Title: A Bayesian Learning Approach to Estimating Unbalanced Spatial Panel Models

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Highly competitive grain commodity markets create incentives for agribusinesses handling grain to use a variety of strategies for reducing variable cost margins. Shuttle train-loading elevators—high-capacity, high-speed grain loading facilities—are a recent example of agribusinesses adopting technologies that improve efficiency and attempt to capture market share. These facilities provide improved rail rates, guaranteed railcar availability, and attract grain from further distances, which has spurred agribusinesses to upgrade existing elevators and build new shuttle-loading facilities across the Great Plains (Bekkerman 2013; Kowalski 2014).

If shuttle-loading facilities reduce the marginal costs of handling a bushel of grain and grain elevators operate in a competitive market, then it seems plausible that some portion of those savings will be passed on to grain producers in the form of stronger basis bids (i.e., higher cash prices). A quantitative test of the level of cost savings pass-through to farmers requires cash bid data from elevators across both space and time. Grain elevators compete for grain in space, but must also adjust their pricing strategies across time if competition from other elevators changes. The amount of any change in basis bids to farmers from reduced transportation costs incurred by elevators will be a function of both the amount of the transportation cost savings and the level of competition faced by new entrants in the grain handling industry.

This study measures the systematic impacts of shuttle-loading elevators on local wheat basis in Kansas and Montana. These states were selected because they are large wheat producing areas, there has been substantial recent growth in the number of shuttle-loading elevators in both states, and agribusinesses continue to explore building additional high-speed grain handling facilities. To identify differences that can be attributed to alternative loading technologies, we model daily nearby basis bid data between January 2004 and July 2013 (2,554 time periods) for 267 Kansas and 30 Montana locations. Due to unsystematic missing observations and/or entry or exit of elevators throughout the time window, these data represent a large unbalanced spatial panel. Existing spatial panel estimation methods are mostly intended for balanced panel data, but are not effective for unbalanced panel because of the computational burden associated with inverting a large spatial weighting matrix.

We propose an alternative approach that provides an efficient, computationally tractable method for estimating unbalanced spatial panel models. Using a dynamic Bayesian network method, we develop an iterative process by which large, unbalanced spatial panel models can be estimated. Preliminary results indicate that shuttle-loading facilities command a small price premium in Kansas and a slightly larger premium in Montana. The estimation also helps glean insights about spatio-temporal responses to market shocks across space and time, helping provide inferences about the breadth and speed of market information transfer.

Background on Basis and Shuttle-Loaders

Knowledge about basis is important to both farmers and grain merchandizers, helping inform them of market information regarding returns to storage, local and downstream demand, and changing costs of transportation. Accurately predicting basis can, therefore, help reduce risk exposure, develop efficient marketing strategies, and hedge variability in grain prices. Many previous studies of basis behavior have focused on two related areas—improving basis prediction and determining factors that help explain variation in basis—but have not explored the empirical effects of grain handling technologies on observed basis values.

Local basis behavior has typically been categorized as having intertemporal and spatial determinants as well as being affected by changes in public policy and the marketing environment. Intertemporal costs are comprised of the carrying costs of storing grain, which include storage costs (on-farm and commercial), demand for grain (e.g. flow), and interest costs of holding grain rather than selling it. Garcia and Good (1983) provide a thorough review of the theory underlying the intertemporal impacts on basis. In addition to analyzing intertemporal relationships, a number of studies demonstrate that wheat basis can be affected by changes in the market structure, including adjustments to loan deficiency payments, introduction of ethanol plants, unanticipated variation in protein content of grain produced in a particular region, and increased transportation costs (Dykema, Klein, and Taylor 2002; Martin, Groenewegen, and Pigeon 1980; Jiang and Hayenga 1997).

The literature has paid less attention, however, to the theory of spatial factors, which is likely due to the general consensus that spatial differences in basis are driven by variation in transportation costs (Strobl, Fortenbery, and Fackler 1992). However, other research suggests that there may be significant impacts on basis from local demand centers, such as ethanol plants in certain areas of the country (McNew and Griffith 2005). This more recent research suggests that demand-side factors associated with differences in grain delivery facilities could also be important determinants of spatial variation in basis bids.

Fortenbery, Zapata, and Kunda (1993) found that shuttle-loading facilities did not pass through the transportation cost savings to farmers. The authors used corn basis levels from 1980 to 1992. This time period is very important because it followed the 1980 Staggers Act, which deregulated the rail road industry and greatly impacted grain shipping through changes in freight rates. One result of the deregulation was an increase in the number of shuttle-loader facilities, which could now take advantage of lower freight rates. Using harvest time basis levels at 16 Corn Belt locations, the authors estimated a spatio-temporal error component model that used elevator concentration measures to determine whether grain companies were able to capture decreased transportation savings rather than passing them on to farmers. The study found no adverse price impacts from deregulation, with basis improvements (i.e., higher cash prices to farmers) more common for locations with less elevator concentration prior to deregulation.

Hauser, Jeffrey, and Baumel (1984) similarly analyzed the period following the Staggers Act, with a focus on shuttle-loading facilities in Iowa and Nebraska. In Iowa, the marketing landscape was relatively saturated with large capacity 25- and 50-car loading facilities prior to the Staggers Act deregulation, while Nebraska had relatively few of these facilities and presented greater entry opportunities. Using a mathematical programming model to estimate the implicit (shadow) prices of shuttle-loader facilities, the author estimated larger shadow prices for Nebraska than Iowa, suggesting possible improvements in local basis were likely to occur in areas with fewer existing shuttle-loading facilities.

The majority of shuttle-loading elevators were built in the largest grain production states of Illinois and Iowa following the Staggers Act. Expansion into the wheat-production regions did not begin until the 2000's when a combination of higher wheat yields and faster harvest times translated to greater demand for efficiency at elevators (Kowalski 2014). Shuttle-loaders have also expanded into the northern Great Plains and Pacific Northwest as international agribusiness firms continue to invest in facilities to assure a steady supply of grain to Asian markets (Bekkerman 2013). The present study contributes to the existing literature by measuring direct impacts of transportation cost savings of shuttle-loaders on local basis bids, and therefore prices received by farmers, giving a more complete picture of the effects of grain handling technology investments by agribusinesses.

Data Description

To quantify the impacts of shuttle-loader elevators on winter wheat basis levels, a panel dataset of daily cash and futures prices was assembled for 297 locations in Kansas and Montana over the 2005 to 2013 period. Cash prices were obtained from the DTN historical database for all Kansas elevators and for the majority of elevators and days in Montana. The remaining prices for Montana were obtained from Cash Grain Bids, Inc. Cash prices represent hard red winter wheat with a protein content of 11% for Kansas and ordinary (10% or less), 11%, 12%, and 13% protein content for Montana wheat. Montana grain prices were averaged across the protein levels to calculate a single winter wheat price for each day and elevator.[1] Futures prices for the nearby (closest contract to expiration at a given point in time) and harvest (July) hard red winter wheat contracts traded on the Kansas City Board of Trade (KCBT), as well as implied volatilities for the nearby contracts, were collected from Bloomberg.[2] Using the cash and futures prices, the nearby basis levels were calculated by subtracting the futures price from the cash price.[3]

Additional information about the elevators in the panel dataset was gathered from a variety of sources. The ability of an elevator to load shuttle trains was determined by directly

[1] While DTN historical databases only report prices for 11%, 12%, and 13% protein level winter wheat marketed in Montana, Cash Grain Bids, Inc. report prices for these protein levels and the ordinary protein level. Because elevators discount lower protein content wheat, the average price is expected to be higher when the ordinary protein level wheat price is excluded. However, the difference is expected to be relatively constant across time and elevators within a common marketing environment (Bekkerman, unpublished data representing Montana elevator protein discount schedules for 22 locations between 2011 and 2013) and can be accounted for using an indicator variable in an empirical specification.

[2] The rollover date for the nearby contract was defined as the first day of the month that the nearby contract was due to expire.

[3] It should be noted that cash bids collected in this manner represent offer prices to buy grain and do not necessarily imply that grain was transacted at these prices for every elevator on every day.

contacting individual elevators and from state and federal elevator licensing records, railroad websites, news releases, and the Kansas Grain and Feed Association's Annual Directory. For each elevator reported to be a shuttle-loader, the year in which they began loading shuttle trains was also recorded. Other elevator characteristics were similarly collected and include information about rail line access, business structure (cooperative or investor-owned firm), and licensed grain holding capacity.

Table 1 provides the descriptive statistics of select variables by state and shuttle-loading capability. The descriptive statistics show that Montana has fewer elevators than Kansas, but the proportion of shuttle-loaders to conventional elevators is higher in Montana than in Kansas. The average capacity of Kansas elevators is approximately 2.5 times larger than the capacity of Montana elevators, but in both states, the grain storage capacity of shuttle-loaders averages five times more than conventional elevators. Interestingly, shuttle-loading facilities in both states are largely privately owned, while conventional elevators are more likely to be operated by a cooperative. The differences between types of grain handling facilities and markets across the two states suggests possible variation in the marketing strategies of elevators in the data, which is likely to be reflected by differences in observed basis.

Figure 1 provides a visual representation of all the Kansas and Montana elevators in the in the data. Shuttle-loader elevators are represented by red circles and conventional elevators are blue. The size of each circle corresponds to an elevator's licensed grain storage capacity, with larger circles representing greater capacity relative to other elevators in the state (not across states). The lines on the map represent rail lines in each state. While all the elevators are located near the rail lines, not every elevator is built close enough to have rail-side access.[4] A visual comparison of the two maps indicates that Kansas has many elevators that are densely clustered as well as an expansive railroad network. Montana has a sparser rail line distribution and fewer facilities. However, many of these facilities have relatively large storage capacities.

Modeling Strategy

We follow Anselin, Le Gallo, and Jayet (2008) in specifying a spatial panel data model that accommodates interactions among spatial units across time. Within this structure, we model variation in nearby basis as

$$\boldsymbol{b} = \lambda(\boldsymbol{I}_t \otimes \boldsymbol{W}_n)\boldsymbol{b} + \boldsymbol{X\beta} + (\boldsymbol{\iota_t} \otimes \boldsymbol{I_n})\boldsymbol{\pi} + \boldsymbol{\rho}(\boldsymbol{I_t} \otimes \boldsymbol{W_n})\boldsymbol{\nu} + \boldsymbol{u}, \quad (1)$$

where the term $\boldsymbol{b}$ represents an $NT\times 1$ vector of nearby basis observations; $\boldsymbol{X}$ is a matrix of explanatory variables, including a binary indicator that indicates whether an elevator has shuttle-loading capabilities, observed basis from the preceding week, observed basis from the corresponding weekday of the preceding year, implied volatility of the nearby Kansas city Board of Trade winter wheat futures contract, and a binary variable indicating whether the cash price data were obtained from the DTN historical database or Cash Grain Bids, Inc.; $\boldsymbol{I}$ is an identity matrix; $\boldsymbol{W_n}$ is a spatial weights matrix in which the weights are represented by the inverse distance between location *i* and *j*, and λ is a vector of spatial autoregressive parameters. The term $\boldsymbol{\varepsilon}$ in equation (1) is specified as a combination of, $(\boldsymbol{\iota_t} \otimes \boldsymbol{I_n})\boldsymbol{\pi}$, a matrix of time-invariant effects where $\boldsymbol{\iota_t}$ is a vector ones and $\boldsymbol{\pi}$ is a vector of elevator-specific indicators; a spatial error component, $\boldsymbol{\rho}(\boldsymbol{I_t} \otimes \boldsymbol{W_n})\boldsymbol{\nu}$, where $|\rho| < 1$ is a spatial error autoregressive parameter and ν is spatially correlated error term; and $\boldsymbol{u}$, an *i.i.d.* white noise term.

[4] Rail-side access refers to an elevator built close enough to the rail line that grain can be loaded directly from storage into a rail car.

In a random effects model, for example, $\pi_i \sim IID(0, \sigma_\pi^2)$ and Mutl and Pfaffermayr (2011) derive the covariance matrix for the spatially correlated disturbance term ε to be

$$\boldsymbol{\Omega}_{\boldsymbol{\varepsilon}} = [\boldsymbol{I_t} \otimes (\boldsymbol{I_n} - \boldsymbol{\rho W_n})^{-1}]\boldsymbol{\Omega}_{\boldsymbol{v}}[\boldsymbol{I_t} \otimes (\boldsymbol{I_n} - \boldsymbol{\rho W_n})^{-1}], \tag{2}$$

where $\boldsymbol{\Omega}_{\boldsymbol{v}} = \sigma_u^2 \left(\boldsymbol{I_t} - \frac{\iota_t \iota_t'}{\boldsymbol{t}}\right) \otimes I_n + (\sigma_u^2 + t\sigma_\pi^2)\left(\frac{\iota_t \iota_t'}{\boldsymbol{t}} \otimes \boldsymbol{I_n}\right)$. Anselin's (1988) general formula for deriving the log-likelihood function for this estimator is used to determine the specific log-likelihood function for the random effects spatial panel model. Millo and Piras (2012) describe the method for estimating the parameters λ, ρ, σ_π^2, σ_u^2, σ_ε^2, and β by iterating between generalized least squares and concentrated likelihood procedures until a convergence criteria is satisfied.

Equation (2) shows that the spatial weighting matrix has a key role in estimating the covariance matrix for a spatial panel model. When data represent a balanced panel, the same spatial relationship among locations exists in each period, which allows the weighting matrix to be simplified to $N \times N$ dimensions. In this case, even with a relatively large number of cross sections, the computational burden for inverting the matrix $(\boldsymbol{I_n} - \boldsymbol{\rho W_n})$ is relatively small. To our knowledge, these panel data structures represent the empirical applications of spatial panel estimators in the literature.

In an unbalanced panel, however, there is a different spatial relationship for each time period, requiring the weighting matrix to have dimensions $nt \times nt$. The covariance matrix $\boldsymbol{\Omega}_{\boldsymbol{\varepsilon}}$ becomes

$$\boldsymbol{\Omega}_{\boldsymbol{\varepsilon}} = [(\boldsymbol{I_{nt}} - \boldsymbol{\rho W_{nt}})^{-1}]\boldsymbol{\Omega}_{\boldsymbol{v}}[(\boldsymbol{I_{nt}} - \boldsymbol{\rho W_{nt}})^{-1}]. \tag{3}$$

With a very small number of cross sections and time periods, this may not present many computational issues. When there are many cross-section units and time periods (e.g., in higher frequency data), however, the computational burden becomes excessive and the estimation frequently fails. In this study, using daily data requires inverting a $629{,}586 \times 629{,}586$ matrix for Kansas and a $70{,}740 \times 70{,}740$ matrix for Montana.

We propose an alternative estimation approach based on a dynamic Bayesian networks (DBN) method. The DBN has been used to develop a probabilistic framework in which model parameters can be learned by recursive forward-backward routines. Within the unbalanced spatial panel structure, the recursive estimation process is used to deconstruct the full unbalanced spatial panel regression based on an $NT \times NT$ weighting matrix into a series of T regressions based on an $N \times N$ weighting matrix. For each individual regression at period t, the $N \times N$ spatial weighting matrix is itself weighted by the marginal probability that the particular spatial weighting matrix is representative of the spatial relationships that existed in the previous periods and that will exist in future periods. That is, the marginal probability of observing a spatial weighting matrix is proportional to the product of the information obtained from its parent (i.e., the weighting matrix observed in period $t-1$) and information from its child (i.e., the weighting matrix observed in period $t+1$). For a weighting matrix, $\boldsymbol{W_t}$, and parent $\boldsymbol{e}^+$ and child $\boldsymbol{e}^-$ information sets, the marginal probability of the weighting matrix is

$$P(\boldsymbol{W_t}|e) \propto \left\{ \sum_{(\boldsymbol{W_{t-1}}, \boldsymbol{W_{t-2}}, \ldots \boldsymbol{W_{t-k}})} P(\boldsymbol{W_t}|\boldsymbol{W_{t-1}}, \boldsymbol{W_{t-2}}, \ldots \boldsymbol{W_{t-k}}) \prod_{\boldsymbol{t=1}}^{\boldsymbol{k}} P(\boldsymbol{W_t}|e^+(\boldsymbol{W_t})) \right\} \prod_{\boldsymbol{s=1}}^{\boldsymbol{l}} P(\boldsymbol{W_s}, e^-(\boldsymbol{W_s})|\boldsymbol{W_t})$$

At the conclusion of the recursive process, we obtain a set of regression parameters that represents information contained in the unbalanced spatial panel structure.

To estimate the recursive process, we assume a state-space model and use the Kalman filter approach in which a forward recursion is used to estimate regression parameters based on observations between periods $t-k$ and t, and then a backward recursion that uses observations between periods T and $t+1$. In this manner, the forward-backward algorithm is an application of a belief propagation structure that initially applies past knowledge to suggest current states, and then further informs the current state information by incorporating the influence of future observations.

Empirical Results

Forthcoming

Conclusions

While having access to large, information-rich datasets is often a "good" problem to have, it can lead to empirical "too-much-of-a-good-thing" roadblocks. As high-frequency, large dimension spatial panel data continue to become more readily available to agricultural economists, these roadblocks are likely to become more apparent. We develop one method for overcoming the dimensionality constraint in large, unbalanced panel regression estimations. Application of this and similar methods is likely to be relevant to studies of agricultural marketing, land and water uses, environmental issues, and other topics that take into account spatial and temporal dependencies.

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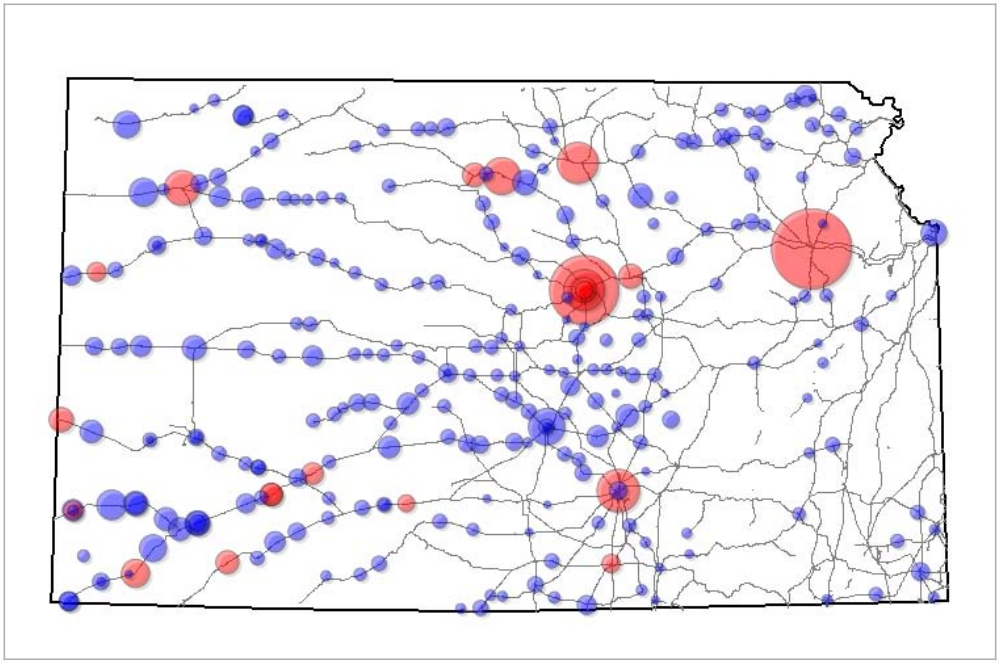
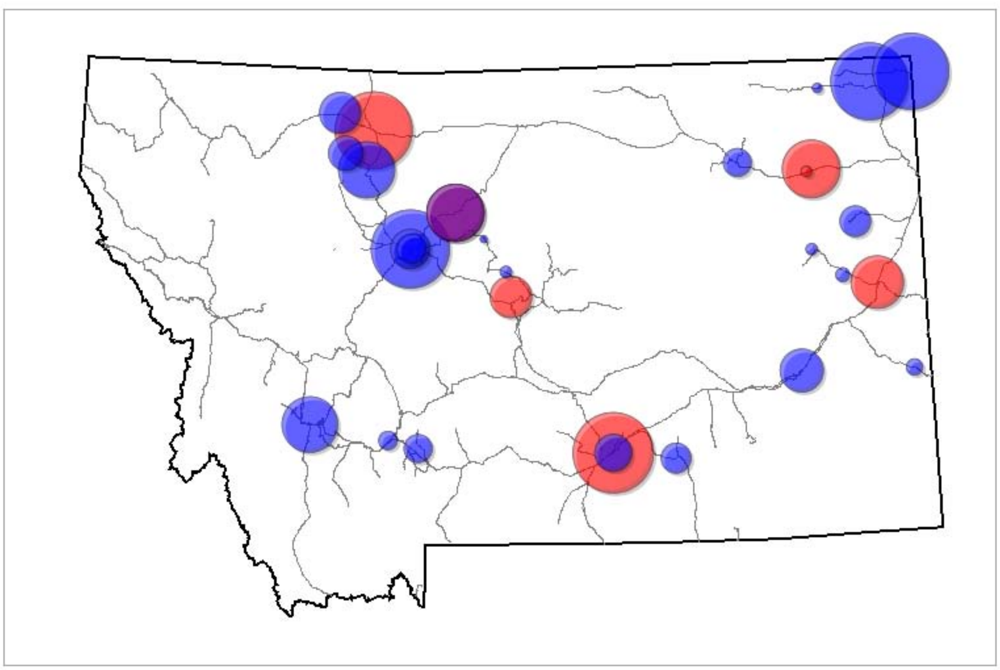
Table 1. Summary Statistics of Select Variables by State and Shuttle-Loading Features

Variable	Mean	Standard Deviation
Kansas		
Proportion elevators in state	0.899	—
Proportion shuttle-loaders	0.087	—
Proportion with rail access	0.693	—
Proportion owned by co-operative	0.640	—
Storage capacity (thousand bu)	1,817.124	3,529.250
Nearby basis (dollars per bu)	-0.594	0.359
Montana		
Proportion elevators in state	0.101	—
Proportion shuttle-loaders	0.256	—
Proportion with rail access	0.800	—
Proportion owned by co-operative	0.570	—
Storage capacity (thousand bu)	715.866	471.562
Nearby basis (dollars per bu)	-0.658	0.590
Shuttle-Loader Elevators		
Proportion with rail access	1.000	—
Proportion owned by co-operative	0.103	—
Storage capacity (thousand bu)	6,126.703	9,151.526
Nearby basis (dollars per bu)	-0.509	0.391
Non-Shuttle-Loader Elevators		
Proportion with rail access	0.672	—
Proportion owned by co-operative	0.627	—
Storage capacity (thousand bu)	1,227.643	1,073.664
Nearby basis (dollars per bu)	-0.608	0.380
KCBT HRWW futures contract implied volatility	32.890	7.790
Total observations	690,525	
Total elevator locations	297	

Notes: Standard errors are presented only for continuous variables. KCBT denotes the Kansas City Board of Trade and HRWW denotes hard red winter wheat.



(a) Grain handling facilities and rail lines in Kansas



(b) Grain handling facilities and rail lines in Montana

Figure 1. Elevator locations and rail lines in Kansas and Montana

Notes: Circles represent the location of a grain handling facility. Red circles represent facilities with shuttle train-loading capabilities and blue circles represent conventional elevators. The size of each circle represents the total storage capacity at the location relative to other elevators in each state. Black lines characterize rail lines.