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Evaluating the Dynamic Nature of Market Risk

This study examines the systematic risk present in major crops for the United States and three corn-belt states. An index of commodities is used in conjunction with cash receipts to generate dynamic estimates of the systematic risk for each crop and state. In our study, we find that beta estimates from a time varying parameter model (FLS) and OLS formulation are substantially different. From our graphs of betas over time, one gains insight into the changing nature of risk and the impact of institutional and macroeconomic events. Systematic risk is shown to increase for most crops over the analyzed period with significant changes in volatility after the collapse of the Bretton Woods Accord.

Keywords: Systematic risk, flexible least squares, single index model, farm policy, macroeconomics

Introduction

Risk has long been important in U.S. production agriculture, but the issue of how agricultural risks have changed over time remains a question. Sumner (2009) provides a revealing 143-year graph of real price trends in corn and wheat with an eye to comparing periods of extreme price fluctuation. He notes a sustained downward trend in real prices after WWII, and suggests that in light of the much lower real prices, "...the real price jumps from 2006 through the middle of 2008 are hard to notice," (Sumner 2009, p. 5). Hamilton (2009) takes the perspective of viewing the long-term real price series on a log scale so that equal movements are equal percentage changes. With respect to price movements he points out that, "The recent move is in fact bigger in percentage terms than the spike of World War I and compares to the 1970s commodity price boom," (Hamilton 2009, p. 1).

When assessing risk, further complicating issues are yields and diversification. If one studies variability in revenue from individual crops the important issue of yield risk is incorporated, but revenue variability does not accurately reflect the risk borne by producers of that crop because part of the variability is diversifiable. Variability that is not diversifiable is referred to in the literature as systematic risk. In this article we view systematic risk in production agriculture as the risk common to all commodities. This risk would not be diversified with other agricultural production activities.

Our question then becomes, how has systematic risk changed over time? Sumner (2009, p.4) recognizes time varying risks when he states, "Many of the most dramatic price movements in the 140-year history have been associated with war and macroeconomic shocks." We assert that the agricultural sector faces these sources of uncertainty as well as others related to general or macroeconomic forces such as exchange rates, recessions, and oil price shocks. In addition, over time new farm bills have provisions targeting

agricultural risk. Some of these factors, many of which are economy wide shocks, are virtually by definition not constant over time.

It is important for entities operating within the agricultural sector to identify, assess, and monitor risks linked to commodities over time. Such understanding of the risk levels facing agriculture is useful for proper planning, policy, education, and management. This article contributes to the literature by demonstrating the value of applying a time varying parameter econometric model to estimation of the classic risk assessment model of financial economics, the single index model. In so doing, we further the empirical understanding of how various types of risk interplay in the agricultural sector over the period 1956 to 2007. We examine the dynamic beta as it relates to five major commodities: corn, soybeans, wheat, lean hogs, and live cattle. These commodities are studied at the United States level as well as for three leading Corn Belt states: Indiana, Illinois, and Iowa.

The remainder of this article is organized as follows. The first section describes the single index model and how it is used to measure systematic risk. The second section outlines the quantitative method for estimating the dynamic beta and the data used in the study. Then, we present the relevant findings of the analysis and close with a discussion of the key points of the study.

Theory and Literature

Sharpe (1964), building on mean-variance portfolio work of Markowitz (1959), was one of the originators of the Capital Asset Pricing Model (CAPM) for which he shared the 1990 Nobel Prize in Economics with Harry Markowitz and Merton Miller. Just prior to his CAPM article, Sharpe (1963) published a closely related paper using what he called a single index model (SIM), which is virtually identical to the CAPM equation, but without equilibrium asset pricing implications. The SIM provides a concise method for investors to understand risk by providing a systematic and nonsystematic risk breakdown. The SIM is represented by the equation:

$$(1) R_{i,t} = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t},$$

where $R_{i,t}$ is the return for asset i in period t and $R_{m,t}$ is the index value in period t . The model parameters are an intercept, α_i , and the change in expected R_i given a change in R_m , β_i . The disturbance term is ε_i . The variance of return on asset i breaks down as: $V(R_i) = \beta_i^2 V(R_m) + V(\varepsilon_i)$. The first term, beta squared times the variance of the index, is systematic risk. The remaining part, the variance of the residual, is diversifiable.

Traditionally, (1) is estimated using ordinary least squares (OLS), yet a number of studies object to OLS's restriction that coefficient estimates are constant across the observed

time period (Jensen, 1969). This discussion developed in the subsequent decades and eventually settled on a consensus that beta, in fact, is not stable.

Although, beta's lack of stability has led some researchers to reject beta as a measure of risk, Fabozzi and Francis (1978) suggest the dynamic nature of beta can be overcome by estimating beta using random coefficient methods (RCM) of Swamy (1970). The authors provide a clear definition of why betas of stocks may be unstable over time. First, macroeconomic effects can change betas for assets during inflationary periods, business cycles, and recessions. Second, institutional effects from political legislation can destabilize betas. Third, credit crunches, bull markets, bear markets, and other market inefficiencies can distort the value of beta in an ordinary least squares context. Francis and Fabozzi (1979) thus specifically addressed the single index model beta under varying macroeconomic conditions. These destabilizing factors apply to agricultural commodities and indicate the need to utilize methods that allow for a changing beta.

Commodities and Farm Level Analysis

A number of previous studies have used the single-index model to measure risk in the agricultural sector. Barry (1980) uses the capital asset pricing model to estimate beta for aggregate U.S. farm real estate. Collins and Barry (1986) examine betas for California crops and generate risk efficient portfolios for farm planning purposes. Turvey, Driver, and Baker (1988) use a SIM for Ontario agriculture to study systematic and non-systematic risk in alternative farm portfolio model specifications and Gempesaw et al. (1988) apply alternative SIM specifications, including a stochastic coefficient model, to Delaware farm sector returns.

These previous SIM applications in agriculture recognize the usefulness of the SIM for risk analysis in general and in particular for its systematic-nonsystematic risk breakdown. However, their focus is on using betas at the farm level for portfolio selection. We build on the existing literature through a dynamic estimation method known as flexible least squares (FLS) to derive betas that change over time. We use a general commodity index to analyze regional risk for a set of commonly produced crops in U.S. agriculture. The method incorporates the concerns of Francis and Fabozzi (1979) and captures beta's response to policy changes and shocks to the macro economy.

Method

There are three leading classes of time-varying parameter models (Rao, 2000). First, parameters are assumed to vary across subsets of observations within the sample but are non-stochastic. Second, parameters are assumed to be stochastic but are generated by a stationary process. Third, parameter dynamics are assumed stochastic yet generated by a nonstationary process. The FLS method is a member of this third class in which parameter movements are assumed to evolve slowly over time.

Time-varying parameter methods have the additional advantage of potentially capturing non-linearities in time series data. Granger (2008, p.1) states that “any non-linear model can be approximated by a time-varying parameter linear model.”

We estimate the dynamic movements of beta using the FLS as presented by Kalaba and Tesfatsion (1988). FLS has been used to examine time-varying betas in previous studies of the stock markets in the U.S. (He, 2005), Korea (He, 2001), and Germany (Ebner and Neumann, 2005). In addition, the method has been applied to agricultural problems such as productivity growth (Dorfman and Foster, 1991), the relationship between cash prices and captive cattle supply (Lee and Kim, 2005), hedging in the dried distiller grains market (Brinker, Parcell, and Dhuyvetter, 2007), demand for pork primal (Parcell, 2002), consumer meat demand (Poray, Foster, and Dorfman, 2001), and confined animal feeding operations’ impacts on residential real estate values (Kuethe Foster, and Florax, 2008).

Flexible Least Squares

We observe commodity returns and index values over a time series, and we wish to estimate a model in which the coefficient estimates are allowed to vary over time. This is achieved by specifying two equations, one which captures the traditional least squares residual and one which examines the dynamic time path of parameter movements.

The SIM (1) can be expressed as a *measurement specification* in FLS:

$$(2) R_{it} - \alpha_{it} - R_{mat,t}\beta_{it} \approx 0.$$

One of the key advantages of the FLS method is that the disturbance terms in equation (2) do not require a complete distributional assumption. The only requirement is that the error terms are assumed to be close to zero.

The other distinct advantage of the FLS method is that coefficient estimates are allowed to evolve slowly over time by means of the *dynamic specification*:

$$(3) \theta_{i,t+1} - \theta_{i,t} \approx 0,$$

where $\theta_{i,t}$ is a vector containing the intercept term $\alpha_{i,t}$ and the slope coefficient $\beta_{i,t}$. Equation (3) therefore captures the dynamic movements of both coefficients in equation (2).

The two specification equations are incorporated in a minimization problem with two residuals components. The measurement specification leads to the traditional sum of squared residuals:

$$(4) r_M^2(\theta|T) = \sum_{t=1}^T (R_{it} - \alpha_{it} - R_{mat,t}\beta_{it})^2.$$

The dynamic specification uses a similar structure to measure the coefficient change:

$$(5) \quad r_B^2(\theta|T) = \sum_{t=1}^{T-1} (\theta_{t+1} - \theta_t)'(\theta_{t+1} - \theta_t).$$

The two minimization criteria are combined in a weighted cost function that penalizes coefficient movements in addition to the traditional residual measurement:

$$(6) \quad C(\theta|\delta, T) = \delta r_B^2 + (1 - \delta) r_M^2, \text{ where } 0 < \delta < 1.$$

The weighting parameter δ forces the coefficient estimates toward or away from a constant value. As δ approaches one, the FLS coefficients approach a constant value, and as δ approaches zero, the coefficient estimates approach random coefficient values. Thus, FLS is a more general model that nests both OLS and RCM estimators. In addition, the FLS algorithm is a generalized form of a number of well-known filters such as those developed by Kalman, Larson-Peschon, and Swerling (Kalaba and Tesfatsion, 1990).

Data

The single index equation (2) requires two variables: a measure of return and an index. This study measures returns for each commodity with annual cash receipts. The United States Department of Agriculture provides annual data on farm receipts for hogs, cattle, corn, soybeans, and wheat for the country as a whole and for individual states. We analyze systematic risk for these commodities in the U.S. as a whole, as well as the individual states of Indiana, Iowa, and Illinois. Cash receipts do not include government payments and provide a good measure for the changing systematic risk of a crop over a geographic region. The data series run from 1956 – 2007 and are normalized by dividing each series by its 1967 value and multiplying by 100.

With respect to the SIM assumption regarding the index, Sharpe (1963, p.5) states “... the assumption (is) that the returns of various securities are related only through common relationships with the same basic underlying factor.” The role of the index is to capture correlated movements in the commodities we are studying. The index chosen for this model is the Reuters-CRB commodity price index (CCI). The index is available monthly from 1956 forward. Several commodities have been added to the index over time to reflect the market environment. Currently, it includes the commodities listed in table 1. The CCI index is the equally weighted average price across commodities and, like our commodity series, is normalized with 1967 equal to 100. For our annual model, the monthly index numbers are averaged over each given year.

Results

We select the optimal smoothing parameter δ for each commodity over the five geographic areas using a specialized J -test suggested by Poray, Foster, and Dorfman

(2001). The test searches over the possible range of parameter to identify the minimum of the incompatibility cost for both the regression and dynamic error. The test takes the following form:

$$(7) J = \min_{\delta} \sqrt{\frac{\sigma_{N,FLS}^2 + \sigma_{D,FLS}^2}{\sigma_{N,OLS}^2 + \sigma_{N,RC}^2}}$$

where $\sigma_{N,FLS}^2$ is the sum of squared measurement errors of FLS given δ , $\sigma_{N,OLS}^2$ the sum of squared errors of the OLS estimate, $\sigma_{D,FLS}^2$ the sum of squared dynamic error of FLS given δ , and $\sigma_{N,RC}^2$ is the sum of squared errors of the random coefficient model. Thus, the test selects the optimal weight between the OLS and RCM specifications as nested by FLS. The optimal smoothing parameters (δ), shown in table 3, are uniformly across all regions and commodities. The calculated weights imply a lean toward the random coefficient aspect of the estimation procedure.

The following section outlines the estimation results related to each commodity for the U.S. and by state. The results are presented graphically and the graphs include a set of policy and macroeconomic events, including farm bills (vertical lines), the end of the Bretton Woods Accord in 1973 (dashed line), and major recession periods (shaded areas). The events are listed in table 2.

General Trends

Results for time varying betas for each commodity are shown in figures 1 through 5. OLS betas, estimated for the U.S. using the entire sample period, are also shown for comparison. The x -axis is marked by year, and the y -axis shows the level of the beta in each period. We focus on our estimated betas because beta is a major factor in the quantitative measurement of systematic risk ($\beta_i^2 V(R_m)$) mentioned earlier. There are a number of common results across all models. First, there is consistent evidence that betas do in fact vary substantially over time. In some cases there are trends in the betas as well as periods of high or low beta. Generally speaking, we find that static OLS estimation over the period presents a drastically different picture of the systematic risk than the dynamic FLS estimates. This confirms our previous discussion about the need for a flexible parameter model for risk estimation. We conclude that it is quite possibly very misleading to estimate SIM models without using time varying parameter methods.

Generally, the commodity graphs show greater beta variation after the failure of Bretton Woods in 1973. This indicates a much different and changing systematic risk for agricultural markets after the transition to more flexible exchange rates. While recessions appear to have little effect on the level of systematic risk, crop betas appear to show a connection to some farm bills. However, the livestock betas do not show this type of response to farm bills. This result is consistent with the predominant focus of policy makers on crop prices and the lack of inclusion of livestock price levels in most farm legislation. Corn and soybean betas have an upward trend throughout the period and

move together. Wheat, hogs, and cattle move significantly but show no direct trend and lack co-movements across time.

Corn

The betas for corn increase over the period and the corn betas tend to move together for all geographic regions analyzed (figure 1). The prominence of the three states studied in corn production likely leads to this similar trend with each other and with the U.S. Corn betas for Illinois were lowest over the entire period and similarly, Iowa corn betas were highest, with Indiana in between. Variability of corn betas after the failure of Bretton Woods appears to increase. Farm bills seem to have an effect on the volatility of corn betas. After the 1985, 1996, and 2002 farm bills, corn betas decrease. Curiously, the sharpest declines are after the 1985 and 2002 farm bills and both of these have the term “security” in the title. This suggests a possible connection between stated goals of policy and actual outcome.

The OLS estimate of the corn beta for the U.S. over the period is much higher than the FLS estimates for most of the period, but the dynamic and OLS betas seem to converge at this higher level near the end of the series. Betas for 2007 show an increase in systematic risk and point to the possible impact of the biofuels policy on systematic risk in corn production.

FLS U.S. corn betas begin the period at values around 0.5, but grow to the 2.0 to 3.0 range after 1990. Thus, for every one unit change in the index, corn receipts change two to three units after 1990.

Soybeans

The results for soybean betas are strikingly similar to the results for corn. The betas for all three states and the U.S. trend upward over the period. Illinois is lowest throughout the period with Iowa and Indiana alternating for highest. Beta patterns for each geographic region mirror one another closely with increased volatility starting in the late 1990's. The impacts from farm bills are not distinct in soybeans, indicating a difference between the policy affects on corn and soybeans and the subsequent risk associated with the soybean market. Soybean betas show a sharp decline after the 2002 farm bill with a slight uptick for 2007, the last year in the series.

In relation to the CRB index, the FLS soybean betas for the U.S. are greater than one for the most of the years analyzed and increases over time. OLS estimation over the whole sample period presents a higher beta than FLS for the U.S. until about 1996, and in the early part of the period the OLS beta is much higher.

Wheat

In contrast to corn and soybeans, the state FLS beta levels decline somewhat over the time span of the study, with the U.S. betas showing no clear trend. The state betas show high volatility from the end of Bretton Woods until about 1990 and then become

relatively stable the rest of the period. The U.S. level betas are relatively steady over the period but higher than the OLS estimate for most years. While the U.S. estimate is similar, the variation from OLS is substantial.

Wheat betas are generally higher than corn or soybean betas until the end of Bretton Woods, at which time corn and soybean betas have increased to the general level of wheat betas. After 1990 state wheat betas are smaller than the U.S. wheat betas. The deviation of U.S. results from state level results for wheat is not surprising given that these particular states are not the leading wheat producers. Similar to corn and soybeans, the betas for Iowa are highest, Illinois the lowest, and Indiana in between.

Cattle

State level cattle betas show a relatively constant and low level over the entire period. In contrast, the U.S. beta increases substantially from the beginning to the end of the period. In general, negative value of beta indicates a movement opposite of the direction of general commodity prices. Negative beta assets are particularly effective at reducing portfolio risk. The U.S. FLS cattle betas are negative until 1970 and trend upward until the early 1990s, but the state level cattle betas are less negative initially and do not show the upward trend.

The U.S. FLS betas are much larger than the state betas for the final 25 years, and they are below the OLS beta for the entire period, although the gap closes significantly at the end of the series. The relatively stable state betas for cattle are much lower than those estimated for corn, soybeans, and wheat.

Hogs

Hog beta levels for each state and the U.S. mirror each other in volatility for the entire time period. There appears to be no appreciable impact from farm bills or macroeconomic factors throughout the series, but the variation is consistent over the entire time frame unlike in the other commodities. A noticeable divergence of hog beta trends for different states begins in the 1980s and continues to the end of the series. Indiana and Illinois decline, while Iowa and the U.S. series are almost perfectly synchronized. Also, beginning in the 1980s, the order of state betas from highest to lowest was Iowa, Indiana, and Illinois, which was the same order found for corn and hogs.

The beginning of the observed divergence corresponds to a period of general changes in hog production techniques which increase over time. Iowa's position as a major hog producing state is without doubt, but the other two states are among the nation's top 10 hog producers. The increased specialization in hog production could account for the increasing divergence over time.

The OLS estimation is much higher than the FLS representation until it converges with Iowa and the U.S. around year 2000. Despite the high levels of variation, the lean hog beta is below one and indicates less systematic risk than crops, but very similar to cattle.

Conclusion

In assessing the systematic risk of a commodity, this study finds great variation in betas for corn, soybeans, wheat, cattle and hogs over time calculated against a single commodity index. Systematic risk, $\beta_i^2 V(R_m)$, depends upon the variance of the index (commodity price volatility) as well as beta. To help summarize the results we graph in figure 7 the square root of systematic risk ($\beta_i \sigma_m$) at the U.S. level for each of the five commodities studied. We calculated the standard deviation of the index (σ_m) for each year using the CRB's monthly data.

Figure 7 accounts for both beta and variance of the index and as a result clearly shows a greater level and volatility of systematic risk for wheat, corn, and soybeans after the Bretton Woods collapse. After 1973, periods of systematic risk expand and collapse for corn, soybeans and wheat (less so for cattle). These periods reflect both changing betas and periods of changing commodity price volatility. Since 2002, systematic risk is expanding for all commodities, but the impact on corn is especially pronounced. Corn, soybean, and wheat systematic risk peaked in the early 1970s and these levels were only exceeded in the final two years for corn and soybeans. Cattle and hog systematic risk is relatively low throughout the period in comparison to corn, soybeans and wheat. Prior to the collapse of Bretton Woods, systematic risk in all five commodities appears to be practically zero when viewed on our graph scaled to contain the level of 2007.

In our study we have found that beta estimates from a time varying parameter model (FLS) and OLS formulation are substantially different. From our graphs of betas over time one gains insight into the changing nature of risk and the impact of institutional and macroeconomic events. This type of analysis lends perspective to policy makers and agricultural economists interested in understanding how policy and markets combine to influence the level of risk present in agricultural commodities.

This paper found large differences on the state level and national levels for different commodities. It is plainly seen that the changing production portfolios for the mid-western states examined impact the risk associated with a given commodity. In particular, the cattle and wheat betas vary greatly from the national estimation. Overall, the risk associated with each commodity is greatly impacted by macroeconomic factors and some farm bill policies. An understanding of changing risk in commodity policies merits this type of analysis.

This analysis allows for a quantitative and visual way to assess risk over time across risk categories. As the beta for a particular crop and region adjust to different factors over time, the level of risk presented in the dynamic representation provides an easy and

effective way to describe and analyze risk to the agricultural sector. Further, the estimation procedure provides a flexible and simple way to visualize the changes in systematic risk over time.

Future research is needed to expand the understanding of the dynamic and spatial nature of beta or look for structural breaks in estimated dynamic betas. In characterizing risk in this manner, a further understanding of how risk adjusts over time for a commodity in a chosen geographical area is attained and interpreted in a rather straightforward manner.

References

- Barry, P. J. 1980. "Capital Asset Pricing and Farm Real Estate." *American Journal of Agricultural Economics*. 62: 549-553.
- Brinker, A., J. Parcell, and K. Dhuyvetter. 2007. "Cross-Hedging Distillers Dried Grains: Exploring Corn and Soybean Meal Futures Contracts." Proceedings NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management.
- Collins, R.A. and P.J. Barry. 1986. "Risk Analysis with Single-Index Portfolio Models: An Application to Farm Planning." *American Journal of Agricultural Economics*. 60: 152-161.
- Dorfman, J. and K. Foster. 1991. "Estimating Productivity Changes with Flexible Coefficients." *Western Journal of Agricultural Economics* 16 (2): 280 – 290.
- Ebner, M. and T. Neumann. 2005. "Time-Varying Betas of German Stock Returns." *Financial Markets and Portfolio Management* 19 (1): 29 – 46.
- Fabozzi, F. J. and J.C. Francis. 1978. "Beta as a Random Coefficient." *Journal of Financial and Quantitative Analysis*. 13(1): 101-116.
- Fabozzi, F. J. and J.C. Francis. 1979. "Mutual Fund Systematic Risk for bull and bear markets: An empirical examination." *Journal of Finance*. 34(5): 1234-1250.
- Gempesaw, C.M., A.M. Tambe, R.M. Nayga and U.C. Toensmeyer. 1988. "The Single Index Market Model in Agriculture." *Northeast Journal of Agricultural and Resource Economics*." 17(2): 147-155.
- Granger, Clive W.J., 2008. "Non-Linear Models: Where Do We Go Next – Time Varying Parameter Models?" *Studies in Nonlinear Dynamics and Econometrics*. 12(3): 1-9.
- Hamilton, J. D. 2009. "The Causes and Consequences of Rising Food Prices: Discussion." *American Journal of Agricultural Economics*. 91: in press.
- He, L. 2001. "Time Variation Paths of International Transmission of Stock Volatility US vs. Hong Kong and South Korea." *Global Finance Journal* 12 (1): 79 – 93.
- He, L. 2005. "Instability and Predictability of Factor Betas of Industrial Stocks: The Flexible Least Squares Solutions." *Quarterly Review of Economics and Finance* 45 (4-5): 619 – 640.

- Jensen, M., 1969. "Risk, the Pricing of Capital Assets and the Evaluation of Investment Portfolios." *Journal of Business* 42 (2): 167-247.
- Kalaba, R. and L. Tesfatsion. 1988. "The Flexible Least Squares Approach to Time-Varying Linear Regression." *Journal of Economic Dynamics and Control* 12: 43 – 48.
- Kalaba, R. and L. Tesfatsion, 1990. "An Organizing Principle for Dynamic Estimation." *Journal of Optimization Theory and Applications* 64 (3): 445 – 470.
- Kuethe, T.H., K. Foster, and R.J.G.M. Florax. 2008. "A Spatial Hedonic Model with Time-Varying Coefficients: A New Method Using Flexible Least Squares." Selected Paper at the American Economics Association Annual Meeting, Orlando, Florida, July 26 – 28.
- Lee, A.C. and M. Kim. 2005. "Time Varying Coefficient: An Application of Flexible Least Squares to Cattle Captive Supply." Selected Paper at the American Economics Association Annual Meeting, Providence, Rhode Island, July 24 – 27.
- Markowitz, H.M. 1959. *Portfolio Selection: Efficient diversification of Investments*, John Wiley and Sons, New York.
- Parcell, J.L. 2002. An Empirical Analysis of the Demand for Wholesale Pork Primals: Seasonality and Structural Change. Department of Agricultural Economics Working Paper No. AEW 2002-11, University of Missouri, Columbia, Missouri.
- Poray, M., K. Foster, and J. Dorfman. 2001. "Measuring an Almost Ideal Demand System with Generalized Flexible Least Squares." Working Paper 01-01, Department of Agricultural Economics, Purdue University.
- Rao, M. 2000. "Estimating Time-Varying Parameters in Linear Regression Models using a Two-Part Decomposition of the Optimal Control Formulation." *The Indian Journal of Statistics* 62: 433 – 467.
- Sharpe, W. F. 1963. "A Simplified Model for Portfolio Analysis." *Management Science*. 9(2):277-93.
- Sharpe, W.F. 1964. "Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk." *Journal of Finance* 19(3): 425-442.
- Sumner, D. A. 2009. "Recent Commodity Price Movements in Historical Perspective." *American Journal of Agricultural Economics*. 91: In press
- Swamy, P. 1970 'Efficient Inference in a Random Coefficient Regression Model.'

Econometrica 38(2): 311-323.

Turvey, C.G., H.C. Driver, and T.G. Baker. 1988. "Systematic and Nonsystematic Risk in Farm Portfolio Selection *American Journal of Agricultural Economics*. 70: 831-836.

Table 1: Commodities in Reuters CCI Index

Corn	Gold	Coffee	Crude Oil
Soybeans	Silver	Sugar	Heating Oil
Wheat	Copper	Cotton	Natural Gas
Live Cattle	Cocoa	Orange Juice	Unleaded Gasoline
Lean Hogs	Nickel	Platinum	

Table 2: Policy and Macroeconomic Events

Farm Bill	Year	Recession Periods
Agriculture Act of 1956	1956	1957-1958
Food and Agricultural Act	1965	1980-1982
Agricultural Act of 1970	1970	1990-1991
Agricultural and Consumer Protection Act	1973	2001-2003
Food and Agriculture Act	1977	
Agriculture and Food Act	1981	
Food Security Act	1985	
Food, Agriculture, Conservation, and Trade Act	1990	
Federal Agriculture Improvement and Reform Act	1996	
Farm Security and Rural Investment Act	2002	
Food, Conservation, and Energy Act	2008	

Table 3: Optimal Smoothing Parameters^a

Commodity	United States	Indiana	Illinois	Iowa
<i>Corn</i>	0.05	0.05	0.05	0.05
<i>Soybeans</i>	0.001	0.05	0.05	0.05
<i>Wheat</i>	0.05	0.05	0.05	0.05
<i>Cattle</i>	0.05	0.05	0.05	0.05
<i>Lean hogs</i>	0.05	0.001	0.001	0.05

^aThe algorithm searches over the interval 0.001 to 0.999 in increments of 0.05.

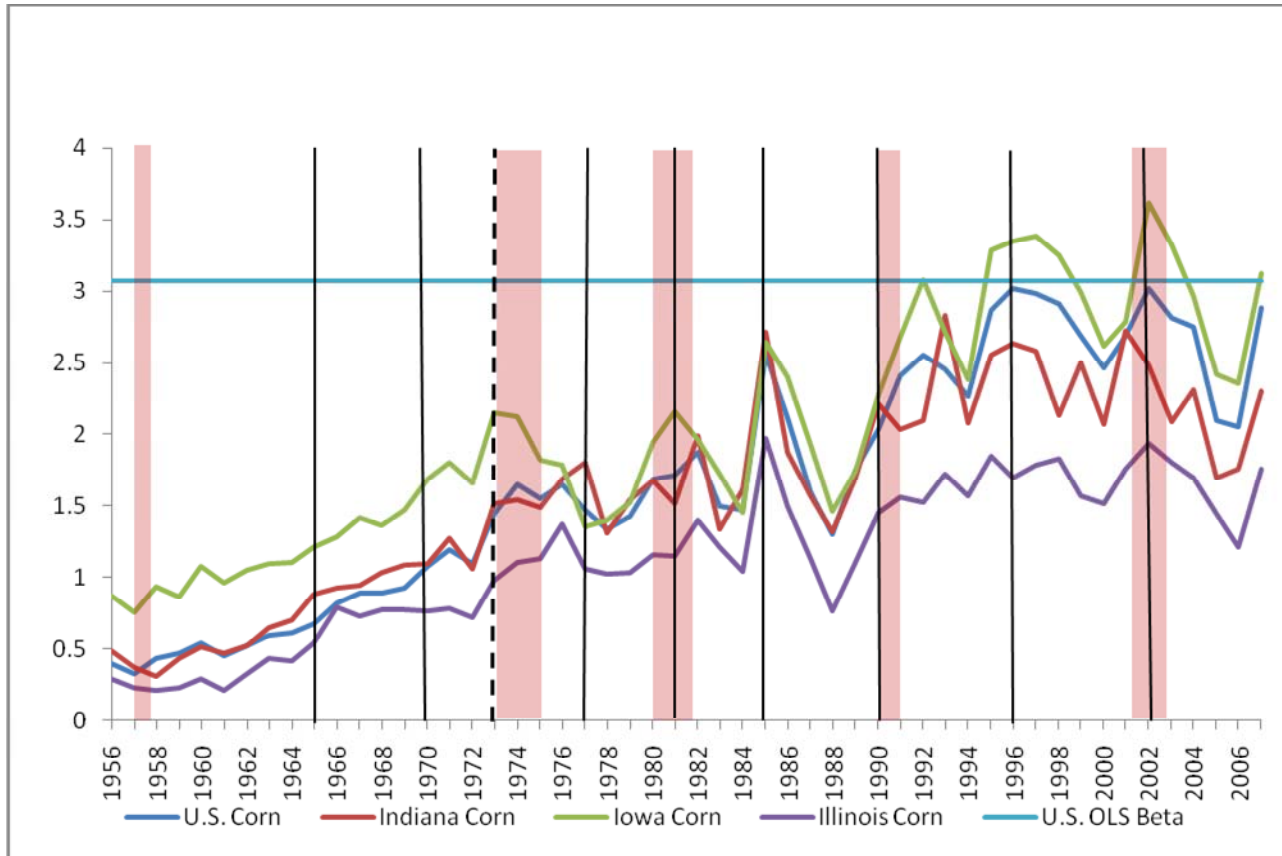


Figure 1: Dynamic beta values for corn

Note: vertical lines indicate farm bills, a dashed line indicates the end of the Bretton Woods Accord, and shaded areas indicate major recession periods.

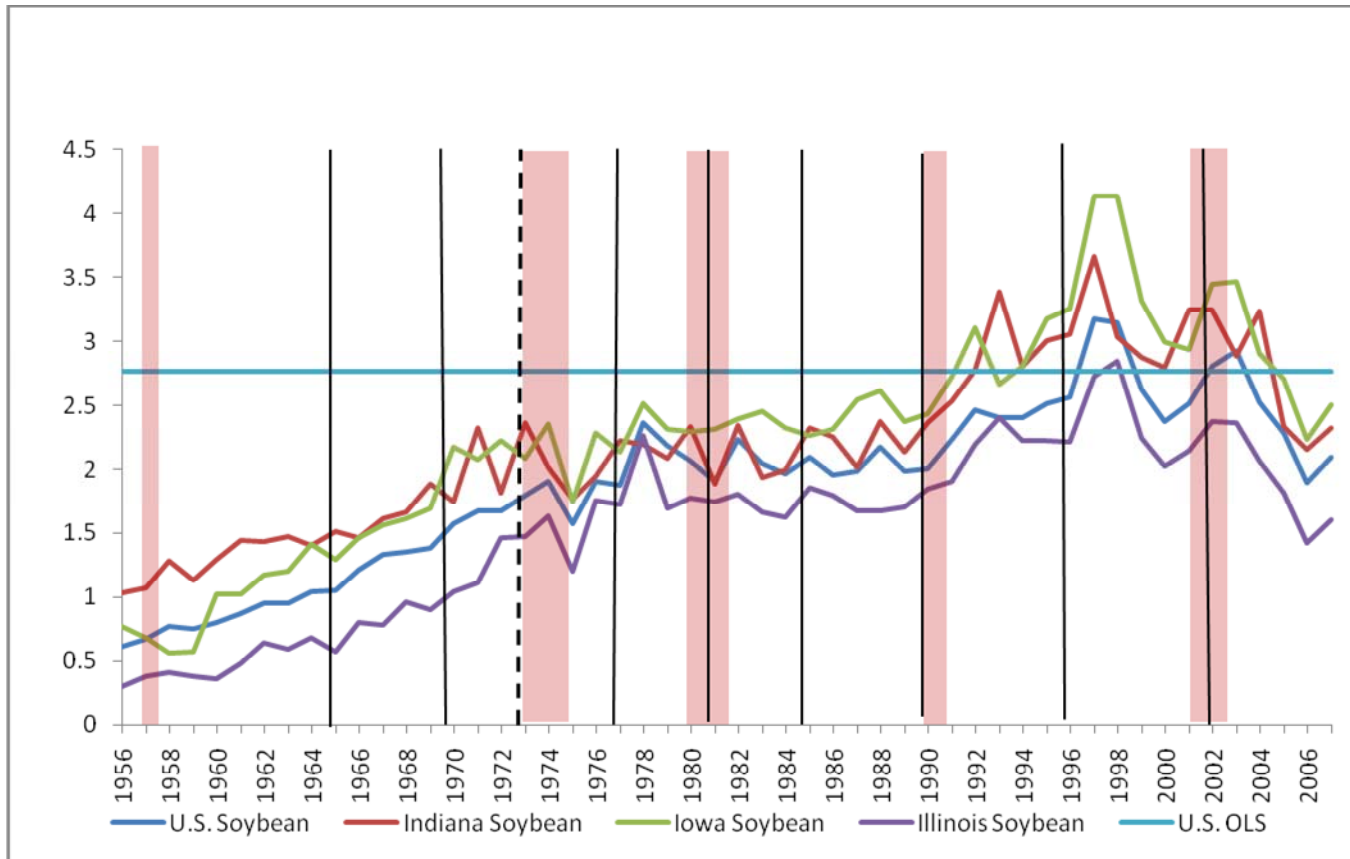


Figure 2: Dynamic beta values for soybeans

Note: vertical lines indicate farm bills, a dashed line indicates the end of the Bretton Woods Accord, and shaded areas indicate major recession periods.

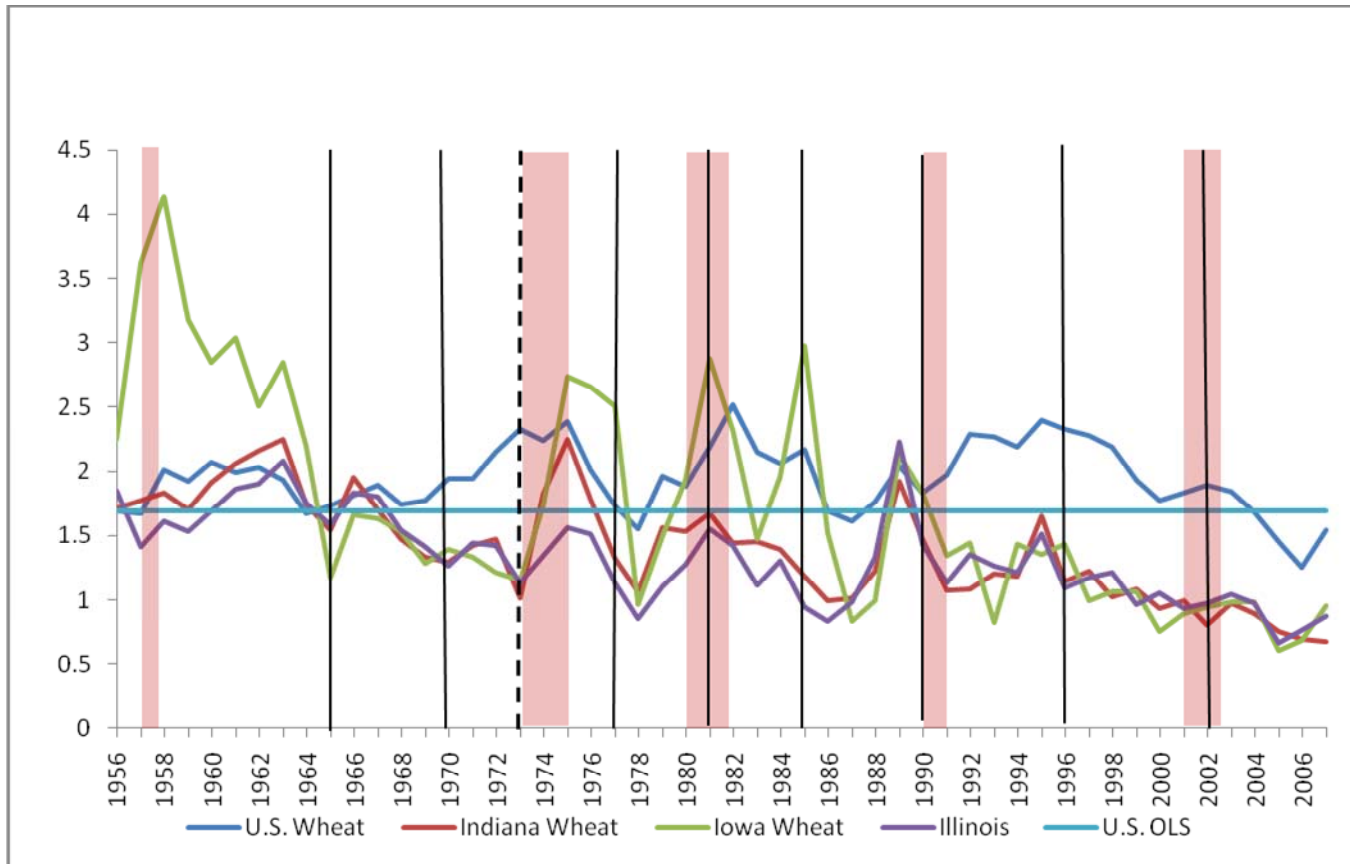


Figure 3: Dynamic beta values for wheat

Note: vertical lines indicate farm bills, a dashed line indicates the end of the Bretton Woods Accord, and shaded areas indicate major recession periods.

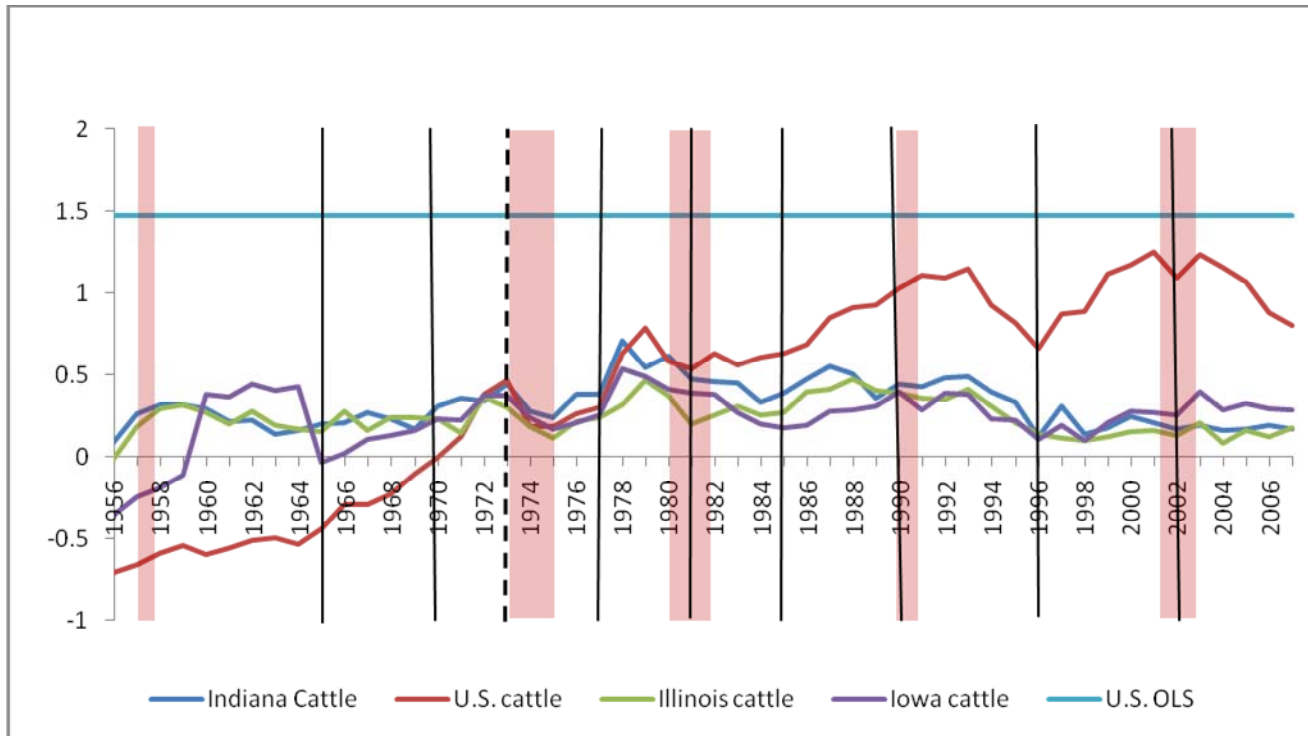


Figure 4: Dynamic beta values for cattle

Note: vertical lines indicate farm bills, a dashed line indicates the end of the Bretton Woods Accord, and shaded areas indicate major recession periods.

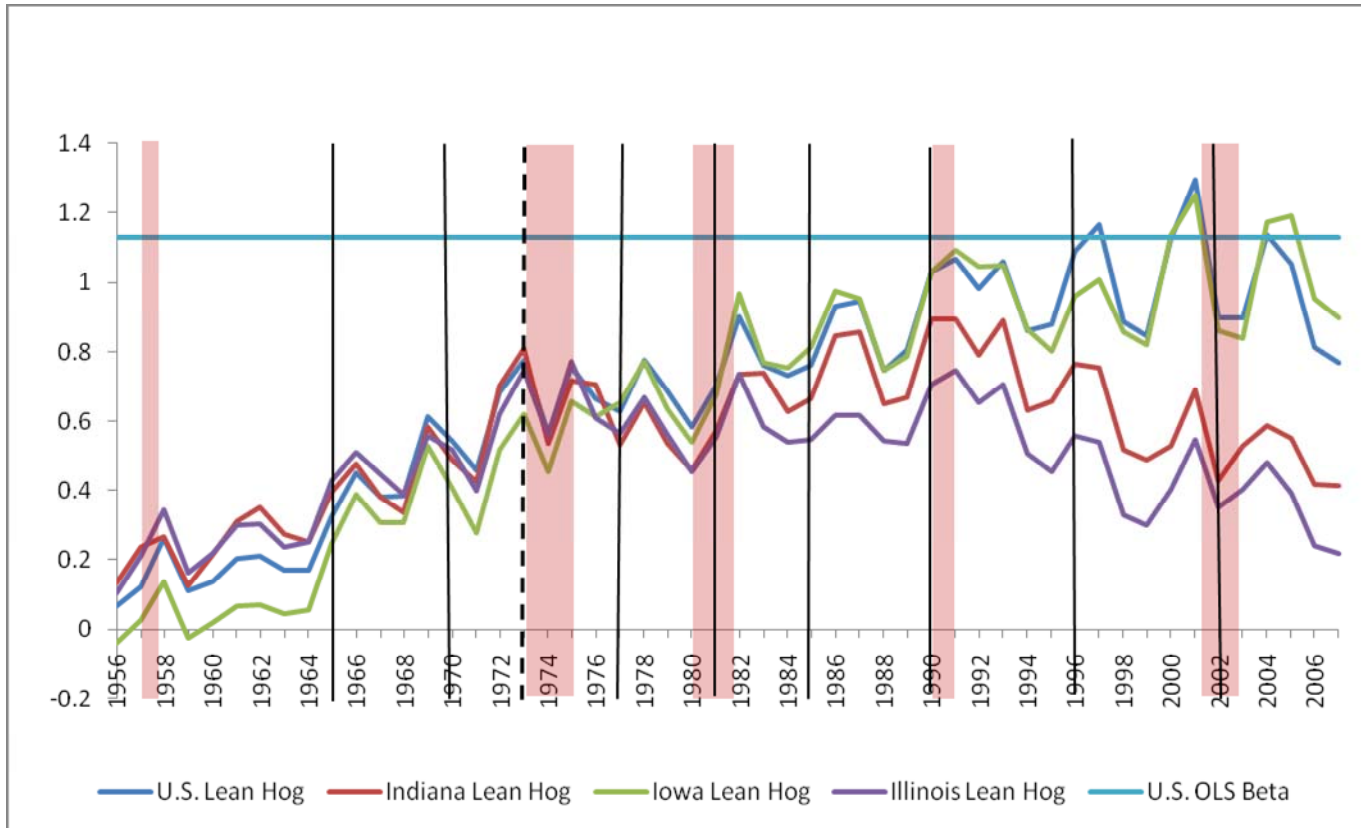


Figure 5: Dynamic beta values for hogs

Note: vertical lines indicate farm bills, a dashed line indicates the end of the Bretton Woods Accord, and shaded areas indicate major recession periods.

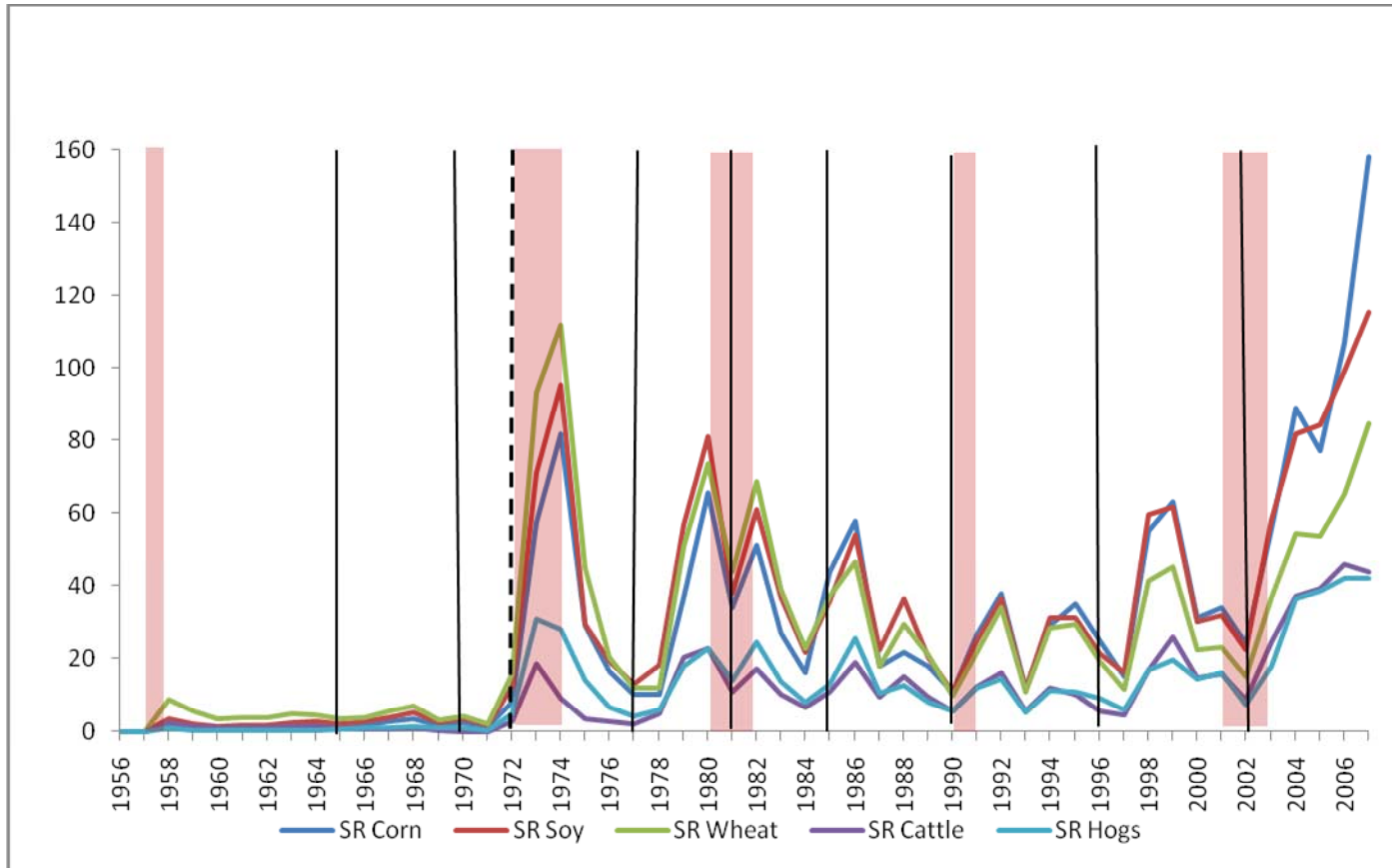


Figure 6: U.S. systematic risk (SR)

Note: vertical lines indicate farm bills, a dashed line indicates the end of the Bretton Woods Accord, and shaded areas indicate major recession periods.