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A Relative Information Approach to Modeling Dynamics of U.S. Farmland Values

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Motivation and Background

Issues relating to farmland values have been at the forefront of the U.S. agricultural policy debate for the past four decades. This is because of farmland's dominance on agricultural producers' balance sheets. For example, the share of real estate on the farm balance sheet increased from 62% in 1950 to 78% in 1981 and currently stands at about 82% (Moss, 2013). Furthermore, 88% of the decline in agricultural assets resulting from the 1980's financial crisis and 82.2% of the increase in agricultural assets between 1986 and 2012 came from real estate.

Given the increasing dominance of farmland values as a percentage of total farm assets over the years and its implications as regards to the opportunity cost of agricultural production, several studies have examined factors that drive farmland values. For example, Shalit and Schmitz (1982) show that using land as collateral for credit drives up land values; in areas where land owners have access to credit and secure these loans with land as collateral, land values increase faster relative to land values in areas where there is no access to credit. Other factors leading to increased farmland values noted in the literature include population and urban growth (Boisvert, Schmit and Regmi 1997; Shi, Phipps, and Colyer 1997; Livanis et al. 2006; Herdt and Cochrane, 1966), market fundamentals (Burt 1986; Featherstone and Baker 1987; Moss 1997; Moss 2013; Just and Miranowski 1993), total factor productivity (Herdt and Cochrane, 1966), and government payments (Latrufee and Le Mouel, 2009; O'Donoghue and Whitaker, 2010; Kropp and Peckham, 2012; Goodwin, Mishra, and Ortalo-Magne, 2011).

More recently, an entropy-based information approach has been used to examine the determinants of increasing farmland values. Moss *et al.* (2007) uses the entropy approach to

explore the content of information contained in changes in relative asset values. Salois *et al.* (2011) extend this approach by developing a dynamic information measure to explore how the information content of farmland values and farm income explain the distribution of farmland values over time. Salois *et al.* (2012) apply this approach to examine the relationship between farmland values, urban pressure and farm income. While there has been considerable research examining the drivers of farmland values, to the best of our knowledge none of the previous studies have taken into consideration how the effects of these factors differ across U.S. states.

Our paper builds upon existing literature by utilizing a richer dynamic panel data set. We define an inequality measure for the farm assets across 46 - states of the U.S. by using an entropy-based approach computed from the state-level farm balance sheet data. The inequality is defined as the measure of information of the message that transforms the share of value of assets in each state into the corresponding aggregate shares. As a result, the inequality measures the dispersion of share of value of assets in each state from the aggregate mean for each asset class. We then use this measure to explore the short-run and long-run relationships of the relative changes in farm asset prices over time, total factor productivity (TFP), and urban pressure. We use panel cointegration and panel error correction models to examine the short-run and long-run effects of TFP and urban pressure on changes in prices of farm assets, which are dominated by farmland values, over time.

Our estimation results show that urban pressure tends to reduce the level of inequality in farm asset values across states in the long-run. On the other hand, differences in TFP seem to increase the level of inequality in asset values across the 46 states. The speed of adjustment from the error correction model is found to be negative and statistically significant, which indicates that the relationship between relative asset prices and other explanatory variables, including the urban pressure and TFP, is indeed a long-run cointegrating relationship, which returns to an equilibrium after a relatively short period of adjustment.

The remainder of the paper is structured as follows: the next section presents the discussion of the empirical model. The third section discusses the data, while the fourth section presents the results and interpretation of the results and the last section presents the conclusion.

The Empirical Model

Following Theil and Moss (1999), we assume N states and m asset categories. A_{skt} represents state s value of asset k at time t which is measured as the share of the total value of assets on all m asset categories at time t. The measure of inequality of the value of assets is expressed as the ratio of the arithmetic mean of the value of assets to the geometric mean of the value of assets. Thus, the measure of inequality of asset k is represented as follows:

$$J_{kt} = -\log N - \frac{1}{N} \sum_{s=1}^{N} \log \frac{A_{skt}}{A_{kt}}$$
(i)

Where $A_{kt} = \sum_{s=1}^{N} A_{skt}$

For all the m asset categories, it can be written as

$$J_{t} = -\log N - \frac{1}{N} \sum_{s=1}^{N} \log A_{kt}$$
(ii)

 J_t can also be expressed as $J_t = \overline{J}_t - \overline{I}_t$

Where $\overline{J_t} = \sum_{kt} A_{kt} J_{kt}$ is the average inequality of the value of assets for the *m* asset categories (weighted according to their shares in the total value of assets) and $\overline{I}_t = \left(\frac{1}{N}\right) \sum_{st} I_{st}$. I_{st} is defined as a measure of information of the message that transforms the share of value of assets in state *s* into the corresponding aggregate shares. It represents a measure of variation in the farm balance sheet and can be computed as follows:

$$I_{st} = \sum_{k=1}^{m} A_{kt} \log \frac{A_{kt}}{(A_{skt}/A_{s,t})}$$
(iii)

Where $A_{s,t} = \sum_{k=1}^{m} A_{skt}$

 $I_{st} = 0$ represents the case where the share of value of assets in state $s (A_{skt}/A_{s.t})$ agree with the aggregate shares (A_{kt}) . Otherwise $I_{st} > 0$.

$$A_{skt} = \frac{V_{skt}}{\sum_{s} \sum_{k} V_{skt}}$$
(iv)

Where V_{skt} is the value of asset k in state s at time t.

Following the urban growth model developed by Capozza and Helsley (1989), the value of farmland at time t in state s can be represented as

$$V_{slt}(t,s) = E\left[\int_{0}^{T} e^{-rt} R_{As}(t,s) dt + \int_{T}^{\infty} e^{-rt} R_{Us}(t,s) dt\right]$$
(v)

Where $R_{As}(t,s)$ represents the net returns to agriculture in state *s* at time *t*, $R_{Us}(t,s)$ is the net returns to urbanization in time *t* at state *s* (which includes the cost of conversion), *r* refers to the discount rate, and *E* represents the expectation with respect to *T*.

Also, as the R_{As}/R_{Us} increases, we expect the time of conversion of farmland to urban uses (*T*) to increase.

$$dV_{slt}(\mathbf{t},\mathbf{s}) = \frac{dh}{dR_A} dR_A(\mathbf{t},\mathbf{s}) + \frac{dh}{dR_U} dR_U(\mathbf{t},\mathbf{s})$$
(vi)

$$dV_{slt}(\mathbf{t},\mathbf{s}) = \alpha_1 dR_A(\mathbf{t},\mathbf{s}) + \alpha_2 dR_U(\mathbf{t},\mathbf{s})$$
(vii)

$$dR_A(t,s) = \beta_0 + \beta_1 dTFP \tag{viii}$$

$$dR_{U}(\mathbf{t},\mathbf{s}) = \gamma_{0} + \gamma_{1} dPopulation$$
(ix)

Equation (v) suggests that farmland value can be divided into two segments: one of which is explained by the net effect of agricultural returns and the other component is explained by net returns to development. Changes in any of these two components result in changes in farmland values. We further hypothesize that changes in net returns to agriculture over the years can be attributed to changes in the total factor productivity. However, a change in net returns to development is solely due to population pressure.

Based on the way the information measure was computed and the panel data structure employed in our analysis, there is a possibility of cross sectional dependence. This may arise as a result of common shocks and unobserved components that may eventually become a component of the error term, spatial dependence, and idiosyncratic pairwise dependence in the disturbances that may not have a specific pattern of common components or spatial dependence (De Hoyos and Sarafidis, 2006).

Such cross section dependence should be taken into account when implementing panel unit root tests. To this extent, we implement Pesaran (2007) panel unit root tests. Pesaran's (2007) panel unit root test controls for the cross section dependence assuming it is caused by a single unobserved common factor in the panel. Pesaran's panel unit root tests modify the standard Augmented Dickey Fuller (ADF) regressions by adding the cross section averages of lags and first-differences of individual series.

After checking for the presence of panel unit roots, we employ residual-based cointegration models for panel data and estimate the short-run and long-run relationships using the Pooled-Mean Group estimator and Mean Group estimator for dynamic heterogeneous panels as follows:

$$\Delta y_{it} = \phi_i (y_{i,t-1} - \theta_i X_{it}) + \sum_{j=1}^{p-1} \lambda_{ij}^* \Delta y_{i,t-1} + \sum_{j=0}^{q-1} \delta_{ij}^{**} \Delta X_{i,t-j} + \mu_i + \varepsilon_{it}$$
(x)

 ϕ_i denotes the error-correction term and the speed of adjustment towards the long-run equilibria (Blackburne and Frank, 2007). An $\phi_i=0$ suggests that no error correction or no long-run relationship exists between the two variables, i.e. they are not cointegrated. However, $\phi_i < 0$ suggests there exists a long-run relationship between the variables and there exists an error-correction representation of the model.

Data

The empirical analysis consists of 46 states excluding Alaska, Hawaii, Louisiana, and New Hampshire. The study made use of data from 1960 to 1999. The restriction of our sample to the time frame and states included are due to data limitations. The TFP data are only available until 1999. Louisiana and New Hampshire are excluded as a result of missing data for certain years because the panel cointegration test requires a balanced panel. Assets and liabilities of state-level farm balance sheets are measured in thousands of U.S. dollars. State-level data on the TFP, population, and farm balance sheet were obtained from United States Department of Agricultural (USDA) Economic Research Service database, U.S. Census Bureau and USDA website respectively. Prior to estimation, the population data were converted into natural logarithms.

Results

Descriptive Statistics

The descriptive statistics for the measure of inequality computed from the components of the farm balance sheet (as described in equation III), TFP, and population are presented in Table 1. As shown in Table 1, the inequality measure is as high as 0.23 with a mean 0.023. TFP ranges from 0.32 to 1.59 with a mean of 0.76.

Table 1. Descriptive Statistics					
bservations	Mean	Std. Dev.	Minimum	Maximum	
1840	0.0231	0.027	0.0001	0.2340	
1840	0.7611	0.221	0.3217	1.5903	
1840	14.9078	1.006	12.5811	17.3164	
	1840 1840	18400.023118400.7611	18400.02310.02718400.76110.221	18400.02310.0270.000118400.76110.2210.3217	

Table 1: Descriptive Statistics

Cross section dependence

The Pesaran (CD) test was used to test for cross sectional dependence under the null hypothesis that the error term is independently and identically distributed (i.i.d) over time periods and cross sectional units. Results from Table 2 suggest that the null hypothesis of no cross sectional dependence can be rejected at 1% level of significance. We also obtained the average absolute correlation of the residuals (ABS). This seems to be relatively high at 0.376.

Table 2: Results of Cross Section Dependence Tests

Result of Cross see	ctional dependence	
Test	Pesaran (CD)	ABS
Statistics	13.603***	0.376
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Notes: ***Significance at the 1% level; **at the 5% level; * at the 10% level.

Order of integration of the series

As a result of the presence of cross section dependence suggested in Table 2, we implemented a Pesaran (2007) panel unit root test, which allows for cross section dependence. Table 3 shows the test statistics and the associated p-values. The optimal lag length is three and is based on the Akaike Information Criterion (AIC). The test was repeated with up to three lags. While the results in levels are mixed, the results of the first difference suggest that the differenced series are all stationary. It can be safely assumed that the measure of information inequality, the TFP and the measure of urban pressure (population) are all integrated of order one [I(1)].

		Specification without trend		Specificat	Specification with trend	
		Levels	First difference	Levels	First difference	
Variable	lags	Zt-bar	Zt-bar	Zt-bar	Zt-bar	
Inequality	0	-2.688	-27.411	-1.754	-25.833	
		(0.004)	(0.000)	(0.040)	(0.000)	
Inequality	1	-1.147	-17.642	-0.988	-15.335	
		(0.126)	(0.000)	(0.161)	(0.000)	
Inequality	2	0.123	-10.416	0.088	-7.454	
		(0.549)	(0.000)	(0.535)	(0.000)	
Inequality	3	0.608	-7.913	-0.066	-5.004	
		(0.729)	(0.000)	(0.474)	(0.000)	
TFP	0	-13.75	-31.289	-13.463	-30.546	
		(0.000)	(0.000)	(0.000)	(0.000)	
TFP	1	-8.389	-27.625	-8.526	-26.085	
		(0.000)	(0.000)	(0.000)	(0.000)	
TFP	2	-3.244	-17.203	-2.862	-14.758	
		(0.001)	(0.000)	(0.002)	(0.000)	
TFP	3	-2.235	-12.934	-2.205	-10.511	
		(0.013)	(0.000)	(0.014)	(0.000)	
Population	0	2.412	-8.069	2.139	-6.060	
		(0.992)	(0.000)	(0.984)	(0.000)	
Population	1	-5.344	-7.479	-4.608	-5.536	
		(0.000)	(0.000)	(0.000)	(0.000)	
Population	2	-4.176	-6.649	-3.951	-4.518	
		(0.000)	(0.000)	(0.000)	(0.000)	
Population	3	-2.730	-5.224	-1.480	-3.050	
		(0.003)	(0.000)	(0.069)	(0.001)	

Table 3: Results of Pesaran Panel Cointegration

Note: p-values are in parenthesis

Cointegration test

The previous results reveal that each individual series has unit root and as a result, we proceed with a test of cointegration. However, due to cross-section dependence in the errors of our panel, we estimate the Westerlund (2007) cointegration test which is robust to the existence of cross section dependence. Due to the presence of common factors that affect cross sectional units, we bootstrapped robust critical values for each of the test statistics using 800 replications.

Table 4 presents the results of the test of the null hypothesis that there is no panel cointegration. The panel statistics (P^t and P^a) and the group mean statistics (G^t and G^a) indicate an existence of long-run relationships between the inequality measure, TFP and total factor productivity. The presence of cross sectional dependence across states in the panel invalidates the statistics of the group mean and panel statistics. As a result, the robust P-values are reported because they take into account the cross-sectional dependence.

Table 4: Results of Westerlund-based Panel Cointegration Test

Estimation with constant but no trend					
Statistic	Value	Z-value	P-value	RobU.S.t P-value	
Gt	-2.831	-5.860	0.000	0.000	
Ga	-9.645	-0.562	0.287	0.055	
Pt	-15.267	-3.533	0.000	0.026	
Ра	-7.839	-2.394	0.008	0.086	

Note: The test for cointegration was implemented using the AIC to choose the optimal lag and lead lengths for each of the series and the Barlett Kernel window width was set to $4(T/100)^{2/9} \approx 3$

Error correction model

We report the results of the Pooled Mean Group (PMG) and Mean Group (MG) estimators. The PMG estimator permits the variation of the intercepts, slopes and error variances across groups but constrains the coefficients of the long-run estimates to be equal across groups (Peseran, Shin, and Smith, 1999). However, the MG estimator allows the intercepts, slope coefficients, and the error variances to vary across the different groups. PMG is estimated using Maximum Likelihood while MG estimation is obtained from unweighted means of the individual coefficients (Blackburne III and Frank, 2007). The restriction of pooling across states (homogeneity) by the PMG estimator results in efficient and consistent estimates when the restrictions are valid. In cases where the restrictions are not valid (that is the true model is

heterogeneous), PMG estimates are inconsistent and MG estimates are appropriate in this case (Blackburne III and Frank, 2007). The Hausman test is used to test the validity of the pooling assumption of PMG in order to choose between the MG and the PMG estimator.

The Hausman Statistic of 0.78 presents the PMG estimator as the efficient estimator under the null hypothesis of pooling. This indicates that constraining the common long-run coefficients resulting from pooling across states gave consistent and efficient estimates. Table 5 presents the results of the normalized cointegrating vector, the coefficients of the short-run dynamics, and the convergence parameter (adjustment coefficient). Similar to Pesaran et al. (1999), the PMG equation was estimated without trend. The results of our estimations show that increases in urban pressure tend to reduce the level of variation of asset values in the farm balance sheet across states in the long-run. On the other hand, differences in TFP seem to increase the level of variation of asset values in the farm balance sheet all statistically significant, which indicates that the relationship between the measure of inequality and other explanatory variables, including the urban pressure and TFP, is indeed a long-run cointegrating relationship that returns to equilibrium after a relatively short period of adjustment.

		Pooled Mean Estimation	Mean Group Estimation
		Statistic	Statistic
Long-run	TFP	0.019	-0.251
		(0.003)	(0.306)
	Population	-0.013	-1.107
		(0.003)	(1.082)
	TFP	-0.004	-0.009
Short-run		(0.004)	(0.006)
	Population	0.007	0.051
		(0.037)	(0.052)
	Adjustment	-0.203	-0.348
		(0.022)	(0.034)
	Hausman test	0.78	

Table 5: Results of the Error Correction Model for the Pooled Mean Group Estimator

Note: The dependent variable is the measure of inequality and standard errors are in parenthesis

Our results provide additional insight into the lingering question of drivers of farmland values. The short-run relationship between the measure of inequality and the variables considered in our estimation suggests that the contemporaneous co-movement between the measure of information inequality across states, the total factor productivity and urban pressure are either less likely to react to past shocks or do not react to past shocks at all. This is evident in the non-significance of the short-run coefficients that explains the adjustment of the states to shocks.

Our results suggest that changes in net returns to development arising from population pressure across states increases farmland values relative to other assets in the balance sheets in states where urban pressure measured by population is increasing fastest. In this case, the balance sheet becomes more concentrated in farmland values. This reduces the level of inequality among states, making the states look more alike. On the other hand, simultaneous changes in net returns to agriculture and development across states relatively increases all assets of the balance sheet and, as a result, states look less alike.

Conclusion

The Agricultural balance sheet is changing over time not only in levels, but also in shares and these changes in shares may affect the financial performance of the sector. This is because the increased share of farmland may imply liquidity difficulties in the sector in periods of financial stress. While our results are preliminary, they suggest that balance sheets become more similar as population grows. This is based on the hypothesis that similarity in population growth comes from growth in the share of real estate on the balance sheet. The empirical results also indicate that balance sheet become less similar as total factor productivity increases.

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