

Nonlinear Modeling of Changing Lag Structure in U.S. Housing Construction*

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Abstract

In this paper, we reconsider the nature of changing lag structure in housing construction. We assume that the U.S. housing construction industry is subject to two regimes determined by the de-trended level of housing units under construction: recession and expansion. The econometric model we employ is a generic nonlinear autoregressive distributed lag model. The results imply that builders seem to change the speed of construction depending on whether the construction industry is in a recession or expansion. The mean lag between housing completions and housing starts is significantly shorter in recession periods than in expansion periods. This conclusion is in line with the so-called *accordion effect*.

Keywords: Nonlinear autoregressive distributed lag models, Accordion effect.

JEL classification: C22, L74.

1 Introduction

This paper is concerned with the empirical modelling of the supply of housing units, in particular, with the relationship between housing starts and completions. This apparently modest problem has received ample attention in the literature. The main contribution of this paper is to provide new insights by applying flexible nonlinear time series models.

The duration between the time a construction of a housing unit begins and the time the housing unit is completed depends on a number of factors like the size of the housing unit, e.g., Merckies and Bikker (1981), the complexity of

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the structure, weather conditions, e.g., Coulson and Richard (1996) and Fergus (1999), and economic conditions, e.g., van Alphen and Merkies (1976), Borooah (1979), van Alphen and de Vos (1985), Merkies and Steyn (1994), and Coulson (1999). While each of these factors are important, we will focus entirely on those related to the underlying economic conditions. Thus, the questions of particular interest to us are; 1. Does the lag structure between housing starts and housing completions change when the construction industry goes into a recession? 2. Is the lag structure longer or shorter when the industry is in a recession or expansion? and 3. How do the changing economic conditions affect the lag structure in the construction industry?

In the existing literature one can find convincing arguments for at least two opposing views regarding a possible asymmetric relationship between housing starts and completions. First, the lag structure between housing starts and housing completions is expected to be shorter when the construction industry is in a recession because contractors have to allocate all of their resources to a few existing projects at hand and they need money flows to survive hard times. Alternatively, it can be argued that since economic expansions typically result in more opportunities, contractors might want to complete existing projects as soon as possible in order to be ready to meet increased demand. Another supporting argument for this second view is that during economic recessions construction companies may have to lay off workers to decrease their costs and to be able to compete better with other companies. Since this implies a reduced capacity, it will take longer to complete existing projects. During economic expansions, however, construction companies are likely to increase their capacity by hiring additional workers and equipment, thus increasing their ability to complete construction projects relatively quickly.

Merkies and Steyn (1994) address the effect of economic conditions on the lag structure in the construction process. Their motivation is an empirical observation by van Alphen and Merkies (1976) who show that the lag pattern between starts and completions has a tendency to contract during slow periods and expand during boom periods, reflecting a given production capacity over projects at hand as business slows down or speeds up. They nickname this observed phenomenon *the accordion effect*.¹ Note that the accordion effect supports the first view described above. Merkies and Steyn (1994) were the first to attempt to explicitly model the relation between construction starts and actual production to provide empirical evidence for the accordion effect.

This paper addresses the same issues but in a different and more formal way. Specifically, we apply flexible nonlinear time series models and provide a statistical hypothesis test for the possible existence of the accordion effect. Unlike our approach, Merkies and Steyn (1994) employ an econometric model which is a variant of the Almon's polynomial lag pattern model and is nonlinear only in the coefficients (which are time varying). They also allow for time dependent variance. However, within their framework they are not able to derive a formal test for the existence of the accordion effect. Alternatively, we

¹Merkies and Steyn (1994), p. 501.

suggest using regime switching autoregressive distributed lag models. Within this class of models we show that identification and estimation of the accordion effect becomes very straightforward. Namely, we propose a simple Wald test based on comparing the estimated "mean lags" under the alternative economic regimes.

We also departure from Merkies and Steyn (1994) by using U.S. data and real variables. In particular, we use the number of housing units started in the past quarters as the explanatory variable and the number of completed houses during a given quarter as the response variable.

The main finding of the paper is that builders actually seem to change the pace of construction under different economic regimes. Builders speed up (slow down) the construction process if the industry is in a recession (an expansion). This empirical finding is in strong support of the accordion effect and has important implications for the supply side of the housing market. In particular, our results indicate that the supply side in a more realistic housing market model should be specified as

$$C^s = \begin{cases} h(S_t, \dots, S_{t-p_r}) & \text{if } r(X) = 1 \\ h(S_t, \dots, S_{t-p_e}) & \text{if } r(X) = 0 \end{cases} ,$$

where C^s and S are the supply of housing completions and starts respectively, $r(X)$ denotes a binary variable such that $r(X) = 1$ indicates recession, e (or $r(X) = 0$) denotes expansion, and X contains economic factors determining whether the economy is in a recession or expansion.

The paper is organized as follows. Section 2 presents the data. Section 3 starts our empirical analysis with a simple unrestricted finite distributed lag model. Section 4 introduces an autoregressive distributed lag model, which addresses the shortcomings of the unrestricted finite distributed lag model. Section 5 presents two regime-switching autoregressive distributed lag models, which assume that the construction industry is subject to two regimes: recession/contraction and expansion. Section 6 concludes.

2 The Data

The data we use consist of monthly observations on the number of new privately owned housing units in the U.S. measured in thousands.² We consider the following three series:

- New privately owned housing units started (i.e., starts), from January 1959 to December 2003.
- New privately owned housing units completed (i.e., completions), from January 1968 to December 2003.

²The data source is the U.S. Census of Bureau and can be obtained at <http://www.census.gov/const/www/newresconstindex.html>.

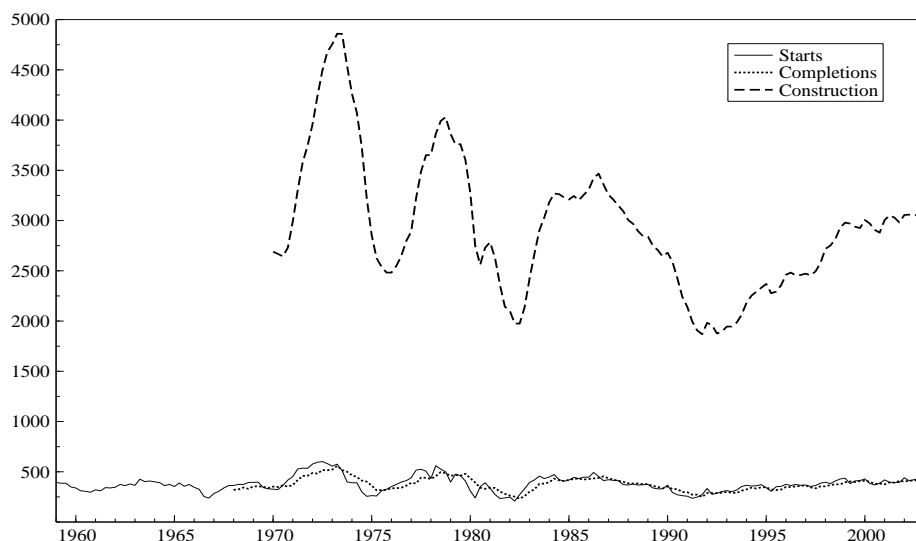


Figure 1: Housing Starts, Completions, and Construction

- New privately owned housing units under construction (i.e., construction), from January 1970 to December 2003.

We aggregate the raw data series to obtain quarterly observations by simply adding the monthly observations within each quarter. This aggregation is performed to ensure parsimony in the estimating equations, as the lag/dependence structure between starts and completions turns out to be relatively long. There is a pronounced seasonality in the series, which we remove using the seasonal adjustment method advocated by Lovell (1963) and discussed in Davidson and MacKinnon (1993). This seasonal adjustment method produces the same results as using seasonal dummies in a linear regression equation. Apart from its simplicity (i.e., transparency), this method is desirable since it does not affect the mean level of the series. Thus, the method makes it possible to interpret the constant term and its significance as an important indicator of the "correctness" of the model.³ Another desirable feature is that the filter is linear and does not introduce "generated" nonlinearities in the data.

Figure 1 illustrates the seasonally adjusted series and Table 1 presents some summary statistics. Several features should be noticed. First, there do not seem to be any apparent trend present in starts and completions while the construction series perhaps exhibits a slight downward trend. Secondly, starts and completions seem to move closely together. Thirdly, there appears to be a lead-lag relation between starts and completions, with starts leading completions.

³This will become clearer when the empirical models are introduced.

Table 1: Summary Statistics for the Quarterly Data

Statistics	Starts	Completions	Construction
Observations	180.00	144.00	136.00
Mean	381.20	378.02	2940.24
Median	374.72	375.41	2899.37
Max	601.86	557.91	4860.55
Min	209.17	232.03	1869.14
Std. Dev.	77.38	63.70	665.67
Skewness	0.47	0.26	0.74
Kurtosis	3.43	2.80	3.50
JB Test p-value	0.02	0.40	0.00

Finally, as shown in Table 1, the mean and the median values for starts and completions are very similar. However, starts are more volatile as shown by the standard deviations and the minimum and maximum values.

To investigate the stationarity of the series further we conduct Augmented Dickey-Fuller (ADF) unit root tests. Although, as previously mentioned, there is no apparent trend in starts and completions series, we do include an intercept as well as an intercept + trend in the tests. Further, we include a sufficiently high number of lags to remove any serial correlation in the error terms in the ADF regressions. Table 2 presents the results of the tests for the seasonally adjusted quarterly series. Note that the augmentation in all cases consists of four lagged differences. The ADF tests strongly reject the unit root hypothesis for all three series at the 1 percent level in the case of intercept and intercept + trend.

It should be noted that these results are in opposition to some previous results on construction data. For instance, Coulson (1999), using the ADF tests, finds that all of the three series have a unit root. However, he uses a different seasonal adjustment method as well as a different sample period. Using the Phillips-Perron test, Lee (1992) concludes that all three series contain a unit root. Lee (1992)'s data set consists of seasonally adjusted (by the Census of Bureau) monthly data from Citibase. It is very likely that the choice of seasonal adjustment method, the sample period, as well as the choice of frequency (temporal aggregation) will affect the power and size of unit root tests in small samples. However, analyzing this issue further is currently outside the scope of our paper. Due to the strong rejection of the unit roots presented in Table 2 we feel relative comfortable proceeding by treating all three series as being (trend-) stationary.

3 Unrestricted Finite Distributed Lag Model

We begin our empirical investigation on the relation between housing completions and housing starts with a linear model, the unrestricted finite distributed

Table 2: The ADF Tests. Critical values computed using McKinnon (1991)

	Starts	Completions	Construction
The Augmented Dickey-Fuller Test			
Augmentation (lags incl.)	4	4	4
Intercept	-4.621	-3.774	-4.423
1% Critical Value	-3.485	-3.497	-3.500
5% Critical Value	-2.885	-2.887	-2.888
10% Critical Value	-2.575	-2.577	-2.578
Intercept + Trend	-5.680	-5.250	-4.871
1% Critical Value	4.009	-4.010	-4.030
5% Critical Value	-3.432	-3.439	-3.446
10% Critical Value	-3.139	-3.142	-3.146

lag (UFDL) model. Although Hendry (1995) and Coulson (1999) criticize the UFDL model in the present context, we find this model attractive as a benchmark model since it is able to explain most of the empirical observations on starts and completions described in Section 2. Moreover, its statistical inadequacies will become useful in developing better models. The UFDL model has previously been studied/fitted by Mayes (1979) under the following general representation

$$Comp_t = C + \sum_{i=m}^p \beta_i Star_{t-i} + \epsilon_t, \quad (1)$$

where $Comp_t$ is the number of housing units completed at time period t , C is the intercept term, $Star_{t-i}$ is the number of housing units started at time period $t - i$, and ϵ_t is the error term, which is assumed to be a white noise process. The minimum and maximum lags, m and p , respectively, are usually chosen by some information criteria. Each β_i is expected to be nonnegative and represents the proportion of starts at time $t - i$ that is completed at time t . The model assumes that the expected number of completed housing units is zero when the number of started housing units at all the included lags is zero. In other words, it is assumed that there cannot be completions without starts. Thus, we expect the intercept term to be statistically insignificant.

Several assumptions associated with the model given by (1) are of importance. First, an implicit assumption in the model is that completed housing units are immediately sold and hence do not sit idle once they have been completed. As such, housing completions represent housing supply. Secondly, housing units are assumed to be homogenous. This is probably not a realistic assumption since our data set includes total units rather than structures with one or more units. Thirdly, the model assumes that the parameters are constant over time, implying that the lag pattern (structure) is time invariant. In other words, builders do not change the pace of construction when they face external shocks like bad weather, business fluctuations in the construction industry, etc.

Finally, it is assumed that builders' plans are realized every period. That is, planned and realized completions are equal in each period. The last two assumptions are obviously unrealistic and will be relaxed later when we formulate more sophisticated models.

Borooah (1979) handles the problems associated with (1) in an alternative way by proposing a second-degree polynomial distributed lag model. Additionally, he employs an optimal adjustment process to address disequilibrium issues in the construction industry.⁴ In order to accommodate the time-variant nature of the data, he uses a modifier, the real value of new building society mortgages, which is linearly added to his model.⁵ Hendry (1986) criticizes Borooah's approach for a number of reasons. First of all, Hendry claims that the model does not imply a long-run equilibrium in which the level of housing starts is equal to that of housing completions. Secondly, the modifier Borooah linearly adds to his model implies that some completions to be never started and results in predicted completions which are negative or larger than existing starts. Finally, the model contains serially correlated residuals, which makes his results doubtful.

Next, we turn to the estimation of the UFDL model. Allowing for a maximum of four years, that is, sixteen lags, the Akaike Information Criterion (AIC) selects the model with ten lags whereas the Schwarz Information Criterion (SIC) selects the model with nine lags. We follow the AIC and estimate the model with ten lags. The results are shown in Table 3. All of the coefficient estimates are nonnegative, as expected. The estimates suggest that approximately 70% of housing starts were finished within a year. This result is similar to previous findings. For example, Borooah (1979) finds that 70% of housing starts were finished within 15 months based on U.K. data, while Mayes (1979) documents that 72% of housing starts in the U.K. are finished within 18 months.

The sum of the estimated coefficients, which is equal to 0.96 with a standard error of 0.02, is not significantly different from unity.⁶ The result implies that approximately 4% of the started buildings are never completed, possibly due to bankruptcy, demolition, fire, conversion, etc. Again, this result is in line with the previous findings; see e.g., Lee (1992) and Coulson (1999). Borooah (1979), estimates that 96% of starts are completed within three years of their start. Note that (1) implies a long-run relation between starts and completions in the form of

$$E(Comp_t) = \underset{(0.0192)}{0.96224} E(Star_t), \quad (2)$$

where 0.96 can be interpreted as the long-run multiplier of $Comp_t$ with respect to $Star_t$.⁷ Since each of the estimated coefficients are nonnegative and their sum is statistically different from zero, the coefficients can be mapped onto a

⁴For a textbook treatment of optimal adjustment process, see Judge et al. (1985, p. 380).

⁵The modifier is an economic variable which is assumed to affect the coefficients of the regression relating the completions and the starts. In other words, Borooah (1979) assumes that the coefficients are themselves linear functions of the modifier.

⁶The test statistic is 3.85 with a p-value of 0.052.

⁷(2) holds, since completions and the starts are stationary and consequently $E(Comp_{t+j}) = E(Comp_t)$ and $E(Star_{t+j}) = E(Star_t)$ for all j , etc. The long-run multiplier is defined as

Table 3: The Unrestricted Finite Distributed Lag Model

Variable	Estimate	Std. Err. ^a	t-ratio	p-value
Constant	6.3366	7.2457	0.8745	0.3834
$Star_t$	0.1670	0.0308	5.4156	0.0000
$Star_{t-1}$	0.2218	0.0457	4.8582	0.0000
$Star_{t-2}$	0.1908	0.0570	3.3471	0.0011
$Star_{t-3}$	0.1156	0.0467	2.4751	0.0146
$Star_{t-4}$	0.0626	0.0442	1.4159	0.1591
$Star_{t-5}$	0.0273	0.0441	0.6185	0.5373
$Star_{t-6}$	0.0431	0.0502	0.8583	0.3923
$Star_{t-7}$	0.0047	0.0575	0.0825	0.9343
$Star_{t-7}$	0.0399	0.0502	0.7943	0.4285
$Star_{t-9}$	0.0315	0.0457	0.6880	0.4927
$Star_{t-10}$	0.0579	0.0303	1.9124	0.0580

^a Newey-West (HAC) standard errors reported

discrete probability distribution as pointed out by Hendry (1995, p. 215). This facilitates interpreting the coefficients of the model as the percentages of housing units started in the past that are finished in the current period.

Overall, the model seems to provide a reasonable fit and the usual F-test overwhelmingly rejects the null hypothesis that the coefficients are all zero. The R^2 and adjusted- R^2 are approximately 0.97. Figure 2 illustrates the normalized lag weights of the model. They do not have a unimodal lag structure, which might be expected in this kind of data, e.g. Merkies and Steyn (1994). The U.S. Census Bureau annually publishes data on the distribution of completions by number of months from start. The distribution is always unimodal, which implies that the estimated lag structure does not fit what we observe. The mean lag is 2.92 with a standard error of 0.09, implying that starts on average are completed with a lag of nine months.

Table 4 presents the results of some diagnostic tests for the UFDL model, indicating that there are some problems with the model. The first thing to notice is that the innovation terms seem to be serially correlated. This is a common problem associated with the UFDL specification as pointed out by Hendry (1986). The Breusch-Godfrey LM test shows that the error terms are serially correlated up to 4 quarters.⁸ In addition, the White test detects the presence of heteroskedasticity in the residuals.

The RESET test detects functional misspecification in the regression equation. The individual parameter stability test due to Hansen (1992b) detects no parameter instability in coefficients on the lags.⁹ However, Hansen's variance

$$\sum_{j=0}^{\infty} dComp_{t+j}/dStar_t \text{ and from (1) it is easily seen to be equal to } \sum_{i=m}^p \beta_i.$$

⁸Results in fact indicate serial correlation of error terms up to order 12. For brevity of exposition, these results are not reported in Table 4.

⁹They are not reported in Table 4 for brevity of exposition.

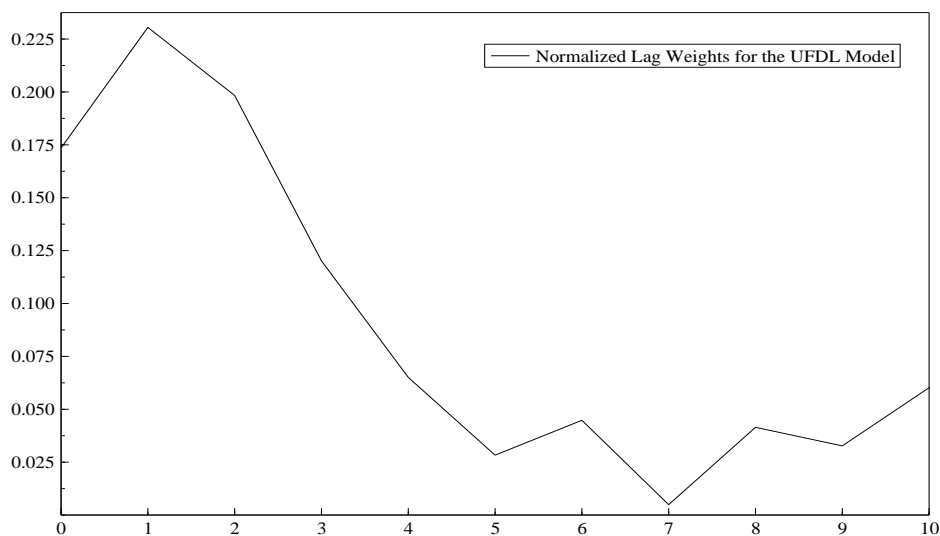


Figure 2: Normalized Lag Weights for the UFDL Model

stability test, shown as HansenV in the table, indicates that the error variance is not stable with a test statistic of 1.15 and 5% critical value of 0.47. This confirms the presence of heteroskedasticity. The model also fails Hansen's joint stability test, shown as HansenJ in the table, with a test statistic of 3.72 and 5% critical value of 3.15.

Although (1) explains many of the important empirical features and is confirming previous findings in the literature, the results in Table 4 indicate that the model is misspecified and needs to be improved. In the next section, the autoregressive distributed lag model will be introduced to address the misspecification issues.

4 The Autoregressive Distributed Lag Model

A natural way to solve the specification issues associated with serial correlation and to some extent also the problem of omitted variables that may cause heteroskedasticity is to include lags of the dependent variable in the equation. In the present context, this strategy leads us to an autoregressive distributed lag (ARDL) model. This model has been fitted to Dutch construction data by Merkies and Steyn (1994) and Steyn (1996). The general form of the model is given by

Table 4: Diagnostic Tests for the UFDL Model

Test	Statistic	p-value
AR(1)	11.9297	0.0007
AR(4)	3.6186	0.0079
RESET	7.3909	0.0074
JB	0.6592	0.7192
White	44.4127	0.0031
F Test	359.4385	0.0000
ARCH(1)	0.2093	0.6473
ARCH(4)	7.5871	0.1079
HansenV	1.1518	0.4700 ^a
HansenJ	3.7162	3.1500 ^a

a: 5% critical value

$$Comp_t = C + \sum_{j=1}^q \alpha_j Comp_{t-j} + \sum_{i=m}^p \beta_i Star_{t-i} + \omega_t,$$

where $Comp$, C , and $Star$ have the same interpretations as before. The model can be labelled as $ARDL(p, q)$. Our main focus is on the reduced form

$$Comp_t = \frac{C}{A(L)} + \frac{\beta_m L^m + \dots + \beta_p L^p}{A(L)} Star_t + \frac{1}{A(L)} \omega_t,$$

where $A(L) = 1 - \alpha_1 L - \dots - \alpha_q L^q$ and L is the lag operator. The coefficient of $Star_t$ gives the lag structure that we are looking for. The ARDL model approximates the finite lag structure of the UFDL model with an infinite lag.

We pick the values of m , p , and q through a series of tests. Starting with a general ARDL(4,4) model, the t/F-test shows that the third and fourth lags can be safely discarded but the second lags should be kept.¹⁰ The AIC selects the ARDL(2,2) specification and the BIC selects the ARDL(2,1) specification. We decide to proceed with the ARDL(2,2) model since it passes the serial correlation test more convincingly. Table 5 shows the estimation results.

All the coefficients, except the second lag of starts, enters the equation significantly. The ARDL(2,2) model variance-dominates the UFDL model with a ratio of 135/142. Though the ratio is not too small, note that the ARDL(2,2) model is much more parsimonious relatively to the UFDL model and involves estimation of only six coefficients. The mean lag, which takes the form

$$\frac{\beta_1 + 2\beta_2}{\beta_0 + \beta_1 + \beta_2} + \frac{\alpha_1 + 2\alpha_2}{1 - \alpha_1 - \alpha_2},$$

is 2.74 with a standard error of 0.20.¹¹ Note that the mean lag of the ARDL model is very close to the mean lag of the UFDL model. Figure 3 shows the

¹⁰The F test statistic is 0.90 with a p-value of 0.465.

¹¹See Hendry (1995), p. 215.

Table 5: Autoregressive Distributed Lag Model

Variable	Estimate	Std. Err. ^a	t-Ratio	p-Value
Constant	8.1991	6.7892	1.2077	0.2293
$Comp_{t-1}$	0.3459	0.0760	4.5503	0.0000
$Comp_{t-2}$	0.2410	0.0594	4.0578	0.0001
$Star_t$	0.1580	0.0298	5.3111	0.0000
$Star_{t-1}$	0.1682	0.0485	3.4693	0.0007
$Star_{t-2}$	0.0569	0.0440	1.2930	0.1982

^a Newey-West (HAC) standard errors reported

normalized lag weights of the ARDL model, now has the desirable unimodal shape for this type of data.

As is well-known, every autoregressive distributed lag model has an equilibrium correction (EqC) representation.¹² One advantage of the ARDL model, in addition to its superior fit to the data in comparison to the UFDL model, is that it takes disequilibrium into consideration. To see this, we write the model in equilibrium correction form as follows:

$$\begin{aligned} \Delta Comp_t = & C + \beta_0 \Delta Star_t - \alpha_2 \Delta Comp_{t-1} - \beta_2 \Delta Star_{t-1} \\ & - (1 - \alpha_1 - \alpha_2) [Comp_{t-1} - \kappa Star_{t-1}] + \omega_t. \end{aligned}$$

The term inside the brackets is the equilibrium correction term and the term in front of $Star_{t-1}$ is the long-run equilibrium term, which takes the following functional form

$$\kappa = \frac{\beta_0 + \beta_1 + \beta_2}{1 - \alpha_1 - \alpha_2}.$$

The equilibrium correction equation implies that as long as the construction industry is in the long-run equilibrium, the term inside the brackets is zero and the change in the level of completions in the current period is determined by the change in the level of starts in the current and last periods and the change in the level of completions in the last period. The long-run equilibrium coefficient is 0.92 with a standard error of 0.0377. As can be seen, the model implies that around 7 per cent of starts were never completed. Since $1 - \alpha_1 - \alpha_2$ is a positive number, a disequilibrium in the form of excess (deficient) completions in the last period has a negative (positive) effect on the change in the level of completions in the current period.

Table 6 shows the results of diagnostic tests for the ARDL(2,2) model. As can be seen, the residuals of the model are now free from serial correlation. The Breusch-Godfrey LM test rejects the null hypothesis of autocorrelation up to order four.¹³ The RESET test, although not too convincingly, does not detect

¹²See any time series econometrics textbook, e.g. Hendry (1995), p. 287.

¹³Again, we tested for neglected serial correlation up to the 12th order, but did not report the results in Table 6 for brevity of exposition.

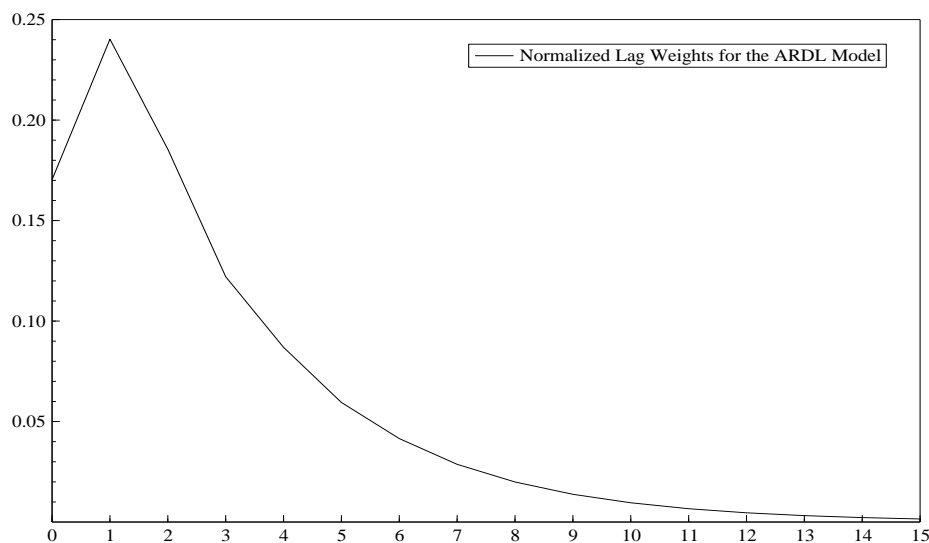


Figure 3: Normalized Lag Weights for the ARDL Model

any specification error in the model. The LM test for ARCH also does not detect any conditional heteroskedasticity. Despite the seemingly good results, one problem with the model is the presence of heteroskedasticity. The White test detects some heteroskedasticity in the errors. Furthermore, although the Hansen’s individual parameter stability test, not reported in Table 6, detects no parameter instability in the individual coefficients even at the 1% level of significance, the variance stability test, shown as HansenV in Table 6, again strongly rejects the null hypothesis that the variance is stable over the sample and the test for joint stability of the coefficients, shown as HansenJ in Table 6, indicates that the coefficients are not jointly stable. As neglected heteroskedasticity can be a result of misspecification of the conditional mean function, these results may indicate that a nonlinear model may provide an improvement over the linear models. We are going to investigate this questions further in the following section.

5 Nonlinear Autoregressive Distributed Lag Models

In order to remove heteroskedasticity, capture the possible changing lag structure caused by business fluctuations in the construction industry, and test the presence of the "accordion effect" we consider the following class of nonlinear

Table 6: Diagnostic Tests for the ARDL Model

Test	Statistic	p-value
AR(1)	0.1708	0.6801
AR(4)	1.3440	0.2498
RESET	2.4277	0.1215
JB	0.7403	0.6906
White	18.1179	0.0530
F Test	824.855	0.0000
ARCH(1)	0.6158	0.4326
ARCH(4)	2.6923	0.6106
HansenV	1.4469	0.4700 ^a
HansenJ	2.2480	1.900 ^a

^a: 5% critical value

”regime switching” models:

$$\begin{aligned}
Comp_t = & C + \left(\sum_{i=1}^{p_1} \alpha_i^1 Comp_{t-i} + \sum_{j=m_1}^{q_1} \beta_j^1 Star_{t-j} \right) G(X_{t-d}; \gamma, c) \\
& + \left(\sum_{i=1}^{p_2} \alpha_i^2 Comp_{t-i} + \sum_{j=m_2}^{q_2} \beta_j^2 Star_{t-j} \right) [1 - G(X_{t-d}; \gamma, c)] + \epsilon_t,
\end{aligned}$$

where $Comp$, C , and $Star$ are as previously defined.¹⁴ The model is basically an autoregressive distributed lag model which allows regime changes. $G(X_{t-d}; \gamma, c)$ is the transition function. We explore two different functional forms for $G(\cdot)$. The first candidate, which we will refer to as the Threshold Autoregressive Distributed Lag (TARDL) model, is given by

$$G(X_{t-d}; c) = I[X_{t-d} \leq c].$$

Here, the transition function is unity whenever the term inside the brackets is true, i.e, whenever the variable X_{t-d} is less than or equal to the value of the scalar parameter c . The transition function is zero otherwise. The second functional form for $G(\cdot)$ we consider is

$$G(X_{t-d}; \gamma, c) = \frac{1}{1 + \exp(-\gamma[X_{t-d} - c])}.$$

This model is labelled the Logistic Smooth Transition Autoregressive Distributed Lag (LSTARDL) model. Notice that both models assume that the construction industry is subject to two regimes and that each regime is determined by the size of the so-called threshold variable, X_{t-d} , relative to the threshold value, c .

¹⁴For estimation we have assumed ”symmetric” adjustment in each regime. More generally one could have allowed for ”asymmetric” adjustment by, for example, fitting an ARDL(2,2) model for regime 1, and an ARDL(2,1) for regime 2.

When the threshold variable falls below (exceeds) the threshold value, we say the construction industry is in regime one (two). Intuitively, one would therefore expect that a good threshold variable would contain information about the general economic conditions in the housing construction industry. In the LSTARDL model, the additional parameter γ determines the smoothness of the transition from one regime to another. If the parameter is a relative small number, the transition is smooth. When γ approaches infinity, the transition function approaches a step function. In this case the LSTARDL model and the TARDL model become identical.¹⁵

The TAR and LSTAR type models have a relatively short history in the time-series literature but have already gained a widespread popularity in theoretical and empirical econometrics. The initial work on the threshold models was carried out by Tong (1978) and Tong (1983). Tong (1990) gives a more detailed analysis. The TAR model can be estimated by conditional least squares. Estimation and testing procedures are discussed in detail in Franses and van Dijk (2000), Hansen (1997), and Hansen (1999), from which our estimation and testing algorithms are adapted. The smooth transition models were introduced to the time series literature by Chan and Tong (1986). Granger and Teräsvirta (1993) and Teräsvirta (1994) popularized them in econometrics literature. Due to the smoothness, the LSTAR type model can be estimated by nonlinear least squares, which obviously is equivalent to maximum likelihood if the error terms are assumed to be Gaussian distributed. Otherwise, nonlinear least squares estimates can be interpreted as quasi-maximum likelihood estimates. A comprehensive review of the estimation and testing procedures can be found in Teräsvirta (1998) and Franses and van Dijk (2000).

One important issue that needs to be addressed prior to estimation is the choice of threshold variable X_{t-d} . This selection is primarily empirically based. We considered several possible candidates including housing starts, housing completions, housing units under construction, mortgage rates, and real construction expenditures. Based on a combination of economic interpretability of the results as well as statistical significance, we choose the de-trended housing units under construction as the threshold variable.¹⁶ This variable was also used/preferred by van Alphen and Merckies (1976). One of the main advantages of using the construction series is that it does not fluctuate too much avoiding too many "spurious" regime shifts.

As simpler models are generally preferred, an important next step is thus to test for the nonlinearity of the conditional mean function in the threshold variable and to find the appropriate lag order for the threshold variable, i.e., estimate the so-called delay parameter given by d . The test for threshold non-

¹⁵We also fitted a version of Hamilton's (1989) Markov regime switching (MS) model to the data but have not reported the results for mainly two reasons. First, by using Hansen's (1992,1996) test we were not able to reject the null of linearity against the MS model. Secondly, the results based on the estimated MS model did not seem sensible from an economic perspective and neglected heteroskedasticity was still present in the residuals (indicating model misspecification).

¹⁶Results based on these alternative choices of threshold variables are available from the authors upon request.

Table 7: Nonlinearity Tests for the NARDL Models

Threshold Variable	TARDL Model		LSTARDL Model	
	Test Statistic	Critical Value ^a	Test Statistic	p-Value
$DCons_t$	10.7372	8.7475	10.957	0.000
$DCons_{t-1}$	21.0816	7.5951	11.872	0.000
$DCons_{t-2}$	19.5415	7.5107	17.461	0.000
$DCons_{t-3}$	26.7051	8.4502	12.670	0.000
$DCons_{t-4}$	35.4680	7.4959	16.384	0.000

^a 5% critical value obtained by bootstrap methods

linearity is based on the hypothesis

$$H_0 : \alpha^1 = \alpha^2 \text{ and } \beta^1 = \beta^2.$$

$$H_1 : \alpha^1 \neq \alpha^2 \text{ and } \beta^1 \neq \beta^2.$$

Hence, under the null there is no difference between the parameters of the two regimes. The test statistic for linearity against the threshold model under the alternative is

$$F = n \left(\frac{\hat{\sigma}^2 - \tilde{\sigma}^2}{\tilde{\sigma}^2} \right),$$

where n is the number of observations, $\hat{\sigma}^2$ is the residual variance under the null hypothesis of linearity, and $\tilde{\sigma}^2$ is the residual variance under the alternative hypothesis of nonlinearity. The testing procedure is explained in Hansen (1999), Franses and van Dijk (2000), and Enders (2004). As noted in Hansen (1999), the test statistic has a nonconventional distribution because of the presence of unidentified nuisance parameters under the null hypothesis. For that reason the critical values are obtained by bootstrapping following Hansen (1999, p. 566). Note, however, that there is a minor difference between Hansen's (1999) framework and our model. Hansen estimates a Self-Exciting Threshold Autoregressive (SETAR) model, for which an autoregressive model (AR) is model under the null hypothesis. The null hypothesis in the current context is the ARDL. Table 7 shows the results from the nonlinearity tests. In the table, $DCons$ represents the de-trended construction series. As can be seen, we reject the null hypothesis that the data generation process is the linear ARDL model for all choices of the delay parameter $d = 1, 2, \dots, 4$ for the de-trended construction series at the usual 5% significance level.

The test of linearity against nonlinearity of the LSTAR type is explained in Teräsvirta (1994), Franses and van Dijk (2000), and Enders (2004). The test exploits that whenever γ is equal to zero, the model is linear. Consequently the null and alternative hypotheses are given as

$$H_0 : \gamma = 0.$$

$$H_1 : \gamma \neq 0.$$

Table 8: Nonlinear Autoregressive Distributed Lag Models

Variables	TARDL		LSTARLDL	
	Estimate	Std. Err. ^d	Estimate	Std. Err.
Regime 1				
Intercept	23.1901	12.8789 ^c	23.5655 ^c	12.9258
$Comp_{t-1}$	0.2485	0.1200 ^b	0.2505 ^c	0.1303
$Comp_{t-2}$	0.1773	0.0890 ^b	0.1766 ^c	0.0932
$Star_t$	0.1665	0.0414 ^b	0.1665 ^a	0.0410
$Star_{t-1}$	0.1855	0.0674 ^a	0.1828 ^a	0.0685
$Star_{t-2}$	0.1428	0.0465 ^a	0.1429 ^a	0.0541
Regime 2				
Intercept	16.1930	16.1774	16.5052	14.1089
$Comp_{t-1}$	0.2937	0.0781 ^a	0.3060 ^a	0.1023
$Comp_{t-2}$	0.3541	0.0521 ^a	0.3458 ^a	0.0811
$Star_t$	0.1809	0.0347 ^a	0.1818 ^a	0.0348
$Star_{t-1}$	0.1394	0.0483 ^a	0.1376 ^a	0.0490
$Star_{t-2}$	-0.0105	0.0526	-0.0141	0.0468

^a Significant at 1%
^b Significant at 5%
^c Significant at 10%
^d Newey-West (HAC) standard errors reported

Since the remaining parameters of the LSTARLDL model are not identified when $\gamma = 0$, Teräsvirta (1994) suggests overcoming the effect of unidentified nuisance parameters by using an auxiliary/approximating equation to test the null hypothesis. This is feasible due to the smoothness of the $G(\cdot)$ in this case. In the present context, this auxiliary equation writes

$$Comp_t = \theta'_0 x_t + \theta'_1 x_t Cons_{t-d} + \theta'_2 x_t Cons_{t-d}^2 + \theta'_3 x_t Cons_{t-d}^3 + \xi_t,$$

where

$$x'_t = [Comp_{t-1} \quad Comp_{t-2} \quad Star_t \quad Star_{t-1} \quad Star_{t-2}]'$$

The test is essentially an F-test that determines whether the coefficients associated with the terms $x_t Cons_{t-d}^i$, $i = 1, 2, 3$ are all zero. The test statistics for various lags of the de-trended construction series are shown in Table 7. As can be seen, we overwhelmingly reject the null hypothesis that the data generation process can be represented by the linear ARDL model in favor of the alternative TAR and/or LSTARLDL models.

Next, Table 8 shows the estimation results for the two models. As can be seen, most of the estimated coefficients are statistically significant. We select $d = 1$, and consequently $DCons_{t-1}$ as the threshold variable, since it produces

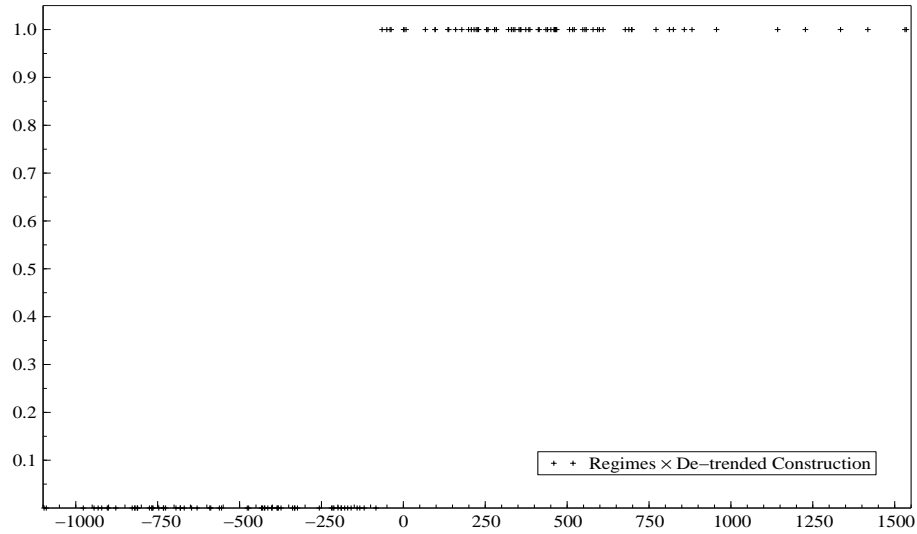


Figure 4: Transition Function for the TARDL Model

the most interpretable results. Furthermore, it seems reasonable that builders change the pace of construction based on the number of housing units under construction in the last quarter. The estimated value of γ is 1256, which indicates that the transitions between the regimes are abrupt and further explains why the estimated parameters reported in Table 8 are very similar for the two models. The estimated threshold values are also very similar for the two models and equal -84 for the TARDL model and -76 for the LSTARDL model. This result implies that if the number of housing units under construction in the last quarter falls more than 80,000 units below the construction trend in the industry, the construction industry is in contraction regime. Figure 4 shows the scatter plot between the threshold variable and the indicator function for the TARDL model. Note that most of the observations fall in the expansion regime, indicating that the construction industry mostly experienced expansion. The transition function for the LSTARDL model looks similar.

The mean lag for the contraction regime is 2.00 with a standard error of 0.22 for the LSTARDL model and 2.00 with a standard error of 0.19 for the TARDL model. The mean lag for the expansion regime is 3.22 with a standard error of 0.47 for the LSTARDL model and 3.22 with a standard error of 0.42 for the TARDL model. The robust standard errors are 0.22 and 0.46, respectively, for the TARDL model. Note that the estimators based on the TARDL model seem to be slightly more efficient. Since the models otherwise provide very similar results, the TARDL model will be our preferred representation. The estimates indicate that builders speed up the construction process during recessions, since

builders complete their projects within a little more than two quarters and slow it down during expansions, since they complete their projects within somewhat more than three quarters. This result is in line with Merkies and Steyn (1994)'s accordion effect.

Within the class of regime switching models we consider it is relative easy to determine/test whether the accordion effect is statistically significant. The idea behind the test is simple. The mean lag for a regime i in, say, the TARDL(2,2) model is given by

$$g(\theta^i) = \frac{\beta_1^i + 2\beta_2^i}{\beta_0^i + \beta_1^i + \beta_2^i} + \frac{\alpha_1^i + 2\alpha_2^i}{1 - \alpha_1^i - \alpha_2^i},$$

where $\theta^i = [\alpha_1^i \ \alpha_2^i \ \beta_0^i \ \beta_1^i]'$ for $i \in \{1, 2\}$. Then the following hypothesis, which implies a necessary condition for the existence of the accordion effect, seems natural

$$\begin{aligned} H_0 & : g(\theta^1) \geq g(\theta^2) . \\ H_1 & : g(\theta^1) < g(\theta^2) . \end{aligned}$$

θ^1 and θ^2 are the regime one and regime two vector of parameters, respectively. If the null hypothesis is rejected, we conclude that the mean lag for the contraction regime is significantly less than the mean lag for the expansion regime. This would imply that builders do change the speed of construction in the recession regime (regime 1). In what follows we only report the results for the TARDL model as the results for the LSTARDL model are similar. The Wald test statistic based on the TARDL model is 5.62 with an asymptotic p-value less than 0.02. Thus, we do reject the null hypothesis that the mean lags are the same under the two regimes. The result supports the existence of a possibly accordion effect in the data.

Figure 5 shows the normalized cumulative lag weights for the first fifteen lags for both regimes based on the coefficient estimations from the TARDL model. As the figure shows, the cumulative normalized lag weight for the recession regime is always above that for the expansion regime. Although builders finish about 15% of housing starts in the current quarter under both regimes, they finish more than half of the projects two quarters later under the recession regime as opposed to 48% under the expansion regime.

In addition, there seems to be an interesting relation between the extent of expansion and the mean lag under the expansion regime (regime 2). The relation indicates that the larger the expansion is, the slower builders are in finalizing constructions. For instance, if the de-trended number of housing units under construction is 0, which is the trend itself, the mean lag under expansion is 3.01, indicating that builders finalize their construction in a little more than three quarters. However, if the de-trended number of housing units equals 100,000, a mild expansion, the mean lag is 3.14. Similarly, if the de-trended number of housing units under construction is 200,000, the mean lag under expansion is

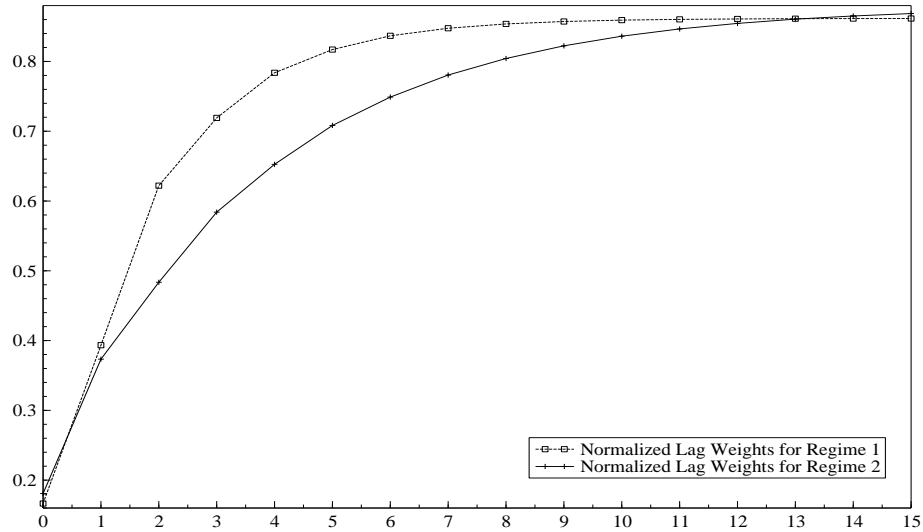


Figure 5: Normalized Cumulative Lag Weights for the TARDL Model

3.36. Finally, when the number of housing units under construction is 600,000, the mean lag under regime 2 is 3.52, more than three and a half quarter, showing that the larger the threshold value, the higher the mean lag under regime 2. The results clearly indicate that the data seem to support the accordion effect. However, one should note that there is no such relation is found for the recession regime, indicating asymmetry between the regimes.

Figure 6 shows the NBER recession periods and the construction industry recession periods, as estimated by the TARDL model. As the figure illustrates, the construction industry cycles seem to follow the NBER cycles with a certain lag. A deviation from this pattern is the recession in the 1990s, where the TARDL predicts a long recession period in the construction industry. However, this prediction is perhaps not surprising if we compare it to Figure 1. There is a clear cut decline in the level of the housing units under construction during this period. A modest decline in the levels of starts and completions is also visible and these observations may imply that the construction industry appears counter-cyclical during that period. A possible explanation for this phenomenon might be demographics. Approximately 75 million American baby-boomers born during the population explosion from 1946 to 1964 entered the 25 to 34 age bracket in the decades prior to the nineties. This age bracket contains most of first-time home buyers of the housing consumption and not surprisingly they snapped up a tremendous number of entry-level homes with positive effects on the housing construction industry. However, during the 1990s, the number of U.S.-born residents aged 25 to 34 dramatically declined as the baby boomers

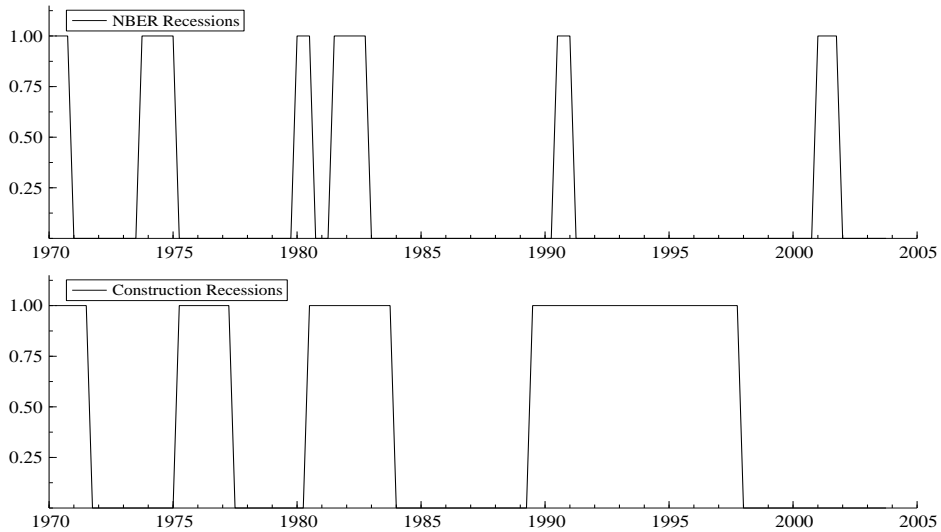


Figure 6: NBER vs. Construction Industry Cycles for the TARDL Model

got older and consequently the entry-level home market was at the brink of a crash, see, e.g., Jaffe (2004). Overall, the TARDL model seems to pick up the recessive period in the housing construction industry.

Table 9 contains diagnostic measures for the TARDL model.¹⁷ As can be seen, the model passes all tests, including the test for neglected heteroskedasticity and seems overall to be statistically well specified contrary to the linear models.

6 Conclusion

The dynamic structure of the housing construction process is complicated. Merkie and Steyn (1994) attempt to model the dynamics using a Dutch construction data set. However, their results, based on a modified polynomial distributed lag model, are far from conclusive; the authors do not statistically identify the existence of the accordion effect, although they claim it exists based on visual inspection.¹⁸

In this paper, we explicitly integrate changing business conditions, represented by the de-trended level of housing units under construction, into our model. We show that there is compelling empirical evidence that the construction industry is subject to two regimes: contraction, reigned when the number of

¹⁷Similar results were obtained for the LSTARDL model.

¹⁸See Figure 2 in Merkie and Steyn (1994), p. 507.

Table 9: Diagnostic Tests for the TARDL Models

Test	Regime 1		Regime 2	
	Statistic	p-value	Statistic	p-value
AR(1)	0.1143	0.7353	0.0140	0.9057
AR(4)	2.6681	0.6148	2.5939	0.6279
RESET	0.2267	0.6358	2.2058	0.8011
JB	0.2673	0.8749	7.9069	0.0192
White	15.1700	0.1260	9.4122	0.4935
F Test	178.9000	0.0000	203.5000	0.0000
ARCH(1)	0.0058	0.9396	2.9632	0.0900
ARCH(4)	0.3837	0.8192	1.3496	0.2627
HansenV	0.4983	0.7480 ^a	0.3469	0.7480 ^a
HansenJ	1.6655	2.1200 ^a	1.8224	2.1200 ^a

a: 1% critical value

housing units under construction is about 80,000 below the construction trend in the industry, and expansion, reigned when it is above that level. Nonlinear autoregressive distributed lag models fitted the data best relative to the other linear models considered. Further, we estimate mean lags for each regime and compare them statistically. We are able to reject the hypothesis that the speed of construction is the same during contractions and expansions which is in support of the accordion effect. We also find an interesting relation between the extent of expansion and the mean lag under the expansion regime. The relation indicates that the stronger the expansion is, the slower the builders are in finalizing their projects, further supporting the accordion effect. However, we are not able to find a similar relation for the contraction regime, indicating asymmetric behavior by the builders in the construction industry. A possible explanation for the accordion effect is that builders have extra capacity to allocate among the existing projects during recession as opposed to expansion. As a by-product of our approach, we are able to identify recession and expansion periods in the U.S. construction industry that compares favorable to the NBER cycles. A long recession seems to be present in the industry during the 1990s, which we speculate was caused primarily by demographic conditions.

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