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Investment and Supply Response: U.S. Hop Farming

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Abstract
The dynamic structure of agricultural supply is the concern of a vast literature. Herein, we address aggregate investment and harvest response for U.S. hop cultivation. Using autoregressive distributed lag (ARDL) methods for the formation of expectations and perennial lags, we find limited evidence of a long-run forcing relationship running from real price to area under cultivation. Short-run dynamics reveal that lagged changes in real price produce complex and highly significant impacts to both acreage and harvest. In an effort to address certain time series structural considerations, split sample estimates (post 1985) show a marked increase in investment and supply response to price. Though not statistically hardened, long-run price elasticities roughly doubled during the small-beer expansion.

Keywords: Hop supply response, ARDL regression, long-run bounds testing
JEL Classifications: C22, E30, Q11

Introduction
The hop (*Humulus lupulus*) is a perennial, climbing plant predominantly grown for the production of beer. The use of hops in brewing dates back to the mid-8th century A.D. (Acitelli, 2013). Industrial interests center on the cultivation of the female plant, where the strobiles or cones flowered are rich in bittering resins and essential oils. Managing a commercial hop farm requires a well-designed agronomic process that promotes quality and high yield. Proper process designs involve investments in suitable acreage, trellising systems, plant propagation, plant health maintenance and harvesting equipment. Most of the U.S. has the climate and soil conditions adequate to grow hops. Optimal acreage for plant health and flowering is found in the Pacific Northwest (PNW)(Henning et al., 2015). Table 1 below portrays how the U.S. ranks in World hop acreage and harvest.[2] Because hop plant bines climb, trellis structures must be constructed to support vertical growth of up to 25 feet.[3] Figure 1 below depicts a conventional V-trellis training system. Vegetative propagation, using rhizome or stem cuttings from mature plants, is the most common hop-yard proliferation method. Replants may take two to three crop seasons to produce a full yield (Kořen, 2007). Seeds are mainly used in genetic breeding programs (Darby, 2013). Plant health considerations involve proper irrigation, fertilization and disease/pest/weed control. Lastly, at a minimum, harvesting equipment includes machinery to take down the bines, strip the cones from the bines, floor ovens to dry and bale presses to package the hops.[4]

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[2] Three-fourths of the 2025 harvest acreage in the U.S. is located in the state of Washington.
[3] Reduced cost, 'low trellis' systems are considered a substitute for small to mid-sized farms (NIFA, 2017).
[4] Post-harvest pelletization or resin/oil extraction equipment, of course, requires additional investment.

Table 1. 2024 World hop acreage and production

	Acres	Acreage Share	Production (M lbs)	Production Share
Germany	50,136	36.5%	102.507	40.8%
U.S.A.	44,793	32.6%	87.072	34.7%
Czech Republic	11,972	8.7%	14.44	5.8%
China	6,672	4.9%	14.33	5.7%
Poland	4,082	3.0%	6.583	2.6%
Europe (balance)	11,080	8.1%	13.197	5.3%
Others	8,714	6.3%	12.886	5.1%
Total	137,449		251.015	

Source: International Hop Growers Convention, Economic Commission Report (2024)

Figure 1. Trellis system

Dynamics of supply have long been forefront in agriculture research. Much of this work focuses on estimating supply structures and response to price. The seminal work of Mark Nerlove (1958) is regarded as the standard framework for dynamic supply models. Nerlove viewed agricultural production as a two-part process: investment or potential production and harvest. Factors relating to investment involve long-run assessment while the harvesting decision is short-run. Nerlove surmised that both are chiefly determined by price expectations. Because availability of specific agricultural investment data is generally lacking, Nerlove proposed the use of 'area under cultivation' or simply desired acreage in time t as a proxy. The relation of desired acreage (A_t^*) to expected price (P_t^*) becomes,

$$A_t^* = a_0 + a_1 P_t^* + a_2 Z_t + u_t, \tag{1}$$

where Z_t represents other observed exogenous factors affecting desired acreage and u_t captures any latent effects. To this, Nerlove added a partial adjustment equation relating desired to actual planted acreage (A_t),

$$A_t - A_{t-1} = \gamma\left(A_t^* - A_{t-1}\right), \tag{2}$$

and an adaptive expectations model that connects expected to actual price (P_t),

$$P_t^* - P_{t-1}^* = \theta\left(P_{t-1} - P_{t-1}^*\right). \tag{3}$$

Correspondingly, desired harvest (H_t^*) can also be expressed as,

$$H_t^* = a_0 + a_1 P_t^* + a_2 Z_t + u_t, \tag{4}$$

where again the model is augmented with a partial adjustment mechanism for harvest and uses the same adaptive expectations for price.

Nerlove's framework was originally applied to annual field crops where time series cointegration and gestation lags were generally ignored. Regression adaptations for perennial crops do appear in the older literature (see Akiyama and Trivedi, 1987 for a review) but suffer from not rigorously addressing possible non-standard statistical distributions in the presence of a variable series unit root. In a more recent review of perennial supply response, Siegle et al., (2024) surveyed 26 papers, post 1987, where 11 used various methods of regression analysis. Regarding the regression treatments, only two rightly addressed series order of integration issues. With no accepted approach to estimating perennial supply response emerging, data availability will dictate the treatment. For hops, the United States Department of Agriculture, National Agriculture Statistics Service (USDA NASS) provides annual surveyed data of aggregate acreage, production (harvest), season average price and inventories (stock) held by suppliers and brewers. This data does not afford the detail necessary to structure an integrated model of factor demands and production analogous to conventional supply theory. It does, however, accommodate a Nerlovian reduced form of investment and harvest.

To model the dynamic features of perennial crops statistically, we will lean on autoregressive distributed lag (ARDL) methods as forwarded by Pesaran and Shin (1999) and the bounds testing methods of Pesaran et al. (2001). The ARDL approach to time series modeling has the advantage of yielding consistent estimates regardless of whether the series are level stationary, I(0), first-difference stationary, I(1), or mutually cointegrated. Most importantly, variable lag selection is not ad hoc. Lag choice is data driven and optimally determined by minimizing certain information criteria. The ARDL framework is particularly valuable as a method for examining cointegrating relationships between variables. The method carefully disentangles the long-run linkages from short-run dynamics. ARDL-based estimators are deemed "super-consistent" and exhibit strong small sample properties (Pesaran and Shin, 1999; Ghatak and Siddiki, 2001).

ARDL framework

A general ARDL(p, q_1, . . . , q_k) dynamic model is defined,

$$y_t = \alpha_0 + \alpha_1 t + \sum_{i=1}^{p} C_i y_{t-i} + \sum_{j=1}^{k} \sum_{l_j=0}^{q_j} B_{j,l_j} x_{j,t-l_j} + \varepsilon_t , \tag{5}$$

where y_t is the dependent variable, α_0 is a constant, $\alpha_1 t$ is a linear trend, p denotes the lag selection for the dependent variable, C_i are the coefficients of the dependent variable lags, k is the number of weakly exogenous $x_{j,t}$ explanatory variables, q_j denotes the lag selections for the explanatory variables, B_j are the coefficients of said regressors and associated lags and, lastly, ε_t is the error term free of serial correlation. Other, stationary, exogenous variables affecting short-term fluctuations of y_t can also be included in Equation (5).[5] This form of the model is an expedient starting point for determining appropriate lag lengths (p, q_j), dependent variable lag coefficients, deterministic components and proper error structure. We simplify the exposition of Equation (5) by setting $k = 1$ where,

$$y_t = \alpha_0 + \alpha_1 t + \sum_{i=1}^{p} C_i y_{t-i} + \sum_{j=0}^{q} B_j x_{t-j} + \varepsilon_t . \tag{6}$$

It is important that lag lengths (p, q) are selected judiciously, particularly for shorter time series. Lag length selection must mitigate residual serial correlation, preserve degrees of freedom and ensure that x_t are weakly exogenous (forcing), free of contemporaneous feedback. Lag selection, therefore, is data driven subject to minimizing certain information criteria. Schwarz (1978) information (SBIC) and Akaike (1987) information (AIC) are convention.

The long-run form and bounds testing requires fitting a reformulation of Equation (6),

$$\Delta y_t = \alpha_0 + \alpha_1 t + \phi_0 y_{t-1} + \phi_1 x_{t-1} + \sum_{i=1}^{p-1} c_i \Delta y_{t-i} + \sum_{j=0}^{q-1} b_i \Delta x_{t-j} + u_t , \tag{7}$$

which is the conditional error correction specification. Long run terms ($\phi_0 y_{t-1}$, $\phi_1 x_{t-1}$) now augment the short-run presentation and first-differencing reduces the lag orders by one. The error correction term (ECT) is then mapped from Equation (7) to (6), $ECT = \phi_0 = -\left(1 - \sum_{i=1}^{p} C_i\right)$. This term represents the speed of adjustment to the long-run when the equilibrium is disturbed. The closer ECT is to zero indicates a slow recovery to the long-run equilibrium.

[5] Inclusion of such variables may effect the critical values for the bounds test (Pesaran et al., 2001).

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Testing for the existence of a long-run form involves the specification of deterministic terms included in the model. Pesaran et al. (2001) distinguishes five cases:[6]

I. No deterministics included ($\alpha_0 = \alpha_1 = 0$); $\mathrm{H}_0 : \phi_0 = \phi_1 = 0$.

II. A restricted constant, no time trend ($\alpha_1 = 0$); $\mathrm{H}_0 : \alpha_0 = \phi_0 = \phi_1 = 0$.

III. An unrestricted constant, no time trend ($\alpha_1 = 0$); $\mathrm{H}_0 : \phi_0 = \phi_1 = 0$.

IV. An unrestricted constant, restricted time trend, $\mathrm{H}_0 : \alpha_1 = \phi_0 = \phi_1 = 0$.

V. Both deterministics are unrestricted, $\mathrm{H}_0 : \phi_0 = \phi_1 = 0$.

Upon bounds rejection of any case specific null[7], the long-run parameters are recovered using,

$$\text{Restricted constant: } \frac{\hat{\alpha}_0}{1 - \sum_{i=1}^{p} \hat{C}_i}, \tag{8}$$

$$\text{Restricted trend: } \frac{\hat{\alpha}_1}{1 - \sum_{i=1}^{p} \hat{C}_i}, \tag{9}$$

$$\text{Forcing variable } (x_t)\text{: } \frac{\hat{\phi}_1}{1 - \sum_{i=1}^{p} \hat{C}_i}, \tag{10}$$

with estimates of C_i as defined in Equation (5). Computation of valid long-run standard errors will follow the *delta* method (Pesaran and Shin, 1999). Recovered long-run variables (Equation (10)) need to be jointly significant for levels inference.[8] Moreover, the *ECT* must be highly significant to rule out degenerate cases.[9]

Data

Table 2 below describes the 76 year time series data as provided by the United States Department of Agriculture, National Agriculture Statistics Service (USDA NASS). Hop acreage proxies as Nerlovian investment; desired area under cultivation. Hop production, of course, represents harvested supply. Real season average price is the key forcing

[6] Banerjee et al. (1998) considers three cases, I, III, V.
[7] Bounds tests have nonstandard distributions. Critical values used will follow the Stata® work of Kripfganz and Schneider (2020).
[8] Conventional critical values are appropriate for this test.
[9] Again, critical values follow Kripfganz and Schneider (2020).

variable considered and because hop farmers/dealers keep an inventory, hop stocks likely influence investment and harvest decisions. Figures 2 - 4 below depict each series graphically. Figure 2 shows the evolution of U.S. hop acreage and harvest. Both series, jointly, map a similar trend and show signs of being nonstationary.[10] The real price series shown in Figure 3 certainly exhibits nonstationarity but does not appear to be trend specific. Lastly, the stock rise shown in Figure 4 follows a rather linear deterministic trend.[11]

Table 2. Data descriptions, sources and descriptive statistics

Hop acreage. Hop acreage harvested in the U.S. by crop year in 1,000s. A hop crop year, for reported metrics, begins September 1. Source: Surveys conducted by the USDA NASS, 1950-2025. Mean 36.016, STD 8.795.
Hop production. U.S. hop production by crop year in millions of pounds. Source: Surveys conducted by the USDA NASS, 1950-2025. Mean 64.325, STD 18.516.
Season average hop price. Average price per pound received by U.S. grower/dealers in a given crop year, inflation adjusted to $2025. Of late, five year forward contracting is convention. Sources: Surveys conducted by the USDA NASS, 1950-2025; Bureau of Economic Analysis for GDP deflator data (Hausman et al, 2012). Mean $4.24, STD 1.22.
Hop stock. All hop inventories held by growers, dealers and brewers in the U.S. as of September 1 of a given crop year in millions of pounds. Source: Surveys conducted by the USDA NASS, 1950-2025. Mean 57.965, STD 30.523.

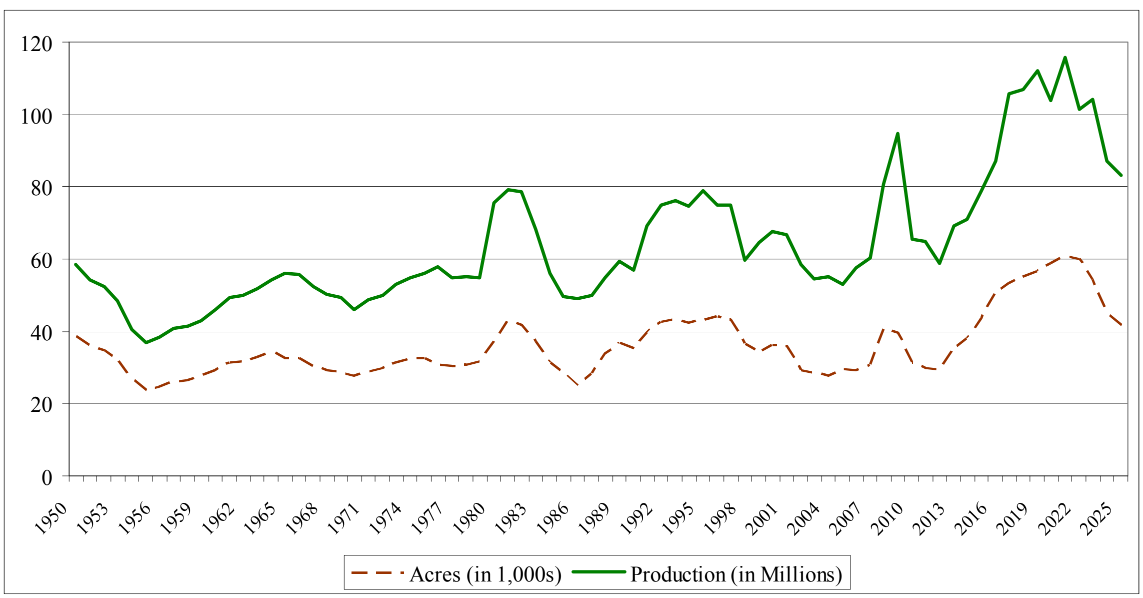

Figure 2. Hop acreage and harvest, in millions of pounds, 1950 - 2025

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[10] The pairwise correlation is 0.9465.
[11] The USDA NASS did not complete a stock survey for the 2012 crop year. We estimated a value for 2012 using the equations found in Table 3 below.

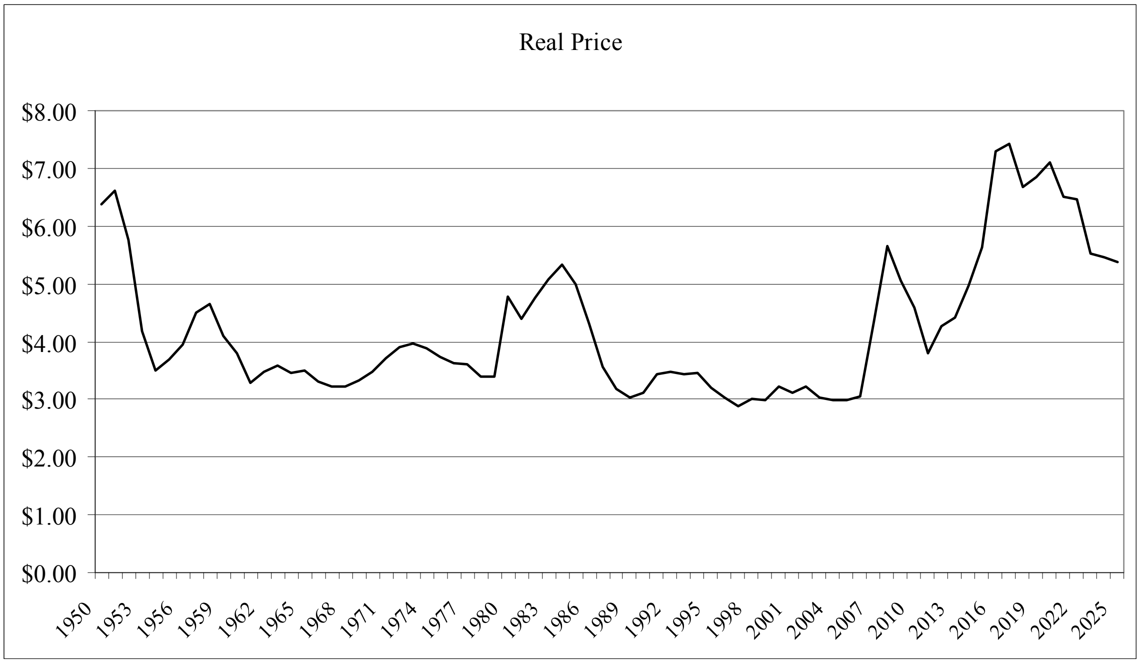

Figure 3. Real season average price per pound, 1950 - 2025

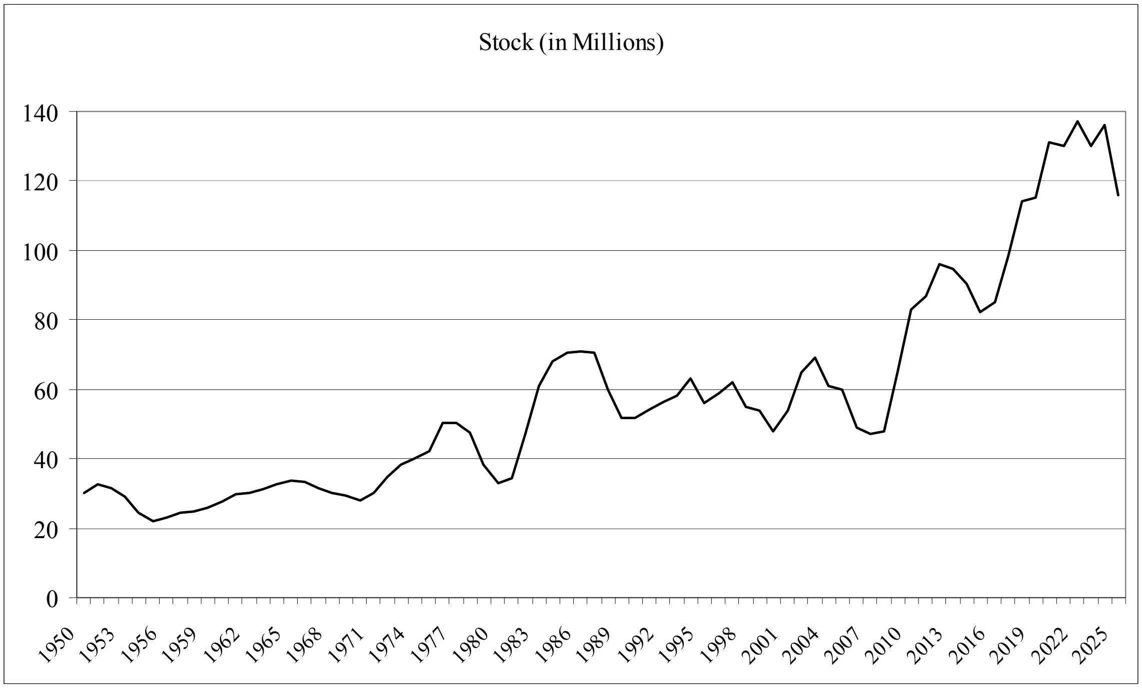

Figure 4. Hop inventory, in millions of pounds, 1950 - 2025

We address our visual assessment of each series with deterministic regressions and conventional unit-root testing. These steps are purposed to assess the need for trend inclusion and to rule out the likelihood that any series is integrated of order two. First, Table 3 presents the results of two regressions for each series. All series are converted to natural logarithms as a means to reduce growth in variance over the 76 year time horizon. Moreover, resulting forcing coefficients are interpreted as elasticities. The center column shows the estimates of regressing the single series data on a constant and linear trend. Phillips and Perron (1988) regressions are shown in the last column. Results confirm trend significance for lnAcres, lnProduction and lnStock. The trend variable is insignificant in both lnPrice equations. Not surprisingly, the lnStock results confirm a highly significant, linear, upward evolution.

Table 3. Constant and trend regressions

Regress series on constant and trend		
Phillips and Perron (1988) equations		
Dependent variable:	**lnAcres**	**ΔlnAcres**
Variable	**Standard**	**Phillips-Perron**
Constant	3.3222***	0.5338***
Trend	0.0063***	0.0013**
lnAcres(-1)	-	-0.1641***
R^2	0.3828	0.1005
Dependent variable:	**lnProd**	**ΔlnProd**
Variable	**Standard**	**Phillips-Perron**
Constant	3.7662***	0.8798***
Trend	0.0096***	0.0025***
lnProd(-1)	-	-0.2356***
R^2	0.6293	0.1326
Dependent variable:	**lnPrice**	**ΔlnPrice**
Variable	**Standard**	**Phillips-Perron**
Constant	1.2752***	0.1329**
Trend	0.0036	0.0012
lnPrice(-1)	-	-0.1290***
R^2	0.0902	0.1096
Dependent variable:	**lnStock**	**ΔlnStock**
Variable	**Standard**	**Phillips-Perron**
Constant	3.1591***	0.5425**
Trend	0.0207***	0.0038**
lnStock(-1)	-	-0.1708**
R^2	0.8512	0.0947

Significance at the < 1% (***), < 5% (**), < 10% (*) levels.

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Second, we need to establish that the underlying stochastic processes generating each variable series are not integrated of order two, I(2). Augmented Dickey and Fuller (1981) and Phillips and Perron (1988) test statistics for standard unit root testing are shown in Table 4. Phillips and Perron (1988) suggested a nonparametric method for controlling serial correlation when testing for a unit root. This method modifies the conventional Dickey and Fuller (1979) statistic so that ordered serial correlation does not affect the asymptotic distribution of the test. The null hypothesis for both tests is the series has a unit root. Trend series are included in the lnAcres, lnProduction and lnStock test estimates. Results indicate a likely mix of integration order and that all variable series have little chance of being I(2).

Table 4. Unit root testing

	lnAcres	**lnProd**	**lnPrice**	**lnStock**
Augmented Dickey-Fuller				
Level, Constant	-	-	-2.5776	-
Level, Constant & Trend	-3.4116*	-3.6709**	-	-3.9192**
1st Diff., Constant	-	-	-6.0863***	-
1st Diff., Constant & Trend	-5.2818***	-7.0771***	-	-5.1187***
Phillips-Perron				
Level, Constant	-	-	-2.3362	-
Level, Constant & Trend	-3.1205	-3.4986**	-	-3.2714*
1st Diff., Constant	-	-	-5.7728***	-
1st Diff., Constant & Trend	-4.7749***	-7.2013***	-	-4.3161***

Significance at the < 1% (***), < 5% (**), < 10% (*) levels.

In order to sort out contemporaneous links among the four variables, a standard vector autoregression (VAR) is performed.[12] Table 5 summarizes the Granger-causality output for two lag length selections. Schwarz information (SBIC) selects two lags, Akaike's information (AIC) selects three. Table 5 presents probability values associated with block lag Wald testing. As shown, price and hop stock Granger-cause acres at the less than 1 percent significance level. Acres, price and hop stock significantly influence harvest, though acres and hop harvest are foreseeably endogenous. Interestingly, only production and hop inventories exhibit contemporaneous feedback.

Table 5. Standard vector autoregression (continued on the next page)

Vector autoregression Granger-causality		
Block exogeneity Wald tests: SBIC 2 lags, AIC 3 lags		
Dependent variable: lnAcres		
Series	**P-value, 2 lags**	**P-value, 3 lags**
lnProd	0.6583	0.1723
lnPrice	0.0009	0.0001
lnStock	0.0002	0.0051

[12] See Stock and Watson (2001) for a superb treatise on VAR methods.

Dependent variable: lnProd		
Series	**P-value, 2 lags**	**P-value, 3 lags**
lnAcres	0.0000	0.0006
lnPrice	0.0000	0.0000
lnStock	0.0007	0.0006
Dependent variable: lnPrice		
Series	**P-value, 2 lags**	**P-value, 3 lags**
lnAcres	0.4895	0.1901
lnProd	0.4465	0.1222
lnStock	0.1014	0.1887
Dependent variable: lnStock		
Series	**P-value, 2 lags**	**P-value, 3 lags**
lnAcres	0.0993	0.1050
lnProd	0.0005	0.0118
lnPrice	0.1694	0.0849

Investment equation

Leaning on the comprehensive analysis above, for each time series, we define a Nerlovian investment function,

$$Acreage_t = f(Price_t, Stock_t), \tag{11}$$

where the dynamic structure of investment is an ARDL process. An advantage of the ARDL model is the flexibility to assign different optimal lag-lengths to different series. In our case, we use a model selection algorithm that minimizes certain information criteria. Table 6 below presents the Equation (5) intertemporal dynamic results for Equation (11). By minimizing Akaike's information (AIC), model p = 2, q_1 = 3, q_2 = 1 is selected when both a constant and linear trend are included. As suspected, it appears that the trend and lnStock series are collinear. The trend variable is highly insignificant (P-value 0.9739) and the test of the lnStock variables jointly equaling zero fails to reject the null. Table 7 below provides re-estimated intertemporal dynamic results after dropping the trend variable.

Without trend, the lnStock variables are jointly significant at the less than 5 percent level. Table 7 also presents diagnostic test results for no serial correlation, no heteroscedasticity and normality of the residuals. All fail to reject the null. Recursive estimation of the intertemproral dynamic model suggests that the coefficients are stable over the sample period. Figure 5 below plots the cumulative sum of recursive residuals (CUSUM), all within critical bounds at the 5 percent significance level (Brown et al., 1975). Moreover, functional form misspecification is rejected at the 5 percent level inferring that non-linearities or asymmetries are not at issue (Ramsey, 1969).

Table 6. ARDL(2,3,1) Intertemporal dynamics regression

Model Selection Criteria: AIC, 180 models evaluated, 5 lag upper limits.			
Dependent variable lnAcres. Constant and trend included.			
Variable	**Coefficient**		
Constant, $\hat{\alpha}_0$	0.4742**	R-squared	0.9244
Trend, $\hat{\alpha}_1$	0.0001	Durbin-Watson	1.9788
lnAcres(-1), $\hat{C}_1$	1.3367***	AIC	-2.4360
lnAcres(-2), $\hat{C}_2$	-0.5497***	lnStock = lnStock(-1) = 0	1.7372
lnPrice	0.1346*		
lnPrice(-1)	0.2005*		
lnPrice(-2)	-0.5016***		
lnPrice(-3)	0.2288**		
lnStock	-0.1266		
lnStock(-1)	0.1768*		

Significance at the < 1% (***), < 5% (**), < 10% (*) levels.

Table 7. ARDL(2,3,1) Intertemporal dynamics regression

Model Selection Criteria: AIC, 180 models evaluated, 5 lag upper limits.			
Dependent variable lnAcres. Constant only.			
Variable	**Coefficient**		
Constant, $\hat{\alpha}_0$	0.4684***	R-squared	0.9244
lnAcres(-1), $\hat{C}_1$	1.3370***	Durbin-Watson	1.9798
lnAcres(-2), $\hat{C}_2$	-0.5499***	AIC	-2.4634
lnPrice	0.1355*	lnStock = lnStock(-1) = 0	4.4282**
lnPrice(-1)	0.2001*	F-Serial correlation[a]	1.8647
lnPrice(-2)	-0.5021***	F-Heteroscedasticity[b]	1.1486
lnPrice(-3)	0.2281**	Jarque-Bera (residuals)	0.7519
lnStock	-0.1258		
lnStock(-1)	0.1780**		

Significance at the < 1% (***), < 5% (**), < 10% (*) levels.
[a] Up to 3 lags. Attributed to Breusch (1978) and Godfrey (1988). See also Bergmeir, et. al. (2018).
[b] Godfrey (1978) and Breusch and Pagan (1979).

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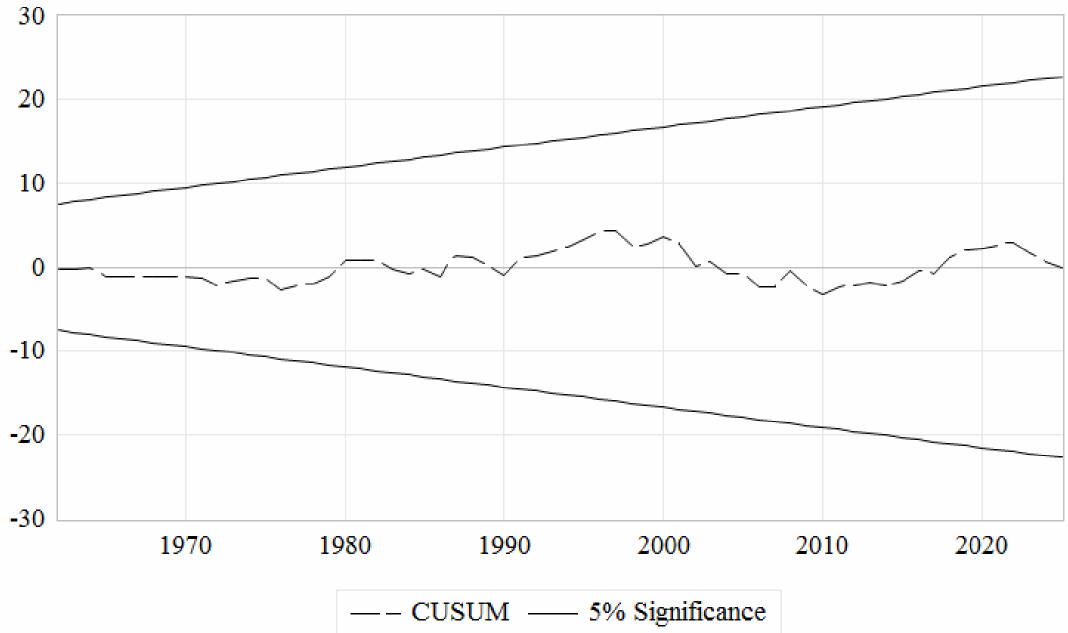

Figure 5. Cumulative sum of recursive residuals, lnAcres on lnPrice, lnStock

Proceeding with the no trend specification, Table 8 below shows the results of estimating a conditional error correction specification for Equation (11). The values of the F-statistics, shown in the far-right column, fail to reject the null of no long-run association, at the less than 5 percent level, evaluated at the upper, I(1), bound. These initial steps do not support a long-run levels relationship under the lag order selected and when the statistically insignificant deterministic trend term is excluded from the specification. Turning to the short-run, evidence of a complicated dynamic running from price to acreage changes is found. Changes in real price with two lags are jointly significant, at the less than 1 percent level, with the second lag term having a negative impact. All price estimates are relatively inelastic. Aggregation of the surveyed data may be responsible for the relatively low elasticity estimates. The lag of acreage change exhibits the largest effect, one step ahead. These short-run dynamics lend some support to the 'sticky acreage' proposition for hops as forwarded by MacKinnon and Pavlovič (2022).

Interestingly, the change in stock variable is negative but insignificant at conventional levels. Because this variable, at levels, is potentially stationary with trend and statistically insignificant in the conditional error correction form, we elected to re-estimate the bounds test with a more parsimonious investment model of acreage on price with constant and trend. Tables 9 and 10 below show these results. Table 11 below provides a side-by-side comparison of error correction estimates from Tables 8 and 10. Not surprisingly, the simplified model results are not that different from the prior estimates with one key exception. The lower right column of Table 11 shows the bounds test rejection of no levels relationship for the unrestricted trend model. While not imperious, this provides some evidence of a long-run relationship running from price to acreage. Accordingly, we recovered a levels estimate for lnPrice, 0.331 using Equation (10), that is significant at the less than 5 percent level. Moreover, the error correction (*ECT*) estimate is the correct sign and significant at the less than 5 percent level using the response-surface Kripfganz and Schneider (2020) critical values for small samples.

Table 8. ARDL(2,3,1) Conditional error correction regression

Dependent variable, Δ lnAcres.			
Variables	**Coefficient**	**Restricted $\hat{\alpha}_0$**	
Constant, $\hat{\alpha}_0$	0.4684***	Bounds F-test[c]	3.9401
lnAcres(-1), $\hat{\phi}_0$	-0.2128***	**Unrestricted $\hat{\alpha}_0$**	
lnPrice(-1), $\hat{\phi}_1$	0.0616	Bounds F-test[c]	5.1226
lnStock(-1), $\hat{\phi}_2$	0.0522**		
Short-run			
Δ lnAcres(-1)	0.5499***		
Δ lnPrice	0.1355*		
Δ lnPrice(-1)	0.2740***		
Δ lnPrice(-2)	-0.2281**		
Δ lnStock	-0.1258		

Significance at the < 1% (***), < 5% (**), < 10% (*) levels.
[c] Critical values follow Kripfganz and Schneider (2020).

Table 9. ARDL(2,3) Intertemporal dynamics regression

Model Selection Criteria: AIC, 30 models evaluated, 5 lag upper limits.			
Dependent variable lnAcres. Constant and trend included.			
Variable	**Coefficient**		
Constant, $\hat{\alpha}_0$	0.6338**	R-squared	0.9202
Trend, $\hat{\alpha}_1$	0.0012**	Durbin-Watson	1.8918
lnAcres(-1), $\hat{C}_1$	1.3369***	AIC	-2.4371
lnAcres(-2), $\hat{C}_2$	-0.5566***	lnP = lnP(-1) = lnP(-2) = lnP(-3) = 0	6.1172***
lnPrice	0.1160*	F-Serial correlation	1.1315
lnPrice(-1)	0.1785*	F-Heteroscedasticity	1.1216
lnPrice(-2)	-0.5361***	Jarque-Bera (residuals)	0.7421
lnPrice(-3)	0.3142***	CUSUM	stable

Significance at the < 1% (***), < 5% (**), < 10% (*) levels.

Table 10. ARDL(2,3) Conditional error correction regression

Dependent variable, Δ lnAcres.			
Variables	**Coefficient**	**Restricted $\hat{\alpha}_1$**	
Constant, $\hat{\alpha}_0$	0.6338***	Bounds F-test[d]	5.4362
Trend, $\hat{\alpha}_1$	0.0012**	**Unrestricted $\hat{\alpha}_1$**	
lnAcres(-1), $\hat{\phi}_0$	-0.2198***	Bounds F-test[d]	8.0001**
lnPrice(-1), $\hat{\phi}_1$	0.0727**		
Long-run			
lnPrice	0.3307**	*ECT*[d]	-0.2198**
Short-run			
Δ lnAcres(-1)	0.5566***		
Δ lnPrice	0.1160*		
Δ lnPrice(-1)	0.2219***		
Δ lnPrice(-2)	-0.3142***		

Significance at the < 1% (***), < 5% (**), < 10% (*) levels.
[d] Critical values follow Kripfganz and Schneider (2020).

Table 11. Comparison of ARDL(2,3,1) to ARDL(2,3)

Dependent variable lnAcres		
Term	**ARDL(2,3,1)**	**ARDL(2,3)**
Constant, $\hat{\alpha}_0$	0.4684***	0.6338***
Trend, $\hat{\alpha}_1$	-	0.0012**
lnAcres(-1), $\hat{\phi}_0$	-0.2128***	-0.2198***
lnPrice(-1), $\hat{\phi}_1$	0.0616	0.0727**
lnStock(-1), $\hat{\phi}_2$	0.0522**	-
lnPrice (levels equation)	-	0.3307**
Δ lnAcres(-1)	0.5499***	0.5566***
Δ lnPrice	0.1355*	0.1160*
Δ lnPrice(-1)	0.2740***	0.2219***
Δ lnPrice(-2)	-0.2281**	-0.3142***
Δ lnStock	-0.1258	-
AIC	-2.4982	-2.4645
Restricted form, Bounds F-test	3.9401	5.4362
Unrestricted form, Bounds F-test	5.1226	8.0001**

Significance at the < 1% (***), < 5% (**), < 10% (*) levels.

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Supply equation

Because of the suspected contemporaneous feedback from the stock variable running to harvest (see Table 5), the reduced form supply response becomes simply,

$$Production_t = f(Price_t). \tag{12}$$

Table 12 shows the intertemporal dynamics of an optimal (3,3) lag model including a constant and trend. Diagnostic efforts confirm no error serial correlation, error normality,

Table 12. ARDL(3,3) Intertemporal dynamics regression

Model Selection Criteria: AIC, 20 models evaluated, 5 lag upper limits.			
Dependent variable lnProd. Constant and trend included.			
Variable	**Coefficient**		
Constant, $\hat{\alpha}_0$	1.1682***	R-squared	0.9111
Trend, $\hat{\alpha}_1$	0.0028***	Durbin-Watson	2.0442
lnProd(-1), $\hat{C}_1$	0.8807***	AIC	-1.9527
lnProd(-2), $\hat{C}_2$	0.0409	lnP = lnP(-1) = lnP(-2) = lnP(-3) = 0	4.9891***
lnProd(-3), $\hat{C}_3$	-0.2571**	F-Serial correlation	1.1399
lnPrice	0.1173	F-Heteroscedasticity	1.5462
lnPrice(-1)	0.3142**	Jarque-Bera (residuals)	1.7835
lnPrice(-2)	-0.5484***		
lnPrice(-3)	0.1961**		

Significance at the < 1% (***), < 5% (**), < 10% (*) levels.

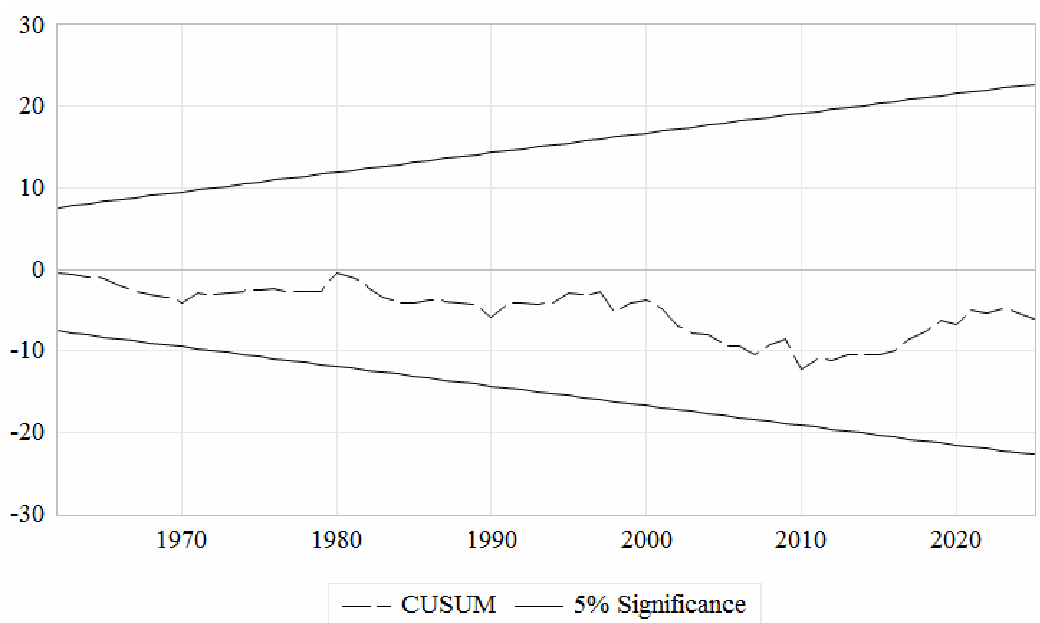

Figure 6. Cumulative sum of recursive residuals, lnProd on lnPrice

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Table 13. ARDL(3,3) Conditional error correction regression

Dependent variable, Δ lnProd.			
Variables	**Coefficient**	**Restricted** $\hat{\alpha}_1$	
Constant, $\hat{\alpha}_0$	1.1682***	Bounds F-test[e]	5.3950
Trend, $\hat{\alpha}_1$	0.0028***	**Unrestricted** $\hat{\alpha}_1$	
lnProd(-1), $\hat{\phi}_0$	-0.3354***	Bounds F-test[e]	7.9283**
lnPrice(-1), $\hat{\phi}_1$	0.0793*		
Long-run			
lnPrice	0.2364*	*ECT*[e]	-0.3354**
Short-run			
Δ lnProd(-1)	0.2162**		
Δ lnProd(-2)	0.2571**		
Δ lnPrice	0.1173		
Δ lnPrice(-1)	0.3523***		
Δ lnPrice(-2)	-0.1961**		

Significance at the < 1% (***), < 5% (**), < 10% (*) levels.
[e] Critical values follow Kripfganz and Schneider (2020).

homoscedasticity, and CUSUM stability (see Figure 6 above). Table 13 provides the conditional error correction form for Equation (12). Again, the bounds test for the unrestricted trend case rejects the null of no long-run relationship at the less than 5 percent level. The *ECT* is significant at the less than 5 percent level using Kripfganz and Schneider (2020) critical values. The recovered long-run elasticity for real price (0.236), however, is only significant at the less than 10 percent level. This indicates that any potential long-run production-price relationship for this time series may be degenerate. Focusing on the short-run, evidence of a complicated dynamic running from price to harvest changes is found. Changes in real price with two lags are jointly significant, at the less than 1 percent level, with the second lag term having a negative impact similar to the investment equation above. All price estimates are again relatively inelastic.

Structural considerations

Relaxation of U.S. states' on-premise beer consumption laws, beginning in the early 1980s, fostered an unprecedented small-beer boom (Elzinga et al, 2015). In 1985, around 70 breweries, mostly large, were operating in the U.S. In 2024, roughly 7,800 'industry members' reported operations to the Alcohol and Tobacco Tax and Trade Bureau (TTB).[13] Eighty percent of the 2024 brewery count produced 1,000 barrels or less for the year.[14] These smaller industry-entrants sought to differentiate their products from big-beer by creatively using hops. Recognizing this, hop grower/dealers began comprehensive breeding programs to develop then market proprietary varietals to the new breweries. This historic small-beer ramp up is said to have structurally changed hop farming in the U.S. (MacKinnon and Pavlovič, 2023). To explore effects on investment

[13] Monthly National Statistical Report - Beer. Report date, January 22, 2026
[14] Interestingly, over 1,000 breweries reported no production for the year 2024 (TTB, 2026).

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and supply response of this perceived structural shift, we split the USDA NASS data and re-estimated the ARDL models for the time period 1985-2025.[15] Figure 7 depicts the cumulative sum of squared recursive residuals for the full sample model, acres on price. As shown, the CUSUM of squares process drifts beyond the 95 percent confidence bounds, slightly, around the year 1985 then returns to stability. This proposed split limits our data to 41 observations. To conserve precious degrees of freedom, we dropped the problematic stock changes from the exploration and remain mindful of parsimonious optimal lag selection.

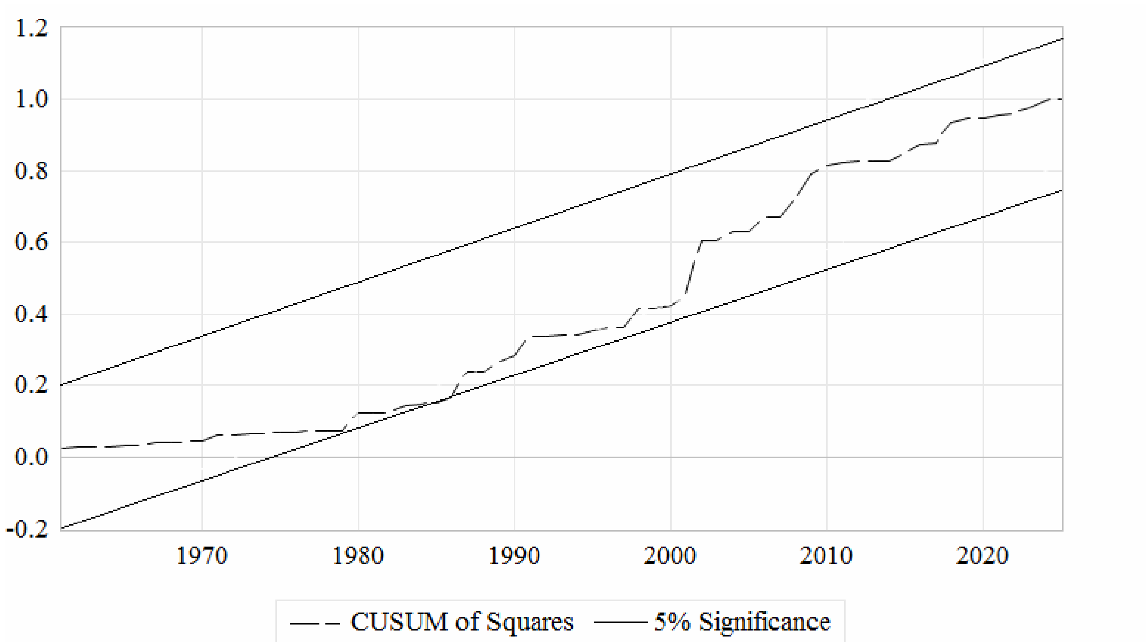

Figure 7. Cumulative sum of squared recursive residuals, lnAcres on lnPrice

Following previous steps, two intertemporal dynamic models were evaluated – with or without a deterministic linear trend. The trend variable was highly insignificant in both the investment and production equations and subsequently dropped from the analysis. Tables 14 and 15 below show the investment response; Tables 16 and 17 below present the harvest results. Despite the small sample size, both reduced form regression equations fit reasonably well and satisfy all diagnostic tests. The right column of Tables 15 and 17 show the F-statistics for the bounds test. In both models, the null of no long-run relationship is affirmed. Out of simple curiosity, we recovered both long-run price coefficients from the error correction specifications for a comparison to the full data models. Regarding the investment response, the long-run price elasticity for the full series was 0.331 compared to 0.622 in the truncated model. For the harvest equation, 0.236 versus 0.568, respectively. Though not statistically hardened, response to price roughly doubled during the small-beer boom.

[15] See Acar et al. (2023) and Perron (2006) on the importance of time series structural break consideration.

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Table 14. ARDL(2,3) Intertemporal dynamics regression

Model Selection Criteria: AIC, 30 models evaluated, 5 lag upper limits.			
Dependent variable lnAcres. Constant only. Data series 1985-2025.			
Variable	**Coefficient**		
Constant, $\hat{\alpha}_0$	0.5568***	R-squared	0.9152
lnAcres(-1), $\hat{C}_1$	1.2495***	Durbin-Watson	1.8933
lnAcres(-2), $\hat{C}_2$	-0.4493***	AIC	-2.1439
lnPrice	0.1922*	F-Serial correlation	2.0703
lnPrice(-1)	0.2069	F-Heteroscedasticity	1.3389
lnPrice(-2)	-0.7350***	Jarque-Bera (residuals)	1.1592
lnPrice(-3)	0.4602***	CUSUM	stable

Significance at the < 1% (***), < 5% (**), < 10% (*) levels.

Table 15. ARDL(2,3) Conditional error correction regression

Dependent variable, Δ lnAcres. Data series 1985-2025.			
Variables	**Coefficient**	**Restricted $\hat{\alpha}_0$**	
Constant, $\hat{\alpha}_0$	0.5568***	Bounds F-test[f]	3.3889
		Unrestricted $\hat{\alpha}_0$	
lnAcres(-1), $\hat{\phi}_0$	-0.1998***	Bounds F-test[f]	4.9450
lnPrice(-1), $\hat{\phi}_1$	0.1242**		
Long-run			
lnPrice	0.6219***	*ECT*[f]	-0.1998*
Short-run			
Δ lnAcres(-1)	0.4493***		
Δ lnPrice	0.1922*		
Δ lnPrice(-1)	0.2749**		
Δ lnPrice(-2)	-0.4602***		

Significance at the < 1% (***), < 5% (**), < 10% (*) levels.
[f] Critical values follow Kripfganz and Schneider (2020).

Table 16. ARDL(2,3) Intertemporal dynamics regression

Model Selection Criteria: AIC, 30 models evaluated, 5 lag upper limits.			
Dependent variable lnProd. Constant only. Data series 1985-2025.			
Variable	**Coefficient**		
Constant, $\hat{\alpha}_0$	0.7357**	R-squared	0.8956
lnProd(-1), $\hat{C}_1$	1.0153***	Durbin-Watson	2.00678
lnProd(-2), $\hat{C}_2$	-0.2259*	AIC	-1.9228
lnPrice	-0.0473	F-Serial correlation	1.9029
lnPrice(-1)	0.9023***	F-Heteroscedasticity	0.8044
lnPrice(-2)	-1.1856***	Jarque-Bera (residuals)	1.7814
lnPrice(-3)	0.4503***	CUSUM	stable

Significance at the < 1% (***), < 5% (**), < 10% (*) levels.

Table 17. ARDL(2,3) Conditional error correction regression

Dependent variable, Δ lnProd. Data series 1985-2025.			
Variables	**Coefficient**	**Restricted $\hat{\alpha}_0$**	
Constant, $\hat{\alpha}_0$	0.7357**	Bounds F-test[g]	2.3589
		Unrestricted $\hat{\alpha}_0$	
lnProd(-1), $\hat{\phi}_0$	-0.2107**	Bounds F-test[g]	3.3119
lnPrice(-1), $\hat{\phi}_1$	0.1197*		
Long-run			
lnPrice	0.5683**	*ECT*[g]	-0.2107*
Short-run			
Δ lnProd(-1)	0.2259*		
Δ lnPrice	-0.0473		
Δ lnPrice(-1)	0.7353***		
Δ lnPrice(-2)	-0.4503***		

Significance at the < 1% (***), < 5% (**), < 10% (*) levels.
[g] Critical values follow Kripfganz and Schneider (2020).

Response increases are also shown in the short-run dynamics. Table 18 below provides the two sample, side-by-side, elasticity comparison. Elasticities for lagged changes in price increased in the truncated sample, markedly so for the supply response. This finding supports MacKinnon and Pavlovič's (2022) Bayesian predictions for U.S. acreage responding to price changes. For the period 1998 - 2020, the time proprietary varieties were becoming dominant in the U.S., MacKinnon and Pavlovič found a higher responsiveness of acreage to price perturbations.

Table 18. Short-run error correction coefficient comparison

Dependent variable, Δ lnAcres	**Full**	**1985-2025**
Δ lnAcres(-1)	0.5566***	0.4493***
Δ lnPrice	0.1160*	0.1922*
Δ lnPrice(-1)	0.2219***	0.2749**
Δ lnPrice(-2)	-0.3142***	-0.4602***
Dependent variable, Δ lnProd		
Δ lnProd(-1)	0.2162**	0.2259*
Δ lnProd(-2)	0.2571**	-
Δ lnPrice	0.1173	-0.0473
Δ lnPrice(-1)	0.3523***	0.7353***
Δ lnPrice(-2)	-0.1961**	-0.4503***

Significance at the < 1% (***), < 5% (**), < 10% (*) levels.

Concluding remarks

The investment and supply response models presented in this paper introduce dynamic elements to aggregate U.S. hop production in two different ways. First, we attempted to empirically reveal long-run relationships by separating them from short-run fluctuations. Most importantly, nonstationarity of all variable series is fully addressed. We do find limited evidence of a long-run forcing relationship running from real season average hop price to acreage decisions. The unrestricted trend (case V) long-run price elasticity is 0.331. Interestingly, accumulating hop inventory (stock) did not impact investment or production in any meaningful way. Second, the formation of expectations and perennial characteristics are introduced, fundamentally, by using the ARDL process. Model lag selection is chosen optimally and is data driven. In all specifications estimated, the optimal price lag was three years. In all models, the change in current price was of little importance in the short-run. Conversely, lagged changes in price produced complex and highly significant impacts. In an effort to address certain structural considerations, split sample estimates (post 1985) show a marked increase in investment and supply response to price. Though not statistically hardened, long-run price elasticities roughly doubled during the small-beer boom.

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