Dynamic Relationships and Price Discovery of Western Alfalfa Markets

Hernan A. Tejeda

Research Fellow
Utah State University
email: hernan.tejeda@usu.edu

Man-Keun Kim

Assistant Professor
Utah State University
email: mk.kim@usu.edu

Dillon M. Feuz

Professor
Utah State University
email: dillon.feuz@usu.edu

Dynamic Relationships and Price Discovery of Western Alfalfa Markets

Abstract
Alfalfa hay exports have substantially increased since 2007 with 99% being shipped from western ports (Putnam et al., 2013), and likely more than 95% of it originating from seven western states (Putnam et al., 2015). This paper determines the dynamic price relationships among alfalfa markets in those western states. Of particular interest is to identify the price discovery process between the spatially separated alfalfa hay markets of Arizona, California, Idaho, Nevada, Oregon, Utah and Washington. Alfalfa hay is the nation's fourth largest crop in terms of total acreage (USDA NASS, 2013). In each of these seven western states, alfalfa is among the top three most important crops in terms of acreage. For many years, the dairy industry in these states has been the dominant market for alfalfa hay. The dairy industry continues to be a major market with alfalfa being the largest feed component for them (more than 50%), and these western states produce approximately 41% of all US production of milk in 2012 (U.S. Dairy statistics). However, the recent surge in alfalfa hay exports is resulting in a new major market for alfalfa hay and may be changing the price discovery process in these markets. The objective of this study is to examine and elucidate the center of price discovery for alfalfa among the seven mentioned western states, by identifying the causal and dynamic price relationships. The concentration and scale of dairies varies considerably by state, and obviously there are spatial differences relating to distance to the ports. Understanding the evolving nature of alfalfa hay prices in these spatially separated markets should have important risk management and policy implications.

Introduction

Alfalfa hay has been experiencing a steady increase in its overseas exports since the early 2000s.

Putnam et al. (2013) note that 99% of these alfalfa exports are shipped from western ports, and

that there has been a substantial surge in exports from 2007 up to date. Moreover, Putnam et al.

(2015) note that most likely more than 95% of these exports originate from the seven western

states of Arizona, California, Idaho, Nevada, Oregon, Utah and Washington. In each of these

states, alfalfa hay is among the top three most important field crops in terms of acreage. In

addition, alfalfa hay is the nation's fourth largest crop in terms of total acreage (NASS, 2013).

   Alfalfa hay is the main feed element of the dairy industry, covering over 50% of the ration

components for dairy cow consumption. The seven western states produced approximately 41%

of all US production of milk in 2012 (U.S. Dairy statistics). Horses and cattle are additionally fed

with alfalfa hay, and its prices have been steadily rising likewise since the beginning of 2000.

This paper investigates the dynamic price relationships among these western spatially separated alfalfa markets that are economically bound through their export operations. Moreover, we study the price discovery process that operates among them, given their relative market integration. The objective is to examine and elucidate the center of price discovery for alfalfa among the seven mentioned western states, by identifying the causal and dynamic price relationships among them. The concentration and scale of the dairy producers varies considerably by state, and there are spatial differences relating from the distance to the ports. Gaining a better understanding of the evolving nature of alfalfa hay prices in these export-related spatially separated markets contributes to the literature through improved risk management information as well as by providing market insight having potential policy implications.

The steady growth in alfalfa exports from 1989 to 2014 can be seen in Figure 1, which includes the percentage that is shipped through western U.S. ports. As may be observed, there is
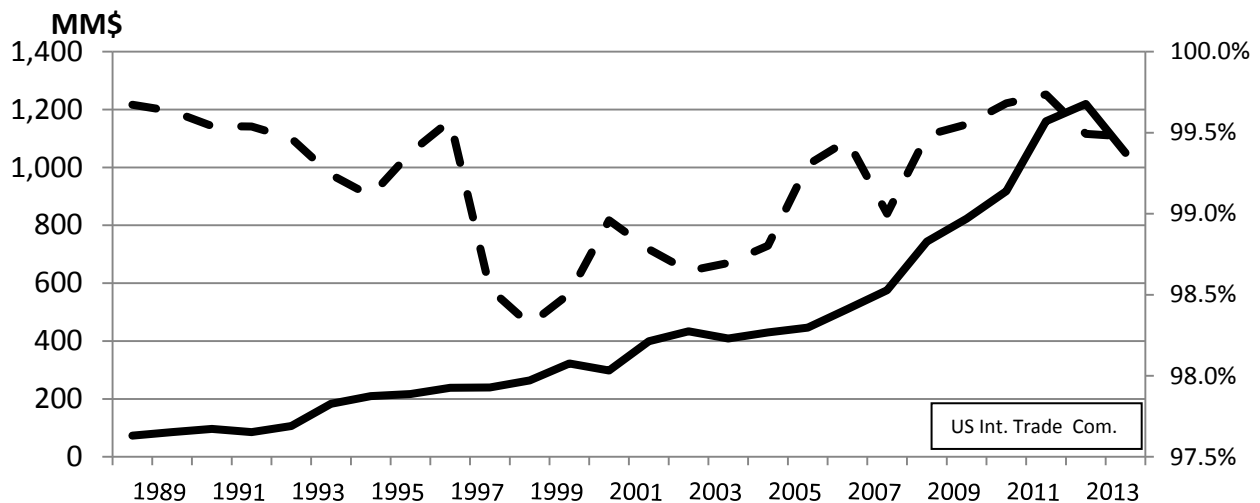

Figure 1: U.S. Alfalfa hay Exports in millions $, and percentage (dashed line) of total exports being shipped through Western ports. i.e, CA, OR, & WA.

a pronounced increase in exports starting from 2000, and it is even more evident beginning in 2007. There is likewise a drop during 2014, which can be attributed to a sharp decrease of nearly

50% in shipments to UAE, in addition to the western port slowdown that affected overall

shipments (Putnam et al., 2015). In the same manner, the increase in export tonnage follows a
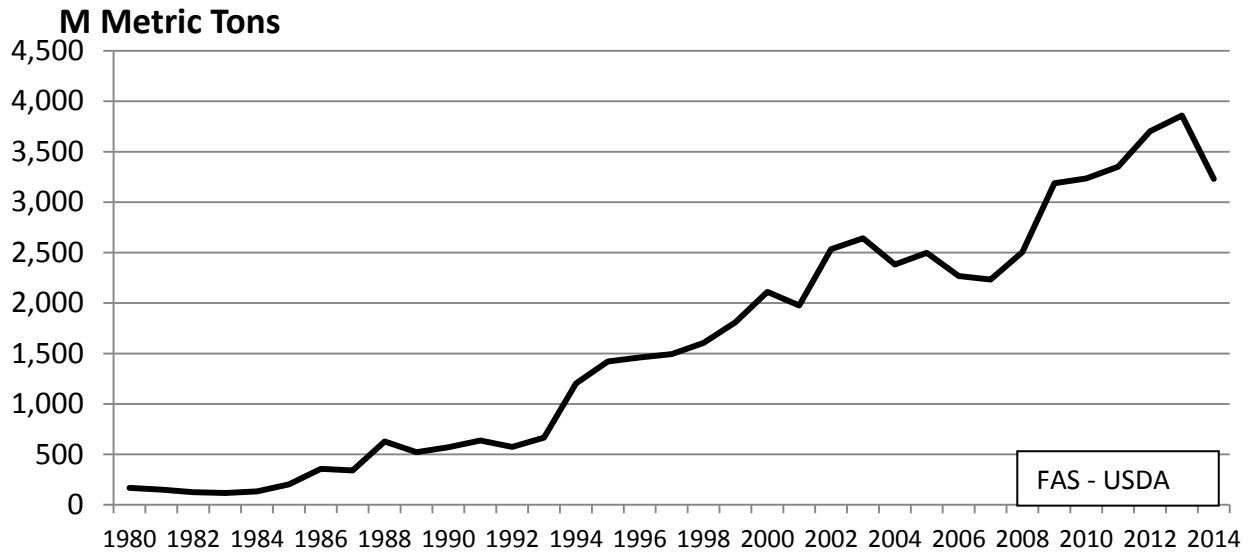
M Metric Tons

Figure 2: U.S. Alfalfa hay Exports in metric tons

similar rising path and is shown in Figure 2; increasing volume-wise by almost a 100% from

2000 onwards before the drop in 2014. The production per each of the seven states is in Figure 3,

with California clearly the largest producer at an average of 6.8 MM metric tons, followed by
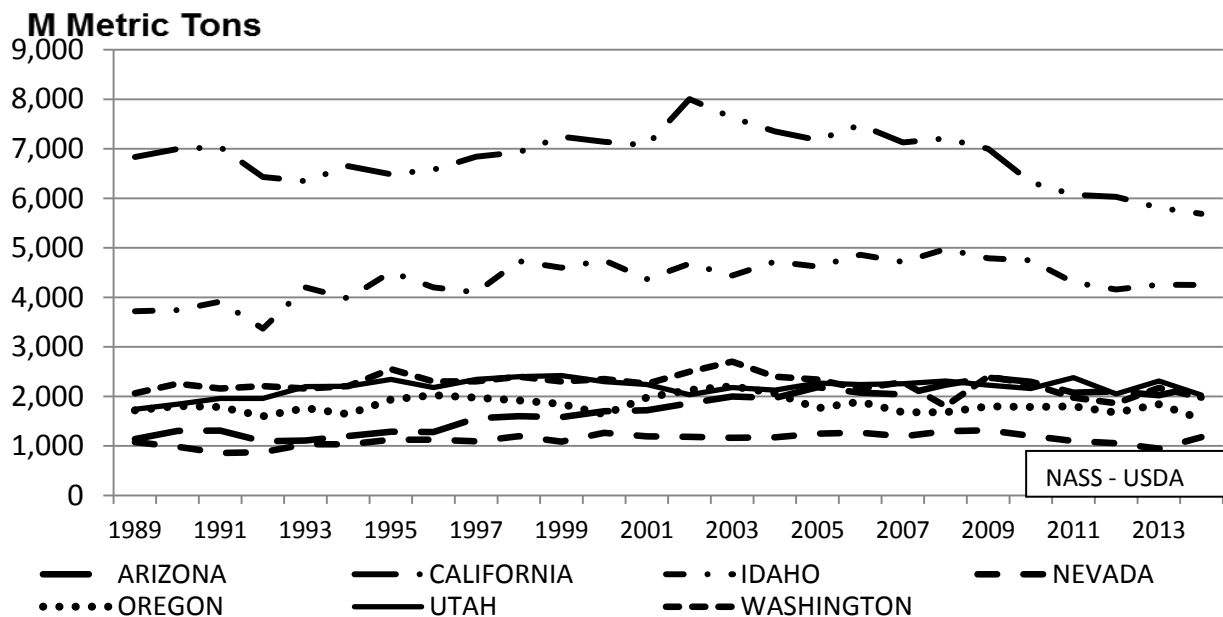
M Metric Tons

Figure 3: U.S. Alfalfa hay Production of Seven Western states in thousands of metric tons

3

Idaho at an average of roughly 4.4 MM metric tons, and then the remaining states between 1.2 and 2.2 MM tons.

The following Figure 4 shows the evolution of average yearly prices for alfalfa hay, per each state from 1990 to 2014. Despite the differences in tonnage from the previous figure, here the prices move much closer together. A noticeable point is that Utah tends to be at the lower end in the evolution of prices, along with Nevada and Idaho. However, near the top it's always a mix between California, Oregon and Washington – which have the ports for export shipment. Relevant to point out is the dip experimented by all prices for the end of 2008 until a better part of 2010, as a direct consequence from the great recession which resulted in a drop of all grain and feed prices.
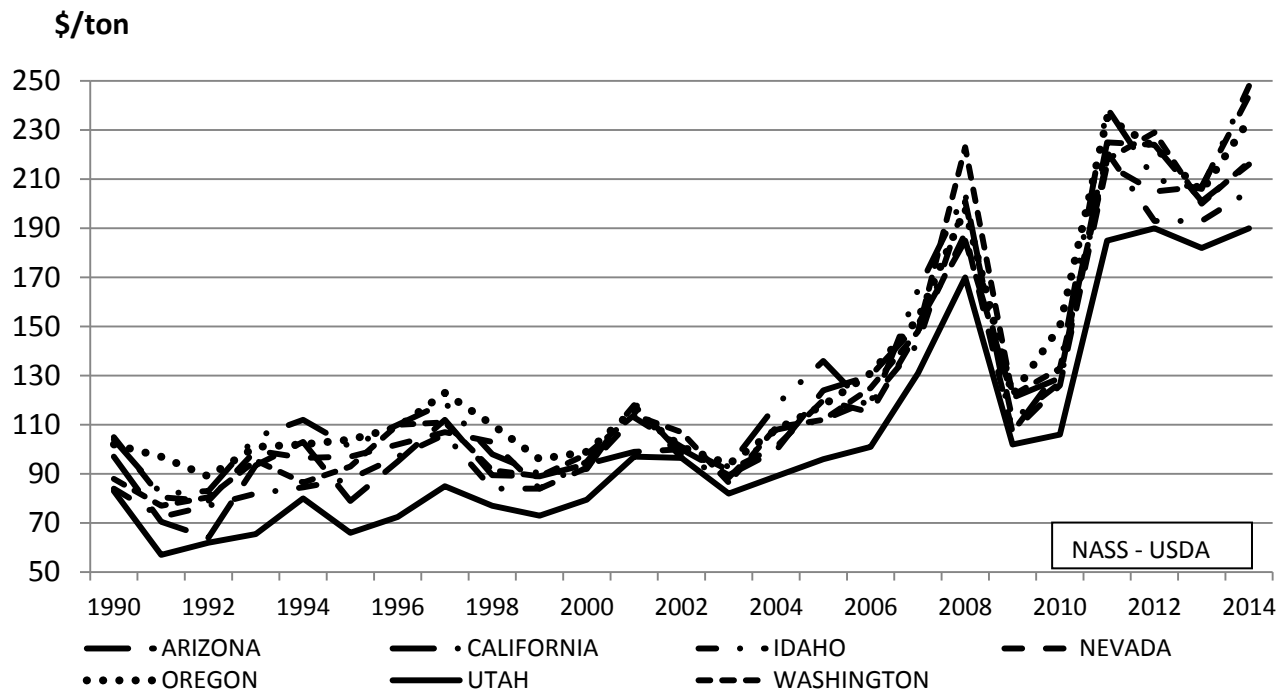
$/ton

Figure 4: Alfalfa Prices Received f Seven Western states in $ per ton

The amount of alfalfa hay exported from the US is still small with respect to the total production. The following Figure 5 shows the volume of alfalfa hay exported over the total
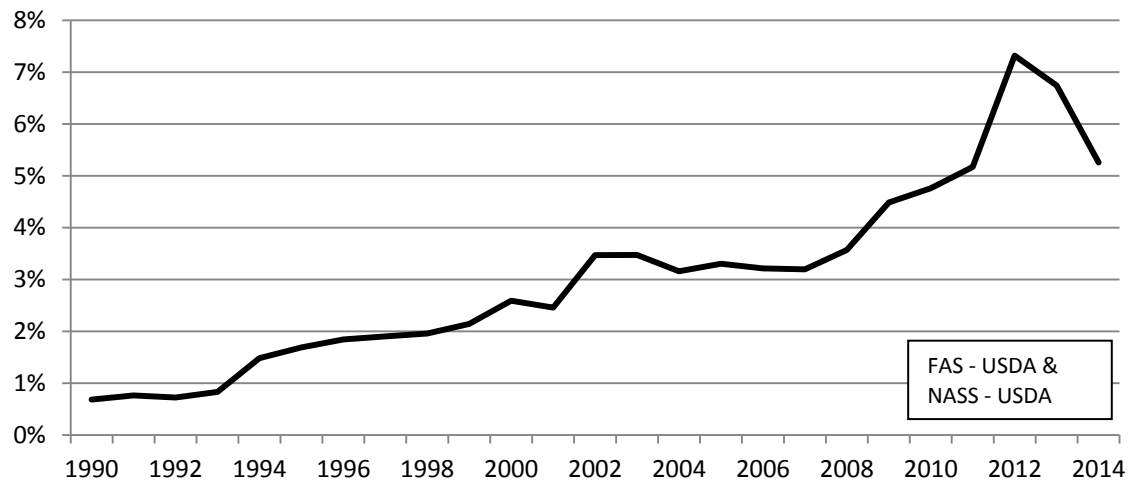
Figure 5: Percentage of U.S. Alfalfa hay Exports (mT) tons to U.S. Alfalfa hay Production (mT)

amount produced in the U.S. It can be seen that the percentage has grown through the years and

yet it remains quite rather modest at just below 8%. However, and as mentioned previously,

given that at least 98% of all U.S. Alfalfa hay export shipments are from western ports, then

under a conservative scenario we may assume that 95% of all U.S. alfalfa hay exports are from

the western states.

Under this scenario, we can see in Figure 6 that up to almost 20% of the alfalfa production in

these western states has been directed for export markets.[1] Thus there is an increasingly sizeable

effect from the alfalfa hay export market in terms of volume and transactions on each of these

seven western states, in comparison to alfalfa producing states from other regions of the country.

This motivates us to investigate the price discovery process of alfalfa hay among these markets.

We employ multivariate time series VAR models with an error correction term (i.e. VECM),

along with Directed Acyclic Graphs (DAG) from Pearl (1995 and 2000) and Spirtes et al. (2000),

to sort-out the dynamic causal relationships among these prices and markets. The DAG

---

[1] Putnam et al. (2015) assume that "…well over 95% of (U.S.) hay exports likely originate from seven western states of CA, WA, OR, ID, UT, NV, and AZ". However, their estimates are that alfalfa exports account for about 11.5% of the seven western states' production.

procedure provides insight into directions of instantaneous causal flows based on contemporaneous correlations. Identifying the directions of contemporaneous causal flows among price innovations is relevant for VAR-type innovation accounting, since it may suggest a data-driven pattern useful for the structural decomposition of the VAR residuals (Swanson and Granger, 1997). This procedure is a substantial improvement over the use of a Cholesky factorization decomposition, which is recursive and thus embodying strong assumptions which may not reflect the 'actual' causal patterns among a set of contemporaneous innovations (Bernanke, 1986). This is useful for assessing the dynamic properties among the markets through Impulse Response Functions (IRFs), as well as to construct forecast error variance decompositions (FEVD).
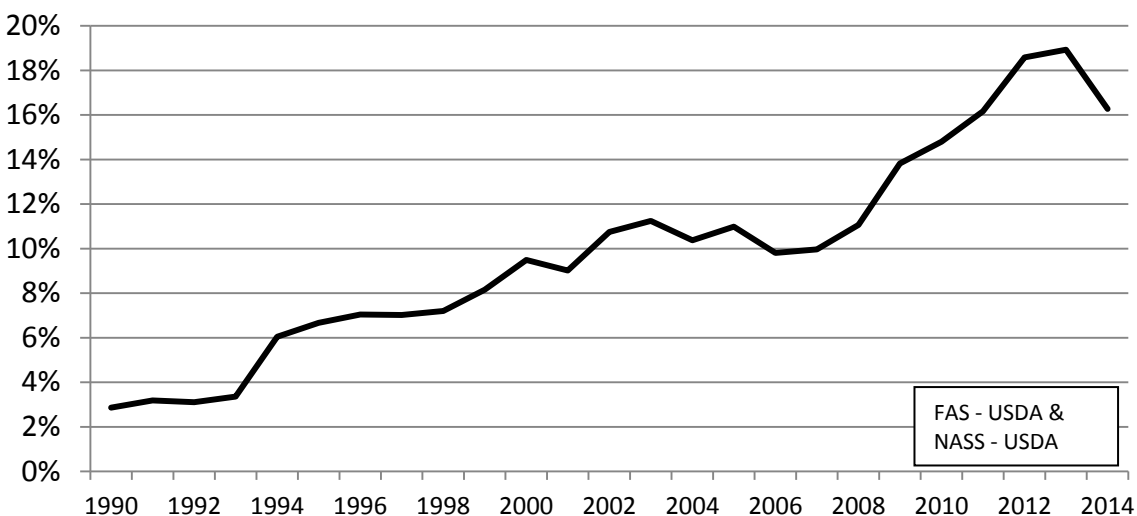
Figure 6: Percentage of Alfalfa hay Exports (in mT) from Seven Western States with respect to their Production (mT)

Prior studies making use of this method in agricultural markets include Bessler and Ackleman (1998) studying farm and retail prices of pork and beef; Bessler and Davis (2004) investigating Texas cash cattle markets; Haigh and Bessler (2004) studying prices relationships among grain in Illinois and export grain at the U.S. Gulf, along with the barge market; McKenzie (2005)

investigating Arkansas soybean basis levels along the Delta and Gulf region considering barge

rate shocks; Awokuse (2007) investigating the integration among China's rice market post food

trade liberalization; and Stockton, Bessler and Wilson (2010) investigating a price discovery

process for cattle markets in Nebraska.

Methods

We apply monthly average cash prices of alfalfa hay for the seven western states (AZ, CA, ID,

NV, OR, UT, and WA), examining from January 2000 to December 2014, encompassing the

period which has experienced the surge in hay exports as seen in Figure 4.

Given the non-stationary nature of the data,[2] we apply vector error correction model (VECM)

to our series of prices after testing for co-integration.[3] The VECM model with p lags is noted as:

$$\Delta \boldsymbol{y}_t = \boldsymbol{\Pi} y_{t-1} + \sum_{i=1}^{p-1} \boldsymbol{\Gamma}_i \Delta \boldsymbol{y}_{t-i} + \boldsymbol{dr}_i + \boldsymbol{e}_t \qquad (t = 1, \dots T) \qquad (1)$$

where Δ is the first difference operator (e.g. $\Delta \boldsymbol{y}_t = \boldsymbol{y}_t - \boldsymbol{y}_{t-1}$); $\boldsymbol{y}_t$ is a ($k \: x \: 1$) vector of prices; $\boldsymbol{\Pi}$

is a ($k \: x \: k$) coefficient matrix of rank r (# of co-integration terms) such that $\boldsymbol{\Pi} = \boldsymbol{\alpha\beta}'$; $\boldsymbol{\Gamma}_i$ is a

($k \: x \: k$) matrix of short-run dynamic coefficients; $\boldsymbol{dr}_i$ is a dummy variable considering the

recession period from third quarter of 2008 to end of 2010, and $\boldsymbol{e}_t$ is a ($k \: x \: 1$) vector of

innovations. We identify the contemporaneous structure of the innovations through the directed

acyclic graph (DAG) analysis of the correlation (covariance) matrix of the $\hat{\boldsymbol{e}}_t$.

The DAG method, as described by Pearl (1995, 2000) and Spirtes et al. (2000), considers a

non-time sequence asymmetry in causal relations among variables. Let A, B, and C be three

variables where A is the cause of B and C, represented by B ← A → C. This suggests that the

unconditional association between B and C is non-zero, but the conditional association between

---

[2] Augmented Dickey-Fuller Unit root tests were applied, showing support in favor of accepting null of non-stationary series.

[3] The Johansen's Co-integration test is applied (Johansen, 1991).

B and C given the information from common cause A, is zero. This infers that common causes

'partition' or 'screen off' associations between their joint effects. Conversely, if B and C both

cause A, represented by B → A ← C, then the unconditional association between B and C is zero

(since neither is depending on A). However, the conditional association between B and C given

the common effect A is non-zero. Thus here it can be inferred that common effects do not

'partition' or 'screen off' associations between their joint causes. These partition or screening-off

attributes of causal relations have been incorporated into the literature of directed acyclic graphs.

A directed graph is a figure that uses arrows and vertices to represent the causal flow among a

set of variables. The graph can be symbolized as an ordered triple (**V**, **M**, **E**) where **V** is a non-

empty set of vertices (e.g. variables), **M** is a non-empty set of marks (symbols attached at the end

of undirected edges), and **E** is a set of ordered pairs where each of one is referred to as an edge.

Adjacent vertices are connected by an edge. A directed acyclic graph has no path that leads away

from a variable and then returns to the same variable. (e.g., A → B → C → A is not acyclic).

DAGs may be used as analytical instruments that represent conditional independence, as

shown by the following recursive probability decomposition:

$$P(v_1, v_2, \ldots \ldots \ldots, v_n) = \prod_{i=1}^{n} P\left(v_i \middle| pr_i\right) \tag{2}$$

where P is the probability of vertices (variables) $v_1, v_2, \ldots \ldots v_n$ and pr_i is the realization of

some subset of variables that precede (i.e. come before in the causal sense) v_i in the order

$(v_1, v_2, \ldots \ldots v_n)$. A d-separation is proposed by Pearl (1995) as a graphical representation of

conditional independence. I.e., d-separation is represented by the conditional independence

relations in (2). According to Pearl (1995), by formulating a DAG where the variables

corresponding to pr_i are represented as 'parents' or direct causes of v_i, then the independencies

implied by (2) can be read off the (DAG) graph employing the notion of d-separation.

Thus in our initial example of three variables A, B, C where A was the common cause of B and C (B ← A → C), if we condition on A, then the association (correlation) between B and C disappears, i.e. conditioning on A, makes B and C become d-separated. However, in an unconditional sense ("avoiding" A), then B and C have an association (correlation) due to their common cause, and are thus d-connected. Conversely, when B and C cause A (B → A ← C), then only under a conditional setting on A would there be an association (correlation) between B and C, or be d-connected. In the case of an unconditional setting between B and C, they would be d-separated. Lastly, the three variables may have a sequential or causal chain relation (A → B → C), where A causes B and B causes C. Here the unconditional association (correlation) between A and C would be non-zero or not be d-separated. However, the association (correlation) between A and C conditional on B would be zero, or they'd be d-separated.

The following result is of essence to these connections: for a directed acyclic graph G with vertex **V**, such that A and B are in **V** and also Z is in **V**, then G linearly implies the correlation between A and B conditional on Z is zero if and only if A and B are d-separated given Z. This notion of d-separation has been incorporated into an algorithm that permits building directed acyclic graphs. Spirtes et al. (2000) have developed the algorithm and programmed into a software titled TETRAD V.[4] Our estimation process made use of this program.

We then make use of standard innovation accounting techniques comprising Forecast Error Variance Decomposition (FEVD) and impulse response functions, which enable us to obtain inferences with respect to the dynamic adjustments in each of the variables from unexpected shocks in the series. The forecast error variance decomposition (FEVD) consists of when the innovations/shocks to each variable is decomposed, permitting the identification of the relative

---

[4] This is the latest version of the software, being superior to TETRAD II which in certain cases may have estimated DAGs with a rather low level of significance (Awokuse and Bessler, 2003).

proportion of the movements in a sequence due to its own shock, over the other shocks to the

variable. In the case that own shocks explain all of the forecast error variance of a specific series,

this variable may be considered exogenous with respect to the other variables in the system.

Conversely, if a large proportion of the FEV from a variable's sequence can be explained by

shocks to one or more of the other variables, then this variable is considered endogenous to the

system. The FEVD approach likewise permits to draw inferences with respect to the magnitude

and degree of influence during the sequence, among the variables in the system.

In addition, impulse response functions (IRF) are determined with standard innovation

accounting. IRFs permit to identify the dynamic adjustments, in terms of direction and

magnitude, for each variable in the system in response to unit shocks in the system's variables.

The IRFs are generated by separately shocking innovations for each of the variables by one

standard deviation.

Results

Unit root test results applying ADF with a trend are in Table 1. Here we can infer that each of the

price series that considers having no lags up to three lags would result in being non-stationary.

We apply AIC, SBC and HQIC criteria to estimate the number of lags in our multivariate series,

with results in Table 2. Thus our 1st differenced VAR with an error correction term (i.e. VEC

model) results in having one lag.

Table 1: ADF Unit root test results for each series, considering a trend

		5% sig level	t-stat AZ	CA	ID	NV	OR	UT	WA
Lags	0	-3.436	-2.006	-2.354	-2.501	-1.918	-2.324	-2.373	-1.902
	1	-3.436	-2.615	-2.734	-2.371	-2.184	-2.449	-2.480	-2.549
	2	-3.436	-3.306	-3.112	-2.700	-2.285	-2.582	-2.282	-2.886
	3	-3.436	-3.385	-3.194	-3.291	-2.461	-2.776	-2.515	-3.010
	4	-3.436	-3.421	-2.982	-3.568	-2.835	-3.106	-2.693	-3.353

Table 2: VAR Optimal lag results

		AIC	HQIC	SBIC	
Lags	0	-12.850	-12.747	-12.596	
	1	-22.084	-21.620	-20.940	**
	2	-21.962	-21.137	-19.929	
	3	-21.766	-20.581	-18.843	
	4	-21.615	-20.068	-17.802	

From the Johansen co-integration test in Table 3, it can be inferred that the series have six co-integrating terms (r = 6).

Table 3: Trace Test on Order of Co-integration

H_o: Rank	Intercepts in the Co-integration relations		Decision
	Trace	Critical value	
r=0	341.015	132.004	R
r<=1	206.555	101.838	R
r<=2	141.731	75.737	R
r<=3	84.886	53.423	R
r<=4	55.220	34.795	R
r<=5	26.668	19.993	R
r<=6	2.534	9.133	FR

We explore the possibility that any one of our market series is not present in the co-integrating space (i.e. not part of a co-integrating vector). The null hypothesis that i-series is not part of the co-integrating space is tested with a test-statistic distributing chi-squared with six degrees of freedom (six co-integrated terms). Table 4 shows the results were the null is rejected for each market. Thus we are confident that all our markets are in the co-integrated vectors. In addition, we consider and test the possibility that some markets may not respond to perturbations in the

Table 4: Test for Exclusion of market from co-integrated space.

LR TEST CHISQ(r)

r	DGF	Crit.: CHISQ_5%	AZ	CA	ID	NV	OR	UT	WA
6	6	12.59	28.96	101.39	50.93	83.67	54.36	38.33	34.56

co-integration vector. I.e., we seek to test the weak exogeneity of each series relative to the long run (co-integrated) equilibrium(s). The null hypothesis is that the particular market does not make adjustment toward the estimated long run relation(s), i.e. that the market is weakly exogenous, and results are below in Table 5. Here the test rejects weak exogeneity for each market and thus each is considered endogenous. However, given California's low statistic value, it may be considered moderately 'weakly-exogenous' and thus moving somewhat independently from the other series.

Table 5: Test for Weak-Exogeneity of markets.

LR TEST CHISQ(r)

r	DGF	CHISQ_5%	AZ	CA	ID	NV	OR	UT	WA
6	6	12.59	66.25	15.95	54.78	87.34	50.20	60.20	63.68

From Spirtes et al. (2000), given that our sample size considers 182 observations, we calculate our (contemporaneous) DAG with a 10% level of significance in order to ensure convergence to the correct (direction) decisions with probability 1. The TETRAD V estimation process to obtain the DAG makes use of the correlation matrix of the innovations from our VECM model, which is in Table 6. The results of our DAG estimation are in Figure 7, where each line is an edge and indicates a relationship between the connected variables.

Table 6: Contemporaneous Correlations of VECM Residuals: Jan 2000 to Dec 2014

State	AZ	CA	ID	NV	OR	UT	WA
AZ	1.000						
CA	0.244	1.000					
ID	0.133	0.132	1.000				
NV	0.178	0.087	0.284	1.000			
OR	0.194	0.066	0.226	0.227	1.000		
UT	0.229	0.034	0.183	0.200	0.273	1.000	
WA	0.346	0.147	0.320	0.137	0.475	0.350	1.000

The arrow at the end of each line specifies the direction of the causal relationships. In this case, California seems to lead the Arizona market in contemporaneous time, which in turn leads Washington. California is the largest producer/seller market by far as shown previously, so being the lead information provider may be anticipated. Washington provides concurrent information to Oregon, Utah and Idaho markets. Washington and Oregon being coastal export-shipping ports would likewise be anticipated to be among the leading markets, and informing the interior states. Nevada receives concurrent information from the Oregon market. In general, the interior states receive their information from coastal states.
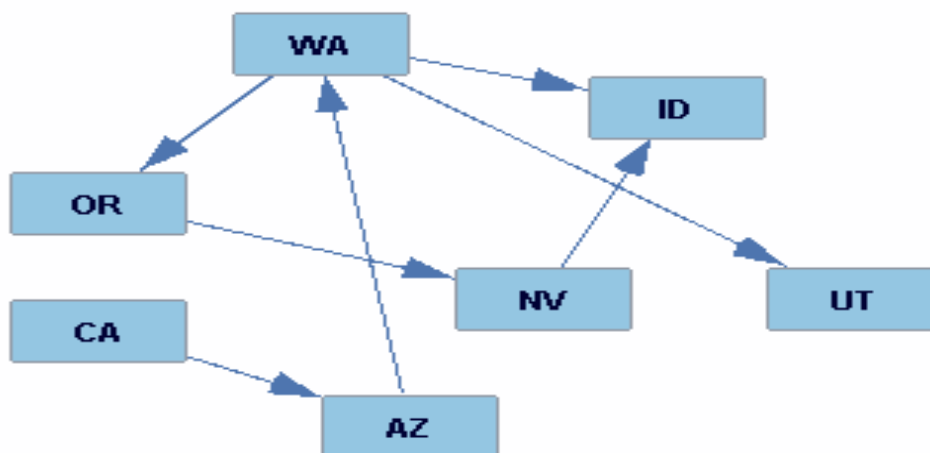

Figure 7: Directed Acyclic Graph on innovations from seven western states alfalfa markets.

We study the dynamic effects of the series through the standard innovation techniques. We first analyze the FEVD for each market considering a period of up to 24 months. Figure 8 shows the decomposition of variance for California and Arizona. For California, we can observe that during the 1st few months this variable behaves exogenously since all its variation only comes from itself. After these initial months, Oregon has a noticeable effect on this market's price variations followed in a smaller scale by Idaho and Washington. In the case of Arizona, from the beginning months onwards, California has a growing impact on this market as it increasingly
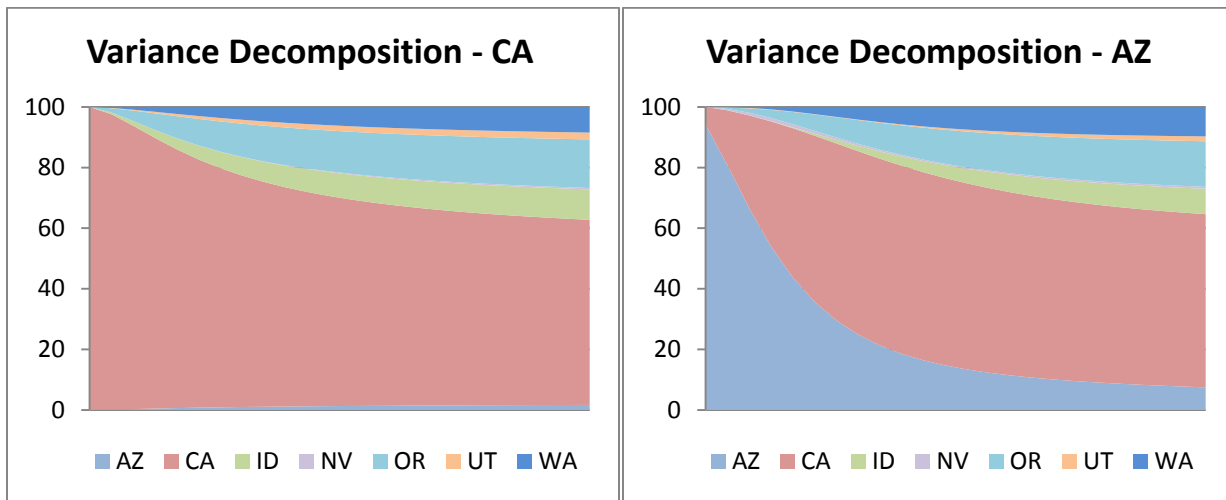
Figure 8: Forecast Error Variance Decomposition (FEVD) allocated to Innovations of California and Arizona market series, respectively.

accounts for the unexpected changes in Arizona prices. In much smaller manner, Oregon and Washington have an effect in Arizona as the sequence progresses. Figure 9 has the FEVD for Washington and Oregon markets. For Washington, there is an immediate effect on the variation of its prices from Arizona, which follows from its concurrent DAG results. However, this effect
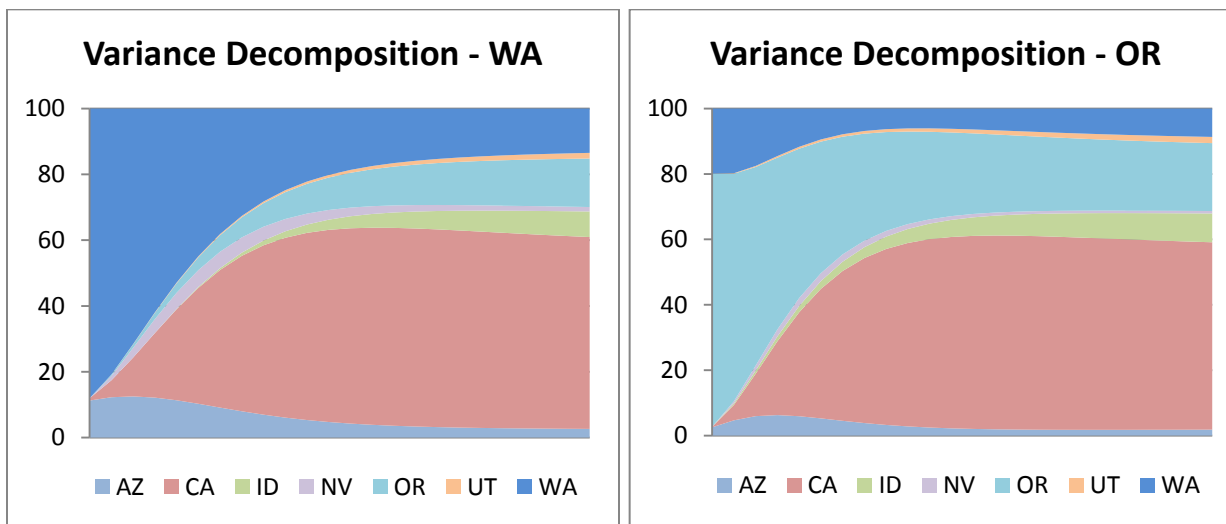

Figure 9: Forecast Error Variance Decomposition (FEVD) allocated to Innovations of Washington and Oregon market series, respectively.

fades within the first few months and California accounts the biggest for unexpected variability in Washington prices. The Oregon decomposition shows that Washington has an immediate

effect, again following the DAG results. However, similarly to Washington, it is California that takes the bear share in the market's unanticipated variability during the following months onwards. In addition, Arizona shows a minor impact from the beginning but it decreases also through the following periods. Figure 10 has the FEVD for Nevada and Utah markets. For Nevada, after the first month in which may behave a bit exogenously given its own affecting variation, it is once again California that has the biggest effect in the market, followed by a distant (much smaller) impact from Oregon and Washington. In the case of Utah, Washington is the only market to have an initial impact in the price variations, again corroborated by DAG results. However, subsequently this effect dwindles and very soon after the first few months California once again is the market accounting for the major unanticipated differences in Utah alfalfa prices. Arizona has a very minor initial effect and Oregon and Idaho likewise have a relative minor increasing
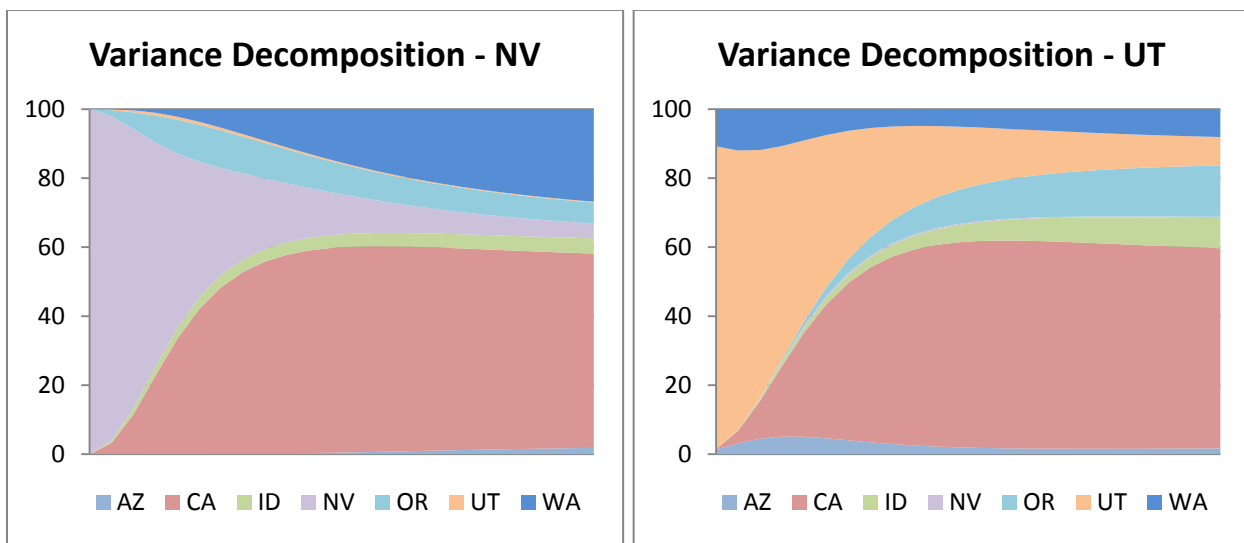

Figure 10: Forecast Error Variance Decomposition (FEVD) allocated to Innovations of Nevada and Utah market series, respectively

impact, though quite small in comparison to California. Figure 11 has the FEVD for Idaho, in which initially Washington has an impact, and in a much smaller scale also Oregon and Nevada.
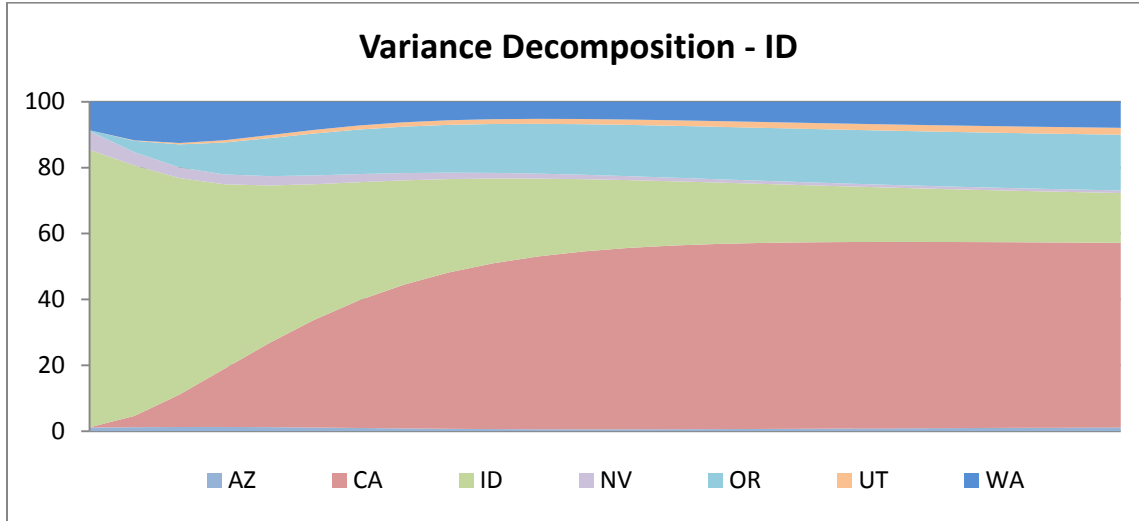
Figure 11: Forecast Error Variance Decomposition (FEVD) allocated to Innovations of Idaho
        market series.

However, for the following months it is California again being the dominant state that impacts

the unexpected variability of its market prices. Washington's initial impact decreases and

Oregon's increases but remains quite lower than California's impact.

   The impulse responses are calculated and shown in Figure 12. These are a one-time-shock to

the innovation of one variable, and leaving the other variables' innovations constant. As

mentioned previously, we applied the DAG method along with the Bernanke (1986)

decomposition to obtain the ordering of variables prior to the calculation of IRF's. The (one-

time) shock is positive and of a magnitude equal to one standard deviation of the innovation of

the particular factor (variable), applied at a contemporaneous period (month zero), and leaving

all other factor's innovations constant for all dates (Hamilton, 1994, pg. 318).

   We find that California has a dominant effect on the price movements of the other markets

(2nd column, Figure 12). Conversely, California prices generally moves only with shocks from

other coastal states, Oregon and Washington, and a bit with Idaho (2nd row, Fig. 12). This latter

may perhaps respond to the size of Idaho's market as it is second among the seven (Figure 3).

Oregon, being a coastal state, and likewise Idaho (again because of its market size), both have a relevant positive effect on price movements by the other states (3rd and 5th column, Figure 12). Both these states respond mainly to shocks from California and each other. Utah has a much smaller positive effect on the other states (6th column, Figure 12, and responds mostly to the three mentioned previously (6th row, Fig. 12).Strangely, shocks from Washington on the other markets generally have a negative impact after a few positive periods. It is not clear at this moment why this would be and more study is necessary.
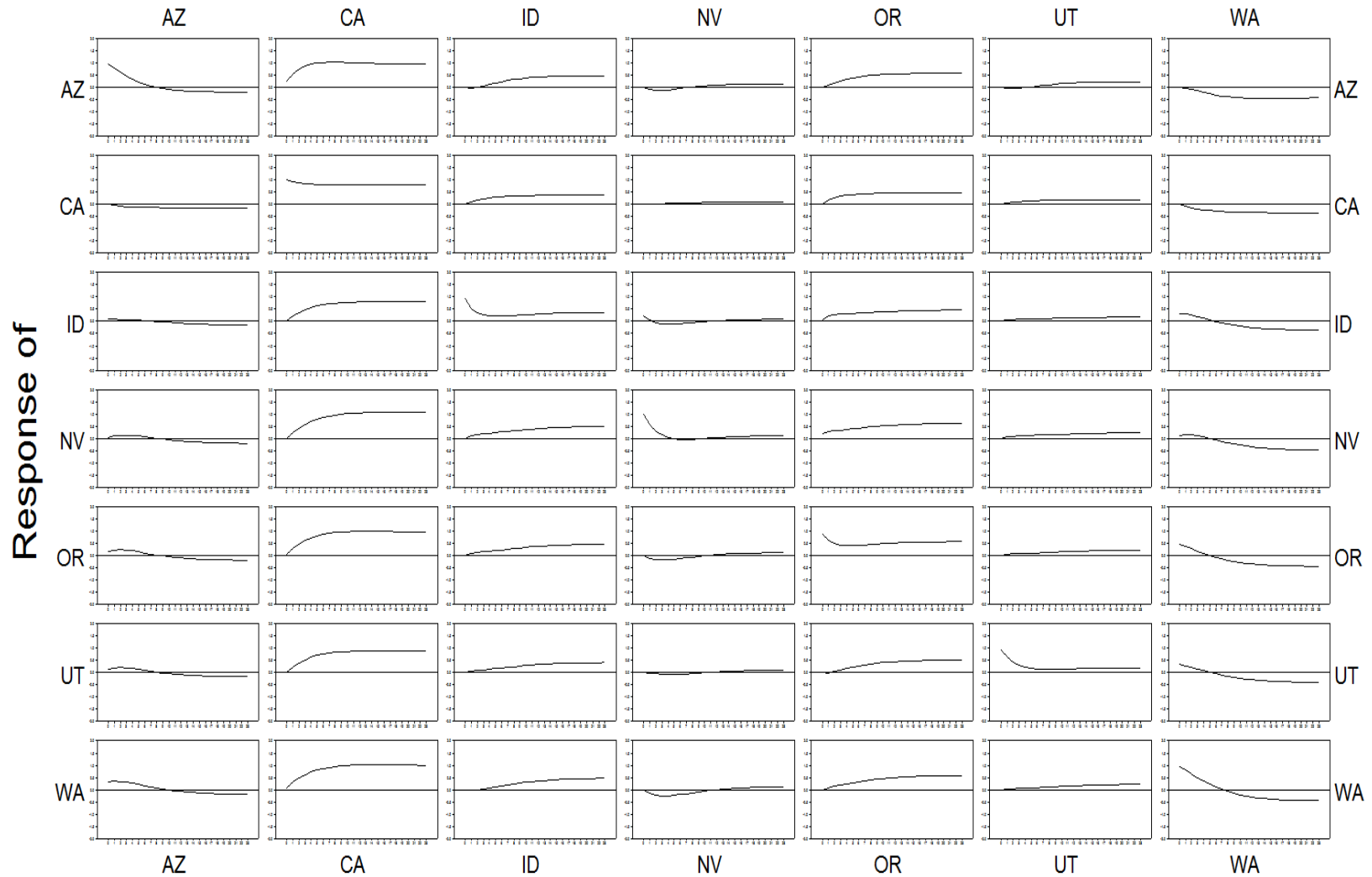
One-time-only Shock to

Figure12: Impulse Response Functions of seven western alfalfa market prices to a one-time shock of each price series

Conclusions

We study the evolution of alfalfa hay prices in seven western states given the increase these markets have experienced in exporting abroad. Specifically, we investigate the price discovery system that operates within these spatially separated but economically integrated markets. We model the price series via a Vector Error Correction Model (VECM), given the non-stationary nature of the prices, as well as from identifying many co-integration terms among them. We likewise apply directed acyclic graphs (DAGs) to identify the contemporaneous structure of the innovation terms from the correlation matrix of the residuals. In addition, we apply standard innovation techniques including forecast error variance decomposition (FEVD) and impulse response functions (IRFs) permitting us to obtain inferences from dynamic adjustments in each of the markets from unexpected shocks.

We find that contemporaneously, California is the leading market, acting weakly exogenous with respect to other endogenous markets. Arizona concurrently receives price information from California, and transmits it to Washington, which in turns leads Oregon, Nevada and Utah with price information. Nevada contemporaneously transmits to Idaho. As anticipated the coastal 'port' states tend to be the price leading informants, given their proximity to export facilities. Nevada, Utah, and Idaho receive their price information from or through Washington, while Arizona from California. This responds to proximity, and more likely to export shipments from internal states.

Regarding the unexpected variation in prices for each market (from FEVD) through a period of 24 months, it is California that takes the major share in each market starting from the 1st few months of analysis. This is anticipated given the state's much larger share of the market, and thus having a main impact on each of the other ones, with Washington being a distant second. As for

18

impulse response functions, it is once again a positive shock from California that produces a positive variation in each the states. Conversely, California is only affected by shocks from Washington and Oregon, the other port states. The inland states, in particular Utah and Idaho, likewise respond mainly shocks to prices from the port states. One result that requires further study is that from shocks to the Washington market, which produced initially positive responses from the other markets, but after a few periods these responses became negative. It is not clear at this moment what may be the explanation for this.

References

Awokuse, TO and Bessler, DA. (2003). Vector autoregression, policy analysis, and directed graphs: an application to the U.S. economy. Journal of Applied Economics, 6: 1–24

Awokuse, T. O. (2007). "Market reforms, spatial price dynamics, and China's rice market integration: A causal analysis with directed acyclic graphs." Journal of Agricultural and Resource Economics, 32: 58–76.

Bernanke, B. S. (1986), "Alternative Explanations of the Money Income Correlation," Econometric Research Program, Research Memorandum No. 321, Princeton University. January.

Bessler, D.A., and Akleman, D.G. (1998). "Farm prices, retail prices, and directed graphs: Results for pork and beef". American Journal of Agricultural Economics, 80, 1145–1149

Bessler, D.A., and E.E. Davis (2004) "Price Discovery in the Texas Cash Cattle Market," Applied Stochastic Models in Business and Industry 20(4):355-378

Haigh, M.S. and D.A. Bessler. (2004) "Causality and Price Discovery: An Application of Directed Acyclic Graphs." Journal of Business 77:1099-1121.

Johansen, S., (1991). Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models. Econometrica 59, 1551–1580

McKenzie, A. M. (2005). The effects of barge shocks on soybean basis levels in Arkansas: A study of market integration. Agribusiness 21: 37–52.

Pearl, J. (1995). Causal diagrams for empirical research. Biometrika 82, 669–710.

Pearl, J. (2000). Causality. Cambridge, Cambridge University Press.

Putnam, D.H., W. Matthews, and D. Sumner, "Hay Exports from Western States have Increased Dramatically", Alfalfa & Forage News, UC Cooperative Extension, November 1, 2013

Putnam, D.H., W. Matthews, and D. Sumner, "Alfalfa and Grass Hay Exports Decline after Sven Years of Dramatic Growth", Alfalfa & Forage News, UC Cooperative Extension, April 28, 2015

Spirtes, P., Glymour, C., and Scheines, R. Causation, Prediction, and Search, Second Edition. The MIT Press, 2001

Stockton, M.C., D.A. Bessler, and R.K. Wilson (2010), "Price Discovery in Nebraska Cattle Markets", Journal of Agricultural and Applied Economics 42: 1-14

Swanson, N.R., and C.W.J. Granger (1997) "Impulse Response Functions Based on a Causal Approach to Residual Orthogonalization in Vector Autoregressions," Journal of the American Statistical Association 92(437):357-67

USDA. National Agricultural Statistics Service. Crop Production. March 8, 2013.