Finding Farms: Comparing Indicators of Farming Dependence and Agricultural Importance in the United States

Douglas B. Jackson-Smith
Department of Sociology, Social Work & Anthropology
Utah State University

Eric Jensen
Department of Agricultural Economics and Rural Sociology
The Pennsylvania State University

Abstract
Many scholars have commented on the changing significance of farming for understanding the dynamics of social and economic change in contemporary rural America. Quantitative analyses of relationships between farming, local socioeconomic conditions, demographic trends, and policy have often relied on an indicator of “farm-dependent” (FD) counties developed by the USDA Economic Research Service. In this article, we argue that measures of economic dependency imperfectly identify the places in the United States where farming is significant, and can paint an incomplete picture of the contemporary geographic distribution and structure of agriculture in the United States. We propose an alternative categorical indicator—agricultural importance (AI)—that provides a better direct measure of the relative size and intensity of farming across diverse U.S. counties. We compare the characteristics of FD and AI counties along a set of dimensions and discuss the strengths and weaknesses of each typology.

Introduction
One of the most significant social and economic changes in the United States over the last 100 years has been the dramatic shift from a nation in which most people had direct ties to farming to one where the overwhelming majority of residents live in urban and suburban environments (Lobao and Meyer 2001). Although agriculture continues to be the predominant land use in most U.S. nonmetropolitan (nonmetro) counties, many have argued that it is relatively unimportant as a direct or indirect source of jobs and income in most rural communities (Friedland 2002; McGranahan 2003). Indeed, researchers and rural economic development practitioners have documented a steady decline in the number of places that are “dependent” on farming for their livelihood (Kassel and Carlin 1999; Salsgiver and Hines 1993; Schluter and Edmondson 1999). The reduced importance of farm income to many rural communities has led to calls for the
fundamental reorientation of federal farm and rural development programs (Dimitri, Effland, and Conklin 2005; Whitener 2005).

While agriculture has become less central to the American way of life in general, its economic importance at the national or regional level is clouded by the unusually low profit margins on most agricultural operations. The result is a sector that generates $221 billion in gross cash income, spends $171 billion in aggregate farm expenses, but returned only $50 billion in net cash farm income in 2002 (U.S. Department of Agriculture [USDA] 2006a). Thus while they may be a relatively small source of direct personal income on most farms, agricultural operations can provide important indirect economic contributions through their patronage of agricultural input and service suppliers, and through the transportation, processing, and marketing of agricultural commodities. Generous estimates suggest that the agro-food system overall directly or indirectly contributes 17 percent of the jobs and 13 percent of the gross domestic product in the United States (Lipton, Edmondson, and Manchester 1998), most of which is generated by the wholesale, retail, and food-service industries.

Because of changes in the structure and organization of the farm sector in the last century, many scholars have sought to examine the social and economic effects of government policies and rural economic restructuring on agricultural places. One common approach has been to use county typology codes developed by the USDA Economic Research Service (ERS) to identify places that have an unusually large share of their income or employment from farming (Cook and Mizer 1994; Ghelfi and McGranahan 2004). In addition, a growing literature has examined the distinctive dynamics of agriculture in metropolitan environments (Heimlich 1989).

This article provides a critical evaluation of the utility of this traditional “farm-dependent” (FD) county classification. In particular, we argue that the economic-dependency approach fails to capture important aspects of the contemporary geographic distribution and structure of agriculture in the United States. When used as a proxy for “agricultural places,” the subset of FD counties can paint an inaccurate picture of the trends and impacts of changes in agriculture in the early twenty-first century. To resolve some of these problems, we propose using a complementary classification scheme that is designed to identify counties and places that have unusually large or intense levels of agricultural activity.

The ERS Economic-Dependency County Typologies

Beginning in the 1970s, a growing number of rural sociologists and rural-development practitioners began to recognize the diversity of
communities in late twentieth century rural America. In response, the ERS developed a set of “economic dependency” codes that established a typology of nonmetro counties based on which economic sector provided unusually large fractions of total personal income in the county (Bender et al. 1985). The original typology identified four economic dependencies: farming-dependent, manufacturing-dependent, mining-dependent, and government-dependent. For example, farming-dependent counties were places where more than 30 percent of total labor-and-proprietor income (LPI) between 1975 and 1979 came from farming. Simultaneously, the ERS established other “policy” codes that classified counties based on characteristics that had important relevance for federal policy—persistent poverty, retirement destination, and federal-lands-dependent. The 1979 typology allowed counties to be coded by more than one economic-dependency code or with both a dependency and policy code, but almost 60 percent of counties were classified into only one county type (Cook and Hady 1993). The most overlap was between persistent poverty and federal-lands counties. The least amount of overlap was found with manufacturing- and farming-dependent counties.

The ERS typology was revised in the early 1990s (using 1989 data) following a decade of dramatic changes to rural America, including the farm crisis and the continued growth of the service sector. The revised typology retained the original seven classifications and added three additional categories—commuting counties, service-sector-dependent counties, and transfers-dependent counties. The new typology also made the economic-dependent categories mutually exclusive to avoid counties with multiple dependencies, included Hawaii and Alaska for the first time, and refined county definitions to increase the precision of the typology. Because of the new definitions, reclassification of some counties to metropolitan status following the 1990 census, and changes in the relative importance of economic sectors, there were several marked changes in the classification of counties under the revised typologies. For example, the number of FD counties declined by 26.3 percent (Cook and Mizer 1994) and increased economic diversity was seen in many nonmetro areas.

In 2004, the ERS typology was once again modified, this time with more pronounced changes to the original definitions (USDA 2006b). Importantly, the new ERS typology changed the methods by which the

1 Davis (1979) and Hoppe (1981) earlier developed two county types (persistently low-income and farming-dependent counties, respectively) that were incorporated into the original ERS typology.
ERS identified FD counties. The two previous typologies defined FD counties as those in which the farming sector represented 20 percent or more of total LPI over a three-year period. The new ERS definition lowered the threshold to 15 percent of either total employment or proprietor income from agriculture in order to be classified as FD (USDA 2006b).

In addition, for the first time the typology included metropolitan (metro) counties\footnote{It is worth noting that two ERS studies assessed the presence of farming-dependence in metro counties earlier than the 2004 revisions (see Hoppe 1981, 1994).} Although this change greatly increases the potential number of counties that could be classified in any of the economic-dependency categories, given their more diversified economic bases, only a tiny handful of metro counties met the 15 percent of employment or income threshold to be classified FD. At the same time, the number of economic-dependency categories was reduced to include farming-dependent, mining-dependent, manufacturing-dependent, federal/state-government-dependent, and services-dependent. The typology added a nonspecialized category for counties that did not meet the criteria for inclusion in any of these categories. Of the four policy classifications from the 1990 codes, only persistent poverty and retirement destination remain in the new typology. The ERS developed five new types of policy classifications—housing stress, low education, low employment, population loss, and nonmetro recreation.

Limitations of Economic-Dependency Typologies

While economic dependency (expressed as a share of total income or employment) presents a view of the relative importance of different sectors to the county economy, it may not provide an appropriate indicator for the overall significance of a particular sector in the broader regional or national economy. This is particularly true for the FD codes the ERS uses. Indicators based on the percentage reliance on income or employment from farming may identify places that are distinctive more for having an unusually low amount of nonagricultural economic activity than unusually high levels of farming activity.

These distinctions were recognized during the early development of the ERS economic-dependency typologies. In that phase, the ERS also evaluated total farm sales as a possible indicator of dependence, but low correlations between sales, employment, and income caused them to be dropped from the analysis. Ross and Green (1985:10) note: “Low correlations with other criterion variables suggested that they were not measuring the same phenomenon. For example, low correlation for
sales per farm with the percentage of income and the percentage of employment from agriculture caused farm sales to be dropped.’’

Other researchers have noted that agricultural employment and income may not be perfectly correlated within a county. In a study classifying counties as ‘‘reliant on agriculture,’’ Salsgiver and Hines (1993) used thresholds of 25 percent of employment and income within a county as their cutting point. Of the 538 counties that they identified as being reliant on agriculture, only 275 counties were high in both income and employment. After separating income from employment, this research concluded that income was more important than employment in determining reliance.

Since the mid-twentieth century, the structure of agriculture in the United States has been changing. Among the most dramatic changes during this agricultural ‘‘transition’’ has been the replacement of labor by capital (Lobao and Meyer 2001). The mechanization of farms and the adoption of labor-saving technologies have diminished the connection between farm employment and farm output. In addition, there is a growing independence between trends in agricultural output and net farm income. In recent decades, farm commodity prices have generally declined while input prices, rents, and other costs of production have increased. This exposes producers to a ‘‘cost-price squeeze’’ (Cochrane 1993) where growth in output may not be reflected by growth in producer incomes.

Other studies have pointed out discrepancies between the ERS definition of FD places and the location of agriculturally important counties. Kassel and Carlin (1999) emphasize that increased economic diversity in nonmetro counties has not necessarily replaced farming activity, but rather diminished farming’s relative share of employment and income within the county. Their research compared FD counties, where at least 20 percent of employment and income come from farming, with what they call ‘‘farming-important’’ counties, in which farming provides 10 to 20 percent of total employment and income. While still using a ‘‘dependency-based’’ measure, their less restrictive measure classified a sizeable number of nonmetro counties as farming important, and unlike most FD counties, these farming-important counties were often experiencing substantial job and population growth.

Schluter and Edmondson (1999) applied the FD concept to state-level data. They found that several factors contributed to a state’s dependence on agriculture. These include the presence of a strong commercial farm sector, concentrated sector supply linkages, and—importantly for our present analysis—the relative scarcity of nonagricultural activity. Their analysis also notes a central problem with using
economic dependency to identify places that are agriculturally significant. Notably, California is the leading producer of fruits and vegetables, has the largest number of workers employed in agriculture, and is the leading state in the U.S. food-and-fiber system, but California is too diverse economically to be classified as an agriculturally dependent state. However, North and South Dakota are both classified as dependent although they collectively contribute less than 1 percent of U.S. employment in the food-and-fiber system.

The FD classification becomes most problematic when characteristics of farms and farm structure in FD counties are used to characterize the broader farming sector in the United States. Petrulis (1985) used a study of FD counties to assess the effects of farm-policy changes on the farm-sector and nonmetro counties. Chan and Elder (2001) used data from FD counties to show that children of farmers are more likely to be civically engaged in their community. Lyson, Torres, and Welsh (2001) relied on the FD codes in their study of the relationships between the scale of farm operations and local community well-being, finding a negative relationship between the two. Each study used data from FD counties as a means to more efficiently collect information about farming, and generalized results to the broader farming community based on the assumption that FD counties are where most farming occurs and are thus typical of farming in general.

The demographic literature commonly uses the FD codes to study the impact of farming on migration patterns and other population trends. In their review of rural migration trends over the last 45 years, Johnson and Fuguitt (2000) used the FD category to conclude that there has been a consistent pattern of out-migration from farming communities to other areas, and they note that the much ballyhooed population turnarounds of the 1970s and 1990s had relatively little impact on population trends in farming areas. In an earlier article, Fuguitt and Heaton (1995) used the FD classification to demonstrate that farming counties had the slowest population growth and the highest dependency ratios and were most impacted by out-migration of younger age groups. Kassel and Carlin (1999) estimated that as much as two-thirds of population growth in farming areas comes from natural increase, though their work focuses only on the subset of FD counties.

The use of the FD codes and similar “dependency”-based approaches can lead to three misconceptions about the broader trends in the U.S. farm sector. First, some researchers suggest that the steady decline in the percentage of income from farming and in the number of FD counties indicates that farming is a declining or disappearing industry (Browne et al. 1992; Drabenstott 2001; Johnson 2001; Vogel
Second, they suggest that most of the important agricultural activity takes place in areas that have relatively simple local economies and are relatively insulated from urban pressure (Kelsohn 2002). Finally, some scholars have misunderstood the codes to indicate places where agriculture is most significant in absolute terms.

A careful reading of statistics on agriculture in the United States challenges each of these misconceptions. For example, while the number of farms (and the amount of farmland) in the United States has gradually declined, the overall volume and commercial value of farm production has continued to grow over the last two decades (USDA 2006c). Similarly, studies of farming in urban contexts suggest that a significant amount of overall farm output is produced in metro counties and in economically robust nonmetro counties adjacent to these urban core areas (Heimlich 1989; Isserman 2001). Studies of metro agriculture find farms in urban areas, although qualitatively different from other farms, are surprisingly vibrant and robust (Heaton 1980; Heimlich 1989; Heimlich and Barnard 1992; Sharp et al. 2002).

To correct for these limitations, we have developed a new county indicator—agriculturally important, or AI—that serves as a compliment to the FD classification in identifying counties with high levels of agricultural production. The remainder of the article outlines the methodology used to create this new indicator and compares it to the widely used FD classification. Specifically, we examine how well the FD and AI counties capture broader trends in farm structure and dynamics of the farm economy. While we focus on the development of a binary indicator variable (AI, non-AI) as a tool for selecting subsets of U.S. counties for studies of agriculture, we also note the value of using parallel continuous indicators of sales volume and sales intensity in multivariate models. Finally, we conclude with a discussion of policy implication for researchers, public officials, and analysts.

**Data and Methods**

The goal of the AI indicator is to develop a mechanism to identify the subset of U.S. counties in which agricultural production is commercially and materially important not only to that specific county but also on a national level. Specifically, we use the market value of agricultural products sold as our main indicator for the overall size of farm production. Total sales is a constant metric that allows commensuration across different commodity sectors and does not bias any particular commodity or type of production as might be the case with a land- or employment-based measure. While sales volume alone is a starting point,
we also recognize that the level of aggregate sales can be influenced by
the size of the county, which varies widely by state and region. To mitigate
against this geographic bias we complement the sales indicator with a
measure of the intensity of production through the use of data on farm
sales per acre of total farmland and cropland. This important second step
in our classification scheme captures counties with intense levels of
production in states with comparatively small county sizes.

Data to construct the AI indicator were taken from the county file of
the 1992 and 2002 U.S. censuses of agriculture. We excluded counties
with less than 50 farms from the analysis because these counties
generally had insufficient data to calculate the variables needed for
determining the classification. A close examination of these counties
also made clear that none would reasonably be considered AI. In
keeping with the most recent version of the ERS typology, we include
both metro and nonmetro counties in our analysis.

We used two distinct criteria to identify counties as AI. The first
criterion ranked all counties by total agricultural sales and classified the
top quartile (over $72.5 million in 2002) as AI. It is worth noting that
high-aggregate-sales counties may reflect the presence of a large
number of moderate- to high-sales farms but also can comprise a small
number of very high sales operations, perhaps surrounded by more
numerous lower-sales-volume farms. The second criterion selects
counties that were in the second quartile for total sales (between
$36.1 million and $72.5 million in 2002), but also in the top quartile of
either “sales per acre of farmland” or “sales per acre of cropland” as
reported in the agricultural census (over $366 and $638 per acre,
respectively, in 2002). As noted above, this second criterion compen-
sated for areas with small county sizes that had relatively intense
agricultural activity. In practice, most AI counties (n = 765) qualified
through the first criterion, while another 197 qualified through the
second criterion (134 meeting both subcriteria, 29 with only high sales
per acre of farmland, and 34 with only high sales per acre of cropland).

Figure 1 shows the distribution of AI counties in the United States
based on the 2002 census of agriculture, and indicates which of the two
AI criteria were used to classify the county.

The patterns in Figure 1 reveal that counties classified by the first
criteria tend to be geographically diverse as these counties are located
in the Pacific states, in a band extending from northwestern Texas
through the upper Midwest, and in parts of Arkansas, Florida, the

A somewhat similar approach was used by Hoppe (1981, 1994) when he ranked
counties by total farm LPI.
Carolinas, Pennsylvania, Delaware, and upstate New York. The use of the second ‘‘intensity’’ criteria identified additional AI counties mainly in the northeastern and southeastern states, where small county sizes and intensive agricultural production predominate.

Results

Overlap of AI and FD Counties

The first step in our analysis was to compare the FD and AI county typologies at two points in time (using the 1992 and 2002 census of agriculture periods, respectively). The results suggest that there is surprisingly little overlap between these two categorization schemes. As indicated in Table 1, only one-third of the counties classified in 1993 as FD would have been considered AI in 1992. Conversely, only 17 percent of the AI counties in 1992 met the ERS definition for farm dependence. The proportion of counties that were AI was virtually identical between the FD and non-FD nonmetro counties. Because the ERS methods excluded all metro counties in 1993, none of the metro counties were considered FD in 1993. However, when viewed through the AI lens,
almost 40 percent of metro counties were among the most important agricultural counties in the United States in the early 1990s. In fact, agricultural importance is more common among metro counties than among nonmetro counties.

In 2004, counties classified by the ERS’s updated FD definition (with lower income thresholds and the inclusion of metro counties) are more congruent with our AI counties (see Table 2). Nearly half of the 440 FD counties in 2004 are also AI. However, over 70 percent of the AI counties in the United States are not considered FD by the ERS. Overall, Pearson correlation coefficients for the AD and FD measures were quite low (0.096 in the 1992–93 versions and 0.140 in the 2002–3 versions).

Figure 2 includes a map of the counties classified as AI, FD, or both. The FD classification scheme clearly captures many more counties in the relatively isolated rural areas in the northern Great Plains, while the AI indicator is more likely to capture counties along the Pacific Rim, in Florida and parts of the eastern seaboard, and in the more fertile and high-rainfall portions of the Upper Midwest. There is an interesting band of overlapping areas that are both FD and AI along the transition zone between the Upper Midwest Corn Belt (to the east) and the Great Plains (to the west). Using a first-order queens contiguity matrix, we calculated join-count statistics and found that FD and AI counties both tend to be geographically clustered within the United States.

---

### Table 1. Comparison of Agriculturally Important and Farm-Dependent Counties, Early 1990s

<table>
<thead>
<tr>
<th>Agriculturally Important Type</th>
<th>ERS County Type (1993)</th>
<th>Farming-Dependent, Nonmetro</th>
<th>Not Farming-Dependent, Nonmetro</th>
<th>Metro</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculturally Important</td>
<td></td>
<td>163</td>
<td>503</td>
<td>300</td>
<td>966</td>
</tr>
<tr>
<td></td>
<td></td>
<td>16.9 (29.3)</td>
<td>52.1 (29.4)</td>
<td>31.0 (37.0)</td>
<td>100.0 (31.4)</td>
</tr>
<tr>
<td>Not Agriculturally Important</td>
<td></td>
<td>393</td>
<td>1,209</td>
<td>510</td>
<td>2,112</td>
</tr>
<tr>
<td></td>
<td></td>
<td>18.6 (70.7)</td>
<td>57.2 (70.6)</td>
<td>24.2 (63.0)</td>
<td>100.0 (68.6)</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>556</td>
<td>1,712</td>
<td>810</td>
<td>3,078</td>
</tr>
<tr>
<td></td>
<td></td>
<td>18.1 (100.0)</td>
<td>55.6 (100.0)</td>
<td>26.3 (100.0)</td>
<td>100.0 (100.0)</td>
</tr>
</tbody>
</table>

*Note: The numbers in each cell, respectively, reflect the total number of counties, row percentage, and column percentage (in parentheses).*

---

4 The join-count statistic measures the spatial autocorrelation of a binary variable (Cliff and Ord 1981). We conducted these tests using the SPDEP package in R. All of the indicators were significant at \( p < .001 \). The existence of spatial correlations is not surprising but requires attention if the AI or FD indicators are used in multivariate models.
Capturing Farming Activity

The second part of our analysis examines how well the AI and FD typologies capture counties where farming takes place in the United States. Table 3 describes the percentage of U.S. farming activity (along a range of indicators) that takes place in AI or FD counties.
Overall, the ERS classified 14 percent of U.S. counties as FD in 2004, while our more inclusive definition for AI counties in 2002 captured 31 percent of counties. In general, the AI counties captured larger proportions of the overall U.S. farms, land, livestock inventories, and commercial farming activity. Moreover, this broader representation usually was larger than the proportionately greater coverage expected from the expanded number of qualifying counties. Over 70 percent of total farm sales and milk-cow inventories, two-thirds of farm workers, over 50 percent of cattle and calf inventories, and over 40 percent of farms and cropland were found in AI counties. By contrast, FD counties represented less than 30 percent of the U.S. totals on all these measures. When the size distribution of farms is considered, it is clear that FD counties have fewer small farms, and more farms with large acreages and moderate sales, than might be expected. By contrast, AI counties contain numerous farms across all size categories, with a heavier representation of the largest commercial operations. Finally, almost half of the total U.S. population lives in AI counties while less than 2 percent lives in counties that the ERS considers FD.

Table 3. Ability of Alternative County Typology Indicators to Capture Farming Activity, Expressed as Percentage of U.S. Totals

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Counties (number)</td>
<td>440</td>
<td>961</td>
</tr>
<tr>
<td>Counties (percentage)</td>
<td>14.3%</td>
<td>31.2%</td>
</tr>
<tr>
<td>Farm numbers</td>
<td>11.2</td>
<td>41.9</td>
</tr>
<tr>
<td>Total acres in farming</td>
<td>26.5</td>
<td>36.7</td>
</tr>
<tr>
<td>Cropland acres</td>
<td>27.1</td>
<td>47.9</td>
</tr>
<tr>
<td>Total value of agricultural sales</td>
<td>25.0</td>
<td>73.4</td>
</tr>
<tr>
<td>Hired farm workers</td>
<td>14.4</td>
<td>65.8</td>
</tr>
<tr>
<td>Livestock inventories</td>
<td></td>
<td></td>
</tr>
<tr>
<td>All cattle and calves</td>
<td>27.2</td>
<td>50.2</td>
</tr>
<tr>
<td>Beef cattle</td>
<td>21.3</td>
<td>32.9</td>
</tr>
<tr>
<td>Milk cows</td>
<td>16.5</td>
<td>76.2</td>
</tr>
<tr>
<td>Farms by sales class</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Under $10,000</td>
<td>7.7</td>
<td>35.4</td>
</tr>
<tr>
<td>Over $100,000</td>
<td>20.9</td>
<td>64.1</td>
</tr>
<tr>
<td>Over $500,000</td>
<td>21.7</td>
<td>73.2</td>
</tr>
<tr>
<td>Farms by acre class</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Under 50 acres</td>
<td>5.9</td>
<td>45.4</td>
</tr>
<tr>
<td>Over 1,000 acres</td>
<td>31.3</td>
<td>41.9</td>
</tr>
<tr>
<td>Total population (2000)</td>
<td>1.7</td>
<td>44.0</td>
</tr>
</tbody>
</table>

Overall, the ERS classified 14 percent of U.S. counties as FD in 2004, while our more inclusive definition for AI counties in 2002 captured 31 percent of counties. In general, the AI counties captured larger proportions of the overall U.S. farms, land, livestock inventories, and commercial farming activity. Moreover, this broader representation usually was larger than the proportionately greater coverage expected from the expanded number of qualifying counties. Over 70 percent of total farm sales and milk-cow inventories, two-thirds of farm workers, over 50 percent of cattle and calf inventories, and over 40 percent of farms and cropland were found in AI counties. By contrast, FD counties represented less than 30 percent of the U.S. totals on all these measures. When the size distribution of farms is considered, it is clear that FD counties have fewer small farms, and more farms with large acreages and moderate sales, than might be expected. By contrast, AI counties contain numerous farms across all size categories, with a heavier representation of the largest commercial operations. Finally, almost half of the total U.S. population lives in AI counties while less than 2 percent lives in counties that the ERS considers FD.
AI Counties and Patterns of Farm-Structural Change

The contrasts with the traditional FD counties discussed above suggest that the AI typology can provide a useful analytical tool for focusing future investigations of agricultural and demographic change. In particular, it can assist in identifying a relatively coherent subset of U.S. counties for more detailed analysis of secondary data. The final part of our article examines differences in farm structure and agricultural trends across AI and non-AI counties. This analysis allows us to see how well AI counties capture broader U.S. farm-structural trends in general. It also enables us to identify the distinctive trends and farm structural attributes of AI versus non-AI and FD versus AI counties.

As is evident in Table 4, farms in AI counties tend to be smaller on average in acreage, with roughly two-thirds the acreage of non-AI counties, but much larger than non-AI counties in farm sales and livestock inventories. AI counties receive almost four times as much gross farm income per farm, and have average sales per acre operated almost double that of non-AI regions. Cattle inventories (on farms that have any cattle) are also twice as large in AI counties on average. Interestingly, a larger percentage of farms in AI counties have relatively small acreages (<10 acre), but a relatively small proportion of AI county farms report very low farm sales (<$10,000). While there are no consistent significant differences in the proportion of large acreage farms across AI and non-AI counties, a notably larger percentage of AI farms reported farm sales exceeding $500,000 per year.

The direction and pace of farm-structural changes in AI and non-AI counties are also distinctive. For example, AI counties experienced much faster losses in farm numbers between 1997 and 2002, but reported almost a 7 percent increase in gross farm sales during the same period (while non-AI counties on average saw gross farm sales decline). This suggests AI counties are more likely to be experiencing patterns of farm intensification and consolidation. Interestingly, there were no significant differences between AI and non-AI counties in the trends for farmland or cropland acreage. Finally, AI counties appear to experience more rapid turnover in farms, as indicated by their higher average farm entry and exit rates.

The right side of Table 4 compares farm-structural characteristics and trends in counties classified into four mutually exclusive groups: AI only (n = 740), FD only (n = 237), both AI and FD (n = 222), and neither AI nor FD (n = 1,877). By examining the characteristics of “pure” AI and FD counties, as well as those that overlap both categories, we can gain better insights into the distinctive patterns of farm-structural trends across the United States.
Table 4. Farm-Structural Characteristics (2002) and Rates of Change (1997–2002) in U.S. Counties by County Type

<table>
<thead>
<tr>
<th></th>
<th>Mean Value by AI Status</th>
<th>Mean Value by AI and FD Categorization</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>AI</td>
<td>Non-AI</td>
</tr>
<tr>
<td>Average farm size (acres)</td>
<td>482.7</td>
<td>766.5</td>
</tr>
<tr>
<td>Median farm size (acres)</td>
<td>224.4</td>
<td>303.1</td>
</tr>
<tr>
<td>Average sales/farm ($1,000)</td>
<td>191.5</td>
<td>54.9</td>
</tr>
<tr>
<td>Average sales/acre ($)</td>
<td>625.9</td>
<td>315.8</td>
</tr>
<tr>
<td>Average cattle inventory b</td>
<td>165.0</td>
<td>83.6</td>
</tr>
<tr>
<td>Percentage of farms</td>
<td></td>
<td></td>
</tr>
<tr>
<td>With &lt; 50 acres</td>
<td>34.1</td>
<td>32.0</td>
</tr>
<tr>
<td>With &gt; 1,000 acres</td>
<td>11.0</td>
<td>12.1</td>
</tr>
<tr>
<td>With &lt; $10,000 sales</td>
<td>49.0</td>
<td>64.0</td>
</tr>
<tr>
<td>With &gt; $500,000 sales</td>
<td>6.7</td>
<td>2.5</td>
</tr>
<tr>
<td>Percentage change 1997–2002</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Farms</td>
<td>−5.3</td>
<td>−2.9</td>
</tr>
<tr>
<td>Acres in farming</td>
<td>−1.9</td>
<td>−2.0</td>
</tr>
<tr>
<td>Crop acres</td>
<td>−3.3</td>
<td>−3.4</td>
</tr>
<tr>
<td>Total sales c</td>
<td>6.8</td>
<td>−1.0</td>
</tr>
<tr>
<td>Hired workers</td>
<td>−19.6</td>
<td>−19.1</td>
</tr>
<tr>
<td>Cattle inventory</td>
<td>−4.3</td>
<td>−8.9</td>
</tr>
<tr>
<td>Estimated entry/exit rates d</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Entry</td>
<td>15.7</td>
<td>14.6</td>
</tr>
<tr>
<td>Exit</td>
<td>22.5</td>
<td>19.0</td>
</tr>
<tr>
<td>Number of cases (range)</td>
<td>942</td>
<td>1,830</td>
</tr>
<tr>
<td></td>
<td>962</td>
<td>2,114</td>
</tr>
</tbody>
</table>

Source: 2002 U.S. census of agriculture.

a Significance of ANOVA F-test: ***p < .001, **p < .01, and *p < .05.

b Mean herd size on farms with any cattle.

c Adjusted for inflation using the all-item consumer price index (CPI).

d Estimated using procedures outlined in Gale (1994).
Initially, it is apparent that farms in pure AI counties are commercially intensive but tend to operate smaller amounts of land. Results suggest that this group operates the least acreage on average, had proportionately more small-acreage farms, but also reported the highest average sales per acre. Given that these AI farms are (by definition) not in FD regions, it is likely that this subset of AI farms is found in more urban locales with more diverse economies and more expensive land (and hence more intensive use of farmland resources). Interestingly, when one ignores those counties that are both AI and FD, the remaining AI counties have a relatively large proportion of small sales-volume farms (which again may reflect the proliferation of intensive commercial farms alongside lifestyle or recreational farms in the urban shadow). Compared to the other groups, the 740 pure AI counties had the fastest rates of farmland and cropland loss between 1997 and 2002, and relatively high rates of growth in the level of total gross farm sales.

Farms in counties that are both AI and FD tend to be significant commercial operations, with the highest average sales per farm (over $300,000), relatively high sales per acre, the largest typical cattle inventories, and the largest proportion of farms with sales over $500,000. We suggest that these 222 counties represent intensively agricultural areas that are, as yet, isolated from urban influences. As such they represent an interesting subset of places that have both significant commercial agricultural sectors and relatively few other income or employment opportunities. Compared to the other groups, they witnessed the most stable farmland and cropland acreage, relatively robust growth in farm sales, and positive increases in cattle inventories.

By contrast, farms in pure FD counties tend to be relatively extensive operations with modest sales volumes. Farms in these 237 counties average just over $100,000 sales per year and operate over 2,000 acres per farm, producing sales per acre that are just one-fifth to one-sixth the levels found in the first two groups. While this group has the largest proportion of 1,000-acre or more farms, it also has relatively few small-acreage, small-sales, or large-sales farms. These counties represent a subset of agricultural communities with few other dynamic economic sectors yet relatively modest levels of commercial agricultural activity. These pure FD counties had the highest rates of loss in farm numbers, the most rapid loss in farm sales, and the lowest rates of farm entry of the four groups.

The fourth group represents the almost 1,900 U.S. counties that are neither FD nor AI. In a sense, they lack a “critical mass” of farming activity in both relative and absolute terms. Farms in these counties tend to be relatively small in acres operated, sales volume, and cattle
inventories. They have a high proportion of farms with less than 50 acres, over two-thirds of farms had less than $10,000 in sales, and relatively few had sales exceeding $500,000 a year. Interestingly, these counties had a relatively high rate of farmland conversion and yet the slowest rate of net farm loss (reflecting an intermediate rate of farm entry and the lowest mean rate of farm exit). Representing more than half the counties in the continental United States, these counties are dominated by a more “recreational” or “lifestyle” form of agriculture.

Discussion

The overall lack of congruence between the traditional FD and new AI county typologies indicates that the conventional ERS classification scheme is an imperfect tool to identify areas in the United States that have significant agricultural activity. To be fair, economic-dependency approaches are designed to highlight places that have few other economic options and where the vicissitudes of the farm economy thus might have deep local impacts, not to find places where an economic activity is particularly sizeable. While very useful for understanding economic dependencies, indicators of farm dependency may not be the best approach for studies of the mainstream trajectory or dynamics of farm-structural change, the interrelationships between demographic and agricultural trends, and evaluations of the impact of farm policies on farm operations, families, communities, or landscapes.

By contrast, the AI typology identifies counties where the farming sector is a significant contributor to regional and national agricultural output, regardless of whether the county is urban or rural, or whether the local economy is highly specialized or diversified. It also serves as a reasonable proxy for counties where the bulk of the nation’s farmers, farm workers, farmland, and livestock are located. Although these counties are not necessarily dependent on agriculture, one could argue that U.S. agriculture is dependent on them.

That said, the AI concept is not without limitations. While sales may be a constant metric across all commodity groups, variation in commodity prices could be biased to capture areas that specialize in higher-valued commodities (for example dairy over beef farms, and specialized vegetable or cash grains over less intensive hay and wheat production). The AI measure also draws attention to counties where the farm sector appears to be more polarized. AI counties include most of the largest-scale farming operations, but also a disproportionately share of both small-acreage and low-sales hobby farms (particularly in more urban areas that are less FD). Finally, because the AI measure is
derived from farms sales, it is unable to capture the importance of agriculture as a visual or aesthetic component of the rural landscape. Increasingly agriculture is valued as much for providing aesthetic and ecosystem services to society (open space, wildlife habitat, water recharge areas, etc.) as for its value in food and fiber production (Nickerson and Hellerstein 2003). It might also be useful to have a county-level indicator that identifies counties with high ratios of farmland to nonfarmland.

In addition, because the AI typology is a dichotomous variable, it is less likely to be useful as an independent variable in multivariate modeling exercises. While it is certainly possible to use total farm sales and sales per acre as separate and more refined continuous measures to reflect the relative size or intensity of a county’s agricultural sector, the use of multiple qualification criteria in our AI indicator precludes us from generating a single continuous measure of “agricultural importance.” Whether a dichotomous or continuous variable format is utilized, it is apparent that indicators of farm sales and sales intensity are spatially clustered; accordingly, efforts to use these indicators in statistical models will need to measure and control for the potential effects of spatial autocorrelation.

Despite these limitations, the AI classification provides a new approach to studying farming at the county level. We view its primary usefulness as a screening tool that identifies a critical subgroup of counties that share certain qualities and that are distinctive from the rest of the country. We have shown how comparing AI and non-AI counties can highlight important agricultural diversity within a specific context (such as metro counties) that otherwise might go unnoticed. The technical measurement of the indicator is robust, unaffected by inflation, and easily calculated across different census periods. This measure alone, or as a compliment to the FD measure, can benefit researchers, policy analysts, and public officials by highlighting the diversity of agriculture across the United States and by easily identifying counties where farming is most intensive and commercially important.

References


\(^5\) Indeed, a number of studies of agricultural trends have used these types of independent variables with some success.


