2000) and Qu and Perron (2007) have dealt with structural breaks in a system of equations. The method used in these studies relies on the assumption of common breaks[37] under which breaks in different parameters[38] occur at the same date. Bai et al. (1998) provide the details of a method that assumes a single break in a multivariate system with stationary regressors. On the other hand, Bai et al. (2000) develop a method of detecting multiple structural breaks in vector autoregressive models with stationary variables.

Qu and Perron (2007) develop a novel approach for detecting multiple structural breaks occurring at unknown dates in linear multivariate regression models with stationary variables.

[33]Nyblom (1989) derives a Lagrange Multiplier test based on MLS for the alternative that the parameters follow a random walk, which is later extended by Hansen (1992) for linear regression models.

[34]These results are omitted to preserve space but available upon request.

[35]See Section 5.2.3 for the details about how the single break date in VECM is estimated.

[36]See, Perron (2006) for a comprehensive literature review.

[37]A common break refers to a break that occurs in all equations at the same date. Throughout this study, breaks are assumed to occur in all equations; and hence; the term *common* is omitted.

[38]These parameters are the regression parameters and the covariance parameters (i.e., the parameters of the covariance matrix of the errors).

The Qu and Perron (2007) methodology allows structural breaks to occur in three scenarios: (1) breaks occurring only in the regression parameters; (2) breaks occurring only in the covariance parameters; and (3) breaks occurring in both the regression and covariance parameters simultaneously. One advantage of the Qu and Perron (2007) methodology is that the dates and the number of breaks are endogenously estimated rather than being imposed ex–ante like some of the methods used in the time series literature. Moreover, it allows the distribution of regressors to differ across regimes and the error process to be autocorrelated as well as conditionally heteroskedastic.

The Qu and Perron (2007) methodology can be applied to various models since it permits incorporating arbitrary valid restrictions on the model parameters. For instance, it can be applied to any VAR with multiple structural breaks where a subset of the parameters does not change across regimes. In essence, the Qu and Perron (2007) methodology is more flexible than those found in the previous studies. It should be emphasized that it encompasses the simpler univariate structural break tests that are presented in Section 5.1. The following subsections present a brief description of the Qu and Perron (2007) methodology and how it is applied in this study.

5.2.1 Model Setup and Estimation

In order to test for multiple structural breaks in VAR with the Qu and Perron (2007) methodology, consider the k-dimensional VAR(1) presented in Eq. 13. It can be extended to a general VAR(p) without any major difficulties.

$$\mathbf{y_t} = \mathbf{c} + A_1 \mathbf{y_{t-1}} + \varepsilon_\mathbf{t} \tag{13}$$

Assume that the dates and the total number of breaks in parameters are unknown in the system. As a matter of notation, let m denote the total number of structural breaks, T denote the sample size, and k denote the number of equations. A subscript j indexes a regime $j = (1, \dots, m+1)$, a subscript t indexes a temporal observation $t = (1, \dots, T)$, and a subscript i indexes the equation $i = (1, \dots, k)$ to which a scalar dependent variable y_{it} is associated. The break dates are denoted by the vector $\mathcal{T} = (T_1, \dots, T_m)$, where $T_0 = 1$ and $T_{m+1} = T$. Hence, there are $m + 1$ unknown regimes with $T_{j-1} + 1 \leq t \leq T_j$ for $j = (1, \dots, m+1)$. The parameter q denotes the number of regressors and $\mathbf{z_t} = (z_{1t}, \dots, z_{qt})'$ is the set of regressors from all equations.[39] Consequently, the model in Eq. 13 can be written in a concise form as

$$\mathbf{y_t} = (I_k \otimes \mathbf{z_t'}) S \beta_\mathbf{j} + \varepsilon_\mathbf{t} \tag{14}$$

where I_k is a $k \times k$ identity matrix; $\beta_\mathbf{j}$ is a $p \times 1$ vector of regression parameters[40] in regime j, where p is the total number of regression parameters used in the system; and $\varepsilon_\mathbf{t}$ is the error

[39] For any VAR, $\mathbf{z_t}$ contains the deterministic terms and the lagged variables. For instance, it becomes $\mathbf{z_t} = (1, y_{1t-1}, \dots, y_{kt-1})'$ for the k-dimensional VAR(1) presented in Eq. 13.

[40] It becomes $\beta_\mathbf{j} = (c_{1j}, A_{11,j}, A_{12,j}, \dots, A_{1k,j}, \dots, c_{kj}, A_{k1,j}, A_{k2,j}, \dots, A_{kk,j})'$ for the k-dimensional VAR(1) presented in Eq. 13

terms with zero mean and covariance matrix Σ_j, which defines the covariance matrix in regime j. The matrix S is of dimension $kq \times p$ with full column rank. It is used to specify which regressors appear in each equation by involving elements that are zero or one. Hence, it is called *selection matrix*.[41] The Qu and Perron (2007) methodology also allows the imposition of a set of r parameter restrictions in the form of

$$g(\beta, vec(\Sigma)) = 0 \tag{15}$$

where $\beta = (\beta_1', \ldots, \beta_{m+1}')'$; $\Sigma = (\Sigma_1, \ldots, \Sigma_{m+1})$; and $g(\cdot)$ is an r–dimensional vector.

The ultimate aim of the Qu and Perron (2007) methodology is to estimate $\Psi = \{\widehat{m}, \widehat{\mathcal{T}}, \widehat{\beta}, \widehat{\Sigma}\}$. For now, suppose that m is known. The estimation of m will be discussed in the next subsection. For the estimation of Eq. 14, it is convenient to rewrite the model as

$$\mathbf{y_t} = \mathbf{x_t'}\beta_\mathbf{j} + \varepsilon_\mathbf{t} \tag{16}$$

where $\mathbf{x_t'} = (I_k \otimes \mathbf{z_t'})S$. To estimate Eq. 16, the Qu and Perron (2007) methodology employs restricted quasi–maximum likelihood assuming serially uncorrelated and normally distributed errors. Then, conditional on the given break dates $\mathcal{T} = (T_1, \ldots, T_m)$, the quasi–likelihood function is defined as

$$L_T(\mathcal{T}, \beta, \Sigma) = \prod_{j=1}^{m+1} \prod_{t=T_{j-1}+1}^{T_j} f\left(y_t | x_t; \beta_j, \Sigma_j\right) \tag{17}$$

where

$$f(y_t|x_t; \beta_j, \Sigma_j) = \frac{1}{(2\pi)^{k/2}|\Sigma_j|^{1/2}} \exp\left\{-\frac{1}{2}\left[y_t - x_t'\beta_j\right]' \Sigma_j^{-1}\left[y_t - x_t'\beta_j\right]\right\} \tag{18}$$

and the quasi–likelihood ratio is

$$LR_T = \frac{\displaystyle\prod_{j=1}^{m+1} \prod_{t=T_{j-1}+1}^{T_j} f\left(y_t | x_t; \beta_j, \Sigma_j\right)}{\displaystyle\prod_{j=1}^{m+1} \prod_{t=T_{j-1}^0+1}^{T_j^0} f\left(y_t | x_t; \beta_j^0, \Sigma_j^0\right)} \tag{19}$$

where $\mathcal{T}^0 = (T_1^0, \ldots, T_m^0)$, β_j^0, and Σ_j^0 indicate the true unknown parameters. Then, the aim is to estimate the values of $(T_1, \ldots, T_m, \beta, \Sigma)$ that maximizes LR_T subject to restrictions $g(\beta, vec(\Sigma)) = 0$. Let $lr_T(\cdot)$ denote the log–likelihood ratio and $rlr_T(\cdot)$ denote the restricted

[41] For any VAR, the matrix S becomes a $p \times p$ identity matrix I_p since VAR uses all of the regressors in each equation by construction (i.e., $kq = p$).

log–likelihood ratio. Then, the objective function is defined as

$$rlr_T(\mathcal{T}, \beta, \Sigma) = lr_T(\mathcal{T}, \beta, \Sigma) + \lambda' g(\beta, vec(\Sigma)) \tag{20}$$

and the estimates are

$$\left(\widehat{\mathcal{T}}, \widehat{\beta}, \widehat{\Sigma}\right) = \underset{(T_1,\ldots,T_m;\beta;\Sigma)}{\operatorname{argmax}} \; rlr_T(\mathcal{T}, \beta, \Sigma) \tag{21}$$

The maximization of Eq. 21 is taken over all partitions $\mathcal{T} = (T_1, \ldots, T_m) = ([T\lambda_1], \ldots, [T\lambda_m])$ in the set

$$\Lambda_\epsilon = \left\{(\lambda_1, \ldots, \lambda_m); |\lambda_{j+1} - \lambda_j| \geq \epsilon,\ \lambda_1 \geq \epsilon,\ \lambda_m \leq 1 - \epsilon\right\} \tag{22}$$

where ϵ is an arbitrarily small positive number between zero and one; and [ ] denotes the integer part of the argument. The parameter ϵ is a trimming fraction that imposes a minimal length for each regime. Thus, it is called *trimming parameter*. An important result of the Qu and Perron (2007) methodology is that the estimates of the break dates $\mathcal{T} = (T_1, \ldots, T_m)$ are not affected by the restrictions imposed on the parameters β and Σ. Instead, the estimates of the break dates are only affected by the underlying structure of the system.

5.2.2 Selection of the Total Number of Breaks

In order to estimate the total number of breaks m, Qu and Perron (2007) use a likelihood ratio test of no structural breaks against m structural breaks. For the given partitions $\mathcal{T} = (T_1, \ldots, T_m) = ([T\lambda_1], \ldots, [T\lambda_m])$, the model can be estimated by quasi–maximum likelihood with the parameter restrictions. Thus, the test is the maximum value of the likelihood ratio over all admissible partitions in the set Λ_ϵ defined in Eq. 22. Then, the test can be constructed as

$$\begin{aligned} \sup LR_T(m, p_b, n_{bd}, n_{bo}, \epsilon) &= \sup_{(\lambda_1,\ldots\lambda_m)\in\Lambda_\epsilon} 2\left[\log \widehat{L}_T\left(\widehat{T}_1, \ldots, \widehat{T}_m\right) - \log \widetilde{L}_T\right] \\ &= 2\left[\log \widehat{L}_T\left(\widehat{T}_1, \ldots, \widehat{T}_m\right) - \log \widetilde{L}_T\right] \end{aligned} \tag{23}$$

where $\log \widehat{L}_T(\widehat{T}_1, \ldots, \widehat{T}_m)$ is the maximum of the log–likelihood obtained by considering only those partitions in Λ_ϵ; $\log \widetilde{L}_T$ is the maximum of the log–likelihood under the null hypothesis of no structural breaks; p_b is the total number of regression parameters that are allowed to change; and n_{bd} and n_{bo} respectively indicate the total number of diagonal and off–diagonal parameters of the covariance matrix of the errors that are allowed to change. As noted before, the Qu and Perron (2007) methodology is particularly flexible in testing many cases of structural breaks. For instance, using the $\sup LR_T(m, p_b, n_{bd}, n_{bo}, \epsilon)$ test, it is possible to test: (1) breaks only in the regression parameters (i.e., $n_{bd} = 0$ and $n_{bo} = 0$); (2) breaks only in the covariance parameters (i.e., $p_b = 0$); and (3) breaks in both the regression and covariance parameters simultaneously (i.e., $p_b \neq 0$, $n_{bd} \neq 0$, and $n_{bo} \neq 0$), which is called *complete pure structural break*.

In empirical applications, it is often the case that the total number of breaks in the system is unknown. Therefore, it needs to be determined by a statistical procedure. In this regard, Qu and Perron (2007) consider a sequential testing procedure based on the null hypothesis of ℓ breaks versus the alternative hypothesis of $(\ell + 1)$ breaks. The procedure performs a one break test for each of the $(\ell + 1)$ segments defined by the partition $(\widehat{T}_1, \ldots, \widehat{T}_\ell)$ and assesses whether the maximum of the tests is significant. More precisely, the test is defined as

$$SEQ_T(\ell + 1 \mid \ell) = \max_{1 \le j \le \ell+1} \sup_{\tau \in \Lambda_{j,\epsilon}} lr_T\left(\widehat{T}_1, \ldots, \widehat{T}_{j-1}, \tau, \widehat{T}_j, \ldots, \widehat{T}_\ell\right) - lr_T\left(\widehat{T}_1, \ldots, \widehat{T}_\ell\right) \tag{24}$$

where $lr_T(\cdot)$ denotes the log–likelihood ratio; $(\widehat{T}_1, \ldots, \widehat{T}_\ell)$ denotes the optimal partition if ℓ breaks are assumed; and $\Lambda_{j,\epsilon} = \{\tau; \widehat{T}_{j-1} + (\widehat{T}_j - \widehat{T}_{j-1})\epsilon \le \tau \le \widehat{T}_{j-1} - (\widehat{T}_j - \widehat{T}_{j-1})\epsilon\}$.

Qu and Perron (2007) also consider a set of tests based on the null hypothesis of no breaks against the alternative hypothesis of an unknown number of breaks given some upper–bound M for m. These tests are called *double maximum tests* since they are based on the maximum of the weighted individual tests for the null hypothesis of no breaks against $m = (1, \ldots, M)$ breaks. The general form of the double maximum test is given as

$$D \max LR_T(M) = \max_{1 \le m \le M} \alpha_m \sup LR_T(m, p_b, n_{bd}, n_{bo}, \epsilon) \tag{25}$$

where α_m denotes the weight for $m = (1, \ldots, M)$. For equal weights (i.e., $\alpha_m = 1$), the test is denoted by $UD \max LR_T(M)$. Whereas, the test is denoted by $WD \max LR_T(M)$ if it applies weights to the individual tests such that the marginal p–values are equal across values of m. A detailed discussion of these tests can be found in Bai and Perron (1998, 2003b).

In practice, Qu and Perron (2007) suggest using the following strategy to determine the number of structural breaks. First, perform one of the double maximum tests to see if at least one break is present. If the test rejects, then the number of breaks can be decided based on testing $SEQ_T(\ell + 1 \mid \ell)$ sequentially until there is no rejection of the null hypothesis.[42] According to Bai and Perron (1998, 2003b), this method leads to the best results and is recommended for empirical applications. However, in the case of VAR with some parameter restrictions, Qu and Perron (2007) suggest using only the $\sup LR_T(m, p_b, n_{bd}, n_{bo}, \epsilon)$ test presented in Eq. 23 to obtain the dates and the total number of structural breaks.[43]

5.2.3 The Application

The present study considers the Qu and Perron (2007) methodology as the primary econometric tool for detecting a single structural break in VECM since it allows imposing arbitrary restrictions on the model parameters and has less restrictive assumptions placed on the error terms. By

[42] In sequential testing, ignore the $SEQ_T(1 \mid 0)$ test and select m such that the $SEQ_T(\ell+1 \mid \ell)$ tests are insignificant for $m \le \ell$).

[43] GAUSS code for the Qu and Perron (2007) methodology and some other explanatory documentation can be found in URL: `https://goo.gl/sJw3eQ`.

construction, the Qu and Perron (2007) methodology best applies to VAR in levels or VAR in first differences since it has an essential precondition. That is, all regressors should be stationary; otherwise, the structural break tests will not be valid.[44] Nevertheless, it can also be applied to VECM with non–stationary and cointegrated variables by imposing valid restrictions on the long–run parameters. VECM satisfies the precondition of stationary regressors by construction since all of the first–differenced terms and the long–run term are stationary, assuming that there is at least one cointegration relation among the variables. However, to ensure the long–run equilibrium of the DGP, all of the long–run parameters (e.g., the parameters of the $\Pi\mathbf{y_t}$ term in Eq. 5a) should be restricted to be constant across regimes while allowing short–run parameters (e.g., the parameters of the Γ_i terms in Eq. 5a) to change across regimes.[45] Fortunately, such a restriction does not affect the estimates of breaks dates as noted before.

An important issue arises while applying the Qu and Perron (2007) methodology to the 6-dimensional VECM(1) presented in Section 4, that is, the curse of dimensionality. In this methodology, the critical values are tabulated using a response surface analysis with the number of regressors not exceeding ten. However, if the actual number is greater than ten, then the reported critical values will not be valid. More precisely, using a 6-dimensional VECM with any lag lengths yields more than ten regressors; and thus, applying any of the structural break tests presented in the previous sections would give invalid results.[46]

Under these conditions, the maximum number of variables that can be used is four (e.g., a 4-dimensional VECM(1) has nine regressors). Therefore, instead of detecting a single structural break in the 6-dimensional VECM(1), the data are separated into various subsamples such that each subsample contains only two, three, or four variables. As a result of this, the dimension of the system is reduced. In each subsample, *Shiller* is included as the first variable, and the rest of the variables are added to cover any possible variable combinations. Then, for each subsample, a lower–dimensional model is constructed using the same lag length that is used in the higher–dimensional model (i.e., 6-dimensional VECM(1)). Finally, for each lower–dimensional model, the structural break tests are performed under the following conditions: (1) the maximum number of breaks is fixed to $m = 1$ in order to target the Great Recession only; (2) all of the long–run parameters are restricted to be constant across regimes; (3) the short–run and covariance parameters are allowed to change across regimes; (4) the trimming parameter is fixed to $\epsilon = 0.25$ in order to prevent possible size distortions of structural break tests (Bai and Perron, 2003b); and (5) only the $\sup LR_T(m, p_b, n_{bd}, n_{bo}, \epsilon)$ test presented in Eq. 23 is used to determine the date of the single structural break as it is suggested by Qu and Perron (2007). The reasoning of this procedure is to determine a single structural break that is statistically significant across

[44]See, assumption A1 in Qu and Perron (2007).

[45]Pierre Perron, one of the authors of Qu and Perron (2007), confirmed that such an application of the Qu and Perron (2007) methodology satisfies the model assumptions.

[46]For instance, the 6-dimensional VECM(1) presented in Section 4 has thirteen regressors, where six of them are the first differences, six of them are in the long–run part, and one constant term. Nevertheless, the Qu and Perron (2007) methodology is applied, and extreme negative critical values are observed for each structural break test.

lower–dimensional models constructed with various subsamples. By doing so, it can be inferred that the higher–dimensional model should have the same break date or at least a close one.

In total, twenty-five lower–dimensional models are constructed. Before performing the structural break tests, the Johansen Cointegration test is conducted to ensure the validity of each model. Only one model does not exhibit any cointegration relationship, which is the model with *Shiller–CB* variable combination. The rest of the models do not have full rank and also show at least one cointegration relationship (i.e., $0 < rk(\Pi) = r < k$) at conventional significance levels; and thus, VECM can be applied. The models with some cointegration relations (i.e., twenty-four of them) are tested for a single structural break as described above. In twenty-two models, 09-2007 is identified as the single structural break date at the 1% significance level. The the model with *Shiller–WPU1331* variable combination does not exhibit a statistically significant break date even though the estimated break date is again the same.

As a result, 09-2007 is selected as the single structural break date for the 6-dimensional VECM(1), which is a close estimation for the start of the Great Recession, 12-2007. The results of this section suggest that the housing market prices and the prices for the primary building materials as a system have experienced a critical structural break in the third quarter of 2007. Therefore, it can be said that at least the short–run price dynamics of these variables have been altered dramatically, and the 6-dimensional VECM(1) applied to the entire data might not be adequate to capture the true price dynamics of these markets. In order to capture the price dynamics before and after the structural break and to compare them, the data are separated into two segments on the structural break date.

6 Estimation and Results for Each Segment

After the structural break date is determined using the Qu and Perron (2007) methodology and the procedure mentioned in the previous subsections, the data are split into two segments on 09-2007 (i.e., the 153$^{\text{rd}}$ observation). Then, the same empirical analyses are conducted on each segment as it is done for the entire data in Section 4. While separating the data into two segments, no transition period is considered. Therefore, the start and the end dates of the 1$^{\text{st}}$ segment are 01-1995 and 08-2007 respectively, and the same dates for the 2$^{\text{nd}}$ segment are 09-2007 and 11-2015. Table 15 and Table 16 present the descriptive summary of the data for each segment.

6.1 Segment 1

This section presents the empirical results for the 1$^{\text{st}}$ segment.

Each series is tested for seasonal unit root with two tests mentioned before, and none of the series are found to have a seasonal unit root in any of the tests. The results of the unit root and stationary tests are omitted since they are similar to the results presented for the entire data (see, Table 3 through Table 6 and Table 27 through Table 30). Thus, it is concluded that each series in the 1st segment is $I(1)$ and the precondition of performing cointegration tests is satisfied.

In order to determine the number of cointegration relations in the multidimensional system, the Johansen trace cointegration is performed with various lag lengths. In overall, the test results presented in Table 17 suggest that there are only two cointegration relations at the 5% significance level. Thus, selecting the lag length with BIC and deciding the number of cointegration relations respectively in Table 17, it is concluded that the multidimensional system in the 1st segment has one lag and two cointegration relations. Then, TYDL Granger–causality tests are performed to reveal causalities between the variables and confirm the cointegration test results. The results in Table 18 show that there are bidirectional Granger–causalities between *Shiller* and the building materials. In essence, these are the only variables that exhibit a Granger–causality in the system.

Since the assumptions of VECM are satisfied, a 6-dimensional VECM is estimated with one lag and imposing the two cointegration relations (i.e., VECM(1)) for the 1st segment. The VECM(1) results along with some model statistics are presented in Table 19. The adjustment matrix α, cointegration matrix β, and composite matrix Π are presented in Table 36, Table 37, and Table 38 respectively. Then, the VECM(1) is converted back to VAR. Table 20 shows the coefficient estimates of VECM(1) in level–VAR form.

The multivariate and univariate diagnostic tests for the model residuals are given in Table 21. The results suggest that there are statistically significant serial correlation and non–normality in the multivariate case. However, ARCH test indicates that the model residuals are homoskedastic after six lags. In the univariate case, these problems are weakened. Specifically, the residuals of *CB*, *WPU1331*, and *LAES* equations show no serial correlation. Moreover, the equations other than *PAAB* and *PACS* exhibit homoskedastic residuals. In general, it seems that the problems with the model residuals are mitigated after the data are split into two on the structural break date.

Finally, impulse response analysis is performed for the 1st segment. Figure 5 illustrates the responses of all variables to a 1% positive shock in each variable individually.[47] The results show that, among all of the variables, *Shiller Index* has the most significant impact on other variables, including itself. A 1% positive shock in *Shiller Index* creates a gradually increasing impact on itself, which finally turns into a permanent change around 10% level. The same shock yields an immediate 15% increase in *Lumber Price* which then becomes statistically insignificant after seven months. On the other hand, the impacts on *Plywood Price* and *OSB Price* become statistically significant only after a couple of months and increase to 18% and 30% until the next nine and five months respectively, then they become statistically insignificant. A 1% positive shock in *Concrete Price Index* generates a statistically significant impulse only on *Shiller Index*, other than itself, which in turn becomes a permanent impact around 2.5% level.

Again, the most intriguing impulse responses are among *Lumber Price*, *Plywood Price*,

[47]As noted in Section 4, all IRFs are interpreted in percentages, and all of the reported responses are positive and statistically significant unless stated otherwise. Also, while interpreting the impulse responses, the focus will be on *Shiller Index*, *Concrete Price Index*, *Lumber Price*, *Plywood Price*, and *OSB Price*.

and *OSB Price*. A 1% positive shock in *Lumber Price* leads to an immediate 0.5% increase in *Plywood Price* which later becomes a permanent increase around 0.75% level. On the other hand, the same impulse produces an immediate 1% increase in *OSB Price* which stays the same in the next months. The response of *Lumber Price* to its impulse gradually declines and reaches a permanent level around 0.7%. The impact of *Lumber Price* on *Shiller Index* starts from a low positive level, but it gradually rises to 0.25%. A similar shock in *Plywood Price* causes immediate 0.75% and 1.75% increases in *Lumber Price* and *OSB Price* respectively and then generates permanent impacts around 0.7% and 1.25% levels. The response of *Plywood Price* to own impulse gradually decreases and becomes a permanent effect around 0.75% level. A 1% positive shock in *OSB Price* results in an immediate 0.35% increase in *Plywood Price* and remains the same in the next months. However, the same impulse leads to an immediate 0.3% rise in *Lumber Price* which gradually decreases to 0.2% level in the long–run. Moreover, it seems that *Shiller Index* has a small positive but gradually increasing response, about 0.1%, to the same impulse in *OSB Price*. In overall, it appears that *Concrete Price Index* has a little but gradually increasing response, around 0.1%, to the impulses in *Lumber Price*, *Plywood Price*, and *OSB Price* separately.

6.2 Segment 2

This section presents the empirical results for the 2nd segment.

All of the series are tested for seasonal unit root, and it is found that none of the series exhibits a seasonal unit root process in any of the two tests mentioned before. Then, the unit root and stationary tests are applied to each series, but the results are omitted since they are similar to the results presented for the entire data (see, Table 3 through Table 6 and Table 27 through Table 30). Hence, it is decided that all of the series in the 2nd segment are $I(1)$ and the precondition of applying cointegration tests is satisfied.

The Johansen trace cointegration test is performed with various lag lengths to identify the number of cointegration relations in the multidimensional system. The results presented in Table 22 suggest that the number of cointegration relations at the 5% significance level is either one or two depending on the lag length selection. In order to be consistent across segments, the lag length is decided using BIC, and the number of the cointegration relations are chosen respectively in Table 22. Thus, it is concluded that the multidimensional system in the 2nd segment has one lag and one cointegration relation. Then, TYDL Granger–causality tests are performed to understand the causalities among the variables and confirm the cointegration test results. The results in Table 23 show that there is a bidirectional Granger–causality between *Shiller* and *WPU1331*, but it is not the case between *Shiller* and other building materials.

A 6-dimensional VECM is estimated with one lag and imposing the one cointegration relationship (i.e., VECM(1)) for the 2nd segment since the series are unit root and cointegrated. Table 24 provides the VECM(1) results along with some model statistics. Table 39, Table 40, and Table 41 display the adjustment matrix α, cointegration matrix β, and composite matrix Π respectively. Then, the VECM(1) is converted back to VAR form. Table 25 presents the estimates of VECM(1) in level–VAR form.

Table 26 shows the multivariate and univariate diagnostic tests for the model residuals. According to the results, there appears to be a statistically significant serial correlation and non–normality in the multivariate case. Whereas, the model residuals are homoskedastic after three lags as suggested by the ARCH test. In the univariate case, the serial correlation problem is disappeared for all equations except *Shiller*. Moreover, the equations other than *CB* and *PACS* exhibit homoskedastic residuals for most of the lag lengths tested. Compared to the results of the entire data and 1st segment, in overall, it seems that the problems with the model residuals are the weakest in the 2nd segment.

Finally, impulse response analysis is performed for the 2nd segment. Figure 6 illustrates the responses of all variables to a 1% positive shock in each variable individually.[48] The results suggest that a 1% positive shock in *Shiller Index* creates a gradually rising impact on itself, and it becomes permanent around 6% level. The same shock results in an immediate 7% increase in *Lumber Price* and then becomes statistically insignificant after two months around 5% level.

A 1% positive shock in *Concrete Price Index* generates a statistically significant impact only on *Lumber Price*, other than itself, only for the first month with a 6% decrease.

In overall, it seems that the statistically significant impulse responses in the 2nd segment are among *Lumber Price*, *Plywood Price*, and *OSB Price*. A 1% positive shock in *Lumber Price* has an immediate 0.25% increase in *Plywood Price*, and it becomes a permanent impact around 0.5% level in the long–run. The same impulse creates a 0.5% increase in *OSB Price*, but it becomes statistically insignificant after five months. The response of *Lumber Price* to its own impulse gradually decreases and reaches a new long–run level around 0.5%. Moreover, among the building materials, *Lumber Price* is the only variable that creates a statistically significant response in *Shiller Index*, a 0.25% increase in the long–run. A similar shock in *Plywood Price* causes an immediate 0.75% increase in *Lumber Price*, but it becomes statistically insignificant after one month around 0.5% level. The response of *OSB Price* and *Plywood Price* to the same shock stay around 1% and 1.3% levels throughout the months considered. A 1% positive shock in *OSB Price* generates 0.3%, 0.3%, and 1% increases in *Lumber Price*, *Plywood Price*, and *OSB Price* respectively, and they remain the same in the next months.

7 Discussion

A comparison of each segment provides useful insights, especially understanding the dynamic price linkages between the housing market and the markets for the primary building materials

[48] As noted in Section 4, all IRFs are interpreted in percentages, and all the reported responses are positive and statistically significant unless stated otherwise. Also, while interpreting the impulse responses, the focus will be on *Shiller Index*, *Concrete Price Index*, *Lumber Price*, *Plywood Price*, and *OSB Price*.

before and after the housing market crisis. Moreover, the results of the entire data (i.e., the case of no structural breaks) can also be helpful to understand how a single structural break alters the results and leads to wrong conclusions.

In both segments, all of the series are found to be a unit root process and cointegrated. However, the number of cointegration relations decreased from two in the 1st segment to one in the 2nd segment.[49] Therefore, it seems that some of the long–run price linkages are weakened or even disappear in the 2nd segment. The same conclusion is also implied by the TYDL Granger–causality test results presented in Table 18 and Table 23. The results indicate that there is a bidirectional Granger–causality between *Shiller-WPU1331*, *Shiller-LAES*, and *Shiller-PAAB* in the 1st segment whereas they disappear in the 2nd segment, except *Shiller-WPU1331*. Moreover, there is a unidirectional Granger–causality between *PACS-Shiller* and *PAAB-WPU1331* in the 1st segment, and *PACS-LAES* in 2nd segment. As a result, combining the cointegration and Granger–causality test results, it is concluded that the structure of the price dynamics between the housing market and the market for primary building materials have changed after the housing market crises.

In order to thoroughly understand how the dynamic price linkages have changed across segments, the impulse responses of each segment are compared impulse by impulse.

First, comparing Figure 5a and Figure 6a suggests that the housing prices and the prices of building materials are more responsive to a shock in *Shiller Index* in the 1st segment than in the 2nd segment. Specifically, a 1% positive shock in *Shiller Index* generates a 10% increase in *Shiller Index* in the 1st segment whereas the same shock result in a 6% increase in the 2nd segment. The difference is even more when the responses in the price of building materials are considered. For instance, the same shock in *Shiller Index* results in up to 18% and 30% increases in *Plywood Price* and *OSB Price* respectively in the 1st segment; however, the responses in the 2nd segment are not statistically significant. Moreover, the response of *Lumber Price* to the same shock in *Shiller Index* is up to an 18% increase for seven months in the 1st segment compared to a 7% increase for only two months in the 2nd segment. In both segments, the response of *Concrete Price Index* to the same shock is statistically insignificant.

Second, comparing Figure 5c and Figure 6c indicates that a 1% positive shock in *Concrete Price Index* yields a 2.5% increase in *Shiller Index* in the 1st segment but the response in the 2nd segment is not statistically significant. Moreover, the same shock increases *Lumber Price* by 6% only in the 2nd segment. In both segments, it seems that the same impulse in *Concrete Price Index* does not have a statistically significant impact on *Plywood Price* and *OSB Price*.

Third, when Figure 5d and Figure 6d are compared, it can be seen that the prices of building materials to a shock in *Lumber Price* are less responsive in the 2nd segment than in the 1st segment. Particularly, *Lumber Price*, *Plywood Price*, and *OSB Price* increase up to 1%, 0.75%, and 1% respectively in the 1st segment; however, they all increase 0.5% in the 2nd segment. On the other hand, *Concrete Price Index* increases by 0.2% in the 1st segment but the impact in the

[49] See, Table 17 and Table 22 and use one lag in both tables since it is suggested by BIC.

2nd segment is not significant. Moreover, in response to the same shock in *Lumber Price*, *Shiller Index* increases by 0.25% in both segments.

Forth, the impacts of *Plywood Price* are compared across segments. As it can be seen from Figure 5e and Figure 6e, the responses of *Lumber Price* and *OSB Price* are approximately same across segments (i.e., a 0.75% increase in *Lumber Price* and a 1.25% increase in *OSB Price*). Moreover, in response to the same shock in *Plywood Price*, *Concrete Price Index* increases by 0.1% only in the 1st segment. In both segments, the response of *Shiller Index* to the same shock is statistically insignificant.

Finally, when Figure 5f and Figure 6f are compared, the results indicate that the responsiveness of the prices of building materials to a shock in *Lumber Price* does not change significantly across segments. The responses are about 0.3%, 0.3%, and 1% for *Lumber Price*, *Plywood Price*, and *OSB Price* respectively in both segments. Moreover, in response to the same shock in *OSB Price*, *Shiller Index* and *Concrete Price Index* increase by 0.1% only in the 1st segment but the responses are statistically insignificant in the 2nd segment.

8 Conclusion

The present research provides empirical evidence on the structural change of the price dynamics between the housing market and the market for primary building materials in the U.S. over the period of housing market crisis (i.e., 01-1995 to 11-2015). For this purpose, first, the Qu and Perron (2007) methodology is applied to identify a single structural break in a VECM framework. The choice of this methodology is led by its decisive advantages compared to the alternative techniques used in the literature. Specifically, the methodology endogenously estimates a structural break in regression and covariance parameters at an unknown date. It also allows the distribution of regressors to differ across regimes and the error process to be autocorrelated as well as conditionally heteroskedastic. Moreover, it can be applied to a VECM by incorporating certain valid restrictions on the model parameters which does not affect the break date estimates. Second, the estimated single breakpoint is used to split the data into two segments. Finally, to investigate the dynamic price linkages across segments, Johansen trace cointegration and TYDL Granger–causality tests, and the standard impulse response analysis are performed for each segment.

Four primary conclusions can be drawn from the results. First, using the monthly price data of U.S. housing and building materials from the last fifteen years, this study finds that there is a single structural break in 09-2007 that appears to have affected the dynamic price linkages between these markets. The timing of the estimated structural break is just three months before the start date of Great Recession, 12-2007. Second, most of the bidirectional Granger–causalities found between housing prices and the prices of building materials have disappeared after the structural break. Third, the prices of building materials have become less responsive to the changes in housing prices after the structural break. Some prices, such as

Plywood Price and *OSB Price*, have even become not responsive at all. Fourth, in general, the impacts of building materials on the housing prices and other building materials are weakened or completely disappeared.

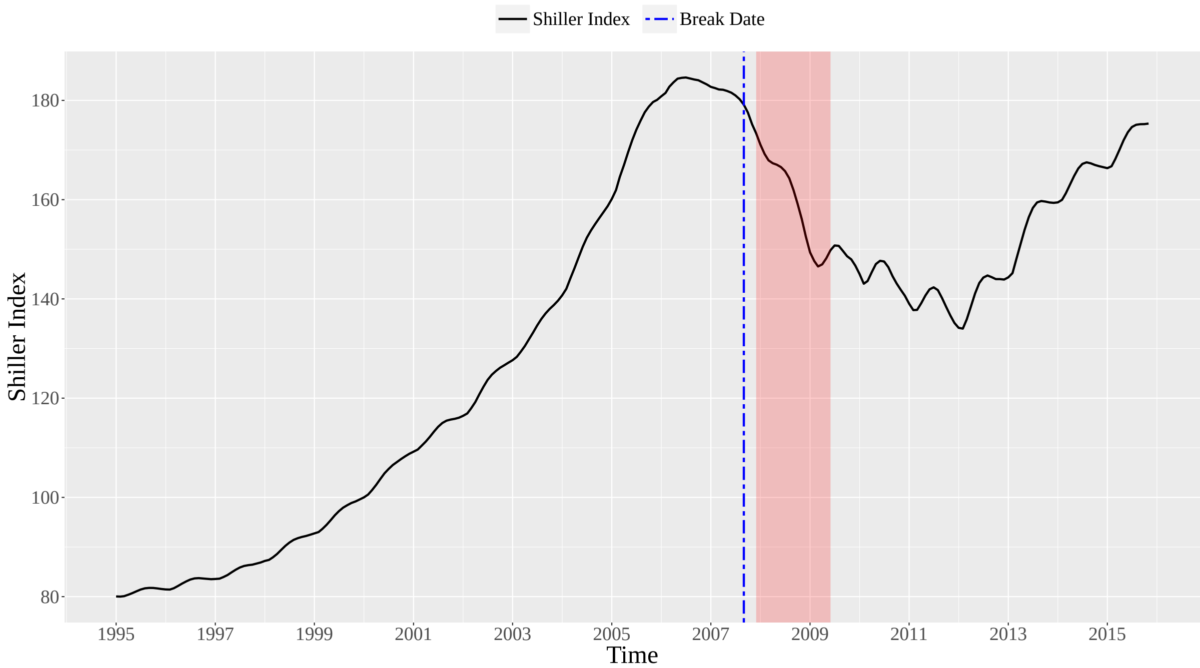
Table 1: Data Description Summary

Variable	Description	Source	# of Obs.
Shiller Index	The S&P CoreLogic Case–Shiller U.S. National Home Price Index, monthly observations. The base month is 01-2001. The designated symbol for the natural logarithmic form is *Shiller*.	S&P (2016a,b)	503
Oil Price	Crude Oil Brent/Global Spot Price in Intercontinental Exchange from Commodity Research Bureau, daily observations. Monthly averages are calculated from daily observations. The designated symbol for the natural logarithmic form is *CB*.	CRB (2016)	7753
Concrete Price Index	Concrete Block and Brick Producer Price Index from U.S. Bureau of Labor Statistics, monthly observations. The original base month is 01-1982 but converted to 01-2001 to match the base month of Shiller Index. The designated symbol for the natural logarithmic form is *WPU1331*.	BLS (2016)	840
Lumber Price	KD Spruce-Pine #2 2×10 from Random Lengths, weekly observations. Monthly averages are calculated from weekly observations. The designated symbol for the natural logarithmic form is *LAES*.	RL (2016)	1124
Plywood Price	Western Plywood Sheathing from Random Lengths, weekly observations. Monthly averages are calculated from weekly observations. The designated symbol for the natural logarithmic form is *PAAB*.	RL (2016)	1124
OSB Price	Southwest OSB Sheathing from Random Lengths, weekly observations. Monthly averages are calculated from weekly observations. The designated symbol for the natural logarithmic form is *PACS*.	RL (2016)	1124

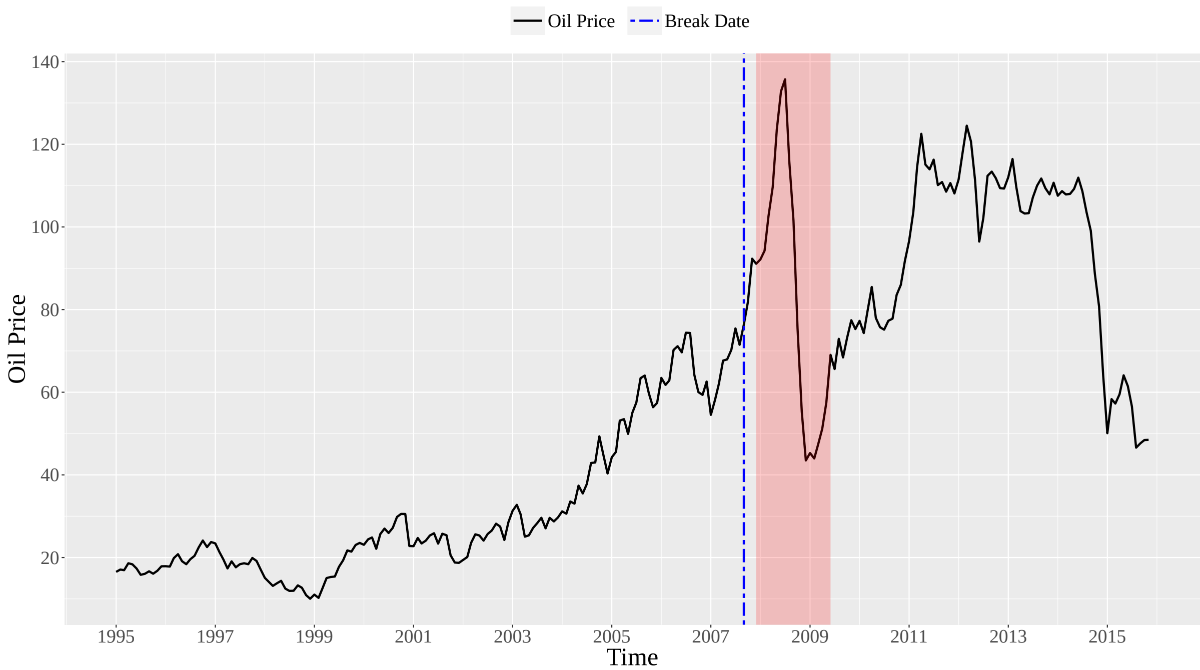
Notes: All variables are in nominal values and seasonally unadjusted.

Table 2: Summary Statistics - Entire Data

Variable	# of Obs.	Min.	Max.	Median	Mean	Std. Dev.	Skewness	Kurtosis
Shiller Index	251	80.01	184.62	141.82	134.34	33.28	−0.24	−1.25
Log Shiller Index	251	4.38	5.22	4.95	4.87	0.27	−0.50	−1.13
Oil Price	251	10.02	135.73	47.29	54.68	35.76	0.51	−1.15
Log Oil Price	251	2.30	4.91	3.86	3.76	0.73	−0.10	−1.36
Concrete Price Index	251	87.79	154.55	120.53	121.06	21.69	0.00	−1.62
Log Concrete Price Index	251	4.47	5.04	4.79	4.78	0.18	−0.11	−1.59
Lumber Price	251	209.50	588.50	349.80	356.50	85.61	0.29	−0.48
Log Lumber Price	251	5.34	6.38	5.86	5.85	0.25	−0.21	−0.65
Plywood Price	251	205.00	435.00	264.25	277.52	52.54	0.71	−0.30
Log Plywood Price	251	5.32	6.08	5.58	5.61	0.18	0.41	−0.80
OSB Price	251	132.50	515.20	194.50	219.05	77.70	1.41	1.65
Log OSB Price	251	4.89	6.24	5.27	5.34	0.31	0.76	−0.16

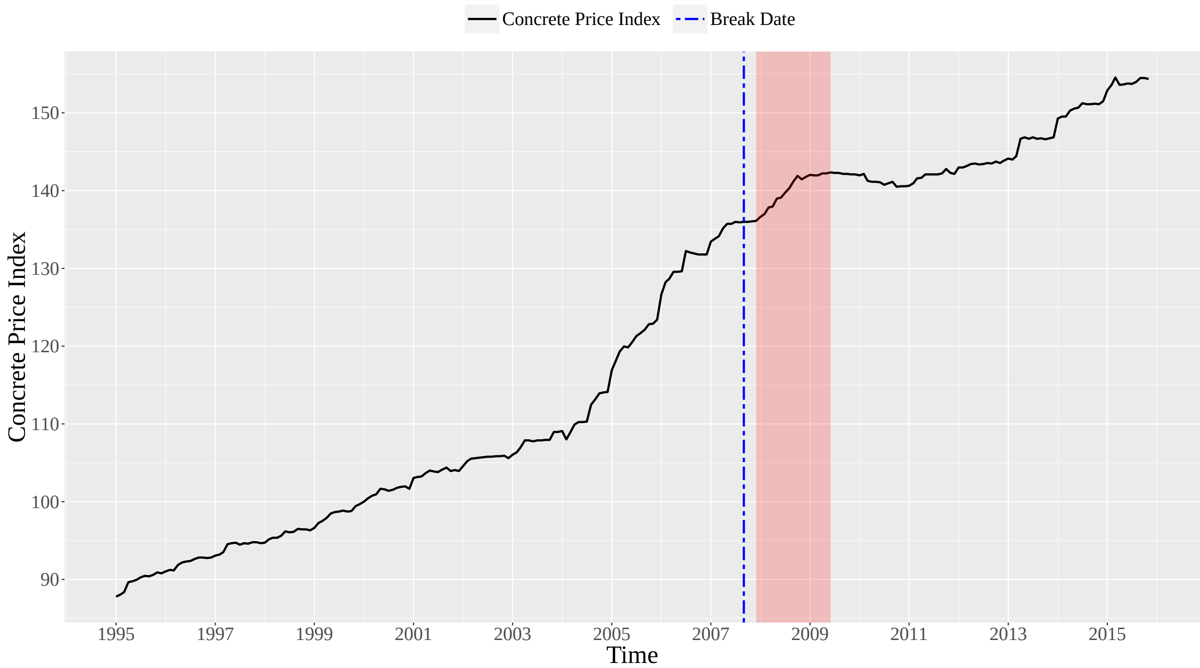


(a) Shiller Index

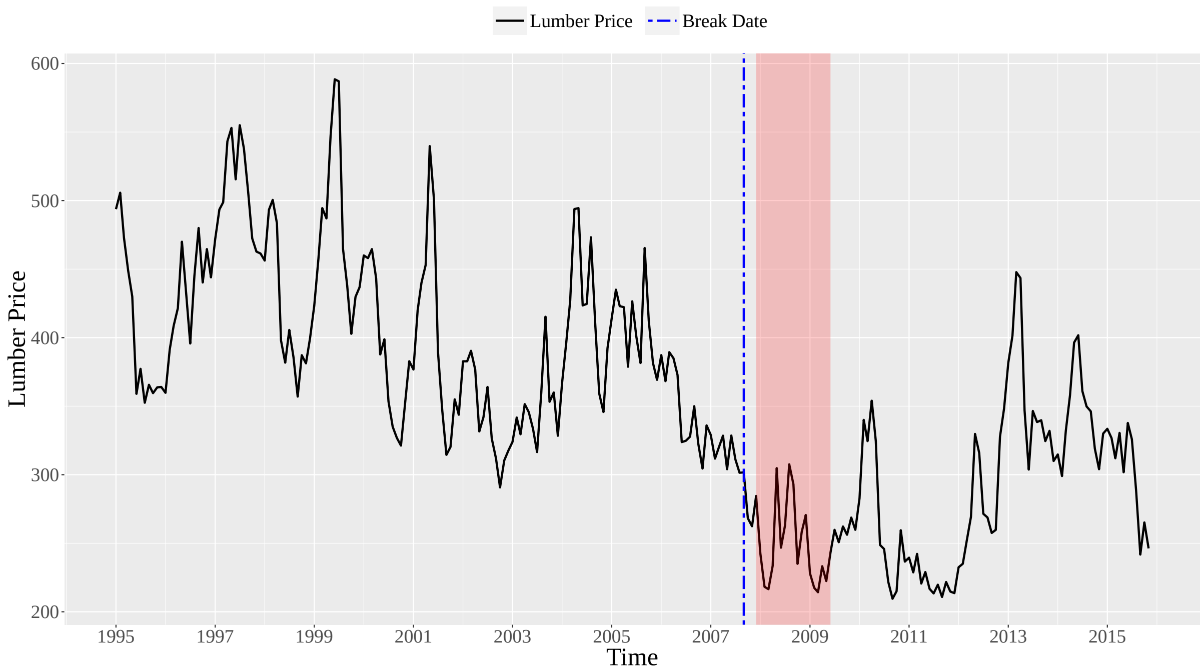


(b) Oil Price

Figure 1: Plots of All Variables

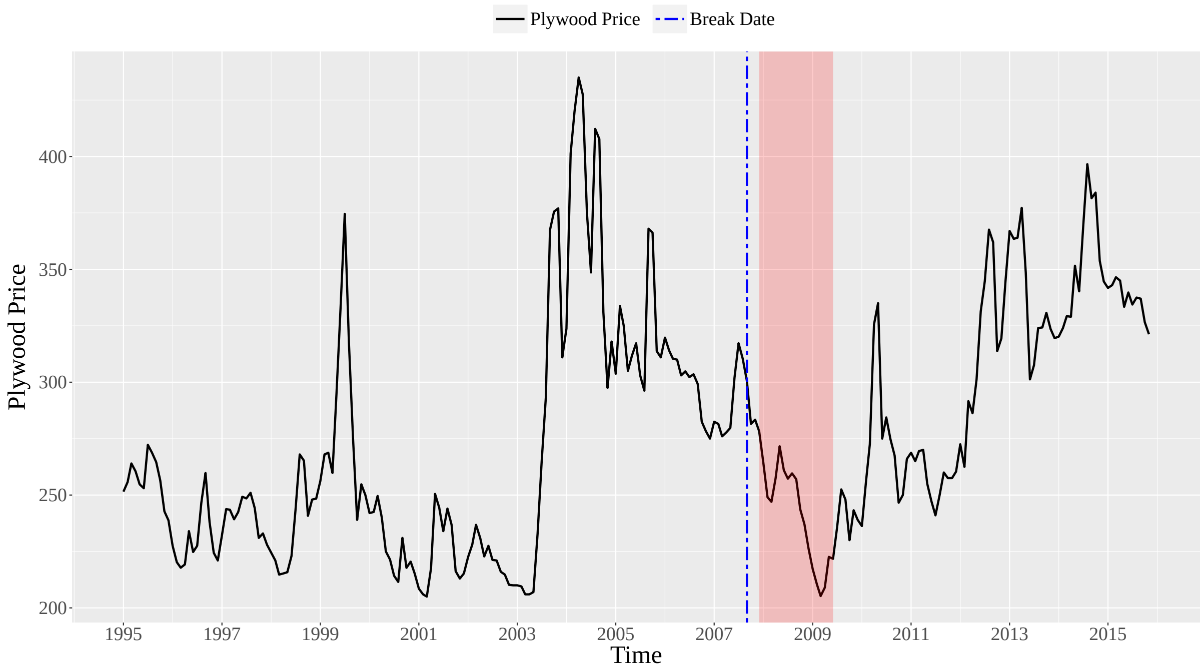


(c) Concrete Price Index

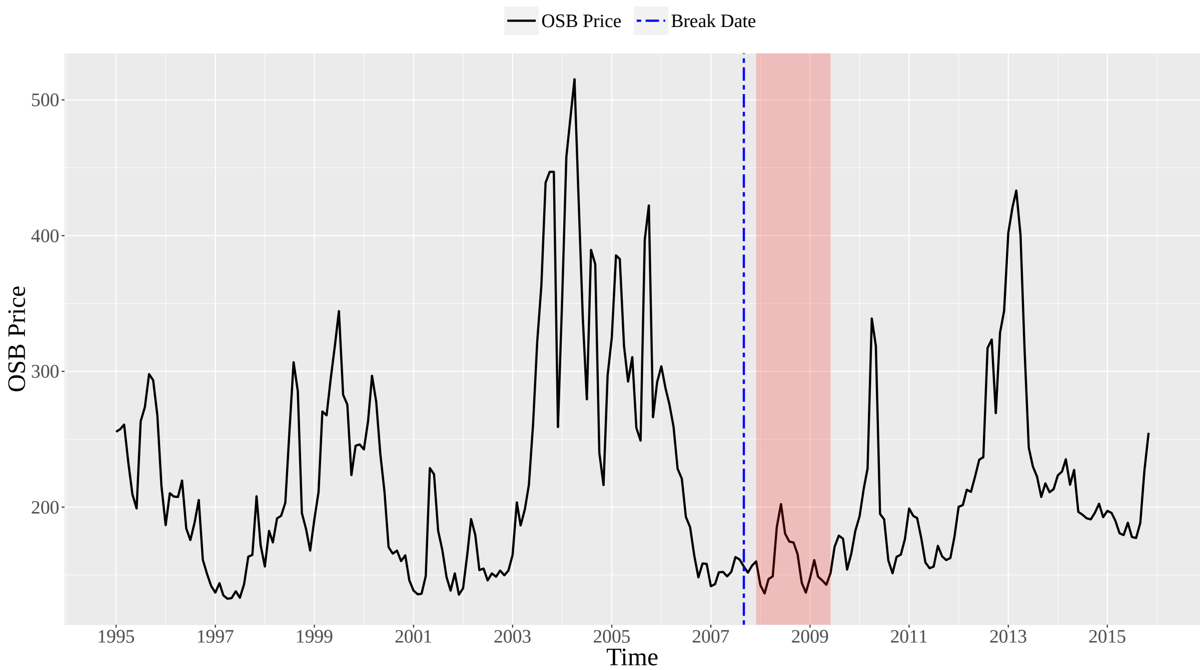


(d) Lumber Price

Figure 1 (continued)



(e) Plywood Price



(f) OSB Price

Figure 1 (continued)

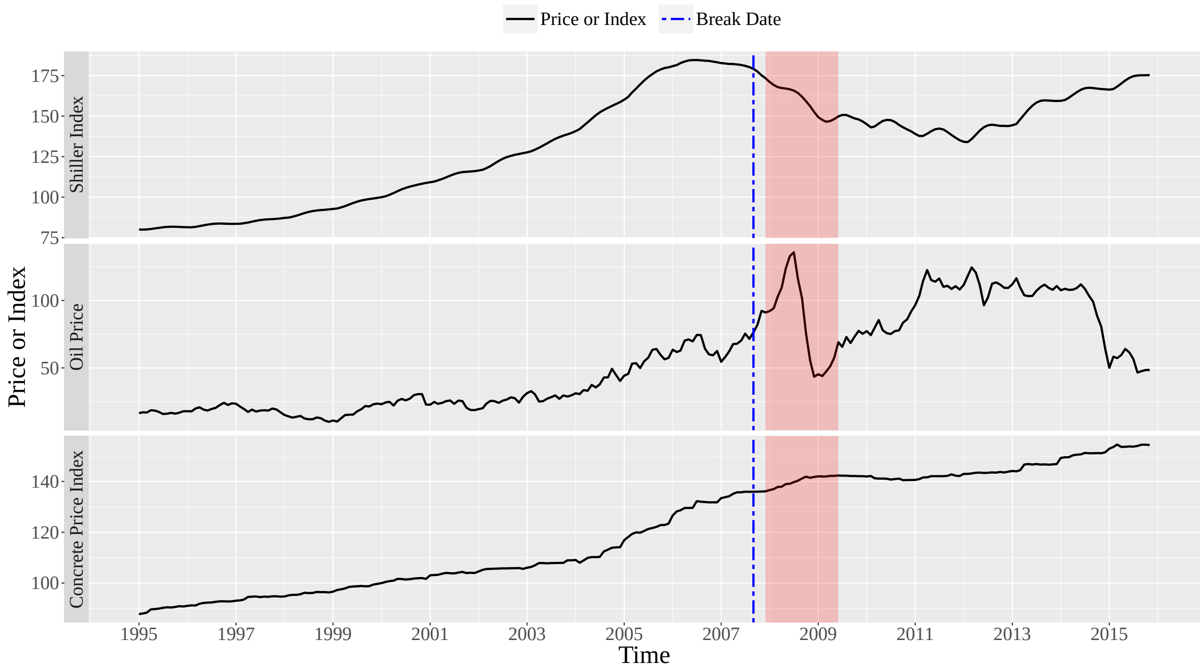


Figure 2: Plots of Non–Wood Variables

Figure 3: Plots of Wood Variables

Table 3: ADF Unit Root Test Results with EAP - Entire Data

	Variable:					
Lag	Shiller	CB	WPU1331	LAES	PAAB	PACS
AIC	Stationary	Unit Root	Unit Root	Stationary	Unit Root	Stationary
BIC	Unit Root	Unit Root	Unit Root	Stationary	Unit Root	Stationary
NPS	Unit Root	Unit Root	Unit Root	Unit Root	Unit Root	Stationary

Notes: All decisions are given at the 5% significance level.

Table 4: PP Unit Root Test Statistics - Entire Data

		Variable:					
Model	Lag	Shiller	CB	WPU1331	LAES	PAAB	PACS
Constant	AIC	-1.59	-1.44	-1.12	-2.96^{**}	-2.86^{*}	-3.65^{***}
	BIC	-1.98	-1.44	-1.12	-2.96^{**}	-2.86^{*}	-3.65^{***}
	Long	-1.45	-1.47	-0.97	-2.71^{*}	-2.71^{*}	-3.62^{***}
	Short	-1.59	-1.51	-1.10	-2.82^{*}	-2.69^{*}	-3.47^{***}
Trend	AIC	-0.85	-1.32	-0.68	-3.99^{**}	-3.46^{**}	-3.65^{**}
	BIC	-0.62	-1.32	-0.68	-3.99^{**}	-3.46^{**}	-3.65^{**}
	Long	-1.12	-1.51	-1.14	-3.91^{**}	-3.32^{*}	-3.62^{**}
	Short	-0.85	-1.65	-0.73	-3.93^{**}	-3.29^{*}	-3.47^{**}

Notes: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 5: ERS Unit Root Test Statistics - Entire Data

		Variable:					
Model	Lag	Shiller	CB	WPU1331	LAES	PAAB	PACS
Constant	AIC	-1.59	-1.44	-1.12	-2.96^{**}	-2.86^{*}	-3.65^{***}
	BIC	-1.98	-1.44	-1.12	-2.96^{**}	-2.86^{*}	-3.65^{***}
	Long	-1.45	-1.47	-0.97	-2.71^{*}	-2.71^{*}	-3.62^{***}
	Short	-1.59	-1.51	-1.10	-2.82^{*}	-2.69^{*}	-3.47^{***}
Trend	AIC	-0.85	-1.32	-0.68	-3.99^{**}	-3.46^{**}	-3.65^{**}
	BIC	-0.62	-1.32	-0.68	-3.99^{**}	-3.46^{**}	-3.65^{**}
	Long	-1.12	-1.51	-1.14	-3.91^{**}	-3.32^{*}	-3.62^{**}
	Short	-0.85	-1.65	-0.73	-3.93^{**}	-3.29^{*}	-3.47^{**}

Notes: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 6: KPSS Stationary Test Statistics - Entire Data

		Variable:					
Model	Lag	Shiller	CB	WPU1331	LAES	PAAB	PACS
Constant	AIC	3.23***	11.04***	5.06***	6.63***	2.50***	0.21
	BIC	9.53***	11.04***	5.06***	6.63***	2.50***	0.21
	Long	1.65***	1.93***	2.16***	1.36***	0.76***	0.07
	Short	4.80***	5.57***	6.31***	3.51***	1.92***	0.17
Trend	AIC	0.86***	0.90***	0.59***	0.61***	0.27***	0.21**
	BIC	2.57***	0.90***	0.59***	0.61***	0.27***	0.21**
	Long	0.44***	0.20**	0.26***	0.15**	0.09	0.07
	Short	1.29***	0.48***	0.74***	0.34***	0.21**	0.16**

Notes: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 7: Johansen Trace Cointegration Test Statistics - Entire Data

	Test Statistic by Lag Length:						*Critical Values:*		
H_0:	$p = 1$	$p = 2$	$p = 3$	$p = 4$	$p = 5$	$p = 6$	10%	5%	1%
$r = 0$	154.20	154.54	145.49	143.02	144.53	130.01	97.18	102.14	111.01
$r \leq 1$	93.47	81.51	82.89	76.25	85.03	83.12	71.86	76.07	84.45
$r \leq 2$	50.71	51.56	51.81	44.35	52.98	53.32	49.65	53.12	60.16
$r \leq 3$	31.35	29.91	29.99	26.40	30.94	31.20	32.00	34.91	41.07
$r \leq 4$	15.09	14.79	14.74	13.01	15.40	14.85	17.85	19.96	24.60
$r \leq 5$	3.24	2.41	2.96	3.15	3.05	3.35	7.52	9.24	12.97

Notes: p indicates the lag length used in the Johansen trace cointegration tests and VECM(p).

Table 8: TYDL Granger–Causality Test Statistics - Entire Data

	Shiller	CB	WPU1331	LAES	PAAB	PACS
Shiller		0.19	6.15**	8.76**	6.86**	3.22
CB	1.71		4.45	0.47	3.14	5.80*
WPU1331	5.27*	0.15		0.88	4.94*	3.42
LAES	5.19*	2.98	1.59		3.96	0.60
PAAB	5.01*	0.26	6.43**	1.20		1.33
PACS	5.71*	1.44	6.18**	0.20	0.47	

Notes: Value in each cell indicates the test statistic for the hypothesis H_0 that is the row variable does not Granger–cause the column variable. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 9: VECM Results - Entire Data

	Equation:					
	ΔShiller	ΔCB	ΔWPU1331	ΔLAES	ΔPAAB	ΔPACS
ECT 1	−0.001	−0.003	0.007***	−0.013	−0.018	−0.015
ECT 2	−0.001***	−0.001	0.002***	0.005	−0.008*	0.001
$\Delta\text{Shiller}_{t-1}$	0.858***	0.378	−0.045	0.941	0.654	0.243
ΔCB_{t-1}	0.006***	0.230***	−0.004	0.077	0.062	0.063
$\Delta\text{WPU1331}_{t-1}$	0.070	0.477	0.049	−0.394	−0.994	−1.620
ΔLAES_{t-1}	0.003	−0.041	−0.001	0.125*	0.118**	0.159
ΔPAAB_{t-1}	−0.004	0.083	−0.004	−0.340**	0.138	−0.183
ΔPACS_{t-1}	0.001	0.039	0.003	0.080	−0.028	0.164
Observations	249	249	249	249	249	249
Residual Std. Error	0.003	0.083	0.004	0.087	0.060	0.133
R^2	0.863	0.076	0.314	0.066	0.092	0.043
Adjusted R^2	0.859	0.045	0.291	0.035	0.062	0.011
F Statistic	189.989***	2.469**	13.802***	2.139**	3.040***	1.353

Notes: ECTs indicate the respective error correction terms. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

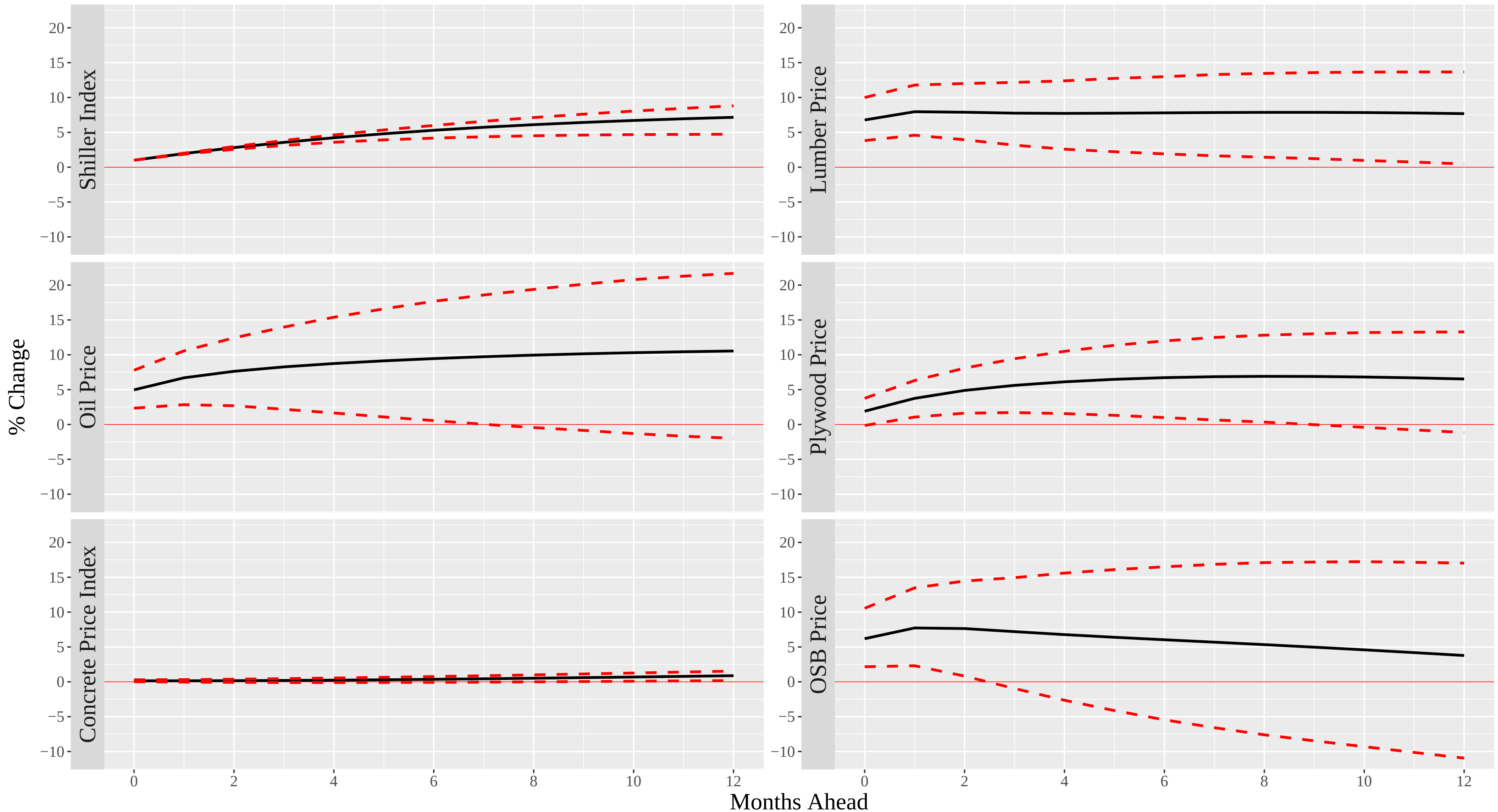
Table 10: Estimated Coefficients of VECM in level–VAR Form - Entire Data

	Equation:					
	Shiller	CB	WPU1331	LAES	PAAB	PACS
Constant	−0.048	−0.044	−0.002	0.854	−0.317	0.530
Shiller_{t-1}	1.857	0.375	−0.038	0.928	0.635	0.228
CB_{t-1}	0.006	1.229	−0.002	0.082	0.054	0.064
WPU1331_{t-1}	0.081	0.492	1.034	−0.532	−0.892	−1.691
LAES_{t-1}	0.007	−0.038	0.003	1.026	0.141	0.095
PAAB_{t-1}	−0.011	0.076	−0.003	−0.213	1.087	−0.105
PACS_{t-1}	0.004	0.042	0.004	0.025	−0.009	1.128
Shiller_{t-2}	−0.858	−0.378	0.045	−0.941	−0.654	−0.243
CB_{t-2}	−0.006	−0.230	0.004	−0.077	−0.062	−0.063
WPU1331_{t-2}	−0.070	−0.477	−0.049	0.394	0.994	1.620
LAES_{t-2}	−0.003	0.041	0.001	−0.125	−0.118	−0.159
PAAB_{t-2}	0.004	−0.083	0.004	0.340	−0.138	0.183
PACS_{t-2}	−0.001	−0.039	−0.003	−0.080	0.028	−0.164

Table 11: Diagnostic Test Statistics for VECM in level–VAR Form - Entire Data

		Univariate Tests by Equation:					
Test	Multivariate	Shiller	CB	WPU1331	LAES	PAAB	PACS
$LB_{(2)}$	130.39***	63.30***	0.02	3.25	1.09	12.79***	9.28***
$LB_{(3)}$	163.48***	66.05***	0.41	3.28	1.25	14.31***	9.37**
$LB_{(4)}$	210.88***	78.46***	1.05	4.31	1.46	14.39***	10.91**
$LB_{(5)}$	267.44***	97.93***	1.46	4.39	5.15	14.48**	12.55**
$LB_{(6)}$	348.91***	130.91***	5.02	4.93	6.01	17.02***	13.30**
$LB_{(9)}$	482.48***	161.41***	8.46	15.80*	6.69	17.90**	15.73*
$LB_{(10)}$	529.58***	170.31***	12.24	15.81	6.69	19.10**	17.99*
$LB_{(12)}$	745.71***	318.13***	14.64	36.45***	11.55	19.50*	18.50
$ARCH_{(2)}$	1138.28***	21.01***	14.14***	0.12	5.58*	35.64***	23.92***
$ARCH_{(3)}$	1542.43***	21.85***	14.43***	0.33	5.59	35.87***	24.28***
$ARCH_{(4)}$	1982.34***	22.50***	14.64***	0.38	9.24*	36.25***	25.68***
$ARCH_{(5)}$	2487.12***	25.04***	14.91**	4.48	10.11*	36.76***	27.88***
$ARCH_{(6)}$	2976.47***	36.64***	15.11**	22.54***	10.19	39.16***	27.88***
$ARCH_{(9)}$	4171.73**	37.19***	20.33**	24.47***	15.28*	40.95***	29.80***
$ARCH_{(10)}$	4568.11**	37.33***	22.41**	24.40***	15.19	41.34***	32.77***
$ARCH_{(12)}$	4977.00	90.21***	26.34***	39.07***	19.05*	45.42***	36.68***
JB	614.07***	195.52***	14.26***	433.30***	0.38	61.56***	97.24***
Skewness	140.35***	0.99***	−0.49***	1.53***	−0.09	0.10	−0.09
Kurtosis	473.71***	6.87***	3.65**	8.69***	3.07	5.43***	6.06***

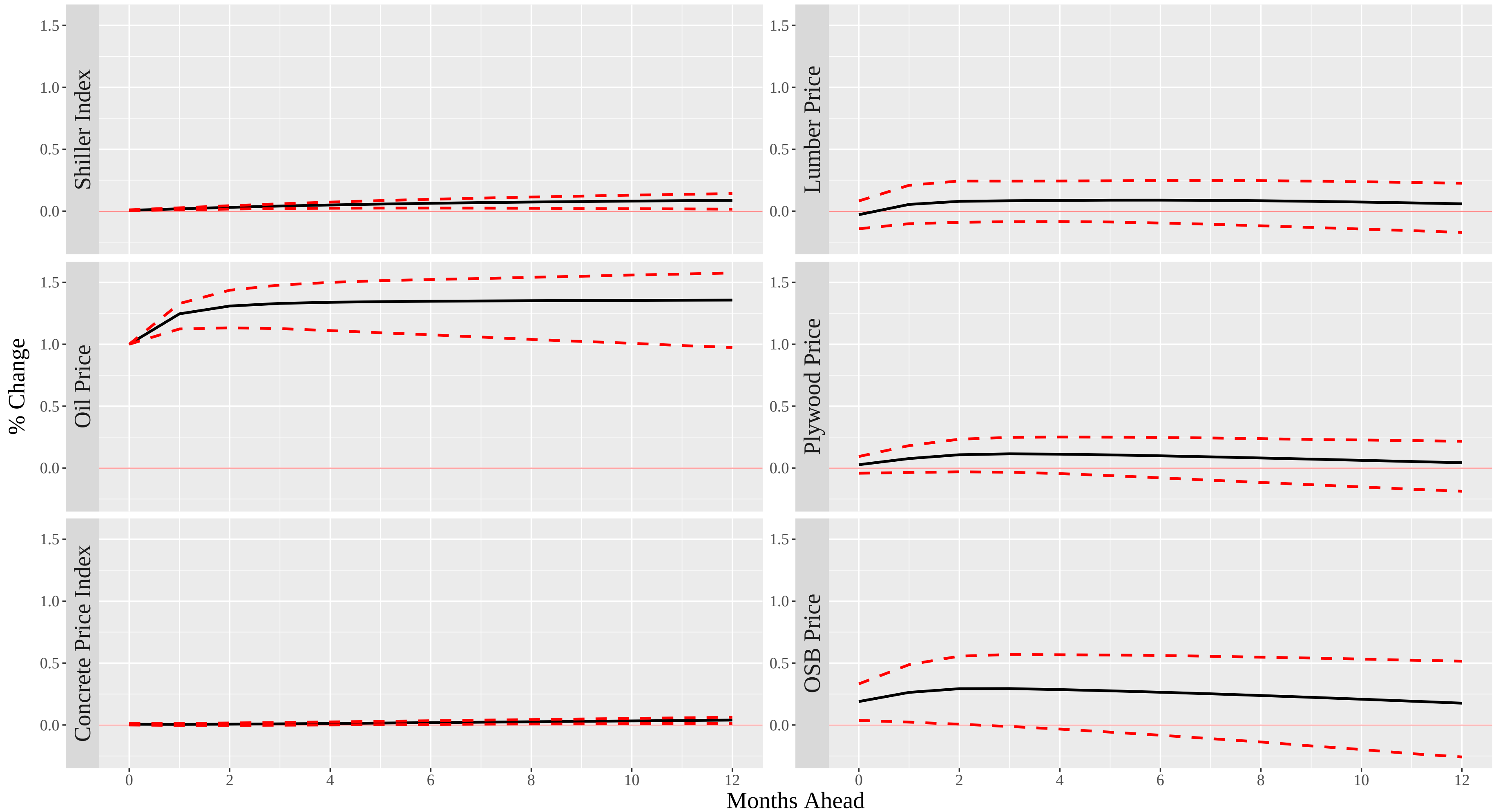
Notes: LB, ARCH, JB, Skewness, and Kurtosis indicate Ljung–Box test for autocorrelation, ARCH test for autoregressive conditional heteroskedasticity, Jarque–Bera test for normality, Skewness test for only skewness, and Kurtosis test for only kurtosis respectively. Values in parenthesis indicate the lag length used in LB and ARCH tests. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.



Notes: All variables are in the natural logarithmic form in the estimation, but the interpretation of IRFs is in percentages with a 90% confidence interval generated with 10000 bootstrap replications.

(a) Response of All Variables to a 1% Positive Shock in Shiller Index - Entire Data

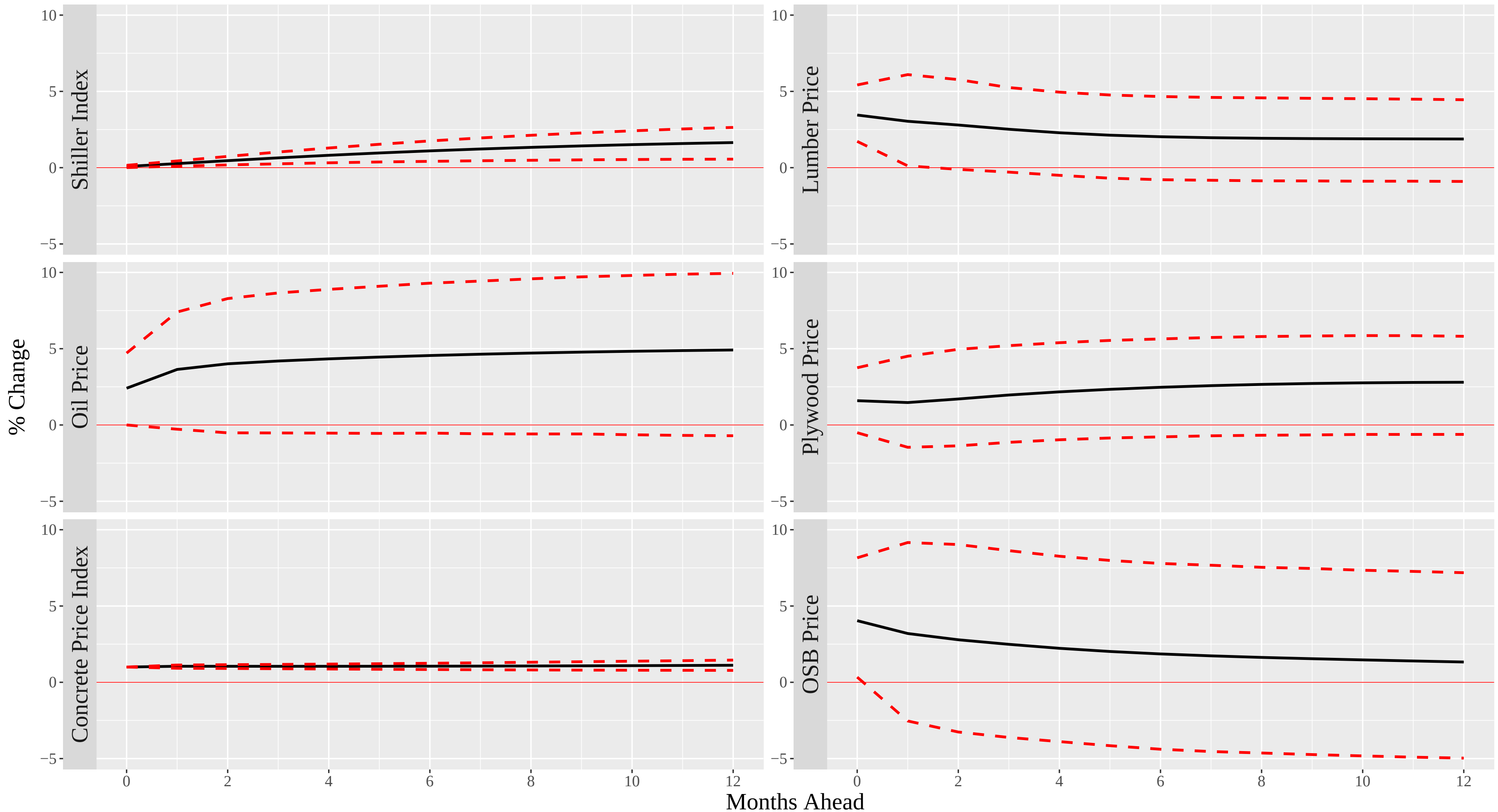
Figure 4: Impulse Responses Analysis - Entire Data



Notes: All variables are in the natural logarithmic form in the estimation, but the interpretation of IRFs is in percentages with a 90% confidence interval generated with 10000 bootstrap replications.

(b) Response of All Variables to a 1% Positive Shock in Oil Price - Entire Data

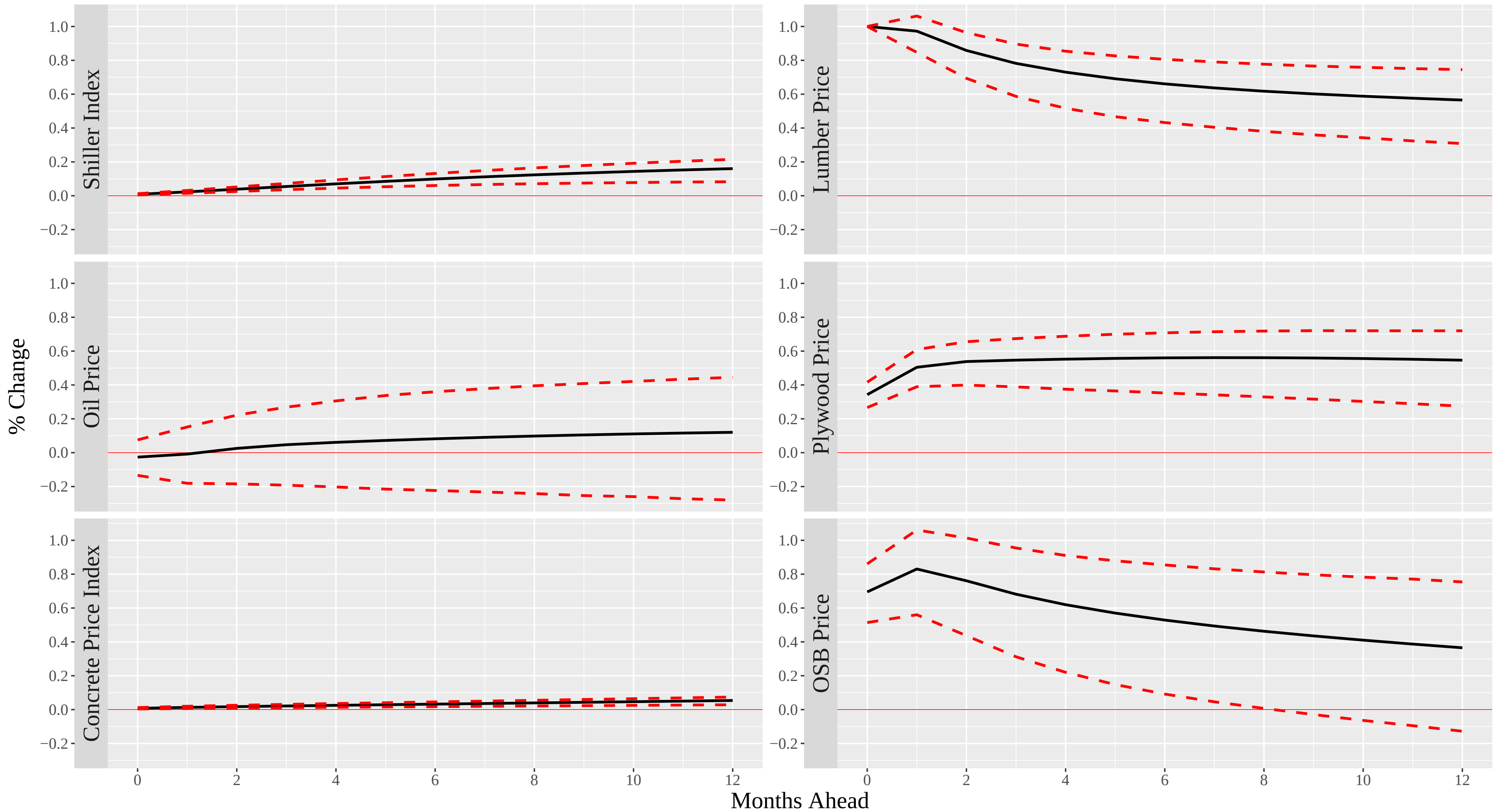
Figure 4 (continued)



Notes: All variables are in the natural logarithmic form in the estimation, but the interpretation of IRFs is in percentages with a 90% confidence interval generated with 10000 bootstrap replications.

(c) Response of All Variables to a 1% Positive Shock in Concrete Price Index - Entire Data

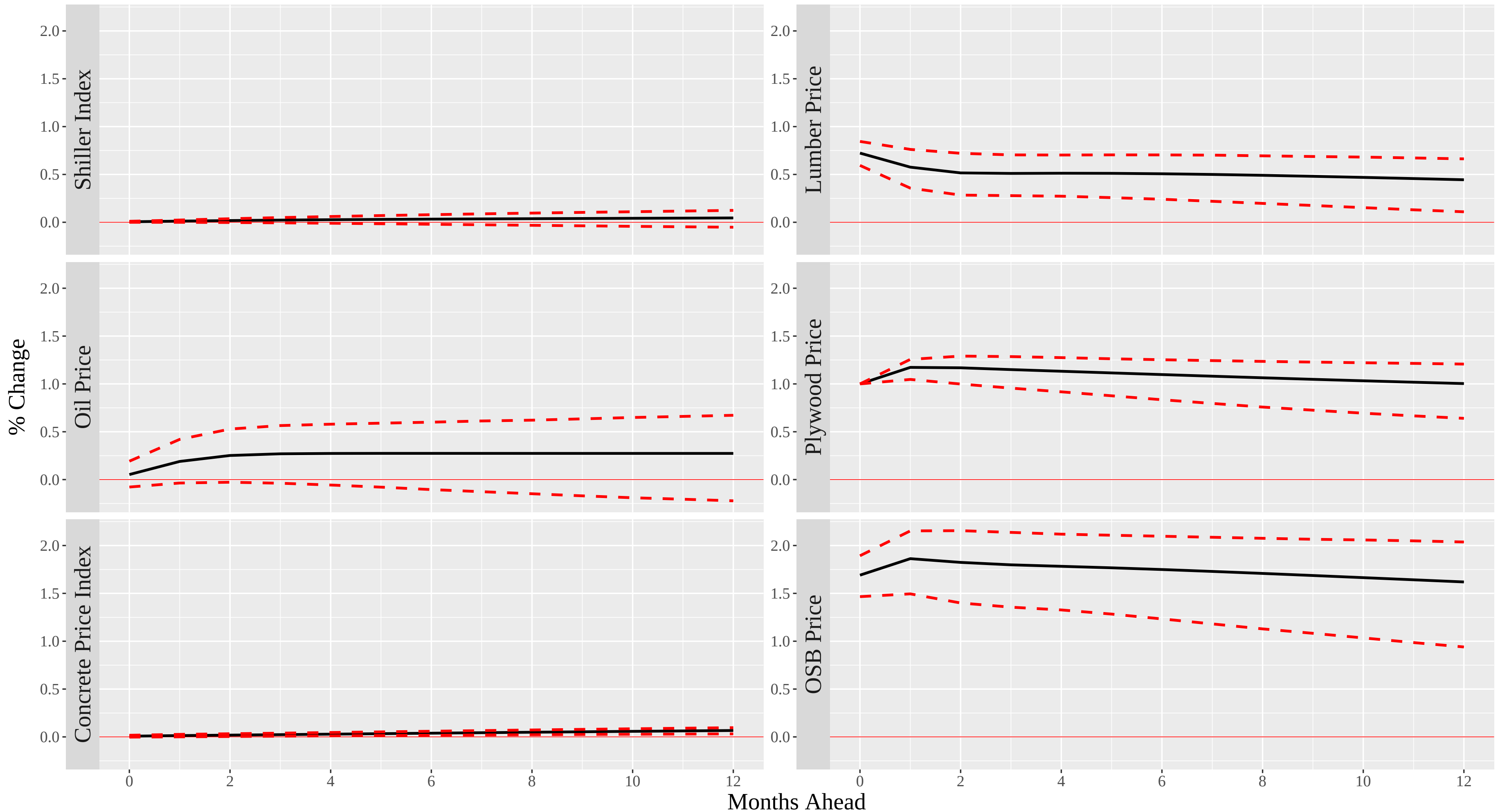
Figure 4 (continued)



Notes: All variables are in the natural logarithmic form in the estimation, but the interpretation of IRFs is in percentages with a 90% confidence interval generated with 10000 bootstrap replications.

(d) Response of All Variables to a 1% Positive Shock in Lumber Price - Entire Data

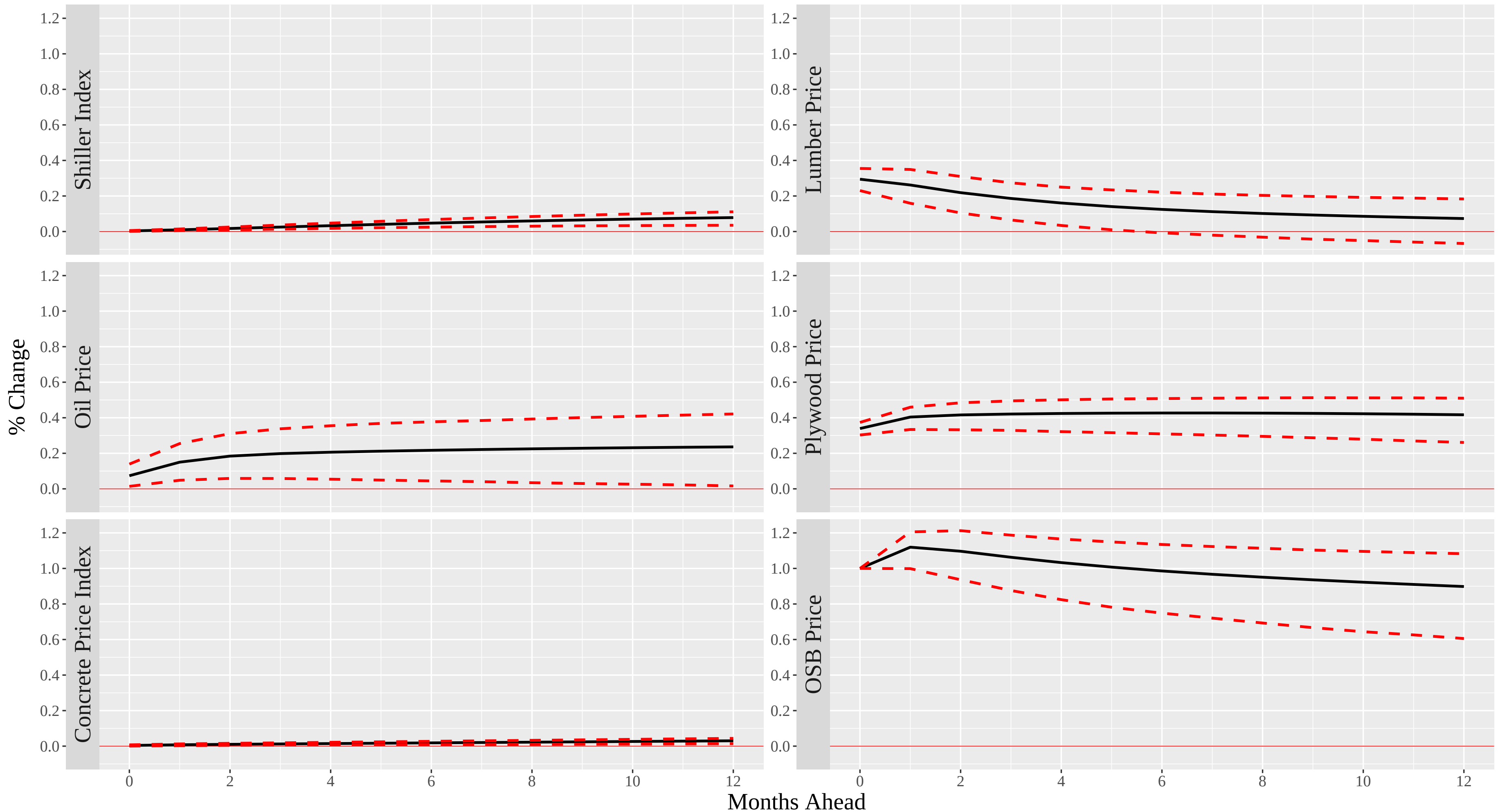
Figure 4 (continued)



Notes: All variables are in the natural logarithmic form in the estimation, but the interpretation of IRFs is in percentages with a 90% confidence interval generated with 10000 bootstrap replications.

(e) Response of All Variables to a 1% Positive Shock in Plywood Price - Entire Data

Figure 4 (continued)



Notes: All variables are in the natural logarithmic form in the estimation, but the interpretation of IRFs is in percentages with a 90% confidence interval generated with 10000 bootstrap replications.

(f) Response of All Variables to a 1% Positive Shock in OSB Price - Entire Data

Figure 4 (continued)

Table 12: EFP and FS Based Structural Break Test Statistics

	EFP Test:	*FS–Based Test:*		
Variable	Rec–CUSUM	SupF	ExpF	AveF
Shiller	8.16***	1052.81***	521.60***	298.38***
CB	6.30***	1116.45***	552.74***	307.41***
WPU1331	8.53***	1654.32***	Inf***	440.39***
LAES	3.90***	284.26***	137.06***	97.15***
PAAB	2.31***	173.09***	81.75***	48.02***
PACS	0.99**	12.91**	3.47***	3.06**

Notes: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 13: BP Structural Break Test Results

Variable	Number of Breaks	Single Break Date
Shiller	5	04-2002
CB	4	07-2004
WPU1331	5	02-2005
LAES	3	05-2006
PAAB	4	07-2003
PACS	4	06-2006

Table 14: Chow Structural Break and NHS Test Statistics

	Chow Test:			*NHS Test:*		
Variable	08-2007	09-2007	10-2007	08-2007	09-2007	10-2007
Shiller	88.72***	84.61***	80.79***	21.33***	21.33***	21.33***
CB	417.17***	403.21***	388.01***	24.05***	24.05***	24.05***
WPU1331	657.49***	633.36***	610.82***	30.69***	30.69***	30.69***
LAES	248.30***	243.71***	234.08***	13.67***	13.67***	13.67***
PAAB	19.21***	18.62***	18.48***	8.24***	8.24***	8.24***
PACS	4.04**	3.58*	3.11*	1.52***	1.52***	1.52***

Notes: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 15: Summary Statistics - Segment 1

Variable	# of Obs.	Min.	Max.	Median	Mean	Std. Dev.	Skewness	Kurtosis
Log Shiller Index	152	4.38	5.22	4.72	4.76	0.29	0.31	−1.33
Log Oil Price	152	2.30	4.32	3.20	3.29	0.52	0.44	−0.74
Log Concrete Price Index	152	4.47	4.91	4.64	4.65	0.12	0.68	−0.54
Log Lumber Price	152	5.67	6.38	5.97	5.99	0.16	0.25	−0.79
Log Plywood Price	152	5.32	6.08	5.52	5.57	0.18	0.80	−0.12
Log OSB Price	152	4.89	6.24	5.33	5.37	0.34	0.52	−0.65

Table 16: Summary Statistics - Segment 2

Variable	# of Obs.	Min.	Max.	Median	Mean	Std. Dev.	Skewness	Kurtosis
Log Shiller Index	99	4.90	5.19	5.02	5.04	0.08	0.17	−1.31
Log Oil Price	99	3.77	4.91	4.60	4.47	0.30	−0.81	−0.52
Log Concrete Price Index	99	4.91	5.04	4.96	4.97	0.03	0.57	−0.57
Log Lumber Price	99	5.34	6.10	5.59	5.63	0.19	0.31	−0.85
Log Plywood Price	99	5.32	5.98	5.65	5.67	0.16	−0.07	−1.13
Log OSB Price	99	4.92	6.07	5.25	5.29	0.26	1.18	1.10

Table 17: Johansen Trace Cointegration Test Statistics - Segment 1

	Test Statistic by Lag Length:						*Critical Values:*		
H_0:	$p = 1$	$p = 2$	$p = 3$	$p = 4$	$p = 5$	$p = 6$	10%	5%	1%
$r = 0$	131.57	126.74	139.94	128.75	128.18	114.24	97.18	102.14	111.01
$r \leq 1$	82.40	78.68	79.84	77.69	82.31	72.54	71.86	76.07	84.45
$r \leq 2$	49.93	48.89	53.80	48.02	51.04	45.74	49.65	53.12	60.16
$r \leq 3$	27.68	28.41	31.41	28.09	29.46	24.44	32.00	34.91	41.07
$r \leq 4$	13.82	15.10	15.35	12.35	13.48	12.23	17.85	19.96	24.60
$r \leq 5$	5.24	5.47	5.37	4.03	3.06	3.65	7.52	9.24	12.97

Notes: p indicates the lag length used in the Johansen trace cointegration tests and VECM(p).

Table 18: TYDL Granger–Causality Test Statistics - Segment 1

	Shiller	CB	WPU1331	LAES	PAAB	PACS
Shiller		0.67	8.53^{**}	6.08^{**}	4.70^{*}	3.45
CB	1.56		2.50	0.15	1.10	1.92
WPU1331	6.10^{**}	0.53		1.49	1.77	1.36
LAES	15.36^{***}	3.55	2.55		0.24	0.05
PAAB	17.21^{***}	0.15	5.24^{*}	0.11		2.09
PACS	4.82^{*}	1.22	3.08	2.86	1.71	

Notes: Value in each cell indicates the test statistic for the hypothesis H_0 that is the row variable does not Granger–cause the column variable. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 19: VECM Results - Segment 1

	Equation:					
	ΔShiller	ΔCB	ΔWPU1331	ΔLAES	ΔPAAB	ΔPACS
ECT 1	0.007***	0.110	0.028***	−0.242**	−0.026	−0.100
ECT 2	−0.001***	−0.008	0.001	0.018	−0.023**	−0.033
ΔShiller$_{t-1}$	0.833***	−0.562	−0.385***	3.776	2.365	4.377
ΔCB$_{t-1}$	0.000	0.048	−0.004	−0.077	0.031	−0.051
ΔWPU1331$_{t-1}$	0.037	0.280	0.051	1.114	−0.546	−1.312
ΔLAES$_{t-1}$	0.001	−0.099	−0.008	0.171	0.109	0.177
ΔPAAB$_{t-1}$	−0.002	0.074	0.004	−0.299*	0.238*	−0.103
ΔPACS$_{t-1}$	0.002	0.058	0.001	0.066	−0.058	0.085
Observations	150	150	150	150	150	150
Residual Std. Error	0.001	0.083	0.005	0.081	0.065	0.149
R^2	0.957	0.059	0.381	0.063	0.110	0.049
Adjusted R^2	0.955	0.006	0.346	0.011	0.060	−0.005
F Statistic	395.814***	1.104	10.916***	1.202	2.203**	0.913

Notes: ECTs indicate the respective error correction terms. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

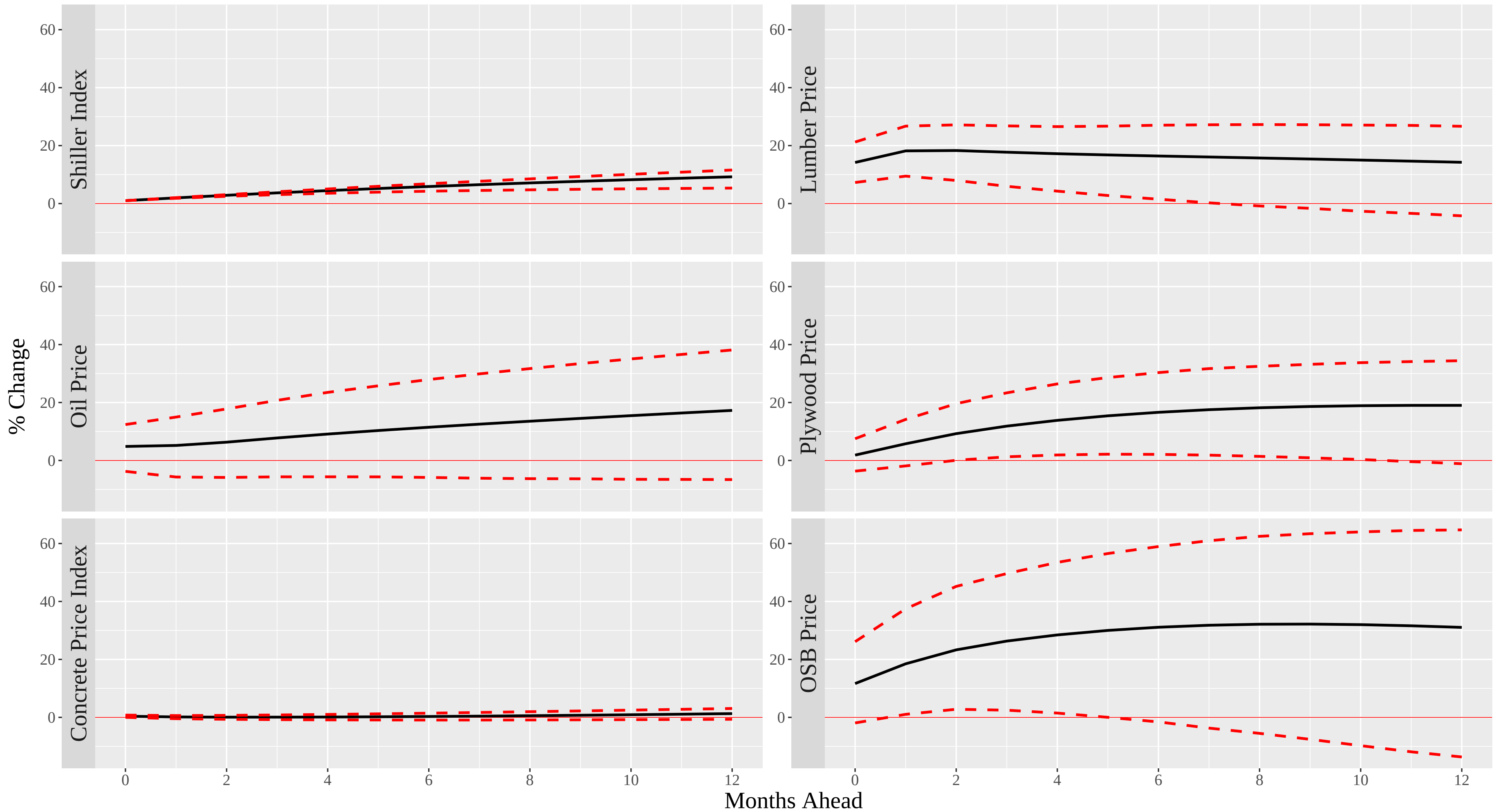
Table 20: Estimated Coefficients of VECM in level–VAR Form - Segment 1

	Equation:					
	Shiller	CB	WPU1331	LAES	PAAB	PACS
Constant	−0.007	−0.008	0.052	0.013	−0.437	−0.695
Shiller$_{t-1}$	1.840	−0.452	−0.357	3.535	2.338	4.278
CB$_{t-1}$	−0.001	1.040	−0.002	−0.059	0.008	−0.084
WPU1331$_{t-1}$	0.031	0.148	0.998	1.405	−0.361	−0.946
LAES$_{t-1}$	0.006	−0.029	0.005	1.018	0.133	0.181
PAAB$_{t-1}$	−0.008	0.002	−0.002	−0.140	1.154	−0.201
PACS$_{t-1}$	0.003	0.081	0.004	0.015	−0.042	1.098
Shiller$_{t-2}$	−0.833	0.562	0.385	−3.776	−2.365	−4.377
CB$_{t-2}$	0.000	−0.048	0.004	0.077	−0.031	0.051
WPU1331$_{t-2}$	−0.037	−0.280	−0.051	−1.114	0.546	1.312
LAES$_{t-2}$	−0.001	0.099	0.008	−0.171	−0.109	−0.177
PAAB$_{t-2}$	0.002	−0.074	−0.004	0.299	−0.238	0.103
PACS$_{t-2}$	−0.002	−0.058	−0.001	−0.066	0.058	−0.085

Table 21: Diagnostic Test Statistics for VECM in level–VAR Form - Segment 1

		Univariate Tests by Equation:					
Test	Multivariate	Shiller	CB	WPU1331	LAES	PAAB	PACS
$LB_{(2)}$	91.50***	37.98***	1.91	3.12	0.27	9.54***	8.00**
$LB_{(3)}$	124.39***	37.98***	2.09	3.12	0.29	10.74**	8.64**
$LB_{(4)}$	158.04***	40.76***	2.11	3.36	1.62	10.86**	9.23*
$LB_{(5)}$	223.79***	52.73***	3.53	4.07	2.17	11.01*	10.52*
$LB_{(6)}$	275.89***	65.29***	3.64	5.15	2.38	15.97**	12.52*
$LB_{(9)}$	401.76***	77.48***	6.66	12.23	3.09	19.70**	17.35**
$LB_{(10)}$	460.93***	81.61***	11.56	12.29	3.49	22.88**	19.14**
$LB_{(12)}$	571.25***	121.53***	15.12	27.84***	7.48	23.36**	19.86*
$ARCH_{(2)}$	1023.83***	1.98	2.06	0.29	3.00	18.70***	12.79***
$ARCH_{(3)}$	1444.74**	2.17	2.19	0.65	3.38	19.13***	14.10***
$ARCH_{(4)}$	1891.03**	2.23	2.63	0.69	4.52	18.91***	14.62***
$ARCH_{(5)}$	2321.43**	2.26	2.67	4.38	5.85	19.63***	16.87***
$ARCH_{(6)}$	2712.22	2.73	4.99	20.91***	5.41	22.17***	16.82***
$ARCH_{(9)}$	2961.00	3.55	6.11	21.27**	7.30	23.40***	17.92**
$ARCH_{(10)}$	2940.00	5.11	9.96	21.10**	7.14	23.45***	19.45**
$ARCH_{(12)}$	2898.00	16.85	15.14	27.60***	13.53	25.80**	24.00**
JB	193.16***	36.51***	5.80**	145.47***	0.07	36.84***	22.65***
Skewness	64.28***	0.72***	−0.45**	1.29***	−0.05	0.46**	0.00
Kurtosis	128.88***	4.94***	3.33	7.08***	2.99	5.25***	4.90***

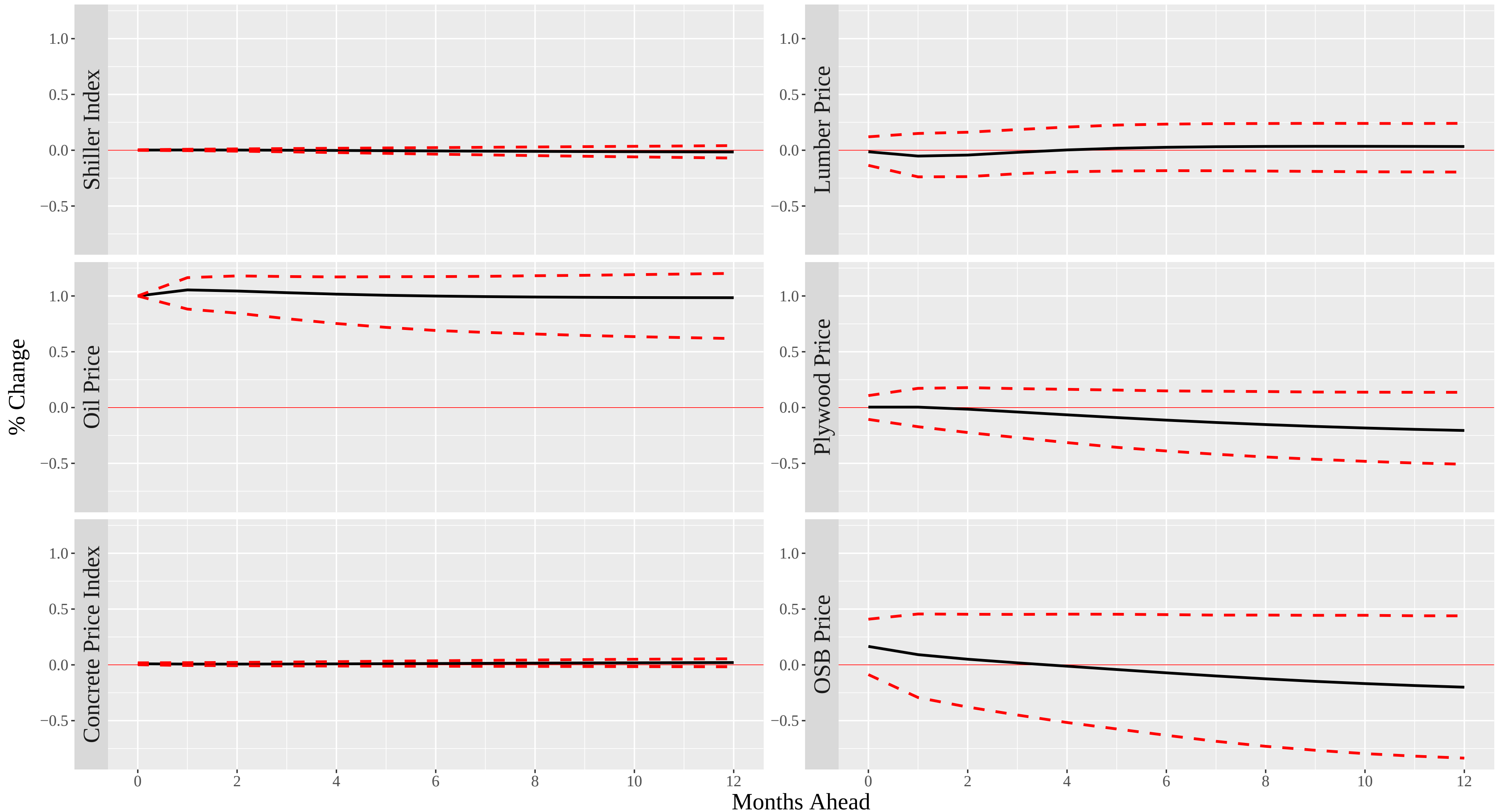
Notes: LB, ARCH, JB, Skewness, and Kurtosis indicate Ljung–Box test for autocorrelation, ARCH test for autoregressive conditional heteroskedasticity, Jarque–Bera test for normality, Skewness test for only skewness, and Kurtosis test for only kurtosis respectively. Values in parenthesis indicate the lag length used in LB and ARCH tests. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.



Notes: All variables are in the natural logarithmic form in the estimation, but the interpretation of IRFs is in percentages with a 90% confidence interval generated with 10000 bootstrap replications.

(a) Response of All Variables to a 1% Positive Shock in Shiller Index - Segment 1

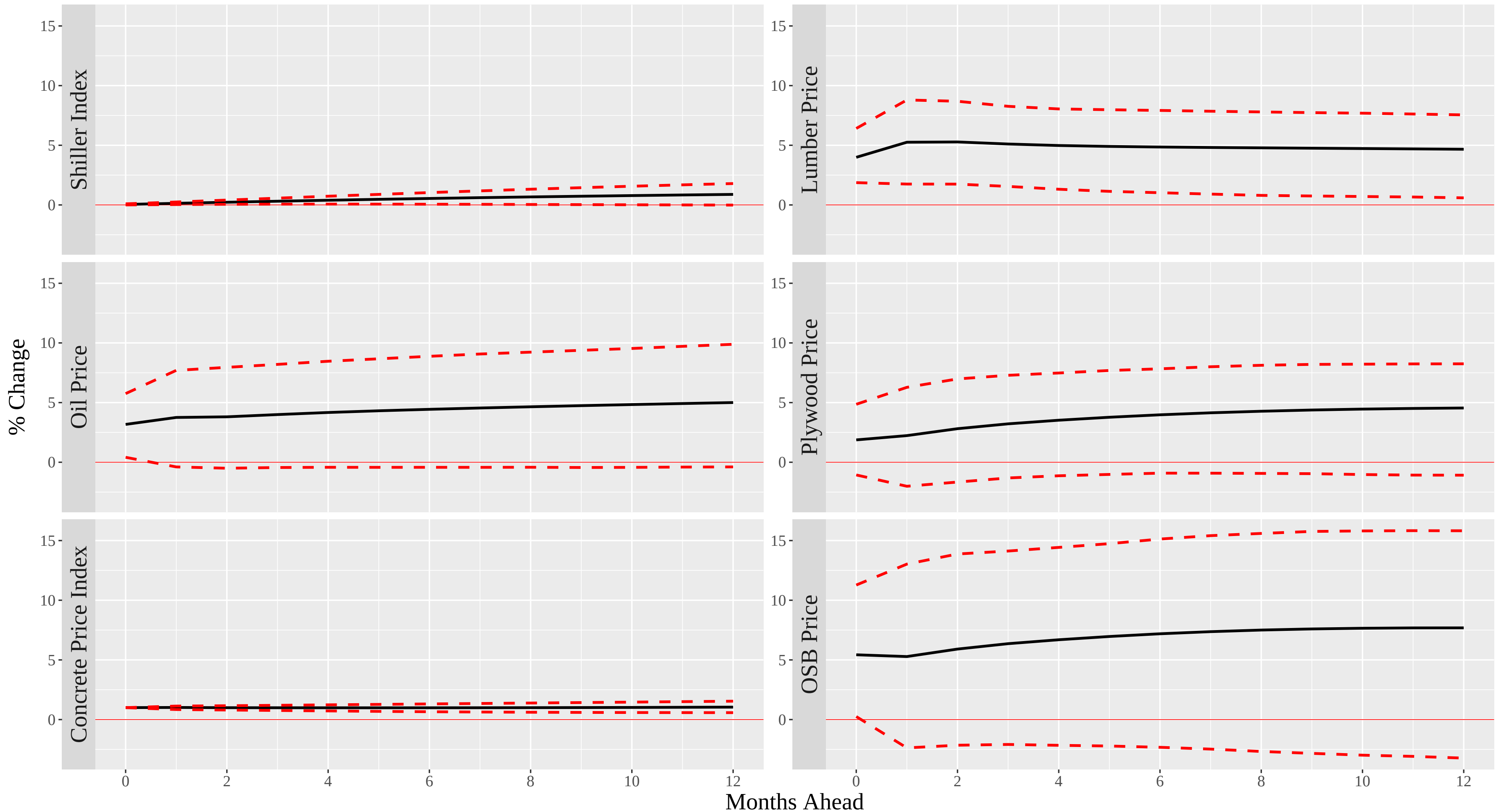
Figure 5: Impulse Responses Analysis - Segment 1



Notes: All variables are in the natural logarithmic form in the estimation, but the interpretation of IRFs is in percentages with a 90% confidence interval generated with 10000 bootstrap replications.

(b) Response of All Variables to a 1% Positive Shock in Oil Price - Segment 1

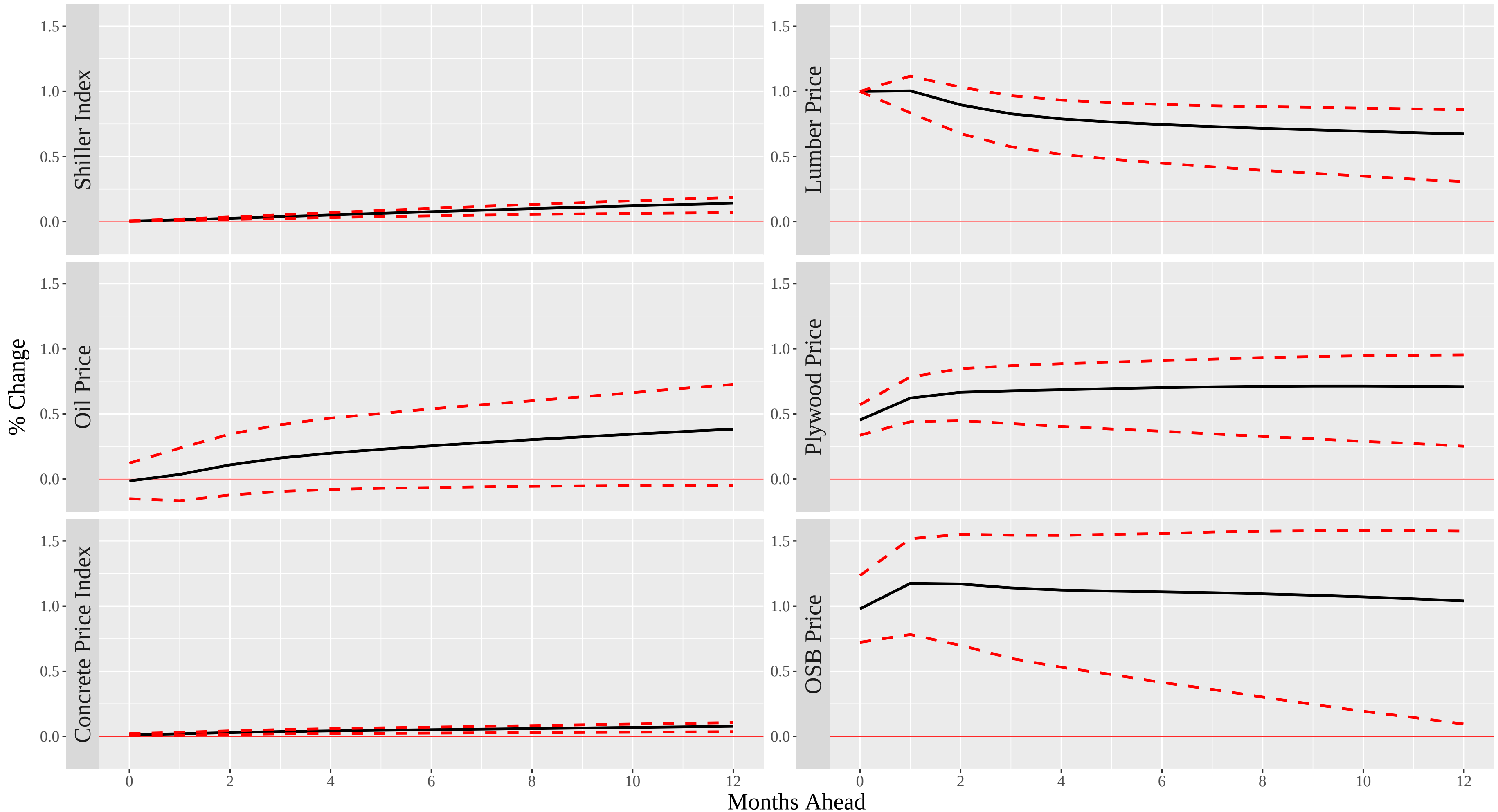
Figure 5 (continued)



Notes: All variables are in the natural logarithmic form in the estimation, but the interpretation of IRFs is in percentages with a 90% confidence interval generated with 10000 bootstrap replications.

(c) Response of All Variables to a 1% Positive Shock in Concrete Price Index - Segment 1

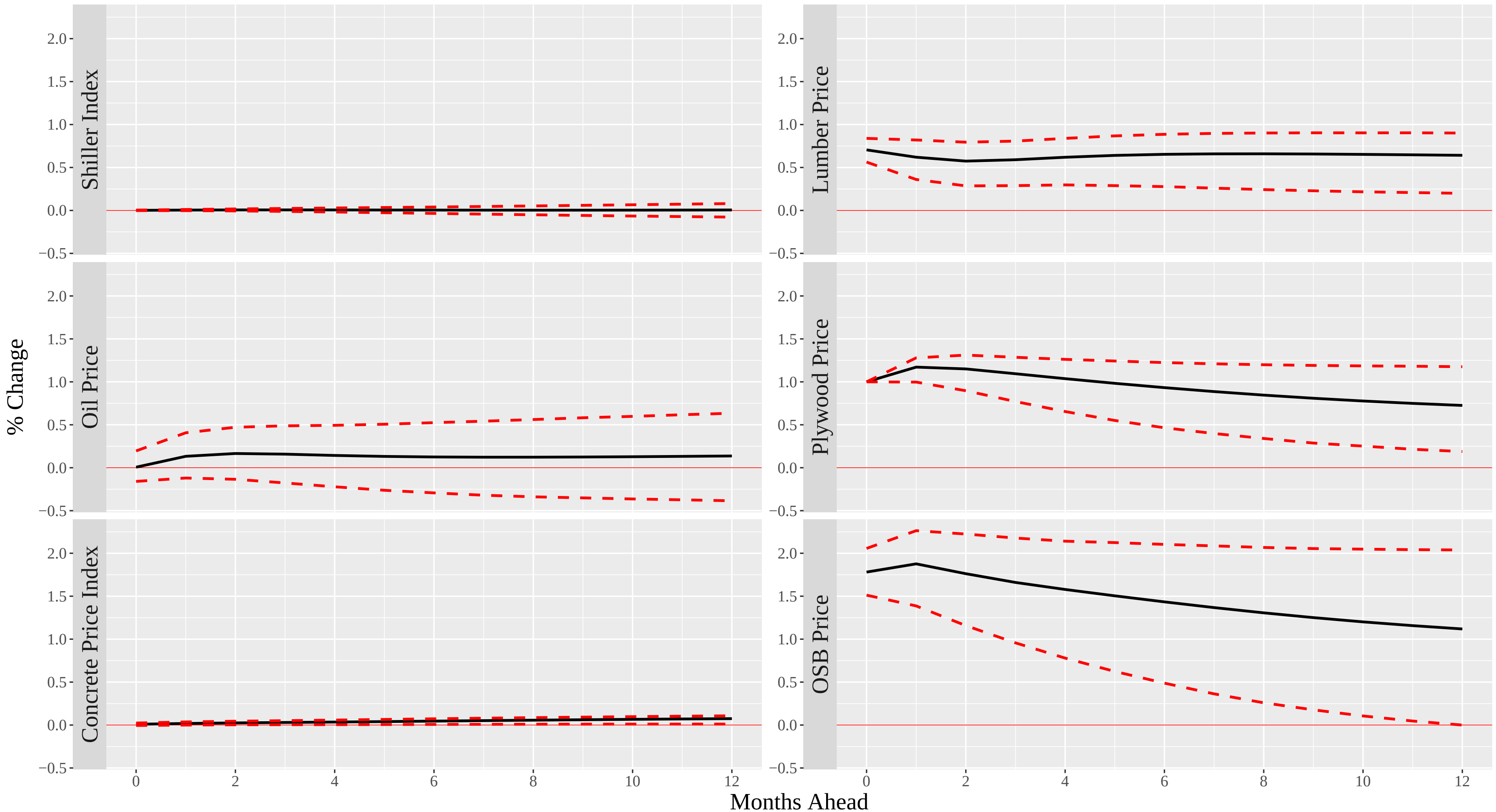
Figure 5 (continued)



Notes: All variables are in the natural logarithmic form in the estimation, but the interpretation of IRFs is in percentages with a 90% confidence interval generated with 10000 bootstrap replications.

(d) Response of All Variables to a 1% Positive Shock in Lumber Price - Segment 1

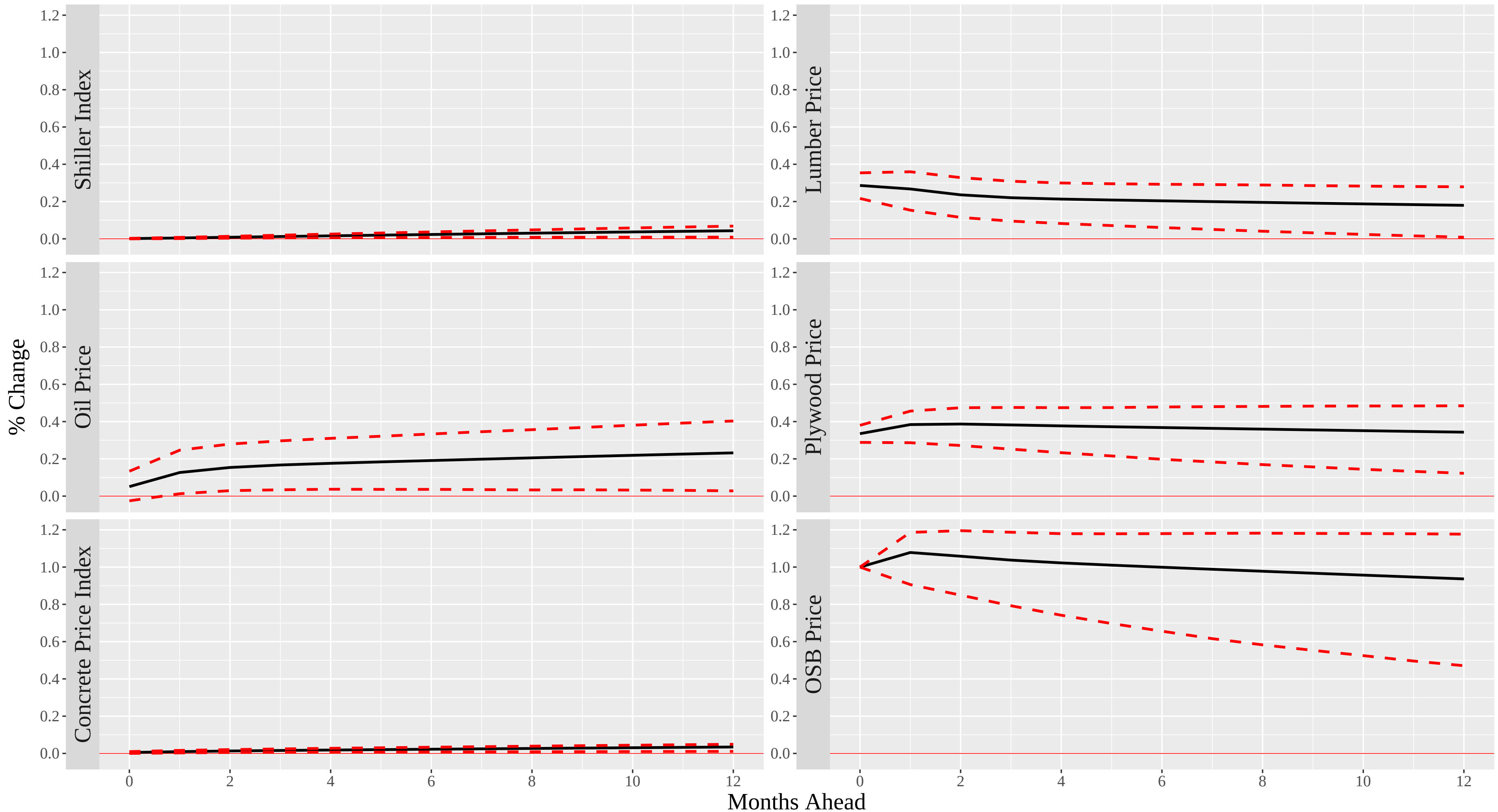
Figure 5 (continued)



Notes: All variables are in the natural logarithmic form in the estimation, but the interpretation of IRFs is in percentages with a 90% confidence interval generated with 10000 bootstrap replications.

(e) Response of All Variables to a 1% Positive Shock in Plywood Price - Segment 1

Figure 5 (continued)



Notes: All variables are in the natural logarithmic form in the estimation, but the interpretation of IRFs is in percentages with a 90% confidence interval generated with 10000 bootstrap replications.

(f) Response of All Variables to a 1% Positive Shock in OSB Price - Segment 1

Figure 5 (continued)

Table 22: Johansen Trace Cointegration Test Statistics - Segment 2

	Test Statistic by Lag Length:						*Critical Values:*		
H_0:	$p = 1$	$p = 2$	$p = 3$	$p = 4$	$p = 5$	$p = 6$	10%	5%	1%
$r = 0$	117.45	133.28	123.54	112.27	153.27	157.85	97.18	102.14	111.01
$r \leq 1$	74.88	79.81	84.66	74.58	80.48	92.16	71.86	76.07	84.45
$r \leq 2$	48.91	51.96	52.79	45.30	41.55	45.59	49.65	53.12	60.16
$r \leq 3$	27.04	28.33	29.79	26.08	23.72	23.39	32.00	34.91	41.07
$r \leq 4$	13.64	11.88	14.05	13.22	12.23	12.12	17.85	19.96	24.60
$r \leq 5$	4.30	4.07	3.71	4.37	5.72	4.34	7.52	9.24	12.97

Notes: p indicates the lag length used in the Johansen trace cointegration tests and VECM(p).

Table 23: TYDL Granger–Causality Test Statistics - Segment 2

	Shiller	CB	WPU1331	LAES	PAAB	PACS
Shiller		0.92	9.03^{**}	4.46	2.87	2.37
CB	10.55^{***}		2.08	7.39^{**}	8.03^{**}	12.43^{***}
WPU1331	8.14^{**}	1.95		6.14^{**}	5.16^{*}	5.88^{*}
LAES	4.17	0.56	0.28		5.78^{*}	0.11
PAAB	0.11	3.05	2.64	5.67^{*}		0.67
PACS	3.14	3.68	4.55	8.08^{**}	0.16	

Notes: Value in each cell indicates the test statistic for the hypothesis H_0 that is the row variable does not Granger–cause the column variable. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 24: VECM Results - Segment 2

	Equation:					
	ΔShiller	ΔCB	ΔWPU1331	ΔLAES	ΔPAAB	ΔPACS
ECT 1	−0.026***	−0.294**	0.019***	0.433***	−0.085	−0.133
$\Delta \text{Shiller}_{t-1}$	0.844***	−0.928	0.024	−0.107	0.283	−2.246*
ΔCB_{t-1}	0.021***	0.548***	−0.007	0.183	0.133**	0.284**
$\Delta \text{WPU1331}_{t-1}$	0.384***	2.498	0.084	−7.519**	−1.013	−2.168
ΔLAES_{t-1}	0.003	−0.041	0.005	0.131	0.147**	0.092
ΔPAAB_{t-1}	−0.021*	0.050	0.001	−0.293	−0.049	−0.204
ΔPACS_{t-1}	0.008	−0.018	−0.001	−0.012	0.005	0.181
Observations	97	97	97	97	97	97
Residual Std. Error	0.004	0.079	0.003	0.091	0.051	0.105
R^2	0.817	0.266	0.156	0.206	0.149	0.140
Adjusted R^2	0.803	0.209	0.090	0.144	0.083	0.073
F Statistic	57.552***	4.659***	2.373**	3.330***	2.248**	2.098*

Notes: ECTs indicate the respective error correction terms. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

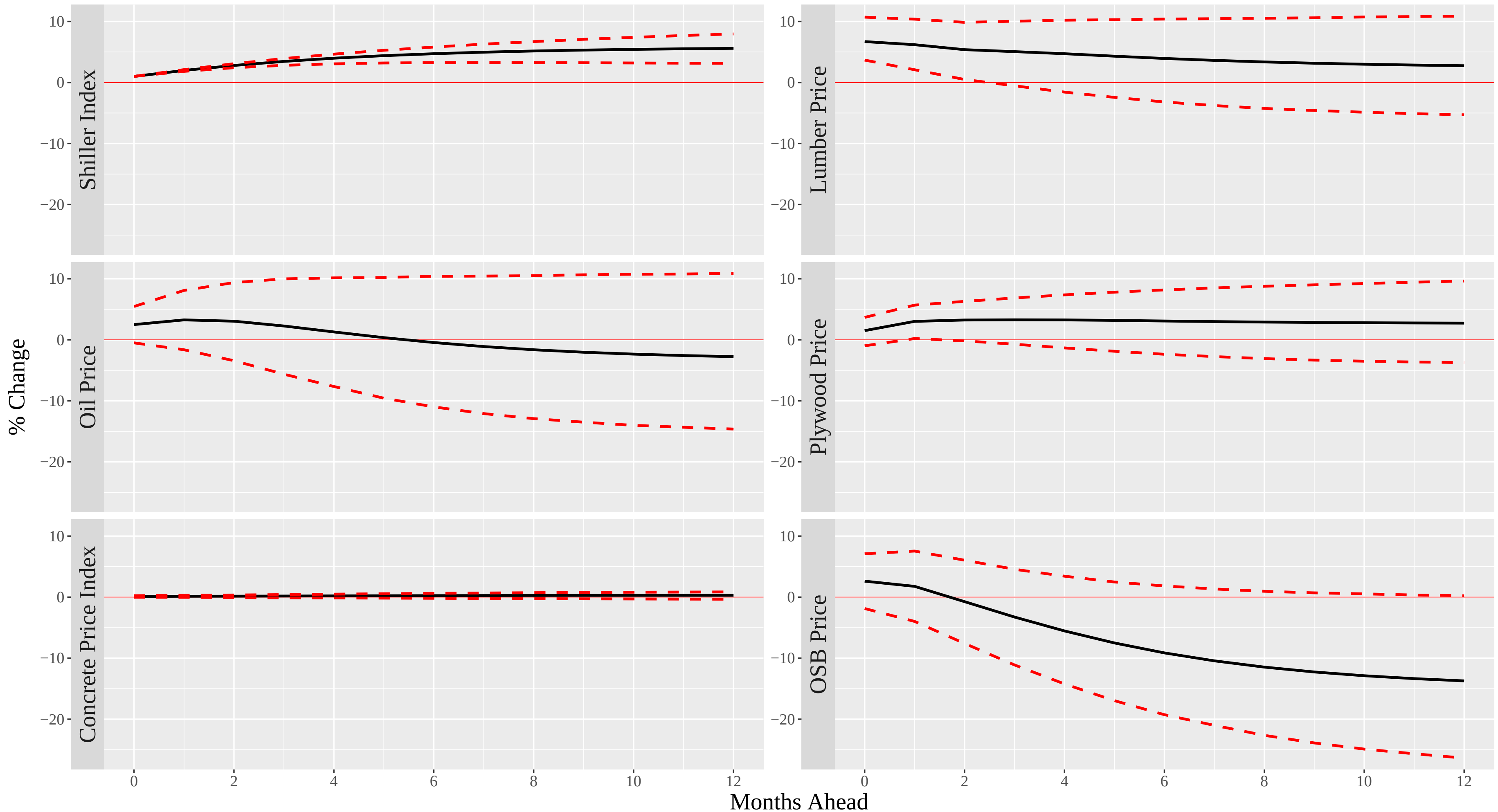
Table 25: Estimated Coefficients of VECM in level–VAR Form - Segment 2

	Equation:					
	Shiller	CB	WPU1331	LAES	PAAB	PACS
Constant	0.151	1.694	−0.109	−2.494	0.488	0.767
Shiller_{t-1}	1.817	−1.222	0.043	0.325	0.198	−2.379
CB_{t-1}	0.016	1.499	−0.004	0.254	0.119	0.262
WPU1331_{t-1}	0.372	2.355	1.093	−7.308	−1.054	−2.232
LAES_{t-1}	0.014	0.082	−0.003	0.950	0.182	0.148
PAAB_{t-1}	−0.014	0.122	−0.003	−0.400	0.972	−0.172
PACS_{t-1}	0.001	−0.093	0.004	0.099	−0.016	1.147
Shiller_{t-2}	−0.844	0.928	−0.024	0.107	−0.283	2.246
CB_{t-2}	−0.021	−0.548	0.007	−0.183	−0.133	−0.284
WPU1331_{t-2}	−0.384	−2.498	−0.084	7.519	1.013	2.168
LAES_{t-2}	−0.003	0.041	−0.005	−0.131	−0.147	−0.092
PAAB_{t-2}	0.021	−0.050	−0.001	0.293	0.049	0.204
PACS_{t-2}	−0.008	0.018	0.001	0.012	−0.005	−0.181

Table 26: Diagnostic Test Statistics for VECM in level–VAR Form - Segment 2

		Univariate Tests by Equation:					
Test	Multivariate	Shiller	CB	WPU1331	LAES	PAAB	PACS
$LB_{(2)}$	78.95***	16.29***	4.64*	1.50	0.03	2.95	1.48
$LB_{(3)}$	101.30***	18.31***	4.67	1.52	0.76	3.23	2.30
$LB_{(4)}$	140.42***	23.67***	5.76	2.75	0.76	4.43	5.45
$LB_{(5)}$	175.26***	28.47***	5.77	5.20	7.51	4.47	5.64
$LB_{(6)}$	223.47***	40.24***	12.03*	5.22	7.59	4.47	5.67
$LB_{(9)}$	320.43***	49.50***	13.40	8.95	8.29	10.84	9.09
$LB_{(10)}$	362.84***	52.27***	13.71	9.69	8.82	12.91	9.26
$LB_{(12)}$	467.62***	116.64***	13.78	11.44	9.68	13.49	10.71
$ARCH_{(2)}$	979.47**	3.42	14.82***	0.15	0.59	11.26***	18.20***
$ARCH_{(3)}$	1350.30	3.40	15.12***	0.32	1.92	11.26**	18.27***
$ARCH_{(4)}$	1770.36	3.59	15.32***	0.79	10.33**	11.64**	23.85***
$ARCH_{(5)}$	1932.00	3.60	16.75***	0.86	14.16**	12.22**	24.17***
$ARCH_{(6)}$	1911.00	5.65	17.23***	1.11	13.67**	12.16*	25.01***
$ARCH_{(9)}$	1848.00	6.66	17.09**	14.80*	10.41	13.53	26.64***
$ARCH_{(10)}$	1827.00	6.54	17.88*	14.64	11.16	15.60	26.39***
$ARCH_{(12)}$	1785.00	22.96**	24.28**	15.37	11.37	15.29	26.18**
JB	257.93***	17.61***	4.43*	248.07***	0.57	20.38***	66.97***
Skewness	55.01***	0.83***	−0.29	1.75***	−0.18	−0.43*	−0.14
Kurtosis	202.93***	4.26**	3.87**	10.01***	3.07	5.08***	7.06***

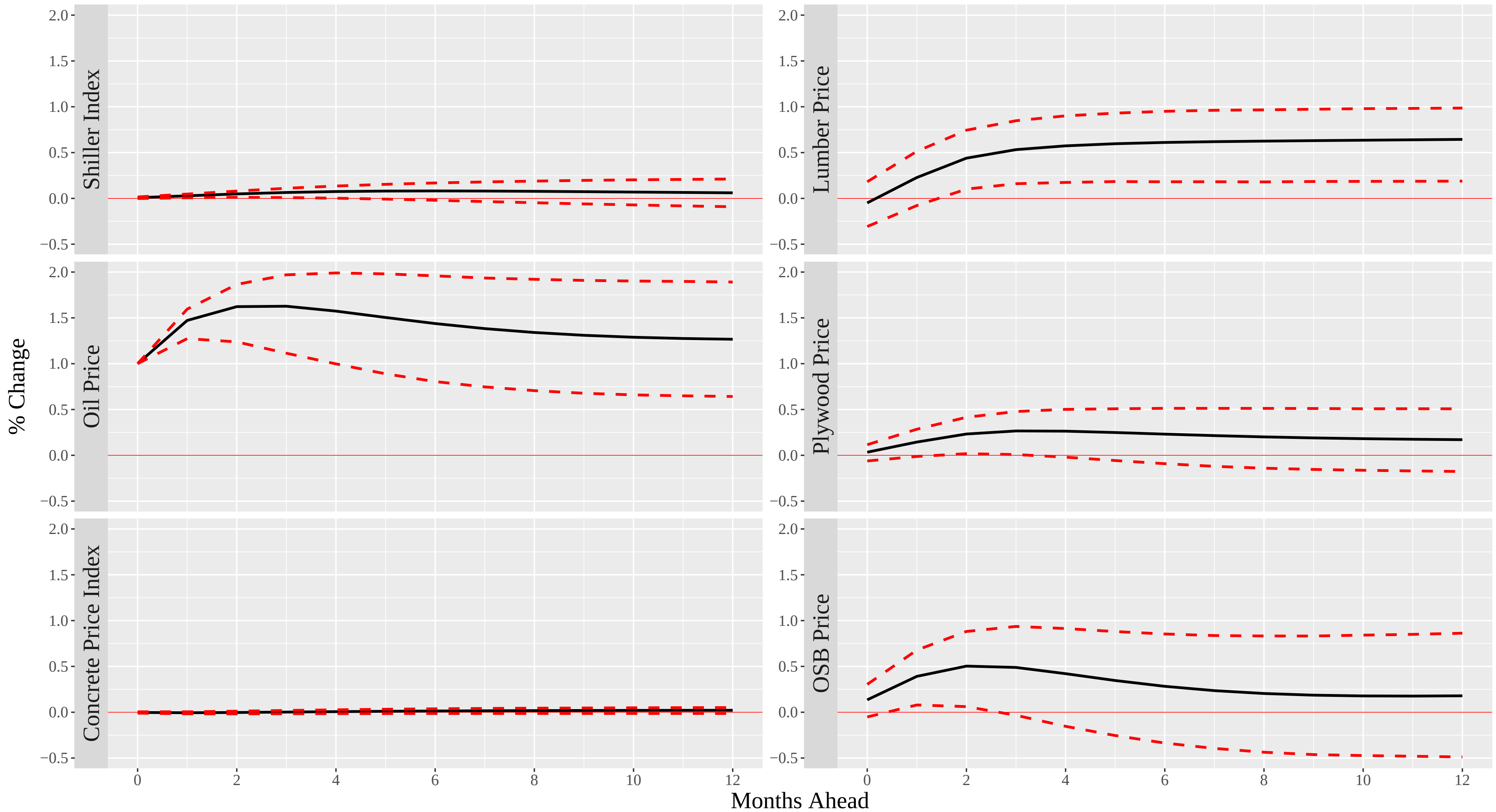
Notes: LB, ARCH, JB, Skewness, and Kurtosis indicate Ljung–Box test for autocorrelation, ARCH test for autoregressive conditional heteroskedasticity, Jarque–Bera test for normality, Skewness test for only skewness, and Kurtosis test for only kurtosis respectively. Values in parenthesis indicate the lag length used in LB and ARCH tests. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.



Notes: All variables are in the natural logarithmic form in the estimation, but the interpretation of IRFs is in percentages with a 90% confidence interval generated with 10000 bootstrap replications.

(a) Response of All Variables to a 1% Positive Shock in Shiller Index - Segment 2

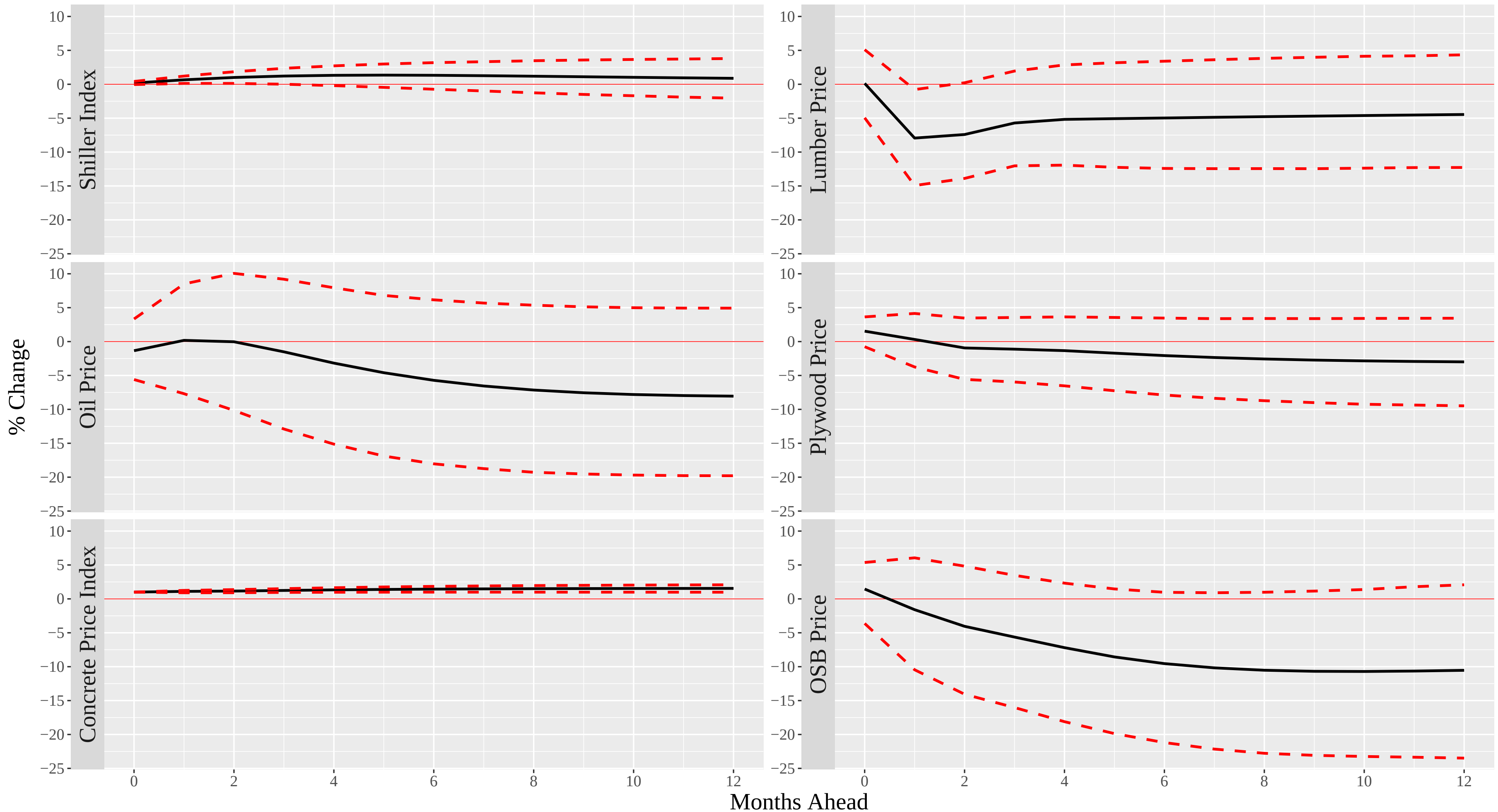
Figure 6: Impulse Responses Analysis - Segment 2



Notes: All variables are in the natural logarithmic form in the estimation, but the interpretation of IRFs is in percentages with a 90% confidence interval generated with 10000 bootstrap replications.

(b) Response of All Variables to a 1% Positive Shock in Oil Price - Segment 2

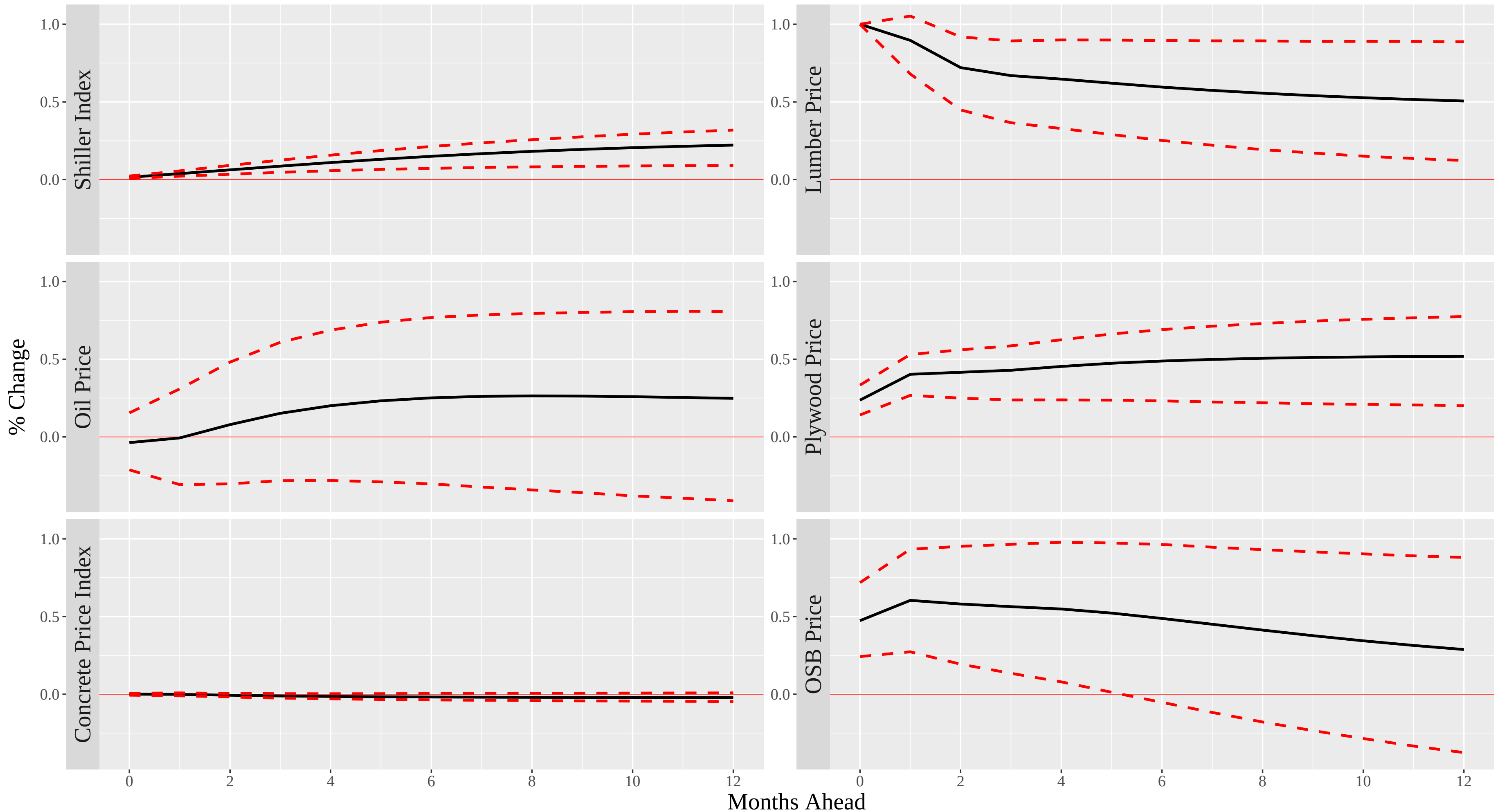
Figure 6 (continued)



Notes: All variables are in the natural logarithmic form in the estimation, but the interpretation of IRFs is in percentages with a 90% confidence interval generated with 10000 bootstrap replications.

(c) Response of All Variables to a 1% Positive Shock in Concrete Price Index - Segment 2

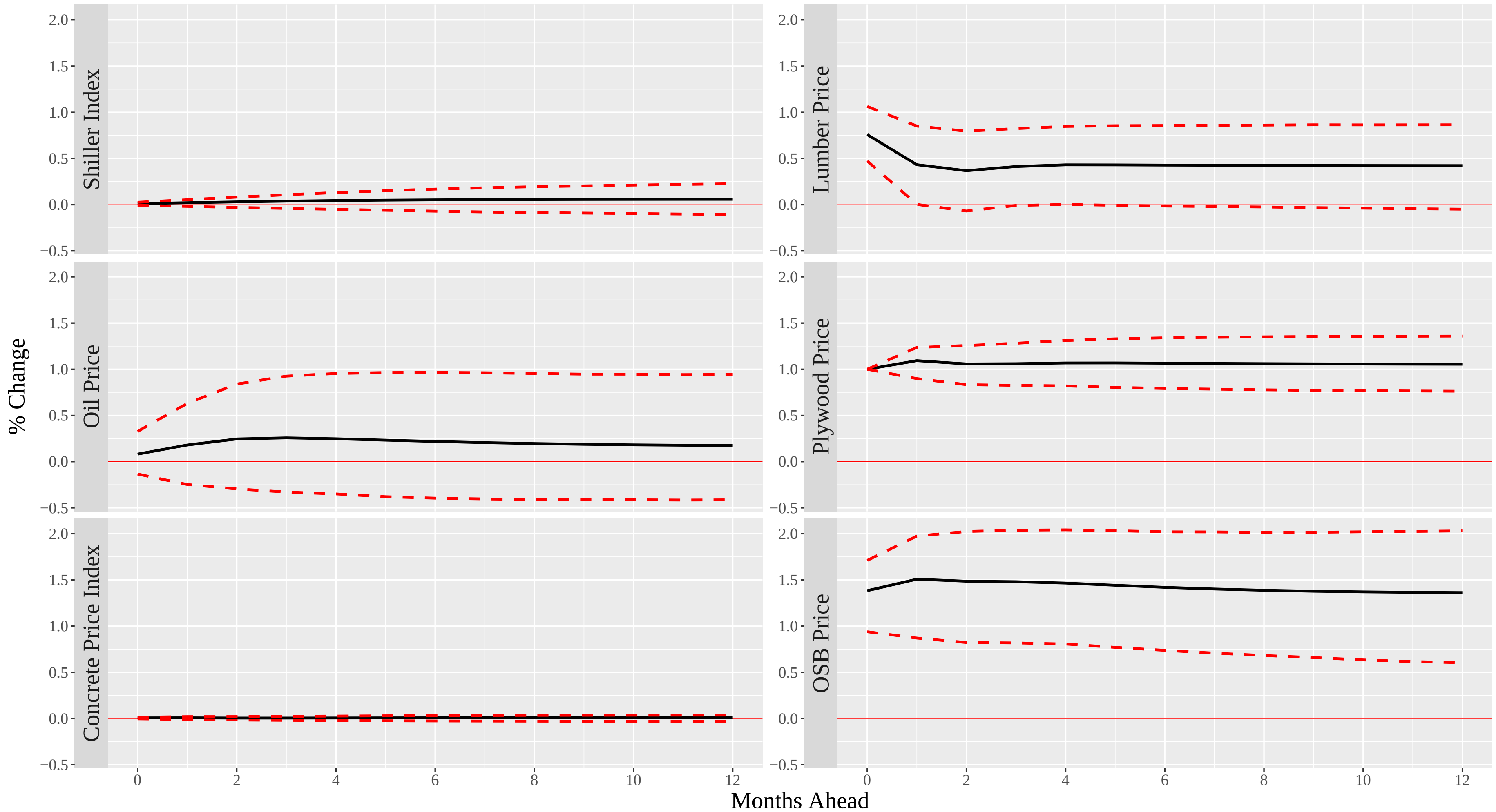
Figure 6 (continued)



Notes: All variables are in the natural logarithmic form in the estimation, but the interpretation of IRFs is in percentages with a 90% confidence interval generated with 10000 bootstrap replications.

(d) Response of All Variables to a 1% Positive Shock in Lumber Price - Segment 2

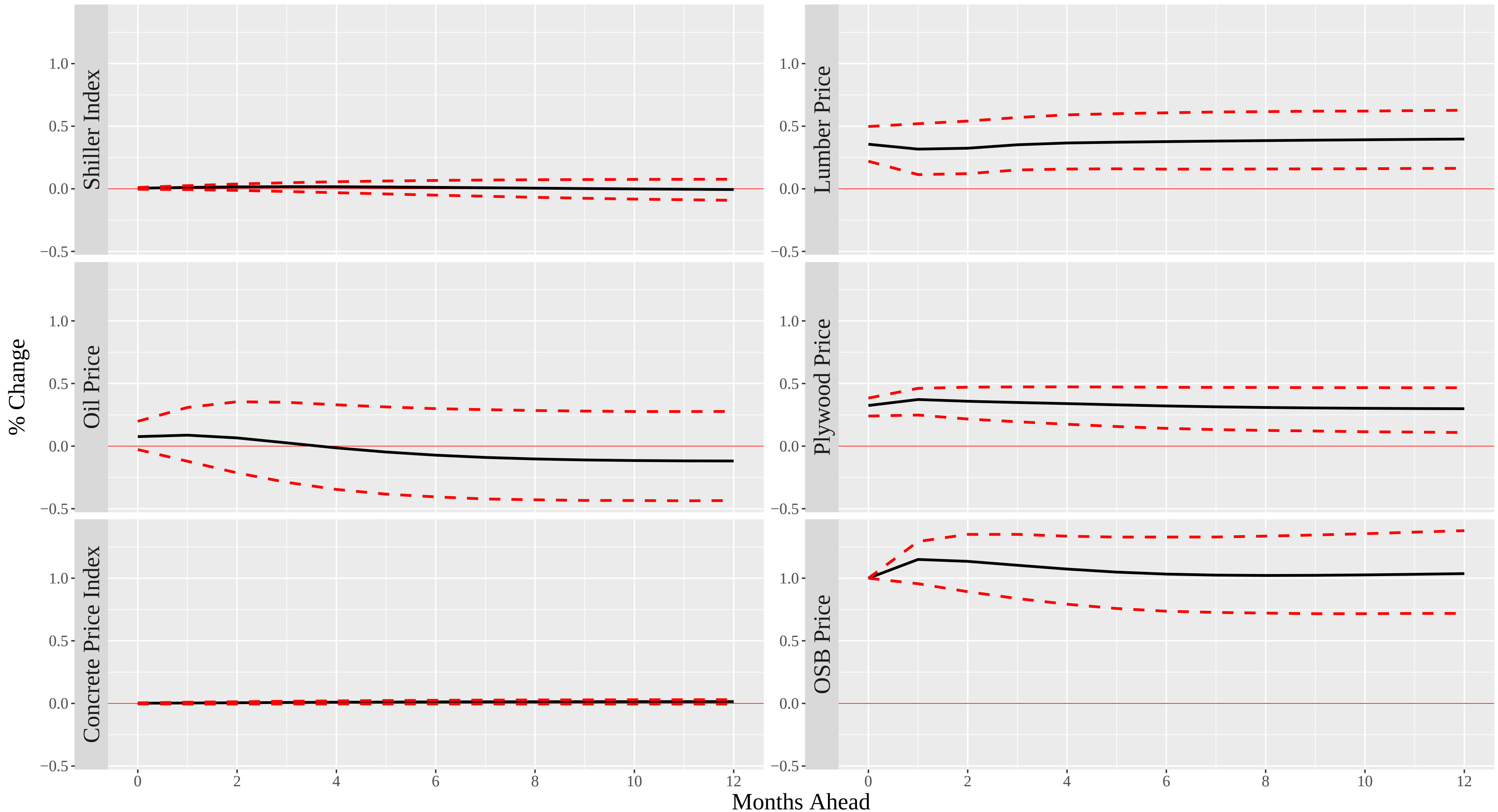
Figure 6 (continued)



Notes: All variables are in the natural logarithmic form in the estimation, but the interpretation of IRFs is in percentages with a 90% confidence interval generated with 10000 bootstrap replications.

(e) Response of All Variables to a 1% Positive Shock in Plywood Price - Segment 2

Figure 6 (continued)



Notes: All variables are in the natural logarithmic form in the estimation, but the interpretation of IRFs is in percentages with a 90% confidence interval generated with 10000 bootstrap replications.

(f) Response of All Variables to a 1% Positive Shock in OSB Price - Segment 2

Figure 6 (continued)

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Appendix

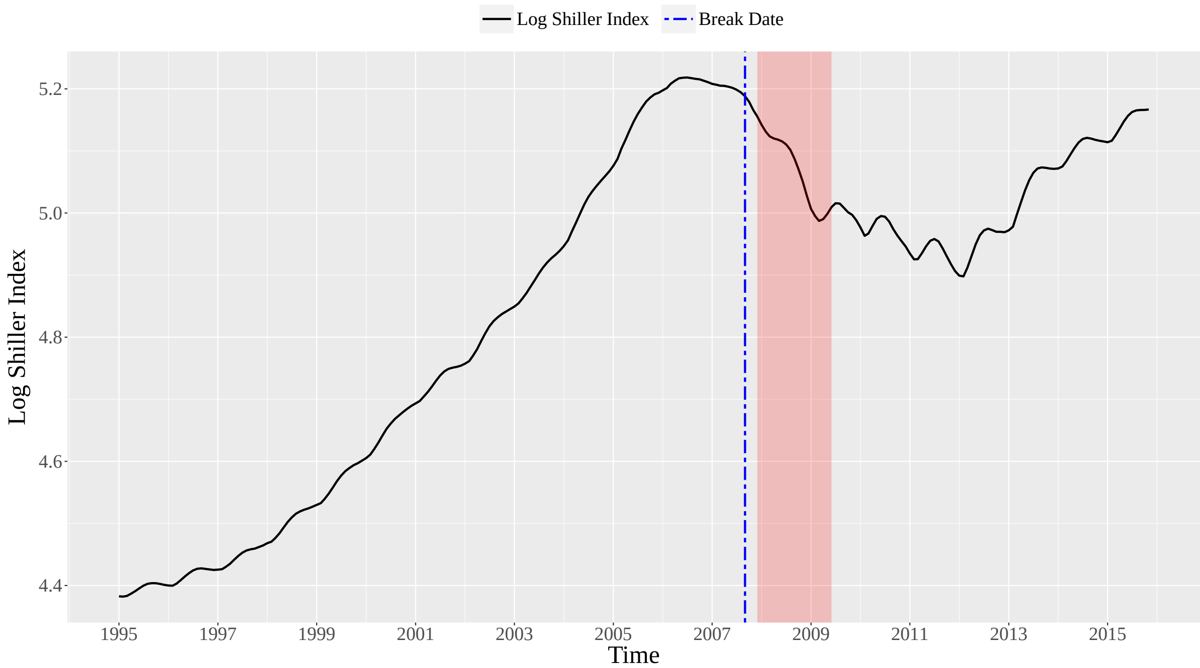
A R Version Information

- R version 3.3.3 (2017-03-06), `x86_64-apple-darwin13.4.0`
- Locale: `en_US.UTF-8/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8`
- Base packages: base, datasets, graphics, grDevices, grid, methods, stats, utils
- Other packages: aod 1.3, bestglm 0.36, boot 1.3-20, CADFtest 0.3-3, car 2.1-6, checkpoint 0.4.3, classInt 0.1-24, cowplot 0.9.2, devtools 1.13.4, dplyr 0.7.4, dygraphs 1.1.1.4, dynlm 0.3-5, fBasics 3042.89, FitAR 1.94, forecast 8.2, Formula 1.2-2, fUnitRoots 3042.79, ggplot2 2.2.1.9000, ggthemes 3.4.0, gridExtra 2.3, gtable 0.2.0, gvlma 1.0.0.2, Hmisc 4.1-1, knitr 1.19, latex2exp 0.4.0, lattice 0.20-35, latticeExtra 0.6-28, leaps 3.0, lgarch 0.6-2, lmtest 0.9-35, ltsa 1.4.6, lubridate 1.7.1, magrittr 1.5, MASS 7.3-47, moments 0.14, NCmisc 1.1.5, NLP 0.1-11, normtest 1.1, nortest 1.0-4, pastecs 1.3-18, plyr 1.8.4, RColorBrewer 1.1-2, reshape 0.8.7, reshape2 1.4.3, sandwich 2.4-0, seasonal 1.6.1, stargazer 5.2.1, stringi 1.1.6, stringr 1.2.0, strucchange 1.5-1, survival 2.41-3, tidyr 0.7.2, tikzDevice 0.10-1, timeDate 3042.101, timeSeries 3042.102, tm 0.7-3, tsDyn 0.9-44, tseries 0.10-42, urca 1.3-0, vars 1.5-2, x13binary 1.1.39-1, XLConnect 0.2-14, XLConnectJars 0.2-14, xtable 1.8-2, zoo 1.8-1
- Loaded via a namespace (and not attached): acepack 1.4.1, assertthat 0.2.0, backports 1.1.2, base64enc 0.1-3, bindr 0.1, bindrcpp 0.2, checkmate 1.8.5, class 7.3-14, cluster 2.0.6, codetools 0.2-15, colorspace 1.3-2, curl 3.1, data.table 1.10.4-3, digest 0.6.15, e1071 1.6-8, filehash 2.4-1, foreach 1.4.4, foreign 0.8-69, fracdiff 1.4-2, glmnet 2.0-13, glue 1.2.0, grpreg 3.1-2, htmlTable 1.11.2, htmltools 0.3.6, htmlwidgets 1.0, iterators 1.0.9, lazyeval 0.2.1, lme4 1.1-15, Matrix 1.2-11, MatrixModels 0.4-1, memoise 1.1.0, mgcv 1.8-22, minqa 1.2.4, mnormt 1.5-5, munsell 0.4.3, nlme 3.1-131, nloptr 1.0.4, nnet 7.3-12, parallel 3.3.3, pbkrtest 0.4-7, pkgconfig 2.0.1, proftools 0.99-2, purrr 0.2.4, quadprog 1.5-5, quantmod 0.4-12, quantreg 5.34, R6 2.2.2, Rcpp 0.12.14, rJava 0.9-9, rlang 0.1.6, rpart 4.1-11, rstudioapi 0.7, scales 0.5.0.9000, slam 0.1-40, SparseM 1.77, spatial 7.3-11, splines 3.3.3, tibble 1.3.4, tools 3.3.3, tseriesChaos 0.1-13, TTR 0.23-2, withr 2.1.1, xml2 1.1.1, xts 0.10-1, yaml 2.1.16

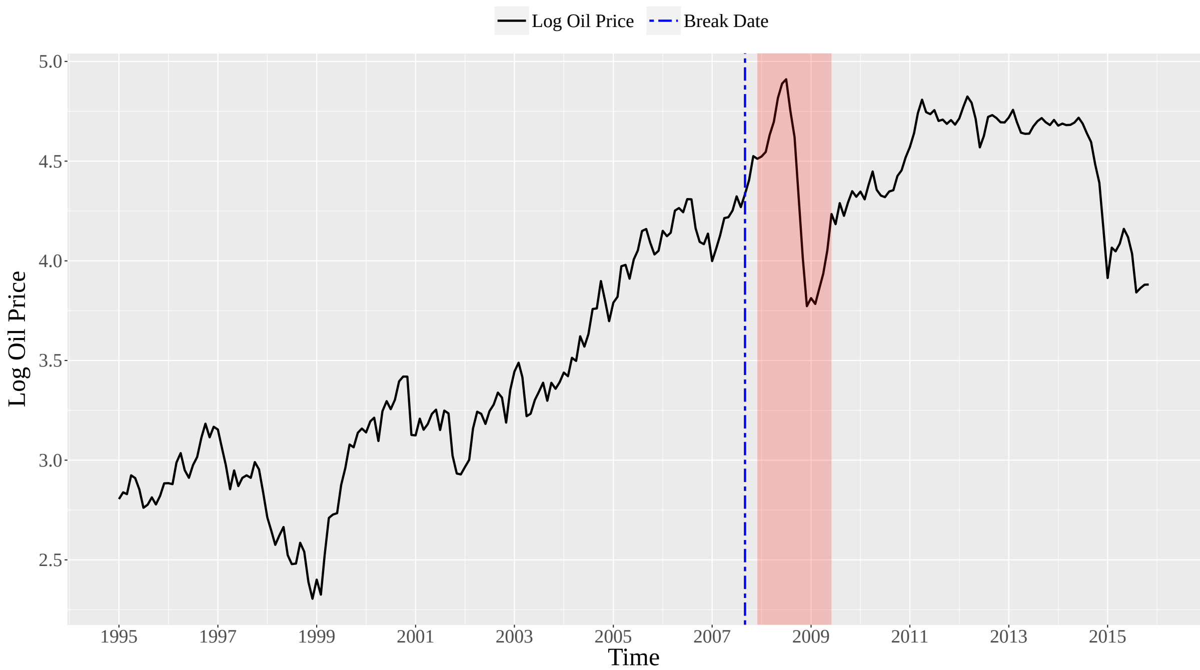
B GAUSS Version Information

GAUSS software used in this study is version 16.04 build 4222.

C Additional Tables and Figures

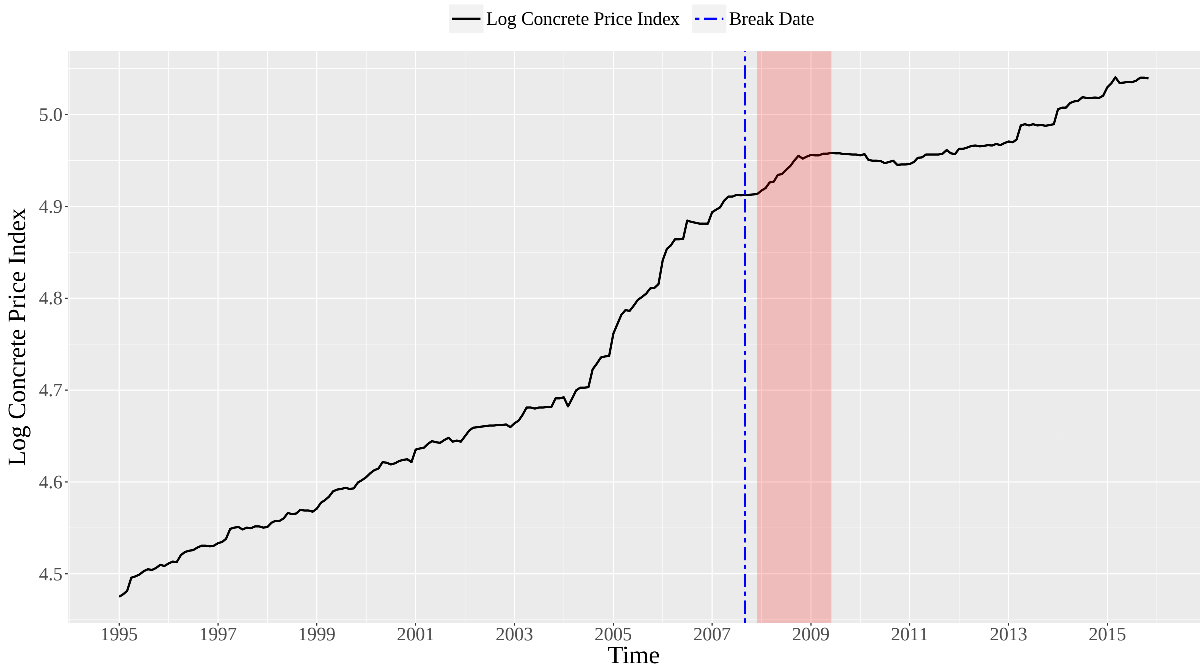


(a) Log Shiller Index

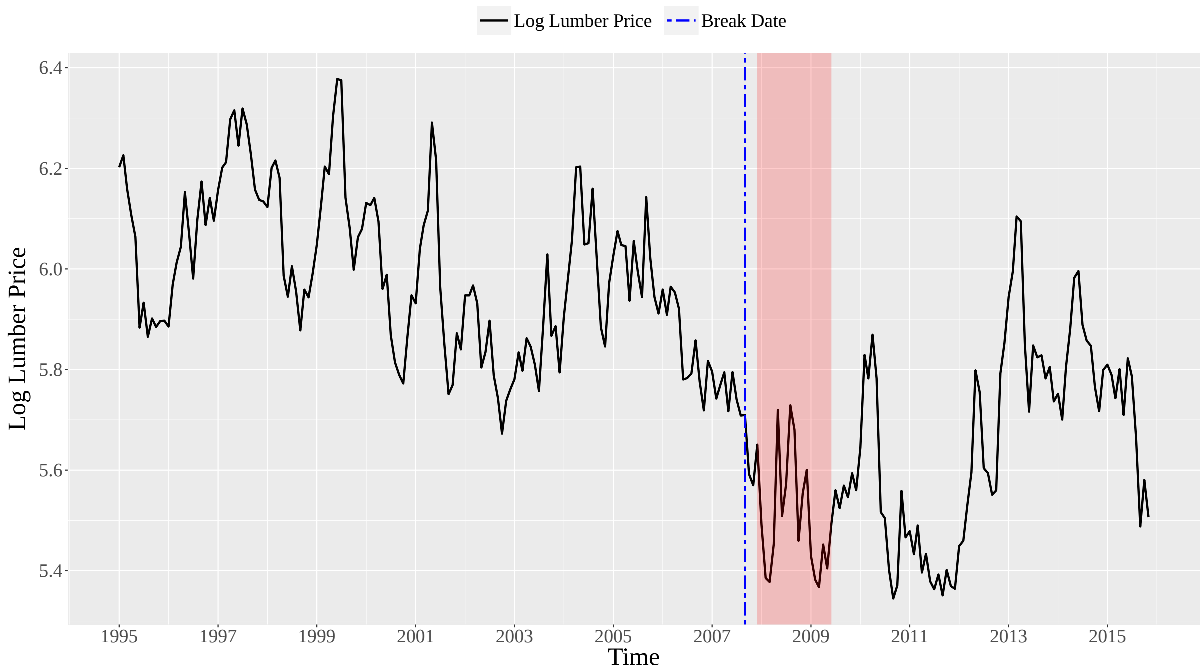


(b) Log Oil Price

Figure 7: Plots of All Variables in Natural Logarithmic Form

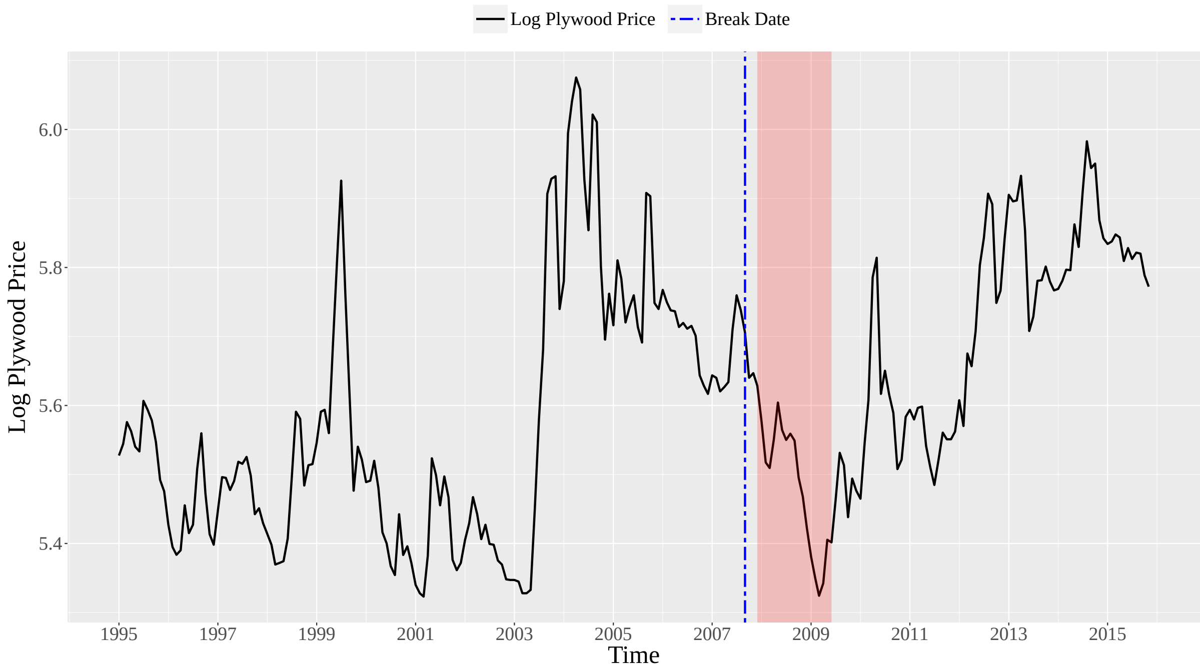


(c) Log Concrete Price Index

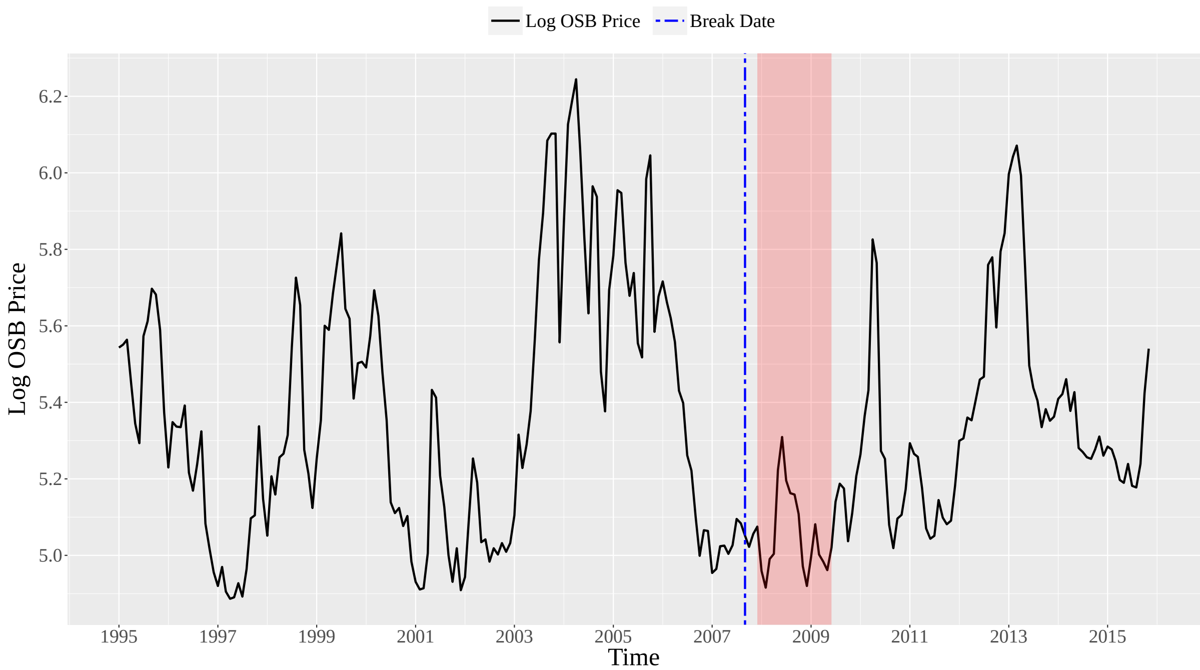


(d) Log Lumber Price

Figure 7 (continued)



(e) Log Plywood Price



(f) Log OSB Price

Figure 7 (continued)

Table 27: ADF Unit Root Test Results with EAP for ΔVariables - Entire Data

	ΔVariable:					
Lag	ΔShiller	ΔCB	ΔWPU1331	ΔLAES	ΔPAAB	ΔPACS
AIC	Unit Root	Stationary	Stationary	Stationary	Stationary	Stationary
BIC	Unit Root	Stationary	Stationary	Stationary	Stationary	Stationary
NPS	Unit Root	Stationary	Unit Root	Stationary	Stationary	Stationary

Notes: All decisions are given at the 5% significance level.

Table 28: PP Unit Root Test Statistics for ΔVariables - Entire Data

		ΔVariable:					
Model	Lag	ΔShiller	ΔCB	ΔWPU1331	ΔLAES	ΔPAAB	ΔPACS
Constant	AIC	-2.96^{**}	-12.19^{***}	-13.56^{***}	-15.57^{***}	-13.00^{***}	-13.76^{***}
	BIC	-2.96^{**}	-12.19^{***}	-13.43^{***}	-15.50^{***}	-13.00^{***}	-13.76^{***}
	Long	-3.47^{***}	-11.96^{***}	-14.62^{***}	-16.50^{***}	-12.78^{***}	-13.76^{***}
	Short	-4.58^{***}	-12.19^{***}	-13.56^{***}	-15.57^{***}	-12.68^{***}	-13.62^{***}
Trend	AIC	-3.04	-12.21^{***}	-13.59^{***}	-15.54^{***}	-12.97^{***}	-13.74^{***}
	BIC	-3.04	-12.21^{***}	-13.47^{***}	-15.46^{***}	-12.97^{***}	-13.74^{***}
	Long	-3.55^{**}	-11.94^{***}	-14.62^{***}	-16.45^{***}	-12.75^{***}	-13.74^{***}
	Short	-4.67^{***}	-12.20^{***}	-13.59^{***}	-15.54^{***}	-12.65^{***}	-13.59^{***}

Notes: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 29: ERS Unit Root Test Statistics for ΔVariables - Entire Data

		ΔVariable:					
Model	Lag	ΔShiller	ΔCB	ΔWPU1331	ΔLAES	ΔPAAB	ΔPACS
Constant	AIC	-0.98	-8.87^{***}	-4.32^{***}	-7.12^{***}	-12.15^{***}	-12.58^{***}
	BIC	-0.98	-8.87^{***}	-10.18^{***}	-11.40^{***}	-12.15^{***}	-12.58^{***}
	Long	-1.86^{*}	-3.18^{***}	-1.95^{**}	-2.20^{**}	-3.77^{***}	-4.27^{***}
	Short	-3.32^{***}	-5.91^{***}	-4.32^{***}	-7.12^{***}	-5.99^{***}	-7.21^{***}
Trend	AIC	-1.14	-9.57^{***}	-4.45^{***}	-7.93^{***}	-12.58^{***}	-12.50^{***}
	BIC	-1.14	-9.57^{***}	-10.33^{***}	-11.88^{***}	-12.58^{***}	-12.50^{***}
	Long	-2.04	-4.45^{***}	-2.07	-3.10^{**}	-4.63^{***}	-4.03^{***}
	Short	-3.54^{***}	-6.88^{***}	-4.45^{***}	-7.93^{***}	-6.54^{***}	-7.07^{***}

Notes: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 30: KPSS Stationary Test Statistics for ΔVariables - Entire Data

		ΔVariable:					
Model	Lag	ΔShiller	ΔCB	ΔWPU1331	ΔLAES	ΔPAAB	ΔPACS
Constant	AIC	0.41*	0.17	0.30	0.02	0.02	0.03
	BIC	0.41*	0.17	0.38*	0.02	0.02	0.03
	Long	0.36*	0.16	0.23	0.04	0.03	0.04
	Short	0.65**	0.15	0.34	0.02	0.03	0.03
Trend	AIC	0.21**	0.10	0.21**	0.02	0.02	0.02
	BIC	0.21**	0.10	0.26***	0.02	0.02	0.02
	Long	0.19**	0.09	0.16**	0.04	0.03	0.03
	Short	0.32***	0.09	0.24***	0.02	0.03	0.02

Notes: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 31: Pairwise Johansen Trace Cointegration Test Statistics - Entire Data

	Shiller	CB	WPU1331	LAES	PAAB	PACS
Shiller		18.85* | 3.12	57.05*** | 5.26	29.52*** | 5.68	26.34*** | 5.41	31.89*** | 5.44
CB			47.76*** | 5.71	20.47** | 2.80	16.23 | 2.68	21.02** | 2.69
WPU1331				63.15*** | 14.92***	58.31*** | 12.25**	59.82*** | 13.74***
LAES					18.56* | 5.21	23.97** | 7.60*
PAAB						27.95*** | 10.08**
PACS						

Notes: The 1st and 2nd values in each cell indicate the test statistics for the hypotheses H_0: $r = 0$ and H_0: $r \leq 1$ respectively. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 32: Pairwise TYDL Granger–Causality Test Statistics - Entire Data

	Shiller	CB	WPU1331	LAES	PAAB	PACS
Shiller		0.78	4.90	10.22**	13.37***	7.36*
CB	3.19		1.74	0.93	3.25	5.10*
WPU1331	9.00**	0.52		0.17	0.37	0.89
LAES	7.42*	0.01	1.39		2.90	0.70
PAAB	0.63	2.53	1.17	5.56*		1.38
PACS	6.86*	2.62	2.13	0.73	0.16	

Notes: Value in each cell indicates the test statistic for the hypothesis H_0 that is the row variable does not Granger–cause the column variable. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 33: Adjustment Matrix α of VECM - Entire Data

	ECT 1	ECT 2
ΔShiller	−0.001	−0.001
ΔCB	−0.003	−0.001
ΔWPU1331	0.007	0.002
ΔLAES	−0.013	0.005
ΔPAAB	−0.018	−0.008
ΔPACS	−0.015	0.001

Notes: ECTs indicate respective error correction terms.

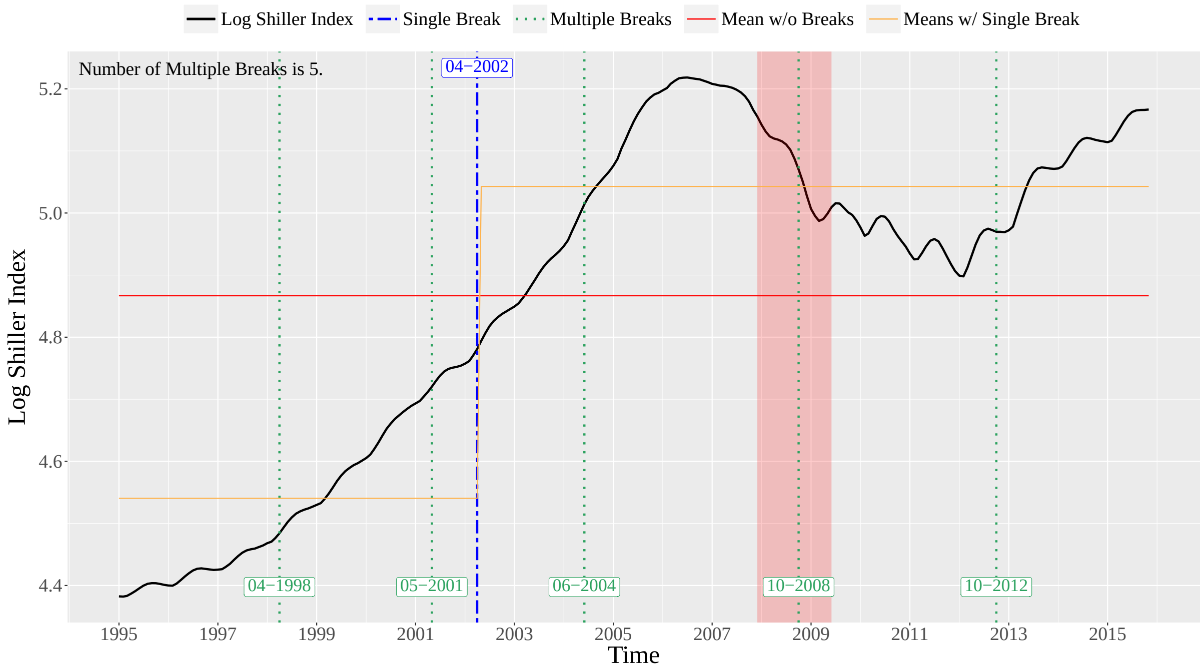
Table 34: Cointegration Matrix β of VECM - Entire Data

	ECT 1	ECT 2
Shiller_{t-1}	1.000	0.000
CB_{t-1}	0.000	1.000
WPU1331_{t-1}	3.473	−19.906
LAES_{t-1}	3.605	−10.773
PAAB_{t-1}	−4.198	15.440
PACS_{t-1}	1.924	−6.456
Constant	−28.763	101.502

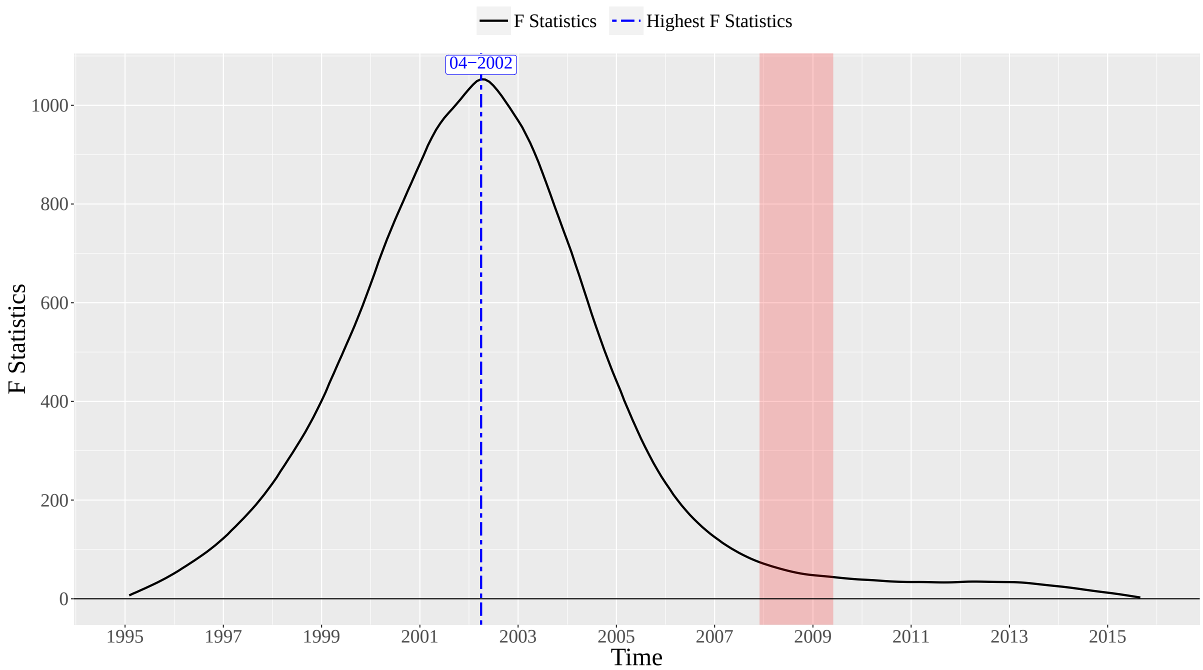
Notes: ECTs indicate respective error correction terms.

Table 35: Composite Matrix Π of VECM - Entire Data

	Shiller_{t-1}	CB_{t-1}	WPU1331_{t-1}	LAES_{t-1}	PAAB_{t-1}	PACS_{t-1}	Constant
ΔShiller	−0.001	−0.001	0.011	0.005	−0.007	0.003	−0.048
ΔCB	−0.003	−0.001	0.014	0.003	−0.007	0.003	−0.044
ΔWPU1331	0.007	0.002	−0.015	0.004	0.001	0.001	−0.002
ΔLAES	−0.013	0.005	−0.138	−0.098	0.128	−0.056	0.854
ΔPAAB	−0.018	−0.008	0.102	0.024	−0.052	0.018	−0.317
ΔPACS	−0.015	0.001	−0.071	−0.065	0.078	−0.035	0.530

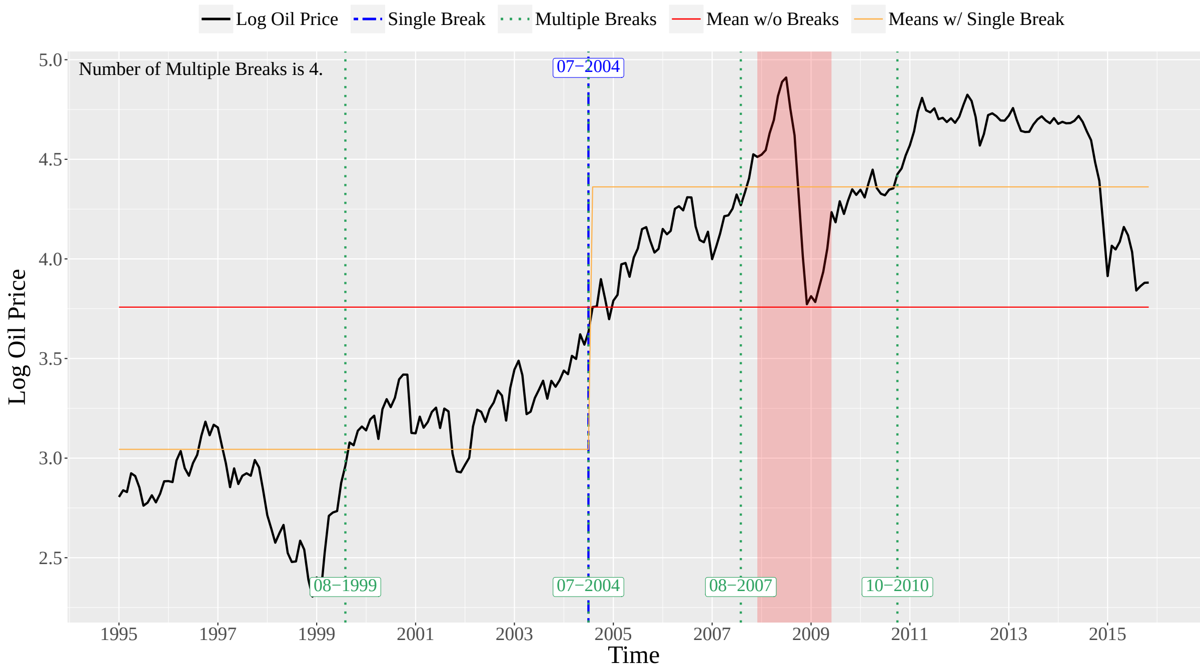


(a) Log Shiller Index

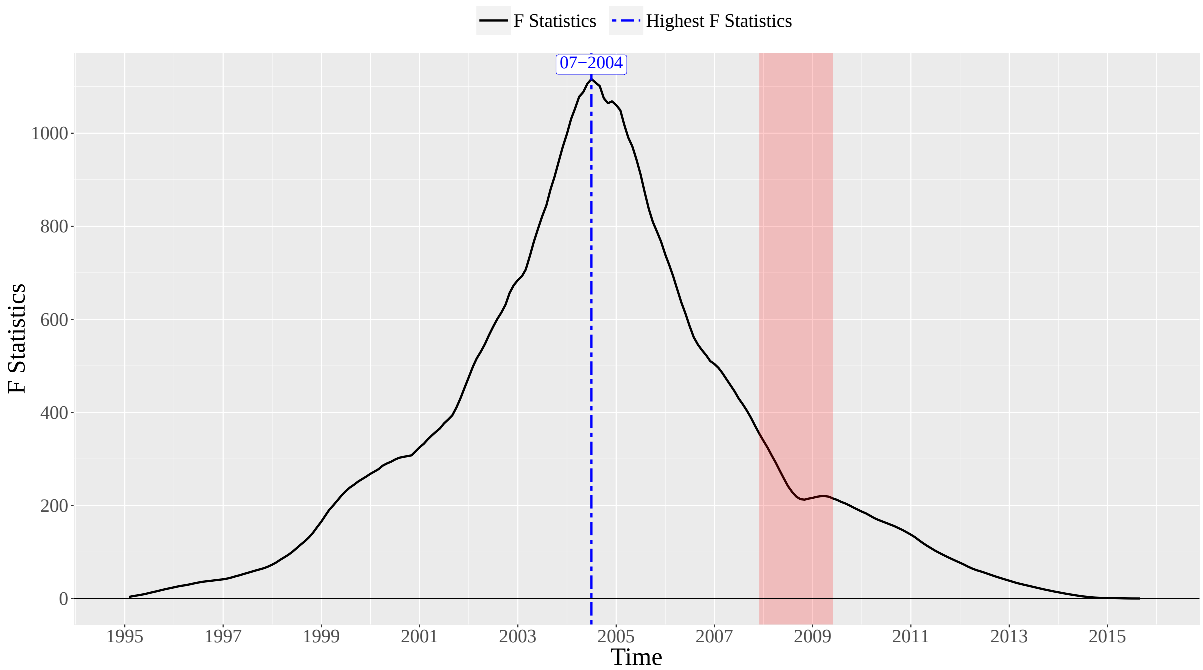


(b) F Statistics for Log Shiller Index

Figure 8: Structural Break Plots for Log Shiller Index

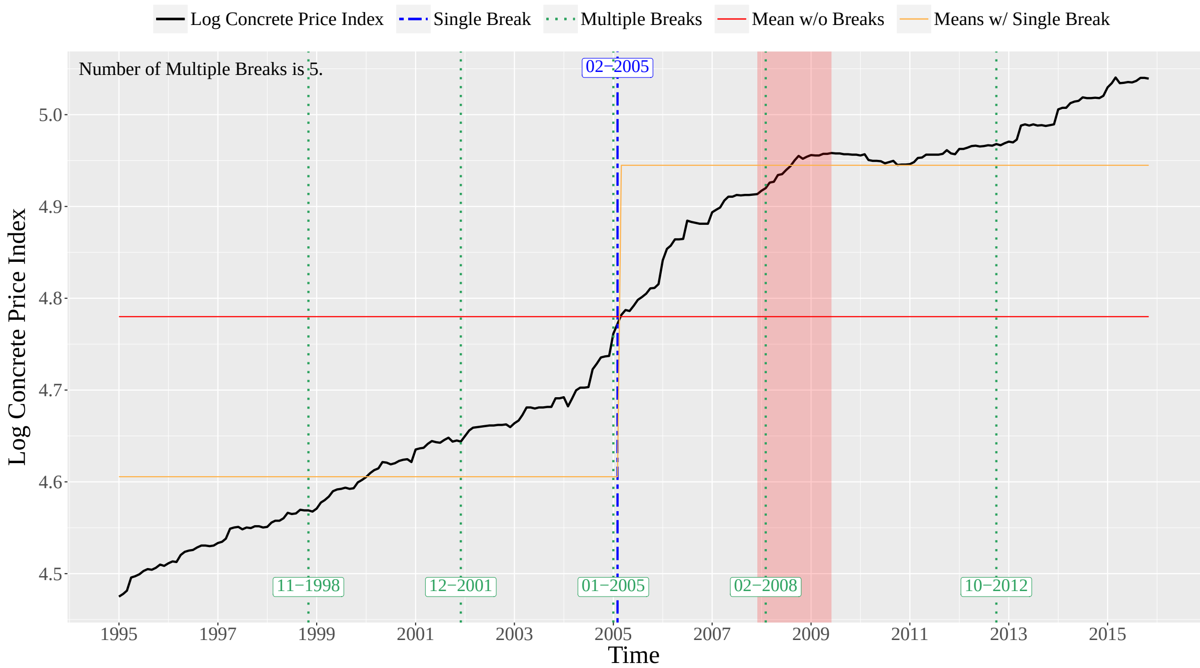


(a) Log Oil Price

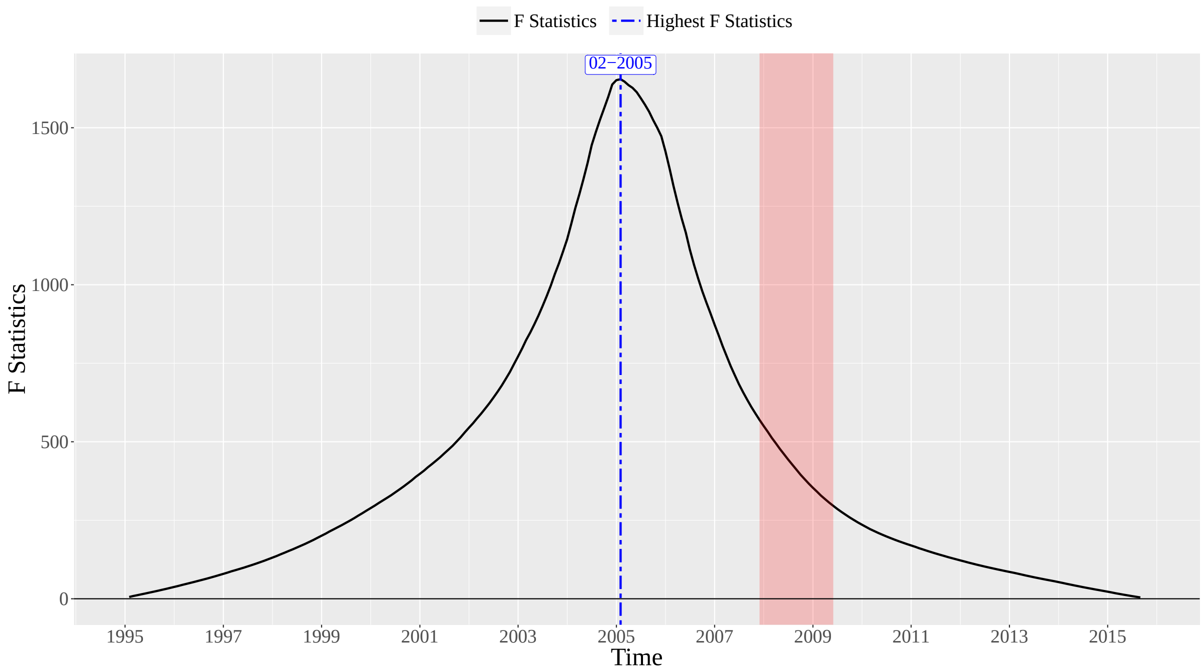


(b) F Statistics for Log Oil Price

Figure 9: Structural Break Plots for Log Oil Price

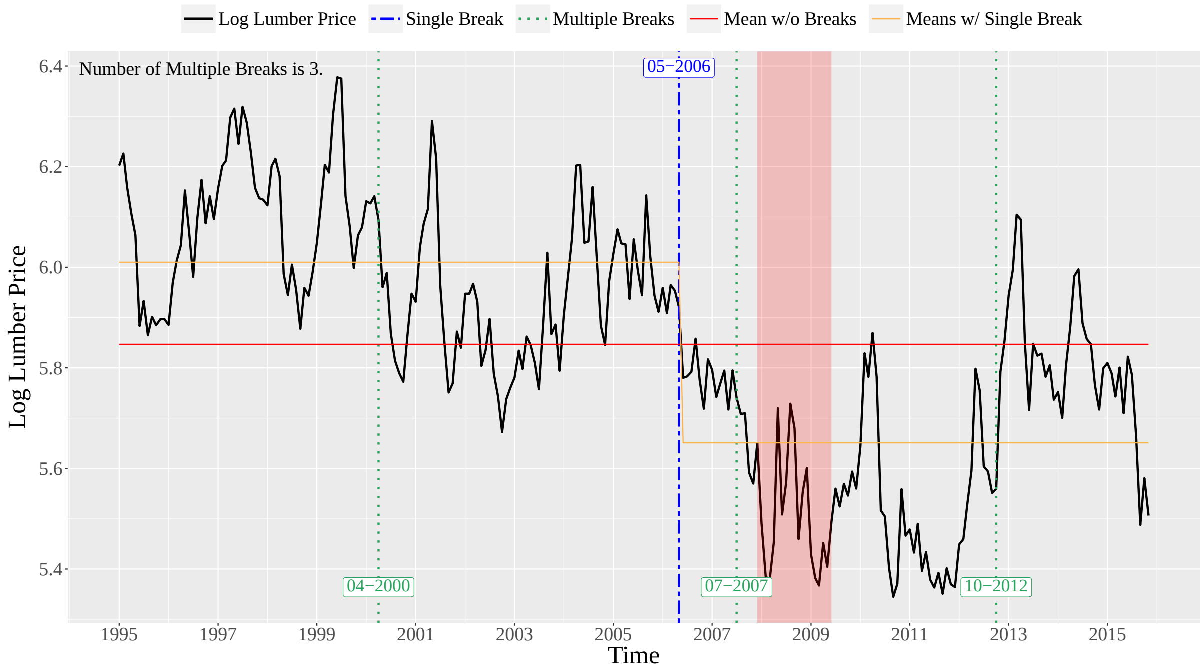


(a) Log Concrete Price Index

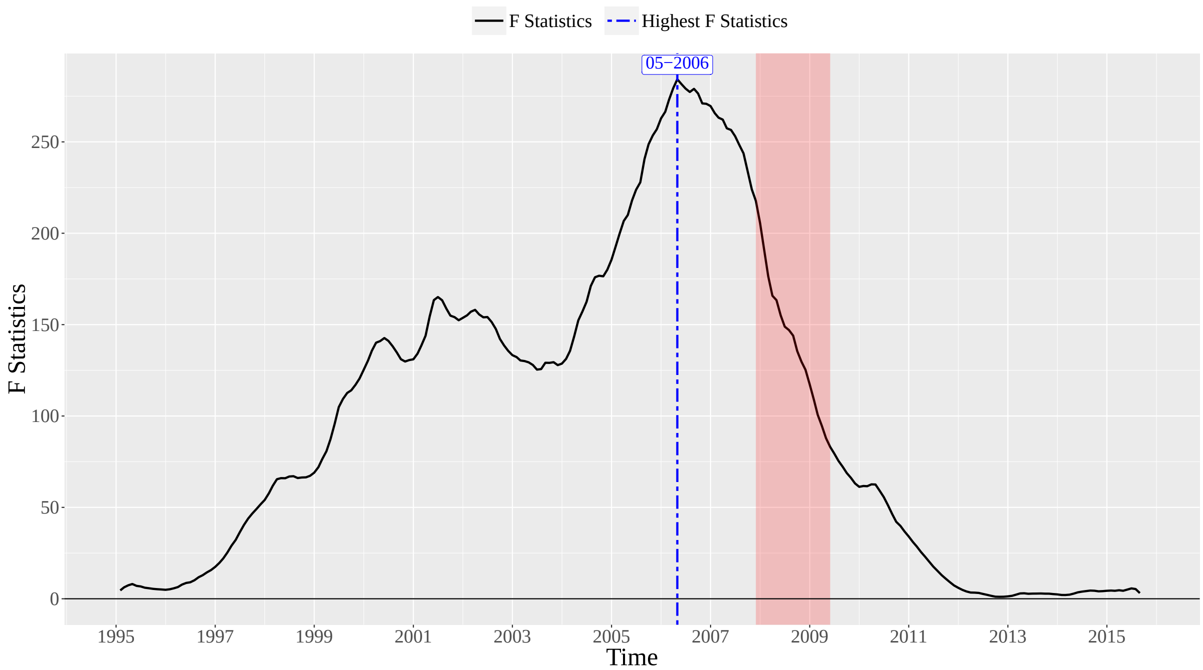


(b) F Statistics for Log Concrete Price Index

Figure 10: Structural Break Plots for Log Concrete Price Index

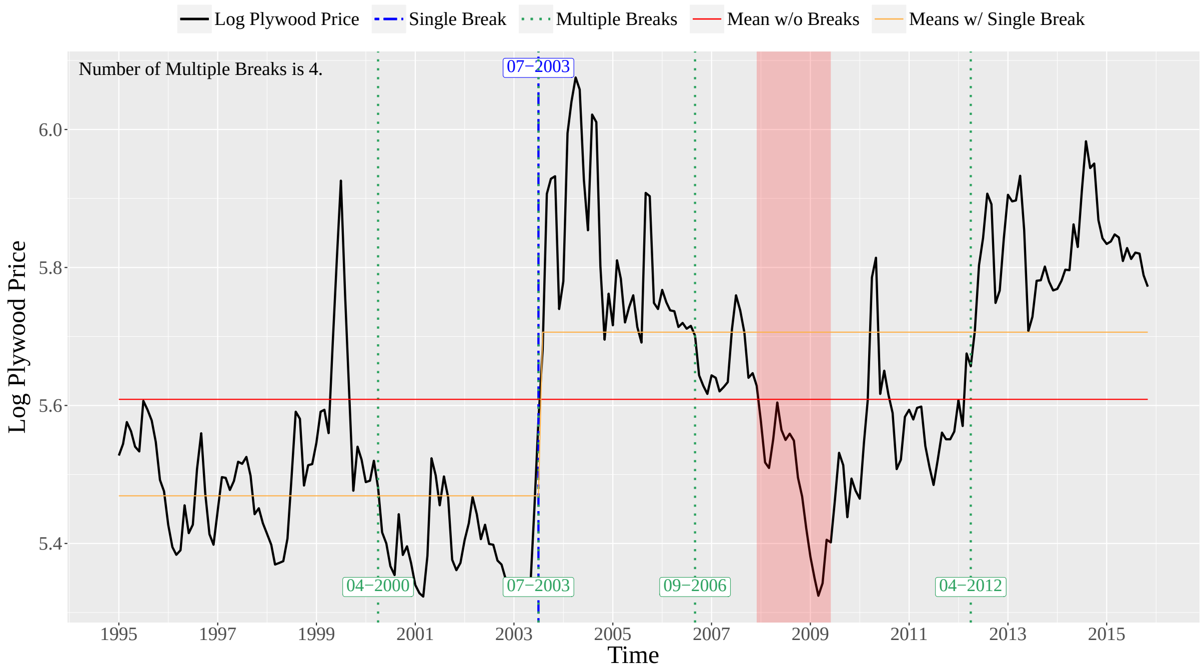


(a) Log Lumber Price

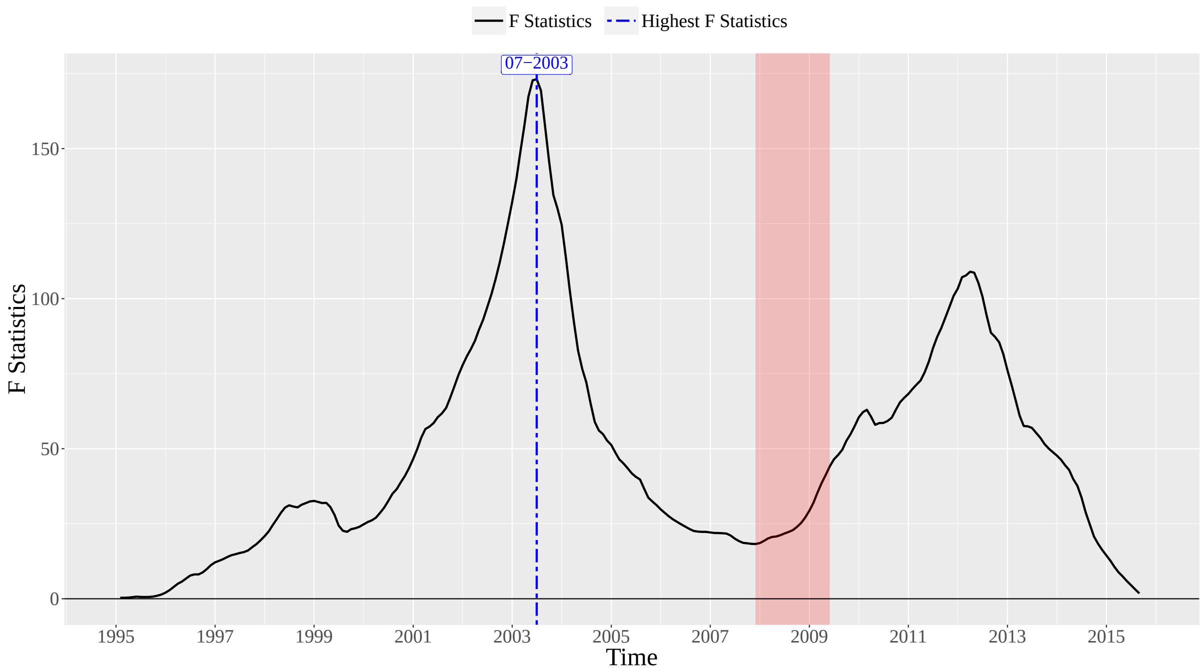


(b) F Statistics for Log Lumber Price

Figure 11: Structural Break Plots for Log Lumber Price

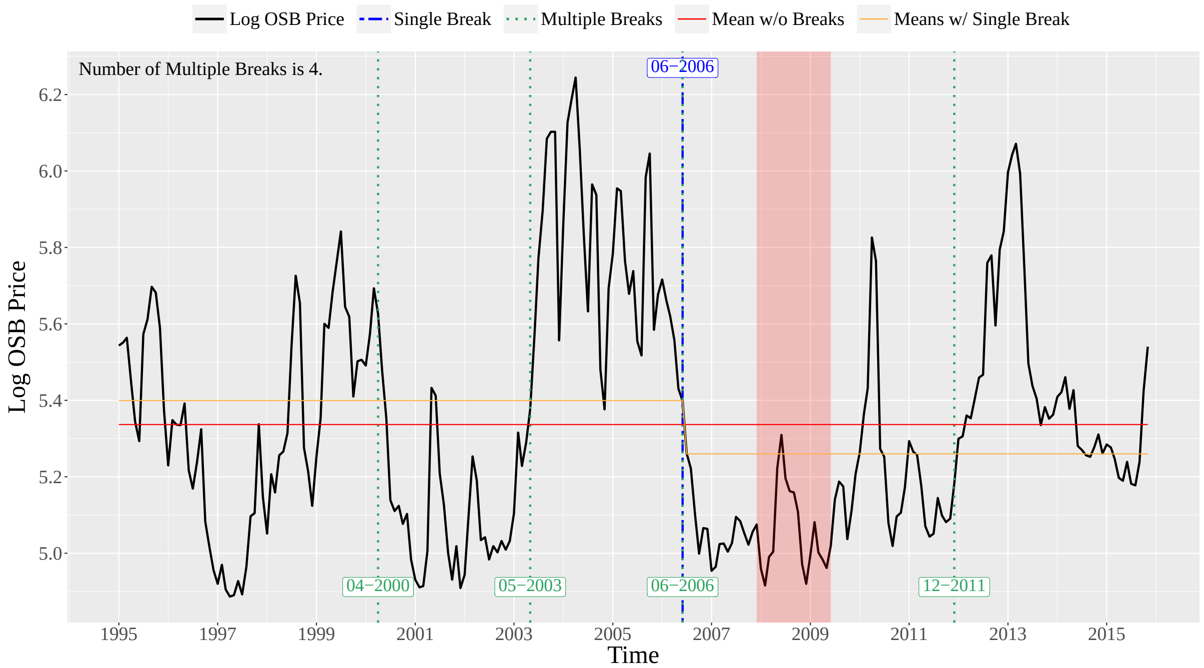


(a) Log Plywood Price

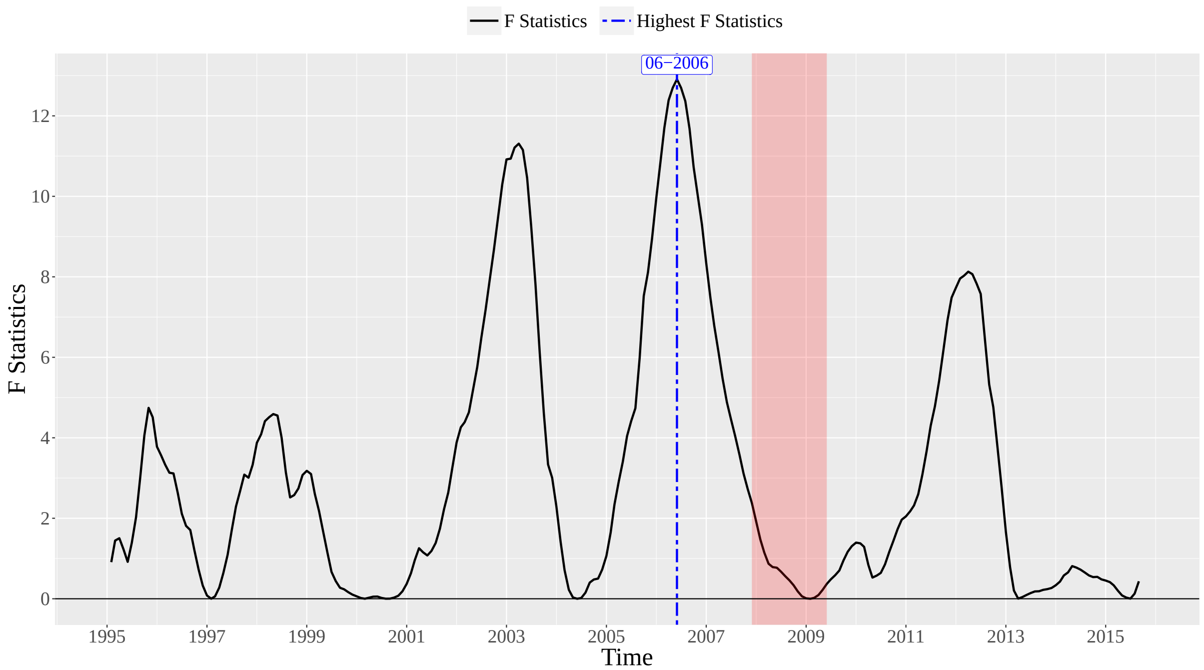


(b) F Statistics for Log Plywood Price

Figure 12: Structural Break Plots for Log Plywood Price



(a) Log OSB Price



(b) F Statistics for Log OSB Price

Figure 13: Structural Break Plots for Log OSB Price

Table 36: Adjustment Matrix α of VECM - Segment 1

	ECT 1	ECT 2
ΔShiller	0.007	−0.001
ΔCB	0.110	−0.008
ΔWPU1331	0.028	0.001
ΔLAES	−0.242	0.018
ΔPAAB	−0.026	−0.023
ΔPACS	−0.100	−0.033

Notes: ECTs indicate respective error correction terms.

Table 37: Cointegration Matrix β of VECM - Segment 1

	ECT 1	ECT 2
Shiller_{t-1}	1.000	0.000
CB_{t-1}	0.000	1.000
WPU1331_{t-1}	−1.648	−6.046
LAES_{t-1}	0.513	−1.640
PAAB_{t-1}	−0.362	4.008
PACS_{t-1}	0.149	−0.846
Constant	1.210	17.282

Notes: ECTs indicate respective error correction terms.

Table 38: Composite Matrix Π of VECM - Segment 1

	Shiller_{t-1}	CB_{t-1}	WPU1331_{t-1}	LAES_{t-1}	PAAB_{t-1}	PACS_{t-1}	Constant
ΔShiller	0.007	−0.001	−0.007	0.005	−0.006	0.002	−0.007
ΔCB	0.110	−0.008	−0.132	0.070	−0.073	0.023	−0.008
ΔWPU1331	0.028	0.001	−0.053	0.013	−0.006	0.003	0.052
ΔLAES	−0.242	0.018	0.291	−0.153	0.158	−0.051	0.013
ΔPAAB	−0.026	−0.023	0.185	0.025	−0.084	0.016	−0.437
ΔPACS	−0.100	−0.033	0.366	0.003	−0.097	0.013	−0.695

Table 39: Adjustment Matrix α of VECM - Segment 2

	ECT 1
ΔShiller	−0.026
ΔCB	−0.294
ΔWPU1331	0.019
ΔLAES	0.433
ΔPAAB	−0.085
ΔPACS	−0.133

Notes: ECTs indicate respective error correction terms.

Table 40: Cointegration Matrix β of VECM - Segment 2

	ECT 1
Shiller_{t-1}	1.000
CB_{t-1}	0.166
WPU1331_{t-1}	0.487
LAES_{t-1}	−0.418
PAAB_{t-1}	−0.247
PACS_{t-1}	0.255
Constant	−5.763

Notes: ECTs indicate respective error correction terms.

Table 41: Composite Matrix Π of VECM - Segment 2

	Shiller_{t-1}	CB_{t-1}	WPU1331_{t-1}	LAES_{t-1}	PAAB_{t-1}	PACS_{t-1}	Constant
ΔShiller	−0.026	−0.004	−0.013	0.011	0.006	−0.007	0.151
ΔCB	−0.294	−0.049	−0.143	0.123	0.073	−0.075	1.694
ΔWPU1331	0.019	0.003	0.009	−0.008	−0.005	0.005	−0.109
ΔLAES	0.433	0.072	0.211	−0.181	−0.107	0.110	−2.494
ΔPAAB	−0.085	−0.014	−0.041	0.035	0.021	−0.022	0.488
ΔPACS	−0.133	−0.022	−0.065	0.056	0.033	−0.034	0.767