Decomposing Local Corn Prices into Hedgeable and Unhedgeable Shocks

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Abstract

We use time series methods to identify the proportion of the variation in local corn prices attributable to shocks that can be protected against using derivatives, and the portion that cannot. Using several recent phenomena as focal points, we decompose the time path of local basis levels at select locations around the Corn Belt into the influence of several explanatory factors, and demonstrate the value of our methodology for measuring the magnitude and duration of market events at disparate spot markets. For example, by comparing the path of residual, idiosyncratic shocks across locations, we identify the impact of the 2014 rail backup. We estimate that transportation problems in the Upper Midwest that year lowered local corn prices in Fargo, ND by up to 43 cents/bu (in April), in Elk Point, SD by up to 37 cents/bu (in September), and in Mitchell, SD by up to 34 cents/bu (in May). Grain market participants at these locations would not have been able to hedge their exposure to these events with liquid derivatives contracts.

Keywords: Basis, corn, drought, futures contracts, grain prices, hedging, rail backup

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Grain market participants regularly trade commodities using the basis, or the difference between the local cash market price and the going price for a reference futures contract. For example, grain elevators often list the price they pay for corn in terms of its relationship to the nearest delivering futures contract. By relating the current local price to an expected future price, the basis provides a market signal to either sell or store, smoothing intertemporal consumption and efficiently guiding commodity inventories through the supply chain.

But even though the expected future price used in the basis calculation is a constant over space at each point in time, the basis surface is not uniform. Many factors differentiate prices from one location to the next. Just as the storage ties together current and future prices at any given location through the possibility of arbitrage, the potential for transportation over space prevents the prices for the same commodity at any two locations from diverging too much. The difference between their prices cannot exceed the shipping cost,[1] or trade occurs and brings prices back into balance. The cost of transportation, then, forms an upper bound on the difference between prices over space. However, within that bound grain prices at any two locations *are* permitted to diverge according to local supply and demand conditions.

The potential for this divergence has important implications in terms of the ability of producers, ranchers, and merchandisers to hedge the price of grain; the tools of hedging, both futures and options, are tied to the difference between the cash price at the delivery location and the futures price for delivery at that location. To the degree that the prices in a local market do not vary with the prices observed in the delivery location specified by the applicable futures contract, local participants' efforts

[1] Plus the time value associated with shipping.

to insulate themselves from the risk of idiosyncratic market shocks are diminished.[2] This is seen even in the case of a classic minimum variance hedge: fewer hedging instruments are optimal as the covariance between the spot and instrument prices decreases. The result is that local shocks—both positive and negative—are felt more strongly, even when production is hedged. In the case of grain, because the price of a futures contract represents the expected forward price in the delivery market, differences between the fundamental conditions in the delivery and local markets directly affect the amount of idiosyncratic risk borne by local market participants. Just how much of the price variation that a given farmer faces is shared by participants in the territory assigned for the delivery of futures contracts, and how much is idiosyncratic to his or her own local market, affected by access to transportation, fuel costs, or nearby feed and ethanol demand?[3]

We seek to identify the proportion of the variation in local corn prices attributable to shocks that can be protected against using derivatives contracts that trade in Chicago, and those that cannot. The former are represented first by changes in the corn basis at Burns Harbor, Indiana, a par delivery location for the Chicago Board of Trade corn futures contract. The price of diesel fuel—which presumably could be hedged using energy derivatives—is also modeled explicitly. The residual variation in local basis represents local shocks that cannot be hedged using traditional means. We use a structural vector autoregressive model to analyze the distinct contribution of each of these factors to the observed time series of spot prices from 2010-2014 at a variety of locations across the US.

Our results paint a portrait of the spatial distribution of price risks, and—another important contribution of our approach—the duration of any divergence in price patterns. At every location we examine, the

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[2] A lower degree of protection can work towards a farmer's advantage or detriment, depending on the relative movement of local prices. The important point is that the protection afforded by hedging tools is less effective.

[3] This question is somewhat analogous to the consideration of asset riskiness as a combination of market-wide and idiosyncratic risk components, as expressed by the Capital Asset Pricing Model (Sharpe, 1964).

correlation between the local and delivery market basis is time-varying. But certain phenomena generate a similar shift at (almost) all observed locations. On the other hand, the composition of local price changes is vastly different based on the location in question: certain points of the production chain are far more susceptible to departing from hedgeable risks than others, for long stretches of time. We interpret these empirical findings about the components of local price variation in the context of known market events. By identifying the structural shocks that explain the path of each local basis through time, we use a counterfactual approach to quantify the impact of the 2012/13 drought, and the rail backup of 2014 in the Upper Midwest.

Background

A variety of factors affect the price of grains. Since at least Working (1927), economists have understood that most of the variation in their prices is explained by supply-side developments, particularly once a crop is planted. Good examples of this phenomenon are found in recent history: following a drought, short crop, and tight supplies of 2012/2013, the 2013/2014 marketing year was a record year for grain and oilseed production in the US and Canada. In that harvest, American farmers produced 552.5 million tons of these commodities, 20% higher than ever previously recorded (Sparger, 2014; USDA-NASS, 2014). On the demand side, satisfaction of the Renewable Fuel Standard places predictable pressures on the corn price, given the amount of legislatively mandated ethanol required for production.

The drought of 2012 impacted agriculture throughout the US (USDA-ERS, 2013), leading USDA to designate over 2,200 counties as disaster areas (USDA, 2013). Despite a rise in total acreage planted to corn of over 5 million acres from the prior year, total production fell by 12.7% to 10.76 million bushels in 2012. The drought affected transportation reliability, as well. Low water conditions that year reduced the relative efficiency of barge shipping; draft restrictions put in place as a result of the drought increased the price of shipping grain down the Mississippi (USDA-AMS, 2012). In contrast, above-average precipitation in 2013 improved growing conditions dramatically.[4] That year, the US generated a record output of 13.8 million bushels of corn and near-record output for soybeans and wheat; Minnesota, Montana, and North and South Dakota all enjoyed record corn production levels that year (***chart to be added***). However, these same states—whose grain supply chain is heavily dependent on rail shipping— faced a particularly harsh winter post-harvest that limited the speed and length of trains. At the same time, improving macroeconomic conditions increased the demand for rail among energy producers in the same region. 2014 was also a record year of domestic oil and gas production in the US, affecting fuel and production costs for the commodity, but also contributing to localized transportation backups as rail networks clogged. In North Dakota, a focal point of rail transportation backups for the winter of 2013/14, crude oil production averaged over 300,000 barrels annually from 2011-2015, an increase of over 400% compared to an average production level of approximately 68,000 barrels from 2006-2010. Taken together, the strain on the rail network due to growing energy and agricultural demand for transportation led to widespread backups and increased shipping costs. BNSF, one of two Class I railroads operating in the West had 16,000 grain cars three days past due in late-March, 2014 (USDA-OCE & AMS, 2015).

On top of naturally low prices due to the bumper crop and high supplies, increased shipping costs from the rail backup reduced the price offered to Upper Midwest farmers for grain harvested in 2013. By comparing average observed basis bids for selected North Dakota grain elevators to a historical year,

[4] https://www.ncdc.noaa.gov/sotc/national/201313

Olson estimates the rail backup lowered North Dakota corn prices by $0.25 and $0.41 in March and April 2014, respectively; he did not find a reduction in prices for the preceding January or February. Likewise, Usset (2014) compares Minnesota corn basis levels from early-2014 to an average of two previous years to estimate that transportation problems reduced corn prices to local farmers by about $0.30 per bushel between March and June. Given overall crop conditions (in a record year) and the substantial heterogeneity of local markets, analyses like these are sensitive to the choice of base year, however, which is meant to represent the counterfactual, i.e., what would have happened to local grain prices absent the transportation issues. USDA-OCE & AMS model the corn basis at six points of origin as a function of several the basis at potential destination locations and transportation costs (and include speed of transport, the ratio of stocks to available storage, and outstanding sales commitments at US ports) to measure the average impact of increases in transportation costs. They estimate that higher transport costs caused by the rail backup would reduce corn prices offered in Minneapolis, MN by an average of $0.17/bu, possibly rising as high as $0.42/bu, relative to the level that would be expected, historically.

Most extant grain basis research focuses on a particular determinant of basis, such as transportation costs (e.g., Li and Thurman, 2013), the market for commodity storage (Garcia and Good, 1983) the influence of nearby ethanol plants (e.g., McNew and Griffith, 2005), or the installation of high-efficiency loading facilities (Bekkerman et al., 2014). Similarly, it is concerned with basis patterns observed in a specific state or sub-region, such as the Texas Triangle Area (Welch et al., 2009) or Kansas (Taylor, Dhuyvetter, and Kastens, 2006).

Our study contributes to the literature by broadening the determinants and geographic area under consideration. An important advantage of our approach is that it permits the use of easy-to-find data, and is not as dependent on sparse or infrequent information—like nearby animal units, location-specific rail tariffs, or ethanol plant production figures—which can limit the empirical value of a model that focuses on more specific factors. As a results, we introduce a method that offers the ability to identify the impact of historical events on local prices, subject to careful consideration of confounding effects.

Researchers have utilized time series methods to varying degrees to explain and forecast basis. Jiang and Hayenga (1997) compared a number of traditional and time series approaches for corn and soybean markets in Northeast Iowa. They concluded that more sophisticated methods generate only minor improvements to straightforward forecasting. Sanders and Manfredo (2006) undertook a similar analysis of Illinois soybean basis for competing methods including ARMA and VAR, finding only minor improvements in time series techniques.

Two recent studies apply time series models to explain the price linkages between domestic local spot markets for crops. McKenzie (2005) uses vector autoregression with ordering assumptions informed by directed acyclic graphs (DAGs) to describe the integration of selected local soybean markets with the Gulf export market. Using innovation accounting, he establishes empirical evidence for lead-lag relationships in price discovery, as well as the proportion of variation in local basis attributable to several determinants. Yu, Bessler, and Fuller (2007) use DAGs and an error-correction approach to explain spatial price linkages in the US corn market.

Model and Methods

Hailu, Maynard, and Weersink (2015) demonstrate that the basis b_t^i at any location i and time t can be decomposed into a spatial component representing the difference between its cash price and the prevailing cash price at a delivery location d for the relevant futures contract, and a temporal component: the carry, or price of storage.[5] The latter is simply the difference between the going cash price at the delivery location, and the expected forward price at that location provided by the futures contract (Working, 1949). The cost of transportation between the local and delivery market τ_t^{id} forms an upper bound between their prices, as predicted by trade theory:

$$(1) \qquad P_t^i \leq P_t^d + \tau_t^{id}$$

$$b_t^{i(S)} \leq \tau_t^{id}$$

Likewise, arbitrage caps the difference in prices at the delivery location between time t and futures contract delivery T at the carry, $c_{t,T}^d$:

$$(2) \qquad P_t^d \leq P_T^d + c_{t,T}^d$$

$$b_t^{d(T)} \leq c_{t,T}^d$$

In a liquid futures market, the first term on the right hand side of (2) is predicted efficiently by the contract price $F_{t,T}$. Without loss of generality, the basis is commonly stated as the local cash price less the futures price of the next-to-deliver, or "nearby" futures contract. By substitution, the local basis can be written as the sum of the contemporaneous difference in prices between the local and delivery markets $b_t^{i(S)}$, and the difference between the going and expected future cash price in the delivery market $b_t^{d(T)}$, which is weakly equal to the sum of the cost of transportation between the local and delivery market, and the carry:

[5] We re-state Hailu, Maynard, and Weersink's (2015) model using new notation to make clear that our focus is on the relationship between local and delivery market prices, rather than domestic and foreign prices.

(3) $$b_t^i = P_t^i - F_{t,T}$$

$$b_t^i = \left(P_t^i - P_t^d\right) + \left(P_t^d - F_{t,T}\right)$$

$$b_t^i = b_t^{i(S)} + b_t^{d(T)}$$

$$b_t^i \leq \tau_t^{id} + c_{t,T}^d$$

As the reference futures contract reaches maturity, under normal conditions $b_t^{d(T)} \to 0$, since the carrying cost approaches zero and the futures market converges to the delivery market cash price.[6] But $b_t^i \to b_T^{i(S)}$, which depends on difference in fundamental conditions between the local and delivery markets (with the transportation cost serving as a maximum). Therefore, when a fully hedged producer (assuming a production level of 5000 bushels of corn) realizes their portfolio at time T, he or she receives a per bushel return of the futures price that was "locked-in" plus $b_T^{i(S)}$:

(4) $$P_T^i + F_{t,T} - F_{T,T} = F_{t,T} + b_T^i$$

$$P_T^i + F_{t,T} - F_{T,T} = F_{t,T} + b_T^{i(S)}$$

Therefore, the less possible it is to capture the idiosyncratic variation represented by $b_t^{i(S)}$ using energy derivatives, less able a market participant is to protect their returns against adverse price movements.

We use time series methods to identify the proportion of variation in the weekly local corn basis due to hedgeable and unhedgeable shocks at a selection of locations around the Corn Belt, from 2010-2014. As a reduced form, a standard vector autoregression (VAR) measures the relationships of a system of

[6] In general, this relationship holds. However, over the late 2000s, major grain futures markets did not converge to cash market prices. Adjemian et al. (2013) and Garcia, Irwin, and Smith (2014) explain that this was due to a market design issue that generated a wedge between futures prices and expected cash prices at the delivery location. Our period of interest does not overlap the period of non-convergence in the corn market.

variables over time by stating each variable in the system as a function of its own lagged values, plus the lagged values of all the other variables in the system. A recursive framework places a triangular structure on the reduced form residuals using an ordering assumption that permits orthogonal "shocks" to variables that come earlier in the order to affect lower variables, contemporaneously.[7] This ordering assumption allows for identification of the structural parameters via a Choleski decomposition of the reduced form variance-covariance matrix. Ultimately, shocks to the lower variables in the order *are* permitted to affect the earlier variables, after a lag defined by their distance in the ordering. As a powerful tool for policy analysis, this technique is common in applied economics (see, e.g., Janzen et al., 2014). The results of VARs are generally displayed via innovation accounting: in this article, we highlight the forecast error variance decomposition (FEVD), and the historical decomposition of forecast errors.

From (3), the basis in any location can be decomposed into (a) spatial and (b) temporal components. Fortunately, the temporal component $b_t^{d(T)}$ is provided directly by the basis in the delivery territory: we use the difference between the average Burns Harbor, Indiana Switching District weekly cash price bid—a par delivery location for the Chicago Board of Trade (CBOT) corn futures contract— and that exchange's nearby futures contract price. The price of fuel, and important proxy for $b_t^{i(S)}$ that could conceivably be hedged by the local price of diesel fuel. The local basis is also calculated with respect to the nearby futures contract.

For each location, the vector of endogenous variables in the VAR is therefore represented by

$$(5) \qquad \boldsymbol{y_t} = (Diesel\ Price_t, Delivery\ Mkt.Basis_t, Local\ Basis_t)$$

The ordering assumption of $Diesel\ Price \rightarrow Delivery\ Mkt.Basis \rightarrow Local\ Basis$ is based on the likelihood that the variables could affect one another contemporaneously. Therefore, while diesel,

[7] Setting the proper order is an important step that should be grounded in economic theory.

delivery market, and local developments could all affect the local basis contemporaneously, shocks to the local basis could only affect diesel and delivery market prices at a lag.

We choose a lag length of 2 for the model at each location according to the Schwarz and Hannan-Quinn information criteria, as shown in table 1. We verified that residuals from the models do not exhibit significant serial correlation using Breusch-Godfrey LM (Breusch, 1978; Godfrey, 1978) and LMF tests (Edgerton and Shukur, 1999); stability of the models is tested using the unit eigenvalue condition (Hamilton, 1994) and CUSUM tests (Brown, Durbin, and Evans, 1975). All basis and diesel price series were further found to be stationary according to Augmented Dickey Fuller (Davidson and MacKinnon, 1993) and KPSS tests (Kwiatkowski et al., 1992), which weigh the evidence against the null of non-stationarity and stationarity, respectively. The VAR representation is then

$$\text{(6)} \qquad \boldsymbol{y_t} = \textstyle\sum_{k=1}^{2} \boldsymbol{A_k y_{t-k}} + \boldsymbol{e_t}$$

We use a recursive system to identify the structural parameters, by premultiplying the terms in (6) by the matrix $\boldsymbol{A_0}$; the SVAR is represented as

$$\text{(7)} \qquad \boldsymbol{A_0 y_t} = \textstyle\sum_{k=1}^{2} \boldsymbol{A_k^* y_{t-k}} + \boldsymbol{\varepsilon_t}$$

For $\boldsymbol{A_k^*} = \boldsymbol{A_0 A_k}$ and $\boldsymbol{e_t} = \boldsymbol{A_0^{-1} \varepsilon_t}$. . Using the SVAR, the structural innovations can be identified from the residual shocks in the VAR according to

$$\text{(8)} \qquad \boldsymbol{e_t} = \begin{pmatrix} e_t^{Diesel} \\ e_t^{Delivery} \\ e_t^{Local} \end{pmatrix} = \begin{bmatrix} a_{11} & 0 & 0 \\ a_{21} & a_{22} & 0 \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{pmatrix} \varepsilon_t^{Fuel} \\ \varepsilon_t^{Carry} \\ \varepsilon_t^{Idiosyncratic} \end{pmatrix}$$

The SVAR decomposes the local basis into a deterministic component[8] and a stochastic component that is itself the summation of the structural shocks from the diesel price, the delivery market basis, and the residual own-shocks. We interpret the first two in the form of "fuel" and "carry" shocks, while the final set of shocks represent idiosyncratic variation in the local basis that cannot be explained by changes in fuel and delivery market conditions. We provide the average effect of these shocks on local prices at various forecast horizons via a FEVD, and also break down the time path of each local basis according to the contribution of these structural shocks in the form of a historical decomposition. Our approach offers the opportunity to estimate the counterfactual local basis level that would have existed had an event not occurred. Using this methodology, we calculate the effect of recent, known commodity market phenomena, in terms of both magnitude and duration, and identify explicitly the portion that could have been hedged.

Data

Geograin.com maintains a database of daily cash price bids for thousands of locations around the US. For tractability, we aggregate these into weekly observations at the county level. Based on geographic factors and historical basis patterns, we focus on seven representative locations in our analysis (see figure 1): Burns Harbor, IN (par delivery location); Grand Island, NE (plains location near ethanol production); Fargo, ND (Midwest location affected by the rail backup); Cedar Rapids, IA (Midwest unaffected by the rail backup); Otoe, NE (strategically located near a main waterway – Missouri River - and two major interstates, I-29 and I-80); Mitchell, SD (located on I-90, a major interstate); and Elk Point, SD (in the midst of livestock farms, and ethanol and biodiesel plants). Our period of interest runs from January 1st, 2010 – December 31st, 2014, comprising a sample size 260 weekly price bids at each

[8] This is made up of the regression constant and trend term, plus the feedback effects provided by the lag structure of the VAR.

location; figure 2 plots the basis values used in our analysis alongside the price of diesel fuel. The latter are collected from US Energy Information Administration reports.

Results and Discussion

Observed Basis Values

The basis plots in figure 2 demonstrate that the paths of local corn prices are highly correlated at times, but diverge quite noticeably at others. Basis levels spend long stretches below zero, indicating a higher future value for grain (in the delivery market), but invert at times (e.g., 2011, 2012, and 2013) just before harvest. The 2011 inversion broke a relatively consistent relationship between the series; all exhibit notably tighter spreads around the carry (represented by the Burns Harbor, IN basis level) after that point up until the 2012 inversion ahead of the drought-affected harvest. Besides for Fargo, ND and Cedar Rapids, IA, those tight spreads continued as limited stocks drew down in advance of the 2013 harvest and basis levels climbed to over +$1/bu at most locations. Following the 2013 harvest, our data exhibit the widest spreads observed over the period of interest. The clearest drivers of that are the very low basis values observed during early-2014 in Fargo, ND, Mitchell, SD, and Elk Point, SD, three locations that were affected by the rail backup. By the end of the sample period (December 2014), the basis levels exhibit about the same relationship as was observed at its outset (January 2010).

Average Effects of Basis Determinants

To identify the average contribution of fuel, carry, and idiosyncratic shocks to each local basis level in the data set, we present an FEVD from our structural VAR in figures 3a-3f. Each FEVD highlights over a set horizon the proportion of the variance in local basis due to shocks to each of the variables in the system, assuming a constant distribution of shocks through time. We interpret the FEVD as the average contribution of each of the modeled factors to variation in the local basis in both the short-run and as the system settles to a steady state. The decompositions in these charts show that in the very short-run (at a one or two week horizon), idiosyncratic shocks explain a high proportion (~70-80%) of the variation in local basis, and fuel shocks play a very small role. But after that, carry shocks dominate; at a 10-week horizon shocks to the price of storage represented by CBOT corn futures explain about 80% of the variation in the local basis in Grand Island and Otoe, Nebraska, Mitchell, South Dakota, and Cedar Rapids, Iowa. But over the long run, fuel shocks gradually increase in all locations. At the horizon of one year shocks to diesel prices explain about 20% of the variation in the local basis in Otoe, NE, Fargo, ND, Mitchell, SD, and Elk Point, SD, while in Grand Island, NE, and Cedar Rapids, IA, they explain about 10% of the variation in the basis, with shocks to the price of storage still dominating the variation in local basis. Local shocks, on average, are a more important driver of long-run local basis levels at some locations than others, settling at a not insignificant level of about 20% in Cedar Rapids, IA, Elk Point, SD, and Mitchell, SD, and about 30% in Fargo, ND, compared to 10-15% in either Nebraska location.

Historical Decomposition

Because the relationship between local basis patterns and the carry is not consistent through time (see figure 2), we also conduct a historical decomposition of the forecast errors from our SVARs. Figures 4a-4f separate the time path of stochastic shocks to the local basis for each modeled location (represented by the red line) into its component structural shocks. Orthogonal fuel (blue bars), carry (green bars), and idiosyncratic (yellow bars) shocks during each week period sum to the stochastic shock; the sum of these bars equals the path of the stochastic basis shock. Adding the stochastic shock to the model's deterministic values yields the original time series of the basis. Figure 4 demonstrates how each shock affected the basis at our locations of interest in terms of the dollar price per bushel of corn offered to farmers.

Fuel shocks are important at certain times over the sample period and tend to operate in the same direction across locations. For example, as diesel prices began to climb in mid-2010 towards a peak in early-2011 (see figure 1) –the blue diesel shock in 4a-f- placed downward pressure on the basis. That is, local grain prices dipped as nationwide transportation costs increased. Then, as diesel prices begin to slide back down in early 2014, the reverse is captured in figure 4, as grain sellers benefitted from reduced shipping costs. We assume that fuel shocks can be hedged using liquid derivatives contracts.

Carry shocks—which can also be hedged using futures and options—dominate local basis changes at most times and locations, and can lead to swings of very large magnitudes. For example, by mid-2013, as grain stocks drew down in the wake of the 2012's drought-affected short crop, the carry inverted substantially: the spot bid for corn in Burns Harbor, IN in July that year was 114.5 cents/bu over the futures contract price for delivery in the same location just 60 days later. That drought shock, which persisted through the beginning of the next harvest (lasting until about October), transmitted to all our sampled locations via the carry, and lead to large increases in the basis everywhere that summer (as shown by the tall cluster of positive green bars). Just as notable, the harvest of 2013 re-established a normal contango market, with futures higher than spot prices; that the crop was a record lowered spot prices even further and placed downward pressure on the prices paid to producers in 4a-f (negative green bars beginning in October 2013). A similar effect can be seen after the notably large corn harvest of 2011—a year that began with storage facilities 40% fuller, according to each crop year's January World Agricultural Supply and Demand Estimates report (USDA, 2012 and 2014).

Although diesel fuel shocks are important basis determinants at times, they do not explain all of the price differences over space. Idiosyncratic shocks represent time-varying local conditions not explained by fuel or carry shocks, including things like isolated surpluses or stockouts, seasonal livestock or ethanol demand, or transportation backups.[9] Developments likes these cannot be hedged using liquid futures or options contracts. The historical decomposition of the SVAR in figure 3 depicts the unhedgeable portion of local basis movements as yellow bars. Echoing our FEVD results, idiosyncratic shocks are more important for some locations (Fargo, ND; Elk Point, SD; and Mitchell, SD) than others (e.g., Otoe, NE). They also contribute a large share to local basis variation at certain times.

For example, in early-2014, idiosyncratic shocks placed significant downward pressure on local basis levels in our North and South Dakota locations (figure 4c-e), but not at our Nebraska or Iowa locations. Given that this period overlaps with the rail backup, and that North and South Dakota were among the hardest hit states (Olson, 2014 and USDA OCE & AMS, 2015), we can use the SVAR results to quantify the effect of the transportation issues that year on the prices offered to grain sellers at each location. Notice that all the panels of figure 4 exhibit positive fuel shocks (blue bars) at that time given the declining price of diesel fuel, as well as contemporaneous negative carry shocks (green bars) are also apparent given the record 2013 corn harvest. As a powerful tool for policy and historical analysis, the SVAR differentiates the degree to which transportation issues reduced prices still further in each of the Upper Midwest figures, by documenting the path that basis values would have taken if the backup had not occurred. Figure 5 plots the idiosyncratic portion of the basis for each location in our model over 2014. In the figure, the North and South Dakota locations (solid lines) exhibit clear depressions in the basis during the time of the rail backup, from February-September (for Fargo and Mitchell), and from February-October (Elk Point). The other modeled locations show negligible local shocks over the same time frame. We therefore estimate that 2014 transportation problems in the Upper Midwest lowered local corn prices in Fargo by up to 43 cents/bu (in April), in Elk Point by up to 37 cents/bu (in September), and in Mitchell by up to 34 cents/bu (in May). All of these estimates are in the ballpark of

[9] Factors (or portions of factors) that operate on the local basis in a constant fashion are soaked up in the deterministic component of the model and are not displayed in figure 3.

prior empirical research about the impact of the rail backup (e.g., Olson, 2014), but by providing both a magnitude and duration of impact, as well as the ability to differentiate effects over space, their usefulness is enhanced. In addition, given that these local price changes were not reflected in the movements of popular derivatives contracts, local market participants were unable to insulate themselves from them.

Conclusion

We model the local basis as a combination of temporal and spatial components, and demonstrate how a structural vector autoregression—a powerful tool for empirical analysis—can be used to estimate the portion of the basis than can be hedged. The residual variation in local prices cannot be protected against using commonly traded derivatives. Using several recent phenomena as focal points, we decompose the time path of local basis levels at select locations around the Corn Belt into the influence of several explanatory factors. We show that the carry explains a large portion of the movements in the basis at all locations. For instance, the drought-affected corn crop of 2012 inverted the carry and led to substantially higher prices at every location. Likewise, the following harvest returned the market to a contango, and the record corn crop widened basis levels (reduced local prices) even further than normal. By focusing on the comparative levels of idiosyncratic shocks during 2014 at locations both in and outside the territory affected by the rail backup, we identify the effect of that event on local prices in terms of a magnitude and duration. Given the ability to differentiate these effects over space, we demonstrate the value of our approach compared to previous efforts.

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Figure 1. Map of representative locations

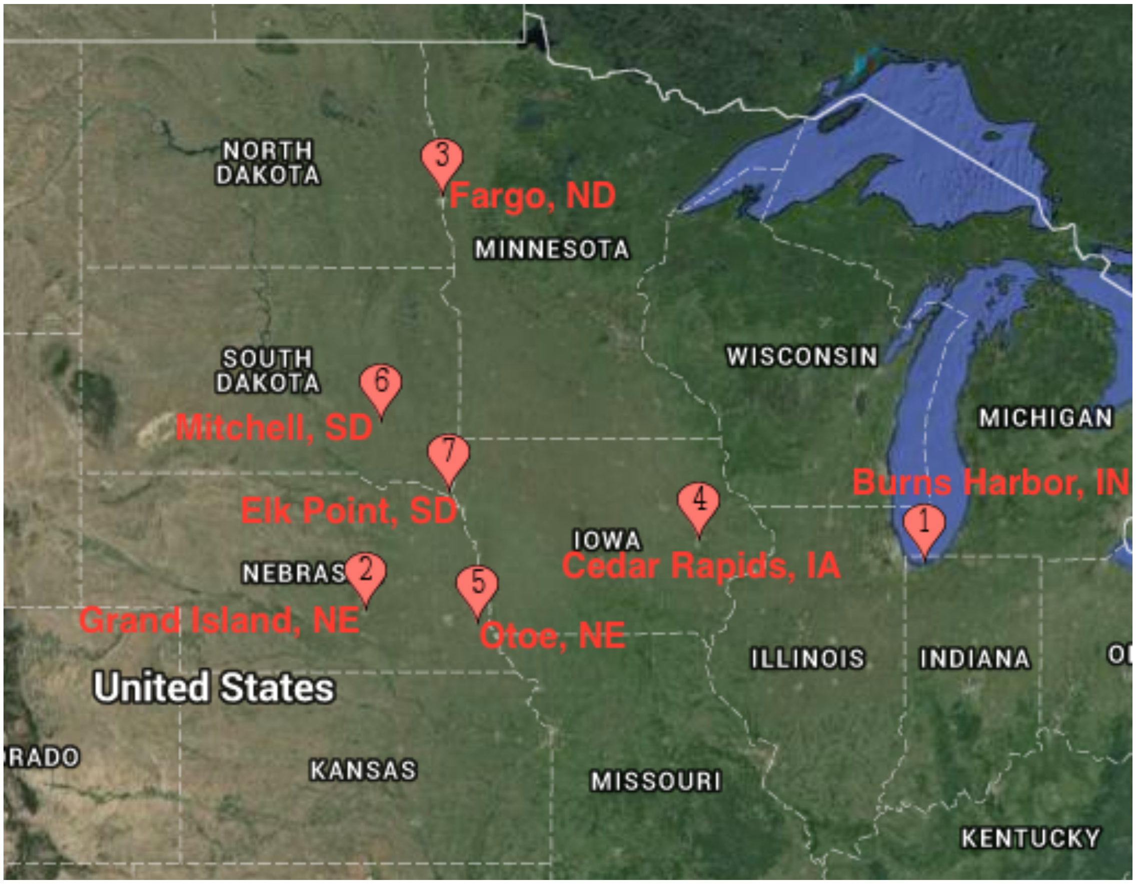

Table 1. Diagnostic tests for basis models

Model/Location	Obs. #	Lags	LM Test	LMF Test	CUSUM	Eigenvalues
Grand Island, NE	260	2	0.3021	0.3386	Stable	Stable
Otoe, NE	260	2	0.7051	0.7431	Stable	Stable
Fargo, ND	260	2	0.3664	0.4046	Stable	Stable
Mitchell, SD	260	2	0.4941	0.5368	Stable	Stable
Elk Point, SD	260	2	0.7193	0.7541	Stable	Stable
Cedar Rapids, IA	260	2	0.4344	0.4712	Stable	Stable

Note: The LM and LMF columns display the p-value associated with the test statistic. The CUSUM and Eigenvalue columns indicate the finding of the tests for model stability.